

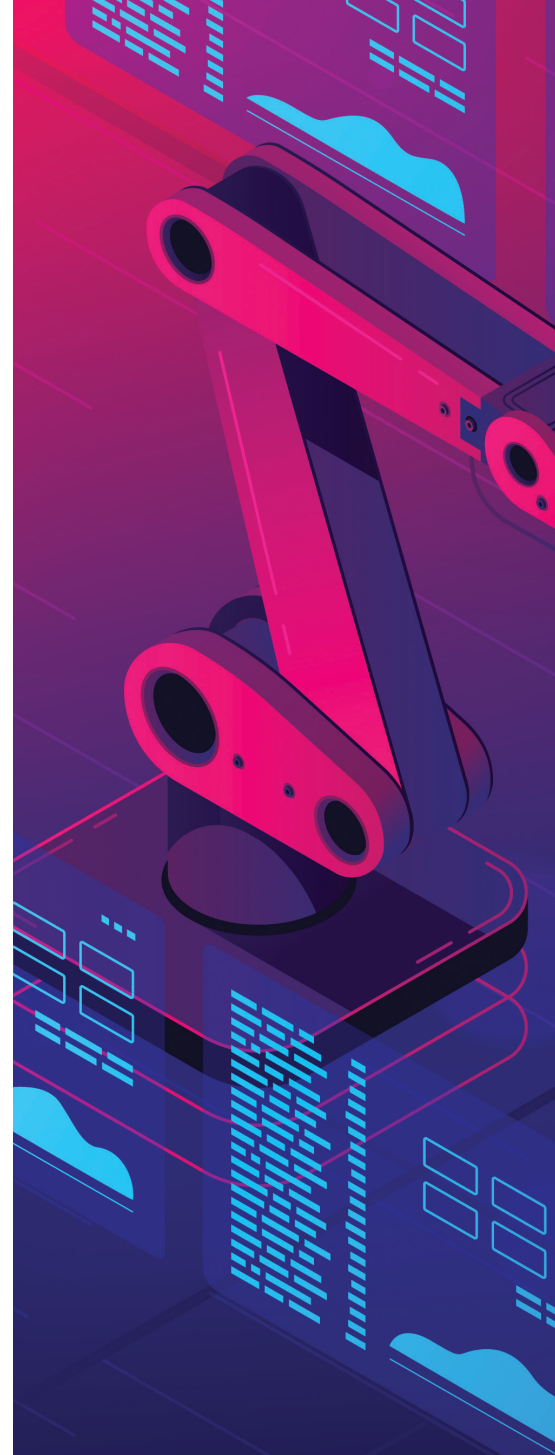
**Automated program repair can relieve programmers from the burden of manually fixing the ever-increasing number of programming mistakes.**

BY CLAIRE LE GOUES, MICHAEL PRADEL, AND ABHIK ROYCHOUDHURY

# Automated Program Repair

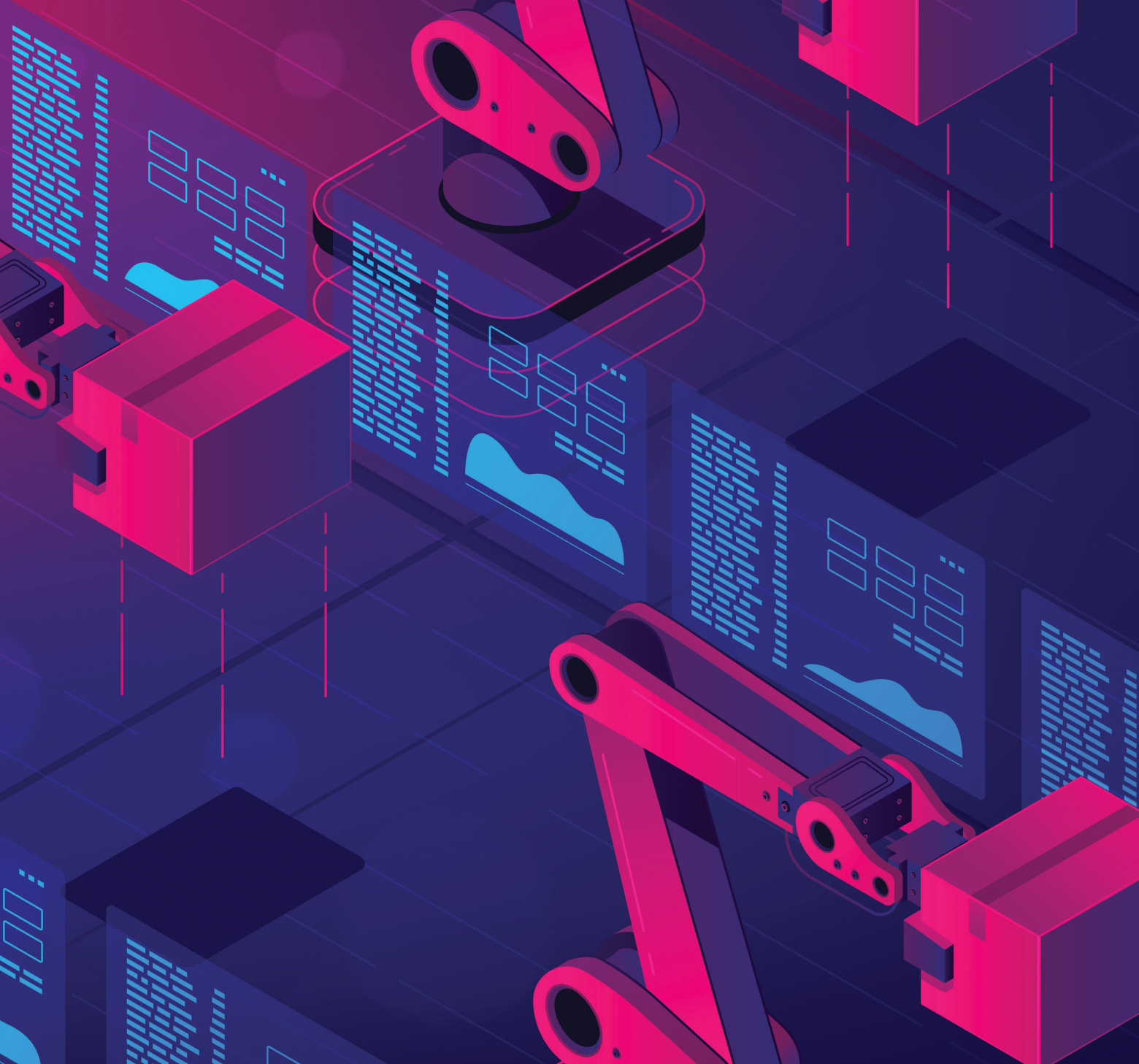
ALEX IS A software developer, a recent hire at the company of her dreams. She is finally ready to push a highly anticipated new feature to the shared code repository, an important milestone in her career as a developer. As is increasingly common in development practice, this kind of push triggers myriads of tests the code must pass before becoming visible to everyone in the company. Alex has heavily tested the new feature and is confident it will pass all the tests automatically triggered by the push. Unfortunately, Alex learns the build system rejected the commit. The continuous integration system reports failed tests associated with a software package developed by a different team entirely. Alex now must understand the problem and fix the feature manually.

