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Automated Test Case Generation to Validate Non-functional Software Requirements

Pingyu Zhang
University of Nebraska - Lincoln, pzhang@cse.unl.edu

AUTOMATED TEST CASE GENERATION TO VALIDATE NON-FUNCTIONAL SOFTWARE REQUIREMENTS

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Pingyu Zhang

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AUTOMATED TEST CASE GENERATION TO VALIDATE NON-FUNCTIONAL SOFTWARE REQUIREMENTS

Pingyu Zhang, Ph.D.

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Advisor: Sebastian Elbaum

A software system is bounded by a set of requirements. Functional requirements describe *what* the system must do, in terms of inputs, behavior, and outputs. We define non-functional requirements to be *how well* these functional requirements are satisfied, in terms of qualities or constraints on the design or on the implementation of a system. In practice, the validation of these kinds of requirements, does not receive equal emphasis. Techniques for validating functional requirements target all levels of software testing phases, and explore both black-box and white-box approaches. Techniques for validating non-functional requirements, on the other hand, largely operate in a black-box manner, and focus mostly on system testing level. As a result, in practice more efforts are focused on validating functional requirements, and only assess non-functional requirements after functional validation is complete.

In this dissertation, we propose a set of automated bounded exhaustive white-box testing techniques that enable cost-effective validation of non-functional requirements from two perspectives. For non-functional requirements defined as qualities of a system, we target load testing for the purpose of performance validation. We present Symbolic Load Generation (SLG), a load test suite generation approach that uses symbolic execution to exhaustively traverse program execution paths, and produce test cases for the ones that may expose worst-case or near worst-case resource consumption scenarios. An assessment of SLG on a set of Java applications shows that it generates test suites that induce program response times and memory consumption several times worse than the compared alternatives, it scales to large and complex inputs, and it exposes a diversity of resource consuming program behavior. We subsequently present CompSLG, a compositional load test generation technique that aims to achieve better scalability than SLG. CompSLG is fully automated to handle software that follows the pipeline architecture, and is evaluated on a group of Unix and XML pipelines. The results show that it generates load tests in situations where SLG fails to scale, and achieves comparable load with a fraction of the cost. We also extend CompSLG to enable the handling of more complex software structures in terms of Java programs, and show the viability of the extended technique through a series of examples.

For non-functional requirements defined as constraints on a system, we target validation of contextual constraints that are imposed by external resources with which the software interacts. We first assessed the magnitude of the problem by conducting a study on fault repositories of several popular Android applications. We then present an approach that amplifies existing tests in an exhaustive manner to validate exception handling constructs that are used to handle such constraints. Our assessment of the approach on a set of Android mobile applications indicates that it can be fully automated, is powerful enough to detect 67% of the faults reported in the bug reports of this kind, and is precise enough that 78% of the detected anomalies correspond to faults fixed by the developers.

Combined, the two proposed techniques advance the field of automated software testing by providing white-box support for non-functional validation.

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Chapter 1

Introduction

In this chapter, we first present the motivation for the research efforts that lead to this dissertation, then summaries the contributions of this research.

1.1 Motivation

A software system, from its inception, is bounded by a set of requirements. A requirement can be either functional or non-functional. Functional requirements describe the behaviors (functions or services) of the system that support user goals, tasks or activities. In other words, it captures *what* the system must do. Non-functional requirements, on the other hand, describe *how well* these functional requirements are satisfied – where "how well" is judged by some externally measurable property of the system behavior.

Hence, non-functional requirements are often defined as qualities or constraints of a system [13]. *Qualities* are properties or characteristics of the system that its stakeholders care about and hence will affect their degree of satisfaction with the system. For example, performance (e.g., throughput, response time, transit delay, or latency) serves as an important measure of the quality of the system. *Constraints*, in this context as defined by Bass et al. [13], are not subject to negotiation and, unlike qualities, are off-limits during design trade-offs. One such example is a contextual constraint, which accounts for elements of an environment into which the system must fit, such as host OS platforms, hardware infrastructures, or other services provided by external resources.

In practice, the validation of the functional and non-functional requirements is not given the same importance. For example, in the popular open source project Eclipse, we observe that validating the core of the Eclipse Editor (release 3.4.1) involves executing a total of 48,693 distinct unit and subsystem tests[1]. Among those tests, more than 80% are functional, and a significant number of tests, 7,761, explicitly target the user interface. As an open source project, functionality and usability are key acceptance criteria for the Eclipse user base, and it makes sense that those requirements were the focus of more than 99% of the test development effort. In comparison, however, the same Eclipse module only includes 21 security tests and a single performance test. From another perspective, there is a huge discrepancy between how functional and non-functional bugs are addressed by the developers in the Eclipse community. According to the Eclipse bug repository [37], there are 4200 bugs associated with the editor module, and 45% of those are labeled as closed and fixed. Among those bugs, over 600 are labeled as performance related, but only 3% are fixed and closed, and only three developers participated in submitting fixes. In light of this situation, it is not surprising that Eclipse has severe non-functional issues. A recent study [36] shows that Eclipse 4.2 is up to 6000 times slower than a previous version (3.8) in some UI operations. Clearly, validation of non-functional requirements seems to matter yet it is not getting proper attention.

In terms of how testing activities are conducted, non-functional requirements are

[1]The number of tests are computed by counting the number of test-java files in each directory labeled as security, interface, etc.

often assessed *after* functional validation is complete. For example, the performance of a system is most likely to be assessed at the end of the development cycle. This choice is largely dependent on the available tool support for non-functional testing, most of which treat the system under test as a black box, and support test automation on the system testing level alone [79]. However, this could lead to disastrous results if it is revealed at this stage that these quality requirements could not be met by the current architecture without significant rework. An experience from Oracle Corporation suggests that performance validation accounts for an average of 2.5% of the total cost of development [88]. However, the cost of fixing poorly performing applications at the end of development cycle is estimated to be 25% of the total cost of development.

We conjecture several reasons for the negligence of non-functional requirements validation. The first reason is the lack of precise and actionable non-functional requirements. Mannion and Keepence outline the characteristics of a high quality non-functional requirement [82]. In reality, many non-functional requirements are specified in loose, fuzzy terms that are open to subjective interpretation [48], which makes testing challenging. The second reason is the lack of cost-effective techniques for validating non-functional requirements. Compared to numerous techniques and tools available for functional testing and validation, tools specifically designed for non-functional purposes are scarce, imprecise, and focus on system testing level. For example, although performance validation plays an important role in the development life cycle, there are only a few tools that support load testing at subsystem testing level [68, 80, 89]. For the tools that do support such activities, most of them focus on profiling and bookkeeping performance trends. They induce load by increasing the input size or the rate at which input is provided [79], which is a rather expensive way of inducing load (e.g., requires additional disk space, bandwidth to execute tests), and may lead to negligence of real performance faults.

In this dissertation we focus on investigating strategies for improving the cost effectiveness of non-functional validation techniques. We reduce the cost of conducting non-functional validation by developing techniques that automatically generate test suites for specific non-functional requirements, and by transforming existing tests into new tests that add non-functional capabilities to the validation process. We improve the effectiveness of the techniques by using program analysis to exhaustively traverse program execution paths, searching for instances of violations of non-functional requirements and producing counter examples (test cases) that allow developers to easily recreate the failing scenarios.

These techniques can be viewed as complementary to the efforts that aim at improving the quality of non-functional requirements. If such requirements are available, our techniques facilitate their validation. If non-functional requirements are not available, the proposed techniques can still be used to expose worst or near worst case scenarios of non-functional properties, which could in turn help to develop more accurate set of non-functional requirements [48, 133].

More specifically, we have targeted two aspects of non-functional testing. For non-functional requirements defined as qualities of a system, we targeted validation of performance properties. We improve cost-effectiveness of performance validation by *automatically generating load tests that focus on smart input value selection* to expose worst or near worst case performance scenarios. For non-functional requirements defined as constraints on a system, we targeted contextual constraints on noisy and unreliable external resources with which a software system must interact. One way to improve the robustness of software that interacts with those external resources is to use exception handling constructs. In practice, however, the code handling exceptions is not only difficult to implement [95] but also challenging to validate [45, 109, 117].

We improve the cost effectiveness of such validation by *amplifying existing tests to exhaustively test every possible execution pattern in which exceptions can be raised*, and produce scenarios in which the exception handling code does not perform as expected. In the following sections we will discuss each approach in detail.

1.2 Non-functional Requirement Validation: Load Testing

Load tests aim to validate whether a system's performance (e.g., response time, resource utilization) is acceptable under production, projected, or extreme loads. Consider, for example, an SQL server that accepts queries specified in the standard query language to create, delete, or update tables in a database. Functional tests would validate whether a query results in appropriate database changes. Load tests, however, would be required to assess whether, for example, for a given set of queries the server responds within an expected time.

Existing approaches to generate load tests induce load by increasing the input size (e.g., a larger query or number of queries) or the rate at which input is provided (e.g., more query requests per unit of time)[79]. Consider again the SQL server. Given a set of tester supplied queries, a load testing tool might replicate the queries, send them to the SQL server at certain intervals, and measure the response time. When the measured response times differ from the user's expectation, which might be expressed as some upper bound determined by the size or complexity of the queries or underlying database, a performance fault is said to be detected.

Current approaches to load testing suffer from four limitations. First, their cost effectiveness is *highly dependent on the particular values* that are used yet there is no support for choosing those values. For example, in the context of an SQL server we studied, a simple selection query operating on a predefined database can have response times that vary by an order of magnitude depending on the specific values in the select statements. Clearly, a poor choice of values could lead to underestimating system response time thereby missing an opportunity to detect a performance fault.

Second, *increasing the input size may be a costly means to load a system.* For example, in the context of a compression application that we studied, we found that to increase the response time of the application by 30 seconds one could use a 75MB input file filled with random values or a 10MB input file if the inputs are chosen carefully. This is particularly problematic if increasing the input size requires additional expensive resources in order execute the test (e.g., additional disk space, bandwidth).

Third, increasing the input size may just force the system to perform *more of the same* computation. In the worst case, this would fail to reveal performance faults and, if a fault is detected, then further scaling is likely to repeatedly reveal the same fault. In functional testing, diversity in the test suite is desirable to achieve greater coverage of the system behavior. Load suites that *cover behaviors with different performance characteristics* are not a focus of current tools and techniques.

Finally, while most load testing focuses on response time or system throughput, there are many other *resource consumption measures* that are of interest to developers. For example, mobile device platforms place a limit on the maximum amount of memory or energy that an application can use.

We introduced an approach (Chapter 3) for the automated generation of load test suites that starts addressing these limitations. It generates load test suites that (a) induce load by using carefully selected input values instead of just increasing input size, (b) expose diversity of resource consuming program behavior, and (c) target a range of consumption measures.

Our white box approach leverages recent advances in symbolic execution to provide smart value selection and diversity in test input generation. However, due to its exhaustive nature and inherent path explosion problem [73], plain exhaustive symbolic execution cannot scale beyond very small programs. To improve scalability we developed a search strategy that is directed towards program paths that consume more resources. Our approach is directed and incremental in exploring possible program paths. The approach is *directed* by a specified resource consumption measure to search for inputs of a given size or structure that maximize consumption of that resource (e.g., memory, execution time). The approach is *incremental* in that it considers program paths in phases. Within each phase it performs an exhaustive exploration of program paths. At the end of each phase, the paths are grouped based on similarity, and the most promising path from each group, relative to the consumption measure, is selected to explore in the next phase. We implemented the approach in the Symbolic Path Finder framework [65] and assessed its effectiveness on three artifacts. The results indicate that the proposed approach can produce suites that induce response times several times greater than random input selection and can scale to millions of inputs, increase memory consumption between 20% and 400% when compared with standard benchmarks, and expose different ways to induce high consumption of resources.

If improving on symbolic execution alone would not lead to desirable scalability suitable for load testing, we reconstruct the analysis compositionally, following a ‘divide-and-conquer’ strategy. We have proposed a compositional approach to generate load tests (Chapter 4). The approach builds on the aforementioned technique to collect the program paths that would lead to an effective load test suite for each system component. The collected paths constitute a performance summary for each component. The approach is compositional in that it analyzes the components’ summaries and their connections to identify compatible paths, as defined by their constraints, which can be solved to generate load tests for the whole system. Key to this process is how path constraints across components must be weighted and relaxed in order to derive test inputs for the whole system while ensuring that the most significant constraints, in terms of inducing load, are enforced. We have implemented the approach by using our previous load generation approach as a subroutine for collecting performance summaries. An evaluation on a group of Unix pipeline artifacts and one XML pipeline shows that the compositional approach achieves scalability beyond that of the previous technique, and has an effectiveness gain of 288% over Random when given the same time to generate tests. In its current form, the compositional approach is fully automated to handle software that follows the pipeline architecture. We have also presented an extension of the approach that enables handling of Java programs, in which each component is a Java method. We have presented a set of new algorithms to handle the added challenges, such as more complex program structures and more sophisticated summary composition strategies. We showed the viability of the extended approach through a series of examples.

1.3 Non-functional Requirement Validation: Exception Handling

Modern software does not execute in isolation. It interacts with external resources that can be noisy and unreliable, and exhibit transient and unpredictable failures [98]. One way to improve software robustness in such a context is to use exception handling constructs. In practice, however, the code handling exceptions is not only difficult to implement [95] but also challenging to validate (e.g., [45, 109, 117]).

We conjecture that the validation challenge is particularly relevant when dealing with systems that must interact with external resources that can be noisy and unreliable, and exhibit transient and unpredictable failures [98]. Consider, for example, an exception handling construct to check for the end of a sequential input stream. The reliability of the stream is rarely in doubt, the end of the file is a certainty, and standard testing frameworks provide mocking support for streams. In contrast, an exception handling construct interacting with noisy and often unreliable localization, communication, and sensor services, cannot make such simplifying assumptions, requiring more complex and hence harder to validate implementations. A standard testing framework, which only supports simple ways of mocking the API calls that invoke those services, cannot accurately model the noisy nature of the external resources, and misses the faults that can only be triggered by specific patterns of exceptions.

To assess the severity of the problem, we conducted a study on fault repositories of eight popular Android applications. The study provides quantifiable evidence of the commonality of faults associated with exception handling code constructs, and more specifically with those related to handling external resources with unpredictable performance that cannot be controlled through standard input manipulation. The results show that 22% of the confirmed and fixed bugs have to do with poor exceptional handling code, and that 12% correspond to interactions with four external resources we deem most relevant to the problem (Section 5.1).

We then presented an exhaustive white box approach to support the detection of such faults (Section 5.3). Our approach is simple, scalable, and effective in practice when combined with a test suite that invokes the resources of interest. The approach is white box in that it first instruments the target program so that the results of calls to external resources of interest can be mocked at will to return exceptions. Then, existing test cases are systematically amplified by re-executing them on the instrumented program under various mocked patterns to explore the space of exceptional behavior. The approach exhaustively tests all patterns, looking for the ones that are effective in exposing faults. When a fault is revealed, the mocking pattern applied with the test serves as an explanation of the failure induced by the external resource. To control the number of amplified tests the approach prunes tests with duplicate calls and call-outcomes to the external resources, and bounds the number of calls that define the space of exceptional behavior explored.

The approach is built on two assumptions. First, it builds on the small scope hypothesis [64], often used by techniques that systematically explore a state space, which advocates for exhaustively exploring the program space up to a certain bound. The underlying premise is that many faults can be exposed by performing a bounded number of program operations, and that by doing so exhaustively no corner cases (test cases that expose faults in extreme situations, such as extreme values for the input parameters) are missed. Several studies and techniques have shown this approach to be effective (e.g., [18, 29, 32]) and we build on those in this work. In our approach, the bound corresponds to the length of the mocked patterns. Second, we assume that the program under test has enough tests cases to provide coverage of the invocations to the resources of interest. The increasing number and maturity of automated test case generation techniques and tools support this assumption. If this assumption holds, then the approach can automatically and effectively amplify the exposure of code handling exceptional behavior.

1.4 Dissertation Statement

In the dissertation we explore the following research statement:

Bounded exhaustive white box testing techniques can cost effectively validate non-functional requirements.

We have investigated this statement from two perspectives. For non-functional requirements defined as qualities of a system, we targeted load testing for the purpose of performance validation. We present a load test suite generation approach by using symbolic execution to exhaustively traverse program execution paths and produce test cases for the ones that expose worst case resource consumption scenarios. For non-functional requirements defined as constraints on a system, we present an approach for validating contextual constraints that are imposed by external resources with which a software interacts. The approach amplifies existing tests in an exhaustive manner to validate exception handling constructs that are used to handle such constraints. Combined, the two proposed techniques complement the field of automated software testing by providing exhaustive support for non-functional validation.

1.5 Contributions of this Research

In this dissertation, we have developed a set of exhaustive white box testing techniques to support automatic validation of non-functional requirements. The contributions of this work are three-fold:

1. **Symbolic Load Generation.** For performance validation we have developed a technique for automated generation of load test suites with support for precise input value selection that is built on state-of-the-art symbolic execution techniques, and equipped with a directed incremental search strategy to tailor the special needs of load generation. An assessment of the approach shows it generates test suites that induce program response times and memory consumption several times worse than the compared alternatives, it scales to large

and complex inputs, and it exposes a diversity of resource consuming program behavior [137] (see Chapter 3 for details).

2. **Compositional Load Generation.** To further improve on the scalability of the symbolic load generation technique, we developed a compositional technique for automated generation of load tests for more complex software systems. The technique is compositional in that it analyzes each software components' performance in isolation, then generates load tests for the whole system by accumulating and stitching each performance summary. An evaluation of the technique on software pipelines shows that it achieves scalability beyond that of the symbolic load generation technique, and has an effectiveness gain of 288% over random when given the same time to generate tests [138]. We further generalize the technique to load test generation for Java programs, provide a conceptual implementation sketch, and illustrate its application through a series of examples (see Chapter 4 for details).

3. **Exception Handling Validation.** For exception handling validation, we first assessed the magnitude of the problem by conducting a study on fault repositories of eight popular Android applications. We then developed a technique that systematically amplifies existing tests to validate exception handling code in an exhaustive manner. Our assessment of the technique indicates that it can be fully automated, is powerful enough to detect 67% of the faults reported in the bug reports of this kind, and is precise enough that 78% of the detected anomalies correspond to faults fixed by the developers. The technique outperforms a state of the art approach [117] in precision and recall. In addition, the feedback from developers and the preliminary case study illustrate the techniques potential to assist developers [136] (see Chapter 5 for details).

1.6 Outline of Dissertation

The remainder of this dissertation is organized as follows: Chapter 2 discusses related work and describes the fundamental concepts that are relevant to the techniques presented in the thesis, such as symbolic execution, performance testing, and techniques for testing of exception handling code. Chapter 3 presents the load test generation technique for standalone programs. In Chapter 4, we introduce the technique for compositional load generation for software pipelines as well as Java programs. In Chapter 5, we present the technique for amplifying tests to validate exception handling code. Finally, in Chapter 6, we provide the overall conclusions for this work, summarize the merit and impact, and present ideas for improvements and future research directions.

Chapter 2

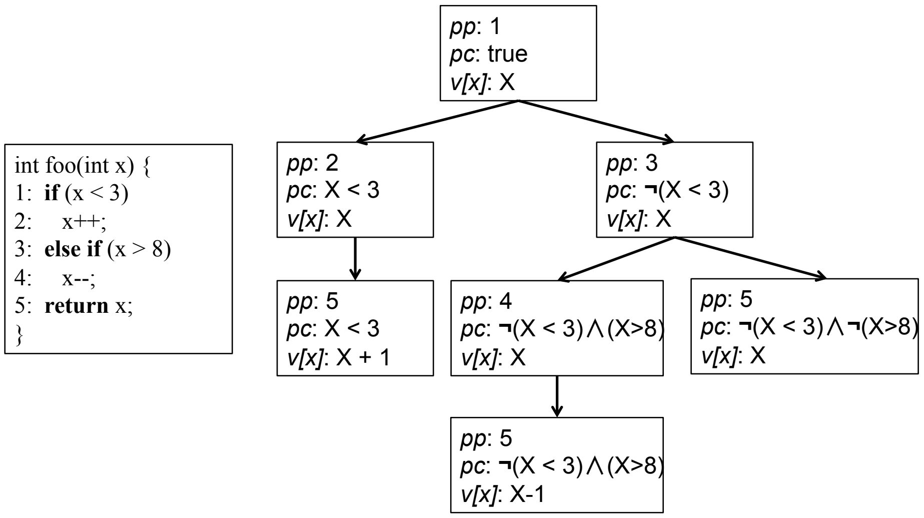
Background & Related Work

In this chapter, we identify key pieces of work that are related to our approaches in the two proposed areas. For our work on load testing, we begin with background information on symbolic execution, a fundamental technique used by our technique. We then discuss recent improvements to symbolic execution and how we benefited from those improvements. We also identify other techniques that aim at load test generation or performance characterization in general, and discuss how they are related to ours. For our work on validating exception handling code, we identify two areas of related work: mining exception handling specifications and exception handling code coverage representations, and discuss how they are related to our technique.

2.1 Symbolic Execution

Symbolic execution [73] simulates the execution of a program using *symbolic values* instead of actual values as inputs. During symbolic execution, when a program variable is read, its corresponding symbolic value is loaded. Memory locations are updated with symbolic values when they are written during symbolic execution.

A *symbolic execution tree* characterizes the execution paths generated during sym-



```
int foo(int x) {
1:  if (x < 3)
2:     x++;
3:  else if (x > 8)
4:     x--;
5:  return x;
}
```

Figure 2.1: Code fragment for foo() and its corresponding symbolic execution tree.

bolic execution. Each node in the tree represents a symbolic program state and the edges represent transitions between states. A *symbolic state* is a "snapshot" of the current execution after the most recent transition. Branching in the symbolic execution tree corresponds to a choice that cannot be precisely determined based on the symbolic state, during symbolic execution. A *path* in the tree is uniquely defined by a conjunction of constraints. Each constraint encodes a branch decision made along the path and is defined as a boolean expression over concrete and symbolic values. The conjunction is called the *path condition.* A path is *feasible* only when the path condition is satisfiable, i.e., there is an assignment of values to variables that makes the formula true; otherwise, the path is considered infeasible. Each time the path condition is updated, an automated *decision procedure* is used to check its satisfiability. When a path condition becomes unsatisfiable, symbolic execution along that path halts and *backtracks* to the previous decision point, and continues on an unexplored path.

Figure 2.1 shows an example code snippet and its corresponding symbolic execution tree. In the code, method *foo()* takes a single integer argument, x, and returns an integer value. It has two branching points (Line 1 and Line 3) and three feasible paths (shown on the right).

Each symbolic state is defined as a triple, (pp, pc, v). The *program position*, pp, denotes the next statement to be executed. The *path condition*, pc, is a conjunction of the constraints on the symbolic variables along the current execution path. The *symbolic value map*, v, is a map from memory locations of the program variables to symbolic expressions representing their current values. For example, in Figure 2.1, the last state of the middle path on the symbolic execution tree (the bottom box) includes pp at Line 5, a pc: $\neg(X < 3) \wedge (X > 8)$, and one symbolic expression $X - 1$ for the variable x.

To illustrate how symbolic execution works, again consider the example in Figure 2.1. When *foo()* is invoked, the path condition is initialized to *true*, and the symbolic value map for variable x contains the symbolic value X (we use capital letters to indicate symbolic values). At Line 1, symbolic execution branches: (1) when $X < 3$, the value of x is incremented at Line 2, and the value $X + 1$ is returned at Line 5; (2) when $\neg(X < 3)$, the execution moves to Line 3 and branches again: (1) when $X > 8$, the value of x is decremented at Line 4, and the value $X - 1$ is returned at Line 5; (2) when $\neg(X > 8)$ the execution moves to Line 5 and returns the original value X. Symbolic execution on this code generates a total of three paths, as illustrated on the right in Figure 2.1.

The simplicity of this example belies the true complexity of performing symbolic execution on real programs. In the next sections, we will describe some of the more challenging aspects of performing symbolic execution in a realistic environment, such as handling complex inputs, scaling up to complex programs, and its application to automatic test generation.

The work in Chapters 3 and 4 are built on symbolic execution techniques, but are unique in their application to load testing, which requires the development of different search heuristics and exposes different tradeoffs and scalability issues.

2.1.1 Generalized Symbolic Execution

Symbolic execution was first introduced as a technique for generating test inputs on scalar inputs. In 1976, King presented an interactive system that provides symbolic execution for programs written in a PL/I style language for testing and debugging [73]. In recent years, thanks to the substantial advances in raw computation power and constraint solving technology, symbolic execution has regained its popularity as a promising technology for test generation research [91].

The rise of object-oriented programing languages in the 90s makes symbolic execution of software written in such languages more challenging: 1) OO programs frequently use dynamically allocated data, such as trees, linked lists, or arrays of unspecified lengths, as inputs. Declaring these types of inputs as symbolic variables is challenging because it would require modeling them in the symbolic heap and updating their structures as the analysis continues. 2) For symbolic execution techniques that correctly model the symbolic heap, the number of possible outcomes for updating a symbolic data structure (such as an symbolic tree) in the heap is prohibitively large, making the technique non-scalable even for tiny examples. 3) A program may use complex library calls in it computation, resulting in non-linear constraints (e.g., strings and high-order mathematical constraints) that can not be solved by traditional decision procedures; or it may make references to native libraries, for which code may not be available to analyze at source code level.

For programs whose inputs are heap-allocated data structures, Khurshid et al. proposed lazy initialization [72]. It starts execution of the program on inputs with uninitialized fields and assigns values to these fields lazily, i.e., when they are first accessed during symbolic execution of the code. It nondeterministically initializes the field to *null*, to a reference of a new object with uninitialized fields, or to a reference of an object created during a prior field initialization. The technique branches on these choices, which effectively systematically treats all aliasing possibilities. This approach eliminates the need to specify an a priori bound on the number of input objects, which is generally unknown.

To solve the problem of poor scalability caused by the introduction of symbolic heap data, Visser et al. proposed state abstraction and subsumption techniques [4, 122]. In this line of work, the authors first described abstraction mapping, an approach that maps heap objects in the symbolic state to a simplified version (e.g., representing a chain of nodes in a linked list with one summarizing node). The authors then present subsumption, a method for examining whether a symbolic state is subsumed by another symbolic state. Subsumption is used to determine when a symbolic state is revisited, in which case the model checker backtracks, thus pruning the state space. In this process, abstraction is used to increase chances of state matching. This effectively explores an under-approximation of program behaviors, but has proved to be effective in generating tests for programs that take container objects as inputs, e.g., binary search trees, arrays.

For symbolic execution involving strings, several approaches have proposed using string solvers [47, 104]. String constraints are collected in conjunction with constraints on scalar variables, and both scalar / string decision procedures are used in satisfiability checks. For other types of complex constraints and native library calls, Pasareanu et al. proposed to solve the problem with uninterpreted functions and mixed concrete-symbolic solving [90]. This technique splits the generated path conditions into two parts: 1) constraints that can be solved by a decision procedure, and 2) complex non-linear constraints with uninterpreted functions to represent external library calls. Simpler constraints are solved first and the solutions (concrete values) are used to simplify the complex constraints; the resulting path conditions are checked again for satisfiability.

Our load test generation technique takes advantage of some of these advances. Our technique support arrays of unspecific length through lazy initialization, and string operations through the use of string decision procedures. Furthermore, we extended the support of external library calls to file system operations through modeling of a symbolic file system, details of which are discussed in Chapter 4.

2.1.2 Dynamic Symbolic Execution

Dynamic symbolic execution aims to improve performance of symbolic execution by combining concrete and symbolic execution, essentially bounding the scope of what is treated as symbolic. First introduced by Godefroid et al. in DART (Directed Automated Random Testing) [51], the idea is to perform a concrete execution on random inputs and at the same time to collect the path constraints along the executed path. These path constraints are then used to compute new inputs that drive the program along alternative paths. More specifically, one can negate one constraint at a branch point to guide the test generation process towards executing the other branch. A constraint solver is called to solve the path constraints and to obtain the test inputs. The program is executed on these new inputs, constraints are collected along the new program path and the process is repeated until all the execution paths are covered or until the desired test coverage is achieved. For example, for the code fragment in Figure 2.1, after exploring the path: $\neg(X < 3) \wedge (X > 8)$, dynamic symbolic execution can negate the branch at Line 3 to explore a new path: $\neg(X < 3) \wedge \neg(X > 8)$.

Whenever symbolic execution gets stuck, dynamic symbolic execution uses concrete values to simplify the constraints, which leads to improved scalability, but loses completeness. Note that both dynamic symbolic execution and generalized symbolic execution aim to help traditional symbolic execution in certain situations, e.g., when there are no available decision procedures or in the presence of native calls, however they use different approaches to achieve this goal. Dynamic symbolic execution uses values from concrete runs to handle situations that decision procedures can not handle, while generalized symbolic execution uses concrete solutions of the solvable constraints in the current path condition to simplify the overall complexity. Implementation-wise, dynamic symbolic execution explores new paths by negating constraints on the current path, which is mostly implemented by code instrumentation, while generalized symbolic execution uses state-space search to explore new paths, which is mostly implemented on top of a state-space exploration framework (usually a model checker). Both techniques are implemented through several tools, which explore different tradeoffs between scalability and completeness. We will discuss those tools in the next section.

2.1.3 Using Symbolic Execution for Automatic Test Generation

One direct application of symbolic execution is the automated generation of test cases that reach certain statements, achieve high degree of coverage, or expose certain bugs. Symbolic execution is well suited for the task, because the path condition to reach a statement in the code when solved, gives exactly the input to reach the statement. There is a large body of work in this research direction, we review some of the most representative ones below.

Symbolic Path Finder. Pasareanu et al. proposed Symbolic Path Finder (SPF) [92], a symbolic execution engine built on the model checking tool called Java Path Finder

(JPF) [65] to enable symbolic execution on Java programs. It is built on generalized symbolic execution, the technique presented in Section 2.1.1. SPF implements a non-standard interpreter of Java bytecode using a modified JPF Java Virtual Machine to enable symbolic execution. SPF stores symbolic information in attributes associated with the JPF program states. The underlying model checker core provides many benefits to the symbolic execution engine, such as built-in state space exploration capabilities, a variety of heuristic search strategies, as well as partial order and symmetry reductions. In addition, it handles complex input data structures and arrays via lazy initialization, and implements state abstraction and subsumption checks. In addition, SPF addresses the issue of scalability with mixed concrete/symbolic execution [92]. The idea is to use concrete system-level simulation runs to determine constraints on the inputs to the units within the system. The constraints are then used to specify pre-conditions for symbolic execution of the units. SPF is used to analyze prototype NASA flight software components and helps to discover several bugs [92, 90].

DART. Proposed by Godefroid et al., DART [51] is the first among the line of work that use dynamic symbolic execution to generate tests (Section 2.1.2). This approach is alternatively named “concolic testing” - aiming to blend concrete and symbolic executions to improve the scalability of traditional symbolic execution approaches. DART, which generates tests for C programs, starts to execute a program with random concrete inputs, gathers symbolic constraints on inputs along the execution, and then systematically or heuristically negates each constraint in order to steer the next execution towards an alternative path. DART is used to generate tests for applications ranging from 300 to 30,000 lines of code, and detected several bugs. Note that SPF also improves scalability by mixing concrete and symbolic executions, but with a different methodology. DART performs concrete execution on whole paths and uses the results to steer towards alternative paths, while SPF interleaves concrete and symbolic executions and uses concrete execution to setup the environment for symbolic execution [92]. In addition, as discussed in Section 2.1.2, both techniques use concrete execution results to handle native library calls, but with different methodologies as well.

CUTE. CUTE [102] is another concolic execution technique for C programs that improves on DART by providing support for heap-allocated dynamic data structures as inputs. The key idea is to represent all inputs with a logical input map, and then collect two separate kinds of constraints, scalar constraints and pointer constraints, as symbolic execution proceeds. The pointer constraints are collected approximately — the only types of pointer constraints allowed are aliasing and null pointers. All other properties of pointers, such as boundary checks and offsets, are ignored. With this improvement, CUTE enables test generation for dynamic data structures such as trees and linked lists.

EXE and KLEE. EXE [24] is a symbolic execution technique designed for systems code in C language, such as device drivers OS kernels. The unique feature in EXE is that it models memory with bit-level accuracy, which is necessary for handling systems code, which often treats memory as raw bytes and casts them in a variety of ways. EXE also uses a custom decision procedure, STP [46], to speedup the solving process. KLEE [23] is a redesign of EXE built on top of the LLVM [74] compiler infrastructure. This design, along with several improvements in storing and retrieving program states, provides further scalability gains to the technique. Another improvement of KLEE is the ability to handle file systems and network operations. It provides symbolic models of these external libraries and supports symbolic execution on these operations. However, neither EXE nor KLEE supports non-linear arithmetic operations, in which case, concrete values are used instead. In terms of scalability, EXE is used to generate tests for applications such as network protocols and Linux kernel modules (e.g., *mount*), ranging from a few hundred to 2K lines of source code. It is shown to successfully generate inputs that detect bugs in these applications. On the other hand, KLEE pushes scalability to a higher level by detecting bugs on applications of 2K-8K lines of code.

Pex. Pex [119], developed by Microsoft Research, is another concolic execution tool to generate test inputs for the .NET platform. It has been released as a plugin for Microsoft Visual Studio and used daily by several groups within Microsoft. Pex uses the Z3 solver [33] as the underlying decision procedure, and uses approximations to handle types of constraints for which Z3 has not supported, such as strings and floating point arithmetic. There have been a number of extensions to Pex, such as support for heap-allocated data [118], which allows test generation for data structures such as trees and linked lists, and new search strategies [127], which use the fitness function in genetic algorithms to guide search.

SAGE. Godefroid et al. proposed a technique called "SAGE: white-box fuzzing" [50], which targets programs whose inputs are determined by some context free grammars, such as compilers and interpreters. The technique abstracts the concrete input syntax with symbolic grammars, where some original tokens are replaced with symbolic constants. This operation reduces the set of input strings that must be enumerated. As a result, the inputs generated by this technique can easily pass the front-end (lexers and parsers) of the software under test, and reach deeper stages of execution, increasing its chance of catching bugs. The technique has been used to validate applications such as a JavaScript interpreter of Internet Explorer 7. In essence, this technique can be viewed as another attempt to combine symbolic and concrete executions. It is unique in that it uses symbolic grammars to reduce the set of input strings for software systems. Since then, similar ideas have been adopted by other researchers to enable validation of applications such as logical formula solvers [81], server-side application architectures [63], web pages [10, 132], and database applications [39].

Our load generation technique, SLG (Chapter 3), is built on top of SPF, and takes advantages of its built-in features, such as support for heap-allocated data, support for string solvers, and mixed concrete / symbolic execution. Furthermore, we have extended SPF to support symbolic file systems, a design that was inspired by the KLEE tool [23].

2.1.4 Search Heuristics in Symbolic Execution

A typical symbolic execution framework often provides a rich set of search heuristics. A search heuristic essentially determines the priority of target branches to explore next. In the extreme, full program behaviors can be explored via an exhaustive strategy. Within this category, there are many well-known search strategies such as breadth-first (BFS) and depth-first search (DFS) strategies. However, each such strategy is biased towards particular branches. While breadth-first search favors initial branches in the program paths, the depth-first search favors final branches.

Most symbolic execution techniques support a mixture of the above heuristics. DART and CUTE use DFS. EXE also uses DFS as its default strategy, but provides an alternative strategy, which is a mixture of best-first (Best-FS) and DFS [23]. The strategy works as follows: the search starts with DFS, after four branches, it uses heuristics to evaluate all forked paths, picks the one with the best progress (in terms of coverage) to continue first, then does another four steps of DFS. The goal of this strategy is to provide some global perspective occasionally, in order to prevent DFS from sinking in a local subtree. SPF also includes strategies like BFS, DFS, and Random, along with other legacy heuristics (such as Best-FS and BEAM) passed down from the model checker JPF [56].

One interesting work by Xie et al. introduces the concept of fitness function from genetic algorithms to the area of concolic execution [127]. The proposed technique, which is termed “fitness function guided search”, assigns fitness values to each explored path. A fitness function measures how close an explored path is in achieving a test target coverage. A fitness gain is also measured for each explored branch: a higher fitness gain is given to a branch if flipping it in the past helped achieve better fitness values. Then during path exploration, the technique would prefer to flip a branch with a higher fitness gain in a previously explored path with a better fitness value. The goal of this technique is to identify high coverage paths quickly, without getting stuck in a large space of less valuable paths.

For our load test generation technique SLG, we developed unique search strategies specifically tailored to our needs. Rather than performing a complete symbolic execution, it performs an incremental symbolic execution to more quickly discard paths that do not seem promising, and directs the search towards paths that are distinct yet likely to induce high load as defined by a performance measure. We will explain the details of this strategy in Chapter 3.

2.1.5 Memoization in Symbolic Execution

Memoization is a technique for giving functions a memory of previously computed values [83]. Memoization allows a function to cache values that have already been calculated, and when invoked under the same preconditions, to return the same value from a cache rather than recomputing each time. Memoization explores the time-space tradeoff, and can provide significant performance gains for programs that contain many computation-intensive calls.

The concept of memoization has also been applied to program analysis techniques, such as software model checking and symbolic execution. Analogous to classical memoization, the results of previous analysis on functions are cached, and then reused accordingly to save time. For example, Lauterburg et al. proposed ISSE (Incremental State-Space Exploration) [75], a model checking technique that stores the state space graph during a full model checking of a program, and then reduces the time necessary for model checking of an evolved version of the program by avoiding the execution of some transitions and related computations that are not necessary. We now discuss the application of memoization in symbolic execution.

