Speeding Up Dataflow Analysis Using Flow-Insensitive Pointer Analysis

Stephen Adams* Thomas Ball* Manuvir Das* Sorin Lerner†

Sriram K. Rajamani* Mark Seigle† Westley Weimer‡

*Microsoft Research †University of Washington ‡UC Berkeley
{sra,tball,manuvir,sriram}@microsoft.com
{lerns,seigle}@cs.washington.edu
weimer@eecs.berkeley.edu

Abstract

In recent years, static analysis has increasingly been applied to the problem of program verification. Systems for program verification typically use precise and expensive interprocedural dataflow algorithms that are difficult to scale to large programs. An attractive way to scale these analyses is to use a preprocessing step to reduce the number of dataflow facts propagated by the analysis and/or the number of statements to be processed, before the dataflow analysis is run.

This paper describes an approach that achieves this effect. We first run a scalable, control-flow-insensitive pointer analysis to produce a conservative representation of value flow in the program. We query the value flow representation at the program points where a dataflow solution is required, in order to obtain a conservative over-approximation of the dataflow facts and the statements that must be processed by the analysis. We then run the dataflow analysis on this "slice" of the program.

We present experimental evidence in support of our approach by considering three client dataflow analyses: pointer analysis, typestate analysis, and temporal property checking. We show that in each case, our approach leads to dramatic speedup.

1 Introduction

In recent years, static analysis has increasingly been applied to the problem of program verification. Two kinds of algorithms for static program analysis have been proposed. Flow-insensitive algorithms such as [DLFR01, HT01, OJ97] scale to large programs, but do not allow strong update. Flow-sensitive algorithms [CRL99, WL95], on the other hand, allow strong update but do not scale to large programs. The absence of strong update adversely affects software engineering and program verification tools, which produce many false positives with conservative analysis. Therefore, these tools often employ costly interprocedural dataflow algorithms [BR01b, CDH+00], even though this choice precludes application to large programs.

This paper is based on two key insights. The first insight is that well-known, flow-insensitive pointer analysis algorithms can be viewed as producing a lightweight, conservative representation of the value flow in a program. The second insight is that by querying this value flow representation before a client dataflow analysis is run, both the number of dataflow facts propagated by the analysis and the part of the program that must be analysed can be reduced.

Three small examples that demonstrate our approach are given in Figure 1.

Figure 1(a) shows a procedure for which we wish to compute the points-to set `*q`. By performing a flow-insensitive "points-to slice", we can remove dataflow facts corresponding to points-to sets for `p` and `r` and statements that do not affect the value of `q`, before computing the points-to set `*q`.

Figure 1(b) shows a procedure whose file I/O related behavior must be summarized for all callers. By performing a "typestate slice", we can remove dataflow facts corresponding to the states of the file handle `g2` and statements that do not affect the state of `g1`, before analyzing `bar`.

Figure 1(c) shows a program fragment on which we wish to determine whether the `abort` function is called. One way to do this is to determine a set of predicates over program variables, construct a boolean program abstraction [BR01a] over these predicates, and then model check the abstraction using dataflow analysis. The predicates required for proving that the `abort` statement is unreachable are `x == 5`, `y == 5`, `x == 10`, and `y == 10`. These predicates can be discovered in two iterations of iterative refinement (see Section 5). By performing a "predicate slice", we can infer the set of constants that flow into variables `x` and `y` and generate these predicates upfront, eliminating the iteration overhead.

These examples show the sort of information we hope to provide to client dataflow analyses. The points-to slice, typestate slice and predicate slice can all be obtained from a flow-insensitive pointer analysis. Each slice reduces the workload of the client dataflow analysis.

Two alternative approaches for achieving the same effect are demand-driven versions of the client dataflow analyses or standard program slicing. Both approaches have drawbacks. Frameworks for demand-driven dataflow [DGS95, HRS95] do not handle a general enough class of dataflow problems to allow application to problems that involve value flow. Program slicing [HRB90] is expensive and may produce overly large slices because it tracks control dependences.

The main contributions of this paper are:

- We show how flow-insensitive pointer analyses can be used to produce a program-point independent graph representation of value flow in a program.
- We show how this value flow representation can be used

```
(a)  void foo() {
       int x, y;
       int *p, *q, *r;
       p = &x;  q = &y;
       r = p;
       *q = 7;  *r = 4;
     }

(b)  FILE *g1, *g2;
     void bar() {
       FILE *l, *m;
       l = g1;
       m = g2;
       fclose(l);
     }
```

```
(c)  void baz(bool b) {
       int x , y;
       if (b) {
         x = 5;
         y = 5;
       }
       else  {
         x = 10;
         y = 10;
       }
       if (x != y)
         abort();
     }
```

Figure 1: Examples of speeding up dataflow analysis. Figure (a) above shows a fragment of C code to be sliced w.r.t. the points-to set `*q`. Figure (b) above shows a fragment of C code to be sliced w.r.t. file I/O behavior. Figure (c) above shows a fragment of C code to be sliced w.r.t. reachability of calls to `abort`.

to perform client-specific program slices that significantly speed up client dataflow analyses.

- We demonstrate the effectiveness of our technique with three specific applications of slicing using the one level flow pointer analysis [Das00]:
  - Points-to slicing: We apply points-to slicing to the benchmarks in SpecInt95. Over all of our benchmarks, 31% of the dereference points in the code have points-to slices that contain less than 1% of the pointer-related assignments in the program. This suggests that our method should speed up flow-sensitive pointer analysis substantially.
  - Typestate slicing: We use typestate slicing to reduce the number of objects whose state is tracked by ESP [DLS01], a typestate checker for large programs. We apply ESP to check file I/O properties of the gcc compiler. Typestate slicing reduces the average number of objects tracked per procedure from 1100 to less than 1, making the dataflow analysis in ESP practical.
  - Predicate slicing: We use predicate slicing to generate a candidate set of predicates for the initial boolean program abstraction used by SLAM [BR01a], a temporal safety property checker. We apply SLAM to check properties of several Windows device drivers. Predicate slicing reduces the running time of SLAM by a factor of 2-10, and allows SLAM to terminate in some cases where it did not terminate before.

