Graspan: A Single-machine Disk-based Graph System for Interprocedural Static Analyses of Large-scale Systems Code

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Abstract

There is more than a decade-long history of using static analysis to find bugs in systems such as Linux. Most of the existing static analyses developed for these systems are simple checkers that find bugs based on pattern matching. Despite many sophisticated interprocedural analyses, few of them have been employed to improve checkers for systems code due to their complex implementations and poor scalability.

In this paper, we revisit the scalability problem of interprocedural static analysis from a “Big Data” perspective. That is, we turn Big Code analysis into Big Data analytics and leverage novel data processing techniques to solve this traditional programming language problem. We develop Graspan, a disk-based parallel graph system that uses an edge-pair centric computation model to compute dynamic transitive closures on very large program graphs.

We implement fully context-sensitive pointer/alias and dataflow analyses on Graspan. An evaluation of these analyses on large codebases such as Linux shows that their Graspan implementations scale to millions of lines of code and are much simpler than their original implementations. Moreover, we show that these analyses can be used to augment existing checkers; these augmented checkers uncovered 132 new NULL pointer bugs and 1308 unnecessary NULL tests, as well as reported 401 fewer false positives in Linux 4.4.0-rc5, PostgreSQL 8.3.9, and Apache httpd 2.2.18.

1. Introduction

Static analysis has been used to find bugs in systems software for more than a decade now (34; 80; 53; 30; 28; 24; 13; 14; 19; 27; 56; 17; 33; 9; 68). Based on a set of systems rules, a static checker builds patterns and inspects code statements to perform “pattern matching”. If a code region matches one of the patterns, a violation is found and reported. Static checkers have many advantages over recent, more advanced bug detectors based on SAT solvers or symbolic execution (17): they are simple, easy to implement, and scalable. Furthermore, they produce deterministic and easy-to-understand bug reports compared to, for example, a symbolic execution technique, which often produces non-deterministic bug reports that are difficult to reason about (26).

Unfortunately, existing static checkers use many heuristics when searching for patterns, which results in both missing bugs or reporting false warnings. For example, Chou et al. (23) and Palix et al. (56) developed nine checkers to find bugs in the Linux kernel. Unfortunately, most of these checkers generate both false negatives and false positives. For instance, their Null checker tries to identify NULL pointer dereference bugs by inspecting only the functions that directly return NULL. However, a NULL value can be generated from the middle of a function and propagated a long way before it is dereferenced at a statement. Such NULL value propagation will be missed entirely by the Null checker.

As another example, the Pnull checker developed recently by Brown et al. (17) checks whether a pointer dereference such as $a = b \rightarrow f$ is post-dominated by a NULL test on the pointer such as $\text{if}(b)$. The heuristic here is that if the developer checks whether $b$ can be NULL after dereferencing $b$, the dereference can potentially be on a NULL pointer. However, in most cases, this dereference occurs in one of the many control flow paths and in this path the pointer can never be NULL. The developer adds the NULL test simply because the NULL value may flow to the test point from a different control flow branch.

Our key observation in reducing the number of false positives and negatives reported by these checkers is to leverage interprocedural analysis. Among the aforementioned nine checkers, six that check flow properties can be easily improved (e.g., producing fewer false positives and false negatives) using an interprocedural analysis, as shown in Figure 1.

While using interprocedural analyses to improve bug detection appears to be obvious, there seems to be a large gap between the state of the art and the state of the practice. On the one hand, the past decade has seen a large number of sophisticated and powerful analyses developed by program analysis researchers. On the other hand, none of these techniques are widely used to find bugs in systems software.

We believe that the reason is two-fold. First, an interprocedural analysis is often not scalable enough to analyze large codebases such as the Linux kernel. In order for such an analysis to be useful, it often needs to be context-sensitive, that is, distinct solutions need to be produced and maintained.
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<tr>
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<td>Double acquired locks and disabled interrupts not appropriately restored</td>
<td>Identify lock/interrupt obj by var names (Negative)</td>
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<td>Derefs post-dominated by a NULL test may not be on NULL pointers</td>
<td>Use a dataflow analysis to filter out cases where the involved pointers must not be NULL</td>
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Table 1. A subset of checkers used by (17) and (56) to find bugs in the Linux kernel, their target problems, their limitations, the potential ways to improve them using a sophisticated interprocedural analysis; the first six have been used by Chou et al. (23) and Palix et al. (56) to study Linux bugs; the last one was described in a recent paper by Brown et al. (17) to find potential NULL pointer dereferences; Positive/negative indicates whether the limitation can result in false positives/negatives.

for different calling contexts (i.e., a chain of call sites representing a runtime call stack). However, the number of calling contexts grows exponentially with the size of the program and even a moderate-sized program can have as large as $10^{14}$ distinct contexts (81), making the analysis both compute- and memory-intensive. Furthermore, most interprocedural analyses are difficult to parallelize, because they frequently involve decision making based on information discovered dynamically. Thus, most of the existing implementations of such analyses are entirely sequential.

Second, the sheer implementation complexity scares practitioners away. Much of this complexity stems from optimizing the analysis rather than implementing the base algorithm. For example, in a widely-used Java pointer analysis (73), more than three quarters of the code is to perform approximations before a user-given time budget runs out. The base algorithm implementation takes a much smaller portion. This level of tuning complexity simply does not align with the “simplest-working-solution” (43) philosophy of systems builders.

**One Stone, Two Birds** Our idea to solve this scalability problem is inspired by the way a graph system enables scalable processing of large graphs. Graph system support pioneered by Pregel (50) provides a “one-stone-two-birds” solution, in which the optimization for scalability is mainly achieved by the (distributed or disk-based) system itself, requiring the developers to only write simple vertex programs using the interfaces provided by the system.

In this paper, we demonstrate a similar “one-stone-two-birds” solution for interprocedural program analysis. Our key observation in this work is that many interprocedural analyses can be formulated as a graph reachability problem (61; 73; 62; 69; 87). Pointer/alias analysis and dataflow analysis are two typical examples. In a pointer/alias analysis, if an object (e.g., created by a malloc) can directly or transitively reach a variable on a directed graph representation of the program, the variable may point to the object. In a dataflow analysis that tracks NULL pointers, similarly, a transitive flow from a NULL value to a variable would make NULL propagate to the variable. Therefore, we turn the programs into graphs and treat the analyses as graph traversal. This approach opens up opportunities to leverage parallel graph processing systems to analyze large programs efficiently.

