Toward a Practical, Path-Based Framework for Detecting and Diagnosing Software Faults

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Abstract

One of the important challenges of developing software is the avoidance of software faults. Since a fault occurs along an execution path, program path information is essential for both detecting and diagnosing a fault. Manual inspection can identify a path where a fault occurs; however, the approach does not scale. Dynamic techniques, such as testing, are also effective to find faulty paths, but only in a sampled space.

This thesis develops a practical, path-based framework to statically detect and then diagnose software faults. The techniques are *path-based* in that both detecting and reporting faults use path information. An important contribution of the work is the development of a demand-driven analysis that effectively addresses scalability challenges faced by traditional path-sensitive analyses. The computed path information is shown to be valuable in automating diagnostic tasks and guiding software testing to quickly exploit faults. A prototype tool, Marple, was developed to experimentally evaluate the research.

Foundations of the thesis are the discoveries of *path diversity* and *fault locality*. *Path diversity* says that if a fault is reported in terms of a program point, the assumption is that all the executions across the same program point have the same property regarding the fault; however, *safe*, *infeasible*, *faulty with various severities and root causes*, and *don't-know* can all traverse the same program point. Given the path type, fault diagnosis can take action accordingly. *Fault locality* demonstrates that instead of a whole program path, often only a path segment of 1–4 procedures, is relevant to a fault. By only focusing on such path segments, fault detection and diagnosis can be more efficient.

To detect path types and path segments, a demand-driven analysis was developed, which achieves interprocedural path-sensitivity and scales up to 570,000 lines of code. Evaluation of

buffer overflow detection shows that the analysis is about 2 times faster than an exhaustive path-sensitive tool. Generality of the technique is achieved via a specification technique and an algorithm that automatically generates path-based analyses for user-specified faults. The techniques are capable of handling both safety and liveness properties as well as both control and data-centric faults, including buffer overflow, integer fault, null-pointer dereference and memory leak.

The usefulness of the path information is demonstrated for computing *fault correlation*, a causal relationship between faults, and for guiding software testing to exploit faults. By grouping the correlated faults, the number of static warnings needed for diagnosis was reduced to about 53%. The correlations also reveal that the propagation of integer faults can lead to not only buffer overflows but also null-pointer dereferences, and resource leaks can cause infinite loops. Our path-guided concolic testing successfully exploits 73% of statically identified faults. Compared to traditional concolic testing, it is 25 times faster over a set of benchmarks on average to trigger the same number of faults.

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Chapter 1

Introduction

1.1 Motivation

Software continues to play a critical role in all aspects of our lives, from personal safety to public health, from phones and appliances used in daily life to vital infrastructures of air traffic control, medical devices and power generation and distribution systems. Due to its ubiquity and importance, software needs to be reliable and robust. In fact, 40% of system failures are attributable to software faults [Marcus and Stern, 2000], and software faults are the direct cause of patient deaths in the Therac-25 radiation therapy [Leveson and Turner, 1993], the Ariane rocket crash [Inquiry Board, 1996], and the Mars Climate Orbiter explosion [Investigation Board, 1999].

Building reliable and robust software is challenging. A primary reason is that software is complex: 1) the code size can be incredibly large, consisting of diverse components; 2) newer and different programming paradigms are used, for example, concurrency and parallelization are becoming more and more important for developing modern software; 3) newly developed code needs to be compatible with legacy code; and 4) software is required to run on a variety of hardware and system environments. Yet software is developed manually, and human beings make mistakes. As a result, human understanding of software does not scale to the rapid growth of software size and complexity, and faults are unavoidably introduced in software during both design and coding. A study commissioned by the Department of Commerce in 2001 shows that for a typical software development project, fully 80% of software development dollars are spent in identifying and cor-

recting software faults; however, despite the effort, software faults cost the U.S. Economy $59.5 billion annually, about 0.6 percent of the gross domestic product (GDP) [NIST, 2002]. Effective fault management tools are desirable to help improve the productivity of software assurance and further remove faults.

1.2 The Problem

Since a fault is produced on an execution path, to detect faults, ideally we should examine each program path and determine if a fault can occur. By Rice's theorem, determining a non-trivial property for a program is undecidable. To achieve a reasonable speed and ensure software still can be shipped on time, we either have to sample a limited number of executions, which potentially will miss an unpredictable number of faults, or we need to reduce the state space by merging program paths. In fact, in many of the tools in the state-of-the-art, faults are detected using conservatively merged information from all paths and reported at a particular program point, which causes imprecision and requires much manual effort to confirm and diagnose the detection results.

Our insight is that program paths are important for both precisely detecting and efficiently diagnosing faults. If a fault is reported in terms of a program point as typical, all executions that traverse the program point are considered as having the same property regarding the fault. Actually, both safe and faulty paths can traverse the same program point. Even for faulty paths, the severity and root causes associated with the fault can be different. If the paths where a fault can occur are given, manual or automatic diagnosis can follow the guidance and take action accordingly based on the type of paths.

To identify a path where a fault occurs, there are three general approaches: manual inspection, dynamic detection and static analysis. The main disadvantage of manual inspection is efficiency. Research shows that on average the estimated speed of code inspection is only 120 lines per person hour [Hatton, 2008]. Code inspection might be useful to review high level design decisions such as software architecture, but it is not practical to manually examine every path of a program for correctness. In practice, manual inspection is often used with static tools to confirm reported warnings

or to help diagnose complex faults triggered in the field.

Dynamic detection executes a program with inputs, and determines the deviation (if any) of the program behavior via the observed symptoms. One advantage of a dynamic tool is soundness, i.e., the fault triggered in detection demonstrates the symptoms that would later manifest in the field. Since execution paths can be obtained, software developers are able to understand the transition of the program states and thus the development of a fault. One drawback of a dynamic tool is that it can only show the presence but not the absence of a bug; that is, often only a limited number of paths and restricted input space can be examined. A dynamic tool would be applied at the late stage of software lifecycle, when program executables and test inputs are available. The bugs found at this stage are considered ten times more expensive to fix than the ones found earlier, e.g., during coding [Kaner et al., 2001].

Another technique is static analysis. Static analysis scans program source code for predefined bug patterns, and reports locations in the code where a fault potentially occurs. Static analysis has been integrated in software development in many software companies. According to data in 2005, a Microsoft program analysis group filed more than 7000 bug reports in one month using their static tools [Das, 2005]. Static analysis requires only program source code and thus can find faults early, when fixing a bug is relatively cheap. In fact, at Microsoft, static tools are deployed at desktops, and code is only allowed to be checked in when it passes the inspection of these tools. Static analysis also outperforms dynamic detection in its full coverage of paths; therefore it potentially finds faults on the paths that a dynamic tool cannot reach. Many dynamic tools rely on the guidance of static information for improved coverage [Sen et al., 2005, Godefroid et al., 2005]. Despite its advantages and initial successes, existent static techniques are limited in their capability of determining and explaining faults, as well as in the high cost of developing, maintaining and using the tools.

This thesis presents a practical, *path-based* framework for statically detecting and then diagnosing faults. A novelty of this work is that our technique is *path-based* in that we not only consider path information in determining a fault, but also compute various path properties for diagnosing a fault. For example, we discovered that most of the time, only a segment of a path, instead of the whole program path, is responsible for producing a fault, and we thus can provide more focus for

fault diagnosis. We also show that paths of different root causes and severity can be distinguished, based on which, we can better schedule the diagnostic tasks. In addition, we find that along fault propagation, different types of faults can interact and then lead to visible consequences; identifying fault relationships and impacts can help group and prioritize faults.

An important contribution of the work is that we make computation of the path information *practical*; that is, the scalability and precision achieved on the framework are applicable for real-world deployed software for a variety of faults. In order to make the expensive path-sensitive feasible, we reduce the state space based on *fault locality*; that is, we detect and report the sequence of, but not the whole, execution along a path for a fault, and only perform an expensive path-sensitive analysis on the portion of the program that is relevant to a fault. Using the automatically computed path information, we identify the relationships of faults along the propagation, which was previously done manually, and guide the dynamic testing to automatically exploit the faults.

1.3 Challenges of Developing a Path-Based Static Framework

The challenges of developing a path-based static framework are 1) to achieve *scalability* and *precision* of the static analysis required by fault detection, 2) to address *generality* of the techniques so that the analysis is applicable for a variety of faults, and 3) to ensure *usability* of both the tool and the results reported by the tool.

Static analysis is potentially imprecise for two reasons. First, in a whole program analysis, it is infeasible to examine all program paths for faults. Instead, approximations, e.g., via merging or abstracting of program paths, have to be applied to reduce the state space. When multiple program states are merged at a program point to derive a summary, imprecision can occur, as reported by path-insensitive analysis [Hallem et al., 2002, Evans, 1996]. Abstraction also can lead to imprecision. For example, in software model checking, programs are mapped to software models such as pushdown automa; however, the traces from the model are not always the paths from the program [Chen and Wagner, 2002].

Another reason for imprecision is that static analysis only considers the program source to

determine the faults. However, program inputs and the external environment are also important for reasoning about the potential program behaviors. Without properly modeling such information, static analysis can make overly conservative or aggressive assumptions. A conservative analysis can lead to *false positives*, i.e., reporting faults which are actually not faults. Contrarily, an aggressive analysis can make "wrong guesses" and lead to *false negatives*; that is, static analysis would miss faults.

Besides precision, scalability is a related challenge that can prevent a static tool from being useful. A scalable static analysis should be able to handle reasonably size software, and importantly, the additional cost of coping with a given increase in code size should be manageable. For example, a naive exhaustive path-sensitive analysis is not scalable, because the analysis cost increases in terms of the growth of path numbers in the program, which can be exponential to the size of the program. To measure scalability, both time and space, e.g., memory or disk storage, used by analysis, need to be considered. Existing techniques for scalability are not ideal in that they either sacrifice the analysis precision [Bush et al., 2000], impact the general applicability [Das et al., 2002, Xie and Aiken, 2007], or require a considerable amount of manual effort to use [Hackett et al., 2006].

Another important goal for designing static analyzers is to reduce the amount of manual effort needed to construct, maintain and use a tool. The goal requires both generality and usability. A general static tool should handle a variety of faults, and especially, it should be able to respond to a new type of fault without requiring the reconstruction of the whole analysis. Achieving generality is challenging. First, we need to determine whether a general algorithm is feasible for identifying a variety of faults; if so, we need a way to specify different faults. The specification for fault patterns should be complete; that is, the specification should include all scenarios in which a fault is potentially manifested in the source code. We also require the fault patterns to be distinctive, using which we can distinguish malicious errors from benign ones. The second challenge to achieve generality is that the precision and scalability tailored for one specific type of fault can be no longer usable. Due to the challenges, generality in the state-of-the-art is mainly restricted to a subcategory of faults, such as typestate [Strom and Yemini, 1986] violations. As a result, repeated efforts have to be expended to build and maintain individual fault detectors.

Usability refers to how easily a static tool can be used, and more specifically, how easily a user can specify faults, configure the tool, or use the bug reports to correct the faults. It should be noted that the focus here is not formal user studies, but whether a static tool considers empirical user experience and integrates features that help reduce manual effort to use the tool. For example, some tools require the use of annotations to help analysis, while both writing and verifying annotations require much manual effort. Another determinant factor of usability is the quality of bug reports. Many static tools only report a program point where a fault potentially occurs. To understand how a fault is developed along executions, code inspectors have to manually explore the paths that traverse the reported program points, which is time consuming and error prone.

The above four challenges are not independent factors, as the techniques used to address one challenge might compromise the other. For example, applying heuristics for scalability impacts precision. Introducing annotations for precision sacrifices usability. The ultimate reason that these challenges exist is that static analysis is undecidable. We thus should develop algorithms that can use the available computation resources for nearly optimal solutions, which means 1) we should avoid computing information that is not needed; and 2) we should avoid repeated computation and instead, reuse intermediate results if possible. In our research, we use these two principles and develop scalable algorithms that handle the requirements of precision, generality and usability.

1.4 An Overview of the Research

This section summarizes the thesis research from three different angles. First, we introduce the development of the five projects in our research process. Second, we list the set of solutions found in our research that addressed the targeted challenges specified in Section 1.3. Finally, we summarize our contributions.

1.4.1 A Description of Five Research Projects

This research is developed in three stages, shown as Figure 1.1. In the *motivation* stage, our goals are to identify the value of paths for detecting and diagnosing faults, and meanwhile to deter-

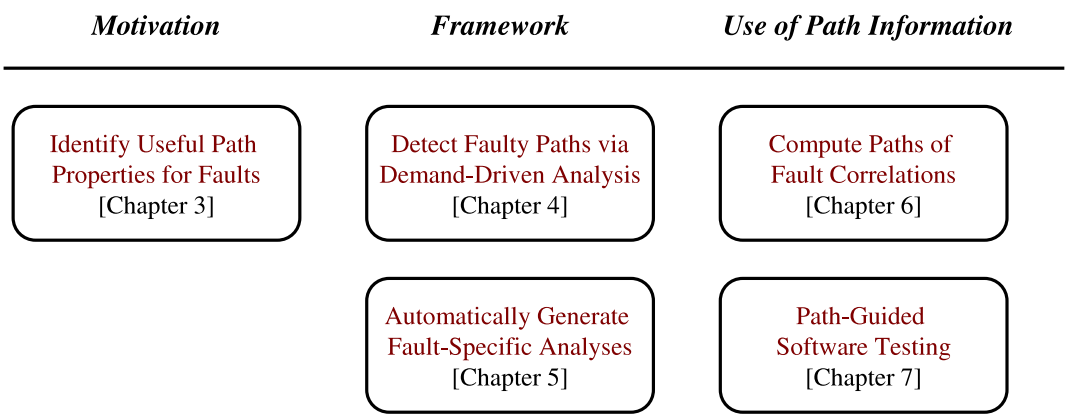


Figure 1.1: Research Process: Five Projects for the Thesis Research

mine path information that is potentially useful in fault diagnosis. In this project, we proposed and experimentally validated two important hypotheses: 1) paths that contain different fault properties (e.g., the presence, type, severity or root cause of a fault) can traverse the same program point, and thus manual and automatic diagnosis can take corresponding actions based on the types of paths; and 2) faults manifest locality, and it is the path segment along a program path that contributes to the cause of a fault. We therefore can use the information identified on path segments to diagnose faults.

In the *framework* stage, we develop the techniques to automatically compute path information regarding faults. The two important contributions include: 1) we demonstrate that demand-driven analysis is feasible and scalable for detecting faulty paths; and 2) we develop a fault model and a specification technique that enable the applications of demand-driven analysis to both data- and control-centric faults as well as faults regarding both liveness and safety properties.

In Figure 1.2, we compare demand-driven analysis with other two categories of techniques previously applied in path-sensitive fault detection. In the figure, each rectangle represents the state space that a static analysis needs to explore: the height of the rectangle indicates the number of paths in a program, and the width displays the length of a path. Each strip in a rectangle represents a path. In the first approach, static analysis exhaustively explores all program paths based on the

structure of the program. More likely, resources would be exhausted before all the faults can be found. In the second approach, static analysis randomly searches paths for faults. Research shows that this approach can find faults more quickly than the first approach [Dwyer et al., 2007]; however, faults also can be missed.

The demand-driven analysis improves the scalability by only collecting the information needed for a fault. Applying *demand-driven* analysis to detect faults, we first perform a low-cost source code scan to identify program points where a fault is potentially observed. We then conduct a path-sensitive analysis only on the code that is relevant to the faults, i.e. the path segments between the program entry and the identified program points. Compared to an exhaustive analysis, demand-driven analysis potentially explores a fewer number of program paths, because only the paths that traverse the program points of interest need to be examined. In the figure, we represent the reduction of the path number using the shortened breadth in the rightmost rectangle. In addition, our path-sensitive analysis starts where a fault potentially occurs and terminates as soon as the decision about the fault is made, when only a segment of paths may be explored. Therefore, the length of a path we analyze is also reduced, shown as the shortened height for each strip in the rightmost rectangle.

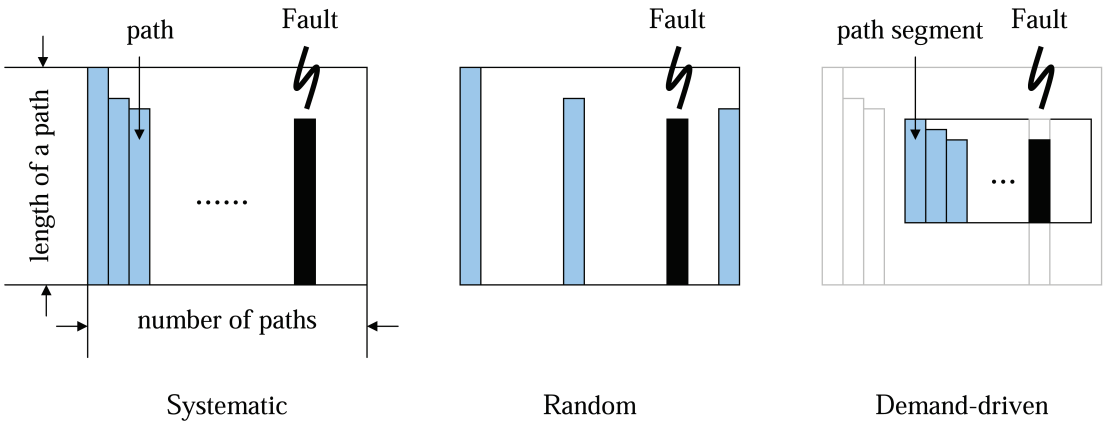


Figure 1.2: Three Types of Path-Sensitive Analysis

In the third stage of our research, shown in Figure 1.1, we study the use of paths for fault diagnosis. In one project, we find that a casual relationship can exist between faults, which we call *fault correlation*, such as “an integer overflow can lead to a buffer overflow”. In practice, code

inspectors manually determine such relationships between faults for understanding the impact of a fault. Using the faulty paths computed, we develop an algorithm to automatically determine fault correlations. In another project, we find that path information is useful to reduce state space of path-based test input generation. We develop a path-guided concolic testing technique that successfully exploits statically identified faults.

We implement our techniques in a prototype tool, called *Marple*, which we use to experimentally evaluate the effectiveness of the techniques.

1.4.2 A Summary of Solutions Provided by the Framework

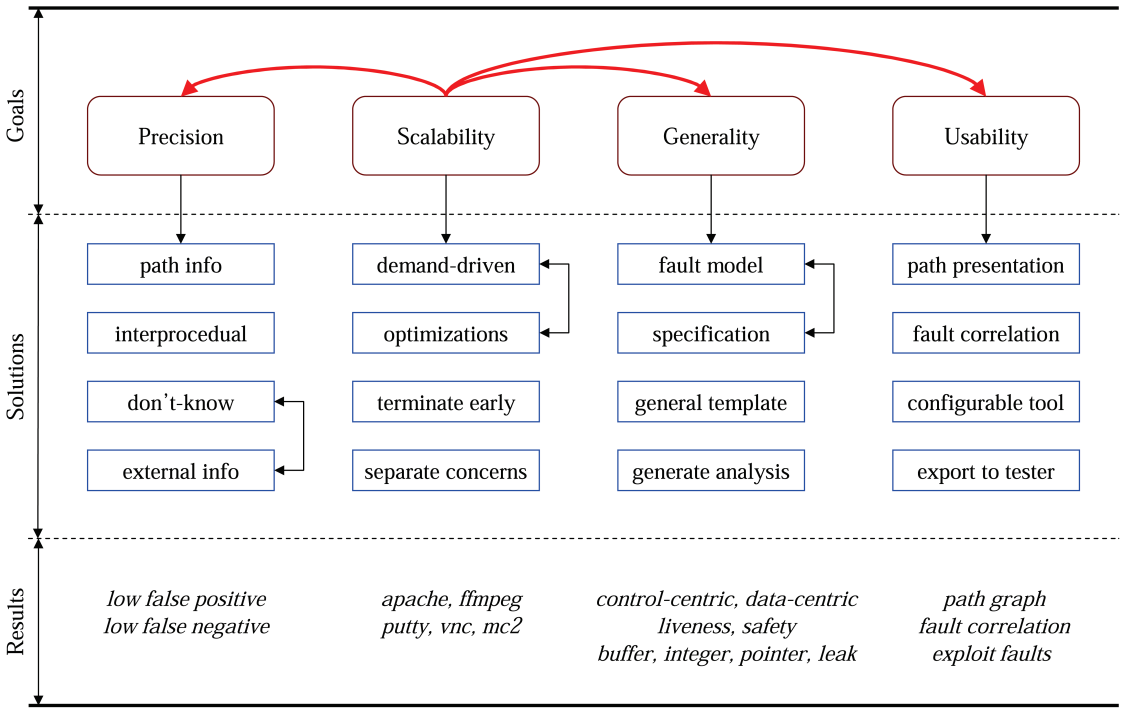


Figure 1.3: Goals, Solutions and Results

The thesis addresses the four challenges of the static fault detection discussed in Section 1.3. In Figure 1.3, we present a summary of our solutions with respect to these challenges. The key that leads to those solutions is the application of a demand-driven, path-based analysis. The figure is divided into three parts. At the top of the figure, we list the four challenges we aim to address.

In the middle of the figure, we present a set of techniques developed to accomplish the goals. At the bottom of the figure, we display results that demonstrate the effectiveness of our techniques in conquering the targeted goals.

In the figure, under *Precision*, we summarize our techniques applied to improve the precision of the analysis. We have pointed out that the two major imprecision sources are: the approximation introduced to reduce the state space and the heuristics applied to model factors beyond program source (see discussion in Section 1.3). We address the first challenge using an interprocedual path-sensitive analysis. For the second source of imprecision, we introduce *don't-know* tags in an analysis to mark positions where imprecision can occur. The idea of don't-know is that we allow heuristics to be introduced to determine faults, but we are aware what and where heuristics are applied. Based on the corresponding results, we can thus decide whether or not to continue applying them. In the figure, we use arrows to connect the boxes of don't-know and external information, indicating that the two techniques are integrated together to handle potential imprecision. By applying the above set of techniques, our experiments report low false positive and false negative rates for analyzing a set of real-world programs.

For scalability, we develop a demand-driven analysis and a set of optimizations based on the analysis. In addition, we integrate two design principles, including *terminate early* and *separate concerns*. *Terminate early* means that the analysis always terminates when the status of the paths is determined, either as safe, containing faults or don't-know; the analysis would not use arbitrary heuristics and allocate computation resources for producing unpredictably imprecise results. *Separate concerns* means we separate complex properties of a path into several individual properties, each of which can be efficiently resolved on the framework. We then compose the properties for the paths that we aim to compute. For example, in our analysis, determining path feasibility and detecting faults are performed in two separate passes of an analysis, so that the infeasible paths identified can be reused in determining different types of faults. The effectiveness of the above techniques is demonstrated in our experiments, where our analysis terminates for large software such as `putty` and `apache` with reasonable time and space overhead.

Generality is achieved via a fault model and a specification technique. We design a general

demand-driven algorithm that can find a variety of faults. Integrating the specification and the general template, we develop solutions to automatically generate individual analyses for user-specified faults. We show that our framework can produce either forward or backward demand-driven analysis, and the generated analyses can handle both safety and liveness properties and both data- and control-centric faults, including buffer overflow, integer faults, null-pointer dereferences and memory leaks.

The usability of our framework focuses on producing useful information for fault diagnosis. We have spoken with software developers in the industry and based on their experience, we have determined features that make a static analyzer easy-to-use. For example, we develop techniques to represent the detected faulty paths; according to code reviewers at Microsoft, path information is very useful for understanding a fault [PC, 2006]. We also identify fault correlations to help understand the propagation and the severity of faults, because we find that security experts actually manually identify such relationships between faults to determine the causes of a vulnerability [Common Vulnerabilities and Exposure, 2010]. Since paths not only can be diagnosed manually, but also can be supplied to dynamic tools for generating test inputs and then producing executions to help debugging, we develop a module to enable other tools to automatically consume the paths. We experimentally demonstrate that concolic testing can follow our generated faulty paths to automatically exploit faults. In addition to improving the presentation of the analysis results, we also develop a configuration tool for better tuning the static analysis. Users thus can make choices on how conservative or aggressive an analysis should be.

Among the four goals, scalability is the prerequisite for the other three, shown by the arrows on the top of the figure. With the improved scalability, we are able to use the additional computation to address precision, generality and usability. The improved generality allows us to explore correlations among different types of faults, and thus further facilitates the usability of the framework.

1.4.3 Contributions

This thesis makes the following contributions:

1. We demonstrate *path diversity*, that is, paths of *infeasible, safe, faulty with various root*

causes and severities and *don't-know* can traverse the same program point. The path classification can guide the fault detection to achieve better precision, and help prioritize and explain detection results for fault diagnosis [Le and Soffa, 2007, Le and Soffa, 2008].

2. We demonstrate that faults manifest locality, i.e., often a fault is relevant to only several procedures along a path, instead of the whole program path. Therefore, by focusing on such path segments, both fault detection and diagnosis can achieve better performance [Le and Soffa, 2007, Le and Soffa, 2008].

3. We develop a demand-driven analysis that statically identifies user-specified faults. In our feasibility study, we applied the analysis to buffer overflow detection and demonstrated its scalability. The work validates the hypothesis that the demand-driven analysis only visits the code that is relevant to the faults and terminates only when a small portion of the code is analyzed [Le and Soffa, 2008].

4. We develop a fault model and a specification language that can specify both control- and data-centric faults as well as both liveness and safety properties [Le and Soffa, 2011].

5. We design an algorithm to automatically generate individual analyses from specifications and a general demand-driven template. The generated analysis can handle one or several types of specified faults. We experimentally show that the generality does not compromise scalability, and the analysis is able to scale at least for identifying buffer overflow, integer faults, null-pointer dereferences and memory leaks [Le and Soffa, 2011].

6. We define fault correlations and demonstrate their values for understanding faults. We also develop algorithms to automatically compute paths along which two faults are correlated [Le and Soffa, 2010].

7. We develop techniques to integrate statically computed path information with the path-based test input generation. In our evaluation, we show that using path-guided concolic testing, we can automatically generate test inputs that exploit our statically identified faults, and with the

guidance of the path information, concolic testing is able to more quickly find faults [Cui et al., 2011].

8. The framework is implemented in a research prototype Marple. It takes the program source and user supplied specifications, and reports the paths with different fault properties for specified faults. The tool is configurable and applicable for analyzing Windows compilable software.

Contributions 1 and 2 are presented in Chapter 3 and contribution 3 in Chapter 4. As the effort of making the framework more generally applied, Chapter 5 includes contributions 4 and 5. The applications of path information are summarized in contributions 6 and 7, which are shown in Chapters 6 and 7 respectively.

1.5 Thesis

The thesis presents scalable, general path-sensitive algorithms for detecting faults and determining fault correlations. It demonstrates that static path information regarding faults can be made:

- **valuable** for both fault detection and diagnosis;
- **practical** in that paths can be identified with reasonable precision and scalability; and
- **broad** to address paths of a variety of faults, and paths of multiple joint properties.

Chapter 2

Background and Related Work

Two key concepts of this thesis are *faults* and *program paths*. We organize the background chapter based on the two concepts. Under *faults*, we define faults and common fault types; we then introduce techniques and terminologies related to detecting and diagnosing faults. Similarly, under *program paths*, we provide definitions related to paths; we then present the existent work on computing and using program paths. At the end of the chapter, we provide information about our implementation and experimentation. In particular, we explain the use of the Microsoft Phoenix [Phoenix, 2004] and Disolver [Hamadi, 2002] in the development of the tool Marple and also our choices of benchmarks for experiments.

2.1 Faults

Definition 2.1: a program *fault* is an abnormal condition caused by the violation of a required property at a program point. The *property* can be specified as a set of constraints to which a program has to conform.

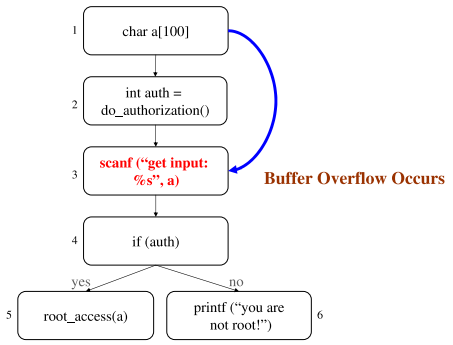
Fault is a dynamic concept, i.e., a fault occurs when a program runs. Research shows that certain types of malfunction in dynamic behavior can be predicted statically using patterns of program source code [Evans, 1996, Bush et al., 2000, Das et al., 2002, Xie et al., 2003, Xie and Aiken, 2007, FindBugs, 2005, Le and Soffa, 2008]. The goal of static fault detection is to apply static analysis on program source to determine the potential occurrence of a fault.

2.1.1 Common Fault Types

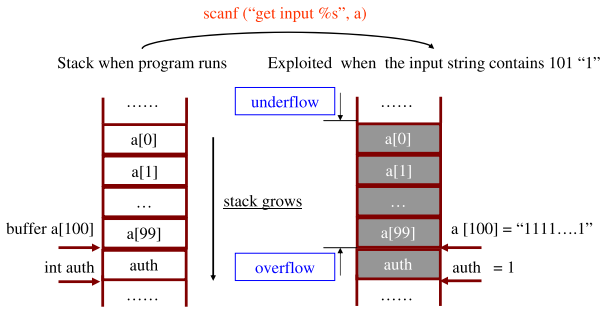
We focus on the following four types of faults, *buffer out-of-bounds*, *integer fault*, *null-pointer dereference* and *resource leak*. They are chosen because 1) these types of faults are commonly seen in software; 2) identifying them is important for software reliability and security, as they can cause programs to crash, hang, slowdown, be exploited or produce incorrect results, 3) they are not simple syntactic faults that can be found during compilation, and instead, only advanced semantic analyzers are able to statically identify them, and 4) the four types are representative for both data and control centric faults, and include both liveness and safety properties.

Definition 2.2: If a write or read of buffer v accesses the memory outside the boundary of v, a buffer *out-of-bounds* occurs. If the access is beyond the buffer, e.g., at the address larger than $[Address(v)+size(v)]$, the fault is a *buffer overflow*; otherwise, if the out-of-bounds access is before the buffer, e.g., at the address less than $[Address(v)]$, it is a *buffer underflow*. A *buffer* is a chunk of memory that stores n $(n > 0)$ number of elements of the same type. In program code, a buffer can be identified using a source variable v; any element in the buffer can be accessed using $v[i]$ (i is the index of the buffer).

Buffer out-of-bounds can occur in the stack, heap or data section, and in all of the three cases, buffer overflow/underflow are exploitable [CERT, 2010]. In Figure 2.1, we show a stack buffer overflow and the exploit targeted to this buffer overflow.



(a) Code with a Buffer Overflow



(b) Exploiting the Buffer Overflow

Figure 2.1: A Stack Buffer Overflow and Its Exploit

In Figure 2.1(a), there is a buffer overflow vulnerability at node 3 on a stack buffer *a*. In Figure 2.1(b), we show that an input *a[100]="111...1"* (with more than a 100 "1") taken at node 3 overflows buffer *a*, and as a result, *auth* located adjacent to the buffer on the stack is overwritten (assuming the memory layout shown as Figure 2.1). Due to the buffer overflow, the value *auth* is controllable by external users, and therefore an unauthorized access can occur at node 5. This buffer overflow is a simplified version of an exploited SSHD vulnerability [Chen et al., 2005].

Next, we introduce three types of integer faults: *truncation error*, *overflow/underflow*, and *signedness error*.

Definition 2.3: An *integer truncation error* occurs when 1) an integer with a larger *width* is assigned to an integer with a smaller width and 2) the destination integer cannot accommodate the value. *Integer width* measures the number of bytes used in the machine to represent a specific type of an integer.

For example, in C and C++, there exist integer types of `char`, `short`, `int`, and `long`; their corresponding sizes are 1, 2, 4, and 8 bytes. When an integer, e.g., 1024, with the `long` type is assigned to the integer of `char` type, a truncation error occurs. Instead of 1024, we would get 0 after the assignment.

Definition 2.4: An *integer overflow/underflow* occurs when an integer arithmetic returns a value that the destination integer cannot accommodate: if the value is larger than the maximum value the destination integer can store, an *integer overflow* occurs; otherwise, if the value is smaller than the minimum value the destination integer can store, an *integer underflow* occurs.

For some languages such as C and C++, the values an integer can store are dependent not only on the integer type, but also its *signedness*. An *unsigned* integer is always non-negative, and all of its bits are interpreted as values. A *signed* integer can represent negative values, and often, its highest bit indicates whether the integer is positive or negative.

Definition 2.5: An *integer signedness error* occurs when a signed integer is converted to unsigned (or when an unsigned integer is converted to signed), and its value cannot be represented by the destination integer.

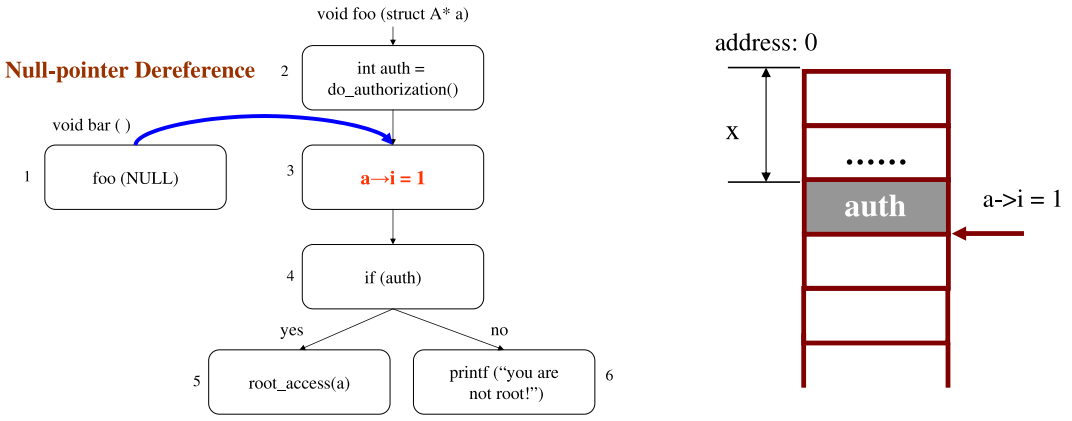
The three types of integer faults listed in Definitions 2.3–2.5 share one commonality: they oc-

cur when a value, either from some integer or integer arithmetic, is assigned to an integer, and the destination integer cannot accommodate the value. The outcomes of the assignment in presence of integer faults are either defined in the language standard or implementation dependent. As the results are often not expected, integer faults can lead to incorrect results, program crashes or exploits [SecurityTeam, 2010, Common Vulnerabilities and Exposure, 2010].

The next category of faults is related to the pointer usage.

Definition 2.6: A *null-pointer dereference* occurs when the program attempts to dereference a pointer whose value is NULL.

Null-pointer dereference can cause the program to crash or even be exploitable. Figure 2.2 shows a proof-of-concept example on how a null-pointer dereference is exploited. In Figure 2.2(a), the pointer dereference *a->i* at node 3 encounters a null-pointer *a*. As a result, the program would access the memory at address *x* (*x* is the offset of variable *i* in *struct A*), which most of the time is not a legitimate user memory space, and thus the program would crash. Sometimes, an authorization token is by chance located at address *x*, as shown in Figure 2.2(b), in which case the assignment at node 3 can change the value of *auth* and allow a non-authorized access at node 5.



(a) a NULL-Pointer Dereference (b) Exploiting NULL-Pointer Dereference

Figure 2.2: An Example of Null-Pointer Dereference

Pointer related faults also include the dereferences of uninitialized, untrusted, or already freed pointers. They are all similar to null-pointer deferences in that the fault occurs when the pointer

dereference is not performed in a proper context.

Finally, the last category of fault is about the usage of resource in software systems.

Definition 2.7: A *resource leak* occurs if some allocated resource is never released. One example is *memory leak*. A memory leak occurs when a chunk of allocated memory is never freed. Memory leaks can slow down or even crash a program. Other resource leak examples include "a file is never closed after open", which can cause a program to crash or leak security sensitive information, or "a lock is never released after acquire", leading to deadlocks.

