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OverHAuL

2

Harnessing Automation for C Libraries via LLMs

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4

July, 2025

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Preface

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35 Acknowledgments

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1 Introduction

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1.1 Motivation

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127 2 Background

128 quarto definitions

129 2.1 Fuzzing

130 What is fuzzing [1].

131 terminology: fuzz campaign, harness, driver, target, corpus

132 Why fuzz?

133 2.1.1 Fuzzing examples

134 Heartbleed [2], shellshock [3].

135 2.1.2 Fuzzer engines

136 C/C++: AFL [4] & AFL++ [4, pp. ++]. LibFuzzer [5].

137 Python: Atheris [6].

138 Java, Rust etc...

139 An example of a fuzz target/harness can be seen in Listing 2.1 [5].

140 OSS-Fuzz: 2016, after heartbleed.

141 2.2 Large Language Models (LLMs)

142 Transformers [7], 2017–2025. ChatGPT/OpenAI history & context. Claude, Llama (1–3) etc.

Listing 2.1 A simple function that does something interesting if it receives the input “HI!”.

```
1 cat << EOF > test_fuzzer.cc
2 #include <stdint.h>
3 #include <stddef.h>
4 extern "C" int LLVMFuzzerTestOneInput(const uint8_t *data, size_t size) {
5     if (size > 0 && data[0] == 'H')
6         if (size > 1 && data[1] == 'I')
7             if (size > 2 && data[2] == '!')
8                 __builtin_trap();
9     return 0;
10 }
11 EOF
12 # Build test_fuzzer.cc with asan and link against libFuzzer.
13 clang++ -fsanitize=address,fuzzer test_fuzzer.cc
14 # Run the fuzzer with no corpus.
15 ./a.out
```

143 2.2.1 Prompting

144 Prompting techniques.

- 145 1. Zero-shot.
- 146 2. One-shot.
- 147 3. Chain of Thought [8].
- 148 4. ReACt [9].
- 149 5. Tree of Thoughts [10].

150 Comparison, strengths weaknesses etc. [11].

151 [12]

152 2.2.2 LLM Programming Libraries (?)

153 Langchain & LangGraph, LlamaIndex [13]–[15]. DSPy [16].

154 Comparison, relevance to our usecase.

155 2.3 Neurosymbolic AI

156 **TODO** [17]–[22].

3 Related work

Automated testing, automated fuzzing and automated harness creation have a long research history. Still, a lot of ground remains to be covered until true automation of these tasks is achieved. Until the introduction of transformers [7] and the 2020’s boom of commercial GPTs [23], automation regarding testing and fuzzing was mainly attempted through static and dynamic program analysis methods. These approaches are still utilized, but the fuzzing community has shifted almost entirely to researching the incorporation and employment of LLMs in the last half decade, in the name of automation [24]–[33].

3.1 Previous projects

3.1.1 KLEE

KLEE [34] is a seminal and widely cited symbolic execution engine introduced in 2008 by Cadar et al. It was designed to automatically generate high-coverage test cases for programs written in C, using symbolic execution to systematically explore the control flow of a program. KLEE operates on the LLVM [35] bytecode representation of programs, allowing it to be applied to a wide range of C programs compiled to the LLVM intermediate representation.

Instead of executing a program on concrete inputs, KLEE performs symbolic execution—that is, it runs the program on symbolic inputs, which represent all possible values simultaneously. At each conditional branch, KLEE explores both paths by forking the execution and accumulating path constraints (i.e., logical conditions on input variables) along each path. This enables it to traverse many feasible execution paths in the program, including corner cases that may be difficult to reach through random testing or manual test creation.

When an execution path reaches a terminal state (e.g., a program exit, an assertion failure, or a segmentation fault), KLEE uses a constraint solver to compute concrete input values that satisfy the accumulated constraints for that path. These values form a test case that will deterministically drive the program down that specific path when executed concretely.

