Automatically Mitigating Vulnerabilities in Binary Programs via Partially Recompilable Decompilation

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Abstract—Vulnerabilities are challenging to locate and repair, especially when source code is unavailable and binary patching is required. Manual methods are time-consuming, require significant expertise, and do not scale to the rate at which new vulnerabilities are discovered. Automated methods are an attractive alternative, and we propose Partially Recompilable Decompilation (PRD). PRD lifts suspect binary functions to source, available for analysis, revision, or review, and creates a patched binary using source- and binary-level techniques. Although decompilation and recomputation do not typically work on an entire binary, our approach succeeds because it is limited to a few functions, like those identified by our binary fault localization.

We evaluate these assumptions and find that, without any grammar or compilation restrictions, 70-89% of individual functions are successfully decompiled and recomputed with sufficient type recovery. In comparison, only 1.7% of the full C-binaries succeed. When decompilation succeeds, PRD produces test-equivalent binaries 92.9% of the time.

In addition, we evaluate PRD in two contexts: a fully automated process incorporating source-level Automated Program Repair (APR) methods; human-edited source-level repairs. When evaluated on DARPA Cyber Grand Challenge (CGC) binaries, we find that PRD-enabled APR tools, operating only on binaries, performs as well as, and sometimes better than full-source tools, collectively mitigating 85 of the 148 scenarios, a success rate consistent with these same tools.

One path for addressing this challenge is automated program repair (APR). Despite active development on many different tools and techniques, most APR methods today operate only on source code [1]. An appealing alternative could lift the entire binary to source, where it can be analyzed, modified, and then recomputed to provide a patched binary. Unfortunately, current decompilation tools suffer scalability issues [2] or focus on readability rather than recompilability [3–5], often producing inaccurate or non-compilable results when applied to a whole binary [2].

Instead, this paper presents a hybrid approach to automated binary repair. Our approach centers on the idea that for most (if not all) binary programs, partial analysis is sufficient for binary repair. These insights guided our approach: fault localization can identify a small set of functions relevant to the vulnerability; decompilers can lift a small set of functions to recomputable source code; binary-source interfaces and binary rewriting can transform them into test-equivalent binaries, even when tools fail for full binaries; the set of compiled binary functions provide sufficient context to enable source-level analyses and transformations, even when those methods only operate on source.

Practically, we provide a mechanism through which partial analysis content can be consolidated to achieve automated patching in an effective manner. However, the underlying technique is laborious, as existing tools are non-existent and generating compatible binary content from source, altering compiled binaries with that content, and ensuring that the result remains executable are all difficult. Our fully-functional prototype addresses these difficulties by automatically resolving the burden of patching source into binaries. Specifically, it analyzes multiple abstractions and generates binary-source interfaces so that decompiler output can be used. To suit our method, only the offset and referenced types for the decompiled function need recovery, significantly reducing the requirement of complete and sound type inference on binary code, an open research problem. We call our decompilation-based, binary-source patching method Partially Recompilable Decompilation (PRD) and its source-based APR-compatible extension to automated binary repair, BinrePaiReD.

1. This work has been submitted to the IEEE for possible publication. Copyright may be transferred without notice, after which this version may no longer be accessible.
Our evaluation focuses on our tool's applicability to automated binary repair, its generality to real-world vulnerabilities, other languages, and performance constraints, as well as its inherent assumptions. Previous evaluations of decompiler output have limited source code, by restricting grammar and types, we evaluate decompiled code's recompilability and behavioral consistency without these restrictions. As automated binary repair is dependent upon fault localization, we gauge our technique's effectiveness identifying functions relevant to vulnerabilities. Our evaluation includes C and C++ x86 programs from multiple datasets, two independently developed and evaluated APR tools (Prophet [6] and GenProg [7]), and off-the-shelf tools (e.g., Hex-Rays and GCC). Our datasets include the DARPA Cyber Grand Challenge (CGC) [8], Rode0Day [9], and C and C++ programs from MITRE CVE. Amazingly, these APR tools perform well on these datasets despite being employed on a small set of functions formed from decompiled source code. Our implementation can extend to other architectures and stripped binaries, assuming decompiler support.

To summarize, the main contributions of this paper are:
- PRD: a fully functional prototype that enables binary repair using high-level source code, the first such to support source-level patching of a binary.
- An empirical validation of our assumptions by evaluation of the individual techniques comprising our solution. Without any grammar or compilation restrictions, we find that 70-89% of individual functions can successfully decompile and recompile with sufficient type recovery (while only 1.7% of full binaries succeed). PRD produces test-equivalent binaries 92.9% of the time.
- An end-to-end evaluation of BinrePaiReD's ability to apply source-based APR tools to mitigate vulnerabilities in CGC binaries. We find that two APR tools, when used with PRD, mitigate vulnerabilities with success rates comparable to, sometimes exceeding, these same tools operating on the full source. They collectively mitigate 85 of 148 unique defects (20 that the winning cyber-reasoning system failed to patch) and provide code that humans can analyze and amend.
- Case studies that demonstrate language (C and C++) and compiler (Clang and GNU) generality, as well as no significant impact to performance.

To further reproducible science, our prototypes, datasets, and our experimental results are available at git@github.com: pdreiter/FuncRepair.git.

## 2 BACKGROUND

We briefly describe the techniques PRD uses for analyzing and manipulating binary content, and those BinrePaiReD employs to localize and repair faults.

### 2.1 Binary Decomposition and Rewriting.

A binary program, or binary, refers to a structured executable file composed of encoded binary instructions. Disassembling is the process of lifting binary instructions to assembly; decompilation is the general process of lifting lower-level abstractions (e.g., assembly) to high-level representations, (e.g., source code). Since much information, like control flow structures, prototypes, variable names, and types, is lost during compiling, decompilers must infer this content. Such inference is unsound, often leading to unreadable output, incorrect results, or failures. Binary rewriting directly alters a compiled binary file, retaining its ability to execute. PRD uses a binary rewriting strategy that appends new content to an existing binary, overwriting with additional calling requirements to detour execution to new binary content (see Section 4).

