Effective and Precise Dynamic Detection of Hidden Races for Java Programs

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ABSTRACT
Happens-before relation is widely used to detect data races dynamically. However, it could easily hide many data races as it is interleaving sensitive. Existing techniques based on randomized scheduling are ineffective on detecting these *hidden races*. In this paper, we propose *DrFinder*, an effective and precise dynamic technique to detect hidden races. Given an execution, *DrFinder* firstly analyzes the lock acquisitions in it and collects a set of "*may-trigger*" relations. Each may-trigger relation consists of a method and a type of a Java object. It indicates that, during execution, the method may directly or indirectly acquire a lock of the type. In the subsequent executions of the same program, *DrFinder* actively schedules the execution according to the set of collected may-trigger relations. It aims to reverse the set of happens-before relation that may exist in the previous executions so as to expose those hidden races. To effectively detect hidden races in each execution, *DrFinder* also collects a new set of may-trigger relation during its scheduling, which is used in its next scheduling. Our experiment on a suite of real-world Java multithreaded programs shows that *DrFinder* is effective to detect 89 new data races in 10 runs. Many of these races could not be detected by existing techniques (i.e., *FastTrack*, *ConTest*, and *PCT*) even in 100 runs.

Categories and Subject Descriptors
D.2.4 [Software Engineering]: Program Verification; **D.2.5 [Software Engineering]**: Testing and Debugging, testing tools; **D.4.1** [**Operating Systems**]: Processing Management – synchronizations, threads.

General Terms
Reliability, verification.

Keywords
Data race, thread scheduling, hidden race, synchronization order

1. INTRODUCTION
A *data race* (or *race* for short) [17] occurs when two or more threads access a same memory location concurrently, and at least one of these accesses is a write [17]. Data race occurrences often indicate other concurrency bugs in the same program [34]. Many dynamic data race detectors are based on the *locking discipline* [40] or the *happens-before* relations (HBR for short) [25]. The locking discipline requires every two concurrent accesses (one of them is a write) to a shared memory location to be protected by a common set of locks. But, such lockset-based detectors are imprecise [18]. HBR-based detectors (or ***HB detectors*** for short) precisely [17] report a data race only if they observe the two accesses involving in a race not ordered by any HBR in an execution/trace. (In this paper, we use the two terms *execution* and *trace* interchangeably.)

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ESEC/FSE'15, August 30 – September 4, 2015, Bergamo, Italy
ACM. 978-1-4503-3675-8/15/08...
http://dx.doi.org/10.1145/2786805.2786839

Some races in a program can be easily exposed in many traces and HB detectors [17][35][37] can effectively detect them. There are other races that are difficult to be detected due to reasons like conditional variables and ad-hoc synchronizations. They can be detected by two most recent techniques *RVPredict* [20] through data flow analysis offline and *Racageddon* [16] through generating specific test inputs for each predicted race.

HB detectors are interleaving-sensitive [49]. They may miss to detect a race if the two accesses of this race are ordered by HBRs in an execution; but the same race can be detected in another execution with a different thread interleaving such that no HBR orders the two accesses. That is, such a race is hidden by *HB edges* in some executions [43]. Some of these races, even on repeated executions, can still be hard to detect [43]. For ease of reference, we refer to such a race as a ***hidden race*** (also known as a "hard" race [43]). This paper focuses on the detection of hidden races.

Existing ***online*** techniques (e.g., [8][15][41][50]) are ineffective to detect hidden races. *Randomized scheduling* techniques (e.g., *PCT* [8] and *ConTest* [15]) only randomly identify changed points [8] or insert random time delays [15] to modify thread priorities. They are ineffective in exposing races whose accesses are separated by consecutive sequences of locking orders [25] among threads. *Active testing* (e.g., [41][50], *Racageddon* and *RVPredict*) techniques are built on top of random (or native) scheduling and/or concurrency bug patterns to produce a predictive trace for potential race analysis. It fails to be successfully applied if no hidden race can be predicted in the predictive run. Besides, they need many runs to deem a potential race as a false positive with confidence. Coverage-driven testing techniques [50] or using adequacy criteria [53] demand either patterns of problematic memory accesses as well as synchronization operations or applicable adequacy criteria as inputs. To the best of our knowledge, there is no effective pattern or adequacy criterion for hidden races discovered yet.

As such, a key challenge for dynamic race detectors is to generate executions that effectively expose hidden races.

Offline techniques [20][43] to may infer hidden races. The Causally-Precedes (*CP*) detector [43] can interestingly predict hidden races in a given trace under limited scenarios. *CP* is however inapplicable if a hidden race is separated by HBR (i.e., HB edges) having conflicting data accesses [43]. Also, analyzing large traces (e.g., running Eclipse for 1 hour of code development) by *CP* is still impractical; besides, *no* online *CP* detector has been invented yet [43]. *RVPredict* [20] confirms each predicted data race via constraint solving. Like other predictive techniques [41], it needs to solve the scheduling constraints for each predicted data race, which may fail.

Our work exploits two observations: (1) many races hidden in one execution can be detected by reversing the direction of one or more consecutive HBRs [25] in another execution, and (2) in real-world programs, only a small proportion of methods generates lock acquisition events, and these methods usually generate events on designated (instead of arbitrary) lock objects.

In this paper, we propose *DrFinder* (Data races Finder), a dynamic technique to detect hidden races by reversing possible HBRs. *DrFinder* is based on *may-trigger relation*. This relation relates a method to a type of lock object in Java programs. It represents that the method *may* directly or indirectly (by calling several other methods) *trigger* a lock acquisition on a lock object of that type.

DrFinder consists of two phases. Figure 1 shows an overview of *DrFinder*. In Phase I, *DrFinder* analyzes each lock acquisition event in a given trace to relate each selected method to the type of the lock object of the event and takes them as a set of *may-trigger* relations (i.e., MTR in Figure 1). In Phase II, it generates a trace for hidden race detection based on the collected set of *may-trigger* relation. Specifically, if a thread generates a lock acquisition event e_1 on a lock of type *c* and some other thread may-trigger a lock acquisition event e_2 on a lock of the same type *c*, *DrFinder* postpones the execution of e_1 until an expected event e_2 occurs. As such, the locking order on these two events that they may form in the trace analyzed in Phase I is reversed. In this way, the races originally hidden by such HBRs are exposed in the later trace.

DrFinder also collects a set of new may-trigger relations in each scheduled execution which is used in the next scheduled execution. This feedback mechanism makes *DrFinder* effective to detect new hidden races in each its scheduled execution.

We have implemented *DrFinder* in the Jikes RVM [3], and evaluated it on the Dacapo benchmarks [6]. The experimental result shows that *DrFinder* finds races that cannot be effectively detected by both native runs, *ConTest*, and *PCT* configured with *FastTrack*. In total, *DrFinder* detects 89 new data races on 5 *Dacapo* benchmarks within 10 runs each. Besides, many of these new races could not be detected by existing techniques in 100 runs.

In summary, the main contributions of this paper are:

- This paper proposes a *may-trigger* relation and a novel hidden data race detector *DrFinder*. *DrFinder* predicts locking orders, and makes decisions on the reversals of locking orders at the *may-trigger* relation level. It profiles *no* memory accesses in Phase I, and only carries forward the *may-trigger* relations between phases.
- It reports the feasibility of *DrFinder* by implementing it as a prototype tool in the Jikes RVM. It presents an experiment to evaluate *DrFinder*. In the experiment, *DrFinder* detects 89 new races and is promising in exposing hidden races. *DrFinder* is scalable to large-scale Java programs (e.g., Eclipse).

In the rest of this paper, Section 2 reviews preliminaries followed by a motivating example in Section 3. Sections 4 and 5 present the design rationales and the details of *DrFinder*, respectively. Section 6 reports the evaluation of *DrFinder*. In Sections 7 and 8, we discuss the related work and conclude this paper, respectively.

