Abstract

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Chapter 1

Finding Substitutable Binary Code By Synthesizing Adapters

1.1 Introduction

Given the large corpus of software available today to an average programmer to reuse, it is desirable to reuse well-tested, bug-free chunks of code that implement some required functionality. Finding such code can be difficult to automate, and there is no guarantee that the code found by such a search will have the exact interface the programmer intends to use. At such times, programmers find themselves writing wrapper code and creating unit tests to check if the wrapped code works as they intended. In this paper, we improve upon a previously presented technique [1] that automates the process of finding functions that match the behavior specified by an existing function, while also synthesizing the necessary wrapper needed to handle interface differences between the original and discovered functions. Use cases for our improved technique include replacing insecure dependencies of off-the-shelf libraries with bug-free variants, reverse engineering binary-level functions by comparing their behavior to known implementations, and locating multiple versions of a function to be run in parallel to provide security through diversity [2].

Our technique works by searching for a wrapper that can be added around one function's interface to make it equivalent to another function. We consider wrappers that transform function arguments and return values. For example, Listing 1.1 shows implementations of the *isalpha* predicate, which checks if a character is a letter, in two commonly-used libraries. Both implementations follow the ISO C standard specification of the *isalpha* function, but the glibc implementation signifies the input is a letter by returning 1024, while the musl implementation returns 1 in that case. The glibc implementation can be adapted to make it equivalent to the musl implementation by replacing its return value, if non-zero, by 1 as shown by the *adapted_isalpha* function. This illustrates the driving idea of our approach: to check whether two functions, f_1

and f_2, have different interfaces to the same functionality, we can search for a wrapper that allows f_1 to be substituted by f_2.

We refer to the function being wrapped around as the *reference* function and the function being emulated as the *target* function. In the example above, the reference function is *glibc_isalpha* and the target function is *musl_isalpha*. We refer to the wrapper code automatically synthesized by our tool as an *adapter*. Our adapter synthesis tool searches in the space of all possible adapters allowed by a specified adapter family for an adapter that makes the behavior of the reference function f_2 equivalent to that of the target function f_1. We represent that such an adapter exists by the notation $f_1 \leftarrow f_2$. Note that this adaptability relationship is not symmetric: $f_1 \leftarrow f_2$ does not imply $f_2 \leftarrow f_1$. To efficiently search for an adapter, we use counterexample guided inductive synthesis (CEGIS) [3]. An adapter family is represented as a formula for transforming values controlled by parameters: each setting of these parameters represents a possible adapter. Each step of CEGIS allows us to conclude that either a counterexample exists for the previously hypothesized adapter, or that an adapter exists for all previously found tests. We use binary symbolic execution both to generate counterexamples and to find new candidate adapters; the symbolic execution engine internally uses a satisfiability modulo theories (SMT) solver. We also implement adapter search using a randomly-ordered enumeration of all possible adapters. We always restrict our search to a specified finite family of adapters.

```
int musl_isalpha(int c) {
  return ((unsigned)c|32)-'a' < 26;
}
int glibc_isalpha(int c) {
  return table[c] & 1024;
}
int adapted_isalpha(int c) {
  return (glibc_isalpha(c) != 0) ? 1 : 0;
}
```

Listing 1.1: musl and glibc implementations of the *isalpha* predicate and a wrapper around the glibc implementation that makes it equivalent to the musl implementation

We implement adapter synthesis to adapt around inputs and outputs in registers and memory. We demonstrate the use of adapter synthesis for the following applications.

- We demonstrate the use of adapter synthesis for adaptably substituting a buggy function with its bug-free variant by finding adaptable equivalence modulo a bug.
- We demonstrate substitution of RC4 key structure setup and encryption functions in mbedTLS (formerly PolarSSL) and OpenSSL by means of synthesizing adapters between their interfaces.
- We present an intra-library evaluation of adapter synthesis by evaluating two of

our adapter families on more than 13,000 pairs of functions from the GNU C library.

- We demonstrate the use of adapter synthesis for reverse engineering at scale using binary symbolic execution-based adapter synthesis. We show that code fragments in a ARM-based 3rd party firmware image for the iPod Nano 2g device can be adaptably substituted by reference functions written for the VLC media player [4]. In this evaluation, we complete more than 1.17 million synthesis tasks, with each synthesis task navigating an adapter search space of more than 1.353 x 10^{127} adapters. We find our adapter synthesis implementation finds several instances of reference functions in the firmware image.

The rest of this chapter is organized as follows. Section 1.2 presents our algorithm for adapter synthesis and describes our adapter families. Section 1.3 describes our implementation, and Section 1.4 presents examples of application of adapter synthesis, large-scale evaluations, and a comparison of two adapter search implementations. Section 1.5 discusses limitations and future work, Section 1.6 describes related work, and Section 1.7 concludes.

1.2 Adapter Synthesis

1.2.1 Algorithm for Adapter Synthesis

The idea behind CEGIS is to alternate between synthesizing candidate expressions and checking whether those expressions meet a desired specification. When a candidate expression fails to meet the specification, a counterexample is produced to guide the next synthesis attempt. In our case, the expressions to be synthesized are adapters that map inputs of the target function to inputs of the reference function and outputs of the reference function to outputs of the target function in such a way that the behavior of the two matches. Our specification for synthesis is provided by the behavior of the target function and we define counterexamples to be inputs on which the behavior of the reference function and target function differ for a given adapter. Our adapter synthesis algorithm is summarized in Figure 1.1. As shown in Figure 1.1, our algorithm takes as input the reference function, the target function, and an adapter family F_A. The algorithm begins with a default adapter and an empty test list. In our implementation, as a default adapter we often use the "zero adapter," which sets every input and output of the reference function to the constant value 0. Until a correct adapter is found or no new adapter can be synthesized, a new counterexample is added to the test list, and any subsequently generated candidate adapters must satisfy all tests in the list. The output of adapter synthesis is either input and output adapters that allow the target function to be substituted by the adapted reference function or an indication that achieving substitutability is not possible using the specified adapter family F_A. Our algorithm is guaranteed to terminate if the space of adapters allowed by F_A is finite [3]. Although

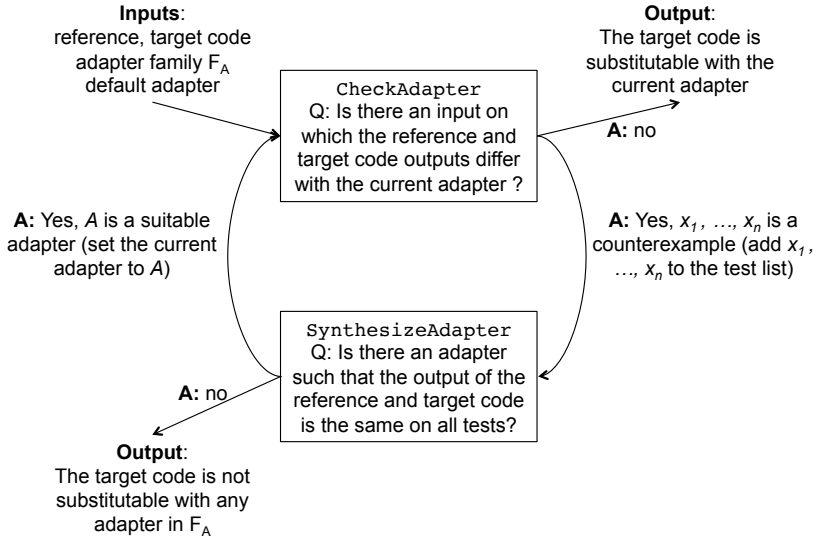


Figure 1.1: Counterexample-guided adapter synthesis

the adapter space and input space may be quite large, in practice we observed that, often, when an adapter was found, the number of steps required to find an adapter was small (see Section 1.4.5).

To generate counterexamples and candidate adapters, our adapter synthesis algorithm uses procedures `CheckAdapter` and `SynthesizeAdapter`, which both rely on symbolic execution. `CheckAdapter` uses symbolic execution to find an input value on which the target function and reference function outputs disagree with a given adapter and `SynthesizeAdapter` uses symbolic execution to search for adapters that cause the target function and reference function to have equivalent output on all inputs in the current test list. Algorithm 1 presents the main adapter synthesis loop, Algorithm 2 presents the `CheckAdapter` procedure that generates counterexamples, and Algorithm 3 presents the `SynthesizeAdapter` procedure that generates candidate adapters. `CheckAdapter` and `SynthesizeAdapter` are both implemented as calls to a symbolic executor.

Adapter synthesis terminates when either `CheckAdapter` or `SynthesizeAdapter` have explored every available execution path without finding a counterexample or new candidate adapter. If `CheckAdapter` fails to find a counterexample, we conclude that the current adapter allows the target function to be substituted by the reference function. If `SynthesizeAdapter` fails to generate an adapter, we conclude that the target function is not substitutable by the reference function with any adapter in F_A. If either `CheckAdapter` or `SynthesizeAdapter` fail due to a timeout, we make no claims about the substitutability of the target function by the adapted reference function. However, our observation from our evaluation is that the majority of adapter synthesis tasks that timed out would eventually lead to the conclusion of no possible adapter. We explore

Input : Target T as a code fragment or a function, reference function R, and adapter family $\mathcal{F}_{\mathcal{A}}$
Output: (input adapter $\mathcal{A}_{in}$, output adapter $\mathcal{A}_{out}$) or *null*

```
[1]  A_in ← default-input-adapter;
[2]  A_out ← default-output-adapter;
[3]  test-list ←empty-list;
[4]  while true do
[5]  |  counterexample ← CheckAdapter (A_in, A_out);
[6]  |  if counterexample is null then
[7]  |  |  return (A_in, A_out);
[8]  |  else
[9]  |  |  test-list.append(counterexample);
[10] |  end
[11] |  (A_in, A_out) ← SynthesizeAdapter (test-list);
[12] |  if A_in is null then
[13] |  |  return null;
[14] |  end
[15] end
```

Algorithm 1: Counterexample-guided adapter synthesis

timeouts in more detail in Section 1.4.5.

1.2.2 Adapter Families

The `SynthesizeAdapter` step synthesizes an adapter from a finite family of adapters. We currently support the following families of adapters, of which the arithmetic and memory substitution adapter families are newly introduced in this work.

Argument Substitution

This family of adapters allows replacement of any reference function argument by one of the target function arguments or a constant. This family is useful, for instance, when synthesizing adapters between the cluster of functions in the C library that wrap around the *wait* system call as shown in Section 1.4.3.

Argument Substitution with Type Conversion

This family extends the argument substitution adapter family by allowing reference function arguments to be the result of a type conversion applied to a target function argument. Since type information is not available at the binary level, this adapter tries all possible combinations of type conversion on function arguments. Applying a type conversion at the 64-bit binary level means that each target function argument itself may have been a *char*, *short* or a *int*, thereby using only the low 8, 16, or 32 bits respectively of the argument register. The correct corresponding reference function argument could

Input : Concrete input adapter $\mathcal{A}_{in}$ and output adapter $\mathcal{A}_{out}$
Output: Counterexample to the given adapters or *null*

```
[1] args ← symbolic;
[2] while execution path available do
[3] |   target-output ← execute T with input args;
[4] |   reference-output ← execute R with input adapt(A_in, args);
[5] |   if ! equivalent(target-output, adapt(A_out, reference-output)) then
[6] |   |   return concretize(args);
[7] |   end
[8] end
[9] return null;
```

Algorithm 2: `CheckAdapter` procedure used by Algorithm 1. T and R are as defined in Algorithm 1.

be produced by either a sign extension or zero extension on the low 8, 16, or 32 bits of the argument register. This adapter family also allows for converting target function arguments to boolean values by comparing those arguments to zero.

Arithmetic adapter

This family allows reference function arguments to be arithmetic combinations of target function arguments. This adapter family has been implemented by Hietala [5].

Memory Substitution

This family of adapters allows a field of a reference function structure argument to be adapted to a field of a target function structure argument. Each field is treated as an array with n entries (where $n \geq 1$), with each entry of size 1, 2, 4, or 8 bytes. Corresponding array entries used by the target and reference functions need not be at the same address and may also have different sizes, in which case both sign-extension and zero-extension are valid options to explore for synthesizing the correct adapter as shown in Figure 1.2. This makes our adapter synthesis more powerful because it can be used in combination with other adapter families that allow argument substitution. This adapter family synthesizes correct adapters between RC4 implementations in the mbedTLS and OpenSSL libraries in Section 1.4.2.

Return Value Substitution

The argument substitution families described above can also be applied on return values. An example of different return values having the same semantic meaning is the return value of the C library function *isalpha* as shown in Listing 1.1. The wrapper function *adapted_isalpha* in Listing 1.1 performs return value substitution.

```
   Input  : List of previously generated counterexamples test-list
   Output: (input adapter A_in, output adapters A_out) or null
[1] A_in ← symbolic input adapter;
[2] A_out ← symbolic output adapter;
[3] while execution path available do
[4]     eq-counter ← 0;
[5]     while eq-counter < length(test-list) do
[6]         target-output ← execute T with input test;
[7]         reference-output ← execute R with input adapt(A_in, test));
[8]         if equivalent(target-output, adapt(A_out, reference-output)) then
[9]             eq-counter ← eq-counter + 1;
[10]        else
[11]            break;
[12]        end
[13]    end
[14]    if eq-counter == length(test-list) then
[15]        return (concretize(A_in), concretize(A_out));
[16]    end
[17] end
[18] return null;
```

Algorithm 3: `SynthesizeAdapter` procedure used by Algorithm 1. T and R are as defined in Algorithm 1. The form of the resulting adapters ($\mathcal{A}_{in}$, $\mathcal{A}_{out}$) is dictated by $\mathcal{F}_{\mathcal{A}}$.