The rest of this paper is structured as follows. In Section 2, we describe our value flow representation, its computation using pointer analysis, and its interface to dataflow clients. We then present three concrete applications of our value flow slicing approach. In Section 3, we explain points-to slicing and demonstrate its effectiveness. In Section 4, we demonstrate the use of typestate slicing in ESP. In Section 5, we show how predicate slicing can be used to aid predicate discovery in SLAM. We discuss related work in Section 6, and conclude in Section 7.

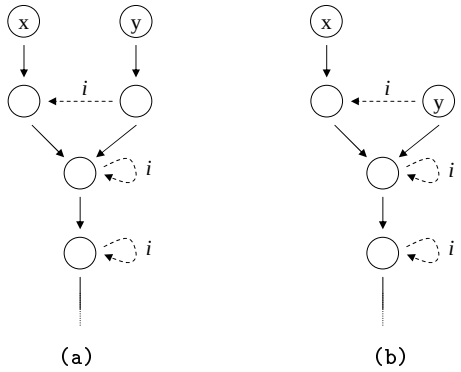


Figure 2: Figures (a) and (b) above show the points-to graphs computed by the one level flow algorithm for i: `x = y` and i: `x = &y`, respectively. Points-to edges are solid arrows. Flow edges are labeled dashed arrows.

2 Value Flow via Pointer Analysis

Pointer analysis algorithms typically produce graph representations ("points-to graphs") of pointer relationships in programs. These graphs encode information about which memory locations hold references to other memory locations. More importantly, these graphs encode constraints that arise from value flow through assignments in the program: every assignment that causes flow of pointer values is represented in the graph.

The key insight of this paper is that if the pointer analysis is modified to process all assignments, rather than just pointer assignments, and if values that are not stored in any memory location are represented explicitly in the graph, the resulting points-to graph encodes a conservative approximation of all value flow in the program. In addition, if the fragments of the graph that result from processing constraints are labeled with the identities of the statements that generated the constraints, the points-to graph encodes slices of the program: each slice represents the set of program statements that contribute to the value of a given expression. In the terminology of program slicing [Tip95], these slices encode flow dependences, but not control dependences. When the client dataflow analysis ignores control dependences (this is typically true of many dataflow analyses, including pointer analysis and the examples considered in this paper) the flow dependence slices encoded in the points-to graph preserve the results produced by the client dataflow analysis.

In this paper we focus on flow-insensitive pointer analyses, which produce a single representation of all of the value flow in the program that is applicable at every point in the program. Flow-sensitive pointer analyses could be used to produce value flow graphs as well: they would produce separate graphs at each program point, though every graph need not encode the entire value flow in the program.

2.1 One Level Flow Pointer Analysis

We demonstrate our approach by using the one level flow pointer analysis [Das00]. The graph fragments produced by the analysis for two kinds of assignments are shown in Figure 2. The points-to graph includes a node for every expression in the program; multiple expressions may map to the same node, but every variable maps to its own distinct

(a)

```
 0: void main() {
 1:   int a, b, c, *x, *y;
 2:   int *z, **p, **q;
 3:   x = &a;
 4:   y = &b;
 5:   p = &y;
 6:   q = &z;
 7:   z = &c;
 8:   p = q;
 9:   *x = 22;
10:   **p = 88;
11: }
```

(b)

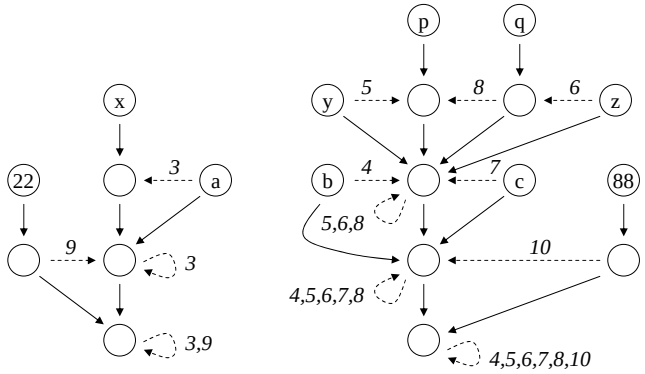


Figure 3: A fragment of C code and its points-to graph, augmented with source code labels and nodes for constants.

node. The graph includes two kinds of edges: points-to edges (written $\rightarrow$) and flow edges (written $\rightarrow_F$). A points-to edge connects (the node of) an expression `e` with (the node of) an expression `*e`. A flow edge $*\,$`e1` $\rightarrow_F$ `*e2` encodes an assignment from `e1` to `e2` in the program. Because the algorithm sometimes merges expressions into the same node, value flow is also encoded in node equality: every node can be viewed as having a flow edge to itself.

As shown in Figure 2, the assignment `x = y` induces an edge $*$`y` $\rightarrow_F$ `*x`, indicating that the value of `y` may flow to `x`, and induces node equality for `**x` and `**y`, `***x` and `***y`, and so on, indicating that the assignment also implicitly creates value flow between `*x` and `*y`, `**x` and `**y`, and so on. The assignment `x = &y` induces an edge `y` $\rightarrow_F$ `*x`, indicating that the address of `y` may flow to `x`. A more detailed discussion of the algorithm can be found in [Das00].

We extend the pointer analysis in two ways: First, we add nodes for values that are not stored in any memory location (*e.g.* constants). Second, we label flow edges with the assignments that induced the edges. We also transitively label all of the self-loop flow edges that are induced at lower (in terms of points-to edges) levels of the graph.

Example 1 A small C program is shown in Figure 3(a). The modified points-to graph computed for this program by the one level flow pointer analysis is shown in Figure 3(b). This graph encodes all of the value flow in the program. For instance, the flow of the value `22` to variable `a` at line 9 is encoded in the flow edge from `*22` to `*a` labeled 9. Notice that the statement at line 3, where `x` is assigned the address of `a`, also contributes to this value flow. The role of this statement is captured by the self-loop flow edge on `*a` labeled 3. □

For our purposes, the points-to graph produced by one level flow has several interesting properties:

- The graph can be computed in almost-linear time.
- Points-to sets can be obtained from the graph in linear time: the set of variables pointed-to by `p` (written $\mathsf{Vars}(*\mathtt{p})$) is obtained by a performing backwards reachability along flow edges from `*p` and including all of the variables encountered along the way.
- Value flow can be queried in linear time: the set of expressions whose values may flow to `e` is obtained by performing backwards reachability along flow edges from `*e` and including all of the expressions with points-to edges to nodes encountered along the way.

