Prioritizing Constraint Evaluation for Efficient Points-to Analysis

Rupesh Nasre
Computer Science and Automation,
Indian Institute of Science,
Bangalore, India – 560012
Email: nasre@csa.iisc.ernet.in

R. Govindarajan
Computer Science and Automation,
Indian Institute of Science,
Bangalore, India – 560012
Email: govind@csa.iisc.ernet.in

Abstract—Pervasive use of pointers in large-scale real-world applications continues to make points-to analysis an important optimization-enabler. Rapid growth of software systems demands a scalable pointer analysis algorithm. A typical inclusion-based points-to analysis iteratively evaluates constraints and computes a points-to solution until a fixpoint. In each iteration, (i) points-to information is propagated across directed edges in a constraint graph $G$ and (ii) more edges are added by processing the points-to constraints. We observe that prioritizing the order in which the information is processed within each of the above two steps can lead to efficient execution of the points-to analysis. While earlier work in the literature focuses only on the propagation order, we argue that the other dimension, that is, prioritizing the constraint processing, can lead to even higher improvements on how fast the fixpoint of the points-to algorithm is reached. This becomes especially important as we prove that finding an optimal sequence for processing the points-to constraints is NP-Complete. The prioritization scheme proposed in this paper is general enough to be applied to any of the existing points-to analyses. We develop a prioritization framework using which we implement prioritized versions of Andersen’s analysis, Deep Propagation, Hardekopf and Lin’s Lazy Cycle Detection and Bloom Filter based points-to analysis. In each case, we report significant improvements in the analysis times (33%, 47%, 44%, 20% respectively) as well as the memory requirements for a large suite of programs, including SPEC 2000 benchmarks and five large open source programs.

I. INTRODUCTION

Static analysis of programs is important to achieve faster runtime execution, more secure code, less buggy programs, invariant guarantees and a better program understanding. As more and more emphasis is laid on guaranteeing secure code, data-race free programs and memory-leak free programs, the demand on scalable and precise static analysis increases. Further, the rapid growth of code bases places even further demand on scalable static analysis techniques. Points-to analysis is an important static analysis which is an enabler for several compiler optimizations. The effectiveness of several compiler optimizations depends heavily on the underlying pointer analysis. Thus, the scalability requirement of pointer analysis and its importance is unquestionable. Indeed, the literature on points-to analysis is rich with several interesting ideas [1], [2], [3], [4], [5], [6], [7]. For analyzing a general purpose C program, it is sufficient to consider all pointer statements of the following forms:

- address-of assignment ($p = \&q$), copy assignment ($p = q$), load assignment ($p = \ast q$) and store assignment ($\ast p = q$) [7].

Load and store assignments are also referred to as complex assignments in literature (e.g., [7]). We use the terms constraint, statement and assignment interchangeably in this article. We deal with flow-insensitive, context-sensitive inclusion-based points-to analyses in this work.

A flow-insensitive analysis iterates over a set of points-to constraints until a fixpoint is obtained. Typically, the flow of points-to information is represented using a constraint graph $G$, in which a node denotes a pointer variable and a directed edge from node $n_1$ to node $n_2$ represents propagation of points-to information from $n_1$ to $n_2$. Each node is initialized with the points-to information computed by evaluating the address-of constraints. Edges are added to $G$ initially by copy constraints and then by complex constraints as the analysis progresses. This is because the edges introduced by complex constraints depend upon the availability of points-to information at nodes which, in turn, depends upon the propagation. Thus, as the analysis performs an iterative progression of the points-to information propagation, new edges get introduced in $G$ due to the evaluation of the complex constraints, resulting in the computation of more and more points-to information at its nodes. When no more edges and no more points-to information can be computed, $G$ gets stabilized and a fixpoint (at the nodes) is reached. An outline of this analysis is given in Algorithm 1.

Algorithms

Algorithm 1 Points-to Analysis using Constraint Graph.

Require: set $C$ of points-to constraints
1: Process address-of constraints
2: Add edges to constraint graph $G$ using copy constraints
3: repeat
4: Propagate points-to information in $G$
5: Add edges to $G$ using load and store constraints
6: until fixpoint

Techniques have been developed for efficient propagation of the points-to information across the edges of a constraint graph, i.e., Line 4 of Algorithm 1. Online cycle elimination [8] detects cycles in $G$ on-the-fly and collapses all the nodes in a cycle into a representative node. This speeds up the
propagation of points-to information since all the nodes in a cycle eventually contain the same points-to information. Wave and Deep Propagation [7] perform a topological ordering of the edges and propagate difference in the points-to information in a breadth-first or depth-first manner. Various heuristics like Greatest Input Rise, Greatest Output Rise, and Least Recently Fired [9] work on the amount and recency of information computed at various nodes in the constraint graph to achieve a quicker fixpoint.

