EXPOSITOR: Scriptable Time-Travel Debugging with First-Class Traces

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***Abstract*—We present EXPOSITOR, a new debugging environment that combines scripting and time-travel debugging to allow programmers to automate complex debugging tasks. The fundamental abstraction provided by EXPOSITOR is the *execution trace*, which is a time-indexed sequence of program state snapshots or projections thereof. Programmers can manipulate traces as if they were simple lists with operations such as map and filter. Under the hood, EXPOSITOR efficiently implements traces as lazy, sparse interval trees whose contents are materialized on demand. EXPOSITOR also provides a novel data structure, the *edit hash array mapped trie*, which is a lazy implementation of sets, maps, multisets, and multimaps that enables programmers to maximize the efficiency of their debugging scripts. In our micro-benchmarks, EXPOSITOR scripts are faster than the equivalent non-lazy scripts for common debugging scenarios. EXPOSITOR to debug a stack overflow and to unravel a subtle data race in Firefox. We believe that EXPOSITOR represents an important step forward in improving the technology for diagnosing complex, hard-to-understand bugs.**

I. INTRODUCTION

"...we talk a lot about finding bugs, but really, [Firefox's] bottleneck is not finding bugs but fixing [them]..."
—Robert O'Callahan [1]

"[In debugging,] understanding how the failure came to be...requires by far the most time and other resources"
—Andreas Zeller [2]

Debugging program failures is an inescapable task for software programmers. Understanding a failure involves repeated application of the scientific method: the programmer makes some observations; proposes a hypothesis as to the cause of the failure; uses this hypothesis to make predictions about the program's behavior; tests those predictions using experiments; and finally either declares victory or repeats the process with a new or refined hypothesis.

There are certain kinds of bugs that can truly test the mettle of programmers. Large software systems often have complex, subtle, hard-to-understand *mandelbugs*[1] whose untangling can require hours or even days of tedious, hard-to-reuse, seemingly sisyphean effort. Debugging mandelbugs often requires testing many hypotheses, with lots of backtracking and retrials when those hypotheses fail. Standard debuggers make it hard to efficiently reuse the manual effort that goes into hypothesis testing, in particular, it can be hard to juggle the breakpoints, single stepping, and state inspection available in standard debuggers to find the point at which the fault actually happened.

Scriptable debugging is a powerful technique for hypothesis testing in which programmers write scripts to perform complex debugging tasks. For example, suppose we observe a bug involving a cleverly implemented set data structure. We can try to debug the problem by writing a script that maintains a *shadow data structure* that implements the set more simply (e.g., as a list). We run the buggy program, and the script tracks the program's calls to insert and remove, stopping execution when the contents of the shadow data structure fail to match those of the buggy one, helping pinpoint the underlying fault.

While we could have employed the same debugging strategy by altering the program itself (e.g., by inserting print statements and assertions), doing so would require recompilation—and that can take considerable time for large programs (e.g., Firefox), thus greatly slowing the rate of hypothesis testing. Modifying a program can also change its behavior—we have all experienced the frustration of inserting a debugging print statement only to make the problem disappear! Scripts also have the benefit that they can invoke libraries not used by the program itself. And, general-purpose scripts may be reused.

A. Background: Prior Scriptable Debuggers

There has been considerable prior work on scriptable debugging. GDB's Python interface makes GDB's interactive commands—stepping, setting breakpoints, etc.—available in a general-purpose programming language. However, this interface employs a callback-oriented programming style which, as pointed out by Marceau et al. [3], reduces composability and reusability as well as complicates checking temporal properties. Marceau et al. propose treating the program as an event generator—each function call, memory reference, etc. can be thought of as an event—and scripts are written in the style of *functional reactive programming* (FRP) [4]. While FRP-style debugging solves the problems of callback-based programming, it has a key limitation: time always marches forward, so we cannot ask questions about prior states. For example, if while debugging a program we find a doubly freed address, we cannot jump backward in time to find the

[1] "*Mandelbug (from the Mandelbrot set)*: A bug whose underlying causes are so complex and obscure as to make its behavior appear chaotic or even nondeterministic." From the *New Hacker's Dictionary* (3d ed.), Raymond E.S., editor, 1996.

corresponding malloc. Instead we would need to rerun the program from scratch to find that call, which may be problematic if there is any nondeterminism, e.g., if the addresses returned by malloc differ from run to run. Alternatively, we could prospectively gather the addresses returned by malloc as the program runs, but then we would need to record *all* such calls up to the erroneous free.

Time-travel debuggers, like UndoDB [5], and systems for capturing entire program executions, like Amber [6], allow a single nondeterministic execution to be examined at multiple points in time. Unfortunately, *scriptable* time-travel debuggers typically use callback-style programming, with all its problems. (Sec. VII discusses prior work in detail.)

B. EXPOSITOR: *Scriptable, Time-Travel Debugging*

In this paper, we present EXPOSITOR, a new scriptable debugging system inspired by FRP-style scripting but with the advantages of time-travel debugging. EXPOSITOR scripts treat a program's *execution trace* as a (potentially infinite) immutable list of time-annotated program state snapshots or projections thereof. Scripts can create or combine traces using common list operations: traces can be filtered, mapped, sliced, folded, and merged to create lightweight projections of the entire program execution. As such, EXPOSITOR is particularly well suited for checking temporal properties of an execution, and for writing new scripts that analyze traces computed by prior scripts. Furthermore, since EXPOSITOR extends GDB's Python environment and uses the UndoDB [5] time-travel backend for GDB, users can seamlessly switch between running scripts and interacting directly with an execution via GDB. (Sec. II overviews EXPOSITOR's scripting interface.)

The key idea for making EXPOSITOR efficient is to employ *laziness* in its implementation of traces—invoking the time-travel debugger is expensive, and laziness helps minimize the number of calls to it. EXPOSITOR represents traces as sparse, time-indexed interval trees and fills in their contents on demand. For example, suppose we use EXPOSITOR's breakpoints combinator to create a trace tr containing just the program execution's malloc calls. If we ask for the first element of tr before time 42 (perhaps because there is a suspicious program output then), EXPOSITOR will direct the time-travel debugger to time 42 and run it *backward* until hitting the call, capturing the resulting state in the trace data structure. The remainder of the trace, after time 42 and before the malloc call, is not computed. (Sec. III discusses the implementation of traces.)

In addition to traces, EXPOSITOR scripts typically employ various internal data structures to record information, e.g., the set s of arguments to malloc calls. These data structures must also be lazy so as not to compromise trace laziness—if we eagerly computed the set s just mentioned to answer a membership query at time t, we would have to run the time-travel debugger from the start up until t, considering all malloc calls, even if only the most recent call is sufficient to satisfy the query. Thus, EXPOSITOR provides script writers with a novel data structure: the *edit hash array mapped trie (EditHAMT)*, which provides lazy construction and queries for sets, maps, multisets, and multimaps. As far as we are aware, the EditHAMT is the first data structure to provide these capabilities. (Sec. IV describes the EditHAMT.)

We have used EXPOSITOR to write a number of simple scripts, as well as to debug two more significant problems. Sec. II describes how we used EXPOSITOR to find an exploitable buffer overflow. Sec. VI explains how we used EXPOSITOR to track down a deep, subtle bug in Firefox that was never directly fixed, though it was papered over with a subsequent bug fix (the fix resolved the symptom, but did not remove the underlying fault). In the process, we developed several reusable analyses, including a simple race detector. (Sec. VI presents our full case study.)

In summary, we believe that EXPOSITOR represents an important step forward in improving the technology for diagnosing complex, hard-to-understand bugs.

II. THE DESIGN OF EXPOSITOR

We designed EXPOSITOR to provide programmers with a high-level, declarative API to write analyses over the program execution, as opposed to the low-level, imperative, callback-based API commonly found in other scriptable debuggers.

In particular, the design of EXPOSITOR is based on two key principles. First, the EXPOSITOR API is purely functional—all objects are immutable, and methods manipulate objects by returning new objects. The purely functional API facilitates composition, by reducing the risk of scripts interfering with each other via shared mutable object, as well as reuse, since immutable objects can easily be *memoized* or cached upon construction. It also enables EXPOSITOR to employ lazy programming techniques to improve efficiency.

Second, the trace abstraction provided by EXPOSITOR is based around familiar list-processing APIs found in many languages, such as the built-in list-manipulating functions in Python, the Array methods in JavaScript, the List module in Ocaml, and the Data.List module in Haskell. These APIs are also declarative—programmers manipulate lists using combinators such as filter, map, and merge that operate over entire lists, instead of manipulating individual list elements. These list combinators allow EXPOSITOR to compute individual list elements on-demand in any order, minimizing the number of calls to the time-travel debugger. Furthermore, they shield programmers from the low-level details of controlling the program execution and handling callbacks.

A. API Overview

Fig. 1 lists the key classes and methods of EXPOSITOR's scripting interface, which is provided as a library inside UndoDB/GDB's Python environment.

a) The execution class and the the_execution object: The entire execution of the program being debugged is represented by the execution class, of which there is a singleton instance named the_execution. This class provides several methods for querying the execution. The get_at(t)[2] method returns a

[2]We use the convention of naming time variables as t, and trace variables as tr.

```
class execution:
    # get snapshots
    get_at(t):          snapshot at time t

    # derive traces
    breakpoints(fn):    snapshot trace of breakpoints at func fn
    syscalls(fn):       snapshot trace of breakpoints at syscall fn
    watchpoints(x, rw):
            snapshot trace of read/write watchpoints at var x
    all_calls():        snapshot trace of all function entries
    all_returns():      snapshot trace of all function exits

    # interactive control
    cont():             manually continue the execution
    get_time():         latest time of the execution

class trace:
    # count/get items
    __len__():          called by "len(trace)"
    __iter__():         called by "for item in trace"
    get_at(t):          item at exactly time t
    get_after(t):       next item after time t
    get_before(t):      previous item before time t

    # create a new trace by filtering/mapping a trace
    filter(p):          subtrace of items for which p returns true
    map(f):             new trace with f applied to all items
    slice(t0, t1):      subtrace from time t0 to time t1

    # create a new trace by merging two traces
    merge(f, tr):               see Fig. 2a
    trailing_merge(f, tr):      see Fig. 2b
    rev_trailing_merge(f, tr):  see Fig. 2c

    # create a new trace by computing over prefixes/suffixes
    scan(f, acc):               see Fig. 2d
    rev_scan(f, acc):           see Fig. 2e
    tscan(f, acc):              see Fig. 3a
    rev_tscan(f, acc):          see Fig. 3b

class item:
    time:               item's execution time
    value:              item's contents

class snapshot:
    read_var(x):
            gdb_value of variable x in current stack frame
    read_retaddrs():
            gdb_values of return addresses on the stack
    backtrace():        print the stack backtrace
    ... and other methods to access program state ...

class gdb_value:
    __getitem__(x):
            called by "gdb_value[x]" to access field/index x
    deref():            dereference gdb_value (if it is a pointer)
    addrof():           address of gdb_value (if it is an l-value)
    ... and other methods to query properties of gdb_value ...
```

Fig. 1. EXPOSITOR's Python-based scripting API. The get_X and __len__ methods of execution and trace are eager, and the remaining methods of those classes return lazy values. Lazy values include trace, snapshot, and gdb_value objects whose contents are computed only on demand and cached.

snapshot object representing the program state at time t in the execution (we will describe snapshots in more detail later). Several methods create immutable, sparse projections of the execution, or traces, consisting of program state snapshots at points of interest: the breakpoints(fn) and syscalls(fn) methods return traces of snapshots at functions and system calls named fn, respectively; the watchpoints(x, rw) method returns a trace of snapshot when the memory location x is read or written; and the all_calls and all_returns methods return traces of snapshots at all function entries and exits, respectively.

For debugging interactive programs, the execution class provides two useful methods: cont resumes the execution of the program from when it was last stopped (e.g., immediately after EXPOSITOR is started, or when the program is interrupted by pressing ^C), and get_time gets the latest time of the execution. If a program requires user input to trigger a bug, we often find it helpful to first interrupt the program and call get_time to get a reference time, before resuming the execution using cont and providing the input trigger.

b) The trace class and the item class: As mentioned above, the trace class represents sparse projections of the execution at points of interest. These traces contain snapshots or other values, indexed by the relevant time in the execution. Initially, traces are created using the execution methods described above, and traces may be further derived from other traces.

The first five trace methods query items in traces. The tr.__len__() method is called by the Python built-in function len(tr), and returns the total number of items in the tr. The tr.__iter__() method is called by Python's **for** x **in** tr loop, and returns a sequential Python iterator over all items in tr. The get_at(t) method returns the item at time t in the trace, or **None** if there is no item at that time. Since traces are often very sparse, it can be difficult to find items using get_at, so the trace class also provides two methods, get_before(t) and get_after(t), that return the first item found before or after time t, respectively, or **None** if no item can be found. The get_at, get_before, and get_after methods return values that are wrapped in the item class, which associates values with a particular point in the execution.

The remaining methods create new traces from existing traces. The tr.filter(p) method creates a new trace consisting only of items from tr that match predicate p. The tr.map(f) method creates a new trace of items computed by calling function f on each item from tr, and is useful for extracting particular values of interest from snapshots. The tr.slice(t0, t1) method creates a new trace that includes only items from tr between times t0 and t1.

The trace class also provides several more complex methods to derive new traces. Three methods create new traces by merging traces. First, tr0.merge(f, tr1) creates a new trace containing the items from both tr0 and tr1, calling function f to combine any items from tr0 and tr1 that occur at the same time (Fig. 2a). **None** can be passed for f if tr0 and tr1 contain items that can never coincide, e.g., if tr0 contains calls to foo and tr1 contains calls to bar, since f will never be called in

this case. Next, tr0.trailing_merge(f, tr1) creates a new trace by calling f to merge each item from tr0 with the immediately preceding item from tr1, or **None** if there is no preceding item (Fig. 2b). Lastly, rev_trailing_merge is similar to trailing_merge except that it merges with future items rather than past items (Fig. 2c).