Example 2 The points-to graph in Figure 3 can be used to answer a number of points-to and value flow queries. A backwards flow query from `**x` picks up `*22`, which means that the value `22` can flow to any variable in the points-to set `*x`, including `a`. Because the query does not pick up any of `b`, `c`, `y`, `z`, `p`, or `q`, all of these variables can be ignored by a dataflow client that is tracking the flow of the value `22` through the program. □

2.2 Slicing Interface

Although the entire value flow graph could be presented to a client analysis, in practice most clients make a series of structured queries to the graph. This interface to the value flow graph is summarized below:

- $\mathsf{Deref}(\mathtt{p}) = \mathtt{q}$ where $\mathtt{p} \rightarrow \mathtt{q}$.
- $\forall \mathtt{v} \in \mathit{ProgVar}$, $\mathsf{N}(\mathtt{v})$ is the node representing `v`.
- $\mathsf{N}(\mathtt{e}) = \mathsf{case}\ \mathtt{e}\ \mathsf{of}\ \mathtt{v} : \mathsf{N}(\mathtt{v});\ *\mathtt{e}' : \mathsf{Deref}(\mathsf{N}(\mathtt{e}'))$.
- $\mathsf{Vars}(\mathtt{e}) = \{\mathtt{v} \in \mathit{ProgVar} \mid \mathtt{v} \rightarrow_F^* \mathtt{e}\}$.
- $\mathsf{PointsToSlice}(\mathtt{e}) = \{l \in \mathit{Lab} \mid \mathtt{r} \xrightarrow{l}_F \mathtt{q}$ and $\mathtt{q} \rightarrow_F^* \mathtt{e}\}$.
- $\mathsf{FlowsInto}(\mathtt{e}) = \{\mathtt{q} \mid \mathsf{Deref}(\mathtt{q}) \rightarrow_F^* \mathsf{Deref}(\mathtt{e})\}$.
- $\mathsf{FlowsTo}(\mathtt{e}) = \{\mathtt{q} \mid \mathsf{Deref}(\mathtt{e}) \rightarrow_F^* \mathsf{Deref}(\mathtt{q})\}$.
- $\mathsf{FlowSlice}(\mathtt{e}) = \{l \in \mathit{Lab} \mid \mathtt{r} \xrightarrow{l}_F \mathtt{q}$ and $\mathtt{q} \rightarrow_F^* \mathsf{Deref}(\mathtt{e})\}$.

The three case studies presented in Sections 3-5 use this interface to the value flow graph. In this description we have not considered objects with structure. The value flow representation can be extended in a straightforward to encode structure field accesses.

3 Points-to Slicing

Over the years many algorithms for precise flow-sensitive context-sensitive pointer analysis have been proposed [WL95, CRL99]. However, these analyses are difficult to scale to large programs. Therefore, a number of flow-insensitive algorithms have been proposed [LH99, Das00, HT01]. Although flow-insensitive algorithms oten produce

Program	LOC	Nodes	Small Deref Slices		Small Function Slices	
			$< 1\%$	$< 10\%$	$< 1\%$	$< 10\%$
compress	1,904	2,234	3.13	93.75	58.33	91.67
li	7,602	23,379	13.64	16.67	49.87	49.87
m88ksim	19,412	65,967	72.28	78.42	69.55	80.62
ijpeg	31,215	79,486	45.38	45.38	52.12	52.12
go	29,919	109,134	80.43	100	98.41	100
perl	26,871	116,490	16.39	17.87	31.25	31.25
vortex	67,211	200,107	42.13	48.24	42.3	46.3
gcc	205,406	604,100	40.34	40.34	44.81	44.81

Table 1: Experimental data on points-to slicing. For each benchmark program, the table above shows the lines of code and the AST node count, the percentage of points-to slices from dereference points whose size is less than 1% and 10% of the number of pointer-related assignments in the program, and the percentage of functions in the program for which computation of all points-to sets requires analyzing less than 1% and 10% of the pointer-related assignments in the program. Slices were computed using one level flow algorithm.

reasonably accurate results [CH00], it is sometimes the case that these algorithms. do not provide satisfactory precision at particular dereference points in a program. Ideally, we would like to have a demand-driven flow-sensitive pointer analysis algorithm that would do just enough work to compute points-to sets at these few dereference points. To our knowledge, such an algorithm has not been proposed in the literature.

One way to achieve the desired effect is to use the points-to graph described in the previous section to perform a "points-to slice" from dereference points of interest, and then apply an exhaustive flow-sensitive pointer analysis on the slice of the program. In this way, we can produce a demand-driven version of any existing pointer analysis.

We first compute PointsToSlice(e). This set of labels represents program points that potentially contribute to the computation of the points-to set for e. The resulting set of program statements does not contain control-flow statements, and in general will not be syntactically valid. In order to produce a program fragment suitable for further analysis, we transform the original program into a program containing IDs at every statement other than those in PointsToSlice(e). We then feed this residual program to an exhaustive, flow-sensitive analysis, suitably modified to apply the identity transfer function at ID statements.

Our approach uses a less precise analysis to compute the slice than the client flow-sensitive pointer analysis. Therefore, the points-to slice may include statements that could be ignored by a truly demand-driven flow-sensitive pointer analysis. Our experimental results suggest that our technique is quite effective in spite of this shortcoming.

