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PropR: Property-Based Automatic Program Repair

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ABSTRACT
Automatic program repair (APR) regularly faces the challenge of overfitting — patches that pass the test suite, but do not actually address the problems when evaluated manually. Currently, overfit detection requires manual inspection or an oracle making quality control of APR an expensive task. With this work, we want to introduce properties in addition to unit tests for APR to address the problem of overfitting. To that end, we design and implement PropR, a program repair tool for Haskell that leverages both property-based testing (via QuickCheck) and the rich type system and synthesis offered by the Haskell compiler. We compare the repair-ratio, time-to-first-patch and overfitting-ratio when using unit tests, property-based tests, and their combination. Our results show that properties lead to quicker results and have a lower overfit ratio than unit tests. The created overfit patches provide valuable insight into the underlying problems of the program to repair (e.g., in terms of fault localization or test quality). We consider this step towards fitter, or at least insightful, patches a critical contribution to bring APR into developer workflows.

CCS CONCEPTS
• Software and its engineering → Search-based software engineering; Automatic programming; Functional languages; Source code generation.

KEYWORDS
automatic program repair, search based software engineering, synthesis, property-based testing, typed holes

1 INTRODUCTION
Have you ever failed to be perfect? Don’t worry, so have automatic program repair (APR) approaches. APR faces many challenges, some inherited from search-based software engineering (SBSE), like overfitting [52, 67], predictive-evaluation in search [73], and duplicate handling [9]. Other challenges are unique to the domain itself, such as deriving ingredients for a fix [41] and producing valid programs [28]. Consequently, APR has open research in all of its core aspects: search-space, search-process, and fitness-evaluation. The research community is shifting its focus towards other solutions, either leaving behind boundaries of search space using generative neural networks [36, 42, 65], or by empirical evidence that fixes are often related to dependencies, not the code itself [4, 14]. Fixes are usually validated by running against the test suite of the program, assuming that a solution that passes all tests is a valid patch. However, Le Goues et al. [54] showed that Program Repair can overfit, i.e., that a fix passes the test suite despite removing functionality or just bypassing single tests.

Usually, generated patches are evaluated against a unit test suite of the buggy program [34]. The fitness is defined as the number of failing tests in the suite [40], making a fitness of zero a potential fix. The problem is the quality of the tests — often not all important cases are covered, and the search finds something that passes all tests but doesn’t provide all wanted functionality [52]. This is considered an overfit repair attempt. A particularly good example for this is the Kali approach [54], that removes random statements of a program. In a later study, Martinez et al. [38] showed that out of 20 of the repair attempts that passed the tests, only one was a real fix. One approach by Ya et al. [71] to address overfitting was to introduce tests generated with EvoSuite [15] to have a stronger test suite, reporting only an improvement in speed, not in found solutions. Unfortunately, EvoSuite introduces a new problem: If the program was faulty (which programs that we are trying to repair are), an automatically generated test suite may assert the faulty behavior and make test-based repairs unable to ever produce a correct program, despite passing the (generated) test suite. Thus, current automated test-case generation is not the be-all and end-all for overfitting in APR.

This work aims to improve APR with addressing the overfitting problem by introducing properties [8] in addition to unit tests. A software property is an attribute of a function (e.g., symmetry, idempotency, etc.) that is evaluated against randomly created instances of input data. Well-written properties often cover hundreds of (unit) tests, making them attractive candidates for fitness evaluation.
We argue that properties can be an improvement to the overfitting challenge in APR. While property-based testing frameworks exist for a range of languages, the practice is particularly natural for functional programming, and widely used in the Haskell community. Therefore, we implement a tool called PropR, which utilizes properties for Haskell-Program-Repair and evaluate the repair rates and overfitting rates for different algorithms (random search, exhaustive search, and genetic algorithms). Our fixes follow a GenProg-like approach [34] of representing patches as a set of changes to the program, with the major difference that our patch ingredients (mutations) are sourced by the Haskell compiler using a mechanism called typed holes [19]. A typed hole can be seen as a placeholder, for which the compiler suggests elements that produce a compiling program. As these suggestions cover all elements in scope (not only those used in the existing code), we overcome to some degree the redundancy assumption [41], i.e., the concept that patches are sourced from existing code or patterns, which is common in GenProg-like approaches.

Our results show that properties help to reduce the overfit ratio from 85% to 63% and lead to faster search results. Properties can still lead to overfitting, and the union test suite of properties and unit tests inherits both strengths and weaknesses. We therefore argue to use properties if possible, and suggest to aim for the strongest test suite regardless of the test-type. The patches from PropR can produce complex repair patterns that did not appear within the code. Even patches that are overfit can give valuable insight in the test suite or the original fault.

Our contributions can be summarized as follows:

1. Introducing the use of properties for fitness functions in automatic program repair.
2. Showing how to generate patch candidates using compiler scope, partially addressing the redundancy assumption.
3. Performing an empirical study to evaluate the improvement gained by properties with a special focus on manual inspection of generated patches to detect eventual overfitting.
4. An open source implementation of our tool PropR, enabling future research on program repair in a strongly typed functional programming context.
5. Providing the empirical study data for future research.