All of the above techniques essentially focus on the propagation order (Line 4 of Algorithm 1) and prioritize the order in which the points-to propagation takes place. However, these techniques do not attempt to dictate which evaluation order of the constraints (Line 5 of Algorithm 1) would prove more beneficial for faster points-to information computation. Specifically, there are two aspects of the constraint evaluation that are not addressed in literature: (i) how many edges a constraint adds, and (ii) where in C a constraint adds edges. We observe that both these parameters are important and can significantly influence the fixpoint computation. It should be noted that neither the propagation order nor the constraint evaluation order changes the fixpoint of the points-to solution.

We develop a framework that deals with the priority ordering of the points-to constraints and the propagation of points-to information. The two criteria mentioned above give rise to a skewed evaluation of important and useful constraints early and in a repeated manner to reach the (same) fixpoint solution faster.

To summarize, while earlier approaches [8], [10], [7] focus on the propagation order of the points-to information, we address the evaluation order of the points-to constraints. Major contributions of this paper are as below.

- We prove that finding a sequence of the points-to constraints to reach the fixpoint in an optimal number of steps in a flow-insensitive inclusion-based analysis is NP-Complete (Section II).
- We develop a priority-based greedy analysis framework for efficient computation of points-to information (Section III). The framework is general and can be used for other static analyses.
- We instantiate our framework by defining constraint priority based on the structure of and the number of points-to facts changed by a constraint. We extend it to a dynamic constraint ordering that can be easily applied to a particular points-to analysis algorithm (Section IV).
- We show the effectiveness of our approach by applying it on top of the state-of-the-art algorithms (Andersens analysis [1], BDD-based Lazy Cycle Detection [11], Deep Propagation [7] and Bloom Filters [12]) for SPEC 2000 benchmarks and five large open source programs (httpd, sendmail, gdb, wine-server and ghostscript) (Section V). Our experimental evaluation shows a significant improvement in the analysis times: 33% in Andersens analysis, 47% in Lazy Cycle Detection, 44% in Deep Propagation and 20% in Bloom Filter based analysis. A positive side-effect of the application of prioritized constraint evaluation is the reduction in the memory requirement of the original analyses: 17% in Andersens analysis and 23% in Deep Propagation.

II. OPTIMAL ORDERING OF CONSTRAINTS

Given our observation that prioritizing the processing of points-to constraints in Line 5 of Algorithm 1 improves the analysis time, it raises the question: does there exist an order in which the constraints should be processed which can ensure optimal number of steps for reaching the fixpoint? For instance, given a set of points-to constraints $a = \&x, b = \&y, p = \&q, *q = b, *p = a$, it takes two iterations to reach the fixpoint, if they are processed in the above order. However, processing the constraints in the following order ensures fixpoint in one iteration:

$$a = \&x, b = \&y, p = \&q, *p = a, *q = b.$$  

Since existing techniques decouple propagation and evaluation of the complex constraints, they do not reorder the constraints, which results in requiring multiple iterations to reach the fixpoint.

In this section, we prove that computing such a sequence even for a restricted scenario where only copy constraints are allowed is NP-Complete.

Theorem 1. Computing the flow-insensitive inclusion-based points-to solution in an optimal number of steps from a set of copy constraints is NP-Complete.

Proof: We reduce Set Cover problem to points-to analy- sis. Consider a Set Cover instance $SC(U, S, K)$ with universe $U$ and a set $S$ of subsets $S_i$. The decision version of the Set Cover problem states that given a universe $U$ and a set $S$ with subsets $S_i$ possibly having elements in common, whether there exists a set of $K$ subsets whose union contains all the elements contained in any $S_i$. The problem $SC(U, S, K)$ is known to be NP-Complete [13].

We reduce $SC(U, S, K)$ to $PTA(C, S, K)$ which is a flow-insensitive points-to analysis over a set of points-to (copy) constraints $C$ with an initial points-to information and the fixpoint defined with respect to pointer $S$. The decision version of PTA checks if the constraints in $C$ can be evaluated in a manner such that the fixpoint with respect to $S$ is reached in $K$ steps. A step indicates evaluation of a constraint.

