Representing and Reasoning about Dynamic Code

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ABSTRACT
Dynamic code, i.e., code that is created or modified at runtime, is ubiquitous in today’s world. The behavior of dynamic code can depend on the logic of the dynamic code generator in subtle and non-obvious ways, e.g., JIT compiler bugs can lead to exploitable vulnerabilities in the resulting JIT-compiled code. Existing approaches to program analysis do not provide adequate support for reasoning about such behavioral relationships. This paper takes a first step in addressing this problem by describing a program representation and a new notion of dependency that allows us to reason about dependency and information flow relationships between the dynamic code generator and the generated dynamic code. Experimental results show that analyses based on these concepts are able to capture properties of dynamic code that cannot be identified using traditional program analyses.

KEYWORDS
Program Analysis, Program Representations, Dynamic Code, Self-Modifying Code, Slicing

1 INTRODUCTION
Dynamic code, i.e., code that is created or modified at runtime, is ubiquitous in today’s world. Such code arises in many contexts, including JIT-compilation, obfuscation, and dynamic code unpacking in malware. Dynamic code raises a host of new program analysis challenges, arising partly from the fact that the behavior of an application containing dynamic code may depend in part on logic that is not part of the application itself, but rather is in the dynamic code generator. As a concrete example, Rabet describes a JIT compiler bug in Chrome’s V8 JavaScript engine that causes some initialization code in the application program to be (incorrectly) optimized away, resulting in an exploitable vulnerability (CVE-2017-5121) [38]. As another example, Frassetto et al. describe how a memory corruption vulnerability can be used to modify the byte code of an interpreted program such that subsequent JIT compilation results in the creation of the malicious payload [14]. To reason about such situations, it would be helpful to be able to start from some appropriate point in the dynamically generated code and trace dependencies back, into and through the JIT compiler’s code, to understand the data and control flows that influenced the JIT compiler’s actions and caused the generation of the problematic code. E.g., for the CVE-2017-5121 bug mentioned above, we might want to perform automated analyses to identify which analyses/transformations within the JIT-compiler led to removal of the program’s initialization code, and which data flows and control-flow logic influenced those transformations. Such analyses, which we refer to as end-to-end analyses, can significantly speed up the process of identifying and fixing such problems.

Unfortunately, existing approaches to (static or dynamic) program analysis do not adequately support such reasoning about dynamic code modification. Traditional program representations, such as control flow graphs, cannot handle the effects of runtime changes to the code, which require accommodating the possibility of some memory locations having different instructions at different times during execution. JIT compilers [15, 23] and dynamic binary translators [34] maintain representations of the code being dynamically modified, but not together with that of the code that performs code modification. Whole-system analyses [11, 13, 21, 53, 54] perform dynamic taint propagation, taking into account explicit information flows via data dependencies but not implicit flows via control dependencies. As we discuss later, they also do not take into account dependencies that can arise through the act of dynamic code modification. Thus, existing approaches to automated reasoning about program behaviors suffer from the following shortcomings:

(a) They do not provide program representations that let us answer questions such as “Which code in the dynamic code generator affected the generation of the faulty application code?” or “What data flows influenced the behavior of those components of the dynamic code generator, and in what ways?”.

(b) They do not support notions of dependence that can allow us to reason about the computation in ways that can help answer such questions.

This paper shows how this problem can be addressed via a program representation that is able to capture the structure and evolution of code that can change dynamically, together with a notion of dependency that arises from the process of dynamic code generation and which is not captured by conventional notions of data and control dependencies. We also discuss an optimized representation that yields significant improvements in space requirements. Experimental results show that our ideas make it possible to reason about dynamic code in novel ways, e.g., we can construct backward dynamic program slices, starting from incorrect dynamically generated JIT-compiled code, to include the JIT-compiler logic responsible for the problem; and detect situations where a dynamic
code generator embeds environmental triggers in dynamically generated code. Such end-to-end analyses are not possible using current approaches to program analysis.

2 BACKGROUND

This section briefly discusses some key concepts relevant to our ideas. It may be skipped by readers familiar with this material.

2.1 Interpreters and JIT Compilers

An interpreter is a software implementation of a virtual machine (VM). Programs are expressed in the VM’s instruction set, with each instruction encoded as a data structure that records relevant information such as the operation, source and destination operands, etc. The computation for each operation x in the VM’s instruction set is performed by a piece of code called the handler for x. The interpreter uses a virtual instruction pointer to access the VM instructions encoding the input program and a dispatch routine to transfer control to appropriate handler code.

While interpretation offers a number of benefits such as portability, it incurs a performance overhead due to the cost of instruction decoding and dispatch as well as the limited scope for code optimization resulting from the fact that the user programs executed by the interpreter are not available for analysis when the interpreter is compiled to machine code. Additionally, modern dynamic languages are often implemented using interpreters, and these incur additional overheads due to runtime type checking.

To address this problem, just-in-time (JIT) compilers are widely used alongside interpreters to improve performance by compiling selected portions of the interpreted program into (optimized) code at runtime. The general idea is to take frequently-executed portions of the program (identified via runtime profiling), apply optimizing transformations, and generate optimized machine code. These optimizations are performed at runtime, as the program is being executed, and results in code that is dynamically created or modified. Some JIT compilers support multiple levels of runtime optimization, where the dynamically created code may be subjected to additional rounds of optimization as execution progresses [45].

2.2 Control Flow Graphs

Program analyses are based on representations of the program’s structure; for concreteness, we focus on control flow graphs (CFGs). CFG construction for static code via static analysis is well-understood [3]. However, this approach is inadequate for dynamic code because code created at runtime is not available for static inspection; instead, we use dynamic analysis. This has the benefit of being able to handle dynamic code; its drawback is that the constructed CFG may not contain all of the program’s code due to incomplete code coverage. We sketch here how CFGs for static code can be constructed from an instruction trace obtained via dynamic analysis. The extension of this approach to dynamic code is discussed in Section 3.4.