### 2.2 Fault Localization.

Fault localization (FL) methods pinpoint the likely locations of a vulnerability or bug by analyzing a program, dynamically or statically. In Spectrum-Based Fault Localization (SBFL), program spectra (characteristics) are obtained through analysis and used to implicate code regions. Spectra can include code coverage, data- or information-flow, call sequences, or program counter samples. SBFL produces suspiciousness scores and ranking (risk evaluation) and does not use other content, like historical development information. To locate vulnerabilities, SBFL map lower-level code elements, like statements and variables, to their execution, then apply metrics. Most methods require access to source, but we localize to function spectra using only the binary and available test contents, calculating suspiciousness scores using multiple SBFL metrics. Specifically, we adapt a hybrid FL method, Rank Aggregation Fault Localization (RAFL) to consolidate the SBFL metrics using weighted ranks to identify the top-\(\chi\) (35%) suspicious functions. We refer to our approach and its output as coarse-grained fault localization (CGFL).

### 2.3 Automated Program Repair.

Automated program repair (APR) methods generate patches for defects in software with minimal or no human intervention. There are many popular methods (see Gazzolla et al. for a survey), but most have adopted a search-based approach, defining transformation operators, e.g., different flavors of mutation, to manipulate existing code, and using test suites to validate repair correctness. Other methods use formal semantics either alone or in combination with mutation-based search. Recently, machine learning (ML) repair like neural machine translation or large language models have proliferated. While most ML models require perfect fault location (source code line or function), they are not currently appropriate for binary repair as they are overwhelmingly trained on source code or natural language. However, PRD could be used in conjunction with ML tools, which may require training or fine-tuning with compiled source code to improve effectiveness. We evaluate PRD using two independently developed mutation-based source-code repair tools, Prophet and GenProg, with its deterministic variant "AE".

Listing 1. Decompiled code for KPRCA_00018's cgc_split, generated by the Hex-Rays disassembler. Low readability of decompiled code does not limit APR tools.

```
int cgc_split() {
    int v0; int result; char v2; card_t v3; card_t v4;
    squarerabbit_t *split_srabbit; squarerabbit_t *srabbit;
    int i; i = 0;
```
3 Motivating Example

To motivate and illustrate our approach, consider KPRCA_00018 (Square_Rabbit) from the DARPA CGC dataset, a casino-inspired game with an integer overflow vulnerability that can crash the program. Let’s assume we need to prevent crashes, but the software is no longer supported, the source is unavailable, and direct binary fault localization and patching are not feasible [27]. However, we have recovered some tests for the buggy binary (100 functional, one crash-inducing) and have access to a source-and-test-based APR tool. Our APR tool does not need source code to be particularly readable, so we rely on decompiled code that recompiles and is test-equivalent to the original. To accomplish this, we assume Hex-Rays as our off-the-shelf decompiler. First, we apply a decompiler to the binary which fails to generate recompilable output for all functions. Although we cannot fully decompile, we can use PRD to address this. By recovering compatible type definitions and decompiling functions individually, we can generate a large proportion of recompilable (87) and test-equivalent (76) functions from the binary.

We localize the likely source of the problem to a small set of suspicious functions, typically less than 20, in the binary (fault localization, successfully implicating a set that includes the vulnerable cg_c_split function, as the most suspicious (tied in rank 1 with one other function).

The next step is generating a patched binary that preserves the expected functionality and repairs the vulnerability. We decompile the suspicious function set, recover compatible types (partial decompilation), and transform them into source that is both recompilable and compatible with binary rewriting via binary-source interfaces. To verify that the resulting binary is test-equivalent to the original binary, we recompile the decompiled code and generated binary-source interfaces, customize the binary content to construct a new binary (partial recomputation and binary rewriting), and check the result for test equivalence. Finally, we address the vulnerability by repairing the decompiled source, either manually or automatically with APR, recompiling and customizing the patch to create a repaired binary.

Using our example, Listing 1 shows the buggy cg_c_split function as decompiled by Hex-Rays (bug appears on lines 10–11: incrementing g_srabbit->split_len results in an integer overflow). Our APR tools successfully identify a developer-equivalent patch (i.e., moving 10 after 11). Altogether, we obtain the ease and benefit of source-level APR, applied to a binary.

4 Partially Re compilable Decomposition

Our functional prototype contribution, PRD enables source-level analysis techniques and vulnerability mitigation, even when only the binary is available. Unlike reassemblers or binary recompilers which operate on low-level software abstractions, PRD enables analyses to be performed at the source code level. While this is a strength of PRD, it comes at the cost of additional requirements, as well as analytical and engineering difficulties. Since compilers do not support combining new content with the non-object binary content, our methodology has to effectively perform linking and locating with all new content. Additionally, any resulting binary must retain the same executional qualities as the original, such as the ability to call and use external and local symbols regardless of their binding.

PRD takes as input a small set of binary functions (identified by fault localization) and consists of three interdependent custom stages that uphold our requirements: partial decompilation, partial recomputation, and binary rewriting, detailed in Figure 1. The output is a single binary, the PRD binary, composed of the original binary, binary-source interfaces, and decompiled function.

While it does not recompile the original source code, PRD does recompile the source code it generates. We consider PRD decompiled code to be this generated source code, i.e., decompiled functions and binary-source interfaces. These binary-source interfaces allow decompiled code to execute original binary content, and when used in conjunction with customized detours, allow original binary content to execute decompiled code. When PRD decompiled code is...
compiled, we consider it to be the PRD recompiled content. As a baseline, PRD succeeds when its output binary is test-equivalent to the original binary.

Our prototype implementation operates on x86 statically- and dynamically-linked Linux ELF executables, compatible with System V ABI and can be extended to x86-64 and stripped binaries with engineering effort. The rest of this section discusses key PRD concepts: partial decompilation, partial recompilation, binary rewriting, and fault localization.