The reduction is performed as below. For each element $s \in S_i$, we create an initial points-to information $S_i \rightarrow \{s\}$, i.e., $S_i$ points-to $s$. For each set $S_i$, we create a copy statement $S = S_i$. This transformation from $SC(U, S, K)$ to $PTA(C, S, K)$ is linear in the number of sets and the number of elements. Thus, SC polynomially reduces to PTA.

If an efficient (polynomial) solution exists for PTA, then the solution can be mapped back to SC. Thus, if there is a sequence of $K$ steps to obtain the fixpoint, and since the
fixpoint would contain all the points-to information, then the subsets \( S_i \) corresponding to the chosen copy constraints \((S = S_i)\) would cover all the elements \( s \in \mathcal{U} \) that correspond to the points-to facts in the fixpoint, forming the set cover.

Similarly, if a set cover of size \( K \) exists, then no other subset would be able to add any new points-to information to \( S \) and the \( K \) subsets would form an optimal sequence of \( K \) steps to obtain the fixpoint over the constraints. Thus, PTA is in NP. (b)

\[ \text{subset would be able to add any new points-to information to the points-to facts in the fixpoint, forming the set cover.} \]

The fixpoint would contain all the points-to information, then the subsets \( S_i \) corresponding to the chosen copy constraints \((S = S_i)\) would cover all the elements \( s \in \mathcal{U} \) that correspond to the points-to facts in the fixpoint, forming the set cover.

\[ \text{Thus, PTA is in NP.} \]

\[ \text{It is easy to see that a given sequence of constraints can act as a polynomial time verifier to check if PTA evaluates to a fixpoint. Thus, PTA is in NP.} \]

From (a) and (b), PTA is NP-Complete.

### III. Prioritized Computation of Constraints

We first explain our priority-based approach using an example, then discuss various priority schemes followed by our prioritization framework. Our priority based approach may be viewed similar to the maximum benefit approach in the online set cover problem [14].

### A. Motivating Example

Consider the program fragment given in Figure 1(a). Let the initial points-to information due to the address-of constraints be \( a \rightarrow \{a, q, r, s, t\} \) and \( p \rightarrow \{b, c, d\} \). Figure 1(b) illustrates the constraint graph \( G \) at the end of different iterations of Andersen’s analysis [1] with points-to information propagated using Deep Propagation [7]. For simpler exposition, we assume that online cycle elimination [8] is not performed.

A node is represented as \( n(P) \) where \( n \) is a pointer and \( P \) is its points-to set computed so far. Directed edge from node \( n_1 \) to \( n_2 \) represents the propagation of points-to information from \( n_1 \) to \( n_2 \). As the behavior of the pointers \( q, r, s, t \) is the same in this example, we use a single node to represent all of them. Prior to Iteration 1, edges \( c \) to \( e \) and \( a \) to \( b \) are added to \( G \) using copy constraints (refer Algorithm 1). Iteration 1 starts with propagating the points-to set \( \{a, q, r, s, t\} \) from node \( a \) to \( b \). Since the points-to set of \( d \) is empty, no information flows to \( e \). The next step of processing complex constraints adds the edges as indicated below.

\[ \begin{align*}
*e &= c: \text{ none.} \\
c &= *a: a \rightarrow c, qrst \rightarrow c. \\
* \text{new edges introduced in this iteration are shown as thick lines. Thus, at the end of the first iteration, the points-to information computed at different nodes as well as the constraint graph are shown in Figure 1(b), Iteration 1.} \\
\text{The analysis continues propagating more points-to information and then adding more edges (shown as thick lines) in each iteration until it reaches the fixpoint in Iteration 5. The final points-to information computed at the nodes by Andersen’s analysis is shown in Figure 1(b) Iteration 5. In all the iterations of the analysis, a fixed ordering of the constraints is used, which is typically the order in which the constraints appear in the program (Figure 1(a)).}
\end{align*} \]

Next, we explain how introducing a prioritized version of Andersen’s analysis would evaluate the same set of constraints. The priority scheme can use various mechanisms for ordering the constraints. We use a mechanism wherein the priority of a constraint is the number of new points-to facts it adds in the previous iteration. Thus, the constraint priority is dynamic and may change across iterations. At the start of the analysis, i.e., before Iteration 1, the constraints can be ordered using any ordering, including the program order. In this example, we choose to use a dependence order. That is, a constraint \( c_1 \) gets more priority over another constraint \( c_2 \) if \( c_1 \) may define a variable that \( c_2 \) uses. Thus, \( p = q \) gets higher priority over \( r = p \). \( r = *p, *p = r \). The constraint ordering at the start of Iteration 1 is shown in the top drawing of Figure 1(c). The value in parentheses following a constraint is the number of new points-to pairs the constraint adds in that iteration. For instance, the constraint \(*a = p \) adds 18 new points-to pairs to \( G \) in Iteration 1.