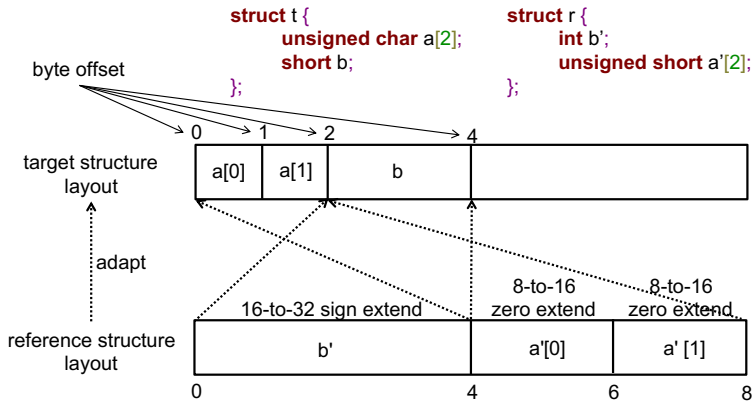
1.2.3 Example

To illustrate our approach, we walk through a representative run of our adapter synthesis algorithm using a pair of target and reference functions that implement similar functionality. Both the target and reference functions are shown in Listing 1.2. Here we will focus only on synthesis of the input adapter, although the general algorithm also produces an adapter that adapts the output of the reference function. A correct input adapter should set the first argument of `reference` to the integer argument y of `target` and set the second argument to the constant 1 to adaptably substitute the `y % 2` operation in `target`. It should also set both the third and fourth arguments of `reference` to the first argument of `target` to adaptably substitute the `x << 1` operation in `target`. We write this adapter as $\mathcal{A}(x, y) = (y, 1, x, x)$.

Step 0: Adapter synthesis begins with an empty counterexample list and a default adapter that maps every argument to the constant 0 (i.e. $\mathcal{A}(x, y) = (0, 0, 0, 0)$). During counterexample generation (`CheckAdapter` in Figure 1.1), we use symbolic execution to search for an inputs x, y such that the output of `target(x,y)` is not equivalent to the output of `reference`$(\mathcal{A}(x, y))$ = `reference(0,0,0,0)`. From `CheckAdapter`, we learn that $x = 1, y = 0$ is one such counterexample.

Step 1: Next, during adapter search (`SynthesizeAdapter` in Figure 1.1), we use symbolic execution to search for a new adapter $\mathcal{A}$ that will make `target(x)` equivalent

Figure 1.2: Memory substitution adapter to make *struct r* adaptably equivalent to *struct t*




```
int target(int x, unsigned y) {
  return (x << 1) + (y % 2);
}
int reference(int a, int b, int c, int d) {
  return c + d + (a & b);
}
int adapted_reference(int x, unsigned y) {
  return target(y, 1, x, x);
}
```

Listing 1.2: Two implementations of similar adaptable functionality

to `reference(`$\mathcal{A}(x, y)$`)` for all inputs x, y in the list [(1,0)]. From `SynthesizeAdapter`, we learn that $\mathcal{A}(x, y) = (y, y, x, x)$ is a suitable adapter, and this becomes our new current adapter.

Step 2: We use `CheckAdapter` to search for a counterexample to the current adapter, $\mathcal{A}(x, y) = (y, y, x, x)$. We find that $x = 0, y = 3$ is a counterexample.

Step 3: Next, we use `SynthesizeAdapter` to search for an adapter $\mathcal{A}$ for which the output of `target(x)` will be equivalent to the output of `reference(`$\mathcal{A}(x, y)$`)` for both pairs of inputs, $x = 1, y = 0$ and $x = 0, y = 3$. `SynthesizeAdapter` identifies $\mathcal{A}(x) = (y, 1, x, x)$ as a suitable adapter.

Step 4: At the beginning of this step, the current adapter is $\mathcal{A}(x, y) = (y, 1, x, x)$. As before, we use `CheckAdapter` to search for a counterexample to the current adapter. We find that `CheckAdapter` fails to find a counterexample for the current adapter, indicating that the current adapter is correct for all explored paths. Therefore, adapter synthesis terminates with the final adapter $\mathcal{A}(x) = (y, 1, x, x)$.

1.2.4 Extensibility

The adapter synthesis algorithm presented in this section is not tied to a source programming language or adapter family. In our implementation (Section 1.3) we target binary x86 and ARM code, and we use adapters that allow for common argument structure changes found in binaries compiled from C and C++ code. Because we work at the binary level, we are also not restricted to working at the level of target functions as described so far. In Section 1.4.5, instead of target functions, we consider target "code fragments." We define a code fragment to be a sequence of instructions consisting of at least one instruction. Inputs to code fragments are the general-purpose registers available on the architecture of the code fragment and outputs are registers written to within the code fragment. We could similarly allow reference functions to be more general code regions.

1.3 Implementation

We implement adapter synthesis for Linux/x86-64 binaries using the symbolic execution tool FuzzBALL [6], which is freely available [7]. FuzzBALL allows us to explore execution paths through the target and adapted reference functions to (1) find counterexamples that invalidate previous candidate adapters and (2) find candidate adapters that create behavioral equivalence for the current set of tests. As FuzzBALL symbolically executes a program, it constructs and maintains Vine IR expressions using the BitBlaze [8] Vine library [9] and interfaces with the STP [10] decision procedure to solve path conditions. We also evaluate adapter synthesis by replacing the symbolic execution-based implementation of adapter search with a concrete implementation that searches the adapter space in a random order.

1.3.1 Test Harness

To compare code for equivalence we use a test harness similar to the one used by Ramos et al. [11] to compare C functions for direct equivalence using symbolic execution. The test harness exercises every execution path that passes first through the function, and then through the adapted reference function. As FuzzBALL executes a path through the function, it maintains a path condition that reflects the branches that were taken. As execution proceeds through the adapted reference function on an execution path, FuzzBALL will only take branches that do not contradict the path condition. Thus, symbolic execution through the target and reference functions consistently satisfies the same path condition over the input. Listing 1.3 provides a representative test harness. If the target is a code fragment instead of a function, its inputs x_1, ..., x_n need to be written into the first n general purpose registers available on the architecture. Since the target code fragment may write into the stack pointer register (`sp` on ARM), the value of the stack pointer also needs to be saved before executing the target code fragment

and restored after the target code fragment has finished execution. On line 2 the test harness executes `TARGET` with inputs x_1, ..., x_n and captures its output in `r1`. If the target is a function, its outputs are its return value and values written to memory. If the target is a code fragment, its output needs to be determined in a preprocessing phase. One heuristic for choosing a code fragment's output is to choose the last register that was written into by the code fragment. On line 6, the test harness calls the adapted reference function `REF` with inputs y_1, ..., y_m, which are derived from x_1, ..., x_n using an adapter `A`. After executing `REF`, the test harness adapts `REF`'s return value using the return adapter `R` and saves the adapted return value in `r2`. On line 7 the test harness branches on whether the results of the calls to the target and adapted reference code match.

```
1 void compare(x1, ..., xn) {
2   r1 = TARGET(x1, ..., xn);
3   y1 = adapt(A, x1, ..., xn);
4   ...
5   ym = adapt(A, x1, ..., xn);
6   r2 = adapt(R, REF(y1, ..., ym));
7   if (r1 == r2) printf("Match\n");
8   else printf("Mismatch\n");
9 }
```

Listing 1.3: Test harness

We use the same test harness for both counterexample search (called `CheckAdapter` in Figure 1.1) and adapter search (called `SynthesizeAdapter` in Figure 1.1). During counterexample search, the inputs x_1, ..., x_n are marked as symbolic and the adapters `A` and `R` are concrete. FuzzBALL first executes the function using the symbolic x_1, ..., x_n. It then creates reference function arguments y_1, ..., y_n using the concrete adapter `A` and executes the reference function. During adapter search, for each set of test inputs x_1, ..., x_n, FuzzBALL first executes the function concretely. The adapter `A` is then marked as symbolic, and FuzzBALL then applies symbolic adapter formulas (described in 1.3.2) to the concrete test inputs and passes these symbolic formulas as the adapted reference function arguments y_1, ..., y_n. During counterexample search we are interested in paths that execute the "Mismatch" side, and during adapter search we are interested in paths that execute the "Match" side of the branch on line 7 of Listing 1.3. For simplicity, Listing 1.3 shows only the return values r_1 and r_2 as being used for equivalence checking.

1.3.2 Adapters as Symbolic Formulae

We represent adapter families in FuzzBALL using Vine IR expressions involving symbolic variables. For example, an adapter from the argument substitution family for the adapted reference function argument y_i is represented by a Vine IR expression that indicates whether y_i should be replaced by a constant value (and if so, what constant value)

or an argument from the target function (and if so, which argument). This symbolic expression uses two symbolic variables, *y_i_type* and *y_i_val*. We show an example of an adapter from the argument substitution family represented as a symbolic formula in Vine IR in Listing 1.4. This listing assumes the target function takes three arguments, *x1*, *x2*, *x3*. This adapter formula substitutes the adapted reference function argument *y1* with either a constant or with one of the three target function arguments. A value of 1 in *y_1_type* indicates *y1* is to be substituted by the constant value given by *y_1_val*. If *y_1_type* is set to a value other than 1, *y1* is to be substituted by the target function argument at the position present in *y_1_val*. We constrain the range of values *y_1_val* can take by adding side conditions. In the example shown in Listing 1.4, when *y_1_type* equals a value other than 1, *y_1_val* can only equal 0, 1, or 2 since the target function takes 3 arguments.

```
y_1_type:reg8_t == 1:reg8_t ? y_1_val:reg64_t :
  ( y_1_val:reg64_t == 0:reg64_t ? x1:reg64_t :
    ( y_1_val:reg64_t == 1:reg64_t ? x2:reg64_t : x3:reg64_t ))
```

Listing 1.4: Argument Substitution adapter

During adapter search, Vine IR representations of adapted reference function arguments are placed into argument registers of the reference function before it begins execution, and placed into the return value register when the reference function returns to the test harness. When synthesizing memory substitution adapters, Vine IR formulas allowing memory substitutions are written into memory pointed to by reference function arguments. We use the registers %rdi, %rsi, %rdx, %rcx, %r8, and %r9 for function arguments and the register %rax for function return value, as specified by the x86-64 ABI calling convention [12]. We do not currently support synthesizing adapters between functions that use arguments passed on the stack, use variable number of arguments, or specify return values in registers other than %rax.

1.3.3 Equivalence checking of side-effects

We allow target and reference code to make system calls and have side-effects on memory. We record the side-effects of executing the target and adapted reference functions and compare them for equivalence on every execution path. For equivalence checking of side-effects via system calls, we check the sequence of system calls and their arguments, made by both functions, for equality. For equivalence checking of side-effects on concretely-addressed memory, we record write operations through both functions and compare the pairs of (address, value) for equivalence. For equivalence checking of side-effects on memory addressed by symbolic values, we use a FuzzBALL feature called *symbolic regions*. Symbolic address expressions encountered during adapted reference function execution are checked for equivalence with those seen during target function execution and mapped to the same symbolic region, if equivalent.

1.4 Evaluation

In this section, we evaluate the performance of adapter synthesis and present its applications using case studies. In Section 1.4.1, we present an example of finding adaptable substitutability modulo a bug—enabling programmers to more easily replace buggy components of their code. In Section 1.4.2, we show how our technique can enable programmers to switch between different libraries with the same functionality. In Section 1.4.3, we show that adapter synthesis can find adapters even within a library. In Section 1.4.4, we compare symbolic execution-based adapter search with concrete enumeration-based adapter search. Finally, in Section 1.4.5, we show how our technique can be used for reverse engineering.

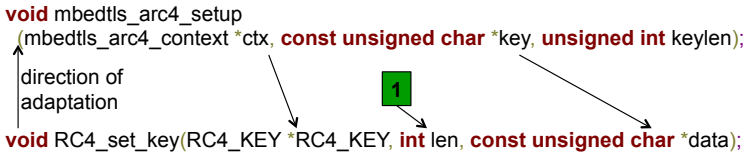
1.4.1 Case Study: Security

```
1  unsigned char lookup1
2      (unsigned char *table, int key) {
3    if(abs(key) > 127) //buggy for key = -2147483648
4      return -1;
5    return table[key+127];
6  }
7
8  unsigned char lookup2
9      (unsigned char *table, int len, int key) {
10   if( !(-(len/2) <= key && key <= (len/2)) )
11     return -1;
12   return table[key+(len/2)];
13 }
14
15 unsigned char adapted_lookup2
16     (unsigned char *table, int key) {
17   return lookup2 (table, 255, key);
18 }
```

Listing 1.5: Two implementations for mapping ordered keys, negative or positive, to values using a C array

Consider a table implementing a function of a signed input. For example, keys ranging from -127 to 127 can be mapped to a 255-element array. Any key k will then be mapped to the element at position $k+127$ in this array. We present two implementations of such lookup functions in Listing 1.5. Both functions, *lookup1* and *lookup2*, assume keys ranging from $-len/2$ to $+len/2$ are mapped in the *table* parameter with *lookup1* being specific to tables of length 255. However, *lookup1* contains a bug caused by undefined behavior. The return value of *abs* for the most negative 32-bit integer (-2147483648) is not defined [13]. Given the most negative 32-bit integer, the eglibc-2.19 implementation of *abs* returns that same 32-bit integer. This causes the check on line 2 of Listing 1.5 to

Figure 1.3: Argument substitution adapter to make *RC4_set_key* adaptably equivalent to *mbedtls_arc4_setup*



not be satisfied, allowing execution to continue to line 5 and causing an out-of-bounds memory access. *lookup2* in Listing 1.5 is a different implementation of an array-based lookup with a different interface than *lookup1*. Checking whether the key is in range is done differently in *lookup2*, causing it to not have the memory access bug present in *lookup1*. For this reason, users of *lookup1* may find it desirable to substitute the use of *lookup1* with *lookup2*. Adapter synthesis can perform such a substitution by adapting *lookup2* to *lookup1* while simultaneously not adapting the out-of-bounds memory access in *lookup1*. Our adapter synthesis implementation synthesizes the correct argument substitution adapter in the *lookup1* ← *lookup2* direction in about 8 minutes. Synthesis of the correct adapter is slowed down by the presence of the *table* pointer in the interfaces of *lookup1* and *lookup2*. The adapter is shown on lines 15-18 of Listing 1.5. This case study shows adapter synthesis can replace a buggy function with its bug-free variant by doing adaptation modulo a bug.