Let G denote the CFG under construction. We process instructions in the execution trace as they are encountered. For each instruction I, its properties (e.g., whether or not it is a control transfer) and its status within G (e.g., whether or not it is already in G) determine how it is processed; we refer to this as "processing I in the context of G." If I has not been encountered previously, it is added as a new instruction. If I follows a conditional or unconditional jump, it should begin a basic block: thus, if I is currently in G and is not the first instruction of its block, the block has to be split and control flow edges added appropriately.

Multi-threading introduces additional complexity because adjacent instructions in the execution trace may be from different threads and thus may not represent adjacent instructions in the code. To handle this, we require that each instruction in the trace be flagged with a value indicating the thread that executed it; we refer to this as the thread-id of the instruction. The CFG construction process separately maintains a summary of the state of each thread; this summary contains information such as the call stack, previous instruction seen, current function being reconstructed, etc. When constructing the CFG G, each instruction I in the trace is now processed in the context of the state summary for its thread, which is obtained from the thread-id for I. Thus, the last instruction from one thread may be appending an instruction to a basic block whereas a different thread could be splitting a different block.

3 REASONING ABOUT DYNAMIC CODE

This section discusses the concepts underlying our approach to representing and reasoning about dynamic code.

3.1 Design Goals

In devising program representations that support end-to-end analysis of dynamic code, we have the following design goals:

1. It should be a natural and scalable generalization of existing program representations.
2. It should provide a basis for extending existing program analyses to handle dynamic code in a natural way.
3. It should be precise enough to distinguish between conceptually distinct dynamic code changes.

The first two goals aim to avoid reinventing the wheel as much as possible. The third is motivated by the fact that dynamic code changes can be quite complex. For example, JIT compilers typically use shared code buffers that may be repeatedly reused to hold different, and possibly unrelated, pieces of dynamically generated code; different dynamically optimized code fragments may involve different runtime optimizations; pieces of dynamically optimized code may sometimes be “deoptimized” to free up space in the shared code buffer; and such deoptimized code and may later get dynamically optimized again, possibly with a different set of optimizations that involve different parts of the JIT compiler. The third goal aims to obtain program representations that are able to separate out the effects of such complex runtime code changes and allow analyses to reason about them.

3.2 Dynamic Code Modification

Dynamic code modification can give rise to different versions of the program, with different instructions and behaviors, at different points in its execution. A representation suitable for end-to-end analysis of dynamic code should keep track of the different versions of the code resulting from dynamic modification. There are two issues to consider here: (1) what constitutes “dynamic code
modification?” and (2) how should such modifications be captured in the program representation? We address these questions as follows. First, we note that in general, heuristic approaches, such as categorizing a memory write as code modification if it targets an executable section of the program’s memory, may not be sufficiently precise, e.g., because permissions on memory pages can be changed during execution, making a non-executable memory region executable. We therefore consider a write to a memory location $\ell$ as “code modification” only if $\ell$ is part of some instruction that is subsequently executed. Second, even small dynamic code modifications can result in arbitrarily large changes to the program’s representation and behavior. In the x86 ISA, for example, the arithmetic instruction “bitwise exclusive or” (opcode: xor; encoding: 0x32) can, by flipping a single bit, be changed to the control transfer instruction “jump short if below” (opcode: jbr; encoding: 0x72), with potentially large effect on the control flow graph.

Based on these observations, we build our program’s CFG using dynamic analysis, as described in Section 2.2, until we encounter an instruction whose memory locations have been modified. At this point we are confronted with a potentially arbitrary change to the program’s behavior and representation. To capture this, we begin construction of a new CFG, which we link to the previously constructed CFG using a special type of edge that we call a “dynamic edge.” Each such linked CFG corresponds to a “phase” of the program’s execution. We make this notion more precise below.

**Terminology.** In some situations, it may make sense to distinguish between code created at runtime prior to being executed (“dynamic code generation”) and code modified at runtime after it has already been executed (“dynamic code modification”). The ideas described here apply to both these situations, and we use the terms “generation” and “modification” of dynamic code interchangeably.

### 3.3 Concepts and Definitions

#### 3.3.1 Phases

The idea behind phases is to partition an execution of a program into a sequence of fragments $\phi_0, \phi_1, \ldots, \phi_i, \ldots$ such that for each $\phi_i$, none of the locations written by the instructions in $\phi_i$ is part of any instruction executed by $\phi_i$. Each $\phi_i$ is referred to as a phase. Execution begins in phase $\phi_0$ with the program’s initial code. When the first dynamic instruction is encountered, we switch to $\phi_1$. Execution continues in $\phi_1$ (including other instructions that may have been created or modified in $\phi_0$) until an instruction is encountered that was modified in $\phi_1$, at which point we switch to $\phi_2$, and so on. This is illustrated in Figure 1. An execution with no dynamic code consists of a single phase.

More formally, given a dynamic instance $I$ of an instruction in a program, let $\text{instr\_locs}(I)$ denote the set of locations occupied by $I$ and $\text{write\_locs}(I)$ the set of locations written by $I$. These notions extend in a straightforward way to a sequence of instructions $S$: $S := \phi_1, \phi_2, \ldots$ with $\phi_i$ for $i > 0$ being such that each $\phi_i$ is a subsequence of $S$ and $\phi_1$ is a phase.

**Figure 1: Phases**

#### 3.3.2 Dynamic Control Flow Graphs

We use the notion of phases to construct control flow graphs for dynamic code: we construct a CFG for each phase of the execution, as discussed in Section 2.2, and link them together using special edges, called dynamic edges, that represent the control flow from the last instruction of one phase to the first instruction of the next phase. We refer to such a CFG as a dynamic control flow graph (DCFG). More formally:

**Definition 3.2.** Given an execution trace $T$, the phases of $T$, denoted $\Phi(T)$, is a sequence $\phi_0, \phi_1, \ldots, \phi_i, \ldots$ of subtraces of $T$ such that the following hold:

- $\phi_0 = T[0 : k]$, where $k = \max_{j} \{ j \mid j \geq 0 \}$ and $\text{write\_locs}(T[0 : j]) \cap \text{instr\_locs}(T[0 : k]) = \emptyset$;
- For $i > 0$, let $\phi_i = T[k : (m - 1)]$, then $\phi_{i+1} = T[m : n]$, where $n = \max_{j} \{ j \mid j \geq m \}$ and $\text{write\_locs}(T[m : j]) \cap \text{instr\_locs}(T[m : n]) = \emptyset$.