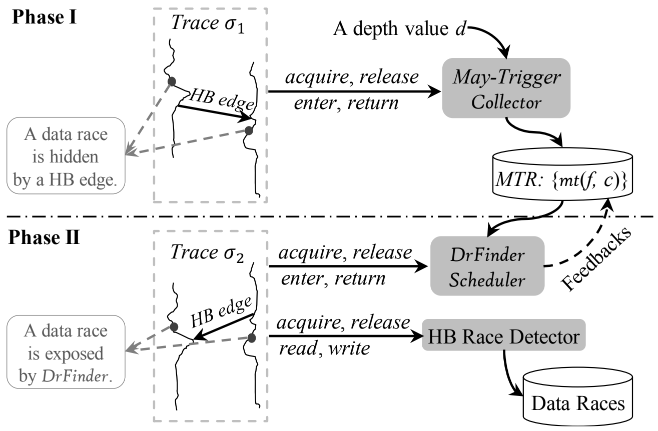


Figure 1. An overview of *DrFinder*.

2. PRELIMINARIES

A multithreaded Java program p contains a set of classes denoted as C. Each class c in C consists of a set of fields and a set of *methods*. We denote the set of all methods of p as M. An object $o \in O$ is an instance of a class c, and the type of o, denoted as $\boldsymbol{type(o)}$, is c. Each lock is an instance of a class.

Each thread t in program p executes a nested sequence of methods. Each method may execute a set of operations $OP = \{ rd, wr, acq, rel, enter, return \}$, where rd and wr mean read and write to a field of a class instance, respectively; acq and rel mean acquisition and release of a lock, respectively; and $enter$ and $return$ mean a call and a return to and from a method, respectively.

An event $e = \langle t, op, o \rangle$ means that a thread t performs an operation $op \in OP$ on an object $o \in O \cup M$. We denote o in e by $\boldsymbol{object(e)}$. A *trace* σ is a sequence of events.

The *Happens-before relation* ($\rightarrowtail$, HBR) [25] in a trace is defined by three rules: (1) if two events α and β are performed by the same thread, and α appeared before β, then $\alpha \rightarrowtail \beta$. (2) if two events $\alpha = \langle t_\alpha, rel, m \rangle$ and $\beta = \langle t_\beta, acq, m \rangle$ are performed by two different threads, and α appeared before β, then $\alpha \rightarrowtail \beta$. (3) if $\alpha \rightarrowtail \beta$ and $\beta \rightarrowtail \gamma$, then $\alpha \rightarrowtail \gamma$.

Two memory events $e_1 = \langle t_1, op_1, v_1 \rangle$ and $e_2 = \langle t_2, op_2, v_2 \rangle$ form a race on v_1 if (1) $t_1 \neq t_2 \wedge v_1 = v_2$, (2) $\{wr\} \cap \{op_1, op_2\} \neq \emptyset$, and (3) neither $e_1 \rightarrowtail e_2$ nor $e_2 \rightarrowtail e_1$.

The relation $e_1 \rightarrowtail e_2$ is called an **HB edge** if $e_1 = \langle t_1, rel, l \rangle$, $e_2 = \langle t_2, acq, l \rangle$, and $t_1 \neq t_2$ [43]. For instance, the two arrows in Figure 2 depict two HB edges $e_1 \rightarrowtail e_9$ and $e_3 \rightarrowtail e_6$, where "*sync*$(o)\{\ldots\}$" denotes a pair of events " $acq(o) \ldots rel(o)$ "; and we will use this short form in Section 3. Given two traces σ and σ' and a pair of events e_1 and e_2, if e_1 and e_2 form a race in σ but does not form any race in σ', then the race is called a **Hidden Race** in σ'.

In a Java program, each thread starts its execution from its method *run*().

3. MOTIVATING EXAMPLE

Figure 2 shows our motivating example, where, each thread (i.e., t_1, t_2, or t_3) executes a sequence of events from top to bottom. These events are memory accesses (i.e., m_1 to m_4) to the locations x and y, and lock acquisition/release events (i.e., e_1 to e_9) on seven lock objects k, n, and o_1 to o_1. The two HB edges $e_1 \rightarrowtail e_9$ and $e_3 \rightarrowtail e_6$ on the two lock objects n and k, respectively, are denoted as arrows. We denote the trace as $\sigma_1 = \langle \ldots, e_1 \ldots, e_9 \ldots, e_3 \ldots, e_6 \ldots \rangle$. The two pairs of accesses to locations x and y (i.e., m_1

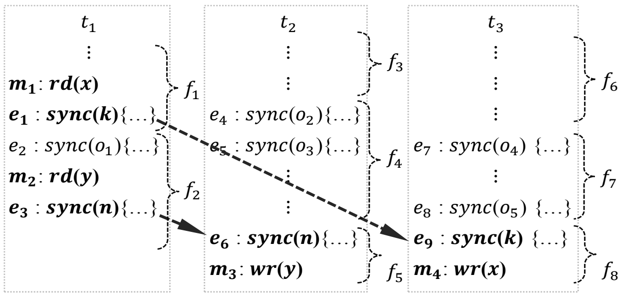


Figure 2. A trace σ_1 hiding two races on *x* and *y* as two HB edges $e_1 \rightarrowtail e_9$ and $e_3 \rightarrowtail e_6$ order the two accesses of each race, respectively.

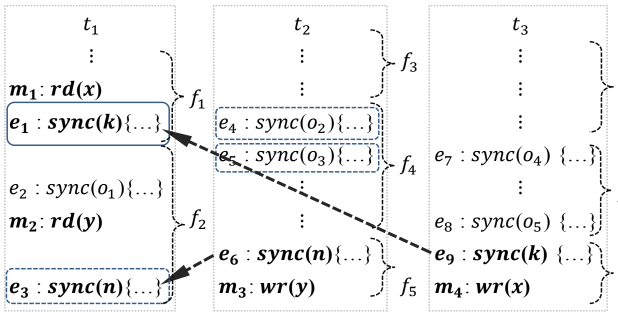


Figure 3. A trace σ_2 generated by *DrFinder*, exposed two races on *x* and *y*.

and m_4, and m_2 and m_3) are ordered by the HB edges $e_1 \rightarrowtail e_9$ and $e_3 \rightarrowtail e_6$, respectively. Hence, no HB detector can detect any race in the trace σ_1.

Next, we reverse the direction of each HB edge shown in Figure 2 to sketch Figure 3, which represents the trace $\sigma_2 = \langle ..., e_9 ..., e_1 ..., e_6 ..., e_3 ... \rangle$ of the same program. An HB detector can now report the two (hidden) races on *x* and *y* in σ_1.

If a native schedule exhibits the trace σ_1 as shown in Figure 2, the probability to observe the trace σ_2 shown in Figure 3 is very low [43]. Hence, the two races may not be easily detected.

Naïve strategy: A naive strategy is to suspend every lock acquisition event observed in a trace before executing the event. For trace σ_2, it suspends the three threads from executing e_1, e_4, and e_7, respectively, producing an occurrence of the suspension of all the threads of the trace (known as thrashing [41]). Thrashing is typically resolved by randomly resuming one of the suspended threads. There is no thoughtful design to ensure $e_9 \rightarrowtail e_1$ in order to expose the hidden race on *x* effectively.

Offline techniques: *CP* [43] can infer these two races from σ_1, providing that no conflicting memory accesses exist inside the synchronization bodies of e_1 and e_9. That is, if *z* is a new location, where e_1 protects a write access to *z* (i.e., $e_1 = sync(k)\{..., wr(z) ...\}$) and e_9 protects a read access to *z* (i.e., $e_9 = sync(k)\{..., rd(z) ...\}$). Then, the race on *x* cannot be detected by *CP* (and the case on *y* is similar). This is restrictive. In their experiment [43], on only 2 out of 11 programs, can *CP* detect 2 and 7 more races than *FastTrack* [17] (an online HB detector).

Online randomized schedulers: *ConTest* [15] inserts a small amount of random time delays on some lock acquisitions. Suppose that e_1 is generated but not executed by t_1 yet. A small time delay in between the generation and execution of e_1 may not be long enough for t_3 to have generated and executed e_9, which depends on both the underlying (native or randomized) scheduler and the sequence of operations performed by t_3 in between the current execution point and e_9. The design of *ConTest* is insensitive to both factors. *PCT* [8] provides a theoretical guarantee to find a concurrency bug, but this guarantee is very low even for the illustrating example. Its guaranteed probability (i.e., $1 \div (n \times k^{BugDepth-1})$) [8], where n is the number of threads and k is the number of instructions executed) also decreases exponentially as *BugDepth* increases. From our first-hand experience, many bugs can be detected using 1 as *BugDepth*, and yet a significant amount of races still cannot be detected using much deeper depths with 100 runs.