The remaining four methods create new traces by computing over prefixes or suffixes of an input trace. The scan method performs a fold- or reduce-like operation for every prefix of an input trace (Fig. 2d). It is called as tr.scan(f, acc), where f is a binary function that takes an accumulator and an item as arguments, and acc is the initial accumulator. It returns a new trace containing the same number of items at the same times as in the input trace tr, where the nth output item out_n is recursively computed as:

$$out_n = \begin{cases} in_n \, ⓕ \, out_{n-1} & \text{if } n > 0 \\ in_n \, ⓕ \, acc & \text{if } n = 0 \end{cases}$$

where f is written infix as ⓕ. The rev_scan method is similar, but deriving a trace based on future items rather than past items (Fig. 2e). rev_scan computes the output item out_n as follows:

$$out_n = \begin{cases} in_n \, ⓕ \, out_{n+1} & \text{if } 0 \leq n < length - 1 \\ in_n \, ⓕ \, acc & \text{if } n = length - 1 \end{cases}$$

Lastly, tscan and rev_tscan are variants of scan and rev_scan, respectively, that take an associative binary function but no accumulator, and can sometimes be more efficient. These two methods are described in Sec. III-B.

c) The snapshot class and the gdb_value class: The snapshot class represents a program state at a particular point in time and provides methods for accessing that state, e.g., read_var(x) returns the value of a variable named x in the current stack frame, read_retaddrs returns the list of return addresses on the stack, backtrace prints the stack backtrace, and so on.

The gdb_value class represents values in the program being debugged at a particular point in time, and provides methods for querying those values. For example, v.__getitem__(x) is called by the Python indexing operator v[x] to access **struct** fields or array elements, deref dereferences pointer values, addrof returns the address of an l-value, and so forth. These gdb_value objects are automatically coerced to the appropriate Python types when they are compared against built-in Python values such as ints, for example; it is also sometimes useful to manually coerce gdb_value objects to specific Python types, e.g., to treat a pointer value as a Python int.

Both the snapshot and gdb_value classes are thin wrappers around GDB's Python API and UndoDB. When a method of a snapshot or gdb_value object is called, it first directs UndoDB to jump to the point in time in the program execution that is associated with the object. Then, it calls the corresponding GDB API, wrapping the return value in snapshot and gdb_value as necessary. In general, the semantics of snapshot and gdb_value follows GDB, e.g., the EXPOSITOR's notion of stack frames is based on GDB's notion of stack frames. We also provide several methods, such as read_retaddrs, that return the result of several GDB API calls in a more convenient form. Additionally, all of GDB's Python API is available and may be used from within EXPOSITOR.

Given a debugging hypothesis, we use the EXPOSITOR interface to apply the following recipe. First, we call methods on the_execution to derive one or more traces that contain events relevant to the hypothesis; such events could be function calls, breakpoints, system calls, etc. Next, we combine these traces as appropriate, applying trace methods such as filter, map, merge, and scan to derive traces of properties predicted by our hypothesis. Finally, we query the traces using methods such as get_before and get_after to find evidence of properties that would confirm or refute our hypothesis.

B. Warm-up Example: Examining foo Calls in EXPOSITOR

To begin with a simple example, let us consider the task of counting the number of calls to a function foo, to test a hypothesis that an algorithm is running for an incorrect number of iterations, for example. Counting foo calls takes just two lines of code in EXPOSITOR. We first use the breakpoints method of the_execution to create the foo trace:

```
-126 foo = the_execution.breakpoints("foo")
```

This gives us a trace containing all calls to foo. We can then count the calls to foo using the Python len function, and print it:

```
-129 print len(foo}
```

Later, we may want to count only calls to foo(x) where x == 0, perhaps because we suspect that only these calls are buggy. We can achieve this using the filter method on the foo trace created above:

```
-133 foo_0 = foo.filter(lambda snap: snap.read_var("x") == 0)
```

Here, we call filter with a predicate function that takes a snapshot object (at calls to foo), reads the variable named x, and returns whether x == 0. The resulting trace contains only calls to foo(0), which we assign to foo_0. We can then count foo_0 as before:

```
-141 print len(foo_0}
```

After more investigation, we may decide to examine calls to both foo(0) and foo(1), e.g., to understand the interaction between them. We can create a new trace of foo(1) calls, and merge it with foo(0):

```
-145 foo_1 = foo.filter(lambda snap: snap.read_var("x") == 1)
-144 foo_01 = foo_0.merge(None, foo_1)
```

We define foo_1 just like foo_0 but with a different predicate. Then, we use the merge method to merge foo_0 and foo_1 into a single trace foo_01 containing calls to both foo(0) and foo(1), passing **None** for the merging function as foo(0) and foo(1) can never coincide. Note that we are able to reuse the foo and foo_0 traces in a straightforward manner; under the

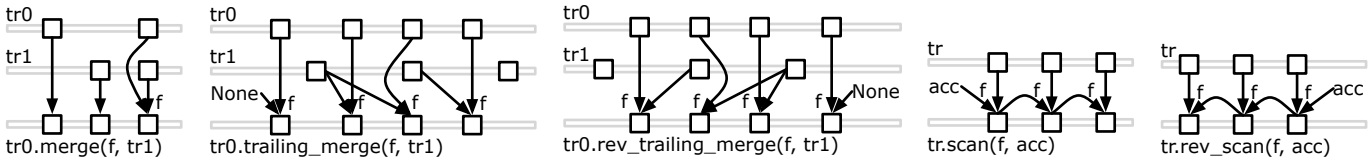


Fig. 2. Illustration of complex trace operations.

hood, EXPOSITOR will also have cached the computation of foo and foo_0 from the earlier and reuse them here.

Finally, we may want to take a closer look at the very first call to either foo(0) or foo(1), which we can do using the get_after method:

```
-162 first_foo_01 = foo_01.get_after(0)
```

We call get_after on foo_01 to find the first item after time 0, i.e., the beginning of the execution, that contains the snapshot of a foo(0) or foo(1) call.

In this example, observe how we began with a simple debugging task that counts all calls to foo in a trace to answer our initial hypothesis, then gradually create more traces or combined existing ones and queried them as our hypothesis evolves. EXPOSITOR is particularly suited for such incremental, interactive style of debugging.

1) Comparison to GDB's Python API: In contrast to EXPOSITOR, it takes 16 lines of code to count foo calls using GDB's standard Python API, as shown below:

```
-168 count = 0; more = True
-167 foo = gdb.Breakpoint("foo")
-166 def stop_handler(evt):
-165     if isinstance(evt, gdb.BreakpointEvent) \
-164             and foo in evt.breakpoints:
-163         global count; count += 1
-162 def exit_handler(evt):
-161     global more; more = False
-160 gdb.events.stop.connect(stop_handler)
-159 gdb.events.exited.connect(exit_handler)
-158 gdb.execute("start")
-157 while more:
-156     gdb.execute("continue")
-155 gdb.events.exited.disconnect(exit_handler)
-154 gdb.events.stop.disconnect(stop_handler)
-153 foo.delete()
```

On line -168, we first initialize two variables, count and more, that will be used to track of the number of calls to foo and to track if the execution has ended respectively. Then, on line -167, we create a breakpoint at the call to foo. Next, we create a callback function named stop_handler on lines -166–-163 to handle breakpoint events. In this function, we first check on lines -165–-164 to see if the breakpoint triggered is the one that we have set, and if so, we increment count on line -163. We also create a callback function named exit_handler on lines -162–-161 to handle stop events which are fired when the program execution ends. This function simply resets the more flag when called.

After that, we register stop_handler and exit_handler with GDB on lines -160–-159, and start the program execution on line -158. GDB will run the program until it hits a breakpoint or the end of the execution is reached, calling stop_handler in the former case, or exit_handler in the latter case. Then, we enter a loop on lines -157–-156 that causes GDB to continue running the program until more is **False**, i.e., the program has exited. Once that happens, we deregister the event handlers from GDB and delete the breakpoint on lines -155–-153, cleaning up after ourselves to ensure that the callbacks and breakpoint will not be unintentionally triggered by other scripts.

It also takes more work to refine this GDB script to answer other questions about foo, compared to EXPOSITOR traces. For example, to count calls to foo(0), we would have to modify the GDB script to add the x == 0 predicate and rerun it, instead of simply calling filter on the foo trace. As another example, if we were given two different scripts, one that counts foo(0) and another that counts foo(1), if would be difficult to combine those scripts as they each contain their own driver loops and shared variables; it would be easier to just modify one of those script than to attempt to reuse both. In contrast, it took us one line to use the merge method to combine the foo_0 and foo_1 traces. Finally, note that EXPOSITOR caches and reuses trace computation automatically, whereas we would need some foresight to add caching to the GDB script in a way that can be reused by other scripts.

C. Example: Reverse Engineering a Stack-Smashing Attack

We now illustrate the use of EXPOSITOR with a more sophisticated example: reverse engineering a stack-smashing attack, in which malware overflows a stack buffer in the target program to overwrite a return address on the stack, thereby gaining control of the program counter [7].

We develop a reusable script that can detect when the stack has been smashed in any program, which will help pinpoint the attack vector. Our script maintains a *shadow stack* of return addresses and uses it to check that only the top of the stack is modified between function calls or returns; any violation of this property indicates the stack has been smashed.

We begin by using the all_calls and all_returns methods on the_execution to create traces of just the snapshots at function calls and returns, respectively:

```
-180 calls = the_execution.all_calls()
-179 rets = the_execution.all_returns()
```

Next, we use merge to combine these into a single trace, passing **None** for the merging function as function calls and

returns can never coincide. We will use this new trace to compare consecutive calls or returns:

```
calls_rets = calls.merge(None, rets)
```

Now, we map over call_returns to apply the read_retaddrs method, returning the list of return addresses on the call stack. This creates a trace of shadow stacks at every call and return:

```
shadow_stacks = calls_rets.map(
    lambda s: map(int, s.read_retaddrs()))
```

We also use map to coerce the return addresses to Python ints.

Then we need to check that, between function calls and returns, the actual call stack matches the shadow stack except for the topmost frame (one return address may be added or removed). We use the following function:

```
def find_corrupted(ss, opt_shadow):
    if opt_shadow.force() is not None:
        for x, y in zip(ss.read_retaddrs(), opt_shadow.force()):
            if int(x) != y:
                return x # l-value of return address on stack
    return None
```

Here, find_corrupted takes as arguments a snapshot ss and its immediately preceding shadow stack opt_shadow; the opt_ prefix indicates that there may not be a prior shadow stack (if ss is at the first function call), and we need to call the force method on opt_shadow to retrieve its value (we will explain the significance of this in Sec. III). If there is a prior shadow stack, we compare every return address in ss against the shadow stack and return the first location that differs, or **None** if there are no corrupted addresses. (The zip function creates a list of pairs of the respective elements of the two input lists, up to the length of the shorter list.)

Finally, we generate a trace of corrupted memory locations using the trailing_merge method, calling find_corrupted to merge each function call and return from call_rets with the immediately preceding shadow stack in shadow_stacks. We filter **None** out of the result:

```
corrupted_addrs = calls_rets \
    .trailing_merge(find_corrupted, shadow_stacks) \
    .filter(lambda x: x is not None)
```

The resulting trace contains exactly the locations of corrupted return addresses at the point they are first evident in the trace.

D. Mini Case Study: Running EXPOSITOR *on* tinyhttpd

We used the script just developed on a version of tinyhttpd [8] that we had previously modified to include a buffer overflow bug. We created this version of tinyhttpd as an exercise for a security class in which students develop exploits of the vulnerability.

As malware, we deployed an exploit that uses a return-to-libc attack [9] against tinyhttpd. The attack causes tinyhttpd to print "Now I pwn your computer" to the terminal and then resume normal operation. Finding buffer overflows using standard techniques can be challenging, since there can be a delay from the exploit overflowing the buffer to the payload taking effect, during which the exploited call stack may be erased by normal program execution. The payload may also erase evidence of itself from the stack before producing a symptom.

To use EXPOSITOR, we call the expositor launcher with tinyhttpd as its argument, which will start a GDB session with EXPOSITOR's library loaded, and then enter the Python interactive prompt from GDB:[3]

```
% expositor tinyhttpd
(expositor) python-interactive
```

Then, we start running tinyhttpd:

```
>>> the_execution.cont() # start running
httpd running on port 47055
```

When tinyhttpd launches, it prints out the port number on which it accepts client connections. On a different terminal, we run the exploit with this port number:

```
% ./exploit.py 47055
Trying port 47055
pwning...
```

At this point, tinyhttpd prints the exploit message, so we interrupt the debugger and use EXPOSITOR to find the stack corruption, starting from the time when we interrupted it:

```
Now I pwn your computer
^C
Program received signal SIGINT, Interrupt
>>> corrupted_addrs = stack_corruption()
                    # function containing Sec. II-C code
>>> time = the_execution.get_time()
>>> last_corrupt = corrupted_addrs.get_before(time)
```

Items in a trace are indexed by time, so the get_before method call above tells EXPOSITOR to start computing corrupted_addrs from the interrupted time backward and find the first function call or return when the stack corruption is detected. We can print the results:

```
>>> print time
56686.8
>>> print last_corrupt
Item(56449.2, address)
```

This shows that the interrupt occurred at time 56686.8, and the corrupted stack was first detected at a function call or return at time 56449.2. We can then find and print the snapshot that corrupted the return address with:

```
>>> bad_writes = the_execution \
        .watchpoints(last_corrupt.value, rw=WRITE)
>>> last_bad_write = bad_writes.get_before(last_corrupt.time)
>>> print last_bad_write
Item(56436.0, snapshot)
```

We find that the first write that corrupted the return address occurred at time 56436.0. We can then inspect the snapshot via last_bad_write.value. In this case, the backtrace of the very first snapshot identifies the exact line of code in tinyhttpd that causes the stack corruption—a socket recv with an out-of-bounds pointer. Notice that to find the bug, EXPOSITOR

[3]GDB contains an existing python command that is not interactive; python-interactive is a new command that we have submitted to GDB, and is available as of GDB 7.6.

only inspected from time 56686.8 to time 56436.0. Moreover, had last_corrupt not explained the bug, we would then call corrupted_addrs.get_before(last_corrupt.time) to find the prior corruption event, inspecting only as much of the execution as needed to track down the bug.

This mini case study also demonstrates that, for some debugging tasks, it can be much faster to search backward in time. It takes only 1 second for corrupted_addrs.get_before(time) to return; whereas if we had instead searched forward from the beginning (e.g., simulating a debugger without time-travel):

```
-187 first_corrupted = corrupted_addrs.get_after(0)
```

it takes 4 seconds for the answer to be computed. Using EXPOSITOR, users can write scripts that search forward or backward in time, as optimal for the task.

III. LAZY TRACES IN EXPOSITOR

As just discussed, EXPOSITOR allows users to treat traces as if they were lists of snapshots. However, for many applications it would be impractical to eagerly record and analyze full program snapshots at every program point. Instead, EXPOSITOR uses the underlying time-travel debugger, UndoDB, to construct snapshots on demand and to discard them when they are no longer used (since it is expensive to keep too many snapshots in memory at once). Thus the major challenge is to minimize the demand for snapshots, which EXPOSITOR accomplishes by constructing and manipulating traces *lazily*.