Several graph systems are available today. These systems are either distributed (such as GraphLab (49), PowerGraph (31), and GraphX (32)) or single-machine (such as GraphChi (41), XStream (66), and GridGraph (92)). Since program analysis is intended to assist developers to find bugs in their daily development tasks, their machines are the environments in which we would like our system to run, so that developers can check their code on a regular basis without needing to access a cluster. Hence, disk-based systems naturally become our choice.

We initially planned to use existing systems to analyze program graphs. Unfortunately, we soon realized that a ground-up redesign (i.e., from the programming model to the runtime engine) is needed to build a graph system for analyzing large programs. The main reason is that the graph workload for interprocedural analyses is significantly different from a regular graph algorithm (such as PageRank) that iteratively performs computations on vertex values on a static graph. An interprocedural analysis, on the contrary, focuses on computing reachability by repeatedly adding transitive edges, rather than on updating vertex values. For instance, a pointer analysis
which the developer only needs to generate the graph and out-of-core support is exploited if the graph is too big to perform label matching and edge addition. In the vertex, all its incoming and outgoing edges need to be visible to the system. Unfortunately, GraphChi supports neither of these features.

More specifically, many interprocedural analyses are essentially dynamic reachability problems in the sense that the addition of a new edge is guided by a constraint on the labels of existing edges. In a static analysis, the label of an edge often represents the semantics of the edge (e.g., an assignment or a dereference). For two edges \( a \rightarrow_{l_1} b \) and \( b \rightarrow_{l_2} c \), a transitive edge from \( a \) to \( c \) is added only if the concatenation of \( l_1 \) and \( l_2 \) forms a string of a (context-free) grammar.

This constraint-guided reachability problem, in general, requires dynamic transitive closure (DTC) computation (37; 86; 64), which has a wide range of applications in program analysis and other domains. The DTC computation dictates two important abilities of the graph system. First, at each vertex, all its incoming and outgoing edges need to be visible to perform label matching and edge addition. In the above example, when \( b \) is processed, both \( a \rightarrow_{l_1} b \) and \( b \rightarrow_{l_2} c \) need to be accessed to add the edge from \( a \) to \( c \). This requirement immediately excludes edge-centric systems such as XStream (66) from our consideration, because these systems stream in edges in a random order and, thus, this pair of edges may not be simultaneously available. Second, the system needs to support a large number of edges added dynamically. The added edges can be even more than the original edges in the graph. While vertex-centric systems such as GraphChi (41) support dynamic edge addition, this support is very limited. In the presence of a large number of added edges, it is critical that the system is able to (1) quickly check edge duplicates and (2) appropriately repartition the graph. Unfortunately, GraphChi supports neither of these features.

This paper presents Graspan, the first single machine, disk-based parallel graph processing system tailored for interprocedural static analyses. Given a program graph and a grammar specification of an analysis, Graspan offers two major performance and scalability benefits: (1) the core computation of the analysis is automatically parallelized and (2) out-of-core support is exploited if the graph is too big to fit in memory. At the heart of Graspan is a parallel edge-pair (EP) centric computation model that, in each iteration, loads two partitions of edges into memory and “joins” their edge lists to produce a new edge list. Whenever the size of a partition exceeds a threshold value, its edges are repartitioned. Graspan supports both in-memory (for small programs) and out-of-core (for large programs) computation. Joining of two edge lists is fully parallelized, allowing multiple transitive edges to be simultaneously added.

Graspan provides an intuitive programming model, in which the developer only needs to generate the graph and define the grammar that guides the edge addition, a task orders-of-magnitude easier than coming up with a well-tuned implementation of the analysis that would give trouble to skillful researchers for months.

Recent work (81; 16) shows the effectiveness of expressing static analyses as Datalog programs. While leveraging Datalog makes analysis implementations easier, existing Datalog engines are designed in generic ways, i.e., not considering the characteristics of the program analysis workload. Furthermore, there does not exist any parallel and out-of-core Datalog engine that can process very large graphs on a single machine. For example, the Linux kernel program graph has more than 1B edges. The fastest shared memory Datalog engine SociaLite (42) quickly ran out of memory while Graspan processed it in four hours (cf. §5.4). While distributed Datalog engines such as Myria (78) and BigDatalog (71) are available, it is unrealistic to require developers to frequently access a cluster in their daily development.

We have implemented fully context-sensitive pointer/alias and dataflow analysis on Graspan. Context-sensitivity is achieved by making aggressive inlining (70). That is, we clone the body of a function for every single context leading to the function. This approach is feasible only because the out-of-core support in Graspan frees us from worrying about additional memory usage incurred by inlining. We treat the functions in recursions context insensitively by merging functions in each strongly connected component on the call graph into one function without cloning function bodies.

Graspan can be readily used as a ‘‘backend’’ analysis engine to enhance existing static checkers such as BugFinder, PMD, or Coverity. We have performed a thorough evaluation of Graspan on three systems programs including the Linux kernel, the PostgreSQL database, and the Apache httpd server. Our experiments show very promising results.

2. Background

While there are many types of interprocedural analyses, this paper focuses on a pointer/alias analysis and a dataflow analysis, both of which are enablers for all other static analyses. This section discusses necessary background information on how pointer/alias analysis is formulated as graph reachability problems. Following Rep et al.’s interprocedural, finite, distributive, subset (IFDS) framework (62), we have also formulated a fully context-sensitive dataflow analysis as a grammar-guided reachability problem. However, due to space limitations, the discussion of this formulation is omitted.

2.1 Graph Reachability

Pioneered by Reps et al. (62; 69), there is a large body of work on graph reachability based program analyses (39; 82; 83; 58; 15; 89; 88; 75). The reachability computation is often guided by a context-free grammar due to the balanced parentheses property in these analyses. At a high level, let us suppose each edge is labeled either an open parenthesis ‘‘(‘‘ or a close parenthesis ‘‘)’’. A vertex is reachable from another vertex if and only if there exists a path between them, the string of labels on which has balanced ‘‘(‘‘ and ‘‘)’’. 
The parentheses ‘(’ and ‘)’ have different semantics for different analyses. For example, for a C pointer analysis, ‘(’ represents an address-of operation & and ‘)’ represents a dereference *. A pointer variable can point to an object if there is an assignment path between them that has balanced & and *. For instance, a string “&**&” has balanced parentheses while “&*&” does not. This balanced parentheses property can often be captured by a context-free grammar.

2.2 Pointer Analysis

A pointer analysis computes, for each pointer variable, a set of heap objects (represented by allocation sites) that can flow to the variable. This set of objects is referred to as the variable’s points-to set. Alias information can be derived from this analysis — if the points-to sets of two variables have a non-empty intersection, they may alias.

