Binary Lifter Evaluation

Eric Schulte
eschulte@grammatech.com

Vlad Folts
vf-olds@grammatech.com

Michael Brown
michael.brown@trailofbits.com

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Binary rewriting gives software developers, consumers, attackers, and defenders the ability to modify both their own and third-party software for instrumentation, customization, optimization, and hardening. Unfortunately, the practical limitations of binary rewriting tools are often glossed over in academic publications in this field, making it unclear to users if and when these tools will work in practice. This, among other challenges, has prohibited the widespread adoption of binary rewriting tools. To address this shortcoming, we collect eight popular binary rewriting tools and assess their generality across a broad range of input binary classes and the functional reliability of the resulting rewritten binaries. Additionally, we evaluate the performance of the rewriting tools themselves as well as the rewritten binaries they produce. We also identify features that are predictive of rewriting success and show that a simple decision tree model trained on these features can accurately predict whether a particular tool can rewrite a target binary.

The goal of this broad evaluation is to provide a state of the practice for binary rewriting tools. We hope our findings will inform potential users of binary rewriting, support binary rewriting tool developers, and set a shared context for future research in this area. The binary rewriters, our corpus of 3344 sample binaries, and the evaluation infrastructure itself are all freely available as open-source software.

1 Introduction

Software supply chains have long been the target of offensive cyber operations by individual and organized actors alike. These supply chains often include software libraries and executables available only as binaries. While the art of reverse engineering binaries is well established, emerging techniques for analyzing, mutating, hardening, and exploiting binaries are now being enabled by advances in binary rewriting.
For binary rewriting tools to be viable, they must generalize to the full variety of programs available on heterogeneous computing platforms and reliably produce functional rewritten binaries. A surfeit of research into binary rewriting applications including instrumentation, optimization, configuration, debloating, and hardening reveals a wide and largely under-emphasized variance in the generality and reliability of binary rewriting tools (Romer et al. 1997; Zhang et al. 2014; Laurenzano et al. 2010; Williams-King et al. 2020; Dinesh 2019; Schwarz et al. 2001; Van Put et al. 2005; Tilevich and Smaragdakis 2005; Qian et al. 2019; Zhang and Sekar 2013; Smithson et al. 2013; Wartell et al. 2012). Frequently, papers presenting these tools only briefly mention large gaps in generality such as support limited to binaries with relocation information and/or symbols – neither of which are typical of commercial off-the-shelf (COTS) software (Williams-King et al. 2020; Dinesh 2019). Similarly, many tools support only a single file format or instruction set architecture (ISA).

While there has been significant research to date seeking to systematize knowledge of general binary rewriting techniques (Wenzl et al. 2019) and evaluate the quality of binary lifters and disassemblers (Meng and Miller 2016; Andriesse et al. 2016), no broad systematic comparative evaluation of binary rewriters has yet been conducted. In this work, we address this important knowledge gap by conducting such an evaluation of 8 binary rewriters across 3344 variant binaries sourced from 34 benchmark programs and 3 production compilers. The tools evaluated in this work are static binary rewriting tools; we exclude dynamic binary instrumentation and rewriting tools (e.g., PIN and DynInst (Luk et al. 2005; Bernat and Miller 2011)) whose runtime harnesses and overhead often make them impractical for the applications considered by this work.

Our work differs from previous surveys in two key ways. First, prior work systematizing knowledge on binary rewriters (Wenzl et al. 2019) focused primarily on their underlying techniques and algorithms and as such did not evaluate their artifacts empirically. In contrast, our evaluation focuses on measuring and comparing the generality and reliability of a broad collection of publicly available binary lifter and rewriter tools. Second, prior works performing comparative evaluation of binary disassemblers and lifters (Meng and Miller 2016; Andriesse et al. 2016) focus on depth achieving near complete measurement of binary analysis accuracy across a small pool of binaries. The difficulties implicit in a truly thorough analysis limits the breadth of these works to small numbers of binaries or to specific classes of binaries. Our evaluation focuses on input program breadth to directly address tool generality and rewritten binary functionality to directly address reliability.

**Summary of Contributions.** In this paper, we first review related work evaluating binary analysis and transformation tools in Section 2. We then describe our experimental methodology to assess the generality and reliability of existing tools in Section 3. Next, we present our experimental results and predictive models derived from them in Section 4. Finally, we discuss the state of the

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1We are not aware of any comparable closed source binary rewriters.
practice in binary rewriting tools and the options for potential users of these tools in Section 5.

2 Background

2.1 Types of Binary Rewriters

**Direct Rewriting.** Zipr (Hiser et al. 2014) lifts a binary into an Intermediate Representation Data Base (IRDB (LLC., n.d.)) upon which transformations may be applied. The IRDB can then be written directly to a binary executable. Similarly, Egalito (Williams-King et al. 2020) lifts a binary into a low-level Intermediate Representation (IR), provides an API for transforming this IR, and provides support for lowering this IR back to a functioning binary.

**Reassemblable Disassemblers.** Uroboros (S. Wang, Wang, and Wu 2015) – superseded by the Phoenix reassemblable decompiler (Phoenix, n.d.) – popularized the idea of reassemblable disassembly (e.g., disassembly to assembly code that could be readily reassembled). Retrowrite (Dinesh 2019) also emits reassemblable assembly code. DDisasm (Flores-Montoya and Schulte 2020) lifts to GrammaTech’s Intermediate Representation for Binaries (GTIRB) (Schulte et al. 2019), and can also directly emit assembly code that can be reassembled.

**LLVM Rewriting.** The now defunct SecondWrite (Smithson et al. 2013) was the first tool to lift binaries to LLVM IR. More recently, McSema (Dinaburg and Ruef 2014) has become the predominant binary lifter to target LLVM IR. Although LLVM has a large user community and provides many analysis, optimization, and hardening passes, there are two properties of its IR that make it difficult for lifters to target. First, it requires type information to represent data. This requires binary type analysis, which is prohibitively difficult at the scale required to rewrite large programs. Instead, many tools explicitly emulate the stack, stack maintenance around function calls, and memory as a large array of bytes. The lack of true types and stack/memory emulation limits the utility of many existing LLVM passes and results in baroque and inefficient rewritten binaries. Second, LLVM IR represents code in static single assignment form resulting in a loss of specificity with respect to the original binary’s concrete machine instructions.

2.2 Related Work

Our work aims to complement and go beyond prior work systematizing knowledge relevant to and evaluating tools for binary analysis, disassembly, lifting, and rewriting. We summarize and compare work related to our own in this subsection.

Andriesse et. al. (Andriesse et al. 2016) reviewed 30 prior publications concerning static disassemblers with the goal of clearly identifying the actual shortcomings of these tools. Their work also includes an evaluation of the accuracy
of nine disassemblers across 981 binaries. They found that modern disassemblers achieve close to 100% accuracy during disassembly, even in the presence of challenging (although rare) compiler-introduced constructs such as inlining data with code and overlapping instructions.

Meng and Miller (Meng and Miller 2016) evaluated seven binary analyzers to determine how their internal algorithms handled eight different challenging code constructs. This evaluation was conducted across a corpus of test programs generated from the SPEC 2006 benchmark set produced at three different optimization levels using two compilers, as well as a number of handcrafted toy programs. They found that while challenging code constructs inhibit code discovery, control-flow graph (CFG) construction, and CFG partitioning, binary analysis algorithms can be improved or supplemented to handle them.

Pang et. al. (Pang et al. 2021) published a broad study of x86 and x86-64 disassemblers. Their work first systematizes the the algorithms, heuristics, and goals of nine open-source disassemblers derived from source code review. Their work also includes a large scale evaluation of disassembly accuracy across 3,328 Linux and 460 Windows binaries. They found that heuristics for handling complex code constructs are indispensable, but are inherently subject to correctness-coverage trade offs.

