A Scalable Mixed-Level Approach to Dynamic Analysis of C and C++ Programs

by

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Abstract

This thesis addresses the difficult task of constructing robust and scalable dynamic program analysis tools for programs written in memory-unsafe languages such as C and C++, especially those that are interested in observing the contents of data structures at run time. In this thesis, I first introduce my novel *mixed-level* approach to dynamic analysis, which combines the advantages of both source- and binary-based approaches. Second, I present a tool framework that embodies the mixed-level approach. This framework provides memory safety guarantees, allows tools built upon it to access rich source- and binary-level information simultaneously at run time, and enables tools to scale to large, real-world C and C++ programs on the order of millions of lines of code. Third, I present two dynamic analysis tools built upon my framework — one for performing value profiling and the other for performing dynamic inference of abstract types — and describe how they far surpass previous analyses in terms of scalability, robustness, and applicability. Lastly, I present several case studies demonstrating how these tools aid both humans and automated tools in several program analysis tasks: improving human understanding of unfamiliar code, invariant detection, and data structure repair.

Thesis Supervisor: Michael D. Ernst
Title: Associate Professor

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Thanks to Brian Demsky for being the first serious user of the tools described in this thesis and for providing bug reports and feature requests that have led to numerous improvements.

Thanks to my co-authors for their work on the following two papers that I have incorporated into my thesis: The contents of Chapter 4 are adapted from *Dynamic Inference of Abstract Types* [23]. The contents of the data structure repair case study (Section 3.4.2) in Chapter 3 are adapted from *Automatic Inference and Enforcement of Data Structure Consistency Specifications* [12].

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Chapter 1

Introduction

1.1 Motivation

Dynamic analysis is a type of program analysis that operates on information gathered from the program at run time. Dynamic analysis can be used for tasks such as optimization (profiling, tracing), error detection (testing, assertion checking, type checking, memory safety, leak detection), error correction (runtime data structure repair, protections against security attacks), and program understanding (coverage, call graph construction, invariant detection); these categories are not mutually exclusive.

The development of scalable and robust dynamic analysis tools for C and C++ programs is important because programs written in these languages are pervasive across all categories of software, including in large safety-critical systems (e.g., operating systems, Internet servers, air traffic control systems). These complex programs stand to benefit greatly from analysis results in terms of improving robustness, security, and performance.

Many kinds of analyses, especially those for software engineering applications, are interested in observing the contents of data structures at run time. Although there exist plenty of highly-scalable C and C++ dynamic analysis tools for tasks such as binary-level profiling and memory leak detection, there is a lack of scalable and robust automated tools for observing data structure contents. It is challenging in practice to make such analysis tools work on large C and C++ programs due to the

```
1.   int globalInt = 42;

2.   int main() {
3.     int localArray[10];     // contents uninitialized
4.     int *a, *b, *c, i, j;   // c and j uninitialized, *c is meaningless
5.     a = &globalInt;
6.     b = (int*)malloc(15*sizeof(int));
       // Heap buffer overflow after i = 14
7.     for (i = 1; i < 100; i+=2) {
8.       b[i] = i;             // Initialize only odd-indexed elements of b
9.     }
10.    return 0;
11.  }
```

Figure 1-1: A C program that demonstrates the memory-unsafe nature of the language

lack of memory safety and source-level complexities inherent in these languages. A useful dynamic analysis tool that deals with data structures must be able to meet the following requirements. This thesis describes a novel approach to dynamic analysis that allows tools built using this approach to meet these requirements better than tools built using existing approaches.

- **Provide memory safety guarantees**

  When C and C++ programs are executed, there is no indication of whether regions of memory have been allocated or initialized to valid values, of the sizes of dynamically-allocated arrays, or of whether there are memory corruption errors. The code in Figure 1-1 shows some examples of how a C program may be memory-unsafe. For instance, variables and pointers may be uninitialized; the analysis must suppress or flag junk values, so as not to corrupt the results. At the point in execution just prior to line 10, the contents of the local variables `localArray`, `c`, and `j` are uninitialized and hold junk values of whatever was on the stack prior to the call of `main()`. Memory may be unallocated or deallocated, making a pointer invalid; dereferences of such a pointer (e.g., `int *c`) yield either junk values or a segmentation fault. Pointer types are ambiguous; a pointer of type `int*` may point to a single integer (e.g., `int *a`), or to an array of integers (e.g., `int *b`). Array lengths are implicit; even if an `int*` pointer is known to

be an array, the run-time system provides no indication of its size. Related to an earlier point, even if the array's size is known, it is not known which of its elements have been initialized (e.g., the even-indexed elements of the array that `b` refers to are all uninitialized). Furthermore, if the target program has memory-related bugs (e.g., the buffer overflow on line 8 when `i > 14`), it is important that the analysis tool not crash, even if the target program attempts an illegal operation. Programs may have latent memory-related bugs which do not disrupt normal execution, but do appear when running under an analysis tool, possibly corrupting the data structures of the analysis tool. In order for an analysis tool to provide accurate information and to be robust against crashes, it must provide these aforementioned memory safety guarantees that are lacking during normal program execution.

- **Handle complexities of C and C++ source code**

  C and especially C++ provide ample opportunities for programmers to write complex and abstruse code that can be difficult to parse (e.g., pointer operations, casts, C++ templates, preprocessor macros). Larger programs are likely to contain more complicated source-level constructs. A useful and scalable analysis tool needs to be able to extract relevant information present in the source code at the right level of detail for the task it attempts to perform.

- **Provide rich language-level information throughout the analysis**

  The execution of a compiled C or C++ program is actually a sequence of simple machine instructions on bytes in memory, but humans perceive the execution in terms of language-level constructs such as statements and functions operating on variables and data structures. An analysis tool, especially one focused on data structures for software engineering tasks, needs to provide results in terms of the language level. Humans (and many follow-on analysis tools) often find language-level information far easier to comprehend and much more useful than data about the compiled binary. This mapping between the machine and language levels must occur throughout the duration of the analysis, because decisions in

the algorithms of many analyses must often be made throughout execution with language-level information taken into consideration.

- **Observe complex nested data structures**

  C and C++ data structures often contain fields that are pointers to other data structures. An analysis tool must be able to recursively traverse within these data structures in a safe manner (so as to not report invalid values or crash the program by dereferencing pointers to unallocated regions of memory) and be able to reach fields deeply nested within several layers of indirection. Only being able to observe top-level variables and arrays of primitive types is not nearly as useful for large programs that make heavy use of complex data structures.

1.2 Source- and Binary-Based Dynamic Analysis

A frequently-used first step for building a dynamic analysis is to augment (instrument) the target program so that, in addition to executing normally, it also outputs the proper information that the analysis desires at run time. The two most common instrumentation techniques are modifying a program's source code and modifying a compiled binary representation of a program; each has its own benefits and drawbacks.

Commonly, source-based analyses have been used when language-level information is required, while binary-based analyses are more common when only machine-level results are needed. There are also trade-offs of implementation work between source and binary-based analysis: often a source analysis requires less initial effort, but a binary analysis is easier to scale to complex target programs.

The mixed-level approach I developed for this thesis combines the best aspects of both source- and binary-based approaches. Before introducing my mixed-level approach, I will first examine the pros and cons of these two previous approaches with regard to meeting the requirements of Section 1.1.

1.2.1 Source-based instrumentation

A source-based instrumentation approach modifies the source code of the target program by adding extra statements that collect data or perform analysis. Code instrumentation by source-code rewriting is the most direct route to constructing a tool that produces language-level output, and it also makes some aspects of tool implementation relatively easy.

An analysis that operates by rewriting a target program's source code can take advantage of the same level of abstraction that the language provides to programmers. It can report results using language-level terms such as functions and variables because it integrates directly into the target program's source code. It can also inherit the portability of the underlying program: as long as the added code has no system dependencies, the instrumented code can be compiled and run on any system where the original program can. More generally, a source-based analysis permits the developer to consider only one level of abstraction, that of the instrumented language. Standard programming tools suffice to examine and debug the output of a source-to-source rewriting tool. Additionally, compiler optimizations automatically reduce the overhead of instrumentation.

The main disadvantage of source-based instrumentation is that it is extremely difficult to provide memory safety guarantees by simply rewriting source code. In order to perform many kinds of dynamic analyses on C and C++ programs, metadata must be kept for pointers to indicate whether they point to an allocated region of memory, how many elements they point to, etc... Without this metadata, an analysis must either sacrifice precision (by not dereferencing pointers) or robustness (by risking crashes from untimely dereferences). Existing work used 'smart pointers' implemented as a wrapper class for ordinary pointers supplemented with metadata [57], but there are scalability limitations due to the complexities of transforming source code that deals with pointers. For instance, the implementor needs to create adapter stubs or summaries for all library code that the target program interfaces with, because their source code is often not available. The difficulty of providing memory

safety guarantees also makes it difficult to add code to traverse complex data structures, which often contain pointers to dynamically-allocated memory.

1.2.2 Binary-based instrumentation

A binary-based approach modifies a compiled executable to add instrumentation code. Some analyses can be most directly expressed at a binary level, and binary-based tools are usually easier to use once written.

The most important advantage of a binary-level analysis is that many analysis problems can be expressed more simply at a lower level of abstraction. At the syntactic level, a binary is a flat list of instructions rather than a nested expression that requires (potentially complex) parsing. At the semantic level, there are fewer machine operations than language-level abstractions, and the machine operations are much simpler. For instance, the language-level description of data has a complex structure in terms of pointers, arrays, and recursive structures. By contrast, the machine-level representation of data is as a flat memory with load and store operations. If the property to be analyzed can be expressed in terms of the simpler machine representation, then the language-level complexities can be ignored. For instance, ensuring memory safety on the binary level is a much easier task than doing so on the source level.

There are also three ways in which binary-based analysis tools can be easier to use. First, a binary tool need not be limited to programs written in a particular language: Language-level differences between programs are irrelevant as long as the programs are compiled to a common machine representation. Second, a binary tool need not make any distinction between a main program and the libraries it uses: execution in a library is analyzed in just the same way as the rest of the program's execution. There is no need to recompile libraries or to create hand-written simulations or summaries of their behavior as is often required for source-based analyses. Third, a binary-based tool requires fewer extra steps to be taken by a user (none, if the instrumentation occurs at run time). A source-based analysis at least requires that a program be processed and then recompiled before running; this can be cumbersome, because compiling a large system is often a complicated process due, in part, to the presence

of conditional compilation and other C preprocessor macros.

One major disadvantage of a binary-based approach to dynamic analysis is that most analyses need some sort of language-level information (e.g., variable names), and that is often impossible to obtain by only looking at the binary code of a target program. For instance, it is very difficult for a binary-only analysis to provide information about the shapes and contents of data structures.

Many existing binary-based dynamic analysis tools incorporate language-level information as a post-processing step in order to produce human-readable output. For instance, a binary-based tool may discover a bug (say, an illegal memory operation) at a particular instruction. After the execution terminates, the tool translates the address, which would not in itself be helpful to a user who is trying to fix the error, to a line number in the program source code. Most uses of source information by binary analyses are limited to this sort of incidental post-processing. However, recall from Section 1.1 that it is often useful to integrate language-level information throughout the duration of the analysis, a feature that is lacking in existing binary-based tools.

1.3 Mixed-Level Approach to Dynamic Analysis

Users often desire the output of an analysis to be in terms of source-level constructs, but a binary analysis can be more natural to implement. Thus, to permit a dynamic analysis to obtain the key benefits of both source and binary analysis, I propose a *mixed-level* approach that performs a binary analysis supplemented with a mapping to the source level used throughout the analysis (and not just as a post-processing step) to interpret machine-level data and operations in terms of language-level constructs such as variables, types, and functions. This approach has the following benefits of a binary-based analysis: ease of ensuring memory safety, reduced dependence on the target program's language and dialect, and ease of use. It has the following benefits of a source-based analysis: full knowledge of variables, types, and data structures, and the ability to report results in a format that a human can reasonably comprehend.

A tool that implements the mixed-level approach performs most of the tracking of

a program's run-time behavior at the instruction level, obtaining the key benefits of a binary-based approach (e.g., ease of ensuring memory safety, simplicity of machine instructions and memory model, ease of use). When it is necessary to use source-level abstractions as the analysis is running, the low-level binary information can be translated into a language-level representation. This translation requires a limited form of source information (obtained, for instance, from debugging information inserted by the compiler), but need not consider all of a language's source-level complexities, thus simplifying implementation and improving robustness.

The mixed-level approach provides many of the benefits of a source-based approach without the drawbacks of dealing with the complexities of parsing C and C++ source code. It is also an improvement over many existing binary-based dynamic analyses that incorporate a small amount of source-level information as a post-processing step in order to produce human-readable output. For many analyses (such as the alias analysis of Section 1.3.1, the value profiling of Chapter 3, and the type inference of Chapter 4), only using source-level information as a post-processing step causes a loss of accuracy, because the results depend upon updating information about source constructs (such as functions and variables) while the analysis is running.

1.3.1 Example: Dynamic alias analysis

As an example of where a mixed-level approach is superior to a purely source-based, purely binary-based, and to a binary-based approach with source information incorporated as a post-processing step, consider an alias analysis, which reports whether two pointer variables might simultaneously refer to the same object. A dynamic alias analysis can detect whether two pointers were ever aliased during a set of executions. The alias results are useful for a profile-directed optimization that transforms the code to check whether the pointers were different, and if so, to use a code path that allocates the pointed-to values in registers [8]. A dynamic alias analysis could be performed naturally using the mixed-level approach: The analysis tool could observe at the machine level each instruction operating on an address, and then record its effect in terms of the corresponding language-level pointers.

By contrast, other commonly used approaches would be much more cumbersome:

- A source-to-source translation tool could track each pointer modification by inserting recording routines for each operator at the source level, but such a strategy is difficult to implement robustly.
- A technique that recorded information in a purely binary form, and then post-processed it to print using source terminology, would not be workable because the mapping between machine locations and language-level pointer expressions is needed to interpret each operation; such an approach would essentially have to store a complete trace.

This pattern of trade-offs applies to many dynamic analyses and demonstrates the applicability of the mixed-level approach: output is desired in terms of source constructs, but a binary analysis would be more natural to implement.

1.4 Thesis Outline

The rest of this thesis is structured as follows.

Chapter 2 describes the Fjalar framework that I have implemented using the mixed-level approach. Fjalar allows for whole- or partial-program instrumentation of binaries and takes advantage of limited language-level information provided by the debugging information compiled into the binary files. Fjalar's API allows tools built upon it to traverse through data structures at run time and safely observe and modify memory values at arbitrary points in execution without risk of crashing or reading uninitialized values. Fjalar is built upon the Valgrind [39] binary translation tool for rewriting x86 executables and currently supports any C or C++ dialect that is compilable by `gcc`.

In addition to building the Fjalar framework, I have used Fjalar to create two dynamic analysis tools, evaluated them in controlled experiments, and applied them to perform several program analysis tasks on real-world C and C++ programs of up to one million of lines of code such as a scientific research tool (RNA-fold), a multi-

player game (Freeciv), an Internet DNS server (BIND), and an air traffic control system (CTAS).

Chapter 3 describes a value profiling tool named Kvasir. Kvasir performs a kind of value profiling for software engineering applications which consists of recording a detailed trace of data structure contents during a target program's execution. It serves as the C/C++ front-end for the Daikon dynamic invariant detection tool, enabling Daikon to find invariants in C and C++ programs. I contrast Kvasir with its predecessor, a source-based tool, and show how a mixed-level approach is superior to a source-based one for this particular application. I also present a case study where I applied Kvasir as part of a data structure repair system.

Chapter 4 describes a novel technique and tool for performing dynamic inference of abstract types. The analysis attempts to partition a target program's variables into sets representing their abstract types, a finer notion of types than the few primitive declared types (e.g., `int`, `float`) that C and C++ provide. The algorithm requires both binary- and source-level information integrated throughout the duration of execution, so it is very suitable for implementation using the mixed-level approach. I built a tool named DynComp to implement this technique. In this chapter, I present the technique, the DynComp tool, the applications of DynComp to program understanding and invariant detection tasks, and contrast it with a previous static approach to abstract type inference.

Chapter 5 lists possibilities for future work and summarizes the contributions of this thesis.

Chapter 2

The Fjalar Framework

I have developed a tool framework named Fjalar that embodies the mixed-level approach of Section 1.3. This chapter provides an overview of Fjalar (Section 2.1) and describes services that its API provides to tools (Section 2.2), how it is implemented (Section 2.3), and a brief tutorial on how to build a basic tool upon it (Section 2.4).

2.1 Overview

I have developed a framework named Fjalar to enable people to construct scalable and robust dynamic analysis tools using the mixed-level approach. Fjalar provides an API that allows tools built upon it to access rich language- and machine-level information at run time, providing services useful for many types of dynamic analyses: binary rewriting, memory allocation and initialization tracking, mapping between memory addresses and language-level terms such as variables and functions, and recursive traversals of data structures during run time. These services make Fjalar particularly well-suited for building dynamic analyses for software engineering applications that are interested in observing data structures.