The remainder of the paper is organized as follows: Section 2 introduces property-based testing and summarizes the related work in the fields of genetic program repair as well as background on typed holes, which are a key element of our patch generation method. In Section 3 we present the primary aspects of the repair tool and their reasoning. Section 4 presents the data used in the empirical study, and declares research questions and methodology. The results of the research questions are covered in Section 5 and discussed in Section 6. After the threats to validity in Section 7 we summarize the work in Section 8. The shared artifacts are described in Section 9.

2 BACKGROUND AND RELATED WORK

2.1 Property-Based Testing

Property-based testing is a form of automated testing derived from random testing [22]. While random testing executes functions and APIs on random input to detect error states and reach high code coverage, property-based testing uses a developer defined attributes called properties of functions that must hold for any input of that function [8]. Random tests are performed for the given property; if an input is found for which the property returns false or fails with an error, the property is reported as failing along with the input as a counter example [8]. Some frameworks will additionally shrink the counter example using a previously supplied shrinking function to offer better insight into the root cause of the failure [8].

There are some variations on property-based testing, e.g. SmallCheck, which performs an exhaustive test of the property [58]. QuickCheck approximates this behavior with a configurable number of random inputs (by default 100 random samples). Figure 1 provides an example comparison of properties and unit tests of a sine function. The properties require an argument Double -> Test and must hold for any given Double. On any single QuickCheck run, 202 tests are performed, forming a much stronger test suite for a comparable amount of code.

A remaining question is whether one cannot just reproduce these 202 tests by unit tests. For a single seed, this is doable — but it is a special strength of properties that the new tests are randomly generated on demand. We hope this addresses the problem of overfitting [52], as there are no fixed tests to fit on as long as the seed changes. Furthermore, we stress that maintaining 2 properties is easier than maintaining 200 (repetitive) unit tests.

2.2 Haskell, GHC & Typed Holes

Haskell. Haskell is a statically typed, non-strict, purely functional programming language. Its design ensures that the presence of side effects is always visible in the type of a function, and it is typical programming practice to cleanly separate code requiring side effects from the main application logic. This facilitates a modular approach to testing in which program parts can be tested in isolation without needing to consider global state or side effects. Haskell’s rich type system and type classes allow tools such as QuickCheck [8] to efficiently test functions using properties, where the inputs are generated by QuickCheck based on a generator for a given datatype.

Valid Hole-Fits. Our tool is based on using the Glasgow Haskell Compiler (GHC), which is widely used in both industry and academia. GHC has many features beyond the Haskell standard, including a

---

Figure 1: Comparison of Properties and Unit Tests for \( \sin \)
feature known as typed holes [19]. A "hole", denoted by an underscore character (_), allows a programmer to write an incomplete program, where the hole is a placeholder for currently missing code.

Using a hole in an expression generates a type error containing contextual information about the placeholder, including, most importantly, its inferred type. In addition to contextual information, GHC suggests some valid hole-fits [19]. Valid hole fits are a list of identifiers in scope which could be used to fill the holes without any type errors. As a simple example, consider the interaction with the GHC REPL shown in Figure 2.

```
GHCi> let degreesToRadians :: Double -> Double
    degreesToRadians d = d * _ / 180
<interactive>:4:30: error:
  · Found hole: _ :: Double
    In the expression: d * _ / 180
Valid hole fits include
  d :: Double (bound at <interactive>:4:22)
  pi :: forall a. Floating a => a (imported from 'Prelude')
```

*Figure 2: Example code with a hole and its valid hole-fits*

Here the definition of degreesToRadians contains a hole. There are just two valid hole-fits in scope: the parameter d and the predefined constant pi. GHC can not only generate simple candidates such as variables and functions, but also refinement hole-fits. A refinement hole-fit is a function identifier with placeholders for its parameters. In this way GHC can be used to synthesize more complex type-correct candidate expressions through a series of refinement steps up to a given user-specified refinement depth. For example, setting the refinement depth to 1 will additionally provide, among others, the following hole-fits:

- negate (_ :: Double)
- fromInteger (_ :: Integer)

In this work we use hole fitting for program repair by removing a potentially faulty sub-expression, leaving a hole in its place, and using valid hole-fits to suggest possible patches.

*Hole-Fit Plugins.* By default, GHC considers every identifier in scope as a potential hole-fit candidate, and returns those that have a type corresponding to the hole as hole-fits. However, users might want to add or remove candidates or run additional search using a different method or external tools. For this purpose, GHC added hole-fit plugins [17], which allows users to customize the behavior of the hole-fit search. When using GHC as a library, this also allows users to extract an internal representation of the hole-fits directly from a plugin, without having to parse the error message.