The evaluations presented in these three works are similar in scale to our work, however our work evaluates the performance of several tools with their own custom disassembly routines not covered in these works (all except uroboros). Further, our work focuses on binary rewriting as opposed to disassembly.

Woodruff et. al. (Woodruff, Carroll, and Peters 2021) proposed Mishegos, a tool for evaluating x86-64 instruction decoders. This work performs a large-scale evaluation of nine x86-64 instruction decoders via a novel differential fuzzing method. Instruction decoding is a component function of binary disassembly, and errors in this task can have cascading effects on binary disassembly such as misidentifying code as data due to an erroneous decoding.

Wenzl et. al. (Wenzl et al. 2019) survey over 50 years of research referencing binary rewriters in their work. Their primary objective is to categorize binary rewriting approaches by end use-case, analysis techniques, code transformation methods, and code generation methods. While this survey covers 67 prior publications, it does not conduct a comparative evaluation of the artifacts generated by these works.

Li et. al. (Li, Woo, and Jia 2020) present a benchmark suite for evaluating binary disassemblers and an accompanying ground truth generator. This suite consists of 879 test binaries built using one Windows and three Linux compilers sourced from 15 different projects. Additionally, this work provides a comparative evaluation of four binary disassemblers using this suite. While similar in scale, provenance, and purpose to our corpus of test binaries, the evaluation performed in this work is geared towards disassembly rather than rewriting.
Dasgupta et al. (Dasgupta et al. 2020) present a method for validating binary lifters that achieves scale by avoiding semantics checks. This tool was used to evaluate McSema (Dinaburg and Ruef 2014) and successfully identified lifter bugs via reference to the standard generated by their method. Their work provides a deep evaluation of one binary lifter over a relatively small pool of benchmark programs, whereas our work presents a broad comparative evaluation of many tools across a large set of real-world program variants using a straightforward lifting and rewriting task as the evaluation mechanism.

3 Methodology

3.1 Tools

We selected eight binary rewriters for our evaluation, listed in Table 1. While our corpus of tools is not exhaustive, it provides excellent coverage of tools that are mature, robust, and scale via automation. We excluded some notable binary rewriting tools, McSema (Dinaburg and Ruef 2014) and Ramblr (R. Wang et al. 2017), from our evaluation because their rewriting workflows involve manual steps and/or lack interfaces that scale via automation. Additionally, the tools evaluated in this work are all publicly available as open source software; we are not aware of any closed source binary rewriting tools.

Table 1: Tools selected for this evaluation and their ISA coverage.

| Tool                  | x86-64 | x86-32 | x86-64 | x86-32 | ARM64 | ARM32 | MIPS64 | MIPS32 | PPC64 | PPC32 |
|-----------------------|--------|--------|--------|--------|-------|-------|--------|--------|-------|-------|
| DDisasm               | ✓      | ✓      | ✓      | ✓      | ✓     | ✓     | ✓      | ✓      | ✓     | ✓     |
| (Flores-Montoya and Schulte 2020) |
| Egalito               | ✓      | ✗      | ✗      | ✗      | ✓     | ✗     | ✗      | ✗      | ✗     | ✗     |
| (Williams-King et al. 2020) |
| McToll                | ✓      | ✗      | ✗      | ✗      | ✓     | ✗     | ✗      | ✗      | ✗     | ✗     |
| (Microsoft, n.d.)    |
| multiverse            | ✓      | ✓      | ✗      | ✗      | ✗     | ✗     | ✗      | ✗      | ✗     | ✗     |
| (Bauman, Lin, and W. Hamlen 2018) |
| Retrowrite            | ✓      | ✓      | ✓      | ✓      | ✓     | ✓     | ✓      | ✓      | ✓     | ✓     |
| (Dinesh 2019)        |
| Urorboros             | ✓      | ✓      | ✓      | ✓      | ✓     | ✓     | ✓      | ✓      | ✓     | ✓     |
| (S. Wang, Wang, and Wu 2015) |
| Zipr                  | ✓      | ✓      | ✓      | ✓      | ✓     | ✓     | ✓      | ✓      | ✓     | ✓     |
| (Hiser et al. 2014)  |

3.2 Benchmark Selection and Variant Generation

In order to obtain realistic evaluation results, we combined benchmark lists compiled by two program managers from the United States Department of Defense to arrive at a diverse list of 33 real-world benchmark programs. We added a
trivial “Hello World!” program to our corpus to provide a low-water mark for program complexity, resulting in a total of 34 benchmarks shown in Table 2.

Table 2: Benchmark programs with size and number of binaries

| Program       | SLOC  | Bins | Description               |
|---------------|-------|------|---------------------------|
| anope         | 65,441| 176  | IRC Services              |
| asterisk      | 771,247| 120  | Communication Framework   |
| bind          | 376,147| 97   | DNS System                |
| bitcoind      | 229,928| 104  | Bitcoin Client            |
| dnsmasq       | 34,671| 176  | Network Services          |
| filezilla     | 176,324| 120  | FTP Client and Server     |
| gnome-calculator | 301  | 20   | Calculator                |
| hello world   | 5     | 148  | Hello World               |
| leafnode      | 12,945| 180  | NNTP Proxy                |
| Libreoffice   | 5,090,852| 44  | Office Suite              |
| libzmq        | 62,442| 67   | Messaging Library         |
| lighttpd      | 89,668| 90   | Web Server                |
| memcached     | 33,533| 84   | In-memory Object Cache    |
| monerod       | 394,783| 148  | Blockchain Daemon         |
| mosh          | 12,890| 176  | Mobile Shell              |
| mysql         | 3,331,683| 110 | SQL Server                |
| nginx         | 170,602| 176  | Web Server                |
| ssh           | 127,363| 88   | SSH Client and Server     |
| openvpn       | 89,312| 180  | VPN Client                |
| pidgin        | 259,398| 180  | Chat Client               |
| pks           | 40,788| 176  | Public Key Server         |
| poppler       | 188,156| 61   | PDF Reader                |
| postfix       | 134,957| 180  | Mail Server               |
| proftpd       | 544,178| 180  | FTP Server                |
| qmail         | 14,685| 152  | Message Transfer Agent    |
| redis         | 14,685| 90   | In-memory Data Store      |
| samba         | 1,863,980| 126 | Windows Interoperability  |
| sendmail      | 104,450| 176  | Mail Server               |
| sipwitch      | 17,134| 128  | VoIP Server               |
| snort         | 344,877| 120  | Intrusion Prevention      |
| sqlite        | 292,398| 180  | SQL Server                |
| squid         | 212,848| 176  | Caching Web Proxy         |
| unrealircd    | 90,988| 132  | IRC Server                |
| vi/vim        | 394,056| 180  | Text Editor               |
| zip           | 54,390| 176  | Compression Utility       |

For each of our 34 benchmarks, we compiled an x86-64 variant of the program using one permutation of the compilers, optimization levels, code layout, symbol
options, and operating systems listed in Table 3. The total size of our corpus of distinct x86-64 program variants is 3344.

Table 3: Variant configuration options.

| Compiler | Flags | Relocation (Position-) | Symbols | Operating Systems |
|----------|-------|------------------------|---------|-------------------|
| clang    | O0    | Independent            | Not Stripped | Ubuntu 16.04²    |
| gcc      | O1    | Dependent              | Stripped  | Ubuntu 20.04      |
| icx      | O2    |                        |          |                   |
|          | O3    |                        |          |                   |
|          | Os    |                        |          |                   |
|          | Ofast |                        |          |                   |
| OLLVM    | fia   | Independent            | Not Stripped | Ubuntu 20.04      |
|          | sub   | Dependent              | Stripped  |                   |
|          | bcf³  |                        |          |                   |

3.3 Evaluation Tasks

We evaluate our selected binary rewriters based on their ability to successfully perform two rewriting tasks and record their progress at multiple checkpoints. In the interest of breadth we use a proxy for successful (i.e., correct) rewriting. Specifically, we consider a rewrite to be successful if the output executable passes a very simple test suite. In practice many binary rewriting tools fail fast when problems arise, meaning they either completely fail to produce a new executable or they produce an executable that is unable to start execution. For a small subset of our benchmark with readily executable test suites with high coverage we also tested programs against the full test suite.