Figure 2-1 provides an overview of the process of running a Fjalar tool on a target program. To prepare the target program for analysis, a user must first compile its source code with `gcc` with DWARF2 debugging information and with no optimizations to produce a binary executable. The user then runs the Fjalar tool with the binary

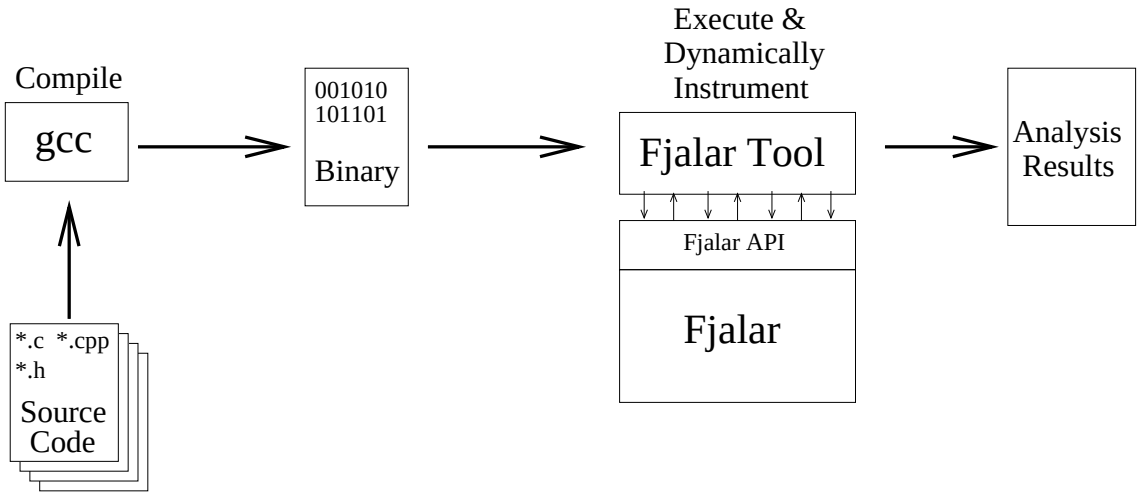


Figure 2-1: Overview of the operation of a tool built upon Fjalar

as input, and the tool dynamically instruments the program to perform the intended analysis (Section 2.4 shows a more detailed example of how to build and run a Fjalar tool). The tool interfaces with Fjalar through an API whose services are described in Section 2.2.

There is little burden on the user of a Fjalar tool; the requirements of DWARF2 debugging information and no optimizations are `gcc` flags (`-g -O0`) that can be easily added as one line to a Makefile or equivalent compilation script. After compilation, the user can invoke a Fjalar tool using a one-line command (such as `fjalar-tool <program-binary>`) to run the analysis.

The primary limitation of Fjalar is that it only works on the x86/Linux platform. Future work (Section 5.1) includes porting Fjalar to additional hardware platforms (e.g., AMD64, PowerPC) and operating systems (e.g., BSD, Mac OS X) as well as to additional languages supported by `gcc` (e.g., Objective-C, Fortran, Java, Ada).

Fjalar is publicly available on the web as a stand-alone source code release (along with documentation and a Programmer's Manual) at `http://pag.csail.mit.edu/fjalar/` and is also integrated into two tools (see Chapters 3 and 4) within the source code distribution of the Daikon dynamic invariant detector (see Section 3.1.1) at `http://pag.csail.mit.edu/daikon/`.

(*Fjalar* is the name of a dwarf in Norse mythology. Two components of the

framework inspired this name: the DWARF debugging information format and the Valgrind tool. *Valgrind* is the name of a legendary gate in Norse mythology.)

2.2 Services Provided by the Fjalar API

Fjalar's API provides the following services to tools:

1. Dynamic binary instrumentation
2. Memory safety guarantees, including reporting dynamic array sizes and indicating which regions of memory are allocated and/or initialized
3. Rich compile-time information about data structures, variables, and functions
4. Customizable memory-safe traversals within data structures and arrays

2.2.1 Dynamic binary instrumentation

A dynamic analysis often requires a means to instrument the target program so that it can provide the desired information at run time. Fjalar uses Valgrind [39], a program supervision framework based on dynamic binary rewriting, to insert instrumentation operations in the target program. Because it operates on machine code, Valgrind is naturally language-independent and makes no distinction between user-written and library code, so analyses built upon it can easily track whole program executions. However, Valgrind is limited to only certain hardware platforms and operating systems, and Fjalar's particular use of Valgrind only allows it to work on x86/Linux.

During the target program's execution, Valgrind translates the x86 instruction stream into a typed assembly language called IR (which is simpler than x86 assembly, thus reducing implementation effort) and allows the tool writer to instrument the IR with tracing or analysis code. The instrumented IR is then just-in-time (JIT) compiled back into x86 code and executed natively. Thus, a tool can insert IR code in the target program that accesses machine-level information about registers, memory, and instructions, giving it the full power of a binary-level analysis.

Fjalar performs one default type of IR instrumentation: inserting hooks at certain points in the target program's execution to call out to execute the tool's code. This feature is useful because tools (such as the ones described in Chapters 3 and 4) need to periodically collect and analyze data gathered at certain points in execution. I have currently implemented support for calling out to the tool's code during the target program's function entrance and exit points. There is an option to make calls to the tool's code only during the entrance and exit points of selected functions, thus enabling partial program analysis.

2.2.2 Memory safety

Fjalar's API allows tools to query any byte of memory anytime during the target program's execution and tell whether that byte has been explicitly allocated by the program and whether it has been initialized to a valid value. It also allows tools to determine array sizes at run time by combining memory allocation information with compile-time information (Section 2.2.3). Given a pointer, Fjalar can determine at any time in execution whether that pointer refers to one element or to an array of elements, and if it is an array, the size of the array at that time. It can then use memory initialization information to tell exactly which elements of that array have been initialized to valid values. This memory-related information is crucial for building accurate and robust dynamic analyses but is not available on the machine-code runtime environment that C and C++ programs execute under (unlike, for example, a Java Virtual Machine runtime environment for Java), thus creating the need for these Fjalar services.

2.2.3 Compile-time language-level information

The services described thus far are for a binary-level analysis, but many dynamic analyses need access to language-level constructs such as variables and functions during execution. Fjalar embodies the mixed-level approach by providing rich compile-time language-level information to tools and integrating it tightly with run-time memory

allocation and initialization information. Given a C or C++ expression that represents a storage location (i.e., an lvalue), Fjalar's API allows a tool to find the address and size of that object at a particular moment in the target program's execution. This language-level information, coupled with Fjalar's memory safety services, allows tools to not only be able to safely access valid regions of memory, but more importantly, to associate semantic meanings with observed memory contents, thus mapping between binary- and language-level information. For example, without language-level information during the analysis, a tool can only tell that a certain block of bytes contains some binary value, but with such information, it can interpret that binary value as an integer, floating-point number, string, data structure, etc...

Fjalar extracts rich language-level information from the debugging information compiled into the target program's binary. It provides tools with direct access to data structures representing compile-time information about functions, variables, and types as well as iterators for these data structures, enabling these services:

- Provides access to function names, addresses, and visibility, and associates parameters and return values with their types
- Provides access to variable names, types, addresses, sizes for static arrays, and visibility (e.g., private, protected, or public member variable, file-static variable)
- Associates struct/class types with their member variables to enable traversals within nested and recursively-defined data structures
- Supports C++ features such as overloaded functions, reference parameters, classes, member variables and functions, and multiple class inheritance
- Creates unique names for global variables and functions to eliminate ambiguity for tools that perform whole-program analysis
- Simplifies typedefs by finding their referred-to types, creates names for unnamed structs/classes, and performs other misc. tasks to disambiguate obscure usage of C and C++ syntax

Fjalar can also export the compile-time structure of a target program to an XML file which hierarchically organizes global variables, functions, formal parameters, local variables, and user-defined types such as typedefs, enums, structs, and classes. This information is useful for debugging or to supplement an analysis.

2.2.4 Data structure traversal

Fjalar gives tools the ability to observe the contents of language-level variables, arrays, and data structures at runtime while maintaining the robustness, coverage, and language-independence of a binary-level analysis. Most non-trivial programs use data structures such as arrays, linked lists, trees, and aggregate types (e.g., structs and classes). Often times, structs and classes contain member variables which are themselves structs and classes (or pointers to such), thus resulting in complex linked and nested data structures. Many kinds of dynamic analyses can benefit from run-time observation of the contents of these data structures, even at times when the target program did not directly manipulate these structures. A tool that only observes data at times when the target program observes or manipulates that data is easier to build and safer (it will not crash if the target program does not crash) but produces limited information. Fjalar enables the construction of more powerful tools that can traverse any data structure in scope and even those not in scope, as long as they contain initialized data. For example, in Figure 2-2, `foo`'s argument `rec` is a structure that contains two pointers and a static array. To observe all of its contents, a tool must be able to follow pointers and recursively traverse inside of structures and arrays, observing the values of the pointers `rec.a`, `rec.b`, `rec.c`, and the arrays referred to by those pointers: `rec.a[]` (an array of 100 integers on the stack), `rec.b[]` (1 allocated but uninitialized integer on the heap), `rec.c[]` (array of 10 uninitialized integers within the struct).

A purely binary-based analysis cannot accomplish such detailed observation absent some indication of how to interpret raw binary values as data structures. It is possible but extremely complicated to accomplish such observation with a source-based analysis, because it must parse and generate complex source syntax which deal

```
struct record {
  int *a, *b;
  int c[10];
};

void foo(struct record rec) {}

int main() {
  int localArray[100];
  ... initialize the 100 ints within localArray ...
  struct record r;
  r.a = localArray;
  r.b = (int*)malloc(sizeof(int));
  foo(r);
}
```

Figure 2-2: A C program that contains structs, arrays, and pointers

with data structures and, more significantly, maintain metadata such as pointer validity, memory initialization, and array sizes. Thus, a mixed-level approach implemented by Fjalar is preferred for robustness and ease of implementation.

Fjalar's API provides recursive data structure traversal functionality, allowing tools to observe the contents of arrays, follow pointers to observe structures such as linked lists and trees, and recursively traverse inside of struct fields, all while ensuring memory safety so that the analysis does not crash the target program.

Here is the general traversal procedure along with features that allow tools to precisely control which data structures to observe and how to traverse through them:

- At every point in the traversal process, Fjalar provides tools with pointers to every variable, every member variable of a struct/class, and to every element of an array, along with corresponding type information. These pointers are guaranteed to point to allocated and initialized memory locations. The tool can pass callback functions (called *action functions*) into the Fjalar traversal functions to allow it to record, analyze, or modify values as the target program executes.

- If the current variable is a pointer, then Fjalar follows the pointer (if it points to an allocated and initialized region of memory) to visit the subsequent variable

resulting from the pointer dereference.

- If the current variable is an array, then Fjalar visits all elements of the array 'simultaneously' by providing an array of pointers to the tool's *action function*, where each element points to an element in the array.

- If the current variable is a struct, union, or class, then Fjalar traverses inside of it by visiting all of the fields. This process is recursive (the depth can be controlled by command-line options).

- Fjalar generates unique names for variables derived from traversing inside of structures and arrays. These names can be parsed more or less as valid C expressions (e.g., `foo->bar.baz[1]` is the name given to the variable derived as a result of dereferencing a struct pointer `foo`, observing its member variable `bar`, which is itself a struct with an array member variable named `baz`, and finally observing the value of the 2nd element of `baz`).

- Fjalar provides numerical parameters for determining how many levels of struct or class objects to traverse. For a linked list, binary tree, or other data structure that contains member variables of its same type, a bound on the traversal depth is required to prevent infinite recursion. For other data structures, an adjustable bound provides a performance versus detail tradeoff.

- Fjalar provides options for selectively tracing only certain variables, such as ignoring global variables, limiting the output of file-static variables, and allowing the user to specify which variables are of interest to the tool, enabling precise partial-program analysis by zooming in on certain interesting data structures within a large program (the case studies in Chapters 3 and 4 often make heavy use of this selection mechanism).

- Fjalar allows the user to specify whether a pointer variable refers to one element or to an array of elements; the traversal can be more precise when the user knows a priori that a particular pointer will always refer to one element.

- Fjalar allows the user to specify what type a pointer variable should be cast to before dereferencing it, which is especially useful for C programs. By default, a pointer is dereferenced as its declared type, but in some C programs, a `void*` pointer is used to emulate runtime polymorphism, so it must be cast to another pointer type before it can be dereferenced to reveal member variables. Also, often times a `char*` pointer is used to refer to a generic memory buffer which contains data of various types, so those pointers must be cast to other types before dereferencing them to observe the buffer contents in a useful form.

All of the aforementioned options related to data structure traversal are more thoroughly documented in the Fjalar Programmer's Manual (`http://pag.csail.mit.edu/fjalar/fjalar_manual.htm`).

The recursive data structure traversal services of Fjalar exemplify the mixed-level approach because, in order to safely and efficiently traverse through arbitrary data structures at any point in execution, both binary- and language-level information is required simultaneously. The mixed-level approach allows for the construction of powerful tools that can trace, analyze, and modify both binary-level components such as instructions, memory, and registers as well as language-level components such as functions, variables, and data structures.

2.3 Implementation

Fjalar is implemented as a C program on top of three existing open-source tools: the Valgrind binary rewriting tool [39], the Valgrind Memcheck memory leak detection tool [46], and the Readelf ELF binary file parser tool from the GNU Binutils package [19]. Fjalar provides a C language API, so a Fjalar tool must be written either in C or in another language (e.g., Python, Java) that provides a C wrapper. This section describes how Fjalar uses code from these tools along with its own code to provide the services described in Section 2.2.

2.3.1 Dynamic binary instrumentation

Valgrind operates by executing a target program under its supervision, translating the x86 instruction stream into its own typed assembly language called IR, dynamically instrumenting the IR, and JIT-compiling the original and instrumentation code back to x86 code to execute natively. I have implemented Fjalar as a Valgrind tool, so any tools built upon Fjalar can directly use the Valgrind API to write code that performs IR instrumentation at run time.

2.3.2 Memory safety

Fjalar utilizes a modified version of the Valgrind Memcheck tool [46] to provide the requisite memory safety guarantees described in Section 1.1. Memcheck is typically used to detect memory errors such as memory leaks, reading/writing unallocated areas of memory, and the use of uninitialized values. It has been successfully used to detect memory errors in large C and C++ programs such as Mozilla, OpenOffice, KDE, GNOME, and MySQL, so it is an extremely practical and scalable tool. Similar to Purify [24], Memcheck tracks whether each byte of memory has been allocated (by assigning an *A-bit* to every byte which is set only when that byte is allocated) and whether each bit of memory has been initialized (by analogously assigning a *V-bit* to every bit). Thus, Memcheck operates by keeping track of 8 *V-bits* and 1 *A-bit* for each byte of memory in the target program's address space. If a particular byte of memory has been allocated for use and is safe to access, then the A-bit for that byte is set. If a particular byte contains a value that has been explicitly initialized by the program, the 8 V-bits for that byte are set (each V-bit corresponds to one bit in memory, so it is possible for only some of the V-bits of a byte to be set; this might happen with bit fields of structs, for instance). Memcheck inserts *redzones* of memory with unset A-bits between `malloc`'ed regions to detect array bounds overflow errors, which are also useful for clearly marking array boundaries in the heap. Because Memcheck is built as a Valgrind tool, it uses the Valgrind API to rewrite the target program's binary to copy and maintain A- and V-bits throughout memory and registers.

Fjalar leverages Memcheck's functionality and scalability by including a modified version of the Memcheck source code into its own code base. Fjalar's API allows tool builders to query the A- and V-bits in order to ensure that memory accesses do not result in segmentation faults or invalid data, respectively. In order to determine the sizes of dynamically-allocated arrays on the heap, the Fjalar API provides a function which takes in a memory address, and if it is a heap address, scans forward and backward until it finds addresses with unset A-bits (guaranteed to be present by the *redzones* that Memcheck inserts). The number of contiguous bytes of allocated memory divided by the number of bytes per element of the type of the pointer equals the size of the array. To find the sizes of static arrays, Fjalar can rely on compile-time language-level information (Section 2.3.3).

2.3.3 Compile-time language-level information

Fjalar obtains compile-time language-level information about functions, variables, and types by parsing the DWARF2 debugging information that is compiled into the target program's binary. I built a debugging information parser on top of a modified version of Readelf (from the GNU Binutils package), a tool that takes as input an ELF binary file (the standard format on Linux systems) and outputs information such as its symbol table and debugging information. Readelf provides a mode that outputs the debugging information as a human-readable text file. I built infrastructure around that code to have it populate Fjalar's data structures instead of outputting text.

The traditional (and intuitively obvious) method of obtaining language-level information is to simply parse the source code of the target program. After all, the relevant information must be present in the source code. Previous researchers in my group used the EDG compiler front end [13] for parsing C and C++ source code. The CIL framework from Berkeley attempts to transform arbitrary C code into a tamer subset of C that is semantically cleaner, and is often used as the front-end for many source-based analyses [37].

However, source code for C and especially for C++ programs is notoriously difficult to parse. Also, a source parser must be modified for different dialects of these

languages. In contrast, debugging information is fairly robust to changes in language dialect and even languages because the format is supposedly language-independent (many languages that `gcc` supports produce similar debugging information). The only thing that it does not contain which is present in the source is control-flow information, but Fjalar only requires information about data, not about control flow. I have found that debugging information provides just the right level of abstraction for obtaining what I need for Fjalar without excessive implementation effort.

The bulk of my implementation effort in this module was to simplify what is found in the debugging information in order to place it in Fjalar data structures for three main kinds of objects: functions, variables, and types. Thus, Fjalar tool builders can ignore all the complexities of source code and of debugging information and easily retrieve relevant compile-time information about data such as the types of the parameters of all functions, the names and types of the member variables of those parameters (if they are structs or classes), the addresses of global variables, etc...