As in the case of unprioritized Andersen’s analysis above, prior to Iteration 1, the copy constraints \( e = d \) and \( b = a \) add edges \( d \) to \( e \) and \( a \) to \( b \) respectively. Iteration 1 of our prioritized approach adds directed edges and computes points-to information as shown in the top drawing of Figure 1(c). Specifically, the constraint \(*a = p \) adds edges from \( p \) to \( qrst \) and \( p \) to \( a \). This allows for addition of the points-to set \( b, c, d \) to those of \( qrst, a \) and \( b, i.e., 18 new points-to pairs. Similarly, the constraint \( c = *a \) adds 4 new edges:

\[ c \rightarrow \{a, b, c, d, q, r, s, t\}. \]

The last constraint \(*e = c \) does not add any edges or new points-to information. Contrasting the state of \( G \) in Iteration 1 of the prioritized Andersen’s analysis with that of Andersen’s analysis, we observe that two additional edges are added in the prioritized analysis, namely \( b \) to \( c \) and \( d \) to \( c \). Thus, compared to Iteration 1 of Andersen’s analysis, Iteration 1 of the prioritized version adds the following additional points-to information to the solution:

\[ a, b, c, d, q, r, s, t \rightarrow \{b, c, d\}, c \rightarrow \{a, b, d, q, r, s, t\}. \]

In general, our priority-based analysis enables addition of more edges to the constraint graph early resulting in more possibilities for early propagation of points-to information. Further note that if the constraint \(*a = p \) is evaluated twice, then the edges from \( p \) to \( b, c, d \) would be added, making provision for propagation of more points-to pairs. We exploit this fact for skewed evaluation in our algorithm (Section IV).

Our priority based analysis framework keeps track of the number of points-to facts that are newly added by each constraint evaluation and accordingly assigns priority to the constraint. Multiple constraints may receive the same priority from forming clusters of constraints. A customary way of representing various priorities is using levels. Thus, constraints which add 1 new points-to facts are assigned a priority level \( P_1 \). As the analysis progresses, constraints are mapped to different priority levels. As an example, since \( c = *a \) adds 8 new points-to pairs in Iteration 1, it is moved to \( P_8 \) (to be used in Iteration 2). Similarly, the constraint \(*a = p \) is moved to \( P_{18} \). The constraint \(*e = c \) remains at \( P_0 \).
Fig. 1. (a) Input constraints and fixed constraint ordering for Andersen’s analysis. (b) Constraint graphs for Andersen’s analysis. (c) Constraint graphs for Prioritized Andersen’s analysis.
The prioritized ordering of the constraints at the start of Iteration 2 (shown in Figure 1(c) Iteration 2) remains the same as in Iteration 1. The new edges added (thick lines) and the points-to information computed at various nodes are as shown in Figure 1(c). In this iteration, the constraint $a = p$ adds 6 new points-to pairs $(d, e \rightarrow \{b, c, d\})$, the constraint $c = a$ adds no new points-to information and the constraint $e = c$ adds 10 new points-to pairs $(d, e \rightarrow \{a, q, r, s, t\})$. Note that the edges $c$ to $b$ and $c$ to $d$ get added in this iteration, whereas in the case of the original Andersen’s analysis, the edges propagated via this edge (pointee set $\{q, r, s, t\}$). The third drawing of Figure 1(c) shows the prioritized ordering of the constraints at the start of Iteration 3, sorted by the number of points-to pairs each constraint added in Iteration 2. The points-to information computed is as shown in Figure 1(c). In this iteration, only $a = e = c$ adds 20 new points-to pairs $(qrst \rightarrow \{a, q, r, s, t\})$.

The method converges after Iteration 4.