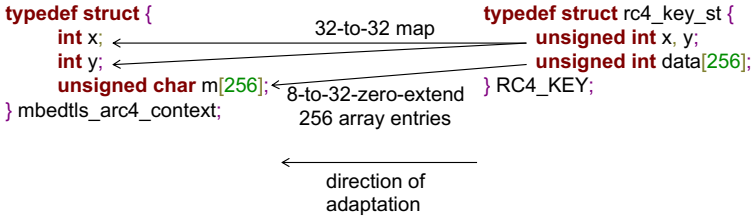
1.4.2 Case Study: Library Replacement

To show that adapter synthesis can be applied to replace functionality from one library with that from another library, we adapt functions implementing RC4 functionality in mbedTLS and OpenSSL.

RC4 context initialization

The RC4 algorithm uses a variable length input key to initialize a table with 256 entries within the context argument. Both cryptography libraries in our example, mbedTLS and OpenSSL, have their own implementation of this initialization routine. Both initialization function signatures are shown in Figure 1.3. Executing each of these initialization routines requires 256 rounds of mixing bytes from the key string into the context. The two initialization routines require the key length and key string arguments at different positions, and use different RC4 context structures (*RC4_KEY* in OpenSSL, *mbedtls_arc4_context* in mbedTLS). The RC4 context arguments contain three fields as shown in Figure 1.4. The first two 4-byte fields are used to index into the third field, which is an array with 256 entries. Each entry in the array is 4 bytes wide in OpenSSL and 1 byte wide in mbedTLS. The correct adapter that adapts the OpenSSL context to the mbedTLS context (mbedTLS ← OpenSSL) performs two mapping operations: (1)

Figure 1.4: Memory substitution adapter to make *RC4_KEY* adaptably equivalent to *mbedtls_arc4_context*



it maps the first two mbedTLS context's fields directly to the first two OpenSSL context's fields and (2) it zero extends each 1 byte entry in the third field of the mbedTLS context to the corresponding 4 byte entry in the third field of the OpenSSL context. The correct adapter for making the *RC4_KEY* structure adaptably equivalent to the *mbedtls_arc4_context* structure is shown in Figure 1.4. The correct adapter in the reverse direction (OpenSSL ← mbedTLS) changes the second mapping operation to map the least significant byte of each 4 byte entry in the third field to the 1 byte entry in its corresponding position.

Performing this adaptation with *mbedtls_arc4_setup* and *RC4_set_key* (the RC4 context initialization functions in mbedTLS and OpenSSL respectively) requires adaptation of side-effects on memory because mixing of the key string into the context is the only output of these functions. Since a memory substitution structure can be used both as input and as output, we have to perform the memory substitution adaptation at least twice. First, the reference function may use the memory substitution structure as input. Hence, we need to adapt the initial byte values of the memory substitution structure to obtain the initial byte values to be used for the reference function. Second, before running the reference function, the target function could have written to the memory substitution structure. Hence, we need to adapt side-effects of the target function on the memory substitution structure in order to compare them with corresponding side-effects on memory from the reference function. The most general memory substitution adapter synthesis allows arbitrary numbers of 1, 2, 4, or 8 byte entries in each field of the 264 ($2\times4+256\times1$) byte mbedTLS context and 1032 ($2\times4+256\times4$) byte OpenSSL context. But this makes the search space of memory mappings very large. We instead only explored adapters where the number of entries in each array was a power of 2. While this reduction is useful in practice, it still gives us a search space of about 4.7 million possible memory substitutions in both directions of adaptation.

Finally, memory substitution must be combined with argument substitution to synthesize adapters between *mbedtls_arc4_setup* and *RC4_set_key*. This combination of argument substitution and memory substitution adapter families creates a search space of 5.593 billion adapters. Our adapter synthesis tool figures out the correct argument,

Table 1.1: Time taken in days for synthesizing adapters between RC4 setup and encryption functions in OpenSSL and mbedTLS

	setup (M ← O)	setup (O ← M)	enc (M ← O)	enc (O ← M)
Concrete enumeration-based adapter search	8.24	5.52	5.65	5.52
FuzzBALL-based adapter search	7.87	6.15	8.54	2.10

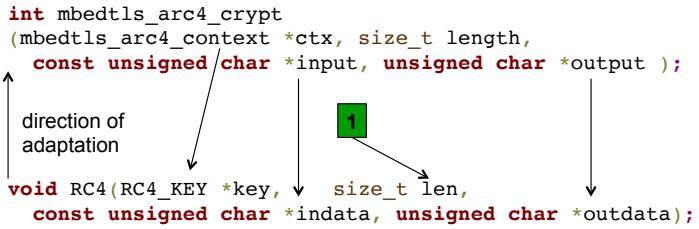
memory, and return value substitutions. It finds adaptable equivalence in both directions of adaptation by checking equivalence between side-effects on the structure objects (*ctx* for *mbedtls_arc4_setup*, *RC4_KEY* for *RC4_set_key*). The correct adapter for adaptably substituting the *mbedtls_arc4_setup* function with the *RC4_set_key* function is shown in Figure 1.3. To setup adapter synthesis between these two function pairs (we synthesized adapters in both directions), we used a symbolic key string of length 1, and hence the synthesis tool correctly sets the key length argument to 1. While we acknowledge that using an input string of length 1 is too small to be useful, we expect the adapter to be correct on strings of length greater than 1 in practice. We also plan to integrate techniques such as path merging [14, 15] to increase the bounds of inputs used in adapter synthesis. While we used an input memory substitution size of 1032 symbolic bytes for memory substitution, both *mbedtls_arc4_setup* and *RC4_set_key* initialize this memory with concrete values in their implementation, thereby causing this adaptation to start with a much smaller symbolic state consisting of a single symbolic input byte.

We present the time taken to synthesize adapters for RC4 setup function pairs in Table 1.1. The execution time shown in Table 1.1 for concrete enumeration-based adapter search is the average execution time taken for adapter synthesis over 10 correctly synthesized adapters for adapting RC4 setup functions. We performed adapter synthesis using concrete enumeration-based adapter search 10 times because concrete enumeration-based adapter search traverses the adapter space in a random order. Using the execution times shown in Table 1.1 and the observation that our adapter synthesis never used more than 1 CPU core and 4 GB of RAM, we estimated [16] the cost of this computation on a Amazon EC2 instance (t2-medium). Table 1.2 shows these estimated costs. These costs suggest that automated adapter search is likely competitive with paying a human programmer to find and verify the correctness of an adapter at the binary level. The time required for adapter synthesis can be further reduced by parallelizing the adapter search in concrete enumeration and reusing the state of adapter search in FuzzBALL-based adapter search. We discuss this further in Section 1.5.

Table 1.2: Estimated cost (in USD) of synthesizing adapters between RC4 setup and encryption functions in OpenSSL and mbedTLS on an Amazon EC2 instance

	setup M ← O	setup O ← M	enc M ← O	enc O ← M	Total
Concrete enum.-based adapter search	$9.17	$6.15	$6.29	$6.15	$27.76
FuzzBALL-based adapter search	$8.76	$6.84	$9.51	$2.34	$27.45

Figure 1.5: Adapter performing argument and memory substitution to make *mbedtls_crypt* in the mbedTLS library adaptably substitutable by *RC4* in OpenSSL



RC4 encryption

The RC4 encryption functions in mbedTLS and OpenSSL take 4 arguments each, three of which are pointers to the RC4 context, the input key string, and the output string, as shown in Figure 1.5. These functions use the RC4 context as input, causing the initial symbolic state to consist of 1032 symbolic bytes for memory substitution and one symbolic byte for the input string. These functions both read from and write to the RC4 context, making two memory substitution adaptations necessary. These functions also encrypt every byte of the input string using a loop where the length of the input string is given as a parameter to the function. Since all arguments to the reference function are symbolic, using a symbolic formula for the length of the input string can easily cause the loop bound to be very large, especially if the symbolic formula for the length allows the possibility of the length being equal to one of the pointer arguments to the reference function. To avoid the encryption loop in the reference function from executing too many times, we restricted every instruction in the reference function to be executed at most twice. Finally, because these functions write to an output string, it is necessary for us to have memory side-effects equivalence checking to capture outputs

that are not part of the return value.

The adapter search space in this case consists of 1.792×10^{12} adapters. The correct adapter for making the *RC4* method adaptably equivalent to *mbedtls_arc4_crypt* is shown in Figure 1.5. Our adapter synthesis tool finds the correct argument and memory substitution adapters in both directions of adaptation. Tables 1.1, 1.2 show the time taken for and estimated cost of adapter synthesis between the RC4 encryption functions in OpenSSL and mbedTLS. Once again, the execution time shown in Table 1.1 for concrete enumeration-based adapter search is the average execution time taken for adapter synthesis over 10 correctly synthesized adapters. We verified the correctness of our adapted context structures by using self-tests present in mbedTLS and OpenSSL.

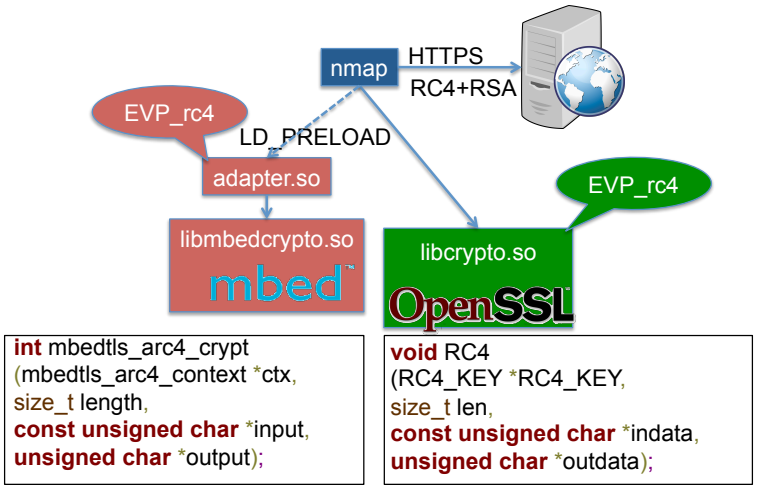
On improving memory substitution performance

On combining the memory substitution adapter family with argument and return value substitution, our adapter synthesis tool encountered a significant slowdown with both RC4 context initialization and encryption. This can be attributed in part to the encoding of memory substitutions in our tool. We enumerate all possibilities of memory substitutions into the formula of every byte in the memory substitution structure, causing the symbolic formulas to be very large. We plan to encode the memory substitution adapter more efficiently in the future to make better use of existing solvers. Another significant cause of the slowdown, in the case of RC4 context initialization, is the slow symbolic execution of 256 rounds of key mixing, once in the target and once in the reference function, because of two symbolic loads and two symbolic stores to memory on every round of key mixing. We plan to integrate loop summarization (for example, as described by Godefroid et al. [17]), and use the theory of arrays for symbolically-indexed memory accesses to speed up this symbolic execution in the future. In the case of RC4 encryption, since we have to adapt the memory substitution structures twice (once for input and once for output) we have to present large formulas to the solver at least twice on every execution path with each query taking a few seconds. This large symbolic state is the cause of significant slowdown during RC4 encryption adapter synthesis. We plan to explore concretization heuristics of symbolic bytes in the future to reduce the number of solver invocations made during RC4 encryption adapter synthesis.

RC4 adapter verification using nmap

We verified the correctness of our RC4 memory substitution adapter using nmap with the setup shown in Figure 1.6. We created adapted versions of the OpenSSL RC4 setup and encryption functions that internally use the mbedTLS context adapted to the OpenSSL context. On a 64-bit virtual machine running Ubuntu 14.04, we compiled the adapted setup and encryption functions into a shared library and setup a local webserver, which communicated over port 443 using the *RC4+RSA* cipher. We used the stock nmap binary to scan our localhost and injected our specially created shared

Figure 1.6: nmap using RC4 encryption in mbedTLS instead of OpenSSL



library using the *LD_PRELOAD* environment variable. The preloading caused the RC4 functions in our shared library to be executed instead of the ones inside OpenSSL. The output of nmap, run with preloading our specially created shared library which used the OpenSSL ← mbedTLS structure adapter, was the same as the output of nmap when using the system OpenSSL library.