2.3.4 Data structure traversal

This module combines the memory safety features of the Fjalar API with the data structures holding compile-time information to provide functionality for traversing through the target program's data structures at run time. I have implemented various file formats to allow the user to specify which variables to trace, whether certain pointers should be considered as pointing to one element or to an array, and whether pointers should be coerced into a different type during traversal (useful for `void*` pointers, for instance). The details of these file formats are described in the Fjalar Programmer's Manual (`http://pag.csail.mit.edu/fjalar/fjalar_manual.htm`).

2.4 Building and Executing a Basic Fjalar Tool

This section briefly describes how to use Fjalar to build a tool and how to invoke that tool on a target program.

2.4.1 A basic Fjalar tool: `basic-tool.c`

I will now describe `basic-tool.c`, a demonstration Fjalar tool that is bundled with the Fjalar source code distribution. It performs a standard data structure traversal described in Section 2.2.4 at all function entrance and exit points, prints out the names of all variables it encounters, and if a particular variable is the dereferenced contents of a pointer, prints out how many elements are in the array. This tool implements the minimum number of functions required of any Fjalar tool. I have included all of the code of `basic-tool.c` in this section, but I will intermix code snippets with their descriptions for greater clarity.

The code below shows fairly standard setup and teardown functions that run when the tool begins and finishes execution, respectively. This tool simply prints out various text messages during those times (using `VG_(printf)()` instead of the standard C library `printf()` because Valgrind requires all tools to use its own version of C library functions). Most non-trivial tools will perform their own initialization, command-line option processing, and clean-up routines using these functions.

```
// Runs before processing command-line options:
void fjalar_tool_pre_clo_init() {VG_(printf)("\nBefore option processing\n\n");}

// Runs after processing command-line options:
void fjalar_tool_post_clo_init() {VG_(printf)("\nAfter option processing\n\n");}

// Prints instructions when the --help option is invoked:
void fjalar_tool_print_usage() {VG_(printf)("\nPrinting usage\n\n");}

// Processes command-line options:
Bool fjalar_tool_process_cmd_line_option(Char* arg) {
  // Return false because we have no options to process
  return False;
}

// Runs after the tool exits:
void fjalar_tool_finish() {VG_(printf)("\nTool is finished!\n");}
```

The `basicAction` function shown below is an *action function* which defines the action that this tool takes for every step of a traversal. The tool passes this as a call-back function into Fjalar's data structure traversal routines. When Fjalar performs

traversals, it calls this function at every variable it reaches, populating this function's parameters with the appropriate contents. For instance, `var` contains information about the current variable active at this step of the traversal, `varName` is the name that Fjalar provides for it (e.g., `foo->bar.baz[1]`), and `varFuncInfo` is the function of the target program that is currently executing while this traversal is occurring. Most importantly for a tool, `pValue` is a pointer to the contents of this variable if it is a single element (`isSequence` is false) and `pValueArray` is an array of pointers to the contents of this variable if it is an array of elements (`isSequence` is true) and `numElts` is the number of elements in the array. Notice that these pointers are of type `void*`, but the `VariableEntry* var` parameter contains enough type information to disambiguate the pointers at run time.

```
TraversalResult basicAction(VariableEntry* var,
                            char* varName,
                            VariableOrigin varOrigin,
                            UInt numDereferences,
                            UInt layersBeforeBase,
                            Bool overrideIsInit,
                            DisambigOverride disambigOverride,
                            Bool isSequence,
                            // pValue only valid if isSequence is false
                            void* pValue,
                            // pValueArray and numElts only valid if
                            // isSequence is true
                            void** pValueArray,
                            UInt numElts,
                            FunctionEntry* varFuncInfo,
                            Bool isEnter) {
  if (isSequence) {VG_(printf)("     %s - %d elements\n", varName, numElts);}
  else {VG_(printf)("     %s\n", varName);}

  // We want to deref. more pointers so that we can find out array
  // sizes for derived variables:
  return DEREF_MORE_POINTERS;
}
```

In `basicAction`, this basic tool simply prints out `varName` and, if it is a sequence, the number of elements in the sequence. It does not actually do anything with the

observed values of the variables during traversal. However, most non-trivial tools would actually use `pValue` and `pValueArray` to observe or even modify the values of variables at run time. Fjalar guarantees that the memory addresses referred to by these pointers are always allocated and their values are initialized as long as the pointers are non-null.

The code below shows two functions that are called whenever the target program enters or exits any functions during execution, respectively (the user can selectively trace only the entrances and exits of particular functions by specifying their names in a file). The basic tool prints out the function name along with "`- ENTER`" or "`- EXIT`", then traverses through all global variables, function parameters, and the return value (only on exit). Notice that the tool passes the address of the `basicAction` function as a function pointer parameter (a callback) to Fjalar's traversal functions in order to specify what happens during each step of the traversal.

```
void fjalar_tool_handle_function_entrance(FunctionExecutionState* f_state) {
  VG_(printf)("[%s - ENTER]\n",f_state->func->fjalar_name);

  VG_(printf)("  Global variables:\n");
  visitVariableGroup(GLOBAL_VAR, 0, 1, 0, &basicAction);

  VG_(printf)("  Function formal parameters:\n");
  visitVariableGroup(FUNCTION_FORMAL_PARAM, f_state->func, 1,
                     f_state->virtualStack, &basicAction);
}

void fjalar_tool_handle_function_exit(FunctionExecutionState* f_state) {
  VG_(printf)("[%s - EXIT]\n", f_state->func->fjalar_name);

  VG_(printf)("  Global variables:\n");
  visitVariableGroup(GLOBAL_VAR, 0, 0, 0, &basicAction);

  VG_(printf)("  Function formal parameters:\n");
  visitVariableGroup(FUNCTION_FORMAL_PARAM, f_state->func, 0,
                     f_state->virtualStack, &basicAction);

  VG_(printf)("  Return value:\n");
  visitReturnValue(f_state, &basicAction);
}
```

The code below shows the constructors and destructors for the 3 'classes' in Fjalar's API – `VariableEntry`, `TypeEntry`, and `FunctionEntry` – that can be sub-classed. Because Fjalar is implemented in C, there is of course no language support for object-oriented programming, so I implemented class inheritance via structural subtyping where, for example, a subclass of `VariableEntry` contains an instance of `VariableEntry` as its first member variable and then adds additional members after it. Then `constructVariableEntry()` needs to be modified to allocate enough space for the extra members of the subclass. Subclassing is very useful for these classes because many Fjalar API functions take objects of these classes as parameters. The basic tool performs no subclassing and thus implements trivial versions of these functions.

```
// Constructors and destructors for classes that can be sub-classed:

// We do not implement any sub-classing so just implement the 'default'
// constructor/destructor by calling VG_(calloc) and VG_(free), respectively
VariableEntry* constructVariableEntry() {
  return (VariableEntry*)(VG_(calloc)(1, sizeof(VariableEntry)));
}

TypeEntry* constructTypeEntry() {
  return (TypeEntry*)(VG_(calloc)(1, sizeof(TypeEntry)));
}

FunctionEntry* constructFunctionEntry() {
  return (FunctionEntry*)(VG_(calloc)(1, sizeof(FunctionEntry)));
}

void destroyVariableEntry(VariableEntry* v) {VG_(free)(v);}
void destroyTypeEntry(TypeEntry* t) {VG_(free)(t);}
void destroyFunctionEntry(FunctionEntry* f) {VG_(free)(f);}
```

2.4.2 Invoking `basic-tool.c` on a target program

These steps allow the tool implemented by `basic-tool.c` to run on a target program:

1. Compile Fjalar along with `basic-tool.c` by setting the appropriate Makefile parameters and running `make` on an x86/Linux machine. (see the Fjalar Program-

mer's manual, `http://pag.csail.mit.edu/fjalar/fjalar_manual.htm`, for more details.)

2. Compile the target program normally with `gcc` (or `g++` for a C++ program), making sure to use the `-g` and `-O0` command-line options to insert DWARF2 debugging information and to disable all optimizations, respectively. Let's say that this generates a binary executable file named `target-prog`. (I have tested Fjalar on various `gcc` versions from 3.0 to 4.0)

3. Execute "`valgrind --tool=fjalar target-prog`" to run the tool on the target program. (The actual invoked executable is Valgrind because Fjalar is actually a Valgrind tool, but it is recommended to create an alias called `basic-tool` to refer to "`valgrind --tool=fjalar`". Then executing "`basic-tool target-prog`" will suffice.)

Because a Fjalar tool operates directly on the binary of a target program, it is extremely easy to use. I have purposely not included a separate evaluation section for Fjalar (i.e., experiments to test its functionality, robustness, scalability, performance, etc...) because the real evaluation of a tool framework is the tools that can be built on top of it. Chapters 3 and 4 describe two tools that I have built, and each chapter contains its own respective evaluation section for those tools and their applications to real-world program analysis tasks.

2.5 Related Work

Much of the Fjalar infrastructure is devoted to tracking uses of memory; this is a key requirement for a rich dynamic analysis of non-memory-safe programs. Most memory tracking analyses aim to detect memory errors in C programs.

Representative recent source-based work is by Xu et al. [57], who rewrite C programs to maintain 'smart pointers' with metadata. Although their approach scales

up to programs as large as 29 KLOC, it suffers from the problems inherent in all source-based approaches: development challenges with parsing C source code, difficulty in supporting additional languages such as C++, and the inability to handle complex language constructs such as integer-to-pointer casts, certain types of struct pointer casts, and the use of custom memory allocation functions. Earlier work includes Safe-C [5] and CCured [38], which analyzes C programs to reduce the cost of dynamic checking.

The best-known binary-based dynamic memory analysis is Purify [24], which performs ahead-of-time binary instrumentation so that the program maintains bits indicating whether each byte of memory is allocated and initialized, and checking them before uses. Memcheck [46], which I use in Fjalar, is similar but is accurate to the bit level and employs a just-in-time compiler. Many similar tools exist with some or all of the capabilities of these tools; for example, another popular approach is using special system libraries (e.g., `malloc` and `free`).

Binary analysis and editing frameworks include ATOM [48], EEL [31], Etch [45], DynamoRIO [7], and Valgrind [39]. These are low-level tools intended for use in binary transformations that improve performance or security, so they make no accommodation for communicating information to a software engineer, much less in terms of source level constructs. Fjalar augments Valgrind's binary-only analysis with language-level information.

2.6 Conclusion

Fjalar is a framework for building dynamic program analysis tools for C and C++ programs, especially those that deal extensively with data structures. By adopting a mixed-level approach, it can be more scalable and useful than pure source- or binary-based analyses for many software engineering applications. Fjalar provides

tools built upon it with memory safety guarantees, rich compile-time information about variables, types, and functions, and the ability to traverse data structures at run time. Its source code is publicly available on the web along with documentation at `http://pag.csail.mit.edu/fjalar/`.

Chapter 3

Kvasir: A Tool for Recording Runtime Values of Data Structures

Kvasir is a value profiling tool that records runtime values of data structures. It serves as the C/C++ front-end for the Daikon dynamic invariant detection tool. I implemented Kvasir using the Fjalar framework because the mixed-level approach allows it to overcome many of the limitations of its source-based predecessor, Dfec (Section 3.1.3). Experiments comparing Kvasir and Dfec confirm the advantages of the mixed-level approach over a source-based approach (Section 3.4.1). I have used Kvasir to analyze real-world C and C++ programs on the order of hundreds of thousands to millions of lines of code and applied it as part of a data structure repair system developed in another research group at MIT (Section 3.4.2) .

3.1 Motivation

This section describes the Daikon tool, requirements for a Daikon front-end, and a previous attempt at building a C/C++ front-end, whose shortcomings were the motivation for Kvasir's inception.

3.1.1 The Daikon dynamic invariant detection tool

The Daikon dynamic invariant detection tool [15] reports likely program invariants by performing machine learning over the values of variables (and other expressions) during a program execution. The result of the analysis is a set of properties, similar to those found in formal specifications or assert statements, that held during the observed executions. For instance, in a program that uses an integer `ind` to index into an array and an integer `arr_size` to represent the size of that array, here is a typical value trace for those variables in the form of `(ind, arr_size)`: `(0, 6), (1, 6), (2, 6), (3, 6), (4, 6), (5, 6)`. This trace can perhaps result from the program executing a loop through a 6-element array. Given the names and types of these variables along with this trace, Daikon could infer invariants like `ind >= 0` and `ind < arr_size`. These are useful statements about variables and their relations that can aid in writing specifications and assertions, generating test cases, refactoring, among many other tasks. Several dozen papers have described over a dozen distinct applications of dynamic invariant detection [42].

Daikon itself is language-independent; its input is a trace of variable names and values. At each *program point* for which likely invariants are desired (by convention, function entrances and exits), the trace indicates the value of each variable that is in scope. At function entrances, these are global variables and formal parameters, and at function exits, they are global variables, formal parameters, and return values. These variables, as well as those that result from traversing inside of data structures held by these variables, are called *relevant variables*, and they permit Daikon to infer procedure preconditions and postconditions. C++ member functions are treated like normal functions with an extra `this` parameter, and generalization over preconditions and postconditions yields object invariants (representation invariants).

Daikon must be coupled with a language-specific front-end that instruments a target program to produce a value trace during execution. Daikon front-ends exist

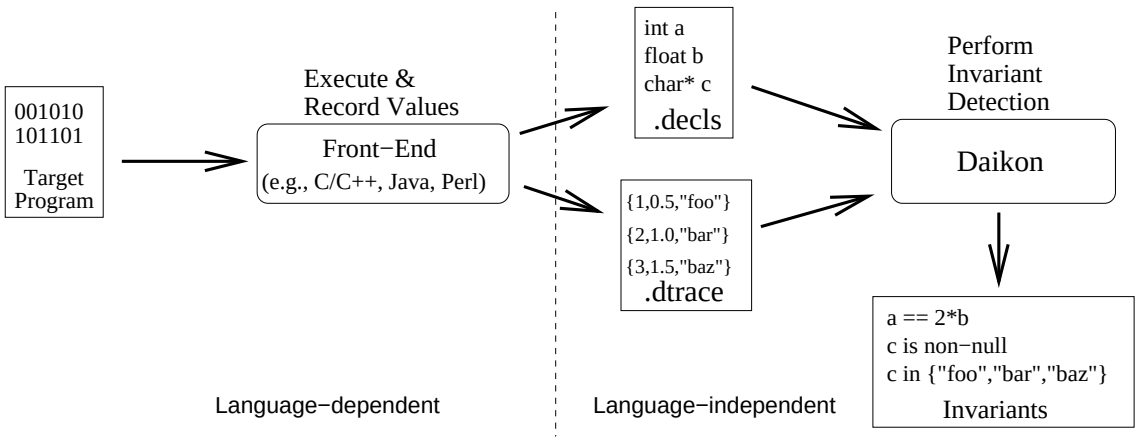


Figure 3-1: The Daikon dynamic invariant detection system

for C/C++, Java, Perl, and several other languages and data formats. Figure 3-1 shows the operation of the invariant detection system. The language-dependent portion of the process on the left side of the dotted line depicts running a target program through a front-end; the front-end must match the language of the target program. The trace generated by the front-end consists of two parts: a `decls` file that contains declarations of variables (their names and types) and program points (their names and parameters), and a `dtrace` file that contains the value trace of the variables, which is formatted to correspond to the declarations in the `decls` file. The trace is language-independent, so in essence, the front-end's job is to translate concrete values in the execution of a program written in a specific language into a language-independent format. Daikon takes as inputs the `decls` and `dtrace` files and performs invariant detection in a language-independent manner.

3.1.2 Requirements for a Daikon front-end

A Daikon front-end is a *value profiling* tool for software engineering applications. Value profiling [8] is a technique that observes the run-time values of variables, expressions, registers, memory locations, etc. It is a general technique that is incorporated in any dynamic analysis that is concerned with what the program computes.

(Purely control-flow-based dynamic analyses, such as coverage tools, need not incorporate value profiling.) A form of value profiling is even implemented in hardware, in order to support speculation, branch prediction, and other optimizations.

Specifically, a value profiling tool for software engineering applications should provide accurate and rich information about the run-time values of arbitrary data structure accesses. The desire for accurate information requires fine-grained tracking of pointer and memory use, to determine when a particular expression's value is meaningless (e.g., uninitialized). The desire for rich information means that it is not enough to merely observe values that the program is directly manipulating at a moment in time; other values may be of interest, even if their uses appear before and/or after that moment. Value profiling for software engineering can be viewed as having the characteristics of three other analyses: traditional value profiling, data structure traversal, and memory error detection. This problem fits into the class of applications that need to bridge the gap between source-based and binary-based analyses. Its output should be in terms of source variables and expressions, and it appears to be an easy source analysis at first glance (just print the values of those expressions), but tracking of memory allocation, initialization, and other low-level details is best done at the binary level.

