Performing Binary Fuzzing using Concolic Execution

by

Steven Valdez

Submitted to the Department of Electrical Engineering and Computer Science
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Abstract

In this thesis, I designed and implemented *Confuzzer*, a system that fuzzes certain classes of closed source binaries using Concolic Execution techniques in order to find vulnerable inputs into programs that could be leveraged by attackers to compromise systems that the binary might be running on. The design of this system allows improved performance on fuzzing programs that have a large branching factor or are heavily based on complex conditionals determining control flow. The system is designed around a Taint/Crash Analysis tool combined with a Path Exploration system to generate symbolic representations of the paths, generating a new set of inputs to be tested. These are implemented using a combination of Intel PIN for the Taint Analysis and Python/z3 for the Path Exploration. Results show that while this system is very slow in instrumenting each run of the binary, we are able to reduce the search space to a manageable level compared to other existing tools.

Thesis Supervisor: Nickolai Zeldovich
Title: Associate Professor

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This work was tested with the help of the Student Information Processing Board for providing machines to test the distributed execution system.

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Chapter 1

Introduction

Finding bugs in existing software and computer systems is difficult, and while manually finding bugs can be effective to a limited extent, a large part of Computer Security has moved to using automated methods for finding bugs within a program. This paper presents *Confuzzer*, a system that helps find bugs in a specific class of closed-source binaries which other existing systems tend to have trouble with. Many existing systems fail to perform well with programs that have a large branching factor and depend on complex conditionals to determine the control flow of the program, and as a result end up exploring only a small part of the program. This can result in vulnerabilities in other parts of the program being completely missing. While the system described is more specialized than existing tools, the goal is to create a system that allows security engineers to look for and attack bugs in programs that have previously been difficult to explore using automated methods.

Automated methods of bug finding are necessary, since even with systems like Bug Bounties and Vulnerability Reward Programs, where bug hunting is distributed among many security researchers with prizes of up to several tens of thousands, the number of bugs in existing systems makes it infeasible to find all of them and prevent attackers from exploiting them [6]. This means that we need automated methods of generating and testing inputs against our target binary, in the hopes that one of the generated inputs will result in a bug being discovered. This method of randomly testing inputs to cause programs to behave incorrectly is called *Fuzzing* and was invented as early as 1988 as part of a graduate class [9]. Since those early days, the art of *Fuzzing* has advanced to a great degree, with advancements in how test cases are actually generated.

Fuzzing systems tend to be divided into 2 main categories. The first is black-box fuzzing, where the fuzzing is performed independently of the program that is being analyzed, and thus tends to result in random inputs being sent to the binary, and results in many inputs that hit the same code path within the binary. As can be imagined, black-box fuzzing is fairly inefficient and can't completely test non-trivial binaries. The second main form of fuzzing is white-box fuzzing, where the fuzzer has knowledge of the binary being run, and can create test inputs based on this knowledge. If source code isn't available, this is sometimes known as grey-box fuzzing since the feedback to the fuzzer is from the machine code that makes up the program, rather than the original higher-level code. The system developed for this thesis falls into the realm of white-box/grey-box fuzzing since the inputs are very much determined by the program execution though we don't require source code.

However, while most existing black-box fuzzing systems work off the idea of using code coverage and input mutation to generate new test cases, the system used in this thesis is based on *Concolic Execution*. Concolic Execution is a specific form of more general Symbolic Execution that was created as part of the CUTE system [10]. Symbolic Execution is a method of evaluating a program, either at the higher-level source code level, or in our case the assembly level, where each operation performed on the input data we are testing is stored as a symbolic expression and whenever we hit some sort of branch we store the branch as a place where different paths might be taken, and then at the end we use all the constraints and symbolic expressions to generate new paths through the program execution. The difference between ordinary Symbolic Execution and Concolic Execution is how we handle branches. In Symbolic Execution, whenever we reach a branch, we create a new thread that continues exploring down each path in the branch, and eventually all the threads complete and we have a massive series of constraints for all possible executions. Meanwhile in Concolic Execution, we initially start with some concrete values for the input and just explore down the path of execution that those values end up taking, and then we try running the program again with new values.

By exploring the program state and building up constraints for each possible execution path, we can solve the constraints for different inputs that should travel down different parts of the program, allowing us to thoroughly test large swaths of the program with fewer inputs. By combining these two ideas together, we hopefully will have a system that can more efficiently test closed source programs and find vulnerabilities in them without having to wait until an attacker starts actively exploiting the vulnerability.

Our implementation of the *Confuzzer* design uses the Intel PIN Dynamic Binary Instrumentation (DBI) tool to do Taint Analysis and then uses z3 and the Python z3 bindings to actually solve the constraints for the various inputs to explore different paths in the binary. In order to run the system at a reasonable speed, and take advantage of the parallelizability of the system, we also need to distribute the taint analysis over multiple machines. While the final design of the system was fairly straightforward, I had a lot of issues in implementing the Intel PIN tool since we didn't have a good Intermediate Representation so we had to handle each individual assembly instruction manually, which resulted in a lot of bugs during the implementation. PIN also didn't have the cleanest memory and API model, resulting in many memory issues while trying to implement the system. In order to avoid these problems in future systems, while still maintaining our goals of closed-source fuzzing, using an alternative DBI or even moving to a emulator such as the User-Mode Emulation might result in an easier implementation.

When testing our implementation compared with other similar systems, we found that the versus other similar systems, execution of the binary was significantly slower than the other fuzzers we had, running at about 3 executions per second on our test cases, versus about 10k executions per second using some of the high end fuzzers we were testing. However our evaluations also shows how we have orders of magnitude fewer test cases that we need to run in order to fully explore the test cases. Overall, from these test cases we see that while the executions are factors slower, the speed-up from the smaller set of test cases needed greatly counteracts these issues, and as a result this fuzzer succeeds at the class of programs we are trying to analyze with this system.

In Chapter 2, we'll give an overview of existing systems in the space, as well as the similarities and differences with the *Confuzzer* system. Next in Chapter 3, we'll talk about the design of the Taint Analysis and Concolic Execution system. Chapter 4 talks about our actual implementation of the system and some of the issues we've had during implementation. Then Chapter 5 will be our evaluation of the system and its performance on some test programs. Chapter 6 will be about future work and improvements that can be made to the system. Finally, Chapter 7 concludes the discussion on our system. We also include an appendix showing the execution of *Confuzzer* on one of our larger test cases.

Chapter 2

Existing Work

Most of the existing work in the area of fuzzers tend to focus on using code coverage and similar metrics in order to direct the test inputs that are being generated. We'll take a look at other metrics that are used by Fuzzers first, before looking at systems that use Concolic Execution to do Path exploration to assist in fuzzing and other similar systems.

We'll also review these existing systems to see the differences between these systems and our design and implementation of the Confuzzer system. As well as their respective advantages and disadvantages.

2.1 Existing Fuzzers

Most of the notable fuzzers that are in use nowadays that don't use symbolic execution systems tend to use some form of evolutionary/genetic mutation to generate new test cases. EFS is an example of such a system, first published in 2007 [3]. Since then, a number of other systems have been designed, including AutoFuzz a fuzzer aimed at trying to determine network protocol information from an initial example of the interaction between Client and Server and then through additional fuzzing to generate mutations of these initial samples [5]. Some systems even go as far as being designed with zero information about the user-input and binary to allow even more general fuzzing [8].

Most of these systems share a similar design in which an initial "seed file" is created with examples of an input to the program, and the system then runs by mutating the inputs to generate new related inputs that might hit other parts of the program execution. Fuzzers tend to have this design since otherwise a lot of the test inputs would fail to gain any useful information as they get blocked by the initial checks that a program might make looking for specific magic numbers or file structures.

While this does limit fuzzers to be more adept at fuzzing certain classes of program or requiring external seed files, the advancements in evolutionary/mutation based fuzzers have allowed for a wide variety of commonly used libraries and programs to be thoroughly fuzzed. We'll take a look at one of the better non-commercial fuzzers to see what sorts of design decisions were made and how it compares to a fuzzer based on symbolic execution principles.

2.1.1 american fuzzy lop

One of the most well-known fuzzer is "american fuzzy lop", a fairly effective fuzzer developed using compile-time instrumentation and genetic algorithms to generate additional test cases to check against the application [13]. Due to some of the optimizations made over other fuzzers, and its use of optimizations at the instrumentation level, it is one of the fastest binary-only fuzzers available [14]. It has found bugs in over 75 different pieces of software and has multiple CVEs dedicated to bugs found by AFL.

In fact, while the software was explicitly designed to not use static analysis or symbolic execution for performance reasons, it was still able to generate input that included unseeded magic values by using the basic path exploration techniques that are included as part of afl-fuzz [12]. The one downside to afl-fuzz is that many of its features and optimizations do require compile-time instrumentation to function and are thus less effective with closed-source binaries.

