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Using inter-procedural side-effect information in JIT optimizations

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Abstract

Inter-procedural analyses such as side-effect analysis can provide information useful for performing aggressive optimizations. We present a study of whether side-effect information improves performance in just-in-time (JIT) compilers, and if so, what level of analysis precision is needed.

We used SPARK, the inter-procedural analysis component of the SOOT Java analysis and optimization framework, to compute side-effect information and encode it in class files. We modified Jikes RVM, a research JIT, to make use of side-effect analysis in local common sub-expression elimination, heap SSA, redundant load elimination and loop-invariant code motion. On the SpecJVM98 benchmarks, we measured the static number of memory operations removed, the dynamic counts of memory reads eliminated, and the execution time.

Our results show that the use of side-effect analysis increases the number of static opportunities for load elimination by up to 98%, and reduces dynamic field read instructions by up to 27%. Side-effect information enabled speedups in the range of 1.08x to 1.20x for some benchmarks. Finally, among the different levels of precision of side-effect information, a simple side-effect analysis is usually sufficient to obtain most of these speedups.

1 Introduction

Over the past several years, just-in-time (JIT) compilers have enabled impressive improvements in the execution of Java code, mainly through local and intra-procedural optimizations, speculative inter-procedural optimizations, and efficient implementation techniques. However, JITs do not generally make use of whole-program analysis information, such as conservative call graphs, points-to information, or side-effect information, because it is too costly to compute it each time a program is executed. However, all non-trivial data types in Java are objects always accessed through indirect references (pointers), so one would expect optimizations using side-effect information to enable significant further improvements in performance of Java programs.

The purpose of the study presented in this paper is to answer two key questions. First, is side-effect information useful for the optimizations performed in a modern JIT, and can it significantly improve performance? Second, what level of precision of the side-effect information and the underlying analyses used to compute it is required to obtain these performance improvements?

To study these questions, we implemented a system consisting of an ahead-of-time inter-procedural side-effect analysis, whose result is communicated to a modified JIT containing optimizations that we adapted to take advantage of the side-effect information.

We implemented the side-effect analyses using the SPARK [15, 16] points-to analysis framework, a part of the SOOT [27] bytecode analysis, optimization, and annotation framework. The side-effect analysis makes use of points-to and call graph information computed by SPARK. The resulting side-effect information is encoded in class file attributes for use by the JIT using the annotation framework [21] included in SOOT.

We chose Jikes RVM [2] as the JIT for our study, and made several modifications to it. First, we added code to read in the side-effect information produced in our analysis. We then modified several analyses and optimizations to take advantage of the information, including local common subexpression elimination, heap array SSA construction, redundant load elimination, and loop-invariant code motion. Finally, we instrumented Jikes RVM both to count the static opportunities for performing optimizations, and to insert instrumentation code to measure the dynamic effects of the improved optimizations.

The contributions of this paper are the following:

- This is the first published presentation of the side-effect analysis that we have implemented in SOOT using points-to and call graph information computed by SPARK.
- To our knowledge, this is the first study of the run-time performance improvements obtainable by taking advantage of side-effect information in a range of optimizations in a Java JIT.
- We present empirical evidence that the availability of side-effect information in a Java JIT can enable significant performance improvements of up to 20%.
- We show that although precise analyses provide significantly more optimization opportunities when counted statically, most of the dynamic improvement is obtainable even with relatively simple, imprecise analyses. In

particular, a side-effect analysis based on a call graph constructed using an inexpensive Class Hierarchy Analysis (CHA) already provides a very significant improvement over not having any side-effect information at all.

The remainder of this paper is organized as follows. Section 2 is devoted to our side-effect analysis in SOOT, the call graph and points-to analyses that it depends on, issues with encoding its result in class file attributes, and the precision variations that we experimented with. In Section 3, we describe how we modified the optimizations in Jikes RVM to take advantage of side-effect information. In Section 4, we present the benchmarks that we used, our experiments, and our empirical results. We discuss related work in Section 5, and we conclude with Section 6.

2 Side-effect analysis in Soot

We implemented side-effect analysis in SOOT [27], a framework for analyzing, optimizing, and annotating Java bytecode. The side-effect analysis depends on two other inter-procedural analyses, call graph construction and points-to analysis. We describe how we construct a call graph in Section 2.1. An important difference from most other work on call graph construction is that to obtain a conservative side-effect analysis, we need to ensure that our call graph includes all methods invoked, including those invoked implicitly by the Java VM. In Section 2.2, we briefly explain the output of SPARK, our points-to analysis framework [15, 16]. Section 2.3 explains how we put the information from these two analyses together and produce side-effect information. In Section 2.4, we briefly note some issues with encoding the side-effect analysis results in class file attributes to communicate them to the JIT. Finally, in Section 2.5, we describe how variations in the precision of the call graph and points-to analyses affect the side-effect information.

2.1 Call Graph Construction

To perform an inter-procedural analysis on a Java program, information about the possible targets of method calls is required. This information is approximated by a call graph, which maps each statement s to a set $cg(s)$ containing every method that may be called from s. Constructing a call graph for a Java program is complicated by the fact that most calls in Java are virtual, so the target method of the call depends on the run-time type of the receiver object.

In our study, we compared two different methods of computing call graphs. First, we computed call graphs using Class Hierarchy Analysis (CHA) [8], an inexpensive method which considers only the static type of each receiver object, and does not require any inter-procedural analysis. Second, we used a points-to analysis (discussed in the next section) to compute the run-time types of the objects that the receiver of each call site could point to, and we determined the target method that would be invoked for each run-time receiver type.

Several important but subtle details of the Java virtual machine (VM) complicate the construction of a conservative call graph suitable for side-effect analysis. In a Java program, methods may be invoked not only due to explicit invoke instructions, but also implicitly due to various events in the VM. Whenever a new class is first used, the VM implicitly calls its static initialization method. The set of events that may cause a static initialization method to be called is specified in [17, section 2.17.4]. In our analysis, we assume that any of these events could cause the corresponding static initialization method to be invoked. Each static initialization method is executed at most once in a given run of a Java program. Therefore, we use an intra-procedural flow-sensitive analysis to eliminate spurious calls to static initialization methods which must have already been called on every path from the beginning of the method. In addition, the standard class library often invokes methods using the `doPrivileged` methods of `java.security.AccessController`. Our analysis models these with calls of the `run` method of the argument passed to `doPrivileged`. Methods may also be invoked using reflection. In general, it is not possible to determine statically which methods will be invoked reflectively, and our analysis only issues a warning if it finds a reachable call to one of the reflection methods. However, calls to the `newInstance` method of `java.lang.Class` are so common that they merit special treatment. This method creates a new object and calls its constructor. In our analysis, we conservatively assume that any object could be created, and therefore any constructor with no parameters could be invoked.

