Dynamic Generation of Likely Invariants for Multithreaded Programs

Markus Kusano, Arijit Chattopadhyay, Chao Wang
Department of ECE, Virginia Tech
Blacksburg, Virginia, USA

Abstract—We propose a new method for dynamically generating likely invariants from multithreaded programs. While existing invariant generation tools work well on sequential programs, we found they are ineffective at reasoning about multithreaded programs both in terms of the number of real invariants generated and in terms of their usefulness in helping programmers. We address this issue by developing a new dynamic invariant generator consisting of an LLVM based code instrumentation front end, a systematic thread interleaving explorer, and a customized invariant inference engine. We show that efficient interleaving exploration strategies can be used to generate a diversified set of executions with little runtime overhead. Furthermore, we show that focusing on a small subset of thread-local transition invariants is often sufficient for reasoning about the concurrency behavior of programs. We have evaluated our new method on a set of open-source multithreaded C/C++ benchmarks. Our experiments show that our method can generate invariants that are significantly higher in quality than the previous state-of-the-art.

I. INTRODUCTION

Methods for dynamically generating likely invariants from sequential software have been used in many applications including program understanding, maintenance, testing/verification, and error diagnosis. However, effective tools for generating such invariants for concurrent software are still lacking. For example, Daikon [1], [2] is a highly successful invariant generation tool for sequential programs written in languages such as Java, C, C++, and Perl. However, as we will show in Section II, for multithreaded programs, Daikon often produces many confusing and incorrect results.

One problem of existing methods such as Daikon is that they depend heavily on the set of execution traces fed to the invariant inference engine. In general, increasing the amount of program behavior exercised in the set of execution traces increases the likelihood that the generated invariants are true. However, generating a sufficiently diversified set of execution traces is difficult for a multithreaded program since the program’s behavior depends not only on the program’s input but also on the thread’s schedules. Thread scheduling, in a typical execution environment, is determined by the underlying operating system and the threading library; naively executing the program many times does not necessarily increase the diversity of the thread schedules.

Another problem of existing methods is that they tend to report too many invariants. Even if many of these reported invariants are real invariants, they are unlikely to be equally useful. It is impractical to assume that the user will have time to sift through all of them individually.

Multithreaded programs, due to the subtle interactions amongst threads and potentially large number of interleavings, pose challenges both in their design and analysis. Typically, when the focus of an analysis is on concurrent nondeterminism, one assumes the sequential part of the computation is correct: instead, the problem comes from rare and complex thread interactions. In such cases, we argue, that the focus should be put on a small subset of thread-local invariants, called the transition invariants, that capture the relations among shared variables directly related to concurrency control. For example, a certain code block should be kept atomic, or instances of certain operations should be made mutually exclusive.

To this end, we propose a new dynamic invariant generation method for multithreaded programs. By leveraging systematic thread interleaving exploration algorithms to generate diversified execution traces, our method significantly improves the quality of generated invariants over existing methods.

The overall flow of our method is shown in Figure 1. Our method takes a multithreaded C/C++ program as input and returns likely invariants as output. First, we instrument the code using a new LLVM based front end to add monitoring capabilities for dynamic analysis. Then, we execute the program under the control of a systematic interleaving explorer. The generated traces are fed to a classifier which separates the passing traces from the failing traces. Finally, we feed a subset of the traces to a customized Daikon invariant inference engine which returns the likely invariants as output.

Another contribution of our work is investigating the impact of different interleaving exploration strategies on the precision and performance of invariant generation. In theory, all possible thread interleavings of a concurrent program should be given to the invariant inference engine to obtain the most precise invariants. However, due to the well-known interleaving ex-
We establish notation in Section III and then present our new invariant generation algorithm in Section IV. We present both runtime optimizations and methods to clarify output to the user in Section V. This is followed by our experimental evaluation in Section VI. We review related work in Section VII and finally give our conclusions in Section VIII.

II. MOTIVATING EXAMPLES

In this section, we present examples to illustrate the problems in existing methods, highlight our main contributions, and demonstrate some potential use cases for our new method.

First, consider the program in Figure 3, which has a global variable named balance being accessed by functions getBalance() and setBalance(). The third function, withdraw(), invokes the previous two functions to deduct a certain amount from balance. Since the global variable balance is protected by a Lock() and Unlock() pair every time it is accessed there is no data-race. However, there can be atomicity violations. The function withdraw() is meant to be executed atomically—without other threads interleaved between the calls to getBalance() and setBalance()—but the atomicity is not enforced. For example, starting with balance=400, if two concurrent threads run withdraw() at the same time, the result may be either 300 or 200.

Existing invariant generation tools do not work well in this case. For example, if we run the program with Daikon’s C front end, most likely we will get a false invariant. The reason is that Daikon relies on the native execution environment to determine the program’s thread schedule at run time, and in this example, since the code in each thread is small—significantly smaller than what can be executed in the Linux kernel’s time slice—all threads will have ample time to run to completion before encountering a context switch.