Example 1 Consider a client of pointer analysis that demands the points-to set for `*x` at line 9 in the program from Figure 3 (a). The sliced program is given in Figure 4 (a). Now consider a slice of `**p` at line 10. The sliced program is given in Figure 4 (b). Note that the inclusion of lines 4 and 5 demonstrate a shortcoming of our approach. Because a flow insensitve analysis is at the heart of the value flow graph, the analysis cannot treat the assignment of `q` to `p` as a strong update. □

3.1 Experiments

In order to test the viability of our approach, we applied our technique to the programs in the SpecINT95 benchmark

```
 0: void main() {
 1:   int a, b, c,*x,*y;
 2:   int *z, **p, **q;
 3:   x = &a;
 4:   ID;
 5:   ID;
 6:   ID;
 7:   ID;
 8:   ID;
 9:   *x = 22;
10:   ID;
11: }
```

(a)

```
void main() {
  int a, b, c, *x,*y;
  int *z, **p, **q;
  ID;
  y = &b;
  p = &y;
  q = &z;
  z = &c;
  p = q;
  ID;
  **p = 88;
}
```

(b)

Figure 4: Figures (a) and (b) above show the program from Figure 3, sliced on `*x` and `**p`, respectively.

suite. Table 1 shows our results, using two different measures.

The first measure is the percentage of all dereference points in the program for which points-to slices are less than 1% and 10% of all pointer-related assignments in the program. Pointer related assignments are those assignments that contribute to actual points-to set computations for some dereference point. Therefore, the numbers in Table 1 are not skewed by the large number of scalar assignments in the programs. The data shows that a significant percentage of dereference points have very small slices. On the average, 31% of all dereferences have slices of size less than 1%, indicating that efficient flow-sensitive computation of these points-to sets over the sliced programs should be possible.

The data also indicates that there are very few slices that are between 1% and 10% of the total program size. The reason for this is that most slices either encounter a single node in the graph that reaches large portions of the pointer-related code in the program (this node has been referred to as the "blob" node in [Das00]), or they avoid the blob node and involve a very small fraction of the code. The small slices that avoid the blob are suitable for traditional exhaustive dataflow analyses.

Table 1 also shows the percentage of functions for which all points-to sets in the body of the function can be computed by a slice that it less than 1% and 10% of the pointer

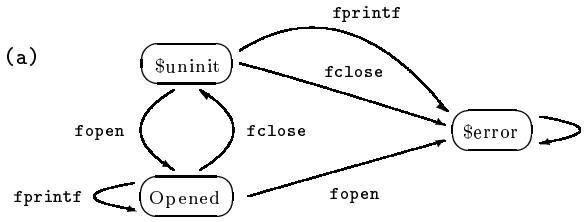


Figure 5: A finite state property that specifies correct usage of a file output library.

related assignments in the program. For these functions, accurate inter-procedural alias information can be obtained in an efficient manner, yielding improved optimization opportunities. The data is skewed by functions that do not contain any dereferences in their body; the points-to slices of these functions are trivially empty. If empty-dereference functions are not considered, 15% of the functions in the benchmarks have small slices on the average.

4 Typestate Slicing in ESP

ESP [DLS01] is a verification tool that identifies violations of programmer specified properties in large C programs. ESP tracks "typestate" [SY86]: As a program executes, it creates values. Every value is associated with a type that is invariant during program execution. Some values are additionally associated with a state that may be updated by certain operations on values. Transitions between states are encoded in a state machine. The machine has a special error state; transitions to the error state indicate violations of the property. An example of a user specified property (valid file output) is given in Figure 5.

The core engine of ESP is an interprocedural dataflow analysis that computes the possible states of every value at every point in the program. Because ESP is intended for application on large programs, the dataflow analysis is performed bottom-up on the call graph, one strongly connected component at a time. As a result, ESP must summarize the typestate behaviour of a function `foo` for all possible callers before any of the callers of `foo` are analyzed. The typestate summary of a function `foo` includes (a) the state changes caused by execution of `foo` on values live before the execution of `foo`, and (b) any new stateful values created by execution of `foo`, and their states on exit from `foo`. In order to compute the summary of a function, ESP first computes the set of memory locations that may hold stateful values at entry to the function, and then performs dataflow analysis for each such value. In a language with type coercion such as C, if we are computing the states of values of a particular type, for instance file handles with type `FILE *`, we must also consider values of all other possible types.

The set of locations that may hold a value at entry to a function `foo` includes all globals, formal parameters of `foo`, and transitive dereference targets of these. We refer to this set as *inNodes* (input interface nodes):

$$reached(v) = \{v\} \cup reached(\mathsf{Deref}(w))$$
$$reached_p(v) = reached(v) - \{v\}$$
$$inNodes(f) = \bigcup_{p \in params(f)} reached(p) \;\cup\; \bigcup_{g \in globals} reached(g)$$

Similarly, the set of locations that may hold a freshly created value at exit from `foo` includes all globals, the return value of `bar`, and dereference targets of these and the formal parameters of `bar`. We refer to this set as *outNodes* (output interface nodes).

$$outNodes(f) = reached(return_f) \;\cup\; \bigcup_{p \in params(f)} reached_p(p) \;\cup\; \bigcup_{g \in globals} reached(g)$$

```
FILE *e, *f, *g, *h;

void foo () {
   int *x, y;
   y = 3;  x = &y;
   g = fopen(...);
   bar(x);
}

void bar (int* p) {
   fprintf (h, "%d", *p);
   fclose (h);
}
```

Figure 6: An example program for typestate analysis. Function `foo` calls `bar` with an integer pointer. Bar prints the value of its dereferenced parameter to `h` and then closes `h`.

Example 3 A small program that manipulates file handles is given in Figure 6. The sets of possible interface nodes for the functions in this program are:

inNodes(`foo`): {`e, *e, f, *f, g, *g, h, *h`}
outNode(`foo`): {`e, *e, f, *f, g, *g, h, *h`}
inNodes(`bar`): {`e, *e, f, *f, g, *g, h, *h, p, *p`}
outNodes(`bar`): {`e, *e, f, *f, g, *g, h, *h, *p`}

In large programs with many globals, the interface node sets can be large enough to make typestate checking infeasible. Clearly, these sets include many locations that contain values whose state is not changed by the called function. A preprocessing step that can eliminate many of the spurious locations from the interface node sets will increase the efficiency of the subsequent typestate analysis.