As shown in the example, a priority based analysis evaluates constraints in such an order that it enables addition of more edges and more useful edges early in the constraint graph to ensure quick fixpoint computation. The propagation of the points-to information via these edges is done by the underlying analysis (Andersen’s method [1] or Deep Propagation [7], etc.) which is not dictated by our method. The above example also suggests that the fixpoint computation of an analysis can be improved by going beyond the conventional mechanism of treating all the constraints with the same priority. Although the example is illustrated in the context of points-to analysis, it is equally applicable to other static analyses such as Mod/Ref analysis. The above example also illustrated two priority schemes – one based on the dependence across constraints based on def-use chain and another based on the amount of information a constraint changes. We carefully categorize different priority schemes in the next subsection and formalize the prioritization framework in Section III-C.

B. Priority Schemes

There are several ways in which the points-to constraints can be prioritized. We classify them into two types.

- **Linguistic scheme**: In this scheme, the constraints are prioritized based on their structure and the constraint variables. For instance, the priority mechanism in the last subsection for ordering constraints prior to Iteration 1 is a linguistic scheme. Another linguistic scheme may prioritize all load and store constraints over copy constraints.

- **Effect-driven scheme**: In this scheme, the constraints are prioritized based on the evaluation effects, e.g., the number of times a constraint gets evaluated or the number of points-to facts it adds (as in the example above).

It is possible to come up with a hybrid scheme that uses a combination of the above two schemes. For instance, one could assign different priority levels based on an effect-driven scheme, and a linguistic scheme can be used to order the constraints within the same priority level.

C. Prioritization Framework

We now formalize our notion of a priority based framework. A prioritized framework $\mathcal{R}$ is a 4-tuple.

\[ \mathcal{R} = (C, \mathcal{P}, F, \leq) \]

- $C$ is the set of input constraints,
- $\mathcal{P}$ is the set of priority levels of size $N_p$,
- $F = \{f_1, f_2, ..., f_i, ..., f_{N_P}\}$ is a family of priority functions such that $f_i$ is the priority function at the $i$th iteration which assigns a priority level $p \in \mathcal{P}$ to a constraint $c \in C$. That is, $f_i(c) = p$, and
- $\leq$ is a partial order defined on the priority levels assigned to a pair of constraints $c_x$ and $c_y$ at the $i$th iteration. If $f_i(c_x) = p_x$ and $f_i(c_y) = p_y$, then $p_x \leq p_y$ iff $p_y$ is at a higher priority level than $p_x$.

IV. PRIORITIZATION ALGORITHM

We instantiate our prioritization framework with a set of two functions. The first function $f_1$ is used for the first iteration whereas the other function $f_2$ is used for the subsequent iterations of the analysis. Thus, $F = \{f_1, f_2, ..., f_i, ..., f_{N_P}\}$. The function $f_1$ assigns priority to a constraint according to its depth in the dependence graph of constraints. Thus, it uses a linguistic scheme to define a constraint priority. For instance, if $c_1$ defines a variable that $c_2$ uses, then $c_1$ gets higher priority than $c_2$. Note that one could use any suitable priority function of choice. The function $f_2$ assigns a priority level to a constraint $c$ in iteration $i + 1$ according to the amount of points-to information newly added by $c$ in iteration $i$. The complete analysis developed using the prioritization framework is given in Algorithm 2. The function evaluate() in Line 10 implements a single iteration of the points-to information computation and propagation using any method like Andersen’s analysis [1], Deep Propagation [7] or Lazy Cycle Detection [10].

Similar to Algorithm 1, our algorithm first processes the address-of and copy constraints (Lines 1–2). Line 3 finds the dependence across constraints and and Line 4 partitions them in different priority levels depending upon the topological ordering of the nodes.

The repeat-until loop at Lines 5–17 iterates through various constraints at various priority levels until none of the constraint evaluations changes the points-to information, suggesting that the fixpoint is reached. Each iteration of this loop corresponds to the different iterations of the points-to analysis illustrated in Figure 1 of Section III.

Constraints in each priority level are processed, starting from the highest priority level, in the for loop (Lines 6–16). In Line 10, the points-to information is computed using an underlying points-to analysis method. The method returns a single integer suggesting the amount of new points-to information computed. Based on the returned integer value, a new priority level is assigned to the constraint (Line 11). If the new priority level is the same as the current priority,
the same constraint may get processed again shortly, as it has changed the points-to information. The repeat-until loop (Lines 8–15) shows that the constraints in the same priority level get processed repeatedly until an inner fixpoint. The number of indirections present in handwritten programs is typically quite small. Hence, looping beyond two iterations gradually reduces the gain (the amount of points-to information added). Therefore, the repeat-until loop from Lines 8–15 iterates for at most \( \text{threshold} \) number of times over the constraints at the same priority level. The condition inner fixpoint takes care of not iterating an \((i+1)\)th time if the \(i\)th iteration does not change the points-to information.