A profiler observes program behavior (such as performance, control flow, or values) but strives not to change that behavior. When it is acceptable to produce only limited information, one way to avoid changes in program behavior is to observe only values that the program directly manipulates. For instance, a value profiler could record the value of a given expression only at instructions that read or write that expression. This ensures that the value is valid, and that the access to it does not cause a segmentation fault or other behavioral change. Software engineers may be helped in some tasks by such limited information, but additional information can be very valuable, for instance for Daikon to generate more useful invariants. A value

```
Original:                              Instrumented by Dfec:

bool g;  // global variable            bool g;  // global variable

int foo(int x) {                       int foo(int x) {
                                         trace_output("foo()::ENTER");
                                         trace_output_int("x", x);
                                         trace_output_bool("g", g);
  ...                                    ...
  return g ? x++ : -x;                   int return_val = g ? x++ : -x;
                                         trace_output("foo()::EXIT");
                                         trace_output_int("x", x);
                                         trace_output_int("return", return_val);
                                         trace_output_bool("g", g);
                                         return return_val;
}                                      }
```

Figure 3-2: Source code before and after instrumentation by Dfec

profiling tool for software engineering, such as a Daikon front-end, should be able to, without causing the program to crash, examine the values of arbitrary data structure elements at arbitrary times, even elements that the target program did not observe or manipulate at those times.

In light of the aforementioned requirements, it is much easier to write a scalable and robust Daikon front-end for a memory-safe language like Java than for C or C++. The problems of unallocated and uninitialized memory, unknown array sizes, and memory corruption are non-existent in a Java Virtual Machine runtime environment. It is actually the challenges of writing a C and C++ Daikon front-end that motivated the initial development of the mixed-level approach and Fjalar framework.

3.1.3 Dfec: A source-based Daikon front-end for C

Before I began development on the Kvasir front-end in January 2004, there already existed a source-based front-end named Dfec (an acronym for "Daikon Front End for C") [36]. Dfec works by rewriting the source code of the target program to insert code that outputs the values of relevant variables during execution.

A user runs Dfec to instrument the target program's source code, compiles the instrumented source, then runs the resulting executable. As the program executes, it outputs the names and values of relevant variables at each execution of a program point. Figure 3-2 shows a function before and after instrumentation. Notice that the global variable `g` is a relevant variable, and also there must be an extra `return_val` variable created to capture the return value of `foo()`.

Dfec uses the EDG C/C++ front end [13] to parse, instrument, and unparse source code. This source code rewriting works well for outputting values, but information about initialized and valid variables and memory must be maintained dynamically. Dfec includes a sophisticated and complex run-time system that associates metadata with each pointer and chunk of memory using 'smart pointer' objects. It inserts code that checks and updates the smart pointer metadata at allocations, assignments, uses, and deallocations of memory.

Dfec suffers from many shortcomings due to the fact that it takes a source-based approach to dynamic analysis (Section 1.2.1), so unfortunately it is not robust or scalable enough to run on programs of even moderate complexity.

The central limitation of Dfec's source-based technique is the difficulty of reliably inserting code at the right places to maintain the memory safety guarantees required of a Daikon front-end (e.g., keeping track of pointer operations to record which data are valid and to ensure that the instrumented program does not dereference an invalid pointer). Smart pointers with metadata is Dfec's attempt to overcome this challenge, but the rewriting of code to use smart pointers is cumbersome and not scalable. For instance, changing a function parameter's type from a regular pointer to a smart pointer creates the need to change it for all calls and declarations, but if it is a library function, then it is often impossible or infeasible to translate library source code, which is either unavailable or much more complex than the target program's code.

In order to circumvent the problem of function prototype incompatibilities caused

by the transformation of regular pointers to smart pointers, Dfec converts smart pointers back into regular pointers before passing them into library functions which take pointers as parameters. Doing so allows the instrumented source code to compile normally. However, the memory tracking and safety benefits of smart pointers are lost when the execution enters library code. The implementor of Dfec manually wrote wrapper functions for a subset of `libc` (e.g., `string.h`) which perform the proper smart pointer bookkeeping operations before delegating to the `libc` versions of the functions. All non-trivial C programs interface with libraries, and it is prohibitive to manually write wrappers for every library function which deals with pointers.

Source code complexity was also a major obstacle in the efforts to extend Dfec to support C++ target programs. Even discounting the difficulties of parsing, C++ is a much more complex language than C at the source level. Though C++ support was originally a goal for Dfec, and the last months of Dfec's development focused on that goal, it was very challenging to make it work robustly. For instance, one source of problems was interactions between the templates used to represent smart pointers, and other uses of templates in the original program.

Dfec also suffers from two other problems that tend to affect source-based analyses. First, though Dfec re-uses an existing source parser, the AST interface alone is rather complex, making maintenance difficult. Second, because Dfec works by processing source code that must then be compiled, it is cumbersome to use, especially for large programs with complex Makefile and configure files that control their build process.

The experiments in Section 3.4.1 and my anecdotal experience confirm that Dfec does not work "out of the box" on C or C++ programs of reasonable size, and even a complete source-based re-implementation would not resolve many of its most debilitating limitations. For the limited number of C programs which Dfec successfully instrumented, many often crashed during execution while trying to dereference pointers to unallocated regions of memory. In theory, the smart pointer objects were supposed

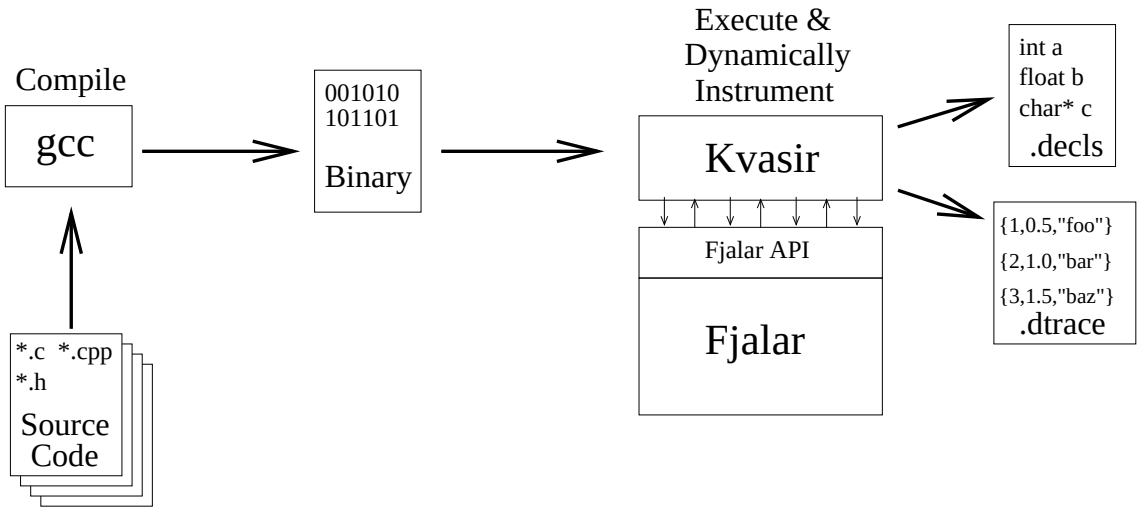


Figure 3-3: Kvasir as a Fjalar tool that produces trace files for Daikon

to provide memory safety and prevent segmentation faults during dereferences, but in practice, C language constructs such as nested pointers to structs, arrays within structs, multiple layers of pointers, and integer-to-pointer casts often misguided the Dfec runtime system into dereferencing an invalid pointer. This experience motivated the development of Kvasir, a new Daikon front-end based on a mixed-level approach.

3.2 Kvasir: A C and C++ Front-End for Daikon

Kvasir (named after the Norse god of knowledge and beet juice) is a C and C++ front-end for Daikon that I implemented based on the mixed-level approach. Kvasir instruments and executes the target program's binary in one step without using the source code. Unlike Dfec, its predecessor, Kvasir works "out of the box" on programs of significant size (see Section 3.4.1), and its scalability and performance surpass those of the Daikon invariant detector itself.

As shown in Figure 3-3, Kvasir is a Fjalar tool that takes a target program's binary as input and produces `decls` and `dtrace` files for Daikon as output. The operation of Kvasir is fairly straightforward for the most part. To generate the `decls` file, Kvasir uses the compile-time information about functions, variables, and types

and the variable traversal features of the Fjalar API (Section 2.2) to output all of the relevant declarations to a file. To generate the `dtrace` file, Kvasir uses the Fjalar API to instrument the target program's binary to pause execution at program points and then to traverse through all relevant variables and output their values to a file, making sure not to dereference pointers to unallocated regions or output uninitialized values.

Kvasir has many options to give the user fine control over what parts of the program to trace. There are file formats in which users can designate which program points and variables to trace, whether to output variable values as scalars or arrays, and whether to coerce a pointer to a certain type before dereferencing it to output its value. There are also command-line options to control how deep to recurse inside of nested data structures and whether to ignore certain classes of variables (e.g., global variables, file-static variables). The Fjalar API provides all of the aforementioned functionality. These features are often very useful when tracing a small portion of a large or long-running program like the data structure repair application of Section 3.4.2 does. When using Daikon to find invariants within a large software system, the user often only cares about certain core modules with interesting data structures, not the majority of the program, which consists of boilerplate code, error handling, file I/O, user interface, etc... Thus, Kvasir's selective tracing options have been very useful in practice; without them, Daikon would not be able to process the vast amounts of collected trace data, but even if it could, it would find lots of invariants that are not interesting to the user.

Kvasir has one additional interesting feature: it can write the `dtrace` trace information to a pipe instead of to a file. Daikon can be connected to the read end of the pipe and detect invariants 'on-the-fly' as the program is executing. This is useful for detecting invariants over a long-running program or an execution that would otherwise produce very large `dtrace` files.

The main advantages of Kvasir over Dfec derive from the fact that C and C++ allow programmers to work directly on the memory level via pointers, so thus, given the appropriate tools, it is much easier and more accurate to take a mixed-level approach by analyzing these programs on the binary level and using source-level constructs only when necessary rather than solely performing a transformation of the source code. Kvasir's use of binary analysis has three interrelated advantages. First, it is precise to the bit level; for instance, Kvasir can print the initialized bits but not the uninitialized ones in a bit vector. Second, the precision is not diminished when libraries are used, since code is treated uniformly regardless of its origins. Contrast this with the hand-written annotations required by a source-based tool such as Dfec. Third, and most importantly, the binary memory tracking is conceptually simple, allowing a simple and robust implementation. Because Kvasir instruments the program binary, it provides full memory tracking coverage unlike Dfec, which only provides such coverage for parts of the program where the source code was available to instrument. Since Kvasir is able to safely examine memory to read values, it does not need any specialized data structures to keep track of pointer variable metadata, thus simplifying its implementation with respect to Dfec. For example, in Figure 2-2, Dfec needs to keep track of several smart pointers to maintain information about the initialization states and number of elements referenced by each pointer within `rec`, but Kvasir can simply follow the pointers, determine the array sizes at runtime, and directly extract the initialized values from memory to report to the `dtrace` file.

Kvasir avoids many of the complexities that stunted Dfec's scalability by not depending on details of the target program's source language. Kvasir's memory tracking is designed with respect to a simple machine model, rather than a complex language semantics. When Kvasir does require language-level information, though, it still saves complexity by using debugging information rather than source code. While the sophisticated structure of debugging information accounts for much of Kvasir's com-

plexity, it is still much simpler than the original source from which it is derived (the compiler abstracts away many source-level details) and the debugging information parsing functionality is well-encapsulated within the Fjalar framework.

The best example of this reduced dependence on source complexities was my experience in adding C++ support to Fjalar and Kvasir (at first, the implementation only supported C). This primarily required additional debugging information parsing code to handle object-oriented features such as member functions and static member variables, and in all required only 4 days of work to get rudimentary functionality and another 2 weeks to add more advanced features and improve robustness. Binaries for C++ programs follow virtually the same calling conventions as those for C programs, so the actual memory, variable, and program point tracking code required almost no modifications. It would likely be just as easy to support other gcc-compiled languages such as Ada, Fortran, Objective-C, and Java.

A final advantage of Kvasir is that it is easy to use. Running a program under Kvasir's supervision is a single step that involves just prepending a command to the normal program invocation. For a program that is normally run as

```
./program -option input.file
```

a user would instead use the command

```
kvasir-dtrace ./program -option input.file
```

It is rarely necessary to modify a program in order for Kvasir to run on it, even for large programs that use many language and system features (see Section 3.4.1).

3.3 Implementation

Kvasir is implemented as a Fjalar tool, much in the same spirit as `basic-tool.c` described in Section 2.4. It adds several command-line options in addition to the ones that Fjalar provides, mostly dealing with how and where to output the `decls`

and `dtrace` files. The bulk of the Kvasir code deals with interfacing with Fjalar and formatting trace output so that it conforms to Daikon's file format. It contains two action functions (analogous to `basicAction()` in `basic-tool.c`) which are passed as callback parameters to the Fjalar traversal functions: one for querying compile-time declarations to output to the `decls` file, and the other for querying memory allocation and initialization and array size information and directly reading values from memory to output to the `dtrace` file. Kvasir piggybacks off of Fjalar for all of the hard work of ensuring memory safety and traversing through data structures.

3.4 Evaluation

I evaluated the Kvasir tool in two ways: performing experiments comparing it to Dfec (Section 3.4.1) and applying it as part of a data structure repair system (Section 3.4.2). Both evaluations confirm that Kvasir is a robust and scalable tool that is able to reliably produce trace files for executions of real-world C and C++ programs.

3.4.1 Experiments

This section compares Dfec and Kvasir in terms of scalability and performance. Scalability was measured by the sizes of programs that Dfec and Kvasir could successfully process and the amount of human effort, if any, required to do so. Performance was measured by the slowdown factors relative to the runtime of the uninstrumented programs.

Scalability

Table 3.1 shows a variety of C and C++ Linux programs. For this experiment, I tried to find widely-used, real-world programs spanning many different domains, as evidenced by the program descriptions. 'Runs to completion' (denoted by a 'Y' in the

Program	Lang.	Description	LOC	Dfec	Kvasir
md5	C	Cryptographic hash function	312	Y	Y
rijndael	C	Cryptographic algorithm	1,208	Y*	Y
bzip2 1.0.2	C	File compression tool	5,123	Y*	Y
flex 2.5.4	C	Fast lexical analyzer generator	11,977	Y**	Y
make 3.80	C	Software build automation tool	20,074	N	Y
xtide 2.6.4	C++	Graphical tide calculator/visualizer	23,768	-	Y
groff 1.18	C++	UNIX document formatting system	25,712	-	Y
civserver 1.13.0	C	Server for multi-player game	49,657	-	Y
ctas	C++	Air traffic controller (one module)	>52,329	-	Y
povray 3.5.0c	C++	3D renderer	81,667	-	Y
perl 5.8.6	C	Programming language interpreter	110,809	-	Y
apache 2.0.54	C	Ubiquitous web server	152,435	-	Y
bind 9.3.1	C	Domain Name System server	152,885	-	Y
xemacs 21.4.17	C	Text editor and work environment	204,808	-	Y*
gcc 3.4.3	C	C preprocessor and compiler	301,846	-	Y*

Y = runs to completion N = failed to run - = did not attempt
$*$ = requires minor modifications reasonable for users to make
$**$ = requires major modifications that would deter most users
(LOC is non-comment non-blank lines of code.)

Table 3.1: Dfec and Kvasir scalability tests for C and C++ Linux programs

table) means that a tool can successfully generate `decls` and `dtrace` files for Daikon for a non-trivial target program execution.

Dfec only ran on the four smallest programs, only one of which, `md5`, worked "out of the box" without any hand modifications to the source code. Any program that uses non-trivial language features (especially those related to pointers) or calls library routines had to be 'massaged' by hand either so that Dfec will accept them as valid input or, more often, so that Dfec's output is a legal program that can still compile. Examples of modifications required for these programs include: For `bzip2`, Dfec's special treatment of the `void*` type failed to be triggered by a type `BZFILE*` when `BZFILE` was a typedef for `void`. I resolved this by directly replacing `BZFILE` with `void`. For `flex`, my colleagues and I made major modifications, including replacing string literals in ternary `?:` operators by variables initialized to those literals in order to resolve an ambiguity related to operator overloading in Dfec's output due to its use of smart pointers. For `make`, a colleague spent several hours trying to bypass Dfec's usual pointer transformations to match the memory layout required by UNIX environment variables, without success. The need to manually edit the target program's source code makes the effort to use Dfec scale up with the target program's size, and that effort was prohibitive for programs larger than ∼10 KLOC.

In contrast, Kvasir runs on both C and C++ programs of up to 300 KLOC, requiring only rare target program modifications for unusual constructs. For `xemacs`, a colleague renamed one of two sets of functions generated by two compilations of a single C source file to avoid having two otherwise indistinguishable functions. For `gcc`, a colleague supplied an extra `--with-gc=simple` configuration parameter to specify a garbage collector that works with the standard `malloc`.

I feel that the user experience in running Kvasir was much better than in running Dfec. All of these programs had Makefiles, so all I needed to do was to add the `-g` and `-O0` options for `gcc` to include debugging information and to disable optimizations,

Program	Base Time	Dfec	Kvasir	Daikon	Valgrind	Memcheck	Kvasir main()
md5	0.14	310	240	500	2.3	15	18
rijndael	0.19	690	5000	2200	7.6	38	86
bzip2	0.18	1100	3500	12000	5.2	28	46
flex	0.41	780	1800	2400	14	49	99
Average		720	2600	4300	7.3	33	62

Table 3.2: Slowdown for programs that were successfully processed by both Dfec and Kvasir. All numbers are slowdown ratios, except that the base run times are given in seconds. All tests were run on a 3GHz Pentium-4 with 2GB of RAM.

respectively, run `make`, and then run Kvasir on the resulting binary. Because all of these programs, regardless of size, compile into one binary with a `make` command, the effort of getting Kvasir to run does not scale with the program's size.