Besides types of faults that can be found in common software, there are also application-specific faults, which only occur in particular software or systems. For example, in UNIX, a call to *chroot* should be immediately followed by the call *chdir*. Our techniques are applicable for both common faults and application specific faults; the discussions in the thesis mainly use common faults presented above as examples.

2.1.2 Background Related to Static Fault Detection and Diagnosis

An important technique we applied to detect faults is *dataflow analysis*. Dataflow analysis was originally developed for optimizing programs in compilers. In recent research, dataflow analysis is also used for software assurance tasks such as fault detection [Das et al., 2002, Hackett et al., 2006, Evans, 1996] and software testing [Duesterwald et al., 1996]. A special dataflow analysis we applied is *demand-driven analysis*, which aims to reduce time and space overhead by only collecting information that is needed [Duesterwald et al., 1997, Bodik et al., 1997b, Heintze and Tardieu, 2001].

2.1.2.1 Dataflow Analysis and Static Fault Detection

Definition 2.8: *Dataflow analysis* identifies a set of values from a program that can satisfy desired data use patterns at program points. A dataflow analysis can be *intraprocedural*, in which only information within the procedure is considered. The analysis also can be *interprocedural*, where information across procedures is also collected. A dataflow analysis can be *forward*, following the direction of program executions, or *backward*, along a reverse direction of program executions.

In a dataflow analysis, the program source code is typically converted to some type of intermediate representation, for example, *control flow graphs*.

Definition 2.9: A *control flow graph (CFG)* of a procedure is a graph $G = (N, E)$, where the nodes in N represent statements of the procedure and the edges in E represent the transfer of the control between two statements. Two distinguished nodes $entry \in N$ and $exit \in N$ represent the unique entry and exit of the procedure. An *interprocedural control flow graph (ICFG)* of a program is a collection of control flow graphs $\{G_i\}$ such that G_i represents a procedure in the program. Suppose $call(s)$ represents the procedure called from a callsite s. Then for each callsite n in an ICFG, there exists an edge from n to the entry of the procedure $call(n)$, and also there exists an edge from the exit of $call(n)$ to n.

Dataflow analysis can compute the following two fundamental classes of program properties.

Definition 2.10: A *safety* property states that "bad things" never happens; a *liveness* property states that "good things" should eventually happen.

For example, in compiler optimizations, "determining whether a variable has a constant value at a program point" is a safety problem, as it requires knowing before reaching the given program point, whether the variable has been assigned to a non-constant value. On the other hand, to determine whether a statement in a program is "dead", we need to know if the defined variable(s) in the statement would eventually be used later along executions; here, we determine a liveness property.

Previous research shows that any program property can be expressed as a conjunction of *safety* and *liveness* properties [Alpern and Schneider, 1985]. Also, assuming a program always terminates, liveness checking can be converted to safety checking [Biere et al., 2002]. In the traditional dataflow analysis, safety properties are determined using a forward dataflow analysis, while computing liveness problems uses a backward analysis [Aho et al., 1986].

Definition 2.11: A *false positive* in static fault detection is a warning reported by static analysis which is not a real fault; a *false negative* is a fault in a program, but not detected by static analysis.

False positives and false negatives are metrics to evaluate the precision of a static fault detector. An ideal fault detector should report zero false positive and zero false negative.

2.1.2.2 Demand-Driven Analysis

Typically, dataflow analysis traverses the ICFG of a program to collect program facts. One of the important decisions is how the ICFG should be traversed to efficiently collect the desired information. For example, in a procedure, there are options of performing a breadth-first or depth-first search. If an interprocedural analysis is conducted, there are also choices of following a *top-down* or *bottom-up* order to traverse the call graph. Top-down analysis starts at the root of an ICFG and traverses its leaves (callees) recursively, while bottom-up analysis summarizes the information from all the leaves and propagates it to the parents (callers). An *exhaustive* dataflow analysis starts at the beginning of a program, and terminates at the exit; the information is collected without a selection, as the analysis does not know which information is potentially useful until the program point that uses the information is reached. *Demand-driven analysis* is different from exhaustive analysis in that the traversal of nodes in an ICFG is completely dependent on the information that is needed, instead of the structure of the ICFG, to reduce time and space overhead [Duesterwald et al., 1997, Heintze and Tardieu, 2001, Bodik et al., 1997b].

To achieve the goal, demand-driven analysis formulates a demand to a set of queries. Driven by these queries, the analysis only visits the parts of the program that are reachable from where the queries are raised, and collects information that is relevant to resolve the queries. Guided by this general paradigm, a concrete demand-driven analysis can be developed to solve specific problems.

Demand-driven analysis is potentially more scalable than exhaustive dataflow analysis for several reasons: 1) the analysis only visits the code reachable from where a query is raised; 2) only information that is useful for resolving a query is collected; 3) the analysis terminates as soon as the resolutions of the query are determined, often when only a small portion of the code is visited; and 4) the information computed for resolving different queries can be reused.

One of the earliest demand-driven analyses computed live variables, dated back to 1978 [Babich and Jazayeri, 1978]. Over the 30 years, research in the area has been focusing on the applications of demand-driven analysis to solve various problems. Demand-driven algorithms have been applied for solving typical dataflow problems [Duesterwald et al., 1997], alias analysis [Heintze and Tardieu, 2001], infeasible path computation [Bodik et al., 1997b], value flow [Bodik and Anik,

1998], range analysis [Blume and Eigenmann, 1995] and software testing [Duesterwald et al., 1996]. Experiments on a demand-driven copy constant propagation framework report speedups of 1.4–44.3 on 14 benchmark programs [Duesterwald et al., 1997]. The demand-driven alias analysis was demonstrated to scale up to millions lines of code [Heintze and Tardieu, 2001]. A demand-driven analysis can be path-sensitive [Le and Soffa, 2008, Bodik et al., 1997b] or path-insensitive [Duesterwald et al., 1997], and forward [Livshits and Lam, 2003] or backward [Bodik et al., 1997b]. Generally, demand-driven analysis follows an opposite direction of a standard data flow analysis. For example, a forward iterative dataflow analysis computes equivalent information as a backward demand-driven analysis for distributive dataflow problems [Duesterwald et al., 1997]. The thesis is the first work that studies and evaluates the capability of demand-driven analysis in determining paths of various types of faults and their correlations.

2.1.3 Related Work on Fault Detection and Diagnosis

Static analysis identifies faults based on the patterns a fault potentially manifest in the code. We first introduce how faults are usually specified for static detectors. Next, we summarize the three representative types of static techniques applied for identifying faults. We also present techniques that further process or use the statically computed information, including fault ranking and static information guided testing and runtime detection.

2.1.3.1 Representing Faults for Static Analysis

For static analysis to identify a particular type of fault, we have to specify code patterns for faults; that is, we should express to static detectors "what do we mean by a fault?" Faults are often represented using the following two fault models: *finite automata* and *assertions*. Finite automata are effective in specifying control-centric faults, i.e., violations of an enforced order of program execution [Chen and Wagner, 2002]. An assertion based model is flexible in that it can specify fault conditions at any program point and express either data or control constraints about program behavior. In static analysis, assertions are often expressed using annotations [ESC-Java, 2000].

Besides using the two fault models, there are three other approaches to integrate fault patterns in a static analyzer. A straightforward approach is to hard-code the safety rules in the analysis, and construct individual static analyzers for each type of fault [Wagner et al., 2000, Brumley et al., 2007]. A more general technique is to first construct a general analysis, and then write additional extensions on top of the general engine to produce fault-specific detectors [Hallem et al., 2002, FindBugs, 2005]. There is also the approach that provides inconsistent rules of the code for static analysis; the assumption is that inconsistency implies a fault [Engler et al., 2001]. Our work develops specification techniques that express both control- and data-centric faults in terms of constraints at program points. Analyses for a specific type of fault are automatically produced.

2.1.3.2 Three Types of Static Approaches for Detecting Faults

Much research has been done for fault detection due to its importance. In Figure 2.3, we provide a spectrum of fault detection and diagnosis techniques in the state-of-the-art, static techniques in the left, dynamic approaches in the right, and in the middle, we show a set of hybrid tools, i.e., techniques that integrate both static and dynamic components. Since our work is static, the focus in this section is to present existing static techniques for faults, as well as their roles in hybrid tools.

Common static techniques for fault detection include *model checking*, *dataflow analysis*, and *type inference*. Model checkers were initially developed to verify small design spaces, such as hardware or protocols. Recently, successes have been accomplished in model checking software. For example, SLAM, a model checker developed by Microsoft, successfully identifies protocol violations in device drivers [Ball et al., 2004]; MOPS reports security violations in millions of lines of code [Chen and Wagner, 2002]. Applied to software, model checkers first abstract software to models such as push down automata (PDA) and also represent faults using finite automata (FA). The software model (e.g., PDA) then is checked against FA for potential violations. If a violation is discovered, a counter example is reported as the trace on the abstract software model. The biggest challenge for software model checking is to manage the potential explosion of the state space; that is, we need to build software models within a reasonable size and meanwhile do not sacrifice much precision. Also, current model checkers [Chen and Wagner, 2002, Henzinger et al., 2002, Visser

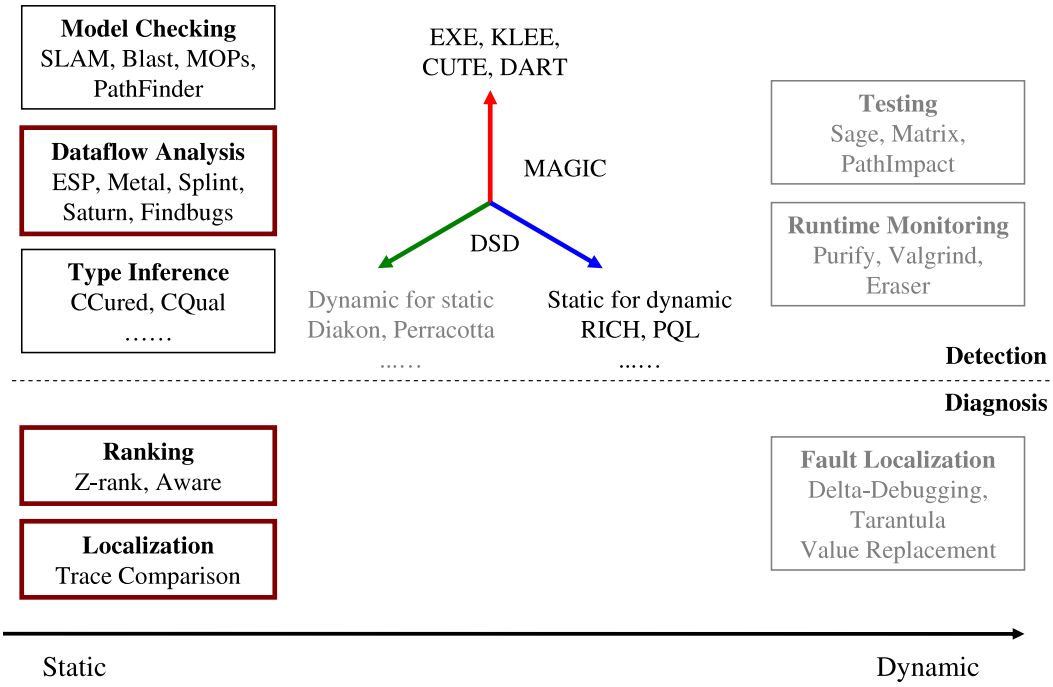


Figure 2.3: Static Analysis for Fault Detection and Diagnosis

et al., 2000] are only able to identify control centric faults such as typestate violations. It is unclear whether we can extend model checkers to handle a more variety of faults.

Dataflow analysis is another category of fault detection techniques. Dataflow analysis traverses a program and collects the information to determine whether a fault pattern is matched. Used with techniques such as symbolic evaluation and constraint solving, dataflow analysis has shown to be effective in detecting many types of faults [Das et al., 2002, FindBugs, 2005, Evans, 1996, Xie and Aiken, 2007, Hallem et al., 2002]. Path-insensitive dataflow analysis merges information at the program points, and the analysis is fast but imprecise [Evans, 1996, FindBugs, 2005]. The techniques developed in this thesis are based on an interprocedural, path-sensitive dataflow analysis. We give a detailed discussion on path-sensitive dataflow analysis in Section 2.2.

Type inference has also been applied to detect software faults. The idea is to develop a set of typing rules as fault patterns. A type inference is performed to determine whether a violation of the typing rules can occur in the code; if so, a fault is reported. This technique has been applied to C programs for detecting memory errors [David and Wagner, 2004, Necula et al., 2005] and

integer faults [Brumley et al., 2007]. However, modeling faults using typing rules is not always straightforward, which restricts the types of faults that actually can be applied. Also, type inference algorithms tend to be conservative, which can lead to many false positives in the fault detection.

2.1.4 Fault Ranking and Localization

Static analysis potentially produces a large number of warnings. Fault ranking and fault localization, shown in the left corner of Figure 2.3, are the two automatic techniques developed to process statically reported warnings.

Fault ranking aims to prioritize real and important faults for static warnings. Often, many factors can indicate the importance of a warning, such as the complexity of the code where the warning is reported or the feedback from code inspectors. Ruthruff *et al.* developed logistic regression models to coordinate these factors [Ruthruff et al., 2008]. Kremenek *et al.* observed that warnings can be clustered in that either they were all false positives or all real faults. Thus diagnosing one can predict the importance of other faults in the cluster [Kremenek et al., 2004, Kremenek and Engler, 2002]. Heckman *et al.* identified alert characteristics and applied machine learning techniques to classify actionable and non-actionable static warnings [Heckman and Williams, 2009]. Compared to the above works which are all based on empirical observations, we compute fault correlations, and statically group and order faults based on the inherent causality between faults, and thus is generally applicable.

Research in fault localization aims to automatically identify the root cause of faults. Static analysis often reports program points where the static violations are detected. However, the actual cause that leads to the violation can be far from where the violation is observed. The only work we found for localizing root causes for static warnings is built on model checkers. It finds statements that occur in the faulty traces but not in the correct ones as likely root causes [Ball et al., 2003]. The techniques are imprecise, because only a limited number of correct traces can be generated and compared, and the statements that occur on the faulty traces but absent from correct traces are not necessarily problematic.

2.1.4.1 Use of Static Information in Hybrid Tools

In the middle of Figure 2.3, we use a three-dimension coordinator to summarize the three potential ways a static and a dynamic analysis can integrate. In the first two approaches, static and dynamic analysis are first performed separately, and in the second stage, the information generated from one analysis is then supplied to another. For example, Perracotta has been applied to dynamically infer API protocols [Yang et al., 2006], which are then used by ESP [Das et al., 2002] to find violations in software. In an opposite direction, static analysis is first applied to pinpoint program points where faults potentially occur; the information then is used to guide runtime detectors [Brumley et al., 2007] and testers (including test input generation and testing) [Csallner and Smaragdakis, 2006].

In the third category of hybrid tools, static and dynamic analysis are performed interactively. An important application is to generate test inputs that execute a targeted path [Cadar et al., 2006, Sen et al., 2005, Godefroid et al., 2005, Cadar et al., 2008]. A representative technique is concolic testing [Sen et al., 2005, Xu et al., 2008, Burnim and Sen, 2008]. In concolic testing, the program under test is concretely executed and symbolically evaluated simultaneously. Instrumentation is inserted to the program to collect the symbolic path constraints and value updates during program execution. The symbolic constraints are solved to generate test inputs targeting a new path. When symbolic values cannot be collected, symbolic expressions are simplified by using the corresponding concrete values.

The planes between the two coordinators in the figure indicate the further opportunities of integrating static and dynamic analysis. For example, DSD applies dynamic inferences to help static analysis find likely faults; the static information is then provided to test input generation to trigger faults [Csallner and Smaragdakis, 2006]. Similarly, static information also can be supplied to concolic testing tools to help further reduce the search space. We developed MAGIC, which applies statically computed path information to guide concolic testing [Cui et al., 2011]. Comparing to program statements, the path information is more precise, as many of the program properties needed for dynamic tools are only valid along some paths. We experimentally show that the path precision brings in further efficiency for guiding dynamic testing, and meanwhile the dynamic testing is able

to confirm static results by exploiting the faults reported in static analysis.

2.2 Program Paths

Here, we introduce the background and related work that are related to program paths.

2.2.1 Terminology Related to Paths

Definition 2.12: A *path* is a sequence of statements in a program, starting at the entry of the program, and ending at the exit of the program. A *path segment* is any subsequence of statements on the path. A *sub-path segment* of a path segment p is a subsequence of statements on p.

Definition 2.13: An input exercises a path, producing an *execution*. If no input can be found to exercise the path, the path is *infeasible*.

Static infeasible path identification is an undecidable problem. Therefore, static analysis will have imprecision: some of the paths identified as faulty might actually be infeasible.

Definition 2.14: *Path conditions*, also called *path constraints*, are a set of control predicates that decide the execution of the path.

Intuitively, path conditions are conditions at branches that a path traverses. An execution would follow a path if all the path conditions are satisfied at runtime. In path-based program testing, we construct program inputs that direct the executions to a desired path.

2.2.1.1 Background on Path-Sensitive Analysis

In dataflow analysis, *sensitivity* describes how the information is handled during the traversal of a program. It is an important measure to distinguish analysis techniques with regard to their precision.

Definition 2.15: *Path-sensitivity* specifies whether a dataflow analysis collects the information with the consideration of program paths. *Path-sensitive analysis* distinguishes the information collected along different paths.

Path-sensitive analysis incorporates flavors of dynamic analysis in that it simulates the executions potentially invoked at the program runtime. As a result, path-sensitive fault detection is more precise and able to provide guidance for fault diagnosis with a sequence of executions that lead to a fault. Meanwhile, since the technique is static, path-sensitive fault detection does not lose the advantages of traditional static analysis, including early reporting of faults as well as a full coverage of program paths and the input space. In path-sensitive fault detection, program facts used to determine faults are collected based on paths, and never merged at the joint points of program control flow. Since not all statically traversed paths can be executed at the runtime, a precise path-sensitive analysis would further remove identifiable infeasible paths to more accurately model dynamic program behavior.

Besides *path-sensitivity*, there are also *flow-sensitivity* and *context-sensitivity*.

Definition 2.16: *Flow-sensitivity* specifies whether the order of the statements is considered in a dataflow analysis. *Flow-insensitive* analysis collects information from a call graph instead of control flow graphs, and the information is collected from procedures without considering the order of the statements. That is, in a flow-insensitive analysis, the information found can be true at any program point in the procedure. *Flow-sensitive analysis*, on the other hand, takes the order of the statements into consideration, and thus the effectiveness of the information is associated with the program points of the procedure.

Definition 2.17: *Context-sensitivity* specifies whether the call history is considered in dataflow analysis. *Context-sensitive* analysis collects information at program points with the consideration of the callers. Global side effects are also considered in that the values of globals are evaluated in the context of a call history.

Path-sensitive analysis considers the order of statements and thus is flow-sensitive. Path-sensitive analysis can be context-sensitive or context-insensitive. An interprocedural path-sensitive analysis records a real call history, and thus is context sensitive; however, a summary based interprocedural analysis can use the path information from procedures in a context-insensitive way.

Traditional iterative dataflow algorithms apply dataflow equations in a flow-sensitive fashion; however, the algorithms apply meet and join operators to merge information, and thus are inherently

path-insensitive. Context-sensitivity is determined by interprocedural propagations in individual dataflow analysis.

2.2.1.2 Related Work on Path-Sensitive Analysis

Path-sensitivity can be achieved using two types of techniques: model checking and dataflow analysis. In model checking, each trace on the software model is examined for correctness. Due to the abstraction, a trace enumerated from the model is often not the exact path from the program, and imprecision can occur. Applying dataflow analysis for paths, dataflow facts propagated from different paths should never be merged at any program point. When a path-sensitive analysis is finished, we report the paths that match a specific fault pattern. For each of the technique, the search of the state space can follow a systematic order, a random sampling or a demand-driven fashion (see Figure 1.2). Based on the above classification, we summarize the representative path-sensitive fault detectors in the state-of-the-art.

In Figure 2.4, the grey boxes are model checkers and the others are dataflow analyzers. From top to bottom, we list the tools in chronological order. At the bottom of the figure, we list the three challenges a path-sensitive static analyzer generally would face, including precision, generality and scalability. Since most of the tools are neither available for use nor report empirical experiences for usability, we are not able to compare their usability. If a tool does not handle any of the challenges, we use an arrow to connect the corresponding box of the challenge and the box of the tool.

In the figure, scalability means whether the analysis can finish with a reasonable path coverage. Most of listed tools manage to finish the analysis. However, Prefix uses a time threshold to terminate with unexplored paths, and thus the technique does not scale with the size of the software. Generality requires the tool to handle a variety of faults, such as both data and control centric faults, without sacrificing scalability and precision. Tools such as ARCHER, ESP, Saturn and MOPS handle the scalability only for a specific type of fault (either buffer overflow or typestate violation), and thus do not meet the requirement of generality [Xie et al., 2003, Das et al., 2002, Xie and Aiken, 2007, Chen and Wagner, 2002]. Precision measures whether the analysis would report high false positive and false negative rates. For example, PRSS randomly explored the search space for faults

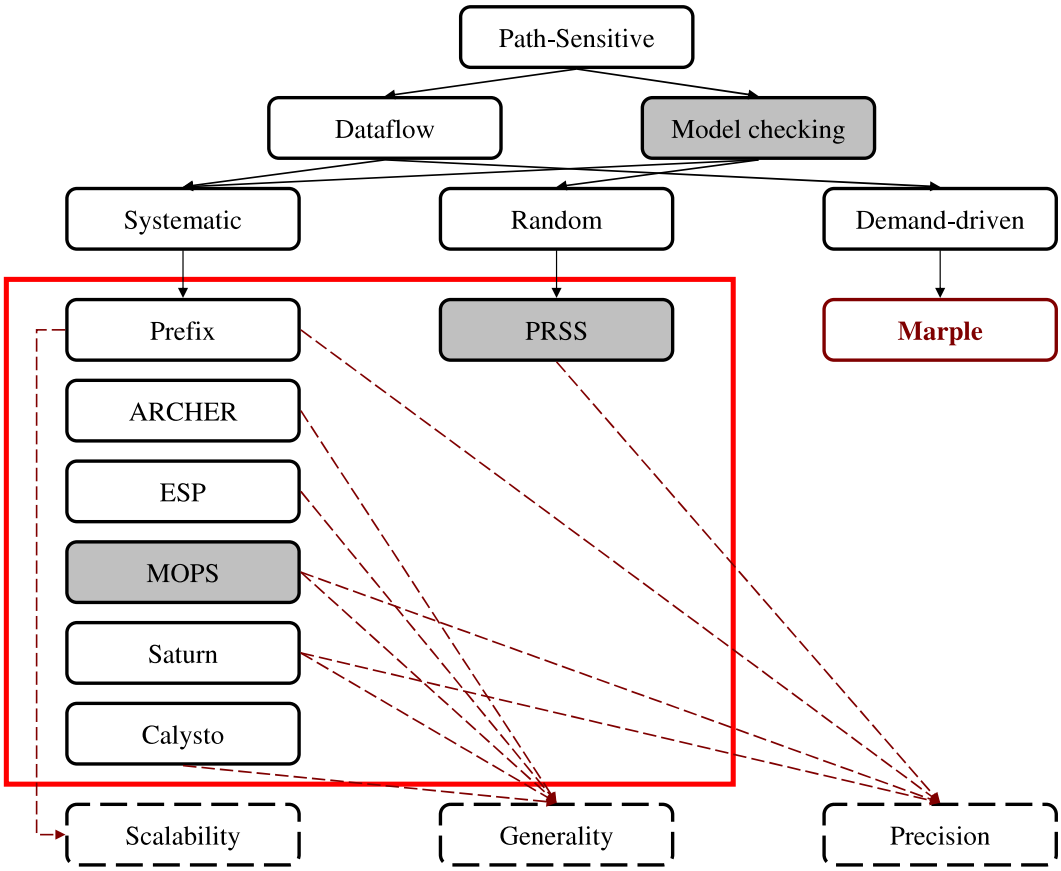


Figure 2.4: Path-Sensitive Analysis: the State-of-the-Art

and can cause false negatives [Dwyer et al., 2007]. None of these fault detectors have shown the scalability and precision to detect both data and control centric faults, as done in Marple.

A detailed comparison for path-sensitive dataflow analysis is shown in Table 2.1. Under *Type of Faults*, we see that Marple is the only one that handles integer faults. 5 out of 7 tools integrate specifications in the analysis. Metal [Hallem et al., 2002] and ESP [Das et al., 2002] provide finite automata for modeling the faults. Prefix [Bush et al., 2000] develops a way to specify library calls. Saturn [Xie and Aiken, 2007] applies a logic programming language to specify summary information at the procedure calls and also inference rules for customizing an analysis. According to the best of our knowledge, none of the above six tools automatically generate a customized analysis from specifications as Marple does.

Tools	Types of Faults			Specification	Path Traversal			Precision		Error Reports
	buf	int	control		exhaustive	path coverage	scalability	path-sensitivity	modeling	
Prefix	×		×	model lib	×	given number	truncation	heuristically merge	ad-hoc	path
Metal			×	automata	×	all	summary	intraprocedurally	dataflow	stmt
ESP			×	automata	×	all	heuristics	heuristically merge	dataflow	path
ARCHER	×			no	×	all (timeout)	summary simple solver	intraprocedurally	linear relation	stmt
Saturn			×	summary	×	all	summary compress Booleans	intraprocedurally	limited bit-accurate	stmt
Calysto			×	no	×	configurable	compact summary	interprocedurally	bit-accurate	stmt
Marple	×	×	×	assertions flow-funcs		relevant	demand-driven caching	interprocedurally	integer,some str,containers	path segment

Table 2.1: Path-Sensitive Dataflow Analysis for Identifying Faults

We also compare the tools in Table 2.1 with regard to the way paths are traversed in the analysis. The comparison on the three metrics under *Path Traversal* shows that Marple is different from the other tools in that we apply a demand-driven algorithm, which allows us to explore only relevant paths, instead of exhaustively along all program paths.

Precision has been compared on the degree of path-sensitivity achieved in the analysis as well as the techniques used to model program facts. The comparison under *path-sensitivity* shows that Calysto and Marple both performed an interprocedural, path-sensitive analysis. Summary based approaches, such as Metal, Saturn and ARCHER do not consider interprocedural path information, and are less precise. ESP applies a heuristic to select the information that is relevant to the faults, while driven by demand, our analysis is able to determine the usefulness of the information based on the actual dependencies of variables, achieving more precision. We model integer computation and some operations of strings and C/C++ containers; compared to bit-accurate modeling technique accomplished by Saturn and Calysto, we are not able to handle integer bit operations; however, the trade-off is a faster analysis.

To report an error, Prefix, ESP and Marple give path information for diagnosis, and Marple provides the path segments that are relevant to a fault. Although the fault detection is path-sensitive, other tools only report a statement where a fault occurs.

2.2.2 Use of Path Information

In the domain of detecting and diagnosing faults, path information is generally used in two ways: 1) to understand fault propagation, and 2) to generate test inputs to trigger faults.

Research in fault propagation has been done for software security [Chen et al., 2003, Ghosh et al., 1998]. To understand the severity of certain types of static faults, Ghosh *et al.* injected faults in programs and dynamically triggered faults to observe their propagation and impact along the execution [Ghosh et al., 1998]. Chen *et al.* discovered that a successful attack performs a set of stages. The finite state machines can be used to model the activities at each stage [Chen et al., 2003]. Similar to our research, both of the above works track the fault propagation along the program paths. However, Ghosh *et al.* obtained fault propagation by running the program, and thus the number of paths that could be explored was limited by the program inputs, while Chen *et al.* manually inspected the exploited paths to understand fault propagation. Besides for software security, fault propagation is also studied for improving software testing. The focus of one effort was to discover how an error can potentially mask another and impact testing coverage [Wu and Malaiya, 1993]. Another study investigated how to propagate an error to the output of the program so that its consequence can be observed [Goradia, 1993].

Techniques for path-based test input generation have three general categories: 1) EXE [Cadar et al., 2006] and KLEE [Cadar et al., 2008] symbolically execute a program along program paths, and generate inputs based on collected symbolic path constraints; 2) SAGE applies trace information and symbolic path constraints to generate test inputs [Godefroid et al., 2007]; and 3) DART [Godefroid et al., 2005], CUTE [Sen et al., 2005], SPLAT [Xu et al., 2008] and CREST [Burnim and Sen, 2008] are concolic testing tools, which use both symbolic and concrete values to generate the test inputs. CREST [Burnim and Sen, 2008] proposes several search strategies to improve the branch coverage for concolic testing. SPLAT [Xu et al., 2008] models buffer operations and determines at runtime whether a buffer overflow can occur at each buffer access; if so, SPLAT generates a test input to trigger the fault. The above techniques all exhaustively explore program paths to generate test inputs, and thus the scalability is an issue. Testing has to give up when a certain number of paths are executed.

The above related work demonstrated the value of program paths for ensuring software security and for improving the productivity of software testing. However, among all the work, the path information is either manually identified or obtained by executing the program. In this thesis,

we developed an approach to statically compute desired path information related to faults. We demonstrated that the automatically identified paths can be used in testing to reduce the state space for test input generation, and faults in a program can be more quickly triggered in path-guided testing [Cui et al., 2011].

2.3 Implementation Support and Benchmarks

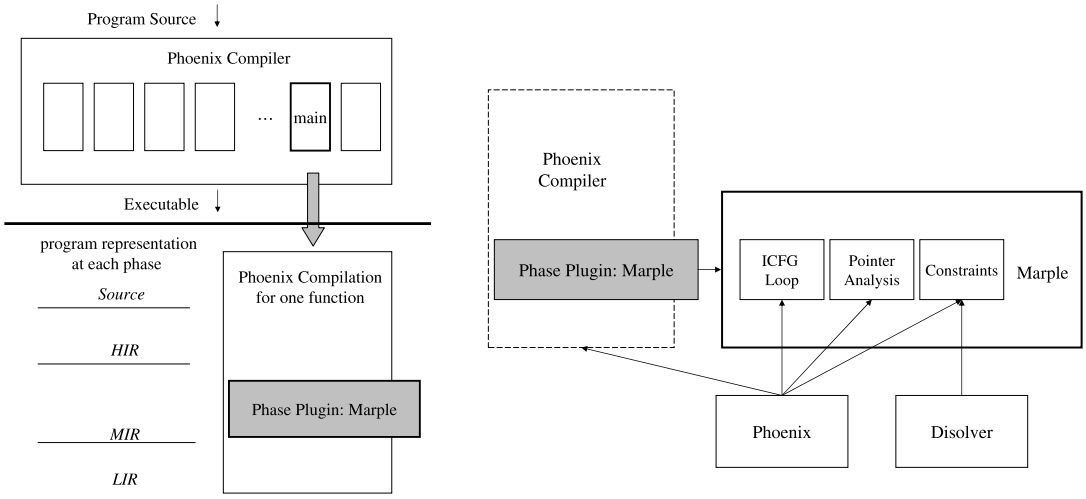
In this section, we provide background related to our implementation and experimentation. In particular, we introduce our experience with the Microsoft Phoenix infrastructure [Phoenix, 2004] and the Disolver constraint solver [Hamadi, 2002], the two external tools we used to build Marple. We also discuss how the benchmarks are selected for conducting experiments.

2.3.1 An Overview of the Microsoft Phoenix and Disolver

Phoenix is a compiler infrastructure developed by Microsoft [Phoenix, 2004]. The infrastructure consists of a Phoenix compiler and a set of libraries that are useful for building customized compiler optimizations and static analysis. As shown in Figure 2.5(a), Marple is built as a phase-plugin to the Phoenix compiler. Phoenix compiles functions of a program one by one via several phases. Intermediate code is generated at phases. During compilation, when an entry of a program is encountered, e.g., main function, and when the Phoenix front end produces an *MIR* (medium level intermediate representation) for the function, Marple is invoked. Marple first calls the Phoenix library to build the ICFG for the program and also to perform an alias analysis; Marple then starts the interprocedural, path-sensitive analysis. During analysis, the Phoenix library is called from time to time, e.g., to help simplify constraints generated in the analysis, or to find the information about certain operands, shown as Figure 2.5(b).

Besides applying Phoenix to simplify constraints, we also apply an external integer constraint solver, the Microsoft Disolver [Hamadi, 2002] for further handling unresolved constraints. Disolver is written in C and was developed at the Microsoft research [Hamadi, 2002]. It takes any numbers of integer constraints, and returns instances if the constraints are satisfiable; if no solutions are found,

we consider that the constraints are never able to be satisfied. The interfaces between Marple and Disolver implement the marshallings and unmarshallings between the Marple and Disolver constraints.



(a) Marple: Phase-plugin to Phoenix (b) Phoenix and Disolver for Marple

Figure 2.5: the Interactions of Phoenix, Disolver and Marple

2.3.2 Phoenix and Disolver for Marple

Here, we give in a detail how Marple is built with the support of Phoenix and Disolver.

2.3.2.1 Intermediate Code

In Phoenix, there exist high-level, medium-level and low-level three types of intermediate representations (HIR, MIR and LIR). During compilation, source code of a program is converted to HIR, MIR, LIR and finally binary executables. At each level, the corresponding analyses and code transformations are performed.

Marple analyzes the MIRs produced by Phoenix. MIR is program-language independent and hardware independent. Loop structures in the code are preserved. Two important differences of MIR and the program source are 1) temporaries are introduced to regulate the instructions. For example, a source level instruction `a = b+c+d` is translated to two MIR instructions `temp=c add`

`d; a = b add temp`. 2) instructions regarding pointer dereference and array subscripts are transformed. For example, the C code `a[b]='x'` is converted to `temp = a subscript b; temp = 'x'` in the MIR.

In our implementation of Marple, we chose to analyze MIRs for two reasons. First, programs written in different languages can be converted to MIR via the front end of Phoenix. Therefore, using MIR as a bridge, Marple is able to analyze programs written in C, C++ and C# code. Second, in Phoenix, many of the typical analyses are implemented for MIR; by applying our analysis also for MIR, we are able to reuse these off-the-shelf analyses, e.g., pointer analysis, in Marple.

2.3.2.2 Modeling Control Flow

Phoenix models the control flow of a program in the ICFG. The challenges of building an ICFG are to handle irregular control flows caused by function pointers, virtual functions, signal handlers and exceptional handling routines. In the version of ICFGs we use, Phoenix handles exceptional handling but not others. We manually resolve some of the function pointers and virtual functions.

Another important control flow analysis is the modeling of the loops. Phoenix provides the basic information about loops such as the loop entries, exits, and back edges. Occasionally (dependent on the patterns of a loop), Phoenix is able to offer more valuable information such as *induction variables*. Induction variables of a loop are variables that get increased or decreased by a fixed amount on every iteration of a loop. Using induction variables, we are potentially able to reason the symbolic updates of a variable in a loop.

2.3.2.3 Modeling Memory: Resolving Aliasing and Handling Aggregates

Pointer analysis determines to which variables or storage locations a pointer refers. It applies before dataflow analysis to determine, for example, whether a definition to a variable occurs through aliasing. Phoenix performs an intraprocedural, flow-sensitive and field-sensitive alias analysis, and provides both *may* and *must* aliasing information.

Scalars are variables in the program that only can hold one value. Scalar types in C, for instance, include `int`, `char`, and `float`. Composite variables, also called *aggregates*, are variables

that can represent a set of scalar values, e.g., array, list, or tree. At the MIR level, Phoenix is able to model a large part of the structures and classes in C and C++. For example, it returns `tree.node` for the element `node` present in the `tree` class, and reports `a[i]` as the $(i+1)^{th}$ elements of array `a`. When a structure is very complex, for instance, in the case of multiple layers of embedded structures, Phoenix will not be able to identify the members of a structure. For example, it reports `a.b.unknown` for the member `a.b.c.d`.

2.3.2.4 Constraints and Algebra Simplification

In Marple, we construct integer constraints for determining faults. In our implementation, the constraints are represented using a small piece of Phoenix MIR code. For example, we write code `_Value(a)>0` to denote the constraint that the value of `a` should be larger than 0. As Phoenix contains an algebra simplification system to optimize its MIR code, by constructing constraints using MIR, we can use this algebra simplification system to simplify our constraints. It should be noted that the capability of the Phoenix's algebra simplification system is limited. For example, Phoenix is not able to process the conjunction or disjunction of multiple constraints. In Marple, we implement some of the algebra rules that Phoenix does not have, and if the constraints still cannot be solved, we send them to an external constraint solver Disolver [Hamadi, 2002] for further evaluation.