However afl-fuzz still accomplishes a great deal while staying true to its original design goals of being fast, usable and reliable for the general use [11]. As afl-fuzz is improved, so to are the optimizations and performance hacks that can be used by

System	Fuzzer	Source Code Required	Execution Layer	Description
Confuzzer	Yes	No	Binary	Fuzzing system using binary-level concolic execution.
KLEE	Yes	Yes	System	LLVM Extension to provide fuzzing through concolic execution.
SAGE	Yes	No	Binary	Windows tool for fuzzing programs using concolic execution.
S^2E	No	No	System	Path Exploration tool to analyze binaries.

Table 2.1: Comparison of Symbolic Execution Systems

other Fuzzing systems aimed at fuzzing primarily closed-source binaries.

2.2 Symbolic/Concolic Execution Systems

There are also a number of Symbolic Execution systems that use Symbolic Execution to perform path exploration for the purpose of fuzzing or doing other sorts of analysis on the program. While almost all the Symbolic Execution systems have a significantly slower run-time than other Fuzzers (sometimes up to 1000x slowdown), they do provide a significant advantage to other fuzzers, as they can find fewer test cases that cover more of the possible execution paths through the program. Some notable ones are KLEE, SAGE, and S^2E. We'll briefly go over each of these to see how they compare to Confuzzer. Table 2.1 also provides an overview of these systems and their features. While many of the systems that we're looking at have some of the properties that we are aiming for in the *Confuzzer* system, none of them have all the properties we are lookiing for. The closest one is SAGE, however SAGE is mostly focused on Windows binaries and has a different set of limitations in the way it handles taint propogation.

2.2.1 KLEE

KLEE is a symbolic execution tool that uses source code and the LLVM compiler to generate tests that attain a high coverage throughout program execution [1]. The general design of KLEE is using LLVM to create an Intermediate Representation (IR) of the program that can be used to easily build up constraints and symbolic formulas throughout the program execution, which can later be solved to generate new test cases that explore other branches.

Unlike the other systems we talk about that don't require source code, KLEE is able to use the source and generated IR in order to create complete constraints for each instruction without any approximations. This allows almost perfect taint analysis in exchange for the source code requirement allowing further optimizations to be performed and tighter constraints when calculating new test cases. However, even with the generated IR, there are still some classes of code that can't be easily instrumented by KLEE, including floating point computation and inline assembly code. KLEE performs fairly well as a Symbolic Fuzzer and is able to handle many programs with available source-code.

2.2.2 SAGE

Moving on, we look over SAGE, a system designed at Microsoft that performs symbolic fuzzing without the need for source code [4]. Between all the existing Fuzzers and Symbolic Execution systems, SAGE ends up being one of the closest in design and performance to Confuzzer, though primarily tested as a Fuzzer targeting Windows executables and environments. SAGE starts with a seed file in order to initially figure out the first path through the binary, and during each iteration it generates new inputs by looking for new paths that can be explored. In order to actually generate the necessary path information and constraints, SAGE uses a combination of iDNA and TruScan which are tools that allow offline analysis of the trace of a program, allowing SAGE to separate the process of Taint Analysis from the actual execution of the program.

While this design does allow for more efficient Taint Analysis, it does suffer some issues when dealing with maliciously written programs which violate the assumptions of stack/heap space made by the Trace programs and might result in incorrect values being stored in the program trace. In addition, this results in SAGE having to effectively run each program execution twice, once to generate the original program trace, and a second time to actually build up the constraint and concrete value equations.

2.2.3 S^{2}E

S^{2}E is a system that provides automatic path exploration to allow other programs and plugins to perform tests across all paths that a program might traverse down [2]. It provides this path exploration using a symbolic execution system that analyzes the program and generates new inputs so that the program travels down new paths. While it isn't primarily a Fuzzer, it would take little effort to add the necessary selectors and analyzers to S^{2}E to create a fuzzing system. Unlike most of the other Symbolic Execution systems we've discussed, S^{2}E doesn't actually instrument the application being analyzed, but rather instruments the entire system to control inputs at all levels of the machine. While this does allow for more general control of the environment, it does come at the cost of having to instrument an entire machine and therefore is theoretically slower than equivalent binary instrumentation.

Unlike the other symbolic execution systems, this system also primarily uses Symbolic Execution, where it attempts to explore all paths simultaneously, and then generates valid test cases once the paths have all been explored. While this works for small programs and limited tainted inputs, this can result in a combinatorial explosion in paths that might prevent the execution from finishing in any reasonable time-frame. S^{2}E also has a focus on plugins/analyzers that look for specific states or conditions being violated, rather than more general problems in the program execution, making it difficult to get the full benefits of a fully symbolic system.

Chapter 3

Design

This section details the overall design of the Confuzzer system. We've split the design into two major parts, the Taint System design and the Concolic System design, as well as an additional section that covers the design of the smaller components of the Confuzzer system.

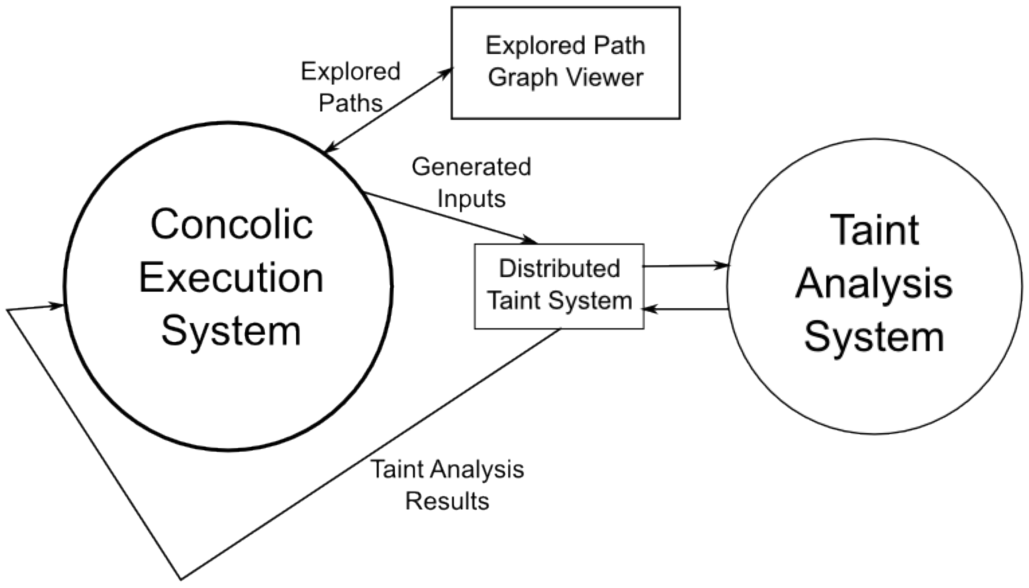


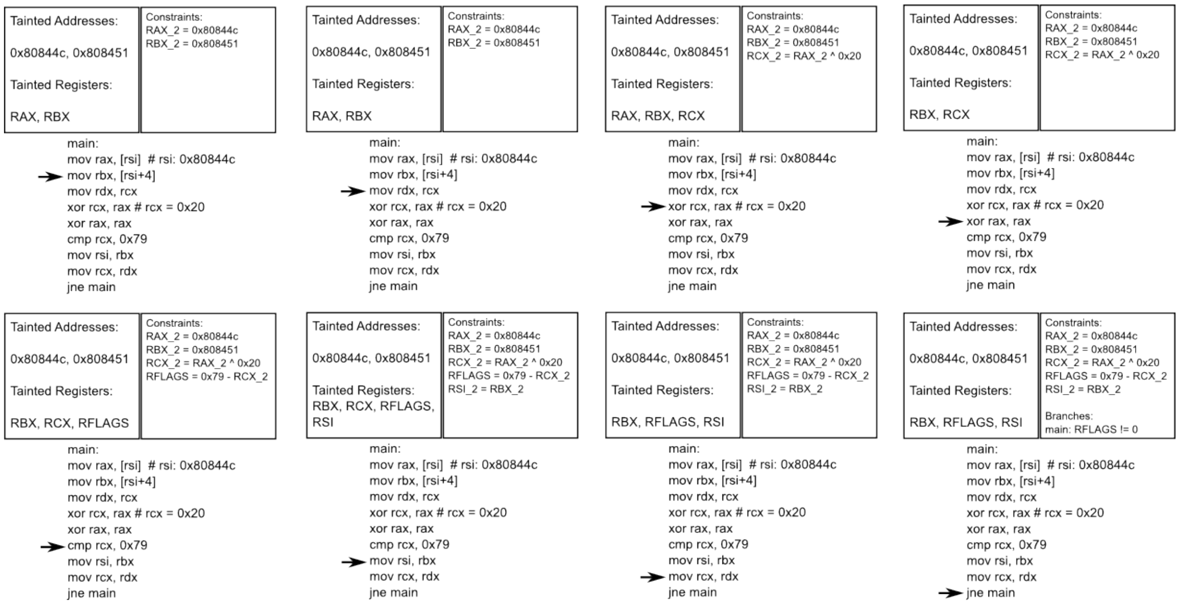
Figure 3-1: Confuzzer Design Overview

Figure 3-1 shows how the various pieces of the design interact and work together. In the following sections we'll cover details about each of these parts. In general, the

Concolic System first generates a default test case that is fed into the distributed Taint System, and as we get results from the Taint System, the Concolic System keeps on generating new constraints and inputs that are repeatedly sent back to the Taint System. In addition, the Concolic System also displays the current explored branches through the UI to give the user an idea of the state of fuzzing and to allow them to prioritize different sections of the program execution.

