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OverHAuL

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Harnessing Automation for C Libraries via LLMs

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Preface

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27 Acknowledgments

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97 1 Introduction

98 1.1 Motivation

- 99 • Memory unsafety is and will be prevalent
- 100 • Software is safe until it's not
- 101 • Humans make mistakes
- 102 • Humans now use Large Language Models (LLMs) to write software
- 103 • LLMs make mistakes [1]

104 Result: Bugs exist

105 1.2 Goal

106 A system that:

- 107 1. Takes a bare C project as input
- 108 2. Generates a new fuzzing harness from scratch using LLMs
- 109 3. Compiles it
- 110 4. Executes it and evaluates it

111 1.3 Preview of following sections (rename)

2 Background

2.1 Fuzz Testing

Fuzzing is an automated software-testing technique in which a *Program Under Test* (PUT) is executed with (pseudo-)random inputs in the hope of exposing undefined behavior. When such behavior manifests as a crash, hang, or memory-safety violation, the corresponding input constitutes a *test-case* that reveals a bug and often a vulnerability [2]. In essence, fuzzing is a form of adversarial, penetration-style testing carried out by the defender before the adversary has an opportunity to do so. Interest in the technique surged after the publication of three practitioner-oriented books in 2007–2008 [3]–[5].

Historically, the term was coined by Miller et al. in 1990, who used “fuzz” to describe a program that “generates a stream of random characters to be consumed by a target program” [6]. This informal usage captured the essence of what fuzzing aims to do: stress test software by bombarding it with unexpected inputs to reveal bugs. To formalize this concept, we adopt Manes et al.’s rigorous definitions [2]:

Definition 2.1 (Fuzzing). Fuzzing is the execution of a Program Under Test (PUT) using input(s) sampled from an input space (the *fuzz input space*) that protrudes the expected input space of the PUT.

This means fuzzing involves running the target program on inputs that go beyond those it is typically designed to handle, aiming to uncover hidden issues. An individual instance of such execution—or a bounded sequence thereof—is called a *fuzzing run*. When these runs are conducted systematically and at scale with the specific goal of detecting violations of a security policy, the activity is known as *fuzz testing* (or simply *fuzzing*):

Definition 2.2 (Fuzz Testing). Fuzz testing is the use of fuzzing to test whether a PUT violates a security policy.

This distinction highlights that fuzz testing is fuzzing with an explicit focus on security properties and policy enforcement. Central to managing this process is the *fuzzer engine*, which orchestrates the execution of one or more fuzzing runs as part of a *fuzz campaign*. A fuzz campaign represents a concrete instance of fuzz testing tailored to a particular program and security policy:

Definition 2.3 (Fuzzer, Fuzzer Engine). A fuzzer is a program that performs fuzz testing on a PUT.

Definition 2.4 (Fuzz Campaign). A fuzz campaign is a specific execution of a fuzzer on a PUT with a specific security policy.

Throughout each execution within a campaign, a *bug oracle* plays a critical role in evaluating the program’s behavior to determine whether it violates the defined security policy:

Definition 2.5 (Bug Oracle). A bug oracle is a component (often inside the fuzzer) that determines whether a given execution of the PUT violates a specific security policy.

In practice, bug oracles often rely on runtime instrumentation techniques, such as monitoring for fatal POSIX signals (e.g., SIGSEGV) or using sanitizers like AddressSanitizer (ASan) [7]. Tools like LibFuzzer [8] commonly incorporate such instrumentation to reliably identify crashes or memory errors during fuzzing.

Most fuzz campaigns begin with a set of *seeds*—inputs that are well-formed and belong to the PUT’s expected input space—called a *seed corpus*. These seeds serve as starting points from which the fuzzer generates new test cases by applying transformations or mutations, thereby exploring a broader input space:

Definition 2.6 (Seed). An input given to the PUT that is mutated by the fuzzer to produce new test cases. During a fuzz campaign (Definition 2.4) all seeds are stored in a seed *pool* or *corpus*.

The process of selecting an effective initial corpus is crucial because it directly impacts how quickly and thoroughly the fuzzer can cover the target program’s code. This challenge—studied as the *seed-selection problem*—involves identifying seeds that enable rapid discovery of diverse execution paths and is non-trivial [9]. A well-chosen seed set often accelerates bug discovery and improves overall fuzzing efficiency.

2.1.1 Motivation

The purpose of fuzzing relies on the assumption that there are bugs within every program, which are waiting to be discovered. Therefore, a systematic approach should find them sooner or later.

— OWASP Foundation [10]

Fuzz testing offers several tangible benefits:

1. **Early vulnerability discovery:** Detecting defects during development is cheaper and safer than addressing exploits in production.
2. **Adversary-parity:** Performing the same randomised stress that attackers employ allows defenders to pre-empt zero-days.
3. **Robustness and correctness:** Beyond security, fuzzing exposes logic errors and stability issues in complex, high-throughput APIs (e.g., decompressors) even when inputs are *expected* to be well-formed.
4. **Regression prevention:** Re-running a corpus of crashing inputs as part of continuous integration ensures that fixed bugs remain fixed.

2.1.1.1 Success Stories

Heartbleed (CVE-2014-0160) [11], [12] arose from a buffer over-read¹ in OpenSSL [13] introduced on 1 February 2012 and unnoticed until 1 April 2014. Post-mortem analyses showed that a simple fuzz campaign exercising the TLS heartbeat extension would have revealed the defect almost immediately [14].

Likewise, the *Shellshock* (or *Bashdoor*) family of bugs in GNU Bash [15] enabled arbitrary command execution on many UNIX systems. While the initial flaw was fixed promptly, subsequent bug variants were discovered by Google’s Michał Zalewski using his own fuzzer [16] in late 2014 [17].

On the defensive tooling side, the security tool named *Mayhem*—developed by the company of the same name—has since been adopted by the US Air Force, the Pentagon, Cloudflare, and numerous open-source communities. It has found and facilitated the remediation of thousands of previously unknown vulnerabilities [18].

These cases underscore the central thesis of fuzz testing: exhaustive manual review is infeasible, but scalable stochastic exploration reliably surfaces the critical few defects that matter most.

2.1.2 Methodology

As previously discussed, fuzz testing of a program under test (PUT) is typically conducted using a dedicated fuzzing engine (see Definition 2.3). Among the most widely adopted fuzzers for C and C++ projects and libraries are AFL [16]—which has since evolved into AFL++ [19]—and LibFuzzer [8]. Within the OverHAuL framework, LibFuzzer is preferred owing to its superior suitability for library fuzzing, whereas AFL++ predominantly targets executables and binary fuzzing.

2.1.2.1 LibFuzzer

LibFuzzer [8] is an in-process, coverage-guided evolutionary fuzzing engine primarily designed for testing libraries. It forms part of the LLVM ecosystem [20] and operates by linking directly with the library under evaluation. The fuzzer delivers mutated input data to the library through a designated fuzzing entry point, commonly referred to as the *fuzz target*.

Definition 2.7 (Fuzz target). A function that accepts a byte array as input and exercises the application programming interface (API) under test using these inputs [8]. This construct is also known as a *fuzz driver*, *fuzzer entry point*, or *fuzzing harness*.

For the remainder of this thesis, the terms presented in Definition 2.7 will be used interchangeably.