We remark that the priority scheme does not require the constraint graph explicitly. The algorithm works on constraints rather than on individual pointers.

A. Algorithm Complexity

Let \( N \) be the number of pointer variables and \( M \) be the number of points-to constraints in a program. Finding dependence across constraints in Line 3 of Algorithm 2 is \( O(MN) \). Each call to evaluate in Line 10 requires \( O(N) \) time. The loop at Line 9 executes \( L \) times where \( L \) is the number of priority levels. The inner repeat-until loop executes at most \( \text{threshold} \) number of times while the outer one at Line 5 executes \( O(M) \) times. Thus, the complexity of the algorithm is \( O(M^2N + MN \times L \times \text{threshold} \times L \times N) \), which is \( O(M^3N + L^2MN) \) since \( \text{threshold} \) is typically a small number (in our implementation it is 2). A good heuristic is to choose \( L^2 \approx O(M) \) in which case, it simplifies to \( O(M^3N) \). Assuming \( M \approx O(N) \), the complexity becomes \( O(M^3) \), same as that of Andersen’s analysis [1] or Deep Propagation [7].

V. EXPERIMENTAL EVALUATION

We evaluate the effectiveness of prioritized points-to analysis using 16 SPEC C/C++ benchmarks and five large open source programs (httpd, sendmail, gdb, wine-server and ghostscript). The characteristics of the benchmark programs are given in Table I. KLOC is the kilo lines of unprocessed source code. Total Inst is the total number of instructions in the LLVM [15] intermediate code after optimizing at -O2 level. Pointer Inst is the total number of pointer instructions processed by the analysis. Func is the number of functions defined in each program. We evaluate the impact of our prioritization approach on the following methods.

- anders: This is the base Andersen’s algorithm [1] that uses a simple iterative procedure over the points-to constraints to reach a fixpoint solution. The underlying data structure used is a sorted vector of pointees per pointer. Our implementation of anders incorporates difference propagation to propagate only the changed points-to
information and implements online cycle elimination [8] and offline variable substitution [16].

- **bddlcd**: This is Lazy Cycle Detection (LCD) algorithm implemented using BDD from Hardekopf and Lin [11] obtained from the first author’s website [17]. We extend it for context-sensitivity.

- **bloom**: The bloom filter method uses an approximate representation for storing both the points-to facts and the context information using a bloom filter. As this representation results in false-positives, the method is approximate and introduces precision loss. For our experiments, we use the medium configuration [12] which results in less than 2% precision loss for the chosen benchmarks.

- **deep**: This is the context-insensitive Deep Propagation method [7] obtained from the first author’s website [18]. The idea is to propagate points-to information in the constraint graph to all the reachable nodes along a path, before the other paths are considered. It uses a sparse bitmap representation to store points-to sets.

**deep** is context-insensitive while other implementations are context-sensitive; further, all methods are flow-insensitive and field-insensitive. Context-sensitivity is implemented using an invocation-graph based approach [19]. For each method a, we denote its prioritized version as p-a. All prioritized versions implement effect-driven scheme with all the optimizations described in Section IV with the number of priority levels set to 203 (see Section V-C). The experiments are carried out on an Intel Xeon machine with 2 GHz clock, 4 MB L2 cache and 4 GB RAM.

### A. Analysis Time

The analysis times (in seconds) of various methods are shown in Table II. Comparing **anders** versus **p-anders**, we observe a 13%–41% reduction in the analysis time (average 33%) due to prioritized scheduling of points-to constraints. This emphasizes the importance of a good constraint order.

In case of **bddlcd**, we observe a larger benefit due to prioritization (44% on an average excluding **gdb**). The benefit is an outcome of an interplay between **bddlcd** algorithm and prioritized scheduling. Cycle detection benefits from evaluating the cyclic constraints together which change an equal number of points-to pairs and hence get grouped into the same priority level. The prioritized scheduling approach evaluates all of them in close-proximity, often giving correct hints to the cycle detection mechanism, resulting in an overall efficient analysis. In case of **gdb**, the prioritized LCD version goes out of memory (see next subsection).