3.1.2 IRIS

IRIS [24] is a 2025 open-source neurosymbolic system for static vulnerability analysis. Given a codebase and a list of user-specified Common Weakness Enumerations (CWEs), it analyzes source code to identify paths that may correspond to known vulnerability classes. IRIS combines symbolic analysis—such as control- and data-flow reasoning—with neural models trained to generalize over

code patterns. It outputs candidate vulnerable paths along with explanations and CWE references. The system operates on full repositories and supports extensible CWE definitions.

3.1.3 FUDGE

FUDGE [33] is a closed-source tool, made by Google, for automatic harness generation of C and C++ projects based on existing client code. It was used in conjunction with and in the improvement of Google’s OSS-Fuzz [36]. Being deployed inside Google’s infrastructure, FUDGE continuously examines Google’s internal code repository, searching for code that uses external libraries in a meaningful and “fuzzable” way (i.e. predominantly for parsing). If found, such code is **sliced** [37], per FUDGE, based on its Abstract Syntax Tree (AST) using LLVM’s Clang tool [35]. The above process results in a set of abstracted mostly-self-contained code snippets that make use of a library’s calls and/or API. These snippets are later **synthesized** into the body of a fuzz driver, with variables being replaced and the fuzz input being utilized. Each is then injected in an LLVMFuzzerTestOneInput function and finalized as a fuzzing harness. A building and evaluation phase follows for each harness, where they are executed and examined. Every passing harness along with its evaluation results is stored in FUDGE’s database, reachable to the user through a custom web-based UI.

3.1.4 UTopia

UTopia [29] (stylized UTOPIA) is another open-source automatic harness generation framework. Aside from the library code, It operates solely on user-provided unit tests since, according to Jeong, Jang, Yi, *et al.* [29], they are a resource of complete and correct API usage examples containing working library set-ups and tear-downs. Additionally, each of them are already close to a fuzz target, in the sense that they already examine a single and self-contained API usage pattern. Each generated harness follows the same data flow of the originating unit test. Static analysis is employed to figure out what fuzz input placement would yield the most results. It is also utilized in abstracting the tests away from the syntactical differences between testing frameworks, along with slicing and AST traversing using Clang.

3.1.5 FuzzGen

Another project of Google is FuzzGen [32], this time open-source. Like FUDGE, it leverages existing client code of the target library to create fuzz targets for it. FuzzGen uses whole-system analysis, through which it creates an *Abstract API Dependence Graph* (A^2DG). It uses the latter to automatically generate LibFuzzer-compatible harnesses. For FuzzGen to work, the user needs to provide both client code and/or tests for the API and the API library’s source code as well. FuzzGen uses the client code to infer the *correct usage* of the API and not its general structure, in contrast to FUDGE. FuzzGen’s workflow can be divided into three phases: **1. API usage inference.** By consuming and analyzing client code and tests that concern the library under test, FuzzGen recognizes which functions belong to the library and learns its correct API usage patterns. This process is done with the help of Clang. To test if a function is actually a part of the library, a sample program is created that uses it. If the program compiles successfully, then the function is indeed a valid API call. **2. A^2DG construction mechanism.** For all the existing API calls, FuzzGen

225 builds an A²DG to record the API usages and infers its intended structure. After completion, this
226 directed graph contains all the valid API call sequences found in the client code corpus. It is built
227 in a two-step process: First, many smaller A²DGs are created, one for each root function per client
228 code snippet. Once such graphs have been created for all the available client code instances, they
229 are combined to formulate the master A²DG. This graph can be seen as a template for correct usage
230 of the library. **3. Fuzzer generator.** Through the A²DG, a fuzzing harness is created. Contrary to
231 FUDGE, FuzzGen does not create multiple “simple” harnesses but a single complex one with the
232 goal of covering the whole of the A²DG. In other words, while FUDGE fuzzes a single API call at a
233 time, FuzzGen’s result is a single harness that tries to fuzz the given library all at once through
234 complex API usage.