To effectively validate an implementation or library, developers are required to author a fuzzing harness that invokes the target library’s API functions utilizing the fuzz-generated inputs. This harness serves as the principal interface for the fuzzer and is executed iteratively, each time with mutated input designed to maximize code coverage and uncover defects. To comply with LibFuzzer’s interface requirements, a harness must conform to the following function signature:

¹<https://xkcd.com/1354/>

Listing 2.1 This function receives the fuzzing input via a pointer to an array of bytes (`Data`) and its associated size (`Size`). Efficiency in fuzzing is achieved by invoking the API of interest within the body of this function, thereby allowing the fuzzer to explore a broad spectrum of behavior through systematic input mutation.

```
1 int LLVMFuzzerTestOneInput(const uint8_t *Data, size_t Size) {  
2     DoSomethingInterestingWithData(Data, Size);  
3     return 0;  
4 }
```

211 A more illustrative example of such a harness is provided in Listing 2.2.

Listing 2.2 This example demonstrates a minimal harness that triggers a controlled crash upon receiving `HI!` as input.

```
1 // test_fuzzer.cpp  
2 #include <stdint.h>  
3 #include <stddef.h>  
4  
5 extern "C" int LLVMFuzzerTestOneInput(const uint8_t *data, size_t size) {  
6     if (size > 0 && data[0] == 'H')  
7         if (size > 1 && data[1] == 'I')  
8             if (size > 2 && data[2] == '!')  
9                 __builtin_trap();  
10    return 0;  
11 }
```

212 To compile and link such a harness with LibFuzzer, the Clang compiler—also part of the LLVM
213 project [20]—must be used alongside appropriate compiler flags. For instance, compiling the harness
214 in Listing 2.2 can be achieved as shown in Listing 2.3.

215 2.1.2.2 AFL and AFL++

216 *American Fuzzy Lop* (AFL) [16], developed by Michał Zalewski, is a seminal fuzzer targeting C and
217 C++ applications. Its core methodology relies on instrumented binaries to provide edge coverage
218 feedback, thereby guiding input mutation towards unexplored program paths. AFL supports several
219 emulation backends including QEMU [21]—an open-source CPU emulator facilitating fuzzing on
220 diverse architectures—and Unicorn [22], a lightweight multi-platform CPU emulator. While AFL
221 established itself as a foundational tool within the fuzzing community, its successor AFL++ [19]
222 incorporates numerous enhancements and additional features to improve fuzzing efficacy.

223 AFL operates by ingesting seed inputs from a specified directory (`seeds_dir`), applying mutations,
224 and then executing the target binary to discover novel execution paths. Execution can be initiated
225 using the following command-line syntax:

Listing 2.3 This example illustrates the compilation and execution workflow necessary for deploying a LibFuzzer-based fuzzing harness.

```
1 # Compile test_fuzzer.cc with AddressSanitizer and link against LibFuzzer.
2 clang++ -fsanitize=address,fuzzer test_fuzzer.cc
3 # Execute the fuzzer without any pre-existing seed corpus.
4 ./a.out
```

```
1 ./afl-fuzz -i seeds_dir -o output_dir -- /path/to/tested/program
```

226 AFL is capable of fuzzing both black-box and instrumented binaries, employing a fork-server
227 mechanism to optimize performance. It additionally supports persistent mode execution as well
228 as modes leveraging QEMU and Unicorn emulators, thereby providing extensive flexibility for
229 different testing environments.

230 Although AFL is traditionally utilized for fuzzing standalone programs or binaries, it is also capable
231 of fuzzing libraries and other software components. In such scenarios, rather than implementing
232 the LLVMFuzzerTestOneInput style harness, AFL can use the standard main() function as the fuzzing
233 entry point. Nonetheless, AFL also accommodates integration with LLVMFuzzerTestOneInput-based
234 harnesses, underscoring its adaptability across varied fuzzing use cases.

235 2.1.3 Challenges in Adoption

236 Despite its potential for uncovering software vulnerabilities, fuzzing remains a relatively underuti-
237 lized testing technique compared to more established methodologies such as Test-Driven Develop-
238 ment (TDD). This limited adoption can be attributed, in part, to the substantial initial investment
239 required to design and implement appropriate test harnesses that enable effective fuzzing processes.
240 Furthermore, the interpretation of fuzzing outcomes—particularly the identification, diagnostic
241 analysis, and prioritization of program crashes—demands considerable resources and specialized
242 expertise. These factors collectively pose significant barriers to the widespread integration of
243 fuzzing within standard software development and testing practices.

244 2.2 Large Language Models

245 Natural Language Processing (NLP), a subfield of Artificial Intelligence (AI), has a rich and ongoing
246 history that has evolved significantly since its beginning in the 1990s [23], [24]. Among the most
247 notable—and recent—advancements in this domain are Large Language Models (LLMs), which have
248 transformed the landscape of NLP and AI in general.

249 At the core of many LLMs is the attention mechanism, which was introduced by Bahdanau et
250 al. in 2014 [25]. This pivotal innovation enabled models to focus on relevant parts of the input
251 sequence when making predictions, significantly improving language understanding and generation

tasks. Building on this foundation, the Transformer architecture was proposed by Vaswani et al. in 2017 [26]. This architecture has become the backbone of most contemporary LLMs, as it efficiently processes sequences of data, capturing long-range dependencies without being hindered by sequential processing limitations.

One of the first major breakthroughs utilizing the Transformer architecture was BERT (Bidirectional Encoder Representations from Transformers), developed by Devlin et al. in 2019 [27]. BERT’s bi-directional understanding allowed it to capture the context of words from both directions, which improved the accuracy of various NLP tasks. Following this, the Generative Pre-trained Transformer (GPT) series, initiated by OpenAI with the original GPT model in 2018 [28], further pushed the boundaries. Subsequent iterations, including GPT-2 [29], GPT-3 [30], and the most current GPT-4 [31], have continued to enhance performance by scaling model size, data, and training techniques.

In addition to OpenAI’s contributions, other significant models have emerged, such as Claude, DeepSeek-R1 and the Llama series (1 through 3) [32]–[34]. The proliferation of LLMs has sparked an active discourse about their capabilities, applications, and implications in various fields.

2.2.1 Biggest GPTs

User-facing LLMs are generally categorized between closed-source and open-source models. Closed-source LLMs like ChatGPT, Claude, and Gemini [32], [35], [36] represent commercially developed systems often optimized for specific tasks without public access to their underlying weights. In contrast, open-source models², including the Llama series [34] and Deepseek [33], provide researchers and practitioners with access to model weights, allowing for greater transparency and adaptability.

2.2.2 Prompting

Interaction with LLMs typically occurs through chat-like interfaces, a process commonly referred to as *prompting*. A critical aspect of effective engagement with LLMs is the usage of different prompting strategies, which can significantly influence the quality and relevance of the generated outputs. Various approaches to prompting have been developed and studied, including zero-shot and few-shot prompting. In zero-shot prompting, the model is expected to perform a specific task without any examples, while in few-shot prompting, the user provides a limited number of examples to guide the model’s responses [30].

