Parallelizing Binary Code Analysis

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Abstract

Binary code analysis is widely used to assess a program’s correctness, performance, and provenance. Binary analysis applications often construct control flow graphs, analyze data flow, and use debugging information to understand how machine code relates to source lines, inlined functions, and data types. To date, binary analysis has been single-threaded, which is too slow for applications such as performance analysis and software forensics, where it is becoming common to analyze binaries that are gigabytes in size and in large batches that contain thousands of binaries.

This paper describes our design and implementation for accelerating the Dyninst binary analysis infrastructure with multithreading. Our goal is to parallelize a commonly used set of binary analysis capabilities, making it easier to parallelize different binary analysis applications. New parallel binary analysis capabilities include constructing control flow graphs, analyzing loop nesting, parsing debugging information, and performing data flow analysis such as register live-ness analysis and program slicing. We cover 146K lines of source code in Dyninst and its software dependencies. A systematic methodology to guide the parallelization is essential: we used data race detection tools to identify unsafe parallelism and employed performance profiling tools to pinpoint performance bottlenecks that merit attention. This methodology guided us to design a new parallel analysis for constructing control flow graphs and identify thread-safety issues widely spread in the codebase. We achieved as much as 25× speedup for constructing control flow graphs and as much as 14× for ingesting DWARF on 64 hardware threads. Binary analysis applications are significantly accelerated with the new parallel Dyninst: we achieve 8× for a performance analysis tool and 7× for a software forensic tool with 16 hardware threads.

1 Introduction

Binary code analysis is a foundational technique for a variety of applications, including performance analysis [2, 10, 21], software correctness [3, 13], software security [15, 35, 36], and software forensics [19, 27]. Important binary code analysis capabilities include constructing control flow graphs (CFGs), analyzing control flow and data flow properties, and extracting source line mappings and data types from debugging information, when it is available. Traditionally, binary analysis applications are single-threaded. However, recent trends in these applications call for improving the performance of binary analysis applications.

In the field of performance analysis, it is becoming common to optimize the performance of large software systems that compile into multi-gigabyte binaries. We have witnessed this trend within software developed by national laboratories and popular machine learning frameworks such as TensorFlow [1]. The developers of these large softwares use the following performance analysis workflow to optimize their code: (1) compile the source code to generate the binary program, (2) measure the performance of the binary during execution, (3) attribute measurements to the corresponding source code (via binary analysis), and (4) optimize the source based on the performance results. These four steps are repeated until developers are satisfied with their software’s performance.

In this performance analysis cycle, binary analysis must be repeated after any source code change because even small code changes can lead to dramatically different binaries, especially with C++ templates and aggressive compiler optimizations. In such a workflow, if the binary analysis in step (3) is slow, it will reduce the throughput and effectiveness of performance analysis. Current single-threaded binary code analysis takes too long to analyze such large binaries. It takes more than 20 minutes to analyze a 7.7GiB shared library from TensorFlow, which would interrupt the workflow of developers tuning the code for production.

In the field of software forensics, researchers have achieved great success in applying machine learning to tasks
including compiler identification [26] and authorship attribution [6, 19, 27]. These machine learning-based software forensics applications require large training sets to be effective, containing hundreds to thousands of binaries. During the development of these forensic applications, the developers typically repeat the following workflow: (1) design a set of binary code features, (2) extract the features with binary analysis to construct a training set, (3) validate the accuracy of a model trained using the new features. These three steps are repeated until the developers are satisfied with the effectiveness of the binary code features.

While the training and tuning of machine learning models have traditionally been regarded as the bottleneck of these software forensics applications, modern machine learning packages often provide support for parallel training and tuning, using multithreading and even GPUs. In such scenario, a serial feature extraction step can be a limiting factor of the development cycle: for example, the feature extraction step in compiler identification [26] may take over 24 hours.

In this paper, we present our design and implementation of parallel binary code analysis to address the speed requirements imposed by these applications. As binary analysis is used in a wide variety of applications, we aim to identify and parallelize a common set of binary analysis primitives to benefit researchers in multiple application domains. The core of our work is a new parallel analysis for constructing control flow graphs (CFG construction), which constructs functions, basic blocks, and edges between basic blocks. CFG construction is used in nearly every binary analysis application, directly or indirectly. Our other parallelized binary analysis operations include parsing DWARF debug information, program slicing, and register liveness analysis. We developed parallel implementations of these operations in the Dyninst binary analysis and instrumentation toolkit [23], a library widely used by researchers in performance analysis, security, and software forensics.

Modern serial CFG construction algorithms are focused on understanding complex machine code generated by compilers [18]. Complex code constructs such as non-returning functions, tail calls and jump tables play key roles in understanding high-level programming constructs, making their analysis important for applications. While function level parallelism is a natural starting point for parallelizing CFG construction, we must address a range of complex issues:

- Functions may share code. Threads analyzing different functions may end up concurrently analyzing shared code and require synchronization.
- Control flow graphs evolve during analysis. As a result, a parallel algorithm for CFG construction needs to consider concurrent changes by others.
- Analysis of indirect control flow such as jump tables relies on sophisticated data flow analysis. We need to make data flow analysis thread-safe and consider concurrent CFG modifications from other threads.
- Current binary code analysis is not designed nor implemented with parallelism in mind. Parallelization exposes the flaws in existing serial analysis for jump tables and tail call identification, and convenient serial programming practices such as the use of lazy initialization and static data are obstacles to parallelization.
- While protecting intricate data structures with mutual exclusion is a tempting way to guarantee correctness, the serialization this induces must be carefully evaluated for its impact on parallelism and performance.

