Precise Pointer Reasoning for Dynamic Test Generation

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Abstract. Dynamic test generation consists of executing a program while gathering symbolic constraints on inputs from predicates encountered in branch statements, and of using a constraint solver to infer new program inputs from previous constraints in order to steer next executions towards new program paths. Variants of this technique have recently been adopted in several bug detection tools, including our whitebox fuzzer SAGE, which has found dozens of new expensive security-related bugs in many Windows applications and is now routinely used in various Microsoft groups.

In this paper, we discuss how to perform precise symbolic pointer reasoning in the context of dynamic test generation. We present a new memory model for representing arbitrary symbolic pointer dereferences to memory regions accessible by a program during its execution, and show that this memory model is the most precise one can hope for in our context, under some realistic assumptions. We also describe how the symbolic constraints generated by our model can be solved using modern SMT solvers, which provide powerful constructs for reasoning about bit-vectors and arrays. This new memory model has been implemented in SAGE, and we present results of experiments with several large Windows applications showing that an increase in precision can often be obtained at a reasonable cost. Better precision in symbolic pointer reasoning means more relevant constraints and fewer imprecise ones, hence better test coverage, more bugs found and fewer redundant test cases.

1 Introduction

Systematic dynamic test generation [6] consists of executing a program while gathering symbolic constraints on inputs from predicates encountered in branch statements, and of using a constraint solver to infer new program inputs from previous constraints in order to steer next executions towards *some* new program paths. This technique is now the foundation of several bug detection tools (see [2, 12, 10] among others), including our whitebox fuzzer SAGE [8]. SAGE can handle large applications and is optimized for handling long symbolic executions at the x86 binary level. Over the last 18 months, it has detected dozens of new expensive security bugs in many Windows applications. SAGE is so effective in detecting

[*] The work of this author was done mostly while visiting Microsoft Research.

```
void single_array(BYTE x, BYTE y) {
    BYTE * a = new BYTE[4];

    a[0] = x;
    a[1] = 0;
    a[2] = 1;
    a[3] = 2;

    if (a[x] == a[y] + 2)
        assert(false);

    delete[] a;
}
```

Fig. 1. An example of a symbolic memory dereference operation. Concretizing the value of a symbolic address results in adding imprecision to the symbolic analysis.

bugs missed by other techniques like static analysis or blackbox random fuzzing that it is now used daily in various Microsoft groups.

Dynamic test generation tools vary by the type of programs they can analyze, the type of constraints their symbolic execution can generate and by the constraint solver they use. Whenever symbolic execution does not know how to generate a symbolic constraint for a program statement depending on some program inputs, the concrete values of those inputs can be used to simplify the constraint as a fallback [6]. However, these concretizations can result in failing to exercise program branches and paths, hence in missing bugs, and also in increasing the number of redundant test cases which *diverge* from their expected program path.

To illustrate this, consider generating test inputs for the method `single_array` in Figure 1 starting with the input tuple {`x = 0, y = 1`}. When the execution encounters the conditional statement `a[x] == a[y] + 2` involving the program inputs `x` and `y`, symbolically evaluating this constraint requires comparing the values at the symbolic memory addresses `&a[x]` and `&a[y]`. If the symbolic execution is not able to reason about symbolic addresses, the concrete values `&a[0]` (since `0` is the concrete value of `x`) and `&a[1]` (since `1` is the concrete value of `y`) of those addresses can be used instead, and the constraint `a[x] == a[y] + 2` is then simplified into `(x != 2)`, which is stored in the path constraint symbolically representing the current execution. Solving the new path constraint `(x == 2)` obtained by negating this constraint results in a new input tuple {`x = 2, y = 1`} which is expected to exercise the other branch of the conditional statement and reach the `assert(false)` statement. However, executing `single_array` with inputs {`x = 2, y = 1`} actually results instead in taking the same program path as the previous one: we call this a *divergence*. Note that concretizing the symbolic addresses resulted in changing the semantics of the condition from trying to find two elements in the array that differ by 2, to assigning the value `2` to the input variable `x`; this imprecision resulted in both generating a redundant test input and missing a reachable statement.

In this paper, we discuss how to precisely reason about symbolic pointer dereferences in the context of dynamic test generation, in order to handle programs with constraints as in the previous example.