1.4.3 Intra-library Adapter Synthesis

The previous section showed an application of adapter synthesis where the target and reference functions came from independently-developed implementations. But, adapter synthesis can also be useful in cases where the target and reference functions were developed within the same library. Synthesizing adapters between binary functions in the same library can expose important relations between adaptably substitutable functions that may not be known to users of the library. It can show relations between functions, by, for example showing that one function can be adaptably implemented in terms of another. Verifying such relations between functions from their binary implementation can provide the users of the library a more detailed picture of the function's behavior. In libraries with a large interface, such as the Ubuntu 14.04 system C library, where it can be challenging to manually identify adaptability relations between functions, performing automated intra-library adapter synthesis can be particularly useful.

Setup

We evaluated our adapter synthesis tool on the system C library available on Ubuntu 14.04 (eglibc 2.19). The C library uses a significant amount of inlined assembly, for

Table 1.3: Adapter Synthesis over 13130 function pairs without memory-based equivalence checking

adapter type	Inequiv.	adapters Found	Timeout	Target function crashed
arg. sub.	8887	382	3014	847
type conv.	8909	383	2989	849

instance, the *ffs*, *ffsl*, *ffsll* functions, which motivates automated adapter synthesis at the binary level. We enumerated 1316 exported functions in the library in the order they appear, which caused functions that are defined in the same source files to appear close to each other. Considering every function in this list as the target function, we chose five functions that appear above and below it as 10 potential reference functions. These steps gave us a list of 13130 ($10 \times 1316 - 2 \times \sum_{i=1}^{5} i$) pairs of target and reference functions. We used the argument substitution and type conversion adapter families combined with the return value adapter family because these families scale well and are widely applicable. We ran our adapter synthesis with a 2 minute timeout on a machine running CentOS 6.8 with 64-bit Linux kernel version 2.6.32 using 64 GB RAM and a Intel Xeon E5-2680v3 processor. To keep the running time of the entire adapter synthesis process within practical limits, we configured FuzzBALL to use a 5 second SMT solver timeout and to consider any queries that trigger this timeout as unsatisfiable. We limited the maximum number of times any instruction can be executed to 4000 because this allowed execution of code which loaded library dependencies. We limited memory regions to be symbolic up to a 936 byte offset limit (the size of the largest structure in the library interface) and any offset outside this range was considered to contain zero.

Results

Table 1.3 summarizes the results of searching for argument substitution and type conversion adapters with a return value adapter within the 13130 function pairs described above. The similarity in the results for the type conversion adapter family and argument substitution adapter family arises from the similarity of these two families. The most common causes of crashing during execution of the target function were missing system call support in FuzzBALL and incorrect null dereferences (caused due to lack of proper initialization of pointer arguments). The timeout column includes all function pairs for which we had a solver timeout (5 seconds), hit the iteration limit (4000), or reached a hard timeout (2 minutes). The search terminated without a timeout for 70% of the function pairs, which reflects a complete exploration of the space of symbolic inputs to a function, or of adapters.

Since there is no ground truth, we manually corroborated the results of our evaluation by checking the C library documentation and source code. Our adapter synthesis

evaluation on the C library reported 30 interesting true positives shown in Table 1.4. The remaining adapters found were correct, but trivial. The first column in Table 1.4 shows the function pair between which an adapter was found (with the number of arguments) and the second column shows the adapter. We use the following notation to describe adapters in a compact way. $f_1 \leftrightarrow f_2$ means $f_1 \leftarrow f_2$ and $f_2 \leftarrow f_1$. # followed by a number indicates reference argument substitution by a target argument, while other numbers indicate constants. X-to-YS represents taking the low X bits and sign extending them to Y bits, X-to-YZ represents a similar operation using zero extension.

Table 1.4: adapters found within eglibc-2.19

$f_1 \leftarrow f_2$ or $f_1 \leftrightarrow f_2$	adapter
abs(1) ← labs(1) abs(1) ← llabs(1)	32-to-64S(#0) and 32-to-64Z(return value)
labs(1) ↔ llabs(1)	#0
ldiv(1) ↔ lldiv(1)	#0
ffs(1) ← ffsl(1) ffs(1) ← ffsll(1)	32-to-64S(#0)
ffsl(1) ↔ ffsll(1)	#0
setpgrp(0) ← setpgid(2)	0, 0
wait(1) ← waitpid(3)	-1, #0, 0
wait(1) ← wait4(4)	-1, #0, 0, 0
waitpid(3) ← wait4(4)	#0, #1, #2, 0
wait(1) ← wait3(3)	#0, 0, 0
wait3(3) ← wait4(4)	-1, #0, #1, #2
umount(1) ← umount2(2)	#0, 0
putchar(1) ↔ putchar_unlocked putwchar(1) ↔ putwchar_unlocked(1)	#0
recv(4) ← recvfrom(6) send(4) ← sendto(6)	32-to-64S(#0), #1, #2, 32-to-64S(#3), 0, 0
atol(1) ↔ atoll(1)	#0
atol(1) ← strtol(3) atoi(1) ← strtol(3) atoll(1) ← strtoll(3)	#0, 0, 10
isupper(1) ← islower(1)	#0 + 32
islower(1) ← isupper(1)	#0 - 32
killpg(1) ← kill(1)	-#0, #1

The last three rows shown in Table 1.4 shows three arithmetic adapters found within the C library using partial automation. The functions *isupper*, *islower*, *kill* have assumptions about conditions that will be satisifed by inputs given to them. We synthesized

the correct adapters by writing wrappers containing preconditions around these three functions.

1.4.4 Comparison with Concrete Enumeration-based Adapter Search

For every adapter family that we have discussed, the space of possible adapters is finite. So instead of using symbolic execution for adapter search, we can find candidate adapters by enumerating concrete adapters until we find one that produces equal side-effects and return values for all previously-found tests. We implement concrete enumeration-based adapter search in C for all the adapter families described in Section 1.2. We use the Pin [18] framework for checking side-effects on memory and system calls for equality. To prevent adapter search time from depending on the order of enumeration, we randomize the sequence in which adapters are generated, ensuring that every adapter had the same probability of being generated. For the adaptable function pairs reported in Section 1.4.3, we synthesized adapters from the type conversion adapter family using both the concrete enumeration- and symbolic execution-based adapter search implementations and captured the total adapter search time. We also counted the size of the adapter search space for every adaptation. In some cases, the adapter search space was too large to be concretely enumerated. For example, the adapter search space for the $killpg \leftarrow kill$ adapter consists of 98.1 million arithmetic adapters. In such cases, we reduced the size of the search space by using smaller constant bounds. Based on the size of adapter search space, we compared the total adapter search times for both adapter search strategies. We present the results from this comparison in Figure 1.7. For concrete enumeration-based adapter search, Figure 1.7 shows the time required to find an adapter has a consistent exponential increase with an increase in the size of adapter search space. But when using binary symbolic execution-based adapter search, Figure 1.7 shows a much slower increase in time required to find the adapter. This occurs because symbolic execution is less affected by an increase in the size of the adapter search space due to an increase in the number of arguments and the number of possible constants in the adapter family.

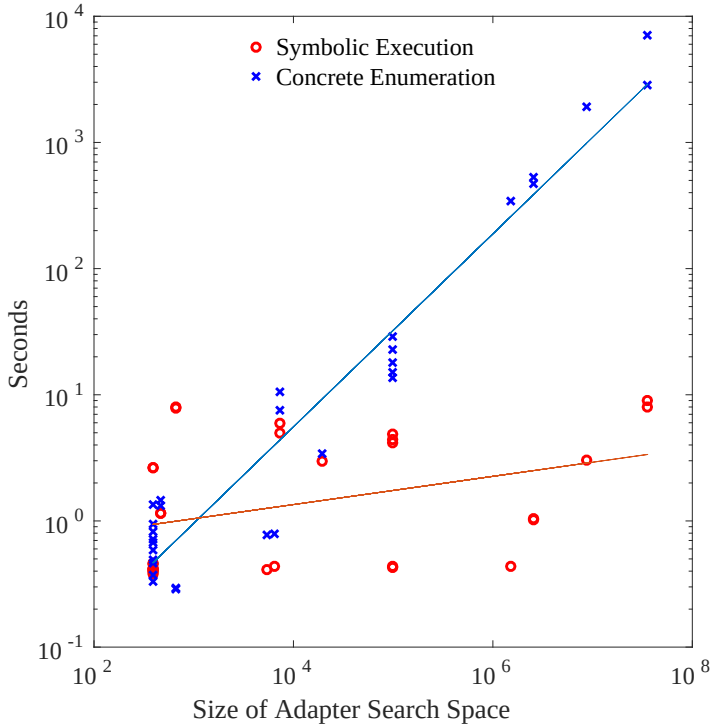
1.4.5 Large-Scale Reverse Engineering

In this section, we show how adapter synthesis can be used for reverse engineering. Our goal is to understand the behavior of fragments of binary code by synthesizing adapters between those fragments and reference functions with known behavior. We evaluate on binary code fragments taken from a ARM firmware image and reference functions chosen from the source code of a popular media player.

Code fragment selection

Rockbox [19] is a free replacement 3rd party firmware for digital music players. We used a Rockbox image compiled for the iPod Nano (2g) device, based on the 32-bit

Figure 1.7: Comparing concrete enumeration-based adapter search with binary symbolic execution-based adapter search for adapters presented in Section 1.4.3



ARM architecture, and disassembled it. We dissected the firmware image into code fragments using the following rules: (1) no code fragment could use memory, stack, floating-point, coprocessor, or supervisor call instructions, (2) no code fragment could branch to an address outside itself, (3) the first instruction of a code fragment could not be conditionally executed.

The first rule disallowed code fragments from having any inputs from/outputs to memory, thereby allowing us to use the 13 general purpose registers on ARM as inputs. The second rule prevented a branch to an invalid address. ARM instructions can be executed based on a condition code specified in the instruction. If the condition is not satisfied, the instruction is turned into a `noop`. The third rule disallowed the possibility of having code fragments that begin with a `noop` instruction, or whose behavior depends on a condition. The outputs of every code fragment were the last (up to) three registers written to by the code fragment. This caused each code fragment to be used as the target code region up to three times, once for each output register. This procedure gave us a total of 183,653 code regions, with 61,680 of them consisting of between 3 and 20 ARM instructions.

To evaluate which code fragments could be synthesized just with our adapter family without a contribution from a reference function, we checked which of these 61,680 code fragments could be adaptably substituted by a reference function that simply returns one of its arguments. Intuitively, any code fragment that can be adaptably substituted by an uninteresting reference function must be uninteresting itself, and so need not be considered further. We found 46,831 of the 61,680 code fragments could not be adaptably substituted by our simple reference function, and so we focused our further evaluation on these 46,831 code fragments that were between 3 and 20 ARM instructions long and non-trivial.

Reference functions

Since our code fragments consisted of between 3 and 20 ARM instructions, we focused on using reference functions that can be expressed in a similar number of ARM instructions. We used the source code of version 2.2.6 of the VLC media player [4] as the codebase for our reference functions. We performed an automated search for functions that were up to 20 lines of source code. This step gave us a total of 1647 functions. Similar to the three rules for code fragment selection, we discarded functions that accessed memory, called other VLC-specific functions, or made system calls to find 24 reference functions. Other than coming from a broadly similar problem domain (media players), our selection of reference functions was independent of the Rockbox codebase, so we would not expect that every reference function would be found in Rockbox.

Results

We used the type conversion adapter family along with the return value substitution family, disallowing return value substitution adapters from setting the return value to be a type-converted argument of the reference function (which would lead to uninteresting adapters). We allowed the reference function arguments to be replaced by unrestricted 32-bit constants, and we assumed each code segment takes up to 13 arguments. The size of this adapter search space can be calculated using the following formula:

$$8 \times \sum_{k=0}^{k=13} (2^{32})^{13-k} \times {}^{13}C_k \times {}^{13}P_k \times 8^k$$

The first multiplicative factor of 8 is due to the 8 possible return value substitution adapters. The permutation and combination operators occur due to the choices of arguments for the target code fragment and reference functions (we assumed both have 13 arguments since most general-purpose registers can be used as input in an arbitrary code fragment). The final 8^k represents the 8 possible type conversion operators that a type conversion adapter can apply. The dominant factor for the size of the adapter

search space comes from the size of the set of possible constants. Our adapter family used unrestricted 32-bit constants, leading to a constants set of size 2^{32}.

With this adapter family set up, we ran adapter synthesis trying to adaptably substitute each of the 46,831 code fragments by each reference function. This gave us a total of 1,123,944 (46831×24) adapter synthesis tasks, with each adapter synthesis search space consisting of 1.353×10^{127} adapters, too large for concrete enumeration. We set a 5 minute hard time limit and a total memory limit of 2 GB per adapter synthesis task. We split the adapter synthesis tasks for each reference function into 32 parallel jobs, creating a total of 768 (32×24) parallel jobs. We ran our jobs on a machine cluster running CentOS 6.8 with 64-bit Linux kernel version 2.6.32 and Intel Xeon E5-2680v3 processors. We present our results in Table 1.5. The first column shows the reference functions chosen from the VLC media player source code. The *#(full)* column reports how many code fragments were found to be adaptably substitutable (represented by the value for *#*), and how many of those exploited the full generality of the reference function (represented by the value of *full*). We report average number of steps and average total running time in the *steps* and *total time* columns respectively.