**Figure 2: DCFG: An example**

Given an execution trace $T$ for a program, let $T[i]$ denote the $i$th instruction in $T$, and $T[i : j]$ denote the sequence (subtrace) $T[i], \ldots, T[j]$. We define the phases of $T$ as follows:

**Definition 3.1.** Given an execution trace $T$, the phases of $T$, denoted $T[\phi_0, \phi_1, \ldots, \phi_i, \ldots]$ of subtraces of $T$ such that the following hold:

- $\phi_0 = T[0 : k]$, where $k = \max_{j} \{ j \mid j \geq 0 \}$ and $\text{write\_locs}(T[0 : j]) \cap \text{instr\_locs}(T[0 : k]) = \emptyset$;
- For $i > 0$, let $\phi_i = T[k : (m - 1)]$, then $\phi_{i+1} = T[m : n]$, where $n = \max_{j} \{ j \mid j \geq m \}$ and $\text{write\_locs}(T[m : j]) \cap \text{instr\_locs}(T[m : n]) = \emptyset$.

**Example 3.3.** Figure 2 gives a simple example of a DCFG. The static CFG of the program under consideration is shown in Figure 2(a). When instruction $I_2$ is executed, it changes instruction $I_1$ to $I_{1a}$ (indicated by the dashed red arrow), where $I_{1a}$ is a conditional branch with possible successors $I_2$ and $I_3$. The following is an execution trace for this program along with its phases:
The first phase, $\varphi_0$, consists of the instruction sequence $i_0, i_1, i_2, i_4$. When control returns to the top of the loop at the end of this sequence, instruction $i_1$ is found to have been changed to $i_f$. This ends $\varphi_0$ and begins $\varphi_1$, which comprises the rest of the trace, $i_1, i_3, i_4, i_1, i_5$. The CFGs corresponding to phases $\varphi_0$ and $\varphi_1$ in Figure 2(b) are $G_0$ and $G_1$ respectively. Finally, the control transfer from $\varphi_0$ to $\varphi_1$ is indicated via a dynamic edge from the basic block of the last instruction of $\varphi_0$ to the basic block of the first instruction in $\varphi_1$, i.e., from the block for $i_4$ in $G_0$ to the block for $i_1$ in $G_1$.

The reader may notice, in Example 3.3, that the basic block containing $i_4$ occurs in both $G_0$ and $G_1$. This illustrates a potential drawback of a naive implementation of DCFGs, namely, that CFG components may be replicated across different phases. It is possible to implement DCFGs to avoid such replication, but in this case it is important to ensure that algorithms that traverse the DCFG (e.g., for slicing) do not follow unrealizable paths. The details for merging phases are discussed in Section 4; Section 6.3.3 briefly sketches the performance improvements we see from implementing sharing of DCFG components across phases.

3.3.3 Codegen Dependencies. Dynamic code modification can induce a dependency between the code performing the modification and the resulting modified code. Consider the following example:

![Algorithm 1](image)

In this example, B is an instruction that adds an immediate value $imm$ to the register $r_0$; the bytes of B containing $imm$ are at address $loc$. Thus, if $loc$ contains the value 5, then $B \equiv \text{add } r_0, 5\text{.'}$. Instruction A writes the contents of register $r_1$ to address $loc$, thereby modifying B. When $B$ is executed, the value added to $r_0$ depends on the value written to address $loc$ by A. Thus, the execution of A affects the behavior of B through the act of dynamic code modification, independent of any data or control dependencies that may exist in the program. We refer to dependencies arising in this way due to dynamic code modification as codegen dependencies. More formally:

**Definition 3.4.** Given an execution trace $T$, a dynamic instance of an instruction $I \equiv T[i]$ is codegen-dependent on a dynamic instance of an instruction $J \equiv T[j]$ ($j < i$) if and only if, for some $loc \in \text{inst}_\text{locs}(I)$, the following hold:

1. $loc \in \text{write}_\text{locs}(J)$, i.e., $J$ modifies the location $loc$; and
2. $\exists k$ s.t. $j < k < i$ : $loc \notin \text{write}_\text{locs}(T[k])$, i.e., $J$ most recently modifies $loc$ before $I$ is executed.

While codegen dependencies resemble data dependencies in some ways, they differ in one fundamental way. If an instruction $I$ is data dependent on an instruction $J$, then $J$ can change the values used by $I$, but not the nature of the computation performed by $I$. By contrast, if $I$ is codegen dependent on $J$, then $J$ can change the nature of the computation performed by $I$, e.g., from an $xor$ instruction to a $jump-if-below$ instruction as discussed earlier.

### 3.4 DCFG Construction

Algorithm 1 shows how we construct a DCFG from an execution trace. The algorithm is based directly on Definition 3.2 and constructs an unoptimized DCFG. The DCFG consists of a sequence of CFGs $\{G_\varphi | \varphi = 0, 1, \ldots, 4\}$, one per phase, linked together by dynamic edges; we refer to the index $\varphi$ for these CFGs as their phase index. The algorithm proceeds as follows. We initialize the phase index $\varphi$ to 0 and the DCFG $G$ to an empty graph. We then iterate through the trace processing each instruction $T[i]$ in turn. If $T[i]$ begins a new phase, we increment the phase index (line 10), reset $W$ to an empty graph, and add this new $V_\varphi$ to the DCFG $G$ (lines 10–12). We then process the instruction $T[i]$ in the context of the CFG $G_\varphi$, as discussed in Section 2.2. At this point, if $T[i]$ is the first instruction of a phase (line 14), it has been added to $G_\varphi$, which means $G_\varphi$ has a basic block for it, so we add a dynamic edge from the basic block of the last instruction of the previous phase to the basic block of the first instruction of the current phase (line 15). Finally, we update the set of written memory locations by adding to the set of locations written by $T[i]$ (line 16). We then continue the process with the next instruction of $T$.