Our graph formulation of pointer analysis is adapted from a previous formulation in (91). This section briefly describes this formulation. The analysis we implement is flow-insensitive in the sense that we do not consider control flow in the program. Flow sensitivity can be easily added, but it does not contribute much to the analysis precision (35). A program consists of a set of pointer assignments. Assignments can execute in any order, any number of times.

**Pointer Analysis as Graph Reachability**

For simplicity of presentation, the discussion here focuses on four kinds of three-address statements (which are statements that have at most three operands):

- a = b  Value assignment  |  a = * b  Load
- *b = a  Store  |  a = &b  Address-of

Complicated statements are often broken down into these three-address statements in the compilation process by introducing temporary variables. Our analysis does not distinguish fields in a struct. That is, an expression a->f is handled in the same way as *a, with offset f being ignored. As reported in (91), ignoring offsets only has little influence on the analysis precision, because most fields are of primitive types.

For each function, an expression graph — whose vertices represent C expressions and edges represent value flow between expressions — is generated; graphs for different functions are eventually connected to form a whole-program expression graph. Each vertex on the graph represents an expression, and each edge is of three kinds:

- **Dereference edge (D):** for each dereference *a, there is a D-edge from a to *a; there is also an edge from an address-of expression &a to a because a is a dereference of &a.

- **Assignment edge (A):** for each assignment a = b, there is an A-edge from b to a; a and b can be arbitrary expressions.

- **Alloc edge (M):** for each assignment a = malloc(), there is an M-edge from a special Alloc vertex to a.

**Figure 1.** A program and its expression graph: solid, horizontal edges represent assignments (A- and M-edges); dashed, vertical edges represent dereferences (D-edge); dotted, horizontal edges represent transitive edges labeled non-terminals. A4 indicates the allocation site at Line 4. OF, VF, and AL represent objectFlow, valueFlow, and alias, respectively.

Figure 1 shows a simple program and its expression graph. Each edge has a label, indicating its type. Solid and dashed edges are original edges in the graph and they are labeled M, A, or D. Dotted edges are transitive edges added by Graspan into the graph, as discussed shortly.

**Context-free Grammar** The pointer information computation is guided by the following grammar:

Object flow:  objectFlow ::= M valueFlow
Value flow:  valueFlow ::= (A alias?)*
Expr alias: alias ::= D valueFlow D

This grammar has three non-terminals objectFlow, valueFlow, and alias. For a non-terminal T, a path in the graph is called a T-path if the sequence of the edge labels on the path is a string that can be reduced to T. In order for a variable v to point to an object o (i.e., a malloc), there must exist an objectFlow path in the expression graph from o to v. The definition of objectFlow is straightforward: it must start with an alloc (M) edge, followed by a valueFlow path that propagates the object address to variables. A valueFlow path is either a sequence of simple assignment (A) edges or a mix of assignments edges and alias paths.

An alias path is represented by D valueFlow D. Each edge has an inverse edge with a “bar” label. For example, for each edge a D b, the edge b D a exists automatically. D represents the inverse of a dereference and is essentially equivalent to an address-of. D valueFlow D represents that if we take the address of a variable a, propagate the address through a valueFlow path to another variable b, and then do a dereference on b, the result is the same as the value in a.

Note that valueFlow and alias mutually refer each other. This definition captures the recursive nature of an alias and valueFlow path. In this grammar, D and D are the open and close parentheses that need to be balanced.

**Example** In Figure 1, e points to A4, since the M edge between them forms an objectFlow path. There is a valueFlow
path from &a to d, which enables an alias path from a to *d. This alias path then induces two valueFlow paths from b to t and from &c to t, which, in turn, contribute to the forming of the valueFlow paths from c to x, making *e and *x alias. Hence, there exists a valueFlow path from e to y, which, together with the M edge at the beginning, forms an objectFlow path from A4 to y. This path indicates that y points to A4. The dotted edges in Figure 1 shows these paths.

A typical way to implement this analysis is to maintain a worklist, each element of which is a pair of a newly discovered vertex and a stack simulating a pushdown automaton. The implementation loops over the worklist, iteratively retrieving vertices and processing their edges. The traditional implementation does not add any physical edges into the graph, but instead, it tracks path information using pushdown automata. The main loop in the implementation carries many data dependencies, making the algorithm difficult to parallelize.

3. Graspan’s Programming Model

In this section, we describe Graspan’s programming model, i.e., the tasks that need to be done by the programmer to use Graspan. There are two main tasks. The first task is to modify a compiler frontend to generate the graph. The second task is to use the Graspan API to specify the grammar. Next, we will elaborate on these two tasks. We will then finish the section by discussing the applicability of Graspan’s programming model to interprocedural analyses.

Generating Graph For Graspan to perform an interprocedural analysis, the user first needs to generate the Graspan graph, which is a specialized program graph tailored for the analysis, by modifying a compiler frontend. Note that since this task is relatively simple, the developer can generate the Graspan graph in a mechanical way without even thinking about performance and scalability. In this subsection, we briefly discuss how we generate the Graspan graph in the context of the pointer/alias analysis. We finish by generalizing graph generation for other interprocedural analyses.

For the pointer/alias analysis, we generate the Graspan graph by making two modifications to the program expression graph described in §2. These modifications include (1) inclusion of inverse edges and (2) context sensitivity achieved through inlining. For the former, we model inverse edges explicitly. That is, for each edge from a to b labeled X, we create and add to the graph an edge from b to a labeled X.

For the latter (achieving context sensitivity), we perform a bottom-up (i.e., reverse-topological) traversal of the call graph of the program to inline functions. For each function, we make a clone of its entire expression graph for each call site that invokes the function. Formal and actual parameters are connected explicitly with edges. The cloning of a graph not only copies the edges and vertices in one function; it does so for all edges and vertices in its (direct and transitive) callees.

For recursive functions, we follow the standard treatment (81) – strongly connected components (SCC) are computed and then functions in each SCC are collapsed into one single function, and treated context insensitively. Clearly, the size of the graph grows exponentially as we make clones and the generated graph is often large. However, the out-of-core support in Graspan guarantees that Graspan can analyze even such large graphs effectively. For each copy of a vertex, we generate a unique ID in a way so that we can easily locate the variable its corresponds to and its containing function from the ID. In the Graspan graph, edges carry data (i.e., their labels) but vertices do not. Finally, the graph is dumped to disk in the form of an edge list.

