Mutagen: Coverage-Guided, Property-Based Testing using Exhaustive Type-Preserving Mutations

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1 INTRODUCTION

Random Property-Based Testing (RPBT) is a popular technique for finding bugs using executable specifications (properties) encoding the expected behavior of our system. Exemplified by frameworks Haskell's *QuickCheck* [?] and a pletora of ports of this tool on other programming languages [?], the most common approach is to instantiate the testing properties using independent, randomly generated inputs.

Users of *QuickCheck* (and RPBT in general) are well aware that one of the biggest challenges while using these frameworks is to provide suitable random data generators that are used to instantiate the testing properties. In some extreme cases, writing highly-tuned random generators capable of exercising every part of a complex system in a reasonable basis can take several thouthands person-hours of trial and error [?].

To alleviate this, there exist several techniques to automatically synthesize random data generators by reyfing the static information present in the codebase, e.g., data type definitions, application public interfaces (APIs), etc. These techniques, however, are unable to synthesize random generators capable of producing data satisfying complex invariants not easily derivable from the codebase, being randomly generated programs are common example of this problem. Moreover, automatically synthesized random generators offer particularly poor results when the testing properties are constrained by sparse preconditions. In this scenario, most of the generated tests are simply discarded before they can be used to test the main components of our system.

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FuzzChick [Lampropoulos et al. 2019] is a property-based testing framework for the Coq programming language that borrows ideas from the fuzzing community to generate highly structured values while using automatically derived generators. Notably, this tool is implemented as an extension of *QuickChick*, Coq's own reimplementation of *QuickCheck*.

Instead of continuously generating random invalid test cases from scratch, *FuzzChick* keeps a queue of interesting previously executed test cases that can be mutated using type-preserving transformations in order to produce new ones. Intuitively, mutating an interesting test case in a small way (at the data constructor level) has a much higher probability of producing a new interesting test case than generating a new one from scratch using a naïve generator. *FuzzChick* is likely to preserve the semantic structure of the mutated data, as mutations are applied directly at the data type level – the random AST in case of generating code.

This tool relies on execution traces to distinguish which test cases resulted interesting and are therefore worth mutating. Mutated test cases are considered interesting for mutation only when they produce new execution traces – any other test case is simply thrown away.

Of course, this hybrid technique is not meant to replace smart manually-written generators. In turn, it provides an acceptable solution that can be used in the early stages of development, and while a better test suite using manually-written generators is still under construction.

In this work, we take a close look at *FuzzChick* for opportunities to improve. Notably, we establish several aspects of its implementation that can be revised — some of these already being identified by the authors of *FuzzChick* on their original work. In particular: (1) *the type-preserving mutations produced by this tool are superficial and rely heavily on randomness to produce diverse mutants*, (2) *using normal queues can cause large delays when interesting values are enqueued frequently*, and (3) *using a power schedule to assing a certain mutation energy to each interesting test case requires fine tuning and can be hard to generalize to work well under different testing scenarios.*

Moreover, we replicated the IFC stack machine case study bundled with *FuzzChick* and observed a noticeable limitation: *after repeating each experiment 30 times, FuzzChick was only able to find 5 out of the 20 injected bugs with a 100% efficacy, the hardest one being found only around 13% of the time after an hour of testing*. Despite this limitation, Lampropoulos et al. show that *FuzzChick* is far better than using normal random testing coupled with naïve random generators by comparing the mean-time-to-failure (MTTF) against *QuickChick*. However, we believe that a proper evaluation ought to use the failure rate as an important metric when comparing RPBT tools.

In this work we introduce Mutagen, a RPBT tool implemented in Haskell that build upon the basic idea behind *FuzzChick*, i.e., code instrumentation and type-preserving mutations.

Unlike *FuzzChick*, mutations in Mutagen are applied *exhaustively*. This is, given an interesting, previously executed test case, our tool precomputes and schedules every possible type-presserving mutation that can be applied to it. This approach has two inherent advantages when compared to *FuzzChick*. On one hand, mutations do not rely on randomness to be generated. Instead, every subexpression of the input test case is mutated on the same basis, which guarantees that no interesting mutation is left behind due to randomness. On the other hand, scheduling mutations exaustively eliminates the need of using a power schedule to assign a given mutation energy to each input test case.

Notably, *scheduling mutations exhaustively within an input test case does not mean that mutations are exhaustive by themselves.* Our tool distinguishes two kinds of mutations, those that can be computed purely, yielding a single mutated value; and those that can be obtained non-deterministically. Pure mutations encode transformations that can be done by swapping data constructor variants or rearranging subexpressions, whereas non-deterministic (random) mutations are useful to represent transformations over large enumeration types, e.g., numbers, characters, etc. In this setting, random mutations let us selectively escape the exhaustiveness of our tool by randomly sampling a small random generator a reduced number of times. This way, our tool avoids, for instance, mutating an given integer into every other integer in the 32 bits range.

Additionally, the testing loop of our tool includes implements two heuristics that help finding bugs faster. In first place, Mutagen uses first-in first-out (FIFO) scheduling with priority to enqueue interesting test cases for mutation. This scheduling algorithm is indexed by the novelty of the test case with respect to the ones already seen. In this light, test cases that discover new parts of the code earlier during execution are given a higher priority while picking the next mutated test case. Additionally, our scheduling lets the testing loop jump back and forth between scheduled test cases as soon as a new more interesting one is enqueued for mutation, eliminating potential delays when the mutation queues grow large.

The second heuristic is used to tune the number of times our tool samples random mutants, i.e., those corresponding to large enumeration types as described above. For this, we keep track of how often we generate interesting test cases. If this frequency suddenly stalls, Mutagen automatically resets the testing loop increasing the amount of times we sample such mutants. This automatically finds a suitable value for this external on the fly.

To validate our ideas, we use two main case studies (described in detail in Section 5): the IFC stack machine used by Lampropoulos et al. on their original work, and a WebAssembly engine written in Haskell. In both case studies, we additionally compare the effect of the heuristics implemented on top of the base testing loop of Mutagen. In the IFC stack machine case study, we compare *FuzzChick* against different variants of our tool, where our results (Section 6) indicate that Mutagen outperforms *FuzzChick* both in terms of time to failure and failure rate. On the other hand, our WebAssembly case study shows the performance of our tool in a more realistic scenario. There, Mutagen is capable of reliaby finding 15 planted bugs in the validator and interpreter, as well as 3 previously unknown bugs that flew under the radar of the existing unit test suite of this engine. All in all, our evaluation encompass ?? hours of CPU time and suggest that testing mutants exhaustively is an appealing technique for finding bugs fast without sacrificing efficacy.

Finally, we discuss related work on Section 7 and conclude on Section 8.

2 BACKGROUND

In this section we briefly introduce the concept of Property-Based Testing along with *QuickCheck*, one of the most popular tools of this sort and often used as the baseline when comparing PBT algoritms. Moreover, we describe in detail the ideas and limitations behind *FuzzChick*, which served as the foundation while designing Mutagen.

2.1 Property-Based Testing and *QuickCheck*

Property-based testing is a powerful technique for finding bugs without having to write test cases by hand. Originally introduced by **?** in tandem with the first version of *QuickCheck*, this technique focuses on aiming the developer's efforts into testing systems via executable specifications using randomly generated inputs. Moreover, tools like *QuickChick* and Isabelle's *QuickCheck* demonstrate that PBT can also be used in the formal verification realm. There, one can quickly spot bugs in system specifications before directing the efforts into pointlessly trying to prove bogus propositions.

In the simplest form, there are four main elements the user needs to provide in order to perform property-based testing on their systems:

- one or more *executable properties*, often implemented simply as a boolean predicates,
- *random data generators*, used to repeatedly instantiate the testing properties,
- *printers*, used to show the user the random inputs that falsify some testing property (the counterexample) whenever a bug is found, and

- *shrinkers*, to minimize counterexamples making them easier to understand by humans.

In this work we focus solely on the first two elements introduced above, namely the testing properties and the random data generators used to feed them. Printers and shrinkers, for the most part, can be obtained automatically using generic programming capabilities present in the compiler, and although being crucial for the testing process as a whole, their role becomes irrelevant when it comes to *finding* bugs.

Perhaps the simplest PBT technique is to repeatedly generate random inputs and instantiate the testing properties until they either get falsified by a counterexample, or we ran a sufficiently large amount of tests — suggesting that the properties holds. *QuickCheck* implements a testing loop that closely follows this simple idea, which is outlined in Algorithm 1, where *P* is the testing property, *N* is the maximum number of tests to perform, and *gen* is the random generator to be used to instantiate *P*.