Tasks. The two tasks we use to evaluate our tools are:

**NOP** This task is a minimal NOP (i.e., No Operation) transform that simply lifts the binary and then rewrites without modification. The NOP transform tests the ability of a binary rewriter to successfully process the input binary, populate its internal or external intermediate representation of the binary, and then produce a new rewritten executable. Despite its name this transform is decidedly non-trivial for most rewriters, evidenced by the fact that rewritten binaries typically look very different from the original due to the undecidable nature of binary disassembly.

**AFL** This task is a more complex transform characteristic of the needs of instrumentation to support gray-box fuzz testing. It evaluates our tools’ ability to extensively transform a binary with instrumentation to support

²Some binaries could be built on this OS due to unavailable dependencies.
³Probability variable set to always insert (100%)
AFL++ (AFL++, n.d.).

This task is important to include as many rewriters cover up analysis errors by incorporating reasonable defaults (e.g., linking code from the original binary on lifting failure, or preserving unidentified symbols which continue to resolve correctly if code is left undisturbed in memory).

**Checkpoints.** For every attempted rewrite operation, we collect a subset of the following artifacts to checkpoint multiple stages of the process:

**IR** For every binary rewriting tool that leverages some form of external IR, we collect that IR at this checkpoint. Specifically, we collect the ASM files generated by tools that emit reassemblable disassembly and the LLVM IR for tools targeting LLVM. Zipr and Egalito use a purely internal IR that are not easily serialized to disk. As such, we do not track successful IR generation for these tools.

**EXE** We next check if the rewriter successfully creates a new executable. In some cases rewritten executables are trivially recreated and are not an indicator of success (e.g., Egalito almost always generates a new executable even if most of them are non-functional). However, in most cases the ability to re-assemble and re-link a new executable indicates that the rewriting tool both successfully disassembled reasonable assembly instructions and generated the required combinations of symbols and included libraries.

### 3.4 Evaluation Metrics

**Functional Metrics.** To measure rewriter correctness, we first observe the rewrite success rate for each tool across all variants for both tasks (i.e., NOP and AFL) at both checkpoints (i.e., IR and EXE). Next, we perform a simple invocation of the NOP rewritten programs (e.g., running help) to ensure the rewrite did not obviously corrupt the program. We refer to this test as the Null Function test. Finally, we execute the AFL rewritten programs with the driver provided by AFL++ to ensure instrumenting the program via binary rewriting did not corrupt the program and that instrumentation was successfully incorporated. We refer to this test as the AFL Function test.

**Non-Functional Metrics.** To measure rewriter runtime performance we observe the total required runtime and the memory high-water mark used by tools during rewriting. This is important as the limiting factor for rewriting is often the amount of available memory because many underlying analyses scale super-linearly in the input binary size.

To determine the performance impacts of rewriting on binaries, we first measure file size impacts using Bloaty (Google, n.d.). Size is an important metric as it measures the degree to which a rewriting tool has inserted dynamic emulation or runtime supports to supplement static binary rewriting that have complexity and efficiency costs. Finally, for successfully rewritten program variants with

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4Each tool we selected except multiverse claims to support AFL++’s instrumentation.
publicly available test suites we measure the impact of rewriting on performance. Specifically, we measure pass rate for all tests in the suite, runtime of the test suite, and the memory consumption high-water mark during execution of the full test suite.

4 Experimental Results

We present binary rewriter success both in aggregate across our entire benchmark set and broken out into cohorts. Each cohort of binaries has like characteristics that highlight the comparative strengths and weaknesses of the evaluated tools.

4.1 Aggregate Rewriting Success Rates

Table 4: Number and percentage of the full suite of 3344 x64 Linux binaries for which the rewriter successfully produces IR, produces a NOP-transformed executable (“EXE”), passes the Null Function test, produces an AFL++ instrumented executable (“AFL EXE”), and passes the AFL Function test

| Tool       | IR  | ELF | Null Func. | AFL ELF | AFL Func. |
|------------|-----|-----|------------|---------|-----------|
| ddisasm    | 3282| 2972| 2861       | 3020    | 2346      |
| %          | 98.05% | 88.80% | 85.48% | 90.23% | 70.09% |
| egalito    | NA  | 3294| 983        | 2493    | 0         |
| %          | NA  | 98.42% | 29.37% | 74.48% | 0.00%    |
| mctoll     | 30  | 30  | 30         | 30      | 30        |
| %          | 0.90% | 0.90% | 0.90%   | 0.90%   | 0.90%    |
| multiverse | NA  | 880 | 362        | NA      | NA        |
| %          | NA  | 26.29% | 10.82% | 0.00%   | 0.00%    |
| reopt      | 3007| 2556| 1134       | 0       | 0         |
| %          | 89.84% | 76.37% | 33.88% | 0.00%   | 0.00%    |
| rewrite    | 817 | 334 | 309        | 330     | 254       |
| %          | 24.41% | 9.98% | 9.23%   | 9.86%   | 7.59%    |
| uboros     | 364 | 216 | 96         | 210     | 0         |
| %          | 10.88% | 6.45% | 2.87%  | 6.27%   | 0.00%    |
| zipr       | NA  | 3059| 2719       | 2705    | 1592      |
| %          | NA  | 91.40% | 81.24% | 80.82%  | 47.56%    |

Our aggregate success results are presented in . Overall, we observed a very broad range of success rates (and by extension levels of support) achieved by our selected binary rewriting tools. For the NOP transform, the tools fall into four distinct categories characterized by the fraction of the universe of potential binaries they can handle:

1. Tools that work only on a tiny fraction (≤5%) of binaries. This group
includes metcoll and uroboros.

2. Tools which work on a few (~10%) binaries. This group includes multiverse and retrowrite.

3. Tools that work on some (~33%) binaries. This group includes egalito and reopt.

4. Tools that work on most (≥80%) binaries. This group includes ddisasm and zipr.

In category (1) we find tools that only handle a very limited set of binaries. For example metcoll only successfully transformed hello-world binaries. The tools in category (2) support a wider range of binaries but in many cases make hard and fast assumptions. For example, multiverse is only able to successfully rewrite binaries compiled by the older versions of clang and gcc available on Ubuntu 16. These tools still do not handle binaries that make use of fairly common code structures (e.g., C++ exceptions). The tools in category (3) largely only work with relocation and debug information, but are able to handle a wide range of the binaries meeting these restrictions. Finally, category (4) tools do not require relocation or debug information and support a wide range of both complex code structures and compiler-specific binary generation behaviors such as multiple forms of jump tables, data intermixed with code, and specialized control-flow constructs.

Given that so many tools require relocation and debug information we present a second view of our results limited to binaries that include this information (i.e., non-stripped, position-independent variants) in . Although position-independent binaries are increasingly common as ASLR becomes the norm, it is still quite uncommon for COTS binaries to include debug information.

Table 5: Number and percentage of 1673 non-stripped, position-independent x64 Linux binaries for which the rewriter successfully reaches task checkpoints and passes functional tests.

| Tool       | IR   | ELF  | Null Func. | AFL ELF | AFL Func. |
|------------|------|------|------------|---------|-----------|
| ddisasm    | 1638 | 1428 | 1373       | 1456    | 1125      |
| %          | 97.91% | 85.36% | 82.07% | 87.03% | 67.24%    |
| egalito    | NA   | 1661 | 492        | 1261    | 0         |
| %          | NA   | 99.28% | 29.41% | 75.37% | 0.00%     |
| metcoll    | 30   | 30   | 30         | 30      | 30        |
| %          | 1.79% | 1.79% | 1.79%      | 1.79%   | 1.79%     |
| multiverse | NA   | 437  | 181        | NA      | NA        |
| %          | NA   | 26.12% | 10.82% | NA      | NA        |
| reopt      | 1504 | 1425 | 684        | 0       | 0         |
| %          | 89.90% | 85.18% | 40.88% | 0.00%   | 0.00%     |
| retrowrite | 817  | 334  | 309        | 330     | 254       |
| %          | 48.83% | 19.96% | 18.47% | 19.73%  | 15.18%    |
The results in show the increase in rewriting success rate that a developer might expect if they compile their binaries with relocation and debug information to support binary rewriting. Unsurprisingly, both Retrowrite and Zipr do much better in this case. However, such binaries are not characteristic of the stripped COTS binaries likely to be received from third parties or found in the wild.