Clustering using random tests

For every target code fragment and reference function pair, we can either find an adapter, find the fragment to not be adaptably substitutable, or run out of time. Our adapter synthesis tool found adaptable substitution using 18 out of the 24 reference functions. For every reference function, we clustered its adapted versions using 100,000 random tests. All adapted versions of a reference function that report the same output for all inputs were placed in the same cluster. The number of clusters is reported in the *#clusters* column. For each reference function, we then manually examined these clusters to judge which adapted versions used the complete functionality of that reference function; these are the cases where describing the functionality of the target fragment in terms of the reference function is mostly likely to be concise and helpful. This took us less than a minute of manual effort for each reference function because we understood the intended semantic functionality of every reference function (we had its source code). We found instances of adapters using the full generality of the reference function for 11 reference functions. Reference functions for which we found no use of full generality are omitted in Table 1.5. We found that a majority of our generated adapters exploit specific functionality of the reference functions. We explored this observation further by manually summarizing the semantics of the 683 adapters reported for `clamp`. We found that these 683 adapters have a partial order between them created by our adapter families of type conversion and return value substitution. We present a subset of this partial order as a Hasse diagram in Figure 1.8 with the most general implementation of `clamp` as the topmost node and functions that use the most specific instances of `clamp` at the bottom. To explain one unintuitive example, the `invert-low-bit` operation on a value `v` can be implemented in terms of `val < N` by setting `val` to the low bit of

Table 1.5: Reverse engineering results using 46831 target code fragments from a Rockbox firmware image and 24 reference functions from VLC media player grouped by the three overall possible terminations of adapter synthesis. The *#(full)* column reports how many code fragments were found to be adaptably substitutable, and how many of those exploited the full generality of the reference function.

	adapter				no adapter	timeout
fn_name	#(full)	#cluster	steps	total time	#	#
clamp	683 (177)	110	12.9	99.3	40553	5595
abs_diff	575 (5)	75	10.5	20.0	46250	6
bswap32	115 (8)	19	8.7	16.6	46708	8
integer_ cmp	93 (5)	15	9.6	21.4	46467	271
even	3 (2)	3	5.7	11.3	46823	5
median	332 (42)	60	13.7	119.2	32171	14328
get_ descr_len	22 (9)	2	9	16.7	46625	184
tile_pos	5617 (407)	909	10.9	53.5	24696	16518
dirac_pic_n _bef_m	330 (2)	18	13.2	25.7	46393	108
RenderRGB	763 (2)	64	10.8	27.5	46061	7
mpga_get_ frame_samples	22 (15)	4	5	7.9	46235	574

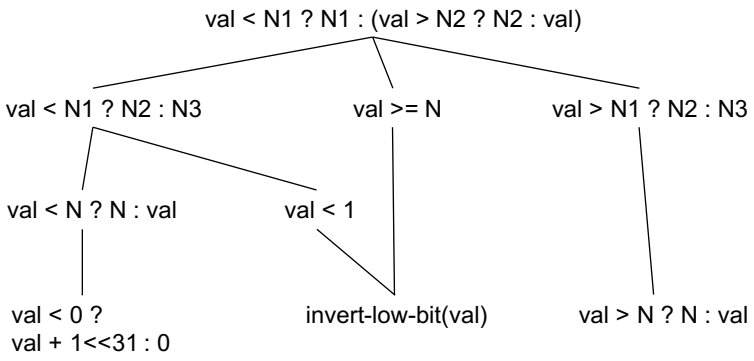


Figure 1.8: Subset of partial order relationship among adapted clamp instances

`v` zero-extended to 32 bits and `N` to 1, and zero-extending the low 1 bit of the return value of `val < N` to 32 bits. Some such functionalities owe more to the flexibility of the adapter family than they do to the reference function. These results suggest it would be worthwhile in the future to prune them earlier by searching for instances of the simplest reference functions first, and then excluding these from future searches.

Timeouts were the third possible conclusion of each adapter synthesis task. The number of timeouts is reported in Table 1.5. We show a histogram of the total running time used to find adapters in Figure 1.9 for the `clamp` reference function. Similar histograms for `tile_pos` and `median` reference functions can be found in Section 1.4.5.

Timeouts with `tile_pos` and `median`

Here we report the histograms of timeouts for the `tile_pos` and `median` reference functions. Please refer to Figures 1.9, 1.10 and 1.11. The number of adapters found after 300 seconds decreases rapidly, consistent with the mean total running time (subcolumn *total time* under column *adapter* in Table 1.5) of 99.3 seconds for the `clamp` reference function. Table 1.5 also shows that the total running time, when our tool concludes with finding an adapter, is significantly less than 300 seconds for all reference functions that reported adapters. Though setting any finite timeout can cause some instances to be lost, these results suggest that a 300-second timeout was appropriate for this experiment, and that most timeouts would not have led to adapters.

1.4.6 Comparing adapter families

We also explored the tradeoff between adapter search space size and effectiveness of the adapter family. We ran all 46,831 target code fragments with `clamp` as the reference function using two additional adapter families beyond the combination of type conversion family with return value substitution described above. The first adapter family allowed only argument permutation and the second allowed argument permututation

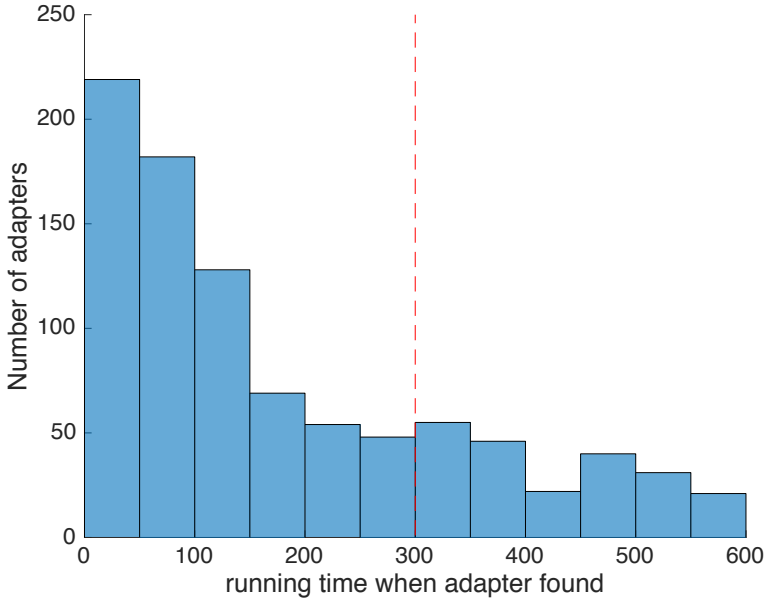


Figure 1.9: Running times for synthesized adapters using `clamp` reference function

along with substitution with unrestricted 32-bit constants. We ran the first adapter family setup (argument permutation + return value substitution) with a 2.5 minute hard time limit, the second adapter family setup (argument substitution + return value substitution) with a 5 minute hard time limit, and the third adapter family setup (argument substitution + return value substitution) was the same as the previous subsection with also a 5 minute hard time limit. We present our results in Table 1.6. As expected, the number of timeouts increases with an increase in the size of adapter search space. Table 1.6 also shows that, for `clamp`, a simpler adapter family is better at finding adapters than a more expressive family, because more searches can complete within the timeout. But, this may not be true for all reference functions. Table 1.6 suggests that,

Table 1.6: Comparing adapter families with 46,831 target code fragments and `clamp` reference function

	size	#-ad	#-inequiv	#-timeout
arg_perm+ ret_sub-2.5m	4.98E+10	9	46803	19
arg_sub+ ret_sub-2.5m	1.3538427E+126	705	45782	344
type_conv+ ret_sub-5m	1.3538430E+126	683	40553	5595

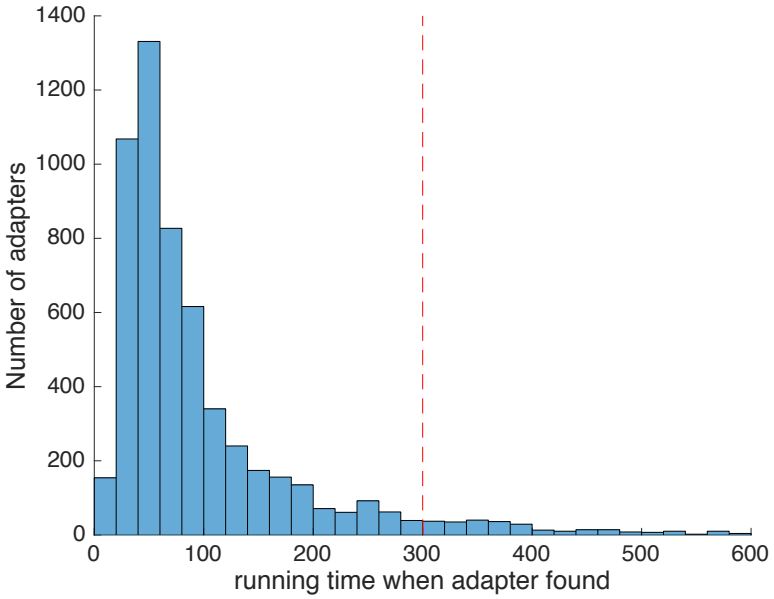


Figure 1.10: Running times for synthesized adapters using `tile_pos` reference function

when computationally feasible, adapter families should be tried in increasing order of expressiveness to have the fewest timeouts overall. We plan to explore this tradeoff between expressiveness and effectiveness of adapter families in the future.

1.5 Limitations and Future Work

We currently represent our synthesized adapters by an assignment of concrete values to symbolic variables and manually check them for correctness. Adapters could instead be automatically incorporated into binary code to replace the original function with the adapted function. This would make the adapters more convenient to use and easier to test automatically. We plan to automate generation of such adapter code in the future.

During every adapter search step, symbolic execution explores all feasible paths, including paths terminated on a previous adapter search step because they did not lead to a correct adapter. Once a candidate adapter is found, the next iteration of adapter search can be accelerated by using information saved from the previous iteration. For example, adapter search can pick up symbolic execution from the last path in the previous iteration that led to a correct adapter. A similar optimization can be utilized for concrete enumeration-based adapter search that uses the same random order of adapters during an adapter synthesis run. Concrete enumeration-based adapter search can be further accelerated by searching for adapters in parallel since checking one adapter is independent of checking other adapters.

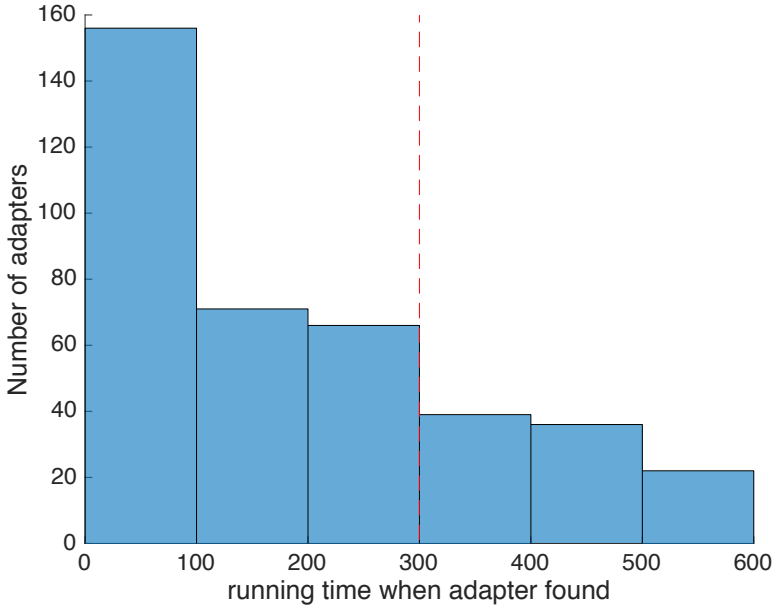


Figure 1.11: Running times for synthesized adapters using `median` reference function

Our tool currently assumes that all behaviors of the target function must be matched, modulo failures such as null dereferences. Using a tool like Daikon [20] to infer the preconditions of a function from its uses could help our tool find adapters that are only correct for correct uses of functions. This would allow us to find equivalence between functions like *isupper* and *islower*, which expect certain types of input.

Adapter synthesis requires us to find if *there exists* an adapter such that *for all* inputs to the target function, the output of the target function and the output of the adapted reference function are equal. Thus the synthesis problem can be posed as a single query whose variables have this pattern of quantification (whereas CEGIS uses only quantifier-free queries). We plan to explore using solvers such as Yices [21] for this $\exists\forall$ fragment of first-order bitvector logic.

Symbolic execution can only check equivalence over inputs of bounded size, though improvements such as path merging [14, 15] can improve scaling. Our approach could also integrate with any other equivalence checking approach that produces counterexamples, including ones that synthesize inductive invariants to cover unbounded inputs [22], though we are not aware of any existing binary-level implementations that would be suitable.

1.6 Related Work

1.6.1 Detecting Equivalent Code

The majority of previous work in this area has focused on detecting *syntactically* equivalent code, or 'clones,' which are, for instance, the result of copy-and-paste [23, 24, 25]. Jiang et al. [26] propose an algorithm for automatically detecting functionally equivalent code fragments using random testing and allow for limited types of adapter functions over code inputs — specifically permutations and combinations of multiple inputs into a single struct. Ramos et al. [11] present a tool that checks for equivalence between arbitrary C functions using symbolic execution. While our definition of functional equivalence is similar to that used by Jiang et al. and Ramos et al., our adapter families capture a larger set of allowed transformations during adapter synthesis than both.