Algorithm 1: *QuickCheck* Testing Loop

```
Function Loop(P, N, gen):
    i ← 0
    while i < N do
        x ← Sample(gen)
        if not P(x) then return Bug(x)
        i ← i+1
    return Ok
```

To illustrate this technique, let us focus on the same motivating example used by Lampropoulos et al., who propose a simple property defined over binary trees. Such data structure can be defined in Haskell using a custom data type with two data constructors for leaves and branches respectively:

```
data Tree a = Leaf a | Branch (Tree a) a (Tree a)
```

The type parameter `a` indicates that trees can be instantiated using any other type as payload, so the value `Leaf Bool` has type `Tree Bool`, whereas the value `Branch (Leaf 1) 2 (Leaf 3)` has type `Tree Int`. Then, we can define tree reflections using a simple recursive function that pattern matches against the two possible constructors, inverting the order of the subtrees whenever it encounters a branch:

```
mirror :: Tree a -> Tree a
mirror (Leaf x)       = Leaf x
mirror (Branch l x r) = Branch (mirror r) x (mirror l)
```

Later, a reasonable requirement to assert for is that `mirror` must be *involutive*, i.e., reflecting a tree twice always yields the original tree. We can simply capture this property using a boolean predicate written as a normal function:

```
prop_mirror :: Tree Int -> Bool
prop_mirror t = mirror (mirror t) == t
```

For simplicity, here we instantiate the tree payload with integers, altough this predicate should clearly hold for any other type with a properly defined notion of equality as well.

With our simple specification in place, the last missing piece is a random generator of trees. In *QuickCheck*, this is usually done via the type class mechanism, instantiating the `Arbitrary` type class, providing a random generator as the implementation of the overloaded `arbitrary` operation:

```
instance Arbitrary a => Arbitrary (Tree a) where
  arbitrary = sized gen
    where
      gen 0 = do { x <- arbitrary; return (Leaf x) }
      gen n = oneof [ do {x <- arbitrary; return (Leaf x) }
                    , do {l <- gen (n-1); x <- arbitrary; r <- gen (n-1); return (Branch l x r)} ]
```

Let us break this definition into parts. The first line states that we will provide an `Arbitrary` instance for trees with payload of type `a`, provided that values of type `a` can also be randomly generated. This allows us to use `arbitrary` to generate `a`'s inside the definition of our tree generator.

Moreover, *QuickCheck* internally keeps track of the *maximum generation size*, a parameter that can be tuned by the user in order to limit the size of the randomly generated values. Our definition exposes this internal parameter via *QuickCheck*'s `sized` combinator, allowing us to parameterize the maximum size of the randomly generated trees. If the generation size is zero (`gen 0`), our generator is limited to produce just leaves with randomly generated payloads. In turn, when the generation size is strictly positive (`gen n`), the generator is able to perform a random uniform choice between generating either a single leaf or a branch. When generating branches, the generator calls itself recursively in order to produce random subtrees (`gen (n-1)`). Notice the importance of reducing the generation size on each recursive call. This way we ensure that randomly generated trees using a generation size `n` are always finite and have at most `n` levels.

Finally, we are ready to let *QuickCheck* test `prop_mirror` against a large number of inputs (100 by default) produced by our brand new random tree generator:

```
quickCheck prop_mirror
+++ OK, passed 100 tests.
```

Should we mistakenly introduce a bug in `mirror`, e.g., by dropping the right subtree altogether:

```
mirror (Branch l x r) = Branch (mirror l) x (mirror l)
```

then *QuickCheck* will quickly falsify `prop_mirror`, reporting a minimized counterexample that we can use to find the root of the issue:

```
quickCheck prop_mirror
*** Failed! Falsified (after 2 tests and 2 shrinks):
Branch (Leaf 0) 0 (Leaf 1)
```

At this point, it is clear that the *quality* of our random generators is paramount to the performance of the overall PBT process. Random generators that rarely produce interesting values will fail to trigger bugs in our code, potentially leaving entire parts of the codebase virtually untested.

Recalling our tree generator, the reader (far from mistaken) might already have imagined better ways for implementing it. For most practical purposes, this generator is in fact quite bad. However, it follows a simple type-directed fashion, and it is a good example of what to expect from a random generator synthesized automatically using a process that knows very little about the values to be generated apart from their (syntactic) data type structure.

As introduced earlier, there exist multiple tools that can automatically derive better random generators solely from the static information present in the codebase. Sadly, these tools lack the domain knowledge required to generate random data with complex invariants — especially those present in programming languages like well-scopedness and well-typedeness.

In particular, automatically derived generators are remarkably uneffective when used to test properties with sparse preconditions. Let us continue with the example by Lampropoulos et al. to illustrate this problem in more detail. For this, consider that we want to use our `Tree` data type to encode binary-search trees (BST) — this requires some minor tweaks in practice. Then, given a predicate `isBST` that asserts if a tree satisfies the BST invariants, we might want to use it as pre- and post-condition to assert that BST operations like `insert` preserve them:

```
prop_bst_insert :: Tree a -> a -> Bool
prop_bst_insert t a =
  isBST t ==> isBST (insert a t)
```

Attempting to test this property using *QuickCheck* does not work well:

```
quickCheck prop_bst_insert
*** Gave up! Passed only 44 tests; 1000 discarded tests.
```

QuickCheck discards random inputs as soon as it finds they do not pass the precondition (`isBST t`). Sadly, most of the inputs generated by our naïve generator suffer from this problem, and the interesting part of the property (`isBST (insert a t)`) is tested very sporadically as a result.

At this point it is reasonable to think that, to obtain the best results when using PBT over complex systems, one is forced to put a large amount of time on developing manually-written generators. In practice, that is most often the case, no automatic effort can beat a well-thought manually-written generator that produces interesting complex values and finds bugs in very few tests. Not all is lost, however. It is still possible to obtain acceptable results automatically by incorporating dynamic information from the system under test into the testing loop. The next subsection introduces the clever technique used by *FuzzChick* to find bugs in complex systems while using simple automatically derived random generators.

2.2 Coverage-Guided Property-Based Testing with *FuzzChick*

To alleviate the problem of testing properties with sparse preconditions while using simple automatically derived random generators, *FuzzChick* introduces *coverage-guided property-based testing* (CGPT) by enhancing the testing process with two key characteristics: (1) *target code instrumentation*, to capture execution information from each test case; and (2) *high-level, type-preserving mutations*, to produce syntactically valid test cases by altering existing ones at the datatype level.

Using code instrumentation in tandem with mutations is a well-known technique in the fuzzing community. Generic fuzzing tools like AFL, libFuzzer or HonggFuzz, as well as language-specific ones like Crowbar use execution traces to recognize interesting test cases, e.g, those that exercise previously undiscovered parts of the target code. Later, such tools use generic mutators to combine and produce new test cases from previously executed interesting ones. *FuzzChick*, however, does this in a clever way. Instead of mutating any previously executed test case that discovers a new part of the code, *FuzzChick* integrates these fuzzing techniques into the PBT testing loop itself.

Since it is possible to distinguish semantically valid test cases from invalid ones, i.e., those passing the sparse preconditions of our testing properties as opossed to those that are discarded early, *FuzzChick* exploits this information in order to focus the testing efforts into mutating valid test cases with a higher priority than those that were discarded.

In addition, high-level mutators are better suited for producing syntactically valid mutants, avoiding the time wasted by using generic low-level mutators that act at the "serialized" level and know very little about the structure of the generated data, thus producing syntactically broken mutants most of the time. This grammar-aware mutation technique has shown to be quite useful when fuzzing systems accepting structurally complex inputs. Tools like Criterion, XSmith and LangFuzz use existing grammars to tailor the generic mutators to the specific input structure used by the system under test. In *FuzzChick*, external grammars are not required. The datatypes used by the inputs of the testing properties already describe the structure of the random data we want to mutate in a concrete manner, and specialized mutators acting at the data constructor level can be automatically derived directly from their definition.

The next subsections describe *FuzzChick*'s testing loop and type-preserving mutations in detail.

2.2.1 *Testing loop.*

Outlined in Algorithm 2, the process starts by creating two queues, *QSucc* and *QDisc* for valid and discarded previously executed test cases, respectively. Enqueued values are stored along with a given mutation energy, that controls how many times a given test case can be mutated before being finally discared.

Once inside of the main loop, *FuzzChick* picks the next test case using a simple criterion: if there are valid values enqueued for mutation, it picks the first one, mutates it and returns it, decreasing its energy by one. If *QSucc* is empty, then the same is attempted using *QDisc*. If none of the mutation queues contain any candidates, *FuzzChick* generates a new value from scratch. This selection process is illustrated in detail in Algorithm 3.

