D-LIFT: Improving LLM-based Decompiler Backend via Code Quality-driven Fine-tuning

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***Abstract*—Decompilers, which reconstruct human-readable source code from binary executables, are vital to many security tasks. Yet, despite recent advances, their output often suffers from syntactic and semantic errors and remains difficult to read. Recently, with the advent of large language models (LLMs), researchers began to explore the potential of LLMs to refine decompiler output. Nevertheless, our study of these approaches reveals significant limitations, such as introducing new errors and relying on unreliable accuracy validation.**

In this paper, we present D-LIFT, an automated decompiler backend that harnesses and further trains LLMs to improve the quality of decompiled code via reinforcement learning (RL). Unlike prior work that overlooks preserving accuracy, D-LIFT adheres to a key principle for enhancing the quality of decompiled code: *preserving accuracy while improving readability*. Central to D-LIFT, we propose D-SCORE, an integrated quality assessment system to score the decompiled code from multiple aspects. In line with our principle, D-SCORE assigns low scores to any inaccurate output and only awards higher scores for readability to code that passes the accuracy check. Specifically, D-SCORE first verifies the syntactic and semantic correctness via the compiler and symbolic execution; only if a candidate is deemed accurate, it then evaluates readability using established metrics to compare the LLM output with the original decompiled code. The score will then be fed back to the LLM for fine-tuning. Our implementation, based on Ghidra and a range of LLMs, demonstrates significant improvements for the accurate decompiled code from the coreutils and util-linux projects. Compared to baseline LLMs without D-SCORE-driven fine-tuning, D-LIFT produces 55.3% more improved decompiled functions, as measured by D-SCORE. Moreover, when selecting the best output among the baseline model, the fine-tuned model, and the original decompiled code, our fine-tuned model yields the best result for 47.3% of functions, whereas the baseline model does so for only 20.9%.

1. Introduction

Binary decompilation is the process of generating high-level source code, with human-comprehensible variables, control flows, and data structures from a binary program. Decompilation has found extensive security applications, such as software reverse engineering [60], vulnerability discovery [22], [40], program patching and hardening [48], and cyber forensics [9]. However, source code generated by decompilers very often has problems in the aspects of syntactic and semantic correctness [11], [16], [37], [72]: A piece of decompiled code may not compile or preserve the semantics of the original binary. Moreover, despite advances in the past decade [7], [8], [12], [33], [35], [66], [67], [70], [71], even with syntactic and semantic correctness, the decompiled code may still be hard for human users to read. In fact, a recent survey [60] found that roughly 70% of reverse engineers still prefer working with the assembly code, due to the incorrectness (i.e., inaccuracy) and/or low readability of the decompiled source code.

In recent years, with the advent of Large Language Models (LLMs), researchers started to explore the potential of LLMs to generate or improve decompiled code [18], [25], [28], [29], [55], [63], [64], [65]. For example, to generate more readable decompiled output, LLM4Decompile [55] introduces supervised fine-tuning (SFT) for the training, and DeGPT [25] introduces a three-role mechanism to help LLMs inference. These LLM-assisted decompilation improvement tools, such as LLM4Decompile and GhidraMCP [31], have rapidly gained attention within the security community. For instance, LLM4Decompile was ranked in 4th place in GitHub Day Trending.

Unfortunately, our analysis of these state-of-the-art, LLM-based decompiled code improvement methods shows significant limitations. For LLM4Decompile, our study (detailed in Section 6.1.3) reveals that, even when the original decompiled code is error-free, new errors are found in 93.2% of its generated functions. For DeGPT, its semantic

correctness check is non-deterministic and does not enhance the LLM's inherent capability to generate more accurate decompiled code. Moreover, our investigation uncovers a unique challenge, multiple valid ground truth possibilities, in improving LLMs for decompilation, as detailed in Section 3.