Memoization at the functional level. Recent work [3, 49] proposes compositional reasoning as a means of scaling up symbolic execution. Godefroid et al. proposed the SMART technique [49], which is intended to improve the scalability of DART. The idea is to reuse *summaries* of individual functions computed from previous analysis. A summary consists of pre-conditions on the functions inputs and post-conditions on the functions output; they are computed "top down", to take into account the proper calling context of the function under analysis. If $f()$ calls $g()$, one can summarize $g()$ the first time it is explored, and reuse $g()$'s summary when analyzing $f()$ later on. Thus, each method is analyzed separately and the overall number of analyzed paths is smaller than in the case where the system is analyzed as a whole. Anand et al. extend the compositional analysis with a demand-driven approach [3], which avoids computing summaries unnecessarily, i.e., summaries that will never be used. Instead, summaries are computed as-needed on the fly.

Memoization on full paths. Application of symbolic execution often requires several successive runs on largely similar programs, e.g., running it once to check a program to find a bug, fixing the bug, and running it again to check the modified program. Similar usage scenarios can also be observed in regression testing and continuous testing [97]. Yang et al. proposed Memoise, a technique as a means of scaling up symbolic execution in this type of usage scenarios [130]. It uses a trie-based data structure to store the key elements of a run of symbolic execution, and it reuses this data to speedup successive runs of symbolic execution on a new version of the program. The savings are achieved in a regression analysis setting, in which multiple program versions are available. However, the exact savings are hard to predict, as they depend on the location of the change, and may vary quite a lot between different changes.

Our technique of compositional load generation is inspired by previous work on compositional symbolic execution, but with different goals and mechanisms. For example, in resolving inconsistencies through constraint relaxation, our technique resorts to the performance tags associated with the path constraints in order to maximize the load that the generated test will induce. To the best of our knowledge, our work is the first one to utilize compositional symbolic execution to generate non-functional tests.

2.2 Automated Techniques for Load Testing

In this section we first present an extensive review of related work on automated techniques for load test generation. Techniques in this area can be roughly categorized into two categories: black-box techniques, which treat the system under test as a black box; and white-box techniques, which have access to the source code of the system under test. We will review techniques in both categories, identify their potential and drawbacks, and discuss how our techniques are related to those. In addition, there is a large body of work on automatic / semi-automatic identification of bottlenecks (or performance bugs) in the source code. Although our current work focuses on generation of load tests, our future goal on load testing includes identifying bottlenecks as well. Therefore, we will present a review on this line of work as well.

2.2.1 Generating Load Tests

Black-box Techniques. There is a large number of tools for supporting load testing activities [79], some of which offer capabilities to define an input specification (e.g., input ranges, recorded input session values) and to use those specifications to generate load tests [108]. For example, a popular tool like Silk [108] provides a user interface and wizards to define a typical user profile and scenario, manipulate the number of virtual users to load a system, and monitor a vast set of resources to measure the impact of different configurations. Clearly, more accurate and richer user and scenario specifications could yield more powerful load tests. Support for identifying the input values corresponding to the most load-effective profiles and scenarios, however, is very limited.

A common trait among these tools is that they provide limited support for selecting load inducing inputs as they all treat the program as a black box. The program is not analyzed to determine what inputs would lead to higher loads, so the effectiveness of the test suite depends exclusively on the ability of the tester to select values. Similar trends appear in load testing techniques and processes in general as they use other sources of information (e.g., user profiles [11], adaptive resource models [14]) to decide how to induce a given load, but still operating from a black box perspective.

One recent advance in this area is the FORPOST technique proposed by Grechanik et al. [55]. The technique is novel in that it uses an adaptive, feedback-directed learning algorithm to learn rules from execution traces of applications, and then uses these rules to select test input data to find performance bottlenecks. It has been shown to help identifying bottlenecks in two applications: an insurance application, for which the inputs are customer profiles; and an online pet store, for which the inputs are URLs selecting different functions in online shopping. When FORPOST is applied to these applications, it automatically learns rules on the bad inputs (high loads) such as: a customer should have home/auto discount, or a customer has viewed more than 16 items, etc. It then uses these rules to derive test inputs, such as customer profiles that have home/auto discounts, that lead to high workloads. Bottlenecks are identified by comparing good with bad test cases: a prominent resource consuming method that occurs in good test cases (high load), but is not invoked or has little significance in bad test cases (low load), is likely to be a bottleneck. This approach works well if there exists a large pool of candidate inputs, the variety among candidate inputs is high, and the properties of the inputs can be expressed by simple rules.

Unlike these black-box techniques, our load test generation technique uses a white-box approach to generate tests. We view black-box approaches as complementary, where a hybrid approach may combine the benefits of both approach in a gray-box performance testing, in which a white-box approach is used to select precise input values, and a black-box approach is used to learn input rules, which in turn would help improving scalability of the white-box approach.

White-box Techniques. Until recently, techniques and tools for performance validation or characterization have treated the target program as a black box. One interesting exception is an approach proposed by Yang et al. [129]. Conceptually, the approach aims to assign load sensitivity indexes to software modules based on their potential to allocate memory, and use that information to drive load testing. Our approach also considers program structure, but a key difference in that, instead of having to come up with static indices, our approach explores the program systematically with the support of symbolic execution to identify promising paths that we later instantiate as tests.

The WISE technique proposed by Burnim et al. proposes to uses symbolic execution to identify a worst-case scenario [20]. The technique utilizes full symbolic execution on small data sizes, and then attempts to generalize the worst case complexity from those small scenarios. This works well when the user can provide a branch policy indicating which branches or branch sequences should be taken or not in order to generalize the worst-case from small examples, which requires an extremely good understanding of the program behavior. The study shows that an ill-defined branch policy fails to scale even for tiny programs like Mergesort.

Our approach is different in two significant respects. First, our work is designed to targets scalability specifically. We characterize the components of a system by performing an incremental symbolic execution favoring the deeper exploration of a subset of the paths associated with code structures. This removes the requirement for a user-provided branch policy. For the entire system, we use a compositional approach to avoid exploring whole program paths and facing path explosion problem. Second, our goal is to develop a suite of diverse tests, not just identifying the worst-case. This requires the incorporation of additional mechanisms and criteria to capture distinct paths that contribute to a diverse test suite, and of a family of performance estimators that can be associated with program paths.

2.2.2 Identifying Performance Problems

Profiling-based Techniques. The most common way of identifying performance problems is through profiling of the system under test. Over the years, profiling tools such as *gprof* [54] has been used to find bottlenecks related to excessive CPU usage.

From the memory consumption perspective, Seward et al. propose Memcheck [103], a tool that performs memory usage profiling of a subject program. The results of Memcheck can be used to help identify memory bottlenecks and other types of memory related errors. Memcheck is built on top of Valgrind [85], a binary instrumentation framework. It maintains a shadow value for every register and memory location, and uses these shadow values to store additional information, which enables tracking of all types of memory operations, such as value initialization, allocation/deallocation, copying, etc. Although programs instrumented with Memcheck typically run 20-30 times slower than normal, it is claimed to be fast enough to use with large programs that reach 2 million lines of code.

However, profiling tools often rely on one specific run of the program under test. Selecting the 'right' input that will expose the resource consumption problems becomes critical, and in practice often leads to missed performance bugs. In recent years, several works have been done to alleviate this problem, either by aggregating information from multiple runs (possibly with order of magnitude difference in input data sizes), in the hope of providing "cost functions" for the key methods in the system, or by mining from millions of traces collected on deployed software systems.

Goldsmidth et al. propose an approach that, given a set of loads, executes the program under those loads, groups code blocks of similar performance, and applies various fit functions to the resulting data to summarize the complexity [52]. This approach is applied to various applications such as a data compression program, a C language parser, and a string matching algorithm, and is able to confirm the expected performance of the implementation of those classic algorithms. Although the approach improves dramatically from single run profiling, the user provided workloads still proves to be critical to the performance of this approach.

Gulwani et al. take a static approach [58]. Their approach instruments a program with counters, uses an invariant generator to compute bounds on these counters, and composes individual bounds together to estimate the upper bound of loop iterations. This approach relies on the power of the invariant generator and the user input of quantitative functions to bound any type of data structures. As a result, this approach is demonstrated to scale only to small examples up to a hundred lines of code.

Coppa et al. propose a new profiling tool, *aprof* [28], that further alleviates the problem of relying user provided workloads. *aprof* also generates performance curves of individual methods in terms of their input sizes. However, instead of allowing users to provide work loads that range orders of magnitude in size, *aprof* only needs a few runs under a typical usage scenario. The key insight is that *aprof* automatically identifies different sizes of inputs to a specific method by monitoring its read memory size in each invocation. The approach is evaluated on a few components in the SPEC CPU2006 benchmarks, and is shown to provide informative plots from single runs on typical workloads. However, *aprof* does not consider alternative types of inputs that are received during runtime, such as data received on-line (e.g., reads from external devices such as the network, keyboard, or timer). The accuracy of the approach would be undermined in those situations.

Zaparanuks et al. propose another profiling tool, *AlgoProf* [133], that attempts to achieve a similar goal as *aprof*, but uses different types of metrics. Instead of using cost metrics such as invocation counts, response times, or instruction counts, *AlgoProf* uses a set of metrics that focus on repetitions, i.e., loop counts, recursions, and data structure access counts. As a result, *AlgoProf* produces cost functions that are more focused on the algorithmic complexity. *AlgoProf* is shown to provide accurate performance plots for classical data structure algorithms such as trees and graphs, and is proved useful in uncovering algorithmic inefficiencies. However, it is not clear whether this type of metrics is as useful in broader types of applications.

Han et al. propose StackMine [60], a tool that takes a different approach to avoid the workload dependent problem. Instead of focusing on a few isolated runs, StackMine works on millions of stack traces collected on the deployed software systems (e.g., Microsoft Windows Error Reporting Tool). It uses machine learning algorithms to mine suspicious traces out of those traces: a sequence of calls appearing a long time across multiple stacks can be a CPU consumption bug; a sequence of calls waiting long time across multiple stacks can be a wait bug. This technique provides an alternative approach to performance debugging in the large, if the user can afford to collect a large amount of stack trace data on deployed products, which is generally expensive and fragmented.

Our work complements these techniques, because we focus on selecting input values that lead to worst case performances. We conjecture that the generated input values can in turn be used to enable a more accurate profiling of the program under test.

Search-based Techniques. Another thread of related works aim to predict overall performance of a system at a stage where only performance evaluation of the constituent components are available [1, 12, 107]. This type of information is valuable, because it can predict performance of systems that are yet to be built, therefore avoiding system architectures that are doomed to lead to bad performance. For example, Siegmund et al. proposed a technique that can predict program performance based on selected features in a software product line environment [107]. The proposed technique models the problem as a search problem, and uses heuristic search to reduce the number of measurements required to detect the feature interactions that actually contribute to performance out of an exponential number of potential interactions.

In a sense, our compositional load generation technique also aggregates performance information of individual components, in order to evaluate performance of the whole system. However, the information we gather are input constraints corresponding to the worst performing program paths, which can enable more accurate compositional analysis, and produce more accurate results.

2.3 Techniques for Detecting Faults in Exception Handling Code

Our work in this field is mainly related to two areas: mining specifications and coverage representations. Additionally, we will review areas of related work on fault injection and mocking, which are techniques used by our work.

2.3.1 Mining Specifications of Exceptional Behavior

Techniques to mine specifications of exceptional behavior (e.g., [2, 117, 124]) operate by mining rules from a pool of source code and then checking a target program for violations of the mined rules. The existing techniques vary in the type of rule structure they target, the scope of the analysis, how the pool is built, and the challenges introduced by the target programming language. So, for example, while Thummalapenta et al. [117] use conditional rules, intraprocedural analysis, a pool of code enriched with code from a public repository, and Java code, Acharya et al. [2] use association rules in C code, which does not support explicit try-catch structures.

The performance of these approaches depends on the quality of the pool of source code, the precision and completeness of the analysis, and the training parameters that define what constitutes an anomaly. It is not evident from the reported studies whether or not exception handling constructs that can take so many different forms and occur in such large scopes can be effectively mined as rules. Our approach is different from these techniques in that it transforms the problem into a state space exploration problem and systemically traverses the space to find faults.

2.3.2 Exceptional Control Flow Representation

Our work is also related to techniques that focus on the development of more precise flow representations and analyses that include control flow edges to and from exception structures [27, 44, 45, 95, 109]. Sinha et al. [109] were among the first to build a program representation with explicit exception constructs, i.e., throw statements and try-catch-finally structures, and propose the use of this representation to calculate links between exceptions and their corresponding handlers. Later, they propose to use this information to build a toolset that helps with test case selection and maintenance [110]. Choi et al. [27] proposed one of the many refinements that followed, either to improve efficiency (e.g., by grouping edges by types) or precision (e.g., by combining the static analysis with some form of dynamic analysis for refinement [21]). Robillard et al. introduced a model and a static analysis tool, Jex, that adopted a similar approach but oriented towards providing development support [95]. Fu et al. [44, 45] extended the control-flow analysis by considering re-throwing exceptions which they argue is common among layered software, and by using the results of exception-flow analysis to improve the coverage of exception handling code through dynamic fault injection. This last piece of work is similar to ours in that we both adopt mechanisms for mocking the APIs. The difference is that this approach is guided to cover the exceptional edges while ours attempts an exhaustive coverage of mocking patterns.

2.3.3 Fault Injection

Fault injection techniques have been used to test the degree of fault tolerance in a system, to increase test coverage, or to simulate certain types of faults. From a broader perspective, fault injection techniques include both hardware and software fault injections. In this section, we only review software fault injection techniques that inject faults at runtime (i.e., dynamically). Static software fault injection (also known as mutation testing), or hardware fault injection, are less related to our work and thus omitted from this review.

The Fault Injection-based Automated Testing (FIAT) platform [101] were among the first to implement software fault injection techniques. The 'fault' defined in this work corresponds to a bit change in memory. By appropriate application, these memory changes are able to emulate faults occurring in other levels of the system, as high as updating a wrong index variable in the source code, or as low as an incorrect register selection within the CPU. FIAT provides mechanisms for user to specify where, when, and how long faults will take effect. However, FIAT is not designed to support precise fault injection, instead, it is mostly used to test the general degree of fault tolerance of a program running on a representative workload. In this scenario, the fault types are simple (such as setting a bit to zero), the fault locations are simple (such as all operands of the ADD instructions), and the fault manifestations are simple (such as machine crash) as well. The technique then systematically and exhaustively injects all possible faults into the system, and statistical techniques are used to characterize faulty behaviors.

Bieman et al. proposed an alternative technique for fault injection aimed at increasing test coverage [16]. This technique automatically identifies assertions in the program, and then steers fault injection towards failing these assertions. For example, if an assertion has a condition ($X > 0$), then the technique deliberately injects values for X what can lead to the violation of the condition. In this way, the corresponding error recovery code can be triggered, and test coverage is eventually increased.

Our exception testing technique presented in Chapter 5 is related to both techniques presented in this section. On one hand, we identify targets, calls to APIs of external resources, as fault injection directions. On the other hand, we use an exhaustive strategy to test the degree of fault tolerance in the applications. Our technique is unique in that we define a space of exceptional behaviors that can be triggered through fault injection by specified external resources, and then inject faults (exceptions) in patterns through mocking to explore each path in the exceptional space, rather than at a single location at a time.

2.3.4 Mocking

Our work is also related to mocking techniques (e.g., [41][42]), and tools (e.g., [35][66]). Mocking was originally developed to support test scaffolding. It allows tests to be written and executed before the system under test is completed, thus directing the programmer to think about the design of code from its intended use, rather than from its implementation. Since then, other software testing approaches have taken advantage of the flexibility provided by mocking techniques to other ends, such as fault injection [42] and carving and replaying of unit tests [38]. Our work can be viewed as a type of fault injection through mocking that focuses on external resources. In our implementation, we use AspectJ to provide mocking capabilities. This decision is based on the availability of a code transformation tool that translates aspect-weaven code into dex binary format that runs on the Android platform [5]. However, our approach does not prescribe a specific mocking tool. For example, the Java-based mocking framework JMock [66] provides a set of APIs to let users create mock classes, and define expected behaviors of a mocked method, such as preconditions for input, and output under various conditions. It also allows a user to setup rules for exceptional behavior, such as the conditions to throw certain types of exceptions, and throwing exceptions in patterns. Therefore, JMock can be used instead of AspectJ in the analysis we introduce in Chapter 5.

Chapter 3

Automatic Generation of Load Tests

In this chapter, we present the design and implementation of SLG, a symbolic execution based load test generation technique. We first introduce the challenges for load generation, then present the algorithm, the parameters it takes, and the implementation details. In the end we describe a thorough evaluation of the technique.[1]

3.1 Challenges

As mentioned in Section 1.2, most existing load testing techniques induce loads by increasing size or rate of the input, without any analysis of the target system to determine what inputs would lead to higher loads. Such techniques provide a rather costly means to load a system, and may force the system to perform more of the same computation. As alluded in Section 2.1, symbolic execution, being a white box exhaustive technique, provides many benefits to load test generation. Instead

[1]Portions of the material presented in this chapter have previously appeared in a paper by Zhang et al. [137].

of focusing on increasing size or rate of input, the generated load tests target actual values that can expose worst case behaviors. Because symbolic execution exhaustively traverses all program paths, it can also lead to a test suite that loads the system in diverse ways. However, plain symbolic execution, or its scalable extension termed *mixed* symbolic execution, is not a cost effective means of generating load tests.

To illustrate this last point, we apply mixed symbolic execution to assess the response time of `TinySQL`, an SQL server that we study in some depth in Section 3.5. Assume that the goal is to validate whether the server can consistently provide response times below 90 seconds for a common query structure like the one in Figure 3.1 operating on a benchmark database. Under this setting the query structure is fixed and the database has concrete data, but the query's parameters are marked as symbolic. Even though this query is rather simple, after 24 hours a mixed symbolic execution for test generation will still be running. It will have generated 274 tests by solving the paths conditions associated with an equal number of paths.

```
SELECT <SYM_FLD> <SYM_FLD>
FROM <SYM_TAB>
 JOIN <SYM_TAB> ON <SYM_COND>
WHERE <SYM_COND> OR <SYM_COND>
```

Figure 3.1: SQL query template.

Figure 3.2 shows a snapshot of the tests generated as a histogram where the x-axis represents `TinySQL` response times in seconds, and the y-axis represents the number of tests that caused that response time. We note that most tests cause a system response time of less than 50 seconds, but there is significant variability across tests ranging from 5 seconds to over 2 minutes. Of all these tests, we are interested in the ones on the right of Figure 3.2 — the ones causing the largest response times and most likely to reveal performance faults. The question we address is how to direct path exploration to obtain only those tests.

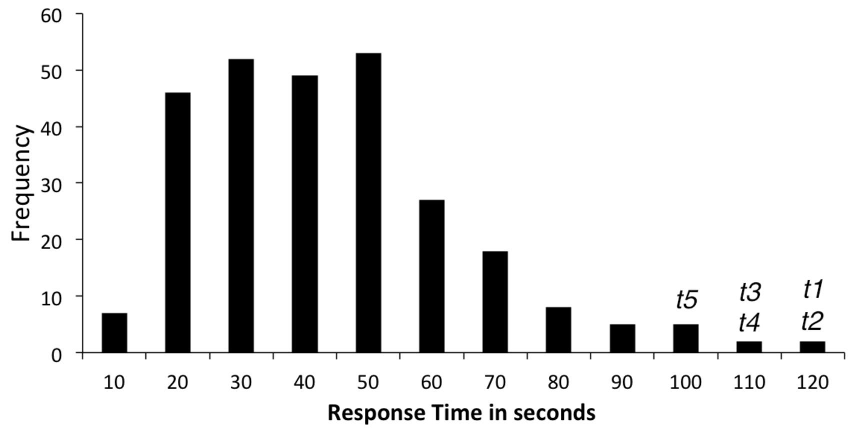


Figure 3.2: Histogram of response time for TinySQL.

3.2 Approach Overview

We now present a white box approach for using symbolic execution to automatically generate load test suites. Rather than performing a complete symbolic execution, it performs an *incremental* symbolic execution to more quickly discard paths that do not seem promising, and *direct* the search towards paths that are distinct yet likely to induce high load as defined by a performance measure.

The approach requires for the tester to: (1) mark the variables to treat as symbolic just like in standard mixed symbolic execution [92], (2) specify the number of tests to be generated, denoted with *testSuiteSize*, and (3) select the performance measure of interest, denoted with *measure*, from a predefined and extendable set of measures. In addition, to control the way that the symbolic execution partitions the space of program paths into *phases* an additional parameter, *lookAhead*, is needed. *lookAhead*[2] represents the number of branches that the symbolic execution looks

[2]In the area of constraint processing, the term *lookAhead* is used to refer to the procedure that attempts to foresee the effects of choosing a value for a branching variable [34]. Specifically, in forward checking, given the current partial solution and a candidate assignment to the current variable, it removes values in the domains of the variables that are still unassigned, which leads to a simpler problem, or detects inconsistency early. In other words, it simplifies the future based the current choice. In our work, *lookAhead* means simplifying the current situation based on a bounded examination of the future.

ahead in assessing whether paths are diverse enough and of high load. (We discuss the selection of values for *lookAhead* in the next section.)

Given the developer supplied parameters, the approach performs an iterative-deepening mixed symbolic execution that checks, after a depth of *lookAhead* branches, whether there are *testSuiteSize* diverse groups of program paths, and if so, it then chooses the most promising path from each group based on *measure*.

Promoting diversity. After every *lookAhead* branches, diversity is assessed on the paths reaching the next depth (shorter paths are deemed as having less load-generating potential and are hence ignored). The approach evaluates diversity by grouping the paths into *testSuiteSize* clusters based on their common prefixes. A set of clusters is judged to have enough diversity when no pair of paths from different clusters have a gap whose length, in terms of branches taken, is within *lookAhead*/*testSuiteSize* of either path in the pair. The intuition is that forcing clusters to diverge by more than *lookAhead*/*testSuiteSite* branches will drive test generation to explore different behaviors that incur high load. This threshold is initiatively chosen based on that bigger test suite means less diversity can be expected among tests. If the diversity among clusters is insufficient, then exploration continues for another *lookAhead* branches. Otherwise, the approach selects the most promising path from each cluster for further exploration in the subsequent symbolic execution phase, and the rest of the paths are discarded.

Favoring paths according to a performance measure. The selection of paths at the end of each phase is performed according to the chosen performance measure. So, for example, if the user is interested in response time, then paths traversing the most time consuming code are favored. If the user is interested in memory consumption, then the paths containing memory allocation actions are favored. Independent

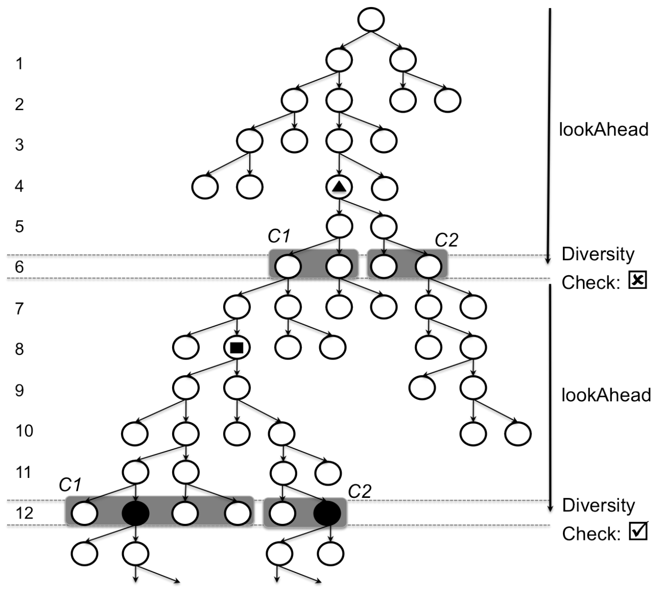


Figure 3.3: Iterative-deepening beam symbolic execution.

of the chosen measure, what is important is that each path has an associated cost performance summary that acts as a proxy for the performance measure chosen by the user. This summary is updated as a path is traversed and is used to select promising paths for load testing.

Illustration. Figure 3.3 illustrates this approach with $testSuiteSize = 2$ and *look-Ahead* $= 6$. These values mean that the common prefix of any pair of paths from two clusters must differ in more than 3 branches for the clusters to be considered diverse enough to enable path selection. The approach starts by performing an exhaustive symbolic execution up to depth 6. Then, it clusters the paths reaching that depth into two clusters – the grayed boxes labelled C1 and C2 at depth 6 in the Figure. These clusters, however, are deemed insufficiently diverse because a gap—whose starting point is marked with a triangle—is found that has a branch length of 2. Hence, the symbolic execution continues until depth 12 where the clustering process is repeated. In this case, the diversity check is successful because the gap—whose starting point is marked with a square—differs in 4 branches, which is more than $lookAhead/testSuitesize$.

The approach in practice. Continuing with `TinySQL` and its query template, when the approach is configured to find values for the query template, to generate 5 tests, to use a $lookAhead = 50$, and to target the maximization of response time, our approach takes 159 minutes to generate a set of tests (11% of the cost of the 24 hours of symbolic execution).

As depicted by annotations $t1 \ldots t5$ in Figure 3.2, the tests identified by the approach do reside on the right hand size of the figure. Two of the generated tests are in the bin labelled 120 seconds (this bin includes all tests that cause response times of 115 seconds or more), 2 are in the 110 seconds bin, and 1 is in the 100 seconds bin. Each of the 5 generated tests takes at least twice the time of the original test from which the template was derived (which took less than 40 seconds).

In addition, as discussed in Section 3.5, the generated tests are diverse. These five tests use many different fields, tables, and filtering clauses. Furthermore, they represent three types of database join operations, each of which impose heavy load on the system in a different way.

3.3 The SLG Algorithm

In this section we provide a detailed description of the approach and its parameterization capabilities to address a broad range of load testing scenarios. We first define key terms, then outline the core algorithm and its components.

Definition 3.3.1 *Path Condition (pc): A conjunction of the necessary constraints for a program path to be taken. A constraint is a symbolic expression over symbolic* *input variables* $\{\Phi_P^1, \Phi_P^2, \cdots, \Phi_P^n\}$ *of program* P*, where the subscripts denote the program and the superscripts denote the variable index. The* **size** *of a path condition is defined in terms of the number of constraints it contains.*

Definition 3.3.2 *Symbolic State: A combination of: (a) symbolic input variables and their associated constraints for a selected subset of program inputs in the form of a path condition, and (b) concrete values for the remaining program inputs.*

Algorithm 1, **SymbolicLoadGeneration (SLG)**, details our load test generation approach. Conceptually, the algorithm repeatedly performs a bounded symbolic execution that produces a set of *frontier* symbolic states based on the branch look ahead, *clusters* those states based on the desired number of tests, and then, if the clusters are sufficiently diverse, selects the most *promising* state from each cluster for further exploration.[3]

Algorithm 1 takes 5 parameters: 1) $\overline{init}$, the states from which the search commences, 2) $testSuiteSize$, the number of tests a tester wants to generate, 3) $lookAhead$, the increase in path condition size that an individual symbolic execution may explore, 4) $maxSize$, the size of the path condition that may be explored by the technique as a whole, and 5) $measure$, the cost measure used to evaluate promising states.

Each of the individual symbolic executions is referred to as a *level* and each level is bounded to explore states that add at most *lookAhead* constraints to the path condition of a previously generated state. This is achieved by incrementing *currentSize* by *lookAhead* and using the result to bound the symbolic execution. If the *currentSize* exceeds the *maxSize*, then the algorithm restricts the bound to produce states with path conditions of at most *maxSize*.

[3]We describe our algorithm here in terms of symbolic states, but it is understood that each such state defines the end of the prefix of a path explored by symbolic execution.

Algorithm 1 SymbolicLoadGeneration ($\overline{init}$, testSuiteSize, lookAhead, maxSize, measure)

```
1: currentSize ← 0
2: $\overline{promising}$ ← $\overline{init}$
3: search ← true
4: while search do
5:     currentSize ← currentSize + lookAhead
6:     if currentSize > maxSize then
7:         currentSize ← maxSize
8:         search ← false
9:     end if
10:    $\overline{frontier}$ ← boundedSE( $\overline{promising}$, currentSize, measure)
11:    $\overline{cluster}$ ← frontierClustering($\overline{frontier}$, testSuiteSize)
12:    if diversityCheck($\overline{cluster}$) $\vee \neg$ search then
13:        $\overline{promising}$ ← selectStates($\overline{cluster}, measure$)
14:    else
15:        $\overline{promising}$ ← $\overline{frontier}$
16:    end if
17:    if largestSize( $\overline{promising}$) < currentSize then
18:        search ← false
19:    end if
20: end while
21: return $\overline{promising}$
```

At Lines 1-2, the first level begins from a set of states, $\overline{init}$, which forms the initial set of promising states, $\overline{promising}$, and the *currentSize* set to zero. At Line 3 the *search* boolean variable is set to *true* and iteration begins at Line 4. Lines 5-9 correspond to increasing *currentSize* and check whether *maxSize* is exceeded. At Line 10, the algorithm performs a level of the search, which corresponds to a call to *boundedSE*(), which attempts to extend states from $\overline{promising}$ to paths of size *currentSize*. As that process proceeds *measure* is used to update an associated performance estimate with each state.

Each time a $\overline{frontier}$ is formed, at Line 11, the function $frontierClustering$ is called to cluster the frontier states into *testSuiteSize* clusters. The clustering process is described below.

The goal of clustering is to identify sets of states that are behaviorally diverse—we measure diversity by differences in the branch decisions required to reach a state. If the clusters of states on the frontier are not sufficiently diverse, then we continue with another level of symbolic execution that attempts to extend the entire frontier another *lookAhead* branches. Should the current $\overline{cluster}$ pass the *diversityCheck*, the function *selectStates*() selects the state from each cluster with the maximum accumulated value for the performance measure (Line 13). Otherwise, the whole $\overline{frontier}$ is copied over to the set of $\overline{promising}$ states and the search resumes (Line 15). We discuss several such measures in Section 3.4.

The iterative-deepening search terminates if no promising state has a path condition whose size is *lookAhead* greater than the previous level's states (Lines 17-18. *largestSize*() returns the largest path condition found in $\overline{promising}$).

When the search terminates, the path conditions associated with the $\overline{promising}$ states can be solved with the support of a constraint solver to generate tests as is done by existing automated generation approaches for functional tests.

3.3.1 Parameterizing SLG

In defining $\overline{init}$ a test engineer selects the portion of a program's input that is treated symbolically. Depending on the program one might, for example, fix the size or structure of the input and let the values be symbolic. An example of the former case is load testing of a program that processes inputs of uniform type but of varying size, such as the `JZlib` compression program. An example of the latter case is load testing of a program that processes structured input, such as the SQL query engine we study. For such a program the structure may be fixed, e.g., the number of columns to select, number of where clauses, etc., in the query, but the column names and where clause expressions are symbolic. In general, treating more inputs symbolically will generate more diverse and higher quality load test suites, but such a test generation may also incur greater cost. We expect that in practice, test engineers will start with a small set of symbolic inputs and then explore larger sized inputs to confirm the observations made on smaller inputs.

The *testSuiteSize* parameter determines how many tests are to be generated. Varying this parameter helps to produce a more comprehensive non-functional test suite for the application under test. Regardless of the size of the test suite, SLG always attempts to maximize diversity among tests. Exactly how many tests are required to perform a thorough testing on the non-functional aspect of interest of the application, however, is a harder question which cannot be assessed with traditional test-adequacy measures, such as code coverage. In practice, selecting a test suite size will likely be an iterative process where test suite size is increased until a point of diminishing returns is reached [105]—where additional tests either lack diversity or a high load.

Bounding the depth of symbolic execution is a common technique to control test generation cost — the *maxSize* parameter achieves this in our approach. The parameter *lookAhead*, however, is particular to an iterative-deepening search as it regulates how much distance the search advances in one iteration. The larger the *lookAhead*, the more SLG resembles a full symbolic execution. Normally a smaller value for *lookAhead* is desired, because a finer granularity would provide more opportunity for state pruning, which is key to the efficiency of our approach. Ultimately state pruning is decided by the diversity among the frontier of states, so a smaller *lookAhead* alone cannot lead to ill-informed pruning. Setting *lookAhead* too small may cause efficiency issues — a value of 1 will degrade the search to breadth first.

Figure 3.4 provides support for this intuition by plotting the quality of tests generated by our approach using *lookAhead* values of 1, 10, 50, 100, 500, 1000 and 30

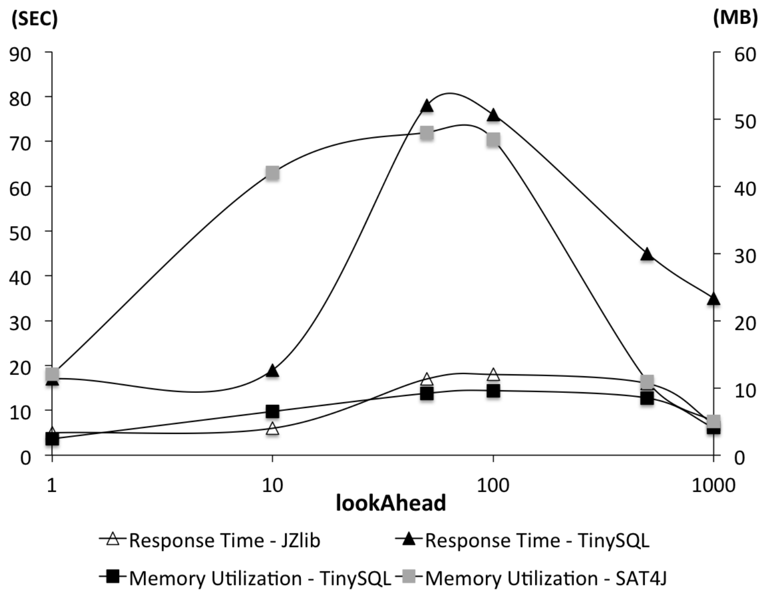


Figure 3.4: Quality of load tests as a function of *lookAhead*.

minutes of test generation time. The original tests for these programs execute an average of 16,000 branches, the selected *lookAhead* values allow multiple iterations. The triangle plots show results for response time tests in seconds on the left axis; the black triangle plots are for the `TinySQL` program and the white triangle for `JZlib`. The square plots show results for maximum memory utilization tests in megabytes on the right axis; the black square is for the `TinySQL` program and the gray square for `SAT4J`. In each plot, the quality of the test rises as the *lookAhead* increases to 50 and then drops off after 100. The reason for such a trend is that when *lookAhead* is smaller than 50, the approach works less efficiently due to inserting many diversity checks prematurely, and when *lookAhead* is larger than 100, much effort is wasted in exploring states that are going to be pruned. We use these insights to support the selection of *reasonable lookAhead* values in the technique evaluations in Section 3.5. In practice, a similar process could be performed automatically to select appropriate values for each system under test.

The last parameter, *measure*, defines how the approach should bias the search to favor paths that are more *costly* in terms of the non-functional measure of interest. The details of how the cost for a path is accumulated as the path is traversed and associated with the end state of that path, which is implemented within $boundedSE()$, and then used to select promising states, which is implemented in $selectStates()$, are abstracted in Algorithm 1. In general, our approach can accommodate many measures by simply associating different cost schemes with the code structures associated with a path. In our studies we explore response time and maximum memory consumption measures through the following cost computations:

a) Response Time Cost. This is a cumulative cost, so the maximal value occurs at the end of the path. We estimate response time by accumulating the cost of each bytecode. We use a very simple and configurable platform-independent cost model that assigns different weights to bytecodes based on their associated cost.

b) Maximal Memory Usage Cost. It attempts to record the largest amount of memory used at any point during a program execution by tracking operations that allocate/deallocate memory and increment/decrement a memory usage value by a quantity that reflects the object footprint of the allocated type. The maximal memory value is only updated if the current usage value exceeds it. As with response time, we find that this simple platform-independent approach strongly correlates to actual memory consumption.

Independent of the chosen performance measure and cost, our approach assumes that the measure constitutes part of a *performance test oracle*. We note that there is a large number of measures explored in the literature, and that they are often specified in the context of stochastic and queueing models [17], extended process algebras [62], programmatic extensions [43], or concerted and early engineering efforts focused on software performance [113]. Because such performance specifications are generally still hard to find, we take a more pragmatic approach by leveraging the concept of a *differential test oracle*. The idea behind differential oracles is to compare the system performance across successive versions of an evolving system to detect performance regressions, across competing systems performing the same functionality to detect potential anomalies or disadvantageous settings, or across a series of inputs considered equivalent to assess a systems's sensitivity to variations in common situations.

3.3.2 Clustering the Frontier and Diversity Checks

A convenient choice of clustering would be to use the classic *K-Means* algorithm [61] and define the number of unique clauses between two PCs as the *clustering distance*. However, this would require comparing across all pairs of PCs of frontier states and quickly run into scalability issues. For example, for the `tinySQL` program, clustering a frontier into 10 clusters at depth 50 requires 2 seconds of execution time, but at depth 100 would require 7 seconds. Doubling the depth caused 3.5 times increase in processing time. In fact, the cost grows exponentially in terms of the explored depth.

To address this challenge, we devised an approximate algorithm that is linear in the number of frontier states. It makes use of the intuition that for frontier states resulting from a depth first search, a pair of neighboring states are more likely to resemble each other than a pair of distant states. Algorithm 2 details the process. It takes $\overline{frontier}$ and the size of resulting cluster K as input, where K is the number of tests to be generated.

At Lines 3-5, it first computes the gap, in terms of the number of unique clauses, between each pair of $pc(s_i)$ and $pc(s_{i+1})$. At Line 6 it sorts the resulting gap vector to find the largest $K-1$ gaps. At Lines 7-13, the algorithm uses the position of these $K-1$ largest gaps to partition the $\overline{frontier}$ into K clusters of various sizes.

