# Towards Bounded Infeasible Code Detection

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- Abstract. A first step towards more reliable software is to execute each statement and each control-flow path in a method once. In this paper, we present a formal method to automatically compute test cases for this purpose based on the idea of a bounded infeasible code detection. The method first unwinds all loops in a program finitely often and then encodes all feasible executions of the loop-free programs in a logical formula. Helper variables are introduced such that a theorem prover can reconstruct the control-flow path of a feasible execution from a satisfying valuation of this formula. Based on this formula, we present one algorithm that computes a feasible path cover and one algorithm that computes a feasible statement cover. We show that the algorithms are complete for loop-free programs and that they can be implemented efficiently. We further provide a sound algorithm to compute procedure summaries which makes the method scalable to larger programs.

## 1 Introduction

Using static analysis to find feasible executions of a program that pass a particular subset of program statements is an interesting problem. Even though in general not decidable, there is ongoing research effort to develop algorithms and tools that are able to solve this problems for a reasonable large number of cases. Such tools can be used, e.g., to automatically generate test cases that cover large portions of a programs source code and trigger rare behavior, or to identify program fragments for which no suitable test case can be found. The later case sometimes is referred to as *infeasible code detection* [3]. Code is considered to be infeasible if no terminating execution can be found for it. Infeasible code can be seen as a superset of unreachable code as there might be executions reaching a piece of infeasible code which, however, fail during their later execution.

In particular, a counterexample for the infeasibility of a piece of code is a terminating execution that executes this code. That is, finding a set of test cases that cover all statements in a program is equivalent to proving the absence of infeasible code. Existing approaches to detect infeasible code do not yet exploit the fact that counterexamples for infeasibility might constitute feasible test cases.

In this paper, we discuss a bounded approach towards infeasible code detection that generates test cases that cover all statements which have feasible executions within a given (bounded) number of loop unwindings. The interesting aspect of bounded infeasible code detection over existing (unbounded) approaches is that counterexamples for infeasibility are likely to represent actual

executions of the program, as compared to the unbounded case, where these counterexamples might be introduced by the necessary over-approximation of the feasible executions.

The paper proposes two novel ideas: the concept of reachability verification condition, which is a formula representation of the program which, similar the weakest-liberal precondition or strongest postcondition, models all feasible executions of a program. But in contrast to existing concepts, a satisfying assignment to the reachability verification condition can directly be mapped to an execution of the program from source to sink. For example, a valuation of wlpcan represent a feasible execution starting from any point in a program, but this does not yet imply that this point is actually reachable from the initial states of the program. Certainly there are ways to encode the desired property using wlp, or sp by adding helper variables to the program (see, e.g., [15,3]), however, we claim that the proposed reachability verification condition provides a better formal basis to show the absence of infeasible code, as it, e.g., can make better use of the theorem prover stack which results in a more efficient and scalable solution. We suggest two algorithms to compute feasible executions of a program based on the reachability verification condition. One uses so-called blocking clauses to prevent the theorem prover from exercising the same path twice, the other algorithm uses enabling clauses to urge the theorem prover to consider a solution that passes program fragments that have not been accessed before. Both algorithms return a set of feasible executions in the bounded program. Further, both algorithms guarantee that any statement not executed by these test cases is infeasible within the given bounds. We do a preliminary evaluation of our algorithms against existing algorithms to detect infeasible code.

Based on the reachability verification condition, as a second novelty, we propose a technique to compute procedure summaries for bounded infeasible code detection. As the presented algorithms return a set of feasible executions, we can extract pairs of input and output values for each execution to construct procedure summaries. The summaries are a strict under-approximation of the possible executions of the summarized procedure. Therefore, the computed summaries are sound to show the presence of feasible executions, but unsound to show their absence. To overcome this gap, we suggest an on-demand computation of summaries if no feasible execution can be found with the given summary. Within the scope of this paper, we do not evaluate the concept of summaries as more implementation effort is required until viable results can be presented.

In Section 3 we explain how we address the problem of computing the weakest-liberal preconditions for general programs. In Section 4 we show how a feasible execution that visits certain blocks can efficiently be expressed as a formula and introduce the concept of reachability verification condition. In Section 5 we present two different algorithms to address the problem of generating test cases with optimal coverage. In Section 6 we show how procedure summaries can be computed with our test case generation algorithm. We present an experimental evaluation of our algorithms in Section 7.

#### 2 Preliminaries

For simplicity, we consider only simple unstructured programs written in the language given in Figure 1.

```
Program ::= Procedure<sup>+</sup>

Procedure ::= proc ProcName(VarId*) [returns VarId] { Block<sup>+</sup> }

Block ::= label : Stmt* [goto label<sup>+</sup>;]

Stmt ::= VarId := Expr; | assume Expr;

| VarId := call ProcName(Expr*);
```

Fig. 1. Simple (unstructured) Language

Expressions are sorted first order logic terms of appropriate sort. The expression after an **assume** statement have Boolean sort. A program is given by a set of *Procedures* each with a unique name. The special procedure named "main" is the entry point of a program. Every procedure contains at least one block of code. A block consists of a label, a (possibly empty) sequence of statements, and non-deterministic **goto** statement that lists transitions to successor blocks. The **goto** statement is omitted for the blocks that have no successors. A statement can either be an assignment of a term to a variable, an assumption, or a procedure call. A call to a procedure is indicated by the **call** keyword followed by the name of the procedure to call, and the (possible empty) list of arguments. A procedure can return a value by writing into the variable mentioned in the **returns** declaration. If this declaration is omitted, the procedure cannot return a value. If the conditional of an assumption evaluates to *false*, the execution blocks. Figure 2 shows a small example of our simple language.

We assume that every procedure contains a unique  $initial\ block\ Block_0$  and a unique  $final\ block$  that has no successor. A procedure terminates if it reaches the end of the final block. A program terminates if the "main" procedure terminates. We further assume the directed graph which is given by the transitions between the blocks is reducible.

The presented language is simple but yet expressive enough to encode high level programming languages such as C [7]. In this paper we do not address the problems that can arise during this translation and refer to related work instead.