To partially verify the correctness of the computed call graph, we instrumented the code to ensure that all methods that are executed at run time were included in the call graph and reachable from the entry points. To do this, we computed the set of methods that are not reachable from the entry points through the call graph, and modified them

to abort the execution of the benchmark if they do get invoked at run time. Although this does not prove that every possible run-time call edge is included in the computed call graph, it does guarantee that every executed method is considered in call graph construction. To further check that our overall optimizations were conservative on the benchmarks studied, we verified that the benchmarks produced identical output in all configurations, including with the optimizations disabled.

2.2 Points-to Analysis

We use the SPARK [15, 16] points-to analysis framework to compute points-to information. For each *pointer* p in the program, it computes a set $pt(p)$ of *objects* to which it may point. The most common kind of *pointer* is a local variable of reference type in the Jimple representation of the code. Local variables appear in field read and write instructions as pointers to the object whose field is to be read or written, and in method invocation instructions as the receiver of the method call, which determines the method to be invoked. In addition, *pointers* are introduced to represent method arguments and return values, static fields, and special values needed in simulating the effects on pointers of native methods in the standard class library. Typically, an *object* is an allocation site; we model all run-time objects created at a given allocation site as a single entity. In addition, we must include special *objects* for run-time objects without an allocation site, such as objects created by the VM (the argument array to the main method, the main thread, the default class loader) and objects created using reflection. For some of these special *objects*, we may not know the exact run-time type. Therefore, we conservatively assume that their run-time type may be any subtype of their declared type.

SPARK performs a flow-insensitive, context-insensitive, subset-based points-to analysis by propagating *objects* from their allocation sites through all *pointers* through which they may flow. SPARK has many parameters for experimenting with variations of the analysis that affect analysis efficiency and precision. In this study, we experimented with four points-to analysis variations. We explain the variations in more detail in Section 2.5.

2.3 Side-Effect Analysis

The side-effect analysis consists of two steps, which are discussed in this section. First, we compute a read and write set for each statement. Second, we use the read and write sets to compute dependencies between all pairs of statements within each method.

For each statement s, we compute sets $read(s)$ and $write(s)$ containing every static field sf read (written) by s, and a pair (o, f) for every field f of *object* o that may be read (written) by s. These sets also include fields read (written) by all code executed during execution of s, including any other methods that may be called, directly or transitively. The read and write sets are computed in two steps. In the first step, we compute only the direct read and write sets for each statement in the program, ignoring any code that may be called from the statement. The result of the points-to analysis is used to determine the possible objects being pointed to by the pointer in each field read or write instruction. In the second step, we continually aggregate the read and write sets of each method and propagate them to all call sites of the method, until a fixed-point is reached. During the propagation, the call graph is used to determine the call sites of each method.

Once the read and write sets for all statements have been computed, for each method, we compute an interference relation between all the read and write sets in the method: $int(m) = \{(set_1, set_2) \mid set_1 \cap set_2 \neq \emptyset\}$. We map the interference relation on read and write sets to four dependence relations between statements (read-read dependence, read-write dependence, write-read dependence, write-write dependence). For example, there is a read-write dependence between statements s_1 and s_2 if $(read(s_1), write(s_2)) \in int(m)$. It is the dependences between statements that we encode in class files for the JIT to use in performing optimizations.

2.4 Encoding Side-Effects in Class File Attributes

All of the analyses described in the preceding sections are performed on Jimple, the three-address intermediate representation (IR) used in SOOT. In order to communicate the analysis results to a JIT, we must convert them to refer to bytecode instructions during the translation of Jimple to bytecode. SOOT includes a universal tagging framework [21] that propagates analysis information through its various IRs, and encodes it in class file attributes. An important complication in this process is that one Jimple statement may be converted to multiple bytecode instructions. However,

Jimple is low-level enough that whenever a Jimple instruction has side-effects, exactly one of the bytecode instructions generated for it has those side-effects. Therefore, for each type of Jimple instruction, we identify the relevant bytecode instruction to the tagging framework, and it attaches the side-effect information to that instruction.

Another complication in communicating the side-effect information is that some methods have a large number of statements with side-effects. Since the dependence relations may have size quadratic in the number of instructions with side-effects, a naive encoding of the dependence relations is sometimes unacceptably large. However, we have observed in those cases, many of the read and write sets in the method are identical. Therefore, we add a level of indirection. Instead of expressing the dependence relations in terms of statements, we enumerate all distinct read and write sets, and express the dependence relations between those sets. For each statement, we indicate which set it reads and writes. The resulting encoding has size $\Theta(m^2+n)$, where n is the number of statements, and m is the number of unique sets. In an earlier study [15, Sections 6.2.2 and 6.2.6], we observed that this encoding limits the annotation size to acceptable levels.

2.5 Analysis Variations

Figure 1: Code examples

```
1  class Box {
2      A a;
3  }
4  abstract class A {
5    int f;
6    abstract void nothing();
7    abstract void maybe();
8    abstract void setF();
9    abstract A id();
10 }
11 class B extends A {
12   void nothing() {}
13   void maybe() { this.f = 1; }
14   void setF() { this.f = 2; }
15   A id() { return this; }
16 }
17 class C extends A {
18   void nothing() {}
19   void maybe() {}
20   void setF() { this.f = 3; }
21   A id() { return this; }
22 }
23 class Main {
24   public static void main(String[] args) {
25      new Main().run(new B(), new C());
26   }
27   void run(A b, A c) {
28     b.f = 4;
29     // insert possible side-effect here
30     int n = b.f; // eliminate this load
31     System.out.println(n);
32   }
33 }
```

(a)

```
1
```

(b)

```
1  c.nothing();
```

(c)

```
1  c.maybe();
```

(d)

```
1  Box b1 = new Box();
2  b1.a = c;
3  c = b1.a;
4
5  Box b2 = new Box();
6  b2.a = b;
7  b = b2.a;
8
9  c.setF();
```

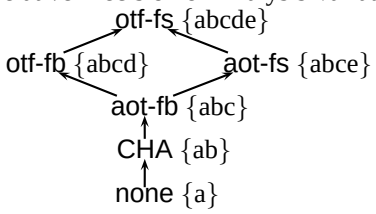
(e)

```
1  c = c.id();
2  b = b.id();
3  c.maybe();
```

In our empirical study presented in Section 4, we compare the effectiveness of six variations of our analysis. In this section, we explain the differences between these variations. In Figure 1, we present examples of code that distinguishes the variations: it may be optimized only if the information provided by specific variations is available.