2.3.3 Challenges of Using External Tools

One of the greatest advantages of using Phoenix and Disolver is their reliability. By using the off-the-shelf components, we saved a lot of implementation efforts. The tradeoff is that we needed to handle additional challenges to use these tools:

- Challenges of working with ongoing projects: Phoenix and Disolver are two ongoing projects, and the APIs they exported were changing over times. As a result, Marple has to be refactored from time to time to stay compatible with the new interfaces. Another problem is that bugs were introduced in the new versions, which prevent us from using some of our old benchmarks.

- Challenges of working with closed source projects: Both Phoenix and Disolver are closed source with limited documentation, tutorials and supports. We had to face a high learning curve at the beginning. After starting to use the tools, we found that the challenge is to get around the internal bugs or to introduce some desired features. For example, we have designed a study of parallelizing Marple for further performance improvement; however, we found that some of the libraries in Phoenix are not reentrant, and we have to give up the experiments. Also, because source code is not available, we are not able to understand and elaborate the capabilities of the analyses Phoenix provides. For example, we cannot predict when the induction variables of loops can be reasoned by Phoenix or what types of aggregates Phoenix surely handles.

- Challenges of using the Windows platform in academia: In order to be compatible with Phoenix, Marple only analyzes programs that can be compiled by the Windows compilers; however, finding widely used Windows open source programs as benchmarks is more difficult than finding ones implemented for UNIX systems. As a result, extra effort had to be spent to port some of the benchmarks. For the same reason, we were not able to use many of the benchmarks that the communities use to perform comparison experiments.

2.3.4 Benchmarks

To evaluate precision, generality, scalability and usability of our techniques, we collected a set of benchmarks, including the buffer overflow benchmarks from Zitser [Zitser et al., 2004], BugBench from Lu [Lu et al., 2005], SPEC CPUINT2000, legacy open sources of `ffmpeg`, `putty`, `vnc` and `apache`, and a Microsoft game project McCommander [Microsoft Game Studio MechCommander2, 2001]. All of the benchmark programs are written in C or C++, and are managed to be compiled by Phoenix. Benchmarks from Zitser [Zitser et al., 2004] are manually constructed programs. Each program consists of a snippet of faulty code selected from the real-world applications of `BIND`, `sendmail` and `wu-ftpd`. BugBench consists of a set of legacy programs, each of which contains some known faults reported by testers or external users. By examining whether we are able to identify these known faults, we can estimate the false negative rate of our techniques.

SPEC CPUINT2000 is used to compare with other tools for performance as well as the capability of fault detection. The large deployed software are used to evaluate the scalability of Marple. To examine the usability and generality of Marple, we selected the benchmarks that are diverse in the program paradigms, e.g., including both object-oriented and procedure based programs, and also various in programming styles, e.g., produced both via open source projects and Microsoft in-house development.

Chapter 3

The Value of Paths for Detecting and Diagnosing Faults

Although various path-sensitive analyses have been developed [Xie et al., 2003, Das et al., 2002, Xie and Aiken, 2007, Chen and Wagner, 2002], a systematical investigation on the value of program paths for software assurance is still lacking. A fundamental reason is that path information is expensive to compute and therefore precise path information is not always available for large software or for desired program properties.

This chapter answers the questions of why path information is important for determining and understanding faults and what types of path information are desirable. In this research, we evaluated two hypotheses regarding the characteristics of a fault occurred in a program.

Our first hypothesis is that paths with different fault properties can traverse the same program point. Along different paths, the transitions of program states are distinctive; some lead to a fault, while others do not. Even if the fault condition is observed at the same program point along different paths, the severity and root causes associated with each path may be different. The diversity of the paths implies that we need to track information along individual paths to detect faults, and we also need to report faults based on paths, so that manual diagnosis and dynamic tools can take actions accordingly to further process statically reported faults.

Our second hypothesis proposes fault locality. Our insight is that although a whole program path can be long, only a certain part of execution is actually responsible for producing the fault. By focusing on the most relevant information on a path, we can save costs for determining and

diagnosing faults. In this chapter, we identify a six-element set of path information as most relevant to a fault. We also explain how to represent and use this information in fault diagnosis.

In our experiments, we validate the first hypothesis by showing that the precision of fault detection can be improved if we distinguish information from different paths, and the types of paths we defined actually do exist in real-world programs. We also experimentally demonstrate that for a set of given faults, the path segments that are responsible for faults only traverse 1-4 procedures on average, manifesting locality.

3.1 Program Points v.s. Paths in Fault Detection and Diagnosis

Intuitively, a program fault is developed along a sequence of execution; when a particular program point is reached, we observe that the program state at the point does not conform to the property as expected (see Definition 2.1). This abnormal condition can manifest immediately at the program point, e.g., causing the program to crash, or the corrupted program state can continue to propagate and manifest later along the execution.

3.1.1 Why Are Paths Important for Fault Detection and Diagnosis

Since the fault is produced after executing a sequence of instructions rather than at a specific instruction, we are not able to statically predict the fault by only matching a syntactic code pattern to each program statement. For the same reason, we should not use a summary of path information at a program point to determine faults. Instead, to achieve a precise fault detection, we need to track the transitions of program states along individual paths to determine if any violation can occur.

Using an example from `Sendmail-8.7.5`, we show that false positives can be avoided when we distinguish information from different paths in fault detection. In Figure 3.1, the `strcpy()` at node 5 is not a buffer overflow. However, a path-insensitive analyzer would merge the facts `[buf = xalloc(i+1), i>=sizeof(buf0)]` from path $\langle 1-3 \rangle$ and `[buf = buf0, i<sizeof(buf0)]` from path $\langle 1,2,4 \rangle$, and get the result `[buf = xalloc(i+1)` $\vee$ `buf = buf0]` at node 5 (symbol $\vee$ represents the union of the two dataflow facts); since `buf0` is a buffer with a fixed length, and `a.q_user`

gets the content from a network package, the analysis identifies node 5 as vulnerable. Whereas, path-sensitive analysis can distinguish that `buf` is set to be `buf0` only along path $\langle 1,2,4\rangle$, while along this path, the length of `a.q_user` is always less than the size of `buf0`, and thus the buffer is safe. In our experiments, our path-sensitive analyzer is aware of the impact of the bounds checking at node 2 and successfully excluded this false positive; however, a path-insensitive detector, Splint [Evans, 1996], incorrectly identified it as a fault.

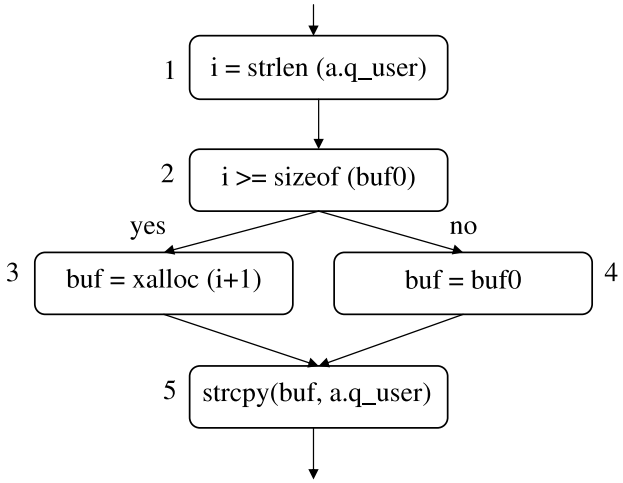


Figure 3.1: An Example from Sendmail-8.7.5

Not only does detecting faults need a consideration of paths, but also reporting a fault should be path-based. Many static tools report faults in terms of the program point where the property violation is perceived. To understand the fault, the code inspector has to manually explore the paths across the point. Among these paths, some might be safe or infeasible, not useful for determining root causes. Even if a faulty path is found quickly, additional root causes may exist along other paths. Without automatically computed path information for guidance, we potentially miss root causes or waste efforts exploring useless information, experiencing an ad-hoc diagnostic process.

Consider a code snippet from `wu-ftpd-2.6.2` in Figure 3.2. The `strcat()` statement at node 8 is vulnerable to a buffer overflow; however, among the paths across the statement, path $\langle 1,2,4-6,8\rangle$ is always safe, while path $\langle 1,2,4-8\rangle$ is infeasible. Only path $\langle 1,3-8\rangle$ can

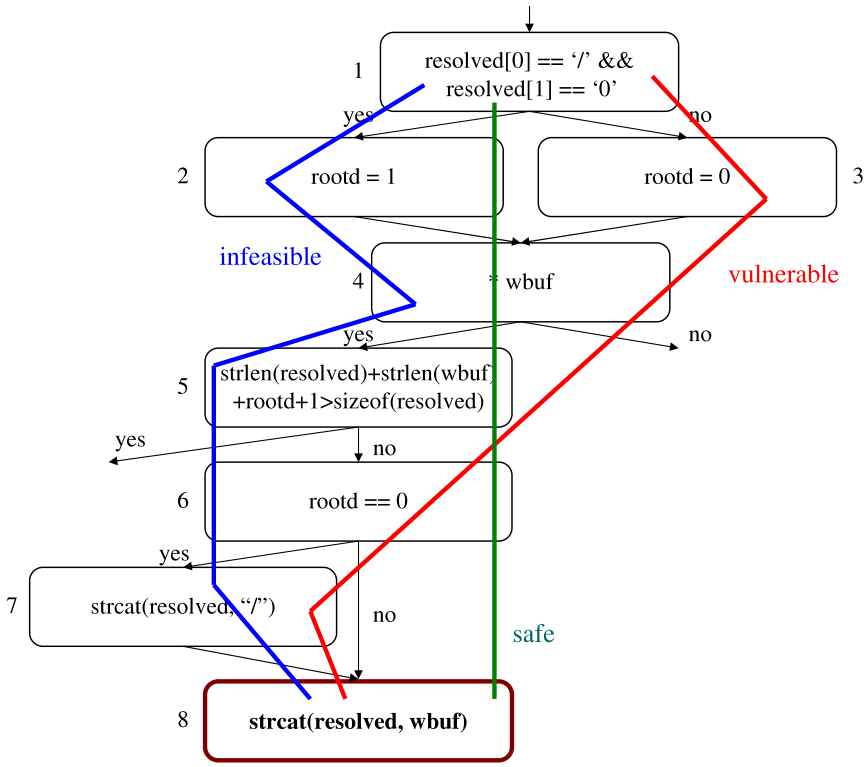


Figure 3.2: Different Paths Cross a Buffer Overflow Statement

overflow the buffer with a $'\backslash 0'$. If a tool only reports node 8 as an overflow, the code inspector may not be able to find this vulnerable path until the two useless paths are examined.

In another example, we show that path information also can help correct the faults, as the root cause of a fault can be path-sensitive; that is, more than one root cause can impact the same faulty statement and be located along different paths. Consider an example from `Sendmail-8.7.5` in Figure 3.3. There exist two root causes that are responsible for the vulnerable `strcpy()` at node 5. First, a user is able to taint the string `login` at node 5 through `pw.pw_name` at node 10, and there is no validation along the path. However, only diagnosing path $\langle 9, 10, 1-5\rangle$ is not sufficient for fixing the bug, as another root cause exists. Due to the loop at nodes $\langle 6, 7\rangle$, the pointer `bp` might already reference an address outside of the buffer `buf` at node 5, if the user carefully constructs the input for `pw.pw_gecos`. This example shows that diagnosing one path for a fix is not always sufficient to correct the fault. Paths containing different root causes should be reported.

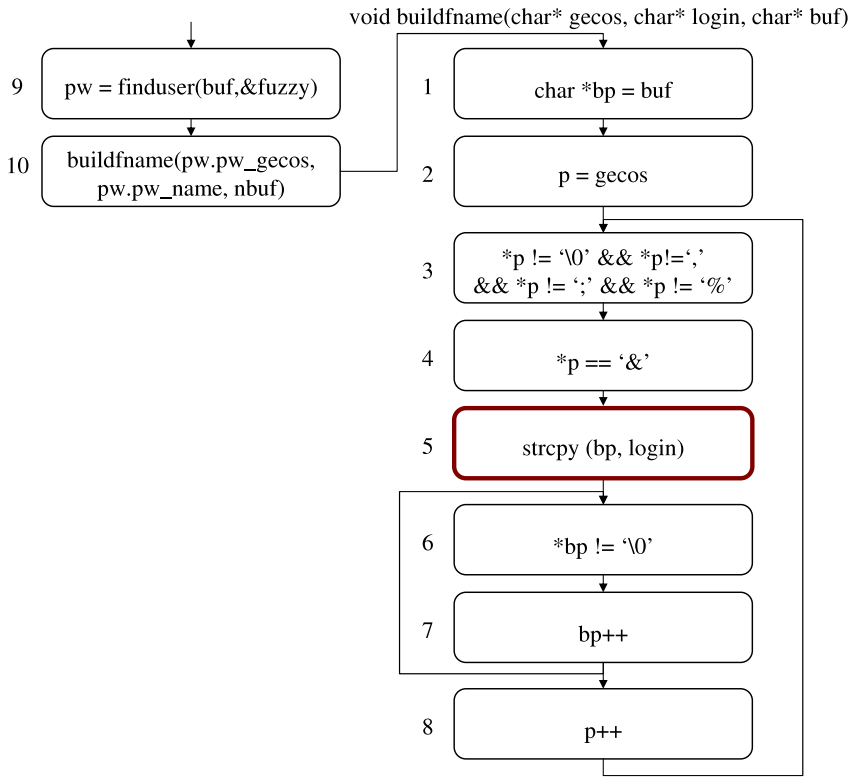


Figure 3.3: Path-Sensitive Root Causes

3.1.2 Path Classification

Knowing the importance of distinguishing paths in fault detection and diagnosis, we develop a path classification to define the types of paths that are potentially useful. The classification includes the following four categories of paths:

Infeasible: Infeasible paths can never be executed. A path that statically is determined as faulty but actually infeasible is not useful for understanding the root cause or for guiding dynamic tools. Although we are not able to prune all of the infeasible paths in a program statically, research [Bodik et al., 1997b] showed that 9–40% of the branches in a program exhibit correlations, and at compile time, we are able to identify infeasible paths caused by these branch correlations. Therefore, detecting these infeasible paths statically is important to achieve more precise fault detection.

Safe: Faults are only observable at certain program points, which we call *potentially faulty points*, where violation conditions can be determined. For example, at a buffer access, we can determine whether a buffer overflow occurs. However, not every path that traverses such a program point is faulty. A proper bounds checking inserted before a buffer access can ensure the safetyness of the buffer. Paths that execute a potentially faulty point but always guarantee to be safe regardless of the input are called *safe* paths.

Faulty with different levels of severities or distinct root causes: When a fault occurs, the severity of the fault, or the root cause of the fault may be different along different paths, even the fault condition is perceived at the same program point. In static analysis, we are able to collect information to predict the severity of a fault, and also distinguish paths that potentially contain distinct root causes. For example, we are able to determine the severity of a buffer overflow by knowing who can, and what contents are allowed to, write to the buffer. A buffer overflow written by an anonymous network user is certainly more dangerous than the one that only can be accessed by a local administrator. A buffer overflow that can be manipulated by any user supplied contents is more serve than the one written by a constant string. Based on the severity, we can prioritize the buffer overflow warnings reported by static analysis. To distinguish paths with different root causes, we highlight statements along a path that are responsible for producing the fault. Two paths with distinctive sequences of impact statements likely contain different root causes.

Don't-Know: Besides the above three categories, there are also paths whose safety cannot be determined statically due to the limited power of static analysis, which we call *don't-know* paths. We further classify them based on the factors that cause them don't-know. The idea is that instead of ad-hoc guessing the values of don't-knows and continuing the analysis with unpredictably imprecise results, we record the locations of these don't-knows as well as the reasons that cause the don't-knows. In this way, code inspectors can be aware of them. Annotations or controlled heuristics can be introduced to further refine the static results if desired. In addition, other techniques such as testing or dynamic analysis can be applied to address the unknown warnings. We summarize the following five don't-know factors:

1. Library calls: The source of library calls is often not available until link time. We model a

set of library calls that are frequently encountered and identify others that might impact the determination of a path as don't-know.

2. Loops and recursive calls: The iteration count of a loop or recursive call cannot always be determined statically. Loops can be classified into three categories: loops that have no impact on the determination of a fault, loops where we can reason their symbolic summary related to the determination of a fault, and also loops where we cannot determine their impact on the fault. The third type of loops is considered as don't-know.

3. Non-linear operations: The capacity of a static analyzer is highly dependent on the constraint solver, since the program property under examination will be finally converted to constraints. Non-linear operations, such as bit operations, result in non-linear constraints which cannot be well handled by practical constraint solvers.

4. Complex pointers and aliasing: Pointer arithmetic or several levels of pointer indirection challenges the static analyzer to precisely reason about memory, especially heap operations. Imprecision of *points-to* information also can originate from the path-insensitivity, context-insensitivity or field-insensitivity of a particular alias analysis used in the detection. In our framework, we apply a pointer analysis integrated in the Microsoft Phoenix framework [Phoenix, 2004] to resolve memory indirection and aliasing, and report those that cannot be handled as don't-know.

5. Shared globals: Globals shared by multiple threads or by multiprocesses through shared memory are nondeterministic.

3.1.3 Experimental Results

Here, we provide two sets of experimental data to demonstrate that: 1) the path types we defined can be found in real-world programs and 2) a path-sensitive analysis is more precise than a path-insensitive analysis.

3.1.3.1 Existence of Path Classification

We selected 9 benchmark programs from BugBench [Lu et al., 2005] and the Buffer Overflow Benchmark [Zitser et al., 2004]. Each benchmark is shipped with a bug report, indicating where a known buffer overflow is located. In the experiment, we take the vulnerable statement, and determine the types of paths that cross the given statement. For buffer overflow, we classify paths as faulty, safe, don't-know and infeasible. Based on the severity of a faulty path, we further distinguish it as *vulnerable* or *overflow-user-independent*: along vulnerable paths, user inputs can control the overflowed buffer, while along overflow-user-independent path, the buffer only can be overflowed with a constant string.

We apply Marple [Le and Soffa, 2008] to determine the types of paths across a given buffer overflow statement. Our experiments consists of two steps. In the first step, we compute paths for a known buffer overflow statement in a benchmark program without considering infeasibility of paths. We then integrated our infeasible path detection module to check the impact of the infeasible paths on the fault detection.

We summarize the identified path types in Table 3.1. Under *Path Types*, we list the number of vulnerable(Vul), overflow-user-independent (CNST), don't-know(UnK) and safe(Safe) paths computed for the given buffer overflow. We mark *yes* under Column *Inf* if infeasible paths are detected in the part of the code where the analysis for path classification can reach [Bodik et al., 1997b]. Our results show that all five types of paths exist in the benchmark programs. Six of nine programs contain vulnerable paths, and two programs have don't-know paths due to the external library. One program has overflow-user-independent paths. Seven out of nine programs have safe paths. Without our paths detection, the code inspectors might explore safe paths which will not be successful in finding the vulnerability. For the program *bc-1.06*, the total number of overflow-user-independent paths is very large and we ran out of memory when we print the paths. Actually, the number of paths is not important because it is not necessary for a code reviewer to inspect every path for diagnosis. In Marple, users can specify the number of paths to be outputted and then after fixing them, they can check if vulnerable paths through the faulty statement still exist.

In Columns *Vul/Vul', CNST/CNST', UnK/UnK'* and *Safe/Safe'*, we use the notation $'$ to indicate

Table 3.1: Different Types of Paths can Cross a Buffer Overflow Statement

Bechmark	Size (kloc)	Path Types				
		Inf	Vul/Vul'	CNST/CNST'	UnK/UnK'	Safe/Safe'
polymorph-0.4.0	0.9	yes	90/90	0/0	0/0	84/0
ncompress-4.2.4	1.9	yes	288/288	0/0	0/0	2016/0
man-1.5h1	4.7	yes	16/16	0/0	0/0	24/24
gzip-1.2.4	5.1	no	1/1	0/0	0/0	0/0
bc-1.06	17.0	yes	0/0	>50,000/>50,000	0/0	>30,000/>30,000
squid-2.3	93.5	yes	0/0	0/0	8/4	4/2
wu-ftp: mapping-chdir	0.2	yes	4320/4320	0/0	0/0	18624/18624
sendmail: ge-bad	0.9	no	48/48	0/0	0/0	648/648
BIND: nxt-bad	1.3	no	0/0	0/0	2/2	0/0

the path numbers after integrating infeasible path detection. Among the 9 programs, we identified infeasible paths for 6 programs at the code relevant to the given fault. Using the infeasible path information, the number of safe paths in three programs and the number of unknown paths in one program are reduced. For example, for *squid-2.3*, 4 out of 8 don't-know paths are actually infeasible. Diagnosing this overflow statement, we should avoid exploring the 4 infeasible paths.

3.1.3.2 Path-Sensitivity in Fault Detection

In this experiment, we compared the fault detection results reported from Marple [Le and Soffa, 2008] and Splint [Evans, 1996], and studied the impact of path-sensitivity on precision of detection results. From our benchmark set, we found five programs that can be successfully analyzed by Splint, listed in the first column of Table 3.2. The first three are from BugBench [Lu et al., 2005], and the last two are from the buffer overflow benchmark [Zitser et al., 2004].

Table 3.2: Comparison of Splint and Marple

Benchmark	Size(kloc)	T_m	T_s	$(V \cup O) \cap T_s$	$U \cap T_s'$
ncompress-4.2.4	1.9	24	14	1/11	7/5/8
gzip-1.2.4	5.1	21	95	8/2	15/3/84
bc-1.06	17.0	110	133	2/4	72/28/105
wu-ftp:mapping-chdir	0.2	6	6	4/0	2/1/0
sendmail:ge-bad	0.9	6	8	2/2	3/1/5

In Table 3.2, Column T_s presents the total number of warnings Splint generates for buffer overflow. Column T_m gives the total number of statements where Marple found that the paths of vulnerable, overflow-user-independent or don't-know go through. Comparing these two columns, we

discovered that even if we do not use any further techniques such as heuristics or modeling of library calls to remove don't-knows, Marple generated less warnings, except for the benchmark `ncompress-4.2.4`. Splint reported 10 less warnings than Marple on this benchmark because it missed 11 statements we identified as overflow. We manually inspected the warnings missed by Splint, and found that these 11 overflows are all real buffer overflows and the first buffer overflow consecutively causes the 10 other overflows on 3 different buffers.

The second column $(V \cup O) \cap T_s$ lists the intersection of statements containing paths of overflow-input-independent and vulnerable reported from Marple and the overflow messages generated by Splint. The number before "/" is the number of statements that are listed in both Splint and Marple results, while the number after "/" is the total number of confirmed overflows generated by Marple but missed by Splint. Column $U \cap T_s'$ compares our don't-know set, U, with the warning set Splint produced excluding the confirmed overflows, annotated as T_s'. In each cell, we present three numbers separated by "/". The first number is the number of statements listed in U but not reported by T_s'. The second number counts the elements in both sets. The third number reports the number of statements from T_s', but not in U. We present a summary of the data from the last two columns in Figure 3.4.

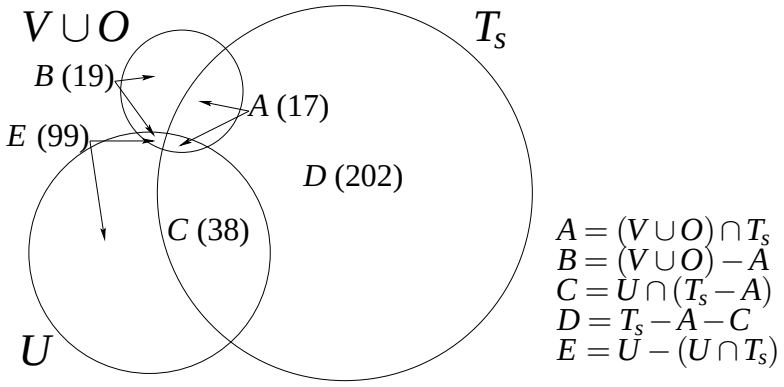


Figure 3.4: Summary of Comparison

The diagram in Figure 3.4 shows that for the 5 programs listed in Table 3.2, Splint and Marple identified a total of 17 common overflows (see set A in Figure 3.4), and Marple detected 19 more flaws that Splint did not report (B). There are 38 warnings both reported by Splint and the don't-know set from Marple (C), and thus these statements are very likely to be an overflow. There are a

total of 202 warnings generated by Splint but not included in our conservative don't-know set (*D*). We manually diagnosed some of these warnings including all sets from `ncompress-4.2.4` and `Sendmail`, 10 from `gzip-1.2.4` and 10 from `bc-1.06` that belong to *D*; we found that all of these inspected warnings are false positives. The number of statements that are in our don't-know set but not reported by Splint is 99 (*E*), which suggests that Splint either ignored or applied heuristics to process certain don't-know elements in the program. In a short summary, our comparison shows that Marple is able to find more faults than Splint and report less false positives.

Limitations. Path-sensitivity is not the only factor that can impact the precision of the analysis. Therefore, we should not conclude that the 202 additional likely false positives reported by Splint are all due to path-insensitive analysis. We inspected several warnings from this set, and found that path-sensitivity is the factor that causes some of the false positives, but not all.

3.2 Selecting and Representing Path Information

Besides distinguishing path types, we also identify information on a path that is potentially useful. We hypothesize that although a program path can be long, faults manifest locality and only a sequence of statements along a path are actually responsible for producing the fault. We thus should focus on the most relevant information along the particular sequence for fault detection and diagnosis.

3.2.1 A Set of Useful Path Information

We identify the following six elements as the most relevant to determine and diagnose a fault on a path: *potentially faulty point*, *property constraint*, *impact point*, *property impact*, *shortest faulty path segment* and *path conditions*. Path conditions are constraints that ensure the execution would follow the path (see Definition 2.14). The other five elements are about faults, defined as follows.

Suppose *P* is a program property and *p* is a program path.

Definition 3.1: If there exists a program point *s* along *p*, at which the violation of *P* can be observed, we say *s* is a *potentially faulty point*.

P holds for path *p* if and only if all executions of *p* satisfy the *property constraints*; *P* is violated if and only if there exists an execution of *p* that does not satisfy the *property constraints*.

Definition 3.2: *Property constraints* defines conditions on the program state at the potentially faulty point.

At source level, given a type of fault, we can pinpoint certain types of statements as potentially faulty points. For example, in a program, the potentially faulty points for buffer overflow are statements that implement the buffer access.

Definition 3.3: Program points on a path that contribute to the production of a fault are *impact points*.

Definition 3.4: At an impact point, any change of the program state that is related to the production of property constraints is called a *property impact*.

Mapped to the program source, the impact points of a fault are a slice of statements along the path that determines the outcome of the property constraints at the potentially faulty point. To statically determine a fault, we need to identify the types of statements that potentially impact points of a fault, and we also need to know changes of the program state at these statements.

Definition 3.5: A *faulty path segment* is the path segment that contains all of the impact points and the potentially faulty point of a fault. The faulty path segment is *shortest* if any sub-path segment is not a faulty path segment.

In Figure 3.5, we summarize the six elements. In the figure, PFS is a potentially fault point; i_1, and i_2 are impact points; and s_1, s_2 and s_3 are program states related to the property constraints at (i.e., right before executing) i_1, i_2 and PFS. The transition between s_1 and s_2 is the property impact at i_1, and the transition between s_2 and s_3 is the property impact at i_2. If a fault is determined as the violation of a safety constraint, the impact points occur before the potentially faulty point along the execution. The shortest faulty path segment *p* is between the first impact point and the potentially faulty point, and *c* is the path condition on the path segment. If a fault is related to a liveness constraint, the shortest faulty path segment is between the potentially faulty point and the last impact point, shown in the rectangle at the right corner of the figure.

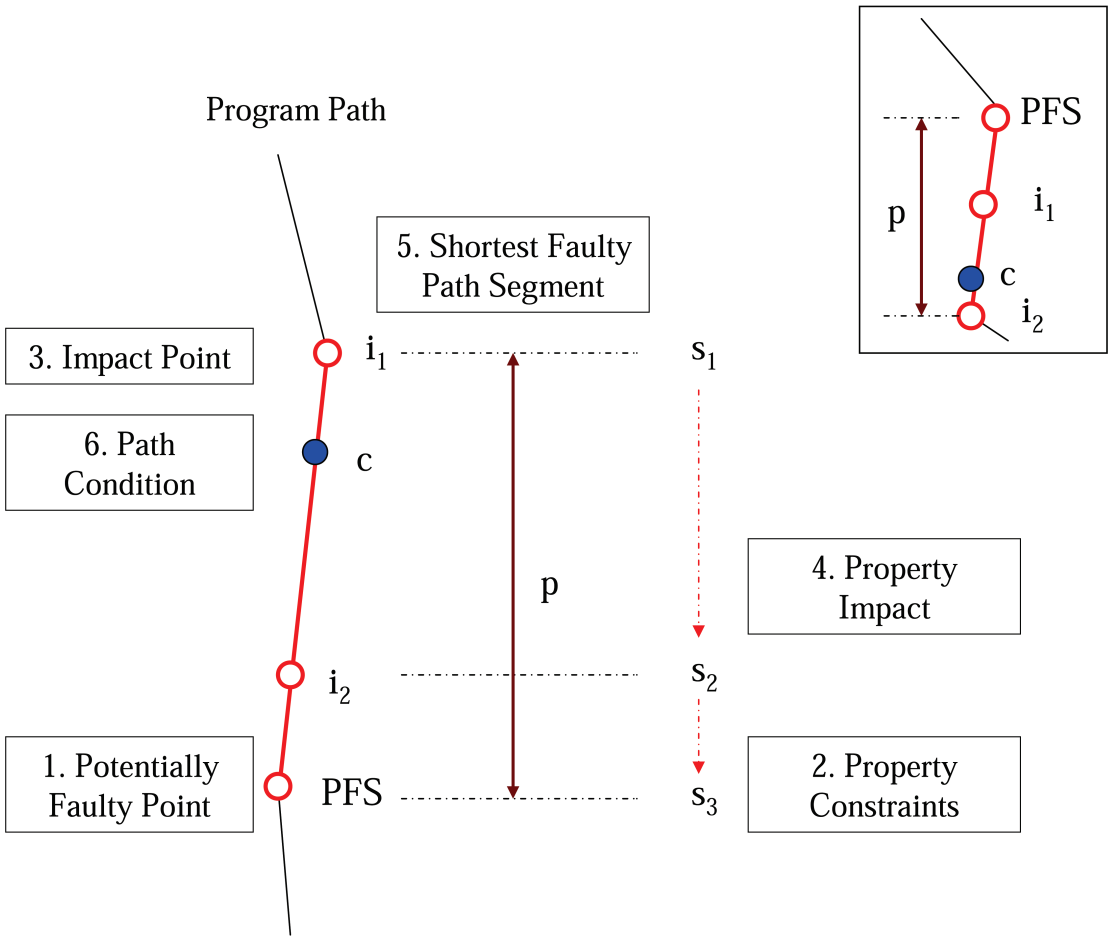


Figure 3.5: Identifying Useful Path Information: the Six Elements

3.2.2 Representing Path Segments Using Path Graphs

There potentially exists a number of faulty path segments. To report these path segments, it is not always feasible to exhaustively enumerate them. In one approach, we can select one path segment to report a fault, randomly or based on the structure of a program, e.g., the shortest path segment; however, the selected path may be a false positive, or too complicated to be understood in fault diagnosis. Sometimes, multiple root causes can exist along different paths, and we have to diagnose more than one path to ensure the correctness of the fixes. Ideally, we should specify all the path segments reported from static analysis in a representation, so that the users can decide how many or what path segments to use. We develop *path graphs* to serve the purpose.

Definition 3.6: Suppose we have a set of path segments $S = \{p_i\}$ on an ICFG $G = (N, E)$, where $p_i = \langle n_{i1}, n_{i2}, ...n_{ik} \rangle$, and $e_{ij} = \langle n_{ij}, n_{ij+1} \rangle \in E$. We denote the set of the statements on a path segment as $N_i = \{n_{ij} | 1 \leq j \leq k\}$, and the set of edges along the path as $E_i = \{e_{ij} | 1 < j \leq k\}$. A *path graph* for a set of path segments S is an annotated graph $G_S = (N_S, E_S)$, where $N_S = \bigcup N_i$ and $E_S = \bigcup E_i$. Each edge of the graph is annotated, specifying which paths contain the edge.

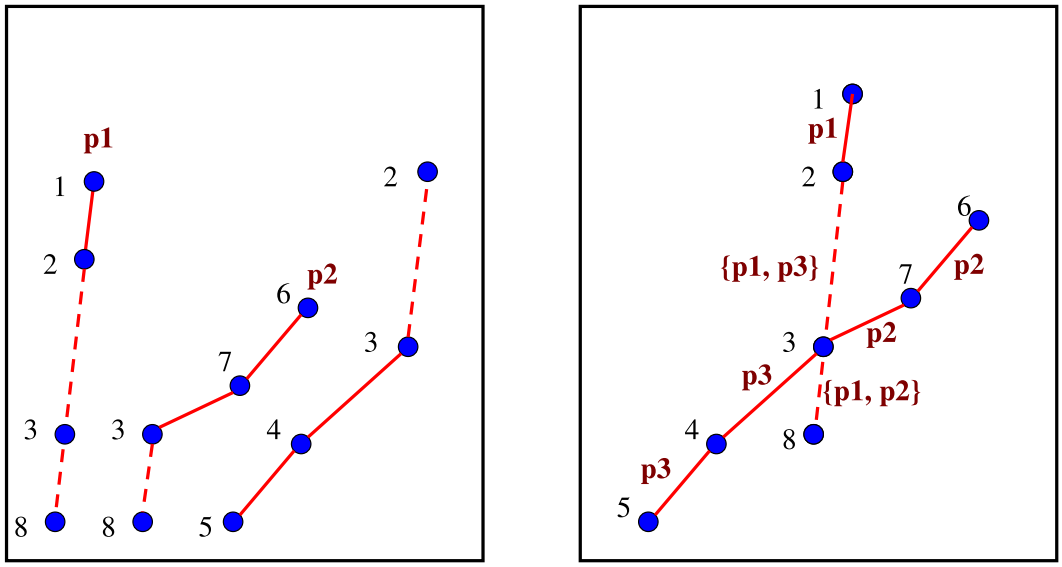


Figure 3.6: Using Path Graph to Represent a Set of Paths: dash lines are shared edges for different paths

In Figure 3.6, we give an example, where a set of path segments are shown in the left, and the path graph that represents the set is shown in the right. The three path segments are: $p_1 : \langle 1,2,3,8 \rangle$, $p_2 : \langle 6,7,3,8 \rangle$, and $p_3 : \langle 2,3,4,5 \rangle$. In the path graph, each edge is marked with a set of path identifications. For example, only path p_1 contains edge $\langle 1,2 \rangle$ but not others; thus path identification p_1 is marked on the edge. Among the edges, edge $\langle 2,3 \rangle$ shared by p_1 and p_3, and $\langle 3,8 \rangle$ shared by p_1 and p_2. Thus, the annotations for the two edges are the set of two path identifications. For each fault we identified, we report a set of path graphs, each of which represent a group of path segments of the same type. For example, paths with different root causes are separated into different path graphs, and we therefore can diagnose one path from a group to ensure all the root causes are considered.

Table 3.3: The Length of the Path Segments Computed for a Given Buffer Overflow

Bechmark	Average Path Size	
	# P/#P'	# B/#B'
polymorph-0.4.0	2.7/2.5	19.0/19.0
ncompress-4.2.4	2.0/2.0	29.3/27.8
man-1.5h1	1.8/1.8	14.3/14.3
gzip-1.2.4	3.0/3.0	5.0/5.0
squid-2.3	1.0/1.0	6.7/6.8
wu-ftp: mapping-chdir	3.8/3.8	33.6/33.6
sendmail: ge-bad	2.0/2.0	35.5/35.5
BIND: nxt-bad	2.0/2.0	23.5/23.5

For each path graph, either the entry (liveness property) or exit (safety property) is the potentially faulty point.