### 4 SPACE OPTIMIZATION OF DCFGS

DCFGs constructed using the straightforward approach described in Algorithm 1 may contain redundancies. This is illustrated in Figure 3, which shows the execution of a program where a function $f$ is JIT-compiled and the resulting code is executed, after which a different function $g$ is JIT-compiled and executed. Suppose that the program’s execution begins in phase $\varphi_0$. The memory writes that
create the JIT-compiled code for \( f \) are thus in \( \phi_0 \). The execution of the JIT-compiled code for \( f \) therefore causes a transition to a new phase \( \phi_1 \). Subsequently executed instructions, including the JIT-compiled code for \( f \) and the JIT-compilation of \( g \), are then a part of \( \phi_1 \). When the JIT-compiled code for \( g \) is executed, there is a transition to a new phase \( \phi_2 \). Thus, the JIT-compiler code executed when compiling \( f \) is part of \( \phi_0 \); while the JIT-compiler code executed when compiling \( g \) is part of \( \phi_1 \). The control flow graphs constructed from these two invocations of the JIT-compiler are therefore replicated, once in \( \phi_0 \) and once in \( \phi_1 \), means that there is potential for a significant amount of redundancy in a naively constructed DCFG. In general, the situation described arises if the same code is invoked multiple times from different phases.

A natural approach to addressing the redundancy problem would be to merge the repeated components of the DCFG. For example, if the JIT compiler is invoked multiple times in the course of execution, as in Figure 3, we can coalesce the various replicated control flow graphs for the JIT compiler into a single copy and redirect all control flow edges accordingly. However, a naive approach to such coalescing can lead to a loss in precision of analysis by propagating information along unrealizable paths, similar to the issue of context-sensitivity in interprocedural program analysis [32, 40, 43, 51].

An important difference between the general problem of context-sensitive interprocedural analysis (i.e., k-CFA) and the issue of merging replicated code in DCFGs is that of the nature and complexity of the context relationships that arise. Programs can have arbitrarily complex call graphs, and increasing the amount of context information maintained during interprocedural analyses can therefore increase the precision of analysis, albeit at increased cost [22]. Phases in a DCFG, on the other hand, have a predictable linear progression, with phase \( n \) transitioning to phase \( n+1 \) on encountering dynamic code. This predictable structure of inter-phase relationships means that, given the phase number of a function or basic block in a DCFG, identifying the phase number of the previous or next phase is straightforward. This allows us to implement this optimization efficiently at all levels of granularity—namely, instructions, basic blocks, edges, and functions—without incurring the complexity and cost of general k-CFA.

Our implementation of merged DCFGs associates a set of phase identifiers with each DCFG component (instruction, basic block, and edge). In the simple case, there are \( N \) identical blocks, each containing the same sequence of instructions, that appear in \( N \) phases \( a_1, \ldots, a_N \). We merge these into a single block, which is then associated with a set of phase identifiers \( \{a_1, \ldots, a_N\} \). The resulting merged block must also account for merging the edges into/out of it. An edge that occurs in a single phase gets the phase identifier for that phase. Shared edges, on the other hand, are edges that connect the same blocks in multiple phases. These are merged into a single edge whose set of phase identifiers is the union of the phase identifiers for the phases in which that edge appears.

Merging basic blocks becomes more complex when sharing similar but non-identical blocks. We take advantage of the similar portions of the blocks using a notion of “splitting a block across a phase.” To split a block across a phase we introduce a new type of edge which we call a “ghost edge.” Conceptually, a ghost edge \( e \) is an intra-block connector and indicates that, for the given phase identifiers associated with \( e \), the two sub-blocks connected by \( e \) should be treated as a single block. Using ghost edges we can split a block, merging the shared components across multiple phases while still keeping unique portions of the block that could not be shared. Figure 4 shows an example of merging sub-parts of a block.

When traversing a merged DCFG, a traversal along the edges and basic blocks of one phase should not take an edge leading out of a shared basic block associated with a different phase if the outgoing edge is not shared between the two phases. We use the sets of phase identifiers associated with basic blocks and edges to enforce this requirement and only allow traversals across components with matching phase identifiers.

## 5 APPLICATIONS

This section discusses a few applications of DCFGs and codegen dependencies to reasoning about dynamic code.

### 5.1 Program Slicing for Bug Localization and Exploit Analysis in JIT Compilers

Program slicing refers to identifying instructions that (may) affect, or be affected by, the value computed by an instruction in a program [2, 30, 48]. Slicing can be static or dynamic; and, orthogonally, forward or backward. By eliminating instructions that are provably irrelevant to the computation of interest, slicing reduces the amount of code that has to be examined in order to reason about it. In the context of dynamic code modification, DCFGs play a crucial role in providing control flow information needed to construct backward slices. Analyses that reason about dynamic code solely through data dependencies, e.g. using taint propagation [11, 13, 21, 54] are unable to capture the effects of control dependencies and therefore are unsound with respect to slicing.

We implemented backward dynamic slicing as an application for evaluating the efficacy of DCFGs and codegen dependencies, with the goal of bug localization and exploit analysis in JIT compilers.
Backward dynamic slicing aims to identify the set of instructions that may have affected the value of a variable or location at some particular point in a particular execution of the program. Our implementation is based on Korel’s algorithm for dynamic slicing of unstructured programs [30]; however, any slicing algorithm for unstructured programs would have been adequate.