In line 28, the code writes a constant to the field `b.f`. In line 30, the constant read out again. Our goal is to optimize away the constant field read. If we substitute each of the code snippets **(a)** through **(e)** on the right of Figure 1 for line 29, the resulting code will never change the value (4) loaded in line 30. However, analyses of different precision are required to prove that the code snippets do not have side-effects affecting the value of `b.f`. Figure 2 gives an overview of the relative precision of the variations, with precision increasing from bottom to top. After each variation, we list the subset of the code snippets that can be optimized using the information provided by the variation.

Figure 2: Relative Precision of Analysis Variations



For the first variation, none, we compute no side-effect information at all, and rely only on the internal analysis in the Jikes RVM JIT for optimizations. In this case, Jikes RVM is able to remove the read in line 30 only when the empty snippet (a) is inserted at line 29. The JIT determines that the field being loaded is the same as the field to which the constant was written, and since no statements have been executed since the write, the value could not have been affected. However, as soon as we insert any method call between the write and read (in each of the code snippets (b) through (e)), the JIT cannot optimize the read, because it knows nothing about the side-effects of the method called.

Our second variation, CHA, is to compute side-effects using a call graph, but without performing any points-to analysis. We construct the call graph using CHA, as described in Section 2.1. In this case, we can optimize code snippet (b), because the analysis determines that the call `c.nothing()` calls the method `nothing()` in either class `B` or `C`, and neither of these methods write to field `f`. However, for the call to `maybe()` in snippet (c), CHA cannot tell which of the two `maybe()` methods will be invoked. Since `B.maybe()` writes to field `f`, the analysis conservatively assumes that `b.f` may be overwritten, and prevents the optimization.

The remaining variations all take advantage of points-to analysis information to compute side-effects. The differences between them are whether the points-to analysis is field-based (fb) or field-sensitive (fs), and whether it uses a call graph computed ahead-of-time (aot), or whether it computes its own call graph on-the-fly (otf). All of the points-to analysis variations determine that `c` can only be of run-time type `B`. Therefore, the call to `c.maybe()` does not write to field `f`, so the read in line 30 can be optimized when code snippet (c) is inserted into line 29.

The distinction between a field-based and field-sensitive analysis defines how the points-to analysis treats pointer flow through fields of heap objects. In a field-based analysis, each field is treated as a *pointer* with a single points-to set. It is assumed that any *object* stored into a field `f` of any object may be retrieved from field `f` of any object. On the other hand, a field-sensitive analysis computes a separate points-to set for each pair $\langle object, field \rangle$. Therefore, if an *object* is written to `b1.a` and read out of `b2.a`, and if `b1` and `b2` cannot point to the same object, then the analysis determines that the *object* will not be read out of `b2.a`. This is illustrated by code snippet (d). In the code, `c` is stored and subsequently stored into and read out of `b1.a`, and `b` undergoes a similar operation through `b2.a`. A field-based points-to analysis cannot distinguish between the field `a` of the two different boxes `b1` and `b2`, and therefore assumes that `c` and `b` could point to the same object, so `b.f` could be written to at the end of the code snippet. A field-sensitive analysis, on the other hand, proves that the `b` and `c` read out of the two boxes are distinct objects, so the call to `c.setF()` does not affect the value of `b.f`.

In order to propagate points-to sets inter-procedurally, a points-to analysis requires an approximation of the call graph. However, we use the result of the points-to analysis to build the call graph. One solution to this circular dependency is to build an imprecise call graph ahead-of-time using CHA, only for the use of the points-to analysis. After the points-to analysis completes, we use the points-to information to construct a more precise call graph to be used in the side-effect analysis. The other alternative is to build the call graph on-the-fly as the points-to analysis proceeds: as points-to sets grow, we add edges to the call graph. Results from our prior work [16] show the latter approach to be more costly, but to produce more precise results. The difference in precision is illustrated by code snippet (e). In the code, `c` and `b` are passed through identity methods that return themselves. An ahead-of-time CHA-

based call graph says that each `id()` method calls may call either of the two `id()` methods, so both objects end up in the points-to sets of both `c` and `b`. Therefore, the analysis cannot determine that the call to `c.maybe()` will not change `b.f`. However, if the analysis builds the call graph on-the-fly, the call graph only contains the single correct target method for each of the `id()` method calls, and the object pointed to by `b` does not flow into the points-to set of `c`. The analysis therefore determines that the call to `c.maybe()` does not write to `b.f`, and the load may be eliminated.

3 Optimizations enabled in Jikes RVM

The JIT compiler that we modified to make use of side-effect information is the Jikes Research Virtual Machine (RVM) [2]. Jikes RVM is an open source research platform for executing Java bytecode. It includes three levels of JIT optimizations (0, 1 and 2). We adapted three optimizations in Jikes RVM to make use of side-effect information: local common sub-expression elimination (CSE), redundant load elimination (RLE) and loop-invariant code motion (LICM). Sections 3.1 to 3.3 describe each of these optimizations and the changes that we made. Because side-effect information refers to the original bytecode of a method, bytecodes that come from an inlined method need to be treated specially. Section 3.4 describes how we dealt with this case.

3.1 Local common sub-expression elimination

The first optimization in Jikes RVM that we modified to make use of side-effect is local CSE. This optimization is only performed within a basic block. The algorithm for performing CSE on fields is described in Figure 3. A cache is used to store the available field expressions. The algorithm iterates over all instructions in a basic block, and processes them. There are two parts in this process. The first is to try to replace each *getfield* or *getstatic* instructions encountered by an available expression. If one is available, it is assigned to a temporary variable and the *getfield* or *getstatic* instruction is replaced by a copy of the temporary. If none is available, a field expression is added to the cache for the *getfield* or *getstatic* instruction. For every *putfield* and *putstatic* instruction, an associated field expression is also added to the cache. The second part is to update the cache according to which expressions the current instruction kills. A call or synchronization instruction kills all expressions in the cache. A *putfield* or *putstatic* of some field X will remove any expression in the cache associated with field X.