3.1 Taint System Design

One of the major parts of this system is the system that keeps track of the spread of Taint through a program from the tainted input that we are testing. While many Taint Analysis systems of various sorts exist, most have to do with doing analysis in the Intermediate Representation of a program that is represented as part of the compilation process. Due to the lack of source code for most programs, we have to design the system to do Taint Analysis on the final running assembly. This presents a lot of complications since x86 assembly doesn't provide nice semantics for figuring out what registers are tainted by an operation or categories to separate the various assembly instructions.



```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RAX, RBX

     main:
     mov rax, [rsi]  # rsi: 0x80844c
  →  mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RAX, RBX

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
  →  mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RAX, RBX, RCX                   RCX_2 = RAX_2 ^ 0x20

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
  →  xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RBX, RCX                        RCX_2 = RAX_2 ^ 0x20

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
  →  xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RBX, RCX, RFLAGS                RCX_2 = RAX_2 ^ 0x20
                                RFLAGS = 0x79 - RCX_2

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
  →  cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RBX, RCX, RFLAGS,               RCX_2 = RAX_2 ^ 0x20
RSI                             RFLAGS = 0x79 - RCX_2
                                RSI_2 = RBX_2

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
  →  mov rsi, rbx
     mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RBX, RFLAGS, RSI                RCX_2 = RAX_2 ^ 0x20
                                RFLAGS = 0x79 - RCX_2
                                RSI_2 = RBX_2

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
  →  mov rcx, rdx
     jne main
```

```
Tainted Addresses:              Constraints:
0x80844c, 0x808451              RAX_2 = 0x80844c
Tainted Registers:              RBX_2 = 0x808451
RBX, RFLAGS, RSI                RCX_2 = RAX_2 ^ 0x20
                                RFLAGS = 0x79 - RCX_2
                                RSI_2 = RBX_2
                                Branches:
                                main: RFLAGS != 0

     main:
     mov rax, [rsi]  # rsi: 0x80844c
     mov rbx, [rsi+4]
     mov rdx, rcx
     xor rcx, rax # rcx = 0x20
     xor rax, rax
     cmp rcx, 0x79
     mov rsi, rbx
     mov rcx, rdx
  →  jne main
```

Figure 3-2: Taint Propagation Example

The basic design of the taint system is that we initially capture any reads from the file descriptor referencing our "tainted input". We can then keep track of any memory addresses or locations that this "tainted input" is stored in. We also mark each of the original reads from the tainted file with a special marker that is then used by the Concolic System. Then, we analyze each instruction in the program and if its a read from a tainted location (memory or register), we create a new constraint representing the instruction and taint the resulting location. In this way, as the program executes the set of tainted registers and addresses slowly changes at each instruction. Finally, we can keep track of any branches that occur in the program and check whether they are controlled by the "tainted input" by seeing if the values the branch is depended on is tainted at that time. Figure 3-2 shows an example of how this system works.

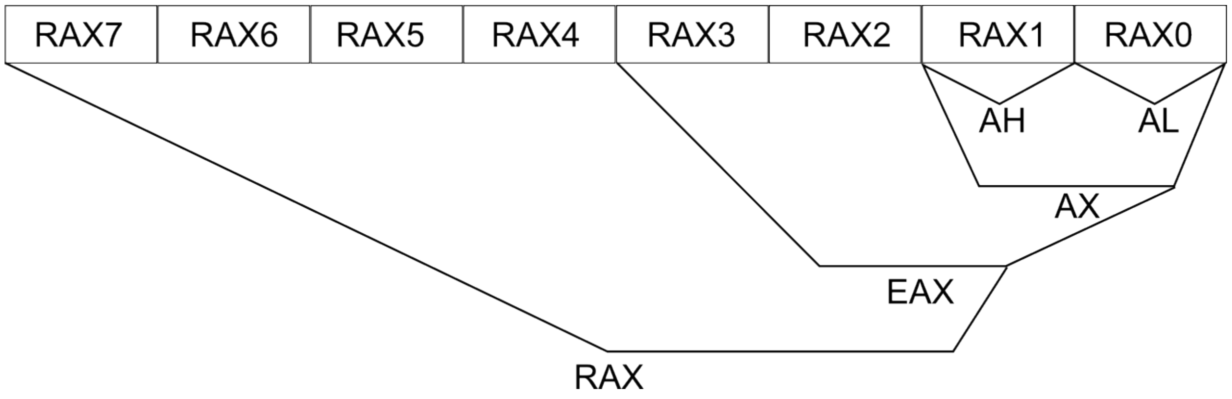


Figure 3-3: Register Chunks Example

However this design doesn't deal with the fact that we have instructions that move registers of differing lengths. In order to deal with this, we instead keep track of each register as chunks of 8 bits. Therefore most registers, which tend to be 64-bit, are made of 8 chunks numbered $RNX0$ through $RNX7$. Depending on the size of the operation that moves data around, we copy over a certain series of register chunks over, keeping the previous values for the uncopied registers. Figure 3-3 shows the layout described and how the various register chunks are related.

Each tainted operation we encounter then generates the constraints depicted in Figure 3-4, which while more than the original design doesn't add that much complexity for z3 to solve against, since most of the constraints are under constrained or

```
Tainted: RAX0_1, RAX1_1

Instructions:
  mov bx, 0x2020
  xor ax, bx


Tainted: RAX0_1, RAX1_1, RAX0_2, RAX1_2
Tainted Instructions:
  RAX_AX_2: xor ax, bx ::: 0x2020 + RAX_AX_1 -> RAX_AX_2


New Constraints:
 RAX_AX_1 = {RAX1_1, RAX0_1}

 RAX_AX_2 = OP(RAX_AX_1 + 0x2020)

 RAX1_2 = RAX_AX_2[1]

 RAX0_2 = RAX_AX_2[0]
```

Figure 3-4: Register Constraints Example

simple substitutions.

Once the Taint Analysis system has finished generating the list of tainted instructions and a semantic for how the registers are altered, it produces a text file listing all the tainted branches that were encountered, along with the list of tainted instructions/constraints. While the instructions are separated into separate registers and rough constraints at the taint analysis stage, it isn't until the generated file enters the Concolic system that the constraints are parsed and turned into a form more suitable for our constraint solver.

3.2 Concolic System Design

The Concolic System has many components working together to generate new inputs and to call out to the Taint Analysis system. It first generates an initial blank input which is sent to the Taint Analysis system. Then, for each input it has sent off it first parses the response, generating SMT constraints representing the state of the program and each branching point. Then it proceeds to attempt to solve the constraints for new inputs that can once again be sent off to the Taint Analysis system. If we have already observed an input, we skip it since we've already parsed it, and once we are unable to generate new inputs that traverse unexplored parts of the program, we conclude the fuzzing. We'll discuss each of these stages in turn.

3.2.1 Taint Analysis Parsing

This stage turns the Taint Analysis output from something like "RFLAGS_0_1: cmp al, 0x6c ::: RFLAGS_0_1 = OP(RAX_0_1, 0x6c)" into a SMT equation of the form "RFLAGS_0_1 == 0x6C - RAX_0_1". We don't generate the actual SMT form until this stage in order to allow the Taint Analysis system to be disconnected from the format of the SMT system we are using. This stage is actually split into two parts, one to handle the parsing of the actual branches that have been encountered and another to parse the general instructions/constraints that we've picked up throughout the execution of the program.