### 2.3 GenProg, Genetic Program Repair & Patch Representation

Search-based program repair centered mostly around the work of Le Goues et al. [34] in GenProg, which provided genetic search for C-program repair. One of the primary contributions was the representation of a patch as a change (addition, removal, or replacement) of existing statements. Genetic search is based around the mutation, creation and combination of chromosomes — the basic building bricks of genetic search. A chromosome of APR is a list of such changes rather than a full program (AST), making the approach lightweight. Utilizing changes is based on the Redundancy Assumption [32], i.e., assuming that the required statements for the fix already exists. The code might just use the wrong variable or miss a null-check to function properly. This assumption has been verified by Martinez et al. [41], showing that the redundancy assumption widely holds for inspected repositories. We adopted the patch-representation in our tool, but were able to weaken the redundancy assumption (see Section 3).

Since GenProgs much has been done in genetic program repair [11] mostly for Java. Particularly, Astor [39] enabled lots of research [61, 66, 69, 70] due to its modular approach, as well as real-world applications [59, 62]. This modularity, mostly the separation of fault localization, patch-generation and search is a valuable lesson learned by the community that we adopted in our tool. Compared to this body of research, our scientific contributions lie within the patch-generation and the search-space (see Section 3.1).

### 2.4 Repair of Formally Verified Programs & Program Synthesis

Another field of research dominant in functional programming is formal verification, in which mathematical methods are used to prove the correctness of programs. Due to its strengths it has been widely applied to various tasks, such as hardware-verification [26], cryptographic protocols [43] or lately smart contracts [6]. But formal verification has also been applied to the domain of program repair and synthesis [30, 60], and some languages can arguably be considered synthesizers around constraints (e.g. Prolog). Using specification-based synthesis in combination with a SAT solver can be effective, however the accuracy is closely tied to the completeness of the post-condition constraints [20]. For Haskell, these approaches revolve around liquid types, which enrich Haskell's type system with logical predicates that are passed on to an SMT solver during type checking [48, 56, 57, 64]. The existing approaches [21, 25, 50] focus primarily on the search-aspects of program synthesis due to the (infinite) search space and often perform a guided search similar to proof-systems. The approach used in the Lifty [51] language is especially relevant: Lifty is a domain-specific data-centric language in which applications can be statically and automatically verified to handle data specified as per declarative security policies, and suggest provably correct repairs when a leak of sensitive data is detected. Their approach differs in that they target a domain-specific language and focus on type-driven repair of security policies and not general properties. Another interesting approach is the TYGAR based Hoogle+ API discovery tool, where users can specify programming tasks using either a type, a set of input-output tests, or both, and get a list of programs composed from functions in popular Haskell libraries and examples of behavior [24]. It is however focused on API discovery and not program repair, although incorporating Hoogle+ into PropR is an interesting avenue for future work. The approach by Lee et al. [35] is in many ways similar; They also operate on student data and find very valuable insights from repair and identical challenges. The approach they developed (FixML) exploits typed holes to align buggy student programs with a given instructor-program based on symbolic execution. FixML is different as it requires a
gold standard, and synthesizes by type-enumeration after symbolic execution. To some degree, this is similar to our implementation of an exhaustive search. Semantics-based repair using symbolic-execution like that of Angelix [44] can be very effective in fixing real-world bugs, and uses symbolic expressions similarly to our typed-holes. However, there are some scalability concerns for symbolic execution, and while they can be mitigated using a carefully chosen number of suspicious expression and their derived angelic forests [44], they can also be mitigated using genetic algorithms and the more lightweight property-based analysis, motivating their usage in PropR. Compared to program synthesis, program repair is better able to take advantage of a “reasonable” baseline program from the developers.

In terms of utilizing specifications, the primary benefit of QuickCheck is the easy adoption for users, whereas formal verification comes with a high barrier of entry for most programs and requires dedicated and educated developers. To some degree we utilize formal verification due to the type-correctness-constraint that already greatly shrinks the search space — while we assert the functional correctness of a fix. To automate the repair process, PropR implements the search methods described in Section 3.4 to find and combine fixes for the whole program repair. An overview of the PropR test-localize-synthesize-rebind (TLSR) loop is provided in Figure 3. The circled numbers (i) in this section refer to the labels in Figure 3.

3.1 Compiler-Driven Mutation

To repair a program, we use GHC as a library in conjunction with custom-written hole-fit plugins as the basis for parsing source code, synthesizing fixes, as for instrumenting and running tests. PropR also parametrizes the tests so that local definitions can be exchanged with new ones, which allows us to observe the effectiveness of a fix. To automate the repair process, PropR implements the search methods described in Section 3.4 to find and combine fixes for the whole program repair. An overview of the PropR test-localize-synthesize-rebind (TLSR) loop is provided in Figure 3. The circled numbers (i) in this section refer to the labels in Figure 3.

\[
\text{len} :: \text{[a]} \rightarrow \text{Int} \\
\text{len} \left[\right] = 0 \\
\text{len} \text{xs} = \text{product} \$ \text{map (const (1 :: Int))} \text{xs} \\
\text{prop}_\text{abc} :: \text{Bool} \\
\text{prop}_\text{abc} = \text{len} \ "abc" = = 3 \\
\text{prop}_\text{dup} :: \text{[a]} \rightarrow \text{Bool} \\
\text{prop}_\text{dup} \text{x} = \text{len} \left(\text{x} \text{++} \text{x}\right) = = 2 \times \text{len} \text{x}
\]

Figure 4: An incorrect implementation of length. We map over the list and set all elements to \(1 \rightarrow \text{Int}\), and take the product of the resulting list. This means that \(\text{len}\) will always return \(1\) for all lists. An expected fix would be to take the sum of the elements, which would give the length of the list.