3.2.3 Experimental Results

We provide the experiment data that demonstrate the fault locality. In this experiment, we took the 9 benchmark programs listed in Table 3.1 (see Section 3.1.3), and computed the length of path segments explored to determine path classification for the given overflow statement. In Table 3.3, we report the average length of the path segments in terms of the number of procedures (not including library calls) and the number of basic blocks that are traversed by the paths. Under *#P/#P'*, we give the procedure counts before (the first number in the column) and after (the second number) the infeasible path module was invoked. Similarly, under *#B/#B'*, we report the block counts before and after considering the impact of path feasibility.

The experimental results show that the path segments that are relevant to a buffer overflow contain about 1–4 procedures on average, manifesting locality. In most of the benchmarks, the faults can be determined by inspecting 2-3 procedures, which implies that an interprocedural analysis is required to identify these faults. The experimental data also show that the number of basic blocks is not always proportional to the number of procedural calls. Inspecting the results, we found that the path segments computed for *sendmail* are actually longer and more complex than the path segments computed for *gzip*, though the path segments from *sendmail* are 1 procedure shorter than the segments from *gzip*. Comparing the results from *# P* and *# P'*, and from *# B* and *# B'*, we found

that the impact of path feasibility on the length of path segments is not significant.

3.3 Conclusions

We have shown in this chapter that path information is valuable for detecting and diagnosing faults, particularly in the following three aspects:

- Path-sensitive analysis is more precise than path-insensitive in identifying faults, as the information needed to determine the property is not merged at branches, and the identifiable infeasible paths can be removed;
- Path information guides the manual diagnosis to follow only faulty paths; meanwhile, paths that differ in severity and root causes can be distinguished; and
- Path segments provide for efficient fault detection and diagnosis.

Based on the potential scenarios of applying path information, we develop a path classification, consisting of types of infeasible, safe, faulty with various severities and distinctive root causes, as well as don't-know. We also identify information on a path that is relevant to determine and understand a fault. This chapter clarifies the goals and motivations of the thesis. In the next chapter, we develop techniques to automatically compute path information identified above.

Chapter 4

Identifying Faulty Paths Using Demand-Driven Analysis

In this chapter, we present an innovative technique that statically identifies the paths along which a fault occurs in a program. We classify program paths that cross a potentially faulty point. To further focus the code inspectors' attention, we report shortest path segments that are relevant to a fault. The scalability of path-sensitive analysis is addressed using a demand-driven analysis. Our insight is that code is not equally faulty over the software. A fault can only occur at certain program points, and only statements that possibly update the property constraints of a fault are relevant to the vulnerability. Therefore, in fault detection, our focus is on the path segments starting from the entry of the program to a potentially faulty point. Only statements that can reach the potentially faulty point should be examined to determine the fault.

In this chapter, we used buffer overflow detection as a case study to evaluate the techniques. In our experiments, we reported a total of 71 buffer overflows over 8 benchmark programs, 14 previously reported and 57 not reported overflows. We demonstrated the scalability of our tool through successfully analyzing a Microsoft online XBox game with over 570,000 lines of code within 35.4 minutes. We also compared our analysis with several existing detectors in terms of precision of the fault detection and speed of the analysis.

4.1 The Challenges

First, we identify challenges of applying a demand-driven analysis to detect paths that contain a particular type of fault.

4.1.1 Applying a Demand-Driven Analysis

In demand-driven analysis, a demand is modeled as a set of queries originating at a statement of interest. For example, applying a demand-driven analysis to determine constants, the query is whether a certain variable in the program is a constant. To identify branch correlation, the query is whether the branch can always be evaluated as true or false.

Applying demand-driven analysis to detect faults, our challenge is to determine the contents and resolutions of a query which can report a fault condition. In addition, we need to decide where in a program a query should be constructed, in which direction the query should be propagated, and when the propagation of the query should be terminated. Also dependent on the contents of the query, we need to identify the potential locations in the source code where the information can be collected for resolving a query, and also the rules to update the query.

4.1.2 Achieving Path-Sensitivity

To achieve path-sensitivity in a demand-driven analysis, we still face some challenges of a traditional path-sensitive analysis. For example, we need to make decisions on how a branch, loop and procedure call should be traversed, and how the low level details of the program source code should be handled, such as pointer aliasing or library calls.

In addition, due to applying a demand-driven analysis, we no longer select the program paths purely based on the structure of the program, and instead, we need to consider the dependency relationships between the demands and the information available in the source code to determine the path traversal algorithm. Accordingly, the strategies of storage and reuse of intermediate results as well as the policies for terminating the analysis need be designed, as they will also be different from traditional exhaustive path-sensitive analysis.

4.2 An Overview of the Analysis

In this section, we provide an overview of our analysis. We first introduce the components and workflow of the analysis. We then use an example to intuitively explain how the analysis works to identify faults. Finally, we show how the analyzer can be used in practice.

4.2.1 The Components and Workflow

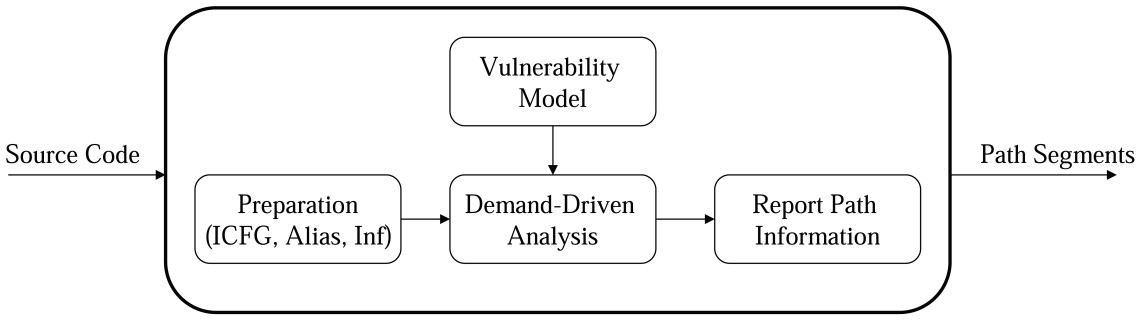


Figure 4.1: Four Components

The analysis takes program source code as input and reports path segments of faults. As shown in Figure 4.1, the analyzer consists of four components. The *Preparation* module implements the initialization routines required before we perform a demand-driven analysis for fault detection. The preparation tasks include: building an ICFG for the program, determining aliasing relationships for the pointers, and identifying infeasible paths. The *Demand-Driven Analysis* module encapsulates the fault detection algorithm. In the analysis, we first construct queries as to whether each potentially faulty point in a program is safe. Starting from where the query is raised, we propagate it forward or backward (depending on the type of fault we detect) along the control flow of the program. Dependent on the contents of the query, symbolic values, ranges or taint information are collected from the program source to resolve the query. The analysis terminates when the query is resolved as safe, faulty, don't-know or infeasible. The *Vulnerability Model* module interacts with the analysis to supply information about the type of fault we aim to detect. The *Report Path Information* module returns the analysis results based on a user required format.

4.2.2 An Example

In Figure 4.2, we use integer faults and null-pointer dereferences as examples to explain how our analysis works to determine faults. In the figure, an integer signedness error occurs at node 11. In the first step, the analysis performs a linear scan and identifies node 11 as a potentially faulty statement, because at node 11, a signedness conversion occurs for integer x to match the interface of *malloc*. We raise a query [*Value(x)* $\geq$ *0*] at node 11, indicating for integer safety, the value of x should be non-negative along all paths before the signedness conversion. The query is propagated backwards to determine the satisfaction of the constraint. At node 10, the query is first updated to [*Value(x)*8* $\geq$ *0*] via a symbolic substitution. Along branch $\langle 8,7\rangle$, the query encounters a constant assignment and is resolved to [$1024 \geq 0$] as safe. Along the other branch $\langle 8,6\rangle$, the analysis derives the information $x \leq -1$ from the false branch, which implies the constraint [*Value(x)*$\geq$ *0*] is always false. Therefore, we resolve the query as unsafe. Path segment $\langle 6,8,10,11\rangle$ is reported as faulty.

Null-pointer dereferences also can be identified in a similar way. Here, our explanation focuses on how infeasible paths are excluded for better precision. In our analysis, identified infeasible path segments are marked on the ICFG, as ip_1 and ip_2 shown in Figure 4.2. To detect the null-pointer dereference, the analysis starts at a pointer dereference discovered at node 13. Query [*Value(p)* $\neq$ *NULL*] is constructed, meaning the pointer p should be non-NULL before the dereference at node 13 for correctness. At branch $\langle 13,12\rangle$, the query encounters the end of the infeasible path and records ip_1 in progress. Along one path $\langle 13,12,9\rangle$, the propagation no longer follows the infeasible path and thus the query drops ip_1. The query is resolved as safe at node 9 because *malloc* implies a non-NULL p (assuming memory allocation succeeds here). Along the other path $\langle 13-10\rangle$, no update occurs until the end of ip_2 is met at node 10. The query thus records ip_2 in progress. When the query arrives at branch $\langle 5,4\rangle$, the start of ip_1 is discovered, showing the query traverses an infeasible path. The analysis terminates. Similarly, the propagation halts at branch $\langle 5,3\rangle$ for traversal of ip_2. The analysis reports node 13 as safe for null-pointer dereference.

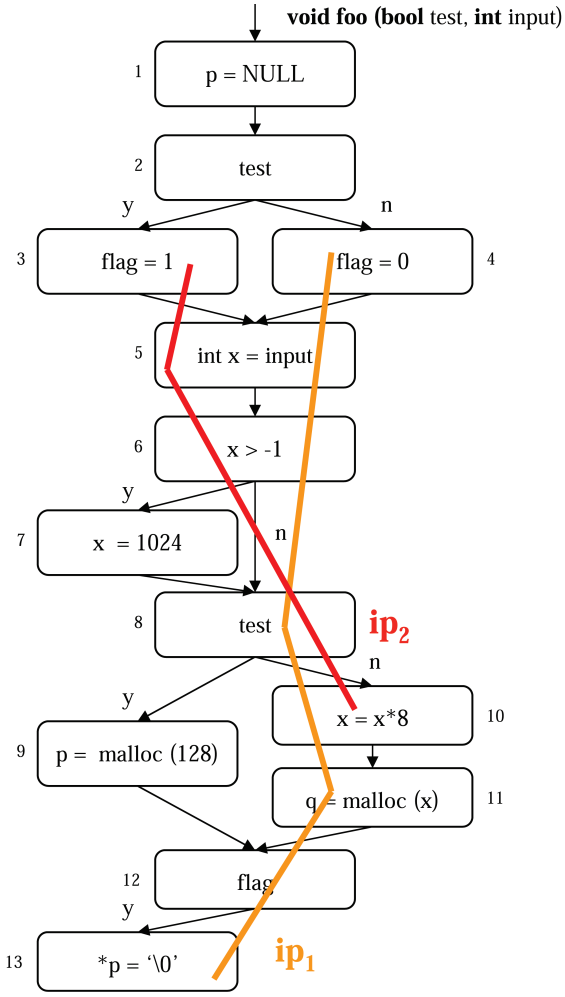


Figure 4.2: Detecting Different Types of Faults

4.2.3 User Scenario

Our analysis can be used both to detect and diagnose faults. If a user would like to diagnose a given faulty statement, she first inputs the source code and requests to analyze the faulty statement. If the analysis returns a faulty path segment, the user then follows the impact points highlighted on the path segment to understand and correct the root cause. Our previous experimental results show that a path segment for a fault typically contains only about 1–4 procedures. After the fix is introduced into the code, the analysis is run again to determine if all faulty paths are eliminated. If not, it returns another faulty path to the user for further diagnosis. The process iterates until all faulty paths are corrected.

If the user prefers to inspect static results to diagnose a fault, rather than using the interactive method, she can request to print path graphs that contain all the faulty and don't-know path segments computed for a given faulty statement. Since each path graph represents a type of paths, the user thus can take a path segment from each graph and determine the fixes.

If the analysis is used for detecting faults, it checks each potentially faulty point, instead of a specified one, and reports paths of requested numbers for the detected faults.

4.3 The Vulnerability Model and the Demand-Driven Algorithm

The two important modules of the analysis are the vulnerability model and the demand-driven algorithm. In this section, we give a detailed description on the two modules and also explain their interactions. We use buffer overflow as an example to elaborate our design.

Table 4.1: Partial Buffer Overflow Vulnerability Model

POS & *UPS*	Q: Constraints	E: Update Equations
`strcpy(a,b)`	$Size(a) \geq Len(b)$	$Len'(a) = Len(b)$
`strcat(a,b)`	$Size(a) \geq Len(a) + Len(b) - 1$	$Len'(a) = Len(b) + Len(a)$
`strncpy(a,b,n)`	$Size(a) \geq Min(Len(b), n)$	$(Len(b) > n \rightarrow Len'(a) = \infty) \vee$ $(Len(b) \leq n \rightarrow Len'(a) = Len(b))$
`a[i] = 't'`	$Size(a) \geq i$	$Len'(a) = \infty$
`char a[x]`	N/A	$Size(a) = x$
`char *a = (char*)malloc(x)`	N/A	$Size(a) = x/8$
$r(x) : Size(x) \leq Len(x)$		

4.3.1 The Vulnerability Model

The vulnerability model for buffer overflow is a 5-tuple: $\langle POS, \delta, UPS, \gamma, r \rangle$, where

1. *POS* is a finite set of possible overflow statements where queries are raised,
2. δ is the mapping $POS \rightarrow Q$, and Q is a finite set of buffer overflow queries,
3. *UPS* is a finite set of statements where buffer overflow queries are updated,
4. γ is the mapping $UPS \rightarrow E$, and E is a finite set of equations used for updating queries, and
5. r is the security policy to determine the resolution of the query.

POS: Buffer overflow only can manifest itself at certain statements, such as where a buffer is accessed. We call such program points *possible overflow statements*. Our analysis raises queries from these points and checks the safety for each of them. A program is free of buffer overflow if no violations are detected on any paths that lead to the possible overflow statements in a program. We recognize that a buffer can be defined only through a string library call or a direct assignment via pointers or array indices. We therefore identify these types of statements as possible overflow statements for write overflow. Table 4.1 presents a partial vulnerability model for buffer overflow. In the first column of the table, the first four expressions are types of possible overflow statements. For the language dependent features, we use C. In the table, the notation $Len(x)$ represents the length of the string in buffer x (including the null character $'\backslash 0'$), $Len'(x)$ indicates the length of the string in buffer x after x is updated, $Size(x)$ is the buffer size of x, $Min(x,y)$ expresses the minimum value among x and y, and $r(x)$ is the security policy to determine if a write to buffer x is safe.

$\delta : POS \rightarrow Q$: The mapping provides rules for constructing a query from a possible overflow statement in the code. We model the buffer overflow query for each possible overflow statement using two elements. The first element specifies whether a buffer access at the statement would be safe, represented as an integer constraint of the buffer size and string length. The second element indicates whether the user input could write to the buffer, annotated as a taint flag. The second column in Table 4.1 displays the query constraints for the four types of possible overflow statements listed in the first column.

UPS: To update a query, the analysis extracts information from a set of program points. We identify two types of sources for information, including statements of buffer definitions and allocations, and statements where we are able to obtain values or ranges of the program variables that are relevant to the buffer size or string length, such as constant assignment, conditional branch and the declaration of the type. In Table 4.1, the first four expressions in the first column are buffer definitions and the next two are buffer allocations, and they are all members of *UPS*.

$\gamma : UPS \rightarrow E$: The mapping formats the information as equations so that the analysis can apply substitution or inequality rules to update queries. In the third column of Table 4.1, we display the equations we derive from the corresponding *UPS*. The symbol ∞ is a conservative approximation

for buffers where $'\backslash 0'$ may not be present.

r: The last part of the vulnerability model is a security policy defined for the analyzer to determine if an overflow could occur. We say a buffer definition is safe if after a write to the buffer, the declared buffer size is no less than the size of the string stored in the buffer (see the last row of Table 4.1). It should be noted that here we only specify the upper bound of the buffer and only model write overflows, but the technique can be easily extended to also include the lower bound and read overflow. Based on how a query conforms to this policy, the query can be resolved as safe, vulnerable, overflow-input-independent, infeasible or don't-know. These answers categorize the paths through which the query propagates.

4.3.2 Interactions of the Vulnerability Model and the Analyzer

Figure 4.3 shows the interaction of the vulnerability model and the analyzer. The analysis first scans the code and identifies the statements that match the possible overflow statements described in the vulnerability model. Queries are constructed from those statements based on the rules defined in the vulnerability model. The analyzer processes a query a time. Each query is propagated backwards from where it is raised along feasible paths towards the program entry. A set of propagation rules are designed in the analyzer to guide the traversal. At the node where information could be collected, the query is updated using the equations. An evaluator follows to determine if the query can be resolved. If not, the propagation continues. If the query is resolved, the search is terminated. To present the computed path graphs, the answers to the query are propagated to the visited nodes to identify path segments of certain types, and statements for understanding root causes are highlighted.

4.3.3 The Algorithm

We present the algorithm for computing buffer overflow paths in Algorithm 1. We only describe the intraprocedural analysis here. Our actual framework is interprocedural, context-sensitive and path-sensitive. The side effects of globals are also modeled.

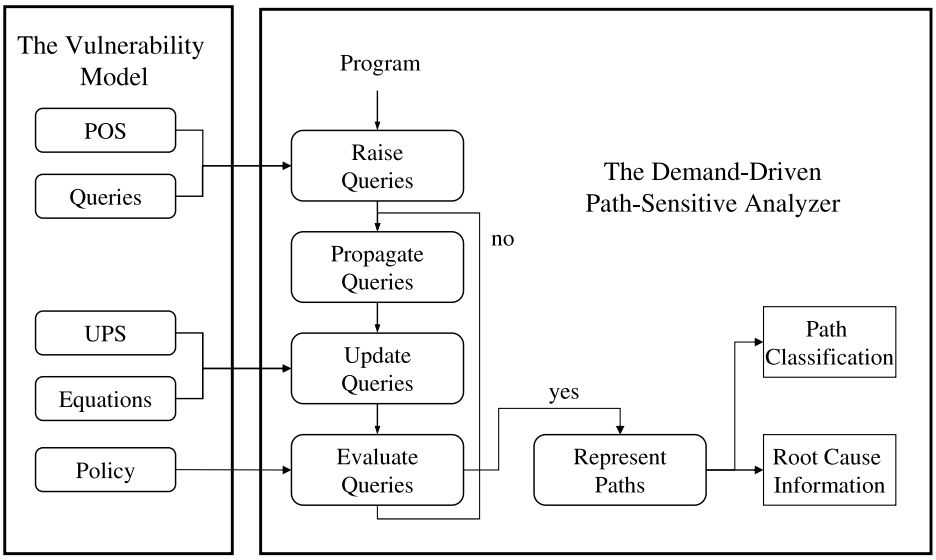


Figure 4.3: Interactions of the Vulnerability Model and the Analyzer

The analysis consists of two phases: *resolve query* and *report paths*. In the first phase, the analysis first identifies the infeasible paths and marks them on the ICFG, at line 1 [Bodik et al., 1997b]. The analysis at lines 2–15 examines the buffers from possible overflow statements one by one and classifies paths that lead to the buffer access. At line 5, the query is constructed based on the query template stored in the vulnerability model `vm.Q`. The analysis uses a worklist to queue the queries under propagation, together with the node to which a query propagates. At lines 6–13, each pair of the node and query is processed.

To update a query, the analysis first determines if the node could impact the buffer we are currently tracking. If so, we extract the information and format it into equations. Procedure `UpdateQ` at lines 16–20 provides details. At line 17, the analysis encounters a node that defines a variable relevant to the current query, but the range or value of this variable is not able to be determined statically. We use `GetUnknown` to record this unknown factor based on rules E defined in the vulnerability model. Line 19 finds that node n is a member of UPS, and the analysis then computes $info$ from node n in `CollectInfo`. Finally, `Resolve` at line 20 consumes the information to update the query.

```
   Input  : ICFG (icfg), Vulnerability Model (vm)
   Output: four types of paths: safe, vulnerable, overflow-input-independent and don't-know
 1 Detect&MarkInfeasibleP(icfg)
 2 foreach s ∈ vm.PVS do
 3     initialize each node n with Q[n] ={}
 4     set worklist to {}
 5     q = RaiseQ (s, vm.Q); add pair(s,q) to worklist
 6     while worklist ≠ ∅ do
 7         remove pair(node i, query q) from worklist
 8         UpdateQ(i, q, vm.S, vm.E)
 9         a = EvaluateQ(i, q)
10         if a ∈ {Vul, OCNST, Safe, Unknown}
11         then  add pair(i, a) to A[q]; else
12         foreach n ∈ Pred(i) do PropagateQ(i, n, q)
13     end
14     ReportP(A[q])
15 end

16 Procedure UpdateQ(node n, query q, ups S, rule E)
17 if n is unknown
18 then info = GetUnknown (n, q, E)
19 else if n ∈ S then info = CollectInfo(n, q, E)
20 Resolve(info, q)

21 Procedure EvaluateQ(node i, query q)
22 SimplifyC(q.c)
23 if q.c = true then a = Safe
24 else if q.c = false ∧ q.taint = CNST then a = OCNST
25 else if q.c = false ∧ q.taint = Userinput then a = Vul
26 else if q.c = undef ∧ q.unsolved = ∅ then a = Unknown
27 else a = Unsolved

28 Procedure PropagateQ(node i, node n, query q)
29 if NotLoop(i, n, q.loopinfo)
30 then
31     status = CheckFeasibility(i, n, q.ipp)
32     if status != Infeasible ∧ !FindCachedQ(q, Q[n])
33     then add q to Q[n]; add pair(n, q) to worklist
34 end
35 else ProcessLoop(i, n, q)
```

Algorithm 1: Categorizing Paths for Buffer Overflow

After the query is updated, `EvaluateQ` at line 9 checks if the query can be resolved as one of the defined answers. Lines 21–27 describes `EvaluateQ` in a more detail. `SimplifyC` at line 22 first simplifies the constraints in the query. Based on the status of the query after the constraint solving, four types of answers can be drawn. For example, at line 26, `Unknown` is derived from the fact that

the constraint *q.c* is undetermined and the unresolved variable set, *q.unsolved*, is empty. If a query is resolved, its answer, together with the node where the query is resolved is recorded in `A[q]` (see line 11). If the query cannot be evaluated to be any of above four types of answers, `Unsolved` is returned and the query continues to propagate at line 12.

`PropagateQ` at line 28–35 interprets the rules we designed for propagating the query through infeasible paths, loops and branches. `CheckFeasibility` at line 31 checks if the propagation from the current node to its predecessor encounters an infeasible path and thus should be terminated. `FindCachedQ` at line 32 determines if the same query has been computed before. At line 35, the analysis processes the loop. We observe that when a query enters a loop, one of the following scenarios could occur: 1) the loop does not update the query, and the query remains the same after each iteration of the loop; 2) the query is updated in the loop and the loop iteration count can be symbolically represented, e.g., loop `for(int i=0; i<c; i++)` iterates *c* times; and 3) the query is updated in the loop and the number of iterations cannot be simply represented using integer variables. For example, we are not able to express the iteration count for the loop `while(a[i] != '\\')` using integer variables. When the first type of loop is encountered, the analyzer stops traversing the loop after it determines that the query does not change in the loop. To deal with the second and third cases, the analyzer reasons the impact of the loop on the query based on the update of the query per iteration, and the number of iterations of the loop; since the initial query at the loop exit is known (note our analysis is backwards), the analysis is able to compute the query at the loop entry. In the third case, we introduce a don't-know factor to represent the iteration count and use it to compute the query at the entry of the loop. If a loop contains multiple paths that can update the query differently, we cannot summarize the update of the query for the loop. Therefore, we will traverse the loop a fixed number of times (requested by the user), and introduce a don't-know factor to indicate that the query update beyond the certain number of iterations is unknown.

If the user is only interested in obtaining one faulty path, the analysis terminates when the first resolution of vulnerable or overflow-user-independent is reached. If the user would like to obtain a classification of the paths across potentially faulty point, the analysis terminates when all the resolutions of the query are reached. The paths the query traverses can be output. If the path graph

is requested, an additional phase has to be performed, shown at line 14 in *report paths*. At this phase, the analysis propagates the answers from the nodes where resolutions are obtained to the nodes that have been visited in the analysis.

Optimizations for Scalability. We developed techniques to further speed up the analysis. One observation is that queries regarding local and global buffers are propagated in a different pattern during analysis. Queries that track local buffers cross into a new procedure only through function parameters or return variables, and the computation for local buffers often does not involve many procedures. However, global buffers can be accessed by any procedure in the program, and those procedures are not necessarily located close on the ICFG. In the worst case, the query cannot be resolved until the analysis visits almost every procedure on the ICFG, and the demand-driven approach cannot benefit much.

To address this challenge, we develop an optimization named *hop*. Our experience analyzing real-world code demonstrates that although global variables can be defined at any procedure, the frequency of the accesses in a procedure is often low, i.e., the procedure possibly just updates the variable once or twice. Our approach is that when we build the ICFG for a program, we record the location of the global definitions in the procedures. Since the analysis is demand-driven, we are able to know before entering a new procedure the variables of interest. If all variables of interest are globals, we can simply search the global summaries at the procedure, and hop the query directly to the node that defines the unresolved variables in the query, skipping most of the irrelevant code. This *hop* technique also can be applied intraprocedurally when we encounter a complex procedure with many branches and loops. Similar to the global hop, we can record the nodes that define local variables in the summary. Although the number of branch nodes could potentially be large, the number of nodes that define variables of interest often is relatively small. Therefore, guided on demand, we are always able to resolve a query within a limited number of hops. In addition to hop, we apply optimizations of advancing and caching as developed by Duesterwald et al. [Duesterwald et al., 1997].

Limitations. Although our framework introduces the concept of don't-know to handle the potential imprecision of the analysis, there is still untraceable imprecision that could impact the de-

tection results. For example, we do not model control flows impacted by signal handlers or function pointers, and do not handle concurrency properties such as shared memory. Another example is that we use an intraprocedural field-sensitive and flow-sensitive alias analyzer from Phoenix [Phoenix, 2004], which is conservative. We also can miss infeasible paths from our infeasible paths detection since identifying all infeasible paths is not computable.

4.4 Experimental Results

The goal of our experiments is to investigate the scalability and capabilities of our analysis for detecting buffer overflow. We selected 8 benchmark programs from BugBench [Lu et al., 2005], the Buffer Overflow Benchmark [Zitser et al., 2004] and a Microsoft Windows application [Microsoft Game Studio MechCommander2, 2001]. All benchmarks are real-world code, and they all contain some known buffer overflows documented by the benchmark designers, which are used to estimate the false negative rate of Marple. We examined the scalability of our analysis using MechCommander2, a Microsoft online XBox game published in 2001 with 570.9 k lines of C++ code [Microsoft Game Studio MechCommander2, 2001].

We conducted two sets of experiments. We first ran our analyzer over 8 benchmark programs and examined the detection results. In the second set of experiment, we evaluated Marple using 28 programs from the Buffer Overflow Benchmark and compared our results with the data produced by 5 other representative static detectors [Zitser et al., 2004]. We applied the metrics of probability of fault detection and false positives for comparison. The results for these two sets of experiments are presented in the following sections.

4.4.1 Path-Sensitive Detection

In this experiment, we ran Marple on every write to a buffer in a program to check for a potential overflow. For each buffer write, we excluded infeasible paths, and categorized paths of interest from program entry to the possible overflow statement into safe, overflow-input-independent, vulnerable and don't-know types. We identified a total of 71 buffer overflows over 8 programs, of which 14

have been previously reported by the benchmark designers and 57 had not been reported before. Among all vulnerable and overflow-input-independent warnings Marple reports, only 1 message is a false positive, which we confirmed manually.

We show the detailed experimental results in Table 4.2. Column *Benchmark* lists the set of benchmarks we used, the first 4 from BugBench, `wu-ftp`, `sendmail`, and `BIND` from the Buffer Overflow Benchmark, and the last XBox application MechCommander2. Column *POS* shows the number of possible overflow statements identified in these programs. Column *Known Bugs* records the number of overflow statements documented in the benchmarks.

Table 4.2: Detection Results from Marple

Benchmark	POS	Known Bugs	Detected Bugs		Path Prioritization			Root Cause Info	
			Known	New	V	O	U	Stmt	Ave No.
polymorph-0.4.0	15	3	3	4	6	1	2	2.9	1.7
ncompress-4.2.4	38	1	1	11	8	4	12	3.9	1.0
gzip-1.2.4	38	1	1	9	7	3	18	4.2	1.7
bc-1.06	245	3	3	3	3	3	108	7.1	1.0
wu-ftp:mapping-chdir	13	4	4	0	3	1	4	6.8	1.0
sendmail:ge-bad	21	2	2	2	3	1	6	6.5	1.2
BIND:nxt-bad	48	1	0	0	0	0	22	N/A	N/A
MechCommander2	1512	1	0	28	28/1	0	487	9.4	1.0

Column *Detected Bugs* summarizes our detection results. It contains two subcolumns. Subcolumn *Known* displays Marple's detection of previously reported overflows. Comparing the results from this subcolumn to the numbers listed under *Known Bugs*, we show Marple detected 14 out of total 16 reported overflows. Marple identified 1 overflow in `BIND` as don't-know, because the analysis is blocked by some library call, and we missed 1 bug in MechCommander2, because we do not model function pointers. Subcolumn *New* shows 57 previously not reported overflows we found in the experiment. We manually confirmed that these overflows are actually real buffer overflows. Many of these overflows are located in BugBench. For example, we found 11 previously not reported overflows in `ncompress-4.2.4` and 9 in `gzip-1.2.4`. Bugbench uses a set of dynamic error detectors such as Purify and CCured to detect overflow [Lu et al., 2005]. These dynamic detectors terminate when the first buffer overflow on the path is encountered; therefore, other overflows on the same path can be missed. We inspected the overflows reported from Marple but not included

in BugBench, and we found that many of the new detected buffer overflows are actually located on the same path as other overflows, but not always involved in the same buffers.

The above results show that Marple not only identified most of the documented overflows, but also discovered buffer overflows that have not been reported by the benchmark designers.

Column *Path Prioritization* presents the results of our path classification. Subcolumns V, O and U show the number of statements Marple reported in the program that contain paths of vulnerable, overflow-input-independent and don't-know. We manually inspected the vulnerable and over-flow-input-independent warnings and identified 1 false positive in MechCommander2. The false positive results from the insufficient range analysis for the integer parameters of a `sprintf()`. Marple can properly suppress false positives because we use a relatively precise path-sensitive analysis, and we successfully prioritized warnings that are truly buffer overflows by categorizing the low confidence results into the don't-know set. For the don't-knows reported in Subcolumn U, we explain what factors cause the don't-know and where the reason for the don't-know appears in the source code.

Consider the benchmark `bc-1.06` as an example to illustrate the don't-know warnings we generate. Among a total of 108 statements that contain don't-know paths, 43 are marked with the factor of complex pointers, 28 result from recursive calls, 15 are caused by loops and 12 are due to non-linear operations. There are also 8 blocked by library calls and 6 dependent on environmental factors such as uninitialized variables. One statement could be labeled with more than one type of don't-know factor, since paths with different don't-know factors can go through the same statement. The computed factors indicate that we can further improve the analysis by applying better memory modeling to resolve pointers, trying to convert non-linear constraints to linear constraints, or annotating the library calls that affect the analysis. The results also help in manual inspection to follow up the don't-know warnings.

The above results validate our hypothesis that although real errors may be in the don't-know set, we are able to report a good number of buffer overflows with very low false positives.

The last column of the table *Root Cause Info* presents the assistance of our analysis for helping identify root causes. In our bug report, we highlight statements that update the query during analysis. We count the number of those statements for each overflow path segment. In Subcolumn *Stmt*,

we report the average count over all overflow path segments in the program. The results suggest that to understand an overflow, the number of statements that the user has to focus on are actually less than 10 on average. We also experimentally validated that the root causes can be path-sensitive. Subcolumn *Ave No*. displays the average number of root causes per overflow for all overflow statements in the program. If the result is larger than 1, there must exist some overflow in the program resulting from more than one root cause. We manually inspected overflow paths and discovered 3 out of 8 programs containing such overflows, and the different root causes for the overflow are all located on different paths.

4.4.2 Buffer Overflow Examples from Results

Here, we show three buffer overflows from two examples which we discovered but had not been previously reported. The first example is from `bc-1.06`. In Figure 4.4, the overflow occurs at line 8, since the number of elements written to buffer `env_argv` is determined by the number of iterations of the `while` loop at line 6 and the `if` condition at line 7. However, the execution of both the `while` loop and the `if` condition are controlled by `env_value`, a string that is set through the environment variable at line 2.

```
1  char* env_argv[30];
2  env_value = getenv("BC_ENV_ARGS");
3  if(env_value != NULL){
4    env_argc = 1;
5    env_argv[0] = "BC_ENV_ARGS";
6    while(*env_value != 0){
7      if(*env_value != ' '){
8        env_argv[env_argc++] = env_value;
9        while(*env_value != ' ' && *env_value != 0)
10         env_value++;
11       if(*env_value != 0){
12         *env_value = 0;
13         env_value++; }
14     }
15     else env_value++; } ...
16 }
```

Figure 4.4: An Overflow in bc-1.06, main.c.

```
1  char SourceFiles[256][256];
2  void languageDirective (void) {
3    char fileName[128]; char fullPath[255];
4    while((curChar!='"') && (fileNameLength<127)){
5      fileName[fileNameLength++] = curChar;
6      getChar();
7    }
8    fileName[fileNameLength] = NULL; ...
9    if(curChar==-1) strcpy(fullPath,fileName);
10   else{
11     strcpy(fullPath,SourceFiles[0]);
12     fullPath[curChar+1] = NULL;
13     strcat(fullPath,fileName); }
14   if((openErr = openSourceFile(fullPath))...)
15 }
16 long openSourceFile (char* sourceFileName){ ...
17   strcpy(SourceFiles[NumSourceFiles],sourceFileName);
18 }
```

Figure 4.5: Overflows in MechCommander2, Ablscan.cpp.

The second example in Figure 4.5 presents two overflows we identified in MechCommander2. At line 13, two strings are concatenated into buffer `fullPath`: the string `fileName`, with the possible length of 127 bytes, and `SourceFiles[0]`, whose maximum length could reach 255 bytes. Both buffers `fileName` and `SourceFile` are accessible to the user, e.g., `getChar()` at line 6 gets the input from a file that users can access, to the global `curChar`, which is then copied into `fileName` at line 5. Therefore, given the size of 255 bytes for `fullPath` at line 3, the overflow can occur at line 13 with the user input. This overflow further propagates to the procedure `openSourceFile` at line 14, and makes buffer `SourceFiles[NumSourceFiles]` at line 17 also unsafe.

4.4.3 Comparison with Other Buffer Overflow Detectors

We also compared Marple with other static buffer overflow detectors using the Buffer Overflow Benchmark developed by Zister et al. [Zitser et al., 2004], in terms of both fault detection and false positive rates. The Buffer Overflow Benchmark contains a total of 14 benchmarks constructed from real-world applications including `wu-ftpd`, `Sendmail` and `BIND`. Each benchmark contains a "bad" program, where several overflows are marked, and a corresponding "ok" version, where overflows in the "bad" program are fixed. Zister et al. evaluated five static buffer overflow detectors:

ARCHER, BOON, UNO, Splint and PolySpace (a commercial tool), with the Buffer Overflow Benchmark. The results show that 3 out of the 5 above detectors report less than 5% of the overflows in the benchmarks, and the other 2 have higher detection rates, but the false positive rates are unacceptably high at 1 false positive in every 12 lines of code and 1 in every 46 lines of code.

The results of the evaluation have been plotted on the ROC (Receiver Operating Characteristic) curve shown in Figure 4.6 [Zitser et al., 2004]. The *y*-axis $p(d)$ shows the probability of detection, computed by the formula $C(d)/T(d)$, where $C(d)$ is the number of marked overflows detected by the tool and $T(d)$ is the total number of overflows highlighted in the "bad" program. Similarly, the *x*-axis $p(f)$ represents the probability of false positives, computed by $C(f)/T(f)$, where $C(f)$ is the number of "ok" statements identified by the tool as an overflow, and $T(f)$ is the total number of fixed overflow statements in the "ok" version of the program. The diagonal line in the figure suggests where a static analyzer based on random guessing would be located. The uppermost and leftmost corner of the plot represents an ideal detector with 100% detection and 0% false positive rates.