Table 1. **The *May-Trigger* relation for methods and lock object types of program shown in Figure 2.**

May-Trigger Relation	*May-Trigger* Relation
$mt(f_1, c_k)$, $mt(f_1, c_1)$, $mt(f_1, c_n)$	$mt(f_5, c_n)$
$mt(f_2, c_1)$, $mt(f_2, c_n)$	$mt(f_6, c_4)$, $mt(f_6, c_5)$, $mt(f_6, c_k)$
$mt(f_3, c_2)$, $mt(f_3, c_3)$, $mt(f_3, c_n)$	$mt(f_7, c_4)$, $mt(f_7, c_5)$, $mt(f_7, c_k)$
$mt(f_4, c_2)$, $mt(f_4, c_3)$, $mt(f_4, c_n)$	$mt(f_8, c_k)$

Our technique: *DrFinder* can effectively reverse the two HB edges $e_1 \rightarrowtail e_9$ and $e_3 \rightarrowtail e_6$ observed in the trace σ_1 when generating the trace σ_2. When observing e_1, it effectively foresees the execution of the event e_9; and similarly, when observing e_3, it effectively foresees the execution of the event e_6. *DrFinder* achieves this prediction via a novel strategy.

We denote the types of the lock objects k, n, o_1 to o_5 as c_k, c_n, c_1 to c_5, respectively, and the methods that contain above events as f_1 to c_8 as shown in Figure 2, where an upper method in a column invokes the method immediately below it (e.g., f_1 invokes f_2).

Specifically, in Phase I, *DrFinder* constructs every may-trigger relation *mt*(*f*, *c*) (see Section 4.3 for definition) between a method *f* and a lock object type *c* observed in σ_1. Each *may-trigger* relation *mt*(*f*, *c*) means that *f* may trigger a lock acquisition event on a lock object of type *c*. Table 1 shows the set of may-trigger relations constructed from σ_1 in Figure 2. (Note that may-trigger relation also considers program call stack, not a single function.)

In Phase II, firstly, suppose that t_2 is executing some events in the method f_3 and t_3 is executing some events in the method f_6. When *DrFinder* observes the event e_1 produced by t_1, it checks the *may-trigger* relations involving f_3 and f_6 (i.e., the two methods being executed by the other two threads t_2 and t_3, respectively), and finds a *may-trigger* relation $mt(f_6, c_k)$, meaning that f_6 may-trigger a lock acquisition event on an object of type c_k, which is the same type as that of e_1. *DrFinder* thus suspends t_1 (depicted as a solid rectangle in Figure 3), and sets t_1 to wait for an event of this object type c_k. It further escorts t_3 to execute all its events until t_3 executes the event e_9, which is the first encountered event on a lock object having the type c_k. *DrFinder* then resumes t_1 to execute e_1 to form the targeted HB edge $e_9 \rightarrowtail e_1$. A further execution of the two threads will execute memory accesses on *x*, which expose the hidden race on *x*.

Next, it is feasible for t_1 to execute e_2 or for t_2 to execute e_4. Because neither $mt(f_4, type(o_1))$ nor $mt(f_2, type(o_2))$ matches any may-trigger relation, *DrFinder* resolves the tie randomly: (1) Suppose that t_1 is selected. When t_1 generates e_3, *DrFinder* finds that $mt(f_4, type(n))$ is a may-trigger relation. Thus, it suspends t_1, and escorts t_2 to execute until t_2 has executed e_6. After that, t_1 executes e_3, and the HB edge $e_6 \rightarrowtail e_3$ is formed. When t_2 executes m_3, the race on *y* is detected. (2) Suppose that t_2 executes e_4 first.

When t_2 further generates e_5, *DrFinder* finds that $mt(f_2, type(o_3))$ does not match any *may-trigger* relation. Thus, both threads t_1 and t_2 may proceed further. So, *DrFinder* resolves the tie randomly. If t_1 is selected to execute first, a race on y is detected. Otherwise, no race is reported because the HB edge between e_3 and e_6 is still $e_3 \rightarrowtail e_6$.

4. DESIGN RATIONALES

In this section, we present the design rationales of *DrFinder*, with the help of two traces σ_1 and σ_2, and their corresponding set of HB edges are Δ_1 and Δ_2, respectively. Besides, there are two threads t_1 and t_2 in two traces and they produce two events e_1 and e_2, respectively, in trace σ_1; however, the two events may not be produced by two threads in trace σ_2.

4.1 Basic Requirements

We recall that a hidden race is difficult to expose in a trace generated by a native scheduler or a pure randomized scheduler. That is, although the two accesses involving in a hidden race may appear in a trace, yet the pair of accesses may be separated by non-trivial numbers of HB edges (e.g., the two accesses m_1 and m_4 in Figure 2). For ease of reference, we refer to such a native or pure randomized scheduler as a default scheduler.

A strategy modeled after the above intuition is as follows: In Phase I, a technique observes the set of HB edges Δ_1 in the trace σ_1 produced by a default scheduler. Then, in Phase II, it aims to reverse the directions of some HB edges in Δ_1 on generating the trace σ_2. That is, if the two events $e_1 \rightarrowtail e_2 \in \Delta_1$, it aims to produce $e_2 \rightarrowtail e_1 \in \Delta_2$ if possible as shown in Figure 4 (a) and (b), respectively.

As such, a dynamic hidden race detector should aim to:

Phase I) keep a (sub)set of HB edges (i.e., Δ_1) in trace σ_1,

Phase II) and schedule a subsequent execution (generating trace σ_2) to reverse HB edges in Δ_1 to expose races hidden in trace σ_1.

However, *DrFinder* does not target to keep any HB edges as which usually incurs high runtime overhead [12][21][41]. It tries to predict HB edges dynamically via the type of locks. In the next two subsections, we present how *DrFinder* achieves this aim to reverse HB edges.

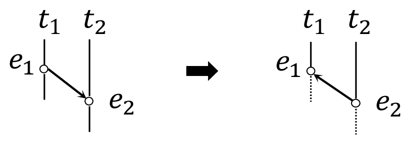
4.2 Reversing Happens-before Edges

Suppose that $e_1 \rightarrowtail e_2$ is an HB edge in Δ_1 as depicted in Figure 4(a), there is a good chance that, using the default scheduler, $e_1 \rightarrowtail e_2$ may also exist in Δ_2. That is, most of HB edges in Δ_1 cannot be easily reversed in Δ_2. Therefore, our target is to actively produce $e_2 \rightarrowtail e_1$ as depicted in Figure 4(b).

Suppose that during the execution (to generate the trace σ_2), both events e_1 and e_2 exist. In theory, a precise but *hypothetical* strategy can be formulated as follows:

> To reverse an HB edge from $e_1 \rightarrowtail e_2$ to $e_2 \rightarrowtail e_1$, the thread t_1 should be suspended when it generates but does not execute the event e_1 until the thread t_2 has executed the event e_2.

However, implementing such a strategy is challenging: if there is no such an event e_2 in trace σ_2, then the HB edge $e_2 \rightarrowtail e_1$ will not exist, and no HB edge needs to be reversed. Hence, above strategy will suspend the thread t_1 until the thread t_2 terminates. If all events (or at least lock acquisition events) in trace σ_1 are logged to check the existence of an event e_2, it is necessary to compute an object abstraction [13][21][41] (e.g., a unique id) for each event.



(a) Observed trace σ_1 (b) Targeted trace σ_2

Figure 4. Reversing an HB edge.

However, before the occurrence of e_2, there is no way to compute an object abstraction for e_2.

Therefore, an effective technique must address a problem: Given an event e_1 to be executed by a thread t_1, how to determine whether some other thread t_2 *will* execute an event e_2 such that $object(e_2) = object(e_1)$ without computing an object abstraction for each event?

4.3 Stack and Type Based Events Predictions

Let us refine the problem further as the two events e_1 and e_2 should be causally related; otherwise, there is no need to consider them to form an HB edge. Suppose that when t_1 is about to execute e_1, thread t_2 is executing an event e^* within the body of a method f_k as shown in Figure 5(a). To ease our explanation, we refer to the current call stack of thread t_2 as stack s. If the event e_2 will occur in future in the execution of t_2, there will be another call stack fragment: s_1 in the below Backward Case or s_2 in the below Forward Case:

- ***Backward Case*** shown in Figure 5(b): after thread t_2 returns from method f_k recursively to a method f_1, and then calls some other methods, an event e_2 from a method $f_d{}'$ is executed. We refer to the two call stack fragments $\langle f_1 \ldots, f_k\rangle$ and $\langle f_1 \ldots, f_d{}'\rangle$ as s' and s_1, respectively, as depicted.
- ***Forward Case*** shown in Figure 5(c): before thread t_2 returns from its execution in method f_k, it further calls some methods and then an event e_2 from a method $f_d{}''$ is executed. We refer to the call stack fragments $\langle f_k \ldots, f_d{}''\rangle$ as s_2, as depicted.