The weakest-liberal precondition [9,2] semantics of our language is defined in the standard way:

$$\begin{array}{c|c} st & wlp(st,Q) \\ \hline \textbf{assume} \ E & E \Longrightarrow Q \\ VarId := Expr & Q[\ VarId/Expr] \\ S; T & wlp(S, wlp(T,Q)) \end{array}$$

```
proc foo(x, y) returns z {
    10:
        goto 11, 12;
11: assume y > 0;
        z := x + y;
        goto 13;
12: assume y <= 0;
        z := x - y;
        goto 13;
13:
}
proc main() {
    10: r := call foo(0, 1);
}</pre>
```

Fig. 2. Example of our Simple Language

A sequence of statements x in our language has a *feasible execution* if and only if there exists an initial valuation V of the program variables, such that in the execution of x all **assume** statements are satisfied.

**Theorem 1.** A sequence of statements  $\mathfrak{L}$  has a feasible execution if and only if there exists a valuation  $\mathcal{V}$  of the program variables, such that  $\mathcal{V} \not\models wlp(\mathfrak{L}, false)$ .

Hence, the initial state of a feasible execution of  $\boldsymbol{x}$  can be derived from a counterexample to the formula representation of the weak-liberal precondition  $wlp(\boldsymbol{x},false)$ .

A path in a program is a sequence of blocks  $\pi = Block_0 \dots Block_n$  such that there is a transition from any  $Block_i$  to  $Block_{i+1}$  for  $0 \le i < n$ . We extend the definition of feasible executions from statements to paths by concatenating the statements of each block. We say that a path  $\pi$  is a *complete path* if it starts in the initial block and ends in the final block. In the following, we always refer to complete paths unless explicitly stated differently. A path is *feasible*, if there exists a feasible execution for that path.

**Theorem 2.** Given a path  $\pi = Block_0 \dots Block_n$  in a program  $\mathcal{P}$  where  $\mathfrak{s}_i$  represents the statements of  $Block_i$ . The path  $\pi$  is called feasible, if and only if there exists a valuation  $\mathcal{V}$  of the program variables, such that  $\mathcal{V} \not\models wlp(\mathfrak{s}_0; \dots; \mathfrak{s}_n, false)$ .

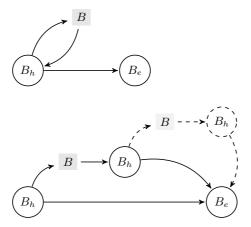
Note that our simple language does not support assertions. For the weakest liberal precondition, assertions are treated in the same way as assumptions. That is, we might render a path infeasible because it's execution fails, but still this path might be executable. As our goal is to execute all possible control-flow paths, we encode assertions as conditional choice. This allows us later on to check if there exist test cases that violate an assertion.

## 3 Program Transformation

As the weakest-liberal precondition cannot be computed for programs with loops in the general case, an abstraction is needed. Depending on the purpose of the analysis, different information about the possible executions of the program has to be preserved to retain *soundness*. E.g., when proving partial correctness [1,2] of a program, the set of all executions that fail has to be preserved (or might be over-approximated), while terminating or blocking executions might be omitted or added.

For our purpose of identifying a set of executions containing all feasible statements, such an abstraction, which over-approximates the executions of a program is not suitable as we might report executions which do not exist in the original program. Instead we need a loop unwinding which does not add any (feasible) executions.

Loop Unwinding. Our loop unwinding technique is sketched in Figure 3. As we assume (w.l.o.g) that the control-flow graph of our input program is reducible, we can identify one unique entry point for each loop, the loop header  $B_h$ , and a loop body B. The loop header contains only a transition to the loop body and the loop exit  $B_e$ . We can now unwind the loop once by simply redirecting the



 $\mathbf{Fig.}$  3. Finite loop unwinding

target of the back-edge that goes from B to  $B_h$ , to  $B_e$  (and thus transforming the loop into an if-then-else).

To unwind the loop k-times, for each unwinding, we have to create a copy of B and  $B_h$ , and redirect the outgoing edge of the B introduced in the previous unwinding to the newly introduced  $B_h$ . That is, the loop is transformed to an if-then-else tree of depth k. This abstraction is limited to finding executions that reach statements within less than (k + 1) loop iterations, however, as the

abstraction never adds a feasible execution, we have the guarantee that this execution really exists.

**Lemma 1.** Given a program  $\mathcal{P}$  and a program  $\mathcal{P}'$  which is generated from  $\mathcal{P}$  by k-times loop unwinding. Any feasible execution of  $\mathcal{P}'$  is also a feasible execution of  $\mathcal{P}$ .

Procedure Calls. Procedure calls are another problem when computing the weakest (liberal) precondition. First, they can introduce looping control flow via recursion, and second, inlining each procedure call might dramatically increase the size of the program that has to be considered. For recursive procedure calls, we can apply the same loop unwinding used for normal loops.

To inline a procedure, we split the block at the location of the procedure call in two blocks and add all blocks of the body of the called procedure in between (and rename variables and labels if necessary). Then, we add additional assignments to map the parameters of the called procedure to the arguments used in the procedure call and the variable carrying the return value of the procedure to those receiving it in the calling procedure.

If inlining all procedure calls is not feasible due to the size of the program, the call has to be replaced by a summary of the procedure body instead. We propose a technique that retains the soundness from Lemma 1 later on in Section 6.

Single Static Assignment. For the resulting loop-free program, we perform a single static assignment transformation [8] which introduces auxiliary variables to ensure that each program variable is assigned at most once on each execution path [12]. For convenience we use the following notation: given a program variable v, the single static assignment transformation transforms an assignment v := v + 1 into  $v_{i+1} := v_i + 1$ , where  $v_{i+1}$  and  $v_i$  are auxiliary variable (and the index represents the incarnation of v). In the resulting program, each variable is written at most once. Hence, we can replace all assignments by assumptions without altering the feasible executions of the program. In that sense, the transformed program is passive as it does not change the values of variables. As single static assignment is used frequently in verification, we refer to the related work for more details (e.g., [12,19,2]).

## 4 Reachability Verification Condition

This section explains how to find a formula VC (the reachability verification condition) such that every satisfying valuation  $\mathcal{V}$  corresponds to a terminating execution of the program. Moreover, it is possible to determine from the valuation, which blocks of the program were reached by this execution. For this purpose VC contains an auxiliary variable  $R_i$  for each block that is true if the block is visited by the execution. From such an execution we can derive a test case by looking at the initial valuation of the variables.