4.1 Partial decompilation

Decomposition output can be produced by automated decompilers, human experts, or a combination (e.g., experts editing decompiler output). While full decompilation refers to the complete decompilation of a binary, we say a decompilation is partial when only certain functions in the binary are decompiled and compatible types are recovered. This design choice mitigates some of the weaknesses and limitations of current binary decompilers and enables source-only analyses (such as APR) on binary code before binary decompilation achieves perfection. The vulnerable functions, inferred types, and other dependencies are extracted from the binary and decompiled to source. To support later PRD stages, additional analyses are necessary to generate compatible binary-source interfaces.

4.1.1 Requirements

Because partial decompilation is required to generate source that is compatible with the later PRD stages, we discuss the constraints necessary to use the decompiled source.

4.1.1.1 PRD recompiled content and its constraints: Because customized detours connect the original binary to decompiled content and all linking and locating is done by PRD, the standard interpreter initializations like constructors, symbol resolutions and relocations, are bypassed for the added decompiled content. To accommodate this, we ensure that the PRD recompiled content fulfills these key requirements: (r1.1) does not require the interpreter and (r1.2) references global, local, and external symbols in original binary content. In Figure 2, we outline the requisite high-level execution flows that PRD enables between original binary content and decompiled content. We focus on the decompiled content and its dependencies (symbols).

4.1.1.2 Binary-Source Interfaces: To satisfy these constraints, we analyze both binary and decompiled content, then generate two complementary binary-source interfaces: unbound symbol and detour interfaces. These allow decompiled code to reference symbols (like callbacks) from the original binary regardless of these symbols’ binding state. We illustrate examples of these interfaces in Listing 2. As the entry point to dynamically-linked functions, the unbound symbol interface wraps a callback with code that allows dynamic linking to behave as if it were being called from the original binary. For the ELF binaries, this interface manages the procedure linkage table, PLT. Similarly, as the entry point to recompiled, decompiled function content, the detour interface manages both PLT and all required symbols used by this content. Together, they ensure the resulting recompiled content is consistent to the original.

The detour interface adds required symbols to the original function prototype, shown in Listing 2 with added void* parameters that harbor values for ebx register and three references: cgc_receive, cgc_mempy, and cgc_calloc. Because cgc_mempy and cgc_calloc are local symbols at calculable locations in the binary, they can be invoked as callbacks from the decompiled code. However, cgc_receive is a symbol whose binding state is indeterminable by decompiled code during runtime, we create an unbound symbol interface to allow decompiled code to interface with its PLT entry. This means that the original binary’s function call and the detour interface have diverged; ergo, a lone jump instruction, e9, will not suffice.

Divergence from the original function call to the detour interface has these implications: (i1) our detour interface is not compatible with the original function call; (i2) the stack state is not consistent upon return from decompiled function; (i3) added references, r, incur a byte-cost, c = 7r + 4, which may overflow the original function. In Section 4.3, we explain how PRD’s binary rewriting phase handles (i1). PRD decompilation addresses (i2) by inserting stack-correcting inline assembly before the detour interface’s return. Note on (i3), when multiple functions are decompiled, the minimum set of required references for any entry function is the union of its calltree’s references.

This approach satisfies our requirements: r1.1 (the binary-source manages references) and r1.2 (the decompiled code uses the original binary’s symbols).

4.1.2 Decomposition

Here, we outline our use of decompilers and their output.

4.1.2.1 Function-specific Decompilation: For PRD to succeed at binary repair, not all binary functions need to be decompiled. Instead, we apply decompilers to a sufficient subset, like CGFL (Section 4.4). This decompiled output is left intact, minus a small set of decompiler-specific keyword substitutions that are necessary for APR and recompilation (e.g., replace DWORD with unsigned int).

4.1.2.2 Compatible Type Recovery: Similarly, it is not necessary to recover the exact types from the binary, instead compatible types are required. For example, a struct foo may contain many fields with different types, but only one of the fields (e.g., foo.bar where bar is an unsigned int) is used in a decompiled function. In partial decompilation, we only need to recover the offset and infer the type of bar for the decompiled function to be suitable for PRD. This significantly reduces the requirement of complete and sound type inference on binary code, an open research problem. To accomplish compatible type recovery, we leverage decompilers’ type inference to reconstruct the necessary compatible types from the binary. Notably, although decompilers can fail to recover all types, PRD can succeed if only referenced compatible types are defined. Since types may be nested, PRD decompilation resolves a definition order for the compatible type definitions to ensure recompilability.

4.1.3 Implementation

Our prototype primarily uses Hex-Rays Decompiler. While Hex-Rays generates an initial decompilation, our custom IDAPython script obtains corresponding local type and function declarations. Note, to aid C++-decompilation, we
Listing 2. Example binary-source interfaces generated by PRD:
unbound symbol (cgc_receive) and detour (det_cgc_read_line)
interfaces, with local symbol callbacks (cgc_calloc) and
(cgc_mempyc).

```c
// EBX mechanism needed to interface with original binary
unsigned int origPLT_EBX = NULL;
// required symbol-2 : typedef function ptr
typedef int (*pcgc_receive)(int s_0, int s_1, int s_2, int s_3);
pcgc.receive lcgc.receive = z__cgc.receive;
unsigned int localorigPLT_EBX = origPLT_EBX;

// Unbound Symbol interface
int cgc.receive( int s_0, int s_1, int s_2, int s_3 )
pcgc.receive lcgc.receive = z__cgc.receive;
asm ( "movl %localorigPLT_EBX,%%ebx
	" "nop
	" "pop %ecx
	" "add $0xc,%esp
	" "pop %ebp
	" "pop %ebx
	" "add $0x14,%esp
	" "nop
	" "pop %eax
	" "push %eax
	" "ret
	" );
return ret;

// required symbol-3 : typedef function ptr
typedef void * (*pcgc.mempyc)(void *, const void *,
cgcssize_t);
pcgc.mempyc cgc.mempyc = NULL;
```

Fig. 2. Program Execution Flows for PRD replacement function for $F_3$
with each fundamental type of execution flow between original and new
binary content outlined by way of numbered arrows. From the original
binary, $F_i \_a$ refer to its binary functions and PLT refers to its Procedure
Linkage Table (ELF). New binary content, i.e., PRD recompiled code,
consists of Decomp($F_3$), the decomposed content for function $F_2$, and
Bin-Src., binary-source interfaces. Subscripts dec specify the detour
interface for a decomposed function, pit the unbound symbol interface
for a dynamically resolved symbol, and local the interface for a local
symbol, whose location is resolved.