Algorithm 2: *FuzzChick* Testing Loop

```
Function Loop(P, N, gen, mut):
    i $\leftarrow$ 0
    TLog, QSucc, QDisc $\leftarrow \varnothing$
    while i < N do
        x $\leftarrow$ Pick(QSucc, QDisc, gen, mut)
        (result, trace) $\leftarrow$ WithTrace(P(x))
        if not result then return Bug(x)
        if Interesting(TLog, trace) then
            e $\leftarrow$ Energy(TLog, x, trace)
            if not Discarded(result) then
                Enqueue(QSucc, (x, e))
            else
                Enqueue(QDisc, (x, e))
        i $\leftarrow$ i+1
    return Ok
```

Algorithm 3: *FuzzChick* Seed Selection

```
Function Pick(QSucc, QDisc, gen, mut):
    if not Empty(QSucc) then
        (x,e) $\leftarrow$ Deque(QSucc)
        if e > 0 then
            PushFront(QSucc, (x, e-1))
        return Sample(mut(x))
    else if not Empty(QDisc) then
        (x,e) $\leftarrow$ Deque(QDisc)
        if e > 0 then
            PushFront(QDisc, (x, e-1))
        return Sample(mut(x))
    else return Sample(gen)
```

Having selected the next test case, the main loop proceeds to execute it, capturing both the result (passed, discarded, or failed) and its execution trace over the system under test. If the test case fails, it is immediately reported as a bug. If not, *FuzzChick* evaluates whether it was interesting (i.e., it exercises a new path) based on its trace information and the one from previously executed test cases (represented by *TLog*). If the test case does in fact discover a new path, it is enqueued at the end of its corresponding queue, depending on whether it passed or was discarded. This process alternates between generation and mutation until a bug is found or we reach the test limit.

The energy assigned to each test case follows that of AFL's power schedule: more energy to test cases that lead to shorter executions, or that discover more parts of the code. Moreover, to favour mutating interesting valid test cases, they get more energy than those that were discarded.

2.2.2 Type-preserving mutations. Mutators in *FuzzChick* are no more than specialized random generators, parameterized by the original input to be mutated. They use a simple set of mutation operations that are randomly applied at the datatype level. In simple terms, these operations encompass (1) *shrinking the value*, replacing its top-level data constructor with one that contains a subset of its fields, reusing existing subexpressions; (2) *growing the value*, replacing its top-level data constructor with one that contains a superset of its fields, reusing existing subexpressions and generating random ones when needed; (3) *returning a subexpression of the same type*; and (4) *mutating recursively*, applying a mutation operation over an immediate subexpression.

Fig. 1 illustrates a *FuzzChick* mutator for our previously used `Tree` data type example. Since trees are parametric, for clarity this definition is also parameterized by a mutator for the payload (`mutate_a`), although this can be abstracted away using the type class system.

In this mutator, branches can be shrinked into leaves by dropping the subtrees, whereas leaves can grow into branches, by reusing the payload and generating two random subtrees. Moreover, branches can be replaced with one of their subtrees. Finally, mutations can be recursively applied over both the payload and the subtrees. At the top level, all these operations are put together using the `oneof` combinator that randomly picks one of them with uniform probability.

```
mutate_tree :: (a -> Gen a) -> Tree a -> Gen (Tree a)
mutate_tree mutate_a (Leaf x) =
  oneof [ do { x' <- mutate_a x; return (Leaf x')}                      -- Mutate recursively
        , do { l <- arbitrary; r <- arbitrary; return (Branch l x r) } ] -- Grow constructor
mutate_tree mutate_a (Branch l x r) =
  oneof [ return l                                                       -- Return subexpression
        , return r                                                       -- Return subexpression
        , return (Leaf x)                                                -- Shrink constructor
        , do { l' <- mutate_tree l; return (Branch l' x r) }             -- Mutate recursively
        , do { x' <- mutate_a    x; return (Branch l x' r) }             -- Mutate recursively
        , do { r' <- mutate_tree r; return (Branch l x r') } ]           -- Mutate recursively
```

Fig. 1. *FuzzChick* mutator for the Tree data type.

2.2.3 Limitations of FuzzChick. Lampropoulos et al. demonstrated empirically that *FuzzChick* lies comfortably in the middle ground between using pure random testing with naïve automatically derived random generators and complex manually-written ones. Their results suggest that CGPT is an appealing technique for finding bugs while still using a mostly automated workflow.

However, the authors acknowledge that certain parts of its implementation have room for improvement, especially when it comes to the mutators design. In tandem with the lack of efficacy observed when replicating the evaluation of the IFC stack machine case study, these observations led us to consider three main aspects of *FuzzChick* that can be improved upon — and that constitute the main goal of this work. In no particular order:

Mutators distribution: if we inspect the mutator defined in Fig. 1, there are two compromises that the authors of *FuzzChick* adopted for the sake of simplicity. On one hand, deep recursive mutations are very unlikely, since their probability decreases multiplicatively with each recursive call. For instance, mutating a subexpression that lies on the third level of a Tree happens with a probability smaller than $(1/6)^3$ =∼ 0.0046, and this only worsens as the type of the mutated value becomes more complex. Hence, *FuzzChick* mutators can only be effectively used to transform to shallow data structures, potentially excluding interesting applications that might require producing deeper valid values, e.g., programming languages, network protocols interactions, etc. Ideally, mutations should be able to happen on every subexpression of the input seed in a reasonable basis.

On the other hand, using random generators to produce neeeded subexpressions when growing data constructors can be dangerous, as we are introducing the very same "uncontrolled" randomness that we wanted to mitigate in the first place! If the random generator produces an invalid subexpression (something quite likely), this might just invalidate the whole mutated test case. We believe that growing data constructors needs to be done carefully. For instance, by using just a minimal piece of data to make the overall mutated test case type correct. If that mutated test case to be interesting, that subexpression can always be mutated later.

Enqueuing mutation candidates: FuzzChick uses two single queues for keeping valid and discarded mutation candidates. Whenever a new test case is found interesting, it is placed *at the end of its corresponding queue*. If this test case happens to have discovered a whole new portion of the target code, it will not be further mutated until the rest of the queue ahead of it gets processed. This can limit the effectiveness of the testing loop if the queues tend to grow more often than they tend to shrink, as interesting mutation candidates can get buried at the end of a long queue that only exercises the same portion of the target code. In the extreme case, they might not processed at all within the testing budget. Ideally, one would like a mechanism that prioritizes mutating test cases that discovers new portions of the code right away, and that is capable of jumping back and forth from mutation candidates whenever this happens. We show in Section 4 how this can be achieved by analyzing the execution information in order to prioritize test cases with novel execution traces.

Power schedule: It is not clear how the power schedule used to assign energy to each mutable test case in *FuzzChick* works in the context of high-level type-preserving mutations. If it assigns too much energy to certain not-so-interesting seeds, some bugs might not be discovered in a timely basis. Conversely, assigning too little energy to interesting test cases might cause that some bugs cannot be discovered at all unless the right mutation happens within the small available energy window — randomly generating the same test case later on does not help, as it becomes uninteresting based on historic trace information.

To keep the comparison fair, the authors replicated the same power schedule configuration used in AFL. However, AFL uses a different mutation approach that works at the bit level. This raises the question about what is the best power schedule configuration when using a high-level mutation approach — something quite challenging to characterize in general given the expressivity of the data types used to drive the mutators.

The next section introduces Mutagen, our CGPT tool written in Haskell that aims to tackle the main limitations of *FuzzChick* using an exhaustive mutation approach that requires very little randomness and no power schedule.

3 MUTAGEN: TESTING MUTANTS EXHAUSTIVELY

In this section we describe the base ideas behind Mutagen, our CGPT tool written in Haskell. On top of them, Section 4 introduces heuristics that help finding bugs faster in certain testing scenarios.

In constrast with *FuzzChick*, Mutagen does not employ a power schedule to assign energy to mutable candidates. In turn, it resorts to mutate them in an exhaustive and precise basis, where (1) each subexpression of a mutation candidate is associated with a set of deterministic mutations, and (2) for every mutable subexpression, each of these mutations is evaluated *exactly once*. There is a small exception to this rules that we will introduce soon.

This idea is inspired by exhaustive bounded testing tools like SmallCheck (in Haskell) or Korat (in Java), that produce test cases exhaustively. In simple words, such tools work by enumerating all possible values of the datatypes used in the testing properties, and then executing them from smaller to larger until a a bug is found, or a certain size bound is reached. The main problem with this approach is that the space of all possible test cases often grows exponentially as we increment the size bound, and the user experiences what it looks like "hitting a wall", where no larger test cases can be evaluated until we exhausted all the immediately smaller ones [?]. In consequence, such tools can only be applied to relatively simple systems, where the space of inputs does not grow extremely fast.

Not to be confused by these tools, in Mutagen we do not enumerate all possible test cases exhaustively. Mutagen uses random generators to find interesting initial seeds, and only then proceeds to execute all possible mutations. Moreover, these mutants will be mutated further only if they discover new paths in the target code, so the testing loop automatically prunes the space of test cases that are worth mutating.