Therefore, to predict the existence of event e_2, thread t_2 should be aware of the method $f_d{}'$ (in Backward Case) or the method $f_d{}''$ (in Forward Case) that executes an event e_2. To do so, it is necessary to record the events that a given method will execute directly or indirectly (i.e., via calling other methods). With such information, given an event e^* from a method f_k, it becomes easy to know whether there will be an event e_2.

However, directly implementing above idea to detect hidden races is ineffective or even does not work. It is because each method, once called, directly (for event within this method) or indirectly (for events out of this method) executes all later events. For example, the method *run*() executes all events. Therefore, to make the prediction of an event effective for detection of hidden races via reversing HB edges, the used stack should be limited. In other words, only some methods in a stack should be used to do prediction, but not all.

Let's further review the two cases. For Backward Case, we can observe from Figure 5(b) that the effective call stack to predict the event e_2 (when thread t_2 is executing an event e^* in method f_k) is only the stack fragments s' and s_1. Similarly, for Forward Case, the effective stack is the stack fragment s_2.

Therefore, we only use the stack fragments s' and s_1, or s_2 to predict events. In theory, the size of the stack s' can range from 1 to infinite. In this paper, we aim to present the basic model of

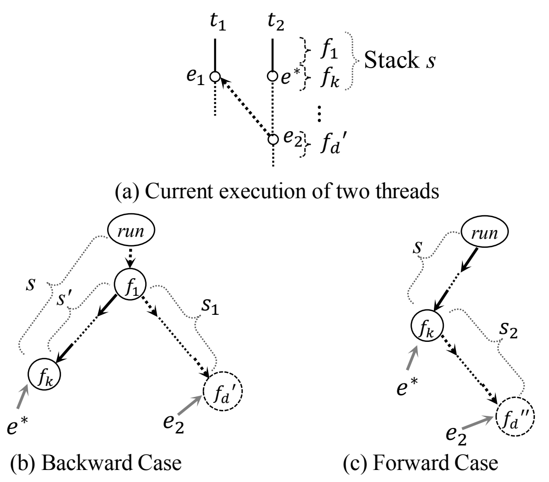


Figure 5. Call stack based prediction of event e_2.

Algorithm 1: *DrFinder.MTCollector*

```
1.  Input: $p$ – a given program
2.  Output: MTR – may-trigger relations
3.  Enabled := all threads in $p$; MTR := $\emptyset$
4.  Stack($t$) := $\emptyset$, for each thread $t \in$ Enabled //method stack
5.  while Enabled $\neq \emptyset$ do
6.    let $t$ be a random thread from Enabled.
7.    let $e := \langle t, op, o \rangle$ be the next event of $t$.
8.    if $op = enter$ then
9.      push $o$ into Stack($t$) //$o$ is a method
10.   else if $op = return$ then
11.     pop out from Stack($t$)
12.   else if $op = acq$ then
13.     for $i$ = 1 to min($d$, Stack($t$).size()) do
14.       let $f$ := Stack($t$).get($i$) //collect lock type
15.       MTR := MTR ∪ { $mt(f$, Type($o$)) }
16.     end for
17.   end if
18.   $execute(e)$
19. end while
```

DrFinder. Hence, we choose the size of s' to be 1, which is a minimal setting. In this case, we have $f_k = f_1$. Therefore, the two cases (i.e., Backward Case and Forward Case) are actually the same one. And the prediction of event e_2 is based on one stack fragment (i.e., s_1 or s_2) to be formed. Thus, we propose our stack based events prediction model **M** to predict the event e_2 as follows:

During the generation of a trace σ_2, if a thread t_2 is executing an event e^* from a method f_k, and there exists a method f_d', such that the method f_d':
(1) contains an event e_2 and
(2) is reachable by thread t_2 via a sequence methods s_1 after executing the event e^*,
then thread t_2 will execute the event e_2.

We refer to the size of the above stack s_1 plus the method f_d' as the ***depth d*** of model **M**. Model **M** looks forward to see whether there will be a sequence of at most d methods (i.e., s_1) with the last method containing an above discussed event e_2.

However, for above prediction model, we still need to address a new problem: given an event e_1 by t_1 and a stack s of t_2, does there exist a method f_d' in the stack contains an event e_2?

We propose the *May-Trigger Relation* to further predict whether a given method will trigger a certain event. Suppose that there is an event e from a method f such that $e = e_2$. Then, we must have $object(e) = object(e_2)$, and $type(object(e)) = type(object(e_2))$. Our insight is that in real-world Java programs, most methods only acquire specific (instead of arbitrary) lock objects, and their method instances often follow the same locking patterns. We propose to use the type of a lock object in a lock acquisition event to predict the possible occurrence of the event e_2 to achieve the reversal of the HB edges from $e_1 \rightarrowtail e_2$ in Δ_1 to $e_2 \rightarrowtail e_1$ in Δ_2.

Formally, ***May-Trigger Relation*** is defined as follows: Given a method f, a type c, and an execution trace σ. If a method f' is reachable from f during the generation of a trace σ by a sequence of at most d methods, and f' produces an event $e = \langle t, acq, o \rangle$ such that $type(o) = c$, then we say f and c forms a *May-Trigger Relation* (*MTR* for short), denoted as $mt(f, c)$.

DrFinder is developed on top of **M** using *MTR* to predict occurrences of events like e_2 to schedule a program to detect hidden races. It uses two pieces of information for its prediction: (1) an event e_1 from a thread t_1, and (2) a method f_1 from a second thread t_2 and a depth d. It interestingly predicts the presence of an event e_2 by checking whether $mt(f_1, type(e_1))$ is a *MTR* identified from σ_1.

4.4 Effective Scheduling via Feedbacks

From above discussion, *DrFinder* executes a program once to collect a set of *MTR* and then schedules the program execution based on the relation set. However, races in a program cannot be dynamically detected in merely one run. Therefore, it is necessary for *DrFinder* to execute a program multiple times to detect more hidden races.

On the other hand, if a same set of *MTR* relation is used in each execution by *DrFinder*, the increment of new races detected is marginal. Actually, after the first scheduling execution by *DrFinder*, the probability to detect new hidden races for *DrFinder* at its other subsequent executions is the same as the existing dynamic techniques (e.g., *FastTrack*) and may be even lower than existing active schedulers (e.g., *PCT*). It is because, the subsequent executions are similar to the first scheduled execution as they are scheduled by *DrFinder* based on a same set of *MTR*.

Therefore, we design *DrFinder*, at each of its executions, to both schedule the execution and collect a new set of *MTR* from the execution being scheduled. The newly collected set of *MTR* is regarded as a feedback to be used in the next execution by *DrFinder*. As such, *DrFinder* is able to effectively schedule each execution based on a set of *MTR* exactly from the previous execution, to detect new hidden races. This feedback mechanism is also depicted in Figure 1.

5. DRFINDER IN DETAILS

5.1 Phase I: May-Trigger Relation Collector

The *MTCollector* algorithm is responsible to collect may-trigger relations, shown in Algorithm 1. Given a program p and a depth d, *MTCollector* executes the program, and collects a set of *may-trigger relations* (i.e., MTR in Algorithm 1) from the observed trace.