4.2 Partial Recompilation
Partial recompilation must recompile high-level source code
to ensure its correct execution in context of the patched
binary, as well as support r1.1 (Section 4.1.1). Because our
binary rewriting strategy appends new binary content, it
must operate even if the memory address of new content is
not known in advance. To satisfy these requirements, par-
tial recompilation creates position-independent, statically
linked content. While position-independent code (PIC) is
ubiquitous, support for both static linking and PIC in a
single shared object is recent, i.e., -shared -static-pie
(supported in GNU 8.4.0 and later), and not behaviorally
consistent across all compilers. We generate our object with
these flags and custom linker script, placing all sections in a
single segment. Although GCC-compatible, we use dietlibc,
a small-footprint libc, to support APR profiling. Our approach
supports executional requirements and r1.1.

4.3 Binary Rewriting
Binary rewriting composes the original binary and PRD-
decomposed source into a single binary that executes cor-
use Ghidra and Hex-Rays. PRD substitutes common primitives such as _DWORD and any Hex-Rays-specific definitions,
resolves a definition order for types, generates the required
binary-source interfaces and resolves the minimum set of
required symbols. These rule-based transformations are a
best-effort heuristic to produce informative decompilation.
To reorient the stack to support detouring with references,
we analyze the initial recompiled PRD source, generate
inline assembly that reconstructs the stack on detour exit,
then insert this assembly snippet in the detour interface (see lines 34-42 of Listing 2).
rectly. Our prototype analyzes, extracts, adds, and manipulates binary content to satisfy our requirements, r1.1-2. Satisfying (i1) (Section 4.1.1.1), we change the effective function call to align with the detour interface, before inserting a jump to it. To accomplish this, we analyze the binary content to generate instructions for each required reference, such that the result adheres to calling convention. We implemented our prototype in Python with LIEF [28].

4.4 Coarse-Grained Fault Localization (CGFL)

Our approach focuses on the minimum requirement, i.e., identifying a small set of functions to decompile and patch, ideally including the vulnerable function. By applying an SBFL variant, i.e., correlating binary function spectra to their execution, a set of suspicious functions can be identified for decompilation. For simplicity, we refer to our FL approach and its output as CGFL.

4.4.1 Requirements

Although the three stages of PRD operate on a small number of implicated functions, if the vulnerable functions are not implicated, BinrePaiReD cannot succeed. Because the binary setting provides different assumptions from most FL methods (Section 2.2), this results in five CGFL requirements: (r2.1) does not require source code or the ability to recompile, (r2.2) prioritizes functions for decompilation, (r2.3) minimizes run-time overhead, (r2.4) avoids functions that cannot support our detouring, and ultimately (r2.5) identifies vulnerable functions. After, finer-grained FL can pinpoint suspicious statements.

4.4.2 Implementation

CGFL uses Valgrind’s [29] callgrind to trace the program under different unit tests (satisfying r2.1–r2.3). Valgrind can efficiently provide function level trace, allowing us to identify function-level spectra. To address requirement r2.4 (detour support), we implemented a screening algorithm that reduces probability of overruns and, for statically-linked programs, culls standard library functions. To avoid detour overruns, we set a minimum function size of 45 bytes, which supports at least six references per detour. This eliminates very small functions with large calltrees (Section 4.1.1.1).

For each qualified function, we calculate suspiciousness scores using five state-of-the-art SBFL metrics (Taranula [30], Ochiai [31], op2 [32], Barinet [33], D2 [34]). Using matrices generated from this content, RankAggreg identifies the top-k suspicious functions [20] (satisfying r2.5: This implicates vulnerable functions in the top 35% over 92% of the time). This generates CGFL: a prioritized, consolidated list of suspicious functions from our function SBFL metrics.

5 Experimental Setup

Our evaluation of PRD and BinrePaiReD includes evaluations of underlying assumptions, as well as studies on end-to-end fully automated scenarios. Additionally, we consider two real-world case studies (Section 6.5.2). Specifically, our evaluation addresses the following research questions:

RQ1. Without any restrictions, how often is decompiled code recompilable?
RQ2. Is decompiled code behaviorally consistent to original binary functions?
RQ3. Does CGFL identify function(s) relevant to the vulnerability?
RQ4. How effective is BinrePaiReD at mitigating vulnerabilities?

Case Study: Generality. Does PRD generalize to real-world vulnerabilities, other languages, and performance constraints?

Next, we describe our datasets and experimental setup.

5.1 Benchmark Datasets

Outlined in Table [1] our four benchmark datasets are: the DARPA Cyber Grand Challenge C binaries (CGC-C) and C++ binaries (CGC-C++); Rode0day 19.11 (Rode0day); and vulnerable, real-world programs (CVE Case Study).

5.1.1 CGC-C and CGC-C++

The DARPA 2016 Cyber Grand Challenge (CGC) provides a dataset of challenge binaries (CBs), each containing realistic vulnerabilities, and a testing framework. We derived our CGC datasets from a Linux variant, trailofbits [35], verified these CBs using a robust variant of the testing environment. This identified 110 valid CGC CBs (100-CGC-C) and 10-CGC-C++, those with at least 9 passing positive and one negative test, i.e., defect scenarios. For our CGC-C evaluations, we consider targets for each CB, a set of functions for decompilation, totaling 190 as some binaries have multiple vulnerable functions.

5.1.2 Rode0day

Rode0day 19.11 inserts hundreds of bugs into Linux binaries, each a collection of stripped binaries and example test inputs. We recompile to ensure that symbol information exists in the binary (required by PRD) and generate unit tests from provided inputs (see Table 1). For our evaluations, we consider both functions and the injected bugs.

