

# 1 Fail Faster

2 Staging and Fast Randomness for High-Performance PBT

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4 Property-based testing (PBT) relies on generators for random test cases, often constructed using embedded  
5 domain specific languages, which provide expressive combinators for building and composing generators.  
6 The effectiveness of PBT depends critically on the speed of these generators. However, careful measurements  
7 show that the generator performance of widely used PBT libraries falls well short of what is possible, due  
8 principally to (1) the abstraction overhead of their combinator-heavy style and (2) suboptimal sources of  
9 randomness. We characterize, quantify, and address these bottlenecks.

10 To eliminate abstraction overheads, we propose a technique based on multi-stage programming, dubbed  
11 Allegro. We apply this technique to leading generator libraries in OCaml and Scala 3, significantly improving  
12 performance. To quantify the performance impact of the randomness source, we carry out a controlled  
13 experiment, replacing the randomness in the OCaml PBT library with an optimized version. Both interventions  
14 exactly preserve the semantics of generators, enabling precise, pointwise comparisons. Together, these  
15 improvements find bugs up to 13× faster.

## 16 1 Introduction

17 Property-based testing is a software testing technique that uses random test inputs to validate logical  
18 specifications [13]. A recent study on PBT usage in industry [21] shows that many practitioners  
19 run their property-based tests very frequently, and with a very short time budget. The faster the  
20 tests fail, the better.

21 One important opportunity for performance improvement is the *generators* that produce random  
22 inputs to the properties under test. These generators are written with the help of *generator libraries*,  
23 usually expressed as embedded domain-specific languages (eDSLs) that provide combinators for  
24 building and composing generators.

25 However, careful measurements show that the performance of existing generator libraries falls  
26 far short of what is possible, for two reasons. First, the high-level design approach followed by  
27 generator combinator libraries introduces layered abstractions that are difficult for compilers to  
28 optimize. Second, the calls a generator makes to its randomness library can constitute a large  
29 proportion of its run-time, magnifying the cost of an inefficient implementation. In this paper, we  
30 characterize, quantify, and address these issues.

31 We address the overhead of many common generator abstractions using *multi-stage programming*  
32 (or *staging*), a well-studied technique for building fast DSLs “without regret” [53]. We refer to  
33 this approach as Allegro. To demonstrate its generality, we implement staged generator DSLs in  
34 two strict functional languages: OCaml and Scala 3. In OCaml, we build AllegrOCaml, based on  
35 Base\_quickcheck—a high-quality PBT library in OCaml, authored by software engineers at the  
36 trading firm Jane Street [61]. In Scala 3, we build ScAllegro, based on ScalaCheck—the language’s  
37 standard PBT library [2].

38 We isolate and quantify the performance benefits of faster randomness, showing that a DSL’s  
39 choice of randomness library has a dramatic effect on its performance. Based on the observation  
40 that the OCaml implementation of Base\_quickcheck’s randomness library is slow in a way that is  
41 simple to fix, we perform a controlled experiment, comparing fast and slow versions of the library  
42 to analyze the impact of faster randomness libraries on generator performance.

Both interventions preserve semantics on the nose: given the same random seed, generators written using AllegroOCaml or ScAllegro produce exactly the same sequence of values as equivalent generators using Base\_quickcheck or ScalaCheck. This semantic equivalence enables pointwise—as opposed to distributional—comparisons of bug-finding effectiveness, ensuring that, if a Allegro generator finds bugs faster, this is attributable *solely* to the staging and randomness library interventions, not lucky choice of seeds.

We evaluate the optimizations with a series of case studies in each generator library, and show that the Allegro generators run faster than their unstaged equivalents. In AllegroOCaml, they run up to 7× faster, and in ScAllegro, up to 13× faster. Using our improved version of Base\_quickcheck’s randomness library in AllegroOCaml, we see even greater gains—more than 12×—showing that both staging and fast randomness play distinct and complementary roles in improving generator performance. Further, we show that AllegroOCaml generators find bugs faster by running our case studies in the Etna platform, which uses generated values as inputs to a buggy system and measures how quickly different generators can detect the bugs. In Etna, AllegroOCaml generators find bugs up to 2.5× faster on average than their Base\_quickcheck counterparts. With fast randomness, the average speedup rises to 3.8×, with some cases exceeding 13×.

In summary, we show that PBT generator DSLs incur significant performance costs across languages and present two interventions that significantly improve their efficiency while preserving their idiomatic style. Concretely, we offer the following contributions:

- (1) We identify two key sources of inefficiency in PBT generator libraries—abstraction overhead and choice of randomness library—both of which significantly impact performance (Section 2).
- (2) We present Allegro, a staging technique that eliminates the abstraction overhead of generators. We apply Allegro to standard generator libraries in both OCaml and Scala 3, showcasing its generality (Section 3).
- (3) We demonstrate that writing generators using Allegro and fast randomness libraries yields substantial performance improvements, both separately and in combination, and we show that these performance improvements extend to significantly improved bug-finding speed (Section 4).

Section 5 discusses how the Allegro technique could be applied to PBT libraries in other languages—Racket, F#, Haskell, and Rust. Sections 6 and 7 present related and future work.

## 2 What are Generator Libraries, and Why are They Slow?

Property-based testing [14] is an approach to software testing that centers around executable specifications of programs called *properties*. For example, if a programmer wants to test an invariant of a binary search tree (BST) implementation that they are working on, they may write a property like

```
prop_insert_invariant t x = isBST t ==> isBST (insert x t)
```

to check that for any tree  $t$  and value  $x$ , if  $t$  is already a valid BST then inserting  $x$  into it also yields a valid BST. Once a developer has a property, they test that property by executing it on hundreds or thousands of random test inputs. These test inputs are usually produced by a *generator*—a program written in some domain-specific language (DSL) that allows the developer to express precisely how values should be sampled.

The standard design for a generator DSL, introduced in Haskell’s QuickCheck library [13] and copied in dozens of other frameworks, is via an embedded *monadic* language [44]. We use the syntax and types from OCaml’s Base\_quickcheck library, which is presented in Figure 1, but similar DSLs can also be found in languages like Haskell, Scala, Python, and many more. The library

```

99  module Bq : sig
100 type 'a t
101 val gen_int : int -> int -> int t
102 val return : 'a -> 'a t
103 val bind : 'a t -> ('a -> 'b t) -> 'b t
104
105 val weighted_union : (int * 'a t) list -> 'a t
106
107 val size : int t
108 val with_size : int -> 'a t -> 'a t
109
110 ...
111 end
112

```

Fig. 1. Some functions from the API of the Base\_quickcheck generator DSL.

provides some basic generators, for example `gen_int` for generating random integers in a range, along with the functions `return` and `bind`. The generator `return x` is the constant generator, always generating the value `x`. Running a generator `bind g k` runs the generator `g`, producing a value `a`, and then runs the generator `k a`.

Together, these three functions are the bare minimum for constructing arbitrary random data generators: `gen_int` provides a base source of randomness, and `return` and `bind` allow generators to be composed to create larger, more complex generators. Figure 2a shows a generator built with these operations; it first samples an int between 0 and 100, names it `x`, samples another between 0 and `x`, and then returns the pair of them.

```

126
127 let int_pair : (int * int) Bq.t =
128   Bq.bind (Bq.gen_int 0 100) (fun x ->
129     Bq.bind (Bq.gen_int 0 x) (fun y ->
130       Bq.return (x,y)))

```

(a) A simple generator using `bind` explicitly.

```

126
127 let int_pair : (int * int) Bq.t =
128   let%bind x = Bq.gen_int 0 100 in
129   let%bind y = Bq.gen_int 0 x in
130   return (x,y)

```

(b) An equivalent generator using the macro for `bind`.

Fig. 2. Simple monadic generators for a pair of ordered integers.

Most languages in which monadic APIs are common expose some sort of syntactic sugar for them. In OCaml,<sup>1</sup> this looks like `let%bind x = e in e'` which desugars to `bind e (fun x => e')`. Figure 2b shows the same generator, written the monadic syntax.

Generator libraries also include other functions that make generator construction easier; some examples of these are included in Figure 1. The `weighted_union` function is a particularly well-used one: it makes making a weighted choice between different generators, allowing the developer to combine different sub-generators into a single program and tune the data distribution. Also important are functions like `size` and `with_size` that are used to control the sizes of generated values and `fixed_point` that is used to define recursive generators.