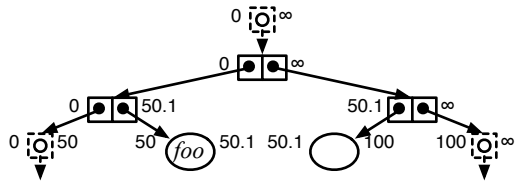
More precisely, all of the trace generators and combinators, including execution.all_calls, trace.map, trace.merge, etc., return immediately without invoking UndoDB. It is only when final values are demanded, with execution.get_at, trace.get_at, trace.get_after, or trace.get_before, that EXPOSITOR queries the actual program execution, and it does so only as much as is needed to acquire the result. For example, the construction of corrupted_addrs in Sec. II-D, line -190 induces *no* time travel on the underlying program—it is not until the call to corrupted_addrs.get_before(time) in Sec. II-D, line -187 that EXPOSITOR uses the debugger to acquire the final result.

To achieve this design, EXPOSITOR uses a lazy, interval-tree-like data structure to implement traces. More precisely, a trace is a binary tree whose nodes are annotated with the (closed) lower-bound and (open) upper-bound of the time intervals they span, and leaf nodes either contain a value or are empty. The initial tree for a trace contains no elements (only its definition), and EXPOSITOR materializes tree nodes as needed.

As a concrete example, the following trace constructs the tree shown on the right, with a single lazy root node spanning the interval $[0, \infty)$, which we draw as a dotted box and arrow.

```
-196 foo = the_execution.breakpoints("foo")
```

Now suppose we call foo.get_before(100). EXPOSITOR sees that the query is looking for the last call to foo before time 100, so it will ask UndoDB to jump to time 100 and then run backward until hitting such a call. Let us suppose the call is at time 50, and the next instruction after that call is at time 50.1. Then EXPOSITOR will expand the root node shown above to the following tree:



Here the trace has been subdivided into four intervals: The intervals $[0, 50)$ and $[100, \infty)$ are lazy nodes with no further information, as EXPOSITOR did not look at those portions of the execution. The interval $[50, 50.1)$ contains the discovered call, and the interval $[50.1, 100)$ is fully resolved and contains no calls to foo. Notice that if we ask the same query again, EXPOSITOR can traverse the interval tree above to respond without needing to query UndoDB.

Likewise, calling get_at(t) or get_after(t) either returns immediately (if the result has already been computed) or causes UndoDB to jump to time t (and, for get_after(t), to then execute forward). These methods may return **None**, e.g., if a call to foo did not occur before/after/at time t.

As our micro-benchmarks in Sec. V will show, if we request about 10-40% of the items in a trace, computing traces lazily takes less time than computing eagerly, depending on the query pattern as well as the kind of computations done. This makes lazy traces ideal for debugging tasks where we expect programmers to begin with some clues about the location of the bug. For example, we start looking for stack corruption from the end of the execution in Sec. II-D, line -187, because stack corruptions typically occur near the end of the execution.

A. Lazy Trace Operations

We implement filter and map lazily on top of the interval tree data structure. For a call tr1 = tr0.map(f), we initially construct an empty interval tree, and when values are demanded in tr1 (by get_X calls), EXPOSITOR conceptually calls tr0.get_X, applies f to the result, and caches the result for future use. Calls to tr0.filter(p) are handled similarly, constructing a lazy tree that, when demanded, repeatedly gets values from tr0 until p is satisfied. Note that for efficiency, EXPOSITOR's does not actually call get_X on the root node of tr0; instead, it directly traverses the subtree of tr0 corresponding to the uninitialized subtree of the derived trace.

The implementation of tr0.merge(f, tr1) also calls get_X on tr1 as required. For a call tr.slice(t0, t1) EXPOSITOR creates an interval tree that delegates get_X calls to tr, asking for items from time t0 to time t1, and returns **None** for items that fall outside that interval.

For the last four operations, [rev_]trailing_merge and [rev_]scan, EXPOSITOR employs additional laziness in the helper function argument f. To illustrate, consider a call to tr.scan(f, acc). Here, EXPOSITOR passes the accumulator to f wrapped in an instance of class lazy, defined as follows:

```
-234 class lazy:
-233     force():        return the actual value
-232     is_forced():    return whether force has been called
```

The force method, when first called, will compute the actual value and cache it; the cached value is returned in subsequent calls. Thus, f can force the accumulator as needed, and if it is not forced, it will not be computed.

To see the benefit, consider the following example, which uses scan to derive a new trace in which each item is a count of the number of consecutive calls to foo with nonzero arguments, resetting the count when foo is called with zero:

```
-238 foo = execution.breakpoints("foo") # void foo(int x)
-237 def count_nonzero_foo(lazy_acc, snapshot):
-236     if snapshot.read_var("x") != 0:
-235         return lazy_acc.force() + 1
-234     else:
-233         return 0
-232 nonzero_foo = foo.scan(count_nonzero_foo, 0)
```

Notice that if lazy_acc were not lazy, EXPOSITOR would have to compute its value before calling count_nonzero_foo. By the definition of scan (Fig. 2d), this means that it must recursively call count_nonzero_foo to compute all prior output items before computing the current item, even if it is unnecessary to do so, e.g., if we had called nonzero_foo.get_before(t), and the call to foo just before time t had argument x=0. Thus, a lazy accumulator avoids this unnecessary work. EXPOSITOR uses a lazy accumulator in rev_scan for the same reason.

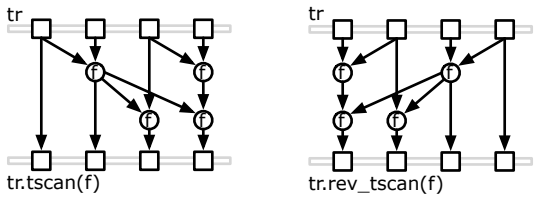
Likewise, observe that in tr0.trailing_merge(f, tr1), for a particular item in tr0 the function f may not need to look in tr1 to determine its result; thus, EXPOSITOR wraps the tr1 argument to f in an instance of class lazy. The implementation of rev_trailing_merge similarly passes lazy items from tr1 to f. Note that there is no such laziness in the regular merge operation. The reason is that in tr0.merge(f, tr1), the items from tr0 and tr1 that are combined with f occur at the same time. Thus, making f's arguments lazy would not reduce demands on the underlying time-travel debugger.

B. Tree Scan

Finally, EXPOSITOR provides another list combinator, *tree-scan*, which is a lazier variant of scan that is sometimes more efficient. The tscan method computes an output for every prefix of an input trace by applying an associative binary function in a tree-like fashion (Fig. 3a). It is invoked with tr.tscan(f), where f must be an associative function that is lazy and optional in its left argument and lazy in its right argument. The tscan method generates an output trace of the same length as the input trace, where the nth output out_n is defined as:

$$out_n = in_0 \,ⓕ\, in_1 \,ⓕ\, \cdots \,ⓕ\, in_n$$

Notice that there is no accumulator, and EXPOSITOR can apply f in any order, since it is associative. When a value at time t is demanded from the output trace, EXPOSITOR first demands the item in_n at that time in the input trace (if no such item exists, then there is no item at that time in the output trace). Then EXPOSITOR walks down the interval tree structure of the input trace, calling f (only if demanded) on each internal tree node's children to compute out_n. Since the interval tree for the input trace is computed lazily, f may sometimes be called with **None** as a left argument, for the case when f forces an interval that turns out to contain no values; thus for correctness, we also require that f treats **None** as a left identity. (The right argument corresponds to in_n and so will never be **None**.)



(a) (b)

Fig. 3. Illustration of tree-scan operations.

Because both arguments of f are lazy, EXPOSITOR avoids computing either argument unnecessarily. The is_forced method of the lazy class is particularly useful for tscan, as it allows us to determine if either argument has been forced, and if so, evaluate the forced argument first. For example, we can check if a trace contains a true value as follows:

```
-275 def has_true(lazyleft, lazyright):
-274     return lazyleft.is_forced() and lazyleft.force() \
-273         or lazyright.is_forced() and lazyright.force() \
-272         or lazyleft.force() or lazyright.force()
-271 has_true_trace = some_trace.tscan(has_true)
-270 last_has_true = has_true_trace.get_before("inf")
```

The best case for this example occurs if either lazyleft or lazyright have been forced by a prior query, in which case either the first clause (line -274) or second clause (line -273) will be true and the unforced argument need not be computed due to short-circuiting.

EXPOSITOR's rev_tscan derives a new trace based on future items instead of past items (Fig. 3b), computing output item out_n as:

$$out_n = in_n \,ⓕ\, in_{n+1} \,ⓕ\, \cdots \,ⓕ\, in_{length-1}$$

Here, the right argument to f is optional, rather than the left.

IV. THE EDIT HASH ARRAY MAPPED TRIE

Many of the EXPOSITOR scripts we have written use sets or maps to record information about the program execution. For example, in Sec. I, we suggested the use of a shadow set to debug the implementation of a custom set data structure. Unfortunately, a typical eager implementation of sets or maps could demand all items in the traces, defeating the intention of EXPOSITOR's lazy trace data structure. To demonstrate this issue, consider the following code, which uses Python's standard (non-lazy) set class to collect all arguments in calls to a function foo:

```
-276 foos = the_execution.breakpoints("foo") # void foo(int arg)
-275 def collect_foo_args(lazy_acc, snap):
-274     return lazy_acc.force().union( \
```

```
-276 class edithamt:
-275     # lookup methods
-274     contains(k):
-273                                         Return if key k exists
-272     find(k):
-271                 Return the latest value for k or None if not found
-270     find_multi(k):
-269                         Return an iterator of all values bound to k
-268
-267     # static factory methods to create new EditHAMTs
-266     empty():
-265                                         Create an empty EditHAMT
-264     add(lazy_eh, k):
-263                                 Add binding of k to itself to lazy_eh
-262     addkeyvalue(lazy_eh, k, v):
-261                                     Add binding of k to v to lazy_eh
-260     remove(lazy_eh, k):
-259                                 Remove all bindings of k from lazy_eh
-258     removeone(lazy_eh, k):
-257       Remove the latest binding of k to any value from lazy_eh
-256     removekeyvalue(lazy_eh, k, v):
-255                 Remove the latest binding of k to v from lazy_eh
-254     concat(lazy_eh1, lazy_eh2):
-253                   Concatenate lazy_eh2 edit history to lazy_eh1
```

Fig. 4. The EditHAMT API.

```
-273         set([ int(snap.read_var("arg")) ]))
-272 foo_args = foos.scan(collect_foo_args, set())
```

Notice that we must force lazy_acc to call the union method which will create a deep copy of the updated set (lines -274–-273). Unfortunately, forcing lazy_acc causes the immediately preceding set to be computed by recursively calling collect_foo_args. As a result, we must compute all preceding sets in the trace even if a particular query could be answered without doing so.

To address these problems, we developed the *edit hash array mapped trie* (*EditHAMT*), a new set, map, multiset, and multimap data structure that supports lazy construction and queries. The EditHAMT complements the trace data structure; as we will explain, and our micro-benchmark in Sec. V-C will show, the EditHAMT can be used in traces without compromising trace laziness, unlike eager sets or maps.

A. EditHAMT API

From the user's perspective, the EditHAMT is an immutable data structure that maintains the entire history of edit operations for each EditHAMT. Fig. 4 shows the EditHAMT API. The edithamt class includes contains(k) to determine if key k exists, and find(k) to look up the latest value mapped to key k. It also includes the find_multi(k) method to look up all values mapped to key k, returned as a Python iterator that incrementally looks up each mapped value. EditHAMT operations are implemented as static factory methods that create new EditHAMTs. Calling edithamt.empty() creates a new, empty EditHAMT. Calling edithamt.add(lazy_eh, k) creates a new EditHAMT by adding to lazy_eh, the prior EditHAMT, a binding from key k to itself (treating the EditHAMT as a set or multiset). Similarly, edithamt.addkeyvalue(lazy_eh, k, v) creates a new EditHAMT by adding to lazy_eh a binding from key k value v (treating the EditHAMT as a map or multimap). Conversely, calling edithamt.remove(lazy_eh, k) creates a new EditHAMT by removing all bindings of key k from lazy_eh. Lastly, calling edithamt.removeone(lazy_eh, k) or edithamt.removekeyvalue(lazy_eh, k, v) creates new EditHAMTs by removing from lazy_eh the most recent binding of key k to any value or to a specific value v. The lazy_eh argument to these static factory methods is lazy so that we need not force it until a call to contains, find or find_multi demands a result. For convenience, the lazy_eh argument can also be **None**, which is treated as an empty EditHAMT.

The last static factory method, edithamt.concat(lazy_eh1, lazy_eh2), concatenates the edit histories of its arguments. For example:

```
-284 eh_rem = edithamt.remove(None, "x")
-283 eh_add = edithamt.addkeyvalue(None, "x", 42)
-282 eh = edithamt.concat(eh_add, eh_rem)
```

Here eh is the empty EditHAMT, since it contains the additions in eh_add followed by the removals in eh_rem. A common EXPOSITOR script pattern is to map a trace to a sequence of EditHAMT additions and removals, and then use edithamt.concat with scan or tscan to concatenate those edits.

B. Example: EditHAMT to Track Reads and Writes to a Variable

As an example of using the EditHAMT, we present one piece of the race detector used in our Firefox case study (Sec. VI). The detector compares each memory access against prior accesses to the same location from any thread. Since UndoDB serializes thread schedules, each read need only be compared against the immediately preceding write, and each write against the immediately preceding write as well as reads between the two writes.

We use the EditHAMT as a multimap in the following function to track the access history of a given variable v:

```
-289 def access_events(v):
-288     reads = the_execution.watchpoints(v, rw=READ) \
-287         .map(lambda s: edithamt.addkeyvalue( \
-286                 None, v, ("read", s.get_thread_id())))
-285     writes = the_execution.watchpoints(v, rw=WRITE) \
-284         .map(lambda s: edithamt.addkeyvalue( \
-283                 edithamt.remove(None, v), \
-282                 v, ("write", s.get_thread_id())
-281     return reads.merge(None, writes)
```

In access_events, we create the trace reads by finding all reads to v using the watchpoints method (line -288), and then mapping each snapshot to a singleton EditHAMT that binds v to a tuple of "read" and the running thread ID (lines -287–-286). Similarly, we create the trace writes for writes to v (line -285), but instead map each write snapshot to an EditHAMT that first removes all prior bindings for v (line -283), then binds v to a tuple of "write" and the thread ID (lines -284–-282). Finally, we merge reads and writes, and return the result (line -281).