In Korel’s slicing algorithm [30], an instruction \( I \) at position \( p \) in a trace \( T \) (i.e., \( I \equiv T[p] \)) depends on an instruction \( J \equiv T[q] \) (written \( I \sim (\text{Korel}) J \)) if and only if, for some source operand \( a \) of \( I \), \( J \) is the last definition of \( a \) at position \( p \). More formally:

\[
I \sim (\text{Korel}) J \iff (\exists \text{ a source operand } a \text{ of } I): \left[ a \in \text{write_locs}(J); \right. \\
\left. (\forall n: q < n < p : a \notin \text{write_locs}(T[n])) \right]
\]

When processing an instruction \( I \), Korel’s algorithm (lines 5 and 16 of Fig. 11 [30]) marks all instructions \( J \) such that \( I \sim (\text{Korel}) J \). To work with dynamic code, we modify this notion to also take codegen dependencies into account, writing the resulting notion of dependency as \( I \sim\sim (\text{Korel}) J \):

\[
I \sim\sim (\text{Korel}) J \iff (\exists \text{ a source operand } a \text{ of } I): \\
\left[ a \in \text{write_locs}(J); \right. \\
\left. (\forall n: q < n < p : a \notin \text{write_locs}(T[n])) \right] \\
(\forall n: q < n < p \Rightarrow a \in \text{write_locs}(T[n]))
\]

Our slicing algorithm is identical to Korel’s except for two generalizations:

1. Codegen dependencies are taken into account in propagating dependencies. In the marking step of the algorithm (lines 5 and 16 of Fig. 11 [30]) we use the \( \sim\sim \) relation rather than the \( \sim \) relation used by Korel [30].
2. The structure of the DCFG is taken into account by treating dynamic edges similarly to jumps (in the terminology used by Korel [30], this corresponds to the notions of \( j\text{-entry} \) and \( j\text{-exit} \)).

5.2 Detecting Environmental Triggers in Malware

Malware sometimes use environmental triggers to evade detection by performing malicious actions only if the right environmental conditions are met, e.g., if the date has some specific value. Current work on detecting such behaviors is geared towards static code, e.g., identifying conditional branches with input-tainted operands [6]. The idea is to use dynamic taint analysis to identify conditional branches of the form ‘\( \text{if expr then behavior}_1, \text{else behavior}_2 \)’ where \( \text{expr} \) is tainted from (i.e., influenced by) some input values. Once such conditionals have been identified, other techniques, e.g., using SMT solvers to generate alternate inputs, can be used to further explore the program’s behavior.

Dynamic code opens up other ways to implement environmental triggers, e.g., by using the environmental input to directly affect what instruction bytes are generated. This idea can be illustrated by adapting an example of evasive behavior, described by Brumley et al. [6], to use dynamic code instead of a conditional. The code, shown in Figure 5, uses bit-manipulation instead of conditionals to evaluate the trigger expression, thereby rendering inapplicable techniques that rely on tainted conditionals. The variable \( \text{day}_\text{bits} \) is set to 1 or 0 depending on whether or not the most significant bit of the value of the expression \( \text{day} \geq 9 \) is 0, i.e., whether or not the predicate \( \text{day} \geq 9 \) is true. Similarly, \( \text{mth}_\text{bits} \) is 1 or 0 depending on whether or not \( \text{month} \geq 7 \) is true. Thus, the variable \( \text{trigger} \) is 1 or 0 depending on whether the environmental trigger—in this example, the predicate \( \text{day} \geq 9 \) & \( \text{month} \geq 7 \)—is true or not. The assignment to \( *\text{(addInstrPtr+11)} \) writes this value into the source byte of an assignment to a variable that is used in a conditional to determine whether the malicious behavior is manifested.\(^1\) Note that the conditional that controls the execution of the \( \text{payload}() \) function is neither data-dependent nor control-dependent on the input; instead there is a codegen dependency between this conditional and the patching instructions, which are data dependent on the input.

Our current implementation generalizes the approach of Brumley et al. [6] to incorporate codegen dependencies: we taint the values obtained from any environmental inputs of interest, then propagate taint in a forward direction. We determine that an environmental trigger is present if either of the following hold:

1. A conditional jump instruction with one or more tainted operands is executed; or
2. There is a codegen dependency where the value written is tainted (equivalently: one or more memory locations containing an executed instruction are tainted).

The first condition is that originally used by Brumley et al. [6], while the second condition incorporates the effects of dynamic code modification. Analysis of the code shown in Figure 5 proceeds as follows. The values obtained from the call \( \text{localtime}() \) are tainted. This causes the variables \( \text{day}_\text{bits} \) and \( \text{mth}_\text{bits} \), and hence the variable \( \text{trigger} \), to become tainted; this tainted value is then written to memory via the assignment

\[ *(\text{addInstrPtr+11}) = \text{trigger} \]

When the function \( \text{hide}() \) is subsequently executed, the location written by the above assignment is found to be a code location, thereby indicating a codegen dependency where the value written is tainted. This indicates the presence of an environmental trigger.

6 Evaluation

6.1 Overview

We built a prototype implementation to evaluate the efficacy of our ideas and ran our experiments on a machine with 32 cores (@ 3.30 Ghz) and 1 TB of RAM, running Ubuntu 16.04. We used Intel’s Pin software (version 3.7) [31] for program instrumentation and collecting instruction-level execution traces; and XED (version 8.20.0) [24] for instruction decoding. We iterate over the instruction trace to construct a DCFG for the execution. We identify dynamic code and determine codegen dependencies using taint analysis: we taint writes to memory, with each memory write getting a distinct taint label. For each instruction in the trace we check whether any of its instruction bytes is tainted, in which case the instruction is flagged as dynamic.

Our evaluations focused on the following questions:

\(^1\)This code relies on the appropriate byte of the modified instruction being at a specific offset—in this case, 11 bytes—from the beginning of that function’s code, and therefore is obviously highly compiler- and system-dependent. This is not atypical of malware, which are usually launched as system-specific binary executables.
We evaluated the capabilities of existing state-of-the-art tools using three widely-used modern dynamic analysis tools that implement backward dynamic slicing: PinPlay [36], angr [44, 47], and Triton [42].

### 6.2 Assessing the Capabilities of Existing Tools

We used the capabilities of existing state-of-the-art tools using three widely-used modern dynamic analysis tools that implement backward dynamic slicing, namely: PinPlay [36] (revision 1.29), angr [44, 47] (commit bd3c6d8 on github), and Triton [42] (build no. 1397).