If the erroneous interleaving never occurs during its analysis, Daikon would report the following false transition invariant for the withdraw() function: balance = orig(balance) - 100, where orig(balance) denotes the original value of balance at the entry point of programs. Our results show that the invariants generated by our new method are often significantly higher in quality than the previous state-of-the-art Daikon. Overall, this paper makes the following contributions:

- We show, through experiments, that existing dynamic invariant generation tools such as Daikon do not work well on multithreaded programs, both in terms of the number of true invariants generated and in terms of the usefulness of these invariants.
- We propose a new method for improving the quality of dynamic invariant generation for multithreaded programs by leveraging selective interleaving exploration strategies.
- We show that transition invariants are the most relevant invariants to help in reasoning about concurrency related behaviors. They are useful in program comprehension and diagnosing concurrency errors.
- We implement the proposed method and demonstrate its efficiency and effectiveness through experiments on a set of multithreaded C/C++ benchmarks.

The remainder of this paper is organized as follows. We present examples to illustrate our new methods in Section II. We establish notation in Section III and then present our new invariant generation algorithm in Section IV. We present both runtime optimizations and methods to clarify output to the user in Section V. This is followed by our experimental evaluation in Section VI. We review related work in Section VII and finally give our conclusions in Section VIII.

explosion problem, the number of thread interleavings can be exponential with respect to the number of concurrent operations. Therefore, we propose the use of selective exploration strategies, as opposed to exhaustive exploration, to reduce runtime overhead. Our experimental evaluation shows that selective exploration often leads to invariants of similar quality to sound reduction methods, such as dynamic partial order reduction [3], but with an order-of-magnitude faster run time.

A third contribution of our work is a focus on generating invariants that are most relevant to concurrency related program behaviors. In general, the invariants generated by an inference engine fall into two categories: state invariants and transition invariants. For example, consider the program in Figure 2, where A.x is initialized to zero. The predicate A.x == 10 at Line 4 is a state invariant—it holds at a thread-local program location and is expressed in terms of the program variables visible at that location. A transition invariant, in contrast, is a predicate that may hold at the entry and exit points of an arbitrary code block and is expressed in terms of two versions of a program variable at the entry and exit points. For example, in Figure 2, the predicate A.x == orig(A.x) + 10 is a transition invariant over the code block from Line 1 to Line 4, where orig(A.x) is the value of variable A.x at Line 1 (the original value) and A.x is the value of variable A.x at Line 4.

For reasoning about concurrency related program behaviors, we argue that it is often sufficient to focus on these transition invariants. The reason is that they capture the no-thread-interference properties, i.e., whether the associated code block is atomic or whether it should be made atomic. By atomic, we mean that the execution of the code block is not affected by the execution of other instructions from concurrently running threads.

Consider the program in Figure 2. A bug can occur if Thread 2 sets the value of p to null when Thread 1 is executing Lines 2–6. If we generate invariants only from the non-buggy runs, we will observe the transition invariant p == orig(p) for the code block from Line 2 to Line 6. Examining the buggy runs, we will see that this invariant no longer holds. The difference in the invariants generated between the passing and failing runs shows the root cause of the bug: p is not constant.

Throughout this paper, we will show how discrepancies between the invariants generated from passing and failing runs, like this example, can be leveraged to understand the software code and diagnose concurrency bugs.

We have implemented our new methods and conducted experiments on a set of open-source multithreaded C/C++
withdraw() and balance denotes the value of balance at the exit point. This is not a true invariant, and reporting it to the user may do more harm than good. That is, it can make the developer believe that withdraw() is atomic, thereby masking the concurrency bug.

Our new method, in contrast, controls the thread scheduling of the program in order to create a diverse and representative set of execution traces. Consequently, the invariant inference engine would produce the following correct invariant for the withdraw() function: balance < orig(balance). This is the correct result and is the best one can infer from the executions of this program (two threads running withdraw() concurrently). That is, the balance always decreases but not necessarily by 100.

Another problem with existing tools is that they often report too many invariants. For example, running Daikon on the benchmark FibBench [4], which has 55 lines of code, would generate 24 likely invariants. Among them, 15 are true invariants (the rest are false), but only three of them are related to the concurrency behaviors of the threads. The others are either specific to the particular program input used in the test runs or the sequential part of the computation. Since our goal is to reason about concurrency related behaviors, our new method allows the user to focus only on the concurrency related invariants, known as transition invariants.

There can be many applications for transition invariants such as balance = orig(balance) - 100 and balance < orig(balance). Here, we give two examples: to help diagnose concurrency bugs and to infer atomic code regions.

During software testing, it is reasonable to expect the user to provide a test oracle which separates failing test runs from passing test runs. We allow users of our new tool to specify correctness conditions using R_assert() which, from the user’s perspective, is identical to the standard C assert() function. For our running example, assume the user asserts that balance = orig(balance) - 100 must hold at the end of the execution. This is illustrated in Figure 3. For the buggy program in Figure 3, if the function withdraw() is executed atomically by both threads, the assertion would pass; but, if the function is not executed atomically, the assertion would fail.

If we run our new invariant generation method on the passing traces only, it would report the transition invariant balance = orig(balance) - 100. In contrast, if we run our new invariant generation method on the failing traces only, it would report the transition invariant balance < orig(balance). The discrepancy between these two sets of results (from passing and failing runs) will help the user diagnose the root cause of the concurrency failure.

Regarding atomic region inference, consider the same example in Figure 3. The transition invariant generated from the passing runs for the code block spanning Lines 13–17 is balance = orig(balance) - 100, which is consistent with the thread-local transition relation of this code block when it is executed without interference from other threads. In other words, the programmer’s design intent, as revealed by all the passing test runs, is that withdraw() should be executed atomically. This suggests that to fix the bug in withdraw(), we need to enforce atomicity around the calls to getBalance() and setBalance() as illustrated in Figure 5.
at the boundary of code blocks of arbitrary size—the user can set the block size as input to our tool as shown in Figure 1. We illustrate this feature using the following example.