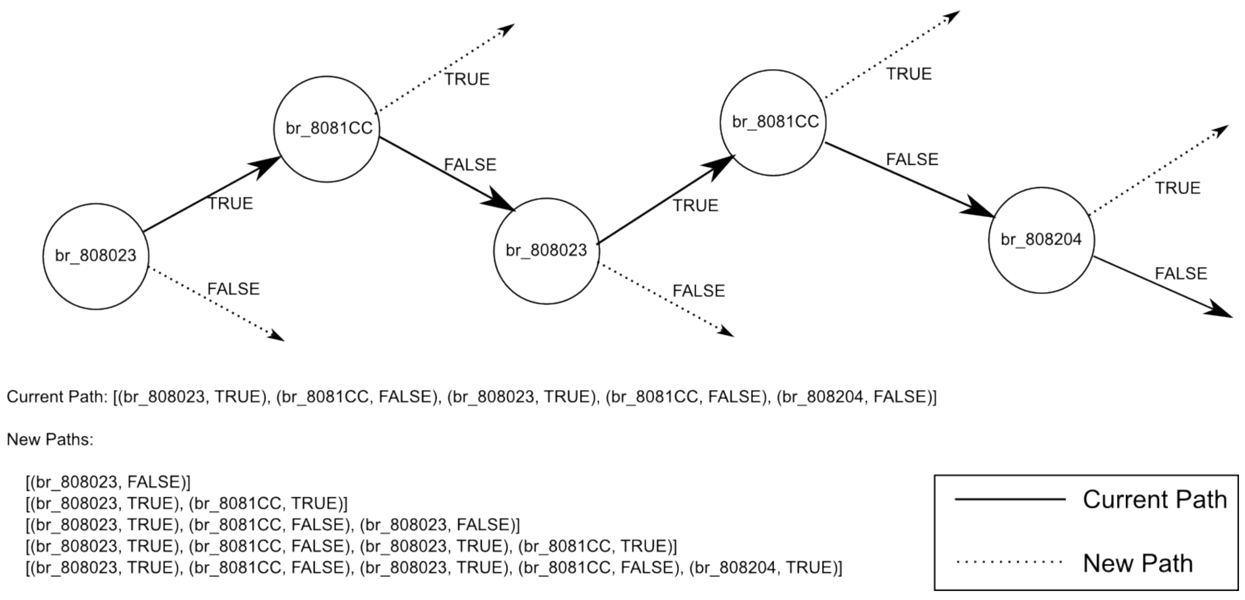
For each branch, we also need to figure out whether the branch was taken during this execution so that the Path Exploration system can determine what branches haven't been visited. Since almost all branches are based on the state of RFLAGS, we also have the Taint Analysis provide the concrete values of RFLAGS so that we can determine whether the path has been taken depending on the opcode of the branch instruction.

For general instructions/constraints, we parse each instruction to convert the opcode into an actual operation between the arguments of the instruction. There are three categories of instructions, those that take a single argument, those that take two arguments, and finally those that also modify RFLAGS. Using both the semantics of the arguments and the opcode, we can determine the appropriate operation to perform between the operations.

Once we've gathered a series of SMT equations representing all the steps of the program execution, as well as a separate series of equations representing each of the branches we've taken, we pass this onto the Path Exploration system to generate subsets of the branch equations for Input Generation.

3.2.2 Path Exploration

Once we've generated the initial SMT equations, we need to start generating the various different sets of branch paths we want to explore in subsequent tests. The way we generate each of these new branch paths is by going through each of the branches we've hit, and keeping all previous branch constraints while we negate the current branch constraint. Figure 3-5 shows the initial path that we've explored, as well as the additional paths we'll try exploring in the new inputs. We don't worry about de-duplicating paths at this point since we'll de-duplicate repeated inputs as part of the input generation phase.



Current Path: [(br_808023, TRUE), (br_8081CC, FALSE), (br_808023, TRUE), (br_8081CC, FALSE), (br_808204, FALSE)]

New Paths:

```
[(br_808023, FALSE)]
[(br_808023, TRUE), (br_8081CC, TRUE)]
[(br_808023, TRUE), (br_8081CC, FALSE), (br_808023, FALSE)]
[(br_808023, TRUE), (br_8081CC, FALSE), (br_808023, TRUE), (br_8081CC, TRUE)]
[(br_808023, TRUE), (br_8081CC, FALSE), (br_808023, TRUE), (br_8081CC, FALSE), (br_808204, TRUE)]
```

Figure 3-5: Path Exploration Example

Once we've figured out which branch constraints to keep and which to negate, we can simply add a new constraint of "AND(branches[:i], NOT(branches[i]))". Once we have all the constraints, we send them to the SMT solver to solve and generate concrete values for all the variables. Once this step is done, the result can be passed to the Input Generation phase to create new test cases.

3.2.3 Input Generation

Once we've solved the SMT equations to find concrete values for each of the variables in the constraints, we actually have to generate an input using these concrete values. While normally straightforward, we have to deal with parts of the tainted file that may never have been read by the current execution of the program or other edge cases. Instead what we do is first find the size of the tainted file that we need to create, by finding the largest value for which a symbol is defined representing the tainted input file and creating an initial array representing the file defaulting to using the null byte. Once we've generated the array, we replace the values that we have concrete values for from the SMT solver and generate a file.

While using null bytes as the default could have problems since some code stops parsing a file at the null-byte, we would have a constraint representing this case in the list of constraints from the program execution, so we don't need to add a special exception for that case.

Its at this stage that we deal with de-duplicating inputs that we already have seen. This prevents us from revisiting paths that we have already analyzed. Another way with dealing with duplicate inputs is to keep track of the sets of paths that have been explored and then checking our new path against that list.

3.3 Minor Component Design

In addition to these major components of *Confuzzer*, we also have a number of other smaller components that are used to help make the system more efficient and to allow greater usability.

3.3.1 Distributed Nodes

One of the first optimizations made to the design is the ability to distribute the workload from a single machine to many. We achieve this by creating workers running on various servers that accept tasks that detail the value that should be used for the

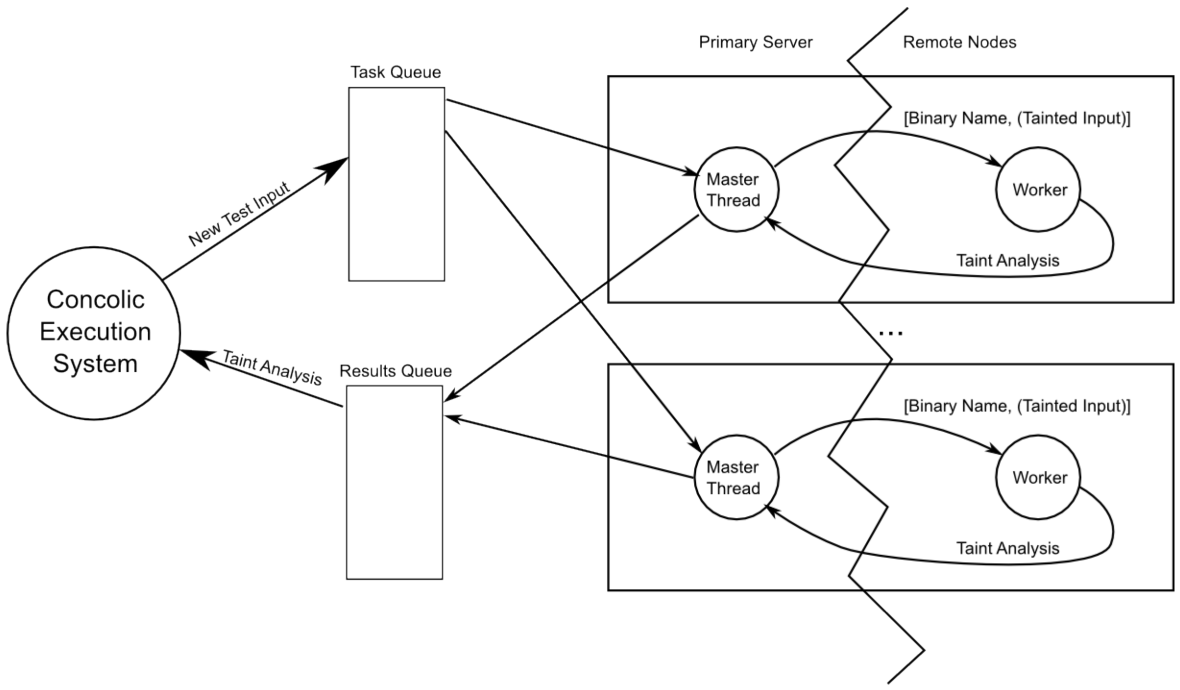


Figure 3-6: Distributed Nodes for Taint Analysis

tainted input, as well as the file name to execute. To prevent malicious use of this system, we require that the binary being tested be uploaded to the servers through a separate channel. Figure 3-6 shows the overall design of the distributed system.