2 Background: Systematic Dynamic Test Generation

Dynamic test generation (see [6] for further details) consists of running the program P under test both concretely, executing the actual program, and symbolically, calculating constraints on values stored in program variables x and expressed in terms of input parameters α. Side-by-side concrete and symbolic executions are performed using a concrete store M and a symbolic store S, which are mappings from program variables, i.e., *memory addresses*, to concrete and symbolic values respectively. A *symbolic value* is any expression e in some theory $\mathcal{T}$ where all free variables are exclusively input parameters α. For any variable x, $M(x)$ denotes the *concrete value* of x in M, while $S(x)$ denotes the *symbolic value* of x in S. For notational convenience, we assume that $S(x)$ is always defined and is simply $M(x)$ by default if no expression in terms of inputs is associated with x in S. We also extend this notation to allow $M(e)$ to denote the concrete value of symbolic expression e when evaluated with the concrete store M. The notation $+$ for mappings denotes updating; for example, $M' = M + [m \mapsto v]$ is the same map as M, except that $M'(m) = v$.

The program P manipulates the memory (concrete and symbolic stores) through statements, or *commands*, that are abstractions of the machine instructions actually executed. A command can be an *assignment* of the form $x := e$ (where x is a program variable and e is an expression), a *conditional statement* of the form `if` e `then` C' `else` C'' where e denotes a boolean expression, and C' and C'' are *continuations* denoting the unique next statement to be evaluated (programs considered here are thus sequential and deterministic), or `stop` corresponding to a program error or normal termination.

Given an input vector $\boldsymbol{\alpha}$ assigning a value to every input parameter α, the evaluation of a program defines a unique finite *program execution* $s_0 \overset{C_1}{\rightarrow} s_1 \ldots \overset{C_n}{\rightarrow} s_n$ that executes the finite sequence $C_1 \ldots C_n$ of commands and goes through the finite sequence $s_1 \ldots s_n$ of program states. Each *program state* is a tuple $\langle C, M, S, pc \rangle$ where C is the next command to be evaluated, and pc is a special meta-variable that represents the current path constraint. For a finite sequence w of statements (i.e., a control path w), a *path constraint* pc_w is a formula of theory $\mathcal{T}$ that characterizes the input assignments for which the program executes along w. To simplify the presentation, we assume that all the program variables have some default initial concrete value in the initial concrete store M_0, and that the initial symbolic store S_0 identifies the program variables v whose values are program inputs (for all those, we have $S_0(v) = \alpha$ where α is some input parameter). We also assume that all program executions eventually terminate. Initially, pc is defined to `true`.

Systematic dynamic test generation [6] consists of systematically exploring all feasible program paths of the program under test by using path constraints and a constraint solver. By construction, a path constraint represents conditions on inputs that need be satisfied for the current program path to be executed. Given a program state $\langle C, M, S, pc \rangle$ and a constraint solver for theory $\mathcal{T}$, if C is a conditional statement of the form `if` e `then` C' `else` C'', any satisfying assignment to the formula $pc \wedge e$ (respectively $pc \wedge \neg e$) defines program inputs that will lead the program to execute the `then` (resp. `else`) branch of the conditional statement. By systematically repeating this process, such a *directed search* can enumerate all possible path constraints and eventually execute all feasible program paths.

The search is exhaustive provided that the generation of the path constraint (including the underlying symbolic execution) and the constraint solver for the given theory $\mathcal{T}$ are both *sound and complete*, that is, for all program paths w, the constraint solver returns a satisfying assignment for the path constraint pc_w *if and only if* the path is feasible (i.e., there exists some input assignment leading to its execution). In this case, in addition to finding errors such as the reachability of bad program statements (like `assert(false)`), a directed search can also prove their absence, and therefore obtain a form of program *verification*.

Theorem 1. *(adapted from [6]) Given a program P as defined above, a directed search using a path constraint generation and a constraint solver that are both sound and complete exercises all feasible program paths exactly once.*

In this case, if a program statement has not been executed when the search is over, this statement is not executable in any context.

In practice, path constraint generation and constraint solving are usually not sound and complete. When a program expression cannot be expressed in the given theory $\mathcal{T}$ decided by the constraint solver, it can be simplified using concrete values of sub-expressions, or replaced by the concrete value of the entire expression.

3 A New Memory Model

We now show how path constraint generation can be made sound and complete in the presence of symbolic pointer dereferences. Throughout the rest of the paper, we use the term *symbolic address* e to refer to a symbolic expression in a given theory $\mathcal{T}$ that is used as an address, and *symbolic content* $*e$ to refer to the content stored at the symbolic address e. We also call $*e$ a *symbolic pointer dereference*, or *symbolic address dereference*. A symbolic address dereference that occurs during the symbolic execution of a conditional statement or of the right-hand side of an assignment statement is called a *symbolic read* operation, while a symbolic address dereference that occurs during the symbolic execution of the left-hand side of an assignment statement is called a *symbolic write* operation. The address where the content of a program variable v is stored is denoted by $\&v$.