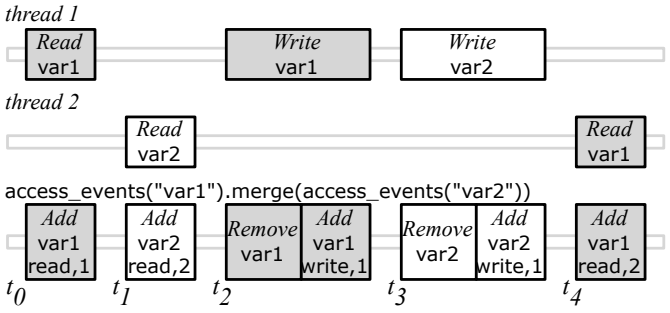


Fig. 5. Example execution with two threads accessing var1 (gray) and var2, and the corresponding EditHAMT operations returned by access_events.

We are not done yet, since the EditHAMTs in the trace returned by access_events contain only edit operations corresponding to individual accesses to v. We can get an EditHAMT trace that records all accesses to v from the beginning of the execution by using scan with edithamt.concat to concatenate the individual EditHAMTs. For example, we can record the access history of var1 as follows:

```
-300 var1_history = access_events("var1").scan(edithamt.concat)
```

We can also track multiple variables by calling access_events on each variable, merging the traces, then concatenating the merged trace, e.g., to track var1 and var2:

```
-303 access_history = \
-302     access_events("var1").merge(access_events("var2")) \
-301         .scan(edithamt.concat)
```

Since trace methods are lazy, this code completes immediately; the EditHAMT operations will only be applied, and the underlying traces forced, when we request a particular access, e.g., at the end of the execution (time "inf"):

```
-302 last = access_history.get_before("inf")
```

To see laziness in action, consider applying the above analysis to an execution depicted in Fig. 5, which shows two threads at the top and the corresponding EditHAMT operations at the bottom. Suppose we print the latest access to var1 at time t_4 using the find method:

```
-310 >>> print last.find("var1")
-309 ("read", 2)
```

Because "var1" was just added at time t_4, answering this query will only force the EditHAMT and query the time-travel debugger at time t_4, and not before.

As another example, suppose we want to find all accesses to var1 from the last access backward using find_multi:

```
-312 >>> for mem_access in last.find_multi("var1"):
-311         print mem_access
-310 ("read", 2)
-309 ("write", 1)
```

Here since all "var1" bindings added prior to time t_2 were removed at time t_2, the results are computed without forcing any EditHAMTs or querying the debugger before time t_2.

C. Implementation

The EditHAMT is inspired by the *hash array mapped trie* (HAMT) [11]. Like the HAMT, the EditHAMT is a hybrid data structure combining the fast lookup of a hash table and the memory efficiency of a trie. The HAMT is a hash-based data structure built in a manner analogous to a hash table. Whereas a hash table uses a bucket array to map keys to values, the HAMT uses an *array mapped trie* (AMT)—a trie that maps fixed-width integer keys to values—for the same purpose. When a hash collision occurs, the HAMT resolves the collision by replacing the colliding entry with a nested HAMT, rehashing the colliding keys, and inserting those keys in the nested HAMT using the new hash values.

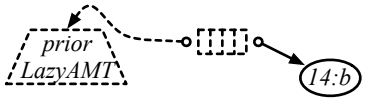
We developed the EditHAMT by making two changes to the traditional HAMT. First, we replaced the AMT with the *LazyAMT*, which supports lazy, rather than eager, updates. Second, we resolve hash collisions, as well as support remove and multiset/multimap operations, using *EditList*s, which are lazy linked-lists of nodes tallying edit operations on the EditHAMT; the tails are lazily retrieved from the prior EditHAMT.

1) LazyAMT: Lazy Array Mapped Tries: The first piece of the EditHAMT is the LazyAMT, which is lazy, immutable variant of the AMT that maps fixed-width integer keys of size k bits to values. We implement the LazyAMT using *lazy sparse arrays* of size 2^w as internal nodes, where w is the bit-width of the array index such that $w < k$, and store key-value bindings as leaf nodes. We will divide the key into w-bit words, where each w-bit word is used to index an internal node during a lookup; the key can be padded as necessary if k is not a multiple of w.

Lazy sparse arrays combine the properties of lazy values and sparse arrays: each element of a lazy sparse array is computed and cached when first indexed, akin to forcing a lazy value, and null elements are stored compactly, like sparse arrays. We implement lazy sparse arrays using two bitmaps to track which elements are initialized and non-null,[4] respectively, and an array to store initialized, non-null elements.

To build the EditHAMT, we need to support two operations on the LazyAMT: adding a key-value binding to a LazyAMT, and merging two LazyAMTs into a single LazyAMT. We will explain how the LazyAMT works by example, using an internal node index bit-width of $w = 2$ bits and a key size of $k = 6$ bits.

a) Adding a key-value binding: When we add a binding such as $14 : b$ to a LazyAMT, we first create a new lazy sparse array representing the root node:

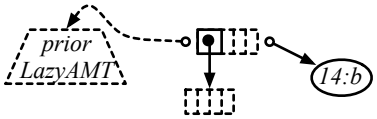


[4]It is more efficient to track non-null elements as many modern processors provide a POPCNT instruction, which counts the number of 1 bits in a word, that can be used to compute the index of a non-null element in the storage array.

Initially, all elements of the root node are uninitialized, which we depict as four narrow dotted boxes; we will use the convention of numbering the boxes from left to right, i.e., in binary, the leftmost box is element 00, and the rightmost box is element 11. In addition, we also maintain a lazy reference to the prior LazyAMT; we do not yet need to know what the prior LazyAMT contains, which we indicate with a dotted arrow. In fact, the lazy reference allows us to further defer the construction of (the root node of) the prior LazyAMT, i.e., the prior LazyAMT may not exist yet when we add the binding $14 : b$; we indicate this with a dotted trapezoid. For example, in EXPOSITOR, we may query UndoDB to determine what binding should be added only when the lazy reference to the prior LazyAMT is first forced. We also need to store the binding $14 : b$, to be added when the LazyAMT is sufficiently initialized.

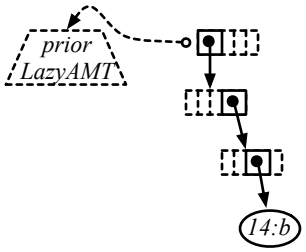
The actual construction of the LazyAMT occurs only when we look up a binding. The lookup is a standard trie lookup, however, since internal nodes are lazy sparse arrays, the elements of those arrays will be initialized as necessary when we access those elements during the lookup. We initialize an element in one of three ways, depending on whether that element is along the lookup path of the binding we previously set aside to be added, and whether we have reached the end of the lookup path. If the element is along the lookup path the binding and we have not reached the end of the lookup path, we create the next internal node and initialize the element to that node. If the element is along the lookup path of the binding and we have reached the end of the lookup path, we initialize the element to a leaf node containing that binding. Otherwise, if the element is not along the lookup path of the binding, we initialize it to point to the same subtrie as the corresponding element (at the same partial lookup path) in the prior LazyAMT, or to be null if the corresponding element does not exist. Note that in the last case, prior LazyAMTs will be recursively initialized as necessary.

For example, suppose that we look up the binding for key 14. First, we split up the key into w-bit words, here, 00 11 10 in binary; this is the lookup path for key 14. Then, we use the first word, 00, to index the root node. We need to initialize the element at 00 as this is the first time we accessed it. Since this particular LazyAMT was created by adding $14 : b$ and the 00 element of the root node is along the lookup path for key 14, we initialize that element to a new uninitialized internal node below the root node:



Here, we depict the initialized element of the root node as a square unbroken box, and a non-lazy reference to the just created internal node as an unbroken arrow.

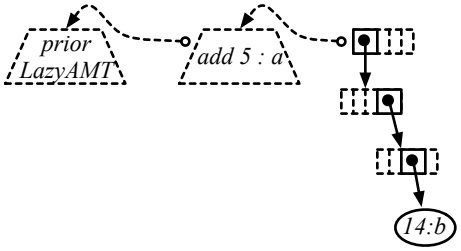
We continue the lookup by using the next word, 11, to index the just created internal node. Since 11 is again along the lookup path, we initialize the corresponding element to another internal node. We repeat the process again with the last word, 10, but now that we have exhausted all bits in the lookup key, we initialize the element for 10 to point to a leaf node containing the binding $14 : b$ that we previously set aside. This results in a partially initialized LazyAMT:



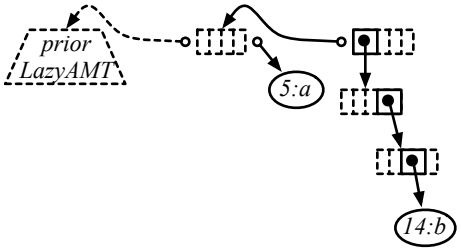
We finish the lookup for key 14 and return b.

The example so far illustrates how the lookup process drives the initialization process in an interleaved manner. Also, since we are looking up a key that was just inserted into the LazyAMT, we did not need to refer to the prior LazyAMT at all. These properties allow LazyAMTs to be constructed lazily, by initializing only as much as necessary to answer lookup queries.

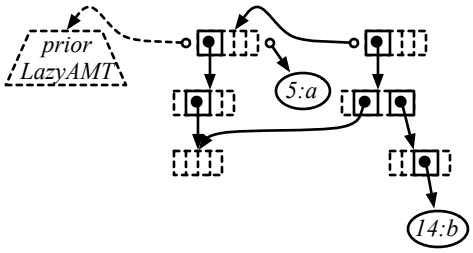
We continue the example by considering the case of looking up a key that was not added by the most recent LazyAMT. Suppose that the immediately prior LazyAMT, when computed, will add binding $5 : a$:



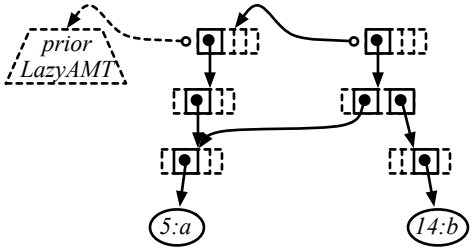
If we then look up key 5, or 00 01 01 in binary, from the rightmost LazyAMT, we would first index 00 of the root node. We have already initialized this element from looking up key 14 before, so we simply walk to the next internal node and index 01. The element at 01 is uninitialized, but it is not along the lookup path of key 14, the key added to the rightmost LazyAMT. To continue the lookup of key 5, we retrieve the prior LazyAMT by forcing our lazy reference to it, causing it to be partially constructed:



Then, we initialize the element at 01 to point to the subtrie under the element at the partial key 00 01 in the prior LazyAMT, partially initializing the middle LazyAMT along the way:



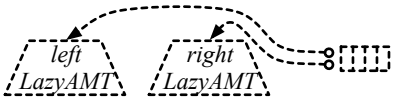
We finish the lookup for key 5 as before, initializing the LazyAMTs a bit more:



Note that we have simultaneously initialized parts of the rightmost LazyAMT and the middle LazyAMT because they share a common subtrie; subsequent lookups of key 5 on either LazyAMT will become faster as a result.

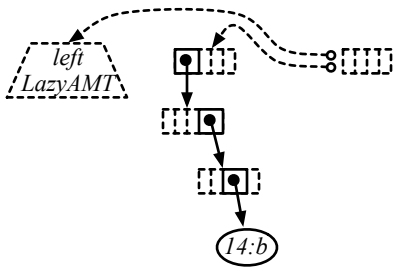
b) Merging two LazyAMTs: The merge operation takes two LazyAMTs as input, which we call *left* and *right*, as well as a function, $mergefn(lazy\text{-}opt\text{-}leftval, rightval)$, that is called to merge values for the same key in both LazyAMTs. As the name of the arguments suggests, $mergefn$ is called in an unusual, asymmetric manner in that it is called for all keys in the *right* LazyAMT, but not necessarily for all keys in the *left* LazyAMT. For each key in the *right* LazyAMT, $mergefn$ is called with a lazy, optional value, representing the value for that key in the *left* LazyAMT, as the $lazy\text{-}opt\text{-}leftval$ argument, and the value for the same key in the *right* LazyAMT as the $rightval$ argument. This approach maximizes laziness in that we can compute a lazy value as soon as we determine a key exists in the *right* LazyAMT without immediately looking up the value for the same key in the *left* LazyAMT. For example, $mergefn$ can be used to create a lazy linked-list by returning $lazy\text{-}opt\text{-}leftval$ and $rightval$ in a tuple.

When we merge two LazyAMTs, we first create a new root node of a new LazyAMT with two lazy references to the input LazyAMTs:

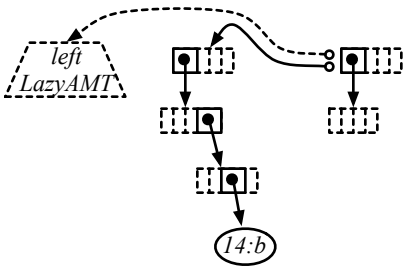


As before, the actual construction of the merged LazyAMT occurs when elements of internal nodes are initialized during lookups. We initialize an element in one of three ways, depending on whether the corresponding element (at the same partial lookup path) in the *right* LazyAMT points to an internal node, points to a leaf node, or is null. If the corresponding element points to an internal node, we create the next internal node and initialize the element to that node. If the corresponding element points to a leaf node, then we call $mergefn$, giving as $lazy\text{-}opt\text{-}leftval$ a new lazy value that, when forced, looks up the same key in the *left* LazyAMT (returning null if the key does not exist), and as $rightval$ the value at the leaf node. Otherwise, if the corresponding element is null, we initialize the element to point to the same subtrie as the corresponding element in the *left* LazyAMT, or to be null if the corresponding element does not exist. Note that both the *left* and *right* LazyAMTs will be recursively initialized as necessary.