As a running example, imagine we had an incorrect implementation of a function to compute the length of a list called \(\text{len}\), with properties, as seen in Figure 4.

3.3 Compiler-Driven Mutation

To repair a program, we use GHC to parse and type-check the source into GHC’s internal representation of the type-annotated Haskell AST. By using GHC as a library, we can interact with GHC’s rich internal representation of programs without resorting to external dependencies or modeling. We determine the tests to fix by traversing the AST for top-level bindings with either a type (\(\text{TestTree}\)) or name (\(\text{prop}\)) that indicates it is a test (\(\text{Test}\)). We use GHC’s ability to derive data definitions for algebraic data types [17] and the Lens library [27] to generate efficient traversals of the Haskell AST.

To determine the function bindings to mutate, we traverse the ASTs of the properties and find variables that refer to top-level bindings in the current module (\(\text{Candidate Selection}\)). We call these bindings the targets.

In our example, both \(\text{prop}_\text{abc}\) and \(\text{prop}_\text{dup}\) use the local top-level binding \(\text{len}\) in their body, so our target set will be \(\{\text{len}\}\).

\[
\text{prop}_\text{abc} :: \text{([a]} \rightarrow \text{Int}) \rightarrow \text{Bool} \\
\text{prop}_\text{abc} \text{f} = \text{f} \ "abc" = = 3 \\
\text{prop}_\text{dup} :: \text{([a]} \rightarrow \text{Int}) \rightarrow \text{[a]} \rightarrow \text{Bool} \\
\text{prop}_\text{dup} \text{f} \text{x} = \text{f} \left(\text{x} \text{++} \text{x}\right) = = 2 \times \text{f} \text{x}
\]

Figure 5: The parametrized properties for \(\text{len}\)
Once we present a new typed hole in it, in a process we call perforation. When we then evaluate the module to an expression representing a fix candidate. Merging two fixes is done by simply merging the two maps. Candidate fixes in ProPR come in three variations, hole-fit candidates, expression candidates, and application candidates.

3.2 Fixes

A fix is represented as a map (lookup table) from source locations in the module to an expression representing a fix candidate. Merging two fixes is done by simply merging the two maps. Candidate fixes in ProPR come in three variations, hole-fit candidates, expression candidates, and application candidates.

Hole-fit Candidates. Using a custom hole-fit plugin, we extract the list of valid hole-fits for that hole, and now have a well-typed replacement for each expression in the target AST.

In an equation for ‘len’:

```
len xs = _ $ map (const (1 :: Int)) xs
```

Valid hole fits include

```
head :: [a] -> a
last :: [a] -> a
length :: Foldable t => t a -> Int
maximum :: (Foldable t, Ord a) => t a -> a
minimum :: (Foldable t, Ord a) => t a -> a
product :: (Foldable t, Num a) => t a -> a
sum :: (Foldable t, Num a) => t a -> a
```

Valid refinement hole fits include

```
fold1 (::_ :: Int -> Int -> Int)
```

Figure 8: Hole-fits for a perforation of `len`, where `product` has been replaced with a hole

We derive hole-fit candidates directly from GHC’s valid hole-fits, as seen in Figure 8, giving rise to the fixes in Figure 9. These take the form of an identifier (e.g., `sum`), or an identifier with additional holes (e.g., `fold1 _`) for refinement fits.

Since we synthesize only well-typed programs, we cannot use refinement hole-fits directly: the resulting program would produce a typed hole error. To use refinement hole-fits, we recursively synthesize fits for the holes in the refinement hole-fits up to a depth of 1.
In our example, we see in Figure 11 that whether they fit a given hole using machinery similar to GHC’s (excepting constants). However, in practical terms, the amount of valid hole-fit synthesis, but matching the type of an expression in-len7 xs
len7
...
len3 xs
len3
...
len1 xs
len1

Figure 9: Candidate fixes derived from the valid hole-fits in Figure 8. The location refers to product in len
configurable by the user. This means that we can generate e.g., fold1 (flip (¬)) when the depth is set to 1, and e.g., fold1 (flip (¬)) (flip (¬)) for a depth of 2, etc. By tuning the refinement level and depth, we could synthesize most Haskell programs (excepting constants). However, in practical terms, the amount of work grows exponentially with increasing depth.

