TBar: Revisiting Template-based Automated Program Repair

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ABSTRACT

Fix patterns (a.k.a. fix templates) are the main ingredients that drive a significant portion of automated program repair (APR) studies in the literature. As fix patterns become widely adopted in various approaches, it becomes critical to thoroughly assess the effectiveness of existing templates to establish a clear baseline for APR. In this paper, we revisit the performance of template-based APR to build comprehensive knowledge about the effectiveness of fix patterns, and to highlight the importance of complementary steps such as fault localization or donor code retrieval. To that end, we first investigate the literature to collect, summarize and label recurrently-used fix patterns. Based on the investigation, we build TBar, a straightforward APR tool that systematically attempts to apply these fix patterns to program bugs. We thoroughly evaluate TBar on the Defects4J benchmark. In particular, we assess the actual qualitative and quantitative diversity of fix patterns, as well as their effectiveness in yielding plausible or correct patches. Eventually, we find that, assuming a perfect fault localization, TBar is able to correctly/plausibly fix 74/102 bugs, while a previous baseline (i.e., kPAR) fixes only 36/55 bugs. Replicating a standard and practical pipeline of APR assessment, we demonstrate that TBar can correctly fix 43 bugs from Defects4J, an unprecedented performance in the literature (including all approaches, i.e., template-based, stochastic mutation-based or synthesis-based APR).

KEYWORDS

Automated program repair, fix template, empirical assessment.

1 INTRODUCTION

Automated Program Repair (APR) has progressively become an essential research field in software maintenance. APR research is indeed promising to improve modern software development by reducing the time and costs associated with program debugging tasks. In particular, given that faults in software cause substantial financial losses to the software industry [5, 49], there is a momentum in minimizing the time-to-fix intervals by APR. Recently, various APR approaches [7, 8, 13, 14, 17, 19, 21, 22, 25, 27, 33, 34, 36, 37, 39, 45, 48, 61, 63, 71, 72] have been proposed, aiming at reducing manual debugging efforts through automatically generating patches.

An early strategy of APR is to generate concrete patches based on fix patterns [19] (also referred to as fix templates [35] or program transformation schemas [13]). This strategy is now common in the literature and has been implemented in several APR systems [10, 13, 19, 20, 33–35, 44, 56]. Kim et al. [19] initiated the usefulness of fix patterns and proposed PAR, an APR tool with 10 fix templates. Saha et al. [56] have later proposed ELIXIR by adding three new templates on top of PAR [19]. Durieux et al. [10] proposed NPEfix to repair bugs throwing null pointer exceptions by using nine pre-defined fix patterns. Long et al. designed Genesis [36] to automatically infer fix patterns for specific three classes of defects. Liu and Zhong [35] explored posts from Stack Overflow to mine fix patterns for program repair. Hua et al. proposed SketchFix [13], a runtime on-demand APR tool with six pre-designed fix schemas. Recently, Liu et al. [34] leveraged the fix patterns of FindBugs static violations [31] to fix semantic bugs.

Although the literature has reported promising results with fix patterns-based APR, to the best of our knowledge, no extensive assessment on the effectiveness of various patterns is performed. A few most recent approaches [13, 34, 35] have reported which benchmark bugs are fixed by each (or some) of their fix patterns. Nevertheless, many relevant questions on the effectiveness of fix patterns remain unanswered.

This paper. Our work thoroughly investigates to what extent fix patterns are effective for program repair. In particular, emphasizing on the recurrence of some patterns in APR, we dissect their actual contribution to repair performance. Eventually, we explore three aspects of fix patterns:

- **Diversity**: How diverse are the fix patterns used by the state-of-the-art? We survey the literature to identify and summarize the available patterns with a clear taxonomy.
- **Repair performance**: How effective are the different patterns? In particular, we investigate the variety of real-world bugs that can be fixed, the dissection of repair results, and their tendency to yield plausible or correct patches.
- **Sensitivity to fault localization noise**: Are all fix patterns similarly sensitive to the false positives yielded by (currently imperfect) fault localization tools? We investigate sensitivity by assessing plausible patches as well as the suspiciousness rank of correctly-fixed bug locations.

Towards realizing this study, we implement an automated patch generation system, TBar (Template-Based automated program repair),

1https://stackoverflow.com/
with a super-set of fix patterns that are collected, summarized, curated and labeled from the literature data. We evaluate TBar on the Defects4J [16] benchmark, and provide the replication package in a public repository:

https://github.com/SerVal-DTF/TBar

Overall, our investigations have yielded the following findings:

1. **Record performance**: TBar creates a new higher baseline of repair performance: 74/102 bugs are correctly/plausibly fixed with perfect fault localization information and 43/81 bugs are fixed with realistic fault localization output, respectively.

2. **Fix pattern selection**: Most bugs are correctly fixed only by a single fix pattern while other patterns generate plausible patches. This implies that appropriate pattern prioritization can prevent from plausible/incorrect patches. Otherwise, APR tools might be overfitted in plausible but incorrect patches.

3. **Fix ingredient retrieval**: It is challenging for template-based APR to select appropriate donor code, which is an ingredient of patch generation when using fix patterns. Inappropriate donor code may cause plausible but incorrect patch generation. This motivates a new research direction: donor code prioritization.

4. **Fault localization noise**: It turns out that fault localization accuracy has a large impact on repair performance when using fix patterns in APR (e.g., applying a fix pattern to incorrect location yields plausible/incorrect patches).

2. FIX PATTERNS

For this study, we systematically review the APR literature to identify program repair approaches that leverage fix patterns. Concretely, we consider the program repair website, a bibliography survey of automated program repair [46], proceedings of software engineering conference venues and journals as the source of relevant literature. We focus on approaches dealing with Java program bugs, and manually collect, from the paper descriptions as well as the associated artefacts, all pattern instances that are explicitly mentioned. Table 1 summarizes the relevant literature that we enumerated and the quantity of identified fix patterns targeting Java programs. Note that the techniques described in the last four papers (i.e., HDRepair, ssFix, CapGen and SimFix papers) do not directly use fix patterns: they leverage code change operators or rules, which we consider similar to using fix patterns.