On the worker side, there is a loop while it waits for a task, and once it receives a task, it creates a new directory with a copy of the binary and all files accessed by the binary. It then runs the Taint Analysis tool on the binary in that directory, and upon completion returns the result of the Taint Analysis to the master. This design is done so that different executions of the binary don't interfere with each other, and to keep a log of all binary executions on disk in case further study of a particular test case might be necessary at a later time.

Meanwhile, on the master side, there are threads for each worker, that pull a task off the synchronized queue (filled by the Input Generation phase) and send them over RPC calls to the various workers. The queue is prioritized based on metrics from the Concolic Execution system and the Graph Viewer (described below). Once a worker has completed its task, the results are stored in another queue to be returned to the Concolic system.

This design allows us to run a lot of tests at the same time without having to wait for each one to complete. Since the slowest part of the system is the Taint Analysis system, this distributed system greatly improves the time it takes to run lots of tests. For larger programs, the Concolic Execution system can also be distributed across multiple nodes when the SMT solving stage takes a considerable amount of time.

3.3.2 Graph Viewer

In addition to the other components, we also generate a graph for each new path that is discovered, and use that to allow a user to prioritize certain branches when performing further tests.

The graph viewer works by creating a separate node for every branching point and an edge for both the TRUE and FALSE paths from each branch. Since we are branching forward from the initial root node, this setup creates a tree structure that represents all possible branches that we know about so far.

In order to build up the tree, we iterate through each path we've visited and create a new node for any new branching points and new edges for the direction that the path travels down. Since the program may sometimes loop back to the same branching point, we need to keep track of the visited path prefix and create a new node whenever the new branch happens with a different prefix than the nodes that we've already drawn, joining paths that have the same prefix and branch.

Experienced users can use the branching pattern and assembly code dis-assembly to select parts of the code to prioritize when generating new paths, allowing the system to explore all the paths in specific critical sections of the code that the user might have reason to believe are more vulnerable to malicious inputs.

Chapter 4

Implementation

The *Confuzzer* system was implemented with a combination of the Intel PIN tool to do binary instrumentation and Taint Analysis, and the z3 Python bindings to actually perform the Concolic Execution step. The current version of the system is available online at `https://github.com/dvorak42/confuzzer`. The rest of this chapter will discuss the implementation of each of these parts, as well as the distributed and graphing components.

4.1 PIN Taint Analysis Tool

In order to do the Taint Analysis on the binary, we ended up implementing an extension for PIN, an Dynamic Binary Instrumenter, to keep track of the tainted state of memory and registers, and to build up a list of all the instructions that operated on tainted locations.

Instead of using a full-system emulator, we ended up choosing to use an application-specific Dynamic Binary Instrumenter (DBI), since it should have a lower overhead than emulating an entire system. Of the popular choices, we ended up using PIN since it was one of the few DBI tools that worked without any need for compile-time injection and allowed us to fully instrument the program with easy access to the state of the registers and memory throughout the program [7]. Another option was DynamoRIO, another similar DBI, however there were fewer systems built on top of it, and had less support at the time.

The PIN plugin takes in the binary that is being analyzed, as well as the names of the tainted inputs to the binary. In order to keep track of tainted values, we first use PIN to instrument any syscalls. Before each syscall, we check the type of the syscall and if it is an "open", we check whether the argument is one of the tainted files that was passed in, and if so keep track of the file descriptors referencing these tainted files. Once we have an open tainted file, we need to check for "read" syscalls and label and taint any memory that is written by the "read" syscall.

Once we have a tainted memory location, we need to start instrumenting all instructions to check whether they are reads from either tainted memory or registers. Since we need to parse the actual registers and memory locations that are being affected by the we have different instrumentation functions based on the number of operands for each operation, and whether they affect registers or memory locations.

The one special case we need to deal with separately is adding an additional "branch" point before predicated instructions. This way, every time that the predicated instruction, we create a new branch point dependent on the state of the RFLAG register. The one problem with this approach is that every instruction will end up instrumented, since we also need to keep track when the taint on registers and addresses are cleared.

In order to keep track of registers and addresses, we create separate lists for each. However, since we have instructions that move different size operands, for each register, we need to separately keep track of each chunk in a register. While we can do bit-level chunking, x86 primarily affects registers at a byte level, so the current implementation uses byte-sized chunks. We also normalize all registers to the largest size ($RDI, RSI, RAX, RBX, \ldots$) when keeping track of the registers. We also need to keep track of the ID of each register, so that as we parse new operations that modify the value of the register, we store it in a newly named variable.

Figure 4-1 shows the pseudocode for actually spreading taint around the various registers and addresses the program accesses. For any operations that use tainted registers and addresses, we increment the ID of the registers being written and then

```
taintRegToReg(instruction, srcReg, dstReg):
  chunkStart, chunkEnd = instruction.offset, instruction.size
  affectReg = []
  for(i in sizeof(dstReg)):
    r1 = {dstReg, i, dstReg.id}
    r2 = {dstReg, i, dstReg.id+1}
    if i < instruction.offset or i > instruction.size + instruction.offset:
      taintEquations.append({'=', r1, r2})

  if isTainted(srcReg):
    s1s = srcReg[chunkStart:chunkEnd]
    s1c = {srcReg, chunkEnd-chunkStart}
    d1s = dstReg[chunkStart:chunkEnd]
    d1c = {dstReg, chunkEnd-chunkStart}
    taintEquations.append({'=', s1s, s1c})
    taintEquations.append({instruction, s1c, d1c})
    taintEquations.append({'=', d1c, d1s})
  else:
    for(i in [chunkStart, chunkEnd]):
      removeTaint(dst)
```

Figure 4-1: Taint Spread Pseudo-code

taint them, as well as adding a constraint representing the assembly instruction. Since we don't want to create constraints for all registers, we also need to get the value of operands that aren't tainted. We do this by copying the memory from the source operand, or by using the Register context that we have to get the current value of an address.

We also need to clear the tainted flag on register and addresses whenever we have an instruction that moves non-tainted values into a register. Without clearing the taint flags, we would end up with almost all the registers and addresses accessed by the program after the original tainted file is read.

Finally we need to keep on propagating any parts of the register that weren't affected by the current instruction. This is actually a simplification of the actual code since we need to cast the register chunks together so that the instruction can operate on them, and then cast it back into separate chunks for further instructions to interact with.

Whenever we encounter a branching point in the program execution, we check whether the RFLAGS register is currently tainted, and if so we add the branch to the list of tainted branches, along with the current value of the RFLAGS register. This allows us to keep track of which direction each branch was taken in. While we could keep track of this by checking what the next executed instruction is, that would require extra bookkeeping.

Separate from the Taint Analysis, we also instrument exception handling in order to deal with the case of segfaults and other crashes. Since we can't trust that standard file descriptors for user input and output are still available at this point, we have to wait until the end of the program's execution to record the crash/segfault.

At the end of the program's execution, we store all the branching points and taint constraints in a file for the Concolic Execution System to parse and use to determine new constraints. In addition, if we recorded a crash or overflow issue, we also update the execution log with that data. Once we've finished with the current execution, the Concolic System then takes over to generate new test cases.

4.2 Concolic System

The Concolic System is implemented using a combination of Python and z3 bindings to parse the file received from the Taint Analysis system. Every time we receive the analysis, we parse it in two stages. The first stage parses the taint constraints into formulas, and the second stage creates the z3 equations.

The first stage parses out the opcode from the assembly instruction and turns it into symbolic notation. We have to do the parsing in two stages since we need to build up the set of variables that will be used by the SMT solver. Some of the assembly opcodes don't have a direct translation to a symbolic equation since we have a limited set of operations we can use with the SMT solver.

The second stage is where we actually create the z3 variables and the constraints are actually added to the system. We mark the z3 variables representing the tainted file inputs differently so that we can later build up the new input file.

We also have a third stage for our actual branch conditions where we use the branch opcode and the value of the RFLAGS register at that time to figure out whether we actually took the TRUE or FALSE path.

Once we've finished parsing all the branches and taint constraints, we can start iterating through each of them and building up a new path constraint using the branches we select for this loop and the rest of the taint constraints. Since we don't have any circular dependencies, and most of the constraints are fairly straightforward, z3 works fairly well at solving the constraints for satisfiable sets of constraints, while converging to unsatisfiability for the paths that are unreachable.

In order to maximize the parts of the program we are exploring early on, we iterate through each branch on the path and keep the previous branch directions, while flipping the direction we are exploring on the current branch. So we create N new paths for every path with N branching points. We then de-duplicate the repeated paths/inputs once we've converted the solutions from the SMT solver into actual input files. A good number of paths will end up being unsatisfiable since there are no inputs to reach that path, or there are contradictory branches from non-optimized or dead code.