---

<sup>1</sup>OCaml actually has a few ways to implement monadic syntax; this is the one provided by Jane Street's libraries.

```

148 module Bq = struct
149   type 'a t = int -> SR.t -> 'a
150
151   let return (x : 'a) : 'a t = fun _ _ -> x
152
153   let bind (g : 'a t) (k : 'a -> 'b t) : 'b t =
154     fun size random ->
155       let a = g size random in
156       (k a) size random
157
158   let gen_int (lo : int) (hi : int) : int t =
159     fun _ random -> SR.int random lo hi
160
161 end

```

Fig. 4. Internals of a Monadic Generator eDSL

161  
 162  
 163  
 164     The generator in Figure 3 uses all of these  
 165     features. It uses `fixed_point` to define a recursive  
 166     generator that reads the current value of  
 167     `size` to determine how to generate a tree. It  
 168     uses `weighted_union` to make a random choice  
 169     between an empty tree and a node, choosing a  
 170     node with weight proportional to the current  
 171     size and choosing a leaf otherwise. When gener-  
 172     ating a node, it uses `with_size` to reduce the  
 173     value of the `size` parameter for future iterations.  
 174

## 2.1 Abstraction

### Overhead of Generator DSLs

175 Just how large is the abstraction overhead of  
 176 monadic generator DSLs, and where does it  
 177 come from? Figure 4 shows the internals of (a  
 178 simplified version of) `Base_quickcheck`. A generator '`'a Bq. t`' is just a function of type `int -> SR.t -> 'a`, taking an `int` representing the current size parameter and a random seed `SR.t`, and returning a generated value '`'a`'. The random seed `SR.t` from `Base_quickcheck`'s randomness library  
 179 called `Splittable_random`, henceforth aliased in code as `SR`. It is an invariant of the generator  
 180 library that every function of this type is deterministic: for a fixed size and seed, it will always return  
 181 the same value, so all of the randomness in testing comes from varying the initial seed. The monad  
 182 functions `return` and `bind` are defined in the usual way: for an instance of the reader monad [44]:  
 183 `return` ignores the size and seed and returns its argument, while `bind` runs `g` and passes the result  
 184 to `k`. The `gen_int` combinator simply calls out to the randomness library `Splittable_random`,  
 185 aliased as `SR` here. Different generator DSLs use variations on this basic design, but the basics are  
 186 the same across the board.

187 Just how much run-time overhead does this monadic abstraction introduce? To illustrate, let's  
 188 return to our running example of a constrained pair of integers, written in both `Base_quickcheck`  
 189 and `ScalaCheck`. Figure 6 shows two versions of the generator, written in both languages. The first  
 190 versions (`int_pair` in `Base_quickcheck` and `intPair` in `ScalaCheck`) are written with the monadic  
 191 generator combinators from their respective libraries. The second versions (`int_pair_inlined`

```

let tree_of g = fixed_point (fun rg ->
  let%bind n = size in
  weighted_union [
    (1, return E);
    (n,
      let%bind x = g in
      let%bind l = with_size (n / 2) rg in
      let%bind r = with_size (n / 2) rg in
      return (Node (l,x,r)))
  ])

```

Fig. 3. A generator using a variety of convenience functions.

197 and `intPairInlined`) are semantically identical to the first, but have been rewritten by (1) inlining all generator combinator definitions, and then (2) repeatedly reducing simplifiable terms like `(fun x -> e) e'` where an anonymous function is defined and then immediately called, to  
 200 `let x = e' in e.`

201

202 Library	203 Generator	204 Average Time per Generation (ns)
203 <code>Base_quickcheck</code>	204 <code>int_pair</code>	205 70
204 <code>Base_quickcheck</code>	205 <code>int_pair_inlined</code>	206 35
205 <code>ScalaCheck</code>	206 <code>intPair</code>	207 458
206 <code>ScalaCheck</code>	207 <code>intPairInlined</code>	208 266

209

210 Fig. 5. Microbenchmarks of generators in `Base_quickcheck` and `ScalaCheck`. Average over 10000 generations  
 211 with random seeds and a fixed size.

212

212 The performance impact of this simplification is large (Figure 5). In both languages, the inlined  
 213 version takes on average half as much time to generate a single pair of ints. Microbenchmarks of  
 214 more realistic generators (see Section 4) show an even more dramatic performance boost. Because  
 215 the inlined versions of the generator are identical to the un-inlined versions except for mechanical,  
 216 semantics-preserving transformations, this performance difference is attributable solely to the  
 217 different machine code generated by the compiler (and not lucky choice of random seeds).

218

```
219
220     def intPair : Gen[(Long,Long)] = for {
221         x <- Gen.choose(0,1000)
222         y <- Gen.choose(0,x)
223     } yield (x,y)

224
225     def intPairInlined : (Gen.Parameters, Seed) =>
226         (Option[(Long,Long)],Seed) = {
227         (p,seed) =>
228             val (x,seed2) = chLng(0,1000)(p,seed)
229             x match {
230                 case None => (None,seed2)
231                 case Some(x) =>
232                     val (y,seed3) = chLng(0,x)(p,seed2)
233                     y match {
234                         case None => (None,seed)
235                         case Some(y) => (Some(x,y),seed3)
236                     }
237             }
238     }

239     (a) Simplifying a Generator in OCaml          (b) Simplifying a Generator in Scala
240
```

241 Fig. 6. Simplifying Generators

242 It might be surprising to readers that this dramatic overhead exists—shouldn't the compiler  
 243 perform this simple optimization? Compilers of effectful and strict functional languages (including  
 244 JIT compilers in the case of Scala 3) do in fact have heuristics to determine if and when to perform

245

this particular kind of simplification.<sup>2</sup> However even in cases as simple as Figure 6, the indirection of return and bind causes these heuristics to not fire. Moreover, the story is even worse for recursive generators, as the heuristics are necessarily even more conservative for optimizing recursive functions.

More complex generators suffer further performance penalties due to *closure allocation*. In cases where the compiler cannot statically eliminate it, running a monadic bind allocates a short-lived closure for the continuation and then immediately jumps into it. In strict functional languages like OCaml and Scala, each individual closure allocation is relatively cheap; but doing lots of allocation in a generator is very costly because each allocation brings us closer to the next costly GC pause. This effect is also magnified in recursive generators: each iteration through the recursive loop re-allocates closures for binds, so the amount of allocation per generated value scales linearly with the number of recursive generator calls.

*Overhead of Choice Combinators.* Like return and bind, combinators like weighted\_union incur a performance penalty at run time. Aside from the previously-discussed issues that compilers cannot see through the abstraction boundary to optimize these programs, choice combinators like weighted\_union come with their own particular abstraction overhead.

In practice, weighted\_union is (almost<sup>3</sup>) always called with an explicitly constructed list, as in weighted\_union [(w1,g1); (w2,g2); (w3,g3)]. This is because the most common use case for weighted\_union is to choose between one of the different constructors of an algebraic datatype, the options for which are always known. This list is allocated at the call site and then never needed after the call to weighted\_union returns. Since the elements of the list and its length n are known, a compiler could in principle unroll the loops in weighted\_union to depth n and specialize the function at each call site to avoid allocating the list. Unfortunately, (almost<sup>4</sup>) no compilers perform this kind of optimization. This allocation (or rather, its tendency to cause GC pauses)—as well as the cost of running the code to traverse arbitrary lists compared to unrolled loops—has a significant impact on performance.

Last, many PBT libraries—including both Base\_quickcheck and ScalaCheck—implement their weighted\_union combinators in ways that are asymptotically more efficient but slower in common cases than a more naive algorithm. Weighted union uses the Fitness Proportionate Selection algorithm [23], which (1) samples a number r between 0 and the sum of the weights, and then (2) finds the first generator for which the cumulative weights in the list before it exceeds r. This second part can be accomplished in  $O(\log_2 n)$  time by a binary search. However, since the lists are short in practice, a linear scan is almost always faster. Moreover, both Base\_quickcheck and ScalaCheck allocate auxiliary data structures (an array in Base\_quickcheck and a BST in ScalaCheck) to perform this search, which incurs further run-time overhead.

## 2.2 Inefficient Randomness Libraries

The core of any PBT generator library is a source of randomness. Different PBT libraries use different randomness libraries implementing different algorithms.<sup>5</sup> Following the original Haskell QuickCheck implementation, Base\_quickcheck uses the SplitMix algorithm [59], implemented by Splittable\_random. Meanwhile, ScalaCheck uses the JSF algorithm [3].

<sup>2</sup>As we discuss in Section 5, purity means that Haskell is a slightly different story. GHC can and often does transformations of this form.

<sup>3</sup>There are some generators where weighted\_union is passed a list which was itself the result of a generator: the well-typed STLC term generator used in Section 4 is an example of this.

<sup>4</sup>GHC is a notable exception here, performing sophisticated list fusion optimizations [20]

<sup>5</sup>The common term for such an algorithm or library is a “Random Number Generator” (RNG). We will avoid this term and instead say “randomness library” to avoid confusing RNG implementations with the PBT generator libraries that use them.