A test case of a program can be found using the weakest (liberal) precondition. If a state satisfies the weakest precondition wp(S, true) of a program S it

will produce a non-failing run. However, it may still block in an assume statement. Since we desire to find non-blocking test cases we follow [3] and use the weakest liberal precondition of false. A state satisfies wlp(S, false) if and only if it does not terminate. Hence we can use  $\neg wlp(S, false)$  to find terminating runs of S.

For a loop-free program, computing the weakest (liberal) precondition is straight forward and has been discussed in many previous articles (e.g., [2,19,11,14]). To avoid exponential explosion of the formula size, for each block

$$Block_i ::= i : S_i; \mathbf{goto} \, Succ_i$$

we introduce an auxiliary variable  $B_i$  that represents the formula  $\neg wlp(Block_i, false)$ , where  $Block_i$  is the program fragment starting at label i and continuing to the termination point of the program. These variables can be defined as

$$WLP: \bigwedge_{0 \le i < n} B_i \equiv \neg wlp\left(S_i, \bigwedge_{j \in Succ_i} \neg B_j\right)$$
$$\wedge B_n \equiv \neg wlp(S_n, false).$$

Introducing the auxiliary variables avoids copying the wlp of the successor blocks. If we are interested in a terminating execution that starts in the initial location 0, we can find a satisfying valuation for

$$WLP \wedge B_0$$

**Lemma 2.** There is a satisfying valuation V for the formula WLP with  $V(B_i)$  = true if and only if there is a terminating execution for the program fragment starting at the block  $Block_i$ .

Proof is given in [3].

Thus a satisfying valuation  $\mathcal{V}$  of  $WLP \wedge B_0$  corresponds to a terminating execution of the whole program. Moreover if  $\mathcal{V}(B_i)$  is true, the same valuation also corresponds to a terminating execution starting at the block  $Block_i$ . However, it does not mean that there is an execution that starts in the initial state, visits the block  $Block_i$ , and then terminates. This is because the formula does not encode that  $Block_i$  is reachable from the initial state.

To overcome this problem one may use the strongest post-condition to compute the states for which  $Block_i$  is reachable. This roughly doubles the formula. In our case there is a more simple check for reachability. Again, we introduce an auxiliary variable  $R_i$  for every block label i that holds if the execution reaches  $Block_i$  from the initial state and terminates. Let  $Pre_i$  be the set of predecessors of  $Block_i$ , i.e., the set of all j such that the final  $\mathbf{goto}$  instruction of  $Block_j$  may jump to  $Block_i$ . Then we can fix the auxiliary variables  $R_i$  using WLP as follows

$$VC: WLP \wedge R_0 \equiv B_0 \wedge \bigwedge_{1 \leq i \leq n} \left( R_i \equiv B_i \wedge \bigvee_{j \in Pre_i} R_j \right).$$

That is, the reachability variable of the initial block is set to true if the run is terminating. The reachability variable of other blocks is set to true if the current valuation describes a normally terminating execution starting at this block and at least one predecessor has its reachability variable set to true.

**Theorem 3.** There is a valuation  $\mathcal{V}$  that satisfies VC with  $\mathcal{V}(R_0) = true$  if and only if the corresponding initial state leads to a feasible complete path  $\pi$  for the procedure. Moreover, the value of the reachability variable  $\mathcal{V}(R_i)$  is true if and only if there is a path  $\pi$  starting in this initial state that visits block  $Block_i$ .

Proof. Let there be a feasible path  $\pi$  and let  $\mathcal{V}$  be the corresponding valuation for the initial variables. If one sets the value of each of the auxiliary variable  $B_i$  and  $R_i$  according to its definition in VC, then VC is satisfied by  $\mathcal{V}$ . Moreover, the  $B_i$  variables for every visited block must be true by Lemma 2. Then also  $\mathcal{V}(R_0)$  must be true, i.e., the reachability variable for the initial state must be true. By induction one can see that  $\mathcal{V}(R_i)$  must also be true for every visited block  $Block_i$ .

For the other direction, let  $\mathcal{V}$  be a satisfying valuation for VC with  $\mathcal{V}(R_0) = true$ . Then also  $\mathcal{V}(B_0) = true$  holds. Hence, by Lemma 2 this valuation corresponds to a feasible path  $\pi$ . Let  $\mathcal{V}(R_i) = true$  for some block. If i = 0 then this is the initial block which is visited by the feasible path  $\pi$ . For  $i \neq 0$  there is some predecessor  $j \in Pre_i$  with  $\mathcal{V}(R_j) = true$ . By induction over the order of the blocks (note that the code is loop-free) one can assume that there is a feasible path starting in this initial state that visits  $Block_j$ . Since  $Block_j$  ends with a non-deterministic **goto** that can jump to  $Block_i$ , the latter block is reachable. Moreover since  $R_i$  is true, also  $B_i$  must be true and by Lemma 2 the valuation corresponds to a terminating run starting at  $Block Block_i$ . Thus, there is a run that starts at the initial state, reaches block  $Block_i$ , and terminates.

Thus VC is the reachability verification condition that can be used to generate test cases of the program that reach certain blocks. To cover all statements by test cases, one needs to find a set of valuations for VC, such that each  $R_i$  variable is true at least in one valuation. The following section will tackle this problem.

#### 5 Covering algorithms

We can now identify feasible executions through a block simply by checking if the reachability variable associated with this block evaluates to true in a satisfying valuation of the reachability verification condition. Further, due to the single static assignment performed before generating the formula, we can identify the initial values for each variable that are needed to force the execution of this path. That is, a valuation  $\mathcal{V}$  satisfying the VC can serve as a test case for a block associated with a reachability variable R, if  $\mathcal{V}(R) = true$ .

**Definition 1 (Test Case).** Given a reachability verification condition VC of a program. Let B be a block in this program, and R be the reachability variable

associated with this block. A test case for the block B is a valuation  $\mathcal{V}$  of VC, such that  $\mathcal{V} \models VC$  and  $\mathcal{V}(R)$  is true.

In the following we present two algorithms to compute test cases for loop-free programs. The first algorithm computes a set of test cases to cover all feasible control-flow path, the second one computes a more compact set that only covers all feasible statements.