Once we've solved the constraint equations, we generate a new test input and place it into a test input queue. Its during this phase that we check whether the input and paths match any of our prioritized branches and if so, we increase their priorities in the Taint Analysis stage. We keep on parsing outputs and generating new paths until we work through our queue of inputs and are unable to generate new unique paths. We also keep track of any paths which result in crashes/segfaults and mark those as interesting inputs.

4.3 Additional Components

While the previous parts are sufficient to actually run the fuzzer, there are a few additional components to improve the system. We also have implemented a distributed system and graph visualization to help with the usability and efficiency of the system.

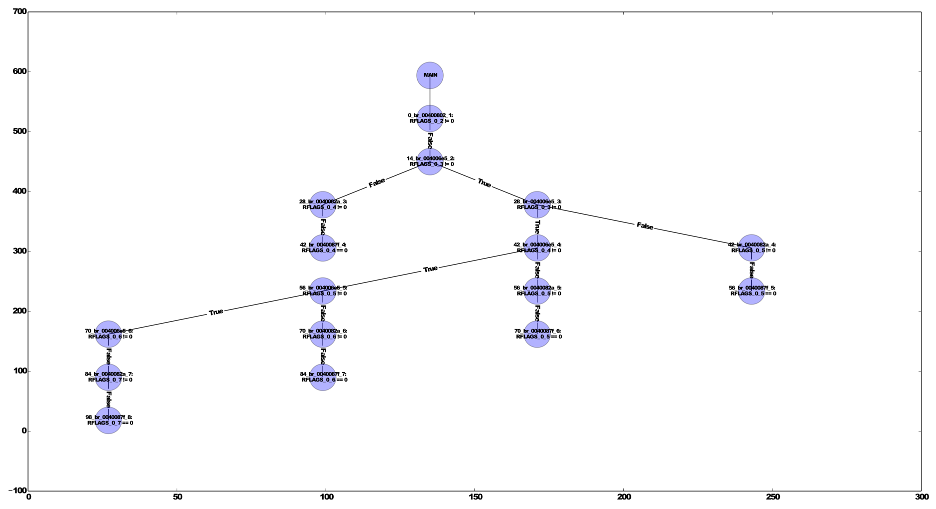

MAIN
0_br_00400802_1: RFLAGS_0_2 != 0
14_br_004006e5_2: RFLAGS_0_3 != 0
28_br_0040082a_3: RFLAGS_0_4 != 0
28_br_004006e5_3: RFLAGS_0_3 != 0
42_br_0040087f_4: RFLAGS_0_4 == 0
42_br_004006e5_4: RFLAGS_0_4 != 0
42_br_0040082a_4: RFLAGS_0_5 != 0
56_br_004006e5_5: RFLAGS_0_5 != 0
56_br_0040082a_5: RFLAGS_0_5 != 0
56_br_0040087f_5: RFLAGS_0_5 == 0
70_br_004006e5_6: RFLAGS_0_6 != 0
70_br_0040082a_6: RFLAGS_0_6 != 0
70_br_0040087f_6: RFLAGS_0_5 == 0
84_br_0040082a_7: RFLAGS_0_7 != 0
84_br_0040087f_7: RFLAGS_0_6 == 0
98_br_0040087f_8: RFLAGS_0_7 == 0
True
False

Figure 4-2: Example Execution Graph

We use xmlrpclib and synchronized Queues in order to communicate between the master and each of the workers. The system is designed to allow each server to support multiple workers per machine. Each worker can run in separate threads, listening for the master using different ports. Additionally, each worker thread can run multiple PIN Taint Analysis processes simultaneously. This allows us to run about 64 analysis operations at the same time, with 8 threads per machines on 8 servers.

To prevent security issues with the RPCs being maliciously used, we require that the binaries that are being used are uploaded to each server through a separate channel. We also have a script that separately fetches all the log files from each run through of the taint analysis in order to store any additional information that the user might want to look over for the crashing test cases.

We use pyplot and graphviz to actually generate the graph of the program execution. Figure 4-2 shows the graph that is generated as part of the execution of binary. In order to give the user an idea of which branch each node represents, we also include the assembly instruction that actually represents the branch.

The user can then input the name of a branch from the graph image into the main thread in order to prioritize it. Since each node is uniquely identified, the name of the branch also includes the prefix branches. The user can prioritize multiple branches in the same part of the program in order to have the system focus on a specific section of the binary.

While these components don't change the correctness of the system, it does make the system faster and allow for the user to prioritize parts of the program that they believe to be vulnerable or critical. There are some additional optimizations that could be made that will be mentioned in the **Future Work** section in Chapter 6.

Chapter 5

Evaluation

Since our goal for this system is to create a Fuzzer that works well with programs that have complicated control flow conditionals or many branches, we are evaluating our system using test cases with these properties. To evaluate *Confuzzer*, we compare its performance on the test cases against both AFL, one of the most popular and successful Fuzzers, as well as against a generic Blind Fuzzer that generates inputs with no feedback information from the binary we are evaluating. Due to the amount of time needed for running the latter tests, we end up calculating expected performance based on testing on a slice of the input space.

We first look at the number of test cases that our fuzzers generate, since programs of similar complexity will have roughly the same branching amounts, giving us a better picture of how each system scales. Our rough results are in Figure 5.1. The estimate for blind fuzzing is based on the number of possible inputs before we are likely to hit a crashing input. We weren't able to make measurements for AFL, since it wasn't

Test Case	Confuzzer	Blind Fuzzing	AFL	Description
test1	8	1.10e12	???	Simple magic value test
test2	6	1.10e12	???	Keygen test using xored value
test4	40494	1.84e19	???	Toy shell example without overflow
test4	40494	1.84e19	???	Toy shell example with overflow

Table 5.1: Test Cases per Fuzzing System

Test Case	Confuzzer	Confuzzer (Distributed)	Blind Fuzzing	AFL
test1	0.21 runs/sec	3.2 runs/sec	2513 runs/sec	9850 runs/sec
test2	0.20 runs/sec	3.1 runs/sec	2497 runs/sec	9879 runs/sec
test3	0.18 runs/sec	2.7 runs/sec	2454 runs/sec	10.8k runs/sec
test4	0.17 runs/sec	2.7 runs/sec	2434 runs/sec	11.3k runs/sec

Table 5.2: Fuzzing Speed

able to determine sufficient information to prioritize certain kinds of input, even with a basic set of example inputs for the test application. One of the advantages of AFL is that it is able to notify the user of crashing inputs while still running, compared to the current implementation of Confuzzer.

We then measure the amount of time each fuzzing system takes to run test cases, to show how the speed of the Confuzzer compares to the other systems. Figure 5.2 shows that the speed of the Confuzzer system is orders of magnitudes slower than the other systems. We actually end up having better timing from AFL than Blind Fuzzing since it forks the binary instead of creating a new process for every test case.

This shows how the Concolic Fuzzer system is able to hone in on specific interesting inputs without having to hit a ton of unnecessary inputs, however the process of finding inputs takes a long time and is heavily dependent on the size of paths in the binary being fuzzed.

While the test cases we are using for the system are a bit artificial, there are many existing programs that have similar constructs, including parsers that search for magic values in order to figure out whether a file is valid, key verification systems that check whether an input is valid to detect some key file is valid, and even network protocols that expect a certain class of inputs.

From the timing results, we could probably end up with a more efficient system by using a combination of *Confuzzer* to generate inputs that pass through taint checks, and then using AFL or another Fuzzer in order to look for alternate inputs past the initial checks in the program. Unfortunately doing this sort of merged Fuzzing requires either some amount of user input to determine when to switch between the systems, or some sort of heuristic to deal with moving between the fuzzers.

The results for AFL also show that its possible that moving from a PIN instrumenter to something using QEMU User Mode Emulation might offer an improvement in the running time of the system. Most of the slowness in running the Confuzzer system comes from the context switching and instrumentation of the binary code. We can increase the speed of the Fuzzer using our distributed system to run multiple instances of the binary and Taint Analysis system. Some of the additional improvements we can apply to *Confuzzer* are covered in the **Future Work** section in Chapter 6.

From the evaluation, we see that this system is able to hit the goals of the system and succeed at beating out other Fuzzers on these special class of difficult binaries that other Fuzzers have failed to get useful/complete results on in a timely manner.

Chapter 6

Future Work

While we currently have a working system, there is still a lot of work that can be done to improve the overall system and create a more efficient and useful system. Similar to the Design, we can split this into two major categories of work, work for the Taint system and work for the Concolic Execution system.

6.1 Taint Analysis Improvements

One of the major improvements to the Taint Analysis system is to switch from using Intel PIN to another instrumentation tool. Some options to explore, given other Taint Analysis and fuzzing tools are using DynamoRIO as its support improves, using full-system emulation, and finally using QEMU's user mode emulation. The final option seems to be most likely to give improved results, given the success that AFL has had with it.