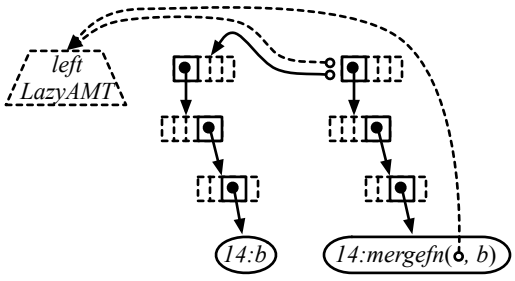
For example, suppose the *right* LazyAMT contains a single binding $14 : b$:



If we look up key 14, or 00 11 10 in binary, we would first index element 00 of the root node. Since this is the first time we accessed this element, we initialize it by looking at the corresponding element in the *right* LazyAMT. The corresponding element points to an internal node, so we initialize the element to a new internal node:



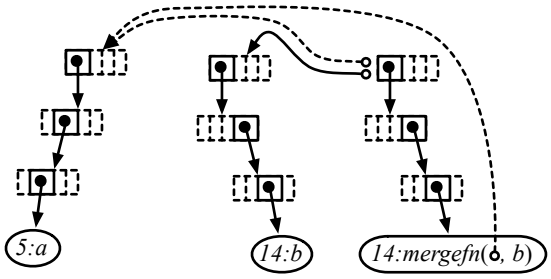
We repeat this process until we exhaust all bits in the lookup key and reach the corresponding leaf node. Because a binding exists for key 14 in the *right* LazyAMT, we initialize a new leaf node that binds key 14 to a merged value by first creating a new lazy value that looks up the key 14 from the *left* LazyAMT, and calling $mergefn$ on that lazy value as well as the value b from the *right* LazyAMT:



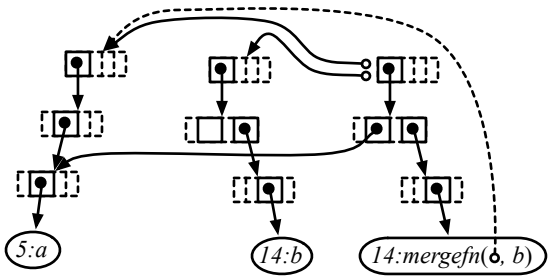
Note that we do not have to force the *left* LazyAMT to be computed immediately; the decision to force the *left*

LazyAMT is deferred to $mergefn$. We finish the lookup by returning the newly merged value.

As another example, suppose the *left* LazyAMT contains a single binding $5 : a$:



If we look up key 5, or 00 01 01 in binary, we would first index element 00 of the root note that is already initialized above. However, when we index element 01 of the next internal node, we would find that the corresponding element in the *right* LazyAMT is null. In this case, we look up the subtrie under the corresponding element in the *left* LazyAMT, and initialize element 01 to it:



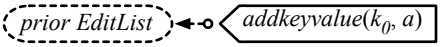
Note that we do not call $mergefn$ in this case. We finish the lookup by walking into *left* LazyAMT to the leaf node for key 5, and returning a.

Finally, we represent the empty LazyAMT as a special instance that simply returns null for all key and partial key lookups, allowing us to avoid building a trie structure with no bindings.

LazyAMT lookups are amortized $O(1)$ time; the LazyAMT has a fixed depth of k/w, so each lookup takes constant time to traverse the internal nodes to a leaf node. Similarly, adding a binding to a LazyAMT or merging two LazyAMTs take only amortized $O(1)$ time and memory to create k/w internal nodes of size 2^w each. The amortization of lookups, adding bindings, and merging LazyAMTs is due to laziness—most of the cost of adding a binding or merging two LazyAMTs is deferred to subsequent lookups. Adding the same key repeatedly would take an additional amortized $O(1)$ memory each time (i.e., prior bindings are never removed, only shadowed). However, this is actually an advantage in EXPOSITOR as we are usually interested in how bindings to the same key change over time.

2) EditList: Lazy Linked-List of Edit Operations: The second piece of the EditHAMT is the EditList, which is a lazy immutable set/map/multiset/multimap implemented as a lazy linked-list of edit operations.

When an operation such as add or remove is applied to an EditList, we simply append a new node to the EditList, labeling it with the given operation and arguments. For example, if we add a binding $k_0 : a$ to an EditList (treating the EditList as a map or multimap), we create a new EditList node labeled $addkeyvalue(k_0, a)$ with a lazy reference to the head of the prior EditList (i.e., the prior node):



We depict the EditList node as a box pointing to the left. Since all operations, including removals, are implemented by appending nodes, we do not need to know what the prior EditList contains, which we depict as a dotted arrow. And, as with the LazyAMT, we keep a lazy reference to the prior EditList which allows us to further delay any computation necessary to determine its contents, i.e., the prior EditList may not exist yet when we perform an addition or removal operation on it, which we depict as a dotted rounded box. Only when we first force the lazy reference to the prior EditList will we need to determine what kind of edit operation the prior EditList contains or if it is null, e.g., by making queries to UndoDB in EXPOSITOR.

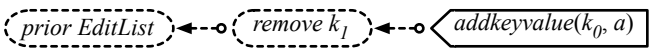
We support several different kinds of edit operations on EditLists, with the corresponding node labels:

- $add(k)$: add element k, treating the EditList as a set or multiset;
- $addkeyvalue(k, v)$: add a binding from key k to value v, treating the EditList as a map or multimap;
- $remove(k)$: remove all elements/bindings for key k;
- $removeone(k)$: remove the latest element/binding for key k, treating the EditList as a multiset or multimap;
- $removekeyvalue(k, v)$: remove the latest binding from key k to value v, treating the EditList as a multimap;
- $concat(lazy\_el)$: concatenate the EditList $lazy\_el$ as a lazy reference at this point.

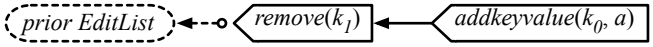
These are the building blocks for the corresponding EditHAMT operations listed in Fig. 4.

We implement EditList lookup in two different ways: one for set membership queries and map lookups, and another for multiset and multimap lookups.

a) Set Membership Queries and Map Lookups: We implement set membership queries and map lookups by traversing the EditList from head to tail (right to left), looking for the first node that contains an edit operation for the given key. For example, if we look up the value for key k_0 in the above EditList, we would start by looking at the head node. Since the head node adds a binding from key k_0, we can finish the lookup and return value a without having to look at the prior EditList. As another example, suppose that the immediately prior node, when we force it to be computed, e.g., by making calls to UndoDB in EXPOSITOR, removes key k_1:



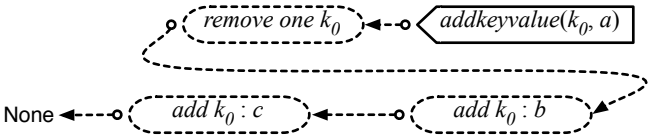
If we look up the value for key k_1, we would first look at the head node and skip it because it does not involve key k_1. Then, we would force the lazy reference to the prior node, causing it to be initialized if necessary, and look at it:



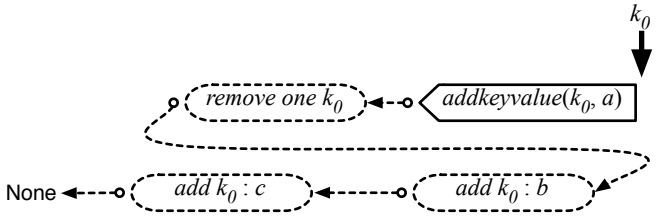
Here, we indicate that the tail has been forced with an unbroken arrow, and that the prior node has been initialized by replacing the dotted rounded box with pointed box. Since the prior node removes key k_1, we know that bindings no longer exist for key k_1, so we can finish the lookup and return null. This example shows that, once we have found a node that involves the lookup key, we no longer need to traverse the rest of the EditList. Also, because the reference to the prior EditList is lazy, the lookup process drives the construction of prior EditLists in an interleaved manner, just as in the LazyAMT.

If we find a $concat$ node during traversal, we handle that node by recursively looking up the concatenated EditList for the given key. If we do not find any relevant nodes in the concatenated EditList, we would then resume the lookup in the original EditList.

b) Multiset and Multimap Lookups: We implement multiset and multimap lookups lazily by returning a Python iterator that allows all values for a given key to be incrementally retrieved, typically via a **for** x **in** values loop. To illustrate how we implement multimap lookups, suppose we have the following EditList:

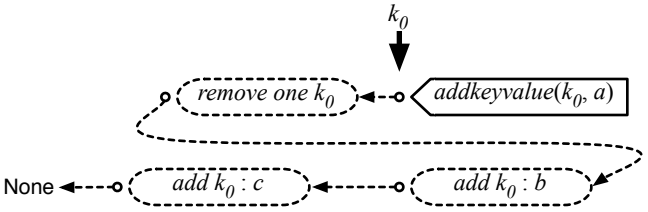


Reading backward from the tail, this EditList binds key k_0 to value c, binds value b and removes it, then binds value a; i.e., it represents a map that contains bindings from k_0 to values a and c but not b. A multimap lookup on this EditList for key k_0 will return an iterator of all values bound to that key:



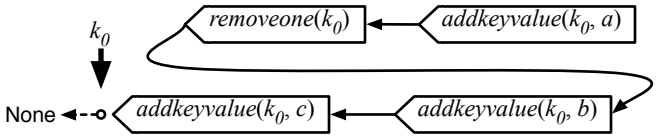
The iterator is associated with the key k_0 and initially points to the beginning of the input EditList, which we depict as a large down-arrow labeled k_0.

The actual lookup does not begin until we retrieve a value from the iterator, which initiates a traversal of the input EditList to find a binding for key k_0:



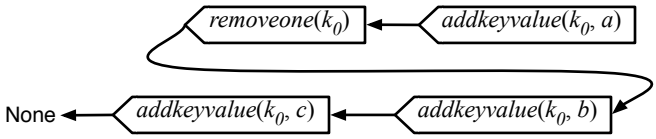
In this case, the head of the input EditList itself contains a binding to value a, so we return the value a and update the iterator to point to the tail of the input EditList (the head of the prior EditList), which we depict by moving the k_0 down-arrow.

If we retrieve a value from the iterator again, the lookup continues from the head of the prior EditList:



The prior node removes the next binding for key k_0; we temporarily note this as a pending removal. The node after that adds a binding for key k_0, but since we have a pending removal, we skip over that node. Next, we reach a node that binds key k_0 to value c, so we return c and update the iterator as before.

If we retrieve a value from the iterator once more, the lookup will reach the end of the input EditList, which we depict as **None**, so we terminate the iterator. At this point, all nodes in the input EditList will have been initialized:



We implement multiset lookups identically by treating $add(k)$ as if key k were bound to itself. Note in particular that, whereas a standard multiset lookup gives us the total number of values for a given key, a lazy multiset lookup allows us to ask if there are at least n values for a given key. As we illustrated above, both multiset and multimap lookups are lazy in that the returned iterator will only initializes as many nodes of the input EditList as retrieved.

EditList set membership and map/multiset/multimap lookups are not particularly fast, since they take $O(n)$, where n is the number of edit operations in the EditList (i.e., the length of the EditList), to traverse the EditList to find a relevant binding. However, applying an edit operation takes only $O(1)$ time and $O(1)$ memory to create and append a single EditList node. Adding an element or binding to the same key repeatedly takes an additional $O(1)$ memory each time, but as we explained for the LazyAMT, this is actually an advantage for EXPOSITOR as we are usually interested in how bindings change over time.

3) EditList + Hash + LazyAMT = EditHAMT: As we described above, the LazyAMT provides fast amortized $O(1)$ set/map lookups, but supports only fixed-width integer keys as well as addition and merging operations; it does not support removal operations or multiset/multimap lookups. Conversely, the EditList supports arbitrary keys, removal operations as well as multiset/multimap lookups, but lookups are a slow $O(n)$ where n is the number of edit operations in the EditList. Both the LazyAMT and the EditList support lazy construction, i.e., we can perform operations such as addition or removal without knowing what the prior LazyAMT or EditList contains. Finally, each LazyAMT operation takes only an additional amortized $O(1)$ time and memory over the prior LazyAMT, and likewise $O(1)$ time and memory for the EditList.

We combine these two data structures to create the EditHAMT, a lazy data structure that is more capable than the LazyAMT and faster than the EditList. The key idea is build multiple EditLists, each containing only edits for keys with the same hash h, which we denote as $editlist(h)$, and use the LazyAMT to map hash h to $editlist(h)$. We can then look up a key k using the following steps:

1) compute the hash h of key k;
2) look up $editlist(h)$ from the LazyAMT of the EditHAMT;
3) look up key k from $editlist(h)$;

The lookup process will cause the underlying LazyAMT or $editlist(h)$ to be initialized as necessary.

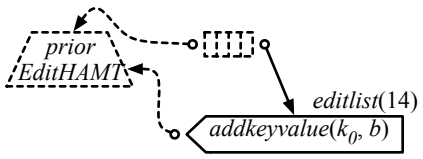
We construct EditHAMTs in one of two ways: we use the LazyAMT addition operation to perform addition or removal operations on an EditHAMT, and the LazyAMT merge operation to concatenate two EditHAMTs.

a) Performing Addition or Removal Operations on an EditHAMT: We take the following steps to perform an addition or removal operation for a given key k on an EditHAMT:

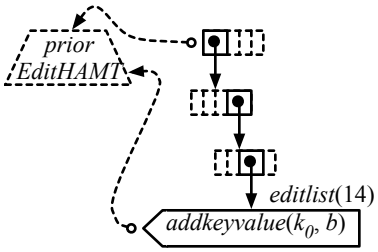
1) compute the hash h of key k;
2) lazily look up the LazyAMT of the prior EditHAMT as $lazyamt'$;
3) lazily look up $editlist'(h)$ from $lazyamt'$, and append the given operation to it to create $editlist(h)$;
4) add a new binding to $lazyamt'$ from hash h to $editlist(h)$ to create the updated EditHAMT;

where by lazily looking up we mean to create a lazy reference that, when forced, looks up $lazyamt'$ or $editlist'(h)$, which allows the construction of the prior EditHAMT to also be lazy. Because both the LazyAMT and the EditList are lazy, the EditHAMT will be mostly uninitialized at first; (parts of) it will be initialized as necessary during lookup.

For example, suppose we add a binding from key k_0 to value b to an EditHAMT, and key k_0 has hash 14. We would create a new LazyAMT that maps hash 14 to a new $editlist(14)$ that appends $addkeyvalue(k_0, b)$ to the prior EditHAMT:

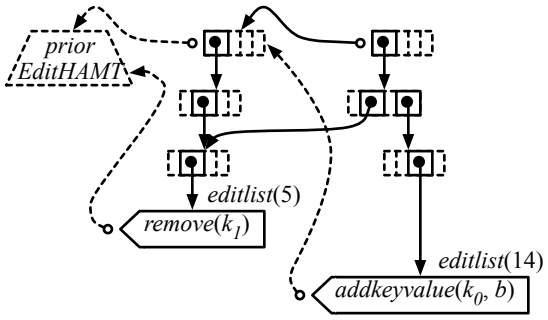


At first, most of the EditHAMT—the LazyAMT as well as the tail of the $editlist(14)$—is uninitialized; we indicate the uninitialized $editlist(14)$ tail as a dotted arrow pointing to the prior EditHAMT. When we look up key k_0, we would look up hash 14 from the LazyAMT to find $editlist(14)$ that we just added, then look up key k_0 from $editlist(14)$. The head of $editlist(14)$ adds key k_0, so we can return value b without looking at the tail. At the end of the lookup, the EditHAMT will be initialized as follows:



This example shows that we can apply an edit operation without knowledge of the prior EditHAMT, and since the key k_0 was just added, we can look up key k_0 without having to consult the prior EditHAMT. Both of these properties are inherited from the underlying LazyAMT and EditList.