Figure 3: Local common sub-expression algorithm

```
1:  for each basic block bb do
2:    for each instruction s in bb do
3:      if volatileField( s ) then
4:        continue
5:      if isGetField( s ) or isGetStatic( s ) then
6:        if if cache.availableExpression( s ) then
7:          replace s by available expression in cache
8:        else
9:          add expression( s ) to cache
10:     else if isPutField( s ) or isPutStatic( s ) then
11:       add expression( s ) to cache
12:     if s is a store of field X then
13:       remove all expressions with field X from cache (excluding expression( s ))
14:     else if s is a call or synchronization then
15:       remove all expressions from cache
```

In this algorithm, we used side-effect information to reduce the set of expressions killed (lines 13 and 15 in Figure 3). When the current instruction is a field store or a call, we only remove from the cache entries that have a read-write or write-write dependence with the current instruction in the side-effect analysis.

An example is shown in Figure 4. Without side-effect information, the compiler would conservatively assume that statement `obj2.x = 10` could write to memory location `obj1.x` and that the call to `nothing()` could write to

any memory locations. In contrast, the side-effect analysis would specify that there is no dependence between these instructions, and thus enable the replacement of the load of `obj1.x` on line 6 by an available expression (line 3).

Figure 4: Local common sub-expression example

```
1  A obj1 = new A();
2  A obj2 = new A();
3  i = obj1.x;
4  obj2.x = 10;
5  nothing();
6  j = obj1.x;
```

3.2 Redundant load elimination

The redundant load elimination algorithm relies on extended Array SSA (also known as Heap Array SSA or Heap SSA) [10] and Global Value Numbering [3]. We explain the general idea of the algorithm below. For a detailed description, please refer to [10].

The algorithm transforms the IR into heap SSA form. A heap array is created for each object field. The object reference is used as the index into this heap array. For example, in the code of Figure 5, there are two heap arrays, X and Y. On line 3, "Heap Array X [a] = ..." means that a store is performed in heap array X at index a (the object reference).

Figure 5: Scalar replacement example

```
1  a = new A();
2  b = new A();
3  a.x = ...          -> heap Array X [a] = ...
4  a.y = ...          -> heap Array Y [a] = ...
5  b.x = ...          -> heap Array X [b] = ...
6  n = a.x            -> n = heap Array X [a]
```

After the transformation to heap SSA form is completed, global value numbers are computed. The global value numbering computes definitely-different (*DD*) and definitely-same (*DS*) relations for object references. The *DD* relation distinguishes two object references coming from different allocation sites, or when one is a method parameter and the other one is the result of a new statement. The *DS* relation returns true when two object references have the same value number (one is a copy of the other). In Figure 5, since a and b are the results of different allocation sites (line 1 and 2), *DD*(a, b) = true and *DS*(a, b) = false.

Once global value numbers are computed, index propagation is performed. The index propagation solution holds the available indices into heap arrays at each use of a heap array. Scalar replacement is performed using the sets of available indices. Note that in the algorithm, these sets actually contain value numbers of available indices. For simplicity, we consider sets of available indices.

In Figure 5, after a.x is assigned on line 3, the set of available indices for heap Array X is {a}. Similarly, {a} is available for heap Array Y after the assignment to a.y on line 4. For the store of b.x on line 5, since global value numbering tells us that *DD*(a, b) = true, we have {a, b} available for heap Array X after line 5. If *DD*(a, b) had returned false, we would have conservatively assumed that a store to heap Array X [b] could have overwritten heap Array X [a], and thus, only {b} would be available after line 5. On line 6, heap Array X is used at index a. Since a is available, a new temporary is introduced and scalar replacement is performed.

For increasing the number of opportunities for load elimination, we used side-effect information during the heap SSA transformation and in the *DD* relation. During the heap SSA construction, without side-effect information, each call instruction is annotated with a definition and a use of every heap array. With side-effect information we annotate

a call with a definition of a heap array, say X, only if there is a write-read or write-write dependence between the call and the instruction using heap array X. Similarly we annotate a call with a use of a heap array if there is a read-read or read-write dependence. We also use side-effect information when the *DD* relation returns false. Two instructions having no data dependence is equivalent to *DD*(a, b) = true, where a and b are the object references used in the instructions.

In Figure 6(a), without side-effect information, since a and b are method parameters, *DD*(a, b) = false. Thus, only {b} is available after line 3. This allows the load of b.x on line 9 to be eliminated. Since it is conservatively assumed that calls can write to any memory location, the available index set after nothing() on line 10 is the empty set. Line 12 represents a merge point of the available index sets after line 7 and 10. The intersection of these two sets is the empty set. After the load of a.x on line 14, {a} is available. Since *DS*(a, b) = false, the load of b.x on line 15 cannot be eliminated.

Figure 6: Redundant load elimination example (a) before (b) after

(a)

```
1  int foo( A a, A b, int n ) {
2    a.x = 2;
3    b.x = 3;
4
5    int i;
6    if( n > 0 ) {
7      i = a.x;
8    } else {
9      i = b.x;
10     nothing();
11   }
12   // Merging point: a phi is
13   // placed here in heap SSA
14   int j = a.x;
15   int k = b.x;
16   return i + j + k;
17 }
18
19 public static void
20     main( String[] args ) {
21   foo( new A(), new A(), 1 );
22 }
```

(b)

```
1  int foo( A a, A b, int n ) {
2    t1 = 2;
3    a.x = t1;
4    t2 = 3;
5    b.x = t2;
6
7    int i;
8    if( n > 0 ) {
9      i = t1;
10   } else {
11     i = t2;
12     nothing();
13   }
14   // Merging point: a phi is
15   // placed here in heap SSA
16   int j = t1;
17   int k = t2;
18   return i + j + k;
19 }
20
21 public static void
22     main( String[] args ) {
23   foo( new A(), new A(), 1 );
24 }
```

Using side-effect analysis, since a.x has no dependence with b.x (line 2 and 3) the available index set after line 3 is {a, b}. Thus, loads of a.x and b.x on line 7 and 9 can be eliminated. The available index set after line 7 is {a, b}, and after line 10, it is also {a, b}, since nothing() has no side-effect. The intersection at the merge point (line 12) results in the set {a, b}. The load of a.x can then be removed on line 14. The available index set after line 14 is {a, b}, allowing load elimination of b.x on line 15. The resulting code after performing load elimination is shown in Figure 6(b).

3.3 Loop-invariant code motion

The LICM algorithm in Jikes RVM is an implementation of the Global Code Motion algorithm introduced by Click [7] and is adapted to handle memory operations. As such, it requires the IR to be in heap SSA form. We provide the basic idea of the algorithm below. For more details, see [7].