The diversity check ensures that the gaps used to partition the $\overline{frontier}$ are of

Algorithm 2 frontierClustering ($\overline{frontier}$, K)

```
1:  $\overline{cluster} \leftarrow \emptyset$
2:  $n \leftarrow |\overline{frontier}|$
3:  **for all** $s_i \in \overline{frontier}, i \in (1, n-1)$ **do**
4:      $\overline{gap}$[i] $\leftarrow$ diff($pc(s_i)$, $pc(s_{i+1})$)
5:  **end for**
6:  $\overline{sortedGap} \leftarrow$ descentSort($\overline{gap}$)
7:  $\overline{largestGap} \leftarrow \overline{sortedGap}$[1, K-1]
8:  **for all** $s_i \in \overline{frontier}, i \in (1, n-1)$ **do**
9:      **if** $\overline{gap}$[i] $\in \overline{largestGap}$ **then**
10:         $\overline{cluster}$.createNewPartition()
11:     **end if**
12:     $\overline{cluster}$.putInCurrentPartition($s_i$)
13: **end for**
14: **return** $\overline{cluster}$
```

sufficient size to promote paths that have non-trivial behavioral differences. The threshold for such a gap could be defined in any number of ways. We use the heuristic $TH_{minPartitionGap} = \frac{lookAhead}{|\overline{cluster}|}$ because it balances the fact that, in general, larger *lookAhead* generates greater diversity while larger values of $|\overline{cluster}|$ tends to reduce the difference between groups of states. This threshold is enforced by checking against the least largest gap that is used to define clusters.

3.3.3 Dealing with Solver Limitations

When Algorithm 1 returns $\overline{promising}$ a typical test generation technique would simply send the path conditions associated with those states to a constraint solver to obtain the test cases inputs. Because path conditions for candidate load tests often contain many tens of thousands of constraints, this basic approach will quickly expose the performance limitations of existing satisfiability solvers. For example, one of the resulting path constraints for `tinySQL` has over 8,000 constraints over 23 variables, and for `JZlib`, an input size of 1000 variables (symbolic bytes) yields over 35,000 constraints.

Algorithm 3 ConstraintLimitedLoadGeneration($\overline{init}$, testSuiteSize, lookAhead, maxSize, measure, maxSolverConstraints)

```
1:  currentSize ← maxSolverConstraints
2:  while currentSize < maxSize do
3:      $\overline{promising}$ ← SymbolicLoadGen($\overline{init}$, testSuiteSize, lookAhead, maxSolverConstraints, measure)
4:      $\overline{init} \leftarrow \emptyset$
5:      for $s \in \overline{promising}$ do
6:          $\overline{inputs} \leftarrow solve(pc(s))$
7:          $\overline{init} \leftarrow \overline{init} \cup$ stateAfterReplay($\overline{inputs}, pc(s)$)
8:      end for
9:      currentSize ← currentSize + maxSolverConstraints
10: end while
11: return $\overline{promising}$
```

We address this issue by defining an outer search, Algorithm 3, that wraps calls to Algorithm 1 in such a way that the maximum number of symbolic constraints considered within any one invocation of Algorithm 1 is bounded. **ConstraintLimitedLoadGeneration(CLLG)** takes the same parameters as SLG plus an additional parameter *maxSolverConstraints*. This parameter can be configured based on the scalability of the constraint solver used to implement symbolic execution.

Algorithm 1 is invoked with *maxSolverConstraints* as the *maxSize* parameter that governs the overall size of the iterative-deepening symbolic execution. At Line 3, the iteration starts by invoking SLG to compute the current set of $\overline{promising}$ states. When $\overline{promising}$ is returned, Algorithm 3 solves the path constraints of each state in $\overline{promising}$ to obtain the input values necessary to reach those states (Line 6). Then, it replays the program using those concrete inputs and, when the program has traversed all the predicates in the path condition, the program state is captured and added to $\overline{init}$ (Line 7). The algorithm terminates when the sum of sizes of the path conditions explored in each of the invocations of *SymbolicLoadGen*() exceeds the *maxSize*.

In essence, Algorithm 3 increases the scalability of our approach by chaining partial solutions together through the use of concrete input values. While this may sacrifice the quality of generated tests, it can help overcome the limitations of satisfiability solvers and allow greater scalability for load test generation. We explore this tradeoff further in Section 3.5.

Finally, we note that when $maxSolverConstraints = maxSize$, CLLG runs a single instance of SLG. Consequently, we use the former as the entry point for our technique.

3.4 Implementation

We have implemented the approach by adapting SPF [92], which is an extensible symbolic execution framework developed at NASA. Figure 3.5 illustrates the key components of the implementation. Our modifications to SPF enable us to use path performance estimators to associate a performance measure with a cost for each path, to use bounded symbolic execution to performance the analysis in phases, and to compute diversity among explored paths. An SMT solver is then used to generate a test suite from the collected path conditions. We then describe these components in details.

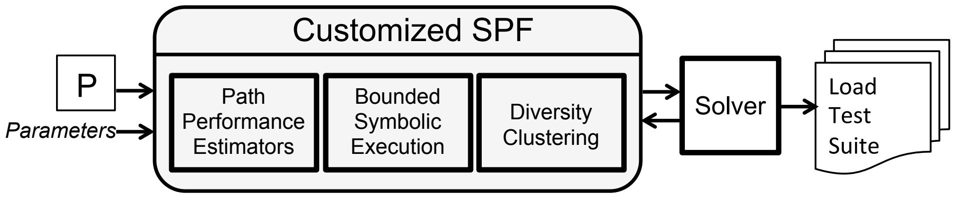


Figure 3.5: Illustration of the SLG implementation.

Path Performance Estimators. We have implemented two performance cost schemes, one aiming to account for the response time and one for maximum memory consumption. For response time, we use a simple weighted bytecode count scheme that assigns a weight of 10 to `invoke` bytecodes and a weight of 1 assigned to all others bytecodes. The implementation allows for the addition of finer grain schemes (e.g., [134]). The memory consumption costing scheme takes advantage of SPF built-in object life cycle listener mechanism to track the heap size of each path, and associates this value with each path. Neither scheme takes into account the JIT behavior or architectural details of the native CPU. In our experience so far these simple schemes has been quite effective. We have designed our implementation for other estimators to be easily added. For instance, a cost estimator related to the number of open files in the system can be easily added by tracking open and close calls on file APIs, and multiple measures can be combined by using a weighted sum of individual measures.

Bounded Symbolic Execution. We run SPF configured to perform mixed symbolic execution. When a phase of symbolic execution finishes, the $selectState()$ function is invoked to compute a subset of the frontier states for further exploration. In the current implementation, the branch choices made along the paths leading to those states are externalized to a file. Then SPF is restarted using the recorded branch conditions to guide execution up to the frontier, and then resume its search towards until the next frontier. This solution is efficient because the satisfiability of the path condition prefix is known from the previous symbolic execution call, thus SPF is simply directed to execute a series of branches and no backtracking is needed for those branches. We note that we have explored alternative mechanisms to avoid recording and replaying path prefixes stored in files and to avoid restarting SPF. We found that none was as efficient in scaling to large programs as the replay approach described above. This approach also has the distinct advantage of allowing the exploration of the recorded path prefixes to proceed in parallel, which is a strategy we plan to pursue in future work. We also use the replay mechanism to implement the

$stateAfterReplay()$ function used in Algorithm 3.3.3.

Diversity Clustering. Algorithm 2 takes advantage of the SPF backtracking support to efficiently compute the $\overline{gap}$ vector on the fly, because each gap between two states s_i and s_{i+1} equals the number of branches s_i needs to backtrack before it can continue on a new path that leads to s_{i+1}.

Test Instantiation. Generating tests from a path condition requires the ability to both solve and produce a model for a given formula. We have explored the use of several constraint and SMT solvers, including Choco [26] (Version 2.04), CVC3 [30] (Version 3.2), and Yices [131] (Version 1.0.12) in a period between Fall 2009 and Summer 2010. Our integration of Yices into SPF has greatly improved the scalability of SPF in general and of our technique in particular. The data reported in our study uses this Yices-based implementation.

3.5 Evaluation

Our assessment takes on multiple dimensions, resources, and artifacts.

First, we assess the approach configured to induce large response times and compared it against random test generation. Then, we explore the scalability of various instantiations of the approach. We do this in the context of JZlib [69] (5633 LOC[4]), a Java re-implementation of the popular Zlib package. This program is well suited for the study because we can easily and incrementally increase the input size (from 1KB to 100MB) to investigate the scalability of the approach and response time is one of its two key performance evaluation criteria. Moreover, we can easily generate what the Spec2000 benchmark documentation [114] defines as the worst load test inputs for

[4]LOC stands for 'Lines Of Code' of a program.

JZlib – random values – to increase response time and use those to compare against our approach. Last, we can use the Zlib package as the differential oracle.

Second, we assess an instantiation of the approach to generate a suite of 10 tests that follow a prescribed input structure with the goal of inducing high memory consumption. We conduct this assessment with SAT4J [100] (10731 LOC) which is well suited for the study in that memory consumption is often a concern for such kind of applications. Furthermore, the SAT benchmarks [99] that already aim to stress this type of applications offer a high baseline against which to assess our approach.

Third, we assess an instantiation of the approach to generate three test suites, one that causes large response times, one that causes large memory consumption, and one that strives for a compromise. We use TinySQL [120] (8431 LOC) and its sample queries and database, as described earlier. Because the tests for this artifact can be easily interpreted (they are SQL queries), we perform a qualitative comparison on their diversity.

Throughout the study we use the same platform for all programs, a 2.4 GHz Intel Core 2 Duo machine with Mac OS X 10.6.7 and 4GB memory. We executed our tool on the JVM 1.6 with 2GB of memory. We configure it to use $lookAhead = 50$ as per the description in Section 3.4 and $maxPCSize = 30000$ in order to keep within the capabilities of the various constraint solvers we used.[5]

3.5.1 Revealing Response Time Issues

Our study considers two load test case generation techniques as treatments: CLLG and Random. Each test suite consists of 10 tests. CLLG is configured to target response time. We imposed a cap of 3 hours for each the test generation strategies.

[5]This number could be adjusted depending on the time available and the selected constraint solvers. As noted earlier, however, all solvers would eventually struggle to process an increasing number of constraints so selecting this bound is necessary.

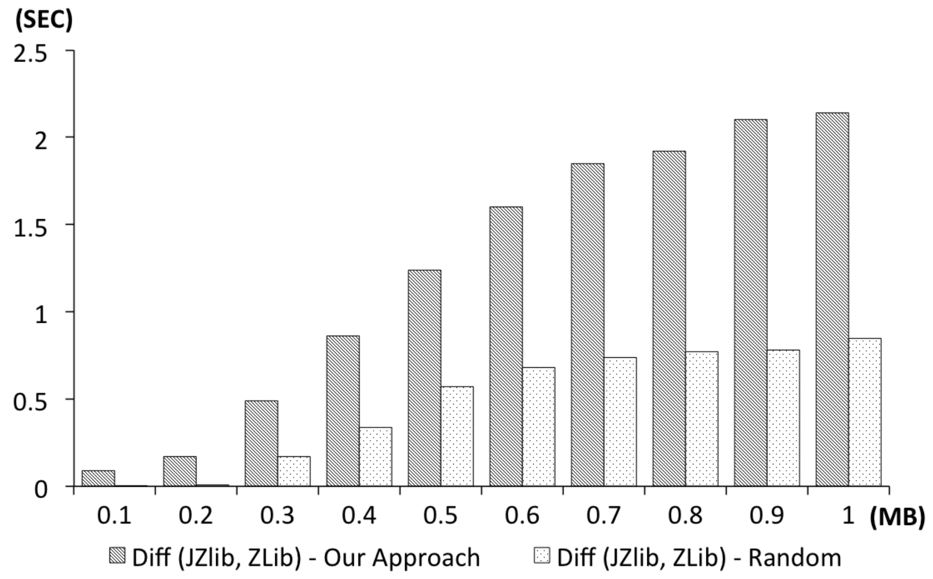


Figure 3.6: Revealing performance issues: response time differences of JZlib vs Zlib when using testing suites generated by CLLG vs Random.

Strategies requiring more time were terminated and not reported as part of the series. For Random test generation we used the whole allocation of 3 hours to simplify the study design, which is conservative in that it may overestimate the effectiveness of the Random test suites in cases were the CLLG suites for the same input size took less than 3 hours to generate. For the Random treatment, we use a random byte generator to create the file streams to be expanded. Another consideration with Random is that, unlike our approach with its built-in selection mechanism, it does not include a process to distinguish the best 10 load tests. This is important as Random can quickly generate millions of tests from which only a small percentage may be worth retaining as part of a load test suite. To enable the identification of such tests, we simply run each test generated by Random once and record its execution time. This execution time, although generally brief, is included in the overall test case generation time.

We first compare the response times of JZlib caused by tests generated with our two treatments. We use Zlib, a program with a similar functionality, as part of a differential oracle that defines a performance failure as: $responseTime_{JZlib} - responseTime_{Zlib} > \delta$. Figure 3.6 describes, for input sizes ranging from 100Kb to 1MB, the ratio in response times between JZlib and Zlib when a randomly generated suite is used (light bars) versus when inputs generated by CLLG are used (dark bars). (The values shown are averaged across the ten tests.) We see that CLLG generates inputs that reveal greater performance differences, more than twice as large as random with the same level of effort. It is also evident that, depending on the choice of δ, our approach could increase fault detection. For example, if $\delta = 1$ sec, then using random inputs will not reveal a performance fault with the input sizes being considered while the tests generate by CLLG would reveal the fault with an input of 0.4MB or greater.

Scalability. To better understand the scalability of the approach and the impact of the $maxSolverConstraints$ bound on the effectiveness of CLLG, we increased the input size up to 100MB and used $maxSolverConstraints$ values of 100, 500, and 1000. We again imposed a cap of 3 hours for each of the test generation strategies. Strategies requiring more time were terminated and not reported as part of the series.

The scalability results are presented in Figure 3.7, which plots the response times averaged across the tests in each suite. The trends confirm the previous observations. The response time of JZlib is several times greater for the test suites generated with CLLG strategies than with those generated by Random.

This is more noticeable for CLLG test suites with greater $maxSolverConstraints$. For example, for an input of 10MB, the suite generated with CLLG-1000 had an average response time that was approximately five times larger than Random and two times larger than that with CLLG-100. However, this strength came at the

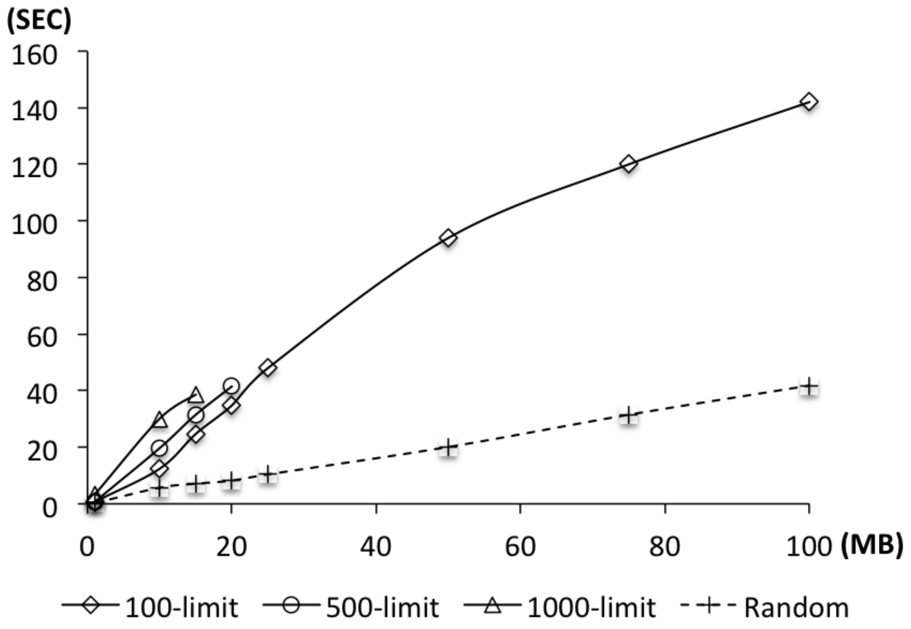


Figure 3.7: Scaling: response times of JZlib with test suites generated by CLLG and Random.

cost of scalability as the former strategy could not scale beyond 15MB. We note similar trends for the other test suites generated with the CLLG strategies, where each eventually reached an input size that required more than the 3 hour cap to generate the test cases. Only the CLLG-100 is able to scale to the more demanding inputs of up to 100MB. Still, the response time of JZlib under the test suite generated with this strategy is more than 3 times greater than the one caused by the Random test suite for approximately the same generation cost. Furthermore, to generate a response time of 40 seconds, a randomly generated test would require on average an input of more than 100MB while CLLG-100 would require a file smaller than 25MB. More importantly, this figure offers evidence of the approach configurability, through the $maxSolverContraints$ parameters, to scale and yet it can outperform an alternative technique that for this particular artifact is considered the worst case [114].

3.5.2 Revealing Memory Consumption Issues

We now proceed to assess 5 test suites of 10 tests generated by our approach to induce high memory consumption in SAT4J. We randomly chose 5 benchmarks from the SAT competition 2009 suite to get a pool of potential values for the number of variables, number of clauses and the number of variables within each clause, and we declare the variables themselves as symbolic. Columns 2 to 4 of Table 3.1 show some of the attributes of the selected benchmarks including the number of variables, number of clauses, and hardness level (assigned based on the results of past competitions, with instances solved within 30 seconds by all solvers labelled as “easy,” not solved by any solver within the timeout of the event labelled as “hard,” and “medium” for the rest.)

Table 3.1 shows the memory consumption results in the last two columns. Column “Original” shows memory consumption of SAT4J when these benchmark programs are provided as inputs, column “Generated” shows the same measure for the average of the ten tests generated with our approach, and Column “% Increase” shows the increase generated tests have over original ones. Overall, the approach was effective in increasing the memory load for SAT4J compared with the original benchmarks. However, the gains are not uniform across instances. The most dramatic gain achieved by our approach, 2.6 times increase in memory consumption, comes from selecting values for `aloul` which is of “medium” hardness. Not surprisingly, the least significant gain comes from `rbcl-xits-06-UNSAT`, which is classified as “hard.” But even for this input with a very large and challenging space of over 47000 clauses the approach leads to the generation of a test suite that on average consumes 20% more memory.

Table 3.1: Load test generation for memory consumption.

Programs	**Description**			**Memory (MB)**		
	Variables	**Clauses**	**Hardness**	**Original**	**Generated**	**% Increase**
aloul-chnl11-13	286	1742	medium	6	22	260%
cmu-bmc-longmult15	7807	24351	easy	35	92	163%
eq-atree-braun-8-unsat	684	2300	medium	11	35	218%
rbcl-xits-06-UNSAT	980	47620	hard	38	45	19%
unif-k3-r4.25	480	2040	medium	6	17	183%

Table 3.2: Response time and memory consumption for test suites designed to increase those performance measures in isolation (TS-RT and TS-MEM) and jointly (TS-RT-MEM).

Test Suite	**Response Time**		**Memory Consumption**	
	Seconds	**% over Baseline**	**MB**	**% over Baseline**
Baseline	45	100	6.6	100
TS-RT	105	234	13	196
TS-MEM	98	217	15	219
TS-RT-MEM	96	213	13	201

3.5.3 Load inducing tests across resources and test diversity

We now assess the approach in the presence of different performances measures and in terms of the diversity of the test suite it generates.

We generate three test suites with 5 tests each for TinySQL (in this study we generate 5 tests instead of 10 because we intentionally want to increase the level of diversity among tests). The first, TS-RT, favors response time. The second, TS-MEM, favors memory consumption. The third, TS-RT-MEM, was generated with an equally weighted sum of the cost for response time and memory consumption. Table 3.2 shows the performance caused by each test suite averaged across the five tests. We use as baseline the original test from which the test template was derived. We report both response time and memory consumption, along with their respective effectiveness over the baseline, for each suite.

The results show that all three test suites are effective at increasing their respective measures. On average, TS-RT forces response times to rise 234% over the baseline, TS-MEM causes a 217% increase over the baseline in terms of memory usage, TS-RT-MEM increases both response time by 213% and memory by 201% over the baseline. By looking at TS-RT and TS-MEM is clear that favoring response time or memory consumption has an effect on their counterpart. As expected, the TS-RT-MEM suite does in between the other two suites in terms of memory consumption. What was a bit surprising is that TS-RT-MEM average response time was lower than TS-MEM. Although the difference is less than 4%, this indicates that when using combinations of performance measures special care must be taken to integrate the different costs schemes to account for potential interactions.

Test suite diversity. We now turn our attention to the issue of test suite diversity. We note that there are no identical queries – TinySQL tests – within each of the generated test suites. Furthermore, all queries complete in different times (differences in tenths of seconds) and consume different memory (differences in KB). We illustrate some of the differences with the sample queries in Table 3.3. Because of space constraints, we only include 3 of the generated queries which, like all others, have various degrees of difference. Some obvious differences are in the fields selected, tables retrieved, and the type of where clauses specifying the filtering conditions. Others are more subtle but still fundamental. For example, while the first query in the Figure is an inner join (it will return rows with values from the two tables with matching track_id), the second one is a cross-join (it will return rows that combine each row from the first table with each row from the second table), and the third one is a self-join (joining content from rows in just one table.) Although this is just a preliminary qualitative evaluation, it provides evidence that the path diversity pursued by the approach translates into behaviorally diverse tests.

Table 3.3: Queries illustrating test suite diversity.

```
SELECT MUSIC_TRACKS.track_name, MUSIC_TRACKS.track_id
FROM MUSIC_TRACKS
JOIN MUSIC_COLLECTION ON
   MUSIC_TRACKS.track_id = MUSIC_COLLECTION.track_id
WHERE MUSIC_TRACKS.track_name <> null OR
   MUSIC_TRACKS.track_id > 0
```

```
SELECT MUSIC_ARTISTS.artst_id, MUSIC_ARTISTS.artst_name
FROM MUSIC_ARTISTS
JOIN MUSIC_EVENTS ON
   MUSIC_ARTISTS.artstid <> null
WHERE MUSIC_ARTISTS.artst_name <> null OR
   MUSIC_ARTISTS.artst_id > 0
```

```
SELECT MUSIC_ARTISTS.artst_name, MUSIC_ARTISTS.artst_country
FROM MUSIC_ARTISTS
JOIN MUSIC_ARTISTS ON
   MUSIC_ARTISTS.artst_name <> MUSIC_ARTISTS.artst_name
WHERE MUSIC_ARTISTS.artst_id > 5 OR
   MUSIC_ARTISTS.artst_country <> null
```

3.6 Summary

So far we have introduced SLG, a symbolic execution based technique capable of generating load test suite automatically. Our assessment of SLG shows that it can induce program loads across different types of resources that are significantly better than alternative approaches (randomly generated tests in the first study, a standard benchmark in the second study, and the default suite in the third study). However, as we will show later in Section 4.1, the cost of generating tests still grows between linearly or exponentially with SLG as program or input size increases. In the next chapter we present a new approach that aims at scaling up the load test generation technique, which uses SLG as a subroutine in its own analysis.

Chapter 4

Compositional Load Test Generation

In this chapter we present our effort in scaling up the load test generation technique. In Section 4.1, we discuss the problems that our load test generation tool SLG faces when applied to more complex software systems. In Section 4.2 - Section 4.4 we present a compositional load test generation technique, CompSLG, that enables handling of complex systems in the form of software pipelines; the algorithms and parameters that controls the techniques; and its implementation details. In Section 4.5 we evaluate CompSLG on four Unix pipeline programs and one XML pipeline. The results show that when reuse of previous analysis results is allowed, CompSLG achieves orders of magnitude savings in test generation time, while maintaining the same level of induced load as SLG. Finally, in Section 4.6, we discuss the challenges on extending CompSLG to enabled handling of more complex systems beyond software pipelines. We present an approach and implementation sketch for handling Java programs, and provide several proof-of-concept examples to show its viability.[1]

[1]Portions of the material presented in this chapter have appeared previously in a paper by Zhang et al. [138]. The material presented in this chapter extends the technique to enable load test

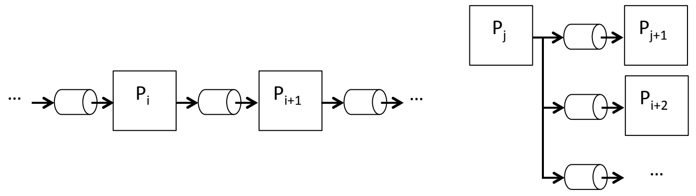
4.1 Motivation

In this section, we first present the definition of software pipelines, then discuss the challenges of load testing pipelines.

4.1.1 Software Pipelines

Many complex systems are formed by composing several smaller programs. The constituent programs may be composed in many different ways. For example, two programs may be chained sequentially so that the output of one is the input of the next; or they could form a call-chain relation in which one program is called inside the other as a subroutine.

Sequential program composition plays an important role in quickly assembling functionality from several processing elements to achieve a specific new functionality. One popular implementation of sequential program composition is called a pipeline [93]. A pipeline is a collection of programs connected by their input and output streams. We consider two types of connections in a pipeline – **linear** and **split**. In a linear pipeline a set of programs $P_1, \cdots, P_n$ are chained so that the output of each P_i feeds directly as input to P_{i+1} (Figure 4.1(a)). In a split pipeline, the output stream of P_j simultaneously feeds into programs $P_{j+1}, P_{j+2}, \cdots$ (Figure 4.1(b)).



(a) Linear (b) Split

Figure 4.1: Pipeline structures.

generation for Java programs.

The *Unix pipeline* is one common instantiation of software pipelines. Each Unix command can be treated as a standalone program executing in a shell environment, or can be chained with others to achieve a combined functionality. For example, the pipeline `grep [pattern] file | sort` achieves the functionality of retrieving information from a file according to a specific pattern, then sorting the results in ascending order. A slightly more complicated example is `find /dir -size 10K | grep -v '.zip' | zip`, which selects files larger than 10K and zips them if they are not zipped already. This pipeline involves three programs and treats not only bytes but also the file system structure.

XML transformations, used extensively on web applications, are another popular type of pipeline. A chain of XML transformations is defined as an *XML pipeline*, expressed over a set of XML operations and an XML transformation language. For example, a three-component linear XML pipeline could 1) validate a webpage against a predefined W3C schema (VALID component); 2) apply a styler transformation for the Firefox web browser (STYLER component); and 3) export the webpage content to an ODF format file that is accessible via OpenOffice (ODF component). The resulting pipeline product is a webpage in ODF format displayed in a way as if it was rendered by a Firefox browser [112].

Another example of pipeline structures are instances of graphical manipulation systems. Such systems allow the user to accomplish complex graphical manipulation tasks by defining a workflow with a chain of modules, each accomplishing one single task. For example, OpenCV [19], an open-source computer vision library originally developed by Intel, provides an interface for users to setup complex pipelines. For example, the following pipeline is included as an example in the OpenCV documentation. The pipeline has three components: 1) resize the input graph (RESIZE component), in which the input is a color image, and the output is a color image of predefined size; 2) convert the graph to a binary graph (BIN component), in which the input is the result of previous component, and the output is a binary image; 3) extract the edges from the objects in the graph (EDGE component) in which the input is the result of the previous component, and the output is a set of vectors encoding the detected edges in the image; The final results of this pipeline can in turn be used as inputs for image understanding algorithms.

4.1.2 Challenges in Load Testing Pipelines

Even for the simplest Unix pipeline example, generating cost effective load tests is not an easy task. Either an increase in input size or program complexity or both can make state of the art load test generation tools fail to scale. To illustrate these points, we use a Java implementation of the Unix shell environment called JShell [67], which includes a set of common Unix commands and provides a bash-like notation for chaining them into pipelines (details of this artifact can be found in Section 4.5.1).

To show how SLG perform when facing larger inputs, we run a pilot study on the pipeline `grep [pattern] file | sort`, treating it as a single program with a single input (the input to `grep`). We initialize the input as a file of various lines numbers of lines (1000, 5000, 10000), each line containing 10 symbolic input values of byte type, and the `[pattern]` in `grep` corresponding to the format of a 10-digit telephone number. We then use SLG[2] to generate ten load tests that attempt to maximize response time on the whole pipeline.

Table 4.1 shows that, on an input with 1000 lines, we obtain ten tests after 109 minutes. The average response time of the ten tests is 4.2 seconds. The generation time is 581 minutes for 5000 lines and goes up to 1355 minutes for an input of 10000

[2]We configure SLG as follows: *testSuiteSize*=10, *lookAhead*=25, *maxSize*=100000 and Yices as the decision procedure.

Table 4.1: SLG on the pipeline `grep [pattern] file | sort` with increasing input sizes.

Program	**Input (# lines)**	**Cost (min)**	**Load (response time in sec)**
grep | sort	1000	109	4.2
grep | sort	5000	581	14.7
grep | sort	10000	1355	37.4

Table 4.2: SLG on pipelines of increasing complexity.

Program	**Input (# lines)**	**Cost (min)**	**Load (response time in sec)**
grep	5000	247	5.8
grep | sort	5000	581	14.7
grep | sort | zip	5000	1516	21.5

lines. For a simple artifact like this, it takes almost 24 hours for SLG to produce tests for inputs of 100KB. The approach struggles to scale up in terms of input size when the whole pipeline is considered at once.

Let's now consider the complexity of the programs under analysis. In Table 4.2 we fix the input size at 5000 but use a more complex artifact on each row. The results suggest that test generation time grows super-linearly with the number of pipeline components. However, the load is not increasing at the same pace. In this case the technique is challenged by the increasing pipeline complexity.

Now, if each pipeline component can be handled by existing approaches, an estimate of the worst overall performance may be obtained by adding the longest response times from each component. In practice, however, such attempts can result in gross overestimations of the pipelines performance as inputs that may drive one component to larger response times may not have the same effect on other components. For example, for the latest pipeline in Table 4.2, the worst case calculated by adding individual components is 32 seconds, while the actual worst case is just 21.5 seconds. Still, as we shall see, this line of thought of reusing the results from each component to generate load tests for the whole program will be central to our approach.

4.2 Overview of a Compositional Approach

Although a large complex program imposes many challenges for a symbolic load test generation approach, if the complex program is composed of several simpler programs, such as the pipeline examples shown in the last section, and each constituent program can be handled by existing approaches, we may devise a new approach that uses the *divide and conquer* strategy to address the illustrated challenges.

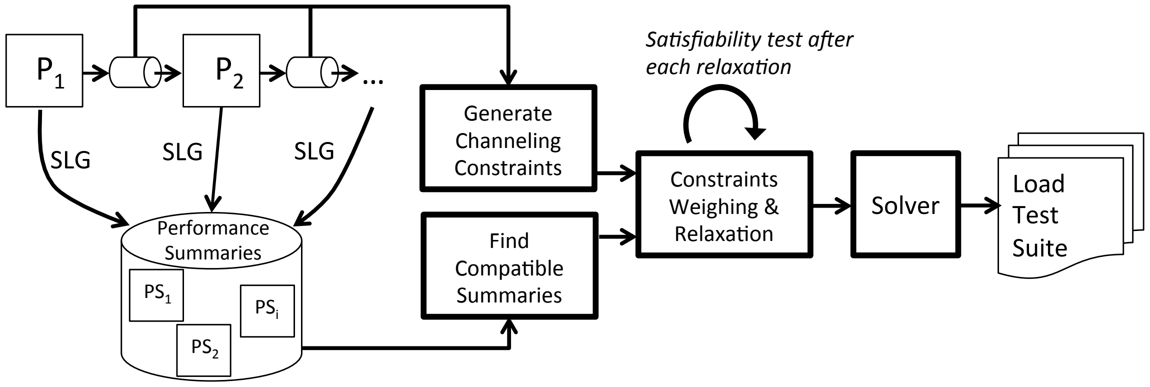

P1
P2
...
SLG
SLG
SLG
Performance Summaries
PS1
PS2
PSi
Generate Channeling Constraints
Find Compatible Summaries
Satisfiability test after each relaxation
Constraints Weighing & Relaxation
Solver
Load Test Suite

Figure 4.2: Illustration of a compositional approach.

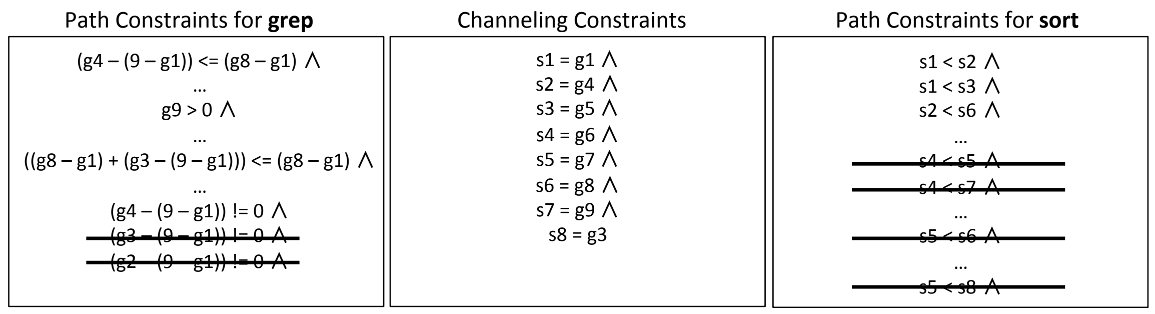
Figure 4.2 shows the key concepts of a compositional load test generation approach. The approach works in four steps. 1) The set of programs (e.g., $P_1, P_2, \cdots$) that form a software pipeline are analyzed by SLG to produce a library consisting of *performance summaries* for each program. A performance summary characterizes one program with a set of path constraints, each representing a program path that induces load according to a performance measure. 2) The approach examines how the constituent programs are composed together, and uses this information as a guideline for selecting compatible path constraints from the library. It also generates a set of *channeling constraints* for each pair of programs. Channeling constraints are equality constraints that bridge the variable sets of two performance summaries computed independently. 3) The selected path constraints and the generated channeling constraints are joined together by conjunction to form a constraint set for the whole program. The resulting constraint set may not be solvable because each constituent constraint encodes a load test of one component, which may not be compatible with the load tests of the other components. Therefore, a constraint weighing and relaxation process is used to remove incompatible constraints, starting from the weakest in terms of their contributions to the program load. The weighing and relaxation process tests the satisfiability of the remaining constraint set after each removal. It iterates until the end product becomes solvable. 4) A solver is used to find a solution that satisfies the constraint set, leading to a load test for the whole program. Steps 2-4 are repeated until a load test suite of desired size is generated.

The approach in practice. Continuing with the `grep [pattern] file | sort` example, we use the same settings as before, only this time we collect performance summaries with SLG, then apply the compositional generation approach on them.

Figure 4.3 illustrates the approach[3]. For steps 1-2, we generate the performance summaries for both `grep` and `sort`, choose one path constraint from each summary (starting from the worst performing ones) and make sure they are compatible by checking for matching output and input sizes (so that they can be executed in a pipeline). The two selected path constraints are shown in Figure 4.3 on the leftmost and rightmost columns. The center column shows the channeling constraints that bridge the two path constraints (which are computed by tracking the output expressions of `grep` in terms of its input variables). Section 4.3.2 describes in detail how to compute the channeling constraints.

The third step involves the conjunction of the three constraint sets, and applying a weighing and relaxation process to remove incompatible constraints. The process starts by removing those constraints that make the least contribution to the load, so

[3]To simplify the presentation, Figure 4.3 depicts a case with the input size of 10 lines, where in the pilot studies the input size varies between 1000 to 10,000 lines.



Path Constraints for **grep**	Channeling Constraints	Path Constraints for **sort**
(g4 – (9 – g1)) <= (g8 – g1) ⋀	s1 = g1 ⋀	s1 < s2 ⋀
…	s2 = g4 ⋀	s1 < s3 ⋀
g9 > 0 ⋀	s3 = g5 ⋀	s2 < s6 ⋀
…	s4 = g6 ⋀	…
((g8 – g1) + (g3 – (9 – g1))) <= (g8 – g1) ⋀	s5 = g7 ⋀	~~s4 < s5 ⋀~~
…	s6 = g8 ⋀	~~s4 < s7 ⋀~~
(g4 – (9 – g1)) != 0 ⋀	s7 = g9 ⋀	…
~~(g3 – (9 – g1)) != 0 ⋀~~	s8 = g3	~~s5 < s6 ⋀~~
~~(g2 – (9 – g1)) != 0 ⋀~~		…
		~~s5 < s8 ⋀~~

Figure 4.3: Path constraints computed for `grep [pattern] file | sort`, with the pattern being a 10-digit phone number. Three sets of constraints are shown, one for `grep`, one for `sort`, one for the channeling constraints connecting them. Crossed out constraints have been removed in order to find a solution.

that the loss in load is minimized, and testing the satisfiability of the remaining ones after each removal. Figure 4.3 depicts a situation where the incompatible constraints have been removed (crossed out), and the remaining constraint set is satisfiable.

Table 4.3 shows the results of redoing the first pilot study (Table 4.1) with the compositional approach. On 1000 lines of input, the approach generated tests of similar quality (4.2 sec vs 4.1 sec) while the generation time is 32% lower. The savings are more impressive as the input size goes up. On an input of 10000 lines, the previous run used almost 24 hours, while the compositional approach finishes in 11 hours and generates tests that induce similar load.

Redoing the second pilot study yields more impressive results. Because the programs under study use the same input size on the three pipelines, the approach is able to reuse the performance summaries collected from a previous artifact to achieve more savings. For example, on analyzing `grep | sort`, we can reuse the summaries computed for `grep` and only need to compute summaries for `sort`. Table 4.4 shows that, in case of `grep | sort | zip`, the compositional approach takes only 12% of the effort of a full SLG, but yields comparable tests.

In practice, the gains in efficiency can in turn improve effectiveness if the testing effort is bounded. For example, assume that a tester is given three hours of test

Table 4.3: Compositional approach on the pipeline `grep [pattern] file | sort` with increasing input size. % in Gen. and Load shows comparison to Table 4.1.