To improve the overall quality while preserving accuracy of the decompiled code using LLMs, we propose D-LIFT[1], an automatic decompilation pipeline with a decompiler front-end and an LLM back-end, which is fine-tuned to improve the quality of the decompiled code. D-LIFT takes a policy model (i.e., baseline model), a decompiler, and a set of real-world binaries as inputs, and provides a code quality-enhanced model to generate more readable decompiled code while preserving accuracy. Unlike prior work that overlooks preserving accuracy, D-LIFT follows a key principle for improving the quality of decompiled code: *preserving accuracy while improving readability*. To this end, we propose D-SCORE, a novel code quality assessment function, which provides comprehensive scoring for LLM-generated decompiled code based on accuracy and readability measurements. Specifically, to assess the accuracy of decompiled code, D-SCORE employs a compiler to generate the syntax feedback and symbolic execution to compare the semantics of the generated code against the corresponding function in the original binary. To assess the readability of decompiled code, D-SCORE computes a score by applying two established readability metrics to compare the LLM's output with the original decompiled code. By leveraging D-SCORE, D-LIFT enhances the LLMs' ability to generate higher-quality decompiled code.

We implement D-LIFT using Ghidra [3] and a number of LLMs, and evaluate D-LIFT using functions from the coreutils [13] and util-linux [58] projects. Overall, as measured by D-SCORE, D-LIFT can improve the quality of 55.3% more functions, compared to the baseline LLMs without D-SCORE-driven fine-tuning. Interestingly, we observe a significant "improve-ability gap" between the accurate and inaccurate decompiled functions originally produced by the decompiler. All LLMs, including baseline and fine-tuned models, face challenges in improving inaccurate decompiled code, with improvement rates of just 8.02% for the originally inaccurate functions compared to 86.2% for the originally accurate ones. Moreover, for functions that are accurately decompiled, when choosing the best output among the baseline model (i.e., decompiler+LLM *without* fine-tuning), the fine-tuned model (i.e., D-LIFT), and the original decompiled code, we find that on average, 47.3% of the top-scoring functions come from D-LIFT, whereas only 20.9% come from the baseline model. Overall, our main contributions are:

- We design D-LIFT, an automatic decompilation pipeline with an LLM-based back-end that is fine-tuned using reinforcement learning to improve the quality of the decompiled code, adhering to the principle of *preserving accuracy while improving readability*.
- We propose D-SCORE, an integrated scoring mechanism designed specifically for decompilation recovery tasks. The framework incorporates existing analytical tools and proven metrics to deliver a balanced evaluation of decompiled code, assessing both syntactic and semantic correctness as well as readability properties to provide effective training feedback to the LLM.
- We implement D-LIFT based on Ghidra and fine-tune three LLMs, and achieve significant decompiled code improvement for widely used benchmark functions.

1. "D-LIFT" reflects the decompilation pipeline with a "**D**ecompiler" front-end and an "**L**LM w**i**th **F**ine **T**uning" back-end.

2. Background and Motivation

2.1. LLM application and training

2.1.1. Applications of LLMs. Large language models (LLMs) have seen wide adoption and investigation, particularly in the domain of code generation. Industry has released numerous LLM-powered tools, e.g., GitHub Copilot [19], Google Gemini Code Assistant [20], and Meta LLaMA Coder [50], to streamline different programming tasks. Academia has mirrored this enthusiasm: the number of publications on code generation rose from 11 in 2022 to 75 in 2023 and then to 140 in 2024—a 1,272% increase [27]. In particular, LLMs have demonstrated promising capabilities across a range of code-to-code generation tasks, including code translation, code completion, automated bug fixing (code repair), and mutant generation. In the security domain, beyond LLM4Decompile, reverse-engineering teams have also leveraged LLMs via Model Context Protocol (MCP) servers to infer variable and function names, producing more readable decompiled output; one such tool, GhidraMCP [31], garnered 4.3k stars on GitHub within its first month after release.

2.1.2. Training LLMs. During LLM training, the most common strategy is to begin with a broad pre-training phase and then follow up with task-specific fine-tuning [36]. The pre-training allows the model to learn linguistic knowledge, such as C coding conventions, into its parameters. Fine-tuning then adapts the pre-trained model to the specific task using two main approaches: instruction tuning and reinforcement learning.

Instruction tuning runs the supervised learning paradigm aiming to align the model's output with a single desired completion. For instance, LLM4Decompile applies Supervised Fine-Tuning (SFT) to align the desired output with the original source code.