As shown by our results in Tables 4 and 5, the AFL transform provides a much better proxy for actual performance of a binary rewriters than the NOP transform. This is true for at least two reasons. First, when applying the NOP transform many relative and absolute locations in a rewritten binary will continue to match their locations in the original binary because no attempt is made to modify the lifted code. This provides a great deal of grace for rewriters that missed code or symbols in the original binary because symbols treated as literals or as data in NOP transformed binaries remains sound surprisingly often. Second, the AFL test is stricter because the rewritten binary actually has to interact with the AFL++ harness to record a successful execution.

Every rewriter included in this evaluation except multiverse provides some out-of-the-box support for AFL++ instrumentation. ddisasm, retrowrite, and uroboros all produce assembly-level IR that an AFL++ provided tool can directly instrument. Similarly mctoll and reopt both produce LLVM IR that an AFL++ provided LLVM pass can directly instrument. Both egalito and zipr do not expose their proprietary IRs but do ship with an AFL++ instrumentation pass compatible with their frameworks.

Despite this broad support, only ddisasm, mctoll, retrowrite, and zipr successfully transform any of our test binaries for use with AFL++. In Egalito’s case, the included AFL++ transform requires a patched afl−fuzz program (Williams-King, n.d.c, n.d.b, n.d.a). Reopt appears to produce LLVM IR that is not suitable for transformation. Further, it appears reopt may only perform well on the NOP transform because it falls back to directly re-linking sections of the original binary when rewriting fails. Uroboros appears to fail to produce any functional AFL transformed binaries not due to any uniform systematic reason but simply because the rewritten assembly code is very brittle due to incorrect analyses during lifting.

### 4.2 Rewriting Success Rates by Compiler

In this section we present the success rates of our binary rewriters broken out by the compiler used to generate variants. Binary rewriting success is often depen-
dent on the compiler used to produce the input binary as many of the heuristics baked into rewriting tools target binary code generation logic or optimizations specific to certain compilers. For example, the Intel compiler (icx) in-lines data into the code section on Linux whereas Clang and GCC do not. As a result of this behavior and other ICX-specific optimizations, some binary rewriters have a significantly lower success rate against ICX-produced binaries.

The results restricted to GCC-compiled variants in are most similar to the aggregate results. This is unsurprising as GCC is the prototypical compiler for Linux systems and represents a middle ground in optimization aggressiveness between the relatively conservative Clang optimizations and the very aggressive Intel optimizations.

Interestingly, the success rate for Clang-compiled variants () across all tools is largely similar to but slightly higher than GCC’s success rate. This could be due to a number of factors including programs more frequently including GCC-only optimizations that prove difficult for binary rewriting tools, GCC leveraging non-standard ELF file format extensions that are not produced by clang, or GCC performing more aggressive optimizations than Clang in some cases.

Our ICX-compiled results are shown in . They vary widely from both GCC and Clang and also across our evaluated tools. DDiSasm performs better on ICX binaries generating an IR in 99% of cases and generating functional AFL rewrites 2% more frequently with these binaries than in aggregate. By contrast, Egalito’s NOP transform success rate drops for ICX-produced variants, mctoll, Multiverse, and Uroboros are unable to process any ICX binaries, and Retrowrite and Zipr both perform significantly worse on ICX binaries although they are still able to successfully generate functional AFL++ instrumented binaries in some cases.

Although we expected the tools to perform worst against ollvm compiled binaries, we were surprised to see that in most cases the binary rewriting success rate increased for these binaries. It is not clear if this is because those programs which could be compiled with ollvm represent the simpler end of our benchmark set, or if there is something about the ollvm transformations that are amenable to binary rewriting if not to traditional reverse engineering.

Table 6: Number and percentage of 1280 GCC-compiled x64 Linux binaries for which the rewriter successfully reaches task checkpoints and passes functional tests.

| Tool   | IR   | ELF   | Null Func. | AFL ELF | AFL Func. |
|--------|------|-------|------------|---------|-----------|
| ddisasm| 1237 | 1146  | 1100       | 1157    | 871       |
| %      | 96.64% | 89.53% | 85.94%     | 90.39%  | 68.05%    |
| egalito| 0    | 1257  | 235        | 1113    | 0         |
| %      | NA   | 98.20% | 18.36%     | 86.95%  | 0.00%     |
| mctoll | 16   | 16    | 16         | 16      | 16        |
### Table 7: Number and percentage of 1176 Clang-compiled x64 Linux binaries for which the rewriter successfully reaches task checkpoints and passes functional tests.

| Tool      | IR   | ELF  | Null Func. | AFL ELF | AFL Func. |
|-----------|------|------|------------|---------|-----------|
| %         | 1.25%| 1.25%| 1.25%      | 1.25%   | 1.25%     |
| multiverse| 0    | 438  | 176        | 0       | 0         |
| %         | NA   | 34.22%| 13.75%    | 0.00%   | 0.00%     |
| reopt     | 1168 | 874  | 387        | 0       | 0         |
| %         | 91.25%| 68.28%| 30.23%    | 0.00%   | 0.00%     |
| retrowrite| 308  | 129  | 124        | 126     | 99        |
| %         | 24.06%| 10.08%| 9.69%     | 9.84%   | 7.73%     |
| uroboros  | 150  | 92   | 16         | 92      | 0         |
| %         | 11.72%| 7.19% | 1.25%     | 7.19%   | 0.00%     |
| zipr      | 0    | 1188 | 1164       | 1030    | 674       |
| %         | NA   | 92.81%| 90.94%    | 80.47%  | 52.66%    |

### Table 8: Number and percentage of 646 ICX-compiled x64 Linux binaries for which the rewriter successfully reaches task checkpoints and passes functional tests.

| Tool       | IR   | ELF  | Null Func. | AFL ELF | AFL Func. |
|------------|------|------|------------|---------|-----------|
| ddisasm    | 1167 | 1034 | 984        | 1057    | 799       |
| %          | 99.23%| 87.93%| 83.67%    | 89.88%  | 67.94%    |
| egalito    | 0    | 1161 | 494        | 1052    | 0         |
| %          | NA   | 98.72%| 42.01%    | 89.46%  | 0.00%     |
| mctoll     | 11   | 11   | 11         | 11      | 11        |
| %          | 0.94%| 0.94%| 0.94%      | 0.94%   | 0.94%     |
| multiverse | 0    | 442  | 186        | 0       | 0         |
| %          | NA   | 37.59%| 15.82%    | 0.00%   | 0.00%     |
| reopt      | 1057 | 901  | 463        | 0       | 0         |
| %          | 89.88%| 76.62%| 39.37%    | 0.00%   | 0.00%     |
| retrowrite | 288  | 147  | 136        | 146     | 108       |
| %          | 24.49%| 12.50%| 11.56%    | 12.41%  | 9.18%     |
| uroboros   | 144  | 92   | 56         | 86      | 0         |
| %          | 12.24%| 7.82%| 4.76%      | 7.31%   | 0.00%     |
| zipr       | 0    | 1021 | 999        | 1010    | 664       |
| %          | NA   | 86.82%| 84.95%    | 85.88%  | 56.46%    |
### Table 9: Number and percentage of 244 Ollvm compiled and obfuscated x64 Linux binaries for which the rewriter successfully reaches task checkpoints and passes functional tests.