2.1 Fix Patterns Inference

Fix patterns have been explored with the following four ways:

1. **Manual Summarization**: Pan et al. [50] identified 27 fix patterns from patches of five Java projects to characterize the fix ingredients of patches. They do not however apply the identified patterns to fix actual bugs. Motivated by this work, Kim et al. [19] summarized 10 fix patterns targeting Java programs. Note that the techniques described in the last four papers (i.e., HDRepair, ssFix, CapGen and SimFix papers) do not directly use fix patterns: they leverage code change operators or rules, which we consider similar to using fix patterns.

2. **Mining**: Long et al. [36] proposed Genesis, to automatically infer fix patterns for three kinds of defects from existing patches. Liu and Zhong [35] explored fix patterns for Java programs from Q&A posts in Stack Overflow. Koyuncu et al. [20] proposed to mine fix patterns at the abstract syntax tree level from bug fixes by leveraging code change differentiating tool [11]. Furthermore, Liu et al. [31] and Rolim et al. [55] proposed to mine fix patterns from static analysis violations. In general, mining approaches yield a large number of fix patterns, which are not always about addressing deviations in program behavior. For example, many patterns are about code style [34]. Recently, AVATAR was proposed as a program repair tool that only selects static analysis violation fix patterns which are likely related to program behaviour [34]. Its authors enumerate a number of heuristics to identify patterns that change data, delete code, change data type, etc. In our study, we follow their approach to focus on patterns which are relevant to APR.

3. **Pre-definition**: Durieux et al. [10] pre-defined nine repair strategies for null pointer exceptions by unifying the related repair templates proposed in previous studies [9, 18, 40]. On the top of PAR [19], Saha et al. [56] further defined three new fix templates to improve the repair performance. Hua et al. [13] proposed an APR tool with six pre-defined so-called code transformation schemas. We also consider operator mutations [43] as pre-defined fix patterns. Indeed the number of operators and mutation possibilities is limited and pre-set. Xin and Reiss [69] proposed an approach leveraging syntax-related code to fix bugs with 34 predefined code change rules at the AST level. Ten of the rules are not for transforming the buggy code but for the simple replacement of multi-statement code fragments. We discard these rules from our study to limit bias.

4. **Statistics**: Besides formatted fix patterns, researchers [14, 63] also explored to automate program repair with code change instructions (at the abstract syntax tree level) that are statistically recurrent in existing patches [14, 32, 42, 62, 76]. The strategy is then to select the top-n most frequent code change instructions as fix ingredients to synthesize patches.

2.2 Fix Patterns Taxonomy

After manually assessing all fix patterns presented in the literature (cf. Table 1), we identified 15 categories of patterns labeled based on the code context (e.g., a cast expression), the code change actions (e.g., insert an "if" statement with "instanceof" check) as well as

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Table 1: Literature review on fix patterns for Java programs.

| Authors | APR tool name | # of fix patterns | Publication Venue | Publication Year |
|---------|---------------|-------------------|-------------------|------------------|
| Pan et al. [50] | - | 27 | TSE | 2009 |
| Kim et al. [19] | PAR | 10 (16*) | ICSE | 2013 |
| Martinez et al. [4] | MultiRepair | 2 | ISTA | 2016 |
| Durieux et al. [10] | NPEfix | 9 | SANER | 2017 |
| Long et al. [36] | Genesis | 3 (108*) | FSE | 2017 |
| D. Le et al. [21] | SS | 4 | FSE | 2017 |
| Saha et al. [56] | ELIXIR | 8 (11*) | ASE | 2017 |
| Hu et al. [13] | SketchFix | 6 | ICSE | 2018 |
| Liu and Zhong [35] | SOFix | 12 | SANER | 2018 |
| Koyuncu et al. [20] | FixMiner | 28 | US Tech Report | 2018 |
| Liu et al. [31] | F4 | 174 | TSE | 2018 |
| Rolim et al. [55] | REVISAR | 9 | UFRSAR Tech Report | 2018 |
| Liu et al. [14] | AVATAR | 13 | SANER | 2019 |

* In the PAR paper [19], 10 fix patterns are presented, but 16 fix patterns are released online. In Genesis, 108 code transformation schemas are inferred for three kinds of defects. In ELIXIR, there is one fix pattern that consists of four sub-fix patterns. These APR tools do not explicitly leverage fix patterns but code change operators or rules, which are similar to fix patterns.
as the targets (e.g., ensure the program will no throw a ClassCastException.). A given category may include one or several specialized sub-categories. Below, we present the labeled categories and provide the associated 35 Code Change Schemas described in simplified GNU diff pattern for easy understanding.

**FP1. Insert Cast Checker.** Inserting an instanceof check before one buggy statement if this statement contains at least one unchecked cast expression. Implemented in: PAR, Genesis, AVATAR, HDRepair¹, SOFix¹, SketchFix¹, CapGen¹, and SimFix³.

```java
+ if (exp instanceof T) {
  var = (T) exp; ......
+ }
```

where `exp` is an expression (e.g., a variable expression) and `T` is the casting type, while “......” means the subsequent statements dependent on the variable `var`. Note that, “+” denotes that the fix pattern is not specifically illustrated in the corresponding APR tools since the tools have some abstract fix patterns that can cover the fix pattern. The same notation applies to the following descriptions.

**FP2. Insert Null Pointer Checker.** Inserting a null check before a buggy statement if, in this statement, a field or an expression (of non-primitive data type) is accessed without a null pointer check. Implemented in: PAR, ELIXIR, NPEFix, Genesis, FixMiner, AVATAR, HDRepair¹, SOFix¹, SketchFix¹, CapGen¹, and SimFix³.

```java
FP2.1: + if (exp != null) {
  //...exp...; ......
+ }
FP2.2: + if (exp == null) return DEFAULT_VALUE;
  //...exp...;
FP2.3: + if (exp == null) exp = exp1;
  //...exp...;
FP2.4: + if (exp == null) continue;
  //...exp...;
FP2.5: + if (exp == null)
  + throw new IllegalArgumentException(...);
  //...exp...;
```

where `DEFAULT_VALUE` is set based on the return type (RT) of the encompassing method as below:

```
DEFAULT_VALUE = {
  false, if RT = boolean; 
  0, if RT = primitive type; 
  new String(), if RT = String; 
  "return", if RT = void; 
  null, otherwise.
```

`exp1` is a compatible expression in the buggy program (i.e., has the same data type as `exp`). FP2.4 is specific to the case of a buggy statement within a loop (i.e., for or while).