Our approach for handling symbolic address dereferences is based on the following observations. A symbolic address e (say a 32-bit address) can potentially point to any memory location within its range of possible values. Considering *all* these 2^{32} possible values for each symbolic address dereference $*e$ would be highly expensive and impractical. In contrast, the current concrete address $M(e)$ of symbolic address e either points to a specific memory location that lies within a valid, well-defined region in memory, or points to an unallocated memory region, which is a *memory-access violation*. A valid memory region is a region of memory with a known starting *address* and a *size*, which we assume here to be both input-independent, i.e., not symbolic (see Section 4). Such a region can reside in the heap, stack or data space of the running process.

Therefore, we propose a memory model which splits the entire universe of possible addresses that each symbolic address e may take into two disjoint sets defined by the concrete value $M(e)$ of that address: the set of concrete addresses contained in the valid memory region including the concrete address $M(e)$, and the rest of the universe. If the concrete address $M(e)$ does not point to a valid memory region, then a memory-access violation is reported. Otherwise, we consider two cases: we *assume* that the symbolic address e is confined within its valid memory region by forcing its value to be between *address* and $address{+}size{-}1$; moreover, we also *assert* that the symbolic address e is confined within its valid memory region by checking separately whether its value could overflow (be greater than $address{+}size{-}1$) or underflow (be less than *address*), hence leading to a possible memory-access violation. Both cases can be implemented by simply injecting the new constraint $address \leq e < address + size$ in the current path constraint, in the style of "active property checking" described in [7].

This model can also be extended to deal with multiple pointer dereferences, such as $**e$. In this case, a *set* of valid memory regions can be associated with a single symbolic pointer dereference, as we will describe later.

To implement this memory model in conjunction with symbolic execution and path constraint generation, we need to (1) extend the symbolic execution to handle symbolic address dereferences, (2) determine the valid memory regions (if any) that may be pointed by a symbolic address, (3) generate constraints involving symbolic addresses and memory regions (including their contents), and (4) translate and then solve those constraints using a constraint solver. We next describe each of those steps in detail.

3.1 Symbolic Execution with Symbolic Address Dereferences

Whenever a symbolic address dereference $*e$ occurs during symbolic execution, the function `get_dereference_expression` shown in Figure 2 is called with the symbolic expression e. This function returns a symbolic expression representing all possible symbolic values that the symbolic pointer dereference $*e$ may return given the current concrete store M and symbolic store S.

To compute this expression, the function `get_dereference_expression` first calls the function `get_memory_regions` (see Figure 2) to determine the set of valid memory regions the symbolic address e may point to and obtain a memory *snapshot* for each of those regions. A snapshot for a valid memory region $\langle address, size \rangle$ is defined as the tuple $\langle address, size, m, s \rangle$ where m and s are snapshots of the concrete store M and symbolic store S within the addresses ranging from *address* to $address{+}size{-}1$. Next, the function `add_bound_constraints` is called in order to add a set of constraints to bound the symbolic address within

```
get_dereference_expression(e) =
    let region_snapshots = get_memory_regions(e)
    add_bound_constraints(e, region_snapshots)
    return create_expression('*', e, region_snapshots)

get_memory_regions(e) =
    let region_snapshots = $\emptyset$
    let concrete_values = expand_and_evaluate(e)
    foreach value $\in$ concrete_values do
        regions_snapshots = region_snapshots $\cup$ get_memory_region_snapshot(value)
    return region_snapshots

get_memory_region_snapshot(address) =
    let $< start, size >$ = get_region_info(address)
    let $s = \emptyset$
    let $m = \emptyset$
    for address : $start \rightarrow start + size - 1$ do
        $m = m + [address \mapsto M(address)]$
        $s = s + [address \mapsto S(address)]$
    return create_region_snapshot(start, size, m, s)
```

Fig. 2. Constructing a symbolic expression to represent a symbolic address content.

each of the valid memory regions. Finally, it creates an expression for the unary dereference operation `(*)` and associates it with the set of memory region snapshots the symbolic address may point to.