| Tool      | IR | ELF | Null Func. | AFL ELF | AFL Func. |
|-----------|----|-----|------------|---------|-----------|
| egalito   | 0  | 636 | 136        | 119     | 0         |
| %         | NA | 98.45% | 21.05% | 18.42% | 0.00%     |
| mctoll    | 0  | 0   | 0          | 0       | 0         |
| %         | 0.00% | 0.00% | 0.00% | 0.00% | 0.00%     |
| multiverse| 0  | 0   | 0          | 0       | 0         |
| %         | NA | 0.00% | 0.00% | 0.00% | 0.00%     |
| reopt     | 575 | 571 | 173        | 0       | 0         |
| %         | 89.01% | 88.39% | 26.78% | 0.00% | 0.00%     |
| retrowrite| 157 | 24  | 23         | 24      | 18        |
| %         | 24.30% | 3.72% | 3.56% | 3.72% | 2.79%     |
| uroboros  | 4  | 0   | 0          | 0       | 0         |
| %         | 0.62% | 0.00% | 0.00% | 0.00% | 0.00%     |
| zipr      | 0  | 622 | 340        | 479     | 144       |
| %         | NA | 96.28% | 52.63% | 74.15% | 22.29%    |

### 4.3 Analysis of Binary Rewriter Success

In this section, we investigate binary formatting options to determine if they are correlates for binary rewriter success. We collected features that may be relevant to binary rewriter performance and are readily available using readelf.
from standard binutils. Specifically we collect:

1. **Position independence**
   
   ```bash
   readelf -h $elf | grep Type | awk '{ print $2 }'
   ```

2. **Stripped or unstripped**
   
   ```bash
   readelf -SW $elf | grep -q .symtab \n   && echo unstripped || echo stripped
   ```

3. **Included sections**
   
   ```bash
   readelf -SW $elf | grep "^[[:digit:]]$" \n   | sed 's/^\./\./g; s/.*$/\\'
   ```

Note that for included sections we eliminate all sections which appeared in every one of our binaries (e.g., .text) and any section which appeared only in binaries from a single program (e.g., .gresource, gnome_calculator).

We collated the success and failure rate across these features for each tool against our corpus of variants considering both rewriting tasks (i.e., NOP and AFL). Then we identified the four most predictive features for rewriting success or failure of the AFL transform for each tool. These features are presented in . In many cases these features are expected and match the advertised capabilities of each tool. For example, retrowrite only supports relocatable (i.e., pi) and non-stripped (i.e., strip) binaries which are its two most predictive features for success.

Next we train a decision tree based on this feature collection to predict the likelihood of success of each rewriter against an example binary when using the AFL transform. Before training we use linear support vector classification to select the most discriminating features for that rewriter. The resulting decision trees are printed as Python code in Appendix 6.1. We evaluate the resulting decision tree using 70% of our binaries for training and reserving 30% for testing. The accuracy of the resulting tree is shown in .

Table 10: Decision tree accuracy predicting binary rewriting success based on simple binary features

| Rewriter   | NOP     | AFL     |
|------------|---------|---------|
| ddisasm    | 90.03%  | 81.47%  |
| egalito    | 87.15%  |         |
| mctoll     | 98.80%  | 98.80%  |
| multiverse | 97.80%  |         |
| reopt      | 67.82%  |         |
| retrowrite | 94.32%  | 93.02%  |
| uroboros   | 96.31%  |         |
| zipr       | 86.65%  | 79.98%  |
As shown in the resulting decision trees, despite their reliance on very simple binary features were very accurate in predicting the changes of tool success. We anticipate two benefits from this analysis. First, tool developers will have insight into properties of binaries that cause their rewriting tools to fail. Second, users can nearly instantaneously run a combination of readelf and our decision tree to see what tools, if any, will reliably transform a given target binary. This is useful when many binary rewriting tools can run for minutes and even hours on a single binary. The success of this simple machine learning model trained on simple inputs indicates promising new directions for the practical application of binary rewriting technology discussed in Section 5. The decision trees and the code used to build and train them are included in our publicly available artifact repository (Grammatech, n.d.).

### 4.4 Size of Rewritten Binaries

shows the size of rewritten binaries as a percentage of the size of the original. A value of 100% means that the rewritten binaries are exactly the same size as the originals, 50% means they are half the size of the originals, 200% means they are twice the size of the originals, and so on. The change in the size of binaries reflects the design decisions made by the rewriting engine and can impact the utility, efficiency, and potential use cases for the rewritten binary.

| Tool        | Rewritten subject size increase |
|-------------|---------------------------------|
| ddisasm     | 91.05%                          |
| egalito     | 168.45%                         |
| mctoll      | 128.22%                         |
| multiverse  | 871.76%                         |
| retrowrite  | 80.65%                          |
| uroboros    | 148.97%                         |
| zipr        | 139.94%                         |

In most cases the rewritten binary is close to or slightly larger than the original. To investigate the specific causes of size changes we collected the changes in size per section per rewriting tool in. Note that in many cases rewriting tools break elf section tables. In these cases bloaty (Google, n.d.), the tool we use to collect section size, is unable to determine sizes for that section in corresponding binaries. In nearly every rewriting tool the largest increase in size of the elf file is in unmapped bytes or bytes that are not accounted for by the section table. This is likely due to at least the following two factors. First, because any extra non-standard runtime harnesses or extra rewriting-specific supports are not properly entered into the section table of the rewritten binary. Second, binary rewriting tools are not penalized for dropping sections...
or breaking parts of the section header table that are not required for execution.

| Section       | ddisasm   | egalito   | mctoll   | multiverse | reopt | retrowrite | uroboros |
|---------------|-----------|-----------|----------|------------|-------|------------|----------|
| .got.plt      | 99.96%    | 100.08%   | 100%     | NA         | 100.38% | 100%       | 99.69%   |
| .data         | 100.42%   | 100.42%   | NA       | NA         | 100.02% | 100.16%    | 101.37%  |
| .dynamic      | 98.31%    | 64.95%    | 94.93%   | NA         | 100.01% | 101.46%    | 100.01%  |
| .rela.dyn     | 98.41%    | 1666.59%  | 100%     | NA         | 100.08% | 99.94%     | 97.61%   |
| .strtab       | 106.11%   | 89.53%    | 97.05%   | NA         | 98.94%  | 108.96%    | 104.05%  |
| .dynsym       | 95.24%    | 100.15%   | 100%     | NA         | 100.75% | 87.06%     | 99.58%   |
| .dynstr       | 95.50%    | 100.41%   | 100%     | NA         | 100.77% | 97.13%     | 99.83%   |
| .symtab       | 116.62%   | NA        | 96.61%   | NA         | 100.29% | 94.72%     | NA       |
| .eh_frame_hdr | 100.21%   | NA        | NA       | NA         | 99.70%  | 93.33%     | 100.93%  |
| .plt          | 99.93%    | 100.14%   | 100%     | NA         | 100.38% | 99.89%     | 99.90%   |
| .rela.plt     | 99.92%    | 99.94%    | NA       | NA         | 100.43% | 99.89%     | 100%     |
| .eh_frame     | 99.81%    | NA        | 98.27%   | NA         | 98.44%  | 93.33%     | 101.43%  |
| [ELF-Program-Headers] | 96.18%    | 94.24%    | 92.76%   | NA         | 94.47%  | 102.23     | 96.85%   |
| [ELF-Section-Headers] | 97.37%    | 72.16%    | 95.98%   | NA         | 103.67% | 93.48%     | 97.30%   |
| .rodata       | 100.07%   | 100.47%   | NA       | NA         | 100.00% | 100.05%    | 100.03%  |
| .text         | 99.18%    | 108.76%   | 103.63%  | NA         | 100.66% | 96.93%     | 97.51%   |
| [Unmapped]    | 130.21%   | 673.91%   | 350.39%  | NA         | 181.97% | 225.88%    | 165.30%  |

For ddisasm and retrowrite the rewritten binaries are slightly smaller on average. This is likely due to symbol and debug information being dropped by the rewriting process. For Egalito, mctoll, uroboros, and zipr the size of the binary increases by a non-trivial amount.