To enhance performance on more complex tasks, several advanced prompting techniques have emerged. One notable strategy is the *Chain of Thought* approach [37], which entails presenting the model with sample thought processes for solving a given task. This method encourages the model to generate more coherent and logical reasoning by mimicking human-like cognitive pathways. A refined variant of this approach is the *Tree of Thoughts* technique [38], which enables the LLM

²The term “open-source” models is somewhat misleading, since these are better termed as *open-weights* models. While their weights are publicly available, their training data and underlying code are often proprietary. This terminology reflects community usage but fails to capture the limitations of transparency and accessibility inherent in these models.

to explore multiple lines of reasoning concurrently, thereby facilitating the selection of the most promising train of thought for further exploration.

In addition to these cognitive strategies, Retrieval-Augmented Generation (RAG) [39] is another innovative technique that enhances the model’s capacity to provide accurate information by incorporating external knowledge not present in its training dataset. RAG operates by integrating the LLM with an external storage system—often a vector store containing relevant documents—that the model can query in real-time. This allows the LLM to pull up pertinent and/or proprietary information in response to user queries, resulting in more comprehensive and accurate answers.

Moreover, the ReAct framework [40], which stands for Reasoning and Acting, empowers LLMs by granting access to external tools. This capability allows LLM instances to function as intelligent agents that can interact meaningfully with their environment through user-defined tools. For instance, a ReAct tool could be a function that returns a weather forecast based on the user’s current location. In this scenario, the LLM can provide accurate and truthful predictions, thereby mitigating risks associated with hallucinated responses.

2.2.3 LLMs for Coding

The impact of LLMs in software development in recent years is apparent, with hundreds of LLM-assistance extensions and Integrated Development Environments (IDEs) being published. Notable instances include tools like GitHub Copilot and IDEs such as Cursor, which leverage LLM capabilities to provide developers with coding suggestions, auto-completions, and even real-time debugging assistance [41], [42]. Such innovations have introduced a layer of interaction that enhances productivity and fosters a more intuitive coding experience. Simultaneously, certain LLMs are trained themselves with the code-generation task in mind [43]–[45].

One exemplary product of this innovation is *vibecoding* and the no-code movement, which describe the development of software by only prompting and tasking an LLM, i.e. without any actual programming required by the user. This constitutes a showcase of how LLMs can be harnessed to elevate the coding experience by supporting developers as they navigate complex programming tasks [46]. By analyzing the context of the code being written, these sophisticated models can provide contextualized insights and relevant snippets, effectively streamlining the development process. Developers can benefit from reduced cognitive load, as they receive suggestions that not only cater to immediate coding needs but also promote adherence to best practices and coding standards.

Despite these advancements, it is crucial to recognize the inherent limitations of LLMs when applied to software development. While they can help in many aspects of coding, they are not immune to generating erroneous outputs—a phenomenon often referred to as “hallucination”. Hallucinations occur when LLMs produce information that is unfounded or inaccurate, which can stem from several factors, including the limitations of their training data and the constrained context window within which they operate. As LLMs generate code suggestions based on the patterns learned from vast datasets, they may inadvertently propose solutions that do not align with the specific requirements of a task or that utilize outdated programming paradigms.

Moreover, the challenge of limited context windows can lead to suboptimal suggestions. LLMs generally process a fixed amount of text when generating responses, which can impact their ability to fully grasp the nuances of complex coding scenarios. This may result in outputs that lack the necessary depth and specificity required for successful implementation. As a consequence, developers must exercise caution and critically evaluate the suggestions offered by these models, as reliance on them without due diligence could lead to the introduction of bugs or other issues in the code.

2.2.4 LLMs for Fuzzing

While large language models (LLMs) demonstrate significant potential in enhancing the software development process, the challenges highlighted in Section 2.2.3 become even more pronounced and troublesome when these models are employed to generate fuzzing harnesses. The task of writing a fuzzing harness inherently demands an in-depth comprehension of both the library being tested and the intricate interactions expected among its various components. This level of understanding is often beyond the capabilities of LLMs, primarily due to their context window limitations, which restrict the amount of information they can effectively process and retain during code generation.

In addition to this issue, the risk of error-prone code produced by LLMs further complicates the fuzzing workflow. When a crash occurs during the fuzzing process, it becomes imperative for developers to ascertain that the root cause of the failure is not attributable to deficiencies or bugs within the harness itself. This additional layer of verification adds to the cognitive load placed upon developers, potentially detracting from their ability to focus on testing and improving the underlying software.

To enhance the reliability of LLM-generated harnesses in fuzzing contexts, it is essential that these generated artifacts undergo thorough evaluation and validation through programmatic means. This involves the implementation of systematic techniques that assess the accuracy and robustness of the generated code, ensuring that it aligns with the expected behavior of the components it is intended to interact with. This strategy can be conceptualized within the framework of Neurosymbolic AI (Section 2.3), which seeks to integrate the strengths of neural networks with symbolic reasoning capabilities. By marrying these two paradigms, it may be possible to improve the reliability and efficacy of LLMs in the creation of fuzzing harnesses, ultimately leading to a more seamless integration of automated testing methodologies into the software development lifecycle.

2.3 Neurosymbolic AI

Neurosymbolic AI (NeSy AI) represents a groundbreaking fusion of neural network methodologies with symbolic execution techniques and tools, providing a multi-faceted approach to overcoming the inherent limitations of traditional AI paradigms [47], [48]. This innovative synthesis seeks to combine the strengths of both neural networks, which excel in pattern recognition and data-driven learning, and symbolic systems, which offer structured reasoning and interpretability. By integrating these two approaches, NeSy AI aims to create cognitive models that are not only more accurate but also more robust in problem-solving contexts.

363 At its core, NeSy AI facilitates the development of AI systems that are capable of understanding
364 and interpreting feedback in real-world scenarios [49]. This characteristic is particularly significant
365 in the current landscape of artificial intelligence, where LLMs are predominant. In this context,
366 NeSy AI is increasingly viewed as a critical solution to pressing issues related to explainability,
367 attribution, and reliability in AI systems [50], [51]. These challenges are essential for ensuring
368 that AI systems can be trusted and effectively utilized in various applications, from business to
369 healthcare.

370 The burgeoning field of neurosymbolic AI is still in its nascent stages, with ongoing research and
371 development actively exploring its potential to enhance attribution methodologies within large
372 language models. By addressing these critical challenges, NeSy AI can significantly contribute to
373 the broader landscape of trustworthy AI systems, allowing for more transparent and accountable
374 decision-making processes [47], [50], [51].

375 Moreover, the application of neurosymbolic AI within the domain of fuzzing is gaining traction,
376 paving the way for innovative explorations. This integration of LLMs with symbolic systems opens
377 up new avenues for research. Currently, there are only a limited number of tools that support such
378 hybrid approaches (Chapter 3). Among these, OverHAuL constitutes a Neuro[Symbolic] tool, as
379 classified by Henry Kautz’s taxonomy [52], [53]. This means that the neural model—specifically the
380 LLM—can leverage symbolic reasoning tools—in this case a source code explorer (Chapter 7)—to
381 augment its reasoning capabilities. This symbiotic relationship enhances the overall efficacy and
382 versatility of LLMs for fuzzing harnesses generation, demonstrating the profound potential held by
383 the fusion of neural and symbolic methodologies.

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 [26] and the 2020’s boom of commercial GPTs [35], 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 [54]–[63].