Algorithm 1 first assigns the set of all threads in p to the set Enabled, null to MTR, and assigns Stack(t) for each thread t in Enabled to empty at lines 3–4. It uses the data structure Stack(t) to keep track of the call stack fragment. It then uses randomized scheduling to execute the program p by selecting the next event e

Algorithm 2: *DrFinder.Agent*

```
1.  Input: $p$ – a given program.
2.  Input: MTR – may-trigger relations returned by MTCollector
3.  Input: RD – an HB race detector (e.g., FastTrack)
4.  Output: MTR' – a set of new may-trigger relations //feedbacks
5.  Enabled := all threads in $p$, MTR' := $\emptyset$
6.  fork(schedule()) //start scheduler (in Algorithm 3)
7.  while Enabled $\neq \emptyset$ do
8.      let $t$ be a random thread from Enabled.
9.      let $e := \langle t, op, o \rangle$ be the next event of $t$.
10.     if $op = acq$ then
11.         allow := DrFinder.Scheduler.requestALock($t$, $o$)
12.         if allow = false then
13.             continue //while loop
14.         end if
15.     end if
16.     execute($e$)
17.     RD.onEvent($e$) //for detection of data races
18.     if $op = acq$ then
19.         DrFinder.Scheduler.lockAcquired($t$, $o$)
20.     end if
21.     update MTR' according to Algorithm 1
22. end while
```

(i.e., $\langle t, op, o\rangle$) from a random thread (lines 6–7) and checks the operation op of the event e:

- If op is either $enter$ or $return$, Algorithm 1 pushes the method o into the Stack(t) or pops out the topmost method from the Stack(t), respectively (lines 8–11).
- If op is acq, Algorithm 1 updates MTR := MTR ∪ {*mt*(f, $type(o)$)}, for each method f in the top d methods in the Stack(t) (lines 13–16) to maintain *may-trigger* relations.

Then, the algorithm executes the event at line 18.

5.2 Part A of Phase II: *DrFinder* Agent

The *Agent* (Algorithm 2) is responsible to execute each event. For the *acq* events, their executions depend on *Scheduler*.

Algorithm 2 accepts the given program p, the set MTR (i.e., *may-trigger* relations) from Phase I, and an HB race detector RD. It returns a set of new may-trigger relations (i.e., MTR'). Algorithm 2 firstly assigns the set of all threads of p to the set Enabled, which is shared by both *Agent* and *Scheduler*, and set MTR' to be empty (line 5). It then starts *Scheduler* (i.e., Algorithm 3 to be presented in Section 5.3) through a *fork*() call (line 6). Next, it takes a next event $e = \langle t, op, o\rangle$ from a random thread t (lines 8–9), and checks the operation op of the event e. If op is acq, *Agent* asks *Scheduler* whether t is allowed to execute e through a function call to requestALock() of *Scheduler* (line 11). If the function returns a *false* value, *Agent* simply keeps e from execution. (Note: the thread t has been removed from Enabled by *Scheduler* at line 10 in Algorithm 3). If requestALock() does not return a *false* value (line 12), *Agent* will both execute and pass e to the race detector RD (lines 16–17). Finally, if e is an acq event, *Agent* also informs *Scheduler* that the thread t has acquired the lock object specified in e via function lockAcquired() (lines 18–20). It also collects a new set of MTR' at line 21 (which is based on Algorithm 1) as the input MTR of the next scheduling execution.

5.3 Part B of Phase II: *DrFinder* Scheduler

Scheduler (Algorithm 3) maintains four data structures: ATHs, RTHs, allowedTH, and allowedLK (lines 1–4), to make scheduling decision:

- ATHs is a set of all the threads in the program p.
- RTHs is a set of pairs of a thread t and a lock object o, each of which representing that t is requesting to acquire the object o, but *Scheduler* suspends this acquisition. Thus, all the threads in this set are waiting to be scheduled by *Scheduler*. For ease of our presentation, we use RTHs.*get*(t) to denote the lock o paired with the thread t.
- allowedTH keeps a particular thread t that both (i) is "escorted" by *DrFinder* with a top priority to execute its lock acquisition events and (ii) is the thread expected by *DrFinder* to acquire a lock object defined by allowedLK.
- allowedLK keeps a lock object o. *DrFinder* expects the thread defined by allowedTH to acquire a lock object having the same type as this lock object.

Scheduler consists of four functions: requestALock(), lockAcquired(), mayTrigger(), and schedule(). In Section 5.2, we have presented that *Agent* (Algorithm 2) invokes the first two functions. We firstly present them followed by presenting schedule() which is the core part of *DrFinder*.

The function requestALock() is called by *Agent* on determining whether to execute the event e (i.e., the lock acquisition on o by t). It checks whether the given thread t is a chosen thread to execute any event (i.e., allowedTH) at line 6. (As such, a targeted HB edge may be formed as soon as it can.) If a *true* value is returned, it indicates that the event e is allowed to execute (line 7); otherwise, the thread t is added to the set RTHs and is also removed from the set Enabled (lines 9–10) so that *Agent* will not pick any event of it for execution (line 8 in Algorithm 2). Next, the function notifies *Scheduler* (that there is a thread to be scheduled, see line 30, to be explained below). On the other hand, if it returns a *false* value at line 12, it indicates that the event e is not allowed to be executed.

The function lockAcquired() is called by *Agent* right after a lock acquisition event e is executed (lines 17–19 in Algorithm 2). It checks whether the executed lock acquisition event e is an event expected by *Scheduler* (line 16). An event $e = \langle t, op, o\rangle$ is an expected event if (1) t is the thread defined by allowedTH (i.e., t = allowedTH) and (2) e operates on a lock object defined by allowedLK (i.e., $type(o)$ = $type$(allowedLK)) at line 16. If so, an expected event occurs and *Scheduler* resets both allowedTH and allowedLK to null (line 17). It then notifies function schedule()that there is no thread marked as "allowedTH" (line 18).

We are going to explain the function schedule(). *Scheduler* is started by *Agent* (at line 5 in Algorithm 2). If no thread is requesting any lock object (i.e., RTHs.*size*() = 0) or there is no event expected by *Scheduler* (i.e., allowedTH $\neq \emptyset$) at line 30, the function schedule() just waits for notifyScheduler() to notify it at either line 11 or line 18.

Once schedule() is notified, the same function selects a random thread t from the set ATHs. It then checks whether there is any thread whose currently executing method f and the type of the given object o match any *may-trigger* relation kept in MTR via mayTrigger() (lines 35–39). All the threads that match this condition are collected as the set CT (line 37), in which a thread t' is randomly selected and escorted by *DrFinder* to execute all its events before t is allowed to continue its execution (line 41). The function then assigns the thread t' and the lock object o to allowedTH and allowedLK, respectively (lines 42–43). If the thread t' is also in the set RTHs, t' will be removed from RTHs and added to Enabled (lines 44–46). *Scheduler* then waits until the thread t' being escorted by *DrFinder* has acquired a lock object having the type

Algorithm 3: DrFinder.*Scheduler*

```
1.  ATHs := all threads in p
2.  RTHs := ∅ //a set of pairs of threads and locks
3.  allowedTH := ∅ //a thread that is expected to acquire a lock
4.  allowedLK := ∅ //the lock expected to be acquired
5.  Function requestALock($t$, $o$)
6.    if allowedTH = $t$ then
7.      return true
8.    else
9.      RTHs.add($t$, $o$)
10.     Enabled := Enabled \ {$t$}
11.     notifyScheduler()
12.     return false
13.   end if
14. end Function
15. Function lockAcquired($t$, $o$)
16.   if allowedTH = $t$ and type(allowedLK) = type($o$) then
17.     allowedTH := ∅, allowedLK := ∅
18.     notifyScheduler()
19.   end if
20. end Function
21. Function mayTrigger($t$, $t'$)
22.   let $o$ := RTHs.get($t$), $f$ := getCurrentMethod($t'$)
23.   if ∃ mt($f$, $c$) ∈ MTR such that $c$ = type($o$) then
24.     return true
25.   end if
26.   return false
27. end Function
28. Function schedule()
29.   while Agent does not exit do
30.     while RTHs.size() = 0 or allowedTH ≠ ∅ do
31.       wait()
32.     end while
33.     $t$ := a random thread from ATHs
34.     CandidateThread CT := ∅
35.     for each thread $t'$ ∈ ATHs do
36.       if $t \neq t'$ and mayTrigger($t$, $t'$) then
37.         CT := CT ∪ {$t'$}
38.       end if
39.     end for
40.     if CT ≠ ∅ then
41.       $t'$ := a random thread from CT
42.       allowedTH := $t'$
43.       allowedLK := RTHs.get($t'$)
44.       if $t'$ ∈ RTHs then
45.         Enabled := Enabled ∪ {$t'$}
46.         RTHs.remove($t'$)
47.       end if
48.       while allowedTH ≠ ∅ do
49.         wait()
50.       end while
51.     end if
52.     Enabled := Enabled ∪ {$t$}
53.     RTHs.remove($t'$)
54.     allowedTH := $t$ //let $t$ to acquire the lock RTHs.get($t$)
55.     allowedLK := RTHs.get($t$)
56.   end while
57. end Function
```

type(`allowedLK`) (see the function `lockAcquired()`) (lines 48–50). Otherwise, if `CT` is empty (line 40), the thread t is allowed to execute (lines 52–55).