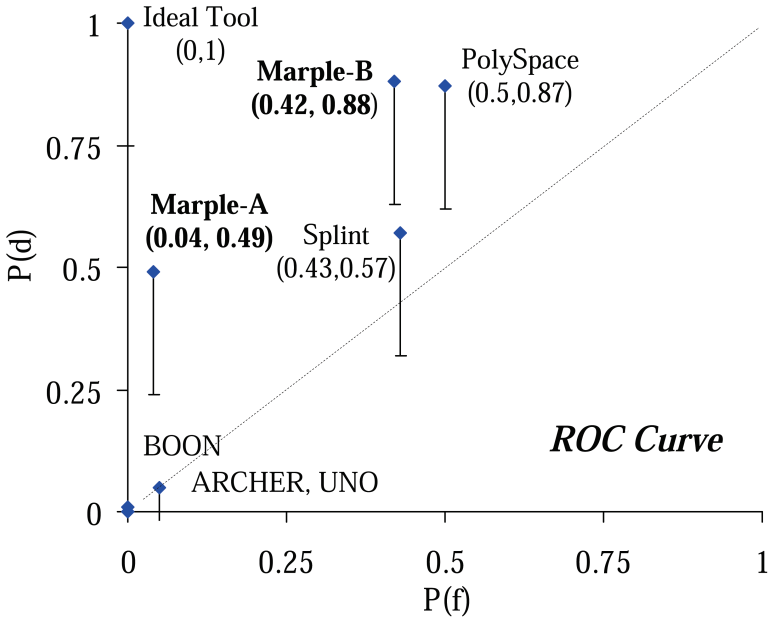


Figure 4.6: Comparison of Marple with other five static detectors on ROC plot

We ran Marple over the Buffer Overflow Benchmark and rendered our results of $p(f)$ and $p(d)$

Table 4.3: Benefit of Demand-Driven Analysis

Benchmark	Size (kloc)	Blocks		Procedures		WorkList Max Size	Time
		Total	Visited	Total	Visited		
polymorph-0.4.0	0.9	323	41	11	4	6	1.3 s
ncompress-4.2.4	0.9	473	269	13	4	56	1.3 s
gzip-1.2.4	5.1	1,218	482	42	17	110	26.2 s
bc-1.06	17.0	3,035	1,489	119	77	677	3.5 min
wu-ftp:mapping-chdir	0.2	84	50	5	5	31	2.1 s
sendmail:ge-bad	0.9	140	81	7	4	12	1.1 s
BIND:nxt-bad	1.3	226	83	9	3	1	0.9 s
MechCommander2	570.9	57,883	25,069	3,259	1,689	944	35.4 min

on the plot. In Figure 4.6, we computed two points for Marple. *Marple_A* is computed using only overflow-input-independent and vulnerable warnings, while *Marple_B* is derived also using don't-know messages, i.e., a don't-know warning is counted both into $C(d)$ as a detection and into $C(f)$ as a false positive. *Marple_A* shows that we can detect 49% of overflows with a 4% false positive rate. *Marple_B* achieves better results both in false positive and negative rates than PolySpace and Splint. Our results indicate that Marple can more precisely detect buffer overflows with high detection and low false positive rates. We discovered that although the don't-know warnings should not miss overflows since they are computed conservatively, we obtained 88% detection rate. The reason for this is that some overflows in the benchmarks are caused by integer errors or they are read overflows, and we have not yet modeled these in our analysis.

4.4.4 Benefit of Demand-Driven Analysis

To evaluate the scalability of our analysis, we measured both the time and memory of analyzing 8 programs. The platform we used for experiments is the Dell Precision 490, one Intel Xeon 5140 2-core processor, 2.33 GHz, and 4 GB memory. Table 4.3 Column *Size* lists the size of benchmark programs in terms of thousands lines of code. Columns *Blocks* and *Procedures* compare the number of total blocks and procedures on the ICFG of a program, listed under Subcolumns *Total*, to the number of blocks and procedures Marple visited during analysis, displayed in Subcolumns *Visited*. The results show that because we direct the analysis only to the code relevant to buffer overflow, the analysis only visited an average of 43% nodes and 52% procedures on the ICFG for 8 programs.

Column *WorkList Size* shows the maximum number of elements in the major worklist in analysis. The actual memory measurement reports that all 8 benchmark programs can be analyzed using less than 4 GB memory.

Column *Time* reports the time that Marple uses to analyze each program. The results show that the analyses for all benchmarks can finish within a reasonable time, and we successfully analyzed MechCommander2 within 35.4 minutes. We compared the performance of our analysis with two path-sensitive tools, ARCHER [Xie et al., 2003] and IPSSA [Livshits and Lam, 2003]. ARCHER uses an exhaustive based search and achieves the speed of analyzing 121.4 lines of code per second [Xie et al., 2003]. IPSSA detects buffer overflows on the SSA annotated with path-sensitive alias information; its average speed for 10 programs in the experiments is 155.3 lines per second [Livshits and Lam, 2003]. Marple reports the speed of analyzing 254.7 lines per second over our benchmark programs.

4.5 Conclusions

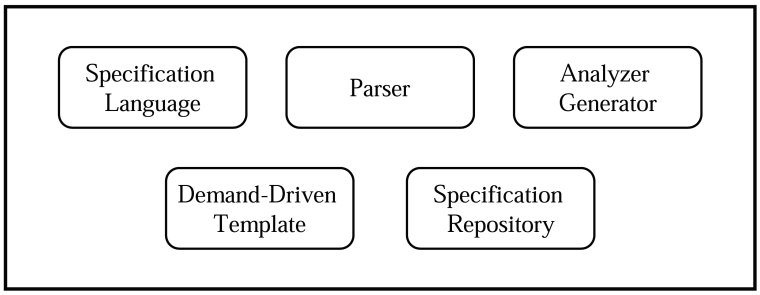
This chapter presents a demand-driven analysis that addresses the challenges of path computation for faults. Both the discussions of the methodology and experimental evaluation focus on buffer overflow detection; however, we show in the next chapter, that the techniques are applicable to detect other types of faults. The main contributions of this work include a vulnerability model that enables the application of demand-driven analysis for detecting faults, and a demand-driven, path-sensitive analysis that achieves the practical precision and scalability. We experimentally show that our analysis can detect faults that are previously not reported in the benchmarks, and 99% of overflows reported by our tool are real buffer overflows. Compared to the other tools in our study, Marple achieves better precision, and is more scalable in detecting and reporting faults.

Chapter 5

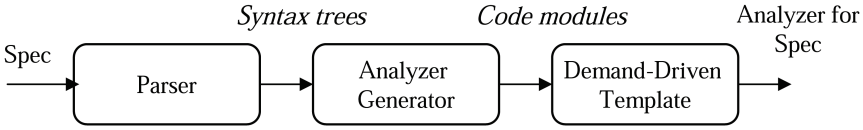
Automatically Generating Path-Based Analysis

In this chapter, we present a novel framework which enables the automatic generation of scalable, interprocedural, path-sensitive analyses that detect user-specified faults. The framework consists of a general algorithm, a specification technique, and a generator that unifies the two to produce an analysis. The key idea is to address the scalability of path-sensitive fault detection in a general demand-driven algorithm and automatically generate the fault-specific parts of the analysis from a specification.

The framework is general in that it can handle both data- and control-centric faults. Data-centric faults require the tracking of variable values and ranges for detection, e.g., buffer overflow and integer faults, while control-centric faults, such as typestate violations, mainly focus on the order of operations. Although different types of information are required to determine different types of faults, there are commonalities in detecting them. Our insight is that 1) many types of faults are only observable at certain types of program statements, and 2) on the paths to such observable points, only certain types of statements can contribute to the failure. By identifying such *potentially faulty points* (see Definition 3.1), we can construct a query at those points regarding whether the fault can occur and propagate the query along the paths for resolutions. Similarly, given *impact points* (see Definition 3.3), we know where to collect information to resolve the query and determine the fault. Therefore, by supplying potentially faulty/impact points and the corresponding actions at the points, we are able to guide a general analysis to locate the desired faults.



(a) Five Components



(b) Work Flow

Figure 5.1: The Framework

In our experiment, we demonstrate that the framework can identify buffer overflows, integer faults, null-pointer dereferences and memory leaks. The detection capability of the produced analysis is comparable with ones that are targeted for a particular type of fault.

5.1 An Overview of the Framework

Our framework takes a user-defined specification and generates interprocedural, path-sensitive analyses that identify path segments of the specified faults. The framework is 1) *general* in that it can handle both data- and control-centric faults, and 2) *scalable and precise* in that the analyses report path segments where a fault occurs and only the code that is relevant to the faults is analyzed.

In Figure 5.1(a), we present the five components of the framework. The *Specification Language* consists of the syntax and semantics of our specification language. The *Parser* and the *Analyzer Generator* translate the specification and produce the parts of the analysis that target the specified fault. A general, path-sensitive, demand-driven algorithm is developed in the *Demand-Driven Template*, which implements our design decisions for handling the challenges of precision and scalability. The *Specification Repository* consists of specifications for common fault types. Rather than having users to specify these faults, the framework provides specifications for a set of fault types,

e.g., buffer overflows, integer faults, null-pointer dereferences and memory leaks. The user also can define her own faults using the language provided by our framework.

As shown in Figure 5.1(b), given a specification, the *Parser* first produces a set of syntax trees. Based on the semantics of the specification, the *Analyzer Generator* generates the code modules that implement the rules for determining the specified faults. The code modules are plugged into the *Demand-Drive Template* to produce the analyzer. The specifications for multiple types of faults can be integrated to generate one analysis that handles a set of types of faults. The advantage of such an analysis is that we can reuse the intermediate results, e.g., feasibility or aliasing information, for analyzing different types of faults, and also explore the interactions of different types of faults [Le and Soffa, 2011].

5.2 Specification Language

The goal of specifications is to express both a fault and the information needed to statically determine the fault.

5.2.1 Fault Signatures and Detection Signatures

A specification consists of *fault signatures* and *detection signatures* for a type of fault the user desires to detect. A fault signature defines "what is a fault". Based on the definition of the fault (see Definition 2.1), we construct the fault signature as pairs of potentially faulty points and property constraints.

For example, a buffer overflow occurs at a buffer access when the length of the string stored in the buffer is larger than the buffer size. To model the fault, we identify the code signatures of buffer read and write, and we define the relation of the string length and buffer size as constraints. Similarly, to model "an opened file has to be closed", we find code signatures of "open file", and construct a constraint as "a close has to follow the open".

Besides the above two examples, we show later that our technique also can model integer fault, null-pointer dereference and memory leak. For those faults that we can model, the constraints

can be about the order of operations, which we call *control-centric*, or otherwise *data-centric* if the constraints define relations of value or range of program variables. Types such as missing a statement or misuse of a variable do not belong to this category.

A detection signature contains a set of information needed to statically determine a type of fault. We model the detection signature based on the dynamic fault behavior. At runtime, a set of changes of program states at certain program points lead to the violation of the property constraints along the execution. Thus, to statically determine the violation of constraints, we need to identify the potential *impact points* (see Definition 3.3) in the program source and their corresponding *property impacts* (see Definition 3.4).

The constraints at a program point can be about the history or future of an execution. For example, it is the values generated along the execution path before reaching the buffer access that contribute to the buffer overflow. On the other hand, in the file-open-close example, we require that for a "file open", the corresponding "file close" should be invoked in the future. Based on the types of constraints, we know where the information that determines the resolutions of the constraints is located. Therefore, we can choose either backward or forward static analysis for fault detection.

5.2.2 Grammar and Semantics

To express a fault signature and detection signature, we introduce *attributes* in our specification to represent an abstraction of program state. *Attributes* are properties of program objects such as program variables or statements. For instance, an attribute can be value, range, or typestate of individual program variables, or relations of multiple variables. To express the fault and detection signatures, the key is to specify the constraints and update rules using attributes of program variables.

The specification language provides a set of commonly used attributes, as well as the operators *computation*, *comparison*, *composition* and *command*. Each attribute takes a program variable(s), and returns an integer, Boolean, or set. Based on the domain, the corresponding computation and comparison operators can be applied. The command operators define common actions for updating a constraint, e.g., symbolic substitution or integration of a constraint.

Specification → **Vars** VarList **FaultSignature** FaultSigList **DetectionSignature** DetectSigList
VarList → Var*
Var → VarType *namelist***;**
VarType → *Vbuffer*|*Vint*|*Vany*|*Vptr*|...
FaultSigList → FaultSigItem ⟨**or** FaultSigItem⟩*
DetectSigList → DetectSigItem ⟨**or** DetectSigItem⟩*
FaultSigItem → **CodeSignature** ProgramPoint **S_Constraint** Condition|
CodeSignature ProgramPoint **V_Constraint** Condition
DetectSigItem → **CodeSignature** ProgramPoint **Update** Action
ProgramPoint → $LangSyntax$|Condition|$LangSyntax$&&Condition
Condition → Attribute Comparator Attribute|!Condition|[Condition]|Condition&&Condition|
Condition || Condition
Action → Attribute:=Attribute|∧Condition|Condition ↦ Action|[Action]|Action&&Action|
Action || Action
Attribute → PrimitiveAttribute(*var*, ...)|Constant|Attribute Op Attribute|*min*(Attribute,Attribute)|
[Attribute,Attribute]|¬Attribute|!Attribute|Attribute ∘ Attribute|[Attribute]
PrimitiveAttribute → *Size*|*Len*|*Value*|*MatchOperand*|*TMax*|*TMin*|...
Constant → *0*|*true*|*false*|...
Comparator →= | ≠ | > | < | ≥ | ≤ | ∈ | ∉
Op → +| − | ∗ | ∪ |∩

Figure 5.2: The Grammar of Specification Language

The grammar of the language is shown in Figure 5.2. In this grammar, we show how a set of advanced language constructs can be composed from the basic construct of attributes. In the grammar, terminals are highlighted: keywords use bold fonts, and the predefined constants, functions and types are italicized.

A specification consists of three sections, shown as the first rule in Figure 5.2. In the first section, we define *specification variable*. The specification variables represent the program objects of interest, such as statements or operands. The rule *Var* shows a variable is defined by a type and a name. A set of built-in types are listed in the production *VarType*. The naming convention for each type indicates to which category of program objects the type refers. For example, a specification

variable that corresponds to a program variable has a type starting with a *V*, followed by a name indicating the type of program variable such as *int*.

After the definition of variables, the grammar provides the fault signature, *FaultSigList*, and the detection signature, *DetectSigList*. *FaultSigList* consists of pairs of potentially faulty points and property constraints, using the keyword **or** for multiple pairs. Similarly, *DetectSigList* lists pairs of impact points and property impacts. The construct *Program Point* provides code signatures or/and conditions to identify the types of program statements of interest. We use keywords **S_Constraint** and **L_Constraint** to distinguish whether the fault is related to a safety or a liveness constraint. The production *Condition* compose constraints of attributes. The basic rule is to connect two *Attribute* with a *Comparator*. A condition is a Boolean. Therefore, a set of Boolean operators can be applied. Symbol [ ] is used to define the priority of the computation. The construct *Action* specifies the actions that can be taken on attributes with the operators of $:=$ for assignment and $\wedge$ for integrating conditions. An action can be conditional and only be performed when a certain condition is satisfied, which we use the operator $\mapsto$ to specify. *Attributes* used to compose *Condition* and *Action* specify the properties of variables. In our specification language, we define a set of commonly used primitive attributes as terminals, shown in the *PrimitiveAttribute* production. A set of operators are defined to compose attributes from these primitive attributes (see the productions *Attributes* and *Op*).

5.2.3 Specification Examples

We show a buffer overflow specification in Figure 5.3. Under *FaultSignature*, the keyword *CodeSignature* provides a set of program points where the buffer constraints have to be enforced. Three examples are the library calls of *strcpy* and *memcpy* as well as the direct assignment to a buffer. We use *S_Constraint* to indicate that the buffer overflow constraint is a safety constraint. It can be specified using a comparator "$\geq$" on attributes of *Size(a)*, the size of buffer *a*, and *Len(b)*, the length of the string *b*. The role of variables such as *a* and *b* is to locate the operands in the code signature for constructing constraints.

Under *DetectionSignature*, we show a set of program points that potentially affect the buffer size

Vars		*Vbuffer* a, b; *Vint* d; *Vany* e;
FaultSignature		
	CodeSignature	$strcpy(a,b)$
	S_Constraint	Size(a)≥Len(b)
or		
	CodeSignature	$memcpy(a,b,d)$
	S_Constraint	Size(a)≥min(Len(b), Value(d))
or		
	CodeSignature	$a[d]=e$
	S_Constraint	Size(a)>Value(d)
DetectionSignature		
	CodeSignature	$strcpy(a,b)$
	Update	Len(a) := Len(b)
or		
	CodeSignature	$strcat(a,b)$
	Update	Len(a) := Len(a)+Len(b)
or		
	CodeSignature	$a[d]=e$ && Value(e)='\0'
	Update	(Len(a)>Value(d) ‖ Len(a)=∞)
		↦ Len(a) := Value(d)
or		
	CodeSignature	$d=strlen(b)$
	Update	Value(d) := Len(b)

Figure 5.3: Partial Buffer Overflow Specification

or string length as well as the update rules for these program points. The first pair says that after a *strcpy* is executed, the length of the string stored in the first operand equals the length of the string stored in the second operand. The third pair introduces a conditional command using the symbol ↦. It says when a '\0' is assigned to the buffer, if the current string in *a* is either longer than *d*, Len(*a*)>Value(*d*), or not terminated, Len(*a*)=∞, we can assign the string length of *a* with the value of *b*. It should be noted that Marple integrates a symbolic substitution module to automatically handle integer computation, e.g., using rules *Value(x):=Value(y)* for the program point $x = y$. The detection signature provided in the specification only gives rules that are potentially useful for determining defined faults; in the case of buffer overflow, the rules are about string libraries and their semantics.

We also present a specification for detecting memory leaks in Figure 5.4. The constraint for

memory leak is that a memory allocation is safe only if a free of the memory is invoked in the future. It is a liveness constraint and defines a control-centric fault. In the specification, we use the attribute *TypeState(a)* to record the order of operations performed on the section of memory tracked by *a*. The *L_Constraint* says that when *TypeState(a)* equals 1, the leak does not occur. Under *DetectionSignature*, the first rule indicates that if a *free* is called on the tracked pointer, *TypeState(a)* returns 1, and the program is safe. The code signatures from the second to fourth rules present the cases when the pointer is no longer associated with the memory: either it is reassigned, or its scope ends. At these program points, we need to determine whether *a* is the only pointer that points to the tracked memory; if so, a memory leak occurs; otherwise, we remove *a* from the reference set, *Ref(a)* (the reference set contains a set of pointers that currently point to the tracked memory). The last rule in the specification adds the aliasing pointer to the reference set.

Vars		*Vptr* a,b; *Vint* c
FaultSignature		
	CodeSignature	$a=malloc(c)$
	L_Constraint	TypeState(a) == 1
DetectionSignature		
	CodeSignature	$free(a)$
	Update	TypeState(a) := 1
or		
	CodeSignature	$a=malloc(c)$
	Update	|Ref(a)|==0↦Ref(a) := {a} ‖
		|Ref(a)|==1↦TypeState(a):=0 ‖
		|Ref(a)|≠1,0↦Ref(a):=Ref(a)-{a}
or		
	CodeSignature	$a=b$
	Update	|Ref(a)|==1↦TypeState(a):=0 ‖
		|Ref(a)|≠1↦Ref(a):=Ref(a)-{a}
or		
	CodeSignature	IsEnd(a)
	Update	|Ref(a)|==1↦TypeState(a):=0
		|Ref(a)|≠1↦Ref(a):=Ref(a)-{a}
or		
	CodeSignature	$b=a$
	Update	Ref(a):=Ref(a)+{b}

Figure 5.4: Partial Memory Leak Specification

5.2.4 User Scenario

To specify a type of fault, the user first needs to identify the program points and the constraints that define the fault. If the faults are data-centric, the user can reuse the detection signatures we developed to compute buffer overflow and integer faults. Additional rules also can be introduced to document the semantics of library functions, or certain types of operators in the program. If the faults are control-centric, the user needs to identify statements that potentially impact the order of operations defined in the constraint. Intuitively, a finite automata, FA, can potentially be converted to our specification: the fault signature can be derived from the end states and their incoming edges of FA, and the detection signature can be obtained from transitions between states in FA. To extend Marple for supporting a new type of fault, in the worst case, we need to add a few new primitive attributes and operators. Our assumption is that the required abstractions in the analysis, i.e., attributes, are always limited to certain types, and it is the composition of the attributes that specify different types of faults and their detection.

5.3 Demand-Driven Template

The above specifications can be integrated in a general static analysis for detecting specified faults. To achieve the scalability and precision that are applicable for a variety of faults, we develop an interprocedural, demand-driven, path-sensitive analysis in the *Demand-Driven* Template, shown in Algorithm 2. The *Demand-Driven Template* is a skeleton of a demand-driven algorithm, which mainly provides query propagation rules that are general for identifying different types of faults. The skeleton has “holes”, where the fault-dependent information is missing. In Algorithm 2, the “holes” are *MatchFSignature* at line 4 and *MatchDSignature* at line 10. *MatchFSignature* examines whether a given program statement matches the code signature of a fault; if it does, a query will be constructed using the constraints in the fault signature. *MatchDSignature* determines whether a given statement matches the code signature for updating a query; if so, the query is updated. The two "holes" will be filled in using the code automatically generated from the *Analyzer Generator*.

```
   Input  : program (p)
   Output: path segments for faults
 1 icfg = BuildICFG(p);AnalyzePtr(icfg); IdentifyInfP(icfg);
 2 set worklist L to {};
 3 foreach s ∈ icfg do
 4 |   MatchFSignature(s)
 5 |   // hole1: raise query q, if s matched code signature
 6 |   if q then add (q,s) to L
 7 end
 8 while L ≠ ∅ do
 9 |   remove (q, s) from L;
10 |   MatchDSignature (q,s);
11 |   //hole2: update query q, if s matched code signature
12 |   a=EvaluateQ (q,s);
13 |   if a ≠Unresolved then add(q,s) to A[q];
14 |   else
15 |   foreach n ∈ Next(s) do PropagateQ(s,n,q);
16 end
17 ReportP(A)
18 Procedure EvaluateQ(query q, stmt n)
19 SimplifyC(q.c, n)
20 if q.c = true then a = Safe
21 else if q.c = false then a = Fault
22 else if q.c = undef ∧ q.unknown ≠ ∅ then a = Don't-Know
23 else a = Unresolved
24 Procedure PropagateQ(stmt i, stmt n, query q)
25  if OnFeasiblePath(i, n, q.ipp) then
26 |   ProcessBranch(i, n, q)
27 |   ProcessProcedure(i, n, q)
28 |   ProcessLoop(i, n, q)
29 end
```

Algorithm 2: the Demand-Driven Template

Using Algorithm 2, we explain a set of design decisions we made to achieve the precision and scalability for the analysis. Without loss of the generality, we use a backward demand-driven analysis as an example to explain this algorithm. As a preparation stage shown at line 1, the analysis first builds an interprocedural control flow graph (ICFG) for the program. The pointer analysis is performed to determine aliasing information and models C/C++ structures. We also conduct a branch correlation analysis to identify infeasible paths; the discovered infeasible paths are marked on ICFG [Bodik et al., 1997a]. The demand-driven analysis for detecting faults is invoked at lines 3-16.

The analysis first performs a linear scan of statements in the ICFG to match the fault signature. If the match succeeds, a query will be returned and added to a worklist at line 6. A query contains the constraints of a fault, as well as in-progress information tracked by the analysis, such as to which nodes it has been propagated.

After the demand is collected, a path-sensitive analysis is performed on the code reachable from where the query is raised. At line 10, if a statement is matched to a detection signature, the query will be updated, either via a general symbolic value substitution, or by fault-specific flow functions. For each update, we evaluate if the query is resolved at line 12.

Lines 18-23 present the evaluation of the query. At line 19, we first simplify the constraints using the algebraic identities and inequality properties. An integer constraint solver is also called to further determine the resolution of the constraint. Considering its performance overhead, we do not invoke the constraint solver at every query update but at a configurable frequency, e.g., when the query is propagated out of a procedure. If the constraint returns *true*, the safety rule always can be satisfied; otherwise, if *false*, a fault is discovered. We report the query as *don't-know* if its resolution is dependent on variables or operations that our analysis cannot handle, e.g., a variable returned from a library or an integer bit operation. The analysis terminates for the query if its resolution is determined.

If the query is not resolved, we continue to propagate it for further information. At line 15, *Next* finds the predecessors (in a backward analysis) or successors (in a forward analysis) of the current node. *PropagateQ* at lines 24-29 integrates a set of propagation rules to handle branches, procedures and loops, where the path-sensitivity is addressed. At line 25, the analysis determines whether the propagation encounters an infeasible path. If not, the propagation proceeds.

When propagating through branches, the query is copied at the fork point, each of which is advanced into separate branches. At the branch merge point, queries from different branches continue to propagate along the paths. We also check at the conditional branch, whether any variables tracked in the constraints are dependent on the condition at the branch; if so, we integrate the condition into the query.

An interprocedural propagation includes the following two cases. If the beginning of the pro-

cedure is reached, the query is propagated to the caller from which the query originally comes to preserve the context-sensitivity. If instead, a procedural call is met, we perform a linear scan for the call to determine if the query can be updated in that call. We only propagate the query in the procedure if the update is possible.

ProcessLoop, at line 28, integrates our strategies to handle loops. We classify loops into three types, based on the update of the query in the loop. We propagate the query into the loop to determine the loop type. If the loop has no impact on the query, the query advances out of the loop. If the iteration count of the loop and the update of the query in the loop can be symbolically identified, we update the query by adding the loop's effect on the original query. Otherwise, we precisely track the loop effect on the query for a limited number of iterations (based on the user's request). If the query is still not resolved, we introduce a "don't-know" tag to record the imprecision.

The analysis terminates when the resolutions for all the queries in the worklist are determined. At line 17, we report path segments that are traversed by the query. The path segments start where a query is raised and end where the resolution of the query is determined. Along the path segment, the constraints of a fault 1) either are always resolved as false, which implies that as long as the execution traverses the path segment, the fault can be triggered, or 2) report violations on some user input, which says any execution that crosses the path segments with a proper input can trigger the fault.

5.4 Generating Analysis

This section presents an algorithm that automatically generates the fault-specific modules, *MatchFSignature* and *MatchDSignature*, in Algorithm 2 from a specification.

5.4.1 An Overview of the Approach

A specification consists of three types of objects: 1) code signatures, 2) constraints and updates composed using the attributes and their operators; and 3) a set of keywords whose roles are to connect the previous two objects to constitute the fault and detection signatures.

The parser first replaces the code signatures encapsulated in the symbol $ with constraints on the operands and operator of the statement. The specification is thus converted into a stream of constraints and updates. Each constraint or update is parsed into a syntax tree, whose leaf nodes are attributes or constants, while the parents are operators for the children. During code generation, the syntax tree is traversed in a bottom up order. At the leaf nodes, we find the code that implements the corresponding attributes from the *attribute library*. This library is developed as a part of the *Analyzer Generator* in the framework. It implements the semantics of a set of predefined attributes. At the parent nodes, we compose the code from their children based on the semantics of the operators. The code produced at the root implements the semantics of the tree. We further integrate the code from syntax trees based on their relations, which are defined by the keywords in the specification, such as *code signature*, *constraint* or *update*.

5.4.2 The Algorithm for Generating Analysis

Algorithm 3 provides in detail the code generation process. The algorithm takes a user-provided specification *spec*, and produces the code modules of *MatchFSignature* and *MatchDSignature*, as well as a repository of calls invoked by the code modules, *R*.

At line 2, we use the grammar, *l.grammar*, to parse a specification. Consider the first pair of *CodeSignature* and *S_Constraint* from the buffer overflow specification in Figure 5.3. As shown in Figure 5.5, the parser introduces the attribute *Op(s)* to represent the operator of statement *s*, and $\texttt{Src}_i\texttt{(s)}$ for the i^{th} operands. Specification variables *a* and *b*, which represent the locations of operands, are replaced accordingly for both the code signature and the constraint. The constraints are converted to syntax trees: *A* for the code signature, and *B* for the buffer overflow constraint. The symbol ∘ in the figure is a composition operator, which performs a function composition between Src_i and *Size*/*Len*.

As shown at line 2 in Algorithm 3, after parsing, a set of pairs of syntax trees, *siglist*, are returned. Each pair of the syntax trees represents either an element of fault signature or an element of detection signature in the specification. The first tree in the pair is produced from the code signature, while the second represents the corresponding constraint or update.

```
   Input  : Specification of Fault (spec)
   Output: Code modules (MatchFSignature, MatchDSignature) A repository of calls invoked by
           code modules (R)
 1 set fs_list, ds_list to {}; initialize R = " "
 2 siglist = Parse(l.grammar, spec)
 3 foreach sig ∈ siglist do
 4     isnode = CodeGenforTree (sig.first, "n")
 5     if IsFSginature (sig) then
 6         raiseQ =CodeGenforTree (sig.second, "n")
 7         case = "If isnode then q=raiseQ;"
 8         add case to fs_list
 9     end
10     else if when (sig.first) then
11         updateQ =CodeGenforTree (sig.second, "n", "q")
12         case = "If isnode then updateQ;"
13         add case to ds_list
14     end
15 end
16 MatchFSignature = GenSignature (fs_list)
17 MatchDSignature= GenSignature (ds_list)
18 Procedure CodeGenforTree (tree t, arglist p1, p2...)
19 alist = SelectAttrImp (t, l.attr)
20 ftree= ComposeFunc (alist, t, l.semantics)
21 Append (R, ftree)
22 return CreateCallSignature (ftree, p1, p2,...)
23 Procedure GenSignature (codelist list)
24 foreach case ∈ list do Append(case,code)
25 return code
```

Algorithm 3: Generate **MatchFSignature** and **MatchDSignature**

Lines 3-15 in the algorithm generate the code modules from the syntax trees. At line 4, *CodeGenforTree* takes *sig.first*, the syntax tree of the code signature, and *"n"*, a variable name, and generates a call that implements the semantics of the tree. The return variable, *isnode*, stores the call signature, while the actual implementation of the call is incorporated in the code repository, *R*. See *CodeGenforTree* at lines 18-22 for details. At line 19, we select attribute functions from the attribute library *l.attr*, which are composed based on the semantics of operators, *l.semantics*, from the syntax tree, *t*. At lines 21 and 22, we add the generated functions to *R* and create a call signature using "*n*" as an actual parameter.

As an example, Figure 5.6 shows the actual code generated for the code signature in Figure 5.5. The *Step 1* box displays the implementation for the attribute *Op*. The function returns the opcode

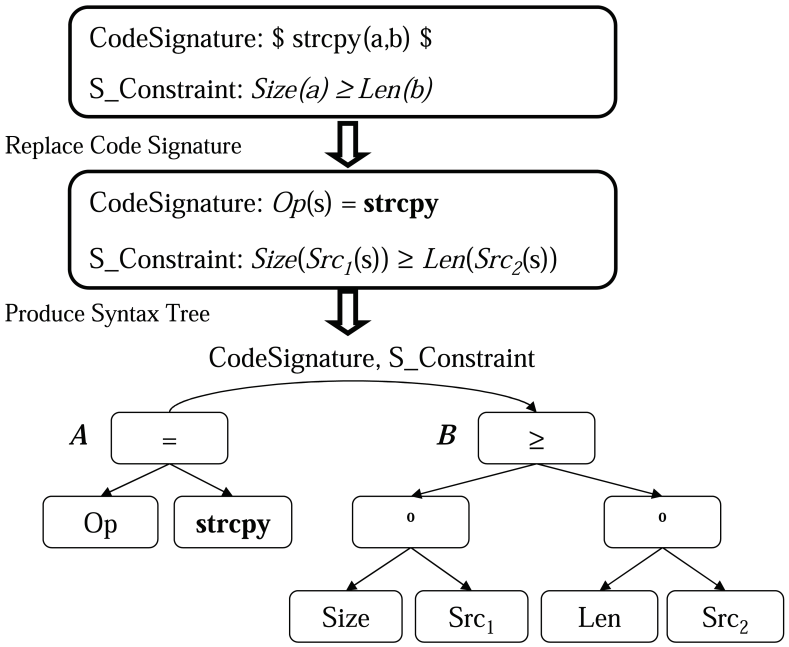


Figure 5.5: Parsing Specification

for a statement from the program. The code in *Step 2* implements the semantics of a comparison operator, $=$, which checks whether the value returns from the left leaf node equals to the one from the right node. In the *Step 3*, the call signature is returned.

Figure 5.6 displays one example for *isnode* at line 4. The code for *raiseQ* and *updateQ* also can be generated in a similar way. At lines 7-8, calls from *isnode* and *raiseQ* are integrated in an *If-Then* clause and added to *fs_list*. At lines 12-13, *isnode* and *updateQ* are combined and added to *ds_list*. *fs_list* consists of cases where a code signature of a fault is matched, and a query is raised, while *ds_list* consists of cases where a code signature for updating the query is matched, and the query is updated. Using the two lists, *GenSigature* produces *MatchFSignature* at line 16 and *MatchDSignature* at line 17. The two code modules can be plugged directly into the Demand-Driven Template at lines 4 and 10 in Algorithm 2

Based on whether the specification integrates *S_Constraint* or *L_Constraint*, *Next* and *PropagateQ* at line 15 in Algorithm 2 will be instantiated using a backward or forward analysis template.

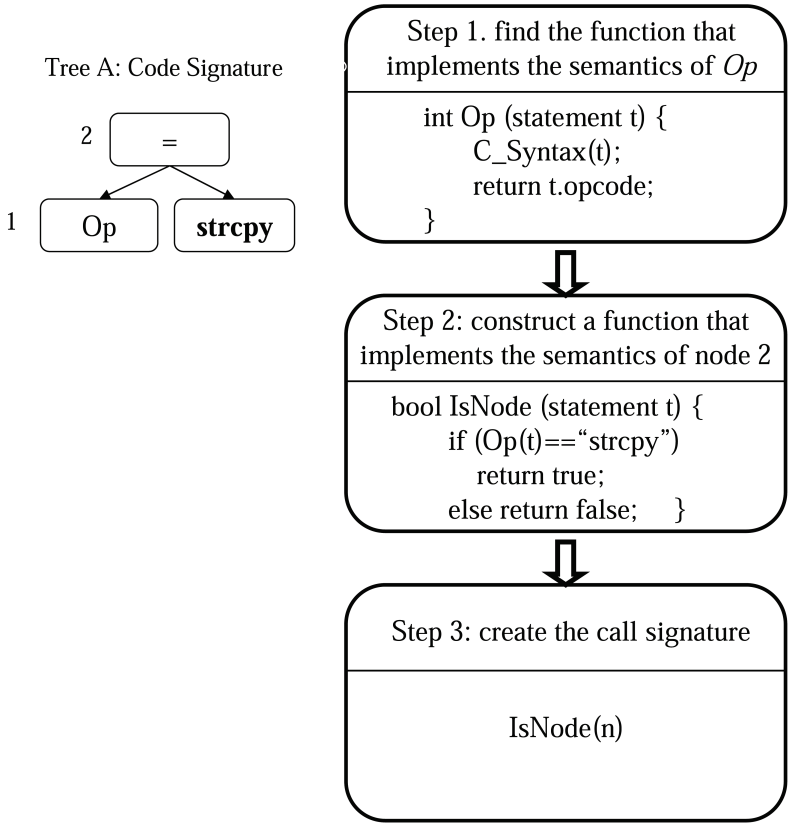


Figure 5.6: Generating Code from Syntax Tree

5.5 Experimental Evaluation

We experimentally evaluate our framework to demonstrate that the analysis we produced can identify multiple types of faults, and the scalability and precision of our detectors are comparable to manually constructed ones and those that only analyze for a specific type of fault.