![Figure 5: Environmental trigger based on dynamic code](image)

**Figure 5:** Environmental trigger based on dynamic code

1. **How capable are existing state-of-the-art dynamic analysis tools at end-to-end reasoning of dynamic code?**

To answer this question we used two small synthetic benchmarks to evaluate three widely-used modern dynamic analysis tools: PinPlay [36], angr [44, 47], and Triton [42].

2. **How effective are our ideas in reasoning about dynamic code in scenarios involving problems in real-world software?**

To evaluate this question, we consider two kinds of experiments: (1) dynamic slicing for bug reports and exploits for the JIT compiler in V8, the JavaScript engine in Google’s Chrome browser; and (2) two benchmarks that use dynamic code for environmental triggers in malware.

3. **What is the performance impact of the merging optimizations discussed in Section 4?**

The bug/exploit proof-of-concept code used in the slicing experiments mentioned are deliberately constructed to crash the software quickly, and thus do not reflect typical application behavior. We use the Jetstream benchmarks (Sec. 6.4) to more accurately evaluate the impact of our memory optimizations on typical application code.

The code for our prototype implementation is available at [GitHub link](https://github.com/skdebray/ASE-2020) and [Arizona link](https://www2.cs.arizona.edu/projects/lynx-project/Samples/ASE-2020). Our data samples are available at [Arizona link](https://www2.cs.arizona.edu/projects/lynx-project/Samples/ASE-2020).
Additionally, to assess the applicability of these tools to real-world software that makes use of dynamic code, we evaluated them on six bug and exploit reports for the V8 JIT compiler. As shown in Table 1, none of them were able to successfully analyze these examples: they all crashed with internal errors when loading V8. All three tools were able to process the LuaJIT example without crashing, but none of the slices they computed contained the JIT compiler or exploit code that created the dynamic code.

### 6.3 Analysis Efficacy on Real-World Examples

To evaluate our approach on real-world software that uses dynamic code, we consider three applications: (1) analysis of exploits involving JIT code; (2) bug localization in JIT compilers; and (3) detection of trigger-based evasive behaviors that use dynamic code. Our goal was to perform end-to-end analyses on these examples, i.e., start from the problematic dynamic code and compute a backward dynamic slice that includes the culprit portions of the dynamic code generator where the bug/security exploit originates. The results are shown in Table 1.

#### 6.3.1 Exploit Analysis. We consider three examples of exploits, two of them involving dynamic code in Google’s V8 JavaScript engine:

1. malicious shellcode originating from an out-of-bounds (OOB) write to the JIT code pages in V8 [9];
2. escape analysis bug in V8’s JIT compiler (CVE-2017-5121) [38]; and
3. malicious bytecode used to escape a LuaJIT sandbox [8].

For each of these exploits, we used the proof-of-concept code to compute a DCFG/backward dynamic slice starting from the dynamically generated exploit code. Separately, we used the write-up for each exploit to determine the bugs responsible for each exploit, identifying the buggy code generator portions in the execution traces recorded for each exploit. We then checked the slice to determine whether the buggy generator code is present in the slice.

The first security exploit we consider entails an OOB write to the JIT code pages within Google’s V8 JavaScript engine [9]. The exploit is a result of array type ambiguity that allows the attacker to write and execute arbitrary shellcode. We constructed a DCFG from an execution trace of the buggy V8 code and computed a backward dynamic slice from the first NOP shellcode instruction in the NOP sled in the attack code. Our backward slice correctly included both the buggy code within V8 that led to the array type ambiguity along with the exploit code that generated the shellcode at runtime.

The second exploit we examined is discussed in detail by Rabet [38]. It arises out of a bug in V8’s escape analysis and causes some variable initializations in the JIT-optimized code to be incorrectly optimized away when performing load reduction. The proof-of-concept code provided causes V8 to crash while executing the optimized dynamic code due to an OOB read. The write-up provided by Rabet proceeds to use this OOB read as a stepping stone towards demonstrating arbitrary code execution. For our analysis of this example, we built our DCFG from the execution trace recorded by Pin and then we computed a backward dynamic slice from the dynamic instruction prior to the exception that is thrown due to the OOB read. We found that the resulting slice correctly included the buggy portions of the load reducer in the escape analysis phase of V8’s JIT compiler, whose optimizations cause the OOB read.

Our final example in this category was with malicious Lua bytecode being used to escape a sandbox in LuaJIT [8]. The proof of concept malicious program corrupts bytecode with the goal of writing shellcode which prints a message. We followed an approach similar to the one we used to slice the V8 OOB write, starting our slice at the beginning of the NOP sled used in the attack. We found that the backward slice computed by our tool correctly picks up the Lua code that generates the shellcode.

The **role of codegen dependencies.** For each exploit example discussed, we computed slices starting at a NOP instruction in the NOP sled generated as part of the shellcode. To assess the role of codegen dependencies, we recomputed these slices ignoring codegen dependencies. We found that, in each case, the resulting slice consisted of just the NOP instruction and nothing else. By contrast, when codegen dependencies were considered, the relevant JIT-compiler code was included in the slice. This demonstrates that codegen dependencies are fundamental to reasoning about the relationship between dynamically generated code and the dynamic code generator that created that code.
6.3.2 Bug Localization. We consider three JIT compiler bugs from Google’s V8 JavaScript engine that were posted to bugs.chromium.org and classified as “Type: Bug-Security.”

(1) Empty jump tables generated by the bytecode generator leading to out-of-bound reads that crash the generated JIT-compiled code [17].

(2) A type confusion bug that leads to a crash after the dynamic code has been generated [18].

(3) Arrow function scope fixing bug, where certain constructs involving a single line arrow function cause a crash [19].