Amidon et al. [27] describe a technique for fracturing a program into pieces which can be replaced by more optimized code from multiple applications. They mention the need for automatic generation of adapters which enable replacement of pieces of code which are not immediately compatible. While Amidon et al. describe a parameter reordering adapter, they do not mention how automation of synthesis of such adapters can be achieved. David et al. [28] decompose binary code into smaller pieces, find semantic similarity between pieces, and use statistical reasoning to compose similarity between procedures. Since this approach relies on pieces of binary code, they cannot examine binary code pieces that make function calls and check for semantic similarity across wrappers around function calls. Goffi et al. [29] synthesize a sequence of functions that are equivalent to another function w.r.t a set of execution scenarios. Their implementation is similar to our concrete enumeration-based adapter search which produces equivalence w.r.t. a set of tests. In the hardware domain, adapter synthesis has been applied to low-level combinatorial circuits by Gascón et al [30]. They apply equivalence checking to functional descriptions of a low-level combinatorial circuit and reference implementations while synthesizing a correct mapping of the input and output signals and setting of control signals. They convert this mapping problem into a exists/forall problem which is solved using the Yices SMT solver [21]. More recently, Katz et al. [31] have applied machine learning to the problem of decompilation of binary code. Their technique predicts decompiled source code, given a fragment of binary code. A primary difference between adapter synthesis and the technique presented by Katz et al. is that, if substitutability is found by adapter synthesis, the match will be exact, whereas the Katz et al's technique finds an approximate match which may not be usable for applications such as library replacement.

1.6.2 Component Retrieval

Component retrieval is a technique [32], [33], [34] that provides a search operator for finding a function, whose polymorphic type is known to the programmer, within a library of software components. The search results contain components whose types are similar but more general (or more specialized). Adapter synthesis shares the same intuition in that, it adapts the more general implementation of a functionlity to the more specific one. Type-based hot swapping [35] and signature matching [36] are related areas of research that rely on adapter-like operations such as currying or uncurrying functions, reordering tuples, and type conversion. Reordering, insertion, deletion, and type conversion are only some of the many operations supported by our adapters. These techniques can only be applied at the source level, whereas our adapter synthesis technique can be applied at source and binary levels

1.6.3 Component Adaptation

Component adaptation is another related area of research, that given a formal specification of a query component, searches a library of components within a set of adaptation architecture theories. This includes techniques for adapter specification [37], for component adaptation using formal specifications of components [38], [39], [40], [41], [42]. Component adaptation has also been performed at the Java bytecode level [43], as well as at low-level C code [44]. Behavior sampling [45] is a similar area of research for finding equivalence over a small set of input samples. However, these techniques either relied on having a formal specification of the behavior of all components in the library to be searched, or provided techniques for translating a formally specified adapter [37].

1.6.4 Program Synthesis

Program synthesis is an active area of research that has many applications including generating optimal instruction sequences [46, 47], automating repetitive programming, filling in low-level program details after programmer intent has been expressed [3], and even binary diversification [48]. Programs can be synthesized from formal specifications [49], simpler (likely less efficient) programs that have the desired behavior [46, 3, 47], or input/output oracles [50]. We take the second approach to specification, treating existing functions as specifications when synthesizing adapter functions.

1.7 Conclusion

We presented a new technique to search for semantically-equivalent pieces of code which can be substituted while adapting differences in their interfaces. This approach is implemented at the binary level, thereby enabling wider applications and consideration of exact run-time behavior. We implemented adapter synthesis for x86-64 and ARM

binary code. We presented examples demonstrating applications towards adaptation modulo a bug, library replacement, and reverse engineering. We present an evaluation to find substitutable code within a library using the C library. Our adapter families can be combined to find sophisticated adapters as shown by adaptation of RC4 implementations. While finding thousands of functions to not be equivalent, our tool reported many instances of semantic equivalence, including C library functions such as *ffs* and *ffsl*, which have assembly language implementations. Our comparison of concrete enumeration-based adapter search with binary symbolic execution-based adapter search allows users of adapter synthesis to choose between the two approaches based on the size of the adapter search space. Our case studies show that adapter synthesis can be applied at scale to reverse engineer binary code using independently-developed codebases, even in the presence of very large adapter search spaces. Our implementation constitutes a novel use of binary symbolic execution for synthesis. Our results show that the CEGIS approach for adapter synthesis of binary code is feasible and sheds new light on potential applications such as searching for efficient clones, deobfuscation, program understanding, and security through diversity.

Chapter 2

Using Path-merging With Adapter Synthesis

Chapter 3

Java Ranger: Static Regions For Efficient Symbolic Execution Of Java

3.1 Introduction

Symbolic execution is a popular analysis technique that performs non-standard execution of a program: operations in the program generate formulas over inputs along every feasible execution through branches in the program, and branch constraints along an execution path are combined into a predicate. Originally developed in the 1970s [51, 52], symbolic execution is a convenient building block for program analysis, since arbitrary behavior in the program can be discovered by adding query predicates for it to the symbolic program representation, and solutions to these constraints are inputs that provide the queried behavior in the program. Some of the applications of symbolic execution include test generation [53, 54], equivalence checking [55, 56], vulnerability finding [57, 58], and protocol correctness checking [59]. Symbolic execution tools are available for many languages, including CREST [60] for C source code, KLEE [61] for C/C++ via LLVM, JDart [62] and Symbolic PathFinder (SPF) [63] for Java, and S2E [64], FuzzBALL [65], and `angr` [58], FuzzBALL [6] for binary code.

However, scalability remains a significant challenge for many applications of symbolic execution. In particular symbolic execution can suffer from a *path explosion*: every symbolic branch that has two feasible sides causes the number of execution paths that need to be explored to be multiplied by two. Real-world software tends to have many branches, thereby creating exponentially many execution paths. Symbolic execution techniques that explore one path at a time are unable to cover all paths within a reasonable time budget. Dynamic state merging [66, 67] provides one way to alleviate scalability challenges by merging dynamic symbolic executors, effectively merging the paths they represent, when the benefit of introducing new symbolic state heuristically

outweighs its cost. Veritesting [68] is another path-merging technique that can dramatically improve the performance of symbolic execution by effectively merging paths. Rather than explicitly merging state representations, veritesting represents a local region of a program containing branches as a disjunctive summary for symbolic analysis. This often allows many paths to be collapsed into a single path involving the region. In previous work [68], constructing such bounded static summaries was shown to allow symbolic execution to find more bugs, and achieve more node and path coverage, when implemented at the X86 binary level for compiled C programs. This motivates investigation using static regions for symbolic execution of Java software (at the Java bytecode level).

Java programmers who follow best software engineering practices attempt to write code in an object-oriented form with common functionality implemented as a Java class and multiple not-too-large methods used to implement small sub-units of functionality. This causes Java programs to make several calls to methods, such as getters and setters, to re-use small common sub-units of functionality. Merging paths within regions in such Java programs using techniques described in current literature is limited by not having the ability to inline method summaries. This is not a major impediment for compiled C code, as the C compiler will usually automatically inline the code for short methods such as `get`. However, Java has an *open world* assumption, and most methods are *dynamically dispatched*, meaning that the code to be run is not certain until a method is resolved at runtime; if inlining is performed at all, it is by the JRE, so it is not reflected in bytecode.

One feature commonly used by Java developers is the use of fields and arrays in Java code. Summarizing non-static field accesses requires finding which object a field access belongs to, an operation which cannot be computed exactly in a static analysis. Instead of summarizing field accesses statically, our interpretation of path-merging for Java code regions computes such a summary only when a summary is instantiated by the symbolic executor. A further generalization of this problem arises with symbolic index-based accesses into array objects. Our interpretation of path-merging supports symbolic indices, by including the possibility of any entry in the array being accessed, in the region's summary. A couple of other improvements in our path-merging technique include include summaries of methods and supporting exceptional behavior in regions.

Not being able to summarize such dynamically dispatch methods can lead to poor performance for näive implementations of bounded static regions. Thus, to be successful, we must be able to inject the static regions associated with the calls into the dispatching region. We call such regions *higher order* as they require a region as an argument and can return a region that may need to be further interpreted. In our experiments, we demonstrate exponential speedups on benchmarks (in general, the more paths contained within a program, the larger the speedup) over the unmodified Java SPF tool using this approach.

Another common feature of Java code that represents the boundary of path merging

is *exceptions*. If an exception can potentially be raised in a region, the symbolic executor needs to explore that exceptional behavior. But, it is possible for other unexceptional behavior to also exist in the same region. For example, it can be in the form of a branch nested inside another branch that raises an exception on the other side. Summarizing such unexceptional behavior while simultaneously guiding the symbolic executor towards potential exceptional behavior reduces the branching factor of the region. We propose a technique named *Single-Path Cases* for splitting a region summary into its exceptional and unexceptional parts.

While summarizing higher-order regions and finding single-path cases is useful to improve scalability, representing such summaries in an intermediate representation (IR) that uses static single-assignment (SSA) form provides a few key advantages. (1) It allows region summaries to be constructed by using a sequence of transformations, with each transformation extending to add support for new features such as heap accesses, higher-order regions, and single-path cases. (2) It allows for simplifications such as constant propagation, copy propagation, constant folding to be performed on region summaries. (3) It makes the construction of region summaries more accessible to users of the symbolic execution tool, thereby making path merging more useful to end-users. In this chapter, we present Java Ranger, an extension of Symbolic PathFinder, that computes such region summaries over a representation we call Ranger IR. Ranger IR has support for inlining method summaries and for constructing SSA form for heap accesses. It also proposes Single-Path Cases as an alternative to multiple transition points as defined by Avgerinos et al. [68].

3.1.1 Motivating Example

Consider the example of Java code shown in Figure 3.1. The `list` object refers to an `ArrayList` of 200 `Integer` objects which have an unconstrained symbolic integer as a field. The checking of each even-indexed entry in `list` introduces a branch, which has both sides feasible, and requires symbolic execution to explore two execution paths instead of the one it was at.

Performing this check over the entire `list` makes symbolic execution need 2^{100} execution paths to terminate (assuming `list` has 200 entries with every even-indexed entry pointing to a new unconstrained symbolic integer). A simple way to avoid this path explosion is to merge the two paths arising out of the `i%2 == 0 && list.get(i) == 42` branch. Such path merging requires us to compute a summary of all behaviors arising on both sides of the branch from lines 11 to 13 until both sides of the branch merge at line 14. If we can construct such a summary beforehand, our symbolic executor can instantiate the summary by reading in inputs to the summary from the stack and/or the heap, and writing outputs of the summary to the stack and/or the heap.

Unfortunately, constructing such a summary for this simple region from lines 11–13 is not straightforward due to the call to `list.get(int)` which is actually a call to `ArrayList<Integer>.get(int)` (`java.util.List<E>.get(int)` is abstract and does

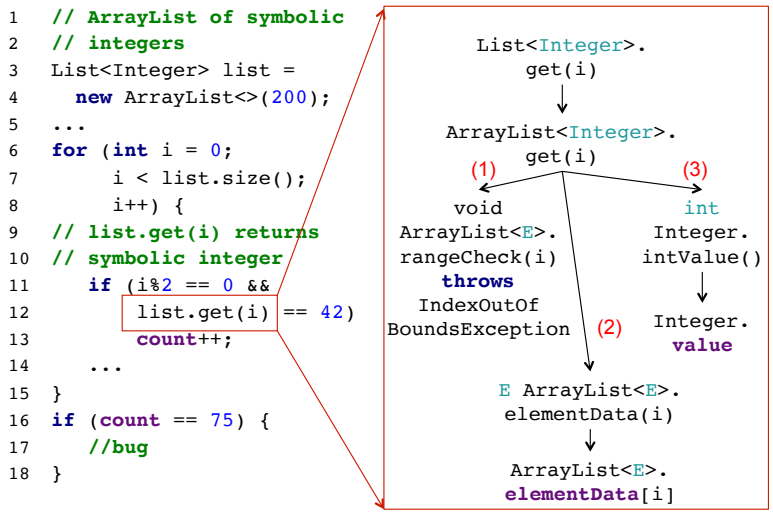


Figure 3.1: An example demonstrating the need for using a multi-path region summary

not have an implementation). `ArrayList<Integer>.get(int)` internally does the following:

1. It checks if the index argument accesses a value within bounds of the `ArrayList` by calling `ArrayList<E>.rangeCheck(int)`. If this access is not within bounds, it throws an exception.

2. It calls `ArrayList<E>.elementData(int)` to access an internal array named `elementData` and get the entry at position `i`. This call results in an object of class `Integer` being returned.

3. It calls `Integer.intValue()` on the object returned by the previous step. This call internally accesses the `value` field of `Integer` to return the integer value of this object.

The static summary of `ArrayList<Integer>.get(int)` needs to not only include summaries of all these three methods but also include the possibility of an exception being raised by the included summary of `ArrayList<E>.rangeCheck(i)`. Our extension to path-merging includes using method summaries, either with a single return or no return, as part of region summaries that have method calls [1]. The method whose summary is to be included depends on the dynamic type of the object reference on which the method is being invoked. In our example, the dynamic type of `list` is `ArrayList`, whereas it is declared statically as having the type `List`. Therefore, the summary of `list.get(i)` pulls in the method summaryof `ArrayList<E>.get(i)`.

[1] We plan to support methods with multiple returns in the future.

Our *Single-Path Cases* extension to path-merging also allows the possibility of exceptional behavior being included in the summary and explored separately from unexceptional behavior by performing exploration of exceptional behavior in the region on its own execution path.

3.2 Related Work

Rewrite this section in your own words

Path explosion is a major cause of scalability limitations for symbolic execution, so an appealing direction for optimization is to combine the representations of similar execution paths, which we refer to generically as *path merging*. If a symbolic execution tool already concurrently maintains objects representing multiple execution states, a natural approach is to merge these states, especially ones with the same control-flow location. Hansen et al. [66] explored this technique but found mixed results on its benefits. Kuznetsov et al. [67] developed new algorithms and heuristics to control when to perform such state merging profitably. A larger departure in the architecture of symbolic execution systems is the MultiSE approach proposed by Sen et al. [69], which represents values including the program counter with a two-level guarded structure, in which the guard expressions are optimized with BDDs. The MultiSE approach achieves effects similar to state merging automatically, and provides some architectural advantages such as in representing values that are not supported by the SMT solver.