Program	**Input (# lines)**	**Cost (min)**	**Load (response time in sec)**
grep | sort	1000	74 (68%)	4.1 (98%)
grep | sort	5000	342 (59%)	13.6 (94%)
grep | sort	10000	615 (45%)	36.1 (96%)

Table 4.4: Compositional approach on pipelines with increasing complexity Previously computed summaries are reused. % in Gen. and Load shows comparison to Table 4.2.

Program	**Input (# lines)**	**Cost (min)**	**Load (response time in sec)**
grep	5000	247 (100%)	5.8 (100%)
grep | sort	5000	153 (26%)	14 (95%)
grep | sort | zip	5000	179 (12%)	19.6 (91%)

generation time, using SLG on the pipeline `grep [pattern] file | sort | zip` with 5000 lines of input will produce load tests that induce 8.3 seconds in response time, while the compositional approach in the same time yields tests that drive load 2.4X higher (last line of Table 4.4).

These data sets clearly convey that efficiency and scalability gains can be achieved by exploring programs independently and then composing their performance summaries, instead of exploring the whole system space at once. Further efficiency gains can be obtained when reusing previously computed components' summaries to save on repetitive computations. Last, when there are limited resources, the gains could translate into increased effectiveness as well.

4.3 The CompSLG Algorithm

A compositional load test generation approach takes *performance summaries* collected on each program in a pipeline, and composes them according to the pipeline structure. We first defines key terms, then outline the core algorithm and its components.

Definition 4.3.1 *Performance Summary (PS): A set of path conditions* $PS_j^s = \{pc_1^j, \cdots, pc_n^j\}$ *for program* P_j *caused by inputs of size* s *that induce load according to a performance measure. Each* pc_i^j *contains the following tags to assist future analysis:* **size** *and* **type** *of the path's input and output, and the* **weight score** *indicating the level of resource consumption (load) when the path is executed.*

A PS_j^s can be computed by applying any symbolic execution based load testing approach (such as SLG) to program P_j with a fixed input size s and type t. Consider the pipeline in Figure 4.4 consisting of `find /dir -size 10K | grep -v '.zip' | zip`. The pipeline takes a symbolic file system (a collection of string, vector, integer and integer array variables representing the name, directory flags, file lists, and file content respectively. Refer to Section 4.4 for more detail) as input, and each program in the pipeline only accesses part of the symbolic file, collecting constraints just on that part. For example, `grep` is the only program that accesses the `name` of the symbolic file. Thus the performance summaries of `grep` need to be collected on the file names (string type) only. To simplify the explanation, we assume the input has one type in the following text. A weight score is an indicator of how much impact a path has in terms of a performance measure (e.g., the response time for a test that traverses that path).

For a set of programs $P_1 \cdots P_n$ and input sizes $size_1, size_2, \cdots$, we compute a library of PS as $PSLib = \{\{PS_1^{size_1}, PS_1^{size_2} \cdots\} \cdots \{PS_n^{size_1}, PS_n^{size_2} \cdots\}\}$. Our compositional analysis takes path conditions generated for different programs and composes them together. First, we need to identify the compatible path conditions that can be stitched. We define compatibility as follows.

Definition 4.3.2 *Compatibility: For two programs* P_i *and* P_{i+1} *in a pipeline* $P_i|P_{i+1}$

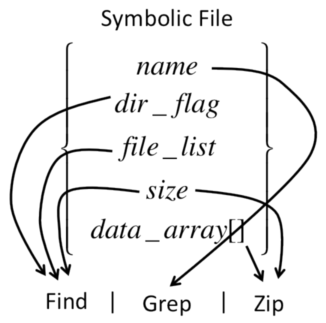


Figure 4.4: Symbolic file modeling.

(the | operator is used to denote a pipe between two programs), two path conditions $pc^i \in PS_i^{size_m}$ *and* $pc^{i+1} \in PS_{i+1}^{size_n}$ *are compatible if* $|O(pc^i)| = size_n$*, where* $O(pc^i)$ *refers to the set of output variables that are confined to the path defined by* pc^i*.*

Next, we need a way to express compatible path conditions in the same *namespace*. This is done through the introduction of *channeling constraints*. A channeling constraint is an equality constraint that connects two variables defined over different contexts [76]. Formally, we define:

Definition 4.3.3 *Channeling Constraints (CC): Given two programs* P_i *and* P_{i+1} *in a pipeline* $P_i|P_{i+1}$*, and* $pc^i \in PS_i$ *and* $pc^{i+1} \in PS_{i+1}$*, channeling constraints CC are equality constraints that map the symbolic input variables of* pc^{i+1}*,* $\{\Phi^1_{P_{i+1}}, \Phi^2_{P_{i+1}}, \cdots, \Phi^n_{P_{i+1}}\}$*, to the corresponding output expressions of* pc^i*,* $\{O^1_{P_i}, O^2_{P_i}, \cdots, O^n_{P_i}\}$*.*

These constraints eliminate the need to solve for ps^{i+1}'s variables, which are now expressed in terms of ps^i's input variables.

Definition 4.3.4 *Unified Constraint Set (UC): Given path conditions* $pc^1 \cdots pc^n$*, where* $pc^1 \in P_1, \cdots, pc^n \in P_n$*, and channeling constraint sets* $CC_1 \cdots CC_{n-1}$*, a unified constraint set is obtained through the conjunction* $pc^1 \wedge CC_1 \wedge pc^2 \wedge \cdots \wedge CC_{n-1} \wedge pc^n$*.*

Algorithm 4 CompSLG($PSLib, T$)

```
1: $\overline{testSuite} \leftarrow \emptyset$
2: while $|\overline{testSuite}| < T$ do
3:     $compPC \leftarrow$ selectCompatiblePC($PSLib$)
4:     $compCC \leftarrow$ genChannelConstraints($compPC$)
5:     $UC \leftarrow$ relaxConstraints($compPC, compCC$)
6:     $\overline{\text{newTest}} \leftarrow$ solve($UC$)
7:     $\overline{testSuite}$.add(newTest)
8: end while
9: return $\overline{testSuite}$
```

In the following sections we will refer to the process of removing individual constraints from the constraint set as *relaxation*, because each removal makes the constraint set easier to satisfy.

Algorithm 4, CompSLG, outlines the process for generating load tests for programs $P_1|\cdots|P_n$ forming a pipeline. The algorithm takes the pre-computed $PSLib$ as input, and has access to the pipeline structure. It also allows the user to specify the number of load tests (T) to generate. The algorithm operates iteratively, generating one test after each iteration of lines 2-8. It first selects a set of compatible path conditions ($compPC$). Then it generates channeling constraints $compCC$ according to the path conditions selection. The conjunction of $compPC$s and $compCC$s are checked for satisfiability. If they are not satisfiable, they are relaxed to ensure that the resulting UC is satisfiable. The UC is subsequently concretized into a test.

In the following sections, we will introduce each of these components in detail. We assume a linear pipeline structure in Sections 4.3.1 - 4.3.3 for a more concise explanation, and briefly discuss the split pipeline structure in Section 4.3.4.

4.3.1 Selecting Compatible Path Conditions

Algorithm 5 shows the process for selecting compatible path conditions. The process takes $PSLib$ as input and starts by selecting a pc^1 from $PSLib$ that represents the

Algorithm 5 selectCompatiblePC($PSLib$)

```
1: $compPC \leftarrow \emptyset$
2: $pc^1_{worst} \leftarrow$ worst-case($PSLib[PS_1]$)
3: $compPC$.add($pc^1_{worst}$)
4: $PSLib$.remove($pc^1_{worst}$)
5: for $i \in (2, n)$ do
6:     $pc^i \leftarrow$ worst-compatible($PSLib[PS_i], pc^{i-1}$)
7:     if $pc^i \neq null$ then
8:         $PSLib$.remove($pc^i$)
9:     else
10:        $pc^i \leftarrow$ SLG($P_i, |O_i|$)
11:        if $pc^i = null$ then
12:            message("Cannot generate compatible summary for $P_i$")
13:            break
14:        end if
15:    end if
16:    $compPC$.add($pc^i$)
17: end for
18: return $compPC$
```

worst case for P_1 (the first component of the pipeline). Then, the process examines the output size associated with pc^1 and finds a pc^2 from the summaries of P_2 with a matching input size at Line 6 of Algorithm 5. The function `worst-compatible` will find a match for pc^2, and if multiple summaries are matched, it will select the one with a higher weight score first. The process operates in this way to find for each pc^{i-1} a matching pc^i. This process continues until all programs have selected compatible pcs. If CompSLG cannot find a compatible pc for a program, it will call the SLG to generate one with the desired attributes, or stop if no such summary can be generated.

Note that we start the selection of compatible paths conditions with the first component of the pipeline and move forward matching pc^{i-1} to pc^i so that, if a compatible pc^i cannot be found, the approach can instruct SLG on the input size to use to produce a compatible load test.

4.3.2 Generating Channeling Constraints

Assume that program P_i takes symbolic variables $\{\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}\}$ as inputs, traverses a path and collects path condition pc^i. After symbolic execution completes, the output of P_i, $\{O^1_{P_i}, O^2_{P_i}, \cdots, O^m_{P_i}\}$, can be expressed in the following way

$$O(pc^i) = \begin{cases} O^1_{P_i} = expr_1(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \wedge \\ O^2_{P_i} = expr_2(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \wedge \\ \cdots \\ O^m_{P_i} = expr_m(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \end{cases} \tag{4.1}$$

where $O(pc^i)$ means the output variables are confined to one path defined by pc^i and $expr_k$ stands for the expression over input symbolic variables $\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}$ that represents the value of $O^k_{P_i}$.

Assume that program P_{i+1} takes symbolic variables $\Phi^1_{P_{i+1}}, \Phi^2_{P_{i+1}}, \cdots, \Phi^m_{P_{i+1}}$ as inputs. Because P_i and P_{i+1} are pipelined, there must a direct mapping between $\Phi^k_{P_{i+1}}$ and $O^k_{P_i}$,

$$I(pc^{i+1}) = \begin{cases} \Phi^1_{P_{i+1}} = O^1_{P_i} \wedge \\ \Phi^2_{P_{i+1}} = O^2_{P_i} \wedge \\ \cdots \\ \Phi^m_{P_{i+1}} = O^m_{P_i} \end{cases} \tag{4.2}$$

where $I(pc^{i+1})$ represents the list of symbolic input variables in pc^{i+1}. Combining (4.1) and (4.2) we obtain the channeling constraint

$$CC = \begin{cases} \Phi^1_{P_{i+1}} = expr_1(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \wedge \\ \Phi^2_{P_{i+1}} = expr_2(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \wedge \\ \cdots \\ \Phi^m_{P_{i+1}} = expr_m(\Phi^1_{P_i}, \Phi^2_{P_i}, \cdots, \Phi^n_{P_i}) \end{cases} \tag{4.3}$$

Algorithm 6 relaxConstraints($compPC, compCC$)

```
1: $UC \leftarrow$ union($compPC, compCC$)
2: while $\neg$ satisfiable($UC$) do
3:     $core \leftarrow$ computeUnsatCore($UC$)
4:     $c \leftarrow$ selectWeakestConstraint($core, compPC$)
5:     removeConstraint($c, UC$)
6: end while
7: return $UC$
```

Algorithm 7 selectWeakestConstraint($core, compPC$)

```
1: for all $c \in core$ do
2:     if $c \in compPC$ then
3:         mark($c$)
4:     end if
5: end for
6: $targetPC \leftarrow$ lowestWeight($compPC$)
7: $c \leftarrow$ marked(leastCost($targetPC$))
8: adjustWeight($targetPC$)
9: return $c$
```

For a linear pipeline there is one CC between each pair of path conditions. CC allows for all constraints to be expressed in terms of P_i's symbolic variables.

4.3.3 Weighing and Relaxing Constraints

If the set of generated constraints is not solvable, then the approach will systematically remove a constraint until it becomes solvable. During each iteration the approach computes an unsatisfiable core of the constraint system under consideration, and then removes one constraint that 1) appears in the unsatisfiable core, 2) appears in the *pc* that has the least weight among all *pc*s, and 3) makes the least contribution to the weight of that *pc*.

Algorithm 6 shows the procedure for weighing and relaxing constraints on *compPC* collected over a set of linearly piped programs and the corresponding channeling constraints $compCC$. The algorithm starts by performing a conjunction of *compPC* and *compCC* into a unified constraint set and tests for satisfiability. If UC is satisfied, there is no need to relax constraints and the algorithm exits. Otherwise, the algorithm repeatedly follows a three-step relaxation process (lines 2-6) until UC is satisfied.

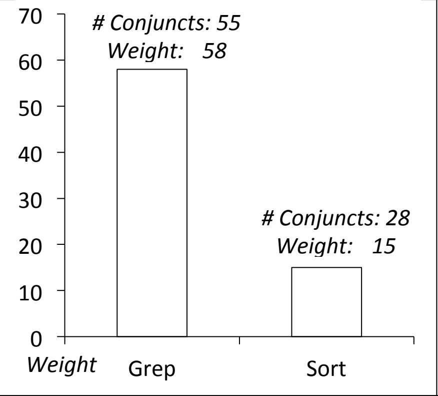
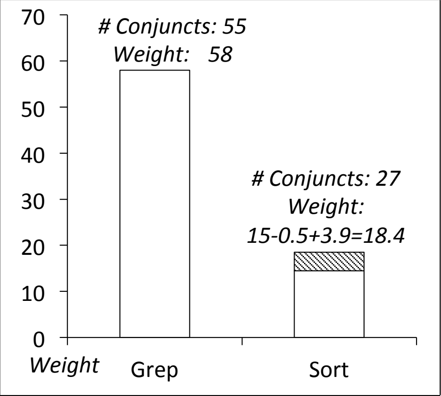
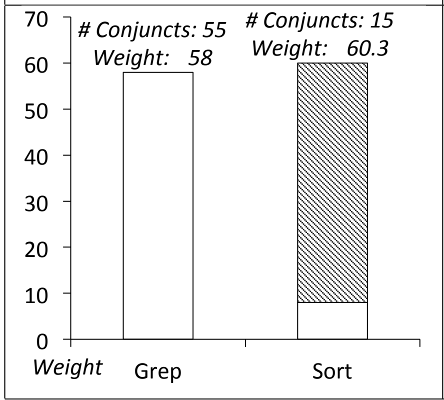
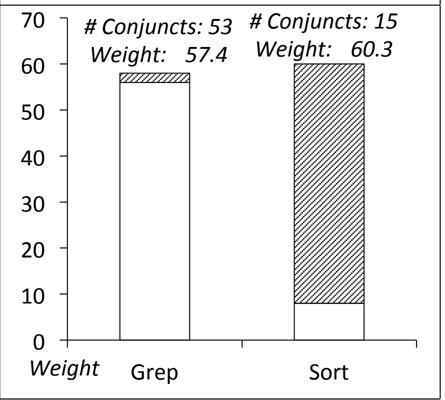
First, an unsatisfiable core[4] of UC is computed. Then the constraint $c \in core$, deemed the weakest in terms of its impact on the load of the system, is removed from UC. In the worst case, UC will be reduced to containing only the constraint from one program, at which time it will be satisfiable because a PS_i contains only feasible paths.

Algorithm 7 details the subroutine for selecting the constraint of the least weight. First, the unsatisfiable *core* and *compPC* are cross compared and constraints that appear in both sets are marked on *compPC* (Lines 1-5). The algorithm then examines the weight score on each pc^i and selects the one with the lowest weight(*targetPC*). If there are more than one pc^i with the same lowest weight, the algorithm will pick one randomly. The algorithm then selects the constraint c that is both marked and has the lowest cost in *targetPC* and returns c (the cost of a constraint c is defined as the difference in the weight of the pc before and after removing c).

Before returning, the weight score for the *targetPC* must be adjusted (Algorithm 7 - line 8). This step is to ensure that past relaxations have an impact on the current selection of the weakest constraint, so that we do not keep relaxing the same pc. Therefore, the algorithm compensates the weight score for the pc^i whose constraint is relaxed at the current iteration. For $pc^1 \cdots pc^n$ with associated weight scores $w_1 \cdots w_n$, after the relaxation of $c \in pc^i$, we compensate w_i by a value determined by $w_1 \cdots w_n$. One possible function we later explore is $max\{w_1, w_2, \cdots, w_n\}/w_i$, where

[4]An unsatisfiable core is a subset of UC which preserves the unsatisfiability but is simplified. A minimum unsatisfiable core ensures that removing any one constraint breaks the unsatisfiability, while a minimal core is the smallest of minimum cores. Here a core is not guaranteed to be either minimum or minimal. As noted in a paper by Liffiton et al. [78], computing such a core is expensive and no practical solver attempts to do so.

Table 4.5: Illustration of weighing and relaxing constraints. White areas correspond to the original weight, shaded areas correspond to the adjusted weights.

Before Relaxation	**After 1st Relaxation**
	
Starting to Relax Grep	**End of Relaxation**
	

the compensation is determined by w_i's ratio to the largest weight score.

Table 4.5 illustrates the process of weighing and relaxing of constraints on the running example. The weight scores are shown as bars on the graph, with the white area indicating the original weight, and the shaded area indicating the adjusted weights. The sum of weights and the number of remaining constraints are also listed at the top of each bar. We can observe that before relaxation, the original weight scores are 58 for `grep` and 15 for `sort`. After removing the first constraint on `sort` (which has a lower weight), its weight score is decreased by 0.5 due to the relaxation (removing the constraint made the path less costly), and increased by $58/15 = 3.9$ due to compensation (so the chances of selecting a constraint from `sort` in the future is less likely). The third cell shows the turning point where after removing 13 constraints, the weight on `sort` has been compensated enough to exceed that of `grep`, whose constraints are starting to be removed. The fourth cell shows the weight scores at the end of relaxation, with `sort` having 13 constraints removed, and `grep` having 2, at which time UC becomes satisfiable.

4.3.4 Handling Split Pipelines

A split pipeline, in which the output of P_j is fed simultaneously to $P_{j+1}, \cdots, P_{j+n}$, can be viewed as a set of parallel linear pipelines $P_j|P_{j+1}, \cdots, P_j|P_{j+n}$. Therefore, we will solve split pipelines in a similar way as presented in Algorithms 4 - 7, with a few modifications. Because in split pipelines, multiple components may share the same predecessor (the splitting component), we need to add a queue data structure at Line 6 of Algorithm 5 to identify the target component on which to invoke *worst-compatible*.

We will discuss more complex structures beyond the realm of pipelines in Section 4.6.

4.4 Implementation

We now discuss the most relevant implementation details of our CompSLG test generator and the support needed to handle the symbolic file system for Unix programs that take a file as input.

CompSLG . CompSLG was implemented on top of SLG (Chapter 3). We build the performance summary libraries by repeatedly invoking SLG on each component of a pipeline. The summaries are stored in XML format. The channeling constraints are computed by implementing a JPF listener that monitors write instructions for the output variables, and traces their symbolic expressions from the stored system states. We use Yices [131] to compute the unsatisfiable core during the constraint weighing and relaxation. We first transform the constraints to a Yices compatible format, and feed it to the solver. Should the solver return unsatisfiable, we then use the `yices_get_unsat_core` API to get the unsatisfiable core of the constraint set.

Symbolic File System Modeling . Certain Unix programs, such as `Find`, take a file directory and a file property as inputs, and browse the directory for files matching such a property. To enable symbolic execution of this type of command, we need to treat the file system symbolically. We implemented several JPF interfaces to handle most file system operations. For each file system operation (e.g. `open`), we check if the action is for a concrete or a symbolic file. For concrete files, we simply invoke the corresponding system call. For symbolic files we emulate the operation with symbolic values (e.g. for `open`, we will return a file handler pointing to a symbolic file with all fields declared as symbolic; for `read`, we will return symbolic bytes of the same size as a concrete read would return). Users can specify size constraints on the symbolic file system being used as inputs. The two size constraints are the number of file objects (files or directories), and the overall size of these files. A symbolic file system can contain as many levels of directories and as many files as desired, catering to the current analysis progress, as long as the two size constraints are not violated.

4.5 Evaluation

We evaluate the cost and effectiveness of CompSLG relative to SLG and Random approaches on various artifacts.

4.5.1 Artifacts

The goal of CompSLG is to generate load tests for larger pipelined programs by composing performance summaries of the constituent parts. To demonstrate the potential of CompSLG we required a set of artifacts conforming to the pipeline computation model. In this study we explore two types of pipelines, one being the Unix pipelines popular among system administrators, the other being XML pipelines used extensively on web servers and other types of data transformation tools.

As mentioned before, CompSLG makes use of SLG, which was implemented as a customized JPF. This limited the selection of artifacts to Java programs that the JPF symbolic execution engine can handle. With that limitation in mind, we selected the Unix programs from a Java implementation of the Unix shell environment called JShell [67]. We enriched the environment with 2 more commands (`grep` and `sort`) so that we could evaluate a variety of common pipelines by composing these commands in different ways. Table 4.6 lists the available programs, their LOC, and the type of input data each one takes (to be described in Section 4.5.3).

Table 4.6: Unix and XML programs.

Program	**LOC**	**Description**	**I/O Data Type**
sort	359	Sorts the input	byte
grep	1051	Retrieves lines according to a pattern	byte
find	1776	Retrieves files according to property	file structure
zip	5313	Compress data	file structure
cat	479	Concatenate and displays files	file structure
cut	894	Extracts information from each line	byte
VALID	850	Validates a webpage	XML
STYLER	2013	Applies a styler transformation	XML
ODF	5512	Transforms a webpage to ODF format	XML

Table 4.7 shows the pipes we study, their description, and how they are initialized for a mixed concrete and symbolic execution. Among them, Artifacts 1 and 2 were distilled from real scripts that we obtained from our Computer Science Department system administrator. Artifact 3 was obtained from a book on Unix system admin-

Table 4.7: Summary of pipeline artifacts.

No.	Program	Source	Description	Initialization
1	find /dir -size 10K | grep -v '.zip' | zip	System admin	Backup script: Finds files larger than 10K and zips them if they are not zipped already	File system can hold 100 files or directories, 1MB of data overall
2	find /dir -name 'mbox' | tee > zip > grep '[[:alnum:]+._-]*@ [[:alnum:]+._-]*' | sort –unique	System admin	Email server management script: Finds all mail box files, zips them, and lists email addresses of all users	File system can hold 100 files or directories, 1MB of data overall
3	find /dir -name '.txt' | cat | grep [[:digit:]]{3}[-]?[[:digit:]]{4} | xargs -ifoo grep foo recordsBook	Unix textbook [115]	Information retrieval script: Filters results through grep of grep	File system can hold 100 files or directories, 1MB of data. recordsBook is a concrete file.
4	cat /var/log/secure.log | grep -i 'user' | cut -d ':' -f 5 | xargs -ifoo grep foo /etc/passwd	COPS [40]	Security check script: find user who accidentally typed password in the id field	1MB of data for secure.log, /etc/passwd is a concrete file
5	VALID | STYLER | ODF	smallx [112]	Validate the content of a webpage and transforms it into ODF format	Sizes vary between 70KB to 280KB

istration [115], and Artifact 4 was abstracted from an instance of the set of security check scripts named COPS [40] (the original script was written in Perl, we extracted the embedded shell pipeline calls that executed the main functionality).

For the XML pipeline we selected a Java implementation called smallx [112] which supports the XML pipeline language XProc [128]. The specific XSLT instance we employed in the study was a three-component linear pipe that: 1) validates a webpage against a predefined W3C schema (VALID); 2) applies a styler transformation for the FireFox web browser (STYLER); 3) exports the webpage content to an ODF format file that is accessible via OpenOffice (ODF). This instance was obtained from the test suite that comes with the smallx package.

4.5.2 Metrics and Treatments

We assess the effectiveness of a load test by measuring its effect on the *response time* of the target program. We measure costs in terms of the *time* necessary for the approach to generate a test suite.

The main treatment in the study is the CompSLG approach as described in Section 4.3. We study three variants of CompSLG, described as follows:

- **No-reuse**: all performance summaries are generated for each artifact on the fly, with no reuse of summaries among artifacts.
- **Incremental-reuse**: the artifacts are analyzed in the order defined in Table 4.6, and summaries are reused when possible. For example, Artifact 2 could reuse the summary generated for `find` in Artifact 1 because they both use the same command and they were invoked with the same input constraints.
- **Full-reuse**: assumes that all summaries were collected previously, so the generation cost only corresponds to the composition effort.

We use two control treatments, SLG and random test generation. SLG is selected as an alternative symbolic load generation approach and Random is used to provide a baseline comparison. For SLG, we apply it to the whole pipeline by treating it as a single program, and we apply it to each component of the pipeline independently, which will reduce the analysis burden, but sacrifices effectiveness in generating a load for the whole pipeline.

For the Random treatment, we treat the pipeline as a single program and we randomly generate one type of input that feeds into the first component. We adopt a generate-and-run scheme for retaining the most effective tests as they are being generated. Random is run for as long as the compositional approach to enable a comparison with the same baseline cost.

We generate 10 tests for all treatments and report average measures of the 10.

4.5.3 Experiment Setup

For Unix pipelines taking a file system as input (e.g., via the `find` command), we initialize it with a symbolic file system and constrain the total number of files and directories it can access. For pipelines taking a single file as input, we simply constrain the size of that file. In Table 4.7, column "Initialization" specifies the *size* constraints we use for the analysis on the Unix pipelines.

For the XML pipeline, we select an input size of 140K, which is reported to be the average size of webpages that exist on the Internet [123]. To explore how CompSLG performs with various input sizes, we also generate tests for two more input sizes, which are 50% and 200% of 140K. In addition to input sizes, we also impose a set of structural constraints on the input to the XML pipeline program. We specify that the input webpage can contain six types of tags (paragraph, heading, hyperlink, image, list, and table tags), and that each of those tags has an upper count of 160 (the associated test suite of smallx uses six types of tags and the maximum usage count of a tag is 160. We use the same settings in our experiment). This set of constraints is to ensure that the approach is not stuck in a local optimum, and the resulting tests are more diverse.

We use SLG as a subroutine for the main treatment (as described in Section 4.4) and as a standalone control treatment. We use the same SLG configuration as in previous empirical studies (Section 3.5), with iterative searches of 50 branches in length and maximum path size of 30000 in order to keep within the capabilities of the various constraint solvers we used. We enforce a generation time cap of five hours across all runs. If exceeded, the analysis is terminated and no results are reported. Throughout the study we use the same platform for all programs, a 2.4 GHz Intel

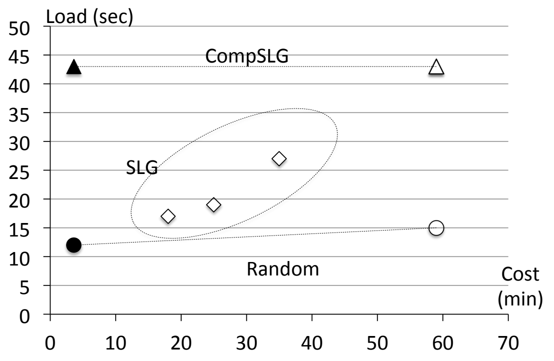
Core 2 Duo machine with Mac OS X 10.6.7 and 4GB memory. We executed our tool on the JVM 1.6 with 2GB of memory.

4.5.4 Results and Analysis

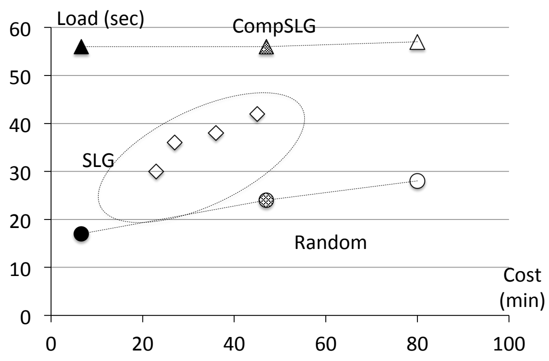
Figure 4.5 shows results on the Unix pipelines. Each figure corresponds to one artifact specified in Table 4.7. The x-axis shows the cost of generating load tests measured in terms of generation time in minutes, and the y-axis shows the effectiveness of running those tests, measured in terms of the average response time in seconds, induced by the 10 tests produced by each treatment. On each figure we plot three sets of data points corresponding to the three treatments used in the study. The triangles refer to CompSLG, with white triangles indicating No-reuse, grey triangles indicating Incremental-reuse, and black triangles indicating Full-reuse; the diamonds refer to the SLG treatment applied to a program in the pipeline to generate input for the whole pipeline, and the circles refer to the Random treatment, with colors matched to each variation of CompSLG. Figure 4.6 shows the results on the XML pipeline in the same format.

We first applied SLG on the whole pipelines and found that none of them could finish within five hours, so they were terminated and are not depicted in the figures. For the rest of the treatments, we describe our findings in terms of effectiveness first and then cost.

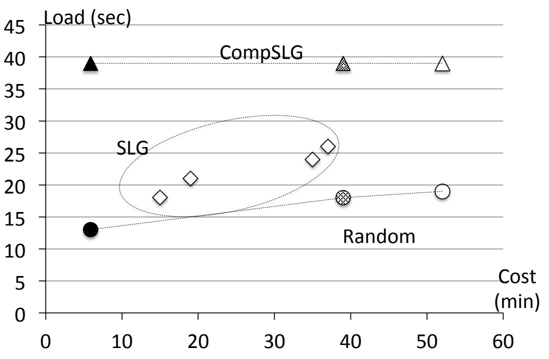
We notice that the various types of CompSLG are all capable of inducing more load than the other treatments across all artifacts. CompSLG produces load tests that generate as much as 4.4X times more load than Random on a Unix pipeline (Artifact 4), and as much as 2.8X on the XML pipeline (280K) with the same cost. We also note that the three variants of CompSLG show almost no variance in terms of effectiveness, indicating that reuse of previously computed summaries does not de-



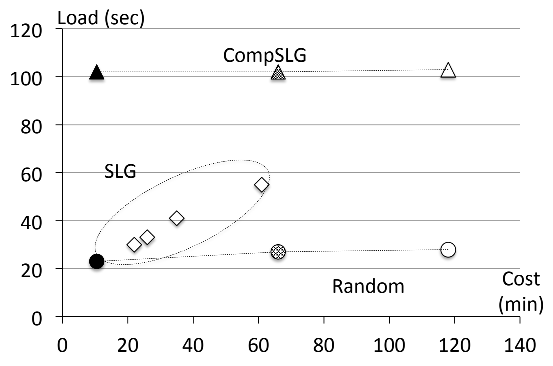
(a) Artifact 1



(b) Artifact 2



(c) Artifact 3

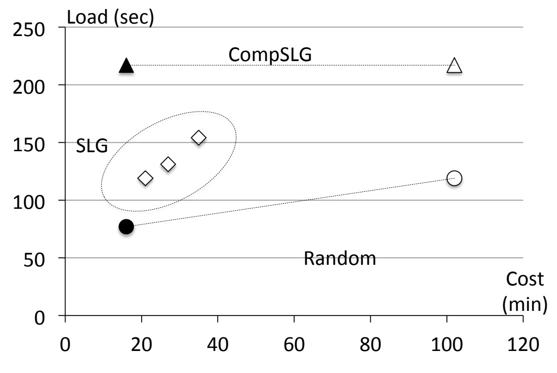


(d) Artifact 4

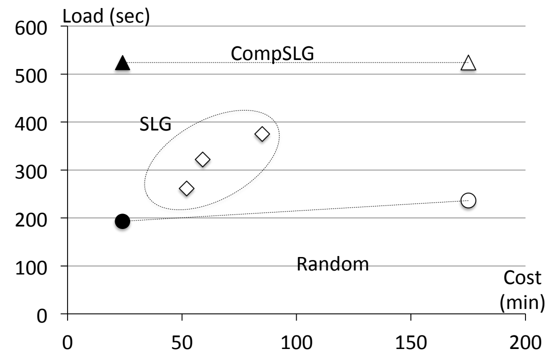
Figure 4.5: Cost-effectiveness of treatments applied to Unix pipelines. Triangles represent CompSLG (blank for No-reuse, shaded for Incremental-reuse, solid for Full-reuse), diamonds represent SLG, and the circles represent Random.

grade load test quality. Random, on the other hand, shows certain level of variance as its effectiveness corresponds directly to the allocated generation time. CompSLG also consistently induces more load in every pipeline than SLG applied to any of the involved components. This makes sense as SLG finds the best inputs for one component which may not necessarily be the best for the pipeline. On average CompSLG induces 1.5X time more load over SLG for the Unix pipelines, and 1.3X for the XML pipeline.

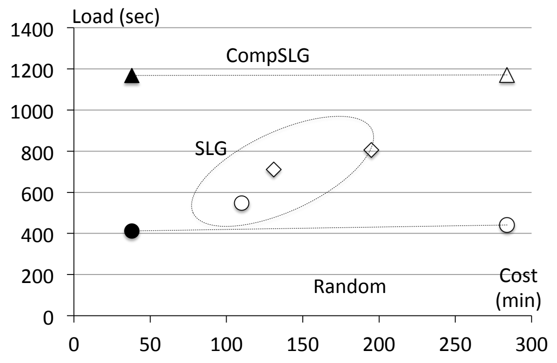
In terms of cost, CompSLG with No-reuse (white triangles) has a higher cost than SLG. However, the cost for CompSLG can be dramatically reduced by reusing performance summaries collected from analysis of previous artifacts. Results on



(a) Size 70K



(b) Size 140K



(c) Size 280K

Figure 4.6: Cost-effectiveness of treatments applied to XML pipeline. Triangles represent CompSLG (blank for No-reuse, solid for Full-reuse), diamonds represent SLG, and the circles represent Random.

Incremental-reuse (grey triangles) indicate that the cost for CompSLG is close to that of SLG, but in all cases achieves a higher load[5]. The savings are more dramatic when we compare the Full-reuse version of CompSLG (black triangles) with other treatments. For the Unix pipelines, on average, CompSLG with Full-reuse took 17% of the time of SLG to generate a load test suite yet achieved an average 45% more load over the non-compositional counterpart. For the XML pipeline, although we do not report any data on Incremental-reuse because size incompatibility prevents such reuse, a similar trend can be observed with Full-reuse, which on average spent 42% of the effort of SLG and achieved 68% more load.

4.6 Exploring CompSLG Extensions to Richer Structures

We now discuss how to extend the existing approach to enable compositional load test generation for structures other than linear software pipelines. We will explore richer structures in the context of Java programs. In this context, each component is a method, and method calling relationships are represented by a call graph (each node represents a component and each edge (f, g) indicates that component f calls component g) [57]. A component may take inputs from various sources, such as input parameters and fields within its scope. A component may also update program states in various ways, such as through return values and writes to fields.

The more complex structure of Java programs adds new challenges to the compositional load generation approach. The approach to handle pipelines, as described previously in this chapter, needs to be updated accordingly to accommodate these

[5]Figure 4.5 - Artifact 1 does not have a grey triangle because it is the first artifact to be analyzed so we do not have precomputed summaries to reuse.

Table 4.8: Handling pipelines vs. Java programs.

Challenge	**Pipelines**	**Java Programs**
Generating channeling constraints	Unidirectional	Bidirectional
	Most inputs through std input stream	Multiple sources of inputs (parameters, fields, etc)
	Most outputs through std output stream	Return values and side effects
Generating performance summaries	High level tags such as input / output sizes are enough for summary matching	Need finer granularity tags such as shapes of input / output
	Performance summaries for individual programs	Performance summaries for individual methods
Composing summaries	Simple structures, composition can be done with greedy forward matching	Complex structures, requires search to find load inducing composition

added difficulties. Table 4.8 summarizes the difference between handling pipelines and handling Java programs. Specifically, three elements of the previous approach need to be updated: generating channeling constraints, generating performance summaries, and composing summaries.

Generating Channeling constraints. The main purpose of channeling constraints is to model the connection from the output of one component, to the input of the next component, so that the constraints of both components can be expressed on the same set of variables. In the context of pipeline programs, *unidirectional* CC would suffice for this purpose, because the outputs of the previous component will be directly used as inputs to the next. In the context of Java programs, each component is a single method. A method may call other methods during its execution, establishing a caller-callee relation. CC in this context need to model both the data connection that flows from the caller to the callee as inputs, and the data connection that flows from the callee to the caller, as outputs. Therefore, we need to establish *bidirectional* CC. In one direction, CC captures the read operations that map the input variables of the callee to the variables used by the caller to pass values. Moreover, the caller may use multiple sources of values, in terms of parameters or fields. In the other direction, CC captures the write operations that map the execution effects of the callee back to the caller in terms of output variables. The new approach for generating channeling constraints needs to accommodate these new challenges.

Generating performance summaries. In the context of pipeline programs, the performance summaries for each component need only to contain high level tags such as input / output sizes to assist summary matching. In terms of Java programs, however, the approach requires richer tags, such as shapes of input / output structures, for the subsequent summary matching. This is because the performance summaries of Java programs are collected at the method level, and are more susceptible to subtle unmatched summaries. As we will show later, summaries that are size matched but not shape matched may have an impact on the generated load.

Composing summaries. For pipeline programs, most execution paths contain all components, except for the rare split pipelines, which can be viewed as a set of parallel linear pipelines in which all components execute. The approach for generating load tests made two assumptions for pipelines: 1) a pipeline only contains a few components (order of tens); 2) a pipeline has a simple structure, even for a split pipeline, which usually contains a few splitting points. Therefore, for linear pipelines, we use a greedy forward matching approach when selecting summaries for each component (as per Section 4.3.1, where we first select a worst case summary for the first component, then moving forward to select a summary for the next component whose input size and type match to output of the previous one. If there are multiple matching summaries for the second component, we select a worst performing one). This does not guarantee a global worst case but produces satisfactory results in practice. For split pipelines, the situation is slightly complicated because a path that contains all components may not correspond to the worst case. However, because the split pipeline only contains a few components and a simple structure, it is usually *affordable* to explore all possible ways of component composition, then pick up the most expensive one for test generation.