The algorithm schedules each intruction early, i.e. finds the earliest legal basic block that an instruction could be moved to (all of the instruction's inputs must dominate this basic block). Similarly, it finds the latest legal basic block for each instruction (this block must dominate all uses of the instruction's result). Instructions such as phi,

`branch` or `return` cannot be moved due to control dependences. Between the earliest and latest legal basic blocks, the heuristic to choose which basic block to place the instruction is to pick the one with the smallest loop depth. Global Code Motion differs from standard loop-invariant code motion techniques in that it moves instructions after as well as before loops.

In Figure 7(a), the compiler first transforms the code into heap SSA form and without side-effect information assumes that method `nothing()` can read and write any memory location. As a result, the compiler will be unable to move the loads of `a.x` and `a.y` outside of the loop. With side-effect information, knowing that method `nothing()` does not read or write to `a.x` or `a.y`, the loads of `a.x` and `a.y` will be moved before and after the loop respectively, resulting in the code in Figure 7(b).

Figure 7: Loop-invariant code motion example (a) before (b) after

(a)

```
1  do {
2    i = i + a.x;
3    j = i + a.y;
4    nothing();
5  } while( i < n );
```

(b)

```
1  t = a.x;
2  do {
3    i = i + t;
4    nothing();
5  } while( i < n );
6  j = i + a.y;
```

3.4 Using side-effect information for inlined bytecode

The side-effect attribute provides information about data dependences between instructions and refers to a bytecode by using its offset. In Figure 8(a), let's assume that calls to `foo()` and `bar()` are inlined, resulting in the code in Figure 8(b). Since an inlined bytecode is associated with its original offset in the IR, it is in general incorrect to retrieve side-effect information for an inlined bytecode in the current method. For example, in the side-effect attribute of method `main()` in Figure 8(b), information about offset `0` is associated with bytecode `b0`, not `b1` or `b2`.

To handle this case, we keep track of inlining sequences for each instruction. When comparing two bytecodes, we retrieve the least common method ancestor of the two bytecode inlining sequences, and use the side-effect information associated with that method. If a bytecode originally comes from that common method, we use its offset. Otherwise, we retrieve the *invoke* bytecode that it comes from in the common method, and use the offset associated with this *invoke* bytecode.

For example, in Figure 8(b), the least common method ancestor for bytecodes `b0` and `b1` is `main()`. Since `b0` originally comes from `main()`, we use its offset (i.e. 0). Since `b1` was not originally part of `main()`, we retrieve the *invoke* bytecode that it comes from in `main()`, i.e. *invoke* `foo`. We then use the offset associated with this *invoke* bytecode (i.e. `1`). Thus, when inquiring about data dependences between bytecodes `b0` and `b1`, we lookup information for offsets `0` and `1` in the side-effect attribute for method `main()`. Similarly, for bytecodes `b1` and `b2` we lookup offsets `0` and `1` in the side-effect attribute of method `foo()` (same result for `b1` and `b3`). For bytecodes `b2` and `b3`, we lookup offsets `0` and `1` in the side-effect attribute of `bar()`.

4 Experiments

4.1 Environment and benchmarks

We modified Jikes RVM version 2.3.0.1 to use side-effect information in the optimizations described in the previous section. We used the production configuration (namely FastAdaptiveCopyMS) in Jikes RVM with the JIT-only option (every method is compiled on first invocation and no recompilation occurs thereafter). We ran the SpecJVM98 [1] benchmarks (size 100) with Jikes RVM at optimization level 1 and 2 using the six side-effect variations described in section 2. A description of the benchmarks is given in Table I. For each benchmark and at each optimization level, we show the number of memory reads per second performed (load density). This shows how important memory operations are in each benchmark. We expect the benchmarks with high load densities, compress, raytrace, mtrt and

Figure 8: Inlining example (a) before (b) after

(a)

```
Offset  main() {
0         b0
1         invoke foo
        }
        foo() {
0         b1
1         invoke bar
        }
        bar() {
0         b2
1         b3
        }
```

(b)

```
Offset
        main() {
0         b0
0         b1
0         b2
1         b3
        }
```

mpegaudio, to benefit most from side-effect analysis. We used the development version of SOOT (revision 1621) to compute side-effect information.

Benchmark	Description	Load density 1000's Level 1	Load density 1000's Level 2
compress	Lempel-Ziv compressor/uncompressor	207383	138570
jess	A Java expert shell system based on NASA's CLIPS system	56371	68353
raytrace	Ray tracer application	106271	127806
db	Performs several database functions on a memory-resident database	7140	11776
javac	JDK 1.0.2 Java compiler	21645	19208
mpegaudio	MPEG-3 audio file compression application	82137	179070
mtrt	Dual-threaded version of raytrace	92599	122821
jack	A Java parser generator with lexical analyzers (now Java CC)	14632	15240

Table I: Benchmark description and load density property

We ran our benchmarks on two different architectures to see whether we would get similar trends in our results. The first system that we used runs Linux Debian on an Intel Pentium 4 1.80GHz CPU with 512Mb of RAM. The second one also runs Linux Debian on an dual processor AMD Athlon MP 2000+ 1.66GHz CPU with 2Gb of RAM. For our experiment, Jikes RVM was configured to run on a single processor machine.

4.2 Results

Our primary goal for this study was to see whether side-effect information could improve performance in JITs, and if so, our secondary objective was to determine the level of precision of side-effect information required. To obtain accurate answers to these questions, we measured for each run the static number of loads removed in local CSE and in the redundant load elimination optimization, and the static number of instructions moved in the loop-invariant code motion phase. These numbers provide us details on how much improvement each optimization achieves statically using side-effect information. We also measured dynamic counts of memory load operations eliminated and execution times (best of four runs, not including compilation time). The architecture-independent dynamic counts help us see whether a direct correlation exists between a reduction in memory operations performed and speedups.

It should be noted that although we used the JIT-only option in Jikes RVM where no method recompilation is expected, some optimizations such as inlining can cause invalidation and recompilation. In this case, for our static numbers, we only counted the number of static loads eliminated (in local CSE or load elimination) or instructions moved (in LICM) in the last method compilation before execution.

To examine the effect of side-effect analysis in both local and global optimizations, we ran our benchmarks using Jikes RVM at optimization level 1 and 2. For level 1, only local CSE uses side-effect information. For level 2, local

CSE, redundant load elimination and loop-invariant code motion use side-effect analysis. We present in the next two sections our results for level 1 and level 2 optimizations.

4.2.1 Optimization level 1

Level 1 optimizations in Jikes RVM include standard optimizations such as local copy propagation, local constant propagation, local common sub-expression elimination, null check elimination, type propagation, constant folding, dead code elimination, inlining, etc. Among these, only local CSE uses our side-effect analysis for eliminating *getfield* and *getstatic* instructions.