The randomness library is the hottest part of the hot path. Indeed, even basic generators—like ones generating a single `int` or `float` uniformly within a range—can sample *unboundedly many* random numbers, since they usually use versions of rejection sampling [67] to find a value within the range. Moreover, generator combinators like `list` usually make  $O(n)$  calls to the `int` or `float` generators. Because of this, the speed of a single sample matters a great deal. Unfortunately, while existing PBT libraries by and large make sensible choices for their randomness libraries, they are not chosen with performance in mind, leading to worse bug-finding power than what is possible.

For example, significantly faster algorithms than SplitMix or JSF exist, such as the Lehmer algorithm [51], WyRand [72], and the xorshiro family of algorithms [7]. These all run between 1.2–1.6x faster per byte than SplitMix in microbenchmarks [39]. Plenty of other known optimizations on top of algorithm choice could also be implemented, including pipelined or even ahead-of-time sampling.

Of course, simply arguing that the randomness library is on the hot path for PBT does not guarantee that a faster sampling leads to measurably faster generation; for that, we need an experiment. The most obvious experiment is to simply swap out the randomness library of either `Base_quickcheck` or `ScalaCheck` one of the aforementioned faster algorithms. But, as discussed previously, AllegrOCaml and ScAllegro are designed to be 100% semantically equivalent replacements for their unstaged counterparts, ensuring that any bug-finding speedups are solely attributable to generator performance and not lucky seeds. Choosing a different randomness library would break this property, making it much more challenging to assess the performance compared to the baseline. To get around this, we exploit a coincidence: `Splittable_random`—the OCaml implementation of SplitMix that `Base_quickcheck` uses—is slow in a way that can be improved *without* changing the algorithm. In particular, due to implementation details related to the OCaml garbage collector, values of the OCaml type `int64` are not machine words, but rather *pointers* to machine words. This means that *all* `int64` operations (both arithmetic and bitwise) must allocate memory cells to contain their output, which has a significant performance benefit. By building a version that uses much faster “unboxed” 64-bit integer arithmetic, we can (a) demonstrate just how much faster bugs can be found just by using a more performant randomness library, and (b) explore which generators benefit the most from faster randomness library.

### 3 How Can I Make My Generator Library Faster?

With a sense of two main inefficiencies in generator libraries, we set out in this section to investigate solutions. We begin with a quick tour through multi-stage programming (Section 3.1), then incrementally build AllegrOCaml, layering on features and functionality (Sections 3.2 through 3.7). Last, we present a controlled experiment demonstrating how a faster randomness library leads to failing faster (3.8).

#### 3.1 Background: Multi-Stage Programming

In multi-stage programming (or simply “staging”), programs execute in multiple stages, with each stage producing code to be run in the next. For the purposes of this paper, we just need two stages: compile time and run time.

*Staging eDSLs.* One of the primary uses of staging is in embedded DSL construction [53, 56, 65]. While embedded DSLs are powerful tools, they have a well-known drawback: the functional abstractions used to build eDSLs tend to prevent compilers from generating efficient machine code. This is *abstraction overhead* [11, 45]: the layers of abstraction that make eDSLs pleasant to use are precisely what prevents them from being fast. Indeed, the root causes of many of the performance issues we discovered in Section 2 are not unique to generator DSLs, but pervasive across eDSLs.

344 In light of this issue, staging is often used as a lightweight compiler for DSLs. The compile-time  
 345 evaluation stage transforms the DSL code, eliminating abstractions to produce code that the host  
 346 language compiler can generate fast machine code for. This recipe has been used to great effect to  
 347 stage eDSLs for stream processing [30, 45], parser combinators [27, 34, 69, 71], and query processing  
 348 [4].

349 Many languages have some degree of staging functionality, including Scala 3 [1], Haskell [57],  
 350 Racket [18], OCaml [28, 70], and Java [68]. For this paper, we have implemented staged PBT  
 351 libraries in both OCaml (using MetaOCaml [28]) and Scala 3 (using `scala.quoted`). All staged  
 352 code presented in the body of this paper is AllegrOCaml code written in OCaml; ScAllegro is very  
 353 similar. We discuss the potential for staged generator DSLs in other languages in Section 5.

354 *Staging in MetaOCaml.* MetaOCaml’s staging functionality is exposed through the type `'a code`.  
 355 A value of type `t code` is an OCaml term of type `t`. Values of `code` type are introduced by *quotes*  
 356 (written `.<...>.`). Quotes delay execution of a program until run time. For example, the program  
 357 `.< 5 + 1 >.` has type `int code`. Note that this is not the same as `.< 6 >.` because brackets delay  
 358 computation, the code is not *executed* until the next stage (run time). Values of type `code` can be  
 359 combined using an *escape*, written `.~(e)` (or just `.~x`, when `x` is a variable). Escaping lets you take  
 360 a value of type `code` and “splice” it directly into a quote. For example, the program `let x = .<1 * 5>.` in  
 361 `.< .~(x) + .~(x) >.` evaluates to `.<(1 * 5) + (1 * 5)>.` MetaOCaml enforces  
 362 correct scoping and macro hygiene, ensuring that variables are not shadowed when open terms are  
 363 spliced in under binders.  
 364

365 The power of staging for optimizing away abstraction overheads comes from defining functions  
 366 that accept and return `code` values. A function `f : 'a code -> 'b code` takes a program  
 367 computing a run-time `'a` and transforms it into a program computing a run-time `'b`. In particular,  
 368 because `f` itself runs at compile time, the fact that the programmer called `f` does not matter at run  
 369 time—the abstraction that `f` defines has been eliminated. A code-transforming function `'a code`  
 370  $\rightarrow$  `'b code` can also be converted *code for a function*—a value of type `('a -> 'b) code`—with the  
 371 following program:

372 `let eta (f : 'a code -> 'b code) : ('a -> 'b) code = .<fun x -> .~(f .<x>.)>.`

373 This program is known as “The Trick” in the partial evaluation and multi-stage programming  
 374 literature [29]. It returns a code for a function that takes an argument `x` and splices in the result of  
 375 calling `f` on just the quoted `x`. For example, the following program

376 `let is_even x = .< .~x mod 2 == 0 >.` in  
 377 `let succ x = .< 1 + .~x >.` in  
 378 `eta (fun x -> succ (is_even x))`

380 reduces at compile time to `.< fun x -> (1 + x) mod 2 == 0 >.` By composing the two  
 381 code-transforming functions together at compile time and only then turning them into a run-time  
 382 function, the two functions are fused together. This is the basis of how staging is used to eliminate  
 383 the abstraction overhead of DSLs. By writing DSL combinators as compile-time functions—and  
 384 calling `eta` at the end on the completed DSL program—we can ensure that any overhead of using  
 385 the combinators is eliminated before run time.

### 386 3.2 Design of a Staged Generator DSL

388 To build a staged version of a generator DSL, we want to rewrite the the generator combinators  
 389 to do as much as possible at compile time. The compile-time stage will then produce simplified  
 390 code, free of any DSL abstraction, that can be compiled and run with different sizes and seeds. Our  
 391 job is thus to carefully bisect the DSL, determining which inputs to generator combinators are  
 392

393 known statically (and can be part of the compile time stage) and which parts are only known at run  
 394 time (and must be treated as code). In the staging literature, this task is known as “binding-time  
 395 analysis,” [26].

396 The crux of our binding time analysis[BCP: the wording here is misleading: it feels like we’re  
 397 implying we’ve implemented a binding-time analysis...] is that the *only* parts of a generator that  
 398 are not known at compile time are the random seed and size parameters. In practice, generators  
 399 themselves are entirely known at compile time. This leads us to define our library’s generator type  
 400 ‘a Gen.t as

401                   ‘a Gen.t = int code -> SR.t code -> ‘a code.

402 That is, a Gen.t is a compile-time function from dynamically known size and seed to dynamically  
 403 determined result.