To be able to find fixes that include constants \( \text{e.g., String or Int} \) or fixes that would otherwise require a high and deep refinement level, we search the program under repair for \textit{expression candidates} \cite{37}. These are injected into our custom hole-fit plugin and checked whether they fit a given hole using machinery similar to GHC’s valid hole-fit synthesis, but matching the type of an expression instead of an identifier in scope. In our example, these would include \( \delta, (\_ :: \text{Int}), (x + x) \), and more. For each expression candidate, we then check that all the variables referred to in the expressions are in scope, and that the expression has an appropriate type. We also look at \textit{application candidates} of the form \( (\_ x) \), where \( x \) is some expression already in the program, and \( \_ \) is filled in by GHC’s valid hole-fit synthesis. This allows us to find common data transformation fixes, such as \text{filter} (\text{not . null}).

Regardless of technical limitations, this approach can be considered a form of \textit{localized program synthesis} exploited for program repair. By using valid hole-fits, we can utilize the full power GHC’s type-checker when finding candidates and avoid having to model GHC’s ever-growing list of language extensions. This allows us to drastically reduce the search space to well-typed programs only.

3.3 Checking Fixes

Once we have found a candidate fix, we need to check whether they work. We apply a fix to the program by traversing the \text{AST}, and substituting the expression found in the map with its replacement. We

\[
\begin{align*}
\text{len1} [] & = 0 \\
\text{len1} \ x s &= \text{head} \ \&\ \text{map} \ (\text{const} \ (1 :: \text{Int})) \ x s \\
\ldots \\
\text{len3} [] & = 0 \\
\text{len3} \ x s &= \text{length} \ \&\ \text{map} \ (\text{const} \ (1 :: \text{Int})) \ x s \\
\ldots \\
\text{len7} [] & = 0 \\
\text{len7} \ x s &= \text{sum} \ \&\ \text{map} \ (\text{const} \ (1 :: \text{Int})) \ x s
\end{align*}
\]

Figure 10: New targets defined by applying the fixes in Figure 9 to the original \text{len}

do this for all targets, and obtain new targets where the locations of the holes have been replaced with fix candidates. For the given \text{len} example, the fixes in Figure 9 give rise to the definitions shown in Figure 10. We then construct a checking program that applies the parametrized properties and tests to these new target definitions and compile the result. A simplified example of this can be seen

\[
\begin{align*}
\text{PropR} \rightarrow \text{mapM} \ (\text{sequence} \\
\rightarrow \text{quickCheck} \ (\text{prop\'_abc \ len1}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_dup \ len1}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_abc \ len2}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_dup \ len2}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_abc \ len3}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_dup \ len3}) \\
\ldots \\
\rightarrow \text{quickCheck} \ (\text{prop\'_abc \ len7}) \\
\rightarrow \text{quickCheck} \ (\text{prop\'_dup \ len7}) 
\end{align*}
\]

\[
\begin{align*}
\rightarrow \text{evaluates to:} \\
\rightarrow ([\text{False, False, False}, [\text{True, True}],[\text{False, False}]
\rightarrow ([\text{False, False}, [\text{False, False}], [\text{True, True}]])
\end{align*}
\]

Figure 11: Checking our new targets from Figure 10

in Figure 11, though we do additional work to extract the results in PropR. It might be the case that the resulting program does not compile: as our synthesis is based on the types, we might generate programs that do not parse because of a difference in precedence (precedence is checked during renaming, after type-checking in GHC). We remove all those candidate fixes that do not compile, obtaining an executable that takes as an argument the property to run, and returns whether that property failed. We run this executable in a separate process: running it in the same process might cause our own program to hang due to a loop in the check. By running in a separate process, we can kill it after a timeout and decide that the given fix resulted in an infinite loop. After executing the program, we have three possible results: all properties succeeded; the program did not finish due to errors or timeout; or some properties failed \( \delta \). In our example, we see in Figure 11 that \text{len3} and \text{len7} pass all the properties, meaning that replacing \text{product} with \text{length} or \text{sum} qualifies as a repair for the program.

3.4 Search

Within PropR, we implemented three different search algorithms: \textit{random search}, \textit{exhaustive search}, and \textit{genetic search} \( \delta \).

All three algorithms share a common configuration: they all have a time budget (measured in wall clock time) after which they exit, and return the results (if any) that they’ve found.

For the \textit{genetic search}, PropR implements best practices and algorithms common to other tools such as Astor \cite{39} or EvoSuite \cite{15}. A mutation consists of either dropping a replacement of a fix, or adding a new replacement to it. The initial population is created by picking \( n \) random mutations. The crossover randomly picks cut points within the parent chromosomes, and produces offspring by swapping the parents’ genes around the cut points. We support environment-selection \cite{23} with an elitism-rate \( \delta \) for truncation. \textit{Elitism} means that we pick the top \( x\% \) percent of the fittest candidates for the next generation, filling the remaining \( (100 - x)\% \) with (other) random individuals from the population. We choose random pairs from the last population as parents and perform environment selection on the parents and their offspring. Our manual sampling of repairs-in-progress on the data points showed that genetic search requires high \textit{churn} in order to be effective: changing a single expression of the program usually failed more properties than it fixed. Hence, the resulting configurations for the experiment have a low elitism- and high mutation- and crossover-rate.