The majority of the scalability problems of Dfec come from limitations of a source-based approach. In general, larger programs are more likely to contain complex source code constructs and interactions with libraries and system interfaces, which are more difficult to properly handle at the source level than at the binary level (especially operations on pointers, which are ubiquitous in C and C++ programs). In contrast, Kvasir's use of dynamic binary instrumentation bypasses all of these limitations and makes it a much more robust and scalable tool. In theory, a perfect source-based analysis could be extremely robust and scalable, but the complexities of transforming source code makes it difficult for real implementations to approach this ideal.

Performance

Both Dfec and Kvasir ran on the order of 1000 times slower than the uninstrumented target programs (see Table 3.2), but most of the overhead was due to writing data traces to `dtrace` files at every program point execution. The `dtrace` files ranged from several hundred megabytes to several gigabytes. For the larger programs of Table 3.2, `bzip2` and `flex`, I configured both Kvasir and Dfec to skip global variables and to print only the first 100 elements of large arrays.

Dfec was somewhat faster than Kvasir because Dfec produces instrumented source code that can be compiled with optimizations to machine code, while Kvasir performs binary instrumentation with Valgrind, which both consumes run time and also yields less-optimized code (x86 code must be translated to Valgrind IR, instrumented, then translated back to x86).

The three rightmost columns of Table 3.2 show the components of Kvasir's slowdown caused by its implementation as a Valgrind tool built on top of Memcheck (both tools are encompassed within the Fjalar framework). The "Valgrind" column shows the ∼10× slowdown of Valgrind running on the target program without any custom instrumentation. The "Memcheck" column shows the ∼30× slowdown of the Memcheck tool, which is required to provide memory safety guarantees for Kvasir. The "Kvasir main()" column shows the ∼60× slowdown of Kvasir when running on the target program but only outputting the trace data for one function, `main()`. This measures the overhead of bookkeeping related to tracing, including the overhead of Fjalar, without the data output slowdown. The rest of Kvasir's slowdown above this factor is caused by the output of trace data for Daikon and is approximately linear in the size of the `dtrace` file. Both Dfec and Kvasir share this unavoidable output slowdown.

I believe that the value profiling overhead could be reduced. However, I have not spent any significant effort on optimizing Dfec or Kvasir, because they usually produce trace output faster than Daikon can process it, so neither is the performance bottleneck in the entire invariant detection system. (Recall that Kvasir can output `dtrace` data to a pipe, and Daikon can detect invariants 'on-the-fly' as the target program is executing; in that case, Kvasir always writes data to the pipe faster than Daikon can read from it.) Kvasir's performance is directly related to the number of program point executions and variables being traced at those program points. Thus, it is completely feasible to trace only selected small portions of an extremely large or

long-running program without a significant slowdown. In fact, this is frequently done for large programs because the user is often interested in certain key functions or data structures (see Section 3.4.2), and also Daikon is currently not scalable enough to produce invariants over all program points and variables in programs larger than ∼10 KLOC. Given its other advantages, Kvasir's performance overhead is completely acceptable for its role as a Daikon front-end for C and C++.

3.4.2 Application: Data structure repair

I have applied Kvasir as part of a runtime data structure repair system. Data structure repair is a technique that repairs corrupt data structures at runtime to conform to certain consistency constraints. For instance, a possible constraint for a doubly-linked list is that for every node `this` (except for the last node), `this->next->prev == this`. The goal of data structure repair is to be able to run an instrumented target program and have that program be more resilient to both bugs and malicious attacks that corrupt data structures. These consistency constraints can be arduous to write by hand, so the system uses Daikon to automatically generate them; after all, they are simply the invariants for data structures and their fields (member variables). The role of Kvasir in this system is to instrument the target program and generate trace files for selected data structures during execution so that Daikon can find consistency constraints for them.

This paper that I co-authored [12] describes three case studies on large C and C++ programs. Although I did not perform the actual data structure repair work, I collaborated closely with those who did by making numerous improvements to Kvasir over the span of a year so that it could run successfully on these programs. This experience helped me to identify inefficiencies, bugs, and limitations in Kvasir and Fjalar and made my tools stronger by giving me concrete incentives for improving them. Here is a summary of the case studies.

Freeciv

Freeciv is a popular open-source multi-player client-server strategy game. The assessment of Freeciv focused on a portion of the server, `civserver`. One key data structure represents the map of the game world. Each tile in this map has a terrain type and cities (with its own nested data structures) may be placed in these tiles as well. I used Kvasir to trace the map data structure (and data structures nested within it) through several regular executions so that Daikon could generate reasonable consistency constraints. Then my colleagues evaluated Freeciv by using a fault injection API to corrupt selected blocks of memory. They first performed randomized fault injections and noted program behavior: When 50 memory locations were simultaneously corrupted, the original Freeciv crashed 92% of the time, but the version augmented with the repair tool only crashed 12% of the time. More significantly, the funders of this project hired an external 'Red Team' to spend one day at MIT to use this API to strategically formulate corruption attacks with full knowledge of the workings of the Freeciv game. The repair system detected 80% of the corruptions and took successful corrective action in 75% of those cases.

The main challenge of this application for Kvasir was to precisely and accurately traverse into deeply-nested data structures and arrays of structures. The map consists of thousands of tiles, each tile may contain a city, each city has certain properties, and those sometimes have interesting fields, etc... Much of the selective program point and variable tracing code owes its refinement to my work on this case study.

BIND

The Domain Name System (DNS) is an Internet service responsible most notably for translating human-readable computer names (such as `www.mit.edu`) into numeric IP addresses (such as `18.7.22.83`). BIND is an open-source software suite that includes the most commonly-used DNS server on the Internet. Because of BIND's ubiquity on

the Internet, it is a frequent target of security attacks, and a number of serious flaws have been found in it over its decades of use. The BIND developers maintain a list of security-critical bugs. In order to assess the effectiveness of data structure repair in protecting BIND from these attacks, we have selected two previously-discovered problems and 'reverse-patched' the latest version of BIND (where these problems have been corrected) so that it exhibits these problems. Both are denial-of-service vulnerabilities: a malicious user interacting with BIND could prevent the server from handling legitimate requests. We were able to apply data structure repair to prevent the denial-of-service attacks (the details of both experiments are in our paper [12]).

I applied Kvasir to trace the data structures that were vulnerable to these two attacks. In performing this case study, I had to implement a pointer-type coercion feature for Fjalar, which allows the user to specify the runtime type of an arbitrary pointer so that Fjalar can traverse inside of its contents. BIND uses various generic pointers to emulate object inheritance in C. Thus, it was necessary to specify the run-time instead of the compile-time types in order to traverse into these data structures to record values of fields that were important for building the consistency constraints.

CTAS

CTAS (Center-TRACON Automation System) is a set of air traffic control tools developed at the NASA Ames Research Center [10]. Versions of this system are deployed at air traffic control centers throughout the United States and are in daily operational use. One interesting data structure is a flight plan that contains 38 fields. This data structure is responsible for keeping track of types of flights, their origins, and their destinations. I ran Kvasir on an execution of CTAS with legal inputs, directing it to only focus on that one data structure. My colleagues processed the resulting trace files through Daikon, found constraints, and re-ran CTAS again, this time using a fault injection system to corrupt flight information within this data

structure. Without the repair tool, many of these faults crash the entire system, which is unacceptable when CTAS is deployed in the real world because an air traffic control system should not shut down simply from bad information about one flight. With the repair tool in place, though, CTAS continues executing normally in the presence of many faults, albeit with some flights having incorrect information. For instance, if a set of legal destinations were {`Boston, Los Angeles, San Francisco, ...`} (the consistency constraint) and the correct destination was `Boston`, then when that field is corrupted to some illegal string, the best that the tool can do is to set the field back to one of the many legal values (e.g., `Los Angeles`), but it is not likely to be the correct one. The important thing, though, is that the program continues to execute correctly, albeit with possibly incorrect values. A simple alert in the user interface could warn operators when a value is potentially incorrect.

CTAS was by far the largest program I attempted to run Kvasir on (over 1 million lines of C++ code), although I only instrumented a much smaller module (∼50 KLOC) that contained the flight plan data structure. In the process of getting Kvasir to run on a program of this size and complexity, I had to make some optimizations to Fjalar in order to speed up the debugging information parsing that occurs as soon as the binary is loaded. Because the binary contains a huge amount of debugging information (for all 1 million lines, not just my 50 KLOC module), it was the first time that I noticed the inefficiencies of this portion of Fjalar. Fortunately, the fix was easy – adding an extra hash table to convert a linear-time lookup into a constant-time one. I also had to make some enhancements to Kvasir's C++ support. Overall, though, I was extremely grateful for the fact that Kvasir operates on one compiled binary because the CTAS project consisted of thousands of source files spread out across many directories, linked together with complex Makefiles and configure scripts. It would have been very difficult to process all of these files with a source-based tool and still have the result compile and run properly.

3.5 Related Work

The closest related work to Kvasir is its predecessor, Dfec [36], a source-based C front-end for Daikon. The limitations of Dfec described throughout this chapter directly motivated the creation of Fjalar and Kvasir.

A debugger designed for interactive use provides some of the same value profiling capabilities as Kvasir, and using some of the same information such as the debugging information. A debugger can stop execution at arbitrary points in the execution, and print the values of arbitrary source-level expressions. Invalid pointer accesses cause a debugger warning, not a segmentation fault. Some software engineering tools have been built on top of the GDB [49] debugger (for example, [2, 20, 6, 9]). However, GDB is not an automated dynamic analysis, nor is it designed for extensibility, and it imposes unacceptably high run-time overheads. Furthermore, it provides no memory validity tracking, a key requirement for a software engineering tool.

3.6 Conclusion

Kvasir is a value profiling tool that serves as a C and C++ front-end for the Daikon dynamic invariant detection tool. It is scalable up to programs of millions of lines of code. Its predecessor, Dfec, could only process C programs up to around 10,000 lines and often required some amount of user effort to work on non-trivial programs. Until the creation of Kvasir, Daikon was only able to run on small C programs and on almost no C++ programs. Kvasir has enabled Daikon to find invariants in large C and C++ programs and thereby broaden its applicability. For instance, Kvasir enabled the data structure repair system to use Daikon to automatically infer consistency properties for data structures within complex, real-world C and C++ programs, a task which would have been impossible with Dfec. Kvasir is publicly available on the web in the source code distribution of Daikon: `http://pag.csail.mit.edu/daikon/`

Chapter 4

DynComp: A Tool for Dynamic Inference of Abstract Types

This chapter presents a novel kind of dynamic analysis that my colleagues and I developed — dynamic inference of abstract types — and describes its implementation, a tool named DynComp that I built using the Fjalar framework. The contents of this chapter are mostly adapted from our paper, *Dynamic Inference of Abstract Types* [23].

An abstract type groups variables that are used for a related purpose in a program. Initially, each run-time value gets a unique abstract type. A run-time interaction among values indicates that they have the same abstract type, so their abstract types are unified. Also at run time, abstract types for variables are accumulated from abstract types for values. The notion of interaction may be customized, permitting the analysis to compute finer or coarser abstract types. Section 4.2 describes our abstract type inference algorithm.

We have produced two implementations of this technique: one operates on compiled binaries of x86/Linux programs written in languages such as C and C++, and the other works on compiled Java programs (bytecodes). The implementation section of this chapter (Section 4.3) will only describe DynComp, the version for compiled

x86/Linux binaries which I built using the Fjalar framework. As will be evident in Section 4.3.2, the nature of our algorithm lends itself well for implementation using a mixed-level approach. Our experiments (Section 4.4) indicate that the analysis is precise, that its results aid humans in program understanding, and that its results improve the precision of a follow-on client analysis.

4.1 Motivation

Even in explicitly-typed languages, the declared types capture only a portion of the programmer's intent and knowledge about variable values. For example, a programmer may use the `int` type to represent array indices, sensor measurements, the current time, file descriptors, counts, memory addresses, and a host of other unrelated quantities. The type `Pair<int,int>` can represent coordinate points, a Celsius/Fahrenheit conversion, a quotient and remainder returned from a division procedure, etc. Different strings or files can represent distinct concepts. Regular expressions can be applicable to different contents. Variables declared with the same generic type, such as `Object` or `Comparable`, need not hold related values.

Use of a single programming language type obscures the differences among conceptually distinct values. This can hinder programmers in understanding, using, and modifying the code, and can hinder tools in performing analyses on the code. Therefore, it is desirable to recover finer-grained type information than is expressed in the declared types. We call these finer types *abstract types*; this chapter presents a dynamic analysis for inferring abstract types.

The abstract type information is useful for program understanding [41].

- It can identify ADTs (abstract data types) by indicating which instances of a declared type are related and which are independent.
- It can reveal abstraction violations, when the inferred types merge values that

should be separate, as indicated by either the declared types or by a programmer's expectations.

- It can indicate where a value may be referenced (only at expressions that are abstract-type-compatible with the value).
- It can be integrated into the program, effectively giving the program a richer type system that can be checked at compile-time. For instance, this could be done using `typedef` declarations in C or ADTs in an object-oriented language.

The finer-grained abstract type information can also be supplied to a subsequent analysis to improve the run time or the results of that analysis. Since our abstract type inference is dynamic, its results are most applicable to a follow-on analysis that does not require sound information (for example, using it as optimization hints), that is itself unsound (such as a dynamic analysis, or many machine learning algorithms), that verifies its input, or that produces results for human examination (since people are resilient to minor inaccuracies). Here are a few examples of such analyses.

- Dynamic invariant detection [15, 32, 25] is a machine learning technique that infers relationships among variable values. Abstract types indicate which variables may be sensibly compared to one another. Directing the detection tool to avoid meaningless comparisons eliminates unnecessary computation and avoids overfitting [16].
- Principal components analysis (PCA) approximates a high-dimensional dataset with a lower-dimensional one, by finding correlations among variables. Such correlations permit a variable to be approximated by a combination of other variables; the reduced dataset is generally easier for humans to understand. Abstract types can indicate variables that are *not* related and thus whose correlations would be coincidental. For example, this could be applied to work that uses PCA over program traces to group program constructs [29].

- Dynamic analysis has been used to detect features (or errors) in programs, by finding correlated parts of the program [55, 44, 56, 14, 21, 22]. Abstract types could refine this information, making it even more useful.
- Abstract types can partition the heap, providing useful information to memory hierarchy optimizations. For example, a group of objects that are likely to be connected in the heap can be allocated on the same page or in the same arena. This can reduce paging when accessing the data structure. A related optimization is to allocate related elements to locations that will not contend for cache lines, reducing thrashing for elements likely to be accessed together.
- Abstract types are related to slices [53, 51], so they can be used for many of the same purposes, such as debugging, testing, parallelization, and program comprehension.
- Abstract types chosen to match the operators used in a later analysis can improve efficiency by allowing the analysis to consider only pairs of variables of the same abstract type, or consider all variables of an abstract type together.

4.2 Dynamic Inference of Abstract Types

We present a unification-based dynamic analysis for partitioning variables into abstract types based on the interactions of the values they held during execution.

Abstract types provide a division of program variables or values into sets of related quantities. For a given program, there are many ways to make this distinction, and different partitions are useful for different purposes. No analysis is guaranteed to produce exactly what the programmer would intend for a given purpose (that is unknowable and inherently subjective, and the program may not perfectly express the programmer's intent), but our goal is to produce information about the program that is sufficiently accurate to be used by people and by follow-on tools.

The key idea of our analysis is to recover information that is implicit in the program. The operations in the program encode the programmer's intent: values that interact in the program must be intended to have the same abstract type (or else the interaction indicates a bug), and values that never interact may be unrelated. More concretely, an operation such as `x+y` indicates that the values of `x` and `y` have the same abstract type. The notion of "interaction" is parameterizable and is further described in Section 4.2.1. Our analysis ignores the underlying type system, including all casts, and unifies the abstract types of two values when they interact.

A *value* is a concrete instance of an entity that a program operates on, such as a particular dynamic instance of the number `42` or the string `"foobar"`. New values can be created via literals, program inputs, memory allocation, or other operations. For example, every time `3 + 5` is executed, a new value is created for 3, a new value is created for 5, and the addition operator creates a new value. By contrast, `x=y` creates no new values — it merely copies one.

An abstract type can be inferred either for variables or for values. Variables are merely containers for values, so a variable can hold many distinct values during its lifetime. For example, in "`x=3; y=3; x=y;`" there are two values (both of which represent the same number), and at the end of execution both variables hold one of them. However, `x` has held two distinct values during its lifetime. This is similar to the way objects in Java work — compare "`x=new Object(); y=new Object(); x=y;`" — but we extend the notion to primitives. Unlike objects, for primitives there is no way to tell by looking at the program state whether two instances of 3 are the same value, but a dynamic analysis can track this information.

Our dynamic abstract type inference works by observing dataflow and value interactions, unifying the sets that represent the abstract types of values that interacted (Section 4.2.1), and then constructing abstract types for variables based on the abstract types of the values they held (Section 4.2.2). It operates dynamically on values

rather than statically on variables (as in [41, 40]), permitting it to produce precise results. We have not observed overfitting to be a problem in practice. If desired, the information can be checked by a type system or similar static analysis, and the combined dynamic–static system is sound, so its results can be used wherever a static abstract type inference's could be.