In addition to switching the Taint Analysis to a different system, we can also reduce the set of instructions that we have to examine by detecting standard functions that we trust and instead of instrumenting the function execution, we add special constraint equations to the Taint log. One example is being able to detect strcmp and other related functions, and replacing them with constraints that represent the possible return values from the functions, rather than having tons of branching points and constraints within the library function itself. There are a couple ways of doing this, from using some heuristic to detect known functions, or actually stubbing out the real library we are optimizing with one that has markers that the Taint Analysis tool would be able to detect and choose to pause instrumentation.

Another improvement that needs to be made to the Taint Analysis system is support for additional types of tainted input, either more general user input from the console, to actual data packets through network sockets. Having these additional forms of tainted input would allow us to test more parts of the code without having to have artificial wrappers that convert a file input into a network or user input.

Finally, the last major improvement to the Taint Analysis system that would be useful is the addition of more ways to detect "bad" or potentially troublesome states, some can be as simple as invalid memory access detection (which already can be done with PIN) or even so far as detecting unintentional control flow hijacking or policy violation. These would allow the system to detect a wider array of potential issues all at once.

6.2 Concolic Execution Improvements

On the Concolic Execution end, one improvement is to the way we handle constraints. If we are able to reduce the number of variables we create when parsing the tainted assembly instructions, we could reduce some of the work z3 has to do when solving the equations. Similarly, if we are able to detect more compound data structures, such as strings, we would be able to combine many of the generated constraints together and use things like z3str for string computations.

Additionally, if we were able to do better path and loop detection, we could improve the search algorithm we use to search more interesting parts of the program space without spending a bunch of time repeatedly working on the same looping structure. Generally, having an improved search algorithm and prioritization would allow us to reach interesting test cases much earlier.

Another overall improvement to the system that should be done in the future is adapting it to work together with other existing Fuzzers. While *Confuzzer* has a advantage on some test cases that other fuzzers have trouble with, the existing fuzzers also have their own advantages on other parts of the program execution. Allowing multiple fuzzers to work together would allow a wider search of the program input space without having all the test cases take as long as the *Confuzzer* test cases take.

Chapter 7

Conclusion

In this thesis, we presented *Confuzzer*, an implementation of a Concolic Execution Fuzzer to help with finding inputs to the program that can cause malicious behavior. Unlike most existing Fuzzers, Concolic Execution allows us to get through sections of the binary that require matching certain values and allowing us to get past sections that would otherwise cause other Fuzzers to take a long amount of time. In implementing this system, we've aimed to design the system to allow the analysis of as many binaries as possible, without requiring source code to perform the analysis. While this prevents us from constructing Intermediate Representations to use in doing the taint analysis, we are still able to parse x86 instructions sufficiently to determine how to spread taint through the program.

While there are still many improvements that could make to the system, the initial prototype is already able to test a class of programs that are difficult to test with the existing systems. Being able to programatically generate test cases is an important step in better securing existing code and doing in-depth testing fast enough to be effective against determined attackers.

Appendix A

Example Program

In order to demonstrate the success of the *Confuzzer* system, we've included the code for a simple test application as well as excerpts from its execution under the Confuzzer system. Using a single execution node, this test took about 14 hours and generated a total of around 40500 unique inputs, without pruning, to the program.

Listing A.1: test4 Source Code

```
#include <stdio.h>
#include <fcntl.h>

int main(void)
{
  int NC = 8;
  char buf[NC];
  char* files[256] = {0};
  int fd = 0;
  int indx = 0;
  int i,j = 0;
  char *r = buf;
  fd = open("script.txt", O_RDONLY);
  read(fd, r, NC);
  close(fd);

  for(i = 0; i < NC; i++) {
    if(buf[i] == 'l') {
      for(j = 0; j < indx; j++) {
        printf("file%d\n", j);
      }
    } else if(buf[i] == 'w') {
      files[256*indx] = "WRITTEN";
      indx += 1;
    } else if(buf[i] == 'd') {
      for(j = 0; j < indx; j++) {
        printf("file%d:\n\t%s\n", j, files[256*j]);
      }

    }
  }
  return 0;
}
```

This program works by taking in 8 instructions as part of a text file, each of which could either "[l]ist" the files that have been created, "[w]rite" a new file, or "[d]ump" the contents of the files. Due to an implementation bug, this code has a memory corruption error if too many files are written. Since this was compiled on a 64-bit system, this tends to occur when more than 4 files are written to memory. Below is a part of the output from the fuzzer, showing the test cases that were sent to the Taint Analyzer, as well as the newly generated test cases from each execution:

```
Testing ./test4 with:                1 l
 Tainted input 'script.txt'          1 w
Left: 1                              1 d
```

```
1 t
1 $l
1 $w
1 $d
1 $ï£¡
1 $_l
1 $_w
1 _ï£¡
1 $_d
Left: 12
2
Left: 12
3 wl
3 ww
3 wd
3 wt
3 w$l
3 w$w
3 w$d
3 w$ï£¡
3 w$_l
3 w$_w
3 w$_d
3 w$_t
3 w$__l
3 w$__w
3 w$__d
3 w$_cï£¡
3 w$ï£¡__l
3 w$ï£¡__w
3 w$ï£¡__d
3 w$Pï£¡Cï£¡
3 w$O_?_l
3 w$O_?_w
3 w$O_?_d
3 w$__c‘ï£¡
3 w$_____l
3 w$_____w
3 w$_____d
3 w$___ï£¡?_
Left: 39
4 ï£¡
Left: 39
5 $_t
5 $__l
5 $__w
5 $__d
5 $_cï£¡
5 $ï£¡__l
5 $ï£¡__w
5 $ï£¡__d
5 $Pï£¡Cï£¡
5 $O_?_l
5 $O_?_w
5 $O_?_d
5 $__c‘ï£¡
5 $_____l
5 $_____w
5 $_____d
5 $_X_c_ï£¡
```

```
5 $___ï£¡?_l
5 $___ï£¡?_w
5 $___ï£¡?_d
5 $‘______
Left: 59
...
Left: 5
Left: 4
Left: 3
Left: 2
Left: 1
40481 wwwwwwl
40481 wwwwwww
40481 wwwwwwd
40481 wwwwwwt
40481 wwwwww$l
40481 wwwwww$w
40481 wwwwww$d
40481 wwwwww$_
Left: 8
40482 wwwwwwll
40482 wwwwwwlw
40482 wwwwwwld
40482 wwwwwwl$
Left: 11
Left: 10
Left: 9
Left: 8
40486 wwwwww$l
40486 wwwwww‘
Left: 9
Left: 8
40488 wwwwwwd
Left: 8
Left: 7
Left: 6
Left: 5
40492 wwwwwwl^D
Left: 5
Left: 4
40494 wwwwwwl$
Left: 4
Left: 3
Left: 2
Left: 1
```

A subset of the crashing inputs that were discovered is below:

```
Crashing Inputs:
        $_wwwwdw
        $_wwwwlw
        $wdwwwdw
        $wdwwwwl
        $wldwwww
        $wlw_www
        $wlwdwww
        $wlww_ww
        $wlwwww
...
```

This along with the remaining crashing inputs covers most of the space of inputs that should crash the program, showing that even with a program that has a combinatorial explosion of paths 4^8, Confuzzer is still able to function in a reasonable amount of time. The 14 hours for 40000 paths matches closely with the results observed by the SAGE system [4]. With the use of N nodes, the time needed to run this test could be reduced by about a factor of N, since the majority of the time was spent in the actual execution of the programs with different inputs.

Appendix B

Example Execution Graphs

Attached is the code and execution graphs for some of the simpler test cases we've been using.