**FP3. Insert Range Checker.** Inserting a range checker for the sub-expression of an array or collection if it is unchecked. Implemented in: PAR, ELIXIR, Genesis, FixMiner, SketchFix, AVATAR, SOFix¹, and SimFix³.

```java
+ if (index < exp.length()) {
  //...exp.get(index)...; ......
+ }
```

where `exp` is an expression representing an array or collection.

**FP4. Insert Missed Statement.** Inserting a missed statement before, or after, or surround a buggy statement. The missed statement is either an expression statement with a method invocation, or a return statement, or a try-catch statement, or an if statement.

**Implemented in:** ELIXIR, HDRepair, SOFix, SketchFix, CapGen, FixMiner, and SimFix.

```java
FP4.1: + method(exp);
FP4.2: + return DEFAULT_VALUE;
FP4.3: + try {
  statement; ......
  + ) catch (Exception e) { ... }
FP4.4: + if (conditional_exp) {
  statement; ......
  + }
```

where `exp` is an expression from a buggy statement. It may be empty if the method does not take any argument. FP4.4 does not include fix patterns FP1, FP2, and FP3, which are used in specific contexts.

**FP5. Mutate Class Instance Creation.** Replacing a class instance creation expression with a cast super.clone() method invocation if the class instance creation is in an overridden clone method. Implemented in: AVATAR.

```java
public Object clone() {
  .... (T) super.clone();
  + ...
```

where `T` is the class name of the current class containing the buggy statement.

**FP6. Mutate Conditional Expression.** Mutating a conditional expression that returns a boolean value (i.e., true or false) by either updating it, or removing a sub conditional expression, or inserting a new conditional expression into it. Implemented in: PAR, ssFix, S3, HDRepair, ELIXIR, SketchFix, CapGen, SimFix, and AVATAR.

```java
FP6.1: - ...condExp1...
  + ...condExp1...
FP6.2: - ...condExp2... Op condExp2...
  + ...condExp2...
FP6.3: - ...condExp1...
  + ...condExp2 Op condExp2...
```

where `condExp1` and `condExp2` are conditional expressions. `Op` is the logical operator ‘||’ or ‘&&’. The mutation of operators in conditional expressions is not summarized in this fix pattern but in FP11.

**FP7. Mutate Data Type.** Replacing the data type in a variable declaration or a cast expression with another data type. Implemented in: PAR, ELIXIR, FixMiner, SOFix, CapGen, SimFix, AVATAR, and HDRepair³.

```java
FP7.1: - ...T1 var ...
  + T2 var ...
FP7.2: - ...(T1) exp...;
  + ...(T2) exp...;
```

where both `T1` and `T2` denote two different data types. `exp` means the being casted expression (including variable).

**FP8. Mutate Integer Division Operation.** Mutating the integer division expressions to return a float value, by mutating its divisor or divider to make them be of type float. Released by Liu et al. [31], it is not implemented in any APR tool yet.

```java
FP8.1: - ...(dividend / divisor... 
  + ...dividend / (double or float) divisor...
FP8.2: - ...dividend / divisor...
  + ...((double or float) dividend / divisor...
FP8.3: - ...dividend / divisor...
  + ...((1.0 / divisor) * dividend...
```

where `dividend` and `divisor` are integer number literals or integerreturned expressions (including variables).
FP9. Mutate Literal Expression. Mutating boolean, number, or string literals in a buggy statement with other relevant literals, or correspondingly-typed expressions. Implemented in: HDRepair, S3, FixMiner, SketchFix, CapGen, SimFix and ssFix†.

FP9.1: \[- \ldots \text{literal1} \ldots + \ldots \text{literal2} \ldots + \ldots \text{exp} \ldots\]

FP9.2: \[- \ldots \text{literal1} \ldots + \ldots \text{exp} \ldots\]

where literal1 and literal2 are of the same type literals, but having different values (e.g., literal1 is true, literal2 is false). exp denotes any expression value of the same type as literal1.

FP10. Mutate Method Invocation Expression. Mutating the buggy method invocation expression by adapting its method name or arguments. This pattern consists of four sub fix patterns:

(1) Replacing the method name with another one which has a compatible return type and same parameter type(s) as the buggy method that was invoked.

(2) Replacing at least one argument with another expression which has a compatible data type. Replacing a literal or variable is not included in this fix pattern, but rather in FP9 and FP13 respectively.

(3) Removing argument(s) if the method invocation has the suitable overridden methods.

(4) Inserting argument(s) if the method invocation has the suitable overridden methods.

Implemented in: PAR, HDRepair, ssFix, ELIXIR, FixMiner, SOFix, SketchFix, CapGen, and SimFix.

FP10.1: \[- \ldots \text{method1} (\text{args}) \ldots + \ldots \text{method2} (\text{args}) \ldots\]

FP10.2: \[- \ldots \text{method1} (\text{arg1}, \text{arg2}, \ldots ) \ldots + \ldots \text{method1} (\text{arg1}, \text{arg2}, \ldots ) \ldots\]

FP10.3: \[- \ldots \text{method1} (\text{arg1}, \text{arg2}, \ldots ) \ldots + \ldots \text{method2} (\text{arg1}, \ldots ) \ldots\]

FP10.4: \[- \ldots \text{method1} (\text{arg1}, \ldots ) \ldots + \ldots \text{method1} (\text{arg1}, \text{arg2}, \ldots ) \ldots\]

where method1 and method2 are the names of invoked methods. args, arg1, arg2 and arg3 denote the argument expressions in the method invocation. Note that, code changes on class instance creation, constructor and super constructor expressions are also included in these four fix patterns.

FP11. Mutate Operators. Mutating an operation expression by mutating its operator(s). We divide this fix pattern into three sub-fix patterns following the operator types and mutation actions.

(1) Replacing one operator with another operator from the same operator class (e.g., relational or arithmetic).

(2) Changing the priority of arithmetic operators.

(3) Replacing instanceof operator with (in)equality operators.

Implemented in: HDRepair, ssFix, ELIXIR, S3, jMutRepair, SOFix, FixMiner, SketchFix, CapGen, SimFix, AVATAR, and PAR†.