4.2.1 Tracking dataflow and value interactions

Our algorithm tracks the flow and interactions of values throughout execution, partitioning values into disjoint sets called *interaction sets*. To accomplish this, it maintains a tag along with each value, which represents the value's abstract type. A global union-find data structure called `value_uf` groups the tags into disjoint interaction sets, each of which contains values that belong to the same abstract type (values that have interacted). Only values of primitive types receive tags; arrays and instances of structs and classes are treated as collections of primitive types. One tag in each set is a canonical representative, called the *leader*, and is used to represent the set when performing operations in `value_uf`.

Tags are created and propagated to reflect the dynamic dataflow that occurs during execution. Every new value created during execution receives a unique tag, which is initially placed in a new singleton set within `value_uf` to denote that it represents a unique abstract type. New values include dynamic instances of literals, inputs such as program arguments and values read from a file, and results of operations such as `+` or memory allocation.

As a value propagates (is copied) during execution, its tag always accompanies it, thus tracking dataflow. For instance, in an assignment `x = y`, when the value stored in `y` is copied into `x`, the tag associated with the value is copied as well. Procedure arguments and return values are treated in exactly the same way. This propagation of tags is somewhat similar to the propagation of abstract identifiers in a static dataflow

analysis, but a key feature is that it occurs only when dataflow actually occurs during execution. In the terminology of static analysis, our technique is completely context-, flow-, and path-sensitive.

Definitions of interaction

In addition to recording dataflow, our analysis classifies values as having the same abstract type (by unifying the sets of their tags in `value_uf`) if they are used together ("interact") in certain operations. The notion of what operations qualify as interactions is parameterizable, and we present 4 useful definitions of interaction among primitive and reference values that we have implemented:

Dataflow - No binary operations are interactions. Thus, every value belongs to a singleton set, which represents a unique abstract type. This tracks dataflow because two variables have the same abstract type if one value transitively flowed from one variable to the other (i.e., via assignment or parameter passing).

Dataflow and comparisons - Under this definition, two values that are operands to a comparison operator (e.g., `<` and `==`) interact, so their tags are unified together in one interaction set within `value_uf`. The result of the comparison is conceptually a boolean value that is unrelated to the operands, so it receives a fresh tag representing a unique abstract type.

Units - This definition ensures that all variables with the same abstract type could be assigned the same units under the usual scientific rules that values may only be added, subtracted, or compared if they have the same units. Thus, these operations are considered interactions, but other operations, such as multiplication and division, are not.

Arithmetic - This is the most inclusive definition of interaction, yielding the fewest abstract types (with the most members). This is the default mode for our

implementations, as we believe it is easier for users to split up sets that are too large than to combine sets that were not recognized as related.

- Comparisons are interactions between operands.
- All arithmetic (`+`, `-`, `*`, `/`, `%`, etc.) and bitwise (`&`, `|`, etc.) operations are interactions between the two operands and the result, so all 3 values have the same abstract type after the operation.
- Shift operations (`<<`, `>>`, etc.) are interactions between the quantity being shifted (left operand) and the result. In practice, we have noticed that the shift amount (right operand) is usually not closely related to the quantity being shifted, so this setting yields more precise interaction sets.

Note that logical operators such as `&&`, `||`, and the ternary `?:` operator do not produce interactions, because no close relationship need exist between the operands, especially in C when operands are often numbers or pointers instead of booleans.

4.2.2 Inferring abstract types for variables

Our analysis infers abstract types for variables based on the interaction sets of values: roughly speaking, variables will be in the same abstract type if they held values from the same interaction set. This section describes two algorithms for constructing abstract types, which give somewhat different results when the interaction sets themselves change over time: the first algorithm is relatively simple, while the second algorithm is more complex, but corresponds to a somewhat more consistent definition of abstract types. In either case, our approach is to compute abstract types separately for variables at certain static points in a program; we call each such location a *site*.

For the first variable type inference algorithm, each site has an associated union-find data structure representing a partition of the variables at the site: before execution, each variable is in its own singleton set. Now, suppose that `x` and `y` are two

```
1.  for each variable v:
2.    Tag leader = value_uf.find(var_tags[v])

      # If var_tags[v] is no longer the leader of its interaction set,
      # then its set has been merged with another set in value_uf
3.    if leader != var_tags[v]:
        # Merge corresponding sets in type_uf and
        # maintain that var_tags[v] is the leader
4.      var_tags[v] = type_uf.union(leader, var_tags[v])

      # If needed, create entry for new value in type_uf
5.    Tag new_leader = value_uf.find(new_tags[v])
6.    if new_leader not in type_uf:
7.      type_uf.make_singleton(new_leader)

      # Merge new tag with existing tags in type_uf
8.    var_tags[v] = type_uf.union(var_tags[v], new_leader)
```

Figure 4-1: Pseudocode for the propagation occurring at each site execution that translates from value interaction sets to abstract types for variables

variables at a particular site, and that on a particular execution they have the values v_x and v_y. The simple algorithm checks whether v_x and v_y are in the same interaction set at that moment of execution, and if so, merges the variable sets containing `x` and `y`. After execution, the abstract types are simply the sets in the union-find structure. A potentially unsatisfying aspect of this algorithm is that while value interactions that occur before the execution of a site affect the abstract types, those that occur afterwards may not, if the variable never again has values from that interaction set.

To avoid the asymmetry in the simple algorithm just described, we developed a more complex algorithm whose definition of abstract type does not depend on the order in which value interactions occur. I have implemented this more complex algorithm in DynComp. The key difference in the second algorithm is that rather than creating abstract types grouping variables directly, it constructs abstract types by first grouping value interaction sets, and then using these groups to define sets of variables. The effect of this choice on the algorithm's results is that its abstract types always correspond to unions of whole value interaction sets, rather than parts

of interaction sets. In other words, if a variable `x` had a value v_x at one execution of a site, the variable `y` had a value v_y at a different execution, and v_x and v_y interacted, then `x` and `y` will be in the same abstract type, even if there was no single execution of the site at which the values of `x` and `y` had interacted or would interact in the future. To implement this approach, the second algorithm does not use a union-find structure representing a partition of variables at each site; instead, it uses a union-find structure representing a partition of value interaction sets.

To be precise, the union-find structure maintains a partition of tag values which at some point were leaders (canonical representatives) of value interaction sets. Such tags are grouped together either as the value interaction sets grow (if an interaction set merged to create a larger one, the old and new leaders are grouped), or as variables take values from different interaction sets on subsequent site executions (the leaders of the previous and current sets are grouped). To maintain the connection between value interaction sets and variables, the algorithm also keeps track, for each variable, of the leader of the interaction set of the most recently observed value of the variable. A pseudocode representation of the steps performed by the algorithm at each execution of a site is shown in Figure 4-1. At each execution of a site, the tool collects the tags for the values of all the variables at the site into an array named `new_tags`; `new_tags[v]` is the tag for the value of the variable `v`. The algorithm first updates the representative tag for each variable value seen on the previous execution, to account for interaction set merges that have occurred between site executions (lines 2–4 of Figure 4-1), and then merges the sets containing the representatives of the previous and current value interaction sets (line 8), creating a new set for the current value if it does not yet exist (lines 5–7). The algorithm's results should also reflect interactions that occur even after the final execution of a site, so it performs a final iteration of propagating merges of interaction sets (as in lines 2–4) for each site at the very end of execution.

At every site at the end of program execution, for every variable `v`, `var_tags[v]` holds the tag for that variable. `type_uf` is the union-find structure that groups tags together into sets which represent the abstract types. All variables at a site with the same tag or with tags in the same set in `type_uf` belong to the same abstract type.

The efficient union-find data structure allows this algorithm to run in almost linear time, $O(n)$, where n is the number of variables. One reason for the algorithm's apparent complexity is to achieve the almost $O(n)$ running time, which is important for scalability. A much more straightforward alternative algorithm works by making a boolean table at each site where each row and column corresponds to a variable. At every site execution, if two variables v_1 and v_2 are holding values that are in the same interaction set, then put a 'check mark' in the table entry for (v_1, v_2). Then at the end of execution, merge pairs of variables with 'check marks' in the table into sets which represent the abstract types. This is $O(n^2)$ in both time and memory, but potentially provides more precision over the $O(n)$ algorithm of Figure 4-1. I have implemented this alternative but have not done much testing to determine whether the precision versus performance tradeoff is worthwhile.

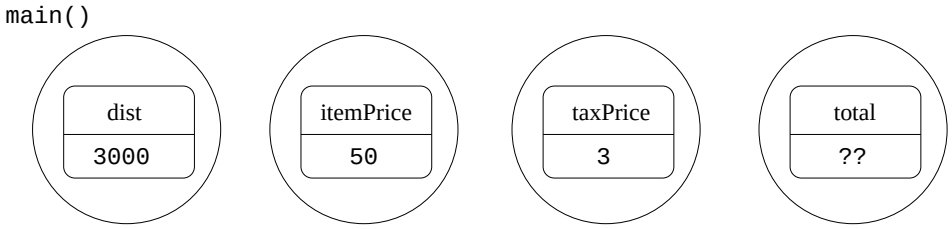
4.2.3 Example

I will use the program in Figure 4-2 to illustrate the operation of the dynamic abstract type inference algorithm. This program performs a simple cost calculation, adding in an extra shipping fee if the distance is greater than 1000 and the year is after 2000. All of the variables are of type `int`, but there are really three abstract types: *Distance*, *Money*, and *Time*. The analysis will be able to find these three types, but of course it will not be able to assign names to those types; that is the user's job. I will now run through the algorithm at a very high level using a series of diagrams.

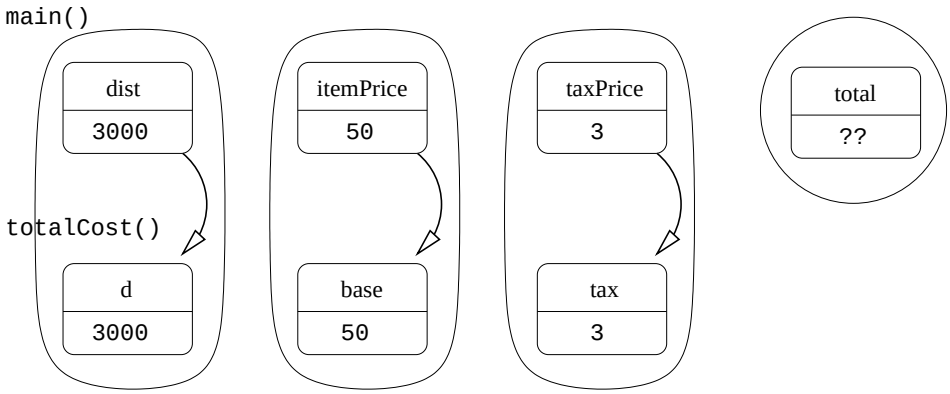
```
1.   int main() {
2.     int dist = 3000;
3.     int itemPrice = 50;
4.     int taxPrice = 3;
5.     int total = totalCost(dist, itemPrice, taxPrice);
6.   }

7.   int totalCost(int d, int base, int tax) {
8.     int year = 2006;
9.     if ((d > 1000) && (year > 2000)) {
10.      int shippingFee = 10;
11.      return base + tax + shippingFee;
12.    }
13.    else {
14.      return base + tax;
15.    }
16.  }
```

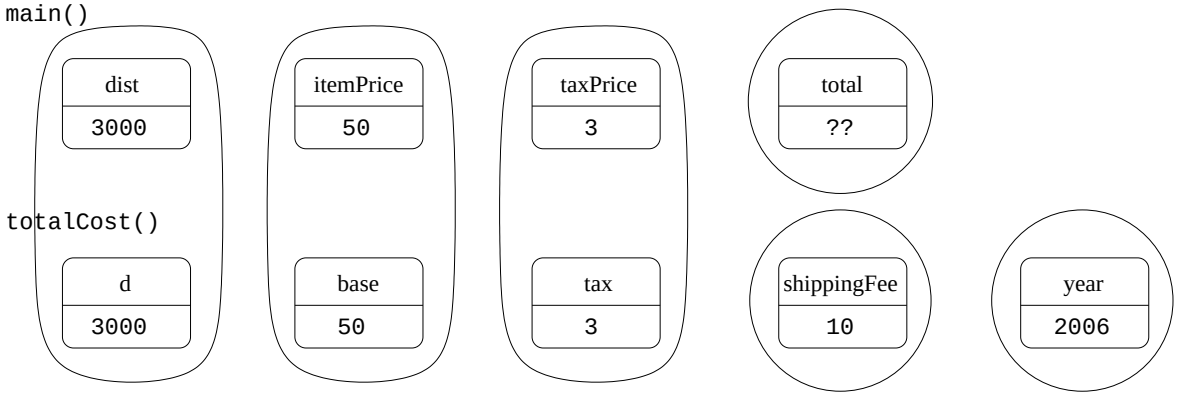
Figure 4-2: An example C program that uses `int` as the declared type for variables of several different abstract types



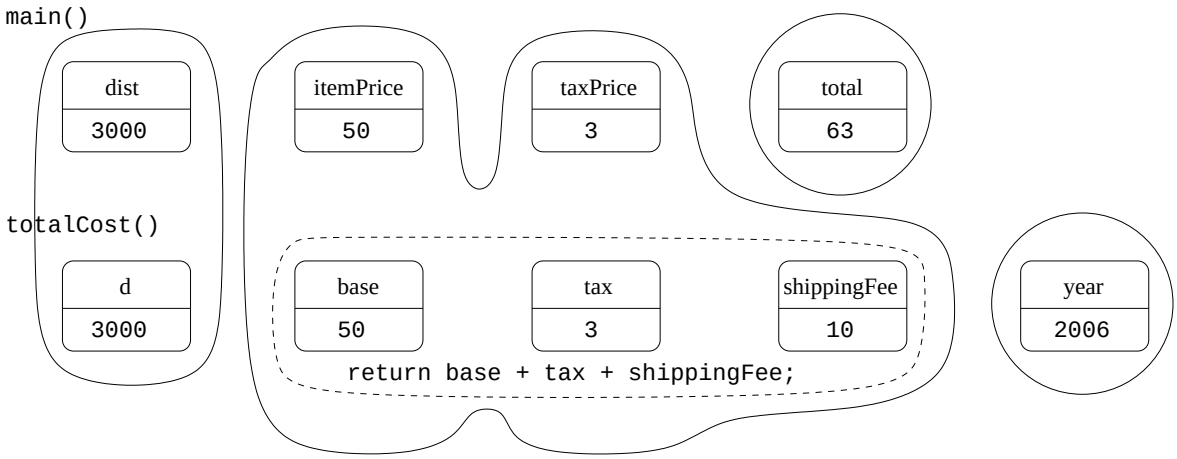
The figure above shows the state of variables and their abstract types while the program is in the middle of executing line 5 in Figure 4-2, just prior to the call to `totalCost()`. 4 local variables have been declared in `main()`. Each receives a fresh tag and is placed in a singleton set, denoted by the circles around each variable/value pair.



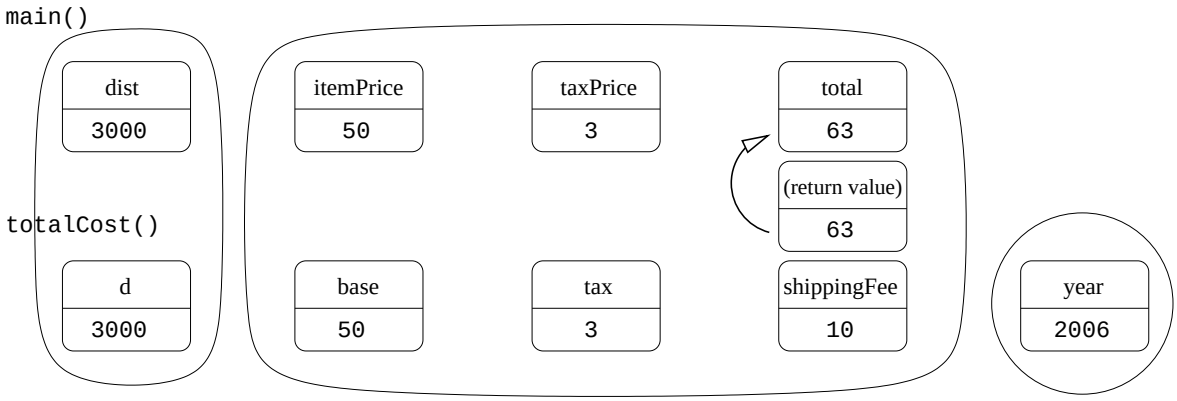
Upon entrance to `totalCost()` in line 7, the values of the 3 arguments from `main()` are copied into the parameters, as shown by the arrows in the figure above. Thus, the 3 argument-parameter pairs belong to the same set because they now hold the same values.



The figure above shows the state after executing line 10. 2 new local variables, `shippingFee` and `year`, are created and placed into singleton sets. Notice that no merging of sets occurs in line 9 because both variables are compared to fresh numeric literals and the `&&` operator does not qualify as an interaction.



Line 11 is where all of the interesting action occurs. The dotted lasso in the figure above shows the merging of the interaction sets of the three variables involved in the addition operation. The solid lasso that surrounds the variables `itemPrice`, `taxPrice`, `base`, `tax`, and `shippingFee` is the one large interaction set that resulted from the merging denoted by the dotted lasso. At this point, it becomes evident that this large set represents the abstract type of *Money*. However, `total` still belongs to a singleton set, but intuitively it also represents some quantity of Money. The next step resolves this disparity.