3.1 Exhaustive Mutations

To describe Mutagen's testing loop, we first need to introduce the mechanism used for testing mutations exhaustively. In contrast to *FuzzChick*, where mutators are parameterized random generators, in Mutagen we define mutations as the set of mutants that can be obtained by altering the input value at the top-level (the root). In Haskell, we define mutations as:

```
mutate (Leaf x)       = [ PURE (Branch def x def) ]   -- Swap constructor
mutate (Branch l x r) = [ PURE l, PURE r              -- Return subexpression
                        , PURE (Leaf x)               -- Swap constructor
                        , PURE (Branch l x l)         -- Rearrange subexpressions
                        , PURE (Branch r x r)         -- Rearrange subexpressions
                        , PURE (Branch r x l) ]       -- Rearrange subexpressions
```

Fig. 2. Mutagen mutator for the `Tree` data type.

```
type Mutation a = a -> [Mutant a]
```

Where `Mutants` come in two flavours, pure and random:

```
data Mutant a = PURE a | RAND (Gen a)
```

Pure mutants are used most of the time, and encode simple deterministic transformations over the top-level data constructor of the input — recursive mutations will be introduced soon. These tranformation can: (1) return an immediate subexpression of the same type as the input; (2) swap the top-level data constructor with any other constructor of the same type, reusing existing subexpressions; and (3) rearrange and replace fields using existing ones of the same type. To illustrate this, Fig. 2 outlines a mutator for the `Tree` data type. Notice how this definition simply enumerates mutants that transform the top-level data constructor, hence no recursion is needed here. Moreover, notice how a default value (`def`) used to fill the subtrees when transforming a leaf into a branch. This value corresponds to the smallest value we can construct in order for the mutant to be type-correct. In practice (`def = Leaf def`), where the inner `def` is the smallest value of the payload — we use the type class system to abstract this complexity away in our implementation. Using a default smallest value is again inspired by exhaustive bounded testing tools, and avoids introducing unnecesary randomness when growing data constructors.

At this point, the reader might consider: what about large enumeration types like integers or characters? Does Mutagen transform them exaustively too? *Certainly not.* Random mutants serve as a way to break exhaustiveness when mutating values of large enumeration types. Instead of trying every possible integer or character, we resolve in using a random generator and sample a small amount of values from it — the precise amount is a tunable parameter of Mutagen. This way, a mutator for integers simply becomes:

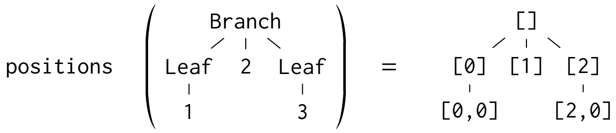
```
mutate n = [ RAND arbitrary ]
```

3.1.1 Mapping top-level mutations everywhere. So far we defined mutations that transform the root of the input. Now it is time to apply these mutations to every subexpression as well. To do so, we will use two functions that can also be derived from the data type definition.

In first place, a function `positions` traverses the mutable candidate and builds a multi-way tree of mutable positions. These positions are essentially a list of indices encoding the path from the root to every mutable subexpression. For instance, the positions of a `Tree` are computed as follows:

```
positions (Leaf x)       = node [ (0, positions x) ]
positions (Branch l x r) = node [ (0, positions l), (1, positions x), (2, positions r) ]
```

In this light, the mutable positions of the value `Branch (Leaf 1) 2 (Leaf 3)` are:



Later, given a desired position to mutate within a candidate, we define another function `inside` that precisely finds the subexpression corresponding to it and applies the mutation. A slightly simplified version of this function for the `Tree` datatype is as follows:

```
inside []       x              = mutate x
inside (0 : pos) (Leaf x)      = [ Leaf x'       | x' <- inside pos x ]
inside (0 : pos) (Branch l x r) = [ Branch l' x r | l' <- inside pos l ]
inside (1 : pos) (Branch l x r) = [ Branch l x' r | x' <- inside pos x ]
inside (2 : pos) (Branch l x r) = [ Branch l x r' | r' <- inside pos r ]
```

This function simply traverses the desired position, calling itself recursively until it reaches the desired subexpression, where the mutation can be applied locally at the top-level (case `inside [] x`). The rest of the function takes care of unwrapping and rewrapping the intermediate subexpressions and is not partically relevant for the point being made.

3.2 Testing loop

Having the exhaustive mutation mechanism in place, we can finally introduce the base testing loop used by Mutagen. This is outlined in Algorithm 5. As it can be observed, we closely follow *FuzzChick*'s testing loop, using qtwo queues to keep mutant candidates, and enqueueing and retrieving interesting test cases from them before falling back to random generation.

The main difference lies in that we precompute all the mutations of a given mutation candidate before enqueueing them. These mutations are put together into lists that we call *mutation batches* — one for each mutation candidate. To initialize a mutation batch (outlined in Algorithm 4), we first flatten all the mutable positions of the input value in level order (recall that positions are stored as a multi-way tree). Then, we iterate over all of them and retrieve all the mutants defined for each subexpression. For each one of these, there are two posible cases: (1) if it is a pure mutant carrying a concrete mutated value, we enqueue it into the mutation batch directly; otherwise (2) it is a random mutant that carries a random generator with it (e.g., a numeric subexpression), in which case we sample and enqueue *R* random values using this generator, where *R* is a parameter set by the user. At the end, we simply return the accummulated batch.

Algorithm 4: Mutants Initialization

```
Function Mutate(x, mut, R):
  muts ← ∅
  for pos in Flatten(Positions(x)) do
    for mutant in Inside(pos, mut, x) do
      switch mutant do
        case PURE $\hat{x}$ do
          Enqueue($\hat{x}$, muts)
        case RAND gen do
          repeat R times
            $\hat{x}$ ← Sample(gen)
            Enqueue($\hat{x}$, muts)
  return muts
```

Finally, the seed selection algorithm (Algorithm 6) simply selects the next test case using the same criteria as *FuzzChick*, prioritizing valid candidates over discarded ones, falling back to random generation when both queues are empty. Since mutations are precomputed, this function only needs to pick the next test case from the current batch, until it becomes empty and can switch to the next precomputed one in line.

Another small difference between Mutagen and *FuzzChick* is the criteria for enqueuing discarded tests. We found that, especially for large data types, the queue of discarded candidates tends to grow disproportionately during testing, making them hardly usable and consuming large amounts of memory. To improve this, we resort to mutate discarded tests cases only when we have some evidence that they are "almost valid." For this, each mutated test case remembers whether its parent (the original test case they derive from after being mutated) was valid. Then, we enqueue discarded test cases only if they meet this condition. As a result, we fill the discarded queue with lesser but

Algorithm 5: Mutagen Testing Loop

```
Function Loop(P, N, R, gen, mut):
    i ← 0
    TLog, QSucc, QDisc ← ∅
    while i < N do
        x ← Pick(QSucc, QDisc, gen)
        (result, trace) ← WithTrace(P(x))
        if not result then return Bug(x)
        if Interesting(TLog, trace) then
            if not Discarded(result) then
                muts ← Mutate(x, mut, R)
                Enqueue(QSucc, muts)
            else if Passed(Parent(x)) then
                muts ← Mutate(x, mut, R)
                Enqueue(QDisc, muts)
        i ← i+1
    return Ok
```

Algorithm 6: Mutagen Seed Selection

```
Function Pick(QSucc, QDisc, gen):
    if not Empty(QSucc) then
        muts ← Deque(QSucc)
        if Empty(muts) then
            Pick(QSucc, QDisc, gen)
        else
            PushFront(QSucc, Rest(muts))
            return First(muts)
    if not Empty(QSucc) then
        muts ← Deque(QSucc)
        if Empty(muts) then
            Pick(QSucc, QDisc, gen)
        else
            PushFront(QSucc, Rest(muts))
            return First(muts)
    else return Sample(gen)
```

much more interesting mutation candidates. Moreover, this can potentially help introducing *2-step mutations*, where an initial mutation breaks a valid test case in a small way, it gets enqueued as discarded, and later a subsequent mutation fixes it by changing a different subexpression.

The next section introduces two heurisitics we added to the base testing loop of Mutagen based on the limitations we found in *FuzzChick*.

4 MUTAGEN HEURISTICS

In this section we introduce two heuristics implemented on top of the base testing loop of our tool. Mutagen enables them all by default, although they can be individually disabled by the user if deemed appropriate.

4.1 Priority FIFO Scheduling

This heuristic tackles the issue of enqueuing novel mutation candidates at the end of (possibly) long queues of not-so-interesting previously executed ones.

FuzzChick uses AFL instrumentation under the hood, which in turn uses an *edge coverage* criteria to distinguish novel executions and to assign each mutation candidate a given energy. In contrast, execution traces Mutagen represent the *path* in the code taken by the program, as opposed to just the set of edges traversed in the control-flow graph (CFG). Using this criteria lets us gather precise information from the each new execution. In particular, we are interested in the *depth* where each new execution branches from already seen ones. Our assumption here is that test cases that differ (branch) at shallower depths from the ones already executed are more likely to discover completely new portions of the code under test, and hence we want to assign them a higher priority.

In this light, every time we insert a new execution path into the internal trace log, we calculate the number of new nodes that were executed, as well as the *branching depth* where they got inserted. The former is used to distinguish interesting test cases (whether or not new nodes were inserted), whereas the latter is used by this heuristic to schedule mutation candidates. Fig. 3 illustrates this idea, inserting two execution traces (one after another) into a trace log that initially contains a single execution path. The second insertion (with trace 1 ⟶ 2 ⟶ 6 ⟶ 7) branches at a shallower depth than the first one (2 vs. 3), hence its corresponding test case should be given a higher priority.