4.1 Eliminating interface nodes via value flow

We use a slicing procedure to eliminate nodes from *inNodes* before the typestate analysis is run. The slicing procedure is based on the following observation: A location `l` must be included in *inNodes(*`f`*)* only if there is some expression `e` such that `e` is an argument to a state changing operation, and the value held by `l` at entry to `f` can flow to `e`. Therefore, we can query the flow-insensitive value flow representation from Section 2 to obtain an over-approximation of the set of locations that must be included in *inNodes(*`f`*)*. We refer to this procedure as "typestate slicing".

A similar procedure can be used to eliminate nodes from *outNodes*. A location `l` must be included in *outNodes(*`f`*)* only if there is some expression `e` such that `e` is the result of a value creation operation, and the value of `e` can flow to `l` at exit from `f`.

ESP uses a language of syntactic patterns to identify state changing operations in the code. The control flow graphs produced by the ESP front-end contain two kinds of distinguished, mutually exclusive, pattern nodes:

- PATTERN(name, p): Represents a call to a function whose name appears along a transition in the protocol, i.e. `fclose(f)`. `p` is the expression on which the operation is applied.
- CPATTERN(name, p): Represents a call to a function which creates fresh stateful values, i.e. `f = fopen(...)`. In this case `p` represents the recipient of the new value.

The set of expressions that are arguments to pattern nodes can then be defined as follows:

$$pNodes(f) = \{n | PATTERN(\_, n) \in f\}$$
$$cpNodes(f) = \{n | CPATTERN(\_, n) \in f\}$$

The sliced sets $inNodes_s$ and $outNodes_s$ are given by:

$$inTargets(f) = pNodes(f) \cup \bigcup_{g \in callees(f)} inNodes_s(g)$$
$$inNodes_s(f) = inNodes(f) \cap \bigcup_{n \in inTargets(f)} \mathsf{FlowsInto}(n)$$

$$outSrcs(f) = cpNodes(f) \cup \bigcup_{g \in callees(f)} outNodes_s(g)$$
$$outNodes_s(f) = outNodes(f) \cap \bigcup_{n \in outSrcs(f)} \mathsf{FlowsTo}(n)$$

The equations above describe a slicing procedure that is applied bottom-up on the call graph, one strongly connected component (SCC) at a time. Although the equations appear to require a fixpoint computation for SCCs containing more than one function, the solution can be obtained by combining a single flow query each for $inNodes_s$ and $outNodes_s$ with intersection operations for each function in the SCC.

Example 4 After typestate slicing is applied, the sets of interface nodes for the functions in the program from Figure 6 are:

$inNodes$(`foo`): {`h`} $outNode$(`foo`): {`g`}
$inNodes$(`bar`): {`h`} $outNodes$(`bar`): {}

4.2 Experiments

We have implemented typestate slicing as a preprocessing step in ESP. The dataflow engine in ESP performs an exhaustive dataflow analysis of the entire code in a strongly connected component for every node in the interface node sets of functions in the SCC. Therefore, the performance of ESP is directly related to the number of interface nodes.

File output in gcc. ESP has been applied to the problem of verifying the file output behaviour of a version of the gcc compiler, taken from the SpenInt95 benchmark suite, using the property specification given in Figure 5. gcc has 140,000 LOC in 2149 functions over 66 files; there are 1,086 global and static variables; the call graph contains a single SCC with over 450 functions.

Typestate slicing applied bottom-up on gcc requires 200 seconds on a Toshiba Tecra 8200 laptop with a 1GHz Pentium III processor and 512MB RAM, running Windows XP. Slicing reduces the number of interface nodes from roughly 1100 to < 1 on average, with a median of 15 for functions with non-empty interface node sets. This dramatic reduction in the sizes of the interface node sets allows ESP to successfully verify gcc in less than 15mins and 750MB of memory. Verification of gcc w.r.t. the file output property would be infeasible if the set of global interface nodes were not pruned.

Registry key leakage in cmd. We have also used ESP to find resource leaks in the command shell interpreter of a version of the Windows operating system. cmd has 40,000 LOC; there are 483 global and static variables. Typestate slicing applied bottom-up on gcc requires 33 seconds on a Compaq Evo W6000 desktop PC with a 2.2GHz Pentium IV processor and 2GB RAM, running Windows XP. Slicing reduces the number of interface nodes from roughly 500 to $<< 1$ on average, with a median of 1 for functions with non-empty interface node sets.

5 Predicate Slicing in SLAM

The SLAM toolkit validates temporal safety properties of programs and interfaces through a process of boolean abstraction [BMMR01, BR01a]. A specification writer describes a monitor or state machine that responds to events (function calls and returns) in the program and transitions to an error state should unsafe behavior happen. SLAM instruments the target program with the specification's state machine and then tries to prove that the specification's error state is not reachable.

The first step in this process involves abstracting the instrumented C program to a boolean program with the same control flow. Boolean programs have all of the control structure of C programs but contain only boolean variables. These boolean variables are chosen to represent predicates over expressions in the original program. For example, a boolean variable might represent "`(*ptr)==2`". The soundness of the boolean abstraction means that if a variable "`(*ptr)==2`" is true at a point L in the boolean program then `(*ptr)==2` will be true at the same point L in the original C program. Given a set of predicates $\mathcal{P}$ and a C program, SLAM can generate the corresponding boolean program. A key property of this transformation is that if the error label is *not* reachable in the boolean program then it is *not* reachable in the original program. Assuming $\mathcal{P}$ has been well-chosen, checking the safety of the original program reduces to checking the safety of the boolean program.

Since the boolean program involves only control flow (`if`, `goto`, function calls) and a finite set of boolean variables, interprocedural dataflow analysis can be used to explore its state-space exhaustively [BR01b]. If the error label is not reachable, the progam adheres to the safety policy. If there is a path to the error label then the path can be checked for feasibility in the original C program. When $\mathcal{P}$ is not sufficiently descriptive the boolean program error path may be infeasible in the original program. Otherwise the tool can produce an error trace demonstrating that the original program does violate the safety policy. When viewed as a dataflow problem, $\mathcal{P}$ is the set of dataflow facts and the boolean abstraction process gives the transition function for every statement in the program.