Within \textit{random search}, we pick (up to a configurable size) evaluated holes at random and pick valid hole-fits at random with
which to fill them. We then check the resulting fix and cache it. The primary reason for using random search is to show that the genetic search is an improvement over guessing. Nevertheless, Qi et al. [53] showed that random search sometimes can be superior to genetic search, further motivating its application. Besides, random search is a standard baseline in search-based software engineering to assess whether more "intelligent" search algorithms are needed for the problem under analysis.

For exhaustive search, we check each hole-fit in a breadth-first manner: first all single replacement fixes, then all two replacement fixes and so on until the search budget is exhausted. Exhaustive search is deterministic apart from inherent randomness in QuickCheck. We use exhaustive search to demonstrate the complexity of the problem, and to show that search is better than enumeration. The deterministic search pattern of exhaustive search would be ideal for a single fix problem such as our example.

The fitness for all searches is calculated as the failure rate number of failures , with a non-termination or errors treated as the worst fitness 1 and a fitness of 0 (all tests passing) marks a candidate patch. Such patches are removed from populations in genetic search and replaced by a new random element.

Within the test-localize-synthesize-rebind loop (Figure 3) we perform one generation of genetic search per loop, and after the selection of chromosomes the program is re-bound and coverage re-evaluated. The authors observed that this is a bit over-engineered for small programs — the fault localization did not greatly change when the programs had only a single failing property. As an optimization, we added a flag to skip the steps (5) to (7) in the loop to speed up the actual search. This configuration was enabled during experiments presented in Section 4. The exhaustive and random search do not perform any rebinding.

3.5 Looping and Finalizing Results

Looping. If there are still failing properties after an iteration of the loop, we apply the current fixes we have found so far to the targets and enter the next iteration of the loop (10), repeating the process with the new targets until all properties have been fixed, or the search budget runs out.

Finalizing and Reporting Results. After we have found a set of valid fixes that pass all the properties, we generate a diff for the original program based on the program bindings and the mutated targets constituting the fix (11). This way the resulting patches can be fed into other systems such as editors or pull requests.

4 EMPIRICAL STUDY

4.1 Research Questions

Given the concepts presented in Section 3, research interests are twofold: How well does the typed hole synthesis perform for APR, and what is the individual contribution of properties. As within the integral approach of PropR, the effects cannot truly be dissected; The only contributions that we can separate for distinct inspection is the use of properties, under which we will investigate the patches generated by PropR.

4.2 Dataset

The novel dataset stems from a student course on functional programming. Within the exercise, the students had to implement a calculator that parses a term from text, calculates results and derivations. While the overall notion is that of a classroom exercise, the problem nevertheless contains real-world tasks asserted by real-world tests. The calculator itself is a classic student-exercise,
3.4 Methodology / Experiment Design

To evaluate RQ1 and RQ2 we perform a grid experiment on the 45 configurations we make a repair attempt on every point in the dataset with the parameters presented in Table 1. For every of the 13 of 30 programs the anonymized data is provided in the reproduction package.

4 RESULTS

The following section answers the research questions in order and presents general information gained in the study. For every entry we performed Fisher exact test based on the repair per seed of every test suite. Each patch was named with a median of 3 patches per successful run. A visualization of the results can be seen in Figure 14 and Figure 15. For every run we performed a grid search test based on the given gold-standard. The conclusion of the discussion is also documented with a short statement. The manual test is also included with the statements.

The search budget starts after a brief initialization, as PropR allows for a maximum of 10 minutes search-budget was determined through probing. We utilize docker and limit every unit test to 300 lines of code (excluding tests) and have at least 5 top level definitions. These common file sizes for Haskell, e.g., PropR itself has an average of 200 LoC per file.

The threshold of 70 has been calculated after seeing 230 patches being generated, which is a sufficient sample for a p-value of 0.05 at an error rate of 10%.

The Vargha-Delaney test [63] to the given pairs of configurations. In the case of equality, a value of 0.5 means that algorithm A and B are equal. A value of 1 means that algorithm A is better than B in 0% of the cases, estimating a similar probability of dominance for future applications on similarly distributed data points. Note that a result of 0.0 does not mean there was no effect — the groups can still be significantly different.

For every run we performed a pairwise Wilcoxon-RankSum test [55] to see if the entries originate from the same population. The Wilcoxon test is a non-parametric test and does not make any assumption on data points to be correct despite not matching the sample-solution. Similarly, work by Nilizadeh et al. [46] utilizes formal verification overfit to unit tests and properties etc. We choose the Vargha-Delaney test, a value of e.g. 0.7 means that algorithm B is better than algorithm A in 70% of the cases, estimating a similar probability of dominance for future applications on similarly distributed data points. Note that a result of 0.0 does not mean there was no effect — the groups can still be significantly different.