In general, the approach of aggressive inlining provides complete information that an analysis intends to uncover. Among all the existing analysis implementations, only Whaley et al. (81) could handle such aggressive inlining but they only clone variables (not objects) and have to use a binary decision diagram (BDD) to merge results. In addition, no evidence was shown that their analysis could process the Linux kernel. On the contrary, Graspan processes the exploded kernel graph (with more than 1B edges) in a few hours on a single machine.

Although this subsection focuses on the generation of pointer analysis graphs, graphs for other analyses can be generated in a similar manner. Here we briefly summarize the steps. First, vertices and edges need to be defined based on a grammar; this step is analysis-specific. Second, if inverse edges are needed in the grammar, they need to be explicitly added. Finally, context sensitivity can be generally achieved by function inlining. The developer can easily control the degree of context sensitivity by using different inlining criteria. For example, we perform full context sensitivity and thus our inlining goes all the way up the top functions of the call graph. If one wishes to perform only one-level context sensitivity, each function only needs to be inlined once.

Specifying Grammar Once the program graph is generated, the user needs to specify a grammar that guides the addition of transitive edges at run time. Unlike any traditional implementation of the analysis, Graspan adds transitive edges (e.g., dotted edges in Figure 1) to the graph in a parallel manner. Specifically, for each production in the grammar, if Graspan finds a path whose edge labels match the RHS terms of the production, a transitive edge is added covering the path and labeled with the LHS of the production.

Since Graspan uses the edge-pair-centric model, it focuses on a pair of edges at a time, which requires each production in the grammar to have no more than two terms on its RHS. In other words, the length of a path Graspan checks at a time must be ≤ 2.

For example, the above mentioned pointer analysis grammar cannot be directly used, because the RHS of both value-Flow and alias have more than two terms. For example, to add a new valueFlow edge, we may need to check more than
2 consecutive edges, which does not fit into Graspan’s EP-centric model. Fortunately, every context free grammar can be normalized into an equivalent grammar with at most two terms on its RHS (62), similar to the Chomsky normal form. After normalization, our pointer analysis grammar becomes:

Object flow: \( \text{objectFlow} ::= M \text{valueFlow} | M \)

Value flow: \( \text{valueFlow} ::= A | \text{valueFlow \alpha} | \text{valueFlow \\beta} \)

Expr alias: \( \alpha ::= T \ D \)

\( T ::= D \text{valueFlow} \)

At the center of Graspan’s programming model is an API `addConstraint` (Label \( \text{lhs}, \text{lhs1}, \text{lhs2} \)), which can be used by the developer to register each production in the grammar. \( \text{lhs} \) represents the LHS non-terminal while \( \text{rhs1} \) and \( \text{rhs2} \) represent the two RHS terms. If the RHS has only one term, \( \text{rhs2} \) should be NULL.

**Graspan Applicability** How many interprocedural analyses can be powered by Graspan? First, we note that pointer analysis and dataflow analysis are already representative of a large number of analysis algorithms that can be formulated as a grammar-guided graph reachability problem. Second, work has been done to establish the convertibility from other types of analysis formulation (e.g., set-constraint (39) and pushdown systems (11; 11; 10)) to context-free language reachability. Analyses under these other formulations can all be parallelized and made scalable by Graspan.

4. **Graspan Design and Implementation**

We implement Graspan in Java in approximately 6000 lines of code. Graspan can analyze programs written in any languages.

4.1 **Preprocessing**

Preprocessing partitions the Graspan graph generated for an analysis. The graph is in the edge-list format on disk. Similar to graph sharding in GraphChi (41), partitioning in Graspan is done by first partitioning vertices into logical intervals. However, unlike GraphChi that groups edges based on their target vertices, one interval in Graspan defines a partition that contains edges whose source vertices fall into the interval. Edges are sorted on their source vertex IDs and those that have the same source are stored consecutively and ordered on their target vertex IDs. The fact that the outgoing edges for each vertex are sorted enables quick edge addition, as we will discuss shortly. Figure 2(a) shows a simple directed graph. Suppose Graspan splits its vertices into three intervals 0–2, 3–4, and 5–6; Figure 2(b) shows the partition layout.

When a new edge is found during processing, it is always added to the partition to which the source of the edge belongs. Graspan loads two partitions at a time and joins their edge-lists (§4.2), a process we refer to as a *superstep*. Given that only two partitions reside in memory at a given time, the size and hence the total number of partitions are determined automatically by the amount of memory available to Graspan.

Preprocessing also produces three pieces of meta-information: a *degree file* for each partition, which records the (incoming and outgoing) degrees of its vertices, a global *vertex-interval table* (VIT), which specifies vertex intervals, and a *destination distribution map* (DDM) for each partition \( p \) that maps, for each other partition \( q \), the percentage of the edges in \( p \) that go into \( q \). The DDM is essentially a matrix, each cell containing a percentage.

Graspan uses the degree file to calculate the size of the array to be created to load a partition. Without the degree information, a variable-size data structure (e.g., `ArrayList`) has to be used, which would incur array resizing and data copying operations. The VIT records the lower and upper-bounds for each interval (e.g., \( (0, [0, 10000]), (1, [10001, 23451]), \) etc.). Graspan maintains the table because the intervals will be redefined upon repartitioning. The DDM measures the “matching” degree between two partitions and will be used by the Graspan scheduler to determine which two to load.

4.2 **Edge-Pair Centric Computation**

Graspan supports in-memory and out-of-core computation. For small graphs that can be held in memory, our preprocessing only generates two partitions, both of which are resident in memory. For large graphs with more than two partitions, Graspan uses a scheduling algorithm (discussed shortly) to load two partitions in each superstep, joins their edge lists, updates their edges, and performs repartitioning if necessary. Each superstep itself performs a fixed point computation — newly added edges may give rise to further edges.

The computation is finished when no new edges can be added. The updated edge lists may or may not be written back to disk depending on the next two partitions selected by the scheduler. This iterative process is repeated until a global fixed point is reached, that is, no new edges can be added for any pair of partitions. Since the VIT and the DDM are reasonably small in size, they are kept in memory throughout the processing.

**In-Memory Edge Representation** The edge list of a vertex \( v \) is represented as two arrays of (vertex, label) pairs, as shown in Figure 2(c). The first array \( (O_v) \) contains “old” edges that have been inspected before and the second \( (D_v) \) contains edges newly added in the previous iteration. The goal of this design is to avoid repeatedly matching edge pairs (discussed shortly).