What if, instead of simply informing Alex of the failing test, the build system also suggested one or two possible patches for the committed code? Although this general use case is still fictional, a growing community



## >> key insights

- Automated program repair is an emerging and exciting field of research that allows for automated rectification of software errors and vulnerabilities.
- The uses of automated program repair can be myriad, such as improving programmer productivity, automated fixing of security vulnerabilities, self-healing software for autonomous devices, and automatically generating hints for solving programming assignments.
- Automated repair can benefit from various techniques: intelligent navigation over a search space of program edits, symbolic reasoning to synthesize suitable code fragments, and techniques that learn from existing code and patches.



of researchers is working on new techniques for automated program repair that could make it a reality. A bibliography of automated program repair research has been composed by Monperrus.<sup>17</sup>

In essence, automated repair techniques try to automatically identify patches for a given bug,<sup>a</sup> which can then be applied with little, or possibly even without, human intervention. This type of work is beginning to see adoption in certain, constrained, prac-

tical domains. Static bug finding tools increasingly provide “quick fix” suggestions to help developers address flagged bugs or bad code patterns, and Facebook recently announced a tool that automatically suggests fixes for bugs found via their automatic testing tool for Android applications.<sup>15</sup>

The problem of bugs motivates a broad array of work on automatically identifying them. Advances in formal verification have shown the promise of fully assured software. However, the pace and scale of modern software development often precludes the application of such techniques from all but

the most safety-critical systems. Lightweight static approaches that rely most commonly on syntactic pattern matching or less complex static analysis are becoming increasingly popular as quality gates in many companies.<sup>7,23</sup> Testing, at multiple levels of system abstraction, remains the most common bug detection technique in practice.

While detecting bugs is a necessary step toward improving software, it leaves the arguably harder task of fixing bugs unsolved. In practice, program repair is challenging for several reasons. A developer must at first understand the problem and localize its root cause in the source code.

<sup>a</sup> We use the colloquial term “bug” to refer to programming mistakes that result in unintended runtime behavior.

Next, she must speculate about strategies to possibly fix the problem. For some of these strategies, the developer will evaluate a potential patch, by applying it and evaluating whether the associated test cases then pass; if not, she might use the failing test cases to conduct additional debugging activities. Finally, the developer must select a patch and apply it to code base. The difficulty of all these tasks is compounded by the fact that complex software projects tend to contain legacy code, code written by other members of an organization, or even code written by third parties.

The promise of automated program repair is in reducing the burden of these tasks by suggesting likely correct patches for software bugs. At a high level, such techniques take as input a program and some specification of the correctness criteria that the fixed program should meet. Most research techniques use test suites for this purpose: one or more failing tests indicate a bug to be fixed, while passing tests indicate behavior that should not change. The end goal is a set of program changes (typically to source code) that leads all tests to pass, fixing the bug without breaking other behavior.

The grand challenge in today's research on automated program repair is the problem of weak specifications. Since detailed formal specifications of intended program behavior are typically unavailable, program repair is driven by weak correctness criteria, such as a test suite. As a result, the generated patches may over-fit the given test suite and may not generalize to tests outside the test suite.<sup>29</sup>

In the rest of this article, we discuss some of the technical developments in automated program repair, including an illustration of the overfitting problem. We start by sketching some of the use-cases of automated program repair.

### Use Cases

This section discusses four practical use cases of automated repair, and reports initial experience based on current repair techniques.

**Fixing bugs throughout development.** Existing continuous integration (CI) pipelines, such as Jenkins, are an important stepping stone for integrating repair into the development process. By regularly building, testing, and



**The grand challenge in today's research on automated program repair is the problem of weak specifications.**



deploying a code base, CI provides the prerequisites for repair tools that use test suites as correctness specifications. Repair can become an activity in CI systems that suggests patches in response to regression test failures, such as for Alex, our hypothetical programmer.

Are we there yet? Existing techniques for automated repair of correctness bugs are typically evaluated for effectiveness using bugs taken from open source projects. Because many techniques require input tests to trigger the bug under repair and to evaluate the technique, such programs and bugs must be associated with one or more failing test cases. These bugs are typically collected systematically by going back in time through code histories to identify bug-fixing commits and the regression tests associated with them. Open source projects whose bugs have been studied in this way include popular Java projects, for example, various Apache libraries, Log4J, and the Rhino JavaScript interpreter, as well as popular C projects, for example, the PHP and Python interpreters, the Wireshark network protocol analyzer, and the libtiff library.

Recently, the Repairnator project<sup>33</sup> has presented a bot which monitors for software errors, and automatically find fixes using repair tools. Another recent work from Facebook<sup>15</sup> describes experiences in integrating repair as part of continuous integration—a repair tool monitors test failures, reproduces them, and automatically looks for patches. Once patches are found, they are presented to the developers for validation. Currently, the effort focuses on automatically repairing crashes in Android apps, however, the project plan is to extend the work to general-purpose repair.