Multiverse is the outlier with rewritten binaries that are nearly nine times the size of the original. This is due to the defining design decision of Multiverse which is that it reassembles all possible disassemblies of the original binary, leading to much more code in the rewritten binary.

It is important to note that the percentages reported in report the size increase for a different domain of binaries for every tool. Specifically they are calculated for binaries the tool can successfully rewrite. As a result, comparing tools with respect to the code size increases in this table is not a direct comparison. Thus, we include to report comparative results for every pair of tools. For each pair of tools we report the relative size of the binaries in the intersection of those programs which are successfully rewritten by both tools. In each cell, the percentage of the successfully rewritten binary sizes by both tools are calculated as a ratio of the row tool to the column tool. For example, multiverse rewritten binaries are just over 9 times bigger on average than ddisasm rewritten binaries. An entry of “NA” indicates that no binaries were successfully rewritten by both tools.
Comparative size of rewritten binaries between rewriting tools. In each cell, the ratio of the rewritten sizes of those benchmark binaries successfully rewritten by both tools are given as the row tool as a percent of the size of the column tool. So, e.g., multiverse binaries are just over 9 times bigger than ddisasm rewritten binaries on average.

| Tool       | ddisasm | egalito | mctoll | multiverse | reopt | retrowrite | uroboros | zipr       |
|------------|---------|---------|--------|------------|-------|------------|----------|------------|
| ddisasm    | 100     | 194.341 | 99.4828| 937.2      | 67.987| 93.9901    | 157.054  |            |
| egalito    | 51.4561 | 100     | 189.775| 463.335    | 59.5564| 60.7094    | 82.2481  |            |
| mctoll     | 100.52  | 100     | 100    | 369.231    | 101.124| 101.124    | 118.198  |            |
| multiverse | 10.6701 | 21.5827 | 27.0833| 100        | 11.0182| 11.0182    | 16.0225  |            |
| reopt      | 92.6033 | 167.908 | 351.829| 854.065    | 87.0065| 87.0065    | 143.244  |            |
| retrowrite | 92.6033 | 164.719 | 98.8889| 907.586    | 114.934| 114.934    | 148.211  |            |
| uroboros   | 64.5098 | 95.5763 | 129.167| 567.148    | 56.2145| 56.2145    | 91.3966  |            |
| zipr       | 63.6723 | 121.583 | 84.6041| 624.122    | 69.8109| 69.8109    | 109.413  |            |

4.5 Binary Rewriter Performance

To accurately and successfully rewrite a binary executable requires significant static analysis. These analyses often scale super-linearly with the size of the program being rewritten. We summarize the average run time of each tool in .

Table 12: Average tool runtime in seconds and memory high-water mark across successfully rewritten binaries.

| Tool       | Runtime (seconds) | Memory high-water Mark (kbytes) |
|------------|-------------------|---------------------------------|
| ddisasm    | 746.79            | 3355465.52                     |
| egalito    | 454.40            | 10433233.07                    |
| mctoll     | 0.00              | 1405.30                        |
| multiverse | 1201.84           | 694814.23                      |
| reopt      | 169.89            | 4061695.00                     |
| retrowrite | 115.07            | 2008647.93                     |
| uroboros   | 19.17             | 93575.58                       |
| zipr       | 380.04            | 1305405.48                     |

As with rewritten program size, the reported averages are skewed because they are calculated across the set of binaries successfully rewritten by each tool. Thus, rewriters that successfully rewrite larger and more complicated binaries have an average that skews higher. To account for this we also present the comparative average in . In each cell, the comparative average tool runtime across successfully rewritten binaries by both tools is expressed as a percentage of the row tool to the column tool. For example, uroboros runtime is roughly 2.3% of the runtime of ddisasm. A significant trend observable in is that tools with higher success
rates tend to run longer than tools with low rewriting success rates. This is not surprising as successful tools perform more analyses and more detailed analyses. They also explicitly handle more portions of the ELF file and more edge cases. All of this takes time.

Comparative runtime in seconds between rewriting tools. In each cell, the ratio of the rewritten sizes of those benchmark binaries successfully rewritten by both tools are given as the row tool as a percent of the size of the column tool. So, e.g., uroboros runtime is roughly 2.3% of the runtime of ddisasm.

| Tool       | ddisasm | egalito | mctoll | multiverse | reopt | retrowrite | uroboros | zipr |
|------------|---------|---------|--------|------------|-------|------------|----------|------|
| ddisasm    | 100     | 163.637 | 3.61924e+08 | 439.571    | 563.515 | 4379.81    | 200.044  |      |
| egalito    | 61.1108 | 100     | 2.19759e+08 | 270.906    | 501.46  | 2123.71    | 128.836  |      |
| mctoll     | 2.76301e-05 | 4.55044e-05 | 100 | 2.25315e-05 | 0.000121456000306700141260177e-05 | 0.000306798 | 0.00141218 | 6.01777e-05 |
| multiverse | 234.958 | 549.3   | 4.43823e+08 | 753.241    | 1963.07 | 20446.2    | 863.876  |      |
| reopt      | 22.7494 | 36.9132 | 8.23357e+07 | 100        | 165.336 | 811.098    | 46.3087  |      |
| retrowrite | 17.7458 | 19.9418 | 3.25947e+07 | 60.483     | 33.4505 | 32.9835    | 6.01777e-05 |      |
| uroboros   | 2.28321 | 4.70874 | 7.08125e-06 | 0.489089   | 12.329  | 298.95     | 1594.57  | 100  |
| zipr       | 49.9891 | 77.6182 | 1.66174e+08 | 215.942    | 303.182 | 1594.57    | 100      |      |

4.6 Binary Rewriter Memory High-Water Mark

As with tool runtime, the memory requirements of a binary rewriter may make rewriting impractical in many circumstances. For a large binary the memory requirements will frequently outstrip the memory available on a standard server class machine. We present the average memory high-water mark during binary rewriting in and for the same reasons as above also present comparative memory high-water marks in . In each cell, the comparative memory high-water mark across successfully rewritten binaries by both tools is expressed as a percentage of the row tool to the column tool. For example, uroboros’ maximum memory consumption is roughly 2.7% of the maximum memory consumption of ddisasm. Again we see that successful tools require more resources during rewriting.

Average tool memory high-water mark in kilobytes for those binaries the tool was able to rewrite.

| Tool       | Memory high-water mark |
|------------|------------------------|
| ddisasm    | 3355465.5287081        |
| egalito    | 10433233.077615        |
| mctoll     | 1405.3086124402        |
| multiverse | 694814.23597679        |
| reopt      | 4061695                |
| retrowrite | 2008647.9376947        |
| uroboros   | 93575.588354773        |
Comparative memory high-water mark in kilobytes between rewriting tools. In each cell, the ratio of the rewritten sizes of those benchmark binaries successfully rewritten by both tools are given as the row tool as a percent of the size of the column tool. So, e.g., uroboros memory consumption roughly 2.7% of the memory consumption of ddisasm.