235 3.1.6 OSS-Fuzz

236 OSS-Fuzz [36], [38] is a continuous, scalable and distributed cloud fuzzing solution for critical
237 and prominent open-source projects. Developers of such software can submit their projects to
238 OSS-Fuzz’s platform, where its harnesses are built and constantly executed. This results in multiple
239 bug findings that are later disclosed to the primary developers and are later patched.

240 OSS-Fuzz started operating in 2016, an initiative in response to the Heartbleed vulnerability [2],
241 [39], [40]. Its hope is that through more extensive fuzzing such errors could be caught and corrected
242 before having the chance to be exploited and thus disrupt the public digital infrastructure. So far,
243 it has helped uncover over 10,000 security vulnerabilities and 36,000 bugs across more than 1,000
244 projects, significantly enhancing the quality and security of major software like Chrome, OpenSSL,
245 and systemd.

246 A project that’s part of OSS-Fuzz must have been configured as a ClusterFuzz [41] project. Cluster-
247 Fuzz is the fuzzing infrastructure that OSS-Fuzz uses under the hood and depends on Google Cloud
248 Platform services, although it can be hosted locally. Such an integration requires setting up a build
249 pipeline, fuzzing jobs and expects a Google Developer account. Results are accessible through a
250 web interface. ClusterFuzz, and by extension OSS-Fuzz, supports fuzzing through LibFuzzer, AFL++,
251 Honggfuzz and FuzzTest—successor to Centipede— with the last two being Google projects [5],
252 [42]–[44]. C, C++, Rust, Go, Python and Java/JVM projects are supported.

253 3.1.7 OSS-Fuzz-Gen

254 OSS-Fuzz-Gen (OFG) [27], [45] is Google’s current State-Of-The-Art (SOTA) project regarding
255 automatic harness generation through LLMs. It’s purpose is to improve the fuzzing infrastructure of
256 open-source projects that are already integrated into OSS-Fuzz. Given such a project, OSS-Fuzz-Gen
257 uses its preexisting fuzzing harnesses and modifies them to produce new ones. Its architecture
258 can be described as follows: 1. With an OSS-Fuzz project’s GitHub repository link, OSS-Fuzz-
259 Gen iterates through a set of predefined build templates and generates potential build scripts
260 for the project’s harnesses. 2. If any of them succeed they are once again compiled, this time
261 through fuzz-introspector [46]. The latter constitutes a static analysis tool, with fuzzer developers
262 specifically in mind. 3. Build results, old harness and fuzz-introspector report are included in a
263 template-generated prompt, through which an LLM is called to generate a new harness. 4. The

264 newly generated fuzz target is compiled and if it is done so successfully it begins execution inside
265 OSS-Fuzz’s infrastructure.

266 This method proved meaningful, with code coverage in fuzz campaigns increasing thanks to the
267 new generated fuzz drivers. In the case of [47], line coverage went from 38% to 69% without any
268 manual interventions [45].

269 In 2024, OSS-Fuzz-Gen introduced an experimental feature for generating harnesses in previously
270 unfuzzed projects [48]. The code for this feature resides in the `experimental/from_scratch` directory
271 of the project’s GitHub repository [27], with the latest known working commit being 171aac2 and
272 the latest overall commit being four months ago.

273 3.1.8 AutoGen

274 AutoGen [25] is a closed-source tool that generates new fuzzing harnesses, given only the library
275 code and documentation. It works as following: The user specifies the function for which a harness
276 is to be generated. AutoGen gathers information for this function—such as the function body,
277 used header files, function calling examples—from the source code and documentation. Through
278 specific prompt templates containing the above information, an LLM is tasked with generating a
279 new fuzz driver, while another is tasked with generating a compilation command for said driver. If
280 the compilation fails, both LLMs are called again to fix the problem, whether it was on the driver’s
281 or command’s side. This loop iterates until a predefined maximum value or until a fuzz driver is
282 successfully generated and compiled. If the latter is the case, it is then executed. If execution errors
283 exist, the LLM responsible for the driver generation is used to correct them. If not, the pipeline has
284 terminated and a new fuzz driver has been successfully generated.