404 The basic functionality of the staged monadic generator DSL can be found in Figure 7.

```
405
406 module Gen = struct
407   type 'a t = int code -> Random.t code -> 'a code
408
409   let return (cx : 'a code) : 'a t = fun size random -> cx
410
411   let bind (g : 'a t) (k : 'a code -> 'b t) : 'b t =
412     fun size random ->
413       .<
414         let a = .~(g size random) in
415           .~(k .<a>. size random)
416       >.
417
418   let int (lo : int code) (hi : int code) : int t =
419     fun size random ->
420       .< SR.int .~random .~lo .~hi >.
421
422   let to_bq (g : 'a code Gen.t) : ('a Bq.t) code =
423     .<
424       fun size random -> .~(g .<size>. .<random>.)
425     >.
426
427
428 end
```

Fig. 7. Basic Staged Generator Library

430 The constant generator `return` runs at compile time. Given `cx : ‘a code`, the code for an ‘a,  
 431 it returns the generator that ignores its `size` and `random` arguments and simply runs[BCP: returns  
 432 the code for?] `cx`. Similarly, `bind g k` sequences generators by passing the result of running  
 433 the generator `g` to the continuation `k`. However, instead of getting access to the particular value  
 434 generated by `g`, the continuation `k` only gets access to code for the value sampled from `g`: we  
 435 know that at run time the code `g` generates will produce *some* ‘a, but at compile time we cannot  
 436 inspect the value. Operationally, `bind` takes code for the `size` and `random` and returns code that (1)  
 437 let-binds a variable `a` to spliced-in code of `g` and then (2) runs the spliced-in continuation `k`. Both  
 438 function applications `g size random` and `k .<a>. size random` run at compile time. `Gen.int` is  
 439 the generator that samples an `int` from the randomness library. Given any `size` and `random` seed, it  
 440 returns a code block that calls `SR.int` with that random seed. Because the lower and upper bounds  
 441

442 might not be known at compile time—they may themselves be the results of calling Gen.int—the  
 443 arguments lo and hi are of type int code and get spliced into the code block as arguments to  
 444 SR.int. Lastly, to\_bq turns a staged generator into code for a normal Base\_quickcheck generator.  
 445 This is just a 2-argument version of “The Trick” from Section 3.1.

446 Returning to our running example, Figure 8 shows the int-pair generator written with the staged  
 447 Gen.t monad, as well as the inlined code that results from calling Gen.to\_bq (changing some  
 448 identifier names for clarity). The code generated is identical to the manually inlined version from  
 449 Section 2.

```
450
451
452 let int_pair_staged : (int * int) Gen.t =
453   Gen.bind (Gen.int .<0>. .<100>.) (fun cx ->
454     Gen.bind (Gen.int .<0> cx) (fun cy ->
455       Gen.return .<(.~cx,.~cy)>.
456     )
457   )
458
459 let int_pair : (int * int) Bq.t code = Gen.to_bq int_pair_staged
460 (* int_pair = .< fun size random ->
461     let x = SR.int random 0 100 in
462     let y = SR.int random 0 x in
463     (x,y)
464     >.*)
```

Fig. 8. Pairs of Ints, Staged

### 3.3 Staging Combinators

In Section 2, we noted that generator combinators like weighted\_union allocate lists in the hot path of the generator. Even though these lists are usually small—at most a few dozen elements—each allocation takes us closer to the next garbage collection, which is bad for performance.

This is an ideal opportunity to exercise another feature of staging: compile-time specialization. Since we almost always know the particular list of choices at compile time, a staged version of weighted\_union can generate *different code* depending on the number of generators in the union. If we use weighted union on a compile-time list of generators g1, g2, and g3, we can emit code that picks between the generators without realizing the list at run time.

Figure 9 shows the code for such a staged weighted union. Crucially, it takes a *compile-time* list weighted\_gens of generators and weights. The weights themselves might only be known at run time—it is common to use the current size parameter as a weight, for instance—so they are codes. Instead of building a data structure representing a histogram of the distribution described by the weights at run time and then traversing it, the compile-time weighted\_union combinator generates a tree of ifs, specialized to the list of weights known at compile time, that picks out the selected generator.

Figure 10 demonstrates a use of this staged weighted union. Given a list of (in this case constant) generators with weights “the current size parameter”, 2, and 1, the generated code first computes the sum of these numbers, samples between 0 and the sum, and traverses the tree of three ifs to find the correct value to return.

```

491 module Gen =
492 ...
493 let pick (acc : int code) (weighted_gens : (int code * 'a t) list) size random : 'a code =
494   match weighted_gens with
495   | [] -> .< failwith "Error" >.
496   | (wc,g) :: gens' ->
497     .<
498       if .~acc <= .~wc then .~(g size random)
499       else
500         let acc' = .~acc - .~wc in
501         .~(pick .<acc'>. gens' size random)
502     >.
503
504 let weighted_union (weighted_gens : (int code * 'a t) list) : 'a t =
505   let sum_code = List.foldr (fun acc (w,_) -> .<.^acc + .^w>.) .<>.
506   weighted_gens in
507   fun size random ->
508     .<
509       let sum = .^sum_code in
510       let r = SR.int .~random_c 0 sum in
511       .~(pick .<r>. weighted_gens size random)
512     >.
513
514
515 let grades : char Bq.t = Gen.to_bq (
516   Gen.bind size (fun n ->
517     Gen.weighted_union [
518       (n, Gen.return .<'a'>);
519       (.<2>, Gen.return .<'b'>);
520       (.<1>, Gen.return .<'c'>);
521     ]
522   )
523   (*
524     .< fun size random ->
525       let sum = size + 2 + 1 + 0 in
526       let r = SR.int random 0 sum in
527       if r <= size then 'a' else
528         let r' = r - size in
529         if r' <= 2 then 'b' else
530           let r'' = r' - 2 in
531             if r'' <= 1 then 'c' else failwith "Error"
532     >.
533   *)
534
535

```

Fig. 9. Staged Weighted Union

```

536
537
538
539

```

Fig. 10. Use of Staged Weighted Union

### 540 3.4 Let-Insertion and Effect Ordering

541 Careful readers might note that the definition of bind (Figure 11a) was more complicated than  
 542 one might expect. Why not define bind in the standard way for a reader monad (Figure 11b)?  
 543 Unfortunately, the latter definition is wrong in our context as it leads to incorrect code being  
 544 generated. For example, consider Gen.bind' (Gen.int .<0>. .<1>.) (fun x -> Gen.return  
 545 .<(. x,. x)>.). This generates the run-time code fun size random -> (SR.int random 0 1,  
 546 int SR.random 0 1), which is incorrect. Instead of generating a single integer and returning it  
 547 twice, it samples two different integers. This matters because, as described in Section 1, AllegrOCaml  
 548 and ScAllegro are intended to be equivalent to their unstaged counterparts.  
 549

```
550 let bind (g : 'a t) (k : 'a code -> 'b t) : 'b t =
551   fun size random -
552     .<
553       let a = .~(g size random) in           let bind' (g : 'a t) (k : 'a code -> 'b t) :
554         .~(k .<a>. size random)           fun size random -> k (g size random) size random
555     >.
556   (a) bind, with a let-binding           (b) bind', the "standard" bind for the reader
557
558   monad
```

558 Fig. 11. bind, two ways

559  
 560 In essence, the behavior of splice  $\tilde{c}x$  in a staged function  $f(cx : 'a code) = \dots$  is to *copy*  
 561 the entire block of code, effects and all. To ensure that the randomness effects of the first generator  
 562 are executed only once but that the value can be used in the continuation multiple times, the correct  
 563 bind let-binds the result of generation to a variable and then passes it to the continuation.  
 564

### 565 3.5 CodeCPS and a Monad Instance

566 Another subtle issue prevents the version of the library design discussed so far from being used as a  
 567 drop-in replacement for an existing generator DSL: the types of `return : 'a code -> 'a Gen.t`  
 568 and `bind : 'a Gen.t -> ('a code -> 'b Gen.t) -> 'b Gen.t` aren't quite right. For the type  
 569 `'a Gen.t` to actually be a monad, these types cannot mention `code`. This is not just a theoretical  
 570 issue; it is a significant usability concern. The syntactic sugar for monadic programming (let%bind  
 571 in OCaml, foreach in Scala, do in Haskell, etc) that makes it smooth can *only* be used if `return` has  
 572 type `'a -> 'a Gen.t` and `bind` has type `'a Gen.t -> ('a -> 'b Gen.t) -> 'b Gen.t`

573 To support convenient monadic programming, we need to adjust the type of `'a Gen.t` slightly.  
 574 An initial attempt is to try type `'a t = int code -> SR.t code -> 'a`. If we strip the `code`  
 575 off the result type, the functions `return (x : 'a) = fun _ _ -> x` and `bind g k = fun size`  
 576 `seed -> k (g size seed)` `size seed` have the proper types for a monad instance. Then, any  
 577 combinators of type `'a Gen.t` before simply become `'a code Gen.t` with this new version.  
 578

579 However, this definition of `bind` doesn't have call-by value effect semantics, as discussed in the  
 580 previous section. And because the type of `g size seed` is now just `'a` (not necessarily `'a code`),  
 581 we cannot perform the let-insertion needed to preserve the CBV effects. To solve this problem,  
 582 we turn to a classic technique from the multistage programming literature: writing our staged  
 583 programs in continuation-passing style [8].