### Repairing security vulnerabilities.

Many security vulnerabilities are exploitable memory errors or programming errors, and hence a relevant target for automated repair. Key software, including popular libraries processing file formats or operating system utilities, are regularly and rigorously checked for vulnerabilities in response to frequent updates using grey-box fuzz testing tools, such as American Fuzzy Lop (AFL<sup>b</sup>). Microsoft recently

<sup>b</sup> <http://lcamtuf.coredump.cx/afl/>



**Figure 1. Simple example for categorizing triangles.**

```

1 int triangle(int a, int b, int c){
2     if (a <= "0" || b <= "0" || c <= "0")
3         return INVALID;
4     if (a == b && b == c)
5         return EQUILATERAL;
6     if (a == b || b != c) // bug!
7         return ISOSCELES;
8     return SCALENE;
9 }

```

announced the Springfield project; Google similarly announced the OSS-Fuzz project. Such continuous fuzzing workflows generate use cases for automated program repair. In particular, repair tools can receive tests produced by grey-box fuzz testing tools like AFL.

Are we there yet? Existing repair techniques are effective at fixing certain classes of security vulnerabilities, specifically integer and buffer overflows. An empirical study conducted on OSS Fuzz subjects<sup>c</sup> shows that integer overflow errors are amenable to one-line patches, which are easily produced by repair tools. For example, these changes add explicit casts of variables or constants, modify conditional checks to prevent overflows, or change type declarations. Existing repair tools<sup>16</sup> have also been shown to automatically produce patches for the infamous Heartbleed vulnerability:

```

if (hbtype == TLS1_HB_REQUEST
    /* the following check being added
    is the fix */
    && payload + 18 < s->s3->rrec.
length) {
    ...
    memcpy(bp, pl, payload);
    ...
}

```

It is functionally equivalent to the developer-provided patch:

```

/* the following check being added is
the fix */
if (1 + 2 + payload + 16 > s->s3->rrec.
length) return 0;
...
if (hbtype == TLS1_HB_REQUEST) {
    ...
}

```

c <https://github.com/google/oss-fuzz>

**Intelligent tutoring.** The computer programming learning community is growing rapidly.

This growth has increasingly led to large groups of potential learners, with often inadequate teaching support. Automated repair can serve as a key component of intelligent tutoring systems that provide hints to learners for solving programming assignments and that automate the grading of students' programming assignments by comparing them with a model solution.

Are we there yet? While repair-based intelligent tutoring remains an open challenge for now, initial evidence on using program repair like processes for providing feedback to students<sup>28</sup> or for automatic grading of student assignments<sup>40</sup> have been obtained. Automated assignment grading can benefit from computation of the "semantic distance" between a student's buggy solution and an instructor's model solution. An important challenge for the future is that programming education requires nuanced changes to today's program repair workflow, since teaching is primarily focused on guiding the students to a solution, rather than repairing their broken solution.

**Self-healing of performance bottlenecks.** With the emergence of a wide variety of Internet of Things (IoT) software for smart devices, drones, and other cyber-physical or autonomous systems, there is an increasing need for online program repair, especially for non-functional properties like energy consumption. Consider a drone used for disaster recovery, such as flood or fire control. The drone software may encounter unexpected or perilous inputs simply by virtue of being faced with an unforeseen physical environment, which may drain the device's battery. There exists a need for online self-healing of the drone software. Au-

tomated repair targeted at non-functional issues, such as performance bottlenecks, can provide such self-healing abilities.

Are we there yet? Current repair techniques for non-functional properties have shown their effectiveness in improving real-world software. Consider two examples of performance-related repair tools. First, the MemoizeIt tool<sup>31</sup> suggests code that performs application-level caching, which allows programs to avoid unnecessarily repeated computations. Second, the Caramel tool<sup>19</sup> has suggested patches for a total of 150 previously unknown performance issues in widely used Java and C/C++ programs, such as Lucene, Chromium, and MySQL, that are now fixed based on the suggested repairs. While these examples are encouraging, the question of how to apply non-functional repair for fully automated self-healing remains open.

### Simple Example

Here, we describe a simple example we will use to illustrate the various state-of-the-art techniques in program repair. The example is selected for didactic purposes rather than to illustrate all the capabilities of repair techniques. Today's techniques apply to significantly more complex programs, as we described previously.

Consider a function that categorizes a given triangle as scalene, isosceles, or equilateral (Figure 1). From the definition of isosceles triangles learned in middle school, we can see that the condition in line 6 should be rectified to

```
(a == b || b == c || a == c)
```

This repair is non-trivial; it goes beyond simply mutating one operator in the condition.

The test suite in Figure 2 captures

**Figure 2. Test suite for the function in Figure 1.**

Test-id	a	b	c	Expected output	Pass/Fail
1	-1	-1	-1	INVALID	Pass
2	1	1	1	EQUILATERAL	Pass
3	2	2	3	ISOSCELES	Pass
4	3	2	2	ISOSCELES	Fail
5	2	3	2	ISOSCELES	Fail
6	2	3	4	SCALENE	Fail

the various triangle categories considered by the function: INVALID, EQUILATERAL, ISOSCELES, and SCALENE. Because the code contains a bug, several of the tests fail. The goal of automated program repair is to take a buggy program and a test suite, such as these, and produce a patch that fixes the program. The test suite provides the correctness criterion in this case, guiding the repair toward a valid patch. In general, there may exist any number of patches for any particular bug, and even humans can find different patches for real-world bugs.

At a high level, the program repair problem can be seen as follows: *Given a buggy program  $P$ , and a test suite  $T$  such that  $P$  fails one or more tests in  $T$ , find a “small” modification of  $P$  such that the modified program  $P'$  passes  $T$ .* The term “small” simply refers to the fact that developers generally prefer a simpler patch over a complicated one. Some techniques even try to find a minimal patch. Others trade off patch size with other goals, such as finding a patch efficiently. A particular risk in automated repair is a “patch” that causes the provided test cases to pass but that does not generalize to the complete, typically unavailable, specification. That is, the patch produced by an automated repair method can overfit the test data. An extreme case of an overfitted repair for the tests in Figure 2 is the following:

```
if (a==-1 && b==-1 && c==-1)
    return INVALID;
if (a==1 && b==1 && c==1)
```

```
    return EQUILATERAL;
if (a==2 && b==2 && c==3)
    return ISOSCELES;
...
```

Of course, such a “repaired” program is not useful since it does not pass any tests outside the provided test suite. This example is deliberately extreme. More commonly, patches produced by current repair techniques tend to overfit the provided test suite by disabling (or deleting) undertested functionality.<sup>29</sup>

### State of the Art

Automatically repairing a bug involves (implicitly) searching over a space of changes to the input source code. Techniques for constructing such patches can be divided into broad categories, based on what types of patches are constructed, and how the search is conducted. Figure 3 gives an overview of the techniques. The inputs to these techniques are a buggy program and a correctness criterion (the correctness criterion is often given as a test suite). Most techniques start with a common preprocessing step that identifies those code locations that are likely to be buggy. Such a fault localization procedure, for example, that by Jones et al.,<sup>8</sup> provides a ranking of code locations that indicates their potential buggy-ness. At a high level, there are two main approaches: *heuristic repair* and *constraint-based repair*. These techniques can sometimes be enhanced by machine learning, which we call *learning-aided repair*.