Consider the program in Figure 6. Within \texttt{thr1()}, the three fields are intended to be updated atomically; similar to the previous example, the programmer asserts the correctness condition using \texttt{R_assert()}. To infer the intended atomic region that spans from Line 6 to Line 12, the capability of generating invariants for arbitrary code blocks is crucial.

Figure 7 shows a section of our tool’s output regarding the transition invariant generated from passing runs. It first starts with a code block size of two and then iteratively expands the block size. A block size of two means that our tool will attempt to generate invariants over any code region containing two consecutive accesses to a shared object. The partitioning of the source code into code regions was performed by our LLVM based instrumentation front end as shown in Figure 1. In Figure 7, \texttt{..main.c_6_12()} means that we consider the block from Line 6 to Line 12 in Figure 6, whereas \texttt{..main.c_9_12()} means that we consider the block from Line 8 to Line 12. With a block spanning Lines 6–12 we cover all the shared memory accesses in \texttt{thr1()}. In both cases, when analyzing the passing runs, we can generate the invariant \( p = \text{orig}(p) \), which indicates that the value of \( p \) is never changed. Amongst all the failing runs, this invariant does not hold. Again, the discrepancies in the invariants generated by the passing and failing runs correctly suggests that in order for the test runs to pass, the code block from Line 6 to Line 12 must be kept atomic.

III. PRELIMINARIES

In this section, we present a formal model for concurrent programs, and introduce the basics of the dynamic invariant generation process.

A. Concurrent Programs

A multithreaded program consists of a set of \textit{shared} variables, and a set of threads \( \{T_1, \ldots, T_n\} \) where \( n \) is the number of threads in the program. Each thread is a sequential program with a set of \textit{thread-local} variables. Let \( st \) be an instruction. An execution instance of \( st \) is called an \textit{event}, denoted \( e = (\text{tid}, l, s, l') \), where \( \text{tid} \) is the thread ID, and \( l \) and \( l' \) are the thread program locations before and after executing \( st \). An event is said to be \textit{visible} if it accesses a shared variable or a thread synchronization object (mutex lock or condition variable). Otherwise, the event accesses only thread-local variables and it is said to be \textit{invisible}. During systematic interleaving exploration and execution trace logging, invisible events will be ignored.

We model each thread \( T_i \) as a state transition system \( M_i \). The transition system of the program, denoted \( M = M_1 \times M_2 \times \ldots \times M_n \), is constructed using interleaving composition. Let \( M = (S, R, s_0) \), where \( S \) is the set of global states, \( R \) is the set of transitions, and \( s_0 \) is the initial state. Each state \( s \in S \) is an \( n \)-tuple of thread program states. Each transition \( e \in R \) is an event from one of the \( n \) threads. An execution trace of \( M \) is a sequence \( \rho = s_0 \xrightarrow{e_0} s_1 \xrightarrow{e_1} s_2 \ldots \xrightarrow{e_n} s_n \), where \( s_0 \xrightarrow{e_0} s_1 \) corresponds to executing event \( e_1 \) in state \( s_0 \) leading to state \( s_1 \).

We use the special event \texttt{halt} to denote normal program termination, and the special event \texttt{abort} to denote faulty program termination, which corresponds to a failed \texttt{R_assert()} statement. An event from thread \( T_i \) may have the following types:

- \texttt{halt}, which denotes the normal program termination;
- \texttt{abort}, which denotes the faulty program termination;
- \texttt{fork(j)} for creating child thread \( T_j \), where \( j \neq i \);
- \texttt{join(j)} for joining back thread \( T_j \), where \( j \neq i \);
- \texttt{lock(lk)} for acquiring lock \( lk \);
- \texttt{unlock(lk)} for releasing lock \( lk \);
- \texttt{signal(cv)} for setting signal on condition variable \( cv \);
- \texttt{wait(cv)} for receiving signal on condition variable \( cv \);
- \texttt{read(v)} for reading of shared variable \( v \);
- \texttt{write(v)} for writing to shared variable \( v \);
- \texttt{mEntry(m)} for entering a function call;
- \texttt{mExit(m)} for returning from a function call;
- \texttt{bEntry(blk)} for starting a code block;
- \texttt{bExit(blk)} for ending a code block.

Here, \texttt{mEntry()} and \texttt{mExit()} are also supported by existing invariant generation tools such as \textit{Daikon}, whereas \texttt{bEntry()} and \texttt{bExit()} are the new additions in our method.

We model thread synchronization events in our method in order to control the execution order during thread interleaving exploration. Using this model, at each moment during a program’s execution, we know which threads are blocked (\textit{disabled}) and which threads are executing (\textit{enabled}).

An enabled thread becomes disabled if (i) it attempts to execute \texttt{lock(lk)} while \( lk \) is held by another thread; (ii) it attempts to execute \texttt{wait(cv)} while the signal on \( cv \) has not yet been set; or (iii) it attempts to execute \texttt{join(j)} while the child thread \( T_j \) is still running. Similarly, a disabled thread becomes enabled if (i) another thread releases the lock \( lk \) by executing \texttt{unlock(lk)}, (ii) another thread sets the condition variable \( cv \) by executing \texttt{signal(cv)}, or (iii) the child thread \( T_j \) terminates.