285 3.2 Differences

286 OverHAuL differs, in some way, with each of the aforementioned works. Firstly, although KLEE
287 and IRIS [24], [34] tackle the problem of automated testing and both IRIS and OverHAuL can be
288 considered neurosymbolic AI tools, the similarities end there. None of them utilize LLMs the same
289 way we do—with KLEE not utilizing them by default, as it precedes them chronologically—and
290 neither are automating any part of the fuzzing process.

291 When it comes to FUDGE, FuzzGen and UTopia [29], [32], [33], all three depend on and demand
292 existing client code and/or unit tests. On the other hand, OverHAuL requires only the bare minimum:
293 the library code itself. Another point of difference is that in contrast with OverHAuL, these tools
294 operate in a linear fashion. No feedback is produced or used in any step and any point failure
295 results in the termination of the entire run.

296 OverHAuL challenges a common principle of these tools, stated explicitly in FUDGE’s paper [33]:
297 “Choosing a suitable fuzz target (still) requires a human”. OverHAuL chooses to let the LLM, instead
298 of the user, explore the available functions and choose one to target in its fuzz driver.

299 OSS-Fuzz-Gen [27] can be considered a close counterpart of OverHAuL, and in some ways it is.
300 A lot of inspiration was gathered from it, like for example the inclusion of static analysis and its

usage in informing the LLM. Yet, OSS-Fuzz-Gen has a number of disadvantages that make it in some cases an inferior option. For one, OFG is tightly coupled with the OSS-Fuzz platform [36], which even on its own creates a plethora of issues for the common developer. To integrate their project into OSS-Fuzz, they would need to: Transform it into a ClusterFuzz project [41] and take time to write harnesses for it. Even if these prerequisites are carried out, it probably would not be enough. Per OSS-Fuzz’s documentation [38]: “To be accepted to OSS-Fuzz, an open-source project must have a significant user base and/or be critical to the global IT infrastructure”. This means that OSS-Fuzz is a viable option only for a small minority of open-source developers and maintainers. One countermeasure of the above shortcoming would be for a developer to run OSS-Fuzz-Gen locally. This unfortunately proves to be an arduous task. As it is not meant to be used standalone, OFG is not packaged in the form of a self-contained application. This makes it hard to setup and difficult to use interactively. Like in the case of FUDGE, OFG’s actions are performed linearly. No feedback is utilized nor is there graceful error handling in the case of a step’s failure. Even in the case of the experimental feature for bootstrapping unfuzzed projects, OFG’s performance varies heavily. During experimentation, a lot of generated harnesses were still wrapped either in Markdown backticks or `tags, or were accompanied with explanations inside the generated .c source file. Even if code was formatted correctly, in many cases it missed necessary headers for compilation or used undeclared functions.`

Lastly, the closest counterpart to OverHAuL is AutoGen [25]. Their similarity stands in the implementation of a feedback loop between LLM and generated harness. However, most other implementation decisions remain distinct. One difference regards the fuzzed function. While AutoGen requires a target function to be specified by the user in which it narrows during its whole run, OverHAuL delegates this to the LLM, letting it explore the codebase and decide by itself the best candidate. Another difference lies in the need—and the lack of—of documentation. While AutoGen requires it to gather information for the given function, OverHAuL leans into the role of a developer by reading the related code and comments and thus avoiding any mismatches between documentation and code. Finally, the LLMs’ input is built based on predefined prompt templates, a technique also present in OSS-Fuzz-Gen. OverHAuL operates one abstraction level higher, leveraging DSPy [16] for programming instead of prompting the LLMs used.