**Heuristic repair.** Heuristic search methods, shown at the left of Figure 3 employ a generate-and-test methodology, constructing and iterating over a search space of syntactic program modifications. These techniques can be explained schematically as follows:

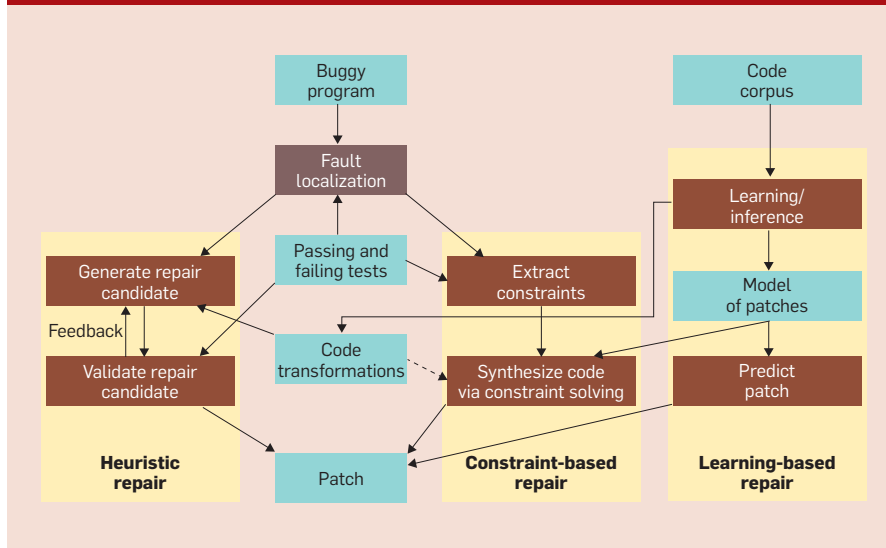
```
for cand ∈ SearchSpace do
    validate cand // break if successful
done
```

with *SearchSpace* denoting the set of considered modifications of the program. Validation involves calculating the number of tests that pass when a suggested patch has been applied. This can amount to a fitness function evaluation in genetic programming or other stochastic search methods.

Heuristic repair operates by generating patches that transform the program abstract syntax tree (AST). An AST is a tree-based representation of program source code that captures important program constructs, while abstracting away syntactic details like parentheses or semicolons. Given fault localization information that pinpoints code locations in the program that are the most likely to be buggy, syntactic techniques render the search tractable by making choices along one of three axes: mutation selection, test execution, and the traversal strategy.

**Mutation selection.** Due to the combinatorial explosion of possible mutations, the number of program variants that can be generated and compiled is typically very large. Techniques thus must limit the type and variety of edits considered for a repair candidate. This in turn defines the search space, with which search-based repair algorithms have great flexibility. However, this flexibility comes at a risk: If the search space is too small, the desired repair may not even be in the search space. For our triangle example (Figure 1), recall that the most natural patch replaces line 6 with  $(a == b \parallel b == c \parallel a == c)$ . If we only consider mutations that modify binary operators, the single-edit search space of the repair algorithm will not contain the developer-provided repair, which requires augmenting the branch condition with new conditions. On the other hand, if the search space is too large, the search can become intrac-

**Figure 3. Overview of repair techniques.**



table, such that the repair may not be found by the algorithm in a reasonable amount of time.

To address this issue, some techniques limit edits to only deletion, insertion, or replacement of code at the statement- or block-level. For code insertion or replacement, a common approach is to pull code from elsewhere in the same program or module, following the plastic surgery hypothesis (that correct code can be imported from elsewhere in the same program)<sup>6</sup> or the competent programmer hypothesis (that programmers are mostly competent, and while they may make a mistake in one portion of a program, they are likely to have programmed similar logic correctly, elsewhere). Such a technique would therefore only consider moving entire blocks or lines of code around, for example, an entire if condition semantically similar to the one shown in Figure 1. This can often work by virtue of the fact that source code is repetitive.<sup>22</sup>

Other techniques have benefited from using more expressive transformation templates, such as guarding a de-reference operation with a null-pointer check. Such transformation templates trade off repair space size for readability and “naturalness” of the resulting patches. Moving from statement-level edits to expression-level edits increases the search space, with the amount of increase depending on the transformation templates used to construct the search space.

However, even if the search space is large, the mutation operators may not support the behavioral change needed by the program or may affect the desired change in ways different from what a human might propose. A technique that may modify operators or insert conditions (copied from elsewhere in the program) would still struggle on this small program, since `(a == c)` never appears verbatim in our example. Such a lack of correct code fragments can result in degenerate behavior on smaller programs that provide little repair material. It also motivates research in intelligently augmenting the search space, for example, by considering past versions of a program.

**Test execution.** Repair candidates are evaluated by running the modified program on the provided set of test cases. Test execution is typically the most

expensive step, as test suites can be large and techniques may need to re-run them many times. Various strategies have been proposed to reduce this cost, including test suite selection and prioritization. Search strategies that do not require a fitness function, for example, based on random or deterministic search, can reduce the cost of testing by simply failing early (at the first test failure). Moreover, such techniques may run the test cases in a heuristic order designed to maximize the chance that, if a test case is going to fail, it is run early in the validation process.