Path Coverage Algorithm. To efficiently generate a set of test cases that covers all feasible control-flow paths, we need an algorithm that checks which combinations of reachability variables in a reachability verification condition can be set to true. That is, after finding one satisfying valuation for a reachability verification condition, this algorithm has to modify the next query in a way that ensures, that the same valuation is not computed again. This procedure has to be repeated until no further satisfying valuation can be found.

```
Algorithm 1: AlqPC
     Input: VC: A reachability verification condition,
                \mathcal{R} = \{R_0, \dots, R_n\}: The set of reachability variables
     Output: \mathcal{T}: A set of test cases covering all feasible paths.
     begin
 1
           \psi \leftarrow \mathit{VC}
 2
 3
           \mathcal{T} \leftarrow \{\}
  4
           \mathcal{V} \leftarrow \mathtt{checksat}(\psi)
 5
           while V \neq \{\} do
  6
                 \mathcal{T} \leftarrow \mathcal{T} \cup \{\mathcal{V}\}
 7
                  \phi \leftarrow false
                 foreach R in R do
 8
 9
                       if \mathcal{V}(R) = true then
10
                             \phi \leftarrow \phi \vee \neg R
11
                       else
                             \phi \leftarrow \phi \vee R
12
                       endif
13
                  endfch
14
                  \psi \leftarrow \psi \wedge \phi
15
                 \mathcal{V} \leftarrow \mathtt{checksat}(\psi)
16
           endw
17
           return \mathcal{T}
18
19
     end
```

Algorithm AlgPC, given in Algorithm 1, uses blocking clauses to guarantee that the every valuation is only returned once. The blocking clause is the negated conjunction of all assignments to reachability variables in a valuation  $\mathcal{V}$ . The algorithm uses the oracle-function **checksat** (see line 4 and 16), which has to be provided by a theorem prover. The function takes a first-order logic formula

as input and returns a satisfying assignment for this formula in form of a set of pair of variable and value for each free variable in that formula. If the formula is not satisfiable, checksat returns the empty set.

The algorithm uses a local copy  $\psi$  of the reachability verification condition VC. As long as checksat is able to compute a satisfying valuation  $\mathcal{V}$  for  $\psi$ , the algorithm adds this valuation to the set of test cases  $\mathcal{T}$  (line 6), and then builds a blocking clause consisting of the disjunction of the negated reachability variables which are assigned to true in  $\mathcal{V}$  (line 8). The formula  $\psi$  is conjuncted with this blocking clause (line 13), and the algorithm starts over by checking if there is a satisfying valuation for the new formula (line 14). The algorithm terminates when  $\psi$  becomes unsatisfiable.

Theorem 4 (Correctness of AlgPC). Given a loop-free and passive program P with verification condition VC. Let  $\mathcal{R}$  be the set of reachability variables used in VC. Algorithm AlgPC, started with the arguments VC and  $\mathcal{R}$ , terminates and returns a set  $\mathcal{T}$ . For any feasible and complete path  $\pi$  there is a test case in  $\mathcal{T}$  for this path.

Proof. There are only finitely many solutions for the variables  $\mathcal{R}$  that will satisfy the formula VC. Due to the introduction of the blocking clause, every solution will be found only once. Hence, after finitely many iteration the formula  $\psi$  must be unsatisfiable and the algorithm terminates. If  $\pi$  is a feasible and complete path, then by Theorem 3 there is a valuation  $\mathcal{V}$  with  $\mathcal{V}(R) = true$  for every block visited by  $\pi$ . Such a valuation must be found by the algorithm before a corresponding blocking clause is inserted into  $\psi$ . The corresponding test case is then inserted into  $\mathcal{T}$  and is a test case for  $\pi$ .

Note that AlgPC is complete for loop-free programs. For arbitrary programs that have been transformed using the steps from Section 3, the algorithm still produces only feasible test cases due to the soundness of the abstraction.

The advantage of using blocking clauses is that AlgPC does not restrict the oracle checksat in how it should explore the feasible paths encoded in the reachability verification condition. The drawback of AlgPC is that, for each explored path, a blocking clause is added to the formula and thus, the increasing size of the formula might slow down the checksat queries if many paths are explored. This limits the scalability of our algorithm. In Section 7 we evaluate how the performance of AlgPC changes with an increasing size of the input program.

Statement Coverage Algorithm. In some cases one might only be interested in covering all feasible statements. To avoid exercising all feasible paths, we present a second algorithm, AlgSC, in Algorithm 2 that computes a compact set of test cases to cover all feasible statements. The algorithm uses enabling clauses instead of blocking clauses that prevent the oracle from computing the same valuation twice. An enabling clause is the disjunction of all reachability variables that have not been assigned to true by previous satisfying valuation of the reachability verification condition.

#### Algorithm 2: AlgSC

```
Input: VC: A reachability verification condition,
                \mathcal{R} = \{R_0, \dots, R_n\}: The set of reachability variables
     Output: \mathcal{T}: A set of test cases covering all feasible statements.
 1
     begin
 2
           \mathcal{T} \leftarrow \{\}
           \mathcal{V} \leftarrow \mathtt{checksat}(\mathit{VC})
 3
           while \mathcal{V} \neq \{\} do
 4
                  \mathcal{T} \leftarrow \mathcal{T} \cup \{\mathcal{V}\}
 5
                 foreach R in R do
 6
                       if V(R) = true then
 7
                             \mathcal{R} \leftarrow \mathcal{R} \setminus \{R\}
 8
                             \mathcal{R} \leftarrow \texttt{RemoveClones}(R, \mathcal{R})
 9
                       endif
10
                 endfch
11
                  \phi \leftarrow false
12
                 foreach R in R do
13
                   \phi \leftarrow \phi \lor R
14
                 endfch
15
                 \mathcal{V} \leftarrow \mathtt{checksat}(\mathit{VC} \land \phi)
16
17
           endw
18
           return \mathcal{T}
19 end
```

The algorithm takes as input a reachability verification condition VC, and the set of all reachability variables  $\mathcal{R}$  used in this formula. Like AlgPC, AlgSCuses the oracle function checksat. First, it checks if there exists any satisfying valuation  $\mathcal{V}$  for VC. If so, the algorithm adds  $\mathcal{V}$  to the set of test cases (line 5). Then, the algorithm removes all reachability variables from the set  $\mathcal{R}$ , which are assigned to true in VC (line 8). While removing the reachability variables which are assigned to true, the algorithm also has to check if this reachability variable corresponds to a block created during loop unwinding. In that case, all clones of this block are removed from  $\mathcal{R}$  as well using the helper function RemoveClones() (line 9). After that, the algorithm computes a new enabling clause  $\phi$  that equals to the disjunction of the remaining reachability variables in  $\mathcal{R}$  (line 13) and starts over by checking if VC in conjunction with  $\phi$  is satisfiable (line 16). That is, conjunction  $VC \wedge \phi$  restricts the feasible executions in VC to those where at least one reachability variable in  $\mathcal{R}$  is set to true. Note that, if the set  $\mathcal{R}$  is empty, the enabling clause  $\phi$  becomes false, and thus the conjunction with VCbecomes unsatisfiable. That is, the algorithm terminates if all blocks have been visited once, or if there is no feasible execution passing the remaining blocks.