FP11.1: \[- \ldots \text{exp1} \text{Op1} \text{exp2} \ldots + \ldots \text{exp1} \text{Op2} \text{exp2} \ldots\]

FP11.2: \[- \ldots (\text{exp1} \text{Op1} \text{exp2}) \text{Op2} \text{exp3} \ldots + \ldots \text{exp1} \text{Op1} \text{exp2} \text{Op2} \text{exp3} \ldots\]

FP11.3: \[- \ldots \text{exp} \text{ instanceof} \text{ T} \ldots + \ldots \text{exp} \text{ != null} \ldots\]

where exp denotes the expressions in the operation and Op is the associated operator.

FP12. Mutate Return Statement. Replacing the expression (excluding literals, variables, and conditional expressions) in a return statement with a compatible expression. Implemented in: ELIXIR, SketchFix, and HDRepair†.

- \[ \ldots \text{return} \ \text{exp1}; \]
  + \[ \ldots \text{return} \ \text{exp2}; \]

where exp1 and exp2 represent the returned expressions.

FP13. Mutate Variable. Replacing a variable in a buggy statement with a compatible expression (including variables and literals). Implemented in: S3, SOFix, FixMiner, SketchFix, CapGen, SimFix, AVATAR, and ssFix†.

FP13.1: \[- \ldots \text{var1} \ldots + \ldots \text{var2} \ldots\]

FP13.2: \[- \ldots \text{var1} \ldots + \ldots \text{exp} \ldots\]

where var1 denotes a variable in the buggy statement. var2 and exp represent respectively a compatible variable and expression of the same type as var1.

FP14. Move Statement. Moving a buggy statement to a new position. Implemented in: PAR.

- \[ \ldots \text{statement}; \]
  + \[ \ldots \text{statement}; \]

where statement represents the buggy statement.

FP15. Remove Buggy Statement. Deleting entirely the buggy statement from the program. Implemented in: HDRepair, SOFix, FixMiner, CapGen, and AVATAR.

FP15.1: \[ \ldots \]

FP15.2: \[ \ldots \text{methodDeclaration}(\text{Arguments}) \{ \ldots ; \text{Statement}; \ldots \]

- \[ \} \]

where statement denotes any identified buggy statement, and method represents the encompassing method.

2.3 Analysis of Collected Patterns

We provide a study of the collected fix patterns following quantitative (overall set) and qualitative (per fix pattern) aspects. Table 2 assesses the fix patterns in terms of four qualitative dimensions:

(1) Change Action: what high-level operations are applied on a buggy code entity in the program? On the one hand, Update operations replace the buggy code entity with another donor code, while Delete operations just remove the buggy code entity from the program. On the other hand, Insert operations insert an otherwise missing code entity into the program, and Move operations change the position of the buggy code entity to a more suitable location in the program.

(2) Change Granularity: what kinds of code entities are directly impacted by the change actions? This entity can be an entire Method, a whole Statement or specifically targeting an Expression within a statement.

(3) Bug Context: what specific AST nodes of code entities are used to match fix patterns.

(4) Change Spread: the number of statements impacted by each fix pattern.

Quantitatively, as summarized in Table 3, 17 fix patterns are related to Update change actions, 4 fix patterns implement Delete...
actions, 13 fix patterns Insert extra code, and only 1 fix pattern is associated to Move change action.

In terms of change granularity, 21 and 17 fix patterns are applied respectively at the expression and statement code entity levels. Only 1 fix pattern is suitable at the method level.

Overall, we note that 30 fix patterns are applicable to a single statement, while 7 fix patterns can mutate multiple statements at the same time. Among these patterns, FP14 and FP15.1 can both mutate single and multiple statements.

3 SETUP FOR REPAIR EXPERIMENTS
In order to assess the effectiveness of fix patterns in the taxonomy presented in Section 2, we design program repair experiments using the fix patterns as the main ingredients. The produced APR system is then assessed on a widely-used benchmark in the repair community to allow reliable comparison against the state-of-the-art.

3.1 TBar: a Baseline APR System
Building on the investigations of recurrently-used fix patterns, we build TBar, a template-based APR system which integrates the 35 fix patterns presented in Section 2. We expect the research community to consider TBar as a baseline APR system: new approaches must come up with novel techniques for solving auxiliary issues (e.g., repair precision, search space optimization, fault locations re-prioritization, etc.) to boost automated program repair beyond the performance that a straightforward application of common fix patterns can offer. Figure 1 overviews the workflow that we have implemented in TBar. We describe in the following subsections the role and operation of each process as well as all necessary implementation details.

3.1.1 Fault Localization.
Fault localization is necessary for template-based APR as it allows to identify a list of suspicious code locations (i.e., buggy statements) on which to apply the fix patterns. TBar leverages the GZoltar framework to automate the execution of test cases for each buggy program. In this framework, we use the Ochiai [1] ranking metric to compute the suspiciousness scores of statements that are likely to be the faulty code locations. This ranking metric has been demonstrated in several empirical studies [51, 59, 68, 73] to be effective for localizing faults in object-oriented programs. The GZolltars framework for fault localization is also widely used in the literature of APR [14, 20, 30, 33, 34, 43, 63, 69, 71, 72], allowing for a fair assessment of TBar’s performance against the state-of-the-art.

3.1.2 Fix Pattern Selection.
In the execution of the repair pipeline, once the fault localization process yields a list of suspicious code locations, TBar iteratively attempts to select the encoded fix patterns from its database of fix patterns for each statement in the locations list. The selection of fix patterns is conducted in a naïve way based on the context information of each suspicious statement (i.e., all nodes in its AST). Specifically, TBar parses the program and traverses each node of the suspicious statement AST from its first child node to its last leaf node. If a node can match any bug context presented in Table 2, a related fix pattern will be matched to generate patch candidates with the corresponding code change schema. If the node is not a leaf node, TBar keeps traversing its children nodes. For example, if the first child node of a suspicious statement is a method invocation expression, it will be first matched with FP10. Mutate Method Invocation Expression fix pattern. If the children nodes of the method invocation start from a variable reference, it will be matched with FP13. Mutate Variable fix pattern as well. Other fix patterns follow the same manner. After all expression nodes of a suspicious statement are matched with fix patterns, TBar further matches fix patterns from statement and method levels respectively.

3.1.3 Patch Generation and Validation.
After a fix pattern is selected for a suspicious statement, the statement will be mutated by following the code change schema of the corresponding fix pattern to generate patch candidates. Each generated patch candidate will be validated with all test cases of the buggy program. If it can make the buggy program pass all test cases successfully, the patch candidate will be considered as a plausible patch. Once such a plausible patch is identified, TBar stops trying other patch candidates for this bug.