With this mechanism in place, we can modify Mutagen's base testing loop by replacing each mutation queue with a priority queue indexed by the branching depth of each new execution. These changes are illustrated in Algorithm 7. Statements in red indicate important changes to the base algorithm, whereas ellipses denote parts of the code that are not relevant for the point being made.

To pick the next test case, we simply retrieve the one with highest priority (the smallest branching depth). Then, whenever we find a new interesting test case, we enqueue it at the beginning of the queue of its corresponding priority. This allows the testing loop to jump immediately onto processing new interesting candidates as soon as they are found (even at the same priority), and to jump back to previous candidates as soon as their mutants become progressively less novel.

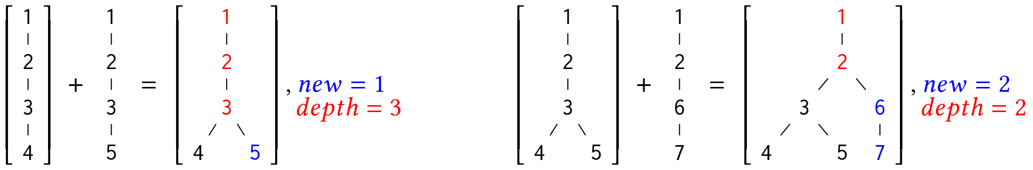


Fig. 3. Inserting two new execution traces into the internal trace log (represented using brackets).

Algorithm 7: Priority FIFO Heuristic

```
Function Loop(P, N, R, gen, mut):
    ...
    x ← Pick(QSucc, QDisc, gen, mut)
    (result, trace) ← WithTrace(P(x))
    ...
    if Interesting(TLog, trace) then
        if not Discarded(result) then
            muts ← Mutate(x, mut, R)
            prio ← BranchDepth(TLog, trace)
            PushFront(QSucc, prio, muts)
        ...

Function Pick(QSucc, QDisc, gen):
    if not Empty(QSucc) then
        (muts, prio) ← DequeMin(QSucc)
        if Empty(muts) then
            Pick(QSucc, QDisc, gen)
        else
            PushFront(QSucc, prio, Rest(muts))
            return First(muts)
    ...
```

Algorithm 8: Trace Saturation Heuristic

```
Function Loop(P, N, gen, mut):
    boring ← 0
    reset ← 1000
    R ← 1
    ...
    while i < N do
        if boring > reset then
            TLog ← ∅
            reset ← reset * 2
            R ← R * 2
        ...
        if not result then return Bug(x)
        if Interesting(TLog, trace) then
            boring ← 0
            ...
        else boring ← boring + 1
        ...
```

4.2 Detecting Trace Space Saturation And Tuning Random Mutations

As introduced in Section 3, our tool is parameterized by the amount of random mutations to be generated over each mutable subexpression defined using a random mutant, e.g., numeric values, characters, etc. But, how many random mutations should we use? A single one? A few tenths? A few hundreds? Clearly, using too little, can put finding bugs at risk. For instance, when the system under test branches on numeric values, we should make sure that we set enough random mutations to test each case in a reasonable basis. Using too many, the other hand, can degrade the performance of the testing loop, as it will spend too much time producing uninteresting mutations. This can happen for instance if the subexpressions defined using random mutants are only used as payloads, and their value does not affect the execution in any way.

Answering this question precisely is not an easy task, and the second heuristic we introduce in this work aims to tackle this issue. We found that, the smaller the number of random mutations we set, the easier it is for the trace log that records executions to start getting saturated, i.e., when interesting test cases stop getting discovered or are discovered very sporadically. Our realization is that we can use this information to automatically optimize the number of random mutations used by our tool. This idea is described in Algorithm 8. The process is simple: (1) we start the testing loop with the amount of random mutations set to one, (2) each time we find that a test is not interesting (i.e. boring), we increment a counter, (3) if we have not produced any interesting test case after a certain threshold (1000 tests seems to be a reasonable value in practice), we increment the amount of random mutations and the threshold by twice the current amount. Additionally, each time this happens we also reset the trace log, so interesting test cases found on a previous iteration can be found and enqueued for mutation again — this time with a higher effort dedicated to producing random mutations.

Then, if the execution of the system under test depends heavily on the values stored at randomly mutable subexpressions, starting with a single random mutation will quickly saturate the trace space, and this heuristic will continuosly increase the random mutations parameter until that stops happening.

5 CASE STUDIES

We evaluated the performance of Mutagen using two main case studies. The first one is a simple abstract stack machine that enforces *noninterference* using runtime checks. The implementation of this case study was originally proven correct by [] in Coq, and subsequently degraded by systematically introducing 20 bugs on its enforcing mechanism. Lampropoulos et al. used this same case study to compare *FuzzChick* against random testing approaches using naïve and manually-written smart random generators. In this work, we replicate their results and compare them against our tool. Worth mentioning, since this case study was originally implemented in Coq, we first translated it to Haskell in order to run Mutagen on its test suite.

The second case study aims to evaluate Mutagen in a more realistic scenario, and focuses on testing *haskell-wasm*, an existing WebAssembly engine written in Haskell of industrial strength. We manually injected 10 bugs in the validator as well as 5 bugs in the interpreter of this engine, and used the reference implementation to find them via differential testing. During this process, we quickly discovered 3 bugs and 2 discrepancies on this engine with respect to the reference implementation. All of them were reported and later confirmed by the authors of *haskell-wasm*.

5.1 IFC Stack Machine

The abstract stack machine used in this case study consists of four main elements: a program counter, a stack, and data- and instruction memories. Moreover, every runtime value is labeled with

Id	Subsystem	Description
1	Validator	Wrong if-then-else type validation on else branch
2	Validator	Wrong stack type validation
3	Validator	Removed function type mismatch assertion
4	Validator	Removed max memory instances assertion
5	Validator	Removed function index out-of-range assertion
6	Validator	Wrong type validation on `i64.eqz` instruction
7	Validator	Wrong type validation on `i32` binary opertations
8	Validator	Removed memory index out-of-range assertion
9	Validator	Wrong type validation on `i64` constants
10	Validator	Removed memory alignment validation on `i32.load` instruction
11	Interpreter	Wrong intepretation of `i32.sub` instruction
12	Interpreter	Wrong intepretation of `i32.lt_u` instruction when operands are equal
13	Interpreter	Wrong intepretation of `i32.shr_u` instruction
14	Interpreter	Wrong local variable initialization
15	Interpreter	Wrong memory address casting on `i32.load8_s` instruction

Table 1. Bugs injected in *haskell-wasm*.

a security level, i.e., L (for "low" or public) or H (for "high" or secret). Labels form a trivial 2-lattice where information can either stay at the same level, or public information can flow to secret one but not the opposite (represented using the familiar $\sqsubseteq$ binary operator). Security labels are propagated throughout the execution of the program every time the machine executes an instruction. There are eight different instructions defined as:

```
data Instr = Nop | Push Int | Call Int | Ret | Add | Load | Store | Halt
```

Control flow is achieved using the `Call` and `Ret` instructions, that let the program jump back and forth within the instruction memory using specially labelled values in the stack respresenting memory addresses. The argument in the `Push` instruction represents a value to be inserted in the stack, whereas the argument of the `Call` instruction encodes the number of elements of the stack to be treated as arguments. Then, programs are simply modeled as sequences of instructions. Finally, machine states can be modeled using a 4-tuple *(pc, stk, m, i)* that represents a particular configuration of the program counter, stack and data- and instruction memories, respectively. To preserve space, we encourage the reader to refer to the work of **?** as well as the original *FuzzChick* paper for more details about the implementation and semantics of this case study.

5.1.1 Single-Step Noninterference (SSNI). This abstract machine is designed to enforce noninterference, which is based on the notion of *indistinguishability*. Intuitively, two machine states are indistinguishable from each other if they only differ on secret data. Using this notion, the particular variant of noninterference we are interested in this work is called *single-step noninterference*. In simple terms, this property asserts that, given two indistinguishable machines states, running a single instruction on both machines brings them to resulting states that are again indistinguishable.

The tricky part about this property is, of course, satisfying its sparse precondition: we need to generate two valid indistinguishable machine states in order to even proceed to execute the next instruction. As demonstrated by Lampropoulos et al., generating two independent machine states using *QuickCheck* has virtually no chances of producing valid indistinguishable ones. However, having the mutation mechanism available, we can use a clever trick: we can obtain a pair of valid indistinguishable machine states by generating a single valid machine state (something still hard but much easier than before), and then producing a similar mutated copy. By doing this, we have a much higher chance of producing two almost identical states that pass the sparse precondition.