Listing B.1: test1 Source Code

```
#include <stdio.h>
#include <string.h>
#include <sys/types.h>
#include <stdlib.h>
#include <fcntl.h>

int strcmp2(char* a, char* b) {
  while((*a == *b) && (*a != '\0')) {
    a++;
    b++;
  }
  return *a - *b;
}


int strcmp3(const char* s1, const char* s2)
{
    while(*s1 && (*s1==*s2))
        s1++,s2++;
    return *(const unsigned char*)s1-*(const unsigned char*)s2;
}
int main(void)
{
  char key[] = "magic";
  char key2[] = "cigam";
  int fd = 0;
  char buf[16] = {0};
  char *r = buf;

  fd = open("key.txt", O_RDONLY);
  read(fd, r, 16);
  close(fd);

  if(strcmp(key, r) == 0) {
    printf("Success!\n");
    return 0;
    //printf("Correct!\n");
  } else {
    if(strcmp2(key2, r) == 0) {
      char ptr[1] = {0};
      strcpy(ptr, "cigamcigamcigam");
      if(strcmp2(ptr, r) == 0) {
        return 2;
      }
    }
    //printf("Wrong %d. %s\n", strcmp3(key, r), ptr);
    return 1;
  }
  return 0;
}
```

Listing B.2: test2 Source Code

```
#include <stdio.h>
#include <sys/types.h>
#include <stdlib.h>
#include <fcntl.h>

int main(void)
{
  char key[] = "\x4f\x43\x45\x4b\x41";
  int fd = 0;
  int i = 0;
  char buf[16] = {0};
  char *r = buf;

  fd = open("key.txt", O_RDONLY);
  read(fd, r, 16);
  close(fd);

  while(i < 5) {
    if((*r ^ 0x22) != key[i])
      return 1;
    r++;
    i++;
  }

  printf("Success!\n");
  return 0;
}
```

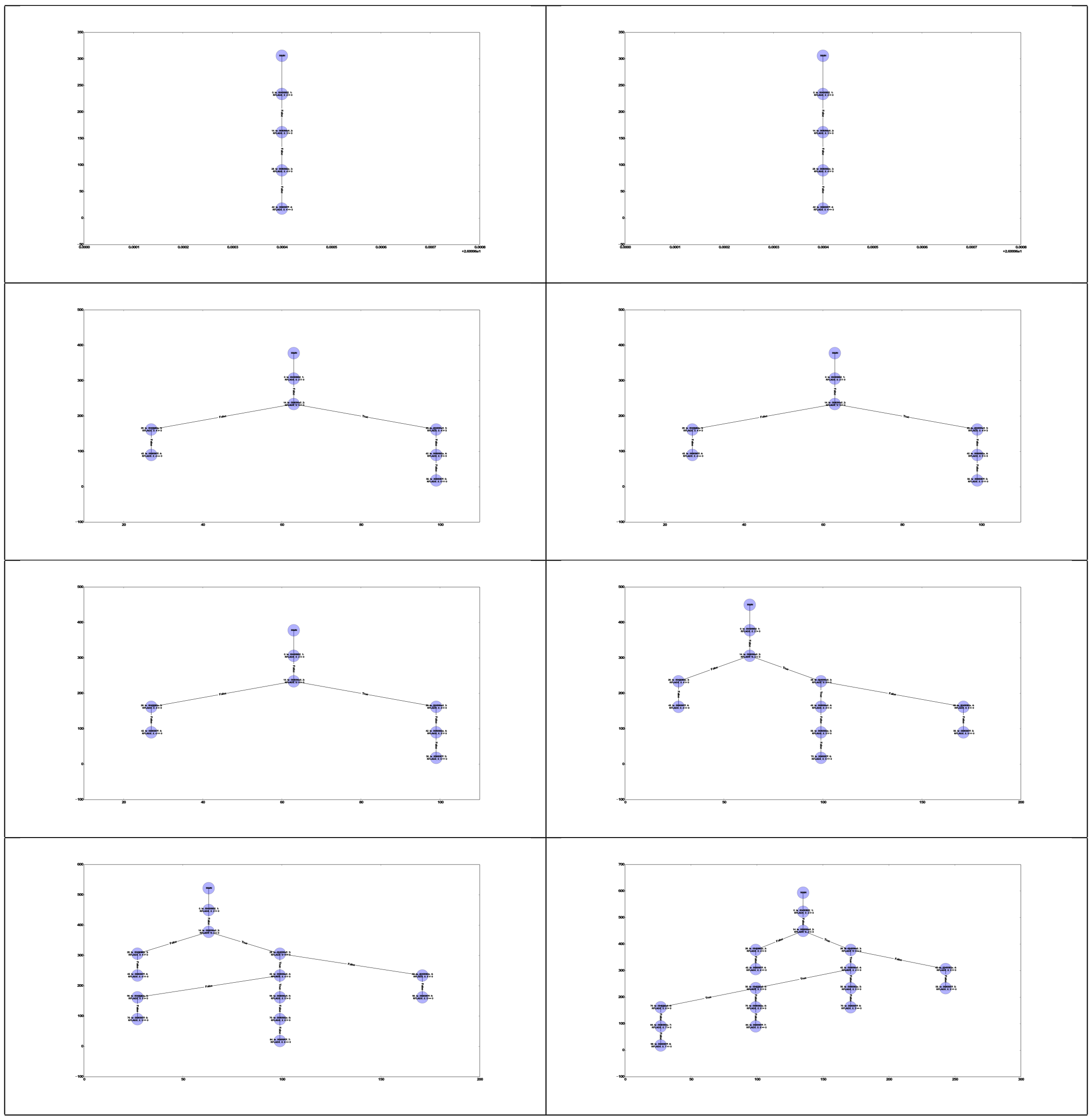


Figure B-1: Example Execution Graphs for test1

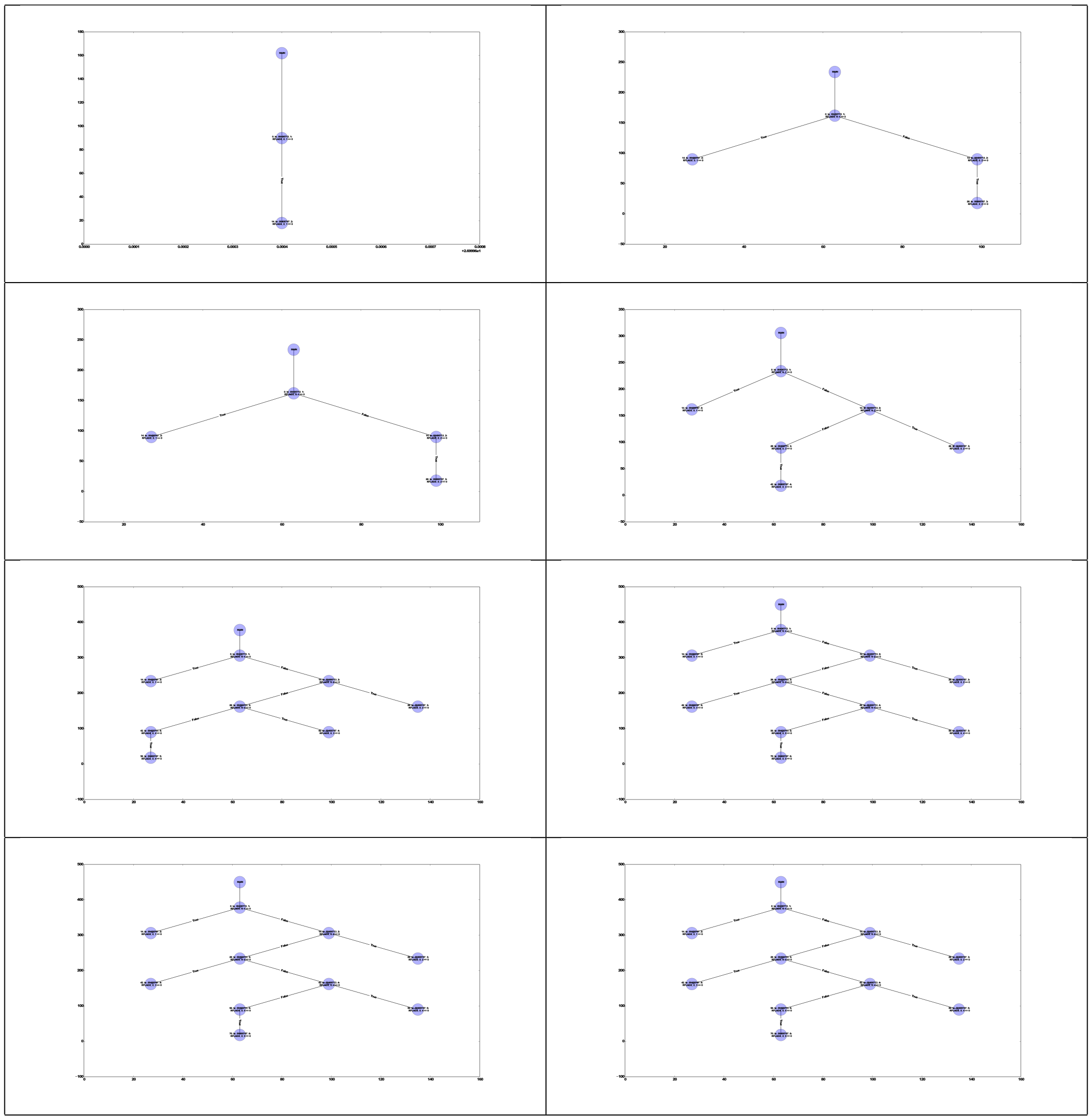


Figure B-2: Example Execution Graphs for test2

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