**Parallel Edge Addition** Algorithm 1 shows a BSP-like algorithm for the parallel EP-centric computation. With two partitions \( p_1 \) and \( p_2 \) loaded, we first merge them into one single partition with combined edge lists (Line 1–2). Initially, for each vertex \( v \), its two arrays \( O_v \) and \( D_v \) are set to empty list and the original edge list of \( v \), respectively (Line 4 and Line 5). The loop between Line 6 and Line 24 creates a separate thread to process each vertex \( v \) and its edge list,
A straightforward approach is that, for each edge already exists. Checking and avoiding duplicates is very simple approach suffers from significant practical limitations. Doing a linear scan of existing edges upon adding an edge has an $O(|E|^2)$ complexity to add edges for each vertex, where $|E|$ is the total number of edges loaded. An alternative is to implement an “offline” checking mechanism that removes duplicates when writing updated partitions to disk. While this approach eliminates the cost of online checks, it may prevent the computation from terminating — if the same edge is repeatedly added, missing the online check would make the loop at Line 6 keep seeing new edges and run indefinitely.

Our algorithm performs quick edge addition and online duplicate checks. Our key insight is that edge addition can be done in batch much more efficiently than individually. To illustrate, consider Figure 2(a) where vertex 0 initially has two outgoing edges $0 \rightarrow 1$ and $0 \rightarrow 4$. Adding new edges for vertex 0 is essentially the same as merging the (outgoing) edges of vertex 1 and 4 into vertex 0’s edge list and then filtering out those that have mismatched labels.

In Algorithm 1, to add edges for vertex $v$, we first compute $V_1$ by intersecting the set of target vertices of the edges in $O_v$ and the set $V$ of all vertices in the loaded partitions (Line 8). $V_1$ thus contains vertices whose edge lists need to be merged with that of $v$. If an out-neighbor of $v$ is not in $V$, we skip it in the current superstep — this vertex will be processed later when its partition is loaded with $v$’s partition.

Next, we add $O_v$ into a list $listsToMerge$ together with $D_{uv}$ of each vertex $u$ in $V_1$ (Line 10 – 12), and merge these lists into a new sorted list (Line 14). Since all input lists are already sorted, function MATCHANDMERGESORTEDARRAYS can be efficiently implemented by repeatedly finding the minimum (using an $O(|V|)$ min-heap algorithm) among the elements in a slice of the input lists and copying it into the output array. This whole algorithm has an $O(|E|\log |V|)$ complexity, which is more efficient, both theoretically and empirically, than scanning edges individually ($O(|E|^2)$) because $|V|$ is much smaller than $|E|$. Furthermore, duplicate checking can be automatically done during the merging — if multiple elements have the same minimum values, only one is copied into the output array. Label matching is performed before copying — an edge is not copied into the output if it has an inconsistent label.
Line 15–20 performs the same logic by computing a new set of vertices \( V_2 \), and merging \( D_v \) and all edges \( (i.e., \; O_u \cup D_u) \) of each vertex \( u \in V_2 \). At Line 20, all the new edges to be added to vertex \( v \) are in mergeResult. Finally, to prepare for the next iteration, \( O_v \) and \( D_v \) are merged (Line 23) to form the new \( O_v \). \( D_v \) is then updated to contain the newly added edges (excluding those that already exist in \( O_v \)).

**Example** Figure 2(c) shows the in-memory edge lists at the end of the first iteration of the loop at Line 6 in Algorithm 1. In the next iteration, thread \( t_0 \) would merge \( O_0 \) with \( D_1 \) and \( D_3 \), and \( D_0 \) with \( O_2 \cup D_2 \) and \( O_3 \cup D_3 \). \( O_0 \) and \( O_1 \) (and \( O_2 \)) do not need to be merged again as it has been done before.

Another advantage of this algorithm is that it runs completely in parallel without needing any synchronization. While the edge list of a vertex may be read by different threads, edge addition can only be done by one single thread, that is, the one that processes the vertex.

### 4.3 Postprocessing

When computation is done, the updated edge lists need to be written back to their partition files. In addition, the degree file is updated with the new vertex degree information. The (in-memory) DDM needs to be updated with the new edge distribution information.

**Repartitioning** If the size of a partition exceeds a threshold \( (e.g., \; \text{a parameter}) \), repartitioning occurs. It is easy for Graspan to repartition an oversized partition since the edge lists are sorted. Graspan breaks the original vertex interval into two small intervals, and edges are automatically restructured. The goal is to have the two small vertex intervals to have similar numbers of edges, so that the resulting partitions have similar sizes. The VIT needs to be updated with the new interval information. Repartitioning can also be triggered in the middle of computation if too many edges are added in a single superstep and the size of the loaded partitions is close to the heap size.

**Scheduling** When a new superstep starts, two new partitions will be selected by the scheduler and loaded. Since a partition on which the computation is done in the previous superstep may be chosen again, Graspan delays the writing of a partition back to disk until the new partitions are chosen by the scheduler. If a chosen partition is already in memory, significant amounts of disk I/O can be avoided.

Our scheduler has two objectives: (1) maximize the number of edge pairs that can potentially match and (2) favor the reuse of in-memory partitions. For (1), the scheduler consults the DDM. While the percentage information recorded in the DDM measures the matching opportunities between two partitions, it is an overall measurement that does not reflect the changes. Hence, we add another field to each cell of the DDM that records, for a pair of partitions \( p \) and \( q \), the change in the percentage of the edges going from \( p \) into \( q \) since the last time \( p \) and \( q \) are both loaded. If \( p \) and \( q \) have never been loaded together, the change is the same as the full percentage.

<table>
<thead>
<tr>
<th>Program</th>
<th>Ver</th>
<th>#LoC</th>
<th>#Inlines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linux kernel</td>
<td>4.4.0-rc5</td>
<td>16M</td>
<td>31.7M</td>
</tr>
<tr>
<td>PostgreSQL</td>
<td>8.3.9</td>
<td>700K</td>
<td>290820</td>
</tr>
<tr>
<td>Apache httpd</td>
<td>2.2.18</td>
<td>300K</td>
<td>58269</td>
</tr>
</tbody>
</table>

**Table 2.** Programs analyzed, their versions, numbers of lines of code, and numbers of function inlines.

Using \( \delta(p, q) \) to denote this change, our scheduler selects a pair of partitions that have the largest \( \delta(p, q) + \delta(q, p) \) score. If multiple pairs of partitions have similar scores \( (e.g., \; \text{in a user-defined range}) \), Graspan picks one that involves an in-memory partition. The delta field in the DDM also determines the termination of the computation — for \( p \) and \( q \) whose \( \delta(p, q) + \delta(q, p) \) is zero, no computation needs to be done on them. Graspan terminates when the delta field in every single cell of the DDM becomes 0.