Considering that some buggy programs have several buggy locations, if a patch candidate can make a buggy program pass a

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Table 2: Change properties of fix patterns.

| Fix Pattern | Change Action | Change Granularity | Bug Context | Change Spread |
|-------------|---------------|--------------------|-------------|--------------|
| FP1.1       | Insert        | statement           | cast expression | single       |
| FP2.1       | Insert        | statement           | a variable or an expression returning non-primitive-type data | dual         |
| FP3         | Insert        | statement           | element access of array or collection variable | single       |
| FP4(1,2,3,4)| Insert        | statement           | any statement  | single       |
| FP5         | Update        | expression          | class instance creation expression and clone method | single       |
| FP6.1       | Update        | expression          | conditional expression | single       |
| FP6.2       | Update        | expression          | variable declaration expression | single       |
| FP7.1       | Update        | expression          | cast expression | single       |
| FP8(1,2,3)  | Update        | expression          | integral division expression | single       |
| FP9(1,2)    | Update        | expression          | literal expression | single       |
| FP10.1      | Update        | expression          | method invocation, class instance creation, constructor, or super constructor | single       |
| FP10.2      | Update        | or statement        | method invocation, class instance creation, constructor, or super constructor | single       |
| FP11.1      | Delete        | expression          | assignment or index expression | single       |
| FP11.2      | Delete        | expression          | arithmetic-index expression | single       |
| FP11.3      | Update        | expression          | instance of expression | single       |
| FP12        | Update        | expression          | return statement | single       |
| FP13(1,2)   | Update        | expression          | variable expression | single       |
| FP14        | Move          | statement           | any statement  | single or multiple |
| FP15.1      | Delete        | statement           | any statement  | single or multiple |
| FP15.2      | Delete        | method              | any statement  | multiple      |

Table 3: Diversity of fix patterns w.r.t change properties.

| Action Type | # fix patterns | Granularity | # fix patterns | Spread | # fix patterns |
|-------------|----------------|-------------|----------------|--------|----------------|
| Update      | 17             | Expression  | 23             | Single | 30             |
| Delete      | 4              | Statement   | 17             | Statement | 30         |
| Insert      | 13             | Method      | 1              | Multiple Statements | 7          |
| Move        | 1              |             |                |        |                |

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3Among these, four sub-fix patterns (FP10) can be applied to either expressions or statements, given that constructor and super-constructor code entities in Java program are grouped into statement level in terms of abstract syntax tree by Eclipse JDT.

4http://www.gzoltar.com
sub-set of previously failing test cases without failing any previously passing test cases, this patch is considered as a plausible sub-patch of this buggy program. TBar will further validate other patch candidates, until either a plausible patch is generated, or all patch candidates are validated, or TBar exhausts the time limitation set for repair attempts.

If a plausible patch is generated, we further manually check the equivalence between this patch and the ground-truth patch provided by developers and available in the Defects4J benchmark. If the plausible patch is equivalent (syntactically or semantically) to the ground-truth patch, the plausible patch is considered as correct. Otherwise, it is only considered as plausible.

We offer a replication package with extensive details on pattern implementation within TBar. Source code is also made publicly available with a GPL licence.

3.2 Assessment Benchmark

For our empirical assessments, we selected the Defects4J [16] dataset as the evaluation benchmark of TBar. This benchmark includes test cases for buggy Java programs with the associated developer fixes. Defects4J is an ideal benchmark for the objective of this study, since it has been widely used by most recent state-of-the-art APR systems targeting Java program bugs. Table 4 provides summary statistics on the bugs and test cases available in the version 1.2.0α of Defects4J which we use in this study.

### Table 4: Defects4J dataset information.

| Project | Chart | Closure | Lang | Math | Mockito | Time | Total |
|---------|-------|---------|------|------|---------|------|-------|
| # bugs | 26    | 135     | 63   | 106  | 38      | 27   | 599   |
| # test cases | 2,205  | 7,927   | 2,245 | 3,602 | 1,457   | 4,130 | 21,566 |
| # fixed bugs by all APR tools [cf. 33, 34] | 13     | 16      | 28   | 37   | 3       | 4    | 101   |

Overall, we note that, to date, 101 Defects4J bugs have been correctly fixed by at least one APR tool published in the literature. Nevertheless, we recall that SimFix [14] currently holds the record number of bugs fixed by a single tool, which is 34.

4 ASSESSMENT

This section presents and discusses the results of repair experiments with TBar. In particular, we conduct two experiments for:

- **Experiment #1:** Assessing the effectiveness of the various fix patterns implemented in TBar. To avoid the bias that fault localization can introduce with its false positives (cf. [33]), we directly provide perfect localization information to TBar.
- **Experiment #2:** Evaluating the TBar baseline APR system in a normal program repair scenario. We investigate in particular the tendency of fix patterns to produce more or less incorrect patches.

4.1 Repair Suitability of Fix Patterns

Our first experiment focuses on assessing the patch generation performance of fix patterns for real bugs. In particular, we investigate three research questions in Experiment #1.

| Research Questions for Experiment #1 |
|-------------------------------------|
| **RQ1.** How many real bugs from Defects4J can be correctly fixed by fix patterns from our taxonomy? |
| **RQ2.** Can each Defects4J bug be fixed by different fix patterns? |
| **RQ3.** What are the properties of fix patterns that are successfully used to fix real bugs? |

In a recent study, Liu et al. [33] reported how fault localization techniques substantially affect the repair performance of APR tools. Given that, in this experiment, the APR tool (namely TBar) is only used as a means to apply the fix patterns in order to assess their effectiveness, we must eliminate the fault localization bias. Therefore, we assume that the bug positions at statement level are known, and we directly provide it to the patch generation step of TBar, without running any fault localization tool (which is part of the normal APR workflow, see Figure 1). To ensure readability across our experiments, we denote this version of the APR system as TBar_p (where p stands for perfect localization). Table 5 summarizes the experimental results of TBar_p.