For each of these bugs we proceeded as follows. To identify the problematic code in the JIT compiler, we examined the corresponding GitHub commits, together with any relevant information in the bug report, to determine the code that was changed to fix the bug. We delineated the problem code so identified using small “marker code snippets”—i.e., small easily identifiable code snippets that do not affect the operation of the JIT compiler—and confirmed that the behavior of the buggy JIT compiler was unaffected. We then used the example code submitted with the bug report to obtain an execution trace demonstrating the bug, and used this trace, together with the DCFG constructed from it, to compute a backward dynamic slice starting from the instruction that crashed. Finally, we analyzed the resulting slice to determine whether the problematic code, as identified above, was included in the slice.

The results of our experiments are summarized in Table 1. Our end-to-end analysis was able to successfully pick up the buggy code for each of the bugs mentioned above in the slice, allowing one to narrow down the functions involved in V8 that lead to the crash.

6.3.3 Performance. Table 2 shows the performance of our prototype DCFG-based slicing implementation on our real-world test inputs (the environmental trigger example is omitted because it does not use backward slicing). These input programs all involve computations of substantial size: the smallest, LuaJIT exploit, has a trace of 464K instructions, while the remaining execution traces range from almost 7.9M instructions (V8 scoping issue bug) to 135M instructions (V8 escape analysis bug). The time taken to read the traces (and do nothing else) is roughly 1M instructions/sec.2

The DCFGs constructed typically range in size from about 22K basic blocks and 62K edges (V8 scoping issue bug) to about 41K blocks and 117K edges (V8 OOB exploit), with a low of 4.6K blocks and 12K edges for the LuaJIT exploit and a high of about 53K blocks and 154K edges for the V8 escape analysis bug. Most of our test programs have 2–4 phases, with the V8 JIT type confusion example an outlier with 9 phases. DCFG construction incurs an overhead of roughly 15× over simply reading a trace: most of the test inputs take roughly 2–3 minutes, with the lowest time being 7.5 seconds for the LuaJIT exploit and the highest being about 30 minutes for the V8 escape analysis bug. Since DCFG construction involves processing each instruction in the execution trace, the time taken depends on the sizes of both the instruction trace and the DCFG.

The overhead incurred by slicing relative to the time taken for DCFG construction ranges from 1.04× for the LuaJIT exploit to 9.5× for the V8 scoping issue bug, with most of the test programs ranging from 3× to 6×. In absolute terms, most of the programs take about 2–10 minutes for slicing, with a low of about 8 secs for the LuaJIT example and a high of about 2.8 hours for the V8 escape analysis bug. Slicing is able to remove about 50%–60% of the instructions in the DCFG, with a high of 71% of the instructions removed for the LuaJIT exploit. These results indicate that our approach is both practical (in terms of time) and useful (in terms of the amount of code removed from the DCFG). Since our approach does not fundamentally alter the slicing algorithm, but rather augments it to work over DCFGs and use codegen dependencies, it is not difficult to adapt our approach to other slicing algorithms with different cost-precision characteristics.

6.3.4 Focusing the analysis: markers and dicing. Given our objective of localizing problems in the JIT compiler code, it is useful to examine the extent to which our approach is able to reduce the amount of actual JIT-compiler code that has to be considered. To

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Our implementation uses Pin to collect an instruction trace that is written to a file on disk. The numbers reported here refer to the time required to read such instruction trace files; the time taken to record the traces and write the trace files, which depends on the tracing tool used and is independent of the ideas described here, is not included.
Table 4: Impact of representation optimization on DCFG size

<table>
<thead>
<tr>
<th>Test program</th>
<th>No. of Instructions</th>
<th>No. of Basic Blocks</th>
<th>No. of Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Orig</strong></td>
<td><strong>Opt</strong></td>
<td>Δ(%)</td>
</tr>
<tr>
<td>base64</td>
<td>781,404</td>
<td>308,748</td>
<td>60.5</td>
</tr>
<tr>
<td>crypto-sha1</td>
<td>1,158,366</td>
<td>319,098</td>
<td>72.3</td>
</tr>
<tr>
<td>date-format</td>
<td>453,177</td>
<td>324,279</td>
<td>28.4</td>
</tr>
<tr>
<td>nbody</td>
<td>394,264</td>
<td>284,973</td>
<td>27.7</td>
</tr>
<tr>
<td>poker</td>
<td>595,329</td>
<td>366,571</td>
<td>38.4</td>
</tr>
<tr>
<td>str-unpack</td>
<td>372,862</td>
<td>251,121</td>
<td>32.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test program</th>
<th>No. of Instructions</th>
<th>No. of Basic Blocks</th>
<th>No. of Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Orig</strong></td>
<td><strong>Opt</strong></td>
<td>Δ(%)</td>
</tr>
<tr>
<td>V8 OOB to JIT Code Pages</td>
<td>193,339</td>
<td>152,723</td>
<td>21.0</td>
</tr>
<tr>
<td>V8 Escape analysis bug</td>
<td>247,264</td>
<td>212,800</td>
<td>13.9</td>
</tr>
<tr>
<td>LuaJIT Exploit</td>
<td>21,389</td>
<td>19,436</td>
<td>9.1</td>
</tr>
<tr>
<td>OOB Read</td>
<td>151,773</td>
<td>133,134</td>
<td>12.3</td>
</tr>
<tr>
<td>JIT Type Confusion</td>
<td>160,526</td>
<td>128,188</td>
<td>20.1</td>
</tr>
<tr>
<td>Scoping issue</td>
<td>101,193</td>
<td>89,675</td>
<td>11.4</td>
</tr>
</tbody>
</table>

Key:
- **Orig**: Value in original-representation DCFG
- **Opt**: Value in optimized-representation DCFG
- Δ: Improvement = (Orig – Opt)/Orig

6.5 Space Optimization: The Impact of Merging

We use two test programs to evaluate the detection of environmental triggers based on dynamic code: one is shown in Figure 5, the other is a variant of the program that uses implicit flows to further disguise the influence of environmental values on the trigger code.