**Reporting Results** Graspan provides an API for the user to iterate over edges with a certain label. For example, for the pointer analysis, edges with the objectFlow label indicate a points-to solution, while edges with the alias label represent aliasing variables. Graspan also provides translation APIs that can be used to map vertices and edges back to variables and statements in the program.

### 5. Evaluation

We built our frontend based on LLVM Clang. Our graph generators for the pointer/alias and dataflow analysis have 1.2K and 800 lines of C++ code. To use Graspan, the pointer/alias analysis has a grammar with five productions \( (\text{e.g., invoking the API function addConstraint five times}) \) while the dataflow analysis has two productions. We first performed the pointer analysis. The dataflow analysis was designed specifically to track NULL value propagation. It was built based on the pointer analysis because it needs to query pointer analysis results when analyzing heap loads and stores.

We used the call graph generated by LLVM to perform inlining. Three large system programs were selected: the Linux kernel, the PostgreSQL database, and the httpd server. Their detailed statistics are reported in Table 2. Linux kernels are not directly compilable with LLVM. Thanks to the LLVMLinux project (6) that provides kernel patches for LLVM compilation, we were able to build the kernel version 4.4.0-rc5 (the latest version supported by LLVM). For the other two systems, we picked their latest versions that could be successfully compiled by LLVM. #Inlines reports the total number of times functions are inlined — the larger this number, the more calling contexts a program has.

Since our goal is to enable developers to run Graspan on development machines, we ran Graspan on a Dell desktop, with a quad-core 3.2GHz Intel i5-4570 CPU, 8GB memory, and a 1TB SSD, running Linux 4.2.0. The size of the Java heap given to Graspan was 6GB. 8 threads were used when the EP-centric computation was performed.

Since our analyses have already achieved the highest level of context sensitivity, we did not compare their precision with
Table 3. Checkers implemented, their numbers of bugs reported by the baseline checkers (BL), and new bugs reported by our Graspan analyses (GR) on top of the BL checkers on the Linux kernel 4.4.0-r5; RE shows total numbers of bugs reported while FP shows numbers of false positives determined manually; to provide a reference of how bugs evolve over the last decade, we include an additional section BL(2.6.1) with numbers of true bugs reported by the same checkers in 2011 on the kernel version 2.6.1 from (56).

<table>
<thead>
<tr>
<th>Checker</th>
<th>BL(4.4.0)</th>
<th>GR(4.4.0)</th>
<th>BL(2.6.1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RE</td>
<td>TP</td>
<td>RE</td>
</tr>
<tr>
<td>Block</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Null</td>
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<td>20</td>
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<tr>
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<td>14</td>
<td>14</td>
<td>+4</td>
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<td>15</td>
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<td>23</td>
<td>+11</td>
</tr>
<tr>
<td>Pnull</td>
<td>218</td>
<td>N/A</td>
<td>-218</td>
</tr>
<tr>
<td>UNTest</td>
<td>N/A</td>
<td>N/A</td>
<td>+118</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<td></td>
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</tr>
<tr>
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<td>0</td>
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<td>NULL</td>
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<td>20</td>
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</tr>
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</tbody>
</table>

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Pnull is a checker implemented by Brown et al. (17); UNTest is a new interprocedural checker we implemented to identify unnecessary NULL tests; ‘+’ means new problems found while ‘−’ represents false positives reduced.

that of existing analyses. The main goal of this evaluation is to (1) demonstrate the usefulness of these interprocedural analyses through the detection of new bugs and reduction of false positives; and (2) show the efficiency and scalability of Graspan when performing such analyses that are extremely difficult to make scalable otherwise.

5.1 Effectiveness of Interprocedural Analyses

To understand the effectiveness of our interprocedural analyses, we re-implemented the seven static checkers listed in Table 1 in Clang. We use these existing checkers as the baseline to understand whether the combination of interprocedural pointer/alias and dataflow analyses are able to improve them in finding new bugs or reducing false positives (as described in Table 1 in §4). Note that our interprocedural analyses are not limited to these checkers; they can be used in a much broader context to find other types of bugs as well (e.g., data races, deadlocks, etc.). We would also like to evaluate our analyses on commercial static checkers such as Coverity and GrammaTech. Unfortunately, we could not obtain a license that allows us to publish the comparisons, and hence, we had to develop these checkers from scratch.

We have added a new interprocedural checker UNTest that aims to find unnecessary, over-protective NULL tests – tests on pointers that must have non-NULL values – before dereferencing these pointers. Although these checks are not bugs, they create unnecessary code-level basic blocks that prevent compiler from performing many optimizations such as common sub-expression elimination or copy propagation, leading to performance degradation. Hence, these checks should be removed for compiler to fully optimize the program.

We manually checked all bug reports from both the baseline checkers and our analyses (except those reported by UNTest as described shortly) to determine whether a reported bug is a real bug. Since some of these checkers (such as Block, Range, and Lock) are specifically designed for Linux, Table 1 only reports information w.r.t. the Linux kernel. For checkers that check generic properties (i.e., Null and UNTest), we have also run them on the two other programs; their results are described later in this section.

For the first six baseline checkers that found many real bugs in older versions of the kernel (used by (56) in 2011 to check Linux 2.6.x and by Chou et al. (23) in 2001 to check Linux 2.4.x), they could find only 2 real bugs in Linux 4.4.0-r5 (with the Size checker). This is not surprising because they were designed to target very simple bug patterns. Given that many static bug checkers have been developed in the past decade (including both commercial and open source), it is likely that most of these simple bugs have been fixed in this (relatively) new version of Linux. For example, the Null checker detected most of the bugs in (56) and (23). In this current version, while it reported 20 potential bugs, a manual inspection confirmed that all of them were false positives.

False Positive Reduction In a recent paper (17), Brown et al. implemented a NULL pointer dereference checker (Pnull in the table) based on a new pattern — if a dereference of a pointer is post-dominated by a NULL test on the pointer, it is considered a potential bug. For instance, the following code snippet shows such a bug:

\[
\begin{align*}
\text{: a } &= \text{ p} \rightarrow \text{f} ; \quad \ldots \quad \text{if ( p ) \{ \ldots \}}
\end{align*}
\]

The intuition here is that the NULL test indicates that the developer thinks the pointer may be NULL at that point, and hence, there is a potential that the dereference (that occurred earlier) may be performed on a NULL pointer.