Reinforcement learning, on the other hand, refines the model through iterative actions and feedback: the model generates candidate output(action), which will be assessed by a reward function that provides feedback, guiding the model toward higher-quality results. In code generation, the feedback usually comes from frameworks, such as unit tests and compilers. Some RL policies, such as PPO [52], also require a single ideal completion to train a critic model that predicts long-term rewards, helping the model choose better actions over time. More recently, Group Relative Policy Optimization (GRPO) [53] achieved promising results on math-related tasks. By normalizing the rewards of candidate

outputs instead of relying on a critic model, GRPO eliminates the limitation of accepting only one ideal completion.

2.2. Decompiled Code Accuracy

The accuracy of the decompiled code, including recompilation syntactic failures and semantic deviations between the decompiled code and the original source code, was first systematically evaluated using Equivalence Modulo Input (EMI) tests [37]. Since then, various methods, including symbolic execution [72], random testing [11], fuzzing [68], and manual inspection [16], have been employed to assess decompiler accuracy. Within these studies, the definition of semantic deviation varies across studies. For example, one [72] may compare function return values between the decompiled code and the binary, while the other [11] may instrument global variables and employ checksum comparisons to evaluate semantic correctness against the original source code.

2.3. Decompiled Code Readability

Quantitative assessment of code readability has long been a topic in software engineering. Buse and Weimer (B&W) [10] led the way by recruiting 120 human evaluators to rate 100 short code snippets, then building a mathematical model, featuring metrics like the number of variables per function, to evaluate the readability.

In the decompilation field, R2I [17] was the first approach to measure readability specifically for decompiled code. It defines a set of features that can be categorized into five feature groups: code quality, user preference, conflicting features, erroneous syntax, and general features. By analyzing these features extracted from the code, it provides relative readability scores across different decompilers. Note that, since R2I focuses on the comparison across different decompilers, many of its features cannot be generically applied to the LLM-generated code.

2.4. Motivations

Although LLM-based code generation is increasingly prevalent, using it to improve decompiled code still faces major challenges.

LLM causes inaccuracy of decompiled code. Though LLMs are widely used for code enhancement [27], they are known to introduce inaccuracies in code generation tasks [46]. In the decompiled-code improvement scenario, we also observe that LLM-refined output frequently shows new errors. Here, we follow the previous work to define the inaccuracy in the decompiled code as either *syntax errors* that prevent successful compilation or *semantic deviations* between the LLM-generated code and the original binary's behavior. As shown in Table 3, an average 44.2% of functions that were originally accurate become inaccurate after LLM processing. For the root cause, as the example shown later in Figure 8, we observed that LLMs frequently make errors on small details, such as omitting brackets or instructions,

```
int main() {
 char a[100];
 unsigned int b=0;
 printf("Enter text:");
 if(fgets(a,sizeof(a),stdin)
      != NULL) {
  while(b<10){
   printf("%c",a[b]);
   b++;
  }
 }
 else
  return 2;
 return 1+1+1;
}
```

```
int main() {
 char c[100];
 int d=0;
 printf("Enter text:");
 if(fgets(c,sizeof(c),
      stdin) != NULL) {
  for(d=0;d<10;d++){
   printf("%c",c[d]);}
 } else {
  return 1+1;
 }
 return 3;
}
```

Figure 1: Two code snippets generate the same binary code. Notably, differences appear in every line except the first and fourth lines.

or referencing the wrong variable, that are hard to spot yet vital for accuracy.

These observations reveal that though LLMs may improve readability, they often introduce incorrectness of decompiled code, a factor that prior studies [11], [16], [37], [68], [72] have identified as vital for effective decompilation. Hence, we propose an overarching principle for improving decompiled code quality: preserving accuracy while improving readability.

However, none of the existing work improves LLMs' code correction (i.e., accuracy) capability. Specifically, LLM4Decompile, while effective at boosting readability, compromises the accuracy of the decompiled code, as shown in Table 3. DeGPT, meanwhile, is unable to improve the LLM's inherent generation capabilities, because its fixes occur only at the inference stage rather than during training. These insights lead us to design a framework that enhances LLMs' ability to correct errors in the decompiled code while improving its readability.