A final challenge of our parallelization is to cover large codebases, containing about 146K lines of source code in Dyninst and its software dependencies. It is impractical to redesign everything from scratch for such a large codebase and no currently active developer is familiar with the entire Dyninst codebase. Therefore, we use a parallelization methodology to strategically identify key performance bottlenecks that should be parallelized and monitor the correctness of the resulting implementation. Using this methodology we redesign algorithms and data structures to support multithreading, identify correctness issues via data race detection tools, and use performance tools to detect bottlenecks that should be addressed in the next iteration. While this methodology does not guarantee the resulting implementation is free of concurrency bugs, it makes the parallelization of large, long-lived, and complex software possible.

We evaluate the performance characteristics of our parallel binary analysis with a number of large binaries, including a 7.7GiB shared library from TensorFlow. We achieved as much as 25× speedup for constructing control flow graphs and as much as 14× for ingesting DWARF on 64 hardware threads, which significantly accelerates client tools that employ binary analysis. We then showcase the benefits of parallelizing binary analysis with two applications. The hpcstruct utility in HPCToolkit [2] is used to relate performance measurement back to source code; we achieved 8× speedup for hpcstruct. BinFeat is a tool for extracting binary code features for software forensics, for which we achieved 7× speedup.

In summary, this work makes the following contributions:

1. A general approach to parallel CFG construction, focusing on parallelizing control flow traversal, which is the core algorithm for many binary analysis tools, including Dyninst, BAP, angr.io, and IDA Pro.
2. Identifying and parallelizing a set of commonly used binary analysis primitives that are critical to reduce execution time in binary analysis applications.
3. Parallelizing hpcstruct which significantly accelerates program structure recovery for performance analysis.
4. Parallelizing BinFeat which significantly speeds up binary code feature extraction for software forensics.
5. A general methodology for parallelizing a large, unstructured codebase, and demonstration of its effectiveness by successful parallelization of a large codebase for binary analysis.

2 Background

This section summarizes typical binary analysis capabilities used by applications and how Dyninst provides these analysis capabilities. We then describe how CFG construction is performed and the challenges of parallelizing CFG construction.

2.1 Binary Analysis Applications

While different binary analysis applications may have different end goals, commonly used analysis capabilities include (AC1) constructing CFGs, (AC2) identifying loops, (AC3) building a mapping between source lines and machine instructions, (AC4) understanding function inlining for templates and inlined functions, (AC5) iterating over functions, basic blocks, edges, and machine instructions, and (AC6) performing data flow analysis such as register liveness analysis. We use two application examples to illustrate how these analysis capabilities are used.

Performance Analysis with HPCToolkit: HPCToolkit is an integrated suite of tools for measurement and analysis of application performance on computers ranging from desktops to supercomputers. To relate performance measurements to an application’s source code, the hpcstruct utility in HPCToolkit relates each machine instruction address to the static calling context in which it occurs. In particular, hpcstruct is able to relate instructions to their original function (AC1) or loop construct (AC2) by inspection of the binary’s final CFG (AC5), and to an inlined function or template (AC4) and source lines (AC3) if DWARF debugging information is available.

Feature Extraction with BinFeat: BinFeat is a tool for extracting binary code features for software forensics tasks, including function entry identification, compiler identification and authorship attribution. Commonly used features include machine instruction sequences, subgraphs of CFGs (AC1), loop nesting levels (AC2), and live register counts (AC6). BinFeat iterates over all functions and blocks to extract these features (AC5).

2.2 Dyninst’s Analysis Capabilities

Dyninst provides several component libraries to fulfill different types of binary analysis. The relevant component libraries for this work include:

- SymtabAPI parses DWARF debugging information and symbol table information and provides interfaces for querying source line mappings (AC3) and function inlining (AC4).
- ParseAPI parses the code sections to construct CFGs (AC1) and loops (AC2) and provide interfaces for inspecting functions, basic blocks, machine instructions and loops (AC5).
- DataflowAPI provides a set of common data flow analyses (AC6) including register liveness analysis, stack height analysis, program slicing (both forward and backward slicing), and symbolic evaluation.

2.3 Towards Parallelizing Dyninst

Most binary analysis tasks have a natural unit of parallelism. For example, machine code can be decomposed into individual functions and DWARF debugging information can be decomposed into compilation units. Therefore, a general approach to parallelization is to analyze or parse each unit of parallelism, and make the analysis of each unit thread safe.

Making analysis thread-safe may not necessarily be easy. While many serial programming practices such as lazy initialization and global variables are convenient, these pose obstacles to parallelization and must be handled with care. Similarly, while mutual exclusion is a common and tempting way to guarantee thread-safety, the resulting performance impact must be carefully evaluated. When building a sophisticated piece of parallel software, we must also consider the thread-safety of code in third-party libraries that we use as building blocks. For example, the DWARF parsing in SymtabAPI uses the Libdw library (a component of Elfunutils [24]) to decode DWARF information.