We re-implemented this checker and ran it on Linux 4.4.0-rc5. It reported 218 potential bugs, which roughly match the number of potential bugs reported in (17). Because our dataflow analysis can identify all variables to which NULL may potentially flow, if our analysis concludes that NULL can never come to a variable, the variable must not receive a NULL value at run time. Hence, we used our dataflow analysis to automatically inspect these 218 bugs. Eventually, our analysis could not find any case in which a NULL value can flow to the pointer being dereferenced.

A manual inspection confirmed this result — we found that in many cases the dereference is in one of the multiple control paths that can reach the NULL test. The pointer can be NULL in a different path (e.g., some function in the path may return an error code, resulting in an uninitialized pointer). In other cases, the tests are just unnecessary — the pointers checked can never be NULL (e.g., other NULL checks already filter out NULL pointers).

Similar results were achieved for PostgreSQL and httpd: our analysis found, respectively, 85 and 98 potential NULL pointers are false positives.
Unnecessary NULL Tests Similarly to pruning false positives in Pnull, we used our interprocedural analyses to identify NULL tests \(i.e.,\ if(p)\) in which the pointers checked must not be NULL. We have identified a total of 1127 unnecessary NULL tests in Linux, 149 in PostgreSQL, 32 in httpd. These are over-protective actions in coding, and may result in performance degradation. Because these warnings are too many to inspect manually, we took a sample of 100 warnings and found these tests were truly unnecessary. This is the first time that unnecessary NULL tests in the Linux kernel are identified and reported.

New Bugs Found Our analyses reported 108 new NULL pointer dereference bugs in Linux, among which 23 are false positives. All of these 85 new bugs involve complicated value propagation logic that cannot be detected by intraprocedural checkers. Figure 3 shows two example bugs.

in Figure 3 (a), function probe_kthread_data invokes probe_kthread_read to initialize pointer data. However, in probe_kthread_read, if a certain condition holds, an error code (-EFAULT) is returned and the pointer never gets initialized. Function probe_kthread_data then returns data directly without any check and the pointer gets dereferenced immediately after the function returns to its caller. In Figure 3 (b), page_private may dereference a NULL pointer since function vmalloc_to_page may return NULL. This bug was missed by the baseline because of the origin of the NULL value and the statement that dereferences it are in separate functions. These types of bugs can only be found by interprocedural analyses. In fact, we show these two bugs because they are relatively simple and easy to understand; most of our bugs involve more than 3 functions and more complicated logic.

For PostgreSQL and httpd, we found 33 and 14 new NULL pointer bugs, none of which were false positives. Our bug reports are all available on BitBucket for download.

Linux Bug Breakdown We have also broken down the new bugs and NULL tests in Linux into modules. Due to space limitations, the result is omitted. We make two observations on this breakdown. First, the code quality of the Linux kernel has been improved significantly over the past decade. Note that the bugs we found are all complicated bugs detected by our interprocedural analyses; the baseline checkers could not find any (shallow) bug in this version of the kernel. Second, consistent with the observations made in both (23) and (56), drivers is still the directory that contains most (NULL Pointer) bugs. This is not surprising as drivers is still the module with the largest size in the kernel codebase. On the other hand, drivers is also the module of which developers are most cautious (possibly due to the findings in (23) and (56)), demonstrated by the most unnecessary NULL tests it contains.

5.2 Graspan Performance

Table 4 reports various statistics of Graspan’s executions. Note that there is a large difference between the initial size and the post-processing size of each graph. For example, in Linux, the number of edges increases 8 times after the computation, while for httpd, the Graspan graph for pointer analysis increases more than 35 times. The computation time depends on both program characteristics and the type of analysis. For example, while the pointer analysis graph for httpd has a large number of edges added, its dataflow analysis graph does not change much and thus Graspan finishes the computation quickly in 4 minutes. We found that this is because our dataflow analysis only tracks NULL values and in httpd the distances over which NULL can flow are often short.

We have also attempted to run these graphs in memory on the desktop we used and all of them except the dataflow analysis of httpd run out of memory. While the initial size of each graph is relatively small, when edges are added dynamically, the graph soon becomes very big and Graspan needs to repartition it many times (reported in Column RP) to prevent the computation from running out of memory.

The Graspan section of Table 5 reports the breakdown of Graspan’s running time into computation, disk writes/reads, and garbage collection. Clearly, the EP-centric computation dominates the execution. While Graspan needs to perform

```
void*probe_kthread_data(
    task_struct *task);
void*data = NULL;
probe_kernel_read(&data);

/* data will be dereferenced
   after return */
return data;
}

long probe_kernel_read
(void *dst){
    page*vmalloc_to_page(...){
        if(page_private(head)
            !="...{
            ...
        }
        return -EFAULT;
    }
    ...probe_kernel_read(x);
}

(a) NULL deref in kernel/kthread.c
(b) NULL deref in mm/swapfile.c
```

Figure 3. Two representative bugs in the Linux kernel 4.4.0-rc5 that were missed by the baseline checkers.

Table 5. A comparison on the performance of Graspan, on-demand pointer analysis (ODA) (91) implemented in standard ways, as well as Socialite (42) processing our program graphs in Datalog. The Graspan section shows a breakdown of the running times into computation time (CT), I/O time (I/O), and garbage collection time (GC); P and D represent pointer/alias analysis and dataflow analysis. OOM means out of memory.
many disk accesses, the I/O cost is generally low because most disk accesses are sequential accesses. Since Graspan is implemented in Java, garbage collection performed by the Java runtime contributes about 10% of the execution time.

We have plotted the relationship between the numbers of edges added and the supersteps. We found that an extremely large number of edges are added within the first 10 supersteps (e.g., more than 500M for Linux), and as the computation progresses, fewer edges are added. This plot is omitted from the paper due to space limitations.

### 5.3 Comparisons with Other Analysis Implementations

**Data Structure Analysis** (44) To understand whether Graspan-based analyses are more scalable and efficient than traditional analysis implementations, we wanted to compare our analyses with existing context-sensitive pointer/alias and dataflow analyses. While we had spent much time looking for publicly available implementations, we could not find anything available except the data-structure analysis (DSA) (44) in LLVM itself. DSA (implemented in 2007) is much more complicated than our pointer/alias analysis implementation — it has more than 10K lines of code while our pointer/alias analysis (i.e., the graph generation part) only has 1.2K lines of code. According to a response from the LLVM mailing list (8), DSA was buggy and removed from LLVM since version 3.3. We tried to use LLVM 3.2 but it could not compile any version of the Linux kernel due to the lack of patches.