For Java programs, both assumptions do not hold anymore. First, the process needs to select summaries for potentially hundreds of components, so a greedy forward matching approach may be too shortsighted when doing so. The negative effects of poorly selected summaries may aggregate in the structure, eventually lead to degradation in induced load. Second, due to the complex structure of Java programs, it is *infeasible* to traverse all possible ways of component composition to determine the worst one.

4.6.1 Richer Channeling Constraints

The added complexity of Java programs calls for a more elaborate definition of the channeling constraints. The new channeling constraints need to capture both the connection that map the values at a call site to the input variables of the called component, and the connection that maps the execution effect of the component back to its call site. It also needs to handle multiple sources of inputs (parameters and fields) and outputs (return values and side effects). We discuss these needs next.

4.6.1.1 Approach to Capture CC_r and CC_w

We start by redefining channeling constraints in the context of Java programs, then present some implementation details and several proof-of-concept examples.

Definition 4.6.1 *Channeling Constraints (CC): Given two components f and g in a system, where f is called by g at call sites CS_g^f, and pc_f, a performance summary of f,* *channeling constraints are equality constraints that map the symbolic input variables of pc_f to CS_g^f, so that pc_f can be reused when computing a summary for g. For every call site cs_i^f, we define two sets of channeling constraints: 1) CC_{ir}^f, which captures the parameters and fields in the system that map to the symbolic input variables of pc_f through read operations. 2) CC_{iw}^f, which captures the execution effects of f back to the corresponding variables in the system through write operations.*

The new definition describes the bidirectional nature of the channeling constraints. In one direction, CC_{ir}^f maps the symbolic input variables of f to its various input sources at its call site cs_i^f. In the other direction, CC_{iw}^f maps the execution effects of f back to call site cs_i^f, ensuring that its effects, both in the form of return values and side effects on the field variables, are accounted for.

As defined, CC_{iw}^f maps the execution effects of f back to the call site cs_i^f. Because the execution effects can be captured by symbolically executing f once, therefore CC_{iw}^f can be generated during the collection of the performance summaries by SLG. To apply CC_{iw}^f to specific call sites, we only need to substitute the generic names of the output variables in CC_{iw}^f with the corresponding variable names at the call site. Such symbolic execution may over-approximate program behaviors at certain call sites, especially when f containing calls to unknown or complex functions, which are treated as uninterpreted functions. In such case, CC_{iw}^f will also over-approximate the execution effects of f. The process of generating CC_{iw}^f is similar to generating CC for pipeline programs (as described in Section 4.3.2), except that for pipelines, the output variables are the ones that are written to the standard i/o streams (pipes), while in this case, the output variables are the return values and updates to the fields.

The process for generating CC_{ir}^f is more complicated. Generally, CC_{ir}^f maps the symbolic input variables of f to its various input sources at cs_i^f. Those input sources, which are carried by variables of the caller, are passed to the callee in terms of parameters or fields. To correctly capture CC_{ir}^{f}, we need to ensure that all write operations to those input variables up to cs_i^f are accounted for by the analysis. For the write operations that are performed by the caller, we need to use a customized symbolic execution (Custom-SE) to generate summaries for those operations up to a call site. The goal of the Custom-SE is to capture the write operations by the caller to the variables that may be used as input sources to f at a particular cs_i^f. However, Custom-SE does not need to capture all write operations at the calling context, as certain optimizations can be applied. First, when Custom-SE is called to generate CC_{ir}^{f} at cs_i^f, it only needs to analyze the code segment in the caller from the point the last callee returns to its call site, to cs_i^f where f is being invoked. This is because all behaviors up to the point of the last call return have already been accounted for by previous analysis. For example, in the calling context of f, if cs_i^f has a predecessor $cs_i^{f'}$ which invokes another component f', Custom-SE only needs to analyze the code segment between the two call sites. Second, assuming that we already have the performance summary of f from SLG, we can determine the types of input variables, and capture write operations on those types only. For example, if f takes only integers as its inputs, then in performing the Custom-SE, we only need capture the write operations on integer variables.

Algorithm 8 illustrates the process of Custom-SE, which we adopt from a previous work on using compositional symbolic execution to test software product lines [106]. The original version was used to compute the edge summaries for the common code that various features interact with. It can be adopted to our needs, because features in a SPL can be viewed as analogous to components in our context. We slightly updated the original algorithm to capture only the write updates to the types of data we are interested in, instead of capturing all writes (Line 14). The algorithm makes use of several helper functions: *branch*() determines whether an instruction is

Algorithm 8 Custom-SE(E, l, e, pc, CC_r, d)

```
if branch(l) then
    l' := target(l, true)
    if SAT(cond(l)$\cup$pc) $\wedge$ (l,l')$\in$ E then
        Custom-SE(l', e, pc$\wedge$cond(l), $CC_r$, d-1)
    end if
    l' := target(l, false)
    if SAT($\neg$cond(l)$\cup$pc) $\wedge$ (l,l')$\in$ E then
        Custom-SE(l', e, pc$\wedge\neg$cond(l), $CC_r$, d-1)
    end if
else
    if l = e then
        return $CC_r$
    else
        $CC_r$ $\cup$= $\pi$(write(l), type(l))
        Custom-SE(E, succ(l), e, pc, $CC_r$, d)
    end if
end if
```

a branch, *target*() returns the target of a branch, *cond*() returns a symbolic condition of a branch, *succ*() returns the successor of an instruction, *write*() returns the set of locations written by an instruction, *type*() returns the type of the data being written, $\pi()$ screens the write locations by a certain data type, and $SAT()$ determines whether a logical formula is satisfiable.

Algorithm 8 takes several parameters as inputs. E is the set of statements bounded by two instructions l and e. Essentially E is a code chop [94], which is a single-entry single-exit sub-graph of the program control flow graph. E can be calculated beforehand using an interprocedural chopping algorithm proposed in [94]. pc and CC_r are set of path conditions and read channeling constraints, both of which are empty at initialization. d is the bound on the length of the path condition that will be explored.

We illustrate how Algorithm 8 operates with the general code template listed in Figure 4.7. It describes a general situation where there are two callees f' and f, and a set of statements between them. Custom-SE$(E, succ(f'), f, \varnothing, \varnothing, d)$ calculates

```
1 caller(...){
2    ...
3    f'(...);
4    ... //Custom-SE applied here
5    f(...);
6    ...
7 }
```

Figure 4.7: Custom-SE Applied to Example Code.

the CC_{ir}^{f} at cs_{i}^{f}, which corresponds to Line 5 of Figure 4.7. E is the code chop bounded by the return of f' and the call to f, $succ(f')$ is the location at which initiate symbolic execution and f is the call that terminates symbolic execution. The initial path condition and read channeling sets are both empty. d is the bound on the length of the path condition that will be determined by the user. We assume that d is sufficiently large to allow symbolic execution to finish at cs_{i}^{f}. However, it may not finish if the number of statements within a path in the chop exceeds d (i.e., an infinite loop in the chop. In that case, the algorithm returns an under-estimating CC_{ir}^{f}, as it did not finish the whole path). The algorithm operates as follows. At Line 1 it checks whether the current instruction is a branching instruction, and if so, explores both true and false branches by invoking Custom-SE recursively (Lines 2-9). If the current instruction is not a branch, it checks if the analysis is completed, at which time it returns with the collected CC_{ir}^{f} (Lines 11-12), or if not finished, collects the write operation of the instruction by adding it to CC_{ir}^{f}, then moves on to the next instruction (Lines 14-15).

In practice the algorithm can be used in various special cases other than the general template shown in Figure 4.7. For example, if f' is not present, then the starting point for Custom-SE would be the first statement of the caller. In another example, f' and f may be called consecutively, without any statements in between. In this case, we just need to set E to empty accordingly. In another, when there is a branch in between f' and f, the algorithm will calculate two sets of CC_rs, one for each distinct path. In Section 4.6.1.3, we will use concrete examples to illustrate these various usage scenarios.

4.6.1.2 Putting It All Together

Now that the processes to obtain CC_r and CC_w are covered, let's explore how they are integrated into the revised CompSLG overall process. Figure 4.8 illustrates such a process for Java programs.

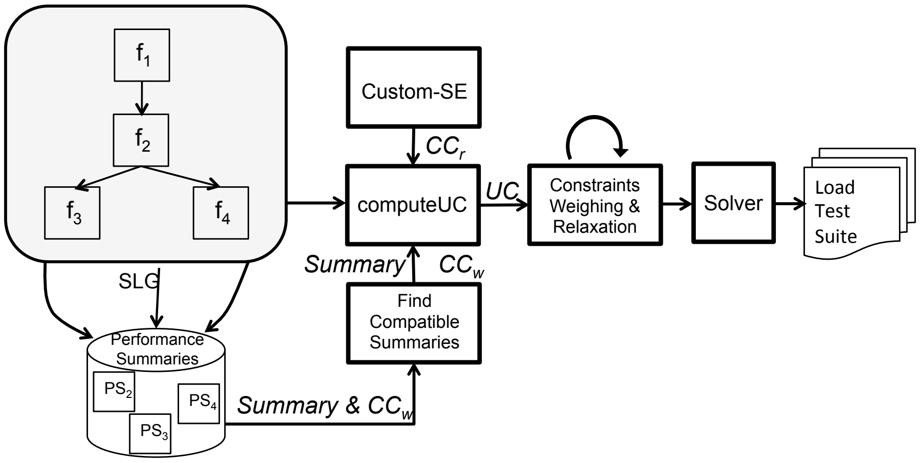


Figure 4.8: Illustration of a compositional approach for Java programs.

In the pipeline approach, all CCs are generated by SLG at the time of collecting performance summaries. In the new approach, there are two types of CCs: CC_w is generated by SLG in the same way as before, and retrieved from the library as needed; CC_r is generated by Custom-SE, which we introduced as Algorithm 8 before. Finally, a new component, computeUC, is used to compute a constraint set for the target method by assembling CC_r, summary and CC_w of each callee of the target method. We will discuss this new component later as Algorithm 10.

Algorithms 9 and 10 formalize the process. Algorithms 9 shows the updated CompSLG algorithm previously introduced in Section 4.3 – Algorithm 4. It takes

Algorithm 9 CompSLG(PSLib, Target, T)

```
1: $\overline{testSuite} \leftarrow \varnothing$
2: while $\overline{testSuite}$ <T do
3:     $UC \leftarrow$ computeUC(PSLib, Target)
4:     $UC \leftarrow$ relax($UC$)
5:     newTest $\leftarrow$ solve($UC$)
6:     $\overline{testSuite}$.add(newTest)
7: end while
8: return $\overline{testSuite}$
```

Algorithm 10 computeUC(PSLib, Target)

```
1: if match(PSLib, Target) then
2:     (summary, $CC_w$) $\leftarrow$ lookup(PSLib, Target)
3:     return (summary, $CC_w$)
4: else
5:     $\overline{calleeSet} \leftarrow$ CFG(Target)
6:     if $\overline{calleeSet} = \varnothing$ then
7:         (summary, $CC_w$) $\leftarrow$ SLG(Target)
8:         return (summary, $CC_w$)
9:     else
10:        $UC \leftarrow \varnothing$
11:        for all $cs_i^f \in \overline{calleeSet}$ do
12:            $CC_{ir}^f \leftarrow$ Custom-SE(Diff($cs_i^{f-1}$, $cs_i^f$), $cs_i^{f-1}$, $cs_i^f$, $\varnothing$, $\varnothing$, d)
13:            (summary, $CC_{iw}^f$) $\leftarrow$ computeUC(PSLib, $f$)
14:            $UC$.add($CC_{ir}^f$, summary, $CC_{iw}^f$)
15:        end for
16:        return $UC$
17:    end if
18: end if
```

three parameters, $PSLib$, the library of performance summaries for the components, $Target$, the target method against which we are generating load tests, and T, the number of tests needed. As before, $PSLib$ is computed beforehand, and the extent of the library is determined by practical constraints such as testing resources. Algorithm 9 operates iteratively, generating one test after each iteration of lines 2-7. In each iteration, it first calls a helper function computeUC to compute UC, a constraint set corresponding to a load inducing path in the target method, then relaxes the set and solves it to generate a test. To keep the presentation simple, Algorithms 9 focuses on the generation and use of channeling constraints to explore the paths of the composition, and does not consider maximizing load. In Section 4.6.3, we will present a new algorithm, Algorithm 11, that addresses this missing piece.

Algorithm 10 computes a constraint set for the target method. At Line 1 it checks if a match already exists in the library, and if so, returns a summary and CC_w. Otherwise, it computes a set of call sites that correspond to all the callees of the target method (Line 5). If $\overline{calleeSet}$ is empty, which means the target method is a leaf method, the algorithm invokes SLG to compute a summary and CC_w (Line 7). If $\overline{calleeSet}$ is not empty, the algorithm loops on each cs_i^f in $\overline{calleeSet}$ to compute a summary for it (Lines 11-15). It invokes Custom-SE to compute CC_{ir}^f, recursively invoking itself to compute summary and CC_{iw}^f, and then returns the aggregated constraint set.

4.6.1.3 Proof-of-Concept Examples

In this section, we will use five examples of increasing complexity to show the applicability of the approach to handle richer channeling constraints. Templates for the code examples are summarized in Table 4.9.

Example 1 (Figure 4.9) deals with a single method call in the main method that does not have side effects. As Table 4.10 shows, the analysis starts by calling computeUC on the main method at Line 3. The constructor call at Line 6 is identified, but omitted due to its empty body (if the constructor is not empty, the process either looks up its summary in the library, or uses SLG to generate one if no match is found). The call to `binarySearch` at Line 8 is then identified, and we assume a match is found in the library. The corresponding CC_r at the call site is generated by calling Custom-SE. The analysis then traverses to the end of main at Line 9, and calculates a summary for main by composing the component summaries with chan-

Table 4.9: Summary of the proof–of-concept examples.

Example	**Characteristics**	**Template**
1	Single function call, no side effects	`main(...){` `...` `r = foo(...);` `...` `}`
2	Single function call, with side effects	`main( ){` `...` `foo(...);` `...` `}`
3	Multiple function calls, with side effects	`main(...){` `...` `foo(...);` `...` `fee(...);` `...` `}`
4	Multiple function calls, with side effects and a predicate	`main(...){` `...` `if(expression){ foo(...); }` `else{ fee(...); }` `...` `}`
5	Multiple nested function calls, with side effects	`main(...){` `...` `foo(...);` `...` `fee(...);` `...` `}` `fee(...){ few(...);}`

neling constraints. The calculated summary is subsequently simplified by removing repetitive constraints and tautologies from the set. This example shows that the approach is capable of reusing a component's summary, if the component does not have side effects.

```
class Demo1{
  public int key;
  public static void main(int i1, int i2, int i3,
          int i4, int i5){
    int[] A = {i1, i2, i3, i4, i5};
    Demo1 demo1 = new Demo1();
    //assume input array is pre-sorted
    int result = demo1.binarySearch(A, demo1.key);
  }
  int binarySearch(int[] A, int key){
    int imin = 0;
    int imax = A.length-1;
    //continue searching while [imin, imax] is not empty
    while(imax >= imim){
      //calculate the midpoint for roughly equal partition
      int imid = (imin + imax)/2;
      //determine which array to search
      if(A[imid] < key)
        imin = imid + 1;
      else if(A[imid] > key)
        imax = imid - 1;
      else
        //key found at index imid
        return imid;
    }
    //key not found
    return null;
  }
}
```

Figure 4.9: Code example 1: single function call, no side effects.

Example 2 (Figure 4.10) deals with a single method call in the main method that has side effects (bubbleSort propagates its changes via array A). As Table 4.11 shows, the analysis starts with the main method. The call to `bubbleSort` at Line 5 is identified, and we assume a match is found in the library (note that it includes CC_w for the fields it writes in A). The corresponding CC_r at the call site is generated

Table 4.10: Constraint composition for code example 1.

Line #	Component	Summary		
		Description	Constraints	Source
5-8	main	target	-	computeUC
8	binarySearch	CC_r	$i1 == s1 \land i2 == s2 \land i3 == s3 \land i4 == s4 \land i5 == s5 \land field.key == s\_key$	Custom-SE
	size = 5 (array)+1(search key)	Summary[6]	$s1 < s\_key \land s2 < s\_key \land s3 < s\_key \land s4 > s\_key \land s5 > s\_key$	library
		CC_w	$result == null$	library
9	main	Summary	$i1 == s1 \land i2 == s2 \land i3 == s3 \land i4 == s4 \land i5 == s5 \land field.key == s\_key \land s1 < s\_key \land s2 < s\_key \land s3 < s\_key \land s4 > s\_key \land s5 > s\_key$	computeUC
9	main	Summary	$i1 < field.key \land i2 < field.key \land i3 < field.key \land i4 > field.key \land i5 > field.key$	simplified

by calling Custom-SE. The analysis then traverses to the end of main at Line 6, and calculates a summary for main by composing the summaries with channeling constraints. The calculated summary is subsequently simplified. This example shows that the approach can reuse a component's summary, and can handle side effects properly.

```
class Demo2{
  public static void main(int i1, i2, i3, i4, i5){
    int[] A = {i1, i2, i3, i4, i5};
    Demo2 demo2 = new Demo1();
    demo2.bubbleSort(A);
  }
  void bubbleSort(int[] A){
    boolean swapped = true;
    int temp;
    while(swapped){
      swapped = false;
      for(int i=1; i <= A.length-1; i++){
        if(A[i-1] > A[i]){
          //swap A[i-1] and A[i]
          temp = A[i-1];
          A[i-1] = A[i];
          A[i] = temp;
          swapped = true;
        }
      }
    }
  }
}
```

Figure 4.10: Code example 2: single function call, with side effects.

Example 3 (Figure 4.11) deals with two method calls in the main method. One of them has side effects. As Table 4.12 shows, the analysis starts with the main method. It first identifies the call to `bubbleSort` at Line 6, then the call to `binarySearch` at Line 7. In this example, both callees have matching summaries that can be reused. The analysis then traverses to the end of main at Line 7, and calculates a summary for main by composing the summaries with channeling constraints. The calculated summary is subsequently simplified. The final summary, in Line 6, captures a worst case scenario for the program, because the `bubbleSort` method is used to sort an array that is already sorted in reverse order, and the `binarySearch` method traverses to the bottom of the search tree. This example shows that the approach is capable of computing a worst case summary for a Java program by composing two worst case summaries for its components together.

Table 4.11: Constraint composition for code example 2.

Line #	Component	Summary		
		Description	Constraints	Source
4-5	main	target	-	computeUC
5	bubbleSort size = 5	CC_r	$i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5$	Custom-SE
		Summary	$s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5$	library
		CC_w	$s5 == i1 \wedge s4 == i2 \wedge s3 == i3 \wedge s2 == i4 \wedge s5 == i1$	library
6	main	Summary	$i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5 \wedge s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5$	computeUC
6	main	Summary	$i1 > i2 \wedge i1 > i3 \wedge i1 > i4 \wedge i1 > i5 \wedge i2 > i3 \wedge i2 > i4 \wedge i2 > i5 \wedge i3 > i4 \wedge i3 > i5 \wedge i4 > i5$	simplified

```
class Demo3{
  public static void main(int i1, int i2, int i3,
        int i4, int i5){
    int[] A = {i1, i2, i3, i4, i5};
    Demo3 demo3 = new Demo3();
    demo3.bubbleSort(A);
    int result = demo3.binarySearch(A, i1);
  }
  void bubbleSort(int[] A){
     ...
  }
  int binarySearch(int[] A, int key){
     ...
  }
}
```

Figure 4.11: Code example 3: multiple function calls, with side effects.

Table 4.12: Constraint composition for code example 3.

Line #	Component	Summary		
		Description	Constraints	Source
4-6	main	target	-	computeUC
6	bubbleSort size = 5	CC_r	$i1 == s1 \land i2 == s2 \land i3 == s3 \land i4 == s4 \land i5 == s5$	Custom-SE
		Summary	$s1 > s2 \land s1 > s3 \land s1 > s4 \land s1 > s5 \land s2 > s3 \land s2 > s4 \land s2 > s5 \land s3 > s4 \land s3 > s5 \land s4 > s5$	library
		CC_w	$s5 == i1 \land s4 == i2 \land s3 == i3 \land s2 == i4 \land s5 == i1$	library
7	main	target	-	computeUC
7	binarySearch size = 5 + 1 for key	CC_r	$s5 == p1 \land s4 == p2 \land s3 == p3 \land s2 == p4 \land s1 == p5 \land key == s1$	Custom-SE
		Summary	$p1 < key \land p2 < key \land p3 < key \land p4 > key \land p5 > key$	library
		CC_w	$result == null$	library
7	main	Summary	$i1 == s1 \land i2 == s2 \land i3 == s3 \land i4 == s4 \land i5 == s5 \land s1 > s2 \land s1 > s3 \land s1 > s4 \land s1 > s5 \land s2 > s3 \land s2 > s4 \land s2 > s5 \land s3 > s4 \land s3 > s5 \land s4 > s5 \land s5 == p1 \land s4 == p2 \land s3 == p3 \land s2 == p4 \land s1 == p5 \land key == s1 \land p1 < key \land p2 < key \land p3 < key \land p4 > key \land p5 > key$	computeUC
7	main	Summary	$i1 > i2 \land i1 > i3 \land i1 > i4 \land i1 > i5 \land i2 > i3 \land i2 > i4 \land i2 > i5 \land i3 > i4 \land i3 > i5 \land i4 > i5 \land i5 < i1 \land i4 < i1 \land i3 < i1 \land i2 > i1 \land i1 > i1$	simplified

Example 4 (Figure 4.12) deals with two method calls in the main method. One of them has side effects. In addition, the main method also contains one predicate, making it fork into two distinct program paths. One path contains both calls, the other contains only one. The two paths are analyzed separately. Tables 4.13 corre-

sponds to the path that contains two calls, and Tables 4.14 corresponds to the path that contains only the call to `binarySearch`. This example shows that the approach can compose summaries for a Java program in multiple ways, and produce a test case for each composition. In the end, two test cases are generated, one for each path. In order to produce a test case with higher load, we need to explore all compositions, generating one test for each composition, comparing them in terms of load, and outputing the one that induces the most load. The fact that the number of tests generated is exponential to the number of predicates makes this strategy infeasible in practice. We discuss how to use heuristics to select a higher loading composition in Section 4.6.3.

```
class Demo4{
  public static void main(int i1, int i2, int i3,
          int i4, int i5){
    int[] A = {i1, i2, i3, i4, i5};
    Demo4 demo4 = new Demo4();
    //check if the array is already sorted
    boolean isSorted = true;
    for(int i = 1; i < A.length; i++){
      if(A[i-1] > A[i]){
        isSorted = false;
        break;
      }
    }
    if(!isSorted){
      demo4.bubbleSort(A);
    }
    int result = demo4.binarySearch(A, i1);
  }
  void bubbleSort(int[] A){
    ...
  }
  int binarySearch(int[] A, int key){
    ...
  }
}
```

Figure 4.12: Code example 4: multiple function calls, with side effects and a predicate.

Table 4.13: Constraint composition for code example 4 (Path 1).

Line #	Component	Summary		
		Description	Constraints	Source
4-15	main (path 1)	target	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 > i5$	computeUC
15	bubbleSort size = 5	CC_r	$i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5$	Custom-SE
		Summary	$s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5$	library
		CC_w	$s5 == i1 \wedge s4 == i2 \wedge s3 == i3 \wedge s2 == i4 \wedge s5 == i1$	library
16-17	main	target	-	computeUC
17	binarySearch size = 5(array)+ 1(search key)	CC_r	$s5 == p1 \wedge s4 == p2 \wedge s3 == p3 \wedge s2 == p4 \wedge s1 == p5 \wedge key == i1$	Custom-SE
		Summary	$p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	library
		CC_w	$result == null$	library
18	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 > i5 \wedge i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5 \wedge s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5 \wedge s5 == p1 \wedge s4 == p2 \wedge s3 == p3 \wedge s2 == p4 \wedge s1 == p5 \wedge key == i1 \wedge p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	computeUC
18	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 > i5 \wedge i1 > i2 \wedge i1 > i3 \wedge i1 > i4 \wedge i1 > i5 \wedge i2 > i3 \wedge i2 > i4 \wedge i2 > i5 \wedge i3 > i4 \wedge i3 > i5 \wedge i4 > i5 \wedge i5 < i1 \wedge i4 < i1 \wedge i3 < i1 \wedge i2 > i1 \wedge i1 > i1$	simplified

Example 5 (Figure 4.13) deals with two method calls in the main method. The `bubbleSort` method is different from previous cases. It contains a call to another

Table 4.14: Constraint composition for code example 4 (Path 2).

Line #	Component	Summary		
		Description	Constraints	Source
4-17	main	target	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 <= i5$	computeUC
17	binarySearch size = 5(array) + 1(search key)	CC_r	$i1 == p1 \wedge i2 == p2 \wedge i3 == p3 \wedge i4 == p4 \wedge i5 == p5 \wedge key == i1$	Custom-SE
		Summary	$p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	library
		CC_w	$result == null$	library
18	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 <= i5 \wedge i1 == p1 \wedge i2 == p2 \wedge i3 == p3 \wedge i4 == p4 \wedge i5 == p5 \wedge key == i1 \wedge p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	computeUC
18	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 <= i5 \wedge i1 < i1 \wedge i2 < i1 \wedge i3 < i1 \wedge i4 > i1 \wedge i5 > i1$	simplified

method `isSorted`. Because `isSorted` can return either $true$ or $false$, `bubbleSort` has two corresponding summaries. To demonstrate that our technique can handle this situation, we assume `bubbleSort` does not have a matching summary in the library. Using the two summaries for `bubbleSort`, we can compose two different summaries for the main method. Table 4.15 corresponds to one of the summaries (in which `isSorted` returns $false$), and Table 4.16 corresponds to the other summary (in which `isSorted` returns $true$). In both tables, computeUC (Algorithm 10) is invoked recursively, once on the target method (`main`), and once on `bubbleSort`, which is a callee of `main`. As a result, there are two compositions in each table, for `bubbleSort` and `main` respectively. In the end, two test cases are generated. This example shows that the approach can compose summaries for a Java program who has multiple callees, and the callees may also contain callees on their own.

```
class Demo5
  public static void main(int i1, int i2, int i3,
            int i4, int i5){
    int[] A = {s1, s2, s3, s4, s5};
    Demo5 demo5 = new Demo5();
    demo5.bubbleSort(A);
    int result = binarySearch(A, i1);
  }
  void bubbleSort(int[] A){
    if(!isSorted(A)){
      boolean swapped = true;
      int temp;
      while(swapped){
        swapped = false;
        for(int i=1; i <= A.length-1; i++){
          if(A[i-1] > A[i]){
            //swap A[i-1] and A[i]
            temp = A[i-1];
            A[i-1] = A[i];
            A[i] = temp;
            swapped = true;
          }
        }
      }
    }
  }
  boolean isSorted(int[] A){
    for(int i = 1; i < A.length; i++){
      if(A[i-1] > A[i]){
        return false;
      }
    }
    return true;
  }
  int binarySearch(int[] A, int key){
    ...
  }
}
```

Figure 4.13: Code example 5: multiple nested function calls, with side effects.

Table 4.15: Constraint composition for code example 5 (Path 1).

Line #	Component	Summary		
		Description	Constraints	Source
4-6	main	target	-	computeUC
10	bubbleSort (call site @6)	CC_r	$i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5$	Custom-SE
10	isSorted	CC_r	$k1 == s1 \wedge k2 == s2 \wedge k3 == s3 \wedge k4 == s4 \wedge k5 == s5$	Custom-SE
	size = 5	Summary	$k1 <= k2 \wedge k2 <= k3 \wedge k3 <= k4 \wedge k4 > k5$	library
		CC_w	$false$	library
10-26	bubbleSort (call site @6)	Summary	$k1 == s1 \wedge k2 == s2 \wedge k3 == s3 \wedge k4 == s4 \wedge k5 == s5 \wedge k1 <= k2 \wedge k2 <= k3 \wedge k3 <= k4 \wedge k4 > k5 \wedge s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5$	computeUC
		CC_w	$s1 == i5 \wedge s2 == i4 \wedge s3 == i3 \wedge s4 == i2 \wedge s5 == i1$	Custom-SE
7	main	target	-	computeUC
7	binarySearch	CC_r	$s5 == p1 \wedge s4 == p2 \wedge s3 == p3 \wedge s2 == p4 \wedge s1 == p5 \wedge key == i1$	Custom-SE
	size = 5(array)+1(search key)	Summary	$p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	library
		CC_w	$result == null$	library
8	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 > i5 \wedge i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5 \wedge s1 > s2 \wedge s1 > s3 \wedge s1 > s4 \wedge s1 > s5 \wedge s2 > s3 \wedge s2 > s4 \wedge s2 > s5 \wedge s3 > s4 \wedge s3 > s5 \wedge s4 > s5 \wedge s5 == p1 \wedge s4 == p2 \wedge s3 == p3 \wedge s2 == p4 \wedge s1 == p5 \wedge key == i1 \wedge p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	computeUC
8	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 > i5 \wedge i1 > i2 \wedge i1 > i3 \wedge i1 > i4 \wedge i1 > i5 \wedge i2 > i3 \wedge i2 > i4 \wedge i2 > i5 \wedge i3 > i4 \wedge i3 > i5 \wedge i4 > i5 \wedge i5 < i1 \wedge i4 < i1 \wedge i3 < i1 \wedge i2 > i1 \wedge i1 > i1$	simplified

Table 4.16: Constraint composition for code example 5 (Path 2).

Line #	Component	Summary		
		Description	Constraints	Source
4-6	main	target	-	computeUC
10	bubbleSort (call site @6)	CC_r	$i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5$	Custom-SE
10	isSorted size = 5	CC_r	$k1 == s1 \wedge k2 == s2 \wedge k3 == s3 \wedge k4 == s4 \wedge k5 == s5$	Custom-SE
		Summary	$k1 <= k2 \wedge k2 <= k3 \wedge k3 <= k4 \wedge k4 <= k5$	library
		CC_w	$true$	library
10-26	bubbleSort (call site @6)	Summary	$k1 == s1 \wedge k2 == s2 \wedge k3 == s3 \wedge k4 == s4 \wedge k5 == s5 \wedge k1 <= k2 \wedge k2 <= k3 \wedge k3 <= k4 \wedge k4 <= k5$	computeUC
		CC_w	$s1 == i1 \wedge s2 == i2 \wedge s3 == i3 \wedge s4 == i4 \wedge s5 == i5$	Custom-SE
7	main	target	-	computeUC
7	binarySearch size = 5(array)+1(search key)	CC_r	$s1 == p1 \wedge s2 == p2 \wedge s3 == p3 \wedge s4 == p4 \wedge s5 == p5 \wedge key == i1$	Custom-SE
		Summary	$p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	library
		CC_w	$result == null$	library
8	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 <= i5 \wedge i1 == s1 \wedge i2 == s2 \wedge i3 == s3 \wedge i4 == s4 \wedge i5 == s5 \wedge s1 == p1 \wedge s2 == p2 \wedge s3 == p3 \wedge s4 == p4 \wedge s5 == p5 \wedge key == i1 \wedge p1 < key \wedge p2 < key \wedge p3 < key \wedge p4 > key \wedge p5 > key$	computeUC
8	main	Summary	$i1 <= i2 \wedge i2 <= i3 \wedge i3 <= i4 \wedge i4 <= i5 \wedge i1 < i1 \wedge i2 < i1 \wedge i3 < i1 \wedge i4 > i1 \wedge i5 > i1$	simplified

4.6.2 Richer Performance Summaries

The technique for handling pipelines needs only to consider the input / output sizes of the summaries when doing summary matching. This is because the pipeline approach works on a coarser granularity. Each component is a single program, and the number of components in a pipeline is usually small (order of tens). For Java programs, because each component is a single method, the approach works at a much finer granularity level. Subtle incompatibilities between summaries can cause removal of key constraints in the performance summaries, and the cumulative effect of such unnecessary reduction may impact the induced load.

The performance degradation is more prominent, when the program under test takes heap-allocated data structures, such as trees and linked lists, as inputs. A modern symbolic execution engine (e.g., Symbolic PathFinder, the framework upon which our technique is built) handles heap-allocated data via lazy initialization. SPF starts execution of the method on inputs with uninitialized fields and it assign values to these fields lazily, i.e., when they are first accessed during the methods symbolic execution. As symbolic execution continues, each node of the execution tree denotes a program state, which consists of the following information: 1) a program counter that tracks the execution progress; 2) a set of constraints collected over symbolic variables of primitive types; 3) the *shape* of the heap-allocated data structure on which the program executes. Here the shape of the data structure is encoded as a set of memory allocations and pointers. The shape information is essential to maintain a precise symbolic execution of the target program.

However, when we use SLG to generate performance summaries, we only store part of the program state: the set of constraints on primitive types. In addition we also store tags on the *size* of inputs / outputs to assist matching. The size tags can be viewed as naive abstractions of the shape information [4], which we omitted in this process. Therefore, when we perform summary matching later, we effectively over-approximate program behaviors, the degree to which is determined by how much the program execution depends on heap-allocated data structures. To handle programs that make heavy use of heap data, we need to use more accurate abstraction of the shape information, when generating performance summaries from program states.

We now use a concrete example to illustrate the severity of the problem. Figure 4.14 lists an example program with an AVL tree implementation. The `main` method of the program contains five consecutive `insert` methods to construct a search tree. For each `insert` method, both input and output are trees, with each output having one more node than the corresponding input. We assume that the `insert` method has sufficient number of summaries (i.e., summaries for trees of sizes up to 10), and want to compose a summary for the `main` method in Figure 4.14.

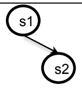
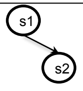
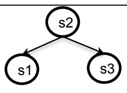
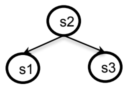
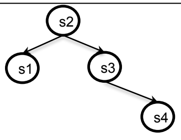
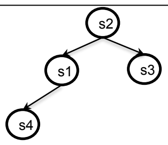
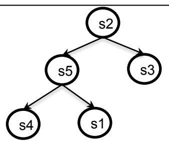
```
AVL insert(int i){
  inserting a node at the end;
  balanceFactor = height(left-subtree)
    - height(right-subtree);
  if (balance_factor > 1){
    rotate left;
  } else if (balance_factor < -1){
    rotate right;
  }
}

main(int s1, s2, s3, s4, s5){
 AVL tree = new AVL();
  tree.insert(s1);
  tree.insert(s2);
  tree.insert(s3);
  tree.insert(s4);
  tree.insert(s5);
}
```

Figure 4.14: Code snippet for the AVL tree: five inserts.

Table 4.17 shows the composition process when only size tags are considered during matching. For each `insert`, it lists the input / output sizes (as well as the

Table 4.17: Handling AVL tree with five inserts (size match).

#	Input		Output		Constraints
	shape	size	shape	size	
1st insert		1		1	–
2nd insert		2		2	$s1 < s2$
3rd insert		3		3	$s1 < s2 \land s2 < s3$
4th insert		4		4	$s1 < s2 \land s2 < s3 \land s3 < s4$
5th insert		5		5	$s1 < s2 \land s2 < s3 \land s4 < s1 \land s5 < s1 \land s4 < s5$

shape of the tree for comparison purpose), and the constraints collected by SLG. In the table, each `insert`'s output size matches the next `insert`'s input size. Table 4.18 shows another scenario in the same format, when the shape of the tree is considered. For example, in Table 4.18 the output tree of the 4th `insert` matches the input tree of the 5th `insert`. While in Table 4.17, the output tree of the 4th `insert` does not match the input tree of the 5th `insert`, although both of them having the same size 4.

Table 4.19 shows the evaluation on the test cases generated from the two scenarios. As shown in the table, the scenario following shape match produces a test case that induces 62% more load than the other scenario. This is because if the shape of the tree is kept as new nodes are inserted, it is more likely to break the balance and force rotation. This example clearly conveys the importance of more precise tags when matching summaries.

Table 4.18: Handling AVL tree with five inserts (shape match).

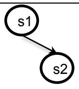
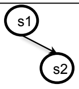
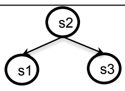
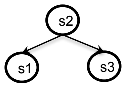
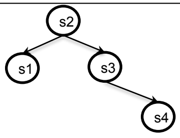
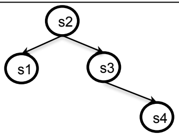
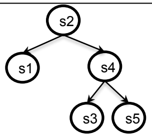
#	Input		Output		Constraints
	shape	size	shape	size	
1st insert		1		1	–
2nd insert		2		2	$s1 < s2$
3rd insert		3		3	$s1 < s2 \wedge s2 < s3$
4th insert		4		4	$s1 < s2 \wedge s2 < s3 \wedge s3 < s4$
5th insert		5		5	$s1 < s2 \wedge s2 < s3 \wedge s3 < s4 \wedge s4 < s5$

Table 4.19: Evaluation: AVL tree with five inserts.

Generated Test	Load (bytecode count)
Size matching scenario	385
Shape matching scenario	517

4.6.2.1 Revisiting the Approach to Generating Performance Summaries

We propose a slightly revised approach for generating performance summaries with more precise metadata describing their properties, in order to enable a more precise summary matching process that follows. First we present a few definitions.

Definition 4.6.2 *Shape Metadata: A set of metadata encoding the shape of the heap-allocated data structure in terms of objects created by memory allocations, and the reference pointers among the objects.*

For example, metadata for a tree data structure (as in the AVL tree example) could include node objects and the children reference within each node. Note that the shape metadata is independent from the symbolic variables kept within the tree, the constraints, or other types of metadata. With shape metadata, we redefine performance summaries and compatibility as well. Both definitions replace the *size* metadata in the pipeline approach with the new *shape* metadata.