**Theorem 5 (Correctness of** AlgSC). Given a loop-free and passive program P with reachability verification condition VC. Let  $\mathcal{R}$  be the set of reachability variables used in VC. Algorithm AlgSC, started with the arguments VC and  $\mathcal{R}$ , terminates and returns a set  $\mathcal{T}$ . For any block in the program there exists a

feasible paths  $\pi$  passing this block if and only if there exists a test case  $\mathcal{V} \in \mathcal{T}$ , that passes this block.

*Proof.* In every iteration of the loop at least one variable of the set  $\mathcal{R}$  will be removed. This is because the formula  $\phi$  will only allow valuations such that for at least one  $R \in \mathcal{R}$  the valuation  $\mathcal{V}(R)$  is true. Since  $\mathcal{R}$  contains only finitely many variables the algorithm must terminate. If  $\pi$  is a feasible path visiting the block associated with the variable R, then there is a valuation  $\mathcal{V}$  that satisfies VC with  $\mathcal{V}(R) = true$ . Such a valuation must eventually be found, since  $VC \wedge \phi$  is only unsatisfiable if  $R \notin \mathcal{R}$ . The valuation is added to the set of test cases  $\mathcal{T}$ .

The benefit of AlgSC compared to AlgPC is that it will produce at most  $|\mathcal{R}|$  test cases, as each iteration of the loop will generate only one test case and remove at least one element from  $\mathcal{R}$ . That is, the resulting set  $\mathcal{T}$  can be used more efficiently if only statement coverage is needed. However, the enabling clause might cause the theorem prover which realizes checksat to take detours or throw away information which could be reused. It is not obvious which of both algorithms will perform better in terms of computation time. Therefore, in the following, we carry out some experiments to evaluate the performance of both algorithms.

Note that, like AlgPC, AlgSC is complete for loop-free programs and sound for arbitrary programs. That is, any block that is not covered by these algorithms is unreachable code (in the loop-free program).

## 6 Procedure Summaries

For large programs, inlining all procedure calls as proposed in Section 3 might not be feasible. However, replacing them by using assume-guarantee reasoning as it is done, e.g., in static checking [1] is not a feasible solution either. Using contracts requires the necessary expertise from the programmer to write proper pre- and postconditions, and thus, it would violate our goal of having a fully automatic tool. If trivial contracts are generated automatically (e.g., [15]), it will introduce feasible executions that do not exist in the original program. This would break the soundness requirement from Lemma 1 that each of the test cases returned by the algorithms AlgPC and AlgSC must represent a feasible path in the (loop-free) program.

Instead of inlining each procedure call, we propose to replace them by a summary of the original procedure which represents some feasible executions of the procedure. The summary can be obtained directly by applying AlgPC or AlgSC to the body of the called procedure. Each valuation  $\mathcal{V}$  in the set  $\mathcal{T}$  returned by these algorithms contains values for all incarnations of the variables used in the procedure body on one feasible execution. In particular, for a variable v, with the first incarnation  $v_0$  and the last incarnation  $v_n$ ,  $\mathcal{V}(v_0)$  represents one feasible input value for the considered procedure and  $\mathcal{V}(v_n)$  represents the value of v after this procedure returns. That is, given a procedure P with verification condition VC and reachability variables  $\mathcal{R}$ , let  $\mathcal{T} = AlgPC(VC, \mathcal{R})$  or  $\mathcal{T} = AlgPC(VC, \mathcal{R})$  or  $\mathcal{T} = AlgPC(VC, \mathcal{R})$  or  $\mathcal{T} = AlgPC(VC, \mathcal{R})$ 

 $AlgSC(VC, \mathcal{R})$  respectively. Furthermore let V be the set of variables which are visible to the outside of P, that is, parameters and global variables. The summary Sum of P is expressed by the formula:

$$Sum := \bigvee_{\mathcal{V} \in \mathcal{T}} \left( \bigwedge_{v \in V} (v_0 = \mathcal{V}(v_0)) \wedge \bigwedge_{v \in V} (v_n = \mathcal{V}(v_n)) \right),$$

where n refers to the maximum incarnation of a particular variable v. The summary can be interpreted as encoding each feasible path of P by the condition that, if the initial values for each variable are set appropriately, the post-state of this execution is established. We need an underapproximation of the feasible executions of the procedure as the procedure summary. Therefore we encode the summary of the previously computed paths and let the theorem prover choose the right path. In practice, in particular when using AlgPC, it can be useful to consider only a subset of  $\mathcal{T}$  for the summary construction, as a formula representing all paths might outgrow the actual verification condition of the procedure.

On the caller side, we can now replace the call to a procedure P by an assumption **assume** Sum where Sum is the procedure summary of P. We further have to add some framing assignments to map the input- and output variables of the called procedure to the one of the calling procedure. We illustrate this step using the following example program:

```
proc foo(a, b) returns c {
    11:
        goto 12, 13;
    12: assume b > 0;
        c := a + 1;
        goto 14;
    13: assume b <= 0;
        c := a - 1;
        goto 14;
    14:
}

proc bar(x) returns z {
    11:
        z := call foo(x,1);
}</pre>
```

Applying the algorithm AlgPC to the procedure foo will result in a summary like:

$$Sum := (a_0 = 0 \land b_0 = 0) \land (c_1 = a_0 - 1)$$
$$\lor (a_0 = 0 \land b_0 = 1) \land (c_1 = a_0 + 1)$$

This summary can be used to replace the call statement in bar after the single static assignment has been performed as follows:

```
proc bar(x) returns z {
```

```
11:
    assume a0=x;
    assume b0=1;
    assume Sum;
    assume z1=c1;
}
```

Note that, to avoid recomputing the single static assignment, when reaching a call statement, we increment the incarnation count for each variable that might be modified by this procedure and the incarnation count of each global variable. Therefore, we have to add frame conditions if a global variable is not changed by the summary (in this example it is not necessary, as there are no global variables).