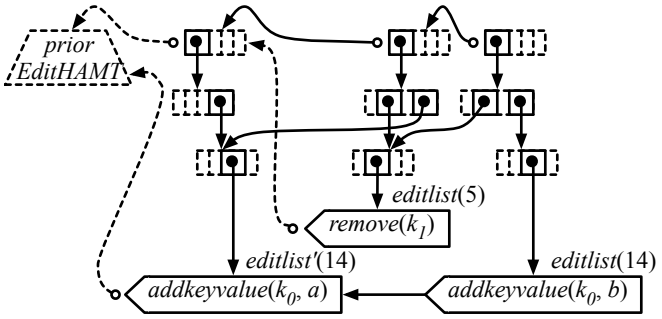
We continue the example by considering the case of looking up a different key that was involved in an earlier edit operation. Suppose that the immediately prior EditHAMT removes key k_1, and key k_1 has hash 5. When we look up key k_1, the EditHAMT will be initialized as follows:



Looking up the $editlist(5)$ from the rightmost LazyAMT causes parts of the middle LazyAMT to be initialized and shared with the rightmost LazyAMT, and since the head of $editlist(5)$ removes key k_1, we can return null without looking at its tail.

The two examples so far do not require traversing the tail of $editlist(h)$. We would need to do so if there was a hash collision or if we perform a multiset or multimap lookup. For example, suppose that an earlier EditHAMT added a binding from key k_0 with hash 14 to value a, and we perform a multimap lookup of key k_0 to find the second value. We have

to initialize the tail of $editlist(14)$ by looking up $editlist'(14)$ from the prior EditHAMT. The immediately prior EditHAMT did not involve key k_0 or hash 14; instead, we will partially initialize the earlier EditHAMT containing $editlist'(14)$ and share it. Then, we retrieve $editlist'(14)$ and initialize it as the tail of $editlist(14)$. At the end of the lookup, the EditHAMT will be initialized as depicted below:

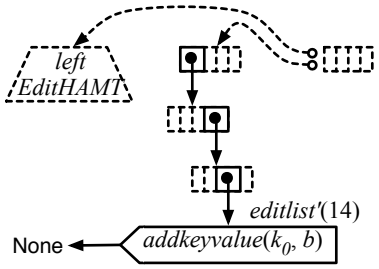


b) Concatenating two EditHAMTs: To concatenate two EditHAMTs, we call the LazyAMT merge operation with:

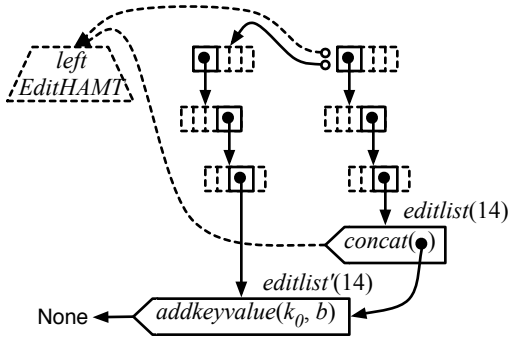
- the older EditHAMT as the *left* LazyAMT;
- the newer EditHAMT as the *right* LazyAMT;
- a *mergefn* function that creates a new $editlist(h)$ by appending an EditList *concat* node containing $editlist'(h)$ from the *right* EditHAMT to the lazy, optional value containing $editlist''(h)$ from the *left* EditHAMT;

where the older and newer EditHAMTs are lazy_eh1 and lazy_eh2, respectively, in Fig. 4.

For example, suppose we concatenate two EditHAMTs, where the *right* EditHAMT contains a single binding $k_0 : b$ and key k_0 has hash 14. We would create a new EditHAMT using the LazyAMT merge operation as described above:

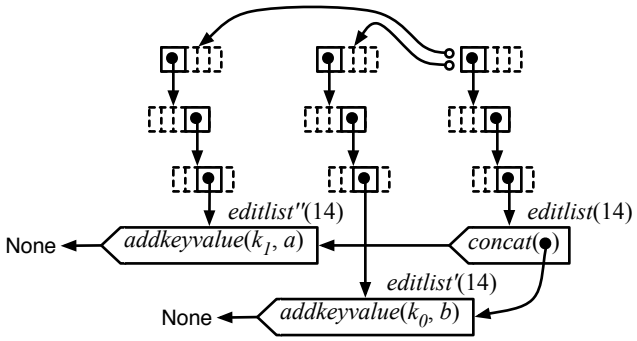


If we perform a map lookup on the concatenated EditHAMT to find the value for key k_0, we would look up the concatenated EditHAMT for hash 14 to retrieve $editlist(14)$ and perform a map lookup on it. This will cause the concatenated EditHAMT to be initialized as follows:



The head of $editlist(14)$ is a *concat* node created by the *mergefn* described above. When we look up key k_0 from $editlist(14)$, we would recursively look up $editlist'(14)$ from the *right* EditHAMT for the same key. Since the head of $editlist'(14)$ adds key k_0, we finish the lookup by returning the mapped value b. We do not have to look at the tail of $editlist(14)$ and can avoid forcing the *left* EditHAMT for now, which is a property inherited from the LazyAMT merge operation.

To consider an example that requires us to force the *left* EditHAMT, suppose that the *left* EditHAMT contains a single binding $k_1 : a$ where key k_1 also has hash 14. If we look up key k_1 from the concatenated EditHAMT, it will be initialized in the following manner:



We would look up key k_1 from $editlist(14)$, and recursively look up $editlist'(14)$ for the same key. Because $editlist'(14)$ does not contain key k_1, we would then resume the lookup in $editlist(14)$, forcing its tail to retrieve $editlist''(14)$ from the *left* EditHAMT, and finally return the mapped value a.

The combination of the LazyAMT and the EditList enables the EditHAMT to support all operations that the EditList supports, reduces the EditList lookup cost to amortized $O(1)$ if we assume no hash collisions, and takes only an additional amortized $O(1)$ time and memory for each edit operation. However, multiset and multimap lookups take amortized $O(n)$ time where n is the number of removeone and removekeyvalue operations.

D. Comparison with Other Data Structures

Compared to Python sets, which are implemented as hash tables, it is more memory efficient to make an updated copy of the EditHAMT, since only a constant number of nodes in the

underlying LazyAMT are created, than it is to make a copy of the bucket array in the hash table underlying Python sets, which can be much larger. This makes it viable to store every intermediate EditHAMT as it is created in a trace, as each EditHAMT only requires an additional amortized $O(1)$ memory over the prior EditHAMT. In our current implementation, a trace of EditHAMTs is cheaper than a trace of Python sets (which requires deep copying) if, on average, each EditHAMT or set in the trace has more than eight elements.

It is also common to implement sets or maps using self-balancing trees such as red-black trees or AVL trees. However, we observe that it is not possible to make these tree data structures as lazy as the EditHAMT. In these data structures, a rebalancing operation is usually performed during or after every addition or removal operation to ensure that every path in the tree does not exceed a certain bound. However the root node may be swapped with another node in the process of rebalancing (in fact, every node can be potentially swapped due to rebalancing). This means that the root node of self-balancing trees is determined by the entire history of addition and removal operations. Thus, we would be forced to compute the entire history of addition and removal operations when we traverse the root node to look up a key, defeating laziness.

We also observe a similar issue arising with hash tables. Hash tables are based on a bucket array that is used to map hash values to keys. Typically, the bucket array is dynamically resized to accommodate the number of keys in the hash table and to reduce hash collisions. However, the number of keys in the hash table is determined by the entire history of addition and removal operations. As a result, we would be forced to compute the entire history of addition and removal operations before we can use the bucket array to map a hash value to a key, defeating laziness.

Furthermore, the EditHAMT suffers much less from hash collisions than hash tables. The LazyAMT in the EditHAMT is a *sparse* integer map, unlike the bucket array in hash tables, and thus can be made much larger while using little memory, which reduces the likelihood of hash collisions.

V. Micro-benchmarks

We ran two micro-benchmarks to evaluate the efficiency of Expositor. In the first micro-benchmark, we evaluated the advantage of laziness by comparing a script written in Expositor against several other equivalent scripts written using non-lazy methods. In the second micro-benchmark, we compared the performance of scripts using the EditHAMT against other equivalent scripts that use non-lazy data structures.

A. Test Program

For both micro-benchmarks, we use the test program in Fig. 6 as the subject of our Expositor scripts. This program consists of two do-nothing functions, foo on line -327 and bar on line -326, and the main function on lines -325–-311 that calls foo and bar in several nested loops.

```
-331 #define LOOP_I 16
-330 #define LOOP_J 16
-329 #define LOOP_K 16
-328 #define LOOP_L 8
-327 void foo(int x, int y) {}
-326 void bar(int z) {}
-325 int main(void) {
-324     int i, j, k, l;
-323     for (i = 0; i < LOOP_I; i++) {
-322         for (j = 0; j < LOOP_J; j++) {
-321             for (k = 0; k < LOOP_K; k++) {
-320                 bar(i * LOOP_K + k);
-319             }
-318             foo(i, i * LOOP_J + j);
-317             for (l = 0; l < LOOP_L; l++) {
-316                 bar(i * LOOP_L + l);
-315             }
-314         }
-313     }
-312     return 0;
-311 }
```

Fig. 6. Micro-benchmark test program

B. Evaluating the Advantage of Trace Laziness

In our first micro-benchmark, we benchmark the advantage of trace laziness using the following procedure. We first start Expositor on the test program in Fig. 6, and run the following script:

```
-320 foo_trace = the_execution.breakpoints("foo")
-319 trace1 = foo_trace.filter(
-318     lambda snap: int(snap.read_arg("x")) % 2 == 0)
```

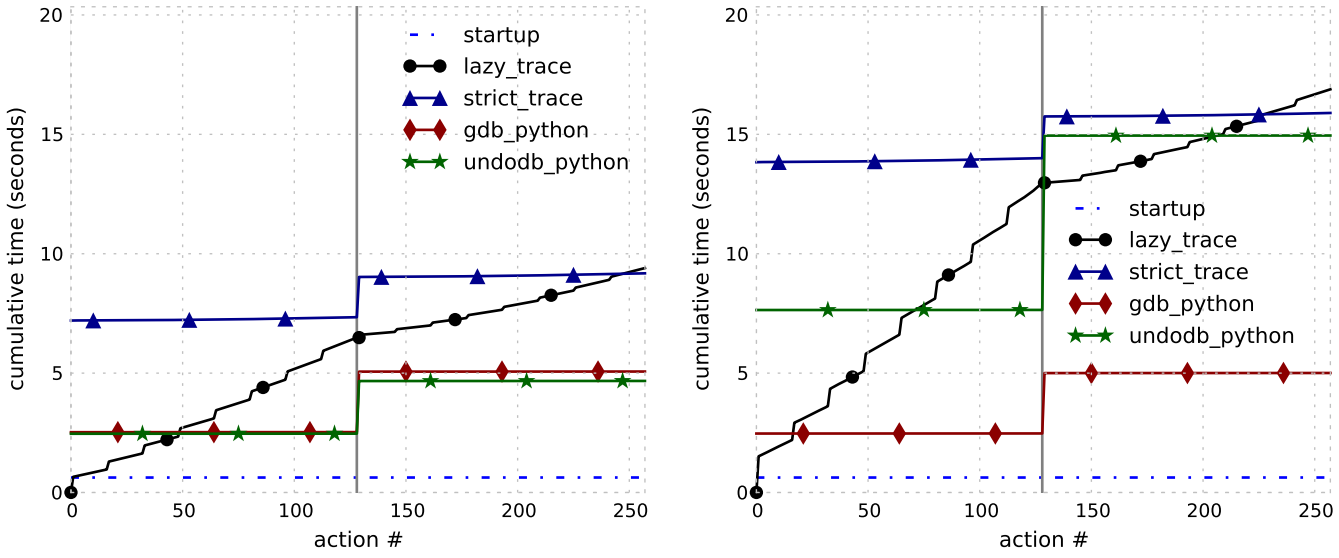
This script creates a trace named foo_trace of calls to foo, and a trace named trace1 that keeps only calls to foo where the argument x is even. We then measure the time it takes to call get_after to find the first item in trace1 after time 0. We repeat this measurement to find the second item, the third item, and so forth, until there are no more items left in trace1. Next, we create another trace named trace2:

```
-327 trace2 = foo_trace.filter(
-326     lambda snap: int(snap.read_arg("x")) % 2 == 1)
```

This trace is similar to trace1, but keeps only calls to foo where x is odd. We then measure again the time it takes to call get_after to find each item in trace2. Finally, we restart Expositor and repeat the entire procedure, but use get_before to find all items in trace1 and trace2 starting from the end of the execution, instead of using get_after.

We compare the above script against several other equivalent scripts that are not lazy, written either in a variant of Expositor with trace laziness disabled, or using the standard GDB Python API with or without UndoDB. We disable trace laziness in Expositor by immediately performing the equivalent of get_after(t) on lazy nodes as they are created, where t is the beginning of the time interval on those nodes, and replacing the lazy nodes by the computed contents.

The results are shown in Fig. 7a for the procedure using get_after, and Fig. 7b for the procedure using get_before. The



(a) get_after

(b) get_before

Fig. 7. The time it takes to get all items in two traces using lazy or non-lazy scripts.

x-axes are labeled "action #", and indicate particular actions that are taken during the benchmarking procedure:

- action 0 corresponds to creating trace1;
- actions 1–128 correspond to calling get_after or get_before repeatedly to get all items in trace1;
- action 129 (the vertical gray line) corresponds to creating trace2;
- actions 130–257 correspond to calling get_after or get_before repeatedly to get all items in trace2.

For scripts using the standard GDB Python API, action 0 and action 129 correspond instead to creating the equivalent of trace1 or trace2, i.e., creating a standard Python list containing the times, rather than snapshots, of the relevant calls to foo. The y-axes indicate cumulative time in seconds, i.e., the total time it takes to perform all actions up to a particular action.