5.5.1 Experimental Setup

In the experiments, we generate an analysis that can identify buffer overflows, integer truncation/signedness errors, null-pointer dereferences and memory leaks. In our implementation, we automatically generated code for *MatchFSignature* at line 4 in Algorithm 2. *MatchDSignature* at line 10 in Algorithm 2 is obtained via interpreting the specification. The detection for the first three types of faults applies a backward analysis, while the analysis for memory leak is forward. The

analysis first performs an infeasible path detection, and then detects each type of fault one at a time.

We construct a benchmark suite, consisting of 9 C/C++ programs: the first five are selected from BugBench [Lu et al., 2005] and the Buffer Overflow Benchmark [Zitser et al., 2004], and the rest are deployed mature applications. Among the nine programs, eight contain 1–2 known faults, which were either reported by users or discovered via static analysis, runtime detection or manual inspection. We estimate false negatives of the analysis by checking whether we are able to identify these known faults. We also use SPEC CPUINT 2000 to compare our memory leak detector with other memory leak detectors.

5.5.2 Detecting Multiple Types of Faults

In the first experiment, we run the generated analysis on the 9 benchmark programs. We evaluate the effectiveness of the analysis using four metrics: detection capability, false negatives, false positives and the path information provided for diagnosis.

In Table 5.1, for each type of fault, we report the number of confirmed faults under Column *d*, the number of the faults that are missed under Column *mf* and the number of false positives under Column *fp*. For each program, we also give the length of the paths for the identified faults, in terms of the minimal and maximum number of procedures, shown under Column *p*. Faults here are counted as the number of statements where the constraint violations are found along some paths. We manually confirmed the data in the table.

Under *Buffer*, we show a total of 33 buffer overflows with 5 false positives. We do not miss any known buffer overflow. Among the 33 identified, 26 are newly discovered buffer overflows. The 5 false positives are all diagnosed as being on infeasible paths. As identification of infeasible paths is undecidable, we cannot exclude all infeasible paths statically. The four programs, *wuftp:mapping-chdir, sendmail:ge-bad, polymophy* and *gzip*, have also been used before to evaluate our manually constructed buffer overflow detector [Le and Soffa, 2008]. The results show that the generated detector is able to report all buffer overflows detected before. Under *Integer*, we report a total of 41 detected integer faults, 33 of which were not previously reported. We missed a fault for *putty* because we do not model function pointers. Besides insufficient infeasible path detection, imprecise

pointer information is also a cause for false positives, which leads to 1 false positive for *apache* and 2 for *ffmpeg*. We identified a total of 8 null-pointer dereferences. The five identified from *apache* are cases where the pointer returned from a *malloc* function is never checked for NULL before use, which is inconsistent with the majority memory allocations called in the program. We missed two null-pointer dereferences in *ffmpeg* as they are related to interactions of integer faults, which we did not model in this experiment. We also identified 2 memory leaks, 1 from *sendmail:ge-bad* and the other from *ffmpeg*, where one cleanup procedure missed a member. For the control-centric faults of null-pointer dereference and memory leak, we only report a total of 3 false positives, compared to 15 generated by the data-centric faults. Our inspection shows that the infeasible paths related to the control-centric faults are often simple, e.g., $p \neq NULL$, and thus easily detected by our analysis; however, integer faults and buffer overflows are more likely located along an infeasible path that is complex and not able to be identified.

Table 5.1: Detecting Multiple Types of Faults

Benchmarks	Size	Buffer Overflow				Integer Fault				Null-Ptr Deref				Memory Leak			
	(kloc)	d	mf	fp	p	d	mf	fp	p	d	mf	fp	p	d	mf	fp	p
wuftp:mapping-chdir	0.2	4	0	0	1-11	0	-	0	-	0	-	0	-	0	-	0	-
sendmail:tTflag-bad	0.2	0	0	1	-	3	0	3	2-2	0	-	0	-	0	-	0	-
sendmail:ge-bad	0.9	4	0	0	1-4	0	-	0	-	2	-	0	1-3	1	-	0	4-4
polymophy-0.4.0	0.9	8	0	0	1-4	0	-	2	-	0	-	0	-	0	-	0	-
gzip-1.2.4	5.1	10	0	2	1-35	15	-	0	1-16	0	-	0	-	0	-	0	-
tightvnc-1.2.2	45.4	0	-	0	-	11	0	0	1-3	0	-	0	-	0	-	0	-
ffmpeg-0.4.9pre	48.1	0	-	0	-	6	0	2	1-1	1	2	0	3-3	1	-	0	2-2
putty-0.56	60.1	7	-	2	1-15	4	1	1	1-29	0	-	1	-	0	-	2	-
apache-2.2.4	268.9	0	-	0	-	2	-	2	1-2	5	-	0	1-3	0	-	0	-

Summarizing the fault detection results from the table, we identified a total of 84 faults of the four types from 9 benchmarks; 68 are new faults that were not previously reported. Inspecting these new faults, we find that many of them are located along the same paths. As a result, the dynamic approaches halt on the first fault and never find the rest. We missed 3 known faults and reported a total of 18 false positives for the detection, mainly due to the precision of pointer analysis and infeasible path detection. Our experimental results demonstrate that the generated analyses are able to identify both control- and data-centric faults with reasonable false positives and false negatives. The results for buffer overflow detection shows that the capability of generated detectors are comparable with manually constructed ones.

Path information about identified faults is also reported. The results under *p* in the table show that although the complete faulty paths can be very long, many faults, independent on the types, can be determined by only visiting 1–4 procedures. The data from *gzip* and *putty* imply that although in general, the faults were discovered by only propagating through several procedures, we are able to identify faults deeply embedded in the program which cross the maximum of 35 procedures. Without path information, it is very difficult for manual inspection to understand how such a fault is produced.

5.5.3 Scalability

To evaluate the scalability of our technique, we collect experimental data about time and space used for our analysis. The machine we used to run experiments contains 8 Intel Xeon E5345 4-core processors, and 16 GB of RAM. All of our experiments finished using memory under 16 GB.

Table 5.2: Scalability

Benchmark	icfg ptr,inf	Buffer		Integer		Pointer		Leak	
		q	*t*	*q*	*t*	*q*	*t*	*q*	*t*
wuftp:mapping-chdir	10.1 s	13	71.4 s	0	0	12	1.1 s	0	0
sendmail:tTflag-bad	12.3 m	1	28.8 m	6	46.6 m	12	17.3 s	0	0
sendmail:ge-bad	5.1 s	32	4.7 s	7	1.2 s	44	4.3 s	2	3.2 s
polymophy-0.4.0	1.8 m	15	8.1 s	3	6.4 s	9	1.2 s	0	0
gzip-1.2.4	25.1 m	39	18.5 m	82	70.9 s	116	6.2 s	2	7.3 s
tightvnc-1.2.2	21.9 m	21	54.9 m	1480	18.3 m	847	1.6 m	27	3.4 m
ffmpeg-0.4.9pre	49.8 m	307	88.1 m	410	33.6 m	1970	4.2 m	76	12.1 m
putty-0.56	26.4 m	150	37.9 m	79	44.1 m	256	3.2 m	14	2.4 m
apache-2.2.4	102.8 m	518	53.0 m	423	160.6 m	2730	9.6 m	21	8.2 m

In Table 5.2, we first give the time used for preparing the fault detection, including building the ICFG, and conducting pointer analysis and infeasible path detection. We then list for each type of fault, the number of queries we raised and the time used for detection (Columns *q* and *t*). The experimental data show that all the benchmarks are able to finish within a reasonable time. The maximum time of 160.6 minutes is reported from analyzing *apache* for integer faults. Adding the columns under *Buffer*, *Integer*, *Pointer* and *Leak*, we obtain the total time for identifying four types of faults. For example, *apache* reports a total time of 231 minutes for fault detection, and the second slowest is *ffmpeg*, which uses 137 minutes. The time used for analysis is not always proportional to

the size of the benchmark or the number of queries raised in the program. The complexity involved to resolve queries plays a major role in determining the speed of the analysis. For example, the small benchmark *sendmail:tTflag-bad* takes a long time to finish because all the faults are related to nested loops.

Another observation is that the identification of control-centric faults is much faster than the detection for data-centric faults, as for the control-centric faults we no longer need to traverse paths of loops to model symbolic update for the query. We also notice that, running on a general framework, our buffer overflow detection is slower than the manually constructed one reported in Chapter 4. Besides the overhead of translating the specification, generality also impacts the speed of analysis in an additional two ways: 1) in order to improve the detection capability of integer faults, null-pointer dereferences and memory leaks, we handle many don't-knows reported by Marple; after don't-know factors are resolved, some queries can continue propagating along the paths and slow down the analysis; and 2) the optimizations we developed in Chapter 4 targeted at detecting buffer overflows are no longer used in the general framework.

5.5.4 Comparing Our Framework with Other Tools

In the second experiment, we analyze SPEC CPUINT 2000 using a memory leak detector produced from our framework. This benchmark has been used by multiple memory leak detectors [Cherem et al., 2007, Clause and Orso, 2010, Orlovich and Rugina, 2006] for evaluation, and we thus are able to get the data for comparison.

In the first and second columns of Table 5.3, 12 programs are listed, and their sizes are given. We compare three existing memory leak detectors with our analysis. The first two [Jeffrey et al., 2008, Orlovich and Rugina, 2006] are static, and their results are displayed under *Tool I* and *Tool II*. Tool I applies a backward analysis. It first assumes that no leak occurs at the current program point. A memory leak is discovered if the collected information contradicts the assumption [Orlovich and Rugina, 2006]. Tool II converts the detection for memory leak to a reachability problem using a guarded value flow graph [Jeffrey et al., 2008]. Neither of the tools is path-sensitive; however the impact of the conditional branch is considered in Tool II. The third tool is dynamic and used to

Table 5.3: Comparison of Memory Leak

CINT2000	size	Marple			Tool I		Tool II		Dynamic
	(kloc)	d	fp	time	d	fp	d	fp	traces
181.mcf	1.3	0	0	2.8 s	0	0	0	0	0
256.bzip2	2.9	1	0	24.5 s	1	0	0	0	10
197.parser	6.4	0	0	26.5 s	0	0	0	0	2
175.vpr	9.6	2	0	268.5 s	0	0	0	1	47
164.gzip	10.0	2	0	8.0 s	1	2	0	0	4
186.crafty	11.3	0	0	56.3 m	0	0	0	0	37
300.twolf	15.1	17	0	25.7 m	0	0	2	0	1403
252.eon	19.3	1	0	58.2 s	-	-	-	-	380
254.gap	31.2	1	0	121.0 s	0	1	0	0	2
255.vortex	44.7	1	1	71.0 s	0	26	0	0	15
253.perlbmk	64.5	1	3	17.1 m	1	0	1	3	3481
176.gcc	128.4	27	2	7.2 h	-	-	35	2	1121

compare false negatives among the static detectors, as memory leaks found in this dynamic tool are always real faults [Clause and Orso, 2010].

Under Column *d*, we report the number of memory leaks that are confirmed to be real, and under *fp*, we give the number of false positives. The numbers under the two columns count the memory allocation sites where a leak can occur along some paths. In dynamic analysis, however, the memory leak is reported as the number of traces that manifest the leak (see Column *traces*). The numbers in the column show whether a memory leak exists in the programs, but it cannot be compared with the number reported under *d*.

Our experimental data show that we are able to report more memory leaks than the other static tools. We identify a total of 53 memory leaks, compared to a total of 3 shown under *Tool I*, and 38 under *Tool II*. We are able to report leaks that neither of the other tools is able to identify. For example, for *vortex*, the result from the dynamic tool shows that there exist leaks in the program; however, neither of the other two static tools reports any faults, while Marple does. Also, we handle the C++ benchmark *eon* and report a memory leak, while the other two tools are only able to analyze C programs. We report a total of 6 false positives, shown under *fp*, compared to 29 reported by Tool I and 6 by Tool II. We are more precise than Tool I because we apply a path-sensitive analysis but they do not. For Tool II, our intuition is that besides using the guards on the value flow graph to help precision, other techniques are also introduced to suppress the false positives, which adversely

impact the detection capability of the tool. Therefore, we are able to report more faults.

We also list the time used to detect the memory leaks. *gcc* takes the longest time, using 7.2 hours, which was still able to finish in a nightly run. Compared to the larger benchmark *apache*, *gcc* is much slower because we find many global pointers in *gcc*; also we encounter more don't-know factors when analyzing *apache*, and thus is able to terminate the analysis early.

5.5.5 Limitations

We use Phoenix to build the ICFG, which currently does not model certain control flows such as function pointers and virtual functions. Therefore, certain parts of the code in a benchmark might not be able to be analyzed. Also, for detecting buffer overflow and memory leak, we only identify a set but not all of the code signatures where a query can be raised for checking safety. For example, we do not construct queries at *realloc* for memory leak. We can miss faults related to such program points.

5.6 Discussion

This chapter addresses the generality of the techniques by showing that we are able to identify both control- and data-centric faults as well as safety and liveness properties. Generality is achieved via a fault model, a specification technique, and a general analysis. Here, we provide a further clarification on how general our techniques actually are from the three perspectives.

In our fault model, faults are considered as violations of property constraints, and the constraints here are specifically about data or control relations on the program objects. For example, many vulnerabilities in web applications, such as cross-site scripting and SQL injection, are caused by improper input validations [Lam et al., 2008] and can be formulated as control violations, which are handled by our framework. We do not consider cases such as missing a statement or use a wrong variable.

The expressiveness of our specification language is determined by its key construct, attributes, and their operators. If a fault is related to some abstraction of program state that no attribute can

express, our framework cannot handle it. For example, currently in our specification language, we are not able to specify deadlock conditions using attributes on the locks.

Also, our techniques are static, and we are thus not able to handle faults whose detection is beyond the capability of static analysis, e.g., performance bugs that cannot be mapped to any code patterns. Furthermore, the types of faults we can handle are restricted by the capability of constraint solvers. For example, our analysis only handles integer constraints, and thus we are not able to find faults related to complex float computation.

5.7 Conclusions

In this paper, we present a unifying framework, which includes a general, scalable analysis, a specification technique, and a generator for automatically generating desired fault detectors. The generated analyses are path-sensitive and interprocedural, and return path segments where a fault occurs. Our experiments show that the produced analyses can identify the common faults of buffer overflow, integer fault, null-pointer dereference and memory leak. Applying a demand-driven, path-sensitive analysis, the fault detection achieves competitive precision and scalability. Although here we mainly focus on traditional faults, with our technique, users can write specifications and identify their own defined faults.

Chapter 6

Path-Based Fault Correlation

Although a number of automatic tools have been developed to detect faults, much of the diagnosis is still being done manually. To help with the diagnostic tasks, we formally introduce *fault correlation*, a causal relationship between faults. We statically determine correlations based on the expected dynamic behavior of a fault. If the occurrence of one fault causes another fault to occur, we say they are correlated. With the identification of the correlated faults, we can better understand fault behaviors and the risks of faults. If one fault is uniquely correlated with another, we know fixing the first fault will fix the other. Correlated faults can be grouped, enabling prioritization of diagnoses of the fault groups. In this chapter, we develop an interprocedural, path-sensitive, and scalable algorithm to automatically compute correlated faults in a program. In our approach, we first statically detect faults and determine their error states. By propagating the effects of the error state along a path, we detect the correlation of pairs of faults. We automatically construct a correlation graph which shows how correlations occur among multiple faults and along different paths. Guided by a correlation graph, we can reduce the number of faults required for diagnosis to find root causes. We implemented our correlation algorithm and found through experimentation that faults involved in the correlations can be of different types and located in different procedures. Using correlation information, we are able to automate diagnostic tasks that previously had to be done manually.

Our work is the first that formally defines and automatically computes fault correlations. The contributions of the work include:

- the definition and classification of fault correlations,
- the identification of the usefulness of correlations in fault diagnosis,
- algorithms for automatically computing correlations,
- correlation graphs that integrate fault correlations on different paths and among multiple faults, and
- experiments that demonstrate the common existence of fault correlations and the value of identifying them.

6.1 Motivation and Challenges

Fault diagnosis, done statically on the program source code, aims to identify and fix the causes of detected faults. Diagnosing faults is challenging for a number of reasons. One reason is that the root cause can be located far from where the fault is detected, while the code around the fault can be complex. Unlike debugging, in fault diagnosis, there is no runtime information available to assist in explaining faults. Also, in static analysis, real faults are often mixed with an overwhelming number of false alarms and benign errors.

In this chapter, we explore relationships among faults for fault diagnosis. We show that a causal relationship can exist between faults; that is, the occurrence of one fault can cause another fault to occur, which we call *correlation*. As an example, in Figure 6.1 we show a fault correlation discovered in `ffmpeg-0.4.8`. The correlation exists between an integer signedness error at node 2 and a null-pointer dereference at node 5, as any input that leads to the integer violation at node 2 triggers the null-pointer dereference at node 5 along path $\langle 1,2,5\rangle$. The trigger can occur because the variable `current_track` at node 2 is not guaranteed to get the unsigned value of `AV_RL32(&head[i+8])` (see the macro definition at the bottom of the figure). If a large value is assigned, the signed integer `current_track` would get a negative value at runtime. When `current_track` is negative, the branch $\langle 2,5\rangle$ is taken and the memory allocation at node 4 is skipped, causing the dereference of `fourxm->tracks` at node 5 to encounter a null-pointer.

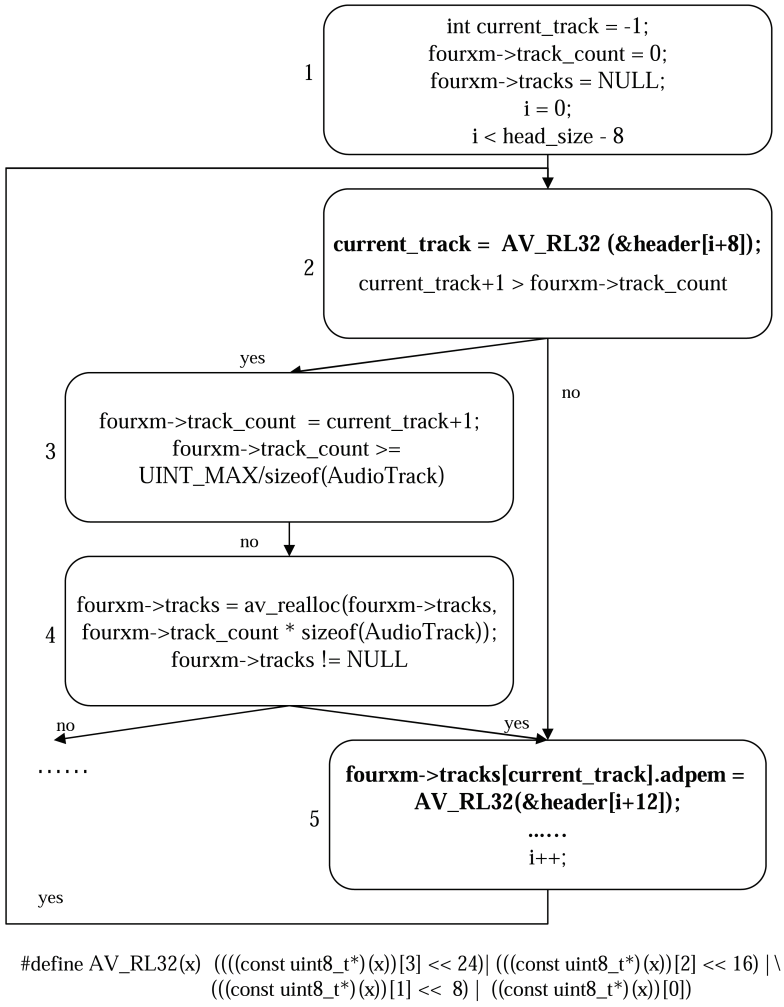


Figure 6.1: Fault Correlation in ffmpeg-0.4.8

Fault correlation is a relationship defined on the dynamic behavior of faults. When a program runs, an initial root cause can propagate and cause a sequence of property violations along the execution before an observed symptom, e.g., crash, is detected. In traditional static tools, the dependencies of those property violations are not identified; either only the first violation is reported or all the violations are reported but as separate faults [Brumley et al., 2007, Evans, 1996, Le and Soffa, 2008, Schwarz et al., 2005]. For the above example, static detection only reports that node 2 contains an integer violation, but it cannot explain whether it is benign or malignant, and if harmful, how severe is the consequence. A static detector for null-pointer dereference also cannot discover

the vulnerability, because the detector may not be aware of any integer violations. When the impact of integer fault is not considered, the static analysis would report the path $\langle 1,2,5 \rangle$ infeasible, as `AV_RL32(x)` always returns a non-negative integer and thus the result of the addition at node 2 should be always larger than `fourxm->track_count`'s initial value 0. However, given the fault correlation, we know that: there exists a null-pointer dereference at node 5; its root cause is the integer fault at node 2; and by fixing the integer fault, the null-pointer dereference can also be fixed.

Fault correlation helps fault management in the following ways: 1) we can detect new faults with introduced fault impact, e.g., the null-pointer dereference shown in Figure 6.1. These faults are impossible to be identified using traditional static detectors; 2) we can confirm and prioritize real faults by revealing their potential consequences; and 3) we can group faults based on their causes.

Determining fault correlations in current static tools is challenging for three reasons. First, identification of correlations of faults requires knowledge of fault propagation, which only can be obtained when program paths are considered; however, exhaustive static analysis based on full path exploration is not scalable. Another reason is that most static tools only detect one type of fault, while correlations often occur among faults of different types as shown in the above example. Also, in order to statically compute the propagation of a fault, the potential dynamic impact of a fault needs to be modeled, which is typically not done in the static tools.

6.2 Defining Fault Correlation

We first define fault correlations. We also provide examples to demonstrate correlations.

6.2.1 Preliminaries

An important concept to define fault correlations is *error state*.

Definition 6.1: The *error state* of a fault is the set of values produced at runtime as a result of property violations.

Intuitively, an error state is the manifestation of a fault. That is, after executing a program statement, there exists a set of values from which we can determine that property constraints are

violated and a fault occurs. The set of values constitute an error state. If a crash would occur, we consider the values that cause the crash as the error state. We model the error state of a fault based on the fault type using constraints. The modeling is empirical and based on the common symptoms of faults a code inspector might use to manually determine fault propagation.

Table 6.1: Error State of Common Faults

Fault Type	Code Signature	Error State
buffer overflow	`strcpy(a,b)`	**len(a)**>size(a)
integer overflow	`unsigned i=a+b`	**value(i)**==value(a)+ value(b)-C
integer signedness	`int j...unsigned i=j`	**value(i)**>2^{31}-1
	`unsigned i...int j=i`	**value(j)**< 0
integer truncation	`unsigned i...uchar j=i`	**value(j)**<value(i)
resource leak	`Socket s=accept(); s=accept()`	**avail(Socket)**== avail(Socket)-1

Table 6.1 lists the error state for several common faults. Under *Code Signature*, we give example statements where a certain type of fault potentially occurs. Under *Error State*, we show constraints about corrupted data at the fault. The type of corrupted data is listed in bold. The first row of the table indicates that when a buffer overflow occurs, the length of the string in the buffer, `len(a)`, is always larger than the buffer size, `size(a)`. From the second to fourth rows, we simulate the effect of integer faults. When an integer overflow occurs, the value stored in the destination integer, `value(i)`, should equal the result of integer arithmetic, `value(a)+value(b)`, minus a type-dependent constant `C`, e.g., 2^{32}. Similarly, when an integer signedness error occurs, we would get an unexpected integer value. For example, when a signed integer casts to unsigned, any results larger than $2^{31} - 1$ (the maximum value a signed 32 bit integer possibly stores) indicates the violation of integer safety constraints [Brumley et al., 2007]. When an integer truncation occurs, for instance, between `uchar` and `unsigned` as shown in the table, the destination integer would get a smaller value than the source integer. In the last row, we use a socket as an example to show that when resource leaks occur, the amount of available resources in the system is reduced, and we model the error state as [`avail(Socket)==avail(Socket)-1`].

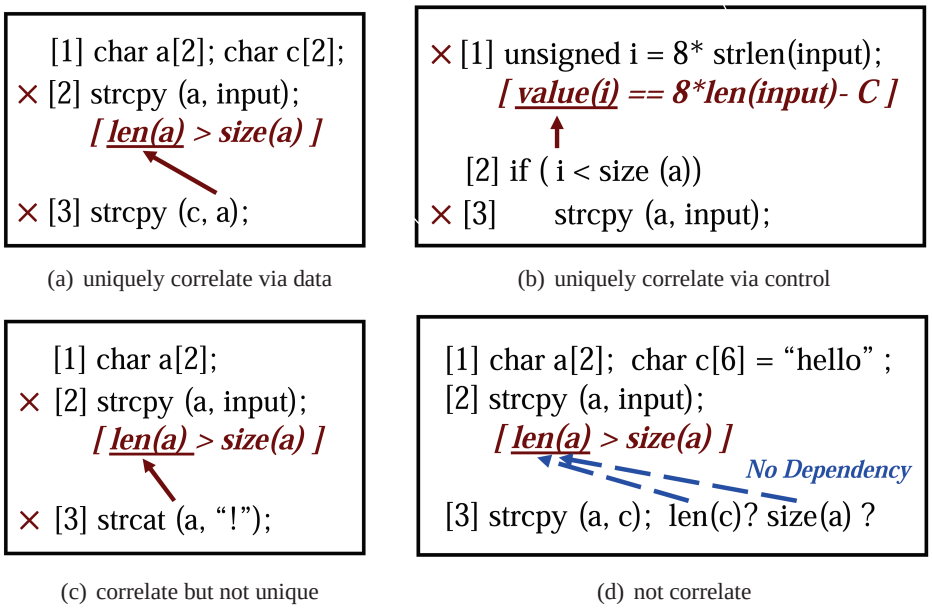


Figure 6.2: Defining Fault Correlation: correlated faults are marked with ×, error state is included in [ ], and corrupted data are underlined

6.2.2 Correlation Definition

Suppose f_1 and f_2 are two program faults.

Definition 6.2: f_1 and f_2 are *correlated* if the occurrence of f_2 along path p is dependent on the error state of f_1. We denote the correlation as $f_1 \rightarrow f_2$. If f_2 only occurs with f_1 along path p, we say f_1 *uniquely correlates* with f_2, denoted as $f_1 \xrightarrow{u} f_2$.

The occurrence of f_2 along p is determined by the property constraints on a set of variables collected along p. If such variables are control or data dependent [Snelting, 1996] on the corrupted data at the error state of f_1, f_1 and f_2 are correlated. Intuitively, given $f_1 \rightarrow f_2$, f_1 occurs first on the path, and the error state produced at f_1 propagates along p and leads to the property violation at f_2. Therefore, f_1 and f_2 have a causal relationship. Given $f_1 \xrightarrow{u} f_2$, f_1 is a necessary cause of f_2, which means, if f_1 does not occur, f_2 cannot occur. If the correlation is not unique, there is other cause(s) that can lead to f_2.

Consider Figure 6.2(a) in which the variable `input` stores a string from the untrusted user. A correlation exists between the buffer overflow at line 2 and the one at line 3, as there exists a

valueflow on variable `a`, shown in the figure, that propagates the error state of the overflow at line 2 to line 3. When the first buffer overflow occurs, the second also occurs. The faults are uniquely correlated.

In Figure 6.2(b), we show a correlation based on control dependency between faults. The integer overflow at line 1 leads to the buffer overflow at line 3, as the corrupted data, `value(i)`, produced at the integer fault impacts the conditional branch at line 2 (on which line 3 is control-dependent).

In Figure 6.2(c), buffer overflow at line 2 correlates with the one at line 3. However, the first overflow is not the only cause for the second because when the overflow at line 2 does not occur, the overflow at line 3 still can occur.

As a comparison, the two buffer overflows presented in Figure 6.2(d) are not correlated. At line 3, both the size of the buffer and the length of the string used to determine the overflow are not dependent on the corrupted data `len(a)` in the error state at line 2.

By identifying fault correlation, we can better understand the propagation of the faults and thus fault behavior. We demonstrate the value of fault correlations in two real-world programs. In the first example, we show given $f_1 \rightarrow f_2$, we can predict the consequence of f_1 through f_2, and prioritize the faults. The correlation also helps group and order faults, as in the case of $f_1 \xrightarrow{u} f_2$, fixing f_1 will fix f_2. See Example 2.

Example 1: Figure 6.3 presents a correlation found in the program `acpid-1.0.8`. In this example, we show how a fault of resource leak can cause an infinite loop and lead to the denial of service. The code implements a daemon that waits for connection from clients and then processes events sent via connected sockets. In Figure 6.3, the `while` loop at node 1 can only exit at node 5, when an event is detected by the `poll()` function at node 2 and processed by the server. Correspondingly, along the paths $\langle (1-4)^*, 1-2, 5 \rangle$, the socket `fd` is created by the function `ud_accept` at node 3, and released by `clean_exit` at node 5. However, if a user does not send legitimate requests, the branch $\langle 2, 3 \rangle$ is always taken, and the created sockets at node 3 cannot be released. Eventually, the list of sockets in the system is completely consumed and no socket is able to be returned from `ud_accept` at node 3. As a result, the condition `fd<0` always returns true. The execution enters an infinite loop $\langle (1-3)^* \rangle$. In this example, the impact of the resource leak makes the execution always

follow the false branch of node 2 and the true branch of node 3, causing the program to hang. With fault correlation information, we can automatically identify that the root cause of the infinite loop is the resource leak. To correct this infinite loop, we can add resource release code in the loop, as shown in the figure.

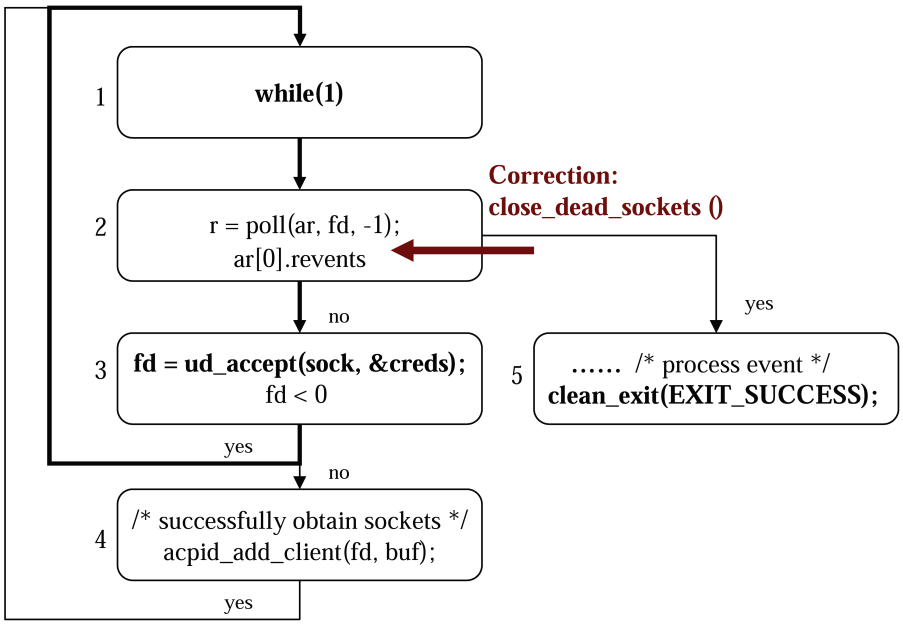


Figure 6.3: Correlation of Resource Leak and Infinite Loop in acpid

Example 2: Static tools potentially report many warnings for a program, especially when they analyze newly written code or legacy but low quality code. Consider the example in Figure 6.4 from `polymorph-0.4.0`. There exist 7 buffer overflows in the code, located at lines 2, 10, 12, 14, 16, 19 and 21. Although these overflows are not all located in the same procedure and even the buffers involved in the overflow are not all the same, we find that correlations exist among them. For example, the overflow at line 2 correlates with the one at line 16 along path $\langle 1-7, 16\rangle$, and line 16 correlates with line 21 along $\langle 16, 17, 21\rangle$. We can group these correlated faults and diagnose them together.

To further understand the correlations in real-world programs, we conducted a study on 300 vulnerabilities in the Common Vulnerabilities and Exposure (CVE) database [Common Vulnera-

```
1  char filename[2048];
2  strcpy(filename, FileData.cFileName);
3  convert_fileName(filename);
4
5  void convert_filename(char* original){
6    char newname[2048]; char *bslash = NULL; ...
7    if(does_nameHaveUppers(original)){
8      for(i=0; i<strlen(original); i++){
9        if(isupper(original[i]))
10         { newname[i] = tolower(original[i]);
11           continue; }
12       newname[i] = original[i];
13     }
14     newname[i] = '\0';
15   }
16   else  strcpy(newname, original);
17   if(clean){
18     bslash = strrchr(newname, '\\' );
19     if(bslash != NULL) strcpy(newname, &bslash[1]);
20   } ...
21   strcpy(original, newname);
22 }
```

Figure 6.4: Correlations of Multiple Buffer Overflows in polymorph

bilities and Exposure, 2010], dated between 2006-2009. We manually identified fault correlations on 8 types of common faults, including integer faults, buffer bounds errors, dereference of null-pointers, incorrect free of heap pointers, any types of resource leak, infinite loops, race conditions and privilege elevations. Our study shows that correlations commonly exist in real-world programs. In fact, the reports suggest that security experts manually correlate faults in order to understand the vulnerabilities or exploits.

Table 6.2 classifies the correlations we found. We mark $*$ if the fault listed in the row uniquely correlates with the fault in the column, and $\times$ for correlations that are not unique. Comparing the rows of *int* and *race* in the table, we found that integer faults and data race behave alike in correlations. Intuitively, both integer violation and data race can produce unexpected values for certain variables, and thereby trigger other faults. From the study, we also found that a fault can trigger different types of faults along different execution paths and produce different symptoms. We mark ✓ in the table if the faults from the column and row can be triggered by the same fault along

different paths.

Table 6.2: Types of Correlated Faults Discovered in CVE

	int	buf	nullptr	free	leak	loop	race	privilege
int	∗	∗ ×	∗	∗	∗	∗ × ✓		∗
buf	∗	∗	✓	∗		✓		∗
nullptr		✓		✓		✓		∗
free		∗	✓					∗
leak			∗			∗		
loop	✓	∗ × ✓	✓					
race	∗	∗ ×	∗	∗	∗	∗		∗
privilege		×						

6.3 Computing Fault Correlation

In this section, we present an algorithm to statically compute fault correlation. The approach has two phases: fault detection and fault correlation. In fault detection, we report path segments where faults occur in terms of path graphs. In fault correlation, we model the error state of detected faults and symbolically simulate the propagation of the error state along program paths to determine its impact on the occurrence of the other faults. The goals of the second phase are to identify 1) whether a fault is a cause of another fault detected in the first phase; and 2) whether a fault can activate faults that had not been identified in the first phase. As the determination of fault correlation requires path information, we use a demand-driven analysis for scalability.

6.3.1 Overview of the Approach

We first review the steps for fault detection shown on the left side of Figure 6.5. The demand-driven analysis first identifies program statements where the violation of property constraints can be observed, namely, *potentially faulty points*. At those statements, the analysis constructs queries as to whether property constraints can be satisfied. Each query is propagated backwards along all reachable paths from where it is raised. Information is collected along the propagation to resolve the query. If the constraints in the query are resolved as `false`, implying a violation can occur, a fault is detected. The path segments that produce the fault are identified as faulty.