5.1.3 Real-World Case Study

Finally, we also consider two real-world programs, podofpdfinfo (PoDoFo-0.9.7 [36]) and jhead (jhead-3.0.6 [37]), not specifically curated for automated repair or binary analysis, which have associated public security vulnerabilities (CVEs). These programs fit the minimum PRD requirement—the vulnerable methods are local symbols.

5.2 External Tools

PRD uses Hex-Rays IDA Pro 7.5 SP2 (Hex-Rays), GCC 8.4.1, and dietlibc. When handling C++, we augment Hex-Rays with the Ghidra SRE Public 10.0.1.

For BinrePaiReD, we use Valgrind for CGFL and apply two APR tools: Prophet (v0.1, Clang-based) and GenProg (v3.2, CIL-based). We used Prophet’s default search algorithm with its profile localizer and three of GenProg’s: default genetic algorithm (“GA”), a deterministic search focused more on static analysis (“AE”) [26], and a “single-edit” repair search. When evaluating program variants, GenProg
replaces standard compilation with PRD tools. Prophet replaces the compiler with custom scripts, relying on environmental variables and dynamic libraries (we make each compatible to PRD). Ultimately, PRD operates seamlessly.

6 EMPIRICAL EVALUATION

In this section, we present the results of our evaluation and explain how they answer our research questions. The first three questions evaluate underlying assumptions, the remaining evaluate our automated approach.

6.1 RQ1: How often is decompiled code recompilable?

To answer this research question, we studied CGC-C, CGC-C++, and Rode0day datasets and place no restrictions on compilation or on the source code grammar. Our evaluation focuses these decompilation features: type recovery, decompilation, basic recompilability, and binary reconstruction. Our type recovery evaluation considers each binary independently. If all specified types are not recovered, then type inference fails for that binary. Decompilation and recompilability evaluations consider each binary function independently and asks how many could be decompiled by Hex-Rays and recompiled. If Hex-Rays fails, then decompilation fails for that function. Basic recompilation per function fails if any dependency is not fully defined, i.e., compatible type recovery, prototype recovery, and decompilation. Although we evaluate basic recompilation with raw decompiler output for function prototype recovery and function content, because this raw output rarely compiles, we use our PRD-transformed types. To assess the impact of type recovery failures on basic recompilation, we include the Incomplete Typing failure rate.

Our results, outlined in Table 2, demonstrate that decompilation succeeds more often than not, but basic recompilation is impacted by type recovery failures. When the decompiler recovered all required types, 70-89% of functions succeed at basic recompilation. Although we evaluated binary reconstruction for each binary, only two CGC-C binaries (Palindrome, Palindrome2) are fully reconstructable, i.e., all of its functions succeed at basic recompilation.

We find that only 1.7% of binaries are fully recompilable, but 70-89% of individually decompiled functions are recompilable when typing succeeds. This strongly supports our insight to use partial, instead of full decompilation.

6.2 RQ2: Is decompiled code behaviorally consistent to original binary functions?

To answer this question, we assessed partially decompiled content on our CGC-C, CGC-C++, and Rode0day datasets: (general) how often can partially decompiled content result in a test-equivalent binary? In both, we applied PRD decompilation to individual functions, extending basic recompilability from Section 6.1 with PRD transformations, e.g., generating PRD binary-source interfaces to create PRD decompiled code. Using this output, we then leveraged PRD’s recompilation and binary rewriting methods to generate a new PRD binary. Finally, each PRD binary is evaluated using the corresponding binary’s test-cases (test-equivalency). For behavioral tests, any disparity between the PRD binary and original is considered a failure, while success of proof-of-vulnerability tests includes mitigation of the vulnerability in addition to consistent behavior.

Our results, shown in Table 2, demonstrate that recompilation of PRD decompiled code performs consistently to basic recompilation from Section 6.1 (i.e., PRD decompilation transformations do not introduce errors and are impacted similarly by incomplete types) and that resulting PRD binaries are often test-equivalent to their original, exceeding 92%. We also evaluated Binary reconstruction and behavior for each binary, like earlier, only two CGC-C binaries (Palindrome, Palindrome2) could be fully reconstructed and could generate test-equivalent PRD binaries for all functions.

These results show that when decompilation succeeds, PRD produces patched binaries that are test-equivalent to the original. PRD provides a solid foundation for source-level transformations.

6.3 RQ3: Does CGFL identify function(s) relevant to the vulnerability?

As most FL methods use source-based or expensive dynamic instrumentation methods, we explore the viability of our CGFL implementation to identify suspicious functions from the vulnerable binary. After confirming compatibility with our implementation, we used our three dataset’s test-cases as stimuli and annotations as ground truth (i.e., vulnerable functions that should be implicated).

For all binaries in our dataset, our results show that the CGFL output contains at least one ground-truth function for 95 of 100 CGC-C, 8 of 10 CGC-C++, and 196 of 206 Rode0day. When accounting for all ground-truths, we see similar
success: 74 CGC-C, 7 CGC-C++, and 196 Rode0day, which succeeds at 95% despite having few tests (Section 5.1.2).

While CGFL succeeds more than 92% with our criteria, when CGFL failed to identify a vulnerable function, we observed three failure types that can be readily explained or mitigated. First, 14 binaries (4 CGC/10 Rode0day) did not exercise any vulnerable function in any negative test (f.1). Second, 10 were in the first three ranks, but ties impacted their selection (f.2), a common failure in SBFL metrics. Third, 1 buggily reimplemented a libc function (f.3). Although (f.1) cannot be addressed by SBFL or by APR, (f.2) can readily mitigated by adding better test content or increasing the size of \( \mathcal{X}_p \) per Section 4.4.1. Finally, (f.3) is a result of our simple heuristic that screens out system functions, statically located in the binary, which could be replaced with a more sophisticated screening process.

Even when few tests are available, our coarse-grained fault localization method works well in practice. CGFL contains the relevant function in 291/316 cases.

6.4 RQ4: How effective is BinrePaiReD at mitigating vulnerabilities?

Our evaluation consists of two scenarios: (plausibility) can APR tools leverage partially decompiled content to find repairs?; (content) does the form and quality of decompiled content impact APR tools?