The function `mayTrigger()` accepts two threads t and t' as its parameters. This function firstly gets the lock object o being requested by t (i.e., paired with t in `RTHs`) and the current executing method f of t' (line 22). It then checks whether the tuple (f, *type*(o)) is a valid *May-trigger* relation (i.e., in the set `MTR`) and returns a *true*-or-*false* result accordingly (lines 23–26).

5.4 Discussion

DrFinder is an active scheduler. It suffers from thrashing [21][41], and may lead the execution to form deadlocks [12][41]. Similar to existing techniques [9][11][12][21][41], when a thrashing occurs, *DrFinder* randomly selects a suspended thread to execute and when a deadlock occurs, the whole execution is restarted (see Section 6.1).

DrFinder actively schedules an execution to produce HB edges that cannot be easily formed in normal executions to expose races. It drives a happens-before based detector (e.g., *FastTrack*) to detect races precisely and report all races. Therefore, like other HB detectors, *DrFinder* is also precise.

Table 2. Descriptive and execution statistics of benchmarks.

Benchmark	Jar Files Size (KB)	# of locks / threads	# of methods (with sync)	# of HB edges
xalan_{06}	81.23	19,565 / 9	1,731 (1.7%)	2,607,853
eclipse_{06}	41,821.53	118,803 / 26	7,581 (4.9%)	22,879,127
xalan_{09}	4,826.81	10,522 / 5	1,869 (1.4%)	3,864,084
pmd_{09}	2,996.30	230 / 5	2,289 (0.2%)	2,288
sunflow_{09}	1,016.91	22 / 9	698 (1.6%)	778
luindex_{09}	878.37	2,612 / 2	804 (14.8%)	217,343
lusearch_{09}	883.02	94,668 / 5	484 (4.6%)	1,371,744
Total	**52,504.16**	**246,422 / 61**	**15,456 (3.8%)**	**30,943,217**

6. EXPERIMENT

This section presents our evaluation on *DrFinder* and its comparison with the state-of-the-art HB race detector *FastTrack*, a random delay scheduler *ConTest*, and a state-of-the-art randomized scheduler *PCT*. All these techniques are reviewed in Sections 1 and 3.

6.1 Implementation and Benchmarks

Implementation. We implemented *DrFinder*, *FastTrack*, *ConTest*, and *PCT* in Jikes RVM [2][3]. Jikes RVM is a Java virtual machine, developed almost in Java language, and could be run on Linux and Mac OSX systems. These tools report a race at the Java class field level [17]. Our tool uses the shadow mechanism [18] to track the state of an execution and adds a *shadow lock* to each object instance to keep the vector clock data and type information. For each memory location (i.e., an instance of a field of a Java class), it allocates a shadow memory to track the reads and writes to this memory location. For each thread, it adds a member in the RVMThread class [2] to keep the Java thread data.

To generate memory and synchronization events in runtime, our tool instruments each class when it is loaded, except those Jikes RVM classes and Java standard library classes. It uses a static escape analysis [5] to identify accesses to provably thread local memory location. It also fully tracks happens-before relations on other program semantics (e.g., accesses to volatile fields [17]).

Our implementation periodically monitors the states of all threads by tracking various synchronizations events and scheduling of *DrFinder* as well as other functions calls (e.g., `sleep()`). Such monitoring is helpful to identify deadlock oucurrences and thrashing occurrences.

Benchmarks. We used the Dapaco benchmark suite [6] to evaluate *DrFinder*. We selected two multithreaded programs from Dacapo 2006-10-M1 ($\texttt{xalan}_{06}$ and $\texttt{eclipse}_{06}$) and five multithreaded programs from Dacapo 2009 ($\texttt{xlan}_{09}$, $\texttt{pmd}_{09}$, $\texttt{sunflow}_{09}$, $\texttt{luindex}_{09}$, and $\texttt{lusearch}_{09}$). Dacapo 2009 includes other multithreaded benchmarks; however, they cannot be run on the latest Jikes RVM 3.1.3 even without our tool. In total, we selected 7 multithreaded benchmarks, including a large-scale real-word program Eclipse ($\texttt{eclipse}_{06}$).

Table 2 shows the descriptive statistics of the benchmarks. The first two columns show the benchmark name and size. The third column

Table 3. **Summary of results on 10 runs for *FastTrack* (*FT*), *ConTest* (*CT*), *PCT*, and *DrFinder* (*DR*) (depth $d = 12$).**

Bench-mark	Total races by				New races by *DR* (%)	Total races	Missed races				Time in seconds (slowdown factor)						Thrash. rate
	FT	*CT*	*PCT*	*DR*			*FT*	*CT*	*PCT*	*DR*	Native	*FT*	*CT*	*PCT*	*DR* (P-I)	*DR* (P-II)	
xalan_{06}	16	16	18	26	13 (+72.2%)	31	15	15	13	5	5.62	30.7 (5.5)	60.3 (10.7)	63.4 (11.3)	11.8 (2.1)	52.3 (9.3)	45.1%
eclipse_{06}	313	308	318	351	54 (+17.0%)	372	59	64	54	21	45.63	119 (2.6)	1,007.9 (22.1)	178.2 (3.9)	56.4 (1.2)	167.2 (3.7)	79.2%
xalan_{09}	12	12	12	20	8 (+66.7%)	20	8	8	8	0	5.43	24.6 (4.5)	35.4 (6.5)	61.8 (11.4)	9.2 (1.7)	41.0 (7.6)	10.9%
pmd_{09}	18	17	18	20	2 (+11.1%)	20	2	3	2	0	3.58	6.9 (1.9)	7.3 (2.0)	15.6 (4.4)	4 (1.1)	12.7 (3.5)	35.1%
sunflow_{09}	5	5	5	17	12 (+240.0%)	17	12	12	12	0	10.36	63.0 (6.1)	84.1 (8.1)	136.7 (13.2)	12.7 (1.2)	99.7 (9.6)	68.7%
luindex_{09}	1	1	1	1	0 (+0.0%)	1	0	0	0	0	2.41	8.4 (3.5)	9.8 (4.1)	21.7 (9.0)	3.2 (1.3)	11.9 (4.9)	33.3%
lusearch_{09}	13	13	13	13	0 (+0.0%)	13	0	0	0	0	6.18	17.2 (2.8)	21.1 (3.4)	49.1 (7.9)	6.8 (1.1)	42.1 (6.8)	12.8%
Sum:	**378**	**372**	**385**	**448**	**89 (+23.1%)**	**474**	**96**	**102**	**89**	**26**	**Avg:**	**3.84**	**8.14**	**8.7**	**1.39**	**6.49**	**40.73%**

shows the numbers of locks and threads in the benchmarks. The last two columns show the numbers of methods (all and those containing lock acquisitions) and the mean number of HB edges in each benchmark over 10 runs. All dynamic data are collected under native scheduling.

6.2 Experimental Setup

Our experiment was performed on an Apple Mac Pro with 2.6GHz Intel Core i5 and 8GB memory running OS X 10.9.2. We compiled Jikes RVM with GNU Class-path 0.98 [1]. We configured *FastTrack* with the native (OS) scheduler, with *ConTest*, with *PCT*, and with *DrFinder*, which are referred to as *FT*, *CT*, *PCT*, and *DR*, respectively. We followed the previous experiments [43] and ran each technique on each subject for 10 times.

6.3 Experimental Results

Table 3 summaries the experimental results. The first column shows the benchmark name. The second major column shows the number of distinct data races reported by each technique in 10 runs. The third major column shows the number of new data races detected by *DR* but not detected by *FT*, *CT*, and *PCT*. The fourth major column shows that the total number of distinct races detected by all four techniques. The fifth major column shows the number of races not detected by each technique compared to the total number of distinct races (i.e., the data in the fourth major column). The sixth major column shows the mean time in seconds for each technique to run each benchmark. It also shows the time of native run (i.e., without any testing tool) and the time needed by both phases of *DR* (as `P-I` and `P-II`, respectively). The overhead of each technique is also calculated. The last column shows the thrashing rate ("`Thrash. rate`") of *DR*. The last row shows either the total ("`Sum`") or the mean value ("`Avg`") of each column.