### Table 5: Number of bugs fixed by fix patterns with TBar_p.

| Project | C | L | M | MC | TC | Total |
|---------|---|---|---|----|----|-------|
| # of Fully Fixed Bugs | 12/13 | 20/26 | 13/18 | 22/35 | 3/3 | 3/6 | 7/10 | 101 |
| # of Partially Fixed Bugs | 2/4 | 3/6 | 1/4 | 1/5 | 0/0 | 1/1 | 8/20 |

*We provide x/y/z numbers: x is the number of correctly fixed bugs; y is the number of bugs fixed with plausible patches. The same notation applies to Table 7.*

Among 395 bugs in the Defects4J benchmark, TBar_p can generate plausible patches for 101 bugs. Among these bugs, 73 bugs are fixed with correct patches. We also note that TBar_p can partially fix 20 bugs with plausible patches, and 8 of them are correct. In a previous study, the kPAR [33] baseline tool (i.e., a Java implementation of the PAR [19] seminal template-based APR tool) was correctly/plausibly fixing 36/55 Defects4J bugs when assuming perfect localization.

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8Partial fix: a patch makes the buggy program pass a part of previously failed test cases without causing any new failed test cases [33].

```java
public String generateToolTipFragment(String toolTipText) {
    return "title=" + ImageMapUtilities.htmlEscape(toolTipText) + " alt=";
}
```

**Matchable fix pattern:** FP9.2.

### Figure 2: Patch and code change action of fixing bug C-10.
While the results of TBar$^p$ are promising, a large portion (79%\(^3\)) of Defects4J’s real bugs cannot be correctly fixed with the available fix patterns. We manually investigated these unfixed bugs and make the following observations as research directions for improving the fix rates:

(1) **Insufficient fix patterns.** Many bugs are not fixed by TBar$^p$ simply due to the absence of matching fix patterns. This suggests

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\(^{3}\)314 bugs = 395 - 73 - 8.
that the fix patterns collected in the literature are far from being representative for real-world bugs. The community must thus keep contributing with effective techniques for mining fix patterns from existing patches.

(2) Ineffective search of fix ingredients. Template-based program repair is a kind of search-based program repair [63]: some fix patterns require donor code (i.e., fix ingredients) to generate actual patches. For example, as shown in Figure 2, to apply the relevant fix pattern FP9.2, one needs to identify fix ingredient “ImageMapUtilities.htmlEscape” as the necessary in generating the patch. In the currently naïve implementation of TBar, donor code fragments are searched within the code available around the buggy code location (i.e., in the same file). Therefore, some bugs cannot be fixed by TBar, although its fix pattern can match with code change actions. With more effective search strategies (e.g., larger search space such as fix ingredients from other projects as in [30]), there might be more chances to fix more bugs.

**RQ1:** The collected fix patterns can be used to correctly fix 74 real bugs from the Defects4J dataset. A larger portion of the dataset remains however unfixed by TBar, notably due to (1) the limitations of the fix patterns set and to (2) the naïve search strategy for finding relevant fix ingredients to build concrete patches from patterns.

Figure 3 summarizes the statistics on the number of bugs that can be fixed by one or several fix patterns. The Y-axis denotes the number of fix patterns (i.e., \( n = 1, 2, 3, 4, 5, \) and \( \geq 5 \)) that can generate plausible patches for a number of bugs (X-axis). The legend indicates that “P” represents the number of plausible patches generated by TBar (i.e., those that are not found to be correct). “\#k\)” where \( k \in [1, 4] \), indicates that a bug can be correctly fixed by only \( k \) fix patterns (although it may be plausibly fixed by more fix patterns).

**Figure 3:** The number of bugs plausibly and correctly fixed by single or multiple fix patterns.

Consider for the bottom-most bar in Figure 3: 66 (= 28+38) bugs can be plausibly fixed by a single pattern (Y-axis value is 1); it turns out that only 38 of them are correctly fixed. Note that several patterns can generate (plausible) patches for a bug, but not all patches are necessarily correct. For example, in the case of the top-most bar in Figure 3, 5 bugs are each plausibly fixed by over 5 fix patterns. However, only 1 bug is correctly fixed by 3 fix patterns.

In summary, 86% (\( \frac{38+10+5+3+10+4}{74} \)) of correctly fixed bugs (74 fully and 7 partially fixed bugs) are exclusively fixed correctly by single patterns. In other words, generally, several fix patterns can generate patches that can pass all test cases but, in most cases, the bug is correctly fixed by only one pattern. This finding suggests that it is necessary to carefully select an appropriate fix pattern when attempting to fix a bug, in order to avoid plausible patches which may prevent the discovery of correct patches by halting the repair process (given that all tests are passing on the plausible patch).

We further inspect properties of fix patterns, such as change actions, granularity, and the number of changed statements in patches. The statistics are shown in Figure 4, highlighting the number of plausible (but incorrect) and correct patches for the different property dimensions through which fix patterns can be categorized.

**RQ2:** Some bugs can be plausibly fixed by different fix patterns. However, in most cases, only one fix pattern is adequate for generating a correct patch. This finding suggests a need for new research on fix pattern prioritization.

Table 6 details which bug is fixed by which fix pattern(s). We note that five fix patterns (i.e., FP3, FP4.3, FP5, FP7.2 and FP11.3) cannot be used to generate a plausible patch for any Defects4J bug. Two fix patterns (i.e., FP9.2 and FP12) lead to plausible patches for some bugs, but none of those patches is correct. These results do not necessarily suggest that the aforementioned fix patterns are useless (or ineffective) in APR. Instead, two reasons can explain their performance:

- The search for donor code may be inefficient for finding relevant ingredients for applying these patterns.
- The Defects4J dataset does not contain the types of bugs that can be addressed by these fix patterns.

In addition, twenty (20) fix patterns lead to the generation of correct patches for some bugs. Most of these fix patterns are involved in the generation of plausible patches (which turn out to be incorrect). Interestingly, we found the cases of six (6) fix patterns which can generate several\(^\text{10}\) patch candidates, some which being correct and others being only plausible, for the same 10 bugs (as indicated in Table 6 with ‘\( \star \)’). This observation further highlights the importance of selecting a relevant donor code for synthesizing patches: selecting an inappropriate donor code can lead to the generation of a plausible (but incorrect) patch, which will impede the generation of correct patches in a typical repair pipeline.

Aside from fix patterns, fix ingredients collected in donor code are essential to be properly selected to avoid patches that are plausible but may yet be incorrect.