3.1 Previous Projects

3.1.1 KLEE

KLEE [64] 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 [20] 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 [54] 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 [63] 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 [65]. 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** [66], per FUDGE, based on its Abstract Syntax Tree (AST) using LLVM’s Clang tool [20]. 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 [59] (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.* [59], 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 [62], 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

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

462 3.1.6 IntelliGen

463 SAMPLE

464 Zhang et al. present IntelliGen [67], a system for automatically synthesizing fuzz drivers by statically
465 identifying potentially vulnerable entry-point functions within C projects. Implemented using
466 LLVM, IntelliGen focuses on improving fuzzing efficiency by targeting code more likely to contain
467 memory safety issues, rather than exhaustively fuzzing all available functions.

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

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

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

484 3.1.7 CKGFuzzer

485 SAMPLE

486 CKGFuzzer [68] is a fuzzing framework designed to automate the generation of effective fuzz drivers
487 for C/C++ libraries by leveraging static analysis and large language models. Its workflow begins by
488 parsing the target project along with any associated library APIs to construct a code knowledge
489 graph. This involves two primary steps: first, parsing the abstract syntax tree (AST), and second,

490 performing interprocedural program analysis. Through this process, CKGFuzzer extracts essential
491 program elements such as data structures, function signatures, function implementations, and call
492 relationships.

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

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

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

507 3.1.8 PromptFuzz

508 SAMPLE

509 Lyu et al. (2024) introduce PromptFuzz [69], a system for automatically generating fuzz drivers using
510 LLMs, with a novel focus on **prompt mutation** to improve coverage. The system is implemented
511 in Rust and targets C libraries, aiming to explore more of the API surface with each iteration.

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

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

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

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

3.1.9 OSS-Fuzz

OSS-Fuzz [65], [70] is a continuous, scalable and distributed cloud fuzzing solution for critical and prominent open-source projects. Developers of such software can submit their projects to OSS-Fuzz’s platform, where its harnesses are built and constantly executed. This results in multiple bug findings that are later disclosed to the primary developers and are later patched.

OSS-Fuzz started operating in 2016, an initiative in response to the Heartbleed vulnerability [11], [12], [14]. Its hope is that through more extensive fuzzing such errors could be caught and corrected before having the chance to be exploited and thus disrupt the public digital infrastructure. So far, it has helped uncover over 10,000 security vulnerabilities and 36,000 bugs across more than 1,000 projects, significantly enhancing the quality and security of major software like Chrome, OpenSSL, and systemd.

A project that’s part of OSS-Fuzz must have been configured as a ClusterFuzz [71] project. ClusterFuzz is the fuzzing infrastructure that OSS-Fuzz uses under the hood and depends on Google Cloud Platform services, although it can be hosted locally. Such an integration requires setting up a build pipeline, fuzzing jobs and expects a Google Developer account. Results are accessible through a web interface. ClusterFuzz, and by extension OSS-Fuzz, supports fuzzing through LibFuzzer, AFL++, Honggfuzz and FuzzTest—successor to Centipede— with the last two being Google projects [8], [19], [72], [73]. C, C++, Rust, Go, Python and Java/JVM projects are supported.

3.1.10 OSS-Fuzz-Gen

OSS-Fuzz-Gen (OFG) [57], [74] is Google’s current State-Of-The-Art (SOTA) project regarding automatic harness generation through LLMs. It’s purpose is to improve the fuzzing infrastructure of open-source projects that are already integrated into OSS-Fuzz. Given such a project, OSS-Fuzz-Gen uses its preexisting fuzzing harnesses and modifies them to produce new ones. Its architecture can be described as follows: 1. With an OSS-Fuzz project’s GitHub repository link, OSS-Fuzz-Gen iterates through a set of predefined build templates and generates potential build scripts for the project’s harnesses. 2. If any of them succeed they are once again compiled, this time through fuzz-introspector [75]. The latter constitutes a static analysis tool, with fuzzer developers specifically in mind. 3. Build results, old harness and fuzz-introspector report are included in a template-generated prompt, through which an LLM is called to generate a new harness. 4. The newly generated fuzz target is compiled and if it is done so successfully it begins execution inside OSS-Fuzz’s infrastructure.

This method proved meaningful, with code coverage in fuzz campaigns increasing thanks to the new generated fuzz drivers. In the case of [76], line coverage went from 38% to 69% without any manual interventions [74].

In 2024, OSS-Fuzz-Gen introduced an experimental feature for generating harnesses in previously unfuzzed projects [77]. The code for this feature resides in the `experimental/from_scratch` directory of the project’s GitHub repository [57], with the latest known working commit being 171aac2 and the latest overall commit being four months ago.

3.1.11 AutoGen

AutoGen [55] is a closed-source tool that generates new fuzzing harnesses, given only the library code and documentation. It works as following: The user specifies the function for which a harness is to be generated. AutoGen gathers information for this function—such as the function body, used header files, function calling examples—from the source code and documentation. Through specific prompt templates containing the above information, an LLM is tasked with generating a new fuzz driver, while another is tasked with generating a compilation command for said driver. If the compilation fails, both LLMs are called again to fix the problem, whether it was on the driver’s or command’s side. This loop iterates until a predefined maximum value or until a fuzz driver is successfully generated and compiled. If the latter is the case, it is then executed. If execution errors exist, the LLM responsible for the driver generation is used to correct them. If not, the pipeline has terminated and a new fuzz driver has been successfully generated.

3.2 Differences

OverHAuL differs, in some way, with each of the aforementioned works. Firstly, although KLEE and IRIS [54], [64] tackle the problem of automated testing and both IRIS and OverHAuL can be considered neurosymbolic AI tools, the similarities end there. None of them utilize LLMs the same way we do—with KLEE not utilizing them by default, as it precedes them chronologically—and neither are automating any part of the fuzzing process.

When it comes to FUDGE, FuzzGen and UTopia [59], [62], [63], all three depend on and demand existing client code and/or unit tests. On the other hand, OverHAuL requires only the bare minimum: the library code itself. Another point of difference is that in contrast with OverHAuL, these tools operate in a linear fashion. No feedback is produced or used in any step and any point failure results in the termination of the entire run.

OverHAuL challenges a common principle of these tools, stated explicitly in FUDGE’s paper [63]: “Choosing a suitable fuzz target (still) requires a human”. OverHAuL chooses to let the LLM, instead of the user, explore the available functions and choose one to target in its fuzz driver.

OSS-Fuzz-Gen [57] can be considered a close counterpart of OverHAuL, and in some ways it is. 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 [65], 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 [71] 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 [70]: “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.

606 No feedback is utilized nor is there graceful error handling in the case of a step’s failure. Even
607 in the case of the experimental feature for bootstrapping unfuzzed projects, OFG’s performance
608 varies heavily. During experimentation, a lot of generated harnesses were still wrapped either in
609 Markdown backticks or `<code>` tags, or were accompanied with explanations inside the generated
610 .c source file. Even if code was formatted correctly, in many cases it missed necessary headers for
611 compilation or used undeclared functions.