Choosing a good set of predicates $\mathcal{P}$ is very important. Two approaches are possible: (1) taking $\mathcal{P}$ to be an approximation to "all of the predicates in the program" (for example, all boolean relations between expressions in the program) generally eliminates false positives but yields a set so large as to make the dataflow analysis infeasible. Such a general approximation of randomly-constructed predicates would link variables that are never meaningfully related by

the flow of values in the original program. (2) taking $\mathcal{P}$ to be the null set, and applying a technique called iterative refinement to generate predicates from infeasible error traces in the boolean program [BR01a]. We initially implemented the second approach in the SLAM toolkit, and observed that SLAM took several iterations to converge on Windows XP device drivers. Using value-flow analysis, we were able to hit a 'sweet-spot' and generate an initial set of predicates detailed enough to eliminate false positives but small enough to make the analysis scale.

We first present a predicate slicing algorithm that works for a restricted ubset of the C language. Given a value-flow graph G for a progam written in that subset, the algorithm produces a set of predicates $\mathcal{P}$ that is provably sufficient to avoid false positives but avoids linking unrelated terms. For C programs that fall outside this restricted subset, the algorithm produces a good set of initial predicates, and the remaining false positives can be eliminated using iterative refinement. This algorithm has been used in practice to produce predicate sets that allow for the rapid analysis of programs for which the naive analysis was either very slow or infeasible.

5.1 Input Language

The restricted subset of C we will consider contains local scoping, procedural abstraction and the following statements:

$$\begin{array}{rcll} s & ::= & v_i \leftarrow n & (n \in \mathcal{Z}) \\ & | & v_i \leftarrow v_j & \\ & | & \mathsf{if}\ (\star)\ s_1\ \mathsf{else}\ s_2 & \\ & | & v_i \leftarrow \mathsf{fun}(v_j, ...) & \\ & | & \mathsf{return}(v_j) & \\ & | & \mathsf{abortif}(v_i \approx v_j) & \end{array}$$

v_i and v_j represent variables. All non-parameter variables are assumed to be initialized before use. Integer constants n form the set of *ground terms* in the program. The if $(\star)$ construct represents a non-deterministic `if`. The $\mathsf{abortif}(v_i \approx v_j)$ statement represents the safety policy: if such a statement can be reached when $(v_i \approx v_j)$ is true, the program violates the safety property. The relational operator $\approx$ is left abstract but is assumed to be deterministic. While severely restricted, this language is motivated by device driver handling of status codes. The codes are enumerated constants defined in header files and no transforming operations (e.g., plus, bitwise-and) may legally be performed on them. However, the safety policy may insist that status codes be propagated or that certain functions be called (or not called) depending on status code values. In such a device driver example the set of ground terms would be the set of status code values considered by the program.

5.2 Predicate Slicing Algorithm

Given a program C in this language, construct its value flow representation G. Intuitively, the algorithm uses G to track all variables and ground terms that can flow into v_i and v_j for every $\mathsf{abortif}(v_i \approx v_j)$ statement and generates predicates to keep track of that flow of values.

Ideally the the algorithm would emit the predicate "`a==b`" if $\mathsf{N}(\mathtt{a}) \rightarrow_F \mathsf{N}(\mathtt{b}) \in G$. Unfortunately, such predicates are often meaningless in scoped programs. For example, in Figure 7, although $\mathsf{N}(\mathtt{r}) \rightarrow_F^* \mathsf{N}(\mathtt{b})$ will be in G, the predicate "`r==b`" cannot be interpreted at any point in the program since `r` is a local variable in `select` and `b` is a local variable in `main`. That predicate is thus not suitable as a dataflow fact for the SLAM toolkit. A similar scoping problem occurs between actual arguments and formal parameters.

We will use the set of ground terms to bridge the gap between variables in different scopes. For example, given that the predicates "`10==r`" and "`10==b`" are true, we can logically conclude "`r==b`" even if we cannot express it as a well-scoped predicate. The predicate slicing algorithm will emit special predicates linking all formal parameters and function return values to an appropriate set of ground terms. These predicates and the transitivity of equality will allow for reasoning that crosses scope boundaries. In the example above, with the predicates "`10==r`", "`5==r`", "`10==b`" and "`5==b`" we have enough dataflow facts to reason about the value of `b` after the call to `select`.

With this intuition in mind, we present the complete algorithm. $\mathsf{Vars}(x)$ is used because many program variables may map to the same graph node x. For each $\mathsf{abortif}(v_i \approx v_j)$:

1. Determine $\mathsf{N}(v_i)$.
2. Let $F_i = \mathsf{FlowsInto}(\mathsf{N}(v_i))$.
3. For every $x, y \in F_i$ with $x \rightarrow_F y$, emit the set of predicates $\{$ "`a==b`" $\mid \mathtt{a} \in \mathsf{Vars}(x) \wedge \mathtt{b} \in \mathsf{Vars}(y) \wedge \mathsf{ShareScope}(\mathtt{a}, \mathtt{b})\}$.
4. Let $T_i = \{\ \mathtt{n} \mid \mathsf{N}(\mathtt{n}) \in F_i\}$ be the set of ground terms `n` that can flow into v_i.
5. For every $x \in F_i$, consider every $\mathtt{a} \in \mathsf{Vars}(x)$. If $\mathsf{return}(\mathtt{a}) \in C$ or `a` is a formal parameter then emit the set of predicates $\{$ "`n==a`" $\mid \mathtt{n} \in T_i\}$.
6. Repeat steps 1–5 with v_j and F_j.

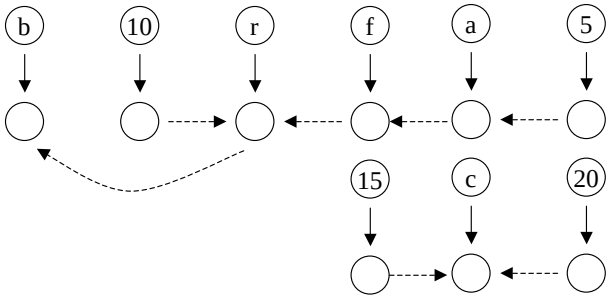
Since the relation $\approx$ is kept abstract, the algorithm generates predicates that keep track of the flow of ground terms throughout the program. Intuitively, the algorithm walks along chains of flow edges and generates equality predicates for every such edge (step 3). Edges that cross scope boundaries are linked using ground terms (step 5). If this set of predicates is used for dataflow analysis, when the $\mathsf{abortif}(\mathsf{v_i} \approx \mathsf{v_j})$ statement is reached some chain of predicates of the form "v_i`==`x", "x`==`y", "y`==n`" should be true. By transitivity, v_i`==n`. A similar value can be obtained for v_j. Given ground term values for v_i and v_j, the safety of the `abortif` statement can be decided statically.