3. Design Challenges

Section 2.4 motivates the need to enhance the LLM in decompiled code improvement. In this section, we summarize the design-level challenges.

Challenge 1: LLM Improvement Method Selection. Improving the code generation capability of LLMs [15], [32], [45], [54], [55] is not new. However, many of them are challenging to adapt for decompiled code improvement. Unlike typical code improvement tasks, decompiled-code enhancement faces a unique challenge: the existence of multiple valid ground truths. Specifically, a single binary may be compiled from multiple semantically equivalent source programs, each of which should be considered a valid ground truth. For instance, as illustrated in Figure 1, two different source files, each around 300 characters long and with an edit distance of 74, produce the same binary output using GCC [1] with `-O2` optimization. In practice, however, researchers typically have access to only one of these source variants as the ground truth. Moreover, many fine-tuning methods, such as supervised fine-tuning (SFT) and the actor-critic paradigm in RL, accept only a single reference to compute the training loss, overlooking the possible existence of a full

set of correct alternatives. This constraint may degrade a model's effectiveness, as exemplified by LLM4Decompile's use of SFT on the source code during training.

Challenge 2: Assessment of decompiled code quality. The assessment of decompiled code quality should reflect the principle of preserving decompiled code accuracy while improving readability. To the best of our knowledge, there is no existing code quality assessment function that addresses these specific requirements.

For accuracy, as introduced in Section 2.2, we mainly focus on two aspects, syntactic correctness and semantic correctness. Since the assessment function must be deterministic, methods such as fuzzing [68] and its derivatives, like `MSSC` [11], are excluded. Additionally, to ensure applicability without the need for source code, we exclude approaches that rely on source-dependent checks, such as unit tests or `Alive2` [39]. That leaves `D-helix` [72], which uses an iterative re-compiler to examine the syntax errors and symbolic execution to check the semantics against the original binary. However, integrating `D-helix` directly into our framework introduces its own challenge. Notably, `D-helix` still relies on certain decompiled code output artifacts, e.g., external function calls, to analyze. Since LLM-generated code frequently omits instructions, these artifacts may be missing or unreliable, undermining `D-helix`'s effectiveness.

For readability, existing metrics [10], [42], [47], [51] each have limitations, e.g., ignoring decompiler-specific artifacts, when applied directly to decompiled code. To the best of our knowledge, R2I [17] is the only metric tailored specifically for decompiled output. However, since it's a relative measure, whose features are derived from multiple decompilers, it cannot assign an absolute score to standalone LLM-generated code. For example, the feature, "number of unnecessary goto labels", is calculated by contrasting angr [61] or RetDec [5] outputs against those from Ghidra [3] and Hex-Rays [2], which cannot be computed when only one decompiler's output is given.

In summary, our principle, preserving accuracy while improving readability, cannot be satisfied by any single metric currently available.

4. Design

D-LIFT is an automatic decompilation pipeline that consists of a decompiler front-end and an LLM back-end capable of improving the quality of decompiled code. Figure 2 illustrates the workflow by which D-LIFT fine-tunes an LLM to produce improved decompiled code output. Three inputs are needed: a policy model (i.e., LLM waiting for training), a set of training binaries, and a decompiler. To improve the policy model's capabilities of generating better decompiled code, D-LIFT employs reinforcement learning (Section 4.1). To guide this training, D-LIFT introduces a multi-aspect assessment/reward metric, D-SCORE, that evaluates the LLM's output code on both accuracy and readability (Section 4.2). Specifically, for accuracy, D-SCORE adopts `D-helix`'s stepwise approach: first verifying syntax (Section 4.2.1), then validating semantics against the original binary (Section 4.2.2). Only if a candidate passes these accuracy checks does D-SCORE move on to assess readability (Section 4.2.3). Once the training is complete, D-LIFT outputs a fine-tuned LLM capable of generating decompiled code with improved accuracy and readability.