**Traversal strategy.** Finally, techniques vary in how they choose which patches to explore, and in what order. GenProg,<sup>37</sup> an early technique proposed in this domain, implements a genetic programming algorithm with a fitness function based on the number of test cases passed by a patched program. Subsequent techniques like PAR<sup>9</sup> have followed, varying in the mutation operators (PAR) or the fitness function. Other techniques simply sample randomly typically restricting themselves to single-edit patches,<sup>21</sup> or in a heuristic, deterministic order as in GenProg AE.<sup>36</sup>

**Constraint-based repair.** In contrast to heuristic repair techniques, constraint-based techniques proceed by constructing a repair constraint that the patched code should satisfy, as illustrated in Figure 3. The patch code to be generated is treated as a function to be synthesized. Symbolic execution or other approaches extract properties about the function to be synthesized; these properties constitute the repair constraint. Solutions to the repair constraint can be obtained by constraint solving or other search techniques. In these approaches, formulation of the repair constraint is the key, not the mechanism for solving it. This class of techniques can be captured via the following schematic:

for test  $t \in \text{test-suite } T$   
     compute repair constraint  $\psi_t$   
 synthesize  $e$  as solution for  $\forall_t \psi_t$

In this case,  $T$  is the test suite used as the correctness criterion to guide repair. The constraint  $\psi_t$  will be computed via a symbolic execution<sup>10</sup> of the

path traversed by test  $t \in T$ . The constraint  $\psi_t$  is often of the form

$$\psi_t \equiv \pi_t \wedge \text{output} = \text{expected}$$

where  $\pi_t$  is the path condition of the path traversed by test  $t$ , output is the symbolic expression capturing the output variable in the execution of  $t$  and expected captures the oracle or expectation. The path condition of a program path is a formula, which is true for those inputs which traverse the path.<sup>10</sup>

**Computing repair constraints and angelix values.** To illustrate constraint-based repair, reconsider our running example from earlier. SemFix,<sup>18</sup> which is representative for constraint-based techniques, substitutes the faulty condition in line 6 with an abstract function  $f(a,b,c)$  on the live variables. In this example,  $f$  is a predicate that takes the integer values  $a,b,c$  and returns true/false. Then, the technique symbolically executes the tests in the given test suite to infer properties about the unknown function  $f$ . These properties are crucial for synthesizing an appropriate  $f$  that can pass all the given test cases.

The first two tests in our test suite do not even reach line 6. Hence, SemFix will not infer any property about the function  $f$  from them. From the last four tests, it can infer the repair constraint

$$f(2,2,3) \wedge f(3,2,2) \wedge f(2,3,2) \wedge f(2,3,4)$$

This is because analysis of the program has revealed that for input exercising line 6 if  $f$  is true, the program returns ISOSCELES and otherwise SCALENE.

Inferring detailed constraint specifications can be difficult, sometimes posing significant scalability issues. This motivates more efficient inference of value-based specifications.<sup>16</sup> In particular, *angelic values* are inferred for patch locations, where an angelic value for a fixed location is one that makes a failing test case pass. Once (collections of) angelic values are identified for each failing test, program synthesis can then be employed to generate patch code meeting such a value-based specification. This is the philosophy embodied in the Angelix tool<sup>16</sup> where angelic values are obtained via symbolic execution (instead of producing repair specifications in the form of SMT constraints via symbolic execution directly). This way of dividing the

repair task into angelic value determination and patch code generation to meet angelic values is symptomatic of semantic repair approaches.

Instead of obtaining angelic values by symbolic execution and constraint solving, they may also be obtained by search, particularly for conditional statements. This is because each occurrence of a conditional statement has only two possible return values: true and false. Techniques that work on enumerating possible angelic values without adopting symbolic execution<sup>13,39</sup> typically try to repair conditional statements exclusively, where the angelic values are exhaustively enumerated until all failing test cases pass. Such techniques adopt the work-flow of semantic repair techniques (specification inference followed by patch generation), with an enumeration step fully or partially replacing symbolic program analysis. Symbolic analysis-based approaches such as Mechtaev et al.<sup>16</sup> on the other hand, avoid exhaustive enumeration of possible angelic values.

*Solving constraints to find a patch.* Once repair constraints or angelic value(s) of a statement to be fixed are obtained, these techniques must generate a patch to realize the angelic value. Finding a solution to the repair constraint yields a definition of the abstract function  $f$ , which corresponds to the patched code. This is often achieved by either search or constraint solving, where the operators allowed to appear in the yet-to-be synthesized function  $f$  are restricted. In this example, if we restrict the operators allowed to appear in  $f$  to be relational operators most search or solving techniques will find the expression  $a == b \ || \ b == c \ || \ a == c$ . Efficient program synthesis techniques (see Alur et al.<sup>2</sup> for an exposition of some recent advances in program synthesis) are often used to construct the function  $f$ .

*Learning-based repair.* Recent improvements in advanced machine learning, especially deep learning, and the availability of large numbers of patches enable learning-based repair. Current approaches fall approximately into three categories that vary by the extent to which they exploit learning during the repair process. **One line of work<sup>14</sup> learns from a corpus of code a model of correct code, which indicates how likely a given piece of code is with regard to the code**

corpus. The approach then uses this model to rank a set of candidate patches to suggest the most realistic patches first. Another line of work infers code transformation templates from successful patches in commit histories.<sup>3,12</sup> In particular, Long et al.<sup>12</sup> infers AST-to-AST transformation templates that summarize how patches modify buggy code into correct code. These transformation templates can then be used to generate repair candidates.

**The third line of work not only improves some part of the repair process through learning, but also trains models for end-to-end repair.** Such a model predicts the repaired code for a given piece of buggy code, without relying on any other explicitly provided information. In particular, in contrast to the repair techniques discussed previously, such models do not rely on a test suite or a constraint solver. DeepFix<sup>5</sup> trains a neural network that fixes compilation errors, for example, missing closing braces, incompatible operators, or missing declarations. The approach uses a compiler as an oracle to validate patch candidates before suggesting them to the user. Tufano et al.<sup>32</sup> propose a model that predicts arbitrary fixes and trains this model with bug fixes extracted from version histories. According to their initial results, the model produces bug-fixing patches for real defects in 9% of the cases. Both approaches abstract the code before feeding it into the neural network. For the running example in Figure 1, this abstraction would replace the application-specific identifiers `triangle` and `EQUILATERAL` with generic placeholders, such as `VAR1` and `VAR2`. After this abstraction, both approaches use an RNN-based sequence-to-sequence network that predicts how to modify the abstracted code.