An accurate model of the sets of enabled and disabled threads at runtime is required since attempts to schedule disabled threads while postponing the execution of enabled threads may lead to artificial deadlocks.

At runtime, our scheduler selects a given event from the set of enabled events. Which event to select is determined by the exploration strategy used by the scheduler. Similarly, the scheduler repeatedly executes the program, systematically exploring new interleavings, until the search strategy’s inter-
leaving coverage criteria is satisfied. We defer discussions of exploration strategies until Section IV. For an in-depth discussion on systematic concurrent program testing refer to [5], [6], [7].

B. Dynamic Invariant Generation

Dynamically generated invariants are predicates that hold over the execution traces produced by test runs. As such, they are not guaranteed to hold for all possible executions of the program. Furthermore, the invariant inference engine often uses a statistical analysis and, in theory, is neither sound nor complete. However, in practice, dynamic invariant generation tools such as Daikon have shown to be useful in a wide range of applications. In general, the number of invariants that can be generated, as well as the likelihood of them being true invariants, depends on the test suite.

Daikon [1], [2] is a highly successful invariant discovery tool that supports programming languages such as C, C++, C#, Eiffel, F#, Java, Lisp, and Visual Basic. For each of these languages, Daikon provides a front end tool for code instrumentation to add logging capability to the target program. The front end tools prepare the program to generate trace logs in a common format, which are then fed to the back end invariant inference engine.

We have developed a new instrumentation tool based on the popular LLVM compiler platform to replace Daikon’s previous front end. The main advantage of our new instrumentation tool is to leverage the large number of static program analysis procedures implemented in LLVM as well as to reduce the runtime overhead caused by instrumentation. We will show through experiments (Section VI) that our LLVM based instrumentation tool can indeed lead to faster dynamic analysis compared to the default front end in Daikon due to its significantly lower instrumentation overhead.

Since Daikon cannot diversify the thread schedules, it may generate many bogus invariants for a multithreaded program. Furthermore, Daikon is effective in generating linear invariants of the form \((ax + by < c)\), but weak in generating more complex invariants such as polynomial invariants \((c_0 + c_1 x + c_2 x^2 + \ldots < 0)\) and array invariants. For the latest development along this line, please refer to the recent work by Nguyen et al. [8], [9]. However, our focus is on improving the expressiveness of the generated invariants, but on improving their quality with respect to concurrency. The vast majority of invariants generated by existing tools such as Daikon capture the sequential program behavior. Our new method, in contrast, focuses on invariants that capture the concurrency behaviors.

IV. UDON: OUR NEW DYNAMIC IN Variant GENERATION TOOL

In this section, we present the three components of our new method: an LLVM based code instrumentation tool, a systematic interleaving exploration tool, and a customized inference engine for Daikon. The overall flow of our tool, called Udon, is illustrated in Algorithm 1, which takes the source code of a multithreaded C/C++ program as input and returns a set of likely invariants as output.

### Algorithm 1 High-level algorithm for Udon

```plaintext
inst_output ← inspect_pass(src_code)
inst_output ← daikon_pass(inst_output)
inst_output ← spacer_pass(inst_output, spacer_size)
trace_file ← gen_traces(inst_output)
thrd_mod_traces ← trace_classifier(trace_file)
invariants ← inv_inference(thrd_mod_traces)
```

A. LLVM Based Code Instrumentation

We developed an LLVM based front end for instrumenting multithreaded C/C++ code. As shown in Algorithm 1, it consists of three code transformation passes.

The first pass, `inspect_pass()`, takes C/C++ code as input and returns an instrumented version of the code as output. Inside this pass, we first identify all the program points where a thread’s schedule needs to be controlled. These program points include the calls to thread synchronization routines, and the read and write operations on shared memory locations discussed in Section III. At each program point, we inject new code before these visible operations to allow the control of the thread at run time by the scheduler. We leverage the conservative static analysis techniques implemented in LLVM to identify these visible operations.

The second pass, `daikon_pass()`, takes the previously instrumented code as input and returns another instrumented version of the code as output. Inside this pass, we inject new code to add event trace generation capabilities to the program. The event trace generated by the program conforms to the common file format as required by the back end invariant inference engine in Daikon [2]. By default, this pass instruments the code only at the function entry and exit points, which is comparable to the original C/C++ front end for Daikon.

The third pass, `spacer_pass()`, takes the previously instrumented code as input and returns the final version of the code as output. Inside this pass, we also inject new code to add logging capabilities not just at the procedural boundaries, but also at the boundary of arbitrary code blocks. This is accomplished by inserting hook function calls to the entry and exit points of these code blocks, which in turn take care of the trace generation at run time.

Note that the events logged as a result of the second and third passes are kept in the same format. From the standpoint of the back end invariant inference engine, there is no distinction between a pair of entry and exit points for a function, and a pair of entry and exit points for an arbitrary code block. Therefore, the back end inference engine does not have to be drastically altered in order to infer invariants at the boundary of arbitrary code blocks. By varying the size of the instrumented code blocks, we can dynamically change the locations where state and transition invariants are generated. This will help us to detect likely atomic regions in the code.