6.4.1 Plausibility.

Because APR tools do not always succeed, we compared the success rate for APR tools applied to the actual source code of the binary (baseline) to the success rate for the same APR tool applied to the PRD decomposed code. Our primary evaluation features an end-to-end use of BinrePaiReD, as shown in Figure 2c. CGFL implicates a subset of the binary, then partially decompiled to create PRD decomposed code, the input to the APR algorithm. To identify repairs, the APR algorithm uses PRD tools to apply source-level patches to the original binary and test content to evaluate the resulting PRD binary’s behavior. Unlike BinrePaiReD, the baseline has access to the entire source.

Using the 157’ defect scenarios from the CGC-C dataset, we assessed baseline and PRD-enabled APR algorithms, limiting each run to 8 hours, outlining results in Table 3. Our primary result shows that PRD-enabled repair, operating only on binaries, performs as well as and sometimes better than full-source repair: PRD-supported algorithms find 51–69 plausible patches, while the full-source baselines find 32–57. Prophet performs slightly better with access to the original source (57 vs. 52) while the GenProg variants perform better in the PRD setting (51–69 vs. 32–48). Collectively, our PRD-supported APR tools mitigated 85 of the 148 scenarios (including 20 that the winning DARBA CGC cyberreasoning system, Mayhem, did not patch). Overall, we find that the success rate for repairs operating on binaries via BinrePaiReD as good as the same tools operating on fullsource \((p < 0.0004, \text{proportions } z\text{-test})\). Because these APR algorithms rely on the global availability of source code, BinrePaiReD should be less likely to succeed due to the reduction in available source. Our results are surprising.

6.4.2 Case Studies: Repair Quality

APR tools can find repairs that overfit the test suite [38], [39], without addressing the root cause of the problem. We do not improve or worsen that orthogonal concern here, instead find that BinrePaiReD inherits the repair quality of its underlying APR method. In our use case, quickly disrupting an exploit is valuable, even if the repair is not general. We focus on GenProg results for simplicity, Prophet results are similar.

First, in cases where GenProg failed to produce a mitigation, the required edit was usually out of scope, like changes to struct fields or unused variables. Other failures involved special constant values or comparators, known tool weakness (cf. [40]). Second, we consider the mitigations that it did find. As multiple solutions were found, we randomly sampled 5–10% and examined their C representations (recall from Section 3.3) BinrePaiReD retains source-level patches, facilitating such analyses. We do not find significant difference in the rate of overfitting between the full-source APR baseline and BinrePaiReD. As a case study, we describe one example that mitigates the vulnerability but does not address it generally (overfits), and then a second example that corrects the defect in a more general way.

6.4.2.1 Lower-Quality: For KPRCA_00013’s first vulnerability, GenProg mutation a(1178,1056) passes all tests and successfully mitigates it. In this edit, the “” character is pushed onto the operator stack in a loop, but the next iteration flags an error since the top of the stack is “”. Although this patch does not address the official vulnerabilities for this CB, it does mitigate this particular exploit, preventing control of the next heap block’s heap metadata.

6.4.2.2 Higher-Quality: NRRFIN_00076’s first defect simulates a vulnerability introduced when a programmer commits unfinished code. The program incorrectly increments *results in a frequent function, leading to the use of an invalid pointer. The mutation found, d(4), correctly deletes the problematic code, eliminating the pointer issues.

Our primary BinrePaiReD result shows that in an endto-end scenario, using PRD to apply a source-level APR tool to binaries produces results that are consistent with and sometimes better than using those same techniques on the corresponding source. This is true both in terms of the rate at which vulnerabilities are mitigated and in terms of repair quality (overfitting).

6.4.3 Study of Input Content on APR Effectiveness

To assess the impact of our informative decomposition approach, we studied a random sample of 21 CGC CBs and their 30 scenarios (Table 3). We consider access to the full source of the program (baseline), the PRD-provided decompiled source for implicated methods (PRD), and a bound
TABLE 4
Experimental BinrePaReD evaluation on 30 scenarios. LOC refers to the lines-of-code for DARPA CGC CB source code and PRD decompiled code; fsn: number of decompiled functions; AST: size of decompiled CIL-AST. Our results for APR tools using full-source are indicated by baseline, with APR$_{prd}$ for PRD (decompiled code) and exact (exact decompilation). We use × for decompiler errors; ✓ APR tool issues; + APR profiling failures that expose vulnerability; ✓ successful repairs; | practice binaries.

| DARPA | TACAS | TACAS | CB | LOC | PRD | fsn | AST | PRD | fsn | AST | PRD | fsn | exact | exact | exact | Mayhem |
|-------|-------|-------|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|-------|-------|--------|
| KPRCA_00013 | 0 | 1 | 44 | 2,160 | 1,917 | 7 | 349 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_00013 | 0 | 2 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_00041 | 0 | 1 | 84 | 1,138 | 510 | 8 | 207 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_00227 | 4 | 2 | 100 | 7,552 | 83 | 3 | 129 | × | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_00227 | 4 | 3 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_00227 | 4 | 4 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_00010 | 1 | 1 | 99 | 1,920 | 744 | 14 | 185 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_00027 | 10 | 0 | 105 | 7,157 | 107 | 3 | 11 | × | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_0009 | 0 | 2 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_0009 | 0 | 3 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_00001 | 0 | 1 | 101 | 43394 | 126 | 3 | 41 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0010 | 0 | 1 | 99 | 228 | 123 | 3 | 14 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0075 | 0 | 1 | 87 | 882 | 178 | 1 | 892 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0033 | 2 | 0 | 100 | 988 | 105 | 1 | 53 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0032 | 0 | 1 | 101 | 1151 | 313 | 3 | 134 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0035 | 0 | 1 | 97 | 6755 | 140 | 1 | 757 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KPRCA_0017 | 0 | 1 | 29 | 1,225 | 162 | 3 | 50 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0017 | 0 | 2 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| KPRCA_0019 | 0 | 1 | 100 | 1,199 | 216 | 3 | 49 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0019 | 0 | 2 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| SMART_0037 | 0 | 1 | 101 | 52123 | 124 | 3 | 26 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| CADET_0001 | 0 | 1 | 99 | 208 | 97 | 4 | 33 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0077 | 0 | 1 | 93 | 1,918 | 129 | 3 | 17 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0077 | 0 | 1 | 151 | 1,031 | 244 | 3 | 17 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0076 | 0 | 1 | 100 | 1,811 | 52 | 3 | 8 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0076 | 0 | 1 | 32 | 1,631 | 111 | 3 | 16 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0020 | 0 | 1 | 92 | 720 | 139 | 6 | 57 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| SMART_0020 | 0 | 2 | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| SMART_0020 | 0 | 1 | 100 | 15,270 | 101 | 1 | 2 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