Given the increasing interest in learning-based approaches toward software engineering problems, we will likely see more progress on learning-based repair in the coming years. Key challenges toward effective solutions include finding an appropriate representation of source code changes and obtaining large amounts of high-quality human patches as training data.

**Repair of non-functional properties.** To help developers improve the

software efficiency, several approaches identify optimization opportunities and make suggestions on how to refactor the code to improve performance. These approaches typically focus on a particular kind of performance problem, for example, unnecessary loop executions<sup>19</sup> or repeated executions of the same computation.<sup>31</sup> Another line of work selects which data structure is most likely to provide the best performance for a given program out of a given set of functionally equivalent data structures.<sup>26</sup> All these approaches suggest code changes but leave the final decision whether to apply an optimization to the developer.

To mitigate security threats, various techniques for repairing programs at runtime have been proposed. These approaches automatically rewrite code to add a runtime mechanism that enforces some kind of security policy. For example, such repair techniques can enforce control flow integrity,<sup>1</sup> prevent code injections,<sup>30</sup> automatically insert sanitizers of untrusted input, or enforce automatically inferred safety properties.<sup>20</sup>

We note that existing techniques to repair non-functional properties typically focus on a particular kind of problem, for example, a kind of performance anti-pattern or attack. This distinguishes them from the core repair literature for fixing correctness bugs, which typically aim at fixing a larger set of errors.

## Perspectives and Challenges

Despite tremendous advances in program repair during the last decade, there remain various open challenges to be tackled by future work. We identify three core challenges: increasing and ensuring the quality of repairs; extending the scope of problems addressed by repair; and integrating repair into the development process.

**Quality.** The quality challenge is about increasing the chance an automatically identified repair provides a correct fix that is easy to maintain in the long term. Addressing this challenge is perhaps the most important step toward real-life adoption of program repair.

*Measures of correctness.* An important aspect of fix quality is whether the fix actually corrects the bug. In practice, program repair relies on measures




of correctness. Finding such a measure is a difficult and unsolved problem, which applies both to patches produced by humans and by machines. To date, researchers have assessed quality using human judgment, crowdsourced evaluations, comparison to developer patches of historical bugs, or patched program performance on indicative program workloads or held-out test cases. The recent work of Xiong et al.<sup>38</sup> provides a novel outlook for filtering patches based on the behavior of the patched program vis-a-vis the original program on passing and failing tests.


*Alternative oracles.* The bulk of the existing literature focuses on test-based repair where the correctness criteria is given as a test suite. Richer correctness properties, for example, assertions or contracts, can be used to guide repair when available.<sup>34</sup> Other approaches consider alternative oracles, such as potential invariants inferred from dynamic executions.<sup>20</sup> Such approaches can follow the “bugs as deviant behavior” philosophy, where deviations of an execution from “normal” executions are observed and avoided. In particular, Weimer et al.<sup>35</sup> provide an overview of various (partial) oracles that can be used for repair.

*Correctness guarantees.* Few of today’s repair techniques provide any guarantees about the correctness of produced patches, which can hinder the application of automated repair, especially to safety-critical software. If correctness guarantees are available as properties, such as pre-conditions, post-conditions, and object invariants, these can be used to guide program repair. The work of Logozzo and Ball<sup>11</sup> reports such an effort where repair attempts to increase the number of property-preserving executions, while reducing the number of violating executions. However, such formal techniques are contingent on the properties to drive the repair being available.

*Maintainability.* Once a correct fix has been detected and applied to the code base, the fixed code should be as easy to maintain as a human fix. Initial work in this domain has investigated the effect that automatically generated patches impact human maintenance behavior.<sup>4</sup> More study is needed to develop a foundational understanding of change quality, especially with respect



**Once repair constraints or angelic value(s) of a statement to be fixed are obtained, these techniques generate a patch to realize the angelic value.**



to the human developers who will interact with a modified system.

A promising avenue for tackling the quality challenge is by leveraging information available from other development artifacts, including documentation or formal specifications, language specifications and type systems, or source control histories of either the program under repair or of the broad corpora of freely available open source software. Such additional information can reduce the repair search space by imposing new constraints on potential program modifications (for example, as suggested by a type system) and increase the probability that the produced patch is human-acceptable.

**Scope.** The scope challenge is about further extending the kinds of bugs and programs to which automated repair applies.

*General-purpose repair.* Research in program analysis has long focused on special-purpose repair tools for specific kind of errors, such as buffer overflow errors,<sup>20</sup> or bugs in domain-specific languages.<sup>24</sup> More recent work, as discussed earlier, focuses on general-purpose repair tools that do not make any assumptions about the kind of bugs under consideration. While automatically fixing all bugs seems out of reach in the foreseeable future, targeting a broad set of bugs remains an important challenge.

*Complex programs and patches.* Many of the key innovations in the initial research in program repair concerned the scalability of techniques to complex programs. For example, search-based techniques moved from reasoning over populations of program ASTs to populations of small edit programs (the patches themselves) and developed other techniques to effectively constrain the search space. Constraint-based repair strategies have moved from reasoning about the semantics of entire methods to only reasoning about the desired change in behavior. These efforts enable scaling to programs of significant size, and multi-line repairs.<sup>16</sup> We anticipate that scalability will periodically return to the fore as program repair techniques engage in more complex reasoning. We emphasize here that program repair techniques should remain scalable with respect to large



programs as well as large search spaces (complex changes).

**Development process.** The final challenge is about integrating repair tools into the development process.

*Integration with bug detection.* Bug detection is the natural step preceding program repair. It is possible to fuse debugging and repair into one step, by viewing repair as the minimal change, which makes the program pass the given tests. We envision future work integrating repair with bug detection techniques, such as static analysis tools. Doing so may enable repair techniques to obtain additional information about possible repairs from static analyses, in addition to the test cases used nowadays. As a first step in this direction, a static analysis infrastructure used at Google suggests fixes for a subset of its warnings.<sup>23</sup> A promising future direction here could be to extend static analysis tools for generating dynamic witnesses or scenarios of undesirable behavior.

*IDE integration.* Most of today's repair tools are research prototypes. Bringing these tools to the fingertips of developers in a user-friendly fashion will require efforts toward integrating repair into integrated development environments (IDEs). For example, an IDE-integrated repair tool could respond to either failed unit or system tests or developer prompting. To the best of our knowledge, this application has not yet been widely explored. Suitably interactive response times are a precondition for such an approach. This research direction will benefit from interaction with experts in developer tooling and human-computer interaction, to ensure tools are designed and evaluated effectively.