B. Systematic Interleaving Exploration

The `gen_traces()` function in Algorithm 1 involves an exploration of the concurrent state space of the program. Due to the well-known interleaving explosion, in general, we cannot afford to naively enumerate all possible thread schedules while diversifying the execution traces for the back
end inference engine. In this work, we build off a set of interleaving exploration strategies to produce a representative subset of thread interleavings.

The baseline search strategy relies on the theory of partial order reduction (POR) [5]. It groups the possible interleavings of a concurrent program into equivalence classes, and then selects one representative interleaving from each equivalence class to explore. Equivalence classes are defined using Mazurkiewicz traces [10]. Two sequences of events are said to be in the same equivalence class if we can create one sequence from the other by successively permuting adjacent and independent events. Two events are dependent if they are from two different threads, access the same memory location, and at least one of them is a write or modify operation; otherwise, the two events are independent. It has been shown [11] that in the context of verifying concurrent systems, exploring one representative interleaving from each equivalence class is sufficient to catch all deadlocks and assertion violations.

One benefit of POR based methods is that they are a sound reduction. The reduced set of interleavings still can capture all possible behaviors of the concurrent program. Therefore, using the explored interleavings as input for the subsequent invariant inference will lead to the best possible result; the explored interleavings form a maximally diversified set of execution traces.

The current state-of-the-art POR based algorithm is dynamic partial order reduction (DPOR) [3]. DPOR computes the dependency relation among events dynamically at run, as opposed to statically at compile time. As a result, DPOR proved to be a practical step forward for POR algorithms. It allowed for realistic programs written in full fledged programming languages such as C/C++ to be verified.

However, due to its exhaustive exploration of the search space, even DPOR may incur a large runtime overhead. As a result, there is a large body of work dedicated to the development of more efficient, yet unsound, exploration strategies. Two methods along these lines are preemptive context binding—when the event trace from both passing and failing executions are posed to statically at compile time. As a result, DPOR proved partial order reduction (DPOR) [3]. DPOR computes the possible behaviors of the concurrent program. Therefore, using all deadlocks and assertion violations.

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Second, we customized the invariant generation engine in Daikon to focus on two types of invariants in a multithreaded program: the state invariants and the transition invariants. Both transition and state invariants are expressed in terms of shared variables—variables accessed by multiple threads in the execution traces. A state invariant is a predicate expressed in terms of the value of variables at a single program location. A transition invariant is a predicate expressed in terms of variable values at two different program locations of the same thread.

In essence, a transition invariant is capable of capturing the non-interference impact of executing an arbitrary code block.

More formally, we consider a program $P$ as a state transition system $P = \langle S, R, I \rangle$, where $S$ is the set of states, $I \subseteq S$ is the set of possible initial states, and $R \subseteq S \times S$ is the transition relation. In general, a transition invariant [12], denoted $T$, is an over-approximation $R^+$ of the transitive closure of $R$ restricted to the reachable state space, i.e., $R^+ \cap (R^*(I) \times R^*(I)) \subseteq T$. Intuitively, a transition invariant summarizes the relation between the pre- and post-conditions of a consecutive set of instructions (transitions) executed by a thread.

Transition invariants are particularly useful in software verification. To verify the concurrent behavior of a program, one typically assumes the sequential computation is correct but the thread interaction is potentially buggy. In this case, transition invariants would conform to the transition relation of a sequential code block in the absence of unexpected thread interference, but would deviate from the transition relation in the presence of thread interference. Therefore, observing that a sequential transition invariant differs from the concurrent transition invariant for the same code block is often indicative of a bug caused by thread interference.

For example, consider a shared counter that is incremented by multiple threads. The sequential (or correct) invariant for the increment operation would be that the counter increases its value by one at a time ($counter = orig(counter) + 1$). However, if the programmer fails to enforce atomicity in the increment operation, this invariant would no longer hold for all possible executions of the program. Clearly, the discrepancy between the sequential (or correct) and concurrent (or incorrect) transition invariants hints at the root cause of the aforementioned bug.

Due to the help of both systematic interleaving exploration techniques and customized invariant inference engines, Udon can more robustly generate high-quality invariants from multithreaded applications than existing methods.

V. OPTIMIZATIONS

The method presented in the previous section addresses the problem of dynamically generating high-quality invariants from multithreaded programs. However, using DPOR may
cause a performance bottleneck due to the exponential growth in the number of interleavings with respect to program size. Another problem of the new method is that the number of reported invariants can still be very large. Despite that many of them are indeed invariants, reporting all of them without filtering can overwhelm the user. In this section, we present our solutions to these problems.

A. Exploring Interleavings Selectively

We address the performance problem by replacing the exhaustive DPOR exploration strategy with efficient, but unsound, selective search strategies. In this context, our goal is to drastically reduce the runtime overhead while maintaining the diversity of the generated interleavings. DPOR is a sound reduction in that it can prune away redundant interleavings without missing any concurrency related program behavior. To this end, it groups all possible thread interleavings into equivalence classes and then tries to explore only one representative interleaving from each equivalence class. However, due to the limited amount of program information available at run time, DPOR still may create many redundant equivalence classes for the purpose of generating invariants.