3.2 Identifying Valid Memory Regions

The function `get_memory_regions` shown in Figure 2 computes the set of possible valid memory regions a symbolic address e may point to by calling the function `expand_and_evaluate` of Figure 3, which either returns the concrete value of e in the case e is a pointer, or returns the set of concrete values e can take in the case e is a pointer dereference. The former case deals with symbolic pointer single-dereferences, which occurs when indexing uni-dimensional arrays, strings and object fields, while the latter case handles symbolic pointer multi-dereferences where a symbolic address depends on previous dereference operations, forming a chain of dereferences, as when indexing multi-dimensional arrays. For each address returned by `expand_and_evaluate`, the function `get_memory_region_snapshot` is called to compute a snapshot of the valid memory region including that address. We assume the function `get_region_info` keeps track of all valid memory regions currently allocated, either statically by the compiler, or dynamically by the memory manager during execution. If a given address is not included in any valid memory region, the function `get_region_info` detects it and reports a memory-access violation.

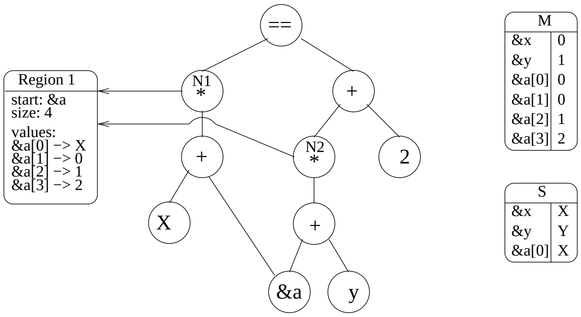
3.3 Adding Bound Constraints

As previously discussed, our memory model both *assumes* and *asserts* that every symbolic address must lie within the bounds of a memory region. Both cases are implemented by adding a *bound constraint* in the current path constraint for every symbolic address dereference. These bound constraints are treated as regular constraints in a path constraint. During a directed search, those constraints

```
expand_and_evaluate($e$) =
    let result = $\emptyset$
    match $e$:
        case $m$: // The symbolic variable $m$
            $result = result \cup M(m)$
        case $+(e', e'')$: // Addition
            let $f'$ = expand_and_evaluate($e'$)
            let $f''$ = expand_and_evaluate($e''$)
            foreach $x \in f'$ do
                foreach $y \in f''$ do
                    $result = result \cup (x + y)$
        case $*e'$:
            let $regions$ = get_memory_regions($e'$)
            foreach $region \in regions$ do
                $result = result \cup$ get_region_concrete_values($region$)
        etc.
    return $result$

get_region_concrete_values($region$) =
    let $values = \emptyset$
    for $address$ : $region.start \rightarrow region.start + region.size - 1$ do
        $values = values \cup region.m(address)$
    return $values$
```

Fig. 3. Partial evaluation of the possible concrete values for a symbolic address.



M	
&x	0
&y	1
&a[0]	0
&a[1]	0
&a[2]	1
&a[3]	2

S	
&x	X
&y	Y
&a[0]	X

Fig. 4. The symbolic expression tree for the `single_array` method. The unary `(*)` operator represent a symbolic memory dereference and is associated with a snapshot of the memory at the time of the dereference.

are eventually negated and solved. A solution of a negated bound constraint represents a potential memory-access violation in the program under test.

Given a set of valid memory region snapshots $\{R_1, R_2, ..., R_n\}$ that may be pointed to by a symbolic address e, the function `add_bound_constraints` adds to the current path constraint a bound constraint of the form

$$\bigvee_i (e == e_i) \wedge (start_i \leq e < start_i + size_i)$$

where $start_i$ and $size_i$ denote the base address and size of region R_i, and where e_i denotes a symbolic expression such that $e == e_i$ holds if and only if e points to R_i. The symbolic expression e_i is computed by symbolically evaluating e except for the last level of dereference in the chain of dereferences defined by e. This computation is illustrated with the following examples.

```
BYTE ** multi_array(BYTE x, BYTE y) {
    BYTE ** a = new BYTE*[2];
    a[0] = new BYTE[2];
    a[1] = new BYTE[3];

    a[0][0]=0; a[0][1]=1;
    a[1][0]=2; a[1][1]=3; a[1][2]=4;

    if (a[x][y] == y + 2)
        assert(false);

    delete[] a;
}
```

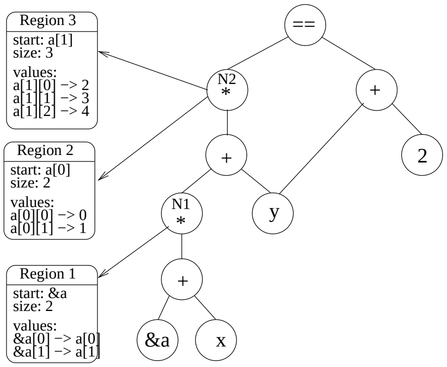


Fig. 5. An example with a symbolic multi-dereference operation.