The startup plot simply marks the time it takes to start up EXPOSITOR (i.e., GDB and UndoDB) from the command line, before running any scripts. The lazy_trace plot corresponds to the script written in EXPOSITOR above. The strict_trace plot corresponds to the same script, but uses a variant of EXPOSITOR with trace laziness disabled. The gdb_python plot corresponds to a script written using the standard GDB Python API without the time-travel features of UndoDB, restarting the execution at action 129 (when the equivalent of trace2 is created), and without caching intermediate computation. Note that because gdb_python does not use time travel, the gdb_python scripts in Fig. 7a and Fig. 7b are the same, i.e., they both run the execution forward only, and gdb_python records times instead of snapshots; plotting gdb_python in Fig. 7b allows us to compare forward execution against backward execution. Lastly, the undodb_python plot uses a nearly identical script as gdb_python, but uses UndoDB to rewind the execution at action 129 instead of restarting the execution, and runs the execution backward in Fig. 7b.

From Fig. 7a, we can see that lazy_trace takes zero time to perform action 0, whereas all the other implementations take some non-zero amount of time. In particular, strict_trace is slower than all other implementations, which suggests that the trace data structure has high overhead when laziness is disabled. Also, undodb_python is slightly faster than gdb_python at action 129, since it is faster to rewind an execution than to restart it.

As we expect from laziness, each call to get_after in lazy_trace takes a small additional amount of time, whereas the other non-lazy implementations do not take any additional time (since all relevant calls to foo have already been found at action 0). When we have found about 40% items from trace1, the cumulative time of lazy_trace reaches that of gdb_python. This tells us that, as long as we do not make queries to more than 40% of an execution, it takes us less time to construct and query a lazy trace, compared to other non-lazy implementations. This is actually the common scenario in debugging, where we expect programmers to begin with some clues about when the bug occurs. For example, a stack corruption typically occurs near the end of the execution, so we would likely only have to examine the last few function calls in the execution.

Furthermore, we observe that the slope of lazy_trace is shallower at actions 130–257. This is because trace2 reuses foo_trace which was fully computed and cached during actions 1–128. Thus, EXPOSITOR does not have to perform as much work to compute trace2. strict_trace also benefits from caching since it uses a (non-lazy) variant of the trace data structure. In contrast, both gdb_python and undodb_python do not reuse any computation, so action 129 takes the same amount of time as action 0.

Fig. 7b shows the results of the benchmark procedure using get_before. We can see that it is much slower to use get_before that get_after—all scripts but gdb_python take longer than in Fig. 7a (gdb_python actually runs forward as we noted above). This is because these scripts has to run the execution in two passes: first to get to the end of the execution, then to execute the get_before calls back to the beginning of the execution. Unlike other scripts, the gdb_python script only has to run forward once and not backward, and so is much faster. Still, lazy_trace can be faster than gdb_python, if queries are made to fewer than about 10% of an execution.

We note that the results of this micro-benchmark actually suggest a lower bound to the advantage of trace laziness. This micro-benchmark is based on a very simple EXPOSITOR script that filters calls to foo using a simple predicate. Therefore, the time used for each script is dominated by the time it takes to set a breakpoint at foo and to run the execution, forward or backward, until the breakpoint. To a lesser extent, the trace data structure in lazy_trace adds overhead to the time used in comparison to gdb_python. The filter predicate in lazy_trace and the equivalent predicate in gdb_python takes very little time in contrast. We expect more complex EXPOSITOR scripts to spend more time in programmer-provided helper functions such as the filter predicate or the scan operator, which will mask the overhead of the trace data structure.

C. Evaluating the Advantage of the EditHAMT

In our second micro-benchmark, we evaluate the advantages of the EditHAMT data structure using the following procedure. We first create a trace of EditHAMTs:

```
bar_maps = the_execution.breakpoints("bar") \
    .map(lambda snap: edithamt.addkeyvalue(
        None, int(snap.read_arg("z")), snap)) \
    .scan(edithamt.concat)
```

For each call to bar(z), we create a new EditHAMT that adds a binding from the argument z to the snapshot of that call. In other words, an EditHAMT in bar_maps at time t contains bindings from arguments z to the corresponding bar(z) calls preceding and including the bar(z) call at time t.

We then create another trace that looks up values from bar_maps:

```
bar_of_foos = the_execution.breakpoints("foo")
    .trailing_merge(
        lambda snap, bar_map:
            bar_map.force().find(int(snap.read_arg("y"))),
        bar_maps)
```

For each call to foo(x, y), we use the trailing_merge method to look up the immediately prior EditHAMT in bar_maps, and then look up that EditHAMT for the most recent bar(z) call where y = z.

Next, we measure the time it takes to call get_after to look up the first item from bar_of_foos, which includes the time it takes to compute the EditHAMTs in bar_maps as necessary, as well as to compute parts of the bar_maps and bar_of_foos traces. We also measure the additional memory used after the call to get_after by Python,[5] which includes the memory required to cache the intermediate computation of the EditHAMTs in bar_maps as well as that of the bar_of_foos and bar_maps traces, but does not include the memory usage of other parts of GDB as well as UndoDB. We repeat these measurements to find the second item, the third item, and so forth, until there are no more items in bar_of_foos. Finally, we restart EXPOSITOR and repeat the entire procedure using get_before to find all items in bar_of_foos starting from the end of the execution, instead of using get_after.

For this micro-benchmark, we set the key size of the EditHAMT to $k = 35$ bits and its internal node index bit-width to $w = 5$ bits, which gives it a maximum depth of 7. These parameters are suitable for 32-bit hash values that are padded to 35 bits. We compare the above script against several other equivalent scripts using other data structures, as well as a script that uses the EditHAMT in a variant of EXPOSITOR with trace laziness disabled as described in Sec. V-B, and a script that uses the standard GDB Python API without the time-travel features of UndoDB and a list of Python dicts (hash table) as the equivalent of bar_maps.

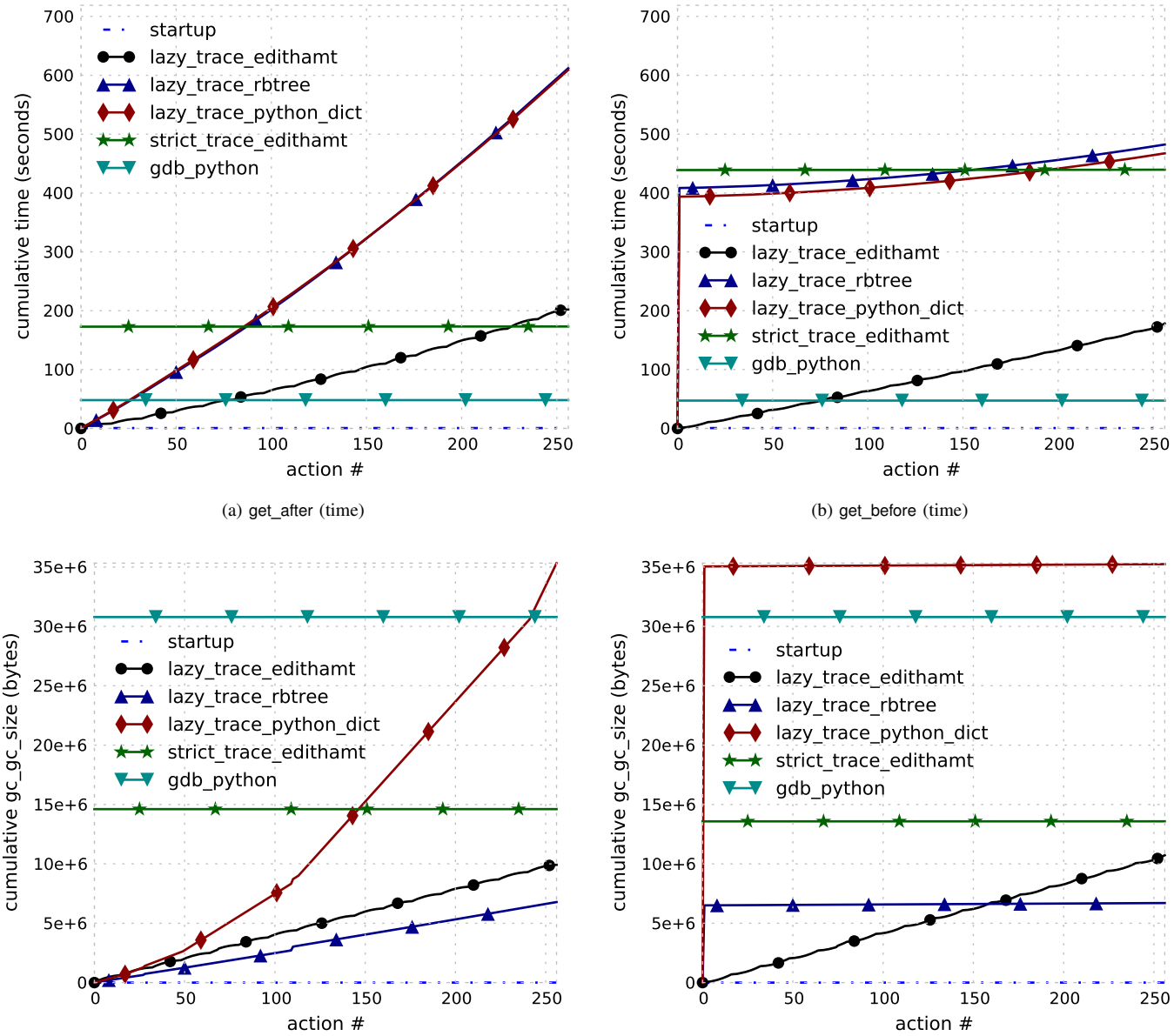
The results are shown in Fig. 8: Fig. 8a and Fig. 8b show the time measurements using get_after and get_before, respectively, while Fig. 8c and Fig. 8d show the memory measurements using get_after and get_before, respectively. The x-axes are labeled "action #", and indicate particular actions that are taken during the benchmarking procedure:

- action 0 correspond to creating bar_maps and bar_of_foos;
- actions 1–256 corresponds to calling get_after or get_before repeatedly to get all items in bar_of_foos.

For the script using the standard GDB Python API, action 0 correspond instead to creating a list of Python dicts mapping the arguments z of bar to times, rather than snapshots, of calls to bar. The y-axes indicate cumulative time in seconds or cumulative memory usage in bytes, i.e., the total time or memory it takes to perform all actions up to a particular action.

The startup plot simply marks the time or memory it takes to start up EXPOSITOR (i.e., GDB and UndoDB) from the command line, before running any scripts. The lazy_trace_edithamt plot corresponds to the EXPOSITOR script above that creates EditHAMTs, which are lazy, in bar_maps. The lazy_trace_rbtree plot corresponds to a similar script, but creates maps based on immutable red-black trees, which are not lazy, instead of EditHAMTs in bar_maps. Likewise, the lazy_trace_python_dict plot creates Python dicts, which are also not lazy, in bar_maps. The strict_trace_edithamt plot corresponds to a script that uses the EditHAMT in a variant of EXPOSITOR with trace laziness disabled as described in Sec. V-B. Lastly, the gdb_python script corresponds to a script written using only the standard GDB Python API without the time-travel features of UndoDB. Note that because gdb_python does not use time travel, the gdb_python scripts in Figs. 8a–8d

[5]We use Python's sys.getsizeof and gc.get_objects functions to measure Python's memory usage.



(a) get_after (time)

(b) get_before (time)

(c) get_after (memory)

(d) get_before (memory)

Fig. 8. The time and memory it takes to get all items in a trace computed by looking up items from an EditHAMT or other data structures.

are all the same, i.e., they all run the execution forward only, and gdb_python records times instead of snapshots; plotting gdb_python in Fig. 8b and Fig. 8d allows us to compare forward execution against backward execution.

From Fig. 8a, we can see that the scripts that use EXPOSITOR, lazy_trace_X, take zero time to perform action 0, whereas strict_trace_edithamt and gdb_python, which are not lazy, take some amount of time to do so, the former more than the latter. This is the result we expect based on the results in Sec. V-B. Also, for lazy_trace_X, each get_after calls takes a small additional amount of time. In particular, lazy_trace_edithamt takes less additional time than lazy_trace_rbtree and lazy_trace_python_dict. This is due to EditHAMT laziness: lazy_trace_edithamt only has to compute as many (parts) of the EditHAMTs in bar_maps as needed to answer the look up in bar_of_foos. In contrast, red-black trees and Python dicts are not lazy, so lazy_trace_rbtree and lazy_trace_python_dict have to compute all prior red-black trees or Python dicts, respectively, in bar_maps, even before answering the lookup in bar_of_foos. Also, since there are many more calls to bar than to foo in the test program (Sec. V-A), and the bar call that matches a foo call occurs within a few calls to bar, lazy_trace_edithamt has to examine fewer bar calls than lazy_trace_rbtree or lazy_trace_python_dict. Furthermore, as long as we make fewer queries than about 30% of the items in bar_of_foos,

it is faster to use lazy_trace_edithamt than it is to use gdb_python. We also note that it is far easier to compose or reuse lazy_trace_edithamt than gdb_python. For example, if we later decide to compare the argument x of foo to the matching bar call, we can easily create a new trace that maps foo calls to their x argument and merge it with bar_of_foos in lazy_trace_edithamt, while we would need to modify and rerun gdb_python to collect the x arguments.

The results are quite different for lazy_trace_rbtree and lazy_trace_python_dict in Fig. 8b—action 0 still takes zero time, but action 1, the very first call to get_before, is very slow, contributing most of the cumulative time by the end of the micro-benchmark. This is because that very first call to get_before retrieves the very last item in bar_of_foos near the end of the execution, which looks up one of the last red-black tree or Python dict in bar_maps to find the matching bar call. As we explained above, since red-black trees and Python dicts are not lazy, lazy_trace_rbtree and lazy_trace_python_dict has to compute all prior red-black trees or Python dicts, respectively, and examine almost all bar calls when performing action 1. These cases highlight the importance of using lazy data structures in EXPOSITOR scripts—non-lazy data structures can completely defeat the advantage of trace laziness.