Definition 4.6.3 *Performance Summary (PS): A set of path conditions $PS_j^s = \{pc_1^j, \cdots, pc_n^j\}$ for program P_j caused by inputs of shape s that induce load according to a performance measure. Each pc_i^j contains the following metadata to assist future analysis:* **shape** *and* **type** *of input and output, and the* **weight score** *indicating its load.*

Definition 4.6.4 *Compatibility: For two programs P_i and P_j in a system, two summaries pc^i and pc^j are compatible if $O(pc^i) = I(pc^j)$, where $O(...)$ and $I(...)$refer to the shape of input and output data that are confined to the path defined by pc^i.*

A shape metadata enabled approach only matches summaries that have the exact same metadata. This will help avoid putting together summaries that contain greater number of incompatible constraints. Therefore we have a greater chance of removing fewer constraints in the resulting product to make it solvable. However, even with the more precise shape metadata, the approach does not guarantee an optimal solution, which means, it may generate a test case that induce relatively high load, but does not represent a worst case scenario. We further discuss these issues next.

Continuing with the AVL tree example, Figure 4.15 shows another code snippet, which builds on the previous one in Figure 4.14, with three more method calls added in the `main` method (`insert`, `delete` and `insert`). Table 4.20 shows the process of composing summaries for the `main` method. To save space the five `insert` calls are omitted (which follows the same process as shown in Table 4.18). Rows 1-3 in Table 4.20 show the composition of the subsequent three calls, which follows the

```
AVL_insert(int i){
  ...
}
main(int s1, s2, s3, s4, s5, s6, s7, s8){
  AVL tree = new AVL();
   tree.insert(s1);
   tree.insert(s2);
   tree.insert(s3);
   tree.insert(s4);
   tree.insert(s5);
   tree.insert(s6);
   tree.delete(s7);
   tree.insert(s8);
}
```

Figure 4.15: Code snippet for the AVL tree: eight calls.

rules of shape matching. For comparison, rows 4-6 depict a global worst case scenario obtained by invoking symbolic execution on the whole `main` method.

Table 4.21 shows the evaluation on the test cases generated from these scenarios. It also lists test cases generated by just performing size matching at each step (because there are multiple ways to perform size-matching-only composition, we generate five tests and report the average load). As shown in the table, the shape matching approach produces tests that induces 28% more load, but is still 40% less than the global worst case.

Table 4.20: Handling AVL tree with eight calls.

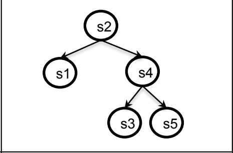
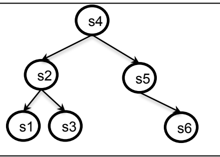
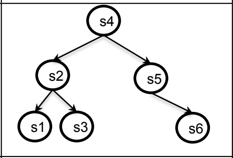
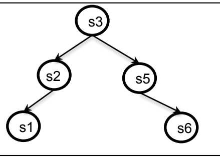
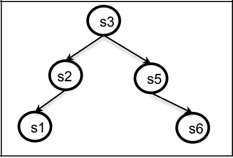
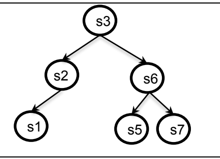
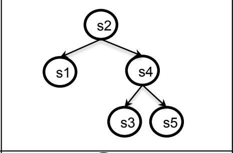
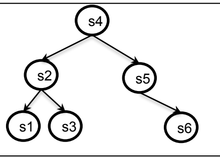
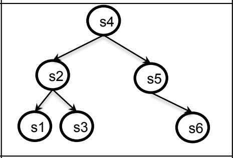
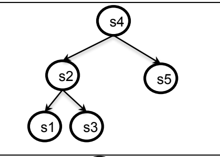
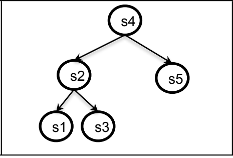
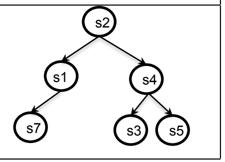
#	**Input**	**Output**
shape matching		
insert		
delete		
insert		
global worst-case scenario		
insert		
delete		
insert		

Table 4.21: Evaluation of the AVL tree example continued.

Generated Test	Load (bytecode count)
Size match only (average of 5 runs)	725
Shape match (rows 1-3)	933
Global worst-case (rows 4-6)	1315

4.6.3 A New Strategy for Summary Composition

The complex nature of Java programs makes the technique for selecting summaries for composition not suitable anymore. We will use a concrete example to illustrate the new challenges. Consider the code snippet in Figure 4.12. The predicate at Line 15 forks the execution into two paths, one containing both calls to `bubbleSort` and `binarySearch`, the other only contains `binarySearch`. The path that contains both calls induces more load, and should be chosen for test generation. One way to identify the more expensive path is to explore both paths. However, the number of paths grows exponentially with respect to the number of predicates. For example, on a program with 4 predicates, the approach may need to traverse 16 paths to identify the most expensive one. On the other extreme, an alternative approach that we have used previously in handling pipelines is to use a greedy forward matching strategy. However, this strategy does not always work for that type of examples, and in general for programs with many paths where the first path may not be the one that induces the most load. A greedy approach would first select a most expensive summary for Lines 9-13. But this early choice will lead to the path that only contains the call to `binarySearch` and skip `bubbleSort` at Line 15, making it a poor choice for load testing.

4.6.3.1 Revisiting the Approach to Composition

Instead of using either exhaustive or greedy strategies, we conjecture that alternative approaches, such as a heuristic search strategy, can be used to solve this problem, hoping that a search strategy would strike a balance between the two extremes. Conceptually, the proposed search strategy works on the component level, in which the static call graph of the program forms the search space of potential compositions. The goal of the search process is to find one composition that corresponds to the

Algorithm 11 CompSLG(PSLib, Target, lookAhead, maxDepth, T)

```
1: currentDepth ← 0
2: search ← true
3: while search do
4:    currentDepth ← currentDepth + lookAhead
5:    if currentDepth > maxDepth then
6:       search ← false
7:    end if
8:    $\overline{frontier}$ ← computeFrontier(PSLib, Target, currentDepth)
9:    $\overline{promising}$ ← selectComposition($\overline{frontier}$, T)
10: end while
11: if $\overline{promising}$ == ∅ then
12:    return null
13: else
14:    for all state ∈ $\overline{promising}$ do
15:       testSuite.add(solve(state))
16:    end for
17:    return testSuite
18: end if
```

worst case performance of the program.

In essence, this problem is similar to finding a program path that corresponds to the greatest load, which we solved through the SLG algorithm. The only difference is granularity: in SLG, the nodes of the search tree are program states, and the edges are instructions (bytecodes in the context of Java); while in the new algorithm, the nodes of the search tree are compositions of explored summaries, and the edges are method invocations. Therefore, we can adapt the SLG algorithm to solve this problem, in an iterative-deepening fashion.

Algorithm 11 redefines the CompSLG algorithm for Java program. The previous definition (Algorithm 9) focuses on application of channeling constraints and did not consider maximizing load. The new definition shown here is modeled after SLG, the algorithm presented in Section 3 (the difference is shown in highlighted lines), and it specifically finds the compositions with the maximal load. The algorithm takes several parameters: PSLib is the library of performance summaries for components;

Target is the target method against which a load test is generated; and T is the number of tests to be generated; *lookAhead* and *maxDepth* are used in the same way as in SLG.

Algorithm 11 invokes a few helper functions. Function `computeFrontier` traverses all possible paths that originate from the target method and up to the designated depth. It returns one constraint set (UC) for each such path. It can be implemented by modifying computeUC (Algorithm 10), with two extensions: 1) computeUC only traverses one path at a time. At Line 2 of Algorithm 10, the lookup function returns only one matching summary. We can update this function to return all matching summaries, allowing computeUC to explore each one (use a queue to hold intermediate results), and return all explored paths; 2) computeUC does not stop at a specified depth. We can use a counter to track recursion depth and stop when exceeding the designated depth.

Function `selectComposition` selects promising paths at each frontier to continue, and prune the others. It uses heuristics to choose a promising path, in terms of its potential to induce load. We can reuse the available heuristics in SLG, such as selecting the paths with the most accumulated weight score, or we can devise new heuristics by taking advantage of the metadata associated with the components. For example, if one component has a summary whose weight dominates the summaries of other components, we can devise a heuristic that always selects the component with the dominating summary. Alternatively, if there are several summaries of comparable weight, we can devise a heuristic that selects distinct summary for each composition. This last heuristic not only steers towards higher load, but also promotes diversity among generated tests.

Algorithm 11 works as follows. As long as the current search depth is less than maxDepth, It iterates on the following steps. First it attempts to explore all possible paths up to *lookAhead* depth (Line 8). Then it uses heuristics to select promising paths to continue on the next iteration (Line 9). When iteration stops, it solves constraints associated to each remaining promising path, and reruns the test suite (Line 14-17). The savings are achieved through pruning of the paths that are not selected to continue.

Revisiting the example. Next we revisit the code snippet in Figure 4.12, applying the new CompSLG algorithm on it. As shown before, this program has two paths. one calls `binarySearch`, the other calls both `bubbleSort` and `binarySearch`. If we set *lookAhead* to 1, after the first iteration, we would have explored two paths: Path 1: up to the call to `bubbleSort`; and Path 2: up to the call to `binarySearch`. The algorithm then selects Path 1 to continue, because `bubbleSort` induces more load than `binarySearch`. On the second iteration it finishes on Path 1 and generates a load test. Note that this example does not explore full potential of the algorithm, because the paths in the example are too short. Clearly for more complex programs with more paths, *lookAhead* would have to be tweaked as well as the other parameters of Algorithm 11 to favor the paths that are best aligned with the interest of the user.

4.7 Summary

This chapter presents a compositional approach, CompSLG, which can automatically generate load tests for complex programs. CompSLG uses emerging symbolic execution based techniques to analyze the performance of each system component in isolation, summarize the results of those analyses, and then perform a global analysis across those summaries to generate load tests for the whole system. CompSLG achieves gains in both efficiency and scalability by avoiding a search on the whole program path space, and by reusing previously computed summaries to save on repetitive computations.

In its current form, CompSLG is fully automated to handle any system that is structured in the form of a software pipeline (such as a Unix pipeline or an XML pipeline). A study of CompSLG revealed that it can generate load tests for pipelines where SLG alone would not scale up, and it is much more cost effective than either SLG applied to single components or Random test generation.

We also investigated how to extend CompSLG to enable its application to Java programs, in which each method considered is a component. The extension includes a new approach to generating channeling constraints, generating performance summaries with more precise metadata, and an adapted strategy for composing summaries. Although the extended version is not yet fully implemented, we showed the viability of the approach with several proof-of-concept examples.

Chapter 5

Amplifying Tests to Validate Exception Handling Code

As part of non-functional requirements, external resources impose contextual constraints on software systems that must interact with them. One way to improve robustness of software is to use exception handling constructs. However, a faulty implementation of exception handling code may introduce bugs that undermine the overall quality of the software. In this chapter we present a white box exhaustive technique for detecting faulty implementations of exception handling constructs. The technique is white box in a sense that it first instruments the target program by adding a mocking device to take the place of the external resources of interest. It then exhaustively amplifies the space of exceptional program behavior explored by each test and associated with an external resource up to a user-defined number of invocations.[1]

We first study the magnitude of the problem in Section 5.1. In Section 5.2 we

[1]Portions of the material presented in this chapter have appeared in a paper by Zhang et al. [136]. The material presented in this chapter provides an extended study of the technique. We will refer to the original study presented in [136] as Phase 1, and the extended study as Phase 2.

present a motivating example showing the difficulties in exposing faulty exceptional behavior and how we propose to solve it. Section 5.3 details the design and implementation of the technique. Section 5.4 presents a two-phase extensive study of the technique.

5.1 Magnitude of the Problem

In this section we study the prevalence of faults associated with code that handles exceptions. The study focuses on free popular applications for the Android platform which rely extensively on APIs that work with external resources like wireless connections, databases, GPS, or bluetooth.

The selection of artifacts for the study was conducted in two phases. Phase 1 consisted of our preliminary assessment of the approach [136]. Phase 2 corresponds to this extended effort for providing a more thorough study of the approach, which includes three new artifacts and a more extensive analysis. For the five applications that were included in Phase 1, the selection process consisted of the following steps. First, we collected a pool of 210 candidate applications from the following sources: Wikipedia [125] (121), Le Wiki Koumbit [77] (40), Trac [121] (15), OpenStreetMap-Wiki [87] (8), and Android Open Source DB [7] (26). We then use statistics provided by Cyrket [31] to identify the applications with more than 50K downloads. This left us with 25 applications. Because we are interested in applications with certain level of development maturity, we refined our selection criteria by retaining applications that 1) had an active and public bug tracking repository (excluded 15 apps), 2) had multiple versions (excluded none), and 3) shipped with a unit test suite (excluded 5 more). These constraints left us with 5 applications: *myTracks* [84], a geo-tagging application; *XBMC remote* [126], a remote control for the XBMC media center; *Bar-*

Table 5.1: Summary of artifacts.

Phase	**Application**	**Resource API**	**Version**	**LOC**	**Unit Test Suite**	
					#	**Execution Time (sec)**
1	Barcode Scanner	android.net	r1220	18170	117	275
	Keepassdroid	android.database / android.net	v0.9.3	7713	34	102
	myTracks	android.database / android.location	r195	5918	55	367
	SipDroidVoIP	android.net	r340	18150	39	135
	XBMC remote	android.net / android.bluetooth	r317	10880	78	234
2	Android Wifi Tether	android.net	r170	18828	76	214
	K-9 Mail	android.net / android.database	r512	34880	215	748
	Open GPS Tracker	android.location / android.database	r195	14156	85	308

code Scanner[2], a retriever of online information; *Keepassdroid* [71], a password keeper that syncs with cloud services; and *SipDroidVoIP* [111], a voice over IP client. All data in Phase 1 was collected between April and August 2011.

In Phase 2, we add three more applications following the same selection process, but use Android market statistics provided by another source called AndroLib [9], because Cyrket has not been accessible since 2012. In addition we excluded the applications that were already selected in Phase 1. In the end we added three new applications: *Open GPS Tracker* [86], a fitness application with GPS tagging function; *K-9 Mail* [70], an email client; and *Android Wifi Tether* [8], an utility application that provides wifi signal broadcasting capability. All data in Phase 2 was collected between September and November 2012.

Table 5.1 provides a summary of the artifacts. The first five applications are from Phase 1, and the other three correspond to Phase 2. Column "Resource API" shows the types of resource APIs the application calls. Because many external resources are managed through APIs, we decided to focus on the ones that use the Android API to

[2]The repository link for this app has not been accessible at the time of dissertation defense.

Table 5.2: Classification of confirmed and fixed bug reports.

Application	**Bug reports - Confirmed and Fixed**			
	Total	**Keywords Screening**	**Exceptions**	**Exceptions with External Resources**
Barcode Scanner	136	72	47	17 (13%)
Keepassdroid	45	29	23	16 (36%)
myTracks	46	28	21	11 (24%)
SipDroidVoIP	252	107	39	27 (11%)
XBMC remote	105	51	39	27 (26%)
Android Wifi Tether	54	32	26	14 (26%)
K-9 Mail	687	289	99	39 (6%)
Open GPS Tracker	100	34	21	14 (14%)
Total	1425	642	315	165 (12%)
Average	178	80	39	21 (12%)

manage communication and sensing, because of their high rate of invocations by the selected applications. The version of each application that we use for the evaluation of the technique presented later in the thesis corresponds to the oldest version against which a bug report is available. Columns “Version” and “LOC” denote the chosen version and lines of code respectively. Column “Unit Test Suite” denotes the number of unit tests shipped with each application, and the time it takes to run the available test suites in the Android emulator [6].

The repositories held more than eight thousand bug reports. Among those, 1,425 were confirmed by the developers and addressed through a code revision. Utilizing the bug repositories’ search facilities we then identified the bug reports that mentioned the keywords *exception, throw*, or *catch*, which resulted in 642 reports. We then examined each of those bug reports to identify the ones that were caused at least in part by incomplete or erroneous coding of exception handlers. We found that 315 of the confirmed and fixed bug reports resulted in either adding new exception handlers, modifying existing handlers, or refactoring handlers in various places. Last, we analyzed each report in further detail to identify the ones that had to do with exceptions thrown when services associated with the localization, bluetooth, database, or network resources were invoked. These are the four types of resources that we deemed interesting because of their noisy, diverse, and unpredictable nature.

Our detailed findings are reported in Table 5.2. Column “Total” shows the total number of reports that were confirmed and linked to a fix. Column “Keywords Screening” corresponds to our initial screening of the reports based on keywords *exception, throw*, or *catch*. Columns “Exception” and “Exceptions with External Resources” report the counts of the more detailed analyses. Even for the small set of four external resources we examined, the data suggests that 22% of the confirmed and fixed bugs have to do with poor exceptional handling code, and that 12% correspond to interactions with external resources.

These findings must be taken in light of the scope of the study. We study eight applications in a domain where we suspected troubles with exception handling because of the types of resources being managed. Still, there are literally tens of thousands of applications like this deployed and we expect for these findings to generalize to them. We also echo the threat to validity often raised when dealing with such open source repositories in terms of their noise, which is compounded by the fact that the analysis of the bug reports required some level of judgement by one of the authors and as such is subject to experimentation bias.

Even in light of these limitations, these findings support what we had informally observed in terms of the magnitude of the problem associated with exceptional behavior caused by external resources. With these issues in mind, we proceed to illustrate what makes exposing these faults difficult and how the proposed approach addresses those challenges.

5.2 Difficulties in Exposing Faulty Exceptional Behavior

Figure 5.1 shows a code excerpt from the Android application XBMC Remote which implements a remote control for the XBMC media player and multimedia center application. Lines 1-5 correspond to a test case driver we incorporated to simplified the setup for presentation. The driver sets an http connection and then attempts to retrieve content from the XBMC media server. It first invokes the method *Connection* at Line 6, which subsequently calls two methods (Lines 12 and 16), *setResponseFormat* attempts to format an http request for subsequent data fetching, and *getSystemInfo* fetches basic system information of the server. If the connection is successful, the *networkManager.netStatus* flag is set to true. After a successful connection, the method *getCurrentlyPlaying* at Line 20 is then called to fetch a list of currently playing music and videos.

All three methods at Lines 12, 16 and 20 use a subroutine *query* (Lines 28-39) to communicate with the server application. The *query* method attempts to establish an URL connection and fetch contents. The API call at line 31 can throw an *IOException* if the connection is down. This exception is caught by the **catch** clause (Line 35), which calls *mErrorHandler.handle*, a centralized error handler (Lines 41-54). When the **catch** clause for *IOException* (line 47) is executed, an attempt to renew the connection is performed.

A bug report issued against this code and deemed high priority by the developers, indicated that the application crashed at launch when the web connection became intermittent[3]. The report's trace log shows that the crash was caused by an elaborated series of successful and failed queries to the API managing the connection. For the

[3] `http://code.google.com/p/android-xbmcremote/issues/detail?id=84`

```
public void test(){
    Connection(...);
    (ICurrentPlaying)list = getCurrentlyPlaying();
    ...
}
public void Connection(...){
    if(setResponseFormat(...)){
        String info = getSystemInfo(...);
        networkManager.netStatus = true;
    }
}
public boolean setResponseFormat(...) {
    if(query('setResponseFormat',...)=='ok') return true;
    else return false;
}
public String getSystemInfo(...) {
    return query(‘GetSystemInfo', ...);
}
//Returns list of media currently playing
public ICurrentlyPlaying getCurrentlyPlaying() {
    list.add(query(‘GetCurrentPlaying',‘music'));
    list.add(query(‘GetCurrentPlaying',‘video'));
    mediaFiles = list.get(‘Filename');
    ...
    return list;
}
//Executes an HTTP API method
public String query(String method, String par) {
    try {
        URL url = formatQueryString(method, par);
        URLConnection uc = url.openConnection();
        String info = uc.getInputStream();
        ...
        return info;
    } catch (Exception e) {
        mErrorHandler.handle(e);
        return "";
    }
}
//Centralized exception handler
public void handle(Exception exception) {
    try { throw exception; }
    catch (NoSettingsException e) {...}
    catch (NoNetworkException e) {...}
    catch (WrongDataFormatException e) {...}
    catch (HttpException e) {...}
    catch (IOException e) {
      if( ! networkManager.netStatus ){
        networkManager.Connection(...);
      } else {
        logger.setMessage('Unknown I/O Exception');
      }
    }
}
```

Figure 5.1: Code excerpt (with comments added for readability) from XBMC Remote Revision 220 with a faulty exception handling mechanism.

failure to be exposed, queries at lines 13 and 17 needed to succeed, but queries at lines 21 and 22 had to throw an exception. These exceptions caused for line 23 to assign null to variable *mediaFiles*, and a subsequent dereference on that variable caused a *NullPointerException* and crashed the application.

Part of the problem lies in the use of the centralized error handler at Line 41. For *IOException*, it first checks if the *netStatus* flag is set (Line 48). If the flag is not set, it means the network connection is down, so the handler attempts to renew the connection by calling *Connection* again. If the flag is set, it is assumed the *IO-Exception* was not caused by a network connection problem, so the handler then logs the exception and returns. Successful calls to query at Lines 13 and 17 set the flag, but subsequent calls to query at Lines 21 and 22 fail, raising exceptions that are not handled correctly by the handler, which ultimately causes the crash.

The code revision in Figure 5.2 was later submitted as a fix. It adds a specific handler in *query* for *IOException* so that, when an *IOException* is thrown, depending on whether network connection is successfully setup, it either attempts to reconnect, or prompts a dialogue for user interaction. Note that this revision did not completely fix the problem, only delayed the failure. If the exceptions are raised in the same pattern as described before, and the user hits “OK” on the prompted dialogue, the application will experience the same crash again.

Similar issues associated with the poor handling of exceptional events triggered by external resources represent 26% of the bugs reported in XBMC Remote.

This motivating example conveys three interesting points. First, writing correct exception handling code is difficult, and even when is known to be incorrect, fixing it can be challenging as well. Second, regarding the difficulties of developing tests for such exceptional scenarios, detecting such faults requires: 1) the control of an external resource (connection) to turn it on and off in a prescribed manner,

```
//Executes an HTTP API method
public String query(String method,String param)
{
  try {
    ...
    URL query=formatQueryString(method,param);
    URLConnection uc = query.openConnection();
    uc.setReadTimeout(mTimeout);
    //connection successful, retrieve content
    BufferedReader rd = new BufferedReader(
      new InputStreamReader(uc.getInputStream()));
    ...
    return results;
  }
  catch(FileNotFoundException e) {
    ...
  }
  catch(MalformedURLException e) {
    ...
  }
  catch (IOException e) {
    if( ! networkManager.netStatus ){
      networkManager.Connection(...);
    }else{
      builder.setTitle("Unknown IO Exception");
      builder.setMessage(...);
      builder.setNeutralButton(...);
    }
  } catch (NoSettingsException e) {
      ...
  }
  return "";
}
```

Figure 5.2: Submitted fix to the previous code in Revision 317.

and 2) the systematic exploration of the space of exceptional program behavior that can be triggered through the invocation of an external resource. Third, regarding the capabilities of existing validation techniques, we note that more precise program representations that include exceptional edges may help to detect components that require additional tests to cover exceptional behavior, but assistance to develop such tests is lacking. We also observe that simply covering exceptional edges may not be enough as some of the sequences of throws resulting in failures are quite elaborate, as illustrated by the previous example. Alternative approaches that mine common occurring patterns of exception handling and use those to detect potential anomalies present different tradeoffs as they may be effective for simpler patterns, but struggle as the space of exceptional constructs becomes richer. We discuss and compare some of these approaches later in Section 5.4.5.

5.3 Test Amplification

We propose an approach for detecting faulty implementations of exception handling constructs through the exhaustive amplification of the space of exceptional program behavior explored by each test and associated with an external resource up to a user-defined number of invocations. Conceptually, the approach first instruments the target program by adding a mocking device to take the place of the external resources of interest, it then amplifies each original test by exposing it to possible resource thrown exceptions by utilizing the mocking device, while monitoring for program failures.

5.3.1 Overview with Example

Following with the example of the previous section, the external resource of interest is *URLConnection*, which is used in the *query* method (line 31). The proposed approach instruments the program to enable the mocking of the *URLConnection* API so invocations to it can throw an exception. The approach is exhaustive in that it explores all the possible mocking patterns bounded by a specified number of invocations to the target resource API, which we call the *mocking length*.

The exploration process with a mocking length of five is illustrated in Figure 5.3. The nodes correspond to calls to the API containing the resource of interest, the edges represent whether an exception is thrown (1) or not (0), and the tree height corresponds to the mocking length. To simplify the explanation, we label the nodes with the line number of the *query* method call sites. A path from the root to a leaf

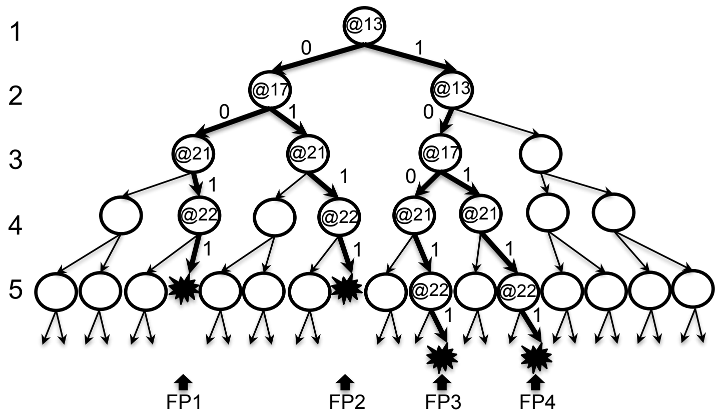


Figure 5.3: Illustration of test amplification up to length 5. Each path from the root to a leaf corresponds to a mocking pattern. 32 patterns are explored and 4 failing patterns (marked as FP1-FP4) are found.

node represents a specific mocking pattern explored by an amplified test. So, for example, the left-most path corresponds to a normal execution of an amplified test where no exceptions are thrown. The right-most path corresponds to a pattern where all calls to the target API throw an exception.

Out of the 2^5 patterns explored, four patterns (labeled FP1 - FP4) revealed terminating program failures (marked with the bolder edges and ending in a star). FP1, for example, corresponds to the mocking pattern that operates normally for the calls to the API launched in lines 13 and 17, but throws an exception at lines 21 and 22 that lead to a crash, matching the situation described previously in the bug report.

For each failure, the approach generates a report that records 1) type of resource API being mocked, 2) mocking pattern, which describes whether to execute a normal call or to throw an exception at each invocation, 3) type of exception being thrown by the target API, and 4) call trace after the exception is thrown. Figure 5.4 contains the failure report corresponding to FP 1 in Figure 5.3. Such failure reports are used to communicate with the user and also as a basis for various types of filters to control the number of tests kept or shown to the user. For example, a simple

```
Mocked Resource API: java.net.URLConnection
Mocking Pattern:
query in setResponseFormat (line 13) -> Normal,
query in getSystemInfo (line 17) -> Normal,
query in getCurrentlyPlaying (line 21) -> Throw -> IOException
query in getCurrentlyPlaying (line 22) -> Throw -> IOException
Trace:
java.io.IOException thrown
xbmc.android.util.ErrorHandler.handle
xbmc.android.util.Connection.query
xbmc.httpapi.client.ControlClient.getCurrentPlaying
xbmc.httpapi.type.ICurrentPlaying.add
xbmc.httpapi.type.ICurrentPlaying.get
...
java.lang.NullPointerException thrown

Thread main exiting due to uncaught exception
```

Figure 5.4: Failure report corresponding to FP1.

failure-filter prunes all reports that did not lead to an exceptional termination caused by the mocked resource. A distinct-failure filter prunes reports with the same type of exception thrown and the same call trace prefix, only reporting the tests with the shorter mocking pattern (the intuition behind this decision is that a shorter pattern is easier to understand and helps debug the failure.) According to this latest filter, in our example, all failure reports had the same type of exception and trace so we just keep FP1.

This example conveys the two assumptions on which the approach is built. First, it builds on the *small scope hypothesis* [64], often used by techniques that systematically explore a state space, which advocates for exhaustively exploring the program space up to a certain bound. The underlying premise is that many faults can be exposed by performing a bounded number of program operations, and that by doing so exhaustively no corner cases are missed. Several studies and techniques have shown this approach to be effective (e.g., [18, 29, 32]) and we build on those in this work. In our approach the bound corresponds to the length of the mocking patterns. Second, we assume that the program under test has enough tests cases to provide coverage of the invocations to the resources of interest. The increasing number and maturity of automated test case generation techniques and tools support this assumption. If this assumption holds, then the approach can automatically and effectively amplify the exposure of code handling exceptional behavior.

Equipped with an intuition of the challenges and the approach, we now proceed to define them more formally.

5.3.2 Problem Definition

Given program P, test suite T, and API R managing a resource of interest to the tester, we formally define the problem as follows.

Definition 5.3.1 *Resource-sensitive function calls: set of calls F in P to functions in R. Each call has an associated target function name and location.*

In the previous example, P is the program shown in Figure 5.1, R is the database API. As a result, F would contain calls to methods in R, such as `openConnection` at line 31.

Definition 5.3.2 *Resource-sensitive function call sequence: $\overline{seq_i} = [f_1, f_2, \ldots, f_n]$, where $f_j \in F$, generated by the execution of $t_i \in T$ on P. Across a test suite T, $SEQ_T = \{\overline{seq}_t | \forall t \in T, \overline{seq}_t = exec(P_F, t)\}$, where P_F stands for program P with calls in F annotated, and function exec executes t on P_F and logs the annotated calls.*

In the motivating example, assuming that the bug report had an associated test t_{84}, and the calls to the database API are annotated, then the resource-sensitive function call sequence is $\overline{seq_{84}} = \{oC, oC, oC, oC\}$, where oC is the abbreviation of function `openConnection`.

Definition 5.3.3 *Space of Exceptional Behavior: each call in $\overline{seq_i}$ can either return normally or raise an exception, defining a space of exceptional behaviors $S_{t_i} = \overline{seq_i} \times (normal, exception)$.*

Definition 5.3.4 *Exception Mocking Pattern: a function mp that defines how to manipulate the behavior of each f in $\overline{seq_i}$, so that the execution of t_i on P is amplified to cover a larger space of exceptional behavior. The space of amplified exceptional behavior bounded by mp on t_i and P is defined as $S_{t_i}^{mp} = \{f_r | \forall f \in \overline{seq_i}, mp(f) \to (f_{rn}, f_{re})\} \subseteq S_{t_i}$, where f_r stands for the return status of f, which has two potential values, f_{rn} and f_{re}, for returning normally or with an exception.*

An exception mocking pattern can be expressed in multiple ways. A regular expression pattern, for example, may define a $S_{t_i}^{mp}$ as a subtree of S_{t_i}. A linear pattern may reduce $S_{t_i}^{mp}$ to one path of the exceptional space. We use linear *mp*s in the scope of this work, because it is simple and sufficient to convey the exhaustive nature of the approach. As defined, the number of linear patterns derived from one $\overline{seq_i}$ grows exponentially with respect to the size of $\overline{seq_i}$. To control this growth, we bound the size of each pattern to a given length k.

Following with the previous example, assuming the resource can raise just one type of potential exception, if we set mocking pattern length k to be 4, the exceptional space $S_{t_i} = \overline{seq_{84}} \times (normal, exception)$ can be covered by 16 (2^4) linear *mp*s, each specifying whether each invocation returns normally or not.

Definition 5.3.5 *Test Amplification for Exceptional Behavior: $\forall t_i \in T$ and its associated $\overline{seq_i}$, we manipulate the return status of $\forall f \in \overline{seq_i}$ according to a mp to cover the exceptional space $S_{t_i}^{mp}$. Consequently, executing T with a set of mps covers $S_T = \bigcup_{\forall t_i \in T} \bigcup_{\forall mp} S_{t_i}^{mp}$, the union of all exceptional behavior spaces bounded by T and the* *set of mps. In the following text we denote the amplified test suite, T with a set of mps, as T_{amp}.*

There are three aspects of T_{amp} worth noticing. First, program dependencies among the invocations may limit the reachability of the S_T nodes. For example, if T does not cover certain feature of the program logic, it is unlikely T_{amp} will explore it's exceptional behavior. There may also be some patterns that are explored through mocking, but could not be experienced in practice given the design of the external resource. For example, when a mobile application is executed without internet connection, it may opt to use locally cached data for online database queries. As a result, certain types of exceptions, such as `SQLiteException`, cannot be thrown. The approach ignores this constraint and explore the full exceptional behavior, which may result in false positives. Second, T_{amp} may reveal invocation sequences that were not in SEQ_T either because of their order of calls or because they include new calls, as exceptions may reveal new execution paths. Such sequences can be translated into new tests that enrich T and consequently S_T. An example in our context would be a test in T_{amp} with a mocking pattern that forces a mobile application to repeatedly renew an internet connection. We can extract a new invocation sequence from the execution of such test, and then use it to enrich S_T. Third, as defined, the number of mocking patterns in T_{amp} can grow exponentially. To control this growth, we bound the size of each pattern with a given number k. In our context, we explored various values of k and found that 10 is sufficiently large for the analysis of the mobile applications we selected (refer to Section 5.4 for more details).

5.3.3 Approach Architecture

Figure 5.5 illustrates the architecture for the systematic amplification of tests. There are five core components.

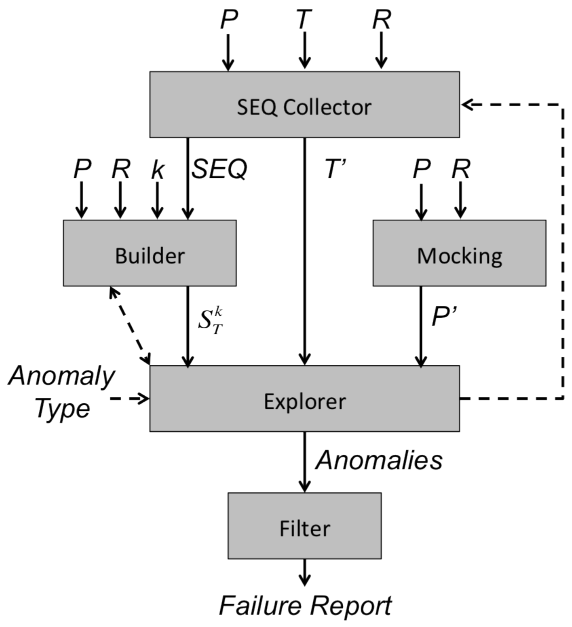


Figure 5.5: Amplification architecture.

The sequence *collector*, takes as input P, R, and T. It instruments P to capture all calls to R, and it then runs all tests in T to produce SEQ_T. Tests that do not contribute a sequence are dropped so that only $T' \subset T$ are further considered. The exceptional space *builder* takes as input SEQ_T, P, R, and bound k. The builder analyzes R by inspecting the API signatures associated with R to derive the types of exceptions that the resource can generate. Given those exception types and SEQ_T, the builder generates S_T^k, a space of the exceptions that may be raised. k is used to bound the space depth. The *mocking* component takes P and R and it generates P' so that all invocations to R can be forced to return an exception of the allowed types. This component facilitates the exploration of a mocking pattern consisting of a sequence of invocations to R that may return normally or raise an exception.

The *explorer* component systematically attempts to amplify the tests in T' to cover S_T^k by mocking the behavior of R as perceived by P' while re-executing the tests. As an amplified test executes, the explorer will check for anomalies. In case where an anomaly is detected, the explorer will generate a trace of invocations to R together with their outcome. The *filter* component will then take those anomalies and report the ones meeting a predefined criteria such as whether to include amplified tests whose mocking patterns and outcome were already revealed by other amplified tests.

The description of the approach architecture overlooks some interesting aspects that we have considered but not fully developed. First, in this work we pursue exhaustive exploration of the space in S_T. However, the architecture also allows more selective exploration of the space to accommodate cost effectiveness tradeoffs. For example, regular expressions could be provided to the *builder* to constrain the space S_T to specific exceptional patterns that are known to be problematic for a particular system or resource.

Second, the dotted line from the explorer to the collector in Figure 5.5 alludes to the potential for establishing a feedback loop where the new invocations of the resources or the new outcomes of existing invocations revealed by the explorer are used to enrich the S_T.

Third, the dotted line between builder and explorer indicates that these processes may be coupled so that the space is defined incrementally as it is being explored. So the *builder*, for example, could define a space for one pattern and pass it to the *explorer*, which in turn will influence the *builder* in the formation of the rest of S_T. This type of lazy space definition may be particularly effective at early stages of the amplification where the size of the space is unknown.

Fourth, the types of anomalies considered could be extended by monitoring for invocation of unexpected handlers due to exception inheritance, or exceptions that are subsumed without proper handling. Such anomalies are often caused by inserting empty handler blocks in the code, just to comply with compiler syntax checking, but ignoring the important exceptions being raised.

Last, our architecture does not prescribe how the instrumentation and exploration should occur. As we shall see, we use AspectJ to provide the mocking capability, but other established frameworks, such as JMock[66] or EasyMock[35], could also be used, and are discussed in Section 2.3.4.

5.3.4 Implementation

In this section we briefly describe the most interesting aspects of an implementation of our approach in the context of Java 1.6 programs and JUnit test suites.

Collection and Mocking. We use AspectJ [116] 1.6.10 to instrument the artifacts to collect SEQ_T, mock the API calls and inject exceptions, and to detect anomalies at run time. Figure 5.6 shows an excerpt of the AspectJ point cut template we used. We first define point cuts for the sites of the calls to the target resource APIs (Line 3). We then define an advice that executes in place of the invocation of the call to the resource API (Lines 6-14). The advice uses a pointer (`currPtr`) to track the exploration progress. It calls method `mockPatternPosition` with `currPtr` as a parameter to check whether to inject exception on the current invocation of the resource API, and throws an exception if the check returns true, otherwise it executes the call normally. The type of exception to be thrown is determined by a call to method `mockExpType` with `currPtr` as a parameter. Both `mockPatternPosition` and `mockExpType` have access to data structures that store the mocking patterns and the type of exceptions to be thrown, which are generated automatically by the *builder* component.