3.4 Examples

Consider again the `single_array` example of Figure 1. Figure 4 shows the expression tree constructed with our memory model while executing the function `single_array` with the input tuple {`x = 0, y = 1`}. Instead of concretizing the dereference operations when evaluating the expression `a[x] == a[y] + 2`, each dereference operation (nodes *N1 and *N2) is now associated with a snapshot of memory corresponding to the possible results of the dereference. In order to cover the `then` branch of the conditional statement, the extended path constraint generated with our memory model is now the conjunction of the constraints:

```
c1: &a[0] == x
c2: &a[1] == 0
c3: &a[2] == 1
c4: &a[3] == 2
c5: &a ≤ &a[x] < &a + 4
c6: &a ≤ &a[y] < &a + 4
c7: *(&a[x]) == *(&a[y]) + 2
```

These constraints are of three types: (1) constraints {`c1, c2, c3, c4`} represent the snapshot of the memory region $Region1$ associated with both dereferences, (2) constraints {`c5, c6`} are the bound constraints for that region, and (3) constraint {`c7`} corresponds to the condition at the branch statement. A constraint solver can easily solve the conjunction of these constraints and generate the new test case {`x = 3, y = 1`} which results in covering the `assert(false)` statement. Additionally, by negating the constraints {`c6, c7`}, we can generate more test cases such as {`x = 10, y = 0`} and {`x = 0, y = 10`} that result in detecting buffer overflows in the program `single_array`.

Consider the second example `multi_array` shown in Figure 5. This program initializes a multi-dimensional array in the heap, and uses the input variables `x` and `y` to index the array. Figure 5 shows the expression tree constructed with our memory model while executing the function `multi_array` with the input tuple {`x = 0, y = 0`}. The expression `a[x][y]` is a chain of dereferences starting with `a[x]` and ending with `a[x][y]`.

While symbolically executing `multi_array`, the symbolic dereference sub-expression `a[x]` is first encountered and evaluated using `get_dereference_expression`. As in the case of `single_array`, `&a[x]` is associated with a single region $Region1\langle \&a, 2\rangle$, the bound constraint $\&a \leq \&a[x] < \&a + 2$ is added to the path constraint to force `&a[x]` within $Region1$, and a symbolic expression (node *N1) corresponding to the dereference operation is returned.

Next, the expression `a[x][y]` is evaluated with `get_dereference_expression`. First, `get_memory_regions` uses `expand_and_evaluate` to compute $\{$`a[0], a[1]`$\}$ as the set of possible concrete values for `&a[x][y]`, and uses these values in order to determine the two regions $Region2\langle a[0], 2\rangle$ and $Region3\langle a[1], 3\rangle$ as the possible valid memory regions that `&a[x][y]` may point to. Then, `add_bound_constraints` adds to the path constraint the following bound constraint:

$$\bigvee \begin{array}{l} (\texttt{\&a[x][y] == a[0] + y}) \land (\texttt{a[0]} \leq \texttt{\&a[x][y] < a[0] + 2}) \\ (\texttt{\&a[x][y] == a[1] + y}) \land (\texttt{a[1]} \leq \texttt{\&a[x][y] < a[1] + 3}) \end{array}$$

Finally, a symbolic expression (node *N2) corresponding to the multi-dereference operation is returned. The symbolic execution proceeds by building a symbolic expression for the condition of the branch statement, as previously described.

3.5 Handling Symbolic Write Operations

An assignment statement of the form $x := e$ consists of an expressions e and of a destination address $\&x$ to store e. When executing an assignment statement, symbolic execution extended with our memory model first inspects the destination address. If the address is concrete, then the memory stores are updated, otherwise a symbolic write need to be handled.

As in a symbolic read, a write operation using a symbolic address can potentially update any of the locations pointed to by the symbolic address. To handle a symbolic write, we first compute the regions that $\&x$ points to using the `get_dereference_expression` described earlier. Then, we associate a *symbolic update* $\&x \mapsto e$ with those regions.