The process of returning from `totalCost()` back into `main()` involves first creating a pseudo-variable that holds the return value (recall that the result of an addition operation belongs to the same interaction set as the operands: `base`, `tax`, and `shippingFee`), copying that value into `total` (denoted by the arrow in the figure

```
1.   int main() {
2.     Distance dist = 3000;
3.     Money itemPrice = 50;
4.     Money taxPrice = 3;
5.     Money total = totalCost(dist, itemPrice, taxPrice);
6.   }

7.   Money totalCost(Distance d, Money base, Money tax) {
8.     Time year = 2006;
9.     if ((d > 1000) && (year > 2000)) {
10.      Money shippingFee = 10;
11.      return base + tax + shippingFee;
12.    }
13.    else {
14.      return base + tax;
15.    }
16.  }
```

Figure 4-3: The program of Figure 4-2 after running our dynamic abstract type inference algorithm

above), and as a result, merging the singleton interaction set of `total` with the large 5-element set. Notice how the dynamic nature of this algorithm provides perfect context-sensitivity via value flows. The analysis could recognize that `total` had the same abstract type as `itemPrice` and `taxPrice`, even though the interaction occurred within another function.

At this point, the target program finishes executing and the analysis terminates, providing a partition of three abstract types for all of the variables. It presents the results in the form of sets of variables belonging to the same abstract type, and the user must use his/her intuition to provide names for these types. In this example, the names could be *Distance*, *Money*, and *Time* for the leftmost, middle, and rightmost sets, respectively. A follow-on tool could re-insert these named types back into the program's source code as `typedef`s or other annotations, as shown in Figure 4-3.

4.3 Implementation

I have implemented a tool named DynComp that performs the analysis described in Section 4.2 on C and C++ target programs for x86/Linux. (A colleague implemented a similar tool for Java programs.) DynComp is built on top of Fjalar, so it computes abstract types for global variables and function parameters at every program point (function entrance and exit) and return values at exit points (that is, the *sites* are function entrance and exit points). Note that the analysis is much more general than my particular implementation (limited by Fjalar's features) and can compute abstract types for any kind of variable either more or less frequently.

4.3.1 Tracking dataflow and value interactions

The value tracking algorithm (Section 4.2.1) is performed purely at the binary level, and operates on all code, including libraries. It is implemented by directly using Valgrind's binary instrumentation API. Instrumentation code maintains a 32-bit integer for every byte of memory and every register, to represent the tag of the value currently stored in that location. This is implemented as a sparse data structure which only allocates tags for memory that is currently in use so that the overhead is only proportional to the amount of memory used by the target program. For every machine instruction that copies values from or to memory or registers, DynComp adds a corresponding instruction to copy the tags of the copied bytes. For every machine instruction that qualifies as an interaction, DynComp adds instructions to merge the sets of the operands' tags in `value_uf`. Values that interact with the stack pointer are treated specially: unrelated pointer values (such as local variable addresses) are not counted as related merely because they are calculated as offsets from `ESP` or `EBP`.

New tags are created in response to two events: dynamic occurrences of literals, and program input. For example, each time the instructions corresponding to the

code `y = 42` are executed, a new tag is assigned to the memory location where `y` is located. Initialization of memory, such as the zero-filling performed by `calloc()`, is another example of new tags created from literals. Valgrind notifies DynComp when a system call such as `read` stores new data in the program's address space; these bytes also receive fresh tags.

To illustrate, consider the code `z = x + y`. This can be compiled roughly into four instructions: a load of the value of `x` into the register `EAX`, a load of `y` into `EBX`, an addition of `EAX` and `EBX`, and a store of `EAX` to wherever `z` is located in memory. For this code, DynComp instruments the binary with instructions to first copy the tag of the value of `x` in memory into the tag of `EAX`, then copy the tag of `y` into the tag of `EBX`, unify (merge) the interaction sets of the tags of `EAX` and `EBX` (because addition is an interaction in the default mode of operation), and finally store the tag of `EAX` (the result) as the tag of the value of `z` in memory.

4.3.2 Inferring abstract types for variables

DynComp subclasses the `FunctionEntry` class from the Fjalar API to add in extra fields to hold per-program-point data structures such as `new_tags`, `var_tags`, and `type_uf` shown in the pseudo-code of Figure 4-1. Then, the conversion between value interactions and variable abstract types (Section 4.2.2) is implemented by creating an action callback function (similar to the one in `basic-tool.c` in Section 2.4) that, during variable traversal at each program point execution, reads the tags of the values of variables from memory into `new_tags` and executes the algorithm of Figure 4-1. The options that DynComp passes into Fjalar to determine which program points and variables to trace control the scope of the analysis. Because most variables hold values that span more than one byte, when those values are read, the interaction sets of tags for all the bytes are merged in `value_uf` to denote that those bytes all represent a single value.

The requirements of the dynamic abstract type inference algorithm demonstrates the power and applicability of the mixed-level approach. This algorithm requires accurate value tracking, which can be done more easily at the binary level, and also a translation from value-based information to variable-based information at every program point (Figure 4-1), which requires source-level information about variables and functions throughout execution. It would be theoretically possible to perform this analysis as a pure binary-only analysis, collecting a full trace of value flow and interactions throughout execution and performing post-processing, but that would be prohibitively inefficient. A pure source-only analysis would be even more impractical because fine-grained value flows are very difficult to trace by instrumenting source code alone. The mixed-level approach makes it possible to access binary- and source-level information throughout the duration of the target program's execution and thus allows the analysis to run quite efficiently in both time and memory.

4.3.3 Optimizations

These optimizations are important to reduce memory overhead for maintaining tags.

Garbage collection of tags: To avoid unbounded memory overhead, I have implemented a garbage collector which periodically scans the tags held in memory and registers as well as in the `type_uf` structures at each site. Unclaimed tags are reused when new values are created.

Eager canonicalization: Tags are replaced by their leaders (the canonical members of sets in `value_uf`) whenever possible to reduce the total number of non-garbage tags in use. For example, when several bytes are copied from one memory location to another, instead of merely copying the tags, DynComp finds the leaders of those tags in `value_uf` and replaces the tags, at both the source and destination locations, with their leaders.

4.4 Evaluation

I evaluated DynComp in several ways. First, I carefully analyzed a small program by hand, to verify that the results were accurate (Section 4.4.1), meaning that they matched up well with human intuition about abstract types. Second, I performed a case study of two programmers who were trying to understand and modify unfamiliar programs; I observed whether the analysis results assisted them in their tasks (Section 4.4.2). Third, I measured how much the inferred types improved the results and efficiency of a follow-on analysis (Section 4.4.3). Fourth, I compared the results of static abstract type inference to our dynamic abstract type inference (Section 4.4.4).

My experiments use the following subject C programs. All line counts are non-comment, non-blank. I ran each program once, on a single input that is also noted below.

- `wordplay` (740 LOC): anagram generator, using a 38KB dictionary
- RNAfold (1804 LOC, of which 706 LOC are in `fold.c`): secondary structure predictor, folding a length-100 RNA sequence, only tracing program points within `fold.c`
- SVM-Light (5834 LOC): support vector machine learning tool, training an SVM on a 474-line input
- `bzip2` (5128 LOC): file compressor, running on a 32KB text file of `gcc` source code
- `flex` (11,977 LOC): lexical analyzer generator, running on the lexical grammar for C
- `perl` (110,809 LOC): scripting language implementation, interpreting a 672-line sorting program from its test suite (our analysis ignored all global variables)

	wordplay	RNAfold	SVM-Light	bzip2	flex	perl
Representation Type	23	42	12	38	190	53
Declared Type	6.2	20	4.5	7.9	87	21
Abstract Type (DynComp)	3.5	18	4.7	1.9	2.4	7.8

Table 4.1: Average number of variables in a type for each site. Section 4.4.1 describes the varieties of type.

4.4.1 Accuracy

Table 4.1 shows the number of variables that share a type in our subject programs, averaged over all function entrances and exits. These averages do not include pointer variables, because abstract types of pointers (as opposed to their contents) are rarely interesting. "Representation types" group all variables into four types based on their machine representation: integer, floating-point, string, and addresses (pointers). "Declared types" group variables by their declared types in the program's source code, thus distinguishing between signed and unsigned integers, integers of different sizes (e.g., `int`, `short`), and type aliases defined using `typedef`. "Abstract types" use the output of DynComp. In general, the abstract types are significantly finer-grained than the declared types, with the exception of SVM-Light, which contained many interactions between variables of different declared types (i.e., `int`s interacting with `short`s); DynComp ignores declared types when performing its analysis, so it can be possible for variables of different declared types to belong to the same abstract type, as demonstrated by SVM-Light.

In order to assess the accuracy of DynComp, I compared its output to a careful manual analysis of the `wordplay` anagram generator program. My hand analysis involved surmising programmer intent by reading code comments and looking at how variables are used throughout the program. It produced abstract types that matched well with human intuition (I did not write this program, so I do not know what abstract types the programmer truly intended to include, but my inferences seem reasonable). The `wordplay` program is small (740 lines); an exhaustive hand

	Global variables	Declarations and comments from `wordplay.c`
Type 1	`keymem`	`char *keymem; /* Memory block for keys */`
	`largestlet`	`char largestlet;`
	`words2mem`	`char *words2mem; /* Memory block for candidate words */`
	`*words2`	`char **words2; /* Candidate word index (pointers to the words) */`
	`*words2ptrs`	`char **words2ptrs; /* For copying the word indexes */`
	`*wordss`	`char **wordss; /* Keys */`
Type 2	`ncount`	`int ncount; /* Number of candidate words */`
	`*lindx1`	`int *lindx1;`
	`*lindx2`	`int *lindx2;`
	`*findx1`	`int findx1[26];`
	`*findx2`	`int findx2[26];`
Type 3	`longestlength`	`int longestlength; /* Length of longest word in words2 array */`
	`max_depth`	`int max_depth;`
Type 4	`*wordsn`	`int *wordsn; /* Lengths of each word in words2 */`
Type 5	`*wordmasks`	`int *wordmasks; /* Mask of which letters are contained in each word */`
Type 6	`rec_anag_count`	`int rec_anag_count;/*For recursive algorithm, keeps track of number of anagrams found */`
Type 7	`adjacentdups`	`int adjacentdups;`
Type 8	`specfirstword`	`int specfirstword;`
Type 9	`maxdepthspec`	`int maxdepthspec;`
Type 10	`silent`	`int silent;`
Type 11	`vowelcheck`	`int vowelcheck;`

Table 4.2: Abstract types inferred by DynComp for all global variables within `wordplay`. A variable with a star (`*`) preceding its name represents the contents that a pointer variable refers to.

examination is not feasible for larger programs. Indeed, the difficulty of such an analysis is a motivation for the DynComp tool.

I ran `wordplay` with DynComp on an 18-letter string to anagram and a 38KB dictionary, achieving 76% coverage of the executable lines. My evaluation considers all 21 global variables. DynComp places them in 11 abstract types, each denoted by a set in Table 4.2. My manual analysis finds 10 abstract types, merging types 3 and 4 in the table; otherwise, my manual analysis, and the code comments, are consistent with DynComp's results.

The declared types and comments indicate that Type 1 represents the abstract type of "words" in the program. Variable `largestlet` represents the largest letter found in some word, and although it is of type `char` instead of `char*`, code inspection confirms that it interacts with characters within the `wordss` array, so thus it has the same abstract type as the other variables in the set.

Type 2 contains variables related to indices into arrays of words. These code comments reveal how the programmer intended to use these variables:

```
/* Create indexes into words2 array by word length.
   Words of length i will be in elements lindx1[i]
   through lindx2[i] of array words2.
...
/* Create indexes into wordss array by first letter.
   Words with first letter "A" will be will be in
   elements findx1[i] through findx2[i] of array wordss.
```

`*lindx1` and `*lindx2` are indices into the array `words2`, and `*findx1` and `*findx2` are indices into the array `wordss`. Thus, all four indices belong to the same abstract type since the contents of the `words2` and `wordss` arrays both belong to the same abstract type. `ncount` interacts with `*lindx2` to produce these indices.

Type 3 contains variables that test whether the base case of a recursive function has been reached, in this line of code:

```
if ((max_depth - *level) * longestlength < strlen(s))
```

Comments in the code indicate that `longestlength` and `*wordsn` should belong to the same abstract type representing "length of word in `words2` array", but DynComp fails to recognize this relationship because their values never actually interact. `longestlength` is initialized with return values of independent calls to `strlen()`, not from cached elements of `wordsn`. DynComp thus places `*wordsn` into its own singleton set (Type 4). No analysis — static or dynamic — that infers abstract types via value interactions could notice this relationship.

Type 5 contains the contents of the `wordmasks` array, which holds "mask[s] of which letters are contained in each word", according to the comments in the declaration. DynComp correctly separates the contents of this integer array from the other integer and integer array content variables in Types 2, 3, and 4.

DynComp correctly placed the remaining variables in singleton sets (Types 6–11) because no interactions occurred among them and variables in other sets.

4.4.2 User studies

Two MIT researchers (who are not members of our research group) who were struggling with reverse engineering problems volunteered to try using DynComp to assist them with their C programming.

RNAfold

The first researcher is a computational biologist who had recently refactored RNAfold, an 1804-line RNA folding program [26]. The refactoring converted 55 `int` variables of the abstract type "energy" into type `double`. The program has hundreds of non-energy-related `int` variables. His hand analysis statically emulated the operation of DynComp, building up sets of related variables by tracing assignments, function calls, and binary operators in the source code. It took him approximately 16 hours of work

to find all the energy variables. He described the process as tedious and error-prone; two iterations were required before he found everything.

I ran DynComp on RNAfold with a test case of a single 100 base pair RNA sequence extracted from a public database (achieving 73% statement coverage of `fold.c`, where the algorithm resides). I showed the inferred sets of abstract types to the researcher and observed his reactions and comments. One 60-element set contained all of the energy variables the researcher had found via manual code inspection. That set also contained 5 index variables, which had interacted with energy variables during complex initialization code. Although the researcher's notion of abstract types did not perfectly match the tool's definition, this minor mismatch was no hindrance: the researcher easily and quickly recognized and filtered out the few non-energy variables.

The DynComp results gave the researcher increased confidence in his refactoring. He estimated that instead of spending approximately 16 hours of manual analysis, he could have set up the test, run the tool, observed the results, and filtered out inaccuracies in 1 or 2 hours.

SVM-Light

The second researcher was trying to understand SVM-Light, a 5834-line support vector machine implementation [27]. His goal was to create a hardware implementation. He was familiar with SVM algorithms but unsure of how SVM-Light implemented a particular algorithm.

I ran SVM-Light once to train the SVM to predict whether income exceeds \$50K/yr based on census data (achieving 37% statement coverage). The DynComp output, the variable names, and the source code and comments confirmed his intuitions about how the mathematical variables in the SVM algorithm mapped into program variables in code. For example, at one particular site, there was a perfect correspondence between his notion of abstract types and what DynComp inferred,

for variables that dealt with calculating error bounds to determine whether to shift the SVM up to higher dimensions.

The researcher noted that the variable `buffer` appeared in large sets at many sites, and he initially suspected imprecision in DynComp. After double-checking the code, though, he saw that `buffer` was used pervasively to hold temporary calculation results for many different operations. He had previously thought that `buffer` was only confined to a few core operations, so he learned a new fact about the program in addition to verifying what he already knew.

4.4.3 Dynamic invariant detection

Section 4.4.2 evaluated whether abstract types are useful to programmers. This section evaluates whether abstract types can improve the results of a follow-on analysis.

As described in Section 4.1, abstract types are applicable to many analyses; for concreteness, our evaluation uses the Daikon dynamic invariant detection system [15] (described in greater detail in Section 3.1.1).

Finer types than those that appear in the program source can aid Daikon in two ways. First, they can improve run-time performance, because there is no need to hypothesize or check properties over variables of different abstract types. More importantly, they can improve output quality by reducing irrelevant output: if fewer properties are hypothesized, then fewer false positives will result. Daikon has been applied to dozens of problems in software engineering and other fields [42], so improving its results is a practical and realistic problem.

Currently, one of the biggest usability limitations of Daikon is the fact that it generates many correct but uninteresting invariants. For instance, it might find for two `int` variables `arr_index` and `cur_year` that `arr_index < cur_year`. This is probably correct if `arr_index` represents an index into a small array and `cur_year` represents a year, but this is an uninteresting invariant because those two variables have dif-

Treatment	Daikon		
	time (sec)	memory (MB)	# invariants
wordplay			
Representation types	7	24	34,146
Declared types	6	24	25,593
Lackwit	5	24	4,281
Abstract types	5	24	2,915
RNAfold			
Representation types	11	66	2,052
Declared types	10	66	2,052
Lackwit	10	66	1,016
Abstract types	10	66	840
SVM-Light			
Representation types	35	30	8,900
Declared types	39	30	8,900
Lackwit	41	30	7,486
Abstract types	35	30	7,758
bzip2			
Representation types	172	151	12,932,283
Declared types	175	151	12,879,392
Lackwit	162	155	549,555
Abstract types	173	156	340,558
flex			
Representation types	>12,384	>1,700	out of memory
Declared types	>10,573	>1,700	out of memory
Lackwit	2285	537	437,608,949
Abstract types	1980	371	8,144,916
Perl (ignoring all global variables)			
Representation types	266	220	1,371,184
Declared types	275	215	1,366,463
Abstract types	276	221	1,029,096

Table 4.3: Effect of types on a follow-on analysis, dynamic invariant detection. All tests were run on a P4 3.6GHz PC with 3GB RAM.

ferent abstract types. DynComp's output can direct Daikon to only find invariants over variables with the same abstract type, thus improving the quality of generated invariants by reducing the number of uninteresting ones.