In case of **bloom**, both the versions (**bloom** and **p-bloom**) analyze all the benchmarks successfully to completion, with **p-bloom** achieving 20% reduction in the analysis time.

The execution times of context-insensitive analysis (deep and p-deep) are significantly lower due to the relatively lower computational requirements of the context-insensitive algorithm. But even in this case, introducing prioritization results in an improvement that is either smaller for benchmarks which require few hundred milliseconds analysis time or not observed (for the benchmarks where the analysis time is a few milliseconds). However, for the larger benchmarks such as httpd, ghostscript and **gdb**, the improvements are significant, resulting in more than 50% reduction in the analysis time. The reason is quite similar to that in case of **bddlcd**. Online cycle detection implemented as part of deep benefits from prioritized scheduling. However, another artifact of deep facilitates higher benefits with prioritized scheduling. Deep Propagation works on the topological ordering of the directed copy edges across pointer nodes in the constraint graph. Effect-driven prioritization of constraints adds copy edges that propagate (approximately) the same number of points-to constraints in an iteration, resulting in most of the propagation path available for deep propagation.

### B. Memory

The memory requirements (in MB) for various methods are shown in Table III. In general, one would expect the memory requirements to remain almost the same. However, the internal structure and implementation of the algorithm play a key role in the overall memory requirement.

**p-anders** consistently requires significantly less memory than **anders**. On an average, the memory requirement for the prioritized version gets reduced by 17%. The memory savings are largely due to the difference propagation and the use of temporary data structures during constraint evaluation. Instead of keeping small difference information for propagation across iterations as in **anders**, our effect-driven prioritized scheme combines difference information together and propagates them along complete paths in consecutive evaluations. This benefit

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1Prioritization improves the performance even in context-insensitive versions of **anders**, **bloom** and **bddlcd**, although by a smaller margin. Due to space limitation, we do not report those numbers here.
is similar in spirit to what Deep Propagation achieves over Wave Propagation [7].

Both bloom and p-bloom complete successfully on all the benchmarks and do not use difference propagation. Hence the memory requirements are quite similar (555 MB versus 539 MB on an average).

p-deep outperforms deep in terms of the memory requirement by 23% on an average. Memory savings are largely due to difference propagation.

On the other hand, p-bddlcd requires 45% more memory than bddlcd. In fact, in case of gdb, p-bddlcd runs out of memory whereas the non-prioritized version completes successfully. Unlike other algorithms discussed here, bddlcd is worklist based. A constraint may get added to the worklist while its another instance is already present. Thus, the worklist size is not bound by the total number of points-to constraints. Having a prioritized scheme requires multiple such worklists to be created, pushing different instances of the same constraint into different worklists based on the current priority of the constraint. Thus, using multiple worklists increases the amount of memory consumed.

C. Effect of configuration parameters

Effect of bucketization. First, we experimented with several values for the number of priority levels. The sensitivity of the analysis time (execution time to complete the points-to analysis) to the number of priority levels (buckets) for p-anders is shown in Figure 2. Note that the values are normalized with respect to anders. To avoid clutter, we show the effect on only four representative benchmarks ghostscript, gdb, perlbench and gzip along with the average over all the benchmarks listed in Table I. We observe that the analysis time steadily reduces with the increasing number of buckets. However, the number of buckets should not be arbitrarily increased. It is important to keep related constraints together so that an inner fixpoint over the related constraints would be beneficial (Section V-A). Using too many priority levels may move related constraints in different priority levels and would reduce the benefit of the inner fixpoint. Further, after a point,
increasing the number of buckets starts giving diminishing returns.

**Effect of skewed evaluation.** We measure for each iteration the number of times (all the constraints in) each priority level reaches an inner fixpoint in the second iteration. We observe that on an average around 84% of the occupied priority levels reach fixpoint in second iteration. This shows the effectiveness of our prioritized ordering which enables faster fixpoint computation.

We would like to note that values of the configuration parameters play an important role in the analysis efficiency and must be chosen carefully. However, our experience suggests that the parameters vary according to the program characteristics and there is no simple rule to arrive at optimal values for all the programs.

**Effect of prioritization.** We counted the average number of new points-to facts generated by each constraint for *anders* and *p-anders* in each iteration for *vortex* (see Figure 3). Due to prioritizing appropriate constraints, *p-anders* computes the points-to facts faster and reaches the fixpoint in 8 iterations compared to 10 as in *anders*. A similar behavior is observed for other benchmarks.