One analysis that cannot be parallelized with the general approach outlined above is the task of CFG construction. It is an inter-procedural analysis and requires a redesign of the core algorithm. We briefly summarize serial CFG construction and the specific challenges for parallelizing CFG construction.

2.3.1 Serial CFG Construction

ParseAPI’s serial analysis is based on definitions and techniques described by Meng and Miller [18]. While there is literature about constructing CFGs from binaries [4, 12, 16, 17, 28], we focus on ParseAPI.

ParseAPI use a permissive CFG representation. The notation \( B[x, y] \) indicates a basic block \( B \) starting at address \( x \) (inclusive) and ending at address \( y \) (exclusive). Control flow edges typically represent actual control flow transfers such as function calls, function returns, and direct branches. An additional call-fallthrough edge at a call site summarizes the execution of a function call. Each edge has a label that indicates whether the edge is inter-procedural or intra-procedural. A function is defined as the basic blocks that are reachable from the function entry by traversing only intra-procedural edges. ParseAPI’s function representation supports non-continuous functions and functions that share code.
ParseAPI uses control flow traversal [28, 33] to construct the CFG. Starting from known function entry points, it follows control flow transfers in the program to discover code and identify function entry points for further analysis. Function symbols extracted from the symbol table are the major source of roots for control flow traversal. While stripping binaries is a common practice for guarding released software against reverse engineering, it is uncommon to remove such information during development.

ParseAPI implements a set of serial analyses to understand complex code idioms found in binaries [18]. First, ParseAPI resolves jump tables using backward slicing to calculate a symbolic expression of the jump target and substitutes the values read from corresponding data regions into the symbolic expression. Second, a call to a non-returning function will never return to its call site, so there should be no call-fallthrough edge at such call sites. ParseAPI identifies non-returning functions by matching function names against known non-returning functions such as exit and abort and uses an iterative analysis to identify functions that always end in a call to a non-returning function. Third, a tail call [9] is a compiler optimization that uses a jump instruction at the end of a function to target the entry point of another function, thus not every branch should be labeled as intra-procedural; ParseAPI uses several heuristics to properly identify these cases.

2.3.2 Challenges for Parallelization

A common compiler optimization is to share binary code between functions with common functionality, such as error handling code and stack tear-down code. This construct is common in compiled code. We have observed this construct in glibc-2.29 (Released Jan. 2019) where common error handling code is shared by multiple syscall wrappers, and within code compiled by the Intel Compiler Suite (ICC). This can also occur logically in functions with multiple entry points: binary analysis tools typically represent such functions as multiple single-entry functions that share code. Thus, Fortran functions with multiple programmer-specified entry points (using the entry keyword), and binaries on Power 8 or newer (the ABI specifies that each function has at least two entry points) lead to functions sharing code.

Functions sharing code make basic control flow traversal operations difficult. For example, if a control flow transfer lands inside an existing basic block, the block must be split. Block splitting is trivial to implement for serial analysis; however, when analysis happens in parallel, multiple threads may concurrently follow control flow transfers to the same basic block and so they must coordinate a split operation.

In addition, handling jump tables, non-returning functions, and tail calls becomes more difficult in parallel analysis. First, during analysis of jump tables, other threads may concurrently add control flow edges to basic blocks that are under this dataflow analysis, which can change the potential expressions available and thus jump targets. Algorithms for this analysis require modifications to consider such concurrent modifications. Second, identification of non-returning functions occurs in parallel with the analysis of the call site, which requires synchronization to ensure threads are able to continue as soon as this is determined. Third, the results of tail call identification heuristics become non-deterministic when executed in parallel. For example, a common heuristic is that a branch to a target known to be in the current function is not a tail call. However, which targets in the current function are known impacts the parsing of its callees and thus is sensitive to thread interleaving. Therefore, tail call heuristics must be modified to account for this situation.

3 Methodology

Dyninst contains over 120K lines of code related to reading ELF sections, interpreting DWARF information, decoding machine instructions, and constructing CFGs. In addition, Elfutils’ Libdw contains over 26k lines of code. Parallelizing such a large volume of code required us to use a careful methodology to focus our attention to what needed it most. Our methodology includes five steps to identify, parallelize, and test a piece of code that will yield overall performance improvement.

1. Use a performance analysis tool such as HPCToolkit [2] to gather performance traces of the code with the aim of identifying code regions whose computational cost justifies an overhaul to add parallelism.
2. Inspect the identified code and choose a candidate parallelization strategy, such as loop-level parallelism, a fork-join parallel programming model, or task-level parallelism. The right choice for a particular code region depends on its code structure as well as the algorithms and data structures that it employs.
3. Use data race detectors to identify data structures and sharing patterns that require synchronization. Candidate tools include logical data race detectors such as cilk screen and happens-before race detectors such as helgrind, the latter available as part of the Valgrind binary instrumentation system [22].
4. Use the performance analysis tool to identify excessive mutual exclusion, unbalanced workloads, and excessive phase-based synchronization that form major bottlenecks.
5. Test the design and implementation with a large suite of test cases and benchmarks.

The above steps are repeated until the overall performance improves satisfactorily.