For this restricted language the above algorithm can be proved correct: the set of generated predicates is always sufficient to statically verify all $\mathsf{abortif}(\mathsf{v_i} \approx \mathsf{v_j})$ statements. The proof is by induction on the length of chains of flow edges leading into v_i in G and makes use of the fact that in this language v_i must always take on a value from T_i (no other values are possible). The algorithm generates a sufficient number of predicates to keep track of the flow of ground terms through the program.

Example 5 Consider the program in Figure 7(a) and the associated value flow representation in 7(b). Let `b` be the variable under consideration. In step 2, $F_\mathtt{b}$ will be $\{10, \mathtt{r}, \mathtt{f}, \mathtt{a}, 5\}$. In step 3 we will emit the predicates "`5==a`", "`f==r`", "`10==r`" (predicates like "`a==f`" have no valid scope). In step 4, $T_\mathtt{b}$ is $\{10, 5\}$. So in step 5, `f` and `r` qualify so we emit the predicates "`5==f`", "`10==f`", "`5==r`" and

```
int select(int f) {
  int r;
  if (*) r ← f;
  else r ← 10;
  return(r);
}
void main() {
  int a,b,c;
  a ← 5;
  b ← select(a);
  if (*) c ← 15;
  else c ← 20;
  abortif(b > c);
}
```

(a)



(b)

Figure 7: An example of predicate slicing. An example program is shown in (a) above. The value flow representation for this program produced by one level flow points-to analysis is shown in (b) above.

Driver Name	Lines of code	Original Runtime	**Improved Runtime**	Generated Predicates	Max Preds In Scope	Missing Predicates
`apmbatt`	2207	299 s	**22 s**	85	10	0
`pnpmem`	3849	1132 s	**125 s**	143	9	4
`floppy`	7562	1063 s	**600 s**	154	16	33
`iscsiprt`	4543	**	**729 s**	146	10	42

Figure 8: Performance of predicate slicing. The table above compares the performance of SLAM with predicate slicing against the performance of SLAM with counter-example driven refinement.

"`10==r`". The algorithm then repeats with `c` as the variable under consideration and generates "`15==c`" and "`20==c`". □

The algorithm can be optimized to produce a smaller set of sufficient predicates if the relation $\approx$ is not abstract (e.g., if it is `<` or `==`) or if one of the arguments is constant. For example, to handle abortif($x == 7$), step 4 can be replaced by "Let $T_i = \{7\}$," since at every point we only care if the value that will flow into x is 7 or not. In addition, because value flow representations often merge source variables of different types into the same node, the algorithm can be refined to emit equality predicates over variables of matching types only.

5.3 Experiments

Figure 8 shows the performance of the predicate slicing algorithm on Windows NT device drivers that have been instrumented with input–output request and locking safety properties. In reality, programs do not fit within the restricted subset of C we presented. For example, the subset does not capture correlations between conditionals: in such cases the algorithm will generate an insufficient set of predicates. SLAM uses a form of counter-example driven refinement to add in those missing predicates. We compare SLAM with the predicate slicing algorithm against SLAM with all predicates generated by counter-example driven refinement.

"Original Runtime" shows the time for SLAM to either find a bug or prove the driver correct using only counter-example driven refinement. In the case of `iscsiprt`, SLAM does not terminate. "Improved Runtime" shows the execution time when SLAM begins with the predicate slice computed using the previous algorithm. "Generated Predicates" gives the number of distinct predicates in the slice. "Missing Predicates" gives the number of necessary predicates not in the slice that must be found by counter-example driven refinement (e.g., those predicates that correlate conditionals).

Using this technique SLAM was able to scale to some previously unreachable real-world device drivers and performs 2–10 times better on others. The predicate slice provides between all and two-thirds of the necessary predicates. However, since SLAM must generally iterate once to find 3–7 missing predicate and each iteration is exponential in the number of predicates already discovered, the net performance increase is more than linear.

6 Related Work

The main idea behind this paper is the use of cheap flow-insensitive value flow information to speed up dataflow. The previous work most similar to our work is that of Ruf [Ruf97] and Zhang et al [ZRL96].

Ruf showed how a unification-based non-standard type inference procedure such as Steensgaard's pointer analysis could be used to partition the data in a program in such a way that dataflow analysis could be scheduled one partition at a time. This reduces the memory footprint of the dataflow analysis [Ruf97]. Ruf's work can be viewed as producing slices using a points-to graph where all flow edges are replaced by node merging. In general, this will lead to larger slices. Ruf also had no mechanism for identifying constraints and using this information to generate slices of the program.

Zhang et al used a unification-based pointer analysis to divide the pointer variables in a program into equivalence classes, such that the points-to sets for each equivalence class could be computed separately using a more expensive

pointer analysis [ZRL96]. Our work generalizes their result by introducing directional flow, and extends their idea to value flow analysis and clients of value flow analysis in general.

Recent work by Foster et al [FTA01] uses a unification-based analysis to compute a set of dataflow facts that are then fed to a flow-sensitive type qualifier system. We believe that their work, which appears similar to the typestate slicing used in ESP, could be classified as an instance of our approach.

Rountev et al developed a framework for combining flow-insensitive global information with flow-sensitive local information [RRL99]. Our work differs from theirs in that our use of flow-insensitive information does not affect the precision of the client analysis, as is the case in their framework. We are merely interesting in improving the efficiency of the subsequent dataflow analysis.

An alternative approach to the one we have presented is to develop demand-driven versions of client dataflow analyses. Previous work on demand-driven dataflow frameworks includes [HRS95] and [DGS95], among others. These frameworks restrict the class of dataflow problems handled, usually to distributive problems, whereas we are interested in value flow problems that are not distributive. It is possible that one can design distributive approximations of value flow analysis that could then be performed from program points of interest, in order to yield more precise slices than those obtained from our flow-insensitive representation.