I measured the effect of the type declarations on Daikon's run time and maximum heap (memory) size, and also on the size of Daikon's output (the number of

hypothesized invariants). For implementation simplicity, Daikon assumes that the type information that it is given is transitive; that is, if variables `a` and `b` have the same abstract type, and so do `b` and `c`, then variables `a` and `c` have the same abstract type. This is not necessarily true in our dynamic context, but DynComp performed this merging (which reduces precision) before presenting the information to Daikon. DynComp's run time was approximately the same as Daikon's, so it is a reasonable preprocessing step.

Table 4.3 shows the results (the rows labeled "Lackwit" are for a static analysis that will be explained in Section 4.4.4). Unfortunately, Daikon's run times and memory usage remained about the same, probably because there is processing involved in discarding irrelevant invariants (my colleagues have not had time to look into optimizing Daikon to take advantage of abstract type information in detail). However, Daikon produced fewer invariants for treatments with smaller average set sizes. As with the results for average set sizes in Table 4.1, the effect tends to be more pronounced on larger programs. For `flex`, abstract type information makes the difference between being able and unable to run Daikon at all, and the more precise dynamically-collected information yields a more than 50-fold decrease in the number of hypothesized invariants. The two rows whose memory usage are labeled ">1,700" indicate incomplete runs that exceeded the maximum memory available to a Java process on this architecture.

In order to verify that the invariants eliminated by the abstract type information produced by DynComp were in fact spurious, I exhaustively examined all the differences between Daikon's output using declared types and abstract types on several smaller examples. For SVM-Light, I performed the hand-evaluation together with the researcher in the user study. He confirmed that all but one eliminated invariant were spurious, because they all falsely related variables of different abstract types. There were several instances of Daikon falsely relating two integer variables, one of which

Abstract types	wordplay	RNAfold	SVM-Light	bzip2	flex	perl
Lackwit (static)	9.1	29	5.6	2.1	14.6	n/a
DynComp (dynamic)	3.5	18	4.7	1.9	2.4	7.8

Table 4.4: Average number of elements in an abstract type, as computed by the static tool Lackwit and the dynamic tool DynComp.

was used as an enumerated value but declared as an `int` and assigned small constant symbolic values defined in `#define` statements. For the one invariant that he said should not have been eliminated, the two variables had a control-flow-based (rather than a dataflow-based) relationship, so our tool was not able to assign them to the same abstract type. I also examined the differences in RNAfold and again saw that almost all eliminated invariants were spurious. Less detailed examinations of other test programs seem to confirm these conclusions.

4.4.4 Comparison to static analysis

Abstract type inference can be performed statically as well as dynamically, and the two approaches have different tradeoffs. This section repeats the evaluation of Sections 4.4.1, 4.4.2, and 4.4.3, using a static abstract type inference tool, Lackwit (described in detail in Section 4.5.1), whose goals and output format are the same as those of DynComp.

Accuracy

Table 4.4 shows the average size of an abstract type as computed by the static tool Lackwit, as compared to those computed by our dynamic tool DynComp. (Lackwit was unable to process `perl`.) The average number of variables in an abstract type is an approximate indication of the precision of each analysis. These numbers alone cannot indicate correctness, so I performed a source code inspection on several programs to determine whether two variables in the same set actually correspond to the same programmer-intended abstract type.

My hand examination of `bzip2` and `flex` focused on the differences in the Lackwit and DynComp output, which I hoped would indicate the strengths and weaknesses of the static and dynamic approaches. Typically the DynComp results were finer and were correct, so far as I could tell.

As in Section 4.4.1, I carefully examined the `wordplay` results. Lackwit assigns the last 6 variables of Table 4.2 to singleton sets (Types 6–11), just like DynComp and my hand analysis. However, Lackwit assigns the first 15 global variables to a single abstract type; in other words, Lackwit is unable to make any distinction among them. By comparison, DynComp assigns them to five distinct abstract types (Types 1–5 in Table 4.2), and the hand analysis assigns them to four distinct abstract types.

Lackwit's static analysis mistakenly groups 15 variables together into one abstract type because of its conservative assumptions about runtime behavior. As one example, consider why it merges types 1 and 3. `wordplay` is invoked from the command line via:

```
wordplay -d<depth> <word> -f <word list file>
```

In C, command-line arguments are passed into the program within the `argv` string array. The static analysis does not distinguish the elements of an array, but gives them all the same abstract type. `wordplay` assigns the numeric value of the `<depth>` argument to `max_depth` (Type 3), and the `<word>` argument interacts with the word variables in Type 1. Thus, Lackwit merges the sets representing types 1 and 3. Other conservative approximations cause Lackwit to spuriously group other variables together into one large set.

User studies

By inspecting the abstract types produced by DynComp for RNAfold, the researcher saw that one particular set contained all the energy variables plus 5 variables of other

abstract types (see Section 4.4.2). Hand-inspection of the abstract types produced by Lackwit revealed that it grouped 10 extraneous variables into that same set in addition to the variables that DynComp placed there, thus making the results strictly worse.

Hand-inspection of the abstract types produced by Lackwit for SVM-Light revealed no significant differences from the results of DynComp.

Dynamic invariant detection

The rows labeled "Lackwit" in Table 4.3 show that the number of invariants that Daikon produced with abstract type information from Lackwit was greater than with information from DynComp. DynComp can partition the variables into smaller and finer abstract types, and this effect propagates to reduce the number of hypothesized invariants.

I compared Daikon's output using the types produced by Lackwit with the types produced by DynComp for several examples. I exhaustively reviewed the differences for RNAfold and SVM-Light and noted mixed results: there were cases where DynComp produced sets of abstract types that more closely mimicked the researcher's notion, and those where Lackwit did. I believe that a more exhaustive or longer test would have been able to improve the results of DynComp.

4.5 Related Work

This section gives additional details about the previous static approaches to abstract type inference, and also compares the present work to more distantly-related research in type inference (including of unit types), points-to analysis, and slicing.

4.5.1 Static abstract type inference

The most closely related project to DynComp is Lackwit [41], which performs a static analysis on C programs with a similar purpose as our dynamic one. Though it can be effective for small programs, and its algorithms are theoretically scalable to quite large programs, Lackwit suffers from some limitations of precision that are almost impossible to avoid in a static analysis.

Lackwit's key implementation technique is to summarize each procedure with a polymorphic type. A type system with parametric polymorphism allows types to contain type variables (conventionally represented by Greek letters) that can be consistently replaced with another type. For instance, a function that returns the first element of a list might have a type "α list $\rightarrow \alpha$", representing the fact that it can be applied to a list of integers, returning an integer (when α is replaced by `int`), or to a list of booleans to return a boolean, and so on. Lackwit effectively devises a new type system for C that is distinct from the usual one: it reflects some of the same structure of data (with mutable references and tuples analogous to pointers and structures), but it allows general polymorphism as in ML, and type constructors can be subscripted by tag variables. For instance, rather than having a single integer type `int`, there is a family $\texttt{int}_\alpha$, $\texttt{int}_\beta$, ... The problem of inferring abstract types then reduces to giving a type to each function; because the type is polymorphic, different uses of the function need not use values of the same abstract type.

For instance, if a function uses two integer arguments together in an operation, the parameters would both get the type $\texttt{int}_\alpha$ (where α is a variable):

```
void f(int a, int b, int c) { a + b; }
// Type: (int_α, int_α, int_β) -> void
....
f(x, y, 5); // x, y both of type int_μ
....
f(z, w, 7); // z, w both of type int_ψ
```

At each site where the function is called, its argument types must have the same tags (both `x` and `y` are of type $\texttt{int}_\mu$), but there is no constraint between different calls ($\texttt{int}_\mu$ and $\texttt{int}_\psi$ can be distinct).

Lackwit constructs these types using the Hindley-Milner type inference algorithm [33]. Its algorithm starts by assigning unique type variables to program variables, and then discovers additional constraints on the type variables by collecting equality constraints from the program and matching the structure of types in a process called "unification". Though the theoretical worst-case running time of the algorithm is superpolynomial, this worst case does not occur in practice: the algorithm's running time is close to linear in the program size. Unfortunately, the theoretical asymptotic scalability of Lackwit does not suffice to make the tool applicable to large programs. In our experience, Lackwit itself runs fairly quickly, but often crashes on attempts to query its database, requiring a slow process of repeated queries. Therefore, we were unable to fairly compare the performance of Lackwit to that of DynComp.

Lackwit's use of polymorphic types improves precision because that provides a limited but efficient form of context sensitivity: the arguments to and value returned by a procedure need not have the same abstract type at every location where the procedure is called. A side effect of this approach is that the abstract types that Lackwit computes for a given procedure are based on the *implementation* of that function, but are independent of the way in which the procedure is *used* by its callers. By contrast, the abstract types computed by our algorithm reflect all of the values passed to a procedure. Lackwit is flow-insensitive: its analysis presumes that a variable has a single abstract type throughout its scope, even if it holds different values at different sites. Because our algorithm tracks values individually, it does not have this limitation. One might imagine using a flow-sensitive static analysis, or making other changes, but many of the limitations of Lackwit observed in previous sections would be shared by just about any static analysis. For instance, in the `wordplay` example discussed in

Section 4.4.4, global variables that should have different abstract types are merged by Lackwit because they are both initialized using elements of the argument array `argv`. It is rare for a static analysis to even give different treatment to elements of an array based on their index; we know of no static analysis that would distinguish between, say, "array elements for which the preceding element was the string `"-d"`" and "array elements for which the preceding element was the string `"-f"`".

4.5.2 Other type inference

Other kinds of type inference can also be performed either statically or dynamically. Lackwit is based on techniques such as Hindley-Milner type inference [33] that have been extensively studied in connection with statically-typed functional languages such as ML [34]. Types can also be statically inferred for languages that have only dynamic types, such as Scheme [18] and Smalltalk [1, 47]; the problem is practically much more difficult in this case. Dynamic approaches to type inference have been tried less frequently, but are relatively lightweight, and can be effective in contexts like reverse engineering when the results are further modified by a developer [43].

4.5.3 Units analysis

Abstract types are intuitively similar to units of measurement. A unit, like an abstract type, is an additional identity that can be associated with a number, and which gives information about what other values can sensibly be operated on together with a value. Also like abstract types, units are poorly supported by existing languages, and can be inferred from a program's operations. "Unit types" [28, 4] might be considered a variant of abstract type, but they have an additional algebraic structure not present in the abstract type systems considered so far. For instance, the unit type of the product of two quantities does not have the unit type of either factor; instead, it has a product unit type. Unit types can be inferred by extending abstract

type inference with algebraic constraint solving; this can be done either dynamically or statically. The "units" mode of DynComp computes an approximation to physical unit types: if DynComp in this mode puts two variables in the same abstract type, they must have the same units, but several different abstract types might represent variables with one set of units, if those variables do not interact directly.

Erwig and Burnett [17] perform an analysis on spreadsheets that they refer to as "unit inference," but like our analysis they do not model the algebraic properties of units. Instead, they introduce a type system that appears to represent a multi-dimensional hierarchical classification of entities (the precise interpretation of their type system is unclear, inasmuch as the system's type constructors do not have the standard interpretation). Rather than simply requiring combined quantities to have the same units, their system requires that values represent a complete level of the hierarchy in each dimension: for instance, adding apples and oranges is appropriate if they are the only kinds of fruit in the spreadsheet, but illegal if bananas also exist. Erwig and Burnett give an algorithm to infer their unit types, but the main challenge is not to infer information from operations, because their spreadsheets already have human-readable annotations in the form of row and column headings; rather the challenge is to infer which combination of header cells describe which data cells, based on the layout.

4.5.4 Points-to analysis

Abstract type inference is particularly important for variables of primitive types such as integers, whose types in the original program rarely give information about their meaning. Though abstract type inference also groups pointer (or reference) variables according to the dataflow between them, and could easily be extended to group pointers with their referents (treating the dereference operation as another kind of interaction), it is usually more useful to distinguish pointers according to what they

point to. This extension gives the problem of points-to or aliasing analysis, which answers questions of the form "what could `p` point to?" or "could `p` and `q` ever point to the same location?". Points-to analysis can be performed dynamically [35], and this is in some ways easier than dynamic abstract type inference because no tags are necessary: the numeric value of a pointer uniquely identifies what it is pointing at.

However, points-to analysis has been studied more extensively as a problem for static analysis. Abstract type inference is one of many problems that are hard to solve statically without accurate information about pointers, since some abstract type must be given to the value produced by a pointer dereference. Lackwit's assignment of polymorphic types to references effectively represents a kind of pointer analysis. Pointer analysis has been studied extensively, but finding the best trade-off between precision and performance for a particular problem is still an area of active research [11, 54]. Many points-to analyses could be converted into abstract type inference algorithms with similar performance and scalability characteristics by adding special-case treatment of operators on primitive types.

The well known almost-linear-time points-to analysis of Steensgaard [50] has an additional connection to our algorithm in its use of an efficient union-find data structure. Like our analysis, Steensgaard's algorithm uses a union-find structure to represent a partition of program variables, but beyond that their uses are rather different. In our algorithm, the goal is to compute an undirected (symmetric) and transitive relation, and the union-find structure represents the equivalence classes of the relation. In Steensgaard's algorithm, the goal is to compute a directed relation, points-to, that is not transitive, and the union-find structure is used to partition the domain of the relation so that an over-approximation to it can be represented in linear space. Steensgaard's algorithm is more closely related to the analysis that Lackwit performs: both were inspired by unification-based type inference.

4.5.5 Slicing

Our dynamic abstract type inference relates variables that are connected by dataflow and by co-occurrence in primitive operations. Those portions of a program that are connected by dataflow and control dependence can be queried using the technique of slicing; a backward slice of a particular statement or expression indicates all the other statements or expressions whose computation can affect the given one. Static slicing approximates this relation, and dynamic slicing [3, 30, 52] computes it exactly for a given computation. In the general case, dynamic slicing amounts to maintaining a full execution trace of a program, and much dynamic slicing research focuses on how to collect and maintain this trace information efficiently. Our analysis considers similar issues with respect to collection, but pre-computes the result for any abstract type query in the compact form of disjoint variable sets. From a program slice, one can construct an abstract type consisting of the variables mentioned in the slice, and conversely the statements that use variables of a given abstract type form a slice. Under this correspondence, our abstract types correspond to slices that ignore control dependencies.

4.6 Conclusion

DynComp is an implementation of a novel technique for dynamic inference of abstract types. Its algorithms for tracing value flows and interactions and then translating into abstract types for variables are most easily implemented using the mixed-level approach of Fjalar, which allows for close integration of source- and binary-level information throughout execution. DynComp helps to improve human understanding of unfamiliar code and also improves the results of invariant detection, a follow-on dynamic analysis. It is publicly available on the web in the source code distribution of Daikon: `http://pag.csail.mit.edu/daikon/`

Chapter 5

Conclusion

5.1 Future Work

One of the wonderful aspects of building a tool framework is that there are many possibilities for both extending the framework and also for building novel tools on top of it. Here is a list of possibilities for future work.

5.1.1 The Fjalar Framework

- Create a more general and flexible traversal mechanism, perhaps implemented as some sort of query language where the user can more precisely specify how to traverse inside of arrays and data structures (an extension of the mechanism described in Section 2.2.4).

- Add support for observing local variables.

- Improve and fix bugs in Fjalar's support for C++ by testing it on additional large C++ programs (there has already been extensive testing on C programs).

- Extend Fjalar to work on additional platforms besides x86/Linux that Valgrind supports, such as AMD64/Linux.

- Extend Fjalar to work on other languages that the `gcc` compiler suite supports, such as Objective-C, Fortran, Java, and Ada.

- Extend Fjalar to support binaries compiled with some optimizations.

- Use Fjalar to build new dynamic analysis tools, such as a dynamic units inference tool that can approximate unit relationships (e.g., physics units), much like how DynComp can approximate abstract types.

5.1.2 Kvasir: A C and C++ Front-End for Daikon

- Generalize the value profiling that Kvasir performs so that it might be useful for other tools besides Daikon, or even extend it to be able to create summaries of data structure form and shapes so that it can present its results to a human to help improve program understanding.

5.1.3 DynComp: Dynamic Inference of Abstract Types

- Perform binary-level basic-block optimizations on the Valgrind IR to improve run time performance and to reduce memory overhead from maintaining tags.

- Improve the user interface beyond its current form, which simply presents sets of variables at each program point, where all variables in a set have the same abstract type.

- Add a query engine and mechanism whereby the user can enter in two variables with the same abstract type and be shown the path of statements (dataflow or interactions) that led to those two variables being grouped into the same abstract type.

5.2 Contributions

This thesis presented a novel mixed-level approach to constructing dynamic analysis tools for C and C++ programs (Chapter 1), a tool framework that implements this approach (Chapter 2), and two dynamic analysis tools built on top of this framework (Chapters 3 and 4). It provided a survey of existing source- and binary-based approaches to dynamic analysis (Sections 1.2 and 2.5) and argued for the advantages of the mixed-level approach over both previous approaches in terms of scalability, robustness, and applicability, especially for the kinds of analyses that deal with observing data structures. Finally, it described several case studies of applying tools built using the mixed-level approach to a variety of program analysis tasks: improving human understanding of unfamiliar code (Section 4.4.2), invariant detection (Sections 3.4.1 and 4.4.3), and data structure repair (Section 3.4.2).

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