584 In Figure 12, following prior work [11, 32], we define the type `'a CodeCps.t = 'z. ('a -> 'z`  
 585 `code) -> 'z code`: a polymorphic continuation transformer with the result type always in `code`.<sup>6</sup>  
 586 The monad instance for this type is the standard instance for a CPS monad with polymorphic return

587 <sup>6</sup>This is an instance of the *codensity* monad [66]—a fact that deserves further investigation.

```

589 module CodeCps = struct
590   type 'a t = { cps : 'z. ('a -> 'z code) -> 'z code }
591
592   let return x = {cps = fun k -> k x}
593
594   let bind (x : 'a t) (f : 'a -> 'b t) : 'b t =
595     {cps = fun k -> x.cps (fun a -> (f a).cps k)}
596
597   let run (t : ('a code) t) : 'a code = t.cps (fun x -> x)
598
599   let let_insert (cx : 'a code) : 'a code t =
600     {cps = fun k -> k .< let x = .~cx in .~(k .<x>.) >.}
601 end
602
603 module Gen = struct
604   type 'a t = int code -> SR.t code -> 'a CodeCps.t
605
606   let return (x : 'a) : 'a t = fun _ _ -> Codecps.return x
607
608   let bind (g : 'a t) (f : 'a -> 'b t) =
609     fun size random ->
610       CodeCps.bind (g size random) (fun x -> (f x) size random)
611
612   let int (lo : int code) (hi : int code) : int code t =
613     fun size random -> let_insert .< SR.int .~random .~lo .~hi >.
614 end
615
616
617
618 type. In prior work, this type is often referred to as the “code generation” monad. This is because a
619 value of type ('a code) CodeCps.t is like an “action” that generates code: CodeCps.run passes
620 the continuation transformer the identity continuation to produce a 'a code. To avoid confusion
621 with random data generators, we refer to this type as CodeCps.t. Most importantly, the CodeCps
622 type supports a function let_insert, which, given cx : 'a code, let-binds let x = .~cx, and
623 then passes .<x>. to the continuation. [HG: I'm getting lost in the inline code again]
624 We can then redefine our staged generator monad type to be 'a Gen.t = int code -> SR.t
625 code -> 'a CodeCPS.t, as shown in Figure 12. The (old) type 'a Gen.t is now written as the (new)
626 type 'a code Gen.t, and this type change carries through all of our combinators. For example,
627 Gen.int now returns int code Gen.t.
628 This gives us the best of both worlds. First, we get a monad instance for 'a Gen.t with the
629 correct types, which lets us use the monadic syntactic sugar of our chosen language. Moreover, we
630 also get to maintain the correct effect ordering: effectful combinators like Gen.int do their own
631 let-insertion, ensuring that a program like Gen.bind Gen.int (fun x -> ...) generates a let-
632 binding for the result of sampling the randomness library. For example, bind (int .<0>..<1>.)
633 (fun cx -> return .<(. cx,.. cx)>.) now correctly generates .< fun size random -> let x
634 = SR.int random 0 1 in (x,x) >. This design is less obviously correct, and does require some
635 care. Rather than bind ensuring correct evaluation order once and for all, individual combinators
636 must be carefully written to ensure that 'a code values that contain effects are let_inserted. To
637

```

Fig. 12. CodeCPS and the Final Gen Monad

638 validate the library, we built a PBT harness to compare staged generators to their Base\_quickcheck  
 639 equivalents over 1,000 random seeds. By differentially testing [41] a large suite of generators in  
 640 this way, we gained confidence that AllegrOCaml is equivalent to Base\_quickcheck.

### 641 3.6 Recursive Generators

642 Generating values of recursive datatypes requires recursive generators. Different generator DSLs  
 643 support recursive generators differently. Some allow recursive generators to be defined as recursive  
 644 functions, while others (including both Base\_quickcheck and ScalaCheck) expose a fixed-point  
 645 combinator to construct recursive generators. Given a step function that takes a “handle” to sample  
 646 from a recursive generator call, it ties the knot and builds a recursive generator.

647 In our setting, letting programmers define recursive generators as recursive functions is out of  
 648 the question. With staged programming, recursion must be handled with care: it is far too easy to  
 649 accidentally recursively define an infinite code value and have the program diverge at compile time,  
 650 when trying to write a code representing a recursive program. To this end, we develop a staged  
 651 recursive generator combinator<sup>7</sup>, whose API is shown in Figure 13. The recursion API consists of  
 652 an opaque type 'a handle, and a function recurse to perform recursive calls. Programmers can  
 653 then define recursive generators by fixed\_point, which ties the recursive knot.

```
655 type 'a handle
656 val recurse : 'a handle -> 'a code Gen.t
657 val fixed_point : ('a handle -> 'a code Gen.t) -> 'a code Gen.t
```

659 Fig. 13. Staged Recursive Generator Combinator API

### 660 3.7 Staging Type-Derived Generators

661 Generators are traditionally handwritten, but some PBT libraries allow users to synthesize them  
 662 automatically from type definitions. Type-derived generators are convenient—the derivation process  
 663 requires no manual effort—but also limited: they are unable to account for constraints not encoded  
 664 in the type. For example, they can generate arbitrary trees, but not binary search trees. When such  
 665 constraints are present, type-derived generators are usually less effective than hand-crafted ones,  
 666 since most generated values will be invalid.

667 The speed of generation becomes particularly important in this setting. In a generator that  
 668 produces only valid values, only a subset of them will trigger a bug; in a type-derived generator,  
 669 however, only a subset of generated values will be valid, and only a subset of *those* will find a  
 670 bug. As a result, many more values must be produced, making it important to do so as quickly as  
 671 possible.

672 The type deriving algorithm follows a compositional pattern. Generators for complex types are  
 673 synthesized by structurally composing generators for their subtypes: base types are mapped to  
 674 primitive generators included in the generator library; product types such as tuples and records  
 675 are handled by sampling each component using bind and aggregating the results; sum types, or  
 676 variants, are generated using a weighted\_union of the generators for each case; for recursive types,  
 677 the entire generator is wrapped in a fixed-point combinator and a recursive handle is used as the  
 678 generator for all recursive occurrences in the type. This compositional approach maps naturally  
 679 to staged generation: to derive a staged generator, we replace each standard combinator with its  
 680 staged counterpart. The derivation algorithm remains unchanged.

681 <sup>7</sup>We actually provide a more general API that allows programmers to define *parameterized* recursive combinators, of type  
 682 '*r* code -> 'a code Gen.t, for any type '*r*.

Our implementation in OCaml uses the PPX (PreProcessor eXtension) system to synthesize staged generators from type definitions. However, any language that supports type-derived generators can implement a staged version using a similar implementation to the original. In Scala, for instance, the same strategy could be realized using type class resolution. In both settings, the result is a three-stage process: a metaprogram—via PPX or type classes—constructs a generator expression composed of staged combinators; this expression is evaluated at compile time to produce a specialized generator; and finally, the generator is executed at run time to produce values.

We implemented this in AllegroOCaml; it is not yet implemented in ScAllegro. We benchmark the results in §4.

### 3.8 Performance Opportunities in Randomness Libraries

As we discussed in Section 2.2, choosing an inefficient randomness library is another impediment to finding bugs fast. To demonstrate that faster random sampling can significantly impact bug-finding power, we use the controlled experiment suggested by OCaml’s inefficient implementation of SplitMix. By replacing this relatively slow randomness library with a faster but semantically equivalent implementation, we can precisely quantify the bug-finding speedup that a better randomness library gives across a range of PBT scenarios.

Note that the performance intervention described here is OCaml-specific. In most other PBT frameworks, the randomness library used operates on machine integers, so this *particular* inefficiency does not exist. However, the insights that we will derive from this experiment in Section 4—about which kinds of generators benefit the most from faster randomness and how it leads to faster bug-finding—are applicable to all languages.

The precise details of the SplitMix algorithm [59] are not important for present purposes; the key fact is that all of its operations are defined in terms of arithmetic and bitwise operations on 64-bit integers. In OCaml, because of details related to the garbage collector, the 64-bit integer type `int64` is represented at run time as a *pointer* to an unscanned block of memory containing (among other things) a 64-bit integer [? ]. This means that all operations that return an `int64` must allocate this block of memory, which has a significant impact on performance. A single call to one of the `Base_quickcheck` library functions—like generating an arbitrary integer—may call into the `Splittable_random` library times. Each call into `Splittable_random` may sample many times from the core SplitMix sampling routine `next_int64`, i.e., using rejection sampling to find a value within a range. Finally, each call to `next_int64` allocates 9 times, and each allocation brings us closer to the next garbage collection pause. While small allocations like these are *very* fast to perform and subsequently collect in OCaml<sup>8</sup>, we will see in Section 4 that they can still have a large performance impact on generators that spend most of their time sampling data. To avoid these allocations, we reimplement SplitMix in C and call out to it with the OCaml FFI. The C version of the library uses proper `int64_t` arithmetic, only boxing and unboxing integers at the call boundaries between OCaml and C code.<sup>9</sup>

## 4 Evaluation

We evaluate the raw generator performance and bug-finding speed of Allegro generators across a range of benchmarks. Our experiments compare generators built using our technique—with and

<sup>8</sup>The OCaml GC is a generational collector [43], and since these allocations are small and mostly very short lived, they will all be minor allocations, never to be promoted.