Another alternative approach is to use standard program slicing techniques, surveyed in [Tip95]. One drawback of program slicing is that it is based on flow-sensitive reaching definition computation, which is likely to be as expensive as exhaustive application of the client dataflow analysis. The other drawback is the inclusion of control dependences, which can lead to larger slices. Control dependences are necessary to provide strict guarantees of correctness, but for dataflow clients that ignore value transfer through control dependences, they are not required. Our value flow representation can be viewed as encoding flow-insensitive reaching definitions. The precision of our value flow can be improved through the use of an SSA form [CFR+91].

7 Conclusions

This paper is based on a simple hypothesis: systems that employ heavyweight interprocedural dataflow analyses can benefit greatly by using a cheap pointer analysis to prune the set of dataflow facts and program statements over which they must operate. We have presented experiments using three different client dataflow analyses to to validate our hypothesis. In all three cases, we obtain significant gains in performance by using a cheap pointer analysis.

References

[BMMR01] Thomas Ball, Rupak Majumdar, Todd Millstein, and Sriram K. Rajamani. Automatic predicate abstraction of c programs. In *Proceedings of the ACM SIGPLAN '01 Conference on Programming Language Design and Implementation (PLDI-01)*, volume 35, pages 203–213, 2001.

[BR01a] Thomas Ball and Sriram K. Rajamani. Automatically validating temporal safety properties of interfaces. In *Proceedings of SPIN '01, 8th Annual SPIN Workshop on Model Checking of Software*, May 2001.

[BR01b] Thomas Ball and Sriram K. Rajamani. Bebop: A path-sensitive interprocedural dataflow engine. In *Proceedings of PASTE '01, ACM SIGPLAN-SIGSOFT Workshop on Program Analysis for Software Tools and Engineering*, June 2001.

[CDH+00] J. Corbett, M. Dwyer, J. Hatcliff, C. Pasareanu, Robby, S. Laubach, and H. Zheng. Bandera: Extracting finite-state models from java source code. In *Proceedings of the 22nd International Conference on Software Engineering*, 2000.

[CFR+91] Ron Cytron, Jeanne Ferrante, Barry K. Rosen, Mark N. Wegman, and F. Kenneth Zadeck. Efficiently computing static single assignment form and the control dependence graph. *ACM Transactions on Programming Languages and Systems*, 13(4):451–490, October 1991.

[CH00] B. Cheng and W. Hwu. Modular interprocedural pointer analysis using access paths: Design, implementation, and evaluation. In *Proceedings of the ACM SIGPLAN 2000 Conference on Programming Language Design and Implementation*, 2000.

[CRL99] R. Chatterjee, B. Ryder, and W. Landi. Relevant context inference. In *Proceedings of POPL '99, 26st ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*, 1999.

[Das00] Manuvir Das. Unification-based pointer analysis with directional assignments. In *Proceedings of the ACM SIGPLAN '00 Conference on Programming Language Design and Implementation (PLDI-00)*, 2000.

[DGS95] Evelyn Duesterwald, Rajiv Gupta, and Mary Lou Soffa. Demand-driven computation of interprocedural data flow. In *Symposium on Principles of Programming Languages*, pages 37–48, 1995.

[DLFR01] Manuvir Das, Ben Liblit, Manuel Fahndrich, and Jakob Rehof. Estimating the impact of scalable pointer analysis on optimization. In *Proceedings of the 8th International Symposium on Static Analysis*, 2001.

[DLS01] M. Das, S. Lerner, and M. Seigle. Path sensitive program verification in polynomial time, November 2001. Submitted to PLDI2002.

[FTA01] Jeffrey S. Foster, Tachio Terauchi, and Alex Aiken. Flow-Sensitive Type Qualifiers. Technical Report UCB//CSD-01-1162, University of California, Berkeley, November 2001.

[HRB90] Susan Horwitz, Thomas Reps, and David Binkley. Interprocedural slicing using dependence graphs. *ACM Transactions on Programming Languages and Systems*, 12(1):26–60, January 1990.

[HRS95] Susan Horwitz, Thomas Reps, and Mooly Sagiv. Demand-driven interprocedural dataflow analysis. In *Proceedings of the ACM SIGSOFT Symposium on Foundations of Software Engineering Notes*, volume 20, 1995.

[HT01] Nevin Heintze and O. Tardeau. Ultra fast aliasing analysis using CLA: a million lines in a second. In *Proceedings of the ACM SIGPLAN '01 Conference on Programming Language Design and Implementation (PLDI-01)*, 2001.

[LH99] D. Liang and M. Harrold. Efficient points-to analysis for whole program analysis. In *Proceedings of the 7th ACM SIGSOFT Symposium on the Foundations of Software Engineering*, 1999.

[OJ97] R. O'Callahan and D. Jackson. Lackwit: A program understanding tool based on type inference. In *Proceedings of the 1997 International Conference on Software Engineering*, 1997.

[RRL99] Atanas Rountev, Barbara G. Ryder, and William Landi. Data-flow analysis of program fragments. In *Proceedings of the ACM SIGSOFT Symposium on Foundations of Software Engineering*, pages 235–252, 1999.

[Ruf97] E. Ruf. Partitioning dataflow analyses using types. In *Conference Record of the Twenty-Fourth ACM Symposium on Principles of Programming Languages*, 1997.

[SY86] R. Strom and S. Yemini. Typestate: A programming language concept for enhancing software reliability. *IEEE Transactions on Software Engineering*, 12(1):157–171, 1986.

[Tip95] F. Tip. A survey of program slicing techniques. *Journal of Programming Languages*, 3(3):121–189, 1995.

[WL95] R. Wilson and Monica Lam. Efficient context-sensitive pointer analysis for C progams. In *Proceedings of the ACM SIGPLAN '95 Conference on Programming Language Design and Implementation (PLDI-95)*, 1995.

[ZRL96] S. Zhang, B. Ryder, and W. Landi. Program Decomposition for Pointer Aliasing: A Step toward Practical Analyses. In *Fourth Symposium on the Foundations of Software Engineering (FSE4)*, 1996.