When applying this methodology, we used HPCToolkit [2] as the performance analysis tool and helgrind as the data race detector. To test our implementation and design, we use HPCToolkit’s hpcstruct utility as the canary to compare a
baseline single-threaded run with multi-threaded runs for thousands of binaries collected from system libraries, executables from Binutils and Elfutils, and executables and shared libraries from Dyninst and HPCToolkit and their dependencies. We also used the Dyninst test suite for testing. Dyninst instrumentation relies on correctly constructing CFGs and some of Dyninst instrumentation capabilities utilize information from DWARF. Therefore, the Dyninst test suite provides an end-to-end testing framework for our parallelization.

We make three observations on this methodology. First, while this methodology does not guarantee the generated parallelization is correct, it points out issues that must be addressed to achieve effective parallelization. Second, when inspecting reports from data race detectors, it is crucial to identify the underlying algorithm and data structure design problems, rather than naively adding mutual exclusion to suppress data races. Third, this methodology enables developers who are not familiar with the target codebase to quickly make progress. Algorithm and data structure redesign requires deep understanding of the relevant code to be effective. This methodology helps developers quickly identify the problematic code that needs rework.

4 Parallel CFG Construction

Our parallel strategy for CFG construction is the result of iteratively applying the methodology described in Section 3 to overhaul Dyninst. Dyninst’s serial code required significant redesign to address the challenges discussed in Section 2.3.2. Instead of completely rewriting the code, we transformed the code into a series of parallel stages with serialization between stages as needed. Section 4.1 describes the stages of our parallel analysis. Section 4.2 presents five invariants for maintaining a consistent CFG, which coordinates creation of functions, basic blocks and edges, and mediates splitting blocks among threads. Finally, Section 4.3 discusses parallel control flow traversal.

4.1 Stages in Parallel CFG Construction

Listing 1 describes three main stages in our parallel analysis. It starts with initializing data structures for analyzing functions defined in the symbol table (Line 1). It is necessary to parallelize this step as we have seen large binaries containing millions of functions. This stage is parallelized with parallel loops. The second stage is the main analysis stage for constructing CFGs. We perform control flow traversal for initialized functions in parallel, during which we may discover more functions. We repeat the control flow traversal until until there are no more functions to analyze (Line 2 - 6). The details of control flow traversal are presented in Section 4.3. The final stage is to finalize the function boundaries for each function (Line 7). This stage performs a parallel graph search from each function entry block, traversing intra-procedural edges to determine which basic blocks belong to which function.

4.2 Control Flow Traversal Invariants

We use Figure 1 to illustrate how our five invariants ensure that threads work correctly with common code.

Figure 1. An example of five threads work with a common area of code. Solid edges represent the progress of threads. Bold solid edges represent actions to take place. Dashed edges represent control flow edges in the CFG.
Invariant 1: Block Creation. There is at most one basic block starting at any given address. This invariant means that if threads branch to the same target concurrently, one and only one thread should create the block and make the block visible to other threads. Maintaining this invariant requires efficient concurrent data structures that synchronize threads branching to the same target, while allowing threads branching to different targets to proceed independently.

In Figure 1a, threads $T_3$, $T_4$ and $T_5$ branch to the same address. According to this invariant, only one thread should create a new basic block. As shown in Figure 1b, $T_4$ creates a new basic block $B_3$. $T_3$ and $T_5$ do not create any new basic blocks and leave the common code area to work with other code. Independently, $T_1$ creates basic block $B_1$ and $T_2$ creates basic block $B_2$.

Invariant 2: Block End. There is at most one basic block ending at any given address. A naive way to implement this invariant is to let a thread check whether a block exists at its current working address. If there exists one, the working thread can end its block. However, this implementation means that there will be a block start lookup after decoding each instruction. This would create a performance hotspot on the concurrent data structure used for Invariant 1. Our design defers the block end check until the working thread reaches a control flow instruction. In this way, the frequency of global data structure lookup is reduced from once per instruction to once per control flow instruction.

As shown in Figure 1b, thread $T_1$, $T_2$ and $T_4$ will independently parse their blocks until they reach the indirect jump instruction. Based on this invariant, only one thread should register the block end address, which is $T_2$ in this example.

Invariant 3: Edge Creation. The thread that registers a block’s end is responsible for creating out-going control flow edges from that block end. This invariant ensures that no redundant control flow edges are created, which avoids redundant expensive jump table analyses and reduces unnecessary block start lookups by avoiding redundant edges. As shown in Figure 1b, because thread $T_2$ registers the block end, $T_2$ continues to perform control flow analysis to resolve the indirect jump targets and create control flow edges. $T_2$ then leaves the common code and continue to works with other code.

Invariant 4: Block Split. The threads that reach a block end but do not register the block end will need to split blocks. Suppose we have block $B_i[x_1, y)$, $B_j[x_2, y)$, ..., $B_n[x_n, y)$ created by n threads, where $x_1 < x_2 < \ldots < x_n < y$. The results of block split should be $B_i[x_1, x_2)$, $B_k[x_2, x_3)$, ..., $B_n[x_n, y)$, with a fall-through edge between each pair of adjacent basic blocks. Since it is inefficient to wait for all the relevant blocks before performing block splits, we design the following eager block split algorithm.