<sup>9</sup>Ideally in the future, one would not need to call out to C for this: the Jane Street bleeding-edge OCaml compiler has support for unboxed types [17], which (among other things) would let us implement a version of SplitMix that does not allocate, directly in OCaml. Unfortunately, the Jane Street branch of the compiler is incompatible with MetaOCaml, which we use to implement the metaprogramming discussed in the previous sections.

736 without our improved SplitMix (“CSplitMix”)—against those implemented with existing generator  
 737 libraries and their default randomness mechanisms. Specifically, we implement semantically  
 738 equivalent staged generator libraries that replicate the behavior of `Base_quickcheck` in OCaml  
 739 and ScalaCheck in Scala, allowing us to assess the effectiveness of our technique across different  
 740 languages and runtime environments.

741 This section presents our experimental setup and addresses the following research questions:

- 742 • **RQ1:** Do generators written using our technique run faster than those written with regular  
     generator combinators?
- 744 • **RQ2:** Do observed generation speedups translate to better bug-finding speed?

746 All experiments were run on a 64-bit Linux machine with 264 GB RAM and a 128-core Intel Xeon  
 747 Platinum 8375C CPU, running Ubuntu 24.04.1 LTS. AllegrOCaml and all OCaml benchmarks were  
 748 compiled with 4.14.1+BER MetaOCaml `ocamlopt`, the native code compiler for OCaml, using compiler  
 749 flag `-O3`. The baseline OCaml generators were written with `Base_quickcheck` 0.16. ScAllegro  
 750 and all Scala benchmarks were run on Scala 3.6.3 and OpenJDK 21.0.6, using ScalaCheck version  
 751 1.17 as the baseline. We used `core_bench` 0.16 [62] in OCaml and `jmh` 0.4.7 [48] for performance  
 752 microbenchmarking. For assessing and comparing PBT techniques, we used the Etna platform [58].  
 753

#### 754 4.1 Benchmarking Generator Speed

755 To answer **RQ1**, we microbenchmark generators, comparing generators written in AllegrOCaml to semantically identical ones in `Base_quickcheck` and generators in ScAllegro to those  
 756 in ScalaCheck. We vary the choice of randomness library in our AllegrOCaml generators, using  
 757 both `Base_quickcheck`’s default `splittable_random` and CSplitMix, as discussed in §3.8. Our  
 758 test cases consist of generators for boolean lists, binary search trees (BSTs), and simply typed  
 759 lambda-calculus (STLC) terms. We implement generators for these benchmarks using a variety of  
 760 *strategies*, varying in structure and sophistication.

761 In AllegrOCaml, our strategies include: type-derived generators for BSTs and STLC terms,  
 762 following the approach described in §3.7; two custom BST generators—one that builds a tree  
 763 incrementally by repeatedly inserting values into an initially empty structure, and another that  
 764 constructs the entire tree in a single pass by generating keys, values, and subtrees at each step;  
 765 a boolean list generator that mirrors the single-pass BST strategy; and a generator for STLC terms  
 766 that is correct by construction (i.e., it produces only well-typed terms).

767 For each strategy, we compare three treatments: our `Base_quickcheck` baseline; a AllegrOCaml  
 768 version using `Base_quickcheck`’s randomness library, `splittable_random`; and a AllegrOCaml  
 769 version using CSplitMix. For each treatment, we measure the time to generate a value (i.e., a BST,  
 770 STLC term, or boolean list), using a random seed, varying generation sizes (10, 100, 1,000, 10,000).<sup>10</sup>  
 771 We run each treatment for 5 seconds and compute the average generation time of a value produced  
 772 in that interval.

773 Our results are summarized in Figure 14. The type-derived AllegrOCaml BST generator achieves  
 774 speedups ranging from 1.30 – 1.38×, which increase dramatically, to 2.13 – 7.76×, when combined  
 775 with CSplitMix. The insertion-based BST generator sees 1.18 – 1.22× speedups with staging alone  
 776 and 3.83 – 6.31× when also using CSplitMix. The single-pass BST generator benefits more from  
 777 staging, with speedups of 2.22 – 2.25×, rising to 9.05 – 9.82× when combined with CSplitMix.  
 778

781 <sup>10</sup>The specific meaning of generation size is a domain-specific implementation detail—in a list generator, size might  
 782 correspond to the desired length of the list, whereas in a tree generator it refer to number of nodes, number of leaves, depth  
 783 of tree, etc. Regardless, our goal is to show that performance trends scale.

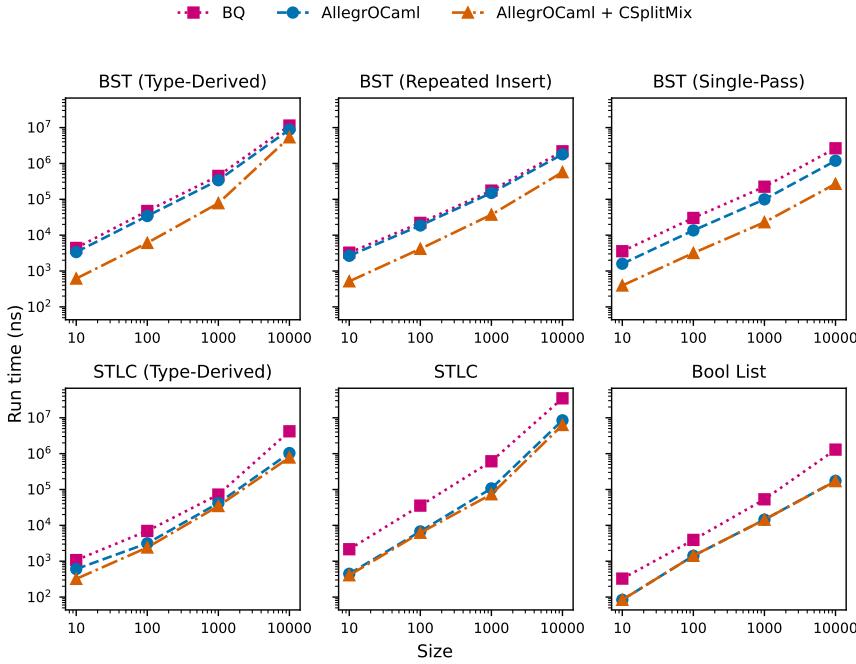


Fig. 14. Time to generate values of varying sizes using each AllegroCaml strategy. Lower is better. Both axes are logarithmic. BQ is Base\_quickcheck.

For STLC, staging accounts for larger performance gains, yielding  $1.73 - 4.05\times$  speedups for the type-derived STLC generator and  $4.10 - 5.71\times$  for the well-typed generator. Adding CSplitMix, these numbers increase to  $2.90 - 5.39\times$  and  $5.33 - 8.33\times$ .

The boolean list generator experiences  $2.77 - 7.47\times$  speedups with staging, and its performance changes only minimally when combined with CSplitMix ( $2.77 - 7.57\times$ ). This is likely because sampling booleans is cheap enough that the overhead of crossing the FFI barrier is comparable to that of generating values directly in OCaml.

The variation in speedups raises a natural question: what determines how much a generator benefits from staging, randomness library optimizations, or both? One likely explanation is that the two techniques address different performance bottlenecks: generators that sample more often benefit more from improved random sampling, while those that rely heavily on generator library combinators gain more from staging. To test this idea, we use measurable proxies that approximate a generator's reliance on its randomness and generator libraries. For the former, we count the number of times a generator invokes the SplitMix sampling routine `next_int64`. For the latter, we use the number of calls to `bind`—the central monadic generator function, extensively used both directly and within other combinators.

We select four strategies with disparate speedup profiles: insertion-based BSTs, single-pass BSTs, boolean lists, and well-typed STLC terms. To determine how often `bind` is invoked, we generate 10,000 values using a fixed generation size of 100 and record the average number of `bind` calls. To determine the number of random samples, we repeat the same test but use Intel ProcessorTrace [25] to capture a 4ms snapshot of processor activity. We then count the number of invocations of `next_int64` and average this over the number of generator calls in the trace.