After the regions are updated symbolically, values in those regions become nondeterministic, in the following sense: any subsequent read operation from these regions are considered symbolic reads, even if the address used in the operation is concrete. For example, consider the code snippet below where `x` is an input variable:

```
BYTE a[4] = {1 ,2 ,3, 4};
a[x]=0;
if (a[3] == 0)
   assert(false);
```

While the expression `a[3]` does not involve any input-dependent expression, the result of `a[3]` is treated as a symbolic read as its outcome depends on the value of `x`: if `x` is 3 then 0 is returned, otherwise 4 is returned. To precisely model such cases, we treat `a[3]` as a symbolic read, and evaluates it using `get_dereference_expression` as described in Section 3.1.

```
z3_translate($e$, $memory$) =
    match $e$:
        case $c$: // a constant c
            return z3_bitvector(c)
        case $m$: // The symbolic variable m
            return z3_bitvector_var(m)
        case $+(e', e'')$: // Addition
            let $f'$ = z3_translate(e')
            let $f''$ = z3_translate(e'')
            return z3_bitvector_add(f', f'')
        case $*e'$: // a dereference expression
            // Translate the region snapshots associated with e'
            let $region\_snapshots = e'.region\_snapshots$
            foreach $region \in region\_snapshots$ do
                for $address$ : $region.start \rightarrow region.start + region.size - 1$ do
                    $memory$ = z3_store($memory$, $address$, $region.s(address)$)

            let $f'$ = z3_translate(e') // Translate the address
            return z3_select($memory$, $f'$)
        etc.
```

Fig. 6. Translating a symbolic expression into a Z3 expression.

3.6 Integration with the Z3 SMT Solver

The memory model presented in the previous sections has been implemented in SAGE [8]. To solve symbolic constraints, we use the Z3 [5] satisfiability modulo theory (SMT) solver. Z3 is a highly efficient SMT solver that targets program analysis problems. Z3 supports several theories including integer arithmetic, fixed-size bit-vectors, arrays, and quantifiers. Z3 also supports sign-extension operations which are very handy for modeling assembly language instructions.

Array types in Z3 are maps from elements of a domain datatype to elements of a range datatype. Arrays are treated as un-interpreted functions, not as an ordered sequence of elements. Z3 provides two operations on maps, *select* and *store*. The *select* operation on a Z3 array takes a variable of the domain datatype and returns an existing element in array of the range type. The *store* operation on an array A takes an index i of the domain datatype and a value v of the range datatype and returns an array A' where $A' = A\ with\ A[i] == v$.

A key advantage of using Z3 is its direct correlation with SAGE's memory model. We can rather easily translate SAGE's symbolic expressions, the memory regions associated with dereference expressions, and the bound constraints to Z3 primitives. Atomic expression representing the constants and the symbolic variable are modeled as 32 bit-vector Z3 terms. Memory is modeled as a Z3 array mapping 32 bit-vectors representing addresses into 8 bit-vectors representing the values.

The translation from SAGE to Z3 is illustrated by the `z3_translate` function shown in Figure 6. Primarily, atomic expression representing the constants and the symbolic variable are translated into 32 bit constants and variables. Binary arithmetic and relational operations are translated into the corresponding Z3 operations. Dereference operation require translating the updates (concrete or symbolic) that occurred on memory. For a dereference operation the address expression is first translated. Then for each region associated with the dereference expression, the updates performed on these regions are translated into *store* operations on memory. Finally the dereference operation is translated into a *select* operation from memory with the symbolic address as an index.

The result of the `z3_translate` on the symbolic expressions representing the program constraints is a Z3 boolean logic formula where, by construction [6], each free variable corresponds to a program input. If Z3 can solve the formula, it also generates a model satisfying the formula and this model can be transformed into a new input assignment to test the program further.

4 Maximum Precision Theorem

Consider a program P containing exclusively (assignment and conditional) statements $st(P)$ whose corresponding symbolic constraints are either expressions in a given decidable theory $\mathcal{T}$ (denoted $st(P) \subset \mathcal{T}$) for which there exists a sound and complete constraint solver, or are symbolic memory dereferences (read or write, single or multi dereferences).

Let such a program P be called *well-formed* if none of its executions can ever trigger a memory-access violation, i.e., a read or write operation outside all current valid memory regions, no matter where those regions reside. In other words, a well-formed program never triggers a memory-access violation even in the presence of an adversarial memory allocator.

Also, let us say that a valid memory region is *input-independent* if its starting *address* and *size* are both input-independent (i.e., do not depend on any input and therefore would only have a concrete value if tracked during symbolic execution).