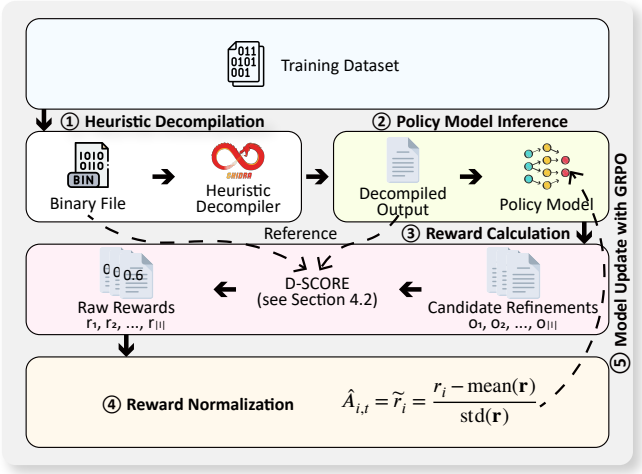


Figure 2: This figure shows how D-LIFT fine-tunes the policy model (i.e., the baseline model). Specifically, it applies GRPO to overcome the inherent complexity of decompilation tasks, where single decompiled code segments can correspond to multiple semantically equivalent source representations.

4.1. LLM Fine-Tuning

The challenge described in Section 3 highlights a critical limitation in current approaches: decompiled code can map to multiple semantically equivalent source representations, each representing a valid ground truth. This multiplicity poses significant training difficulties for supervised fine-tuning (SFT) approaches, such as LLM4decompile, which are designed to work with only one correct answer. Although reinforcement learning generates multiple candidates during training, theoretically providing access to various valid solutions, conventional RL policies maintain the single ground truth constraint when computing the loss. Fortunately, Group Relative Policy Optimization (GRPO) [53] overcomes this constraint by generating the loss from the normalized rewards across multiple candidate outputs. ,

Figure 2 illustrates how D-LIFT integrates GRPO into our workflow. ① Given a training binary, denoted as *bin*, D-LIFT invokes the heuristic decompiler to produce a original decompiled output, denoted as o_g. ② Using the o_g as input, the policy model generates a set of candidate refinements,$\{o_1, o_2, ...\}$. ③ For each candidate, o_i, D-LIFT computes a reward, r_i, using D-SCORE (see Section 4.2 for details). ④ Next, GRPO normalizes these rewards, $\mathbf{r} = \{r_1, r_2, ...\}$ within each candidate group according to its standard formulation:

$$\hat{A}_{i,t} = \tilde{r}_i = \frac{r_i - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})} \quad (1)$$

⑤ Finally, GRPO uses these normalized rewards, $\hat{A}_{i,t}$, to compute the loss for fine-tuning the model as follows:

$$J_{\text{GRPO}}(\theta) = \mathbb{E}_{q,\{o_i\}_{i=1}^{G}\sim\pi_{\theta_{\text{old}}}} \left[\frac{1}{G}\sum_{i=1}^{G}\frac{1}{|o_i|}\sum_{t=1}^{|o_i|}\min\left(r_t(\theta)\hat{A}_{i,t}, \text{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_{i,t}\right) \right] - \beta D_{\text{KL}}\left(\pi_\theta \| \pi_{\text{ref}}\right) \quad (2)$$

Given that the decompilation task accepts multiple valid ground truths, D-LIFT eliminates the KL-divergence weight by setting β to zero, thereby removing dependence on a single reference solution. In practice, setting β to zero not only reduces memory and computational overhead but also improves training effectiveness, in line with recent findings [24], [38]. The additional variables referenced in Equation (2) serve to modify the policy model parameters, with detailed definitions available in the original GRPO research publication [53].

4.2. Reward Function Design

Figure 3 shows the overall procedure of D-SCORE. As a reward function, D-SCORE takes three inputs: the original decompiled code, o_g, the original binary, *bin*, and a candidate refinement from the policy model, o_i, and outputs a comprehensive score r_i reflecting both accuracy and readability of o_i. Formally, r_i is defined as follows:

$$\begin{aligned} r_i = {} & \mathbb{1}(\ \text{cond}_{syn}\ )\cdot\left(R_{syn}\right) \\ & + \mathbb{1}(\neg\ \text{cond}_{syn}\ )\cdot(\mathbb{1}(\ \text{cond}_{sem}\ )\cdot R_{sem}(o_i, bin) \\ & + \mathbb{1}(\neg\ \text{cond}_{sem}\ )\cdot R_{read}(o_i, o_g))), \\ \text{where} \quad & \text{cond}_{syn} = \left(R_{syn}(o_i) == syn_{pen}\right), \\ & \text{cond}_{sem} = \left(R_{sem}(o_i) == ret_{pen} || call_{pen}\right) \end{aligned} \quad (3)$$