Another approach to achieve path merging is to statically summarize regions that contain branching control flow. This approach was proposed by Avgerinos et al. [68] and dubbed "veritesting" because it pushes symbolic execution further along a continuum towards all-paths techniques used in verification. A veritesting-style technique is a convenient way to add path merging to a symbolic execution system that maintains only one execution state, which is one reason we chose it when extending SPF. Avgerinos et al. designed and implemented their veritesting system MergePoint for the application of binary-level symbolic execution for bug finding. They found that veritesting provided a dramatic performance improvement, allowing their system to find more bugs and have better node and path coverage in a given exploration time. The static regions used by MergePoint are intra-procedural, but they can have any number of "transition points" at which control can be returned to regular symbolic execution. Avgerinos et al. do not provide details about how MergePoint represents memory accesses or integrates them with veritesting, though since MergePoint was built as an extension of the same authors' Mayhem system, it may reuse techniques such as symbolic representation of loads from bounded memory regions [70].

The veritesting approach has been integrated with another binary level symbolic execution engine named `angr` [58]. However angr's authors found that their veritesting implementation did not provide an overall improvement over their dynamic symbolic

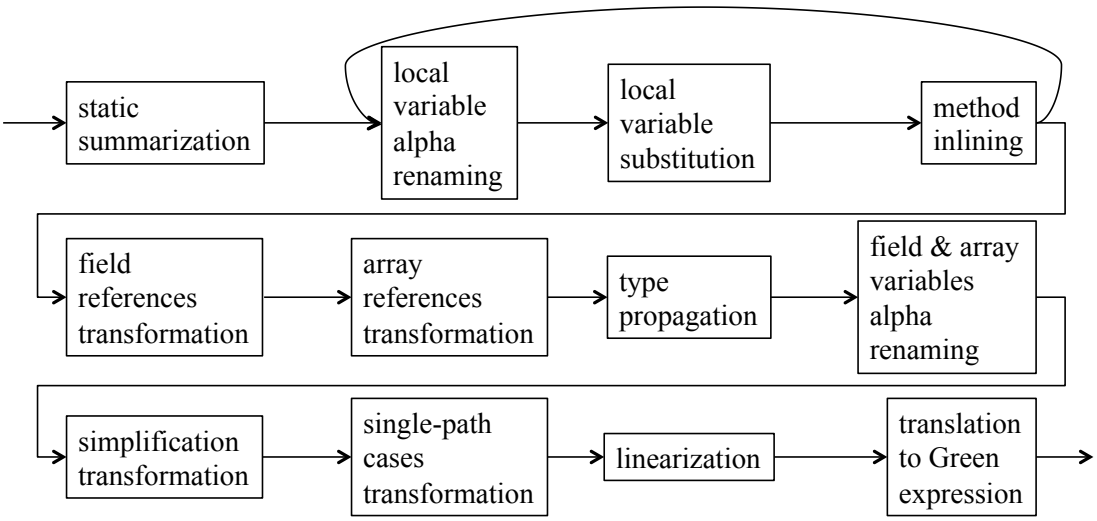
execution baseline: though veritesting allowed some new crashes to be found, they observed that giving more complex symbolic expressions slowed down the SMT solver enough that total performance was degraded. We have also observed complex expressions to be a potential cost of veritesting, but we believe that optimizations of the SMT solver interface and potentially heuristics to choose when to use static regions can allow them to be a net asset.

The way that Java Ranger and similar tools statically convert code regions into formulas is similar to techniques used in verification. In the limit where all relevant code in a program can be summarized, such as with WBS and TCAS-SR in Section 3.4, Java Ranger performs similarly to a bounded symbolic model checker for Java. SPF and Java Ranger build on Java Pathfinder (JPF) [71], which is widely used for explicit-state model checking of Java and provides core infrastructure for instrumentation and state backtracking. Another family of Java analysis tools that use formula translation (also called verification condition generation) are ESC/Java [72], ESC/Java2 [73], and OpenJML [74], though these tools target static error checking and verification of annotated specifications.

Perhaps the most closely related Java model checking tool is JBMC [75], which has recently been built sharing infrastructure with the similar C tool CBMC. JBMC performs symbolic bounded model checking of Java code, transforming code and a supported subset of the standard library into SMT or SAT formulas that represent all possible execution paths. (The process by which JBMC transforms its internal code representation into SMT formulas is sometimes described as (static) symbolic execution, but it has more in common with how Java Ranger constructs static regions than with the symbolic execution that vanilla SPF performs.) In cases that Java Ranger can completely summarize, we would expect its performance to be comparable to JBMC's; an experimental comparison is future work. But static region summaries are more important as an optimization to speed up symbolic execution on software that is too large and/or complex to be explored exhaustively.

A wide variety of other enhancements to symbolic execution have been proposed to improve its performance, including caching and simplifying constraints, summarizing repetitive behavior in loops, heuristic guidance towards interesting code, pruning paths that are repetitive or unproductive, and many domain-specific ideas. A recent survey by Baldoni et. al. [76] provides pointers into the large literature. One approach that is most related to our higher-order static regions is the function-level compositional approach called SMART proposed by Godefroid [77]. Like Java Ranger's function summaries, SMART summarizes the behavior of a function in isolation from its calling context so that the summary can be reused at points where the function is used. But SMART uses single-path symbolic execution to compute its summaries, whereas Java Ranger uses static analysis: this makes Java Ranger's summary more compact at the expense of requiring more reasoning by the SMT solver. Because SMART was implemented for C, it does not address dynamic dispatch between multiple call targets.

Figure 3.2: Overview of transformations on Ranger IR to create and instantiate multi-path region summaries with higher-order regions



3.3 Technique

To add path merging to SPF, we first pre-compute static summaries of arbitrary code regions with more than one execution path and we also pre-compute method summaries. To bound the set of code regions we analyze, we start by specifying a method M in a configuration file. Next, we construct a set containing only the class C that contains M. We then get another set of classes, C', such that every class in C' has at least one method that was called by a method in a class in C. This step which goes from C to C' discovers all the classes at a call depth of 1 from C. We continue this method discovery process up to a call depth of 2. While we can increase the call depth in our method discovery process, we found that summarizing arbitrary code regions with more than 2 calls deep, did not lead to practically useful region summaries. After obtaining a list of methods, we computed static summaries of regions in these methods and method summaries as explained in Section 3.3.1. After computing static region and method summaries, we process them as a sequence of transformations described in the next section 3.3.3 and summarized in Figure 3.2.

3.3.1 Statement Recovery

The regions of interest for our technique are bounded by the branch and meet of a given acyclic subgraph. The intuition is that path explosion during execution of loops is driven by conditional logic within the loop, rather than the loop itself. Starting from an SSA form, the first transformation recovers a tree-shaped AST for the subgraphs of interest. While this step is not strictly necessary, it substantially simplifies subsequent

transformations.

The algorithms are similar to those used for those used for decompilation [78] but with slightly different goals:

- The algorithm must be *accurate* but need not be *complete*. That is, obfuscated regions of code need not be translated into a tree form.
- The algorithm must be *lightweight* in order to be efficiently performed during analysis. Thus, algorithms that use global fixpoint computations are too expensive to be used for our purposes.

Starting from an initial SSA node, the algorithm first finds the immediate post-dominator of all *normal* control paths, that is, paths that do not end in an exception or return instruction. It then looks for nested self-contained subgraphs. If for any graph, the post-dominator is also a predecessor of the node, we consider it a loop and discard the region.

The algorithm systematically attempts to build regions for every branch instruction, even if the branch is already contained within another region. The reason is that it may not be possible to instantiate the larger region depending on whether summaries can be found for *dynamically-dispatched* functions, and whether references are *uniquely determinable* for region outputs.

3.3.2 Region Definition

Once the statement of a multi-path region has been recovered, its corresponding environment is populated. This includes identifying region boundary and creating local variable inputs, outputs, type, and stack slot tables for the region. The region boundary is used to identify boundaries of the region w.r.t local variables. This is used later to constrain the computation and population of Ranger IR environment tables. For example, the local variable input table is populated with first *use* in the region boundary that map to a given stack slot. The output table is populated with the last *def* of a local variable at merge point of the region. The local variable type table is populated for all variables that lay within the boundaries of the region, this is initially done by inquiring the static analysis framework, WALA [79] but is later changed by inferring types of local variables at instantiation and during type propagation transformation 3.3.3.

We also construct a stack slot table as part of a region's Ranger IR summary. The stack slot table maps Ranger IR variables to a stack slot, if they correspond to a local variable in the source code. We populate the stack slot table by obtaining a variable to stack slot mapping from WALA. We also assume that, if at least one variable used in a ϕ-expression is a local variable, then all variables used in that ϕ-expression must belong to the same stack slot. We use this assumption to further propagate stack slot information in the stack slot table across all ϕ-expressions encountered at merge points of regions.

3.3.3 Instantiation-time Transformations

Renaming Transformation: In Alpha renaming transformation, all Ranger IR variables are renamed to ensure their uniqueness before further processing takes place. This is particularly important not only to ensure uniqueness of variables among different regions, but also to ensure uniqueness of variable names of the *same* region which might be instantiated multiple times on the same path, i.e., a region inside a loop will be instantiated multiple times.

Local Variable Substitution Transformation: During this transformation we eagerly bring in all dynamically known constant values, symbolic values and references from stack slots into the region for further processing.

Higher-order Regions Transformation: This transformation is initiated when a method invocation is encountered during local variable substitution. At this point, we perform three steps. (1) the region that corresponds to the called method is retrieved and alpha renaming of Ranger IR variables corresponding to local variables is applied on it. (2) Ranger IR expressions that correspond to the actual parameters are evaluated and used to substitute the formal parameters by repeatedly applying local variable substitution transformation over the method region. (3) When no more higher-order regions can be inlined, the resulting substituted method region is inlined into the outer region.

If the method region has a single return value, then the original method invocation is replaced with an assignment to the returned expression. We dont currently support instantiation of method regions with multiple return statements, support for which requires another transformation that we talk about in Section 3.6.

Field References SSA form: The field references transformation translates reads and writes of fields in Java bytecode into corresponding Ranger IR statements. In order to translate all field accesses to SSA form, this transformation creates a summary of the semantics represented by the field accesses in the region. This transformation constructs a new field access variable for every field assignment on every path within the region. This new field access variable construction makes use of two monotonically increasing subscripts. It uses a path subscript to distinguish between assignments to the same field on the same execution path. It uses a global subscript to distinguish between assignments to the same field across execution paths. At the merge point of the region, field assignments done on the same field are merged using Gated Single Assignment (GSA) [80]. Each merged field access variable has its own path and global subscripts and represents the output of the region into its field. The path subscript helps us resolve read-after-write operations on the same execution path and find the latest write into a field on an execution path. The global subscript helps us distinguish between field accesses across multiple execution paths.

Array References SSA form: The array references transformation translates reads and writes of arrays in Java bytecode into corresponding Ranger IR statements. In order to translate all array accesses to SSA form, this transformation creates an execution

path-specific copy of every array when it is first accessed within a region. Reads and writes of arrays are then done on a path-specific copy of the array. All array copies are merged at the merge point of multi-path regions. The merged array copy represents array outputs of the region.

Type Propagation: Ranger IR needs to have type information for its variables so that it can construct corresponding correctly-typed Green variables during the final transformation of the region summary to a Green formula. Having accurate type information is also important for looking up the correct higher-order method summary. As part of region instantiation, Java Ranger infers types of Ranger IR variables in the region summary by using JPF's runtime environment. Types of local variables are inferred during the local variable substitution transformation and types of field reference and array reference variables are inferred during their respective transformations. Using these inferred types, the type propagation transformation propagates type information across assignment statements, binary operations, and variables at leaf nodes of γ functions.

Simplification of Ranger IR: The Ranger IR constructed by earlier transformations computes exact semantics of all possible behaviors in the region. Representation of such semantics as a formula can often lead to unnecessarily large formulas, which has the potential to reduce the benefits seen from path merging [58]. For example, if an entry in an array is never written to inside a region, the array reference transformation can still have an array output for that entry that writes a new symbolic variable into it. The region summary would then need to have an additional constraint that makes the new symbolic variable equal the original value in that array entry. Such conjuncts in the region summary can be easily eliminated with constant propagation, copy propagation, and constant folding [81]. Ranger IR also has statement and expression classes that use a predicate for choosing between two statements (similar to an `if` statement in Java) and two sub-expressions (similar to the C ternary operator) respectively. When both choices are syntactically equal, the predicated statement and expression objects can be substituted with the statement or expression on one of their two choices. Such statements and expressions were simplified away to use one of their two choices. Ranger IR performs these two simplifications on such predicated statements and expressions along with constant folding, constant propagation, and copy propagation.

Single Path Cases: This transformation collects path predicates inside a region that lead to *non-nominal* exit point. This is an alternative approach to that was presented in [68]. In our work we define non-nominal exit point to be points inside the region that either define exceptional behavior or involve behavior that we cannot summarize, i.e, object creation and throw instructions. The intuition here is that, we want to maximize regions that Java Ranger can summarize, even if the summarization is only partial. We use this pass of transformation to identify such points, collect their path predicates and prune them away from the Ranger IR statement. The outcome of this process, is a more simplified and concise statement that represent the nominal behavior of the

Ranger region. The collected predicate is later used to guide the symbolic execution to explore non-nominal paths, which Java Ranger had not summarized.