612 Lastly, the closest counterpart to OverHAuL is AutoGen [55]. Their similarity stands in the
613 implementation of a feedback loop between LLM and generated harness. However, most other
614 implementation decisions remain distinct. One difference regards the fuzzed function. While
615 AutoGen requires a target function to be specified by the user in which it narrows during its
616 whole run, OverHAuL delegates this to the LLM, letting it explore the codebase and decide by
617 itself the best candidate. Another difference lies in the need—and the lack of—of documentation.
618 While AutoGen requires it to gather information for the given function, OverHAuL leans into the
619 role of a developer by reading the related code and comments and thus avoiding any mismatches
620 between documentation and code. Finally, the LLMs’ input is built based on predefined prompt
621 templates, a technique also present in OSS-Fuzz-Gen. OverHAuL operates one abstraction level
622 higher, leveraging DSPy [78] for programming instead of prompting the LLMs used.

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

- 626 1. Implementing a feedback mechanism between harness generation, compilation, and evalua-
627 tion phases,
- 628 2. Using autonomous ReAct agents capable of codebase exploration,
- 629 3. Leveraging a vector store for code consumption and retrieval.

4 OverHAuL’s Design

In this thesis we present *OverHAuL* (**H**arness **A**utomation with **L**LMs), a neurosymbolic AI tool that automatically generates fuzzing harnesses for C libraries through LLM agents. In its core, OverHAuL is comprised by three LLM ReAct agents [40]—each with its own responsibility and scope—and a vector store index reserving the given project’s analyzed codebase. An overview of OverHAuL’s process is presented in Figure 4.1. The objective of OverHAuL is to streamline the process of fuzz testing for C libraries. Given a link to a git repository [79] of a C library, OverHAuL automatically generates a new fuzzing harness specifically designed for the project. In addition to the harness, it produces a compilation script to facilitate building the harness, generates a representative input that can trigger crashes, and logs the output from the executed harness.

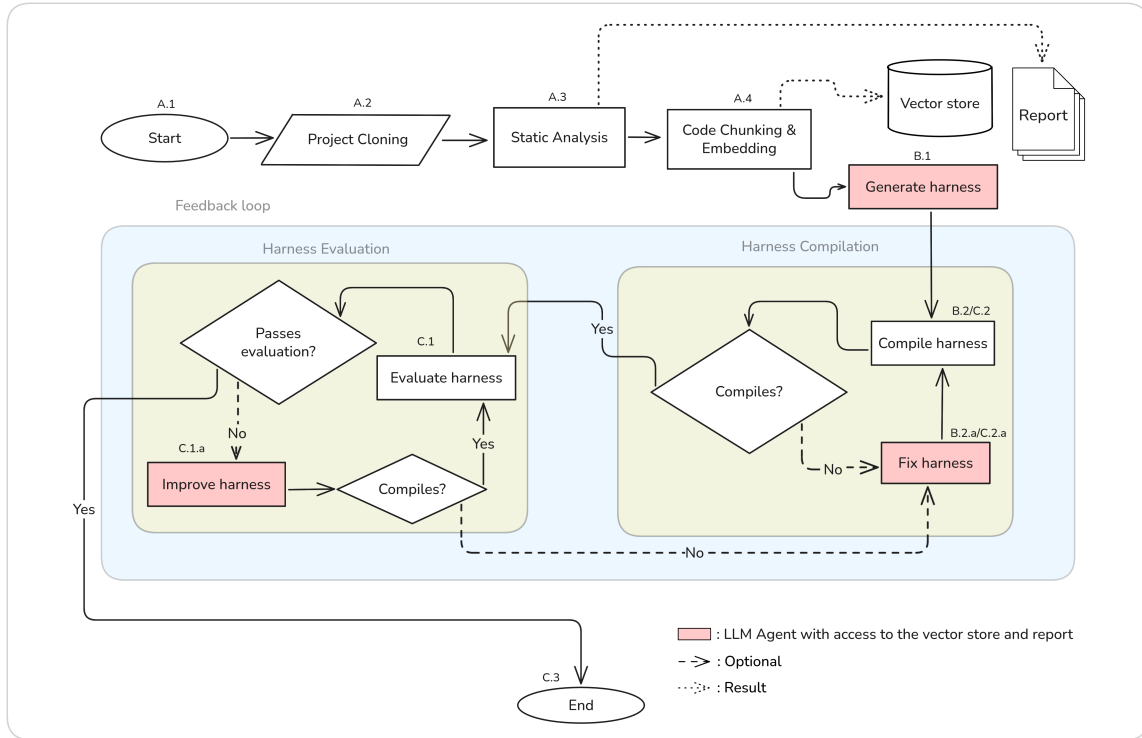


Figure 4.1: Overview of OverHAuL’s automatic harnessing process.

As commented in Section 3.2, OverHAuL does not expect and depend on the existence of client code or unit tests [59], [62], [63] nor does it require any preexisting fuzzing harnesses [57] or any documentation present [55]. Also importantly, OverHAuL is decoupled from other fuzzing projects, thus lowering the barrier to entry for new projects [57], [65]. Lastly, the user isn’t mandated to specify manually the function which the harness-to-be-generated must fuzz. Instead, OverHAuL’s

agents examine and assess the provided codebase, choosing after evaluation the most optimal targeted function.

OverHAuL utilizes autonomous ReAct agents [40] which inspect and analyze the project’s source code. The latter is stored and interacted with as a set of text embeddings [80], kept in a vector store. Both approaches are, to the best of our knowledge, novel in the field of automatic fuzzing harnesses generation. OverHAuL also implements an evaluation component that assesses in real-time all generated harnesses, making the results tenable, reproducible and well-founded. Ideally, this methodology provides a comprehensive and systematic framework for identifying previously unknown software vulnerabilities in projects that have not yet been fuzz tested.

Finally, OverHAuL excels in its user-friendliness, as it constitutes a simple and easily-installable Python package with minimal external dependencies—only real dependency being Clang, a prevalent compiler available across all primary operating systems. This contrasts most other comparable systems, which are typically characterized by their limited documentation, lack of extensive testing, and a focus primarily on experimental functionality.¹

4.1 Architecture

OverHAuL can be compartmentalized in three stages: First, the project analysis stage (Section 4.1.1), the harness creation stage (Section 4.1.2) and the harness evaluation stage (Section 4.1.3).

4.1.1 Project Analysis

In the project analysis stage (steps A.1–A.4), the project to be fuzzed is ran through a static analysis tool and is sliced into function-level chunks, which are stored in a vector store. The results of this stage are a static analysis report and a vector store containing embeddings of function-level code chunks, both of which are later available to the LLM agents.

The static analysis tool Flawfinder [81] is executed with the project directory as input and is responsible for the static analysis report. This report is considered a meaningful resource, since it provides the LLM agent with some starting points to explore, regarding the occurrences of potentially vulnerable functions and/or unsafe code practices.

The vector store is created in the following manner: The codebase is first chunked in function-level pieces by traversing the code’s Abstract Syntax Tree (AST) through Clang. Each chunk is represented by an object with the function’s signature, the corresponding filepath and the function’s body. Afterwards, each function body is turned into a vector embedding through an embedding model. Each embedding is stored in the vector store. This structure is created and used for easier and more semantically meaningful code retrieval, and to also combat context window limitations present in the LLMs.

¹I.e. “research code”.

4.1.2 Harness Creation

Second is the harness creation stage (steps B.1–B.2). In this part, a “generator” ReAct LLM agent is tasked with creating a fuzzing harness for the project. The agent has access to a querying tool that acts as an interface between it and the vector store. When the agent makes queries like “functions containing `strcpy()`”, the querying tool turns the question into an embedding and through similarity search returns the top $k = 3$ most similar results—in this case, functions of the project. With this approach, the agent is able to explore the codebase semantically and pinpoint potentially vulnerable usage patterns easily.