In conclusion, OverHAuL constitutes an *open-source* tool that offers new functionality by offering a straightforward installation process, packaged as a self-contained Python package with minimal external dependencies. It also introduces novel approaches compared to previous work by

1. Implementing a feedback mechanism between harness generation, compilation, and evaluation phases,
2. Using autonomous ReAct agents capable of codebase exploration,
3. Leveraging a vector store for code consumption and retrieval.

TODO να συμπεριλάβω και τα:

3.2.1 IntelliGen [[20250711141156]]

SAMPLE

IntelliGen: Automatic Fuzz Driver Synthesis Based on Vulnerability Heuristics Zhang et al. (2021) present **IntelliGen**, a system for automatically synthesizing fuzz drivers by statically identifying potentially vulnerable entry-point functions within C projects. Implemented using LLVM, IntelliGen focuses on improving fuzzing efficiency by targeting code more likely to contain memory safety issues, rather than exhaustively fuzzing all available functions.

The system comprises two main components: the **Entry Function Locator** and the **Fuzz Driver Synthesizer**. The Entry Function Locator analyzes the project’s abstract syntax tree (AST) and classifies functions based on heuristics that indicate vulnerability. These include pointer dereferencing, calls to memory-related functions (e.g., `memcpy`, `memset`), and invocation of other internal functions. Functions that score highly on these metrics are prioritized for fuzz driver generation. The guiding insight is that entry points with fewer argument checks and more direct memory operations expose more useful program logic for fuzz testing.

The Fuzz Driver Synthesizer then generates harnesses for these entry points. For each target function, it synthesizes a `LLVMFuzzerTestOneInput` function that invokes the target with arguments derived from the fuzzer input. This process involves inferring argument types from the source code and ensuring that runtime behavior does not violate memory safety—thus avoiding invalid inputs that would cause crashes unrelated to genuine bugs.

IntelliGen stands out by integrating static vulnerability estimation into the driver generation pipeline. Compared to prior tools like FuzzGen and FUDGE, it uses a more targeted, heuristic-based selection of functions, increasing the likelihood that fuzzing will exercise meaningful and vulnerable code paths.

3.2.2 CKGFuzzer [[20250711203054]]

SAMPLE

CKGFuzzer is a fuzzing framework designed to automate the generation of effective fuzz drivers for C/C++ libraries by leveraging static analysis and large language models. Its workflow begins by parsing the target project along with any associated library APIs to construct a code knowledge graph. This involves two primary steps: first, parsing the abstract syntax tree (AST), and second, performing interprocedural program analysis. Through this process, CKGFuzzer extracts essential program elements such as data structures, function signatures, function implementations, and call relationships.

Using the knowledge graph, CKGFuzzer then identifies and queries meaningful API combinations, focusing on those that are either frequently invoked together or exhibit functional similarity. It generates candidate fuzz drivers for these combinations and attempts to compile them. Any compilation errors encountered during this phase are automatically repaired using heuristics and domain knowledge. A dynamically updated knowledge base, constructed from prior library usage patterns, guides both the generation and repair processes.

Once the drivers are successfully compiled, CKGFuzzer executes them while monitoring code coverage at the file level. It uses coverage feedback to iteratively mutate underperforming API combinations, refining them until new execution paths are discovered or a preset mutation budget is exhausted.

380 Finally, any crashes triggered during fuzzing are subjected to a reasoning process based on chain-
381 of-thought prompting. To help determine their severity and root cause, CKGFuzzer consults an
382 LLM-generated knowledge base containing real-world examples of vulnerabilities mapped to known
383 Common Weakness Enumeration (CWE) entries.

384 3.2.3 PromptFuzz [[20250713225436]]

385 SAMPLE

386 Lyu et al. (2024) introduce PromptFuzz [49], a system for automatically generating fuzz drivers using
387 LLMs, with a novel focus on **prompt mutation** to improve coverage. The system is implemented
388 in Rust and targets C libraries, aiming to explore more of the API surface with each iteration.