Building and Exploration. Our builder and explorer work independently. First, the builder analyzes the signatures of the methods in R invoked by P as indicated by

```
public aspect OnlineMocking{
    //define point cut
    public pointcut detect(): call(* Resource.targetF(...));

    //define advice
    around():detect()
    {
        if(mockPatternPosition(currPtr)){
            throw newException(mockExpType(currPtr++));
        } else{
            //execute the original API
            Resource.targetF(...);
        }
    }
}
```

Figure 5.6: Excerpts of aspect for online mocking and error injection.

SEQ to determine the type of exceptions they can throw. It then derives the space of exceptions. The explorer then attempts to perform a depth first space search, amplifying each test with each of its mocking patterns, and running them one at a time. For each $t_i \in T'$, the explorer will clone each test up to 2^{m^k} times, where m is the number of types of exceptions the invocations can throw, and k is the bound set by the user. Each cloned test is then coupled with a unique mocking pattern to amplify its behavior.

As an amplified test executes, the explorer will check for two types of anomalies: abnormal termination (program terminates due to uncaught exceptions) or abnormal execution time (duration of amplified test is greater than the non-amplified by a certain threshold).

Explorer Optimization. During exploration of a particular amplified test, at a point where an API call is examined, and the mocking pattern dictates that an exception should be thrown, if the following three properties match to a previous instance: 1) the call stack (the programing path from *main* to the API call); 2) the API being called; and 3) the type of exception being thrown, then throwing the exception will expose the same behavior as in the previous case. To exploit this, we store a snapshot of the call stack of the test execution before each mocked exception, and when executing another amplified test, at each point where an exception is to be thrown, if the current call stack matches one of the stored snapshots, we skip exploring the test any further, and move on to the next test. This strategy leads to performance gains at the cost of sacrificing completeness. A match means throwing the exception under consideration will not lead to any new exception handling behavior for this instance of API call. However it is not guaranteed that the current amplified test will not result in any new behavior in the future. In practice, as per our empirical findings, the optimization did not miss any anomalies that was detected with the un-optimized approach, and contributed to 5% - 12% savings in execution time of the approach.

The Android Environment. Android applications compile into dex format (Android bytecode) and execute on the Dalvik VM and the Android Virtual Device (AVD) [6]. This imposes a challenge as we also want to run that code with AspectJ, which requires a custom compiler to weave aspects into original class files. However, as AspectJ performs code injection on the bytecode level, and dex files (Android bytecode) rely on class files, it is possible to adopt the following process: 1) Let Java compiler compile Java code to class files; 2) Let AspectJ compiler (iajc) inject point cuts and advices to class files; 3) Let Android code generator (dx) transform the new class files and create dex files. We developed a custom Ant build script to automate the double transformation process.

5.4 Evaluation

In this section we address the following research questions:

- RQ1: How cost effective are the amplified tests in detecting anomalies in exceptional handling code?
- RQ2: To what extent do the detected anomalies represent real faults?

5.4.1 Study Design and Implementation

We studied the Android applications and the resources listed in Table 5.1. For each of those resources, we collected the checked exceptions that could be thrown from public methods as defined by the Android SDK Specification [6] (i.e., for the methods in *android.bluetooth* class, the included exceptions are *ConnectionTimeoutException*, *SocketTimeoutException*, *UnknownHostException*, for methods in *android.database* class, the included exceptions are *CursorIndexOutOfBoundsException*, *SQLException*, *StaleDataException*, etc.). In total we identified 17 exception types that could be thrown by the classes *java.net, android.database, android.location* and *android.bluetooth.*

We set the approach parameters as follow. To set the approach mocking length we mimic the process a tester would follow. Ideally a tester would select the smallest mocking pattern length that still detects all the faults. This value, however, is *not* known in advance, and it is different across programs, tests, and resources. So the tester must pick a reasonable starting value that may be refined over time. Similarly, we select a length of 10 which seems reasonable considering the time it takes to explore the exceptional space of these applications. This decision also echoes with Jackson's small scope hypothesis [64] which conjectures that exhaustive testing up to a small bound will detect most faults. As described next, our findings confirm this hypothesis, as the majority of the faults can be detected with a length of 5. To further explore the effect of mocking lengths on the effectiveness and efficiency of the approach, in Section 5.4.2.3 we redo the experiment with mocking lengths of 1, 3, 5 and 7, hoping to gain a better understanding on how to select an optimal mocking length that balances cost and effectiveness of the approach. We set the filtering component to remove duplicate reports (those that include the same failing trace of invocations to R, thrown exceptions, and test outcome), whether produced by a single test or across different tests.

We assess the effectiveness of the approach by generating T_{amp} from the unit test suites that came with the artifacts, and then running the amplified tests on the respective artifact. We analyze the anomalies revealed by the amplified tests from two perspectives. First, we compare them against the bug reports in terms of precision (the degree to which a detected anomaly maps to a bug report in the repository) and recall (the degree to which bug reports in the repository are included in the set of detected anomalies). For the anomalies that are not matched to bug reports, we run them in later versions of the programs to check whether they disappear, as the code may have been fixed but such fix may not have been reported. Second, for the three applications studied as part of Phase 2, we further study the anomalies by requesting feedback from the applications' developers. We measure costs in terms of the *size* of the amplified test suite and the *time* required to generate and execute it. We also perform an in-depth analysis on how the mocking length parameter affects cost and effectiveness. We discuss other costs in Section 5.4.4.

The Android applications required different Android API versions ranging from 1.6 to 2.2. The study was conducted using a 2.4 GHz Intel Core 2 Duo machine with 4 GB memory, running Mac OS X 10.6.6.

5.4.2 RQ1: Cost Effectiveness in Detecting Anomalies

We study this research question by amplifying the unit tests that came with the artifacts, executing them and analyzing the behaviors they expose. We start by presenting the result with mocking length of 10 and discuss its effectiveness in exposing anomalies. Then we will repeat the study with various decreasing mocking lengths to explore its effect on the tradeoff between cost and effectiveness. Finally we present a characterization of the mocking patterns that do expose anomalies, in the hope of discovering certain patterns that are more effective in detecting anomalies.

5.4.2.1 Results with Mocking Length=10

We start by providing a characterization of the original test suite, T, in Table 5.3. For each artifact-resource combination, we report the number of original tests exercising each one of the resources and the time required to execute them. We also report coverage on the try-catch blocks that the original test suite achieved through JMeter [59], with the assistant of a simple instrumentation that marks the try-catch blocks in the source code. To facilitate a quicker comparison, in Column "# Original Tests" we copied the number of tests in the original test suites associated with the applications from Table 5.1. We note that the initial test screening process helped to eliminate many original tests that do not reach the target exceptional constructs. For example, for Barcode Scanner, just 18% of the original tests were able to exercise the external resource *android.net*.

In Table 5.4, we provide a characterization of the amplified test suite, T_{amp}. Columns "Amplification Time", "# Tests Amplified", and "Execution Time" columns indicate the cost of amplifying the screened test suite (in seconds), the number of amplified tests and their execution times (in hours) respectively. For comparison reasons we also include coverage on the try-catch blocks which are achieved by T_{amp}, and its

Table 5.3: Characterization of the original test suites.

Application	# Original Tests	Resource	# Tests after Initial Screen	Execution Time (sec)	Coverage
Barcode Scanner	117	java.net	21	39	21%
Keepassdroid	34	android.database	12	31	12%
		java.net	27	54	
myTracks	55	android.database	21	38	7%
		android.location	39	73	
SipDroidVoIP	39	java.net	32	67	10%
XBMC remote	78	java.net	41	92	23%
		android.bluetooth	19	39	
Android Wifi Tether	76	java.net	42	106	15%
K-9 Mail	215	java.net	115	254	21%
		android.database	57	145	
Open GPS Tracker	85	android.database	37	64	14%
		android.location	55	121	

improvement over the original test suite.

First, we note that the test amplification time for T_{amp} is trivial. For the biggest application with the most tests, K-9 Mail, the generation time was 24 seconds, 9% of the original test suite execution time. Second, as expected for an exhaustive testing exploration approach, the number of amplified tests and time required to execute them are generally large, with the most prominent case being the *K-9 Mail* and *java.net* combination which took more than 34 hours to finish. As we later show, our length choice may have been too conservative and hence unnecessarily costly. The cost is compensated, however, with noticeable coverage gains and anomalies detected. The T_{amp} suite provides on average a gain of 62% of coverage on the catch-blocks, hinting at the potential of the automated amplification to expose new exceptional behavior.

Next, we analyze the impact of these newly explored behaviors. Table 5.5 accounts for the anomalies the amplified test suite found, and provides a characterization of the mocking patterns that revealed those anomalies. As per our setting on the filter component, if an anomaly is revealed by multiple patterns, we count the shortest one,

Table 5.4: Characterization of the amplified test suites.

Application	Resource	Amplify Time (sec)	# Amplified Tests	Execution Time (hrs)	Coverage (gains)
Barcode Scanner	java.net	17.1	17,921	10.1	81% (+60%)
Keepassdroid	android.database	3.5	9,721	7.5	75% (+63%)
	java.net	6.8	18,856	17.3	
myTracks	android.database	5.9	17,734	14.3	81% (+74%)
	android.location	8.1	31,543	22.7	
SipDroidVoIP	java.net	6.2	24,476	17.6	74% (+64%)
XBMC remote	java.net	7.5	33,255	18.6	76% (+53%)
	android.bluetooth	5.4	16,547	9.5	
Android Wifi Tether	java.net	10.7	35,512	14.2	73% (+58%)
K-9 Mail	java.net	24.1	91,117	34.5	71% (+50%)
	android.database	11.4	40,623	11.4	
Open GPS Tracker	android.database	7.6	31,125	17.6	79% (+65%)
	android.location	12.3	44,258	21.3	

which we deem easier for the user to trace the problem (the rest of the patterns are ignored for all other counts). The amplified test suite identified 211 unique anomalies, an average of 26 per application. Of those anomalies, 61% corresponded to mocking patterns that consisted of more than a single throw in response to a call to the API. This clearly shows that throwing more complex exceptions can greatly help detecting anomalies. There are three anomalies (in *XBMC remote*, in *Keepassdroid*, and in *K-9 Mail*) that require mocking length of 10 to be detected. These three are infinite loops which require an "All Throw" mocking pattern of length 10 to detect the issue. All considered, we found that the average mocking pattern length to detect an anomaly is just over 3, with 2 throws on average per pattern, indicating that the cost of the approach could be drastically reduced by selecting a much tighter exploration bound.

5.4.2.2 Controlling the Mocking Length Parameter for Cost Effectiveness

To better convey the effects of the mocking pattern length on testing costs and fault detection effectiveness, we repeated the study with mocking lengths 1, 3, 5 and 7. Figure 5.7 shows the results of the study in each program and resource. In each

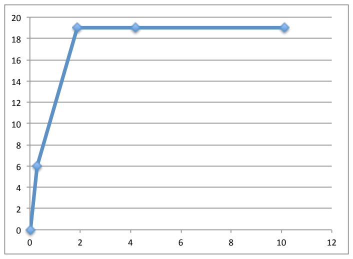
Table 5.5: Anomalies detected.

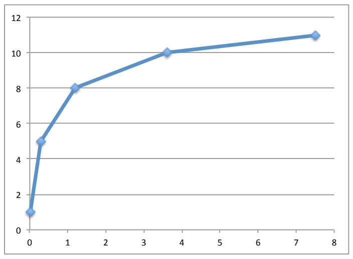
Application	# Anomalies Detected	Mocking Pattern		
		# More Than A Single Throw	Avg Length	Max Length
Barcode Scanner	19	9 (47%)	2.6	5
Keepassdroid	11	9 (82%)	5.1	10
	18	10 (56%)	2.1	5
myTracks	19	12 (63%)	3.4	5
	9	5 (56%)	3.2	5
SipDroidVoIP	16	9 (56%)	1.9	4
XBMC remote	14	8 (57%)	4.8	10
	9	6 (67%)	3.1	4
Android Wifi Tether	10	10 (100%)	3.1	4
K-9 Mail	39	19 (49%)	2.1	4
	16	10 (63%)	2.1	10
Open GPS Tracker	14	10 (71%)	3.2	5
	17	11 (65%)	2.8	4

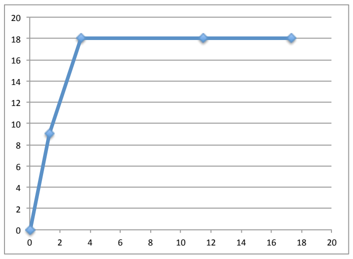
graph, there are five data points, corresponding to the results of executing one T_{amp} generated with a distinctive mocking length (from left to right: 1, 3, 5, 7, and 10). The X-axis corresponds to cost in terms of execution time in hours, and the Y-axis corresponds to the number of anomalies found.

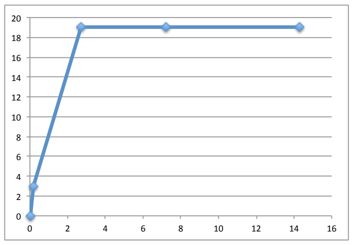
From all 13 graphs, we can observe a similar trend, in which the curve becomes saturated as the the mocking length increases, but at different rates. Out of the 13 graphs, 10 reached saturation at mocking length of 5. For most programs, further investment in amplifying testing resources does not translate into more detection power. For the other three graphs (5.7(b), 5.7(g), 5.7(l)), the saturation point was not reached, as increasing the mocking length still leads to the detection of more anomalies. However, given enough testing resources (in this case, more test execution time), they will become saturated, as the approach will exhaust all possible mocking patterns eventually.

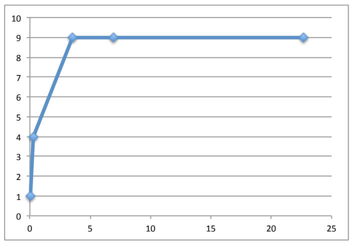
For all artifacts, T_{amp} generated with a mocking length of 1 detected only 2% of the anomalies, as it did not explore a large part of the interesting exceptional behavior. With a length of 5, 96% of the anomalies detected with a length of 10 were found

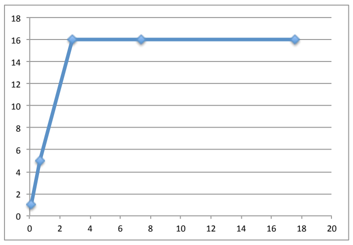

(a) Barcode Scanner - net

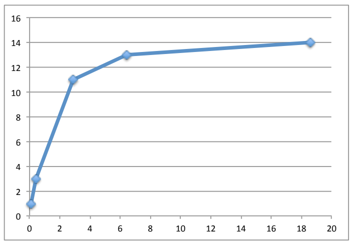

(b) Keepassdroid - database

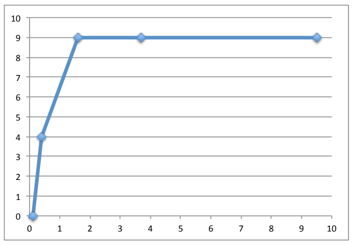

(c) Keepassdroid - net

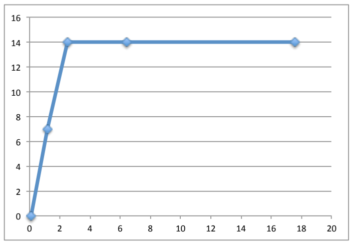

(d) myTracks - db

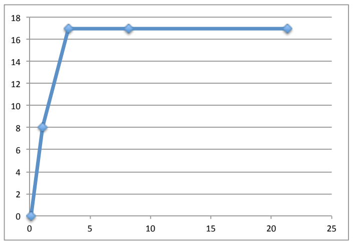

(e) myTracks - location

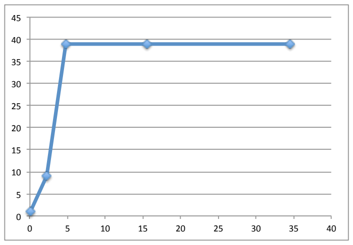

(f) SipDroidVoIP

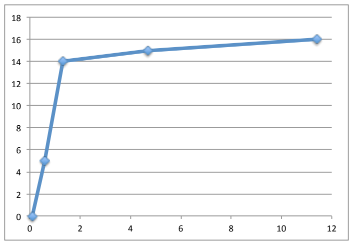

(g) XBMC Remote - net


(h) XBMC Remote - bluetooth


(i) Open GPS Tracker - db


(j) Open GPS Tracker - loc


(k) K-9 Mail - net


(l) K-9 Mail - database

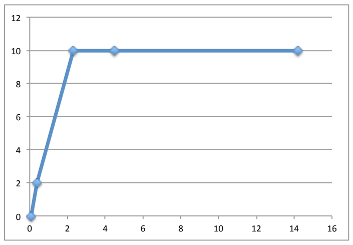

(m) Android Wifi Tether

Figure 5.7: Anomalies detected by T_{amp} under various mocking lengths for application-resource combinations. Each observation corresponds to a mocking length (from left to right: 1, 3, 5, 7, and 10). X-axis represents cost in terms of execution time in hours, and Y-axis represents the number of anomalies detected.

with less than 5% of the cost. Overall these results confirm that our choice of 10 as the default mocking length is indeed conservative. It also shows the flexibility of our approach. In situations where testing resources are limited, a tester can use a smaller mocking length, while retaining most of the detection powers of the tool. However, it is worth noting that a bound of 5 would have missed 8 anomalies that corresponded to faults in *Keepassdroid*, *XBMC remote* and *K-9 Mail*, so the savings may come at a cost for some artifacts. As discussed previously, in certain cases, there are anomalies that can only be detected by patterns of length 10 (like the three instances of infinite loops).

5.4.2.3 A Closer Look at the Mocking Patterns

To better understand the role of the mocking patterns in detecting these anomalies, we analyze the mocking patterns that effectively detected anomalies in the previous study with mocking length of 10. We categorize the patterns in the following categories: 1) Single Throw - 1st, in which only the first instance of the API call throws an exception, and all the other instances return normally; 2) All Throw, in which all instances of API invocations throw exceptions; 3) Single Throw - not 1st, in which only one instance of the API invocation throws an exception, but its location in the sequence of API calls can be anywhere except the first instance; 4) Multi Throw - One Transition, in which multiple instances of the API calls can throw exceptions, but there can only be one transition either from non-throwing to throwing, or vice versa; for example, a pattern of three throws followed by 2 normal returns falls into this category; 5) Multi Throw - Multi Transition, in which multiple instances of the API calls can throw exceptions, and multiple transitions occur as well. For example, a pattern of intermittent throw / normal execution falls into this category. The first two categories, Single Throw - 1st and All Throw, are most likely supported by existing frameworks (e.g. the Eclipse

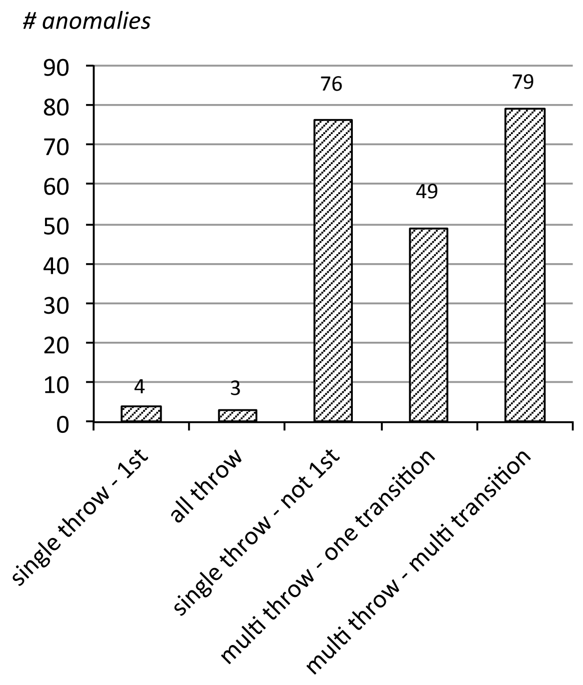


Figure 5.8: Categorization of mocking patterns.

IDE for Android application development provides support for mocking of APIs that can be configured to throw a single exception or throw exceptions at all times). The third category, which represents instances of one arbitrary exception being thrown, is often used in manual test cases for exception handling code. The fourth and fifth categories, which correspond to patterns that describe intermittent resource on/offs over a period of time, are unlikely to be used in existing testing processes or tools.

The results (Figure 5.8) show that the majority (97%) of the anomalies are in fact detected by the more complex patterns in the last three categories. Patterns in the category of Multi Throw - Multi Transition detected the most anomalies. This shows that intermittent patterns, in which throw and normal returns are interleaved, are most effective in detecting anomalies. These data explains, at least in part, why manual test cases often fail to detect bugs in exception handling code. Without an exhaustive testing approach it is difficult for a tester to come up with the complex patterns that do expose bugs of this type.

In summary, investigation of RQ1 suggests that *an amplified test suite can provide significant coverage gains of exception handling code, detect many anomalies in existing popular applications, and do so through the exploration of patterns that are non-trivial.* We now proceed to investigate these anomalies.

5.4.3 RQ2: Anomalies & Failures

We now assess whether the anomalies we found contributed to real faults. We strike at RQ2 from two perspectives. First, we compare the anomalies found by the approach against the bug reports of the applications in terms of precision and recall. For the anomalies that are not matched to bug reports, we execute the amplified tests that revealed them on the newest version of the applications, evaluating whether the anomalies are still present. We conjecture that if the anomalies are not present, that means that code revisions removed them in the new versions, thus they were potential real faults. Second, for the three applications studied as part of Phase 2, we further study the anomalies by seeking feedback from the application developers for confirmation, and then report their comments.

5.4.3.1 Precision and Recall

We start the assessment of the detected anomalies by mapping them to real bug reports. We compute the percentage of bug reports associated with the anomalies found and the percentage of anomalies that are included in the bug reports. The first metric gives us a notion of the approach completeness (also refer to as recall) while the second provides a lower bound on the approach preciseness. We note that both metrics are inherently limited (e.g., they assume that all faults have been found and that all found faults have a bug report) but they are useful to pinpoint strengths and weaknesses of the approach.

The process to map anomalies to bug reports is as follows. First, we search among the bug repository for instances of the location (call to target API or exception) where an anomaly was detected. If the resulting bug report includes a stack trace, which is often the case, we will match it with the stack trace associated with the anomaly. Otherwise, we retrieve the submitted fix to the bug, and inspect the code to determine if the fix was applied to the ill coded exception handling module that was captured by the anomaly reported by the amplified test.

Out of the 211 detected anomalies, 137 of them are matched to bug reports. The other 74 anomalies may be false positives, or they may correspond to real faults that are yet to be reported. To investigate this possibility, we run the 74 amplified tests that detected these anomalies on the newest version of the applications. If the anomalies are not present, that means that code revisions removed them as the applications evolve, thus they could have been real faults. For the five applications from Phase 1, the new versions corresponds to the latest version available on June 2011. For the three newly added applications, the new versions corresponds to that of October 2012.

In this step, 27 out of the 74 remaining anomalies that appear in older versions are not present in the latest versions, which adds credibility to the value of the anomalies detected by the approach. We also note that the 47 remaining anomalies are induced by amplified tests with more complex mocking patterns, with an average length of 3.6, as compared to the amplified tests that detected all 211 anomalies, which had an average mocking pattern length of 3.1. This result may indicate that the remaining anomalies represent faults that are harder to find.

Figure 5.9 combines the results from the previous steps. Each bar represents the total number of anomalies detected by the amplified suite for one artifact, and the

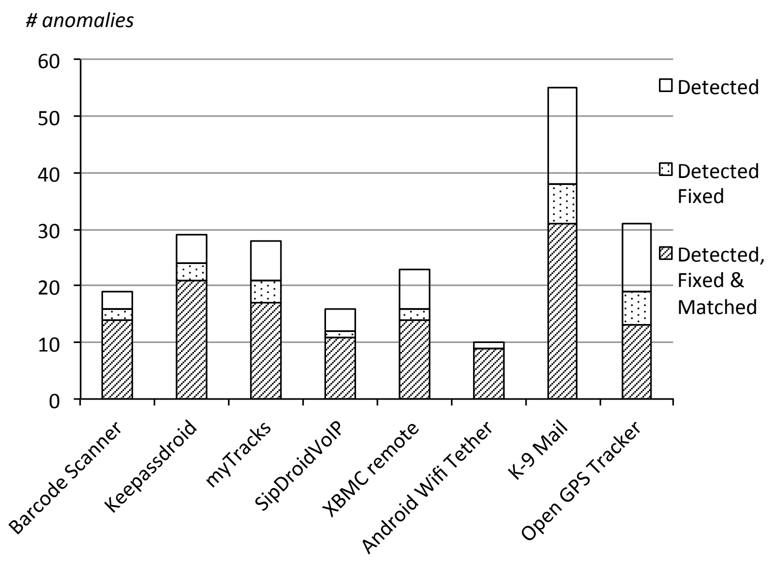


Figure 5.9: Mapping detected anomalies to bug reports.

three levels of shade indicate the number of anomalies that were 1) detected by our approach, fixed by the developers, and matched to bug reports; 2) detected and fixed in a later version, but could not be matched to a bug report[4]; 3) just detected by our approach.

Figure 5.9 suggests that, on average, 65% of the anomalies can be traced to faults reported in the bug repositories. Furthermore, 13% of the anomalies, although not matched, are fixed in later versions, indicating that these detected anomalies may expose exceptional behaviors in practice. On average, only 22% of the detected anomalies have unconfirmed status, which may constitute faults that are yet to be found or false positives. For example, myTracks has a simulation mode through which locations are defined via a KML file. If such mode is activated, the location API calls cannot fail because they do not interact with real location providers. Our tool overlooks this possibility and mocks such API calls, which may lead to false positives. On the other

[4]Note that an anomaly that was detected, fixed but not matched could be the result of either: 1) the issue was fixed as a side effect of other submitted code changes; 2) the problematic code module was refactored during program evolution; or 3) it was not reported.

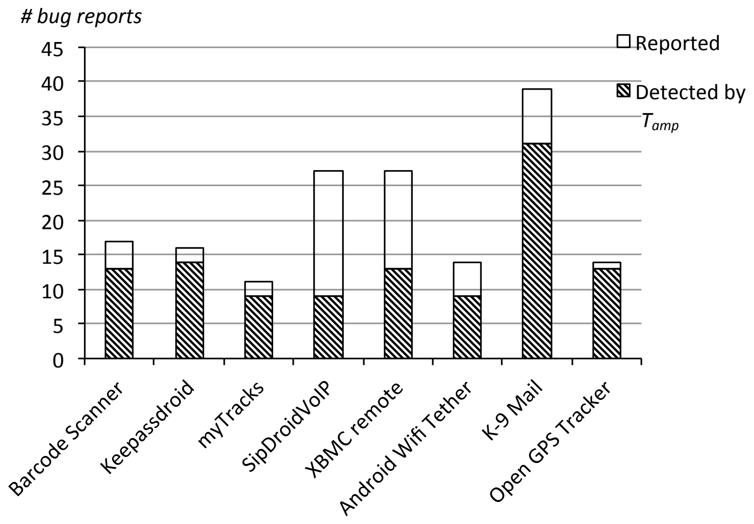


Figure 5.10: Mapping bug reports to anomalies.

hand, as we shall see in the next section, some anomalies are indeed undetected faults.

We now look at the results on mapping from bug reports associated with external resources to the anomalies (Figure 5.10). The shaded portions of the bars represent bug reports that had a correspondent anomaly exposed by T_{amp}, and the white parts represent bugs that were reported in the bug tracking systems. *On average, 67% of the reported bugs are matched to the anomalies detected by* T_{amp}.

We then proceeded to analyze those numbers in more detail to determine under which circumstances our approach failed to detect a reported bug. The most common reason was the limited coverage of the available unit test suite. For example, myTracks Issue #172 describes a crash when saving a new marker to a track. The triggering condition for this bug requires pausing and resuming tracking before inserting a new marker. This workflow, however, was not covered by any of the original tests. Another report in in K-9 Mail (Issue # 475) describes a situation where the received email has a *.gif* file as an attachment, opening the file in the mail viewer caused a crash. This, too, was not covered by the original tests. A second reason was the lack of control on some of the external factors other than the invocation of resource APIs.

For example, myTracks issue #137 describes a bug where the user gets many error messages when trying to upload tracks to the Google Maps service. Reproducing the bug requires controlling two factors: a Google authentication API that fails all the time, and a specific scheduling order for two threads. Our approach controls the first factor, but does not have control over the second.

While the first shortcoming can be addressed by devoting more testing efforts, the second issue requires extending our approach to include a more sophisticated instrumentation mechanism to capture and replay the threads schedule.

5.4.3.2 Feedback From Application Developers

According to Figure 5.9, there are 56 (26%) anomalies whose status cannot be determined. Treating them as false positive is to our disadvantage because we suspect that some of them may correspond to real faults that are yet to be reported, thus we cannot find a match in the bug repository. In order to further investigate these anomalies, we sent some of them to the applications' developers, asking them to examine the anomalies, and provide feedback to either confirm or reject our findings.

The process is as follows. First, we selected the three newly added applications *Open GPS Tracker*, *K-9 Mail* and *Android Wifi Tether*, because their high level of recent activities made us believe it is more likely to reach the right developers. The three applications have 30 anomalies whose status is undecided (12 for *Open GPS Tracker*, 17 for *K-9 Mail* and 1 for *Android Wifi Tether*). We decided to send a sample of these anomalies to the developers in order to increase our chances of getting feedback from them. We randomly selected three anomalies from *Open GPS Tracker*, three from *K-9 Mail* and the one from *Android Wifi Tether*, for a total of seven anomalies. Second, we contacted the developers, explaining our intent. Once they agreed to participate, we sent them materials to familiarize them with our tool

Table 5.6: Summary of feedbacks from developers.

Application	**Anomaly No.**	**Status**	**Comment**
Android Wifi Tether	#1	confirmed	"...will fix and include in the next release"
K-9 Mail	#1	confirmed	"The pattern you described is helpful because it will help us replay the bug in the simulator"
	#2	no reply	-
	#3	no reply	-
Open GPS Tracker	#1	confirmed	"...have not seen similar things before, but I suppose it could lead to a crash in the situation you described. I believe adding an extra check to guard *DBConnection* would improve on robustness."
	#2	confirmed	"...has been reported recently"
	#3	no reply	-

and explain to them the key concepts like mocking patterns and mocking length. The actual anomaly report we sent out is the same as the one shown in Figure 5.4, plus the execution environment, version numbers, and simulator screen shots[5]. We asked the developers to confirm or reject the anomalies, and to comment on the value of the report and on the tool in general.

We received feedback from developers of the three applications. For the seven anomalies they reviewed, four are confirmed to be real faults, including two that were reported by other users *after* we completed our study on the bug reports. Table 5.6 shows the status of these anomalies and the developer's comments. In the column "Status", "confirmed" means the anomaly has been confirmed by the developer, while "no reply" means that we did not get feedback from the developer. These results, although preliminary, confirm our conjecture that a portion of the anomalies whose status are not confirmed are indeed real bugs (57% in this case).

[5]A simulator screen shot shows the status of the mobile phone screen at the time of the anomaly.

5.4.4 Threats to Validity

In addition to the limitations we mentioned in Section 5.1 regarding the scope of the programs we studied and the potentially noisy nature of analyzing bug reports, we introduced some other threats in this section. More specifically, our choice of versions was deliberate to maximize the number of faults that could be detected. In practice, the deltas will be smaller and is not certain how the collected metrics will be affected. Second, the metrics we utilized are just partial proxies for the cost effectiveness of the approach and are highly context dependent. In a more realistic setting, the cost of the approach would also include the time required by developers to interpret the tool's outputs and exclude the false positives. Third, our focus was on particular types of exceptions that we deemed interesting based on our experience. Although the approach is applicable to other exception handling constructs and resources, its cost effectiveness may vary according to the difficulties associated with particular the resources. Fourth, our study on developer feedback was preliminary and focused only on three developers and a subset of the detected anomalies.

5.4.5 Extended Domain and Alternative Approach

In this section we briefly compare the proposed approach against the CAR-Miner tool developed by Thummalapenta et al. [117]. This tool represents one of the latest attempts targeting the detection of errors in exception handling code. Instead of amplifying or generating a test suite, CAR-Miner mines exception handling rules from the source code of a pool of applications and then checks whether a target program violates those rules.

Our comparison with CAR-Miner is focused on HsqlDB, the artifact on which CAR-Miner detected the most faults [117]. HsqlDB is a database application with almost 30KLoc in version 1.7.1 (the one used in the original study) and 551 unit tests. We take advantage of the public availability of this application to examine its bug reports as we did for the Android applications in Section 5.1. The examination, which was conducted in summer of 2010, found 178 confirmed bug reports that led to code revisions. Among them, 58 (32%) were caused by poorly handled exceptions and 14 were caused by the external resource *java.db* (the core external resource used by this application). This seems to indicate that the proper handling of exceptions in HsqlDB is as challenging as for the Android applications, but the effect of external resources is smaller as the Android applications seem to rely more heavily on external sensors and communication services.

CAR-Miner detected 51 instances of broken rules in HsqlDB and the authors were able to map 10 of those to bug reports. Upon closer examination we noticed that three of those bug reports were later rejected by the developers, which leaves CAR-Miner with seven broken rules that map to reported bugs. One of these three instances, #1896443 is particularly interesting because it points to one of the limitations of this type of approaches in their analysis scope. The use of intraprocedural analysis means that longer exception handling patterns are often missed.

Amplifying the HsqlDB test suite with our approach resulted in 97,280 amplified tests that take 19.4 hours to execute and find 22 anomalies. Among the anomalies found are the 7 confirmed faults found by CAR-Miner, and two other faults from the repository. One such instance, bug report #1800705, shows a case where a raised exception caused a DB connection not to close properly. Again, because the exception is not thrown by an explicit API call in the method but rather by a chain of exception re-throws that propagated a lower level exception to the current method, CAR-Miner is not able to detect it. In terms of false positives, as expected, the mining approach reported over 85% of false positives (51 anomalies reported from which 7 were confirmed faults). For our approach, the same criteria gives a false positive rate of 59% (9 of 22 were confirmed bugs).

5.4.6 Preliminary Case Study

To start addressing some of the limitations we identified in terms of the scope of the work and its lack of development context, we performed an initial case study of the approach assisting Android applications developers. Our case study was conducted in the convenient context of BusLinc [22], an application for the Android platform being developed by a team of senior Computer Science students at University of Nebraska-Lincoln, two professional Android developers, and the IT division of the Lincoln StarTran transportation service. The application communicates with StarTran's location server and, combined with a smartphone's current location, can provide users detailed bus route, nearest bus stop, and real-time bus schedule information.

The application primarily uses two types of resource APIs, a network API that communicates with a server, and a location API that is used to obtain the device physical location. We use our approach to assist with the testing of exception handling behaviors of the network API, which was used more extensively than the location API. We generated 2048 amplified tests based on just two automated system tests provided by the developers. In 20 minutes the approach reported 4 distinct anomalies, all of which were terminations caused by poorly handled exceptions, and involved non-trivial mocking patterns whose lengths range between 2 and 4.

One such anomaly reflected a situation where the network communication succeeded in checking server availability and route updates, but failed at retrieving the actual bus routes. Consequently, the route object was stored as a null pointer and a subsequent reference to the object crashed the application. Two other anomalies of similar type were detected, one for checking out the bus stops, the other for vehicles.

The last anomaly was associated with the logic for displaying a route on the Google Maps overlay, where the waypoints on the route were null objects due to a network failure in updating them.

We met with two of the student developers to gain further insights on these anomalies. During the meeting, the developers were directed towards the code locations with the poorly implemented exception handlers that caused the crashes, and were asked to construct failing scenarios for the network API usage that could lead to these crashes. After 15 minutes, the developers failed to identify scenarios for any of the four failures. We then provided and explained the failure reports. With those at hand, the developers recognized and confirmed the problems. Based on these preliminary findings, it seems that the approach was useful in revealing non-obvious problems with their exception handling constructs.

5.5 Summary

In this chapter we have introduced a simple yet cost effective approach aimed at amplifying existing tests to validate exception handling code associated with external resources. The technical merit of the approach resides in defining the challenge as a coverage problem over the space of potential exceptional behavior, and the systematic manipulation of the environment to cover that space. Although our focus was motivated by faults triggered by noisy and unreliable external resources, the approach could be beneficial in other scenarios where there is limited understanding or confidence on an API.

The findings of our studies indicate that amplified suites are powerful enough to detect over 200 anomalies, the majority (97%) of which are detected under complex mocking patterns. These anomalies eventually led to code fixes 65% of the time and included 78% of the reported bugs. Our approach outperforms a state of the art approach in precision and recall. In addition, the feedback from developers and the preliminary case study illustrate the approach's potential to assist developers.

Chapter 6

Conclusions and Future Work

In this chapter, we first summarize the techniques presented in Chapters 3 to 5. We then identify the limitations of these techniques, and discuss possible solutions on how to overcome the limitations. In the end, we conclude this dissertation by identifying several areas of future work that are related to our research on non-functional validation.

6.1 Summary and Impact

In this dissertation, we presented several techniques that enable cost-effective validation of non-functional software requirements. Specifically, we targeted two aspects of non-functional testing. For non-functional requirements defined as qualities of a system, we targeted validation of performance properties. There are many existing techniques that target performance validation, however, they do not provide support for choosing the critical values that expose worst cases, but focusing on increasing size and rate of input, which is a rather expensive way of inducing load, and may lead to negligence of real performance faults. We improved cost effectiveness of performance validation by automatically generating load tests that focus on smart input value selection to expose worst case performance scenarios in diverse ways. We subsequently introduced a compositional load test generation technique that targeted more complex software systems, to which the previous technique failed to scale. For non-functional requirements defined as constraints on a system, we targeted contextual constraints on noisy and unreliable external resources with which a software system must interact. One way to improve robustness of software is to use exception handling constructs. In practice, however, the code handling exceptions is not only difficult to implement but also challenging to validate. We improved the cost effectiveness of such validation by amplifying existing tests to exhaustively test every possible pattern in which exceptions can be raised, and produce scenarios in which the exception handling code does not hold.