Consider the busy-waiting example in Figure 8, which has two threads $T_1, T_2$ communicating via the variable $x$ ($x = 1$ initially). Under DPOR, the systematic exploration would generate infinitely many interleavings. Each interleaving corresponds to a different execution of the loop by the first thread. Each of these interleavings belongs to a separate equivalence class (since dependent memory locations are being updated) so each must be tested. Notice that, except for the first two interleavings, denoted $c(ab)$ and $(ab)c(ab)$, respectively, none of the other interleavings of the form $(ab)^kc(ab)$, where $k = 2, 3, ..., c$ can offer new concurrency scenarios.

In this paper, we propose to avoid generating an excessive number of execution traces during interleaving exploration by using a selective search, as opposed to an exhaustive search. The aim of a selective search is to cover a small subset of high-risk concurrency scenarios, while avoiding the redundant ones as shown in the example in Figure 8. The rationale is that, in practice, programmers often make implicit assumptions regarding the concurrency control of threads, e.g., certain code blocks should be mutually exclusive, certain code blocks should be atomic, and a certain operation order should be obeyed. Concurrency bugs are frequently the result of these implicit assumptions being broken, leading to data races, atomicity violations, and order violations. The goal of a selective search is to maximize the coverage of such scenarios while reducing the runtime overhead.

One popular selective search strategy proposed in the context of software testing is preemptive context bounding (PCB) [6]. PCB explores interleavings with only a bounded number of involuntary context switches. The strategy can be effective in concurrency testing because, in practice, many concurrency bugs can be exposed using a small number of context switches. We note that although PCB is effective in practice, the number of explored interleavings remains exponential with respect to the number of concurrent threads. Furthermore, it is not effective on the example in Figure 8, where all interleavings have exactly one context switch.

Another popular, and more scalable, selective search strategy is the history-aware predecessor set (HaPSet) [7] based reduction. It can be viewed as an improvement over PCB since the number of explored interleavings is no longer exponential with respect to the number of concurrent operations or threads. This is accomplished by focusing on covering only the ordering combinations of read/write instructions in the program, which is opposed to the many instances of these instructions.

Formally, a program statement $st$ is defined as a tuple $(file, line, thr, ctxx)$, where $file$ is the file name, $line$ is the line number, $thr$ is the thread ID, and $ctxx$ is the bounded calling context. Given a set $T = \{\rho_1, ..., \rho_n\}$ of interleavings and a statement $st \in Stmt$ that accesses a shared object, the History-aware Predecessor Set, or HaPSet[$st$], is defined as the set $\{st_1, ..., st_k\}$ of statements such that, for all $i : 1 \leq i \leq k$, an event $e$ produced by $st$ is immediately dependent upon an event $e_i$ produced by $st_i$ in some interleaving $\rho \in T$.

Consider again the example in Figure 8. After exploring the first two interleavings, denoted $c(ab)$ and $(ab)c(ab)$, respectively, the HaPSet computed over these interleavings are as follows: HaPSet[$a$] and HaPSet[$c$] = $\{a\}$. Since $a$ and $c$ are the only two conflicting program statements in the program, all possible HaPSet combinations have already been covered. Therefore, the interleaving exploration stops since no other interleaving can lead to a HaPSet scenario.

We shall show through experiments in Section VI that faster interleaving exploration algorithms such as PCB and HaPSet are often as good as DPOR in terms of generating high-quality invariants. At the same time, these algorithms can be orders-of-magnitude faster, which makes Udon practically useful.

B. Focusing on Transition Invariants

By default, the number of invariants generated by our method—as well as other similar tools such as Daikon—can be large. However, not all of these invariants are useful for reasoning about the concurrency related program behaviors. For example, among the 22 likely invariants generated for FibBench [4] by Daikon, only three are related to concurrency, whereas the others are specific to the sequential part of the computation. Therefore, in this work, we propose to focus on only the transition invariants over shared variables. In the remainder of this section, we show why transition invariants are useful in helping the user understand the software code and diagnose concurrency bugs.

Let us assume that a multithreaded program has some assertions that would be satisfied in most cases, but may fail in some rare interleavings. Furthermore, regarding the concurrency control, there is no formal documentation other than the source code that describes the programmer’s intent. In this case, we classify the execution traces of the program into two groups: the passing traces and the failing traces. To
help the user understand the root cause of the concurrency error manifested in the failing traces, we leverage the two sets of invariants generated by Udon from the set of passing and failing traces and identify the discrepancy between them.

Formally, let \( I_p \) and \( I_f \) be the likely invariants generated from the passing and failing traces, respectively. As a result, \( I_d = I_p \setminus I_f \) consists of all the invariants satisfied by the passing but not the failing traces. Our conjecture is that the discrepancy often provides information to help understand why the error occurs. In the following example, we show that \( I_d \) can indeed help a programmer understand the root cause.

Consider Figure 9, where a parameterized number of threads share a global counter \( \text{sum} \) initialized to zero. \( \text{NUM} \) is the number of threads that execute the function \( \text{thread()} \) concurrently. These threads are created, run, and joined inside \( \text{main}() \) before it checks the value of \( \text{sum} \). The test oracle provided by the programmer is shown on Line 6, which states that the expected result is \( \text{sum} = \text{NUM} \). The assertion passes in runs where each thread executes the function \( \text{thread()} \) atomically, but fails in runs where the threads interfere with each other. Specifically, depending on how they interfere with each other, the value for \( \text{sum} \) ranges from 1 to \( \text{NUM} \).