A procedure summary can be seen as a switch case over possible input values. That is, the summary provides the return values for a particular set of input values to the called procedure. Any execution that calls the procedure with other input values becomes infeasible. In that sense, using procedure summaries is an under-approximation of the set of feasible executions and thus sound for our purpose.

**Lemma 3 (Soundness).** Given a loop-free procedure P which calls another loop-free procedure P'. Let  $P^{\#}$  be the version of procedure P where all calls to P' have been replaced by the summary of P'. Any feasible execution of  $P^{\#}$  is also a feasible execution of P.

Using these summaries is a very strong abstraction as only a very limited number of possible input values is considered as the set of feasible executions of the called procedure is reduced to one per control-flow path (or even less, if algorithm AlgSC is used). In particular, this causes problems if a procedure is called with constant values as arguments. In the example above, inlining only works if the theorem prover picks the same constant when computing the summary that is used on the caller side (which is the case here). If the constants do not match, the summary might provide no feasible path through the procedure, which is still sound but not useful. In that case, a new summary has to be computed where the constant values from the caller side are used as a precondition for the procedure (e.g., by adding an appropriate assume statement to the first block of the called procedure) before re-applying algorithm AlgPC or AlgSC.

The benefit of this summary computation is that it is fully automatic and the computation of the summary is relatively cheap, because the called procedure has to be analyzed at least once anyway. However, it is not a silver bullet and its practical value has to be evaluated in our future work. We do not consider procedure summaries as an efficient optimization. They rather are a necessary abstraction to keep our method scalable.

## 7 Experiments

We have implemented a prototype of the presented algorithms. As this prototype still is in a very early stage of development, the goal of this experiments is only to evaluate the computation time of the queries needed to cover all feasible statements in comparison to similar approaches. Other experiments, such as the applicability to real world software remain part of future work.

We compare the algorithms from Section 5 with two other approaches that compute a covering set of feasible executions: A worst-case optimal approach AlgFM from [16] and a query-optimal approach AlgVSTTE from [3]. The worst-case optimal approach checks if there exists a feasible control-flow path passing each minimal block. A block is minimal, if there exists no block that is passed by a strict subset of the executions passing this block [15,4]. Each implementation uses helper variables to build queries that ask the theorem prover for the existence of a path passing through one particular block. The query-optimal approach [3] uses helper variables to count how many minimal elements occur on one feasible execution and then applies a greedy strategy to cover as many minimal elements as possible with one valuation of the formula. Note that the purpose of AlgFM and AlgVSTTE is slightly different from the purpose of the algorithms in this paper. The AlgFM and AlgVSTTE use a loop-free abstraction of the input program that over-approximates the set of feasible executions of the original program (see, [15]). On this abstraction they prove the existence of blocks which cannot be part of any terminating execution. To be comparable, we use the same abstraction for all algorithms. That is, we use AlgFM and AlgVSTTE to check the existence of statements that do not occur on feasible executions. Since both algorithms are complete for loop-free programs, they return the same result as AlgSC.

Note that the result and purpose of all algorithms is slightly different. However, all of them use a theorem prover as an oracle to identify executions that cover all feasible statements in a program.

For now, our implementation works only for the simple language from Section 2. An implementation for a high-level language is not yet available. Hence the purpose of the experiments is only to measure the efficiency of the queries. Therefore, we decide to use randomly generated programs as input data. Generated programs have several benefits. We can control the size and shape of the program, we can generate an arbitrary number of different programs that share some property (e.g., number of control-flow diamonds), and they often have lots of infeasible control-flow paths. We are aware that randomly generated input is a controversial issue when evaluating research results, but we believe that, as we want to evaluate the performance of the algorithms, and not their detection rate or practical use, they are a good choice. A more technical discussion on this issue follows in the threats to validity.

Experimental Setup. As experimental data, we use 80 randomly generate unstructured programs. Each program has between 2 and 9 control-flow diamond shapes, and each diamond shape has 2 levels of nested if-then-else blocks (i.e., there are 4 distinct paths through each diamond). A block has 3 statements, which are either assignments of (linear arithmetic) expressions to unbounded integer variables or assumptions guarding the conditional choice. Each program

Algorithm	Queries (total)	Time (sec)
AlgPC	69777	13.12
AlgSC	854	11.81
AlgFM	1760	$145,\!45$
AlgVSTTE	512	$615,\!51$

**Table 1.** Comparison of the four algorithms in terms of total number of queries and computation time for 80 benchmark programs.

has between 90 and 350 lines of code and modifies between 10 and 20 different variables.

For each number of control-flow diamonds, we generated 10 different random programs and computed the average run-time of the algorithms. This is necessary to get an estimate of the performance of each algorithm, as their computation time strongly depends on the overall number of feasible executions in the analyzed program.

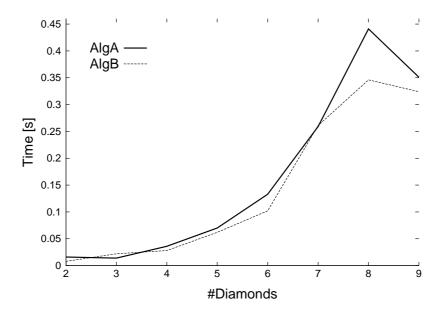
For a fair comparison, we use the theorem prover SMTInterpol <sup>3</sup> in all four algorithms. For each algorithm, we record how often the theorem prover is asked to check the satisfiability of a formula and we record the time it takes until the theorem prover returns with a result. All experiments are carried out on a standard desktop computer with ample amount of memory.

Discussion. Table 1 shows the summary of the results for all algorithms after analyzing 80 benchmark programs. Figure 5 gives a more detailed view on the computation time per program. The x-axis scales over the number of control-flow diamonds ranging from 2 diamonds to 9. Figure 6 gives a detailed view on the number of queries. As before, the x-axis scales over the number of control-flow diamonds.

The algorithms AlgPC and AlgSC are clearly faster than AlgFM and AlgVSTTE. Overall, AlgSC tends to be the fastest one. Figure 4 shows the computation time for AlgPC and AlgSC in a higher resolution. It turns out that the difference between the computation time of AlgPC and AlgSC tends to become bigger for larger programs. As expected, AlgSC works a bit more efficient as the size of the formula is always bounded, while AlgPC asserts one new term for every counterexample found. However, comparing the number of theorem prover calls, there is a huge difference between AlgPC and AlgSC. While AlgSC never exceeds a total of 20 queries per program, AlgPC skyrockets already for small programs. For a program with 10 control-flow diamonds, AlgPC uses more than 2000 theorem prover calls, where AlgSC only need 10. Still, AlgSC is only 0.03 seconds faster on this example (< 10%).