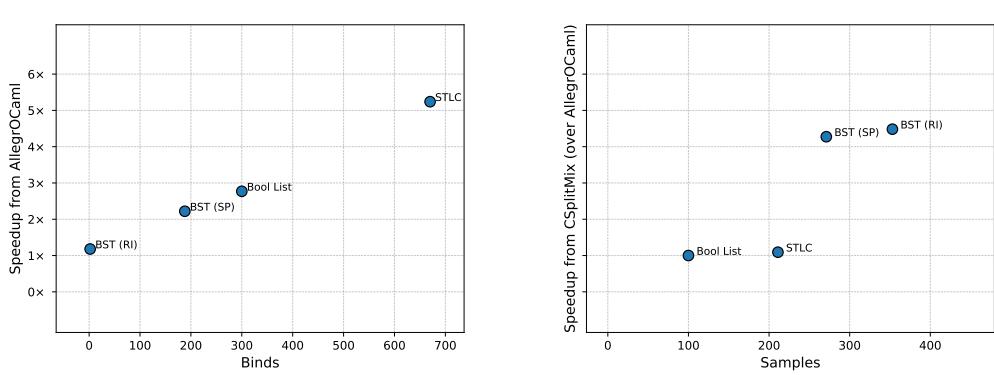


Fig. 15. Left: Speedup from staging (compared to Base\_quickcheck) versus the number of bind calls. Right: Speedup from CSplitMix (compared to AllegroCaml alone) versus the number of random samples.

Figure 15 summarizes the results. The left plot shows a clear linear relationship between performance benefit from staging and number of calls to bind. The right plot shows a separation between generators that sample heavily (BST strategies) and those that do not (STLC and Bool List), with the former seeing significantly greater speedups from CSplitMix.

From these results, we conclude that staging and randomness library choice play distinct and complementary roles in generator performance. Sampling-heavy generators see greater improvements from faster randomness libraries, while combinator-heavy ones benefit more from staging. Since both factors influence performance significantly, generator libraries should use both in order to handle diverse workloads.

In ScAllegro, we implement a subset of the AllegroCaml strategies: the boolean list generator, single-pass BST generator, and well-typed STLC term generator.<sup>11</sup> We did not implement an optimized version of ScalaCheck’s randomness library, but our experimental setup was otherwise the same as in OCaml.

As shown in Figure 16, ScAllegro achieves an even greater performance gain—purely from staging—over ScalaCheck than AllegroCaml does over Base\_quickcheck. In particular, the single-pass BST strategy is  $4.89 - 6.51 \times$  faster, the boolean list generator is  $6.86 - 13.41 \times$  faster, and STLC is  $5.43 - 9.70 \times$  faster. This difference arises from ScalaCheck’s representation of generators as functions of type `size -> seed -> Option[A]`: each generator combinator must construct and then pattern-match on these `Option` values, introducing significant boxing and unboxing overhead at each step. Staging eliminates this overhead. These results show that the Allegro approach generalizes well across languages.

## 4.2 Benchmarking bug-finding speed

To answer RQ2, we evaluate the bug-finding speed of our BST and STLC case studies using Etna [58]. Etna allows users to measure the effectiveness of different generator implementations by injecting bugs into the system under test and recording the time taken for a relevant property to fail in response. Each case study includes a diverse set of *tasks*, where a task consists of a specific bug-property pair designed to test a specific aspect of the system (e.g., BST includes tasks that test insertion, deletion, and union operations). In particular, BST has 37 tasks, and STLC has 20.

<sup>11</sup>The type-derived strategies are excluded, since ScAllegro does not currently support type derivation.

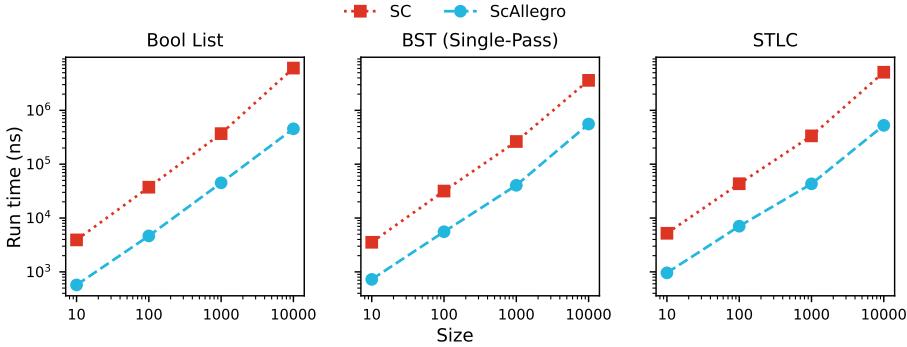


Fig. 16. Time to generate values of varying sizes using each ScAllegro strategy. Lower is better. Both axes are logarithmic. SC is ScalaCheck; Staged is ScAllegro.

Strategies for BST and STLC are implemented in AllegroOCaml; they are unchanged from their description in §4.1. Etna does not support Scala, so we were unable to test ScAllegro’s bug-finding speed in Etna, but we expect the results in this section to extend to ScAllegro.

It is worth noting that the time-to-failure of a given strategy on a given seed is not necessarily representative of the strategy’s average time-to-failure over a large number of trials. We normalize by computing the relative performance, or the “speedup.” This works in most cases, but it is not perfect. For example, it is theoretically possible to choose a seed such that the *first* value produced by a generator discovers the bug, which would eliminate any differential speedup, and likewise if both generators fail to find the bug. To account for these cases, we repeat the above process over 30 random seeds—that is, all strategies run on the same seed so that they produce identical sequences of values, and this process is repeated 30 times. Although the variance *between* seeds in Etna can be vast, timing results are replicable for a *given* seed. Across 1,000 trials using the same seed, the observed variance in time-to-failure was less than a nanosecond.

We run each strategy on all tasks using a 60-second timeout. If a bug is not found within this limit, the task is considered “unsolved.” We exclude tasks where all strategies fail to find the bug from our dataset, as they provide no basis for comparison. Similarly, we exclude tasks where the Base\_quickcheck strategy completes in under 5ms, as such negligible run times do not yield meaningful insights into relative performance. Across all 30 seeds, these filters remove 28/600 (4.67%) of type-derived STLC’s tasks, 168/600 (28%) of STLC’s tasks, 149/1110 (14.42%) of type-derived BST’s tasks, 268/1110 (24.1%) of single-pass BST’s tasks, and 371/1110 (33.42%) of insertion-based BST’s tasks. More sophisticated strategies tend to find bugs very quickly, leading to a higher number of filtered tasks. By applying these filters, we ensure that our reported speedups reflect optimizations that meaningfully impact performance.

Our results are summarized in Figure 17, which shows the geometric average of individual-task speedups for each strategy and benchmark. Trends in bug-finding speed reflect trends in performance from §4.1. The distribution of speedups in Figure 18 reveals substantial variability, with most tasks clustering near the median and a long tail of outliers achieving much larger gains. STLC shows a more bimodal distribution of speedups than the other benchmarks, which we attribute to the heterogenous difficulty of its tasks: some tasks regularly hit the 60-second timeout, while others finish in a fraction of a second. We find that “easier” tasks—those that run on the order of milliseconds—regularly achieve speedups in the range of 4 – 9×, whereas tasks that run on the

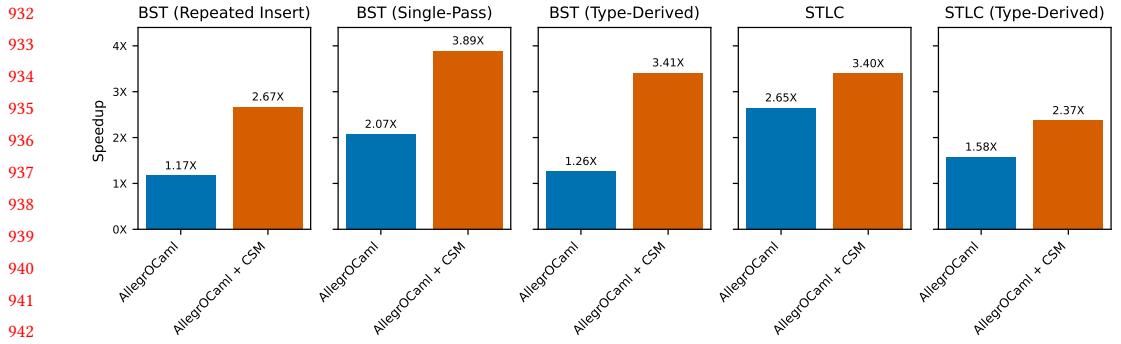


Fig. 17. Geometric average of all speedups—relative to `Base_quickcheck`—for each strategy and benchmark, showing that staging leads to better bug-finding speed across the board. CSM is CSplitMix.

order of seconds achieve more moderate speedups of up to 3.5 $\times$ . Overall, these results give strong evidence that AllegroCaml consistently benefits bug-finding speed, sometimes drastically.