| Tool     | ddisasm | egalito | mctoll | multiverse | reopt | retrowrite | uroboros | zipr |
|----------|---------|---------|--------|------------|-------|------------|----------|------|
| ddisasm  | 100     | 31.8241 | 238771 | 362.347    | 82.6124 | 162.217    | 3631.61  | 261.96|
| egalito  | 314.228 | 100     | 741944 | 1431.48    | 259.7  | 489.282    | 11511.5  | 828.157|
| mctoll   | 0.0418812 | 0.0134781 | 100 | 0.229632 | 0.0345991 | 0.0874121 | 1.64368 | 0.111593|
| multiverse | 27.5979 | 6.98578 | 43547.9 | 100 | 18.6142 | 63.6278 | 822.128 | 104.691|
| reopt    | 121.047 | 38.506 | 289025 | 537.224    | 100    | 202.12     | 4336.39  | 318.145|
| retrowrite | 61.6458 | 20.4381 | 114401 | 157.164    | 49.4755 | 100        | 251.503  | 154.504|
| uroboros | 2.7536  | 0.868699 | 6083.9 | 12.1636    | 2.30607 | 39.7609    | 100      | 8.17977|
| zipr     | 38.1737 | 12.075 | 89611 | 95.5195    | 31.4322 | 64.7234    | 1222.53  | 100  |

### 4.7 Functionality Against Full Test Suite

For three benchmark programs with readily available test suites we check the degree to which successful execution of the Null Function test predicts successful execution of the complete test suite.\(^5\) Our results are presented in . In each cell we report the number of binaries that completely pass the full test suite and the number of binaries that pass the Null Function test as “full/null”. We report this for each binary rewriter as well as for the original input binaries files. There are up to 60 binaries for each program due to the multiple build options (e.g., compiler, optimization level, pie, stripped, etc.). We do not include ICX-compiled binaries due to the extra runtime dependencies they require that impose significant extra burden when running full test suites in the test environment.

Overall we find a weak correlation with only 258 rewritten programs passing their full test suite of the 395 rewritten programs that passed their Null Function tests. However, it is worth noting that some original binaries (i.e., inputs to the binary rewriter) that pass the Null Function test do not pass the full test suite (e.g., redis when compiled with −Ofast).

\(^5\)We report full results for only three benchmark programs due to the dearth of high-quality test suites for real-world programs and the high level of effort required for properly configuring them.
Table 13: Number of binaries passing their full test suite compared to the number of binaries passing the Null Function test.

| Tool    | lighttpd | nginx | redis |
|---------|----------|-------|-------|
| original| 30/30    | 60/60 | 26/30 |
| ddisasm | 0/30     | 60/60 | 26/30 |
| egalito | 18/18    | 18/18 | 10/10 |
| multiverse| 0/0    | 0/0   | 0/0   |
| reopt   | 2/19     | 4/60  | 2/8   |
| retrowrite| 0/9    | 16/26 | 0/0   |
| uroboros| 0/0      | 0/0   | 0/0   |
| zipr    | 28/30    | 58/58 | 22/30 |

Note that we disable one test in redis because it looks for a specific symbol in the stack trace. This is sufficiently internal that we believe it does not compromise program soundness for binary rewriters to change this behavior. Most otherwise correct rewrites do change this stack introspection behavior.

4.8Rewritten Binary Performance Against Full Test Suite

The performance of rewritten binaries is critical to many use cases for static binary rewriting. If performance degradation falls below that of dynamic binary rewriting then in many cases dynamic rewriting is a better alternative as it is able to leverage dynamic information and harnessing to more reliably execute the rewritten program. We report the average change in runtime and memory high-water mark for successfully rewritten programs as they run against their full test suite in . Only those rewriters which produced binaries capable of passing all tests are included. For each rewriter, the percentage change in average runtime and change in memory high-water mark is calculated only over successfully rewritten binaries. With the exception of Reopt-rewritten binaries which had resource consumption at least an order of magnitude over the original, runtime and memory consumption of the rewritten binaries is close to that of the original binary. This is especially true of the memory high-water mark.

Table 14: Performance of rewritten binaries when run against the full test suite.

| Tool   | Runtime (seconds) | Memory High-water Mark (kbytes) |
|--------|-------------------|---------------------------------|
| ddisasm| 109.43%           | 100.21%                         |
| egalito| 104.45%           | 99.85%                          |
| reopt  | 1324.66%          | 51937.17%                       |
| retrowrite | 103.84% | 100.17%                        |
Table 14: Performance of rewritten binaries when run against the full test suite.

| Tool | Success Rate 1 | Success Rate 2 |
|------|----------------|----------------|
| zipr | 102.50%        | 102.38%        |

## 5 Discussion

We identify several trends with respect to binary rewriter IR from our results. First, rewriting via LLVM IR appears to be infeasible given the current state of binary type analysis. Only one binary (the trivial hello-world) was successfully instrumented for AFL++ using an LLVM rewriter (mctoll). Additionally, non-trivial NOP-transformed binaries successfully produced with reopt had dramatically increased runtime and memory consumption as compared to the original. Second, direct rewriting as performed by Egalito and Zipr successfully produced executables even in the presence of analysis errors; however their output binaries also demonstrated a higher functional failure rate. Conversely, reassemblable disassemblers were more likely to raise errors during re-assembling and re-linking and thus fail to create an executable.

During our evaluation, we communicated with the developers of our evaluated tools to share our partial results and our benchmark set. Unsurprisingly, the best-performing tools in our evaluation, ddisasm and zipr, had sufficient development resources to respond to specific failures encountered in our work. Thus, their performance against this evaluation set likely outperforms their expected performance in general. This is indicative of a defining characteristic of binary rewriting at this point in time; binary rewriting is eminently practical in many particular cases that have been addressed and considered by tool developers, but impossible in the general case as the universe of binary formats and features is simply too large with too many edge cases to handle.

We believe that our evaluation indicates that practical applications of binary rewriting should be preceded by a scoping stage. In this stage, the target binary is classified as either “in scope” or “out of scope” for the binary rewriting tool(s) of interest. While scoping can be accomplished via traditional binary analysis, the high success rate demonstrated by our simple predictive model with trivially collected features shows that accurate scoping can be conducted with little effort. Further, the relative simplicity of our model implies that more reliable and potentially accurate predictive models are easily within reach. With such a model, users of binary rewriting tools can quickly ensure their target binaries meet the expectations of the available rewriting tools before initiating expensive binary rewriting tasks at scale. For binaries that are likely to fail during static rewriting, the user could either conserve their resources by forgoing binary rewriting or spend them employing more expensive techniques such as dynamic binary rewriting where necessary.
6 Conclusion

In this work, we presented a comparative evaluation of eight binary rewriting tools on two rewriting tasks across a corpus of 3344 variant binaries produced using three compilers and 34 source programs. Our evaluation measured the performance of the tools themselves as well as the performance and soundness of the rewritten binaries they produce. In general, our evaluation indicates that binary rewriters that avoid lifting to machine-independent IRs (e.g., LLVM IR) were most successful in terms of generality and reliability. Additionally, we identified binary features that are predictive of rewriting success and showed that a simple decision tree model trained on these features can accurately predict whether a particular tool can rewrite a target binary. The findings and artifacts contributed by this evaluation are intended to support users and developers of binary rewriting tools and drive rewriter adoption and maturity.

Artifact Availability

We have made the full set of artifacts generated in this work including our evaluation infrastructure, corpus of test binaries, predictive models, and the evaluated tools publicly available at: https://gitlab.com/GrammaTech/lifter-eval (Grammatech, n.d.).