When running our benchmarks with Jikes RVM at optimization level 1 (which also includes all level 0 optimizations), the use of the five side-effect variations (CHA, aot-fb, aot-fs, otf-fb and otf-fs) produced identical static and dynamic counts, and similar runtimes. To avoid repeating identical results, we grouped these five side-effect variations under the name any in the side-effect column of Tables II and III. As expected, the execution times of runs using these five side-effect variations are almost identical. We thus also grouped them under any in the second column of Table IV, and reported the average execution times of runs using these five side-effect variations.

Benchmark	Side-Effect	Local CSE performed		
		getfield	getstatic	total
compress	none	108	1	109
	any	112 (3.70 %)	2 (100.00 %)	114 (4.59 %)
jess	none	229	0	229
	any	245 (6.99 %)	1	246 (7.42 %)
raytrace	none	166	0	166
	any	188 (13.25 %)	1	189 (13.86 %)
db	none	130	0	130
	any	133 (2.31 %)	3	136 (4.62 %)
javac	none	415	0	415
	any	431 (3.86 %)	1	432 (4.10 %)
mpegaudio	none	340	174	514
	any	347 (2.06 %)	176 (1.15 %)	523 (1.75 %)
mtrt	none	166	0	166
	any	188 (13.25 %)	1	189 (13.86 %)
jack	none	470	1	471
	any	663 (41.06 %)	2 (100.00 %)	665 (41.19 %)

Table II: Level 1 static counts for local CSE

Table II shows that using side-effect information in local CSE increased the number of static opportunities for load elimination by 2% to 41%, but only resulted in a decrease of up to 0.87% of dynamic *getfield* and *getstatic* instructions (Table III). As a result, most benchmarks have similar execution times with or without side-effect analysis. However, the use of side-effect information produced speedups of 1.08x and 1.06x for mpegaudio on our Intel and AMD systems, and 1.02x for raytrace on both systems (Table IV).

These results show that the simplest side-effect analysis, CHA, is sufficient for level 1 optimizations in Jikes RVM. Only local CSE uses side-effect analysis, and since it is only performed on basic blocks (typically small in Java programs), the effect is minimal.

4.2.2 Optimization level 2

The more advanced and expensive analyses and optimizations in Jikes RVM are level 2 optimizations. They include redundant branch elimination, heap SSA, redundant load elimination, coalescing after heap SSA, expression folding, loop-invariant code motion, global CSE, and tranforming while into until loops. As described in section 3, we made use of side-effect information in the heap SSA construction, redundant load elimination, and loop-invariant code motion.

Benchmark	Side-Effect	getfield	getstatic	total
compress	none	1871398009	33418641	1904816650
	any	1871397929 (0.00 %)	33418641	1904816570 (0.00 %)
jess	none	209404162	2326905	211731067
	any	209402840 (0.00 %)	2326905	211729745 (0.00 %)
raytrace	none	287993152	1359	287994511
	any	287979508 (0.00 %)	1359	287980867 (0.00 %)
db	none	160088294	96012	160184306
	any	160087709 (0.00 %)	96012	160183721 (0.00 %)
javac	none	149595624	4028976	153624600
	any	149407295 (0.13 %)	4028946 (0.00 %)	153436241 (0.12 %)
mpegaudio	none	456136442	52215347	508351789
	any	455026631 (0.24 %)	52215346 (0.00 %)	507241977 (0.22 %)
mtrt	none	291501667	2063	291503730
	any	291474379 (0.01 %)	2063	291476442 (0.01 %)
jack	none	50029731	1534965	51564696
	any	49579043 (0.90 %)	1534977 (0.00 %)	51114020 (0.87 %)

Table III: Level 1 dynamic counts

(a)

Benchmark	Side-Effect	Time(s)	Speedup
compress	none	9.215	
	any	9.395	0.98x
jess	none	4.583	
	any	4.615	0.99x
raytrace	none	4.276	
	any	4.198	1.02x
db	none	22.023	
	any	22.054	1.00x
javac	none	11.047	
	any	11.215	0.99x
mpegaudio	none	8.874	
	any	8.219	1.08x
mtrt	none	4.744	
	any	4.727	1.00x
jack	none	6.095	
	any	6.108	1.00x

(b)

Benchmark	Side-Effect	Time(s)	Speedup
compress	none	9.185	
	any	9.184	1.00x
jess	none	3.756	
	any	3.77	1.00x
raytrace	none	2.71	
	any	2.662	1.02x
db	none	22.434	
	any	22.453	1.00x
javac	none	7.097	
	any	7.177	0.99x
mpegaudio	none	6.189	
	any	5.85	1.06x
mtrt	none	3.148	
	any	3.087	1.02x
jack	none	3.524	
	any	3.509	1.00x

Table IV: Level 1 running time (a) Intel (b) AMD

Our benchmarks were run at optimization level 2 in Jikes RVM (all level 0 and 1 optimizations are also performed), and produced identical counts and similar runtimes for the side-effect variations aot-fb, aot-fs, otf-fb and otf-fs (except for one case in compress, where the static number of loads eliminated is 388 for aot-fb and aot-fs, and 389 for otf-fb and otf-fs). Thus, we grouped these four variations of side-effects that are based on points-to analysis under the name PTA in Tables V to IX. In Table IX, the time under PTA is the average runtime of these four variations.

Benchmark	Side-Effect	Load Elimination performed			
		getfield	getstatic	aload	total
compress	none	359	4	0	363
	CHA	386 (7.52 %)	5 (25.00 %)	0	391 (7.71 %)
	PTA	388 (8.08 %)	5 (25.00 %)	0	393 (8.26 %)
jess	none	722	1	129	852
	CHA	1050 (45.43 %)	2 (100.00 %)	149 (15.50 %)	1201 (40.96 %)
	PTA	1106 (53.19 %)	3 (200.00 %)	196 (51.94 %)	1305 (53.17 %)
raytrace	none	342	1	32	375
	CHA	613 (79.24 %)	2 (100.00 %)	84 (162.50 %)	699 (86.40 %)
	PTA	613 (79.24 %)	2 (100.00 %)	127 (296.88 %)	742 (97.87 %)
db	none	243	1	2	246
	CHA	274 (12.76 %)	4 (300.00 %)	2	280 (13.82 %)
	PTA	274 (12.76 %)	4 (300.00 %)	3 (50.00 %)	281 (14.23 %)
javac	none	1519	26	90	1635
	CHA	1842 (21.26 %)	30 (15.38 %)	101 (12.22 %)	1973 (20.67 %)
	PTA	1847 (21.59 %)	30 (15.38 %)	108 (20.00 %)	1985 (21.41 %)
mpegaudio	none	706	212	367	1285
	CHA	804 (13.88 %)	216 (1.89 %)	370 (0.82 %)	1390 (8.17 %)
	PTA	804 (13.88 %)	216 (1.89 %)	426 (16.08 %)	1446 (12.53 %)
mtrt	none	342	1	32	375
	CHA	613 (79.24 %)	2 (100.00 %)	84 (162.50 %)	699 (86.40 %)
	PTA	613 (79.24 %)	2 (100.00 %)	127 (296.88 %)	742 (97.87 %)
jack	none	678	2	69	749
	CHA	999 (47.35 %)	16 (700.00 %)	69	1084 (44.73 %)
	PTA	999 (47.35 %)	16 (700.00 %)	69	1084 (44.73 %)