These results show that, even though AlgSC might be slightly more efficient than AlgPC, the number of queries is not an important factor for the computation time. In fact, internally, the theorem prover tries to find a new counterexample by changing as few variables as possible which is very close to the idea of

<sup>3</sup> http://ultimate.informatik.uni-freiburg.de/smtinterpol/

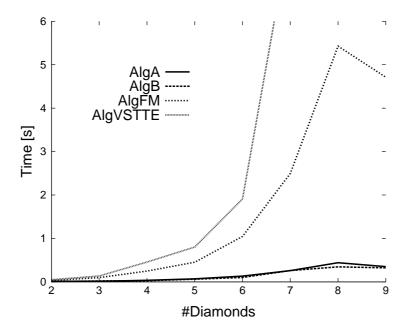


**Fig. 4.** Runtime comparison of the algorithms proposed in Section 5. The ticks on the x-axis represent the number of control-flow diamonds in the randomly generated programs.

AlgPC. AlgSC, which queries if there exists a counterexample through a block that has not been visited so far, will internally perform the same steps as AlgPC and thus, the performance gain is only rooted in the smaller formulas and reduced communication between application and prover. However, the results also show that, when using a theorem prover, computing a path cover with AlgPC is not significantly more expensive than computing only a statement cover with AlgSC.

The computation time for AlgFM and AlgVSTTE are significantly higher than the one for the presented algorithms. For AlgFM, some queries, and thus some computation time, could be saved by utilizing the counterexamples to avoid redundant queries. However, the number of queries cannot become better than the one of AlgSC due to the kind of queries. The most significant benefit of AlgPC and AlgSC over AlgFM is that they don't have to inject helper variables in the program. In fact AlgPC and AlgSC also use one variable per block to encode the reachability, but this variable is added to the formula and not to the program. Thus, it is not considered during single static assignment, which would create multiple copies for each variable.

For the query-optimal algorithm AlgVSTTE, the computation time becomes extremely large for our random programs. This is due to the fact that AlgVSTTE tries to find the best possible counterexample (that is, the one with the most previously uncovered blocks) with each query. Internally, the theorem prover will exercise several counterexamples and discard them until the best one



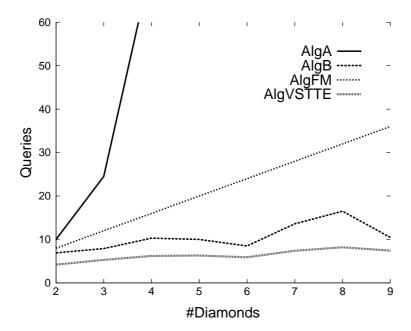
**Fig. 5.** Computation time for each algorithm. The ticks on the x-axis represent the number of control-flow diamonds in the randomly generated programs.

is found. The procedure is similar to the one used in AlgPC and AlgSC: the theorem prover computes a counterexample and then assures that this example cannot be found again, and then starts over. But in contrast to AlgVSTTE, our algorithms do not force the theorem prover to find a path that satisfies additional constraints, and, hence, relaxing the problem that has to be solved by the theorem prover. Even though one might find benchmarks where AlgVSTTE is significantly faster than AlgFM, the algorithms AlgPC and AlgSC will always be more efficient since they pose easier (and, hence, faster) queries to the theorem prover.

The presented results should not be interpreted as an argument against a query-optimal algorithm. We rather conclude that the place for such optimizations is inside the theorem prover. Modifying the way, the theorem prover finds a new counterexample can lead to tremendous performance improvements. However, such changes have to consider the structure of verification conditions and thus will exceed the functionality of a general theorem prover.

Threats to validity. We emphasize that the purpose of the experiments is only to evaluate the performance of AlgPC and AlgSC. These experiments are not valid to reason about practical use or scalability of the method.

We report several internal threats to validity: The experiments only used a very restricted background theory. However, the path reasoning described in this paper prunes the search space for the theorem prover even if we use richer logics



**Fig. 6.** Number of call to the theorem prover for each algorithm. The ticks on the x-axis represent the number of control-flow diamonds in the randomly generated programs.

including arrays or quantifiers. As shown in our experiments, the algorithms proposed in this paper pose easier problems to a theorem prover. This won't change if we switch to richer logics since our algorithms only limit the theorem prover to reason about feasible paths while all other algorithms pose additional constraints on such a path. If we use richer logics we only limit the number of paths. But still it remains easier to just find a path than to find one that satisfies some additional condition.

We have chosen randomly generated programs as input for two reasons. First, we wanted to be able to scale the number of paths and use the most difficult shape of the control structure for our techniques. Hence, we had to scale the number of diamonds in the control flow graph. Second, we did not implement a parser for a specific language. Existing translations from high-level languages into unstructured languages are not suitable for our algorithms as they overapproximate the set of infeasible executions to retain soundness w.r.t. partial correctness proofs. These translations might both over- and under-approximate the set of feasible executions of a program and thus violate our notion of soundness. However, for the purpose of comparing the performance of the different algorithms, the experiments are still valid.

In our experiments we only used SMT interpol to answer the queries. For the comparison of AlgPC with the other algorithms, the choice of the theorem prover can make a significant difference. SMT interpol tries to find a valuation for a formula by making as few changes as possible to the previous valuation. If a theorem prover chooses a different strategy, in particular AlgSC might become much fast. However, we are not aware of any theorem prover that uses this kind of strategy.

#### 8 Related Work

Automatic test case generation is a wide field ranging from purely random generation of input values (e.g., [22]) to complex static analysis. The presented algorithms can best be compared to tools that provide automatic white-box test case generation. Probably the most notable tools in this field are PREfix [6] and Pex [23]. Both algorithms use symbolic execution to generate test cases that provoke a particular behavior. Pex further allows the specification of parameterized unit tests. Symbolic execution analyzes a program path-by-path and then uses constraint solving to identify adequate input to execute this path. In contrast, our approach encodes all paths into one first-order formula and then calls a theorem prover to return any path and the input values needed to execute this path. In a way, symbolic execution selects a path and then searches feasible input values for this path, while our approach just asks the theorem prover for any path which is feasible. One advantage of our approach is that it might be more efficient to ask the theorem prover for a feasible path than checking for each path if it is feasible.