Based on Invariant 2 (block end), only one block $B_i[x_1, y)$ will register its end at $y$. When another block $B_j[x_2, y)$ reaches $y$, the working thread can look up $B_i$ as the registered block. Depending on the relationship between $x_i$ and $x_j$, we have two cases:

- If $x_i > x_j$, $B_j$ is split into $[x_j, x_i)$ while $B_i$ is untouched. We then register $B_i$ at block end address $x_i$, which will trigger a new iteration of block split when another block has already registered block end at $x_i$. As shown in Figure 1c, $T_1$ splits blocks $B_1$, registers $B_i$ ending at 0xA and then leaves the common code.
- If $x_i < x_j$, $B_i$ is split into $[x_i, x_j)$ while $B_j$ is untouched. We then replace $B_i$ with $B_j$ for block end address $y$, register $B_i$ for block end address $x_j$, and move outgoing edges from $B_i$ to $B_j$. Similar to the first case, registering $B_i$ at $x_j$ may recursively require another block split. As shown in Figure 1d, $T_4$ splits $B_2$ and moves control flow edges from $B_2$ to $B_3$.

For both cases, each iteration of the block split algorithm ends with a smaller block end address. Therefore, our block split algorithm is guaranteed to converge.

Invariant 5: Function Creation. There is at most one function starting at any given address. This invariant has similar properties and requirements to Invariant 1 for creating blocks.

4.3 Parallel Control Flow Traversal

Listing 2 presents the algorithm for control flow traversal. Coupled with the invariants defined in Section 4.2, control flow traversal can be performed in parallel.

The traversal is repeated until there are no more unanalyzed basic blocks (Line 2). For each unanalyzed block $b$, we use routine linearParsing to decode instructions until a control flow transfer instruction is encountered (Line 4). Modifications to Dyninst’s instruction decoding code add thread-safety to support this.

Routine registerBlockEnd follows invariant 2 (block end) to register the block end (Line 5). Only the thread that successfully registers the block end will see a non-empty set of control flow edges returned, following invariant 3 (edge creation). All other threads reaching the same block end will see an empty set of edges and will follow invariant 4 (block split) to split the blocks (Line 7).

The thread that creates the control flow edges will proceed to traverse the edges (Line 8 - 12). If we encounter a function call, we may need to create a new function, following invariant 5 (function creation) at Line 10. If we encounter a call-fallthrough summary edge or return edge, we process non-returning functions (Line 11). Handling non-returning functions will be discussed in more detail in Section 4.3.1. If we encounter other types of edges, such as indirect, direct or conditional branches, we create new basic blocks based on invariant 1 (block creation) at line 12.

In the rest of the section, we discuss how we improve the handling of non-returning functions, tail calls and jump tables in the context of parallel analysis.
Listing 2. The algorithm of control flow traversal.

4.3.1 Non-returning Functions

Serial ParseAPI implements the non-returning function analysis presented by Meng and Miller [18]. Each function has a return status, with three different values: UNSET, RETURN, and NORETURN. A function’s return status is initialized with NORETURN if it is known to be a non-returning function, otherwise a function’s return status is UNSET. Three main components in the non-returning function analysis are: (1) a function’s return status is set to RETURN if we find a return instruction; (2) if we encounter a call site calling to a function with UNSET return status, we do not parse the call-fallthrough edge until the callee’s return status is set to RETURN; (3) if there is a cyclic dependency between functions’ return statuses, all functions in the cycle are non-returning.

We identified that component (2) introduces dependencies between the analysis of functions. Serial ParseAPI will resume the caller once the analysis of the callee is finished. However, if the callee is a large function, the callers may have to wait for a long time. Such dependencies between functions limit parallelism.

We improve the non-returning function analysis to eagerly notify its callers once a function’s return status is set to RETURN. This simple improvement works well in practice because a large function may have many return instructions in it. As soon as we encounter one return instruction, we know this function is RETURN and we can resume the analysis of its callers.

4.3.2 Tail Calls

Serial ParseAPI uses three heuristics to determine whether a branch is or is not a tail call: (1) a branch to a known function entry is a tail call; (2) a branch to a basic block that is reachable through only intra-procedural edges of the current function is not a tail call; (3) if there is stack frame tear down before the branch, it is a tail call.

Parallelization exposes the flaws of these heuristics: the results of the heuristics depends on the order of analysis. In parallel, the order of analysis is non-deterministic from the threads’ interleaving, causing these heuristics to generate non-deterministic results. Listing 3 is an example where function A and B branch to the same address. If A is analyzed first, because leaveq tears down the stack frame, we will treat the branch in A as a tail call and create a new function at the branch target; later when we analyze B, we find that B branches to a known function entry, so the branch is in B also a tail call. In this case, function B will not include block at 0x400. On the other hand, if B is analyzed first, because there is no stack frame tear down before the branch in B, we will not treat the branch as a tail call, and the block at 0x400 will be part of B. Therefore, the function boundary of B is determined by the order of analysis.

To address the issue exposed by non-determinism, we correct tail call identification results during the function finalization stage. The rationale is that during finalization, all the basic blocks and edges have been created, so we have complete information about the CFG. For any branch that have been determined to not be a tail call, if there is a function at its target, we correct it to be a tail call.