More bugs are fixed by Update change actions than any by any other actions. Similarly, fix patterns targeting expressions fix more bugs correctly than patterns targeting statement and method granularity levels. However, fix patterns mutating whole statements have a higher rate of correct patches among their plausible generated patches. Finally, fix patterns changing only single statements can correctly fix more bugs than those touching multiple statements. Fix patterns targeting multi-statements have however a higher rate of correctness.

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\(^{10}\)We remind the reader that in this experiment TBar generates and assesses all possible patch candidates for a given pair "bug location - fix pattern" with varying ingredients.
4.2 Repair Performance Comparison: TBar vs State-of-the-art APR tools

Our second experiment evaluates TBar in a realistic setting for patch generation, allowing for reliable comparison against the state-of-the-art in the literature. Concretely, we investigate two research questions in Experiment #2.

Research Questions for Experiment #2

RQ4. What performance can be achieved by TBar in a standard and realistic repair scenario?
RQ5. To what extent are the different fix patterns sensitive to noise in fault localization (i.e., spotting buggy code locations)?

In this experiment we implement a realistic scenario, using a normal fault localization (i.e., no assumption of perfect localization as for TBar$_p$) on Defects4J bugs. To enable a fair comparison with performance results recorded in the literature, TBar leverages a standard configuration in the literature [33] with GZoltar [6] and Ochiai [1]. Furthermore, TBar does not utilize any additional technique to improve the accuracy of fault localization, such as crashed stack trace (used by ssFix [69]), predicate switching [75] (used by ACS [71]), or test case purification [74] (used by SimFix [14]).

With respect to the patch generation step, contrary to the experiment with TBar$_p$ where all positions of multi-locations bugs were known (cf. Section 4.1), TBar adopts a “first-generated and first-selected” strategy to progressively apply fix patterns, one at a time, in various suspicious code locations: TBar generates a patch $p_i$, using a fix pattern that matches a given bug. If $p_i$ passes a subset of previously-failing test cases without failing any previously-passing test case, TBar selects $p_i$ as a plausible patch for the bug. Then, TBar continues to validate another patch $p_{i+1}$ (which can be generated by the same fix pattern on the same code entity with other ingredients, or on another code location). When $p_{i+1}$ passes a subset of test cases as $p_i$, if $p_{i+1}$ is generated for the same buggy code entity as $p_i$, $p_{i+1}$ will be abandoned; otherwise, TBar takes $p_{i+1}$ as another plausible patch as well. Through this process, TBar creates a patch set $P = \{ p_i, p_{i+1}, \ldots \}$ of plausible patches. Here, as soon as any patch can pass all the given test cases for a given bug, TBar takes it as a plausible patch for the given bug, which is regarded as a fully-fixed bug, and all $p_i \in P$ will be abandoned. Otherwise, our tool yields $P$ as the set of plausible patches that can each partially fix the given bug.

We run the TBar APR system against the buggy programs of the Defects4J dataset. Table 7 presents the performance of TBar in comparison with recent state-of-the-art APR tools from the literature. TBar can fix 81 bugs with plausible patches, 43 of which are correctly fixed. No other APR tool had reached this number of fixed bugs. Nevertheless, its precision (ratio of correct vs. plausible patches) is lower than some recent tools such as CapGen and SimFix which employs sophisticated techniques to select fix ingredients. Nonetheless, it is noteworthy that, despite using fix patterns catalogued in the literature, we can fix three bugs (namely CI-86,L-47,M-11) which had never been fixed by any APR system.

RQ3: There are noticeable differences between successful repair among fix patterns depending on their properties related to implemented change actions, change granularity and change spread.

It is noteworthy that TBar performs significantly less than TBar$_p$ (43 vs. 74 correctly fixed bugs). This result is in line with a recent study [33], which demonstrated that fault localization imprecision is detrimental to APR repair performance. Table 6 summarizes information about the number of bugs each fix pattern contributed to fix with TBar$_p$. While only 4 fix patterns did not lead to the generation of any plausible patch when assuming perfect localization. With TBar, it is the case for 13 fix patterns (see Table 8). This observation further confirms the impact of fault localization noise.

We propose to examine the locations where TBar applied fix patterns to generate its plausible but incorrect patches. As shown in Figure 5, TBar has made changes on incorrect positions (i.e., non-buggy locations) for 24 out of the 38 fully-fixed and 15 out of the 16 partially-fixed bugs.

Figure 5: The mutated code positions of plausibly but incorrectly fixed bugs.

Even when TBar applies a fix pattern to the precise buggy location, the generated patch may be incorrect. As shown in Figure 5, 14 patches that fully fix Defects4J bugs mutate the correct locations: in 3 cases, the fix patterns were inappropriate; in 2 other cases, TBar failed to locate relevant donor code; for the remaining, TBar does not support the required fix patterns.

Finally, Figure 6 illustrates the impact of fault localization performance: unfixed bugs (but correctly fixed by TBar$_p$) are generally more poorly localized than correctly fixed bugs. Similarly, we note that many plausible but incorrect patches are generated for bugs which are not well localized (i.e., several false positive buggy locations are mutated leading to plausible but incorrect patches).

Figure 6: Distribution of the positions of buggy code locations in fault localization list of suspicious statements. C and P denote Correctly- and Plausibly- (but incorrectly) fixed bugs, respectively. F and U denote Fixed and Unfixed bugs.

RQ5: Fault localization noise has a significant impact on the performance of TBar. Fix patterns are diversely sensitive to the false positive locations that are recommended as buggy positions.
Table 7: Comparing TBar against the state-of-the-art APR tools.

| Proj. | GenProg | Kali | JMRepair | HIRepair | Nopet | ACS | ELIXIR | JAID | ssFix | CapGen | SketchFix | FixMiner | LSRepair | SimFix | kPAR | AVATAR |
|-------|---------|------|----------|----------|-------|----|--------|------|-------|--------|-----------|----------|----------|--------|------|--------|
| C     | 0/7     | 6/6  | 1/4      | 0/2      | 1/6   | 2/2| 4/7    | 2/4  | 3/7   | 4/4    | 4/8       | 4/8      | 5/8      | 5/9    | 4/8  | 3/10  |
| CI    | 0/0     | 0/0  | 0/0      | 0/0      | 0/0   | 0/0| 0/0    | 0/0  | 0/0   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 8/12  |
| L     | 0/0     | 0/0  | 0/0      | 0/0      | 0/0   | 0/0| 0/0    | 0/0  | 0/0   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 0/0   |
| M     | 0/0     | 0/0  | 0/0      | 0/0      | 0/0   | 0/0| 0/0    | 0/0  | 0/0   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 0/0   |
| Mc    | 0/0     | 0/0  | 0/0      | 0/0      | 0/0   | 0/0| 0/0    | 0/0  | 0/0   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 0/0   |
| T     | 0/2     | 0/2  | 0/1      | 0/1      | 0/1   | 1/1| 0/2    | 0/2  | 0/4   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 0/0   |
| Total | 0/2     | 0/2  | 0/1      | 0/1      | 0/1   | 1/1| 0/2    | 0/2  | 0/4   | 0/0    | 0/0       | 0/0      | 0/0      | 0/0    | 0/0  | 0/0   |