5.1.2 IFC Rules. In this abstract machine, the enforced IFC rules are implemented using a rule table indexed by the operation that the machine is about to perform. Such table contains: the dynamic check that the abstract machine needs to perform in order to enforce the IFC policy, along with the corresponding security label of the program counter and the operation result after the operation is executed. For instance, to execute the `Store` operation (which stores a value in a memory pointer) the machine needs to check that both the label of the program counter and the label of the pointer together "can flow" to the label of the destination memory cell. If this condition is not met, the machine then halts as indication of a violation in the IFC policy. After this check, this operation overwrites the value at the destination cell and updates its label with the maximum sensibility of the involved labels. In the rule table, this looks as follows:

Operation	**Precondition Check**	**Final PC Label**	**Final Result Label**
`Store`	$l_{pc} \vee l_p \sqsubseteq l_v$	l_{pc}	$l_{v'} \vee l_{pc} \vee l_p$

Where l_{pc}, l_p, l_v, and $l_{v'}$ represent the labels of: the program counter, the memory pointer, and the old a new values stored in that memory cell. The symbol $\vee$ simply denotes the join of two labels, i.e., the *maximum* of their sensibilities.

In this case study, we systematically introduce several bugs on the IFC enforcing mechanism by removing or weaking the checks stored in this rule table.

5.2 WebAssembly Engine

WebAssembly is a popular assembly-like language designed to be an open standard for executing low-level code in the web, although it has become increasingly popular in standalone, non-web contexts as well. WebAssembly programs are first validated and later executed in a sandboxed environment (a virtual machine), making this language an attractive target for virtualization in *functions-as-a-service* platforms. The language is relatively simple, in esence (1) it contains only four numerical types, representing both integers and IEEE754 floating point numbers of either 32 or 64 bits; (2) values of these types are manipulated by writing functions using sequences of stack instructions; (3) functions are organized in modules and must be explicitly imported and exported; (4) memory blocks can be imported, exported and grown dinamically; among others.

Unlike most other programming languages, its behavior is fully specified, and WebAssembly programs are expected to be consistently interpreted across engines — despite some subtle details that we will address soon. For this purpose, the WebAssembly standard provides a reference implementation with all the basic functionality expected from a compliant WebAssembly engine.

In this work, we are interested on using Mutagen to test the two most complex subsystems of *haskell-wasm*: the *validator* and the *interpreter* — both being previously tested using a unit test suite. Our tool is an attractive match for testing *haskell-wasm*, as the space of WebAssembly programs that can be respresented using its AST contains mostly invalid ones, and automatically derived random generators cannot satisfy all the invariants required to produce interesting test cases. Here, we avoided spending countless hours writing an extensive property-based specification to mimic the reference WebAssembly specification. Instead, we take advantage of the readily available reference implementation via differential testing. In this light, our testing properties assert that any result produced by *haskell-wasm* matches that of the reference implementation.

Unsurprisingly, this engine had several subtle latent bugs that were not caught by the existing unit tests and that we discovered using Mutagen while developing the test suite used in this work. Moreover, Mutagen exposed two discrepancies between *haskell-wasm* and the reference implementation. Not severe enough to be classified as bugs, these discrepancies trigger parts of the WebAssembly specification that are either not yet suported by the reference implementation (multi-value blocks), or that produce a well-known non-deterministic undefined behavior allowed by the specification (NaN reinterpretation). These findings are briefly outlined in Table 2.

The rest of this section introduces the test suite we used to test the different parts of *haskell-wasm.*

5.2.1 Testing the WebAssembly Validator. We begin by designing a property to test the WebAssembly validator implemented in *haskell-wasm.* To keep things simple, we can simply assert that, whenever a randomly generated (or mutated for that matter) WebAssembly module is valid according to *haskell-wasm*, then the reference implementation agrees upon it. In other words, we are testing for false negatives. In Haskell, we write the following testing property:

```
prop_validator m =
  isValidHaskell m ==> isValidSpec m
```

Where the precondition (`isValidHaskell m`) runs the input WebAssembly module `m` against the *haskell-wasm* validator, whereas the postcondition (`isValidSpec m`) serializes `m` to a file, runs it against the reference implementation validator and checks that no errors are produced.

We want to remark that, although here for simplicity we only focus on finding false positives, in a realistic test suite, one would also want to test for false negatives, i.e., when a module is valid and *haskell-wasm* rejects it. This can be easily done by inverting the direction of the implication (<==) in the property above. However, the resulting property is much slower, as every tested module will always be serialized and run against the reference implementation.

5.2.2 Testing the WebAssembly Interpreter. Testing the WebAssembly interpreter is substantially more complicated than testing the validator, since it requires running actual programs. To achieve this, we need the generated test cases to comply a with stable interface that can be invoked both by *haskell-wasm* and the reference WebAssembly implementation.

To keep things simple here as well, we use a stub definition that provides a module that initializes a memory block and exports a single function. This module can be instantiated by providing the definition of the single function, along with a name and a type signature. In Haskell:

```
mk_module ty name fun =
  emptyModule { types     = [ ty ]
              , functions = [ fun ]
              , exports   = [ Export name (ExportFunc 0) ]
              , mems      = [ Memory (Limit 1 Nothing) ]
              }
```

Using this stub module, we can define a testing property parameterized by the function type signature, the function implementation and a list of invocation arguments:

```
prop_interpreter ty fun args =
  (discardAfter 20)
  (do let m = mk_module ty "f" fun;
      resHs   <- invokeHaskell m "f" args
      resSpec <- invokeSpec    m "f" args
      return (equivalent resHs resSpec))
```

This property instantiates the module stub using the input function and its type signature, and uses it to invoke both the *haskell-wasm* and reference implementation interepreters with the

Id	Subsystem	Category	Description
1	Validator	Bug	Invalid memory alignment validation
2	Validator	Discrepancy	Validator accepts blocks returning multiple values
3	Interpreter	Bug	Instance function invoker silently proceeds after arity mismatch
4	Interpreter	Bug	Allowed out-of-bounds memory access
5	Interpreter	Discrepancy	NaN reinterpretation does not follow reference implementation

Table 2. Bugs and discrepancies found by Mutagen in *haskell-wasm.*

provided arguments. Then, the property asserts whether their results are equivalent. Interestingly, equivalence in this context does not imply equality. Non-deterministic operations in WebAssembly like NaN reinterpretations can produce different equivalent results (as exposed by the discrepancy #5 in Table 2), and our equivalence relation needs to take that into acount. Notice that we additionally set a 20ms timeout to discard potentially diverging programs with infinite loops.

Using this testing property directly might not sound like a great idea, as randomly generated lists of inputs will be very unlikely to match the type signature of randomly generated functions. However, it lets us test what happens when programs are not properly invoked, and it quickly discovered the bug #3 in *haskell-wasm* mentioned above. Having solved this issue in *haskell-wasm*, we proceed to define a more useful specialized version of `prop_interpreter` that fixes the type of the generated function to take two arguments (of type `I32` and F32) and return an `I32` as a result:

```
prop_interpreter_i32 fun i f =
  prop_interpreter (FuncType { params = [I32, F32], result = [I32]}) fun [VI32 i, VF32 f]
```

This specilized property let us generate functions using this fixed type and invoke them with the exact number and type of arguments required. In our experiments (presented in next section), we use this property when finding all the injected bugs into the *haskell-wasm* interpreter. Worth mentioning again, a realistic test suite should at least include different variants of this property testing functions of several different types.

6 EVALUATION

All the experiments were performed in a dedicated workstation with an Intel Core i7-8700 CPU running at 3.20GHz, and equipped with 32Gb of RAM. We ran each experiment 30 times except for the ones involving the bugs on the WebAssembly interpreter, which were run 10 times. From there, we followed the same approach taken by Lampropoulos et al. and collected the Mean-Time-To-Failure (MTTF) of each bug, i.e., how quickly a bug can be found in wall time. In all cases, we used a one-hour timeout to stop the execution of both tools if they have not yet found a counterexample.

Additionally, we collected the Failure Rate (FR) observed for each bug, i.e. the proportion of times each tool finds each bug within the one-hour testing bugdet. We found this metric crucial to be analyzed when replicating *FuzzChick*'s results, as opposed to just paying attention at the MTTF.

In both case studies, we additionally show how the FIFO scheduling and trace reset heuristics described in Section 4 affect the testing performance by disabling them when using our tool. We call these variants *no FIFO* and *no reset*, respectively. In the case of *no reset*, the amount of random mutations is no longer controlled by this heuristic, so we fixed it to 25 random mutations throughout the execution of the tool.

6.1 IFC Stack Machine

The results of this case study are shown in Fig. 4, ordered by the failure rate achieved by *FuzzChick* in decreasing order — notice the logarithmic scale used on the MTTF. As introduced earlier, *FuzzChick* can only find 5 out of the 20 bugs injected with a %100 success rate within the one hour testing budget. In turn, our tool manages to find every bug on all runs, and taking less than a minute in the worst absolute case. These results are somewhat pesimistic towards *FuzzChick* if compared to the ones presented originally by Lampropoulos et al.. However, we want to remark that our experiments encompass 30 independent runs instead of the 5 originally used when presenting *FuzzChick*. Moreover, since the MTTF simply aggregates all runs, regardless of if they found a bug or timed out, this metric is quite sensitive to the particular timeout used on each experiment, and will tend to inflate the results as soon as the failure rate goes below 1. For this reason, additionally comparing the failure rate between tools gives us a better estimation of the reliability of both tools, where Mutagen shows a clear improvement.