389 The workflow begins with the random selection of API functions, extracted from header file
390 declarations. These functions are used to construct initial prompts that instruct the LLM to generate
391 a simple program utilizing the API. Each generated program is compiled, executed, and monitored
392 for code coverage. Programs that fail to compile or violate runtime checks (e.g., sanitizers) are
393 discarded.

394 A key innovation in PromptFuzz is **coverage-guided prompt mutation**. Instead of mutating
395 generated code directly, PromptFuzz mutates the LLM prompts—selecting new combinations of API
396 functions to target unexplored code paths. This process is guided by a **power scheduling** strategy
397 that prioritizes underused or promising API functions based on feedback from previous runs.

398 Once an effective program is produced, it is transformed into a fuzz driver by replacing constants
399 and arguments with variables derived from the fuzzer input. Multiple such drivers are embedded
400 into a single harness, where the input determines which program variant to execute, typically via a
401 case-switch construct.

402 Overall, PromptFuzz demonstrates that prompt-level mutation enables more effective exploration
403 of complex APIs and achieves better coverage than direct code mutations, offering a compelling
404 direction for LLM-based automated fuzzing systems.

405 4 Overview

- 406 1. How is it different?
 - 407 2. What does it offer?
 - 408 3. Example uses
 - 409 4. Scope of Usage
-
- 410 1. In what contexts does it work?
 - 411 2. Prerequisites

412 4.1 Architecture

- 413 • **System diagram**
- 414 • Main Library Architecture/Structure
- 415 • LLM usage
- 416 – Prompting techniques used (callback to Section [2.2.1](#)).
- 417 • Static analysis
- 418 • Code localization(?)
- 419 • Fuzzers
- 420 • GitHub Workflow/Usage
- 421 • “Iteration budget”

422 5 Evaluation

423 5.1 Benchmarks

424 Results from integration with 10/100 open-source C/C++ projects.

425 5.2 Performance

426 5.3 Issues

427 5.4 Future work

428 5.4.1 Technical future work

429 5.4.2 Architectural future work/extensions

- 430 1. Build system
- 431 2. More (static) analysis tools integrations
- 432 3. General *localization* problem

6 Future Work

The prototype implementation of OverHAuL offers a compelling demonstration of its potential to automate the fuzzing process for open-source libraries, providing tangible benefits to developers and maintainers alike. This initial version successfully validates the core design principles underpinning OverHAuL, showcasing its ability to streamline and enhance the software testing workflow through automated generation of fuzz drivers using large language models. Nevertheless, while these foundational capabilities lay a solid groundwork, numerous avenues exist for further expansion, refinement, and rigorous evaluation to fully realize the tool’s potential and adapt to evolving challenges in software quality assurance.

6.1 Enhancements to Core Features

Enhancing OverHAuL’s core functionality represents a primary direction for future development. First, expanding support to encompass a wider array of build systems commonly employed in C and C++ projects—such as GNU Make, CMake, Meson, and Ninja [50]–[53]—would significantly broaden the scope of libraries amenable to automated fuzzing using OverHAuL. This advancement would enable OverHAuL to scale effectively and be applied to larger, more complex codebases, thereby increasing its practical utility and impact.

Second, integrating additional fuzzing engines beyond LibFuzzer stands out as a strategic enhancement. Incorporation of widely adopted fuzzers like AFL++ [44] could diversify the fuzzing strategies available to OverHAuL, while exploring more experimental tools such as GraphFuzz [28] may pioneer specialized approaches for certain code patterns or architectures. Multi-engine support would also facilitate extending language coverage, for instance by incorporating fuzzers tailored to other programming ecosystems—for example, Google’s Atheris for Python projects [6]. Such versatility would position OverHAuL as a more universal fuzzing automation platform.