The harness generated by the agent is then compiled using Clang and linked with the AddressSanitizer, LeakSanitizer, and UndefinedBehaviorSanitizer. The compilation command used is generated programmatically, according to the rules described in Section 4.5. If the compilation fails for any reason, e.g. a missing header include, then the generated faulty harness and its compilation output are passed to a new “fixer” agent tasked with repairing any errors in the harness (step B.2.a). This results in a newly generated harness, presumably free from the previously shown flaws. This process is iterated until a compilable harness has been obtained. After success, a script is also exported in the project directory, containing the generated compilation command.

4.1.3 Harness Evaluation

Third comes the evaluation stage (steps C.1–C.3). During this step, the compiled harness is executed and its results evaluated. Namely, a generated harness passes the evaluation phase if and only if:

1. The harness has no memory leaks during its execution This is inferred by the existence of `leak-<hash>` files.
2. A new testcase was created *or* the harness executed for at least `MIN_EXECUTION_TIME` (i.e. did not crash on its own) When a crash happens, and thus a testcase is created, it results in a `crash-<hash>` file.
3. The created testcase is not empty This is examined through `xxd`’s output given the crash-file.

Similarly to the second stage’s compilation phase (steps B.2–B.2.a), if a harness does not pass the evaluation for whatever reason it is sent to an “improver” agent. This agent is instructed to refine it based on its code and cause of failing the evaluation. This process is also iterative. If any of the improved harness versions fail to compile, the aforementioned “fixer” agent is utilized again (steps C.2–C.2.a). All produced crash files and the harness execution output are saved in the project’s directory.

4.2 Main Techniques

The fundamental techniques that distinguish OverHAuL in its approach and enhance its effectiveness in achieving its objectives are: The implementation of an iterative feedback loop between the LLM agents, the distribution of responsibility across a swarm of distinct agents and the employment of a “codebase oracle” for interacting with the given project’s source code.

714 4.2.1 Feedback Loop

715 The initial generated harness produced by OverHAuL is unlikely to be successful from the get-go.
716 The iterative feedback loop implemented facilitates its enhancement, enabling the harness to be
717 tested under real-world conditions and subsequently refined based on the results of these tests.
718 This approach mirrors the typical workflow employed by developers in the process of creating and
719 optimizing fuzz targets.

720 In this iterative framework, the development process continues until either an acceptable and
721 functional harness is realized or the defined *iteration budget* is exhausted. The iteration budget
722 $N = 10$ is initialized at the onset of OverHAuL’s execution and is shared between both the
723 compilation and evaluation phases of the harness development process. This means that the
724 iteration budget is decremented each time a dashed arrow in the flowchart illustrated in Figure 4.1
725 is followed. Such an approach allows for targeted improvements while maintaining oversight of
726 resource allocation throughout the harness development cycle.

727 4.2.2 React Agents Swarm

728 An integral design decision in our framework is the implementation of each agent as a distinct
729 LLM instance, although all utilizing the same underlying model. This approach yields several
730 advantages, particularly in the context of maintaining separate and independent contexts for each
731 agent throughout each OverHAuL run.

732 By assigning individual contexts to the agents, we enable a broader exploration of possibilities during
733 each run. For instance, the “improver” agent can investigate alternative pathways or strategies
734 that the “generator” agent may have potentially overlooked or internally deemed inadequate
735 inaccurately. This separation not only fosters a more diverse range of solutions but also enhances
736 the overall robustness of the system by allowing for iterative refinement based on each agent’s
737 unique insights.

738 Furthermore, this design choice effectively addresses the limitations imposed by context window
739 sizes. By distributing the “cognitive” load across multiple agents, we can manage and mitigate the
740 risks associated with exceeding these constraints. As a result, this architecture promotes efficient
741 utilization of available resources while maximizing the potential for innovative outcomes in multi-
742 agent interactions. This layered approach ultimately contributes to a more dynamic and exploratory
743 research environment, facilitating a comprehensive examination of the problem space.

744 4.2.3 Codebase Oracle

745 The third central technique employed is the creation and utilization of a codebase oracle, which is
746 effectively realized through a vector store. This oracle is designed to contain the various functions
747 within the project, enabling it to return the most semantically similar functions upon querying
748 it. Such an approach serves to address the inherent challenges associated with code exploration
749 difficulties faced by LLM agents, particularly in relation to their limited context window.

By structuring the codebase into chunks at the level of individual functions, LLM agents can engage with the code more effectively by focusing on its functional components. This methodology not only allows for a more nuanced understanding of the codebase but also ensures that the responses generated do not consume an excessive portion of the limited context window available to the agents. In contrast, if the codebase were organized and queried at the file level, the chunks of information would inevitably become larger, leading to an increase in noise and a dilution of meaningful content in each chunk [82]. Given the constant size of the embeddings used in processing, each progressively larger chunk would be less semantically significant, ultimately compromising the quality of the retrieval process.

Defining the function as the primary unit of analysis represents the most proportionate balance between the size of the code segments and their semantic significance. It serves as the ideal “zoom-in” level for the exploration of code, allowing for greater clarity and precision in understanding the functionality of individual code segments. This same principle is widely recognized in the training of code-specific LLMs, where a function-level approach has been shown to enhance performance and comprehension [83]. By adopting this methodology, we aim to foster a more robust interaction between LLM agents and the underlying codebase, ultimately facilitating a more effective and efficient exploration process.

4.3 High-Level Algorithm

A pseudocode version of OverHAuL’s main function can be seen in Algorithm 4.1. It represents the workflow presented in Figure 4.1 and uses the techniques described in sections 4.1 and 4.2. It is important to emphasize that, within the context of this algorithm, the `HarnessAgents()` function serves as an interface that bridges the “generator”, “fixer” and “improver” LLM agents. The agent that is used upon each function call depends on the values of the function’s arguments. This results in the *harness* variable representing all generated, fixed or improved harnesses. This approach is adopted for making the abstract algorithm simpler and easier to understand.

Algorithm 4.1 OverHAuL

Require: *repository***Ensure:** *harness, compilation_script, crash_input, execution_log*

```
1: path ← REPOCLONE(repository)
2: report ← STATICANALYSIS(path)
3: vector_store ← CREATEORACLE(path)
4: acceptable ← False
5: compiled ← False
6: error ← None
7: violation ← None
8: output ← None
9: for i = 1 to MAX_ITERATIONS do
10:   harness ← HARNESSAGENTS(path, report, vector_store, error, violation, output)
11:   error, compiled ← BUILDHARNESS(path, harness)
12:   if  $\neg$ compiled then
13:     continue ▷ Fix harness
14:   end if
15:   output, accepted ← EVALUATEHARNESS(path, harness)
16:   if  $\neg$ accepted then
17:     continue ▷ Improve harness
18:   else
19:     acceptable ← True
20:     break
21:   end if
22: end for
23: return compiled  $\wedge$  acceptable
```

775 4.4 Installation and Usage

776 The source code of OverHAuL is available in <https://github.com/kchousos/OverHAuL>. OverHAuL
777 can be installed by cloning the git repository locally, creating and enabling a Python3.10 virtual
778 environment [84] and installing it inside the environment using Python’s PIP package installer [85],
779 like in Listing 4.1.