Within the above equation, X_{pen} represents the penalty score because of error X, and R_Y represents the reward return from each specific check in field Y. Note that, following our principle, we also define:

$$syn_{pen} < ret_{pen} < call_{pen} < min(R_{read}) \quad (4)$$

To generate r_i, specifically, ① D-SCORE checks for syntax errors (See Section 4.2.1). If any is found, it returns a syntax error score syn_{pen}. ② Otherwise, it verifies semantic equivalence between o_i and *bin*. If o_i fails the semantic check, D-SCORE returns a score, R_{sem}, based on the symbolic matching with the *bin* (See Section 4.2.2). ③ Only when o_i passes both syntax and semantic checks, D-SCORE defers to the readability component and returns a readability score, R_{read} (See Section 4.2.3).

4.2.1. Syntax Metric. Since D-LIFT uses `D-helix`'s framework to examine accuracy, D-SCORE adopts `D-helix`'s `Recompiler`. As an iterative recompilation tool, `Recompiler` automatically initializes undefined variables, injects required system libraries, and translates special pseudo-instructions

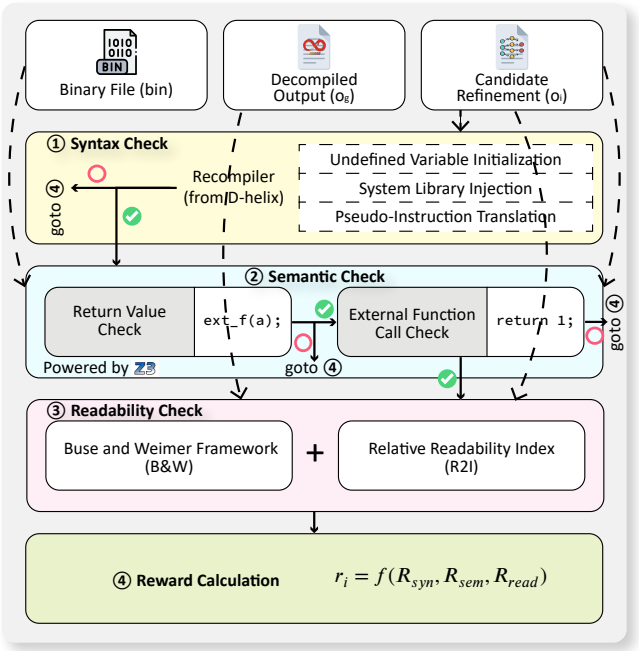


Figure 3: D-SCORE Framework, following our principle of *preserving accuracy while improving readability*.

(e.g., CONCAT) into function calls. For each candidate code o_i from the policy model, D-SCORE submits it to `Recompiler` and obtains a syntax score, R_{syn}, based on `Recompiler`'s feedback. Specifically, D-SCORE assign $R_{syn}(o_i)$ to syn_{pen} when the o_i cannot be recompiled and 0 otherwise. Formally:

$$R_{syn}(o_i) = \begin{cases} syn_{pen}, \text{ if } o_i \text{ cannot be compiled.} \\ +0, \text{ otherwise} \end{cases} \quad (5)$$

Note that syn_{pen} contributes directly to D-SCORE (as shown in Equation (3)), ensuring a clear penalty for any syntax error.

4.2.2. Semantics Metric. Once the o_i passes the syntax check, D-SCORE runs symbolic execution to conduct the semantic check between the original binary and o_i's IR. In addition to the behavior of return values, we also consider the behavior of external function calls in our semantic equivalence check.