If we only consider the succesfull runs where *FuzzChick* does not time out, we observed a peculiarity. This tool either finds bugs relatively quickly (after a few thouthands tests) or does not find them at all within the time budget, which suggest that its power scheduler assigns some mutation candidates too little energy before they become uniteresting and get ultimately discarded. Under this consideration, it is fair to think that *FuzzChick* might be a better choice if we set a shorter timeout and run it several times. Thus, to be an improvement over *FuzzChick*, our tool must be able to find bugs not only more reliably, but also relatively fast!

Table 3 shows a comparison between the mean number of tests required by both tools to find the first failure when we only consider successful runs. Additionally, as adviced by [?] when comparing random testing tools, we computed the non-parametric Vargha-Delaney A_{12} measure [?]. Intuitively, this measure encodes the probability of Mutagen to yield better results than *FuzzChick*. As it can be observed, using an exhaustive mutation approach can be

Bug	*FuzzChick*	Mutagen	A_{12} measure	
			Value	Estimate
1	13974.9	3632.7	0.89	large
2	23962.9	7122.3	0.90	large
3	19678.5	4633.9	0.89	large
4	20398.4	16831.2	0.72	medium
5	17348.1	2326.6	0.94	large
6	10727.1	2312.9	0.92	large
7	5070.7	332.9	0.91	large
8	5596.4	298.7	0.90	large
9	16402.4	26342.5	0.51	negligible
10	11553.0	25044.5	0.55	negligible
11	11304.3	2536.8	0.82	large
12	18507.3	14482.7	0.65	small
13	17961.5	13454.9	0.65	small
14	10621.9	3928.3	0.78	large
15	23866.3	43678.2	0.23	large
16	25321.7	27602.0	0.54	negligible
17	28515.6	52344.9	0.47	negligible
18	24218.6	123401.3	0.14	large
19	18638.9	30682.3	0.45	negligible
20	18883.1	15841.9	0.60	small
		Mean	0.67	medium

Table 3. Mean tests until first failure and effect size comparison between *FuzzChick* and Mutagen when considering only succesfull runs. Estimates in blue and red indicate results favouring *FuzzChick* and Mutagen, respectively.

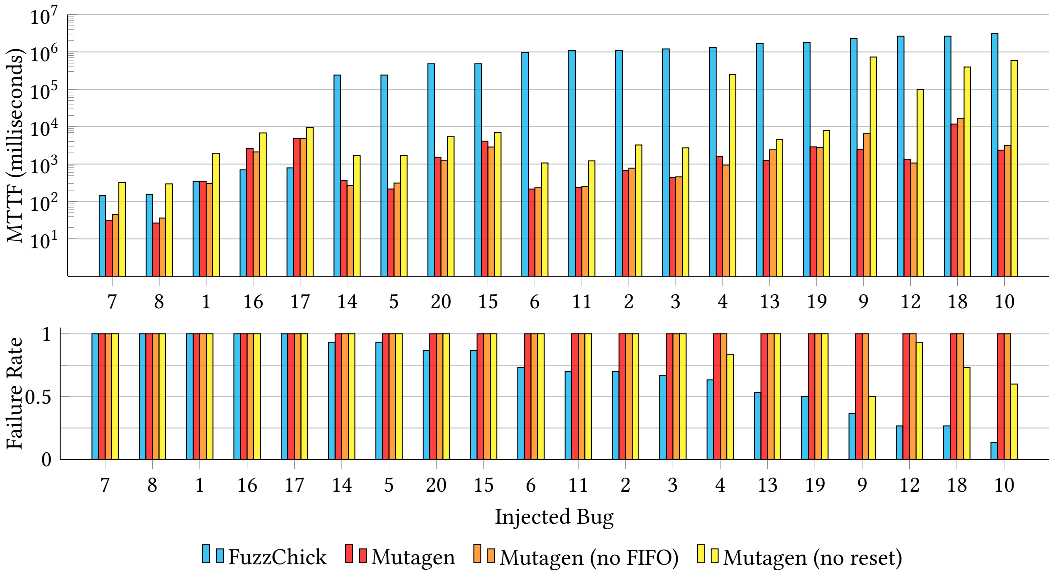


Fig. 4. Comparison between *FuzzChick* and Mutagen across 20 different bugs for the IFC stack machine.

not only more reliable, but also faster, where Mutagen is likely to find bugs faster that *FuzzChick* in 14 of the 20 bugs injected into the abstract machine.

In terms of the Mutagen heuristics, we can also arrive to some conclusions. In first place, this case study does not seem to be affected by using a FIFO scheduling. Upon inspection, we found that the reason behind this is that the mutation candidate queues remain empty most of the time (generation mode), and when a new interesting candidate gets inserted, all its mutants (and their descendents) are processed before the next one is enqueued.

On the other hand, disabling the trace saturation heuristic (*no reset*) we observed two interesting effects: havig fixed the amount of random mutations to 25 adds a seemingly constant overhead when finding most of the (easier) bugs, suggesting that we are spending worthless time mutating numeric subexpressions inside the generated machine states and that a smaller number of random mutations could be equally effective to find such bugs. However, some of the hardest to find bugs cannot be reliably exposed using this amount of random mutations (#4, #9, #12, #18 and #10), suggesting that one should increase this number even further to be able to discover all bugs within the time budget. In consequence, we believe this heuristic is effective at automatically tunning this internal parameter of our tool, especially when the user is unsure about what the best value for it might be.

6.2 WebAssembly Engine

The results of this case study are shown in Fig. 5, ordered by the mean-time-to-failure achieved by Mutagen. Given that we used different properties to test the WebAssembly validator and interpreter, we will focus on these results independently.

Firstly, we focus on the bugs injected in the validator (Fig. 5 left). There, we can quickly conclude that *QuickCheck* is well suited to find most of the bugs — it merely finds a counterexample for the easier bugs #4 and #5 in just 1 out of 30 runs! The reason behind this simple: WebAssembly modules comprise several different interconnected components, e.g., types and functions definitions, memory blocks, imports, exports, etc. All these components need to be valid and agree with each other in order for the module to be correctly validated (modulo the injected bugs). Using an automatically derived generator that generates each one of these components independently is virtually unable to produce valid WebAssembly modules. Using the same random generator, however, Mutagen is able to consistently find every bug in less than 20 seconds in the absolute worst case.

In terms of the heuristics implemented in our tool, we can observe two clear phenomena. On one hand, disabling the FIFO schedulng (case *no FIFO*), the hardest-to-find bugs (#7, #8 and #1) are no longer found on every run. Moreover, although bugs #2, #9, #8 and #6 are found with %100 success rate across runs, it takes several times longer for Mutagen to find them. On the other hand, disabling the the trace saturation heuristic (case *no reset*) and using a fixed number of 25 random mutation does not affect the effectiveness of our tool, apart from adding again a mostly constant overhead on the time required to find every bug — suggesting that the value we arbitrarily chose for this parameter is too large and should be left to be handled automatically by our tool.

If we now pay attention to the bugs injected into the interpreter (Fig. 5 right), we notice that finding bugs requires substantially more time (minutes instead of seconds), since both interpreters need to validate and run the inputs before producing a result to compare. Perhaps more interestingly, we can observe a significant improvement on the performance of *QuickCheck* in terms of failure rate. This is of no surprise: we deliberately reduced the search space by using a module stub when defining `prop_interpreter` in our test suite. Nonetheless, Mutagen still outperforms *QuickCheck* both in terms of failure rate and mean time to failure. Moreover, by disabling the FIFO scheduling we observe that the performance of our tool gets more unstable, where the bugs #12 and #11 take substantially less time to be found, whereas the bugs #15 and #14 cannot be found on every run.