780 To use OverHAuL, you need to provide a secret key for using OpenAI’s API service. This key can
781 be either stored in a .env file in the root directory, like so:

```
1 # cat .env
2 OPENAI_API_KEY=<API-key-here>
```

782 Or it can be exported in the shell environment:

Listing 4.1 OverHAuL’s installation process.

```
1 $ git clone https://github.com/kchousos/overhaul; cd overhaul
2 ...
3 $ python3.10 -m venv .venv
4 $ source ./venv/bin/activate
5 $ pip install .
6 ...
7 $ overhaul --help
8 usage: overhaul [-h] [-c COMMIT] [-m MODEL] [-f FILES [FILES ...]] [-o OUTPUT_DIR] repo
9
10 Generate fuzzing harnesses for C/C++ projects
11
12 positional arguments:
13   repo                  Link of a project's git repo, for which to generate a harness.
14
15 options:
16   -h, --help            show this help message and exit
17   -c COMMIT, --commit COMMIT
18                       A specific commit of the project to check out
19   -m MODEL, --model MODEL
20                       LLM model to be used. Available: o3-mini, o3, gpt-4o, gpt-4o-mini,
21                       gpt-4.1, gpt-4.1-mini, gpt-3.5-turbo, gpt-4
22   -f FILES [FILES ...], --files FILES [FILES ...]
23                       File patterns to include in analysis (e.g. *.c *.h)
24   -o OUTPUT_DIR, --output-dir OUTPUT_DIR
25                       Directory to clone the project into. Defaults to "output"
26 $
```

```
1 $ export OPENAI_API_KEY=<API-key-here>
2 $ overhaul <repo-link>
```

783 Once these preliminary steps are completed, OverHAuL can be executed. The primary argument
784 required by OverHAuL is the repository link of the library that is to be fuzzed. Additionally, users
785 have the option to specify certain command-line flags, which allow them to control the checked-out
786 commit of the cloned project, select the OpenAI LLM model from a predefined list, define specific
787 file patterns for OverHAuL to search for, and determine the directory in which the project will be
788 cloned. A sample successful execution can be presented in Figure 4.2.

789 In this example, the dateparse repository is cloned into the ./output/dateparse directory, which is
790 relative to the root directory of OverHAuL. Following a successful execution, this directory will
791 contain a new folder named harnesses, which will house all the generated harnesses formatted as
792 harness_n.c—where n ranges from 1 to $N - 1$, with N representing the total number of harnesses
793 produced. The most recent and verifiably correct harness will be designated simply as harness.c.

```

} overhaul https://github.com/dvhar/dateparse -m gpt-4.1
2025-07-17 00:55:18.887 | INFO | overhaul.cli.parse_arguments:184 - Cloning project's repo in the output/dateparse directory...
2025-07-17 00:55:18.976 | INFO | overhaul.core.harnesser:_init_:167 - Initializing LLM...
2025-07-17 00:55:18.991 | INFO | overhaul.cli.main:243 - Iteration 1 of harnessing...
2025-07-17 00:55:18.991 | INFO | overhaul.core.harnesser:harness:207 - Calling LLM to generate a harness...
2025-07-17 00:55:22.837 | DEBUG | overhaul.rag.ragger:rag_tool:88 - Agent using RAG: "Show the functions in dateparse.c that contain a strcpy call, especially near lines 405, 800, and 1242."
2025-07-17 00:55:25.807 | DEBUG | overhaul.rag.ragger:rag_tool:88 - Agent using RAG: "Provide the full implementation (signature and body) of the dateparse function in dateparse.c."
2025-07-17 00:55:30.207 | DEBUG | overhaul.rag.ragger:rag_tool:88 - Agent using RAG: "Show the full signature and body of the function int dateparse(const char* datestr, date_t* t, int *offset, int stringlen) in dateparse.c."
2025-07-17 00:55:34.176 | DEBUG | overhaul.rag.ragger:rag_tool:88 - Agent using RAG: "Show the definition of struct parser and the typedef of date_t as used in dateparse.c and dateparse.h."
2025-07-17 00:55:38.581 | DEBUG | overhaul.rag.ragger:rag_tool:88 - Agent using RAG: "Show the definition of struct parser and the typedef of date_t from dateparse.h."
2025-07-17 00:56:01.897 | INFO | overhaul.io.file_manager:write_harness:60 - Writing harness to project...
2025-07-17 00:56:01.898 | INFO | overhaul.io.file_manager:write_harness:92 - Harness written to output/dateparse/harnesses/harness.c
2025-07-17 00:56:01.898 | INFO | overhaul.core.builder:build_harness:63 - Building harness...
2025-07-17 00:56:01.899 | INFO | overhaul.core.builder:build_harness:140 - Starting compilation of harness: harnesses/harness.c
2025-07-17 00:56:02.345 | INFO | overhaul.core.builder:build_harness:149 - Harness compiled successfully
2025-07-17 00:56:02.345 | INFO | overhaul.core.evaluator:evaluate_harness:81 - Evaluating harness...
2025-07-17 00:56:02.345 | INFO | overhaul.core.evaluator:evaluate_harness:90 - Starting execution of harness...
2025-07-17 00:56:02.417 | INFO | overhaul.core.evaluator:evaluate_harness:119 - Harness execution completed in 0.07 seconds.
2025-07-17 00:56:02.419 | INFO | overhaul.core.evaluator:evaluate_harness:181 - New testcases created (1): [{"crash-dfaa340e98889cd82d2cd680cf96fd04552a2b4", 1752702962.4113252}]
2025-07-17 00:56:02.419 | SUCCESS | overhaul.cli.main:282 - All done!

```

Figure 4.2: A successful execution of OverHAuL, harnessing [dvhar’s dateparsing C library](#), using OpenAI’s gpt-4.1 model. Debug statements are printed to showcase the interaction between the LLM agents and the codebase oracle (Section 4.2.3).

Additionally, the dateparse directory will include an executable script named `overhaul.sh`, which contains the compilation command necessary for the harness. A log file titled `harness.out` will also be present, documenting the output from the latest harness execution. Lastly and most importantly, there will be at least one non-empty crash file included, serving as a witness to the harness’s correctness.

4.5 Scope

Currently, OverHAuL is designed to generate new harnesses specifically for medium-sized C libraries. Given the inherent complexity of dealing with C++ projects, this is not a feature yet supported within the system.

The compilation command utilized by OverHAuL is created programmatically. It incorporates the root directory along with all subdirectories that conform to a predefined set of common naming conventions. Additionally, the compilation process uses all C source files identified within these directories. Crucially, it is important that no `main()` function is present in any of the files to ensure successful compilation. For this reason any files or directories that include “test”, “main”, “example”, “demo”, or “benchmark” in their paths are systematically excluded from the compilation process. This exclusion also decreases the “noise” in the oracle, as these files do not constitute part of the core library and would therefore not contain any functions meaningful to the LLM agents.

Lastly, No support for build systems such as Make or CMake [86], [87] is yet implemented. Such functionality would exponentially increase the complexity of the build step and is beyond the scope of this thesis.