Linearization: Ranger IR contains translation of branches in the Java bytecode to if-then-else statements defined in the Ranger IR. But the if-then-else statement structure needs to be kept only as long as we have more GSA expressions to be introduced in the Ranger IR. Once all GSA expressions have been computed, the Ranger IR need not have if-then-else statements anymore. The γ functions introduced by GSA are a functional representation of branching, which lets us capture the semantics of everything happening on both sides of the branch. Since the linearization transformation is done after every field and array entry has been unaliased and converted to GSA, dropping if-then-else statements from the Ranger IR representation of the region summary reduces redundancy in its semantics and converts it into a stream of GSA and SSA statements.

Translation to Green: At this point Ranger region contains only compositional statements as well as assignment statements that might contain GSA expressions in them. This transformation starts off by translating Ranger variables to Green variables of the right type using the region type table. Then Ranger statements are translated. More precisely, compositional statements are translated into conjunction, assignment statements are translated into Green equality expressions. For assignment statements that have GSA expressions, these are translated into two disjunctive formulas that describes the assignment if the GSA condition or its negation were satisfied.

The sequence in which these Ranger IR transformations are performed should not matter. This sequence of transformations should be run up to a fixed point so that we can have resolve local variable, field, and array inputs in an arbitrary order, as was seen with the motivating example described in Figure 3.1. Currently Java Ranger does not support such a fixed point computation, but we plan to automate this computation in the future.

3.3.4 Checking Correctness Of Region Summaries

The Ranger IR computed as a result of performing the transformations described in Figure 3.2 should correctly represent the semantics of the summarized region. If it does not, then using the instantiated region summary can cause symbolic exploration to explore the wrong behavior of the subject program. We checked the correctness of our instantiated region summaries by using equivalence-checking as defined by Ramos et al. [55]. We designed a test harness that first executes the subject program with a set of symbolic inputs using SPF and capture the outputs of the subject program. Next, the test harness executes the same subject program with the same set of symbolic inputs using Java Ranger and capture the outputs of the subject program once again. Finally, the test harness compares outputs returned by symbolic execution with SPF and Java Ranger. If the outputs do not match, then a region summary used by Java Ranger did not contain all the semantics of the region it summarized. We symbolically execute all execution paths through this test harness. If no mismatch is found between outputs

on any execution path, we conclude that all region summaries used by Java Ranger must correctly represent the semantics of the regions they summarized. We performed correctness-checking on all results reported in this paper.

3.4 Evaluation

3.4.1 Experimental Setup

We implemented the above mentioned transformations as a wrapper around the Symbolic PathFinder [63] tool. To make use of region summaries in Symbolic PathFinder, we use an existing feature of SPF named *listener*. A listener is a method defined within SPF that is called for every bytecode instruction executed by SPF. Java Ranger adds a path merging listener to SPF that, on every instruction, checks (1) if the instruction involves checking a symbolic condition, and (2) if Java Ranger has a pre-computed static summary that begins at that instruction's bytecode offset. If both of these conditions are satisfied, Java Ranger instantiates the multi-path region summary corresponding to that bytecode offset by reading inputs from and writing outputs to the stack and the heap. It then conjuncts the instantiated region summary with the path condition and resumes symbolic execution at the bytecode offset of the end of the region. Our implementation, named Java Ranger, wraps around SPF and can be configured to run in four modes. (1) In mode 1, it runs vanilla SPF without any path merging enabled. (2) In mode 2, it summarizes multi-path regions only and instantiates them if they are encountered. (3) In mode 3, it summarizes and instantiates methods, by utilizing high ordder regions, along with multi-path regions as done in mode 2. (4) In mode 4, it uses single-path cases along with multi-path region and method summaries used in mode 3.

3.4.2 Evaluation

In order to evaluate the performance of Java Ranger, we used the following benchmarking programs commonly used to evaluate symbolic execution performance. (1) Wheel Brake System (WBS) [82] is a synchronous reactive component developed to make aircraft brake safely when taxing, landing, and during a rejected take-off. (2) Traffic Collision Avoidance System (TCAS) is part of a suite of programs commonly referred to as the Siemens suite [83]. TCAS is a system that maintains altitude separation between aircraft to avoid mid-air collisions. (3) Replace is another program that's part of the Siemens suite. Replace searches for a pattern in a given input and replaces it with another input string. We used the translation of the Siemens suite to Java as made available by Wang et al. [84]. We also manually created a variant of TCAS by converting regions of code with return statements on every execution path to regions of code with a single return statement at the merge point of the region. We refer to this variant of TCAS as TCAS-SR (TCAS with Single Returns). We also created variants of WBS, TCAS, and TCAS-SR by running them for multiple steps.

Bench mark Name	Java Ranger mode	# exec paths	run time (msec)	# solver queries	solver time (msec)	# inst. regs	# inst. methods	# inst.
WBS-1step	1	24	273	46	53	0	0	0
WBS-1step	2	1	548	0	0	6	0	6
WBS-1step	3	1	582	0	0	6	0	6
WBS-1step	4	1	663	6	65	6	0	6
TCAS-SR-1step	1	392	4115	2798	3792	0	0	0
TCAS-SR-1step	2	18	999	74	428	19	0	107
TCAS-SR-1step	3	1	512	0	0	4	28	4
TCAS-SR-1step	4	1	619	4	72	4	28	4
Replace	1	1715	3470	5482	2763	0	0	0
Replace	2	1080	3.0E+04	1.30E+04	2.5E+04	17	0	977
Replace	3	632	3.7E+04	10259	2.9E+04	24	113	806
Replace	4	345	1.1E+05	7020	1.0E+05	26	122	501
TCAS-1step	1	392	4698	2798	4287	0	0	0
TCAS-2steps	1	1.5E+05	2.2E+06	1.1E+06	2.1E+06	0	0	0
TCAS-1step	4	178	6848	1719	5349	13	0	445
TCAS-2steps	4	3.2E+04	1.4E+06	3.1E+05	1.2E+06	13	0	8.0E+04
TCAS-SR-2steps	1	1.5E+05	1.7E+06	1.1E+06	1.7E+06	0	0	0
TCAS-SR-2steps	4	1	643	8	106	4	56	8
TCAS-SR-3steps	4	1	704	12	116	4	84	12
TCAS-SR-10steps	4	1	1087	40	354	4	280	40
WBS-2steps	1	576	775	1150	418	0	0	0
WBS-3steps	1	1.4E+04	9806	2.8E+04	8364	0	0	0
WBS-4steps	1	3.3E+05	2.2E+05	6.6E+05	1.9E+05	0	0	0
WBS-5steps	1	8.0E+06	5.3E+06	1.2E+07	4.4E+06	0	0	0
WBS-2steps	4	1	971	20	401	15	0	20
WBS-3steps	4	1	1344	35	769	16	0	35
WBS-4steps	4	1	1919	50	1235	16	0	50
WBS-5steps	4	1	2165	65	1523	16	0	65
WBS-6steps	4	1	3239	80	2479	16	0	80
WBS-10steps	4	1	3895	140	3163	16	0	140

Table 3.1: Java Ranger Performance on WBS, TCAS, TCAS-SR, and Replace

We ran WBS, TCAS, TCAS-SR, and Replace using Java Ranger and present our results from instantiating region summaries in Table 3.1. Table 3.1 shows that Java Ranger achieves a significant improvement using path-merging with WBS. The "# exec paths" column is the number of execution paths required to completely explore the benchmark. "runtime (msec)" is the time taken for dynamic analysis (excludes static analysis time). "# inst. regs" is the total number of regions that were instantiated at least once when running each benchmark. "# inst. methods" is the number of higher-order regions that were used and "inst." is the total number of instantiations that was done when running the benchmark. Table 3.1 shows that we achieve a significant improvement using path-merging with WBS. Java Ranger outperforms SPF when running TCAS too but it doesn't allow path merging to summarize the entire program to a single execution path, as in the case with WBS. We manually analyzed TCAS and found the only barrier to our path-merging was the presence of several code regions containing a return instruction on every execution path. We manually performed a semantics-preserving transformation to the source code of TCAS to create another version, TCAS-SR, that has a single return value at the end of all such multi-path regions. We plan to automate this transformation in the future, see future work section 3.5. Table 3.1 shows the benefit of such a *multiple-returns-to-single-return* transformation. It allows Java Ranger to summarize the entire TCAS-SR program into a single execution path. This is made possible by the use of higher-order regions as shown in Table 3.1. In mode 2, Java Ranger explores 18 execution paths with TCAS-SR, whereas in mode 3 (mode 2 + higher-order region support), it needs to only explore a single execution path because it can instantiate 28 higher-order method summaries. The bottom half of Table 3.1 also shows the benefits of path-merging with Java Ranger increase as we run more steps of WBS, TCAS, and TCAS-SR. We ran as many steps of each of these 3 benchmarks as possible with a 6 hour timeout using Java Ranger in modes 1 (runs Java Ranger without path merging) and 3 (runs Java Ranger with multi-path region summaries and higher-order region summaries). While, in mode 1, Java Ranger can only run 5 steps of WBS in less than 6 hours, in mode 4 (path merging with multi-path regions, higher-order regions, and single-path cases), Java Ranger can easily execute up to 10 steps in less than 4 seconds. A similar benefit is seen with TCAS-SR where Java Ranger in mode 1 can only run 2 steps of TCAS-SR in 6 hours, but in mode 4, it can easily run up to 10 steps of TCAS-SR in about 1 second.

However, the performance of Java Ranger when running Replace is quite different from that seen when running WBS, TCAS, and TCAS-SR. While Java Ranger reduces the total number of execution paths with every increase in mode, the path reduction isn't as significant. More importantly, it also makes an order of magnitude more solver calls thereby increasing the total runtime.

We further investigated this drop in performance of Java Ranger when running Replace by exploring the space of potential regions to instantiate. We obtained the list of regions that are instantiated at least once when running Replace with Java Ranger

in mode 3 (using high order and multi-path region summaries). This step produced a list of 24 regions. Next, we sampled the space of all possible subsets of this set of 24 regions by (1) randomly enumerating the space up to 11500 subsets of all possible subsets of 24 regions, (2) enumerating the space in the order of set size up to all subsets of 3 regions from a set of 24 regions. With both methods of enumeration, we searched for the least amount of time Java Ranger needs to instantiate at least one region with Replace. We found this least time to be 26.3 seconds which is still more than the 3.47 seconds Java Ranger needs to run Replace in mode 1 (running vanilla SPF with no path merging). In the fastest runs with at least one region instantiation in both methods of enumeration, Java Ranger finished exploration with the same number of execution paths as that explored during mode 1. The result of this analysis, combined with a significant increase in the number of solver queries with Java Ranger's path-merging modes, points toward the conclusion that every instantiation of a multi-path region in Replace causes another branch to be symbolic. This conclusion is also in alignment with the observation made by Kuznetsov et al. [67] that path merging can sometimes have a net negative effect on the performance of symbolic execution. We plan to integrate heuristics for estimating the side-effects of introducing new symbolic state as a result of path merging on symbolic execution performance with Java Ranger in the future.

3.5 Future Work

While Java Ranger has the potential to scale to large real-world Java programs, there are a number of directions along which it can be further improved.

- Java Ranger attempts to perform path merging as aggresively as possible. This path merging strategy doesn't optimize towards making fewer solver calls. We plan to work towards implementing heuristics that can measure the effect of path merging on the rest of the program.

- Java Ranger is most useful when it can merge multiple execution paths into one summary. But such merging causes an increase in the size of the summary, and consequently, the path condition. Once a summary has been communicated to the solver, it need not be sent again as long as it remains the same. This requires us to use the solver in an incremental mode, where we use previously-constructed state in the solver for future solving. Our current implementation of Java Ranger sends the entire path condition to the solver with every query, making every query even more expensive in the presence of large multi-path region summaries. We plan to integrate incremental solving with Java Ranger in the future.

- Multiple return instructions that appear on all execution paths inside a multi-path region can be simplified to a single return value of the region. We implemented this transformation manually in TCAS but we plan to automate it in the future. Such automation would allow us to summarize regions with return instructions.

- While statically summarizing regions gives dynamic symbolic execution a performance boost to explore more paths efficiently, generating test cases that covers all summarized branches is one of the fundamental roles of dynamic symbolic execution that is currently unsupported. This is an extension that we intend to investigate in our future work.

- While path merging can potentially allow symbolic execution to explore interesting parts of a program sooner, the effect of path merging on search strategies, such as depth-first search and breadth-first search commonly used with symbolic execution, remains to be investigated. We plan to explore the integration of such guidance heuristics with path merging in the future.

- Java Ranger can summarize methods and regions in Java standard libraries. This creates potential for automatically constructing summaries of standard libraries so that Java symbolic execution engines can prevent path explosion originating from standard libraries.

3.6 Conclusion

We presented Java Ranger as a path merging tool for Java. It works by systematically applying a series of transformations over a statement recovered from the CFG. This representation provides the benefit of modularity and makes path-merging for Java symbolic execution more accessible to end users. Java Ranger has its own IR statement and it supports the construction of SSA for fields and arrays. Java Ranger provides evidence that inlining summaries of higher-order regions can lead to a further reduction in the number of execution paths that need to be explored with path merging. It supports the exploration of exceptional behavior in multi-path regions via Single Path Cases which is an alternative technique for summarizing unexceptional behavior while simultaneously capturing exceptional behavior of a region. Java Ranger reinterprets path merging for symbolic execution of Java bytecode and has the potential to allow symbolic execution to scale up to exploration of real-world Java programs.

Chapter 4

Program Repair Using Adapter Synthesis

Chapter 5

Conclusion and Discussion

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