To answer RQ1 we perform a pairwise Wilcoxon-RankSum test [49] on the data points grouped by their test configuration. The Wilcoxon test is a non-parametric test and does not make any assumption on data points being normally distributed. For every run we performed a pairwise Wilcoxon-RankSum test [55] to see if the entries originate from the same population. The Wilcoxon test is a non-parametric test and does not make any assumption on data points to be correct despite not matching the sample-solution. Similarly, work by Nilizadeh et al. [46] utilizes formal verification overfit to unit tests and properties etc. We choose the Vargha-Delaney test, a value of e.g. 0.7 means that algorithm B is better than algorithm A in 70% of the cases, estimating a similar probability of dominance for future applications on similarly distributed data points. Note that a result of 0.0 does not mean there was no effect — the groups can still be significantly different.
showed that 4 of the 13 repaired entries were significantly better in producing repairs with properties (E1, E3, E4, and E14 from Table 2).

A global Fisher exact test and Wilcoxon-RankSum test showed no statistical significant difference between the test suites (p-values of 10%-20%). Whether properties are beneficial is a highly specific topic, and we expect it more to be a matter whether the bug is properly covered by the test suite. We argue that properties can produce stronger test suites than unit tests, but whether they are applicable and well implemented is ultimately up to the developers.

Figure 14: Solved Entries per Test-Suite and Algorithm

Figure 14 shows genetic search outperforming exhaustive search in any test suite configuration, and most effectively for properties.

Figure 15: Venn-Diagram of Solved Entries per Suite

Figure 15 shows the overlap of solved entries by test suite. It shows that four entries were uniquely solvable by using only properties and one entry was uniquely solvable by the combined test suite. All entries solved by unit tests have also been solved by the properties. This does not necessarily imply that properties are better — the patches can still be overfit and are to be evaluated in RQ3.

Summary RQ1

Properties do not significantly help with producing patches. In our study, properties found unique patches that unit tests did not produce. The difference between results in genetic and exhaustive search were greatest for the properties.

RQ 2 — Repair Speed. We grouped the results per seed and compared the median time-to-first-result for each test suite. All two-way hypothesis-tests reported a significant p-value of less than 0.01, proving that there are significant differences in distributions.

In particular, we performed a test\(^2\) whether properties are faster than unit tests in finding patches, which was the case with a p-value of 0.02. The Vargha and Delaney effect size test showed an estimate of 0.28 which is considered a medium-effect size, showing that properties are faster than unit tests.

An overview of the time-to-first-result can be seen in Figure 16. We would like to stress that similar to some results of RQ3, the test suites’ speed seems to behave in such a way that the slowest and hardest test determines the magnitude of search. Properties do not have a significant overhead by design, which is positively surprising. The cost of their execution is compensated by the speedup in search.

Figure 16: Distribution of Time to First Patch per Entry

Summary RQ2

Genetic Search finds patches faster for properties than for unit tests. The combined test suite also yields combined search speed.

RQ 3 — Manual Inspection. From the sample of 70 patches the authors agreed on 49 to be overfit and 21 to be fit. Given the overall population of 230 and an error rate of 10%, we expect 62 to 76 of total patches to be correct. This results in a total non-overfit rate of 27% to 33%. In particular, patches in the sample found for unit tests were overfit in 85% of cases (19/23), but the properties were overfit in 64% of cases (21/33). The combined test suite overfit in 63% (9/14) cases.

These are not evenly distributed — some programs are only repaired overfit while others are always well fixed. Hence, we deduce that of the 13 Entries that have fixes, 3 to 4 have non-overfit repairs. This estimates an effective repair-rate of 10% or respectively 13%, which performs similar to the rates reported by Astor [38] (13%)

\(^2\)Wilcoxon-RankSum with less
and better than GenProg \cite{38}(1\%-4\%). Arja \cite{72} reports an effective repair rate of 8\% which we slightly outperform.

A typical example found by manual inspection was adding space-stripping to the addition-case of showExpr, as seen in Figure 17.

\begin{verbatim}
prop_unit_showBigExpr :: Bool
prop_unit_showBigExpr = strip (showExpr expr) == strip res
   where
   res = "sin (2.1 * x + 3.2) + 3.5 * x + 5.7"
   strip = filter (not . isSpace)
   arg = Expr.sin (add (mul (num 2.1) x) (num 3.2))
   expr = add (add (add (mul (num 3.5) x) (num 5.7)) arg
\end{verbatim}

Figure 18: The unit test corresponding to the fix in Figure 17

There is a single unit test (see Figure 18) to assert a printed addition without spaces. Within the patch only the "*" case gets repaired — this is due to the precedence of the expression which is correctly picked up. Hitherto, the change in the addition actually removes all white-space and correctly passes the test. This (actually) solves the unit test as expected and is therefore arguably not truly overfitting. Nevertheless, a developer would perform the string-stripping on all cases, not only on the addition. Here we see a shortcoming of the test suite — this would have not been possible if we had a property showing the printed output was not useless despite the overfitting: the suggested patches clearly show the shortcomings of the test suite. The proposed overfit patches help developers with fault localization and improving the test suite. In particular, as properties and unit tests are not exclusive, developers can consider a test-and-repair-driven approach, where they adjust the test suite and program iteratively assisted by the repair tool. We consider this approach attractive for class-room settings, where the programs are of lower complexity and allow for fast feedback. While we don’t expect PropR to be enough to solve the tasks for the students, it clearly shows where the problems in the tests or code are. Exploring class-room usage is an interesting direction for future work.