Table V: Level 2 static counts for redundant load elimination

Table V shows that using side-effect information in RLE increased static opportunities for load removal by 7% to 98%. There were very few improvements for removing *getstatic* instructions, but the increase was large for removing *getfield* and *aload* (array load) instructions for some benchmarks (jess, raytrace, mtrt and jack). Interestingly, PTA improved over CHA for all benchmarks except jack.

In Table VI, we show static counts of instructions moved during LICM. The last two columns are the total instructions moved when LICM is performed on high-level (HIR) and low-level (LIR) intermediate representation in Jikes RVM. Note that memory operations are not moved during LICM on LIR; interestingly, the use of side-effect in HIR optimizations enabled some other transformations that allowed some instructions to be moved during LICM on LIR. We see in Table VI that side-effect analysis increased the number of moved *getfield* (up to 18%), in one case of a *putfield*, and the total during HIR (up to 14%). For only one benchmark (jess), using PTA side-effect information allowed more instructions to be moved than CHA. There were no *putstatic*, *aload* or *astore* instructions moved. Note that since RLE is performed before LICM, improved side-effect information can cause loads that would have been moved in LICM to be removed in RLE. Therefore, to measure the impact of side-effect information on LICM, we disabled RLE when collecting the static LICM counts. We do not show static counts for local CSE, which are minimal because redundant load elimination is performed before local CSE.

Level 2 optimizations using side-effect information reduced total dynamic load operations in the range of 1% to 19% (Table VIII). Side-effect analysis enabled a reduction in *getfield* operations (up to 27%), but only reduced *getstatic* and *aload* instructions by up to 3% (Table VIII). For most benchmarks, using PTA side-effect information allowed a larger reduction of dynamic loads than CHA.

Table IX shows speedups achieved for compress, raytrace, mtrt and mpegaudio. The speedups vary from 1.08x to

Benchmark	Side-Effect	getfield	getstatic	putfield	total HIR	total LIR
compress	none	87	0	1	118	29
	any	90 (3.45 %)	0	1	122 (3.39 %)	29
jess	none	139	0	0	280	250
	CHA	144 (3.60 %)	0	0	287 (2.50 %)	251 (0.40 %)
	PTA	161 (15.83 %)	0	0	309 (10.36 %)	255 (2.00 %)
raytrace	none	87	0	47	184	54
	any	96 (10.34 %)	0	47	210 (14.13 %)	56 (3.70 %)
db	none	61	0	0	88	31
	any	64 (4.92 %)	0	0	92 (4.55 %)	32 (3.23 %)
javac	none	44	0	5	116	479
	any	48 (9.09 %)	0	6 (20.00 %)	121 (4.31 %)	479
mpegaudio	none	128	27	1	299	98
	any	152 (18.75 %)	27	1	327 (9.36 %)	102 (4.08 %)
mtrt	none	87	0	47	184	55
	any	96 (10.34 %)	0	47	210 (14.13 %)	57 (3.64 %)
jack	none	23	0	2	39	58
	any	23	0	2	39	58

Table VI: Level 2 static counts for LICM

Benchmark	Side-Effect	getfield	getstatic	aload
compress	none	836681238	29585886	450569851
	CHA	713879612 (14.68 %)	29585886	450569851
	PTA	694156483 (17.03 %)	29585886	450569851
jess	none	193400124	2326905	74199530
	CHA	177280681 (8.33 %)	2326905	74197591 (0.00 %)
	PTA	141340271 (26.92 %)	2326572 (0.01 %)	74188965 (0.01 %)
raytrace	none	278990954	1359	70558731
	CHA	217369769 (22.09 %)	1359	70189162 (0.52 %)
	PTA	217369769 (22.09 %)	1359	70125938 (0.61 %)
db	none	160085986	96012	113165950
	CHA	154814883 (3.29 %)	96012	113165950
	PTA	154814883 (3.29 %)	96012	113165950
javac	none	129704466	3728755	3947221
	CHA	123962720 (4.43 %)	3726381 (0.06 %)	3947158 (0.00 %)
	PTA	123962933 (4.43 %)	3726306 (0.07 %)	3947133 (0.00 %)
mpegaudio	none	258084245	16092989	796126083
	CHA	254421559 (1.42 %)	16075411 (0.11 %)	794492856 (0.21 %)
	PTA	254421559 (1.42 %)	16075411 (0.11 %)	773557981 (2.83 %)
mtrt	none	282145314	2063	71578275
	CHA	220136202 (21.98 %)	2063	71124467 (0.63 %)
	PTA	220136202 (21.98 %)	2063	70998019 (0.81 %)
jack	none	46154208	1534965	5727775
	CHA	42805654 (7.26 %)	1530924 (0.26 %)	5727775
	PTA	42805654 (7.26 %)	1530924 (0.26 %)	5727775

Table VII: Level 2 dynamic count for loads instructions

Benchmark	Side-Effect	total
compress	none	1316836975
	CHA	1194035349 (9.33 %)
	PTA	1174312220 (10.82 %)
jess	none	269926559
	CHA	253805177 (5.97 %)
	PTA	217855808 (19.29 %)
raytrace	none	349551044
	CHA	287560290 (17.73 %)
	PTA	287497066 (17.75 %)
db	none	273347948
	CHA	268076845 (1.93 %)
	PTA	268076845 (1.93 %)
javac	none	137380442
	CHA	131636259 (4.18 %)
	PTA	131636372 (4.18 %)
mpegaudio	none	1070303317
	CHA	1064989826 (0.50 %)
	PTA	1044054951 (2.45 %)
mtrt	none	353725652
	CHA	291262732 (17.66 %)
	PTA	291136284 (17.69 %)
jack	none	53416948
	CHA	50064353 (6.28 %)
	PTA	50064353 (6.28 %)

Table VIII: Level 2 dynamic total load count

1.17x on our Intel system, and from 1.02x to 1.20x on AMD. On both systems, mpegaudio has the largest speedup. These benchmarks are the ones with the highest load densities (Table I), and the ones that we expected would benefit the most from side-effect information.