6.3.1 Summary of Results

Effectiveness. From Table 3 (the second and third major columns), *DR* detects more races on 5 out of 7 benchmarks by 11.1% to 240.0%. On the remaining two benchmarks, all four techniques detect the same set of data races. In total, *DR* detects 89 more new races from all benchmarks. We find that *FT*, *CT*, and *PCT* detect almost the same set of data races (where the difference is at most 10). This is consistent with an intuition that the random sleep strategy used by *CT* is not quite effective and randomized scheduling strategy used by *PCT* is also not quite effective without a larger number of runs.

Performance. From the column on time, we observe that *FT* has the best performance, which is expected. The overhead of *CT* on top of *FT* ranges from 0.11x to 5.28x except on $\texttt{eclipse}_{06}$. For *PCT*, it incurs about 2.2x higher overhead than *DR* on average.[1] The overhead of the Phase I of *DR* is only 0.39x. The overhead of *DR* (Phase II) on top of *FT* ranges from 1.1x to 4.0x. On average, *DR* only incurs 2.65x on top of *FT*.

On $\texttt{eclipse}_{06}$, *CT* incurs a heavy overhead, which is 19.5x on top of *FT*; but, *DR* only incurs 1.1x on top of *FT*. Although $\texttt{eclipse}_{06}$ included 26 threads, in most of the execution time, there are only two active threads. We find that *DR* is able to suspend these two threads according to their locking orders most of the time. But, *CT* has to delay each lock acquisition by a random period. As a result, the total time overhead of *CT* is much heavier than that of *DR* on this benchmark.

Thrashing Rate. From the last column of Table 3, *DR* is able to make successful thread suspension decisions in nearly 60% of all cases. In the remaining cases (40.73%), thrashing occurred. We have inspected these thrashing occurrences and found that about half of them were caused due to the type of the unique and global instance of *Class Loader* class used by the Dacapo test harness to load each class instead of the program under test. (This harness strictly speaking is not a part of each benchmark.) In our experiment, we have not seen any deadlock occurrence.

6.3.2 Comparison on Not Detected Races

Table 3 also shows the total number of distinct races detected by all four techniques in the fourth major column. It also shows the number of races that are not detected by each technique but detected by other three techniques in the fifth major column. Overall speaking, among all 474 detected races detected by all four techniques on all the benchmarks, *DR* only misses 26 races; however, *FT*, *CT*, and *PCT* misses 96, 102, and 89 races, respectively.

From above analyses, we find that *DR* is effective in exposing hidden races; but it may be unable to expose some races that can be detected by HB detectors with randomized or native scheduling. We argue that this is not a major issue. It is because, in practice, one may run a program with random or native scheduling to detect these races (e.g., configured in Phase I of *DR*) followed by detecting the hidden races in Phase II of *DR*. We have checked the races not detected by *DR* and found that almost all 26 races have been detected by *FT* in each of 10 runs, and the remaining ones can be detected by *FT* in at least one run.

6.3.3 Comparison on Races Detected in 10 Runs

Figure 6 shows the cumulative number of races detected in the experiment by the four techniques on each benchmark except on $\texttt{luindex}_{09}$ (on which, all three techniques detected exactly one race in each run). The x-axis shows these 10 runs and y-axis shows the cumulative number of races detected.

[1] Note that, there is a parallel version of *PCT* known as *PPCT* [33] that has the same effectiveness but runs faster than *PCT*. Hence, the time overhead of *PCT* in Table 3 is for reference only and we do not discuss the overhead of *PCT* in the next paragraph. We believe our *DrFinder* could also be implemented in parallel and we leave it as a future work.

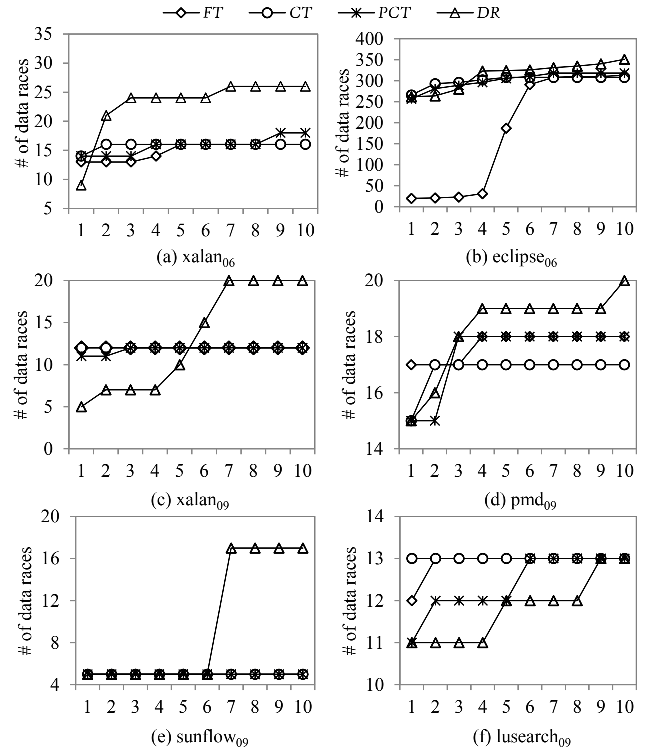


Figure 6. Number of distinct races detected in 10 runs by FT, CT, PCT, and DR.

Figure 6 shows that FT, CT, and PCT almost always detect the same numbers of races except on `eclipse06`. This indicates that they have similar race detection ability among all 10 runs (where the detected races are almost the same ones). Whereas, DR has an increasing trend on the number of detected races. Apparently, DR may detect fewer races in some runs (e.g., the first five runs on `xalan09`). But, we have shown in Table 3 that DR actually exposes more races.

To measure the ability of DR on the detection of new races with increasing number of runs, we further analyze the cumulative number of 89 new data races detected by DR in the first "i" (where i is from 1 to 10) runs. We normalize this cumulative number by the total number of new races detected by DR on the corresponding benchmark. The result is shown in Figure 7. Note that we do not show the result on `luindex09` and `lusearch09` in Figure 7 as no new races is detected on them.

Figure 7 shows that on each benchmark except `eclipse06`, all the new races detected by DR were detected in the first 7 runs. On `eclipse06`, almost on each run, more new races were detected by

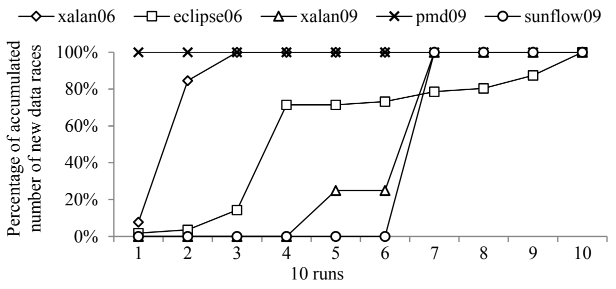


Figure 7. Cumulative number of new races detected by DR in each run but missed in all the 10 runs by FT, CT, and PCT.

DR; and moreover, more than 71.43% new races were detected in the first 4 runs. Therefore, we tend to believe that DR is able to effectively detect hidden races, even on large-scale multithreaded programs (e.g., `eclipse06`), which cannot be detected by FT, CT, and PCT in 10 runs (or even up to 100 runs, see Section 6.3.5).

6.3.4 DrFinder with Different Depths

In our main experiment, we have set the depth to 12. To evaluate the ability of DR on its detection of hidden races with different depths, we repeated the main experiment for DR but set the depth from 2 to 20 with step 2 in turn, where each configuration was also conducted for 10 runs. The results are summarized in Table 4. In each data cell, the format is "x (y)" where the "x" is the total number of races detected by DR with corresponding depth and the "y" is the number of new races that cannot be detected by FT, CT, and PCT in their10 runs. On each benchmark, if DR is able to detect most new races among all its depths, we mark the corresponding cell with gray color. Similarly, we do not mark cells corresponding to `luindex09` and `lusearch09` (as the data in the either entire row shows that there is no new race detected).

From Table 4, we observe that with different depths, DR is generally able to detect more races than that detected by FT, CT, and PCT. DR also detects new races in almost all these depths, where the exception is on `sunflow09`.