5 Evaluation

To thoroughly assess the performance and effectiveness of OverHAuL, we established four *research questions* to direct our investigative efforts. These questions are designed to provide a structured framework for our inquiry and to ensure that our research remains focused on the key aspects of OverHAuL’s functionality and impact within its intended domain. By addressing these questions, we aim to uncover valuable insights that will contribute to a deeper understanding of OverHAuL’s capabilities and its position in contemporary automatic fuzzing applications:

- **RQ1:** Can OverHAuL generate working harnesses for unfuzzed C projects?
- **RQ2:** What characteristics do these harnesses have? Are they similar to man-made harnesses?
- **RQ3:** How do LLM usage patterns influence the generated harnesses?
- **RQ4:** How do different techniques affect the generated harnesses?

5.1 Experimental Benchmark

To evaluate OverHAuL, a benchmarking script was implemented¹ and a corpus of ten open-source C libraries was assembled. This collection comprises of: Firstly, GitHub user dhvar’s dateparse library, which is also used as a running example in OSS-Fuzz-Gen’s [57] experimental from-scratch harnessing feature (Section 3.1.10). Secondly, nine other libraries chosen randomly² from the package catalog of Clib, a “package manager for the C programming language” [88], [89]. Each library is described below.

1. [dvhar/dateparse](#): A library that allows parsing dates without knowing the format in advance.
2. [clibs/buffer](#): A string manipulation library.
3. [jwerle/libbeaufort](#): A library implementation of the Beaufort cipher [90].
4. [jwerle/libbacon](#): A library implementation of the Baconian cipher [91].
5. [jwerle/chfreq.c](#): A library for computing the character frequency in a string.
6. [jwerle/progress.c](#): A library for displaying progress bars in the terminal.
7. [willem/cbuffer](#): A circular buffer implementation.
8. [willem/torrent-reader](#): A torrent-file reader library.
9. [orangeduck/mpc](#): A type-generic parser combinator library.
10. [h2non/semver.c](#): A semantic version v2.0 parsing and rendering library [92].

¹<https://github.com/kchousos/OverHAuL/blob/master/benchmarks/benchmark.sh>

²From the subset of libraries that do not have exotic external dependencies, like the X11 development toolchain.

842 5.1.1 Local Benchmarking

843 To run the benchmark locally, one would need to follow the installation instructions in Section [4.4](#)
844 and then execute the benchmarking script, like so:

```
1 $ ./benchmarks/benchmark.sh
```

845 The cloned repositories with their corresponding harnesses will then be located in a subdirectory of
846 `benchmark_results`, which will have the name format of `mini__<timestamp>__ReAct__<llm-model>__<max-`
847 `exec-time>__<iter-budget>`. “Mini” corresponds to the benchmark project corpus described above,
848 since a 30-project corpus was initially created and is now coined as “full” benchmark. Both the mini
849 and full benchmarks are located in `benchmarks/repos.txt` and `benchmarks/repos-mini.txt` respectively.
850 To execute the benchmark for the “full” corpus, users can add the `-b full` flag in the script’s
851 invocation. Also, the LLM model used can be defined with the `-m` command-line flag.

852 **6 Results**

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

854 7 Implementation

855 –depth 1 output/

856 embedder model openai Source code is processed and chunked using Clang [33]. The chunks are
857 function-level units, found to be a sweet-spot between semantic significance and size [82], [83].
858 This results in a list of Python dicts, each containing a function’s body, signature and filepath. Each
859 chunk’s function code is then turned into an embedding using OpenAI’s “text-embedding-3-small”
860 model. faiss store and index A FAISS [36] vector store is created. Each function embedding is stored
861 in it (with the same order, as to correspond with the previous list containing the metadata).

862 same order code chunks

863 Prompting techniques used (callback to Section 2.2.2). Sample prompt

864 [78]

865 1. Why instead of langchain or llamaindex? [93], [94]

866 libclang Python package

867 7.1 Development environment

868 uv, ruff, mypy, pytest, pdoc

869 7.2 Equipment

870 desktop pc cpu, memory

871 7.3 models used

872 gpt-4.1

873 7.4 Reproducibility

874 github workflow actions, artifacts, summary

8 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.

8.1 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 [86], [87], [95], [96]—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++ [19] could diversify the fuzzing strategies available to OverHAuL, while exploring more experimental tools such as GraphFuzz [58] 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 [97]. 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 [62], [63], 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.

8.2 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 [43]–[45], 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.

8.3 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 [88], 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 [55], [57].

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.

8.4 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.

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

952 **9 Discussion**

953 more powerful llms -> better results

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

956 **9.1 Threats to Validity**

957 **10 Conclusion**

958 Recap

959 Performed a literature review of similar projects.

960 Presented the algorithm *and* the implementation.

961 generative AI disclaimer à la ACM?

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A Abandoned Techniques

During its development, OverHAuL went through several iterations. A number of approaches were implemented and evaluated, with some being replaced for better alternatives. These are:

1. One-shot harness generation

Before the iterative feedback loop (Section 4.2.1) was implemented, OverHAuL attempted to operate in a straightforward pipeline, with just a “generator” agent being tasked to generate the harness. This meant that at either the compilation step or evaluation step, any failure resulted in the execution being terminated. This approach put too much responsibility in the response of a single LLM query, with results more often than not being unsatisfactory.

2. Chain-of-Thought LLM instances

The current implementation of ReAct agents has effectively supplanted the less effective Chain of Thought (COT) LLM modules [37]. This shift underscores a critical realization in the harness generation process: the primary challenge lies not in the creation of the harness itself, but rather in the necessity for real-time feedback during execution. This is the reason why first employing COT prompting offered limited observed improvements.

COT techniques are particularly advantageous when the task assigned to the LLM demands a more reflective, in-depth analysis. However, when it comes to tasks such as knowledge extraction from a codebase oracle and taking live feedback from the environment into consideration, ReAct agents demonstrate greater efficiency and effectiveness.

3. Source code concatenation

Initially, there was no implementation of a codebase oracle. Instead, the LLM agents operated with a Python string that contained a concatenation of all the collected source code. While this method proved effective for smaller and simpler projects, it encountered significant limitations when applied to more complex codebases. The primary challenge was the excessive consumption of the LLM’s context window, which hindered its ability to process and analyze larger codebases effectively. As a result, this approach became increasingly unsustainable as project complexity grew, underscoring the need for a more robust solution.

4. {index, read}_tool usage for ReAct agents

The predecessor of the oracle comprised a dual-system approach for code exploration, integrating the index_tool and the read_tool. The index_tool offered the LLM agent a structured JSON object that delineated the project’s architecture, including all relevant file paths. On the other hand, the read_tool required a file path as input and returned the file’s content, albeit truncated to a maximum of 4000 characters. While this methodology presented an improvement in scalability over earlier systems, several limitations persisted.

1232 Firstly, the LLM was constrained to searching through the codebase strictly in file-specific
1233 terms, which limited its efficacy in understanding the broader context of code relationships.
1234 Furthermore, the imposed character limit on the `read_tool` meant that certain portions of the
1235 codebase remained inaccessible, impeding the agent’s analytical capabilities. Even if this
1236 character limit were to be lifted, the resultant output would still occupy a significant portion
1237 of the context window, particularly in larger and more intricate projects. As such, while this
1238 approach offered advancements in code exploration, it still fell short.