The next theorem formally states that the memory model presented in this paper is *the most precise there is* for any program P as defined above whose valid memory regions are all input-independent.

Theorem 2. *For any well-formed program P as defined above whose valid memory regions are all input-independent, the memory model and associated path constraint generation presented in Section 3 are both* sound and complete *given a sound and complete constraint solver for the decidable theory $\mathcal{T}$ such that $st(P) \subset \mathcal{T}$. In this case, a directed search with this path constraint generation and constraint solver will thus exercise all feasible program paths exactly once.*

Proof: (sketch) Consider any program path w and its corresponding path constraint pc_w. Since program P is well-formed, every symbolic pointer dereference $*e$ points to a value stored in some valid memory region. In that case, all possible memory regions e may possibly point to are determined using the algorithm of Section 3.2, and results in bound constraints for those regions as described in Section 3.3. Then, given a sound and complete solver for $\mathcal{T}$ such that $st(P) \subset \mathcal{T}$, the path constraint pc_w is satisfiable assuming the bound constraints *if and only if* there is an input assignment that exercises the path w. □

Note that, if a memory-region overflow or underflow is possible along path w, it will be detected provided that (1) every concrete pointer dereference is checked for out-of-bound access violation, *and* (2) every symbolic memory dereference is preceded in the path constraint pc_w by a bound constraint whose negation is checked. As shown in [7], both checks (1) and (2) are actually necessary (i.e., one does not subsume the other). However, in presence of memory-access violations, the program is no longer "well-formed" and the theorem does not hold: although memory-access violations may (and will typically) be detected, it is no longer guaranteed that all feasible program paths will eventually be exercised.

Our memory model assumes that all valid memory regions are input-independent, i.e., that the *address* and the *size* of every memory region are "concrete". In a security setting where program inputs are viewed as controlled by an attacker, assuming that all valid memory regions have a concrete base *address* is equivalent to assuming memory allocation (such as calls to `malloc()`) is not controllable by the attacker, which is often a realistic assumption. With this assumption, our memory model cannot be used to generate test inputs to violate assertions like `assert(&a > &b)` where `&a` and `&b` are base addresses of dynamically-allocated memory regions.

A more practical limitation is our assumption that valid memory regions cannot have symbolic *sizes*. Indeed, the amount of memory allocated by a program can sometimes depend on some program input or the number of those inputs. However, symbolic reasoning about memory allocation with symbolic sizes is largely orthogonal to reasoning about symbolic address dereferences, which is the main focus of our paper, and this other problem can be addressed using other techniques [14].

5 Related Work and Discussion

The memory model defined in this paper generalizes and extends previously published ones [12, 2] in the context of dynamic test generation. The simple model in [12] only handles symbolic pointer equalities and inequalities, but does not support pointer arithmetic, multi-dereferences or symbolic writes, and cannot be used find the assertion violations in the examples of Figures 1 and 5.

The memory model of [2] is more precise and handles both pointer arithmetic and symbolic pointer single dereferences. But it does not handle symbolic pointer multi-dereferences and does not discuss how to deal with symbolic write operations. Although it can deal with the example of Figure 1, it cannot handle the example of Figure 5. Moreover, [2] does not discuss when (i.e., for which programs) its memory model is sound and/or complete. In contrast, the previous section precisely states when our memory model is sound and complete, that is, it formalizes under which assumptions our memory model is the most precise there is. Note that our implementation does not use the optimizations and iterative constraint-refinement scheme discussed in [2] for translating array constraints into SAT constraints as we use a SMT solver (namely Z3) which directly supports array theories.

Memory models used in traditional static program analysis [4, 11] are *abstractions* of the stack and heap of the analyzed program. In contrast, our memory model is very precise and is used in conjunction with a symbolic execution of a specific program path and concrete execution.

Recent work [3, 13, 1] discusses how to perform bit-precise reasoning using static analysis and symbolic execution. The idea is to generate a single SAT formula (possibly refined iteratively) representing the entire program, i.e., all the possible program executions at once. This approach requires models for all system calls and external libraries. Existing implementations often have a strongly-typed view of memory and do not support arbitrary pointer casting operations. Moreover, whole-program formula encodings typically become unsound and/or incomplete in the presence of loops and recursion. Scalability is also problematic and bit-precise analysis is often only intraprocedural, not interprocedural. In contrast, dynamic test generation considers whole program executions one by one, which is expensive, but its (interprocedural) symbolic execution can handle arbitrary system calls and libraries by using testing and concrete values as a fallback. This way, all bugs found are guaranteed to be sound (no false alarms), although full path coverage cannot typically be achieved for large realistic applications and bugs may be missed. However, in practice, we often have no alternative, as the complexity and size of applications like those considered in the next section are beyond the scope of applicability of current interprocedural bit-precise static analysis tools.