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8 Appendix

8.1 Predictive Models

Listing 1: Decision tree to predict the success of AFL instrumentation with ddisasm. Accuracy of 81.47%.

```python
def ddisasm_tree(note_abi_tag, interp, strip, rela_plt, pi):
    if not note_abi_tag:
        if not interp:
            if strip:
                if interp:
                    return {'FAIL': 50.0, 'PASS': 112.0}
                else:  # not interp
                    return {'FAIL': 37.0, 'PASS': 33.0}
            else:  # not strip
                return {'FAIL': 12.0, 'PASS': 0.0}
        else:  # interp
            if rela_plt:
                if interp:
                    return {'FAIL': 47.0, 'PASS': 910.0}
                else:  # not interp
                    return {'FAIL': 92.0, 'PASS': 368.0}
            else:  # not rela_plt
                return {'FAIL': 10.0, 'PASS': 0.0}
    else:  # note_abi_tag
        if not strip:
            return {'FAIL': 53.0, 'PASS': 0.0}
        else:  # strip
            if not interp:
                if interp:
                    return {'FAIL': 64.0, 'PASS': 11.0}
                else:  # not interp
                    return {'FAIL': 22.0, 'PASS': 3.0}
            else:  # interp
                if not pi:
                    return {'FAIL': 53.0, 'PASS': 0.0}
```
if interp:
    return {'FAIL': 215.0, 'PASS': 168.0}
else:  # not interp
    return {'FAIL': 82.0, 'PASS': 38.0}
else:  # pi
    return {'FAIL': 0.0, 'PASS': 15.0}

Listing 2: Decision tree to predict the success of AFL instrumentation with mctoll. Accuracy of 98.80%.

def mctoll_tree(note.abi_tag, strip, pi, got.plt, data.rel.ro, symtab, note.gnu.build_id):
    if note.abi_tag:
        return {'FAIL': 1672.0, 'PASS': 0.0}
    else:  # not note.abi_tag
        if strip:
            if not pi:
                if not got.plt:
                    if data.rel.ro:
                        if not symtab:
                            return {'FAIL': 5.0, 'PASS': 6.0}
                        else:  # symtab
                            return {'FAIL': 3.0, 'PASS': 0.0}
                    else:  # not data.rel.ro
                        if symtab:
                            return {'FAIL': 21.0, 'PASS': 4.0}
                        else:  # not symtab
                            return {'FAIL': 3.0, 'PASS': 0.0}
                else:  # got.plt
                    return {'FAIL': 17.0, 'PASS': 0.0}
            else:  # not pi
                if symtab:
                    if got.plt:
                        return {'FAIL': 21.0, 'PASS': 0.0}
                    else:  # not got.plt
                        if not note.gnu.build_id:
                            return {'FAIL': 98.0, 'PASS': 6.0}
                        else:  # note.gnu.build_id
                            return {'FAIL': 80.0, 'PASS': 3.0}
                    else:  # not symtab
                        return {'FAIL': 69.0, 'PASS': 0.0}
                else:  # not strip
                    return {'FAIL': 334.0, 'PASS': 0.0}

Listing 3: Decision tree to predict the success of AFL instrumentation with retrowrite. Accuracy of 93.02%.
Listing 4: Decision tree to predict the success of AFL instrumentation with zipr.
Accuracy of 79.98%.

```python
def retrowrite_tree(note.gnu.build_id, pi, got.plt,
                    note.abi_tag, rela.plt,
                    data.rel.ro, interp):
    if note.gnu.build_id:
        if not pi:
            return {'FAIL': 531.0, 'PASS': 0.0}
        else: # pi
            if got.plt:
                return {'FAIL': 169.0, 'PASS': 0.0}
            else: # not got.plt
                if note.abi_tag:
                    if rela.plt:
                        if data.rel.ro:
                            return {'FAIL': 36.0, 'PASS': 50.0}
                        else: # not data.rel.ro
                            return {'FAIL': 78.0, 'PASS': 64.0}
                    else: # not rela.plt
                        return {'FAIL': 8.0, 'PASS': 0.0}
                else: # not note.abi_tag
                    if data.rel.ro:
                        return {'FAIL': 64.0, 'PASS': 32.0}
                    else: # data.rel.ro
                        return {'FAIL': 11.0, 'PASS': 0.0}
        else: # not note.gnu.build_id
            return {'FAIL': 1166.0, 'PASS': 0.0}

    if not got.plt:
        if got.plt:
            if interp:
                if interp:
                    return {'FAIL': 19.0, 'PASS': 114.0}
            else: # not interp
                if rela.plt:
                    return {'FAIL': 82.0, 'PASS': 36.0}
                else: # rela.plt
                    return {'FAIL': 4.0, 'PASS': 0.0}
        else: # not got.plt
```
else: # interp
    return {'FAIL': 17.0, 'PASS': 113.0}
else: # not interp
    if not pi:
        return {'FAIL': 30.0, 'PASS': 103.0}
    else: # pi
        return {'FAIL': 26.0, 'PASS': 108.0}
else: # not got.plt
    if interp:
        if not pi:
            return {'FAIL': 10.0, 'PASS': 26.0}
        else: # pi
            return {'FAIL': 7.0, 'PASS': 24.0}
    else: # not interp
        if pi:
            if rela.plt:
                return {'FAIL': 14.0, 'PASS': 0.0}
            else: # not rela.plt
                if not note.gnu.build_id:
                    if not pi:
                        return {'FAIL': 29.0, 'PASS': 5.0}
                    else: # pi
                        return {'FAIL': 21.0, 'PASS': 10.0}
                else: # note.gnu.build_id
                    return {'FAIL': 13.0, 'PASS': 0.0}
            else: # not pi
                return {'FAIL': 0.0, 'PASS': 15.0}
    else: # got.plt
        if not pi:
            if interp:
                if got.plt:
                    if not note.abi_tag:
                        if not note.gnu.build_id:
                            return {'FAIL': 4.0, 'PASS': 10.0}
                        else: # note.gnu.build_id
                            return {'FAIL': 11.0, 'PASS': 76.0}
                    else: # note.abi_tag
                        if not note.gnu.build_id:
                            return {'FAIL': 0.0, 'PASS': 14.0}
                        else: # note.gnu.build_id
                            return {'FAIL': 7.0, 'PASS': 29.0}
                else: # not got.plt
                    return {'FAIL': 0.0, 'PASS': 16.0}
            else: # not interp
                if not note.abi_tag:
                    if not strip:
if got.plt:
    if not note.gnu.build_id:
        return {'FAIL': 41.0, 'PASS': 133.0}
    else:  # note.gnu.build_id
        return {'FAIL': 10.0, 'PASS': 45.0}
else:  # not got.plt
    if not note.gnu.build_id:
        return {'FAIL': 23.0, 'PASS': 43.0}
    else:  # note.gnu.build_id
        return {'FAIL': 41.0, 'PASS': 34.0}
else:  # strip
    return {'FAIL': 21.0, 'PASS': 0.0}
else:  # note.abi_tag
    if got.plt:
        if not strip:
            if not note.gnu.build_id:
                return {'FAIL': 63.0, 'PASS': 55.0}
            else:  # note.gnu.build_id
                return {'FAIL': 31.0, 'PASS': 27.0}
        else:  # strip
            return {'FAIL': 4.0, 'PASS': 0.0}
    else:  # not got.plt
        if rela.plt:
            return {'FAIL': 6.0, 'PASS': 0.0}
        else:  # not rela.plt
            if not note.gnu.build_id:
                return {'FAIL': 32.0, 'PASS': 9.0}
            else:  # note.gnu.build_id
                return {'FAIL': 30.0, 'PASS': 6.0}
        else:  # pi
            if not note.gnu.build_id:
                if note.abi_tag:
                    return {'FAIL': 30.0, 'PASS': 0.0}
                else:  # not note.abi_tag
                    if got.plt:
                        if not note.abi_tag:
                            if interp:
                                return {'FAIL': 13.0, 'PASS': 1.0}
                            else:  # not interp
                                return {'FAIL': 134.0, 'PASS': 39.0}
                        else:  # note.abi_tag
                            if interp:
                                return {'FAIL': 8.0, 'PASS': 3.0}
                            else:  # not interp
                                return {'FAIL': 98.0, 'PASS': 21.0}
                        else:  # not got.plt
if interp:
    return {'FAIL': 0.0, 'PASS': 9.0}
else: # not interp
    if not note.abi_tag:
        return {'FAIL': 40.0, 'PASS': 22.0}
    else: # note.abi_tag
        return {'FAIL': 37.0, 'PASS': 7.0}
else: # note.gnu.build_id
    return {'FAIL': 355.0, 'PASS': 0.0}