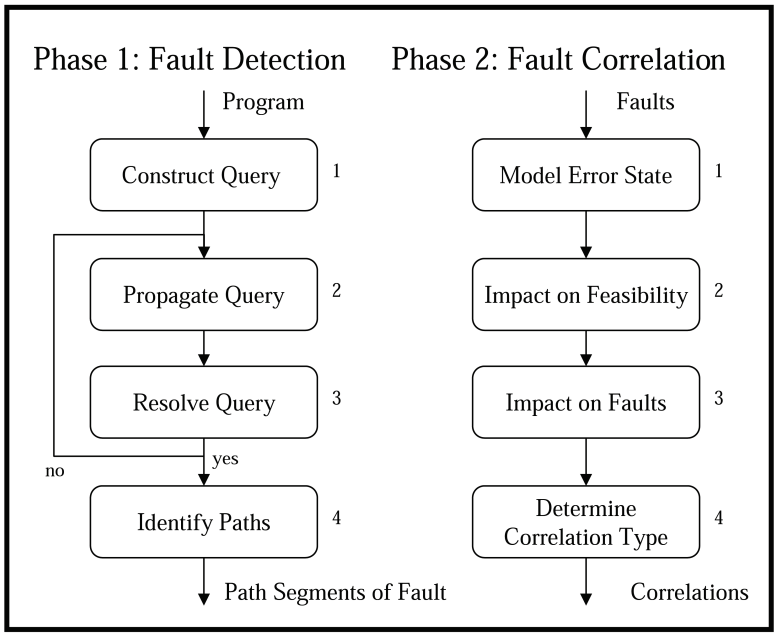


Figure 6.5: Fault Detection and Fault Correlation

To improve the precision of the fault detection, we run an infeasible path detection using a similar query based algorithm, where the query is constructed at a conditional branch as to whether the outcome of the branch can always be true or false [Bodik et al., 1997b]. After the infeasible paths are identified and marked on the ICFG, we run various fault detectors. In the fault detection, when the query that is being used to determine faults encounters an infeasible path, the propagation terminates.

In the analysis, we cache queries and the resolutions at statements where the queries have been propagated. Both the cached query and the identified path segments will be reused to compute fault correlations. All the detected faults are checked for correlation in the next phase.

We developed four steps to determine the fault correlation, shown on the right in Figure 6.5. In the first step, we model the error state of f_1 based on its fault type (see Table 6.1). The error state is instrumented on ICFG as a constraint. For example, for the integer fault in Figure 6.1, we insert [`value(current_track)<0`] at node 2, and for the resource leak in Figure 6.3, we add at node 3 [`avail(Socket)==avail(Socket)-1`]. Next, we examine whether the error state of f_1

can change the results of branch correlation analysis, as an update of the conditional branch can lead to the change of feasibility, which then impacts the occurrence of f_2. In the following step, we determine the impact of f_1 directly on f_2, and finally we check if the identified correlation is unique.

6.3.2 Examples to Find Correlations

Based on the definition of fault correlation, for $f_1 \rightarrow f_2$ to occur, we require two conditions: 1) there exists a program path p that traverses both f_1 and f_2; and 2) along p, constraints for evaluating f_2 are dependent on the error state of f_1. In this section, we use examples to show how the steps of fault detection and fault correlation presented in Figure 6.5 proceed to determine the two conditions.

6.3.2.1 Correlation via Direct Impact on Faults

In Figure 6.6, we show an example on the left, and the actions taken in the analysis on the right. Under *Fault Detection*, we present the transitions of the query in fault detection phase. Each table describes the propagation of a query along one path. The first column of the table gives the nodes where a query propagated and updated. The second column lists the query after being updated and cached at the node. In Table Q_5, we show that, to detect integer overflow, we identify node 5 as a potentially faulty point and raise the query [`value(i)*8<C`] (`C` is the type-dependent constant 2^{32}), inquiring whether the integer safety constraints hold. The query is propagated backwards and resolved as `false` at node 4 due to a user determined input `i`, shown in the second row of Table Q_5. Path $\langle 4,5\rangle$ is thus determined as faulty and marked on ICFG. The query is also propagated to node 3 and resolved as `true` (this path is not listed in the figure due to space limitations). Similarly, to detect buffer overflows, we identify nodes 8, 10 and 11 as potentially faulty and raise queries to determine their safety. Table Q_8, Q_{10} and Q_{11} present the propagation of the three queries. Take Q_8 as an example. At node 8, we raise an initial query [`value(i)`$\leq$`size(p)`], inquiring whether the buffer constraints are satisfied. At node 6, the query is first changed to [`8*value(i)`$\leq$`value(x)`]. A symbolic substitution at node 5 further updates the query to [`8*value(i)`$\leq$`8*value(i)`]. We thus resolve the query as `true` and report the buffer at node 8 safe. In the fault detection phase, we

identify three faults, an integer overflow at node 5, and buffer overflows at nodes 10 and 11. We determine in the next step whether the correlation exists for these faults.

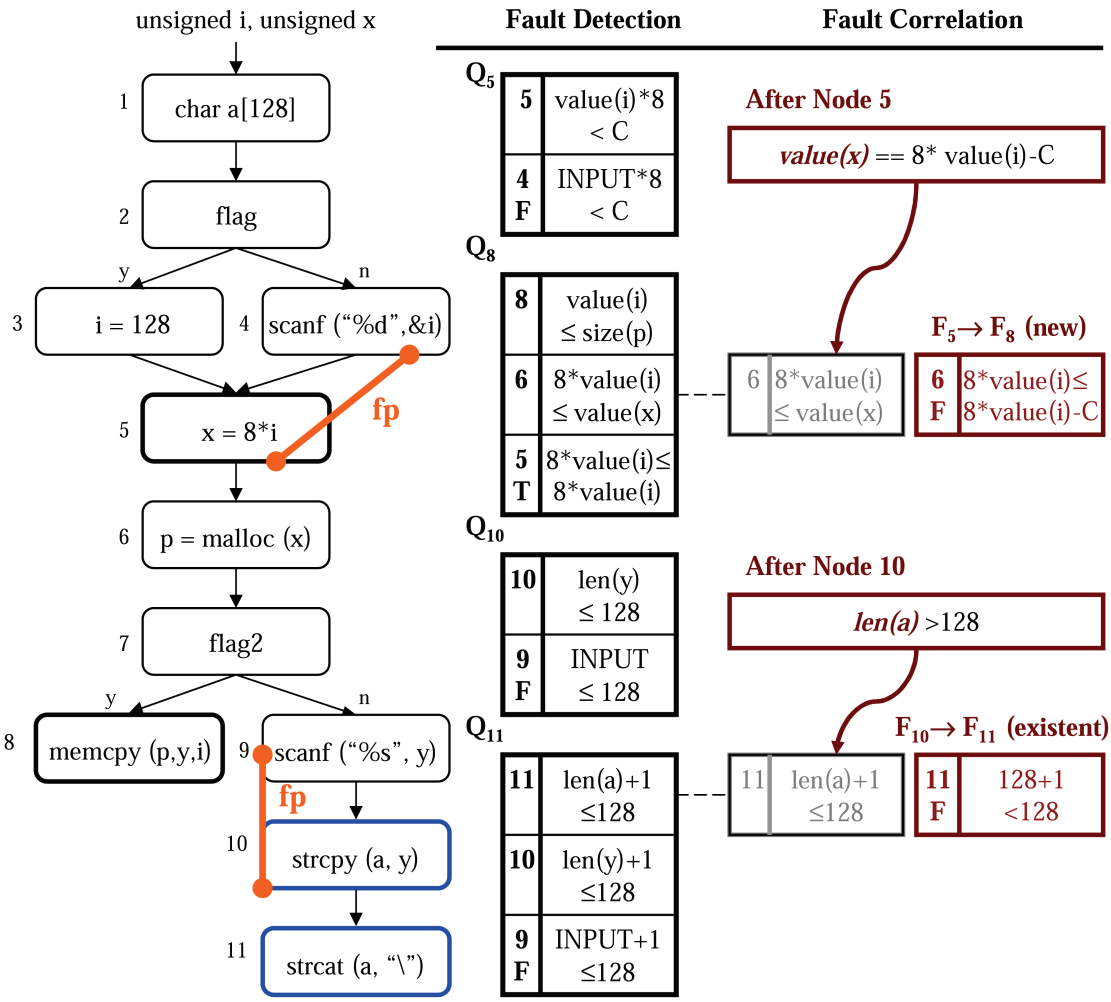


Figure 6.6: Correlation via Direct Impact

Under *Fault Correlation* in Figure 6.6, we list the steps for computing correlations. We first model the error state. For the integer overflow at node 5, we introduce `[value(x)==8*value(i)-C]` as an error state, shown in the first box under *Fault Correlation*. We italicized `value(x)` to indicate it is the corrupted data at this fault. Conceptually, we need to propagate the error state along all program paths in a forward direction to examine if the corrupted data `value(x)` can impact the occurrence of the faults at nodes 8, 10 and 11. Since our analysis is demand-driven, to determine

such impact, we actually propagate the queries raised at nodes 8, 10 and 11 in a backward direction toward the fault located at node 5, and determine if the error state can update the queries. As such backward propagation has been done in fault detection, we can take advantage of cached queries to compute correlation. In the figure, all queries listed in the tables are cached in the corresponding nodes after fault detection. From Table Q_8, we discover that at the immediate successor(s) of the integer fault, i.e., node 6, query [`8*value(i)≤ value(x)`] has been propagated to and is cached. The query is dependent on the corrupted data `value(x)` at the error state. We use a bold arrow in the figure to show the dependency. The query is thus updated with the error state and reaches a new resolution `false`. In this case we discover a fault that was not reported in fault detection. Using a similar approach, we introduce the error state [`len(a)>128)`] after node 10 for a buffer overflow. With this information, the query for checking buffer overflow at node 11 is resolved to `false`. In this case, two previously identified faults are determined as correlated.

To determine $f_1 \xrightarrow{u} f_2$, we examine when f_1 is fixed, whether f_2 still can occur. As for $f_1 \xrightarrow{u} f_2$, f_1 is the necessary cause of f_2, and fixing f_1 ensures the correctness of f_2. Our approach is to replace the inserted error state with the constraints that imply the correctness of the node. For example, in Figure 6.6, we replace the error state at node 5 with [`value(x)==8*value(i)`], and at node 10 with [`len(a)≤128`]. With the new information, node 8 is determined as safe, indicating the correlation of node 5 and node 8 is unique, while node 11 still reports unsafe, showing the correlation between nodes 10 and 11 is not unique.

In our approach, the two conditions for determining fault correlation are ensured by two strategies. First, in fault correlation, if queries are updated with the error state of f_1 and still not resolved, we continue propagating the updated query along the faulty path of f_1, which assure f_2 and f_1 are located along the same path. For instance, in the above example, if the buffer overflow query raised at node 8 is not resolved at node 5 with the error state, it would continue to propagate along path $\langle 5,4\rangle$ for resolution, as the error state is only produced along the faulty path $\langle 5,4\rangle$. Second, we establish the dependency between f_2 and f_1 by assuring the error state of f_1 can update the queries of f_2 and the variables in the queries are dependent on the corrupted data in the error state.

6.3.2.2 Correlation via Feasibility Change

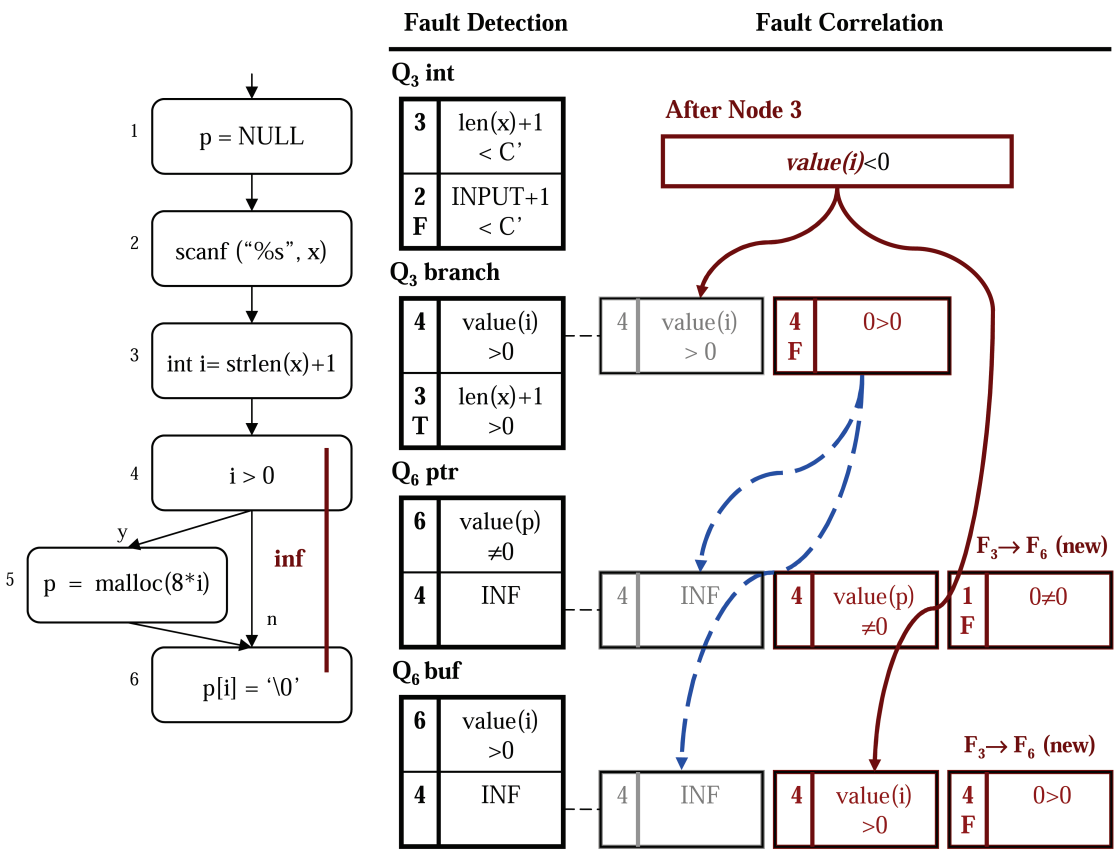


Figure 6.7: Correlation via Feasibility Change

The error state of f_1 also can impact f_2 indirectly by changing the conditional branches f_2 depends upon, shown in Figure 6.7. The program is a simplified version of Figure 6.1. Under *Fault Detection*, we list the query transitions to detect infeasible paths and faults. Under *Fault Correlation*, we show the query update in fault correlation. In this example, our focus is to present how an integer error found at node 3 changes the branch correlation at node 4 and then impacts other faults. An error state [`value(i)<0`] is modeled after node 3. Examining cached query at node 4, we find that the error state can update the branch query [`value(i)>0`] and resolve it to `false`. The change of the resolution implies that the path this query propagated along is no longer infeasible as identified before. Therefore, all the queries that are control dependent on this branch are potentially impacted, and we need to evaluate all the queries cached at node 4 for new resolutions. For example,

we restart the query [`value(p)`$\neq$`0`] from node 4 and resolve it at node 1 as `false`, and a null-pointer dereference is discovered. Similarly, we restart the buffer overflow query [`value(i)>0`] at node 4, where we find the query is resolved as `false` with the information from the error state. In this case, the error state of the integer fault first impacts the branch and activates the propagation of the query at node 4; then the error state also has a direct impact on the query and changes its resolution to `false`.

6.3.3 The Algorithm of Fault Correlation

For identifying fault correlations, Algorithm 4 takes the inputs $icfg$ and n, where $icfg$ represents the ICFG with fault detection results (including the cached queries and marked faulty paths), and n is the node where the fault is detected. Our goal is to identify all the correlations for the fault at node n.

At line 2, we model the error state. For each query cached at the immediate successor(s) of the fault, we identify queries that are dependent on the error state. See lines 3–5. If the query is resolved after updating with the error state, we add it to the set of resolved queries A at line 7. Otherwise, if the updated query was used to compute faults, we add it to the list FQ at line 8. If the query was used to compute branch correlation, we add it to the list IQ at line 10. Lines 11–12 collect queries stored at the branch $q'.raise$. The faults associated with these queries are potentially impacted by the feasibility change, and thus need to be reevaluated. After queries are classified to the lists FQ and IQ, we compute the feasibility change at line 17 using IQ and then determine the impact of the error state directly on the faults at line 18 using FQ.

The determination of the resolutions of updated queries is shown in `Resolve` at line 19. The analysis is backwards. At line 21, we first propagate the queries to the predecessors of the faulty node. We then use a worklist to resolve those queries at lines 23–28. `Propagate` at line 30 indicates that we need to only propagate the queries along feasible and faulty paths. After a query is resolved at line 26, we identify paths and mark them on ICFG at line 29. For branch query, they are adjusted infeasible paths, while for queries to determine faults, the paths show where the correlation occurs.

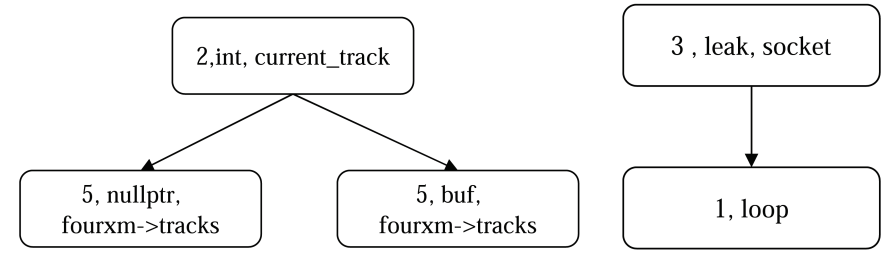
```
   Input  : ICFG with fault detection results (icfg);
            faulty node (n)
   Output: Correlations for n
 1 initialize IQ = {} and FQ = {}
 2 er = ModelErrState (n);
 3 foreach m ∈ Succ(n) do
 4 |   foreach q ∈ Q[m] do
 5 |   |   q' = UpdateWithErrState (er, q);
 6 |   |   if q' ≠ q then
 7 |   |   |   if q'.an = resolved then add q' to A
 8 |   |   |   else if IsFaultQ(q') then add q' to FQ
 9 |   |   |   else
10 |   |   |   |   add q' to IQ
11 |   |   |   |   foreach x ∈ Q[q'.raise] do
12 |   |   |   |   if IsFaultQ(x) then add x to FQ
13 |   |   |   end
14 |   |   end
15 |   end
16 end
17 Resolve(IQ)
18 Resolve(FQ)
19 Procedure Resolve (querylist Q)
20 foreach q ∈ Q do
21 |   foreach p ∈Pred(n) do Propagate (n, p, q)
22 end
23 while worklist ≠ ∅ do
24 |   remove (i, q) from worklist
25 |   UpdateQ(i, q)
26 |   if q.an = resolved then add q to A
27 |   else foreach p ∈Pred(i) do Propagate (i, p, q)
28 end
29 IdentifyPath(A)
30 Procedure Propagate (node i, node p, query q)
31 if OnFeasiblePath(i, p, q.ipp)∧
32    OnFaultyPath(i, p, q.fpp) then
33 add (p, q) to worklist
```

Algorithm 4: Compute Fault Correlations

6.4 Correlation Graphs

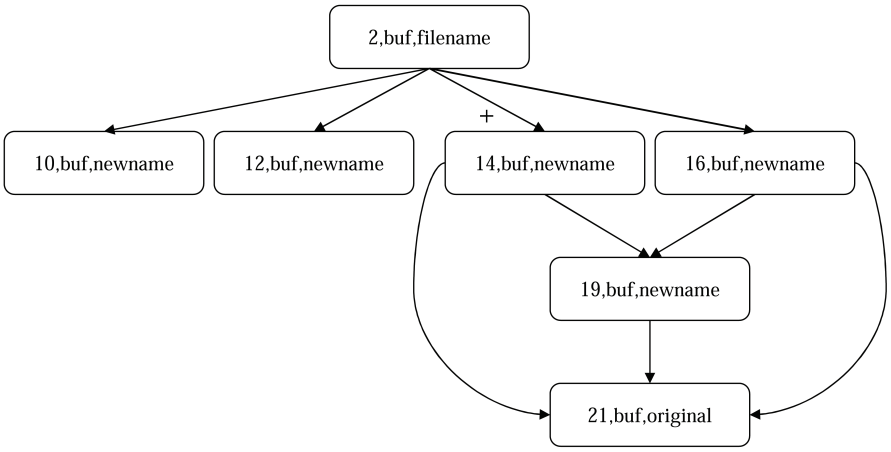
Our algorithm computes the correlation between pairs of faults. We integrate individual fault correlations in a graph representation to present correlations among multiple faults and along different paths for the whole program.

Definition 6.3: A *correlation graph* is a directed and annotated graph $G = (N, E)$, where N is a set of nodes that represent the set of faults in the program and E is a set of directed edges, each of which specifies a correlation between two faults. The *entry nodes* in the graph are nodes that do not have incoming edges, and they are the faults that occur first in the propagation. The *exit nodes* are nodes without outgoing edges, and they are the faults that no longer further propagate. Annotations for a node introduce information about a fault, including its location in the program, the type, and the corrupted program objects at the fault if any. Annotations for the edge specify whether the correlation is unique and also the paths where the correlation occurs.



(a) graph for Figure 6.1

(b) graph for Figure 6.3



(c) graph for Figure 6.4

Figure 6.8: Correlation Graphs for Examples: + marks a correlation that is not unique

The correlation graph groups faults of the related causes for the program. The entry nodes of the graph and the nodes whose correlation are not unique should be focused to find root causes. Using the correlation graph, we can reduce the number of faults that need to be inspected in order to fix all the faults. In Figure 6.8, we show the correlation graphs for examples we presented before,

Figure 6.8(a) for Figure 6.1, 6.8(b) for Figure 6.3, and 6.8(c) for Figure 6.4.

In Figure 6.1, we have shown a correlation of integer fault and null-pointer dereference along path $\langle 1,2,5\rangle$. Actually the integer fault at node 2 also correlates with a buffer bounds error at node 5 along path $\langle (1-5)^+,1,2,5\rangle$. See Figure 6.8(a). If the buffer bounds error continues to cause privilege elevation, the correlation graph would show a chain of correlated faults to help understand the exploitability of the code. On the other hand, if both the null-pointer dereference and buffer underflow at node 5 are reported via a dynamic detector, using the correlation graph, we are able to know the two failures are attributable to the same root cause and can be fixed by diagnosing the integer fault at node 2. Similarly, the relationship of the resource leak and infinite loop shown in Figure 6.3 is depicted in Figure 6.8(b).

The correlation graph in Figure 6.8(c) integrates all correlations for 7 buffer overflows in Figure 6.4. To use this graph for diagnosis, we start from the entry node of the graph, as it indicates the root cause of all 7 correlated faults. Diagnosing the entry node we discover that when the input `FileData.cFileName` is copied to the `filename` buffer at line 2, no bounds checking is applied. We thus introduce a fix for line 2. The correlation graph indicates that all other correlated faults can be fixed except the fault at line 14, as in the graph, the edge from the fault at line 2 to the fault at line 14 indicates the existence of an additional root cause. We thus diagnose line 14 and introduce the second fix.

6.5 Experimental Results

To demonstrate that we are able to automatically compute fault correlations and show that fault correlations are helpful for fault diagnosis, we implemented our techniques and chose three types of common faults as case studies: buffer out-of-bounds, integer truncation and signedness errors, and null-pointer dereference. In the experiments, we first run fault detection and update the ICFG with faults detected. We model the error state of integer and buffer faults using the approaches shown in Table 6.1 and then determine the fault correlation. It should be noted that although in our experiments, we use our fault detector to identify faults and then compute fault correlations, our

technique is applicable when faults are provided by other tools. We used a set of 9 programs for experimental evaluation: the first five are selected from benchmarks that are known to contain 1–2 buffer overflows in each program [Lu et al., 2005, Zitser et al., 2004]; the rest are deployed mature applications with a limited number of faults reported by our fault detector. The experimental data about fault correlation are presented in the following four sections. The results have been confirmed by manual inspection.

6.5.1 Identification of Fault Correlations

In the first experiment, we show that fault correlations can be automatically identified. Table 6.3 displays identified correlations. In the first column of the table, we list the 9 benchmark programs. Under *Faults from Detection*, we display the number of faults identified for each program in our fault detection. Buffer bounds errors are reported in Column *buf/corr*. Integer faults are listed in Column *int/corr* and the null-pointer dereferences are shown in Column *ptr/corr*. In each column, the first number gives the identified faults and the second lists the number of detected faults that are involved in fault correlation. Our fault detector reports a total of 80 faults of three types, 51 of which are involved in fault correlation.

Under *Fault Correlations*, we list the number of pairs of faults in the program that are found to be correlated. For example, under *int_buf*, we count the pairs of correlated faults where the cause is an integer fault, which leads to a buffer overflow. Comparing the integer faults involved in the correlations under *int_buf* and *int_ptr* with the ones found in fault detection, we can prioritize the integer faults with severe symptoms. In the last column of *Fault Correlations*, we give a total number of identified correlations. In our experiments, we found fault correlations for 8 out of 9 programs. Correlations occur between two integer faults, an integer fault and a buffer overflow, an integer fault and a null-pointer dereference, two buffer overflows, as well as a buffer overflow and an integer fault.

The experiments also validate the idea that the introduction of error states can enable more faults to be discovered. We identify a total of 25 faults during fault correlation from 5 benchmarks, including buffer overflows, integer faults, and null-pointer dereferences, shown under *Faults during*

Correlation.

Consider the benchmark `gzip-1.2.4` as an example. We discover a total of 25 faults and 22 pairs of them are correlated. A new buffer overflow is found after introducing the impact of an integer violation. Buffer overflow correlates with integer fault when `strlen` is called on an overflowed buffer which later is assigned to a signed integer without proper checking. We also found that the new faults generated during fault correlation can further correlate with other faults. In `putty-0.56`, two integer faults found during fault correlation resulted from another integer fault are confirmed to enable a buffer overflow. The propagation of these faults explains how the buffer overflow occurs.

Table 6.3: Automatic Identification of Fault Correlations

Benchmarks	Faults from Detection			Fault Correlations						Faults during Correlation
	buf/corr	*int/corr*	*ptr/corr*	*int_int*	*int_buf*	*int_ptr*	*buf_buf*	*buf_int*	*total*	
wuftp:mapping-chdir	4/4	0	0	0	0	0	7	0	7	0
sendmail:tTflag-bad	0	3/1	0	0	1	0	0	0	1	1 (buf)
sendmail:ge-bad	4/4	0	1/0	0	0	0	3	0	3	0
polymorph-0.4.0	8/8	0	0	0	0	0	13	0	13	0
gzip-1.2.4	9/9	15/7	0	0	7	0	9	6	22	1 (buf)
ffmpeg-0.4.8	0	6/2	1/0	0	10	1	0	0	11	11 (1 ptr, 10 buf)
tightvnc-1.2.2	0	11/8	0	9	8	0	0	0	17	7 (2 int, 5 buf)
putty-0.56	7/6	4/2	0	3	3	0	4	0	10	5 (3 int, 2 buf)
apache-2.2.4	0	2/0	5/0	0	0	0	0	0	0	0

6.5.2 Characteristics of Fault Correlations

We also collected the data about the characteristics of fault correlations, shown in Table 6.4. In Column *Unique/Not*, we count, for all the correlations identified, how many are uniquely correlated (see the first number in the column) and how many are not (see the second number). The data demonstrate that both types of correlations exist in the benchmarks. Column *Dir/Indir* shows whether a correlation occurs directly between two faults or indirectly as a result of feasibility change. The first number summarizes the direct correlations and the second number counts the indirect ones. The results show that most correlations are discovered via direct query interactions, and only two programs report the correlations identified from feasibility change. We also investigated the distances between the correlated faults. The experimental data under *Inter/Intra* show that along the correlated paths, the two faults can be located either intraprocedurally or interpro-

cedurally. Therefore an interprocedural analysis is required for finding all correlations. A related metric is the distance of correlated faults along the correlation paths in terms of number of procedures. Column *Corr-Proc* gives both the minimum and maximum numbers of procedures between two correlated faults in the benchmark. We are able to find the correlation where two faults are 19 procedures apart.

Table 6.4: Characteristics of Fault Correlations

Benchmarks	Unique/Not	Dir/Indir	Inter/Intra	Corr-Proc
wuftp:mapping-chdir	4/3	7/0	7/0	1–10
sendmail:tTflag-bad	1/0	1/0	0/1	1–1
sendmail:ge-bad	0/3	3/0	0/3	1–1
polymorph-0.4.0	11/2	13/0	8/5	1–3
gzip-1.2.4	12/10	21/1	15/7	1–19
ffmpeg-0.4.8	11/0	1/10	0/11	1–1
tightvnc-1.2.2	14/3	17/0	16/1	1–2
putty-0.56	10/0	10/0	2/8	1–3

6.5.3 Computing Correlation Graphs

A correlation graph is built for each benchmark in the experiments. In Table 6.5, we first give the size of benchmarks in terms of thousands lines of code. In Column *Node*, we report the total number of nodes in the correlation graph. The nodes include faults identified from fault detection and fault correlation. The types of identified faults are listed in Column *Type*. For example, for the program `ffmpeg-0.4.8`, we find faults of all three types. In Column *Group*, we provide the number of groups of correlated faults for each program. We obtained the number by counting the connected components in each correlation graph. The results show that although the number of faults can be high in a program, many of the faults can be grouped and diagnosed together. For 7 out of 9 programs, the faults are clustered to less than a half of fault groups which will assist diagnosis.

Under *Analysis Cost*, we report the analysis costs for computing correlation graphs, including the time used for detecting faults (see the first number in the column) and the time used for computing fault correlations (see the second number). The machine we used to run experiments is the Dell Precision 490, one Intel Xeon 5140 2-core processor, 2.33 GHz, and 4 GB memory.

The experimental data show that the analysis cost for fault detection is not always proportional to the size of the benchmarks; the complexity of the code also matters. For example, the analysis for `sendmail:tTflag-bad` takes a long time to finish because all the faults are related to several nested loops. The additional costs of computing fault correlations for most of the benchmarks are under seconds or minutes, except for `gzip-1.2.4`, which contains the most faults among the benchmarks and many faults are found to impact a large chunk of the code in the program. The data suggest that the important factors that determine the analysis cost of fault correlation are the number of faults and the complexity of their interactions.

Table 6.5: Correlation Graphs and their Analysis Costs

Benchmarks	Size(kloc)	Node	Type	Group	Analysis Cost
wuftp:mapping-chdir	0.2	4	1	1	3.9 m/43.2 s
sendmail:tTflag-bad	0.2	4	2	3	108.0 m/5.6 s
sendmail:ge-bad	0.9	5	2	2	10.8 s/3.7 s
polymorph-0.4.0	0.9	8	1	1	39.4 s/9.3 s
gzip-1.2.4	5.1	25	2	9	29.3 m/90.0 m
ffmpeg-0.4.8	39.8	18	3	7	114.2 m/3.4 m
tightvnc-1.2.2	45.4	18	2	6	60.3 m/2.4 m
putty-0.56	60.1	16	2	7	62.8 m/1.2 m
apache-2.2.4	268.9	7	2	7	217.8 m/2.1 s

6.5.4 False Positives and False Negatives

In our experiments, both false positives and false negatives have been found. Because we isolate don't-know warnings for unresolved library calls, loops and pointers, our analysis does not generate a large number of false positives. In fault correlation, we consider the following two cases as false positives: 1) at least one of the faults involved in correlation is false positive; and 2) both faults in the correlation are real faults, but they are not correlated. In our buffer overflow detection, we report a total of 7 false positives for all programs, 1 from `sendmail:tTflag-bad`, 4 from `gzip` and 2 from `putty`. For integer fault detection, we report a total of 10 false positives, 3 from `sendmail:tTflag-bad`, 2 from `polymorph`, 2 from `ffmpeg`, 1 from `putty` and 2 from `apache`. We find 25 correlations reported are actually false positives, 23 of which are related to case (1), and 2 to case (2) where the correlation paths computed are confirmed as infeasible. However, we did not find that any new faults reported during fault correlation (see the last column in Table 6.3)

are false positives. Interestingly, we found false positive faults can correlate with each other and thus be grouped. In our implementation, we have applied such correlations to quickly remove false positives and improve the precision of our analysis. We exclude the false positives when reporting the faults and fault correlations in Tables 6.3, 6.4 and 6.5.

We miss fault correlations mainly in two cases: 1) we report correlated paths between two faults as don't-know; and 2) the correlation occurs among the types of faults not investigated in our experiments. For example, in the benchmark `tightvnc-1.2.2`, three integer faults are reported as not correlated, shown under *Faults from Detection* in Table 6.3; however, our manual inspection discovers that these faults can cause buffer read overflow, which was not considered in our fault detection.

6.6 Conclusions

As faults become more complex, manually inspecting individual faults becomes ineffective. To help with diagnosis, this chapter shows that identifying a causal relationship among faults helps understand fault propagation and group faults of related causes. With the domain being statically identifiable faults, this chapter introduces definitions of fault correlation and correlation graphs, and presents algorithms for their computation. Our experiments demonstrate that fault correlations exist in real-world software, and we can automatically identify them. The benchmarks used in our experiments are mature applications with few faults. However, determining correlation is especially important for newly developed or developing software which would have many more faults. Although the fault correlation algorithm is tied to our fault detection for efficiency, a slightly modified correlation algorithm would work if faults are discovered by other tools and presented to the correlation algorithm.

Chapter 7

Path-Guided Concolic Testing

Concolic testing [Sen et al., 2005] has been proposed as an effective technique to automatically test software. The goal of concolic testing is to generate test inputs to find faults by executing as many paths of a program as possible. However, due to the large state space, it is unrealistic to consider all of the program paths for test input generation. Rather than exploring the paths based on the structure of the program as current concolic testing does, in this research, we generate test inputs and execute the program along the paths that have identified potential faults.

We present a path-guided testing technique that combines static analysis with concolic testing. A novelty of our work is that our technique is path-based, i.e., we direct dynamic testing to the path segments rather than a program point. Compared to program points, path information is more precise, and can help further reduce the search space for test input generation.

This research addresses three challenges. Considering that the number of suspicious paths can still be huge, we need to develop a representation of path information used in testing. Also, static analysis produces false positives and false negatives. We need to understand the impact of the potential imprecision in guiding test input generation. Furthermore, not every execution that exercises a faulty path necessarily triggers the fault; besides path constraints, we also need to track fault conditions for test input generation.

Our technique proceeds in three steps. First, the program under test is analyzed by a path-sensitive static analysis tool. Both the suspicious statement and corresponding path segments along

which a fault could occur are identified, represented using a *path graph*. Second, reachability relationships from each branch to these path segments are computed. In the third step, we execute the program with an initial input, and use the reachability information and the path graph to select the paths of interest. During execution, we generate test inputs that 1) can reach a suspicious statement along a corresponding suspicious path segment, and 2) can trigger the fault condition at the suspicious statement.

We have implemented our techniques in a tool called MAGIC (MArple-GuIded Concolic testing). Currently, this tool handles buffer overflows for C programs; however the technique is applicable for multiple types of faults, including both data- and control-centric faults. In our experiments, MAGIC confirmed 73% of statically reported faults. It failed to trigger 5 static faults whose detection requires an environment which is different from where MAGIC is running, and it missed 2 faults due to the capability of concolic testing. Compared to concolic testing, MAGIC found about 2.5 times more faults, and using the path information, MAGIC triggers the faults 1.1–66.3 times faster over a set of benchmarks.

The main contributions of this chapter include:

- automatic test input generation to exploit statically identified faults,
- application of static path information for reducing the cost of dynamic testing,
- the implementation of the techniques for detecting buffer overflows, and
- an experimental study that demonstrates the effectiveness of our technique.

7.1 An Example

First, we use an example to intuitively explain the techniques. In Figure 7.1, we show a piece of code adapted from the benchmark wu-ftp [Zitser et al., 2004]. This example contains three paths and two buffer write statements at lines *6* and *10* respectively. A buffer overflow exists at line *10*. Using this example, we compare how traditional concolic testing and our technique find this buffer overflow.

Applying concolic testing for buffer overflow [Xu et al., 2008], we first execute the program with an initial input. We assume in the first run, *argc=1*, which means that no command line argument is supplied to the program. Under this input, the program takes the execution path $\langle 2,3,4(T),5\rangle$. During execution, the symbolic path constraint [*argc !=2*] is collected. As the goal of concolic testing is to cover as many paths as possible, in the second run, the tester inverts the path constraint to [*argc=2*], aiming to exercise the branch *4(F)*. Suppose a command line argument *"a"* is generated for *argv[1]*. Running this input, path $\langle 2,3,4(F),6,7,8(F),10\rangle$ is taken. Along this path, the tester checks the buffer safety at lines *6* and *10*, and determines that both lines 6 and 10 are safe for this execution. Meanwhile, the tester also derives that line 10 can be an overflow if the length of argv[1] is larger than 8. Using this buffer overflow condition, the tester can generate an input "aaaaaaaaa" for *argv[1]*, which leads the execution to path $\langle 2,3,4(F),6,7,8(F),10\rangle$, and exploits the buffer at line 10. Since there are still paths that have not been covered, the concolic testing continues to invert the path constraint at line 8, aiming to take branch *8(F)*. A string *"."* is generated as the input for *argv[1]* to exercise $\langle 2,3,4(F),6,7,8(T),9\rangle$.