**On-demand Pointer Analysis** (91) As no other implementations were available, we implemented the context-sensitive version of Zheng and Rugina’s C pointer analysis (91) ourselves. We took the expression graph generated by our frontend and used a worklist-based (sequential) algorithm to compute transitive closures. The ODA section of Table 5 reports its performance. For all but httpd, ODA either ran out of memory or took a very long time (longer than one day) on the same desktop where we ran Graspan. For example, when processing Linux, it ran out of memory in 13 minutes. When we moved it onto a server with 32 2.60GHZ Xeon(R) processors and 32GB memory, it took this implementation 3.5 days to analyze Linux and it consumed 29GB out of the 32GB memory. On the contrary, Graspan finished processing Linux in 4.5 hours with less than 6GB memory on the desktop with a much less powerful CPU (due to exploited parallelism).

### 5.4 Comparisons with Other Backend Engines

**Datalog** Since Datalog has been used to power static analyses, it is important to understand the pros/cons of using Graspan v.s. a Datalog engine as the analysis backend. While there are many Datalog engines available (42; 7; 78; 71), SociaLite (42) and LogicBlox (7) are designed for shared-memory machines while the others (78; 71) are distributed engines running on large clusters. Since a distributed engine is not a choice for code checking in daily development tasks, we focused our comparison against shared-memory engines. LogicBlox is a commercial tool that has been previously used to power the Doop pointer analysis framework (16) for Java. However, it was the same licensing issue that prevented us from publishing comparison results with LogicBlox. Hence, this subsection only compares Graspan with SociaLite, a Datalog engine developed by Stanford that has been demonstrated to outperform LogicBlox and other shared-memory engines.

The **SociaLite** section of Table 5 reports SociaLite’s performance on the same desktop. SociaLite programs were easy to write — it took us less than 50 LoC to implement either analysis. However, SociaLite clearly could not scale to graphs that cannot fit into memory. For both the pointer/alias and the dataflow analysis, it ran out of memory for Linux and PostgreSQL. For httpd, although SociaLite processed the graphs successfully, SociaLite took much longer than Graspan.

**GraphChi** To understand whether other graph systems can efficiently process the same (program analysis) workloads, we ran GraphChi — a disk-based graph processing system — because GraphChi is the only available system that supports both out-of-core computation and dynamic edge addition. GraphChi provides an API add_edge for the developer to add an edge; it maintains a buffer for newly added edges during computation and uses a threshold to prevent the buffer from growing aggressively. When the size of the buffer exceeds the threshold, the edge adding thread goes to sleep and the function always returns false. The thread periodically wakes up and checks whether the main data processing thread comes to the commit point, at which the edges in the buffer can be flushed out to disk. We ran GraphChi on the same desktop to process the Linux dataflow graph. GraphChi ran into assertion failures in 133 seconds with around 65M edges added. This is primarily because GraphChi was not designed for the program analysis workload that needs to add an extremely

### Table 4. Graspan performance: reported are the numbers of vertices and edges before (IS) and after (PS) being processed by Graspan. Graspan’s pre-processing time (PT), numbers of supersteps taken (#SS), total running time (T), and numbers of times repartitioning has occurred (RP).

<table>
<thead>
<tr>
<th>Prog</th>
<th>IS=(E,V)</th>
<th>PS=(E,V)</th>
<th>PT</th>
<th>SS</th>
<th>T</th>
<th>RP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linux</td>
<td>(129.3M, 48.6M)</td>
<td>(1.5B, 48.6M)</td>
<td>192 secs</td>
<td>563</td>
<td>4.2 hrs</td>
<td>24</td>
</tr>
<tr>
<td>PSQL</td>
<td>(177.3M, 37.6M)</td>
<td>(1.1B, 37.6M)</td>
<td>127 secs</td>
<td>1025</td>
<td>3.8 hrs</td>
<td>73</td>
</tr>
<tr>
<td>httpd</td>
<td>(4.5M, 1.0M)</td>
<td>(155M, 1.0M)</td>
<td>4 secs</td>
<td>24,443</td>
<td>3.2 hours</td>
<td>102</td>
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</table>

<table>
<thead>
<tr>
<th>Prog</th>
<th>IS=(E,V)</th>
<th>PS=(E,V)</th>
<th>PT</th>
<th>SS</th>
<th>T</th>
<th>RP</th>
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</thead>
<tbody>
<tr>
<td>Linux</td>
<td>(49.5M, 42.7M)</td>
<td></td>
<td>4 secs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSQL</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>httpd</td>
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</tr>
</tbody>
</table>
large number of edges (with many duplicates) dynamically; neither were other existing graph systems.

6. Related Work

Static Bug Finding Static analysis has been used extensively in the systems community to detect bugs (29; 25; 84; 80; 53; 30; 28; 24; 13; 14; 19; 27; 56; 17; 33; 9; 68; 67; 45; 46; 1) and security vulnerabilities (20; 18; 38). Engler et al. (28) use a set of nine checkers to empirically study bugs in OS kernels. Palix et al. (56) implemented the same checkers using Coccinelle (55). Commercial static checkers (2; 3; 5; 4) are also available for finding bugs and security problems. There exists a body of work that makes program analysis declarative (81; 16) — analysis designers specify rules in Datalog and these rules are automatically translated into analysis implementations. However, existing Datalog engines do not support disk-based computation on a single machine.

Grammar-guided Reachability There is a large body of work that can be formulated as a context-free language (CFL) reachability problem (85). Work by Reps et al. (61; 62; 36; 59; 63) proposes to model realizable paths using a context-free language that treats method calls and returns as pairs of balanced parentheses. CFL-reachability can be used to formulate a variety of static analyses, such as polymorphic flow analysis (58), shape analysis (60), points-to and alias analysis (75; 73; 91; 74; 89; 74; 83; 82; 83; 88; 15), and information flow analysis (48). The work in (39; 51; 40) studies the connection between CFL-reachability and set-constraints, shows the similarity between the two problems, and provides implementation strategies for problems that can be formulated in this manner. CFL-reachability has also been investigated in the context of recursive state machines (11), streaming XML (10), and pushdown languages (12).

Graph Systems State-of-the-art graph systems include disk-based systems (41; 66; 92; 79; 47; 90; 34), shared-memory systems (72; 54), as well as distributed systems (50; 49; 31; 21; 77; 32; 65; 22; 57; 52; 76). Graspan is designed specifically for program analysis workload.

7. Conclusion

Graspan is the first attempt to turn complicated “Big Code” analysis into scalable “Big Data” analytics, opening up a new direction for scaling various sophisticated interprocedural analyses (e.g., symbolic execution, theorem proving, etc.) to large systems.

References