4.3.3 Jump Table Analysis

Serial Dyninst implements a jump table analysis that uses backward slicing and symbolic execution. During the backward slicing, other threads may modify the CFG by creating new control flow edges, creating new blocks, and splitting blocks. The non-determinism of parallel analysis causes backward slicing to derive different symbolic expressions.

We address the non-determinism issue with a fixed-point analysis. The key insight here is that if the current analysis misses control flow edges or basic blocks created by other threads, the current analysis may miss a subset of indirect jump targets, but will never derive wrong jump targets. Therefore, we repeat the jump table analysis when the analysis of the function is done, which may find new basic blocks and trigger more analysis.

5 Thread-Safe Binary Analysis

A general parallelization pattern is to identify a parallelism unit and provide thread-safe analysis. This pattern can be applied to intra-procedural analysis, where the unit of parallelism is a function and intra-procedural analysis is then thread-safe by definition. Example intra-procedural analyses include constructing loop nesting, register liveness analysis, and program slicing. This pattern can also be applied to parallel DWARF parsing, where the parallelism unit is a compilation unit (a source file).
However, making the implementation of analysis thread-safe is complicated by the widespread uses of static and global variables and lazy initialization in the codebase. Data race detectors are designed to identify such offending variables in large codebases, but we have to suppress several types of false positives to make them effective.

### 5.1 Effective Use of Data Race Detectors

While we found data race detectors to be helpful in identifying races in the codebase, we also found that many false positives resulted from the lack of automatic support for the synchronization interfaces in use. Some cases could be handled by using more standard synchronization or recompiling dependencies (such as OpenMP), but for most we had to add “annotations” to our code to mark locations of interest and ensure the detector would understand its parallel semantics.

In Intel’s iclkscreen’s case, annotations take the form of API calls for a “fake” lock, identified by the address given as an argument. In cases where this was not sufficient, another annotation could be used to clear the access history for a region of memory, allowing the thread to insert it into a shared data structure without triggering reports. Valgrind’s annotations are quite different, taking the form of specialized macros that describe a happens-before ordering between threads, correlated again via an address argument.

While we found that “fake” locks generally had to be inserted around the usage of the difficult synchronization primitives, we also found that happens-before annotations could more often be written directly inline with the synchronization at work. Even so, language-specific synchronization constructs such as C++’s static initialization were not able to be annotated; for those cases we rewrote the code to explicitly use an annotated call_once.

While these could not handle every case, we were able to reduce 1000s of race reports to a mere 15, the remaining caused by the internals of TBB. Language and library support for data race annotations would have significantly accelerated our development and testing.

### 5.2 Parallel DWARF Parsing

A binary’s DWARF information is organized in a forest-like structure with a tree for each compilation unit. Since source files are typically of similar sizes across a project we simply used an OpenMP parallel for loop to process each of the CUs in parallel, accumulating their information in structures allocated in parallel by a previous phase. This resulted in thousands of race reports, which we handled first by mutex locks and then later by using concurrent data structures such as those discussed in Section 6.1 and Section 6.2. Some races were caused by code within Libdw, and in cases where the performance would suffer from full mutual exclusion we applied more significant modifications by implementing a resizeable hash table [8, 20, 34] in Libdw.

```
1 tbb::concurrent_hash_map<Address, Block*> blocks;
2 bool attemptToCreateBlock(Address a) {
3     Block* b = new Block(a);
4     if (blocks.insert((a, b)) { // Successfully registered the new block.
5         return true;
6     } else { // Block already exists.
7         delete b;
8         return false;
9     }
10 }
```

Listing 4. Example implementation of invariant 1 (block creation).

### 6 Implementation Experiences

Careful implementation that follows our parallelization design is crucial for correctness and high performance. We present several code examples and lessons we learned in our work.

#### 6.1 Sample Implementations of Invariants

In Section 4.2 we presented five invariants for parallel control flow traversal. An efficient implementation of these is the foundation for scalable parallel binary code analysis.

Listing 4 is a code example of our implementation for invariant 1 (block creation). This code example can be easily adapted to implement invariant 5 (function creation). Recall that two requirements for invariant 1 are (1) threads that branch to the same address should be synchronized and only one thread should create a new block, and (2) threads that branch to different addresses can make progress independently. Our implementation uses the concurrent hash map provided by Intel’s Threaded Building Blocks library [14] to fulfill these two requirements, which provides entry-level reader-writer locks. The insert method of concurrent_hash_map ensures that only one of the concurrent insertions with the same key will succeed (Line 5). Therefore, we can use the return value of insert to determine whether the current thread has successfully created a block and should continue analysis of the block (Line 7). Threads that see a false return value knows that another thread has created the block and can move on to other work (Lines 9 - 10).

Listing 5 is a code example showing how invariant 2 (block end), invariant 3 (edge creation), and invariant 4 (block split) fit together. concurrent_hash_map exposes the entry-level reader-writer locks via an “accessor” semantic. We can obtain an “accessor” for the existing entry in the table (inserting one if requested and not already present). The accessor acts as a read or write lock on the entry, and other threads that are trying to obtain a conflicting accessor will wait until the holding thread releases its own accessor. Line 4 ensures only one block is registered for a block end address, enforcing invariant 2. The accessor ensures that edges creation (Line 6) and block splitting (Line 10) are mutually exclusive. This
Listing 5. Example implementation for invariant 2 (block end), invariant 3 (edge creation), and invariant 4 (block split).