*Interactivity.* As program repair gets integrated into development environments, interacting with the developer during repair is important. While the focus in the past decade has been on fully automated repair, putting the developer back into the loop is necessary, in particular, due to the weak specifications (test suites) often used to guide program repair. User interactivity may be needed to yield expected outputs of additional test inputs that are generated to strengthen the test-suite driving repair.<sup>27</sup> It is of course possible to filter plausible



**Automated program repair remains an enticing yet achievable possibility that can improve program quality while improving programmers' development experience.**



but possibly incorrect patches by, for example, favoring smaller patches or favoring patches “similar” to human patches. Nevertheless, the developer still needs to explore the remaining large set of patch suggestions.

*Explaining repairs.* A strongly related problem is to explain repair suggestions. One idea worth pursuing is to compute and present the correlation of patches based on program dependencies and other semantic features, which allow the developer to loosely group together plausible patches. Explaining repairs is needed particularly in its application to programming education.<sup>40</sup> Instead of merely fixing a students' incorrect program to the model correct program, it is useful for the repair tool to generate hints of what is missing in the students' repair. Such hints may take the form of logical formulae capturing the effect of repairs, which are gleaned from constraint-based repair tools; these hints may be presented in natural language, instead of logic, for easy comprehension by the learners.


## Conclusion

Automated program repair remains an enticing yet achievable possibility that can improve program quality while improving programmers' development experience.

Technically speaking, automated repair involves challenges in defining, navigating, and prioritizing the space of patches. The field benefits from past lessons learned in search space definition and navigation in software testing, as embodied by the vast literature in test selection and prioritization. The GenProg tool<sup>37</sup> is just one example of how genetic search, which has been useful for testing, can be potentially adapted for repair. At the same time, automated repair comes with new challenges because it may generate patches that overfit the given tests. This is a manifestation of tests being incomplete correctness specifications. Thus, there is a need for inferring specifications to guide repair, possibly by program analysis. The Semfix and Angelix tools<sup>16,18</sup> are a few examples of how the repair problem can be envisioned as one of inferring a repair constraint, and they have shown the scalability of such constraint-based techniques.

Conceptually speaking, automated program repair closes the gap between the huge manual effort spent today in writing correct programs, and the ultimate dream of generating programs automatically via learning approaches. Given the challenges of generating multiline program fixes in program repair, we can thus imagine the difficulty of generating explainable programs automatically.

Pragmatically speaking, automated program repair also makes us keenly aware of the challenges in managing changes in software engineering projects, and the need for automation in this arena. Today, manual debugging and maintenance often takes up 80% of the resources in a software project, prompting practitioners to long declare a legacy crisis.<sup>25</sup> In the future, program repair can provide tool support by repairing bugs from complex changes in software projects. This can help resolve a dilemma of developers when managing program changes: “Our dilemma is that we hate change and love it at the same time; what we really want is for things to remain the same but get better.”<sup>d</sup>

**Acknowledgments.** The authors acknowledge many discussions with researchers at the Dagstuhl seminar 17022 on Automated Program Repair (Jan. 2017). Claire Le Goues acknowledges support of the U.S. National Science Foundation under grants no. CCF-1750116 and CCF-1738253. Michael Pradel acknowledges support of BMWF/Hessen within CRISP and support of the DFG within the ConcSys and Perf4JS projects. Abhik Roychoudhury acknowledges support of National Research Foundation Singapore, National Cybersecurity R&D program (Award No. NRF2014NCR-NCR001-21). 

d Quote by Sydney J. Harris.