### D. Comparison with priority queue

In all our experiments the buckets are implemented as a hashtable wherein the priority level acts as the key. One may argue that the prioritization can possibly be more efficiently implemented as a priority queue. Theoretically, a priority queue incurs, on an average, an O(log n) complexity for each insertion and removal of an element. In our hashtable-based implementation, insertion and removal are O(1) operations, given a reference to a constraint. To study how the two implementations perform in practice, we developed a priority queue-based analysis with C++ STL. Our preliminary results on SPEC 2000 benchmarks indicate that the hashtable-based analysis requires 33% – 93% lesser time than the priority queue-based analysis. Although more experimentation is necessary to draw further conclusions, it seems clear that the priority levels implemented as a hashtable perform better than that implemented as a true priority queue.

### VI. Related Work

We refer the reader to the survey on pointer analysis techniques by Hind and Pioli [20].

Several novel techniques have been developed to improve upon the original Andersen’s analysis [4], [21], [22], [23]. Binary Decision Diagrams (BDD) [4], [23] are used to store points-to information in a succinct manner. The idea of bootstrapping [6] uses divide and conquer strategy by partitioning the set of pointers into disjoint alias sets using a fast and less precise algorithm (e.g., [2]) and later, a more precise algorithm analyzes each partition. Nasre et al. [24] convert points-to constraints into a set of linear equations and solve it using a standard linear solver. Storing complete context information alleviates the need to store the complete context information.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Context-sensitive</th>
<th>Context-insensitive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>anders</td>
<td>p-anders</td>
</tr>
<tr>
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</tr>
<tr>
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<td>615</td>
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<tr>
<td>average</td>
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<td>862</td>
</tr>
</tbody>
</table>

* The average is calculated ignoring the OOM entry.

**TABLE III**

**MEMORY REQUIREMENT (MB)**

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2 Due to constraints getting evaluated multiple times in *p-anders*, the notion of iteration is not well defined.
Inclusion based analysis can also be improved using several novel enhancements proposed in literature. Online cycle elimination [8] breaks dependence cycles amongst pointer variables on the fly. Offline variable substitution [16] operates over constraints prior to the constraint evaluation to find out pointer equivalent variables. Except for the offline variable substitution, all the other enhancements operate dynamically on the constraint evaluations. Our linguistic scheme based on dependences across constraints falls in the offline category. However, in general, similar to the effect-driven scheme, it is dynamic in nature and can be used online to update the constraint dependences as more points-to information gets computed. The linguistic scheme also finds resemblance with the node listing approach [26] for dataflow analysis of structured programs.

Wave and Deep Propagation techniques [7] perform a breadth-wise and depth-wise propagation of points-to information in a constraint graph. Various techniques proposed for worklist management [9] also identify heuristics to reach the fixpoint faster. Specifically, Greatest Output Rise (GOR) algorithm comes close to our effect-driven priority scheme. However, similar to Deep and Wave Propagation, the worklist management algorithms deal with the propagation of points-to information in the constraint graph and are orthogonal to our prioritized analysis of the points-to constraints. Our prioritized framework is more comprehensive and applicable to a variety of existing techniques.

VII. Conclusions

In this paper, we proposed a prioritized order of processing constraints in the points-to analysis method to improve its efficiency. First, we proved that finding an optimal sequence of points-to constraints for even a restricted flow-insensitive version is NP-Complete. Subsequently, we identified two new dimensions for evaluating points-to constraints: how many edges a constraint adds and where in the constraint graph it adds edges. Based on this observation, we presented a prioritized framework for evaluating a set of points-to constraints.

We illustrated the generality of the proposed framework by implementing prioritized versions of Andersen’s analysis, Lazy Cycle Detection using BDD, Bloom-filter based analysis and Deep Propagation. Experimental evaluation shows that the presented priority scheme can greatly benefit the state-of-the-art algorithms to reach a fixpoint faster. In addition to improving the analysis time, the proposed approach also reduces the memory requirement of the algorithms that use difference propagation.

While the framework is illustrated in the context of points-to analysis, the idea of prioritized evaluation is general and applicable to other static and dynamic analyses. We believe that further work on prioritizing constraints can open up interesting possibilities for performing optimizations.

ACKNOWLEDGMENT

We thank Aditya Kanade, Akash Lal, Aditya Thakur and Kapil Vaswani for helpful comments.

REFERENCES