When given the passing traces, Udon will generate the transition invariant \( \text{sum} == \text{orig(sum)} + 1 \) for the \( \text{inc()} \) function. However, when given the bad traces, Udon will generate the transition invariant \( \text{sum} > \text{orig(sum)} \), which covers cases in which \( \text{sum} \) is increased by 2, 3, ..., \( \text{NUM} \). By comparing the two sets of transition invariants, we can see the difference in behavior of the passing and failing runs. In the passing runs, \( \text{sum} \) is always incremented, whereas in the failing runs, it is not.

Another possible application of transition invariants is to help the user identify atomic regions. When the transition relation of a code region is consistent with the transition invariant generated for the same code region, we say that section has been executed atomically. Furthermore, if the transition invariant is generated from passing traces only—and they are not satisfied by the bad traces—we can assume that the code region is intended to be atomic. For example, the function \( \text{thread()} \) in Figure 9 and the function \( \text{withdraw()} \) in Figure 3 are intended to be atomic, whereas only the fixed version of \( \text{withdraw()} \) in Figure 5 is atomic. The atomic code regions inferred in this way can help the user comprehend the software code and diagnose failed execution traces.

VI. EXPERIMENTS

We have implemented the proposed method in a software tool called Udon. Udon can handle unmodified C/C++ code written using POSIX threads to automatically generate dynamic invariants. We used LLVM to create a new front end for Daikon [2] and a modified version of Inspect [13], [14] for systematic concurrent program exploration.

We evaluated Udon on 19 open source programs. The first set of programs come from the 2014 Software Verification Competition [4]. These programs, while small in terms of lines of code, implement complex low-level synchronization algorithms such as Peterson’s [15] and Dekker’s [16] solutions to the mutual exclusion problem. The second set of programs are real-world applications: \texttt{fescaan} is a parallel directory scanner and \texttt{nbdts} [17] is a C implementation of several non-blocking concurrent data structures. All tests were run on a machine with a 2.60 GHz Intel Core i5-3230M CPU and 8 GB of RAM running a 64-bit Linux OS.

Our experimental evaluation was designed to answer the following research questions:

- Can the previous state-of-the-art method, Daikon [2], generate correct invariants for concurrent programs?
- Can our new method, Udon, robustly generate high-quality invariants for concurrent programs?
- Can Udon scale to programs of realistic size and complexity?

A. Results

Table I shows the results of an experiment comparing the performance of Udon against Daikon [2]. For each test program, both Daikon and Udon were used to generate invariants. By design, Udon needs to re-run the program multiple times in order to explore the concurrent behavior of a program, whereas Daikon runs the program only once. In order to create a fair comparison, we also allowed Daikon to run each test program the same number of times as Udon. We refer to the multi-run Daikon strategy as Daikon* and the single-run strategy as Daikon in Table I.

Columns 1–4 of Table I show the program name, lines of code (LoC), number of program program points, and number of monitored shared variables, for each test. Columns 5–7 and 8–10 show the total number and the number of incorrect invariants generated by Daikon, Daikon*, and Udon respectively. For experiment purposes only, we manually inspected the results to verify if the invariants were true. Finally, Columns 11–13 and 14–16 show the number of runs and run time in seconds for each method.

First, the results show that Daikon generates incorrect invariants for every test program. The cause of this is clear: since Daikon only exercises a small portion of the concurrent behavior of a program — even if it runs the program multiple times — it fails to observe many different states of the program and, as a result, deduces incorrect invariants. Comparing Columns 8 and 9 of Table I shows that running Daikon multiple times on the same program has little to no effect at reducing the number of incorrect invariants. The likely cause of this is that simply re-running a concurrent program repeatedly explores only a small portion of the entire interleaving space.

Second, Columns 7 and 10 show that Udon is capable of generating a large number of correct invariants for each test program. On average, Udon produces only one incorrect invariant per test. Compared to Daikon and Daikon*, Udon produces, on average, over an order of magnitude fewer incorrect invariants. The incorrect invariants generated by Udon are

```c
1 void thread()
2 {
3     sum = sum + 1;
4 }
5 int main()
6 { // create, run, and join (NUM) threads...
7     R_assert (sum==NUM);
8 }
```

Figure 9. Concurrent program with multiple threads updating a counter.
due to the fact that HaPSet [7], the default concurrent coverage metric used by Udon, can skip certain interleavings where new values of memory could have been explored. As a result, the invariants are generated based on an incomplete exploration of the program.

Finally, we examine the scalability of our method. Columns 15 and 16 of Table I show that, on average, using our new LLVM based front end for instrumentation results in a five times speedup over the previous, Daikon, front end. The reason is that Daikon's front end for C/C++ (called Kvasir) uses Valgrind [18] to dynamically instrument the executable every time it runs the program. Whereas Udon instruments the program only once at the compile time. As a result, using our new front end should provide a speed up when analyzing both sequential and multithreaded C/C++ programs.

Table II shows a breakdown of the invariants generated by Udon. We classified each invariant into one of two categories: transition invariants over shared variables and all other (regular) invariants. Transition invariants were generated with respect to the entry and exit of each function. Table II shows that by considering only transition invariants we can present the user with a more manageable output compared to considering all invariants. As shown in the previous sections, these transition invariants present a concise summary of the concurrency behavior of a program.