Concolic testing terminates either when 1) no more new paths can be further executed due to incapability of solving complex constraints, 2) all of the paths in a program have been executed, or 3) a time threshold is reached. Considering that there is an exponential number of paths, often only a small portion of the program paths are actually covered by concolic testing [Godefroid et al., 2005] [Sen et al., 2005]. For this example, concolic testing covers all the three paths of the program and generates a total of three test inputs. Buffer write statements at lines 6 and 10 are checked for each path that exercises them.

Our observation is that not all of the buffer write statements are equally suspicious for buffer overflows. Even for a suspicious statement, not all the paths that traverse it are faulty. To save the cost of test input generation, we should direct the testing along suspicious paths.

Applying our technique, we first statically identify that line *10* is suspicious for buffer overflow along path segment $\langle 6,7,8(F),10\rangle$, and line *6* is safe, which implies that no checks are needed for this statement at run time. We then perform a reachability analysis, and find that branch *4(F)* reaches the suspicious path segment, but branch *4(T)* cannot. Based on the above static information,

```
1  main(int argc, char **argv){
2    char mapped_path[10];
3    char *path;
4    if(argc != 2 )
5      return;
6    strcpy(mapped_path,''/'');
7    path = argv[1];
8    if(path[0] == '.'))
9      return;
10   strcat(mapped_path, path);
11 }
```

Figure 7.1: Comparing Concolic Testing and MAGIC Using an Example

we run a concolic testing. The program is first executed with no arguments along path $\langle 2,3,4(T),5\rangle$. As branch *4(F)* can reach the suspicious path segment, we inverse the symbolic path constraint and generate an input *"a"*. Under this input, the program executes $\langle 2,3,4(F),6,7,8(F),10\rangle$. Since the suspicious path segment is traversed, the tester determines if the buffer overflow is triggered. As the buffer overflow is not triggered under this input, the tester integrates the buffer overflow condition at line *10*, and generates a new input *"aaaaaaaaaa"* to exploit the buffer overflow.

With the static information, we do not need to explore the program nodes that cannot reach the suspicious path segment, e.g., branch *4(T)*. Only paths that cross a suspicious path segment are checked for buffer overflow. For instance, no effort is needed to generate test input for path $\langle 2,3,4(F),6,7,8(T)\rangle$. Testing can be terminated early when the potential faults are triggered. We exploit the overflow at line *10* by only generating two test inputs, and the possibility of buffer overflow is checked only once along one path.

7.2 An Overview of MAGIC

This section provides a high level description of MAGIC, including the components of MAGIC and their interactions.

7.2.1 The Components

MAGIC consists of five components, shown in Figure 7.2. Marple and the reachability analyzer are the two static components. Marple is a static path-sensitive analyzer that reports the suspicious statements as well as the suspicious path segments. The reachability analyzer calculates reachability relationships from each branch of the program to the suspicious path segments. The dynamic testing components are built based on concolic testing, including a program instrumentor, a test input generator and a test driver. The program instrumentor inserts statements to the program to collect symbolic constraints and concrete values during testing. The test input generator generates test inputs using symbolic path constraints and fault conditions. The test driver executes the program with test inputs and performs symbolic evaluation simultaneously.

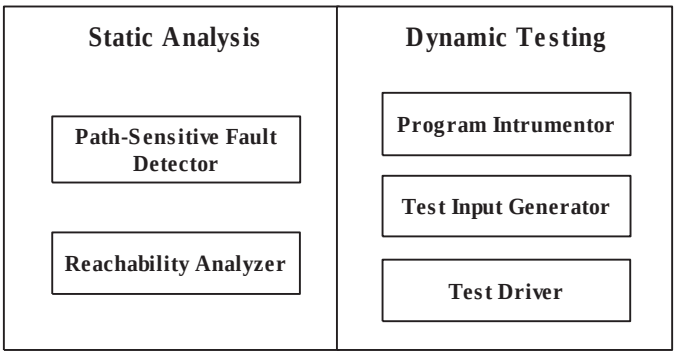


Figure 7.2: The Components of MAGIC

Our testing components make several improvements on traditional concolic testing. First, we use boundary values to initiate the test input, which is experimentally shown to achieve a better branch coverage than using a fixed given value as the input. Another enhancement is that we dynamically change the program state at runtime when a fault is perceived to avoid the crash of the program; otherwise, manual effort has to be involved to fix the fault before testing can continue. Furthermore, we model program operations that are potentially related to the production of a certain type of fault. For instance, to trigger a buffer overflow, we handle string libraries and pointer operations. Concolic testing might never be able to exercise desired paths if these operations are not modeled. In addition to path constraints, we also construct fault conditions for test input generation.

The goal is to ensure the generated inputs not only can exercise a desired path but also trigger faults.

7.2.2 The Workflow of MAGIC

As shown in Figure 7.3, MAGIC first statically analyzes the program and reports suspicious statements and path segments. Based on the program source and the path segments, MAGIC runs a reachability analysis to determine, for each branch, whether the execution at the branch is able to reach any of the suspicious path segments. MAGIC instruments the program to collect information needed at runtime. Testing runs on the instrumented program with an initial test input. During execution, the tester determines whether the current execution can traverse any suspicious path segment. Meanwhile, the tester collects concrete and symbolic values; when a suspicious fault is encountered, the symbolic constraints regarding path constraints and fault conditions are solved by a constraint solver for potential test inputs. Testing terminates when a program input is discovered that can trigger the fault, or the paths that traverse the set of suspicious path segments are all examined, which show that the suspicious statement is likely safe along the reported suspicious path segments. The details of static and dynamic components are presented in Section 7.3 and 7.4.

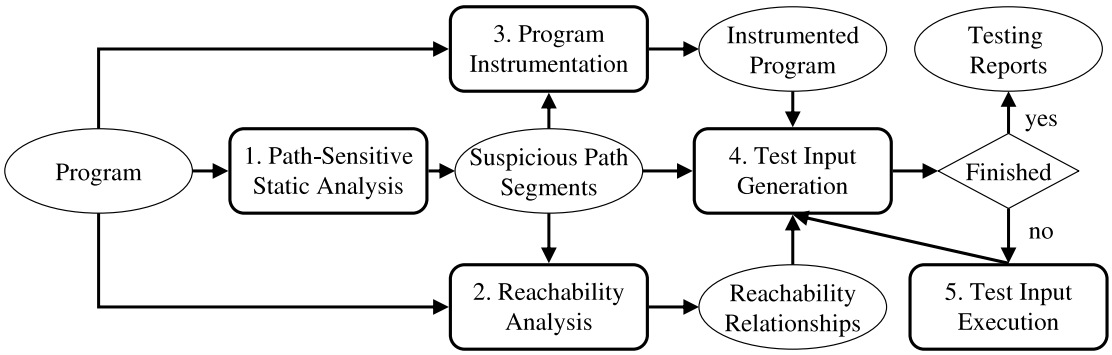


Figure 7.3: The Workflow of MAGIC

7.3 Obtaining Static Path Information

In MAGIC, a program is first analyzed using our path-sensitive analysis to obtain *suspicious statements* and corresponding *suspicious path segments*. Here, we consider both *faulty* and *don't-know* path segments reported by Marple as suspicious and any statement where a suspicious segment can traverse is a *suspicious statement*. In this section, we first describe our choice of static information provided to dynamic testing, and we then present the reachability analysis customized for our purpose.

7.3.1 The Choice of Path Information

To determine what path information we should provide to dynamic components, we first need to understand the semantics of two types of suspicious path segments. In our analysis, a path segment is determined as faulty if: 1) along the path segment, the fault always occurs independent of program inputs, e.g., a buffer overflow with a constant string, or 2) there exists an entry point along the path segment, where users can supply an input to trigger the fault, e.g., a buffer overflow with an external string. As its determination is independent on any other information beyond the path segment, any execution that traverses the faulty path segment (with a proper input supplied at the entry point along the path segment for the second case) can trigger the fault. A don't-know path segment is determined when the query encounters don't-know factors. If the don't-know factors are resolved, the query is potentially propagated further before being determined as faulty, in which case, the don't-know path segment can be viewed as a partial faulty path segment. Some of the don't-know paths can be safe and thus executions along don't-know paths do not necessarily trigger the fault.

There is also the choice on the number of suspicious path segments we should present. In testing, we only need to demonstrate the exploits of the buffer overflow along one execution. However, presenting one path segment for test input generation is not sufficient. The reasons are twofold. First, static information can be imprecise. For example, even a buffer overflow potentially occurs at the statement, a suspicious path segment randomly picked from the static results can be infeasible.

Although we have applied a static analysis to remove some of the infeasible paths, infeasible path detection is an undecidable problem, and we can not remove all of them for a program. The second reason is that concolic testing is not always able to generate a test input to exercise a given path, as some of the symbolic constraints are too complex to solve. We also can choose to enumerate all of the suspicious path segments; however, this solution is not scalable as there potentially exists a large number of suspicious path segments, and both storing and accessing them at runtime can incur unacceptable overhead. There is also the choice of using a fixed number of path segments. The challenge is to determine a reasonable number and also strategies to select the path segments.

In our work, we applied *path graphs* (see Definition 3.6) to represent a set of suspicious path segments that end at the same suspicious statement. Each path graph contains a type of paths for a fault. The path graphs are generated by Marple. In Marple, computation of path graphs is a forward analysis following the fault detection. As shown in Chapter 4, in fault detection, queries are propagated backwards for resolutions. During propagation, queries are stored at each program node. To construct the path graph, we start at the node where a fault or don't-know resolution was derived. These nodes are first added to the graph as entry nodes. Marple then determines for each successor, whether the query at the current node was actually propagated from either of its successors; if so, the successor(s) is added to the graph, and an edge between the predecessor and successor is also added into the graph. The process continues until the suspicious statement, where the query was initially raised, is reached.

For example, we show in Figure 7.4 (a) and (b), two suspicious path segments ending at the same suspicious statement r. s_1 and s_2 are two resolution points. Figure 7.4(c) is the path graph constructed for the suspicious path segments in (a) and (b).

The choice here is whether we use the annotations on the path graph in testing. The tradeoff is that using the annotated path graph, more information needs to be compared at runtime, incurring additional performance overhead; if annotations on the edges are not considered when we use the path graph, some path-sensitive information is potentially lost and we potentially lead the test input generation to some safe path. In MAGIC, we use the path graphs without annotations.

In concolic testing, generating an input that potentially covers a path segment in a path graph

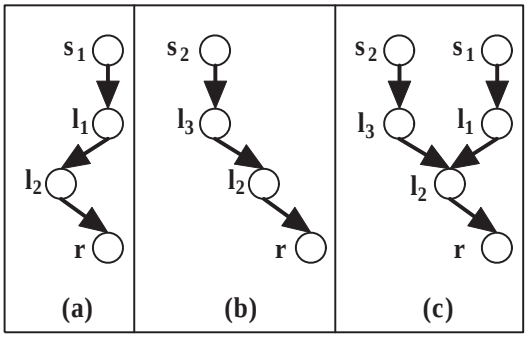


Figure 7.4: A Path Graph for Two Suspicious Path Segments

is more efficient than generating an input based on individual path segments. The reasons are as follows. Concolic testing generates a test input for a new path by inverting a particular branch. Given a path, concolic testing potentially needs to invert a set of branches from an initial execution, and take several iterations before a desired test input can be generated. On the other hand, if a set of path segments are given in a graph, concolic testing has more flexibility in choosing which path to exploit. The testing terminates as long as any suspicious path segment in the graph is triggered.

7.3.2 Reachability Analysis

In our dynamic testing, we need to generate test input for the path that starts at the beginning of the program and traverses any path segment in path graphs. We use reachability analysis to determine whether any of the branches in a program can actually reach the entries of the path graphs; if not, we terminate the test input generation along the corresponding branch.

Algorithm 1 takes the interprocedural control flow graph of a program (ICFG), and a set of path graphs reported by our analysis as inputs. The results of reachability are stored in a map, where for each branch, we report a set of entries of path graphs that the branch can reach. In Algorithm 1, lines *1-5* determine for each branch statement, whether the entries of the path graph can be reached. The core analysis is achieved in a recursive procedure *Reach* (see line *8*). At line *10*, we get the immediate successors of the current branch b. For each successor b_i, if b_i is an entry of the path graph, then we add it to the set *reachable* at line *13*; otherwise, we recursively call procedure *Reach* on b_i at line *14*.

Algorithm 1. Calculating Reachability Relationship

INPUT: *icfg*: the ICFG of the program, *G*: a set of path graphs

OUTPUT: *reachability*: a **map**<branch, <**set**> entries of path graphs>

```
1   for each branch statement b in icfg
2       initialize reachable {}
3       Reach(b, &reachable)
4       reachability[b] := reachable
5   end
6   return reachability
7
8   PROCEDURE: Reach(statement b, set reachable)
9   //recursively traverse statements can be reached from b
10      set successors := immediate successor statements of b in icfg
11      for each statement  b_i in successors
12          if b_i is an entry of any path graph g ∈ G
13              reachable.push(b_i)
14          Reach(b_i, reachable)
15      end
16  end
```

7.4 Dynamic Testing

In our dynamic testing, we apply the reachability information and the suspicious statements/-path segments computed above. Since collecting and solving symbolic constraints are important for generating the test input, we symbolically model fault conditions, as well as the semantics of certain program statements that are relevant to trigger faults. In this section, we first present the goals of program instrumentation and techniques. We then show our modeling techniques for four types of program statements. Finally, we explain how the static information is used to generate test inputs.

7.4.1 Program Instrumentation

Instrumentation is inserted in the program source. Dynamic testing runs on the instrumented programs and takes actions according to the instrumentation. A general goal is to collect symbolic path constraints and fault conditions needed for test input generation at runtime. Four types of actions are applied based on the types of program statements:

- if an input statement is encountered, we add a new input variable into a *symbolic map*. The symbolic map records the symbolic values of current live variables, and also symbolic path constraints and fault conditions;
- if a binary and unary variable operation is met, we record the symbolic values of the results;
- for conditional branches, we record the conditions for both false and true branches in the symbolic map; and
- for a suspicious statement, such as *strcpy* or pointer dereferences, we construct fault conditions to determine inputs that can trigger the fault.

7.4.2 Buffer Overflow Vulnerability Model

One main difference of MAGIC and concolic testing is that MAGIC is focused to trigger particular types of fault. Here, we describe the vulnerability model we developed for buffer overflow. In this model, we provide a mapping from a buffer write statement to an overflow condition. We also provide the actions we take at statements related to buffer and pointer operations. For each buffer, we not only consider the buffer size and the string length, but also the contents of the buffer up to a certain number of bytes. We specify a buffer using a 3-tuple (*size*, *L*, *C*), where:

- *size* is a symbolic expression for the size of the buffer;
- $L = \{len_1, len_2, ..., len_n\}$ is a set of symbolic expressions representing the lengths of strings stored in the buffer, as shown in Figure 7.5. Since $'\backslash 0'$ can occur multiple times in a buffer, we record string lengths that are relevant to every $'\backslash 0'$ for precision. Dependent on the location of the pointer *p* to the buffer, the string obtained via *p* can be relevant to any of recorded lengths.

Table 7.1: Modeling Buffer Overflow Conditions

Suspicious Operations	Overflow Conditions
Suppose p_d = ($addr_d$, off_d) Suppose p_s = ($addr_s$, off_s) *strcpy*(p_d, p_s)	(b_d ($size_d$, L_d, C_s) := $\delta(addr_d)) \neq null$; ($b_s$ ($size_s$, L_s, C_s) := $\delta(addr_s)) \neq null$; $Len(b_s, p_s)$ - off_s >= $size_d$ - off_d
Suppose p_d = ($addr_d$, off_d) Suppose p_s = ($addr_s$, off_s) *strcat*(p_d, p_s)	(b_d ($size_d$, L_d, C_s) := $\delta(addr_d)) \neq null$; ($b_s$ ($size_s$, L_s, C_s) := $\delta(addr_s)) \neq null$; $Len(b_s, p_s)$ - off_s + $Len(b_d, p_d)$ >= $size_d$
Suppose p = ($addr$, off) *p := var	(b ($size$, L, C) := $\delta(addr)) \neq null$; $off > size$

- $C = c_1, c_2, ..., c_v$ is a sequence of symbolic expressions representing the first v characters of the buffer [Xu et al., 2008]. The tradeoff here is that the more content of a buffer is modeled, more precise the symbolic analysis can achieve, however, with higher overhead.

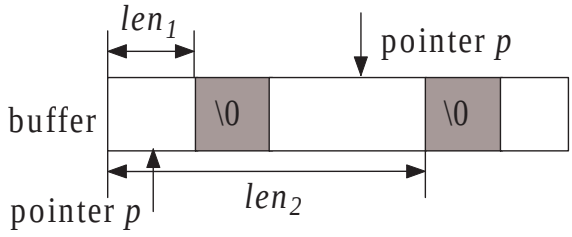


Figure 7.5: Multiple Strings in a Buffer

We use a pair (*addr*, *off*) to specify a pointer to a buffer, where *addr* is the beginning of the buffer and *off* specifies the symbolic offset from *addr*. In Table 7.1, we show how buffer overflow conditions can be constructed based on the type of program statements at runtime. In the first column, we show three examples of suspicious statements. We explain the construction of buffer overflow conditions in the second column. Consider the first row of the table as an example. p_s and p_d are two pointers. A string in the buffer pointed to by p_s is copied to the buffer pointed to by p_d. At runtime, when such a suspicious statement is encountered, we first find in the symbolic map the buffers associated with p_s and p_d. This action is specified using δ in the second column. If the mapping is successful, shown as $b_d \neq null$ and $b_s \neq null$ in the table, we determine whether the string from p_s copied to p_d potentially cause an overflow (see Figure 7.6).

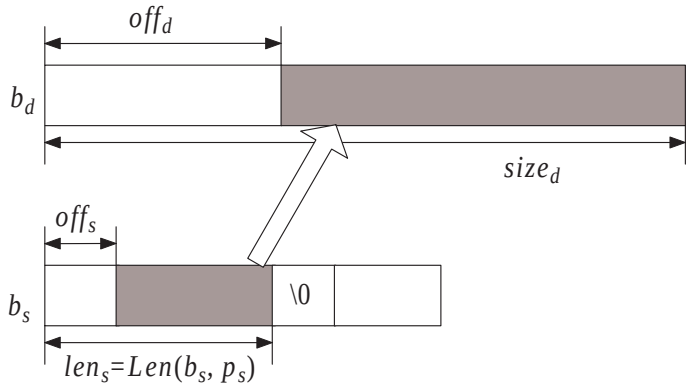


Figure 7.6: Buffer Overflow Condition

In the figure, we show that the available buffer space is $[size_d - off_d]$. The string being copied has a length of $[len_s - off_s]$, where len_s represents the length of the string stored in buffer *s*. As we mentioned in Figure 7.5, multiple string lengths can be recorded for a buffer, and we need to select a proper length depending on the location of the pointer. We use $Len(b_s, p_s)$ to represent this action. The second column first row in the table indicates that if the string length is larger than or equal to the available buffer size, a buffer overflow can occur.

Besides operations modeled by concolic testing [Sen et al., 2005], our testing components also model additional buffer and pointer operations. Table 7.2 presents a partial list. In the first column, we present the type of program statements, and in the second column, we specify actions MAGIC takes at the statement to construct the symbolic map. Consider the first row of the table. When the program executes the statement *p* (*addr*, *off*) := *input*(*size*), MAGIC creates a new buffer *b* on the symbolic map. The three parameters of a buffer are initialized: the size of the buffer is *size*, a string length is also *size*, and the first *n* bytes of characters are set based on the input string. After the buffer is created, MAGIC establishes a mapping between the buffer and the pointer using *addr:=&b* and *off:=0*.

7.4.3 Path-Guided Test Input Generation

Algorithm 2 takes the path graphs of suspicious path segments reported by Marple, and generates the program inputs that can trigger faults.

Table 7.2: Symbolic Semantics of String and Pointer Operations

Operations	Symbolic Semantics
p (*addr*, *off*) := *input(size)*	create a buffer b (*size*, {*size*}, {c_1, c_2, ..., c_n}), *addr* := *&b*, *off* := *0*
p (*addr*, *off*) := *malloc(size)*	create a buffer b (*size*, {}, {}), *addr* := *&b*, *off* := *0*
suppose p = (*addr*, *off*) *free*(p)	b := δ(*addr*) delete b
suppose *str* = (*addr*, *off*) *char str*[*size*]	create a new buffer b (*size*, {*size*}, {}), *addr* := *&b*, *off* := *0*
suppose $p_d = (addr_d, off_d)$ suppose $p_s = (addr_s, off_s)$ $p_d := p_s \pm v$	$add_d := add_s$, $off_d = off_s \pm v$
suppose p = (*addr*, *off*) **p* := *'\0'*	*b (size, L, C)* := δ*(addr)* $L := L \cup \{off\}$

At line *2*, initial program inputs are generated. Primitive input variables are given value *0*, and strings are initialized as empty strings. If boundary values of the inputs are known, MAGIC uses their lower and upper bounds.

In the second step, MAGIC executes the program with the generated inputs (see *Run_Program* at line *3*). During execution, MAGIC collects both the branches that the execution covers and the symbolic path constraints at the branches. When a path is discovered to traverse a suspicious path segment in any given path graph, MAGIC determines if a buffer overflow occurs; if not, MAGIC integrates the buffer overflow conditions with a set of path constraints and generates a new test input. If a buffer overflow is confirmed, MAGIC removes the path graph corresponding to this suspicious statement. Also, when a buffer overflow is determined, MAGIC allocates a new memory space for the buffer with the overflowed size and continues the execution, in an attempt to trigger more faults along the same execution. When the execution terminates, we store a sequence of branches and symbolic path constraints, collected along the execution, into the branch list *B* and the constraint list *C*.

Path_Guided_Search at line *6* uses the branch list *B* and the constraint list *C* collected from the previous execution to generate test inputs that excise the suspicious paths. The *for* loop at line *8* examines the collected branch one by one in a reverse order; for each branch, MAGIC determines

whether its *paired branch* is either able to reach the entries of any path graph in G (see line *11*) or on a suspicious path segment (see line *15*). If so, at line *21*, MAGIC attempts to generate a new test input using a set of path constraints collected along $\langle B[1], B[2], ..., B[i-1] \rangle$ with the inverted path constraint at branch $\overline{B[i]}$. The generated input at line *23* executes path $\left\langle B[1], B[2], ..., B[i-1], \overline{B[i]} \right\rangle$. If the current branch cannot reach the entries of the path graphs or is not on any suspicious path segment, MAGIC proceeds to examine the next branch at line *8* in the same way. The testing process terminates when all suspicious statements are triggered or all suspicious path segments are covered.

Algorithm 2. Path-Guided Test Input Generation

INPUT: G{g_1, g_2, ..., g_l}: a set of path graphs of suspicious path segments

```
1   initialize branch list B {} and constraint list C {}
2   I = GenInitInput()
3   Run_Program(I, &B, &C)
4   Path_Guided_Search(B, C)
5
6   PROCEDURE: Path_Guided_Search(branchlist B, constraintlist C)
7       bool inversePath := false
8       for(i:=sizeOf(B); i >= 1 ; i- -)
9           get the PairedBranch B[i]
10          for each suspicious path graph g_k in G
11              if B[i] can reach any stop point in g_k
12                  inversePath := true
13                  break
14              end
15              else if path⟨B[1],...B[i-1],B[i]⟩ traverses a path segment in g_k
16                  inversePath := true
17                  break
18              end
19          end
20          if(inversePath = true)
21              I' := solve (C[1] ∩ C[2] ∩ ... ∩ C[i-1] ∩ ¬ (C[i]))
22              initialize branch list B' {} and constraint list C' {}
23              Run_Program(I', &B', &C')
24              Path_Guided_Search(B', C')
25          end
26      end
27  end
```

7.5 Implementation and Evaluation

We implemented MAGIC for testing buffer overflows. Our goals are to evaluate its capability for generating inputs to detect and trigger faults and also to determine its performance. For comparison, we also constructed two other tools. Tool I implements the techniques of SPLAT [Xu et al., 2008], which model buffer lengths and the first several bytes of buffer content on top of basic concolic testing to trigger buffer overflows. Different from MAGIC, it does not use boundary values as initial inputs, and terminates when a fault is found. In the experiments, we needed to fix the fault and run the tool again until no more faults were found. We constructed Tool II by isolating the dynamic testing components from MAGIC; that is, it does not use any static information. Comparing Tool II and MAGIC, we can determine the usefulness of the path information in guiding test input generation.

MAGIC is implemented on top of CREST [Burnim and Sen, 2008] and Marple [Le and Soffa, 2008]. Both MAGIC and Tool I are implemented using Microsoft Phoenix SDK[1], and applied the Yices constraint solver [2]. The machine used for experiments is the Intel Duo Core 2.26 GHz processor with 2GB memory. We selected a set of benchmark programs, including wu-ftp:mapping-chdir, sendmail:ge-bad, polymorph-0.4.0 and gzip-1.2.4. The first two are buffer overflow benchmarks [Zitser et al., 2004], containing typical and realistic buffer overflows. Polymorph-0.4.0[3] is a real-world program, used to simplify file names in UNIX. Gzip-1.2.4[4] is a file compression program.

We ran a preliminary set of experiments to determine the time threshold we could use for the tools. The experimental results show that for all of the benchmarks, testing either terminates within *1500* seconds, or is no longer able to trigger more faults beyond *1500* seconds. Thus, in our experiments, we decided to double the number and set the time threshold at *3000* seconds for all three tools. The goal is to ensure that for most of the benchmarks, testing terminates before reaching this threshold, and even when the termination is forced by the time threshold, the number of faults

[1] http://connect.microsoft.com/Phoenix
[2] http://yices.csl.sri.com/
[3] http://sourceforge.net/projects/polymorph/
[4] http://www.gzip.org/

reported by the tools reflect the actual detection capability of the tools.

7.5.1 Capability of Triggering Faults

We first ran experiments to determine the capability of the three tools for triggering faults. The results are shown in Table 7.3. The first two columns give the benchmark programs and their sizes. For each tool, we show the number of faults triggered, the number of faults that were missed and the total time that it takes to finish the testing. By manually confirming suspicious statements/path segments reported from Marple, we are able to know the number of buffer overflows a testing tool is supposed to trigger. We therefore can determine the number of faults missed in testing. For *gzip-1.2.4*, Marple reports 9 buffer overflows. Four of these require specific environment variables to have long lengths that are not possible in the system where MAGIC runs. In this testing environment, MAGIC does not miss any faults for this benchmark. In addition to the fault detection capability, we also report the performance of dynamic testing. The performance of static analysis can be found in Chapter 4.

Table 7.3: Comparison of Testing Time and Fault Detection Capability

Benchmarks	Size (kloc)	Tool I: SPLAT techniques			Tool II: MAGIC without Static Information			MAGIC		
		Detect	Miss	Time	Detect	Miss	Time	Detect	Miss	Time
wu-ftp:mapping-chdir	0.2	2	0	1342 s	5	0	1325 s	5	0	20 s
sendmail:ge-bad	0.9	3	1	1618 s (crash)	4	0	1459 s	4	0	171 s
polymorph-0.4.0	0.9	0	7	>3000 s	5	2	>3000 s	5	2	>3000 s
gzip-1.2.4	5.1	3	2	463 s	5	0	1071 s	5	0	951 s

Comparing the results of Tool I and Tool II, we find that more faults are triggered using Tool II than Tool I. Across all benchmarks, Tool I missed *10* faults and Tool II only missed *2*. The reasons for being able to trigger more faults in Tool II are: 1) MAGIC models string contents more carefully, e.g., tracking multiple $'\backslash 0'$ for a buffer; and 2) MAGIC uses boundary values, instead of a fixed default value, which enables more branches to be covered in testing. The times used in testing are comparable for the two tools, except for gzip-1.2.4, where Tool II executes more paths than Tool I due to the use of the boundary value, and thus takes longer to terminate. Since more paths are executed, more faults are found. The constraint solver is crashed when we run Tool I for *sendmail:ge-bad* after 1618 seconds.

Comparing Tool II to MAGIC, we discover that 1) both the tools trigger the same number of faults, which shows Marple does not report false negatives that can impact this testing, and 2) MAGIC is more efficient to find these faults. The testing time is reduced because paths which do not traverse any suspicious path segment are avoided. Among the benchmarks, the time reduction in gzip-1.2.4 is the least. One reason is that for this benchmark, Tool II is not able to cover a certain number of paths due to complex symbolic constraints, and thus testing terminates early. Another reason is that for this benchmark, some of the don't-know path segments are short, and thus in MAGIC, the guidance is not significant.

7.5.2 The Effort to Generate Test Inputs

In another experiment, we compared the effort of generating test inputs with the three tools. Table 7.4 presents the experimental results for each tool. Under *Attempts*, we display the number of paths (or path segments) that are targeted for test input generation, i.e., the number of times that symbolic constraints are sent to the constraint solver for potential test inputs. Under *Generated*, we give the number of test inputs that are successfully generated from the constraint solver. The numbers count both the test inputs that can trigger faults, and the inputs generated in the process of searching for suspicious path segments. Under *Time*, we show the total time spent in the constraint solver in generating test inputs from the symbolic constraints.

Table 7.4: Comparison of Test Input Generation Costs

Benchmarks	Tool I: SPLAT techniques			Tool II: MAGIC without Static Information			MAGIC		
	Attempts	Generated	Time	Attempts	Generated	Time	Attempts	Generated	Time
wuftp:mapping-chdir	13995	1748	30.9 s	7828	1254	19.4 s	23	20	0.2 s
sendmail:ge-bad	1335	1084	54.5 s	30377	1201	3.9 s	5362	253	0.7 s
polymorph-0.4.0	492061	3335	116.7 s	46019	1615	66.7 s	227	122	0.7 s
gzip-1.2.4	4258	485	8.7 s	12533	1178	25.6 s	5687	1178	5.0 s

Our experimental results show that MAGIC largely reduces the search space for generating test inputs, as both the number of paths explored and the number of test inputs generated in the testing process reported by MAGIC are much less. The time used for test input generation is also reduced accordingly.

7.6 Conclusions

This chapter presents MAGIC, a path-guided concolic testing framework for automatically generating test inputs to exploit statically identified faults. MAGIC consists of both the static and dynamic components: the static components include a path-sensitive analyzer, and a reachability analyzer; and dynamic components implement concolic testing that in particular is able to trigger buffer overflows in a program. Our experiments show that in MAGIC, the dynamic testing confirms statically reported buffer overflows, and also determines some of the don't-know static warnings as faulty. MAGIC also helps classify false positives, as if no inputs can be generated to exploit the suspicious path, we are more confident that the suspicious path is safe. We also find that guided by the path information, our testing runs 1.1–66.3 times faster than concolic testing over a set of benchmarks. Although we only implemented buffer overflow detection for our experiments, more types of faults can be included.

Chapter 8

Conclusions and Future Work

This thesis presents a practical framework that statically computes and reports path information to predict dynamic fault behavior. The main insight is that path information is essential for addressing the precision problem faced by traditional static analysis. In addition, if program paths are given, we are able to explore likely-dynamic behaviors, such as propagation of a fault or interactions of multiple faults, which has not been done in traditional static analysis. The computed path information is shown not only helpful for understanding and fixing the faults [Le and Soffa, 2007, Le and Soffa, 2008, Le and Soffa, 2010], but also useful for guiding dynamic testing to exploit the faults [Cui et al., 2011].

An important contribution of this work is that we developed a demand-driven analysis to address the state space explosion problem faced in path-sensitive analysis, and make the computation of path properties feasible for a variety of faults and for large deployed software [Le and Soffa, 2008]. With the improved scalability, we are able to further apply techniques to make path computation more precise, general and usable [Le and Soffa, 2011].

8.1 Contributions and Impact

This thesis demonstrates that static computation of paths of certain fault properties can be valuable (see Chapter 3, 4, 6 and 7), practical (Chapter 4 and 5) and broadly applied (Chapter 5 and 6). We developed a set of path-based techniques which compute and use path information for detecting

and diagnosing faults. In the following, we summarize the contributions of our work from these three aspects:

- Identification of Path Information: We demonstrated *path diversity* and *fault locality*. *Path diversity* says paths across the same program point can differ in the presence, the root cause or severity of a fault, or its analyzability with regard to static analysis. Therefore, using path information, we can more precisely characterize the behavior of potential executions. A path classification is developed including the types of *infeasible*, *faulty with various consequences and root causes*, *safe*, and *don't-know*. *Fault locality* says that faults often are only relevant to a sequence of execution, instead of the whole program path, based on which, we developed efficient algorithms to detect and diagnose the path segments that contain faults.

- Computation of Path Information: We developed a demand-driven analysis to automatically detect paths of a type of fault, and the path information is reported in path graphs. Using a fault-model and specification technique, we automatically generated path-based analyses to detect user-specified faults. Generality is achieved for computing both safety and liveness properties, and both control and data-centric types of faults, including buffer overflows, integer faults, null-pointer deferences and memory leaks.

- Utilization of Path Information: Based on the paths of multiple faults, we developed an algorithm to automatically compute the relationships between multiple faults. Fault correlations are shown to be valuable in grouping faults and prioritizing diagnostic tasks. Using path information, we also developed a hybrid test input generation technique, which generates test inputs to confirm statically identified faults, and can more quickly trigger faults compared to traditional concolic testing.

The prototype tool, Marple, developed in this research has been used to study *reducing the cost of test input generation using static information* and *parallelization of static analysis* [Mitali Parthasarathy and Soffa, 2010]; it also has been used to teach basic concepts of static analysis and the Microsoft Phoenix Infrastructure. The Phoenix and Disolver groups have integrated our feedback and bug reports for developing Phoenix and Disolver.

With the results of this thesis, industry can better understand the value of precise and rich path information for reducing the manual cost of fault detection and diagnosis; the techniques related to scalability, precision and generality of static path computation can be integrated into the industrial software assurance process to further improve productivity.

8.2 Future Work

Future work includes:

- Further exploring the use of paths. Static path information is interesting because it specifies likely dynamic behavior but has a broader coverage than dynamic traces. In this thesis, we have shown that paths are useful to guide testing. Similarly, path information also can benefit other dynamic tools, such as runtime monitors or instrumentors. In addition, we also can compare information between paths, or between paths and dynamic traces to derive interesting properties. The challenge here is to identify and represent the path information for a particular application to achieve desired functionality and efficiency.

- Investigating the application of the framework to identify other types of faults. We have demonstrated the effectiveness of our framework in detecting the four types of faults. However, we hypothesize that our techniques are applicable to any types of faults that traditional static analysis handles, and will be more efficient. For example, it is interesting to model and handle concurrent bugs with our framework. When multithreading is involved, the state space we need to handle is even bigger, the question is how much demand-driven analysis can help here to further improve the scalability and precision of fault detection.

- Researching more types of fault interactions and their values for software assurance. We have shown a causal relationship between faults and their computation. Other fault relationships may exist, e.g., one fault can disable another or multiple faults may collaborate to cause a vulnerability. With more types of faults integrated into or our framework and more types of fault relationship considered, we can predict more interesting properties regarding fault

propagation and potential dynamic symptoms, e.g., we would like to determine the potential impact of a data race in a program.

- Processing the don't-know warnings. We have shown that testing can exploit some of the don't-know paths to confirm them as vulnerable. Based on the don't-know factors, these warnings can be further refined by other solutions. For example, we can apply a statistical analysis to reason the potential behavior of certain parts of source code.

- Parallelizing our demand-driven, path-sensitive algorithm: Demand-driven analysis is naturally parallel. Our initial exploration shows there exists a potential to further speed up the analysis. For example, each query for determining the safety of each potentially faulty point is independent, and thus can be parallelized. Also, for resolving each query, the propagation of the queries along different paths can be run in parallel. The challenge is to enable parallelization and meanwhile maximize the reuse of the intermediate results.

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