In which the CGC-provided source is used for the same implicated methods (exact), i.e., the exact source function replaces the decompiled function. We observe that GenProg and Prophet separately produce 28 candidate patches with baseline, with PRD, and 34 with exact decompilation. This echoes the RQ1 finding that state-of-the-art decompilation tools have room to improve in end-to-end usage scenarios.

In addition, Table 4's LOC values offer a partial explanation for how decompilation can perform comparably to full source: the decompilation applies only to the implicated functions (reducing effective LOC by 95%), while the full source provides the entire source code to the APR tool. This supports our insight that CGFL, if accurate at implicating a relevant subset, can help downstream stages (such as decompilation or program analysis/transformation).

Our secondary BinrePaReD result shows that decompilation can strongly impact quality, but current decompilers' weaknesses are mitigated by fault localization filtering.

6.5 Case Study: Generality
Our previous results establish some generality, but for a binary-facing technique it is also important to consider multiple languages, real-world programs and defects, and execution overhead.

6.5.1 Application to C++
We have shown that PRD can partially decompile and recompile binaries produced from C++ (see Table 2) for individual functions. Because we cannot directly evaluate baseline APR algorithms on C++ (an unsupported language), in this end-to-end assessment, we focus on evaluating further compatibility with BinrePaReD, i.e., multiple C++ functions. Using the GCC-C++, we evaluate PRD's applicability to BinrePaReD specifically using each binary's CGFL as the decompile set. For each binary, we applied PRD to its CGFL, totaling 149 functions (includes decompiled C++ class methods). Although we generate test-equivalent PRD binaries for 7 of the 10 binaries, recompilation failures (94) dominate test (10) and decompilation (9) failures, like our Section 6.2 results. These results indicate that the PRD framework is not only extensible to C++ binaries, but can potentially allow repairing C-like binaries with C-based APR tool. Because APR tools overwhelmingly favor other languages over C++, our results improve tool applicability.

6.5.2 Real-world Vulnerabilities.
We detail PRD and CGFL effectiveness for two real-world programs that contain known vulnerabilities (see Table 1). CVE-2021-30472: For tests, we used the developer’s recommended example PDFs and the CVE input, bug4 for podofpdfinfo. This exploit hits a vulnerability in PdfEncryptMD5Base::ComputeEncryptionKey (f1) before PdfEncryptMD5Base::ComputeOwnerKey (f2) vulnerability. We applied our CGFL approach (Section 4.4.1). All SBFL metrics identified f1 in rank 1 (10 ties) of 265 with f2 at rank 147—echoing the bug precedence. We successfully applied PRD to both methods. Because Hex-Rays incorrectly lifted the stack canary using x86-64 content, we had to manually correct this with the equivalent x86 inline assembly. Using the GCC-G++ compiled binary and this content, PRD successfully generated a test-equivalent binary for f2, while f1 improved on test-equivalency, mitigating the vulnerability. Specifically, the decompiler generated a large number of local variables for f1, changing the stack such that the original vulnerability was no longer intact.

CVE-2021-3496: We applied our same methods to jhead. CGFL implicated the function, ProcessMakerNote, as rank 3 of 42. Notably, it inlines the reported buggy function ProcessCanonMakerNoteDir. PRD successfully generated a test-equivalent binary from a Clang binary.
By manually applying the necessary bug fixes (less than 3 lines were changed), we produce PRD-binaries that both pass all tests, resolving the CVE-reported bugs for both jhead and podofpdfinfo, successfully applying PRD to two real-world issues.

6.5.3 Performance Analysis.

Using perf stat, we consider run-time and compile-time performance for PRD binaries. For run time, we compared 100 PRD binaries to their counterparts over 5,163 tests and found that the difference in performance was not statistically significant (user: \( p < 0.970 \); system: \( p < 0.277 \), two-tail t-test). For compile time, an overhead relevant to APR algorithms, we sampled 25 CGC CBs and respective single-detour PRD binaries, generating each 25 times. We found that generating a PRD binary is statistically less expensive than compiling the binary from source (user: \( p < 0.0 \); system: \( p < 8.4845 \times 10^{-92} \), two-tail t-test). These results imply that PRD does not induce a performance overhead on APR tools.

We show that PRD can be applied to C++ binaries and real-world CVEs. Our rate of producing test-equivalent binaries for our C++ benchmark, 24.2%, is comparable to our rate for C. We find that both CGFL and PRD are successful on 2 of 2 real-world CVEs. We find negligible overhead for producing and running PRD binaries.

7 Discussion

With an initial analysis identifying a relevant set of functions which is then decompiled, PRD enables manual and automated mitigation of binary-level exploits. PRD produces a new binary that executes new content instead of the original.

If a complete test suite is not available, then this relevant subset identification may be impacted. However, our CGFL evaluation of Rode0days indicated a 95% success rate despite a limited test suite, i.e., one behavioral and one exploit.

The current limitations of decompilers are addressed by identifying a small function set, which increases decompilation accuracy and subsequent recompilability. On average, this approach reduced the lines-of-code (LOC) by an average of 95% from original to decompiled source (Section 6.4.3). It is interesting that our BinrePaiReD results with this reduction are consistent with full-source APR. We leave to future research what role restricting the program search space to a functional subset plays in APR tool efficiency.