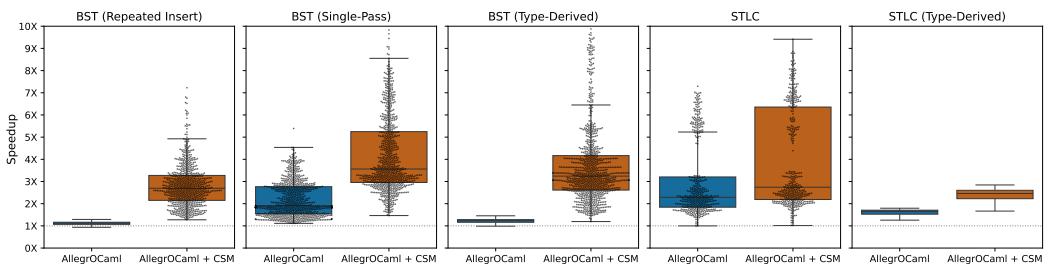


Fig. 18. Distribution of individual-task speedups across strategies and benchmarks. Gray dots represent tasks. Plots with extremely low variance have no swarm overlay. CSM is CSplitMix.

In addition to AllegroCaml’s overall bug-finding speed, we evaluate the performance of its type-derived generators—specifically, whether they can transform previously intractable tasks into tractable ones. Out of 78 tasks that initially timed out, 30 (38.4%) completed successfully using AllegroCaml alone, and 50 (64.1%) completed successfully after adding CSplitMix. This shows that staged type-derived generators can provide significant performance improvements for free, without any additional effort from the user.

## 5 Beyond OCaml and Scala

In the years since the original QuickCheck paper [13], PBT has had remarkable success in languages outside of the Haskell world from which it came [2, 24, 61]. For this reason, readers who are users and developers of PBT libraries in *other* languages—including non-strict or procedural ones—might be curious about how the techniques brought to bear on OCaml’s `Base_quickcheck` and Scala’s `ScalaCheck` in this paper might be imported to their favorite language.

We begin by noting that the principle of choosing fast random number generators is completely language-agnostic. In languages like OCaml, where runtime value representations make natively-implemented randomness library inefficient, calling out to a C implementation or using standard libraries written in C is a surefire win. In other languages, serious thought should be put into using as fast of a randomness library as possible, as opposed to picking up any suitable option off the

shelf. Next, we discuss language-by-language the degree to which the staging-related insights of this paper are portable.

**Racket** is the next target that we intend to test on. The entire Racket philosophy is intertwined with using macros to build small eDSLs like the ones we use to write generators, and so it seems a natural fit. However, the racket macros literature, while extensive, does not usually concern itself with staging for performance purposes. For this reason, we—the authorship team of this paper, devoid of much Racket expertise—decided to not use Racket as a test case in this paper.

**Haskell** is home to the original PBT implementation, and so it is natural to ask why we have not built a Allegro in it yet. The basic answer is that the Haskell compiler (GHC) is designed specially to eliminate the run-time overhead of monadic abstractions! Indeed, because Haskell is pure, GHC can aggressively inline and beta-reduce nearly anything as part of its normal optimiation steps. This means that in many cases, the impact of a staged PBT library (and indeed, all staged monadic DSLs) negligible. For complex enough programs however, the heuristics GHC uses can degrade, leading to performance overheads for monadic code. For this reason, Haskell does have a multi-stage programming system called Template Haskell [57], which is sometimes to build eDSLs in contexts where one does not want to rely on the optimizer’s heuristics. In short: it is possible to build a Allegro version of Haskell QuickCheck, but the benefits would be much less pronounced.

F# has both multi-stage programming capabilities [42] and a well-used PBT library called FsCheck [19]. The internals of FsCheck’s generator eDSL are very similar to both Base\_quickcheck and ScalaCheck, so we expect that building an Allegro in F# is primarily an engineering effort.

**Rust** shares some similarities with functional languages, and indeed, it is host to a number of property-based testing libraries [10, 52]. However Rust does not structurally encourage monadic eDSLs—it does not have a special monadic syntax—and so PBT libraries in Rust ask programmers to define generators directly as seed  $\rightarrow$  value functions. For this reason, staging does not seem directly applicable to any of the PBT libraries in Rust.

## 6 Related Work

*Speeding up Property-Based Testing.* Our work is unique in its approach to speeding up PBT, but it is certainly not the only work focused on making PBT faster.

Perhaps the best-explored approaches to speeding up bug-finding with PBT is by changing the order in which test inputs are sampled. Feedback-driven mechanisms like Targeted PBT [40] and Coverage-Guided PBT [37] have the potential to speed up testing by changing the generation order to try to find “interesting” inputs faster. Separately, enumerative approaches to PBT [9, 54] try to get to bugs faster by leveraging the “small-scope hypothesis” and attempting to quickly exhaust the list of small inputs to the program under test. All of these approaches can have significant performance benefits in practice, but they are largely orthogonal to our contributions; we expect Allegro could be used to speed these existing techniques to varying degrees.

Similarly orthogonal to our approach are techniques for quickly filtering out inputs that are invalid for testing. Some of these approaches work statically, by automatically deriving generators that produce valid inputs by construction [38], while others filter dynamically via laziness [12] or by solving satisfiability problems [36, 55, 60]. In all cases, these approaches could be further improved by insights from Allegro.

The most direct comparison to our work is QuickerCheck [35], an implementation of Haskell’s QuickCheck that exploits the inherent parallelism of PBT to achieve significant performance gains. QuickerCheck, like Allegro, was designed with performance engineering in mind, taking seriously the idea that PBT is a performance critical task. Still, despite their similar motivations and considerations, the solutions are entirely different and complementary.

*Multi-Stage Programming.* Staging’s roots come from quasiquotation in LISP [6], where the unified representation of data and code allows for sophisticated metaprogramming. Quasiquotation-style macros were introduced to the ML family of languages by Nielson and Nielson’s Two-Level Functional Languages [47] and MetaML [63], which in turn quickly inspired MetaOCaml [28] (and more recently MacoCaml [70]) in OCaml, Lightweight Modular Staging in Scala [53], Template Haskell in Haskell [57], and more. In addition to implementations, researchers have studied the type-theoretic foundations of multi-stage languages [15, 16, 46], as well as ways of combining multi-stage types with other sophisticated features like dependent types [32]. Meanwhile, the Racket community continues the LISP tradition with a long and fruitful line of work studying how macros and metaprogramming can be used to build extensible DSLs [18, 33, 64].

Back in the ML-family world, the primary use of staging is building embedded DSLs with minimal performance overhead, an idea which has come to be known as “abstraction without regret” [49, 50, 53, 56, 65]. This technique has been applied across a range of domains, including Big data processing [5], stream processing [30, 45], query processing [4], and parser combinators [27, 34, 69, 71]. This work on staged parsers is the closest analogue to ours—indeed, PBT research has drawn an explicit link between parsing and generation, framing generators as “parsers of randomness” [22]. However, this equivalence is primarily theoretical. PBT generators are (a) not actually implemented as parsers of random sequences, and (b) support choice-based combinators like `weighted_union` that parsers do not. For this reason, we must build staged generator libraries from scratch and cannot simply use existing staged parser libraries.

## 7 Conclusion & Future Work

In this paper, we identified, studied, and proposed potential solutions to two important sources of inefficiency in PBT generator libraries: abstraction overhead and choice of randomness library. In the future, we hope to continue to investigate and push the boundaries of PBT generator performance.

On the abstraction overhead side, we hope to employ some of the many tricks for better code generation that have been written about in the staging literature. For example, MetaOCaml includes a primitive floating let-insertion [31] that yields optimal let placement, which we did not use in AllegrOCaml. Another trick we hope to use is GADT-based techniques for unpacking the states of recursive functions. Currently, the AllegrOCaml recursion combinator introduces some overhead from boxing and unboxing the accumulator values at each recursive call. As noticed in other work [32], this overhead can be eliminated using a type-level heterogenous list to represent the state at compile time.

On the randomness libraries side we plan to investigate fast randomness libraries that are not equivalent to SplitMix, such as Lehmer [51], WyHash [72], and variants of xoroshiro [7]. We also want to try techniques to speed up sampling such as pipelining, using SIMD instructions, or even generating random numbers ahead of time. Last, we hope to investigate the degree to which actual statistical randomness matters in PBT.

## 1069 Data Availability Statement

For artifact evaluation we will submit (1) the source code of AllegrOCaml and ScAllegro as well as (2) the code for our version of Etna, which we have modified slightly to (a) support parallelism, and (b) pass deterministic seeds to all versions of a single strategy. These programs are not available publicly or anonymized at the time of submission. The dataset for our evaluation is produced by a combination of Etna and microbenchmarks in the AllegrOCaml and ScAllegro sources. It is also not available publicly at the time of submission, but the artifact will contain the means and instructions to reproduce it.

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