Automatic Load Test Generation. In Chapter 3, we presented SLG, an approach that automatically generates load test suites by performing a focused form of symbolic execution. Symbolic execution, being a white box exhaustive technique, provides many benefits to load test generation. It can potentially generate load tests that target input values that can expose worst case behaviors. Furthermore, because symbolic execution exhaustively traverses all program paths, it can also lead to a test suite that loads the system in diverse ways. To improve scalability, SLG considers program paths in phases. Within each phase it performs an exhaustive exploration. At the end of each phase, the paths are grouped based on similarity, and the most promising path from each group, relative to the consumption measure, is selected to explore in the next phase.

We implemented SLG on top of the Symbolic Path Finder framework, and assessed its cost effectiveness on three real world Java applications: JZlib (5633 LOC), a data compression application; SAT4J (10731 LOC), a SAT solver; and TinySQL (8431

LOC), a database management system. Our assessment of SLG shows that it can induce program loads across different types of resources that are significantly better than alternative approaches (randomly generated tests in the case of JZlib, a standard benchmark in the case SAT4J, and the default suite in the the case of TinySQL). Furthermore, we provide evidence that the approach scales to inputs of large size and complexity and produces functionally diverse test suites.

For more complex software systems on which SLG failed to scale, in Chapter 4 we presented CompSLG, a technique that generate load tests compositionally, using SLG as a subroutine in its own analysis. CompSLG uses SLG to analyze the performance of each system component in isolation, summarizes the results of those analyses, and then performs an analysis across those summaries to generate load tests for the whole system. We have presented novel approaches to solve 1) how to generate channeling constraints, which are key to connect constraint systems of different components; 2) how path constraints across components must be weighted and relaxed in order to derive test inputs for the whole system while ensuring that the most significant constraints, in terms of inducing load, are enforced.

CompSLG is fully automated to handle any Java system that is structured in the form of a software pipeline. A study of CompSLG revealed that it can generate load tests for Unix and XML pipelines where SLG alone would not scale up, and it is much more cost effective than either SLG applied to single components or Random test generation. We also investigated how to extend CompSLG to enable its application to Java programs, in which each method considered is a component, resulting in a much more complex structure than a pipeline. The extension includes a new approach to generating channeling constraints, generating performance summaries with more precise metadata, and an adapted strategy for composing summaries. Although the extended version is not yet fully implemented, we showed the viability of the approach with several proof-of-concept examples.

For years techniques and tools for performance validation or characterization have treated the target program as a black box. We are among the first to advocate and develop a more precise technique for such activities, and the outcome of this research provides efficient solutions that solve this fundamental problem. We believe our notion of compositional analysis in generating test cases is also inspirational to researchers aiming to scale symbolic execution based techniques.

Validation of Exception Handling Code. In Chapter 5, we presented an automated technique to support the detection of faults in exception handling code that deals with external resources. The technique was motivated by the idea of small scope hypothesis [64], which stated that many faults could be exposed by performing a bounded number of program operations, and that by doing so exhaustively no corner cases are missed. The technique is simple, scalable, and effective in practice when combined with a test suite that invokes the resources of interest. The approach first instruments the target program so that the results of calls to external resources of interest can be mocked at will to return exceptions. Then, existing test cases are systematically amplified by re-executing them on the instrumented program under various mocked patterns to explore the space of exceptional behavior. When an amplified test reveals a fault, the mocking pattern applied with the test serves as an explanation of the failure induced by the external resource. To control the number of amplified tests the approach prunes tests with duplicate calls and call-outcomes to the external resources, and bounds the number of calls that define the space of exceptional behavior explored.

The technique was assessed on a set of eight Android mobile apps, and the findings of our studies indicate that the technique is powerful enough to detect over 200 anomalies, the majority (97%) of which are detected under complex mocking patterns. These anomalies eventually led to code fixes 65% of the time and included 78% of the reported bugs. Our approach also outperforms a state of the art approach in terms of precision and recall. In addition, the feedback from developers and a preliminary case study illustrate the approachs potential to assist developers.

This technique was the first in the software testing field to transform the problem of exception handling code validation into the established area of search space exploration, and the first to use the idea of bounded exhaustive testing to solve it. Our modeling of external resource as patterns could illuminate future research in related areas.

6.2 Limitations

In this section, we identify key limitations to the techniques presented in Chapters 3-5. Generally, there are two types of limitations: limitations caused by the *design* of a technique, and limitations caused by the *implementation* of a technique. Table 6.1 summarizes both types of limitations, which we discusses in detail below.

Limitations in Symbolic Load Generation (SLG). For the Symbolic Load Generation (SLG) technique presented in Chapter 3, the key limitation by design is the selection of the values for parameters of the technique, such as the *lookAhead* parameter that controls how much distance the search advances in each iteration of iterative-deepening, and the *maxSolverConstraints* parameter, which determines how many constraints to collect before calling the solver in CLLG. As stated in Chapter 3, the *lookAhead* parameter is essential in controlling the efficiency of the SLG algorithm, and the *maxSolverConstraints* is used to balance the tradeoff between the quality of the generated tests and the scalability of the CLLG algorithm. The existing technique

Table 6.1: Summary of limitations.

Technique	**Limitations**	
	by design	**by implementation**
SLG (Chapter 3)	• Sensitivity of parameters	• Lack of support for resources other than time and memory • Solver and symbolic execution engine capabilities
CompSLG (Chapter 4)	• Find a compatible summary for reuse • Lack of support for exceptions	• Same as above
Exception handling validation (Chapter 5)	• Limited by existing tests • Imprecise API modeling	• Lack of support for other platforms

does not support automatic selection of the values for these parameters, instead, we select the values by gathering insights from a few trial runs with a range of values. This situation imposes a limitation to the applicability of the technique, as selecting the optimal values of the parameters might be a costly process. We conjecture that this limitation can be removed by selecting the values dynamically. For example, an initially large value for *lookAhead* could be set during the initialization phase of the program under test, then smaller values could be set to the parameter, as the program execution deepens.

Implementation-wise, the SLG technique only supports load generation for two types of resources, namely, response time and memory consumption. However, we have designed our implementation so that other types of resources can be easily added. For instance, the resource of energy consumption can be added by tracking the energy footprint of individual Java bytecode. SLG is also limited by the symbolic execution engine and the SMT solver that is used to carry out symbolic execution.

This limitation can be relieved by incorporating more powerful engines and solvers to the technique.

Limitations in Compositional Load Generation (CompSLG). For the CompSLG technique presented in Chapter 4, there are two key limitations introduced by the design of the technique. First, as presented in Section 4.6.2, a precise summary (such as the one that preserves the shape of input/output objects) can lead to a precise compositional analysis, which ultimately leads to better load inducing test suites. However, keeping precise summaries may countermine the savings achieved through a compositional analysis, as the technique may not be able to find a matching summary from the library, instead, it is forced to generate a new summary that matches the particular specification. We conjecture two directions that can help overcome this limitation. On one hand, the technique should provide a flexible definition that allows various levels of approximations for the performance summary. Depending on the complexity of the program under test, the technique may choose to produce summaries on different levels of approximation suitable for the situation. On the other hand, in case that a precise summary matching cannot be achieved, the technique should provide a mechanism that allows a broader selection of summaries to be reused. For example, in `bubbleSort`, if a matching summary, which has an input of 1001 integers, cannot be found in the library, but a summary that has an input of 1000 integers is present in the library, the technique can reuse the one 1000 integers in place for the one with 1001 integers. Similar reusing mechanisms can also be applied to summaries that preserve shape of input / output objects. Note that this selection will lead to an under-approximation in the analysis, which may have implications for the quality of the generated tests.

Second, the CompSLG technique for Java programs does not consider the presence of exceptions that can be thrown at runtime by the program under test. When an exception is thrown, the program will take alternative execution paths that cannot be encoded solely by constraints on the symbolic input variables. It is also possible that a load-inducing execution path is the one with the presence of exceptions. For example, a path that repeatedly encounters network connection exceptions and repeatedly tries to reconnect can be an expensive path in terms of response time. To enable CompSLG to generate this type of test cases, we need to 1) update the definition of the performance summary to allow encoding of exception throwing patterns, in addition to the constraints on the symbolic input variables; 2) use an updated control flow graph that features exception control flow edges to guide the compositional analysis.

Limitations in exception handling code validation. For the exception validation technique presented in Chapter 5, there are two key limitations caused by the design of the technique. First, the exception handling behavior exposed by the amplified test suite is limited by the coverage of the original test suite. As shown in Section 5.4.3, if the original test suite misses certain regions of the code, the amplified test suite is likely to miss the same region. This limitation can be relieved by establishing a feedback loop where the new invocations of the resources revealed by amplifying the existing test cases can be used to enrich the pool of tests to be amplified, which in turn will lead to more behavior coverage by the technique.

Second, the technique for exception testing is built as an exhaustive approach. It is shown to be an effective technique, but the cost of applying it is high. For example, in our study presented in Chapter 5, the cost of applying the technique to Android apps ranges from 4 hours to 24 hours, depending on the size of the original test suite, the mocking length, and the complexity of the program under test. We plan to investigate the interplay between the technique and real world usage rules of the external resources, which may help inform what mocking patterns are worth exploring, thus enabling a more selective exploration instead of an exhaustive approach. For example, when an Android app runs without access to data connection, the app may use certain mechanism to reroute database queries to locally cached data, instead of submitting the queries online. As a result, certain types of exceptions, such as `SQLiteException`, could not occur in reality. Our current implementation ignores this situation and incorrectly mocks the full behavior. To overcome this limitation we will leverage the usage rules of the APIs to eliminate this type of over-approximation.

6.3 Future Work

In this section, we identify several areas of future work related to our research on non-functional validation. We first describe a few directions towards improving the proposed techniques. We then present a few long term research goals that involve pushing a more precise and scalable non-functional validation both to the millions of desktop programmers, and to the cloud computing systems.

Extension of CompSLG to richer structures. In Chapter 4 we presented an extension of CompSLG that enables load test generation for Java programs. In its current form, this extension is largely manual, and requires a non-trivial implementation to be fully automated. Our first goal is to automate this proposed technique, and to assess it on a rich set of applications.

In the long term, we also plan to investigate different automatic software decomposition techniques. The cost effectiveness of the compositional load generation technique is affected by how the system under test is decomposed. Much work has been done on automatic software decomposition, with various focuses on testing [25], visualization [15], and maintenance [53]. We plan to create our own flavor of software decomposition with a focus on how it will make it easier for load generation technique to analyze it later on.

Seamless non-functional test generation in the IDE. For desktop programming, it is predicted that the steady improvements in automatic test case generation, software bug finding, and code verification techniques will make it far easier for a programmer in the future to quickly write software that is reliable, maintainable, and malleable [96]. In a few years, the advances in computational power will enable IDEs to run constantly as many relevant tests as possible all the time while the programmer is working [97]. This will provide nearly instant feedback when semantic bugs arise.

As part of future work, we propose to build the technology that enables such instant feedback on non-functional properties of the code. To achieve this goal, we plan to test waters by first integrating the load generation technique into the Eclipse IDE. It will be deployed as an early warning system, constantly generating load test cases for the available code, and raising flags for abnormalities such as excessive CPU or memory usage. The challenges for building this technology involves 1) significantly speedup the current test generation techniques to match the expectations of seamless continuous test generation paradigm; and 2) intuitively reduce false positives to avoid overwhelming the user with false error messages.

Load testing in the cloud. The popularity of cloud computing in recent years has provided cost effective ways of scaling expensive computations. As part of future work, we propose to speedup the non-functional test generation techniques presented in this dissertation by utilizing cloud computing powers. Towards this goal, the following aspects must be considered 1) how to adapt the existing algorithms so that a trade-off between communication overhead and accuracy of path selection heuristic can be achieved; and 2) how to balance load among worker nodes.

From a different perspective, performance is an important requirement for applications in the cloud. In extreme cases, near real-time responsiveness is preferred on services such as banking fraud detection, etc. Despite this, the performance of a cloud system is always evaluated with benchmarks that either use random or predefined input data [135]. Running on an heterogeneous environment, knowing what type of workload would expose worst case performance scenarios for a cloud system is very important for a system engineer to estimate the potential of the system he manages. Our load generation technique can be extended to enable generating workloads for such systems. To achieve this, factors that have not been considered, such as network latency, disk access latency, and data locality, have to be explicitly considered when deriving new methods.

Bibliography

[1] A. A. Abdelaziz, W. M. W. Kadir, and A. Osman. Article:Comparative Analysis of Software Performance Prediction Approaches in Context of Component-based System. *International Journal of Computer Applications*, 23(3):15–22, June 2011. Published by Foundation of Computer Science.

[2] M. Acharya and T. Xie. Mining API Error-Handling Specifications from Source Code. In *Proceedings of the 12th International Conference on Fundamental Approaches to Software Engineering: Held as Part of the Joint European Conferences on Theory and Practice of Software, ETAPS 2009*, FASE '09, pages 370–384. Springer-Verlag, 2009.

[3] S. Anand, P. Godefroid, and N. Tillmann. Demand-driven Compositional Symbolic Execution. In *Proceedings of the Theory and Practice of Software, 14th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'08/ETAPS'08, pages 367–381. Springer-Verlag, 2008.

[4] S. Anand, C. S. Păsăreanu, and W. Visser. Symbolic Execution with Abstraction. *International Journal on Software Tools Technology Transfer*, 11(1):53–67, Jan. 2009.

[5] Android-aspectj tool. `http://code.google.com/p/android-aspectj/`, 2011.

[6] Android developers doc. `http://developer.android.com/index.html`.

[7] Android open source db. `http://www.aopensource.com/`.

[8] Android wifi tether code host. `http://code.google.com/p/myandroid-wifi-tether/`, 2012.

[9] Androlib website. `http://www.androlib.com/appstats.aspx`, 2012.

[10] S. Artzi, A. Kiezun, J. Dolby, F. Tip, D. Dig, A. Paradkar, and M. D. Ernst. Finding Bugs in Dynamic Web Applications. In *Proceedings of the 2008 International Symposium on Software Testing and Analysis*, ISSTA '08, pages 261–272. ACM, 2008.

[11] A. Avritzer and E. J. Weyuker. The Automatic Generation of Load Test Suites and the Assessment of the Resulting Software. *IEEE Transactions on Software Engineering*, 21(9):705–716, Sept. 1995.

[12] S. Balsamo, A. Di Marco, P. Inverardi, and M. Simeoni. Model-Based Performance Prediction in Software Development: A Survey. *IEEE Transactions on Software Engineering*, 30(5):295–310, May 2004.

[13] L. Bass, P. Clements, and R. Kazman. *Software Architecture in Practice*. Addison-Wesley Longman Publishing Co., Inc., 1998.

[14] M. Bayan and J. a. W. Cangussu. Automatic Feedback, Control-based, Stress and Load Testing. In *Proceedings of the 2008 ACM Symposium on Applied Computing*, SAC '08, pages 661–666. ACM, 2008.

[15] D. Beyer. CCVisu: Automatic Visual Software Decomposition. In *Companion of the 30th International Conference on Software Engineering*, ICSE Companion '08, pages 967–968. ACM, 2008.

[16] J. M. Bieman, D. Dreilinger, and L. Lin. Using Fault Injection to Increase Software Test Coverage. In *Proceedings of the The Seventh International Symposium on Software Reliability Engineering*, ISSRE '96, pages 166–. IEEE Computer Society, 1996.

[17] G. Bolch, S. Greiner, H. de Meer, and K. Trivedi. *Queueing Networks and Markov Chains: Modeling and Performance Evaluation with Computer Science Applications*. Wiley-Interscience, 1998.

[18] C. Boyapati, S. Khurshid, and D. Marinov. Korat: Automated Testing based on Java Predicates. In *Proceedings of the 2002 ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA '02, pages 123–133. ACM, 2002.

[19] G. Bradski. The OpenCV Library. *Dr. Dobb's Journal of Software Tools*, 2000.

[20] J. Burnim, S. Juvekar, and K. Sen. WISE: Automated Test Generation for Worst-case Complexity. In *Proceedings of the 31st International Conference on Software Engineering*, ICSE '09, pages 463–473. IEEE Computer Society, 2009.

[21] R. P. Buse and W. R. Weimer. Automatic Documentation Inference for Exceptions. In *Proceedings of the 2008 International Symposium on Software Testing and Analysis*, ISSTA '08, pages 273–282. ACM, 2008.

[22] Buslinc code host. `http://code.google.com/p/android-unl2011/`.

[23] C. Cadar, D. Dunbar, and D. Engler. KLEE: Unassisted and Automatic Generation of High-coverage Tests for Complex Systems Programs. In *Proceedings of the 8th USENIX Conference on Operating Systems Design and Implementation*, OSDI'08, pages 209–224. USENIX Association, 2008.

[24] C. Cadar, V. Ganesh, P. M. Pawlowski, D. L. Dill, and D. R. Engler. EXE: Automatically Generating Inputs of Death. In *Proceedings of the 13th ACM Conference on Computer and Communications Security*, CCS '06, pages 322–335. ACM, 2006.

[25] A. Chakrabarti and P. Godefroid. Software Partitioning for Effective Automated Unit Testing. In *Proceedings of the 6th ACM & IEEE International Conference on Embedded Software*, EMSOFT '06, pages 262–271. ACM, 2006.

[26] Choco solver. `http://www.emn.fr/x-info/choco-solver/doku.php`.

[27] J.-D. Choi, D. Grove, M. Hind, and V. Sarkar. Efficient and Precise Modeling of Exceptions for the Analysis of Java Programs. *SIGSOFT Softw. Eng. Notes*, 24(5):21–31, Sept. 1999.

[28] E. Coppa, C. Demetrescu, and I. Finocchi. Input-sensitive Profiling. In *Proceedings of the 33rd ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '12, pages 89–98. ACM, 2012.

[29] D. Coppit, J. Yang, S. Khurshid, W. Le, and K. J. Sullivan. Software Assurance by Bounded Exhaustive Testing. *IEEE Transactions on Software Engineering*, 31(4):328–339, 2005.

[30] Cvc3 solver website. `http://www.cs.nyu.edu/acsys/cvc3/`.

[31] Cyrket mobile app statistics. `http://www.cyrket.com/m/android/`.

[32] B. Daniel, D. Dig, K. Garcia, and D. Marinov. Automated Testing of Refactoring Engines. In *Proceedings of the the 6th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The*

foundations of Software Engineering, ESEC-FSE '07, pages 185–194. ACM, 2007.

[33] L. De Moura and N. Bjørner. Z3: an Efficient SMT Solver. In *Proceedings of the Theory and Practice of Software, 14th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'08/ETAPS'08, pages 337–340. Springer-Verlag, 2008.

[34] R. Dechter. *Constraint Processing.* Morgan Kaufmann Publishers Inc., 2003.

[35] Easymock website. `http://easymock.org/`.

[36] Eclipse bug 362718 - workbench performance tests. `https://bugs.eclipse.org/bugs/show_bug.cgi?id=362718`.

[37] Eclipse bug repository. `https://bugs.eclipse.org/bugs/`.

[38] S. Elbaum, H. N. Chin, M. B. Dwyer, and M. Jorde. Carving and Replaying Differential Unit Test Cases from System Test Cases. *IEEE Transactions on Software Engineering*, 35:29–45, January 2009.

[39] M. Emmi, R. Majumdar, and K. Sen. Dynamic Test Input Generation for Database Applications. In *Proceedings of the 2007 International Symposium on Software Testing and Analysis*, ISSTA '07, pages 151–162. ACM, 2007.

[40] D. Farmer and E. H. Spafford. The COPS Security Checker System, 1994.

[41] S. Freeman, T. Mackinnon, N. Pryce, and J. Walnes. Mock Roles, Objects. In *Companion to the 19th annual ACM SIGPLAN Conference on Object-oriented Programming Systems, Languages, and Applications*, OOPSLA '04, pages 236–246. ACM, 2004.

[42] S. Freeman and N. Pryce. Evolving an Embedded Domain-specific Language in Java. In *Companion to the 21st ACM SIGPLAN Symposium on Object-oriented Programming Systems, Languages, and Applications*, OOPSLA '06, pages 855–865. ACM, 2006.

[43] S. Frolund and J. Koistinen. QML: A Language for Quality of Service Specification. Technical Report 10, HP Laboratories, 1998.

[44] C. Fu and B. G. Ryder. Exception-Chain Analysis: Revealing Exception Handling Architecture in Java Server Applications. In *Proceedings of the 29th International Conference on Software Engineering*, ICSE '07, pages 230–239. IEEE Computer Society, 2007.

[45] C. Fu, B. G. Ryder, A. Milanova, and D. Wonnacott. Testing of Java Web Services for Robustness. In *Proceedings of the 2004 ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA '04, pages 23–34. ACM, 2004.

[46] V. Ganesh and D. L. Dill. A Decision Procedure for Bit-vectors and Arrays. In *Proceedings of the 19th International Conference on Computer Aided Verification*, CAV'07, pages 519–531. Springer-Verlag, 2007.

[47] I. Ghosh, N. Shafiei, G. Li, and W.-F. Chiang. JST: an Automatic Test Generation Tool for Industrial Java Applications with Strings. In *Proceedings of the 2013 International Conference on Software Engineering*, ICSE '13, pages 992–1001. IEEE Press, 2013.

[48] M. Glinz. Rethinking the Notion of Non-Functional Requirements. In *in Proceedings of the Third World Congress for Software Quality (3WCSQ'05*, pages 55–64, 2005.

[49] P. Godefroid. Compositional Dynamic Test Generation. In *Proceedings of the 34th Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*, POPL '07, pages 47–54. ACM, 2007.

[50] P. Godefroid, A. Kiezun, and M. Y. Levin. Grammar-based Whitebox Fuzzing. In *Proceedings of the 2008 ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '08, pages 206–215. ACM, 2008.

[51] P. Godefroid, N. Klarlund, and K. Sen. DART: Directed Automated Random Testing. In *Proceedings of the 2005 ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '05, pages 213–223. ACM, 2005.

[52] S. F. Goldsmith, A. S. Aiken, and D. S. Wilkerson. Measuring Empirical Computational Complexity. In *Proceedings of the the 6th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering*.

[53] R. Gopal and S. Schach. Using Automatic Program Decomposition Techniques in Software Maintenance Tools. In *Software Maintenance, 1989., Proceedings., Conference on*, pages 132–141, 1989.

[54] S. L. Graham, P. B. Kessler, and M. K. Mckusick. Gprof: A Call Graph Execution Profiler. In *Proceedings of the 1982 SIGPLAN Symposium on Compiler Construction*, SIGPLAN '82, pages 120–126. ACM, 1982.

[55] M. Grechanik, C. Fu, and Q. Xie. Automatically Finding Performance Problems with Feedback-directed Learning Software Testing. In *Proceedings of the 2012 International Conference on Software Engineering*, ICSE 2012, pages 156–166. IEEE Press, 2012.

[56] A. Groce and W. Visser. Model Checking Java Programs Using Structural Heuristics. In *Proceedings of the 2002 ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA '02, pages 12–21. ACM, 2002.

[57] D. Grove, G. DeFouw, J. Dean, and C. Chambers. Call Graph Construction in Object-oriented Languages. In *Proceedings of the 12th ACM SIGPLAN Conference on Object-oriented Programming, Systems, Languages, and Applications*, OOPSLA '97, pages 108–124. ACM, 1997.

[58] S. Gulwani, K. K. Mehra, and T. Chilimbi. SPEED: Precise and Efficient Static Estimation of Program Computational Complexity. In *Proceedings of the 36th Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*, POPL '09, pages 127–139. ACM, 2009.

[59] E. Halili. *Apache JMeter*. Packt Publishing, 2008.

[60] S. Han, Y. Dang, S. Ge, D. Zhang, and T. Xie. Performance Debugging in the Large via Mining Millions of Stack Traces. In *Proceedings of the 2012 International Conference on Software Engineering*, ICSE 2012, pages 145–155. IEEE Press, 2012.

[61] J. A. Hartigan and M. A. Wang. Algorithm AS 136: A K-Means Clustering Algorithm. *Journals of the Royal Statistical Society*, pages 100–108, 1979.

[62] H. Hermanns, U. Herzog, and J. P. Katoen. Process Algebra for Performance Evaluation. *Theory of Computer Science*, 274(1-2):43–87, 2002.

[63] G. Hughes and T. Bultan. Interface Grammars for Modular Software Model Checking. In *Proceedings of the 2007 International Symposium on Software Testing and Analysis*, ISSTA '07, pages 39–49. ACM, 2007.

[64] D. Jackson and C. Damon. Elements of Style: Analyzing a Software Design Feature with a Counterexample Detector. *IEEE Transactions on Software Engineering*, 22(7):484–495, 1996.

[65] Java path finder website. `http://babelfish.arc.nasa.gov/trac/jpf`.

[66] Jmock framework. `http://www.jmock.org/index.html`.

[67] Jshell. `http://geophile.com/jshell/`.

[68] Junitperf website. `http://www.clarkware.com/software/JUnitPerf.html`.

[69] Jzlib website. `http://www.jcraft.com/jzlib/`.

[70] K-9 mail code host. `http://code.google.com/p/k9mail/`, 2012.

[71] Keepassdroid code host. `http://code.google.com/p/keepassdroid/`, 2011.

[72] S. Khurshid, C. S. Păsăreanu, and W. Visser. Generalized Symbolic Execution for Model Checking and Testing. In *Proceedings of the 9th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'03, pages 553–568. Springer-Verlag, 2003.

[73] J. C. King. Symbolic Execution and Program Testing. *Communications of ACM*, 19(7):385–394, July 1976.

[74] C. Lattner and V. Adve. LLVM: A Compilation Framework for Lifelong Program Analysis & Transformation. In *Proceedings of the International Symposium on Code Generation and Optimization: Feedback-directed and Runtime Optimization*, CGO '04, pages 75–. IEEE Computer Society, 2004.

[75] S. Lauterburg, A. Sobeih, D. Marinov, and M. Viswanathan. Incremental State-space Exploration for Programs with Dynamically Allocated Data. In *Proceedings of the 30th International Conference on Software Engineering*, ICSE '08, pages 291–300. ACM, 2008.

[76] Y. C. Law, J. H. Lee, and B. M. Smith. Automatic Generation of Redundant Models for Permutation Constraint Satisfaction Problems. *Constraints*, 12(4):469–505, Dec. 2007.

[77] Le wiki koumbit: Open source android applications. `https://wiki.koumbit.net/AndroidFreeSoftware`.

[78] M. H. Liffiton and K. A. Sakallah. Algorithms for Computing Minimal Unsatisfiable Subsets of Constraints. *J. Autom. Reason.*, 40(1):1–33, Jan. 2008.

[79] Load test tools. `http://www.softwareqatest.com/qatweb1.html`.

[80] Loadunit website. `http://loadunit.sourceforge.net`.

[81] R. Majumdar and R.-G. Xu. Directed Test Generation Using Symbolic Grammars. In *Proceedings of the 22nd IEEE/ACM International Conference on Automated Software Engineering*, ASE '07, pages 134–143. ACM, 2007.

[82] M. Mannion and B. Keepence. SMART requirements. *SIGSOFT Software Engineering Notes*, 20(2):42–47, Apr. 1995.

[83] D. Michie. "Memo": Functions and Machine Learning. *Nature*, 218(1-2):19–22, 1968.

[84] mytracks code host. `http://code.google.com/p/mytracks/`, 2011.

[85] N. Nethercote and J. Seward. Valgrind: a Framework for Heavyweight Dynamic Binary Instrumentation. In *Proceedings of the 2007 ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '07, pages 89–100. ACM, 2007.

[86] Open gps tracker code host. `http://code.google.com/p/open-gpstracker/`, 2012.

[87] Open street map wiki. `http://wiki.openstreetmap.org/wiki/Android#OpenSource`.

[88] Oracle application environment testing. `http://www.oracle.com/us/products/consulting/resource-library/application-environment-testing-ds-1900126.pdf`.

[89] Perftestplus website. `http://www.perftestplus.com/load.htm`.

[90] C. S. Păsăreanu, N. Rungta, and W. Visser. Symbolic Execution with Mixed Concrete-symbolic Solving. In *Proceedings of the 2011 International Symposium on Software Testing and Analysis*, ISSTA '11, pages 34–44. ACM, 2011.

[91] C. S. Păsăreanu and W. Visser. A Survey of New Trends in Symbolic Execution for Software Testing and Analysis. *Int. J. Softw. Tools Technol. Transf.*, 11(4):339–353, Oct. 2009.

[92] C. S. Păsăreanu, P. C. Mehlitz, D. H. Bushnell, K. Gundy-Burlet, M. Lowry, S. Person, and M. Pape. Combining Unit-level Symbolic Execution and System-level Concrete Execution for Testing NASA Software. In *Proceedings of the 2008 International Symposium on Software Testing and Analysis*, ISSTA '08, pages 15–26. ACM, 2008.

[93] C. V. Ramamoorthy and H. F. Li. Pipeline Architecture. *ACM Comput. Surv.*, 9(1):61–102, Mar. 1977.

[94] T. Reps and G. Rosay. Precise Interprocedural Chopping. In *Proceedings of the 3rd ACM SIGSOFT Symposium on Foundations of Software Engineering*, SIGSOFT '95, pages 41–52. ACM, 1995.

[95] M. P. Robillard and G. C. Murphy. Static Analysis to Support the Evolution of Exception Structure in Object-oriented Systems. *ACM Transactions on Software Engineering Methodology*, 12(2):191–221, Apr. 2003.

[96] D. Saff and M. D. Ernst. Reducing Wasted Development Time via Continuous Testing. In *Proceedings of the 14th International Symposium on Software Reliability Engineering*, ISSRE '03, pages 281–. IEEE Computer Society, 2003.

[97] D. Saff and M. D. Ernst. Continuous Testing in Eclipse. In *Proceedings of the 27th International Conference on Software Engineering*, ICSE '05, pages 668–669. ACM, 2005.

[98] M. Sama, S. G. Elbaum, F. Raimondi, D. S. Rosenblum, and Z. Wang. Context-Aware Adaptive Applications: Fault Patterns and Their Automated Identification. *IEEE Transactions on Software Engineering*, 36(5):644–661, 2010.

[99] Sat competition website. `http://www.satcompetition.org/`.

[100] Sat4j website. `http://www.sat4j.org/`.

[101] Z. Segall, D. Vrsalovic, D. Siewiorek, D. Yaskin, J. Kownacki, J. Barton, R. Dancey, A. Robinson, and T. Lin. FIAT-fault Injection based Automated Testing Environment. In *Fault-Tolerant Computing, 1988. FTCS-18, Digest of Papers., Eighteenth International Symposium on*, pages 102–107, 1988.

[102] K. Sen, D. Marinov, and G. Agha. CUTE: a Concolic Unit Testing Engine for C. In *Proceedings of the 10th European Software Engineering Conference held jointly with 13th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, ESEC/FSE-13, pages 263–272. ACM, 2005.

[103] J. Seward and N. Nethercote. Using Valgrind to Detect Undefined Value Errors with Bit-precision. In *Proceedings of the Annual Conference on USENIX Annual Technical Conference*, ATEC '05, pages 2–2. USENIX Association, 2005.

[104] D. Shannon, I. Ghosh, S. Rajan, and S. Khurshid. Efficient Symbolic Execution of Strings for Validating Web Applications. In *Proceedings of the 2nd International Workshop on Defects in Large Software Systems: Held in conjunction with the ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA 2009)*, DEFECTS '09, pages 22–26. ACM, 2009.

[105] E. Sherman, M. B. Dwyer, and S. Elbaum. Saturation-based Testing of Concurrent Programs. In *Proceedings of the the 7th joint meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on the Foundations of Software Engineering*, ESEC/FSE '09, pages 53–62. ACM, 2009.

[106] J. Shi, M. B. Cohen, and M. B. Dwyer. Integration Testing of Software Product Lines Using Compositional Symbolic Execution. In *Proceedings of the 15th International Conference on Fundamental Approaches to Software Engineering*, FASE'12, pages 270–284. Springer-Verlag, 2012.

[107] N. Siegmund, S. S. Kolesnikov, C. Kästner, S. Apel, D. Batory, M. Rosenmüller, and G. Saake. Predicting Performance via Automated Feature-interaction Detection. In *Proceedings of the 2012 International Conference on Software Engineering*, ICSE 2012, pages 167–177. IEEE Press, 2012.

[108] Silk performer. http://microfocus.com/products/SilkPerformer.

[109] S. Sinha and M. J. Harrold. Analysis and Testing of Programs with Exception Handling Constructs. *IEEE Transactions on Software Engineering*, 26(9):849–871, Sept. 2000.

[110] S. Sinha, A. Orso, and M. J. Harrold. Automated Support for Development, Maintenance, and Testing in the Presence of Implicit Control Flow. In *Proceedings of the 26th International Conference on Software Engineering*, ICSE '04, pages 336–345. IEEE Computer Society, 2004.

[111] Sipdroidvoip code host. http://code.google.com/p/sipdroid/, 2011.

[112] Smallx. http://code.google.com/p/smallx/.

[113] C. Smith and L. Williams. *Performance Solutions: a Practical Guide to Creating Responsive, Scalable Software*. Addison Wesley Longman Publishing Co., Inc., 2002.

[114] Spec. http://www.spec.org/cpu2000/CINT2000/164.gzip/docs/164.gzip.

[115] D. Taylor. *Teach Yourself Unix System Administration in 24 Hours*. Sams Publishing, 2003.

[116] The aspectj project website. http://www.eclipse.org/aspectj/.

[117] S. Thummalapenta and T. Xie. Mining Exception-handling Rules as Sequence Association Rules. In *Proceedings of the 31st International Conference on Software Engineering*, ICSE '09, pages 496–506. IEEE Computer Society, 2009.

[118] S. Thummalapenta, T. Xie, N. Tillmann, J. de Halleux, and Z. Su. Synthesizing Method Sequences for High-coverage Testing. In *Proceedings of the 2011 ACM*

international conference on Object oriented programming systems languages and applications, OOPSLA '11, pages 189–206. ACM, 2011.

[119] N. Tillmann and J. De Halleux. Pex: White Box Test Generation for .NET. In *Proceedings of the 2nd International Conference on Tests and Proofs*, TAP'08, pages 134–153. Springer-Verlag, 2008.

[120] Tinysql website. `http://www.jepstone.net/tinySQL/`.

[121] Trac: Open source android applications. `http://trac.osuosl.org/trac/replicant/wiki/ListOfKnownFreeApps`.

[122] W. Visser, C. S. Păsăreanu, and R. Pelánek. Test Input Generation for Java Containers Using State Matching. In *Proceedings of the 2006 International Symposium on Software Testing and Analysis*, ISSTA '06, pages 37–48. ACM, 2006.

[123] Report on Average Web Page Size. `http://www.websiteoptimization.com/speed/tweak/average-web-page/`.

[124] W. Weimer and G. C. Necula. Mining Temporal Specifications for Error Detection. In *Proceedings of the 11th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'05, pages 461–476. Springer-Verlag, 2005.

[125] Wikipedia: List of open source android applications. `http://en.wikipedia.org/wiki/List_of_open_source_Android_applications`.

[126] Xbmc remote code host. `http://code.google.com/p/android-xbmcremote/`, 2011.

[127] T. Xie, N. Tillmann, J. De Halleux, and W. Schulte. Fitness-guided Path Exploration in Dynamic Symbolic Execution. In *Dependable Systems Networks, 2009. DSN '09. IEEE/IFIP International Conference on*, pages 359–368, 2009.

[128] Xproc. `http://www.w3.org/TR/xproc/`.

[129] C.-S. D. Yang and L. L. Pollock. Towards a Structural Load Testing Tool. In *Proceedings of the 1996 ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA '96, pages 201–208. ACM, 1996.

[130] G. Yang, C. S. Păsăreanu, and S. Khurshid. Memoized Symbolic Execution. In *Proceedings of the 2012 International Symposium on Software Testing and Analysis*, ISSTA 2012, pages 144–154. ACM, 2012.

[131] Yices. `http://yices.csl.sri.com/`.

[132] F. Yu, C. Wang, A. Gupta, and T. Bultan. Modular Verification of Web Services Using Efficient Symbolic Encoding and Summarization. In *Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, SIGSOFT '08/FSE-16, pages 192–202. ACM, 2008.

[133] D. Zaparanuks and M. Hauswirth. Algorithmic Profiling. In *Proceedings of the 33rd ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI '12, pages 67–76. ACM, 2012.

[134] L. Zhang and C. Krintz. Adaptive Code Unloading for Resource-constrained JVMs. In *Proceedings of the 2004 ACM SIGPLAN/SIGBED Conference on Languages, Compilers, and Tools for Embedded Systems*, LCTES '04, pages 155–164. ACM, 2004.

[135] L. Zhang, X. Ma, J. Lu, T. Xie, N. Tillmann, and P. de Halleux. Environmental Modeling for Automated Cloud Application Testing. *IEEE Software*, 29(2):30–35, 2012.

[136] P. Zhang and S. Elbaum. Amplifying Tests to Validate Exception Handling Code. In *Proceedings of the 2012 International Conference on Software Engineering*, ICSE 2012, pages 595–605. IEEE Press, 2012.

[137] P. Zhang, S. Elbaum, and M. B. Dwyer. Automatic Generation of Load Tests. In *Proceedings of the 2011 26th IEEE/ACM International Conference on Automated Software Engineering*, ASE '11, pages 43–52. IEEE Computer Society, 2011.

[138] P. Zhang, S. Elbaum, and M. B. Dwyer. Compositional Load Test Generation for Software Pipelines. In *Proceedings of the 2012 International Symposium on Software Testing and Analysis*, ISSTA 2012, pages 89–99. ACM, 2012.