Third, the evaluation component of OverHAuL presents an opportunity for refinement through more sophisticated analysis techniques. Beyond the current criteria, incorporating dynamic metrics such as differential code coverage tracking between generated fuzz harnesses would yield deeper insights into test quality and coverage completeness. This quantitative evaluation could guide iterative improvements in fuzz driver generation and overall testing effectiveness.

Finally, OverHAuL’s methodology could be extended to leverage existing client codebases and unit tests in addition to the library source code itself, resources that for now OverHAuL leaves untapped. Inspired by approaches like those found in FUDGE and FuzzGen [32], [33], this enhancement would enable the tool to exploit programmer-written usage scenarios as seeds or contexts, potentially generating more meaningful and targeted fuzz inputs. Incorporating these richer information sources would likely improve the efficacy of fuzzing campaigns and uncover subtler bugs.

6.2 Experimentation with Large Language Models and Data Representation

OverHAuL’s reliance on large language models (LLMs) invites comprehensive experimentation with different providers and architectures to assess their comparative strengths and limitations. Conducting empirical evaluations across leading models—such as OpenAI’s o1 and o3 families and Anthropic’s Claude Opus 4—will provide valuable insights into their capabilities, cost-efficiency, and suitability for fuzz driver synthesis. Additionally, specialized code-focused LLMs, including generative and fill-in models like Codex-1 and CodeGen [54]–[56], merit exploration due to their targeted optimization for source code generation and understanding.

Another dimension worthy of investigation concerns the granularity of code chunking employed during the given project’s code processing stage. Whereas the current approach partitions code at the function level, experimenting with more nuanced segmentation strategies—such as splitting per step inside a function, as a finer-grained technique—could improve the semantic coherence of stored representations and enhance retrieval relevance during fuzz driver generation. This line of inquiry has the potential to optimize model input preparation and ultimately improve output quality.

6.3 Comprehensive Evaluation and Benchmarking

To thoroughly establish OverHAuL’s effectiveness, extensive large-scale evaluation beyond the initial 10-project corpus is imperative. Applying the tool to repositories indexed in the clib package manager [57], which encompasses hundreds of C libraries, would test scalability and robustness across diverse real-world settings. Such a broad benchmark would also enable systematic comparisons against state-of-the-art automated fuzzing frameworks like OSS-Fuzz-Gen and AutoGen, elucidating OverHAuL’s relative strengths and identifying areas for improvement [25], [27].

Complementing broad benchmarking, detailed ablation studies dissecting the contributions of individual pipeline components and algorithmic choices will yield critical insights into what drives OverHAuL’s performance. Understanding the impact of each module will guide targeted optimizations and support evidence-based design decisions.

Furthermore, an economic analysis exploring resource consumption—such as API token usage and associated monetary costs—relative to fuzzing effectiveness would be valuable for assessing the practical viability of integrating LLM-based fuzz driver generation into continuous integration processes.

6.4 Practical Deployment and Community Engagement

From a usability perspective, embedding OverHAuL within a GitHub Actions workflow represents a practical and impactful enhancement, enabling seamless integration with developers’ existing toolchains and continuous integration pipelines. This would promote wider adoption by reducing barriers to entry and fostering real-time feedback during code development cycles.

503 Additionally, establishing a mechanism to generate and submit automated pull requests (PRs) to the
504 maintainers of fuzzed libraries—highlighting detected bugs and proposing patches—would not only
505 validate OverHAuL’s findings but also contribute tangible improvements to open-source software
506 quality. This collaborative feedback loop epitomizes the symbiosis between automated testing tools
507 and the open-source community. As an initial step, developing targeted PRs for the projects where
508 bugs were discovered during OverHAuL’s development would help facilitate practical follow-up
509 and improvements.

510 7 Discussion

511 more powerful llms -> better results

512 open source libraries might have been in the training data results for closed source libraries could
513 be worse this could be mitigated with llm fine-tuning

514 8 Conclusion

515 Recap

516 8.1 Acknowledgements

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