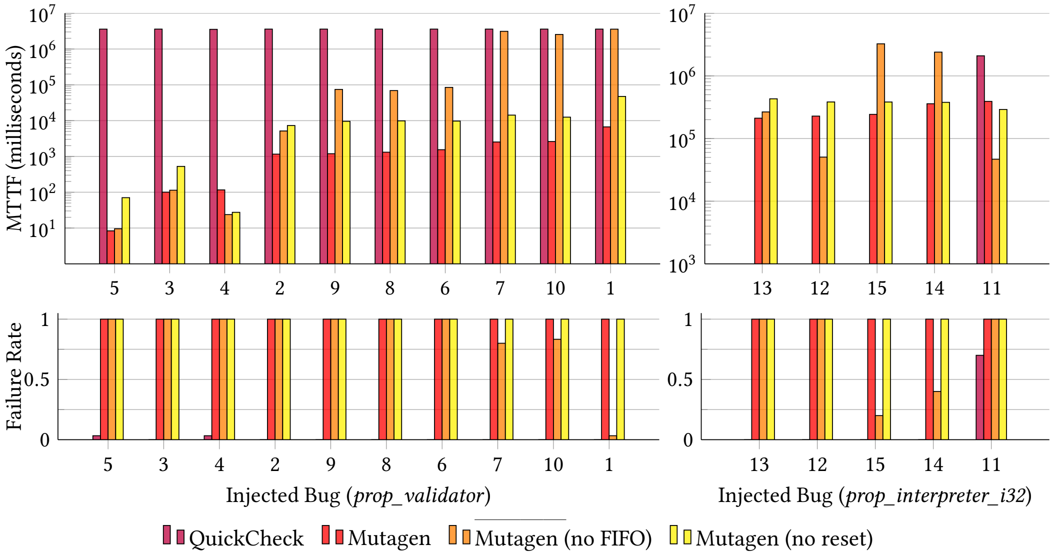


Fig. 5. Comparison between *QuickCheck* and Mutagen across 15 different bugs injected into *haskell-wasm*.

Finding where the best tradeoff lies in cases where the heuristics cause mixed results like this is an interesting direction to aim future work.

Finally, this case study gives us the opportunity to analyze the overhead introduced by the code instrumentation and internal processing used in Mutagen versus the stateless black-box approach of *QuickCheck*. Table 4 compares the total number of executed and passed test per second that we obtained using each tool. It is easy to conclude that Mutagen executes tests several times slower than *QuickCheck*– roughly 16x and 70x slower when testing *prop_validator* and *prop_interpreter_i32*, respectively. Part of the reason behind this slowdown is that the code instrumentation our tool currently uses is built upon a superficial tranformation that logs traces at the user level. We anticipate that a large portion of the overhead could be reduced considerably by integrating the instrumentation directly into the Haskell runtime — a substantial challenge to tackle in the future.

More importantly, in the same time, our tool is capable of running many more tests that pass the sparse preconditions than *QuickCheck*, and which ultimately lead us to finding bugs.

Property	*QuickCheck*		Mutagen	
	total	passed	total	passed
prop_validator	42136	0.00028	2583	539.19
prop_interpreter_i32	134000	23.16	1890	372.75

Table 4. Mean number of tests per second executed by each tool on the WebAssembly case study.

7 RELATED WORK

There exists a vast literature on fuzzing and property-based testing. To preserve space, in this section we only focus on three main topics: automated random data generation using static information, fuzzing using coverage information, and exhaustive bounded testing tools, all of which inspired the design of Mutagen.

Automated Random Data Generation. Obtaining good random generators automatically from static information (e.g., grammars or datatype definitions) has been tackled from different angles.

In Haskell, DRAGEN [?] is a meta-programming tool that synthezises random generators from datatypes definitions, using stochastic models to predict and optimize their distribution based on a target one set by the user. DRAGEN2 [?] extends this idea adding support for generating richer random data by extracting additional static information like library APIs and function input patterns from the codebase. Similarly, [?] developed a polinomial tuning mechanism based on Boltzmann samplers [?] that synthesizes generators with approximate-size distributions for combinatorial structures like lists or trees.

Exploiting some of the ideas described above, *QuickFuzz* [??] is a generational grammar-based fuzzer that leverages existing Haskell libraries describing common file formats to synthesize random data generators that are used in tandem with off-the-shelf low-level fuzzers to find bugs in massively used programs.

Automatically deriving random generators is substantially more complicated when the generated data must satisfy by (often sparse) preconditions. [?] developed an algorithm for generating inputs constrained by boolean preconditions with almost-uniform distribution. Later, [?] extends this approach by adding a limited form of constraint solving controllable by the user in a domain-specific language called *Luck*. Recently, [?] proposed a derivation mechanism to obtain constrained random generators directly by defining their structure using inductively defined relations in Coq.

We consider all these generational approaches to be orthogonal to the ideas behind Mutagen. In principle, our tool is tailored to improve the performance of poor automatically derived generators. However, more specialized generators can by used directly by Mutagen, and combining them with type-preserving mutations using a hybrid technique is an appealing idea that we aim to address in the future.

Coverage-guided Fuzzing. *AFL* [M. Zalewski 2010] is the reference tool when it comes to coverage-guided fuzzing. *AFLFast* is an extension to AFL that uses Markov chain models to tune the power scheduler towards testing low-frequency paths. In Mutagen, the scheduler does not account for path frequency. Instead, it favours a breadth-first traversal of the execution path space. Similar to our tool, *CollAFL* [?] is a variant of AFL that uses path- instead of edge-based coverage, which helps distinguishing executions more precisely by reducing path collisions.

When the source code history is available, *AFLGo* [?] is a fuzzer that can be targeted to exercise the specific parts of the the code affected by recent commits in order to find potential new bugs. Back to PBT, a related idea called *targeted property-based testing* (TPBT) is to use fitness functions to guide the testing efforts towards user defined goals. *Target* [?] is a tool that implements TPBT using optimization techniques like hill climbing and simulated annealing.

Moreover, a popular technique is to combine coverage-guided fuzzing with ideas borrowed from symbolic execution tools like *KLEE* [?] to avoid getting stuck in superficial paths [??]. When using off-the-shelf symbolic executors, this technique is often limited by the path explosion problem, altough recent tools like *QSYM* [?] demonstrate that using tailored concolic executors can help overcoming this limitation.

Most of these ideas can potentially be incorporated in our tool, and we keep them as a challenge for future work.

Exhaustive Bounded Testing. A popular category of property-based testing tools does not rely on randomness. Instead, all possible inputs can be enumerated and tested from smaller to larger up to a certain size bound.

Feat [?] formalizes the notion of *functional enumerations.* For any algebraic type, it synthesizes a bijection between a finite prefix of the natural numbers and set of increasingly growing values of the input type. Later, this bijection can be traversed exhaustively or, more interestingly, randomly accessed. This allows the user to easily generate random values in a uniform basis simply by sampling natural numbers. However, values are enumerated based only on their type definition, so this technique is not suitable for testing properties with sparse preconditions expressed elsewhere.

SmallCheck [**?**] is a Haskell tool that also follows this idea. It progressively executes the testing properties against all possible inputs values up to a certain size bound.

On the object-oriented realm, *Korat* [**?**] is a Java tool that uses method specification predicates to automatically generate all (nonisomorphic) test cases up to a given small size.

Being exhaustive, these approaches rely on prunning mechanisms to avoid populating unevaluated subexpresions exhaustively before the computational cost becomes too restrictive. *LazySmallCheck* is a variant of *SmallCheck* that uses lazy evaluation to automatically prune the search space by detecting unevaluated subexpressions using lazy evaluation. In the case of *Korat*, pruning is done by instrumenting method precondition predicates and analyzing which parts of the execution trace correspond to each evaluated subexpression.

In this work we use exhaustiveness as a way to reliably enforce that all possible mutants of an interesting seed are executed. In contrast to fully-exhaustive testing tools, Mutagen initially relies on randomness to find initial interesting mutable candidates. In terms of pruning, it is possible to instruct Mutagen to detect unused subexpressions (using a technique similar to that of *LazySmallCheck*) to avoid scheduling mutations over their corresponding positions. This could, in principle, improve the overall performance when testing properties that tend to short-circuit, leaving parts of the input unevaluated. In our case studies, however, we observed that their preconditions tend to be quite strict when mutating from passed test cases, fully evaluating their input before executing the postcondition. Thus, we do not expect to see considerable improvements by applying this idea in this particular scenario. Gathering empirical evidence about using prunning via lazy evaluation in Mutagen is an effort that we keep as future work.

8 CONCLUSIONS

We presented Mutagen, a coverage-guided, property-based testing framework written in Haskell. Inspired by *FuzzChick*, our tool uses coverage information to guide automatically derived mutators producing high-level, type-preserving mutations. However, instead of relying heavily on randomness and power schedules to find bugs, our tool uses an exhaustive mutation approach that generates every possible mutant for each interesting input candidate, and schedules it to be tested exactly once. This is in turn inspired by exhaustive bounded testing tools that focus on testing every possible input value of the system under test.

Our experimental results indicate that Mutagen outperforms the simpler approach taken by *FuzzChick* in terms of both failure rate and tests until first failure. Moreover, we show how our tool can be applied in a real-world testing scenario, where it quickly discovers several planted and existent previously unknown bugs.

As already indicated throughout this work, there are several direction for future work we aim to investigate: combining Mutagen with specialized generators; improving the code instrumentation in order to effectively target mutations towards specific parts of the code; and evaluating the effect of lazy prunning; among others. In addition, we want to investigate how to redefine our automatically synthesized mutators in a stateful manner. This way, it would be possible to apply mutations that preserve complex properties of the generated data simply by construction, e.g., mutations that *always* produce well-typed subexpressions that refer only to identifiers in scope. The main challenge will be to achieve this while keeping the testing process as automatable as possible.

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