Figure 10 compares the scalability of three interleaving exploration strategies implemented in Udon. HaPSet [7] is the default strategy, DPOR [3] is theoretically the ideal strategy (since it will lead to the most precise results), and PCB [6], which is a widely used strategy in the testing literature (we used a context bound of two). In this experiment, we ran Udon on the Indexer benchmark from SVCOMP'14 varying the number of threads in the program. Here, the x-axis denotes the number of threads, and the y-axis denotes the number of interleavings explored by each strategy. The result shows that the number of interleavings quickly explodes under DPOR. Under PCB, the increase in the number of interleavings is slower, since only the interleavings with a bounded number of preemptive context switches are explored; nevertheless, the growth is still (predictably) exponential with respect to the number of threads. In contrast, the increase in the number of interleavings is the smallest under HaPSet.

To quantify the effect of different interleaving exploration strategies on the quality of the generated invariants, we ran Udon on the benchmarks using HaPSet [7], PCB [6], and DPOR [3], respectively. For PCB, we used a context bound of two. The results are summarized in Table III. Here, we compare the number of runs, time, and number of incorrect invariants. An x in a column indicates the test took longer than two hours. Column 1 shows the name of the test program, Columns 2–4 and 5–7 show the number of runs and time of HaPSet, PCB, and DPOR, respectively. Finally, Columns 8–10 show the number of incorrect invariants found by each method.

First, since DPOR provides a sound guarantee to explore all relevant thread schedules, it produces no incorrect invariants. However, DPOR suffers from an exponential increase in run time relative to the length and number of threads in a program. As a result, DPOR failed to finish analyzing nbds-hashtable while both HaPSet and PCB were able to finish in a reasonable time. However, if a user desires high invariant accuracy at the cost of longer run time, Udon is capable of using DPOR instead of HaPSet.

Since both HaPSet and PCB skip interleavings where new memory values could be encountered, they both suffer from incorrect invariants being generated. However, on average, HaPSet performs significantly better than PCB in terms of
The main advantage of dynamic invariant generation is scalability: they have been applied to realistic applications where a tradeoff between precision and scalability.

Other dynamic invariant generation tools include DIDUCE [28], DySy [29], Agitator [30], and Iodine [31]. However, existing dynamic generation tools tend to lack either in precision or in scalability. Our method, in contrast, relies on dynamic analysis.

Static Techniques. There is a large body of work on using static analysis [19], [20] for invariant generation, whose main advantage is that the reported invariants are true for every reachable state of the program. Typically, invariants generated by these techniques are predicates expressed in some linear abstract domains, such as difference logic, octagonal, or polyhedral. There are also methods based on constraint solving [21], [22], [23], which can generate more complex invariants such as polynomial and non-linear invariants. Recent advances in SMT solving [21], [22], [23], which have been highly successful in practice.

Dynamic Techniques. There is also a large body of work on dynamic invariant generation, including tools such as Daikon [1], [2], which have been highly successful in practice. The main advantage of dynamic invariant generation is scalability: they have been applied to realistic applications where static techniques fail to scale. Other dynamic invariant generation tools include DIDUCE [28], DySy [29], Agitator [30], and Iodine [31]. However, existing dynamic generation tools do not work well on multithreaded programs due to the nondeterminism in thread scheduling. Our contribution, Udon, fills the gap by solving the issue of nondeterminism with respect to dynamic invariant generation.

Hybrid Techniques. There are also hybrid techniques for invariant generation, which leverage both static analysis and dynamic analysis to improve performance. For example, Nguyen et al. [8], [9] proposed a method for generating invariants expressed as polynomials and linear relations over a limited number array variables. Such invariants have been difficult to generate by existing methods. There are also hybrid techniques based on random testing [32] and guess-and-check [33], which first generate a set of candidate invariants from concrete execution data and then verify them using SMT solvers.

Interleaving Exploration. There is a large body of work on using selective interleaving exploration techniques for testing concurrent programs, including ConTest [34], CHESS [6], [35], [36], CTrigger [38], CalFuzz [39], PENELOPE [40], and Maple [41], and property guided pruning techniques [42], [43] implemented in Inspect. Recent empirical evaluations of such techniques can be found in [44], [45], [46]. However, the focus of this paper is not on improving software testing, but on leveraging the related techniques for generating high-quality invariants. In this sense, our work is orthogonal to these existing methods.

Atomicity Inference. Various methods have been proposed for inferring atomicity and detecting concurrency bugs. They may rely on static analysis [47], dynamic analysis [48], [49], [50], [51], [40], [52], or symbolic analysis [53], [54], [55], [56], [57], [55] techniques. However, their focus is primarily on discovering the intended order of conflicting events from different threads. The thread-local transition invariants generated by our new method is similar to the likely deterministic specifications generated by the Determin tool [58], which has its own construct for specification of invariants. The main difference is that Determin relies on a given set of thread schedules, whereas in our work, different schedules are generated automatically.

VII. RELATED WORK

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VIII. CONCLUSIONS

We presented a new method for dynamically generating invariants from multithreaded programs. We used selective interleaving exploration to simultaneously improve invariant quality while keeping runtime overhead low. We also proposed the use of thread-local transition invariants to help the user understand the code and diagnose concurrency errors. We implemented our method and evaluated it on a set of multithreaded C/C++ programs. Our experiments show that, when compared to the state-of-the-art, such as Daikon, our new method produces better invariants while remaining scalable.

IX. ACKNOWLEDGMENTS

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