Another observation from Table 4 is that when depth values are within 4 and 12, DR is likely to detect a significant amount of new races on top of FT, CT, and PCT. And these depths values also lead to a larger amounts of total races. We also highlight these cells in gray color in the last row of Table 4.

In future, we will study both how the depth values affect the ability of DR and non-parametric strategies to determine the depth.

6.3.5 Further Evaluation on New Races

In the 10 runs by all techniques, DR detects 89 new races. We further repeatedly ran other three techniques more times until either

Table 4. The total number of data races detected by DR with depths from 2 to 20 (with Step 2) in 10 runs.

Bench-mark	***DR*** with a different Depth (total number of races and number of new races)									
	2	4	6	8	10	12	14	16	18	20
$xalan_{06}$	28 (16)	31 (15)	30 (15)	27 (15)	27 (15)	26 (13)	31 (15)	26 (15)	27 (15)	27 (15)
$eclipse_{06}$	306 (13)	337 (43)	336 (42)	343 (46)	336 (41)	351 (54)	316 (21)	301 (18)	284 (15)	312 (15)
$xalan_{09}$	18 (7)	18 (7)	18 (7)	18 (6)	18 (7)	20 (8)	17 (6)	12 (6)	11 (5)	13 (1)
pmd_{09}	20 (2)	18 (1)	19 (2)	20 (2)	20 (2)	20 (2)	20 (2)	20 (2)	20 (2)	20 (2)
$sunflow_{09}$	5 (0)	5 (0)	6 (0)	5 (0)	14 (9)	17 (12)	6 (1)	6 (0)	5 (0)	5 (0)
$luindex_{09}$	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)
$lusearch_{09}$	13 (0)	13 (0)	13 (0)	13 (0)	12 (0)	13 (0)	13 (0)	13 (0)	13 (0)	13 (0)
Sum:	**391 (38)**	**423 (66)**	**423 (66)**	**427 (69)**	**428 (74)**	**448 (89)**	**404 (45)**	**379 (41)**	**361 (37)**	**391 (33)**

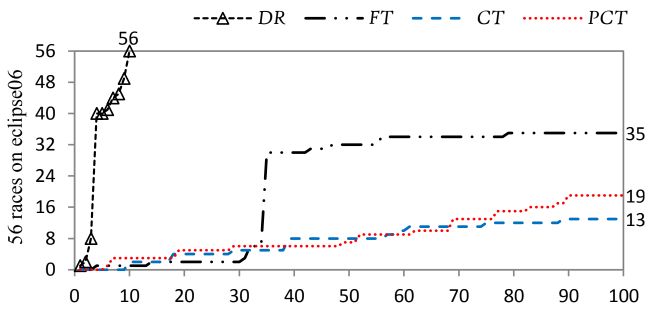


Figure 8. Cumulative effectiveness of *FT*, *CT*, and *PCT* in 100 runs on the 56 races that can only be detected by *DR* in 10 runs.

(1) they detect the same number of distinct races as that detected by *DR* or (2) the number of runs is up to 100 on each benchmark except on luindex$_{09}$ and lusearch$_{09}$. On these two benchmarks, other three techniques already detect the same set of races as *DR* in 10 runs.

We found that on eclipse$_{06}$, xalan$_{06}$, xalan$_{09}$, and pmd$_{09}$, other three techniques could not detect as many races even exhausting all 100 runs as what *DR* detects in the 10 runs. On sunflow$_{09}$, all three techniques need more than 25 runs to catch up with *DR*.

Because eclipse$_{06}$ is the largest one in our benchmarks, we further analyzed the ability of *FT*, *CT*, and *PCT* on detecting the 56 new races from eclipse$_{06}$ that are only detected by *DR* but missed by all the other three in their 10 runs in the main experiment. The result is shown in Figure 8, where we also list the 56 races for comparison. It shows that *FT*, *CT*, and *PCT* were able to detect only 35, 13, and 19 races out of the 56 races in all 100 runs. (Note that, in a run, *FT* detects 17 races. Excluding these 17 races, it detects less races than that by *PCT* in all 100 runs.) This experiment, once more, illustrates that *DR* is effective on detecting hidden races.

7. RELATED WORK

Many techniques on data race detection have been proposed. They mainly fall into two groups: static techniques [22] [32][36] [46] and dynamic techniques [17][35][40][43][49]. Static techniques like *RELAY* [46] and *LockSmith* [36] rely on statically but imprecisely identifying memory-accessing statements that may concurrently visit same memory locations without the protection of the same locksets. *Chord* [32] reduces the number of false warnings by using several stages of refinement on the entire data race warning set. But, it loses the soundness guarantee of reporting all data races in a program.

Many dynamic detectors use the locking discipline [40][42] to predict races. However, this discipline is not necessarily to be obeyed even for data-race-free programs so that many false positives may be generated using such a strategy. HB based dynamic ones [17] [35] can precisely report data races. However, they are sensitive to particular thread interleaving (even with improvement [45][47]) which provides less coverage than those using the lockset strategy.

RaceMob [23] statically detects data race warnings and distributes them to a large number of user processes to validate real races. However *RaceMob* only works on limited scenarios where a distributed user site computation is available. Active testing techniques [41][37] need runs for confirmation after an imprecise race detection phase. In such a run, the schedules are guided by the set of data race warnings to trigger real data races. This kind of approach is able to confirm real races but cannot eliminate false positives.

DrFinder takes another approach by using a precise data race detector, i.e., *FastTrack* [17], in the first place. With the inherent limitation of the *sensitivity* on thread interleaving, an effective thread scheduling technique such as *DrFinder* is a desirable complement with HB detectors (if used in our Phase I) to provide precise data race reports with high coverage.

Thread Scheduling techniques are more promising to detect races than pure stress testing. Systematic scheduling techniques such as model checking [48][30], are in theory able to exhaustively execute every schedule. However, due to the state explosion problem, enumerating each schedule is not practical for real-world programs. *Chess* [30] sets a heuristic bound on the number of pre-emptions to explore the schedules. Also, although systematic approaches avoid executing previously explored schedules and are more scalable than pure model checking techniques [14], they usually incur large overheads and fail to scale up to handle long running programs. Although improvement for *Chess* exists [4], finding the positions for such bounded exhaustive exploration from a large trace to effectively expose hidden races is challenging [24].

Another type of scheduling technique is based on some coverage criteria of concurrent programs [7][19]. For example, *Maple* [50] relies on patterns (i.e., *iRoots* [50]) to mine certain coverage to expose concurrency bugs. However, *Maple* is insensitive to detect races requiring reversing more than one HB edge. Existing experiments (e.g., [10]) have shown that on a large benchmark like Chromium, there may be 16 million or more HB edges in a trace. It is challenging to select an effective subset of all such HB edges to confirm given patterns as *Maple* is designed to confirm one pattern per confirmation run. Besides, the relation between the coverage of a specific metric and targeted concurrency bugs cannot be verified in theory. A previous empirical study [26] has shown that different criteria have different effectiveness on different testing techniques. This increases the difficulty of choosing a suitable criterion.

DrFinder is specially designed to detect hidden races based on our may-trigger relation. Unlike above reviewed systematic scheduling techniques or coverage based techniques that have to restrict their scheduling bounds [30][50], *DrFinder* is able to scale up to large-scale programs (i.e., Eclipse in our benchmark) and does not require any bug patterns.

8. CONCLUSION

This paper presents a dynamic technique *DrFinder* to detect hidden races in multithreaded Java programs. It tries to reverse possible HB edges based on a type based *May-trigger Relation*. The experiment shows that *DrFinder* is promising in detecting hidden races and detected 89 news races that were missed by existing techniques *FastTrack*, *ConTest*, and *PCT*. Many new races detected by *DrFinder* in 10 runs cannot be detected by other techniques even in 100 runs. *DrFinder* is also efficient as it incurs less overhead than other active scheduling techniques *CT* and *PCT*. In future, we will extend our basic model of *DrFinder* proposed in this paper to further validate its ability on detection of hidden data races.

9. ACKNOWLEDGEMENTS

We thank anonymous reviewers for their invaluable comments and suggestions on improving this work. We also thank Dr. W.K. Chan and Mr. Chunbai Yang at City University of Hong Kong for their help on the preliminary version of this work. This work is partially supported by the National Natural Science Foundation of China (NSFC) under grant No. 91418206.

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