Listing 6. Implementation example for a thread-safe efficient map with multiple keys, discussed in Section 6.2.

6.2 Multi-Keyed Map Implementation

One of the more interesting structures we parallelized within Dyninst was a storage for symbols, supporting lookups by any of its four properties: byte offset, mangled name, "pretty" human-readable name and demangled "typed" name. The original implementation used a template class from Boost [5] to implement this, a very customizable structure called a multi_index_container. Since the Boost implementation is not thread-safe, after contention for its mutex lock became a notable bottleneck we redesigned the structure for concurrency as shown in Listing 6.

The key insight is that no lookups occur in parallel with an insertion or modification, so synchronization is only needed during writes. Two writes only conflict if the Symbol they are working with is the same, so we use the entry-level lock on the master table to mediate between threads. The thread which inserts on the master table proceeds to update the corresponding entries in the by* tables, retaining its lock to ensure that any other modifications to the collective entries occur in a total order. Once all modifications are complete, later lookups are able to use the by* tables directly, giving the same semantics as the original structure.

6.3 Performance Improvements

We summarize two implementation lessons that are beneficial for improving performance, starting with replacing parallel loops with task parallelism. As described in Section 4, we use a parallel for loop to perform parallel control flow traversal and collect new functions to analyze. The problem with this implementation is that analysis of newly collected functions will not start until all existing functions have been analyzed. This can cause significant idleness when the analysis of functions is imbalanced. To address this issue, our improved implementation uses OpenMP tasks as the parallel programming model and we launch a new task as soon as we discover a new function to analyze.

The second lesson is to use a thread local cache to reduce redundant calculations while not incurring thread synchronization overheads. For invariant 2 (block end) discussed in Section 4.2, we let each thread parse their blocks without any synchronization until reaching a control flow instruction. This design causes redundant instruction decoding between overlapping blocks analyzed by different threads. However, while functions sharing code is common, most of the code blocks in a binary are still not shared. This means that most of the time, a thread is going to branch into a block that was created by itself, not created by other threads. Therefore, we implemented a thread local cache that maintains the addresses that have been analyzed by the thread and use this cache to reduce redundant decoding.

6.4 Application Parallelization

Even if Dyninst's analysis capabilities are parallelized, binary analysis applications need to reduce serial execution to achieve good speedup. Based on our experiences of parallelizing two applications (HPCToolkit and BinFeat), we summarize a design pattern for parallelizing binary analysis applications.

Listing 7 shows an example code snippet to write parallel binary analysis applications. Line 2 uses the parallel CFG construction algorithm described in Section 4 to construct a CFG. Line 3 and 4 get the list of functions in the binary and sort the functions to address load balancing between threads. Sorting is important as functions will have different

```cpp
class Symtab::indexed_symbols {
    concurrent_hash_map<std::string, vector<Symbol*>> byMangledName;
    concurrent_hash_map<std::string, vector<Symbol*>> byPrettyName;
    concurrent_hash_map<std::string, vector<Symbol*> byTypedName;
    bool insert(Symbol* s) {
        accessor a;
        if(master.insert(a, {s, s->getOffset()}))
            return false; // Already inserted, no need to continue
        accessor a1;
        byOffset.insert(a1, s->getOffset());
        a1->second.push_back(s); }
        accessor a2;
        byMangledName.insert(a2, s->getMangledName());
        a2->second.push_back(s); }
        // ... etc...
        return true;
    }
};
```
Listing 7. Code example of utilizing Dyninst for parallel binary analysis applications.

sizes, which can cause notable unbalance if a large function is scheduled last in a work queue. Therefore, we sort the functions in decreasing order so that large functions are processed first. Within the parallel loop, the user can apply intra-procedural analysis in parallel to different functions.

To complete the parallelization of a binary analysis application, an application developer will also need to parallelize application-specific logic that is not related to binary analysis. For example, BinFeat needs to build a global feature index after extracting features from every functions in a binary. This operation can be parallelized with a reduction operation, which is a generic parallel computing primitive.

7 Evaluation

We evaluated the performance of our parallelization using hpcstruct, a utility in HPCToolkit for performance analysis, and BinFeat, a feature extraction tool for software forensics.

7.1 HPCToolkit’s hpcstruct

We use four large binaries to illustrate the effectiveness of our parallelization for speeding up performance analysis, including two binaries from Lawrence Livermore National Laboratory (LLNL1 and LLNL2\(^1\)), one large binary from Argonne National Laboratory (Camellia), and one shared library from TensorFlow [1].

Sizes of relevant sections of the four binaries are given in Table 1. LLNL1 is a Power little-endian 64-bit binary, LLNL2 and TensorFlow are x86-64, and Camellia is a Power big-endian 32-bit binary. LLNL1, LLNL2 and Camellia were compiled by their corresponding software development teams, while TensorFlow binary is from our parallelization for speeding up performance analysis, including two binaries from Lawrence Livermore National Laboratory (Camellia), and one shared library from TensorFlow [1].