A higher level of precision of side-effect information made a difference in performance for compress and mpegaudio. Using PTA side-effect vs CHA increased the speedup of compress from 1.08x to 1.11x on Intel, and 1.02x to 1.05x on AMD. For mpegaudio, it went from 1.11x to 1.17x on Intel and from 1.15x to 1.20x on AMD.

These results show that using side-effect analysis in global optimizations improved opportunities for load elimination and moving instructions, reduced dynamic load operations, and improved performance in runtimes. Benchmarks with higher load densities benefited most from side-effect information. The results also show that points-to analysis improves side-effect information compared to only using CHA, but that the differences between points-to analysis variations are negligible.

5 Related Work

Early side-effect analyses for languages with pointers by Choi *et. al.* [4] and Landi *et. al.* [14] made use of may-alias analysis to distinguish reads and writes to locations known to be different. These analyses were mainly targeted at analysis of C, so the call graph was assumed to be mostly static. Therefore, in comparison with our work, in that setting, the information about pointers was most important, while the call graph was much easier to compute.

In contrast, Clausen's [6] side-effect analysis for Java was based on a call graph constructed with a CHA-like analysis, but it did not use any pointer information. This analysis computed read and write information for each field, ignoring which specific object contained the field read or written. In comparison with our work, Clausen's analysis is most similar to our CHA-based side-effect analysis. Clausen applies his analysis results in an ahead-of-time early Java bytecode optimizer to a similar set of optimizations as we do: dead code removal, loop invariant removal, constant propagation, and common subexpression elimination.

(a)

Benchmark	Side-Effect	Time(s)	Speedup
compress	none	10.423	
	CHA	9.635	1.08x
	PTA	9.386	1.11x
jess	none	4.889	
	CHA	4.945	0.99x
	PTA	4.872	1.00x
raytrace	none	4.38	
	CHA	3.93	1.11x
	PTA	3.905	1.12x
db	none	22.625	
	CHA	22.605	1.00x
	PTA	22.471	1.01x
javac	none	10.962	
	CHA	11.138	0.98x
	PTA	11.142	0.98x
mpegaudio	none	9.319	
	CHA	8.41	1.11x
	PTA	7.932	1.17x
mtrt	none	4.681	
	CHA	4.201	1.11x
	PTA	4.208	1.11x
jack	none	6.097	
	CHA	6.122	1.00x
	PTA	6.101	1.00x

(b)

Benchmark	Side-Effect	Time(s)	Speedup
compress	none	9.503	
	CHA	9.316	1.02x
	PTA	9.03	1.05x
jess	none	3.949	
	CHA	3.962	1.00x
	PTA	4.002	0.99x
raytrace	none	2.735	
	CHA	2.607	1.05x
	PTA	2.615	1.05x
db	none	23.212	
	CHA	23.222	1.00x
	PTA	23.141	1.00x
javac	none	7.154	
	CHA	7.21	0.99x
	PTA	7.231	0.99x
mpegaudio	none	5.977	
	CHA	5.175	1.15x
	PTA	4.987	1.20x
mtrt	none	2.88	
	CHA	2.788	1.03x
	PTA	2.796	1.03x
jack	none	3.505	
	CHA	3.47	1.01x
	PTA	3.51	1.00x

Table IX: Level 2 running time (a) Intel (b) AMD

When evaluating the precision of points-to analyses, it is common to report the size of the points-to sets at field read and write instructions, as in [18, 23]. Rountev and Ryder [24] evaluate their points-to analysis for precompiled libraries in this way. Other points-to analysis work [13, 19, 25, 26] takes this evaluation one step further, by also computing read and write sets summarizing the effects of entire methods, rather than just individual statements, and propagating this information along the call graph. This is similar to the read and write set computation we mention in Section 2.3. In general, these studies conclude that differences in precision of the underlying analyses do have a significant effect on the static precision of side-effect information.

Chowdhury *et. al.* [5] study the effect of alias analysis precision on the number of optimization opportunities for a range of scalar optimizations. However, they only measure the static number of optimizations performed (rather than their run-time effect), and their benchmarks are mostly pointer-free C programs, some translated directly from FORTRAN, so they find, unsurprisingly, that alias analysis precision has little effect.

Studies measuring the actual run-time impact of code optimized using side-effect information are surprisingly rare. Ghiya *et. al.* [11, 12] measure the effectiveness of side-effect information on the run-time efficiency of code produced by an optimizing compiler for C. Like us, they find that some improvements are possible, and that even simple, imprecise alias information enables most of the improvements. Diwan *et. al.* [9] perform a similar study in a compiler for Modula-3, with type-based alias analyses. They perform redundant load elimination, loop invariant code motion, and common subexpression elimination, and also find improvements comparable to ours and Ghiya *et. al.*'s. They also agree that much of the improvement is possible even with simple type-based analyses. Razafimahefa [22] performs loop invariant code motion using side-effect information on Java in an ahead-of-time bytecode optimizer, and reports run-time speedups comparable with ours on an early-generation Java VM.

Pechtchanski and Sarkar [20] present a preliminary study of a framework which allows programmers to provide annotations indicating absence of side-effects. These annotations are communicated to Jikes RVM and used for optimizations. Only limited, preliminary, empirical results of the effect of these annotations are provided, and verification of the correctness of the programmer-provided annotations has yet to be done.

In summary, existing work on other languages largely agrees with our findings on Java. Some side-effect infor-

mation is useful for real run-time improvements from compiler optimizations. Although precision of the underlying analyses tends to have large effects on static counts of optimization opportunities, the effects on dynamic behaviour are much smaller; even simple analyses provide most of the improvement. Important distinctions of our work from previous work are that we provide a study of run-time effects of side-effect information on Java, and that we show how to communicate analysis results from an off-line analyzer to a JIT.

6 Conclusion

In this study, we showed that side-effect analysis does improve performance in just-in-time (JIT) compilers, and that relatively simple analyses are sufficient for significant improvements. On level 1 optimizations, side-effect analyses had little impact on performance, except for one benchmark. On level 2 optimizations, however, our results showed an increase of up to 98% of static opportunities for load removal, a reduction of up to 27% of the dynamic fields reads, and execution time speedups ranging from 1.08x to 1.20x. As we expected, using side-effect analysis had the largest impact on the benchmarks with high load densities.

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