6 DISCUSSION

Overfitting on Properties. Similar to the overfitting of empty patches shown in RQ3, we had cases of patches where one or more failing properties exhibited inconsistent behavior, and an overfit patch was considered a successful patch. We observed an example that changed the simplification of multiplication to return 0 whenever a variable was in the term. This satisfies the property and should fail other properties such as multiplicative associativity, but (in rare cases) Quick-Check produced examples for the other properties that also evaluate to 0. This overfitting shows that a test suite is not better just because it is utilizing properties. APR-fitness is still only as good as the test suite — properties help define better test suites and well-written properties positively influence APR.

Exploitable Overfitting. A noticeable side effect of the tool is that if the repair overfits, it produces numerous (bad) patches, as can be seen from the number of generated proposals. However, the repairs’ output is not useless despite the overfitting: the suggested patches clearly show the shortcomings of the test suite. The proposed overfit patches help developers with fault localization and improving the test suite. In particular, as properties and unit tests are not exclusive, developers can consider a test-and-repair-driven approach, where they adjust the test suite and program iteratively assisted by the repair tool. We consider this approach attractive for class-room settings, where the programs are of lower complexity and allow for fast feedback. While we don’t expect PropR to be enough to solve the tasks for the students, it clearly shows where the problems in the tests or code are. Exploring class-room usage is an interesting direction for future work.

Drastically Increased Search-Space. Due to the novel approach to finding repair candidates, the search space drastically increased as compared to using existing expressions or statements only. This can be seen with the absence of random-search findings. Other studies showed at least some results with random search, sometimes reporting random search as most successful \cite{53}. As we find (many) patches with exhaustive search, the problems are generally solvable with small changes. This implies that the only reason for random search to yield no results is the increased search space.

This finding motivates further investigating the genetic search and its optimization for more complex problems that do not achieve timely results with exhaustive search. We consider it worthwhile to revisit existing datasets, that were not solvable due to the redundancy assumption in most repair tools, using a typed hole approach.

Transference to Java. As Java is the most prominent language for APR, it begs the question of which results can be transferred from Haskell into more mainstream approaches. Properties are supported
by JUnit-Plugins\(^3\) and can easily be added to any common test suite and build-tool. The positive effects of properties as presented in Section 5 only require Java programs with sufficient properties. However, the current Java-ecosystems are not utilizing properties; even less sophisticated JUnit-Features, such as parametrized tests, are not widely adopted. This is in stark contrast to functional programming communities, where tools like QuickCheck are popular.

The hole-fitting repair approach cannot be easily reproduced for Java; The JavaC, unlike GHC, is not intended to be used as a library. Nevertheless, Java is strictly typed and the basic hole-fitting approach can be integrated using meta-programming libraries like Spoon \([47]\). Many challenges remain: As Java’s methods are not pure functions, they cannot be just transplanted. Side effects can wreak havoc and just on a technical level polymorphism, that is involved in the counter-examples. However, it should be possible

4https://pandoc.org/

5https://www.haskell.org/alex/

3https://github.com/pholser/junit-quickcheck

Our analysis of 230 patches show that we reach an effective repair rate of 10%-13% (comparable to other state-of-the-art tools) but have a reduced rate of overfitting (from 85% to 63% when applying properties). The novel approach for patch generation produces a greatly increased search space and promising patches on manual inspection. We observed that properties did not increase the number of programs for which patches were found, but solutions were less overfit and found faster. Overfitting based on unit tests persisted into the combined test suite. Similarly, we have observed that properties can produce cases of overfitting too.

Our results attest to the stronger utilization of language-features for patch generation to overcome the redundancy assumption, i.e., only reusing existing code. Using the compiler’s information on types and scopes, the created patches are semantically correct and come in a much greater variety, which was reported as a missing feature for many APR tools. Our manual analysis motivates to use the generated patches (if not directly applicable) as guidance for fault localization or to improve the test suite.

8 CONCLUSION

The goal of this paper is to introduce a new automatic program repair approach based on types and compiler suggestions, in addition to utilizing properties for repair fitness and fault localization. To that end, we implemented PropR, a Haskell tool that utilizes GHC for patch-generation and can evaluate properties as well as unit tests. We provided a dataset with 30 programs and their unit tests and properties. On this dataset we performed an empirical study to compare the repair rates for different test suites and search-algorithms, and manually inspect the generated patches.

9 ONLINE RESOURCES

PropR is available on GitHub under MIT-license at https://github.com/Tritlo/PropR. The reproduction package which includes the data, evaluation and a binary of PropR is available on Zenodo https://doi.org/10.5281/zenodo.5389051

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