`\(^1\)` Due to export control, we are unable to disclose the names of these binaries until approved by LLNL.

\(^2\)`Results for LLNL2 are based on one run for each thread count. We have limited access to the binary and cannot repeat the experiment.
within hpcstruct in Figure 2, which presents a performance trace of hpcstruct running on TensorFlow with 64 threads. The contents of each phase are as follows:

1. Read data from disk into an internal buffer.
2. (SymtabAPI) Parse DWARF type information in parallel and store in appropriate data structures. Imbalance in the sizes of compilation units can cause some idling.
3. (SymtabAPI) Parse address to function and line mappings from DWARF and store in a serial structure optimized for accelerated lookup.\(^3\)
4. (ParseAPI) Parse text regions in parallel to identify functions and construct the final CFG.
5. Convert line map and parsing results into a "skeleton" suitable for export.
6. Query Dyninst structures in parallel to fill the "skeleton" with the final data to be serialized.
7. Serialize data and write to disk in parallel with queries to mitigate the effects of serial processing.

Although our parallelization (2 and 4) scales well, the overall execution of hpcstruct has difficulties scaling. As per Amdahl’s Law, the serialization in application code (1, 5-7) and remaining difficulties (3) prevent our speedup from scaling past 13×. Applications with less serialization will see larger speedups.

7.2 BinFeat
Software forensic researchers typically use real world software to construct their training sets. We follow their practice and construct a set of binaries to analyze. We compiled Apache HTTP Server [29], Redis [32], Mysqlslap [30], and Nginx [31] with GCC-6.4.0 and -O2 optimization. Our data set contains 504 binaries. This experiment is ran on a x86-64 machine with 18 cores, 72 threads, 48MB L3 cache.

Table 3 shows the performance results for BinFeat. We achieved 7× overall using 32 hardware threads, but did not gain any improvement with 64 threads. Extracting instruction features (18×) and control flow features (16×) scale well to 64 threads.

The extraction of data flow features has only 9×. We find that its performance is hurt by imbalanced workload between threads. Note that we extract features from each function in parallel. Data flow analysis typically has a higher time complexity compared to analyzing instructions and traversing control flow graphs. Therefore, the analysis of large functions will dominate the whole execution.

CFG construction has only 4×. We identify two factors that limit its performance. First, the issue of imbalanced workload also applies to CFG construction as CFG construction uses a complicated data flow analysis to analyze jump table. Second, the analysis of function calls can cause task dependencies, because the caller cannot continue to parse the call-fallthrough edges until the return status of the callee is determined. Note that these two issues do not show up for large binaries used in the hpcstruct experiments. We find that large binaries contain sufficient number of functions to keep threads busy to hide these two issues.

8 Discussion
Benefiting other applications: Our work provides a general framework for researchers to parallelize their binary analysis applications. For example, software vulnerability searching calculates binary code similarity [7, 11] to match known vulnerable code. The calculation of binary code similarity utilizes binary analysis capabilities of analyzing machine instruction characteristics, control flow, and data flow. Our work has parallelized several common analysis capabilities and it will be interesting to see how our work benefits other binary analysis applications.
Compiler assisted analysis: Our work opportunistically use information from the compiler (such as providing correct and detailed labels in the code and DWARF). However, this is not the whole solution and we cannot rely on sufficient or even accurate compiler support. Surprisingly often for even the most widely-used compilers, the compiler-provided information is incomplete or inaccurate. One key issue is that binary analysis applications do not typically control which compiler to use to generate the binaries. For performance analysis, software developers often use the compiler and optimization flags that lead to greatest performance, which often leads to less accurate debugging information. Software forensic analysts deal with binaries collected from the wild, whose compiler generated information is often intentionally removed to defend against analysis. Therefore, while we use compiler assistance when available, we cannot not rely on its presence.

Other forms of parallelism: We focus on multithreading as the mechanism for parallelization. Other forms of parallelism can be used to further improving the performance of binary analysis applications. For example, BinFeat can benefit from node level parallelism by distributing the analysis of different binaries to different machines. We believe this type of parallelism is possible for certain specific applications, and is orthogonal to our work. Binary analysis application developers can benefit from our work and seek additional parallelization opportunities if necessary.

9 Conclusion
With the increasing size of software and the need for analyzing a large batches of binaries, adding multithreaded parallelism speeds up binary analysis, but doing so requires principled algorithm and data structure redesign and careful attention to implementation. Our work covers 146K lines of Dyninst and Libdw, both originally written with only sequential execution in mind. Without a good methodology for parallelization, we would have needed line-by-line code inspection to identify unsafe code; for a project of this size this was infeasible. The use of performance tools and data race detectors focused our attention to important problems, leading us to a redesign of parallel CFG construction algorithm, a large set of thread-safe analysis for parsing DWARF debugging information, analyzing loops, and data flow analysis, as well as a general pattern for parallelizing binary analysis applications. We evaluated our parallel binary analysis with a performance analysis tool hpcstruct and a software forensics tool BinFeat, achieving 25× for parallel CFG construction, 14× for ingesting DWARF, 8× for hpcstruct, and 7× for BinFeat using 64 hardware threads. Our results show that our parallel binary analysis can significantly speed up binary analysis applications, cutting the wait time of their users and developers.

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