Many other approaches to static analysis-based automatic test case generation and bounded model checking exist but, due to the early stage of the development of the proposed ideas, a detailed comparison is subject to future work.

In [10] test cases are generated from interactive correctness proofs. The approach of using techniques from verification to identify feasible control-flow paths for test case generation is similar to ours. However, they generate test cases from a correctness proof, which might contain an over-approximation of the feasible executions. This can result in non-executable test cases. Our approach underapproximates the set of feasible executions and thus, any of the generated test cases can be executed.

Using a first-order formula representation of a program and a theorem prover to identify particular paths in that program goes back to, e.g., ESC [11] and, more recently, Boogie [19,12,1]. These approaches use similar program transformation steps to generate the formula representation of a program. However, the purpose of these approaches is to show the absence of failing executions. Therefore, their formula represents an approximation of the weakest precondition of the program with postcondition true. In contrast, we use the negated wlp with postcondition false. Showing the absence of failing executions is a more complicated task and requires a user-provided specification of the intended behavior of the program.

In [14], Grigore et al propose to use the strongest postcondition instead of the weakest precondition. This would also be possible for our approach. As mentioned in Section 4, the reachability variables are used to avoid encoding the complete strongest postcondition. However, it would be possible to use sp and modify the reachability variables to encode wlp.

Recently there has been some research on wlp based program analysis: in [17], an algorithm to detect unreachable code is presented. This algorithm can be seen as a variation of AlgSC. However, it does not return test cases. The algorithms AlgFM [16,15], and AlgVSTTE [3] detect code which never occurs on feasible executions. While AlgFM detects doomed program points, i.e. control-locations, AlgVSTTE detects statements, i.e. edges in the CFG. If a piece of code cannot be proved doomed/infeasible, a counter example is obtained which represents a normal-terminating executions. The main difference to our approach is that their formula is satisfied by all executions that either block or fail. We do not consider that an execution might fail and leave this to the execution of the test case.

There are several strategies to cover control-flow graphs. The most related to this work is [3], which has already been explained above. Other algorithms such as, [5,4,13] present strategies to compute feasible path covers efficiently. These algorithms use dynamic analysis and are therefore not complete.

Lahiri et al [18] used a procedure similar to one of our proposed algorithms to efficiently compute predicate abstraction. They used an AllSMT loop over a set of *important* predicates. One of our algorithms, AlgPC, lifts this idea to the context of test case generation and path coverage. Our second algorithm, AlgSC cannot be used in their context since the authors of this paper need to get all satisfying assignments for the set of predicates. In contrast, we are only interested in the set of predicates that are satisfied in at least one model of the SMT solver.

## 9 Conclusion

We have presented two algorithms to compute test cases that cover those statements respectively control-flow paths which have feasible executions within a certain number of loop unwindings. The algorithms compute a set of test cases in a fully automatic way without requiring any user-provided information about the environment of the program. The algorithms guarantee that these executions also exist in the original program (with loops). We further have presented a fully automatic way to compute procedure summaries, which gives our algorithm the potential to scale even to larger programs.

If no procedure summaries are used, the presented algorithms cover *all* statements/paths with feasible executions within the selected number of unwindings. That is, besides returning test cases for the feasible statements/paths one major result is that all statements that are not covered cannot be covered by *any* execution and thus are dead code.

The experiments show that the preliminary implementation already is able to outperform existing approaches that perform similar tasks. The experiments also show that computing a feasible path cover is almost as efficient as computing

a feasible statement cover with the used oracle even for procedures of up to 300 lines of code.

Due to the early stage of development there are still some limitations which refrain us from reporting a practical use of the proposed algorithms. So far, we do not have a proper translation from high level programming language into our intermediate format. Current translations into unstructured intermediate verification languages such as Boogie [1] are built to preserve all failing executions of a program for the purpose of proving partial correctness. However, these translations add feasible executions to the program during translation which breaks our notion of soundness. Further, our language does not support assertions. Runtime errors are guarded using conditional choice to give the test case generation the possibility to generate test cases that provoke runtime errors. A reasonable translation which only under-approximates feasible executions is still part of our future research.

Another problem is our oracle. Theorem provers are limited in their ability to find satisfying valuations for verification conditions. If the program contains, e.g., non-linear arithmetic, a theorem prover will not be able to find a valuation in every case. This does not affect the soundness of our approach, but it will prevent the algorithm from covering all feasible paths (i.e., the approach is not complete anymore). To make these algorithms applicable to real world programs, a combination with dynamic analysis might be required to identify feasible executions for those parts where the code is not available, or where the theorem prover is inconclusive.

Future Work. Our future work encompasses the development of a proper translation from Java into our unstructured language. This step is essential to evaluate the practical use of the proposed method and to extend its use to other applications.

One problem when analyzing real programs is intellectual property boundaries and the availability of code of third-party libraries. We plan to develop a combination of this approach with random testing (e.g., [21]), where random testing is used to compute procedure summaries for library procedure(s) where we cannot access the code.

The proposed procedure summaries have to be recomputed if the available summaries for a procedure do not represent any feasible execution in the current calling context. Therefore, we plan to develop a refinement loop which stores summaries more efficiently.

Another application would be to change the reachability variables in a way that they are only true if an assertion inside a block fails rather than if the block is reached. This would allow us to identify *all* paths that violate assertions in the loop-free program. Encoding failing assertions this way can be seen as an extension of the work of Leino et al in [20].

In the theorem prover, further optimizations could be made to improve the performance of AlgSC. Implementing a strategy to find new valuations that, e.g., change as many reachability variables as possible from the last valuation could lead to a much faster computation of a feasible statement cover. In the

future, we plan to implement a variation of the algorithm AlgVSTTE [3] inside the theorem prover.

We believe that the presented method can be a powerful extension to dynamic program analysis by providing information about which parts of a program can be executed within the given unwinding, what valuation is needed to execute them, and which parts can never be executed. The major benefit of this kind of program analysis is that it is user friendly in a way that it does not require any input besides the program and that any output refers to a real execution in the program. That is, it can be used without any extra work and without any expert knowledge. However, more work is required to find practical evidence for the usefulness of the presented ideas.

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