Looking at memory usage, Fig. 8c shows that each get_after call in lazy_trace_edithamt and lazy_trace_edithamt takes a small additional amount of memory. EditHAMTs use slightly more memory than red-black trees, partly because, due to EditHAMT laziness, we do not compute as many (parts of) EditHAMTs as red-black trees. Also, the memory cost of EditHAMTs is exaggerated in our Python-based implementation, since it makes extensive use of closures which are rather costly memory-wise in Python.[6] We believe that an implementation of EditHAMTs in more efficient languages such as C or OCaml would use much less memory. In contrast, lazy_trace_python_set is quite expensive, using an increasing amount of memory after each get_after call. This is because Python dicts are implemented using hash tables, and since each dict in bar_maps has to be distinct, we have to make a deep copy of the dicts. This eventually takes $O(n^2)$ memory where n is the number of bar calls in the execution, which is confirmed by Fig. 8c. The gdb_python script uses almost as much memory as lazy_trace_python_dict by the end of the micro-benchmark, since they both create many Python dicts, except that gdb_python stores them in a Python list which has lower overhead than a trace. The strict_trace_edithamt script also uses a lot memory, more than lazy_trace_edithamt by the end of the micro-benchmark, since strict_trace_edithamt has to create every EditHAMT in bar_maps (the EditHAMTs themselves are lazy), unlike lazy_trace_edithamt which only creates EditHAMTs in bar_maps when they are looked up.

We see a similar pattern in Fig. 8d for memory usage as in Fig. 8b for time usage: action 1 of lazy_trace_rbtree and lazy_trace_python_dict contributes almost all of the cumulative memory usage by the end of the execution. As we explained above for Fig. 8b, this is due to having to compute almost all red-black trees or Python dicts in bar_maps.

VI. FIREFOX CASE STUDY: DELAYED DEALLOCATION BUG

To put EXPOSITOR to the test, we used it to track down a subtle bug in Firefox that caused it to use more memory than expected [12]. The bug report contains a test page that, when scrolled, creates a large number of temporary JavaScript objects that should be immediately garbage collected. However, in a version of Firefox that exhibits the bug (revision c5e3c81d35ba), the memory usage increases by 70MB (as reported by top), and only decreases 20 seconds after a second scroll. As it turns out, this bug has never been directly fixed—the actual cause is a data race, but the official fix instead papers over the problem by adding another GC trigger.

Our initial hypothesis for this bug is that there is a problem in the JavaScript garbage collector (GC). To test this hypothesis, we first run Firefox under EXPOSITOR, load the test page, and scroll it twice, temporarily interrupting the execution to call the_execution.get_time() just before each scroll, time $t_{scroll1}$ and time $t_{scroll2}$, and after the memory usage decreases, t_{end}. Then, we create several traces to help us understand the GC and track down the bug, as summarized in Fig. 9.

We observe the GC behavior using a trace of the calls to (gc_call) and returns from (gc_return) function js_GC (Fig. 9a).[7] Also, we find out when memory is allocated or released to the operating system using mmap2 and munmap traces of the same-named system calls (Fig. 9b). Printing these traces reveals some oddly inconsistent behavior: the GC is called only once after $t_{scroll1}$, but five times after $t_{scroll2}$; and memory is allocated after $t_{scroll1}$ and deallocated just before t_{end}. To make sense of these inconsistencies, we inspect the call stack of each snapshot in gc_call and discover that the first js_GC call immediately after a scroll is triggered by a scroll event, but subsequent calls are triggered by a timer.

We now suspect that the first scroll somehow failed to trigger the creation of subsequent GC timers. To understand how these timers are created, we write a function called set_tracing that creates a trace for analyzing set-like behavior, using EditHAMTs to track when values are inserted or removed, and apply set_tracing to create timer_trace by treating timer creation as set insertion, and timer triggering as set removal (Fig. 9c). This trace reveals that each js_GC call creates a GC timer (between gc_call and gc_return snapshots), except the js_GC call after the first scroll (and the last js_GC call because GC is complete).

To find out why the first js_GC call does not create a GC timer, we inspect call stacks again and learn that a GC timer is only created when the variable gcChunksWaitingToExpire is nonzero, and yet it is zero when the first js_GC returns (at

[6] In 32-bit Python 2.7.1, a closure over a single variable takes 108 bytes, and each additional variable takes 28 bytes.

[7] The index=−1 optional argument to execution.breakpoints indicates that the breakpoint should be set at the end of the function.

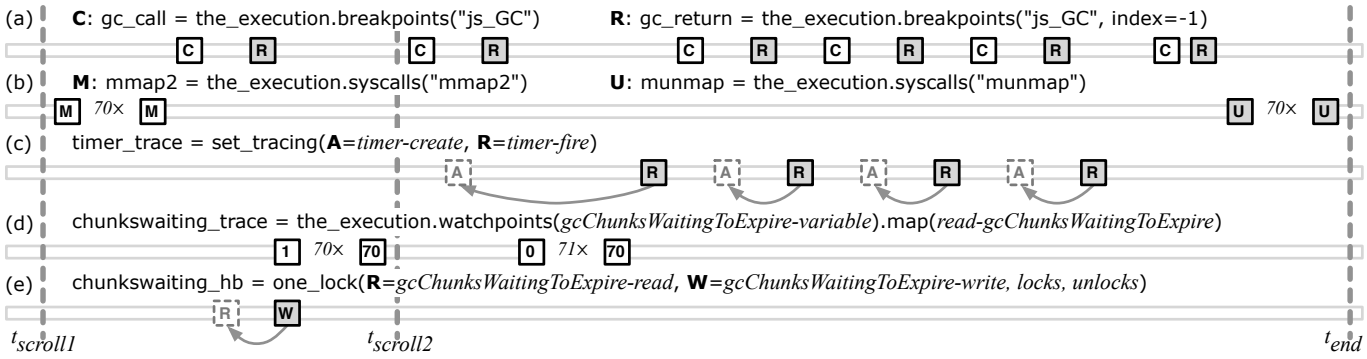


Fig. 9. Timeline of items in traces used to debug Firefox.

the first gc_return snapshot). Following this clue, we create a watchpoint trace on gcChunksWaitingToExpire and discover that it remained zero through the first js_GC call and becomes nonzero only after the first js_GC returns. It stayed nonzero through the second scroll and second js_GC call, causing the first GC timer to be created after that (Fig. 9d).

We posit that, for the GC to behave correctly, gcChunksWaitingToExpire should become nonzero at some point during the first js_GC call. Inspecting call stacks again, we find that gcChunksWaitingToExpire is changed in a separate helper thread, and that, while the GC owns a mutex lock, it is not used consistently around gcChunksWaitingToExpire. This leads us to suspect that there is a data race. Thus, we develop a simple race detection script, one_lock, that works by comparing each access to a chosen variable against prior accesses from different threads (Sec. IV-A explains how we track prior accesses), and checking if a particular lock was acquired or released prior to those accesses. For each pair of accesses, if at least one access is a write, and the lock was not held in one or both accesses, then there is a race, which we indicate as an item containing the snapshot of the prior access. We apply this race detector to gcChunksWaitingToExpire and confirm our suspicion that, after $t_{scroll1}$, there is a write that races with a prior read during the first js_GC call when the timer should have been created (Fig. 9e).

To give a sense of EXPOSITOR's performance, it takes 2m6s to run the test page to $t_{scroll2}$ while printing the gc_call trace, with 383MB maximum resident memory (including GDB, since EXPOSITOR extends GDB's Python environment). The equivalent task in GDB/UndoDB without EXPOSITOR takes 2m19s and uses 351MB of memory (some difference is inevitable as the test requires user input, and Firefox has many sources of nondeterminism). As another data point, finding the race after $t_{scroll1}$ takes 37s and another 5.4MB of memory.

The two analyses we developed, set_tracing and one_lock, take only 10 and 40 lines of code to implement, respectively, and both can be reused in other debugging contexts.

VII. RELATED WORK

EXPOSITOR provides scripting for time-travel debuggers, with the central idea that a target program's execution can be manipulated (i.e., queried and computed over) as a first-class object. Prior work on time-travel debugging has largely provided low-level access to the underlying execution without consideration for scripting. Of the prior work on scriptable debugging, EXPOSITOR is most similar to work that views the program as an event generator—with events seeded from function calls, memory reads/writes, etc.—and debugging scripts as database-style queries over event streams or as dataflow-oriented stream transformers. None of this scripting work includes the notion of time travel.

A. Time-Travel Debuggers

Broadly speaking, there are two classes of time-travel debuggers. *Omniscient debuggers* work by logging the state of the program being debugged after every instruction, and then reconstructing the state from the log on demand. Some examples of omniscient debuggers include ODB [13], Amber (also known as Chronicle) [6], Tralfamadore [14], and TOD [15]. In contrast, *replay debuggers* work by logging the results of system calls the program makes (as well as other sources of nondeterminism) and making intermediate checkpoints, so that the debugger can reconstruct a requested program state by starting at a checkpoint and replaying the program with the logged system calls. Several recent debuggers of this style include URDB [16] and UndoDB [5] (which we used in our prototype) for user-level programs, and TTVM [17] and VMware ReTrace [18] for entire virtual machines. EXPOSITOR could target either style of debugger in principle, but replay debugging scales much better (e.g., about 1.7× recording overhead for UndoDB vs. 300× for Amber). Engblom [19] provides a more comprehensive survey on time-travel debugging techniques and implementations.

The above work focuses on implementing time travel efficiently; most systems provide very simple APIs for accessing the underlying execution, and do not consider how time travel might best be exploited by debugging scripts.

Similarly, GDB's Python environment simply allows a Python program to execute GDB (and UndoDB) commands in a callback-oriented, imperative style. This is quite tedious, e.g., just counting the number of calls to a particular function takes 16 lines of code (Sec. II-B1), and cannot be composed with other scripts (e.g., to refine the count to calls that satisfy

predicate p). EXPOSITOR's notion of traces is simpler and more composable: function call counting can be done in one or two lines by computing the length of a breakpoint trace; to refine the count, we simply filter the trace with p before counting (Sec. II-B).

Tralfamadore [20] considers generalizing standard debugging commands to entire executions, but does not provide a way to customize these commands with scripts.

Whyline is a kind of omniscient debugger with which users can ask "*why did*" and "*why didn't*" questions about the control- and data-flow in the execution, e.g., "*why did this Button's visible = true*" or "*why didn't Window appear*" [21]. Whyline records execution events (adding 1.7× to 8.5× overhead), and when debugging begins, it uses program slicing [22] to generate questions and the corresponding answers (imposing up to a 20× further slowdown). Whyline is good at what it does, but its lack of scriptability limits its reach; it is hard to see how we might have used it to debug the Firefox memory leak, for example. In concept, Whyline can be implemented on top of EXPOSITOR, but limitations of GDB and UndoDB (in particular, the high cost of software watchpoints, and the inability to track data-flow through registers) makes it prohibitively expensive to track fine-grained data-flow in an execution. We plan to overcome this limitation in future work, e.g., using EDDI [23] to implement fast software watchpoints.

B. High-Level (Non-callback Oriented) Debugging Scripts

EXPOSITOR's design was inspired by MzTake [3], a Scheme-based, interactive, scriptable debugger for Java based on *functional reactive programming*. In MzTake, the program being debugged is treated as a source of *event streams* consisting of events such as function calls or value changes. Event streams can be manipulated with combinators that filter, map, fold, or merge events to derive new event streams. As such, an event stream in MzTake is like a trace in EXPOSITOR. Computations in MzTake are implicitly over the most recent value of a stream and are evaluated eagerly as the target program runs. To illustrate, consider our example of maintaining a shadow stack from Sec. II-C. In MzTake, when the target program calls a function, a new snapshot event `s` becomes available on the `calls` stream. The `calls_rets` stream's most recent event is the most recent of `calls` and `rets`, so MzTake updates it to `s`. Since `shadow_stacks` is derived from `calls_rets`, MzTake updates its most recent event by executing `map(int, s.read_retaddrs())`).

This eager updating of event streams, as the program executes, can be less efficient than using EXPOSITOR. In particular, EXPOSITOR evaluates traces lazily so that computation can be narrowed to a few slices of time. In Sec. II-C, we find the *latest* smashed stack address without having to maintain the shadow stack for the entire program execution, as would be required for MzTake. Also, EXPOSITOR traces are time indexed, but MzTake event streams are not: there is no analogue to `tr.get_at(i)` or `tr.slice(t0, t1)` in MzTake. We find time indexing to be very useful for interactivity: we can run scripts to identify an interesting moment in the execution, then explore the execution before and after that time. Similarly, we can learn something useful from the end of the execution (e.g., the address of a memory address that is double-freed), and then use it in a script on an earlier part of the execution (e.g., looking for where that address was first freed). MzTake requires a rerun of the program, which can be a problem if nondeterminism affects the relevant computation.

Dalek [24] and Event Based Behavioral Abstraction (EBBA) [25] bear some resemblance to MzTake and suffer the same drawbacks, but are much lower-level, e.g., the programmer is responsible for manually managing the firing and suppression of events. Coca [26] is a Prolog-based query language that allows users to write predicates over program states; program execution is driven by Prolog backtracking, e.g., to find the next state to match the predicate. Coca provides a `retrace` primitive that restarts the entire execution to match against new predicates. This is not true time travel but re-execution, and thus suffers the same problems as MzTake.

PTQL [27], PQL [28], and UFO [29] are declarative languages for querying program executions, as a debugging aid. Queries are implemented by instrumenting the program to gather the relevant data. In principle, these languages are subsumed by EXPOSITOR, as it is straightforward to compile queries to traces. Running queries in EXPOSITOR would allow programmers to combine results from multiple queries, execute queries lazily, and avoid having to recompile (and potentially perturb the execution of) the program for each query. On the other hand, it remains to be seen whether EXPOSITOR traces would be as efficient as using instrumentation.

VIII. CONCLUSION

We have introduced EXPOSITOR, a novel scriptable, time-travel debugging system. EXPOSITOR allows programmers to project a program execution onto immutable traces, which support a range of powerful combinators including `map`, `filter`, `merge`, and `scan`. The trace abstraction gives programmers a global view of the program, and is easy to compose and reuse, providing a convenient way to correlate and understand events across the execution timeline. For efficiency, EXPOSITOR traces are implemented using a lazy, interval-tree-like data structure. EXPOSITOR materializes the tree nodes on demand, ultimately calling UndoDB to retrieve appropriate snapshots of the program execution. EXPOSITOR also includes the EditHAMT, which lets script writers create lazy sets, maps, multisets, and multimaps that integrate with traces without compromising their laziness. We ran two micro-benchmarks that show that EXPOSITOR scripts using lazy traces can be faster than the equivalent non-lazy scripts in common debugging scenarios, and that the EditHAMT is crucial to ensure that trace laziness is not compromised. We used EXPOSITOR to find a buffer overflow in a small program, and to diagnose a very complex, subtle bug in Firefox. We believe that EXPOSITOR holds promise for helping programmers better understand complex bugs in large software systems.

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