## References

- Abadi, M., Budiu, M., Erlingsson, U. and Ligatti, J. Control-flow integrity. In *Proceedings of the 12th ACM Conference on Computer and Communications Security*, 2005, ACM, 340–353.
- Alur, R., Singh, R., Fisman, D. and Solar-Lezama, A. Search-based program synthesis. *Commun. ACM* 61 (2018), 84–93.
- Brown, D.B., Vaughn, M., Liblit, B. and Reys, T.W. The care and feeding of wild-caught mutants. In *Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering*, (Paderborn, Germany, Sept. 4–8, 2017), 511–522.
- Fry, Z.P., Landau, B., and Weimer, W. A human study of patch maintainability. In *Proceedings of the Intern. Symp. on Software Testing and Analysis*, 2012, 177–187.
- Gupta, R., Pal, S., Kanade, A. and Shevade, S. DeepFix: Fixing common C language errors by deep learning. Assoc. for the Advancement of Artificial Intelligence, 2017.
- Harman, M. Automated patching techniques: The fix is in. *Commun. ACM* 53 (2010), 108–108.
- Johnson, B., Song, Y., Murphy-Hill, E. and Bowdidge, Z. Why don't software developers use static analysis tools to find bugs? In *Proceedings of the Intern. Conf. on Software Engineering*, 2013, 672–681.
- Jones, J.A., Harrold, M.J. and Stasko, J. Visualization of test information to assist fault localization. In *Proceedings of the ACM/IEEE Intern. Conf. on Software Engineering*, 9.
- Kim, D., Nam, J., Song, J. and Kim, S. Automatic patch generation learned from human-written patches. In *Proceedings of the ACM/IEEE International Conference on Software Engineering*, 2013.
- King, J.C. Symbolic execution and program testing. *Commun. ACM* 19 (1976).
- Logozzo, F. and Ball, T. Modular and verified automatic program repair. In *Proceedings of Object-Oriented Programming Systems Languages and Applications*, 2012.
- Long, F., Amidon, P. and Rinard, M. Automatic inference of code transforms for patch generation. In *Proceedings of the ACM SIGSOFT Intern. Symp. on Foundations of Software Engineering*, 2017.
- Long, F. and Rinard, M. Staged program repair with condition synthesis. In *Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering*, 2015.
- Long, F. and Rinard, M. Automatic patch generation by learning correct code. In *Proceedings of the ACM Intern. Symp. on Principles of Programming Languages*, 2016.
- Marginean, A., Bader, J., Chandra, S., Harman, M., Jia, Y., Mao, K., Mols, A. and Scott, A. Saffix: Automated end-to-end repair at scale. In *Proceedings of the Intern. Conf. on Software Engineering*, Software Engineering in Practice track, 2019.
- Mechtaev, S., Yi, J. and Roychoudhury, A. Angelix: Scalable multiline program patch synthesis via symbolic analysis. In *Proceedings of the ACM/IEEE Intern. Conf. on Software Engineering*, 2016.
- Monperrus, M. Automatic software repair: A bibliography. *ACM Computing Surveys* 51, 1 (2017).
- Nguyen, H.D.T., Qi, D., Roychoudhury, A. and Chandra, S. SemFix: Program repair via semantic analysis. In *Proceedings of the ACM/IEEE Intern. Conf. on Software Engineering*, 2013.
- Nistor, A., Chang, P.-C., Radoi, C. and Lu, S. Caramel: Detecting and fixing performance problems that have non-intrusive fixes. In *Proceedings of ICSE*, 2015.
- Perkins, J.H. et al. Automatically patching errors in deployed software. In *Proceedings of the Symp. on Operating Systems Principles*. ACM, 2009.
- Qi, Y., Mao, X., Lei, Y., Dai, Z. and Wang, C. The strength of random search on automated program repair. In *Proceedings of the Intern. Conf. on Software Engineering*, 2014.
- Ray, B., Hellendoorn, V., Godhane, S., Tu, Z., Bacchelli, A. and Devanbu, P. On the “naturalness” of buggy code. In *Proceedings of the 38th Intern. Conf. on Software Engineering* (Austin, TX, USA, May 14–22, 2016), 428–439.
- Sadowski, C., Aftandilian, E., Eagle, A., Miller-Cushon, L. and Jaspan, C. Lessons from building static analysis tools at google. *Commun. ACM* 61, 4 (Apr. 2018), 58–66.
- Samimi, H., Schäfer, M., Artzi, S., Millstein, T., Tip, F. and Hendren, L. Automated repair of HTML generation errors in PHP applications using string constraint solving. In *Proceedings of the 34th Intern. Conf. on Software Engineering*, 2012.
- Seacord, R., Plakosh, D. and Lewis, G. *Modernizing Legacy Systems: Software Technologies, Engineering Processes and Business Practices*. Addison Wesley, 2003.
- Shacham, O.M., Vechev, M.T. and Yahav, E. Chameleon: Adaptive selection of collections. In *Proceedings of Conf. on Programming Language Design and Implementation*, 2009, ACM, 408–418.
- Shriver, D., Elbaum, S. and Stolee, K.T. At the end of synthesis: narrowing program candidates. In *Proceedings of the Intern. Conf. on Software Engineering*, 2017.
- Singh, R., Gulwani, S. and Solar-Lezama, A. Automated feedback generation for introductory programming assignments. In *Proceedings of the Intern. Conf. on Programming Language Design and Implementation*, 2013.
- Smith, E.K., Barr, E., Le Goues, C. and Brun, Y. Is the cure worse than the disease? overfitting in automated program repair. In *Proceedings of the International Symposium on Foundations of Software Engineering (FSE)*, 2015.
- Su, Z. and Wassermann, G. The essence of command injection attacks in Web applications. In *Proceedings of Symp. on Principles of Programming Languages*, 2006, 372–382.
- Toffola, L.D., Pradel, M. and Gross, T.R. Performance problems you can fix: A dynamic analysis of memoization opportunities. In *Proceedings of Conf. on Object-Oriented Programming, Systems, Languages, and Applications*, 2015.
- Tufano, M., Watson, C., Bavota, G., Di Penta, M., White, M. and Poshvanyk, D. An empirical investigation into learning bug-fixing patches in the wild via neural machine translation. In *Proceedings of Intern. Conf. on Automated Software Engineering*, 2018.
- Urli, S., Yu, Z., Seinturier, L. and Monperrus, M. How to design a program repair bot? insights from the repairator project. In *Proceedings of Intern. Conf. on Software Engineering*, Track Software Engineering in Practice, 2018.
- Wei, Y., Pei, Y., Furia, C.A., Silva, L.S., Buchholz, S., Meyer, B. and Zeller, A. Automated fixing of programs with contracts. In *Proceedings of ACM Intern. Symp. on Software Testing and Analysis*, 2010.
- Weimer, W., Forrest, S., Kim, M., Le Goues, C. and Hurlley, P. Trusted software repair for system resiliency. In *Proceedings of 46th Annual IEEE/IFIP Intern. Conf. on Dependable Systems and Networks Workshops*, 2016.
- Weimer, W., Fry, Z. and Forrest, S. Leveraging program equivalence for adaptive program repair: Models and first results. In *Proceedings of ACM/IEEE Intern. Conf. on Automated Software Engineering*, 2013.
- Weimer, W., Nguyen, T.V., Le Goues, C. and Forrest, S. Automatically finding patches using genetic programming. In *Proceedings of ACM/IEEE Intern. Conf. on Software Engineering*, 2009.
- Xiong, Y., Liu, X., Zeng, M., Zhang, L. and Huang, G. Identifying patch correctness in test-based program repair. In *Proceedings of Intern. Conf. on Software Engineering*, 2018.
- Xuan, J., Martinez, M., Demarco, F., Clement, M., Marcote, S.L., Durieux, T., Le Berre, D. and Monperrus, M. Nopol: Automatic repair of conditional statement bugs in Java programs. *IEEE Trans. Software Engineering* 43, (2017).
- Yi, J., Ahmed, U.Z., Karkare, A., Tan, S.H. and Roychoudhury, A. A feasibility study of using automated program repair for introductory programming assignments. In *Proceedings of ACM SIGSOFT Intern. Symp. Foundations of Software Engineering*, 2017.

Claire Le Goues (clegoues@cs.cmu.edu) is an associate professor at Carnegie Mellon University, Pittsburgh, PA, USA.

Michael Pradel (michael@binaervarianz.de) is a professor at the University of Stuttgart, Germany.

Abhik Roychoudhury (abhik@comp.nus.edu.sg) is a professor at the National University of Singapore.

© 2019 ACM 0001-0782/19/12



Watch the authors discuss this work in the exclusive *Communications* video.  
<https://cacm.acm.org/videos/automated-program-repair>