While decompiled source is less readable than the original, it is better than assembly. This is not an impediment for APR, as evidenced by the similar success rates for full-source vs. BinrePaiReD repairs. We can extend C-based APR tools to C++ binaries by decoupling into C-like source.

7.1 PRD Limitations and caveats.

BinrePaiReD and PRD are not applicable for tools that use whole-program analysis (such as the use of symbolic execution by Angelix [41]) or interpreted languages. While our implementation focuses on 32b ELF and System-V, with engineering effort, PRD is compatible with other binary formats, ABIs, and stripped binaries, assuming calling conventions are upheld and decompiler support. PRD is compatible with ASLR binaries. We do not handle self-modifying or self-checking binaries. The most serious challenge to BinrePaiReD arises from limitations of current decompilers. When we fail to generate test-equivalent PRD binaries, decompilation caused most failures. Our transformations are limited to currently known and mitigated decompiler weaknesses. Our evaluations indicate there is some brittleness, particularly with compiler-instrumented binaries and type recovery. Our motivating example (Section 5) and the end-to-end repair results (Section 6.4) demonstrate the full pipeline with Hex-Rays.

7.2 Decompilation failures.

Although decompilation techniques have achieved impressive results, modern decompilers still struggle to generate satisfactory results when the binary (1) is compiled from a non-C language, (2) contains manual assembly code, or (3) contains self-modifying or obfuscated code. Improvements in decompilation enhance PRD’s generality and quality.

7.3 Unsound decompilation results.

Decompilers do not always generate decompiled code that preserves the semantics of the original binary. While determining the equivalence of two arbitrary binaries is undecidable in general, this problem can be addressed by requiring byte-level equivalence between the original binary code and the recompiled (but unpatched) code [4]. Akin to Equivalence Modulo Input testing [42], we validate the generated binary against existing test cases, i.e., test-equivalency, assuming adequate coverage.

8 Related Work

Our approach and evaluation rely on recent progress in three major research areas: binary patching and rewriting, APR, and binary code decompilation.

8.1 Binary Patching and Rewriting

There are dynamic and static binary rewriting techniques. Dynamic binary rewriting or dynamic binary instrumentation inserts user code at specified binary locations at runtime, e.g., Pin [43], Valgrind [29], and DynamoRIO [44]. These techniques can introduce prohibitively high overhead and are unused in production binary patching. Static binary rewriting techniques, like Egalito [45] and LIEF [28], perform code transformation and relocation. They have much lower runtime overhead than dynamic methods and suit generic tasks like binary patching and control-flow integrity enforcement. Ramblr [46] and ddisasm [47] convert binary code into assembly that can later be reassembled into a new binary. E9Patch performs in-binary byte editing in AMD64 binaries to allow insertion of a few chunks of code [48]. CGC finalists used either in-place binary editing or reassembly to apply patches [49–51]. Unlike PRD, no existing solutions transform binary code to high-level source.
8.2 Automated Program Repair

Three recent surveys [21], [22], [52] review more than a decade of this work. Most APR techniques work on source code instead of binary content. Some exceptions are Schulte et al.’s [13] executables and Orlov and Sipper’s early work [56], [57] on Java bytecode. Since Java bytecode is interpreted by the Java Virtual Machine, any incompatible, we omit its discussion. Similarly, Angelix [41]’s symbolic execution is incompatible. Tools that assume perfect FL are incompatible [58]. Closely related tools, e.g., RSRepair [59], Kali [60], and SPR [61] require similar modifications to those we made for our tested tools. Other tools, like CodePhage [42], CodeCarbonCopy [63] are compatible with PRD but would require more modifications. OSS-Patcher [64] targets third-party, open-source libraries for automatic binary patching, but requires both source and source-based patches. Current ML-based repair methods, like CoCoNut [58] or VulRepair [24], are not compatible with binary repair, as they not only operate on source code, but also rely on perfect fault localization, i.e., the buggy location is annotated in the input (usually the source code line or context surrounding it). However, any ML tool could easily leverage PRD for both input and binary repair.

8.3 Binary Code Decompilation

The quality of binary code decompilation relies on advances in binary code extraction, (control flow) structural analysis, and type inference. Binary code extraction on non-obfuscated binaries is equivalent to control flow graph recovery, where state-of-the-art approaches work in a compiler-, platform-, and architecture-agnostic manner with high precision [47], [65], [66]. Structural analysis has progressed significantly: Schwartz et al. reduced the number of goto statements [67]; Yakdan et al. proposed pattern-independent control-flow structuring to eliminate goto statements and improve readability [5]. Decompilers often use static analyses or type inference due to their intrinsic requirement in code coverage (e.g., [68–71]). Rapid progress in decompilation has enabled the recomputation of compiled code—deemed impossible by most researchers until recently. Liu et al. show that the output of modern C decompilers is generally recompilable [2], when grammar and types are restricted. Similarly, Harrand et al. present a method that mitigates Java decompiler failures by merging outputs [72]. Both confirm that decompilers make mistakes and may generate incorrect output.

9 Conclusion

Security-critical vulnerabilities that arise after software is deployed must be addressed quickly, even when recomputation is not possible. Further, 15–25% of sampled post-release operating system bug fixes are reported to have end-user visible impacts such as information corruption [73]. We present a new way to patch binaries when recompiling from source is not an option. While it cannot yet replace full-source, we show that decompilation generates recompliable code for most functions. By focusing on only the vulnerable functions, state-of-the-art decompilers can produce recompliable code that is amenable to source-level code repair tools. We CGFL to identify a buggy function set, partial decompilation to lift part of the source to source, where repairs are developed and applied, then generates a PRD binary addressing the problem. Our implementation and datasets are available at git@github.com:pdreiter/FuncRepair.git.

Today’s tools are better at finding vulnerabilities than they are at patching them. We hope our methods will improve that capacity by leveraging recent advances in source-level APR. Although APR is an active area of research and used in industry, that potential has not been equally realized for binary code. BinrePaiReD using PRD helps to address these shortfalls.

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