6.4 Detecting Environmental Triggers

We built two detectors to demonstrate the utility of DCFGs and codegen dependencies for this purpose. In the first case, we taint the input source and propagate the taint forward in the execution trace. If there is a codegen dependency from an instruction with tainted operands to an instruction that is later executed, an input-dependent value may be influencing the instruction bytes of some dynamic instruction, and we report that there is dynamic input-dependent program behavior. In the second case, we compute a backward dynamic slice with the slicing criterion being the dynamically modified code location at the point where it is executed.

Table 4 gives the results of these experiments. The two columns labeled ‘**Original**’ refer to the size of the DCFG and the backward slice computed without markers, i.e., as shown in Table 2; the columns labeled ‘**Dicing**’ refer to the size of the DCFG and slice when markers are used; the columns labeled ‘**Improvement**’ show the percentage improvement due to dicing. The columns labeled Δ_{DCFG} and Δ_{slice} show, respectively, the reductions in the size of the DCFG and the slice when irrelevant code is excluded. These are in the range 35%–85% for DCFG size and 26%–84% for slice size. The JIT Type Confusion bug sample is an outlier, with almost all of the dependent value may be influencing the instruction bytes of some tainted operands to an instruction that is later executed, an input-dependent value may be influencing the instruction bytes of some dynamic instruction, and we report that there is dynamic input-dependent program behavior. In the second case, we compute a backward dynamic slice with the slicing criterion being the dynamically modified code location at the point where it is executed.

Our implementations correctly detect that environmental values influence dynamic program behavior for our benchmarks. To assess the state of the art, we tested these programs using two widely used analysis tools: S2E, a widely used symbolic execution engine [10], and angr. In each case, we found that the input values used to patch the function hide() in Figure 5 are silently concretized and only the false path is explored. As a result, these tools are unable to identify the environment-dependent aspect of the program’s behavior.
Improvement (%)

0 20 40 60 80

Key: + : basic blocks
x : instructions

Figure 6: Space optimization improvements vs. DCFG size

7 SUMMARY AND DISCUSSION

Our design goals, in Section 3.1, were to devise a program representation that naturally and scalably generalizes existing representations; allows existing analyses to be extended to dynamic code in a simple and natural way; and is precise enough to distinguish between conceptually distinct dynamic code modifications. DCFGs provide a natural generalization of the well-known notion of control flow graphs to dynamic code and thus satisfy the first goal. Section 5.1 shows how we extend slicing to dynamic code in a straightforward way, thereby satisfying the second goal. For the third goal, DCFGs allow us to distinguish the code structure of individual JIT-compiled functions by separating out the different code modifications in different DCFG phases, with the space optimizations of Section 4 ensuring scalability; codegen dependencies then make it possible to identify and reason about the code components and value flows in the dynamic code generator relevant to the code modifications in each such phase. As far as we know, no other existing system can do this.

8 RELATED WORK

Anckaert et al. describe a program representation for dynamic code that is capable of representing multiple versions of the code as it is modified during execution [4]. However, this work does not have a notion of codegen dependencies and as a result is of limited utility for applications that involve reasoning about causal relationships between the dynamic code generator and the dynamic code.

Debray and Yadegari discuss reasoning about control dependencies in interpreted and JIT-compiled code [52]. While the goals of this work are similar to ours, its technical details are quite different. In particular, it does not aim to provide a program representation capable of supporting arbitrary dynamic code, but instead is narrowly focused on control dependency analysis in interpretive systems. It also makes assumptions, such as the ability to map each dynamically generated instruction to a unique byte-code instruction it originated from, that render it inapplicable to contexts not involving interpreters, such as the dynamic-code-based environmental triggers discussed in Sections 5.2 and 6.4.

Korczyński and Yin discuss identifying code reuse/injections using whole-system dynamic taint analysis [29]. While this work captures codegen dependencies, it does not propose a program representation that can capture the code structure for the different phases that arise during execution. As a result, this approach is not suitable for analyses, such as program slicing, that require information about the control flow structure of the code. Dalla Preda et al. describe a notion of phases to characterize the semantics of self-modifying code [12], however this work was never implemented and the technical details are very different from ours.

There is a large body of literature on program slicing (e.g., see [30, 39, 46, 50, 55]), but all of this work focuses on static code. There is a lot of work on dependence and information flow analyses (e.g., see [20, 27, 35]), but these typically do not consider end-to-end analysis of dynamic code. Several authors have discussed taint propagation in JIT-compiled code, but focusing on taint propagation in just the application code rather than on end-to-end analyses [13, 28, 41]. Whole-system analyses [11, 13, 21, 53, 54] focus on issues relating to dynamic taint propagation through the entire computer system. Such systems provide end-to-end analyses but typically consider only explicit information flows (= data dependencies), not implicit flows (= control dependencies); they are thus of limited use for reasoning about behaviors, such as conditional dynamic code modification (i.e., where the dynamic code generated may depend conditionally on input and/or environmental values), which are common in applications such as JIT compilers.

There are a number of systems that reason about program behavior using dynamic analysis, and therefore are able to perform some kinds of analysis on dynamic code [36, 42, 44, 47]. Our experiments indicate that these systems do not keep track of multiple versions of code resulting from dynamic code modification, and so cannot fully capture the dependences arising from runtime code changes.

Cai et al. [7] and Myreen [33] discuss reasoning about dynamic code for the purposes of program verification using Hoare logic. We have not seen any implementations to apply their work towards modern software that utilizes dynamic code (i.e. a javascript engine). Furthermore, our work is more specific in that we seek to provide a program representation capable of representing dynamic code.

9 CONCLUSIONS

Dynamic code is ubiquitous in today’s world. Unfortunately, existing approaches to program analysis are not adequate for reasoning about the behavior of dynamic code. This paper discusses how this problem can be addressed via a program representation suitable for dynamic code as well as a new notion of dependencies that can capture dependencies between the dynamic code and the code that generated it. Experiments with a prototype implementation of backwards dynamic slicing based on these ideas show, on a number of real-world examples, that these ideas make it possible to work back from the faulty code to the JIT compiler logic that led to the generation of the faulty code.

ACKNOWLEDGMENTS

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