Table 8: Per-pattern repair performance.

| Correct | FP1 | FP2 | FP3 | FP4 | FP5 | FP6 | FP7 | FP8 | FP9 | FP10 | FP11 | FP12 | FP13 | FP14 | FP15 | FP16 | FP17 |
|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|------|------|
| Accuracy | | | | | | | | | | | | | | | | | |
| Avg. position | | | | | | | | | | | | | | | | | |

5 DISCUSSION

Overall, our investigations reveal that a large catalogue of fix patterns can help improve APR performance. However, at the same time, there are other challenges that must be dealt with: more accurate fault localization, effective search of relevant donor code, fix pattern prioritization. While we will work on some of these research directions in future work, we discuss in this section some threats to validity of the study and practical limitations of TBar.

Threats to Validity. Threats to external validity include the target language of this study, i.e., Java. Fix patterns studied in this paper only cover the fix patterns targeting at Java program bugs released by the state-of-the-art pattern-based APR systems. However, we believe that most fix patterns presented in this study could be applied to other languages since fix patterns are illustrated as abstract syntax tree level. Another threat to external validity could be the fix pattern diversity. Our study may not consider all available fix patterns so far in the literature. This threat, we systematically reviewed research work on pattern-based program repair in the literature.

Our strategy of fix pattern selection can be a threat to internal validity. While our strategy naively matches patterns based on the context information around buggy locations. More advanced strategies would give a higher probability to select appropriate patterns to fix more bugs.

Limitations. TBar applies a single fix pattern to a single buggy location once. Our assumption here is that it is not necessary to iteratively apply fix patterns to the same location. This might be a limitation of our tool. If the tool applies multiple fix patterns to a single location iteratively, the search space could be expanded. However, this can cause search space explosion.

6 RELATED WORK

Fault Localization. In general, most APR pipelines start with fault localization (FL), as shown in Figure 1. Once the buggy position is localized, APR tools can mutate the buggy code entity to generate patches, which might fix a given bug. To identify defect locations in a program, several automated FL techniques have been proposed [67]: slice-based [41, 65], spectrum-based [3, 52], statistics-based [28, 29], etc.

Spectrum-based FL (SBFL) techniques are widely adopted in APR pipelines since they identify bug position at the statement level. SBFL techniques rely on the ranking metrics (e.g., Trantula [15], Ochiai [2], Op2 [47], Barinel [3], Dstar[66]) to calculate the suspiciousness of each statement. GZoltar [6] and Ochiai have been widely integrated into APR systems since their effectiveness has been demonstrated in several empirical studies [51, 59, 68, 73]. As reported by Liu et al. [33] and studied in this paper, this FL configuration still has a limitation on localizing buggy locations. Therefore, researchers tried to enhance FL techniques with new techniques, such as predicate switching [71, 75] and test case purification [14, 74].

Patch Generation. Patch generation is another key process of APR pipeline, which is, in other words, searching for another shape of a program (i.e., a patch) in the space of all possible programs [26, 38]. If the search space is small, it might not include the correct patches. [63]. To reduce this threat, a straightforward strategy is to expand the search space, however, which could lead to other two problems: 1) at worst, there still is no correct patch in it; and 2) the expanded search space includes more plausible patches that enlarge the possibility of generating plausible patches before correct ones [30, 63].

To improve repair performance, many APR systems have been explored to address the search space problem. GenProg [27, 61] leveraged stochastic method to search patches. Synthesis-based APR systems [37, 71, 72] explored to limit the search space on conditional bug fixes by synthesizing new conditional expressions with variables identified from the buggy code. Pattern-based APR tools [10, 13, 14, 19, 21, 25, 34–36, 56] are designed to purify the search space by following code change schemas to mutate buggy code entities with retrieved donor code. Other APR pipelines focus on specific search methods for donor code or patch synthesizing strategies, to address the search space problem, such as contract-based [7, 60], symbolic execution based [48], learning based [4, 12, 39, 54, 58, 64], and donor code searching [17, 45] APR techniques. Various existing APR tools have achieved promising results on fixing real bugs, but there is still an opportunity to improve the performance; for example, mining more fix patterns, improving pattern selection and donor code retrieving strategy, exploring a new strategy for patch generation, and prioritizing bug positions.

Patch Correctness. The ultimate goal of APR systems is to automatically generate a correct patch that can resolve the program defects. At the beginning, patch correctness is evaluated by passing all test cases [19, 25, 61]. However, these patches could be overfitting [23, 53] and even worse than the bug [57]. Since then, APR
systems are evaluated with the precision of generating correct patches [14, 34, 63, 71]. Recently, researchers start to explore automated frameworks that can identify patch correctness for APR systems automatically [24, 70].

7 CONCLUSION

In software engineering literature, fix patterns (a.k.a. fix templates) have been studied in various scenarios to understand bug fixes in the wild. They are further implemented in different program repair pipelines to generate patches automatically. Although template-based program repair tools have achieved promising results, no extensive investigation on the effectiveness of fix patterns was conducted. We fill this gap in this work by revisiting the repair performance of fix patterns via a systematic study assessing the effectiveness of a variety of fix patterns summarized from the literature. In particular, we build a straightforward template-based APR tool, TBar, which we evaluate on the Defects4J benchmark. On the one hand, assuming a perfect fault localization, TBar is capable of fixing 74/102 bugs correctly/plausibly. On the other hand, in a normal/practical APR pipeline, TBar can correctly fix 43 bugs despite the noise of fault localization false positives. This constitutes a record performance in the literature on Java program repair. We expect TBar to be established as the new baseline APR system, leading researchers to propose better techniques for substantial improvement of the state-of-the-art.

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