During execution, valid memory regions need to be tracked by instrumenting dynamic memory allocation. Fairly efficient solutions to this problem are well-known. In SAGE, this is done using TruScan [9].

Our precise memory model may sound expensive. But note that this is very much a "pay as you go" model: for instance, if a program never performs any symbolic pointer dereference, no constraints like those discussed in this paper will ever be generated. The next section presents results of experiments that shed light on this cost/precision tradeoff.

6 Experiments

This section presents results of preliminary experiments with our SAGE implementation of the precise memory model introduced in this paper. The goal of these experiments is to estimate the benefit and cost of this memory model. Specifically, we evaluate two configurations: (Old) no symbolic pointer handling and (New) symbolic read operations with single and multi pointer dereferences.

Experiments were performed with the following applications: a GIF image processor, a PDF reader, an animated icons parser, a cryptographic certificate processor, and a ZIP file decompressor. We used the single generation (Gen1) mode of SAGE in which the target application is executed concretely and symbolically on one well-formed seed input file, all the constraints in the path constraint for that execution are negated and solved one-by-one in conjunction with the corresponding prefix of the path constraint (see [8]), and all the resulting new test cases obtained from each satisfiable constraint are executed concretely to see whether they exhibit a crash. We measured the total running time of

Benchmark	GIF		PDF		ANI		Crypto		ZIP	
Mode	Old	New	Old	New	Old	New	Old	New	Old	New
Total Time (s)	185	190	1,060	1,190	80	80	310	315	420	420
Symb. Exec. Time (s)	35	35	190	220	11	10	32	100	35	35
Solver Time (s)	15	17	160	180	2	2	8	65	1.5	1.5
# Tests Generated	54	54	1,124	1,251	129	129	193	167	147	147
# Constraints	499	541	1,782	1,928	318	318	350	352	272	272
Initial Coverage	83,000	83,000	41,760	41,760	19,100	19,100	73,100	73,100	131,200	131,200
Gen1 Coverage	89,500	89,700	45,870	45,940	20,300	20,300	76,000	75,800	133,200	133,200

Fig. 7. Microbenchmark statistics.

each SAGE session including testing the new generated test inputs, the time it took to perform the single symbolic execution, the time taken by the constraint solver, the number of constraints in the path constraint generated by the symbolic execution, the number of those constraints that were successfully negated and solved to yield a new test case, the (rounded) initial instruction coverage obtained by running the target program with the seed input, and the (rounded) total (Gen1) instruction coverage obtained after also running the target program with all the new test inputs generated.

Results are summarized in Figure 7. The ANI and ZIP programs do not use any input in any indirect memory accesses. As a result, there were no symbolic dereference constraints: the new memory model did not have any effect on these programs. The new GIF run generated more constraints than the old run, but the same number of constraints were successfully inverted in both runs. Apparently, some of the constraints that were inverted in the old run become unsatisfiable and are not inverted in the new run due to increased precision. As a result SAGE generates fewer divergences and the overall quality of the generated tests is better in the new run as witnessed by the marginally better coverage produced by the new run. Note that the symbolic execution and constraint solving times are not affected by the overhead of the new memory model in those three experiments.

The new PDF run generates more constraints and more tests. Although overall coverage is a little better as a result, this comes at a cost: the running time is slightly higher both because there are more tests to evaluate and because of the overhead in symbolic execution and constraint solving.

In the Crypto example, we see that although almost no additional constraints are added by the new run, a significant number of constraints are no longer satisfiable because they contain additional symbolic pointer expressions. Although symbolic execution and constraint solving incur an overhead with the new memory model, this time is made up overall because there are fewer new tests to run and evaluate. The marginal decrease in coverage for the new run is likely caused by divergences arising from symbolic-execution imprecision that is unrelated to the memory model.

These results are promising in that we do not observe a drastic overall time increase as a result of introducing the new memory model. Therefore, even a small chance of finding a new bug thanks to increased precision justifies the memory model presented here. At the time of this writing, we do not have enough experience using the new memory model in production-testing mode inside Microsoft to comment on the overall impact of the new memory model.

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