For the return values check, we mostly follow `D-helix`'s approach, which employs symbolic execution and `SMT` solver. Specifically, as shown on the left side of Figure 4, given the decompiled code, D-SCORE symbolizes the input arguments and runs the symbolic execution to generate the symbolic model, `Symbolic-Model-Ret`, a mathematical model that encapsulates function behavior by mapping formula inputs to function arguments and formula outputs to function return values. After that, D-SCORE runs the `SMT` solver on `SMT-RET` to compare the symbolic models between the original binary and the decompiled code.

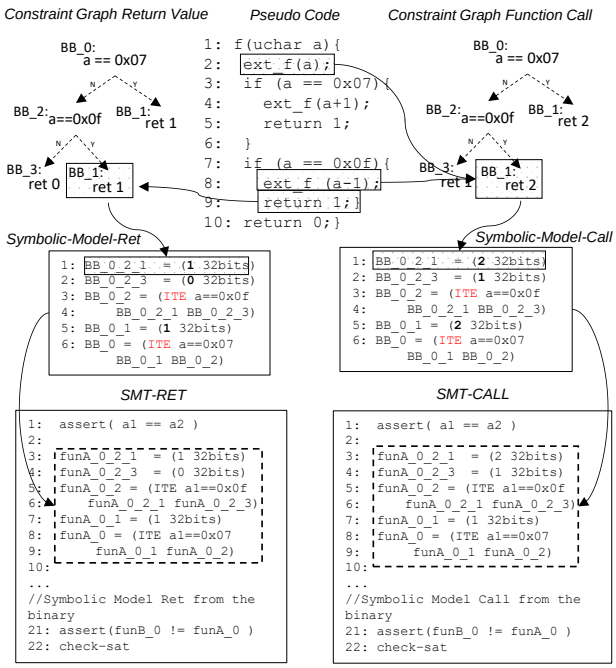


Figure 4: The workflow of semantic check in D-SCORE. The left side shows how the return value is checked, and the right side shows how the external function call is examined.

When checking the behavior of the external function call, however, directly applying `D-helix` to test LLM-generated code (e.g., o_i) can yield many false negatives. This limitation stems from `D-helix`'s fundamental dependence on decompiled code to establish ground truth for verifying external function calls. Specifically, it models external function calls by approximating return values through the sum of the least significant bytes of those arguments. However, this external function call modeling process is only initialized when an external function call is detected within the decompiled code. Since instructions, including function calls, are often omitted in the LLM-generated code, `D-helix` may *not* properly initialize its function call modeling procedures, leading to possible false negatives.

To model the external function call in LLM-generated code in a better way, D-SCORE counts how many external functions are invoked, as shown on the right side of Figure 4. Specifically, to identify valid external calls in each decompiled function, we first extract and save the names of all invoked external functions in the original decompiled output, o_g, to a file as our ground truth. After that, during the symbolic execution of the LLM-generated code, we build a symbolic model called `Symbolic-Model-Call` to model the external function call behavior. Unlike `Symbolic-Model-Ret` tracking the return value, this model uses the ground-truth file to track the number of matching function calls in the LLM-generated code for each execution path. Finally, we run `SMT` solver on `SMT-CALL` to compare the function call-count symbolic models between the original binary and the decompiled code. Note that we ignore the arguments in our semantic checks because compilation removes this information, and existing recovery techniques [34] cannot reliably reconstruct it.

Formally, we define our semantics metric as follows:

$$R_{sem}(o_i) = \begin{cases} ret_{pen}, \text{ if } (check_{ret}(o_i) == false) \\ call_{pen}, \text{ if } (check_{ret}(o_i) == true \\ \qquad\qquad \&\& \ check_{call}(o_i) == false) \\ +0, \text{ otherwise} \end{cases} \tag{6}$$

, where $check_{ret}(o_i)$ is Boolean result of running `SMT` on `SMT-RET`, and $check_{call}(o_i)$ is result of running `SMT` on `SMT-CALL`.

4.2.3. Readability Metric. To evaluate the readability of each candidate refinement, o_i, fairly, we generate a relative readability score by directly comparing it against the original decompiled code, o_g. To do this, we customize established software-engineering readability measures by incorporating selected R2I features as follows:

$$R_{read}(o_i, o_g) = \gamma \cdot R_{b\&w}(o_i, o_g) + \delta \cdot R_{R2I}(o_i, o_g) \tag{7}$$

To compute $R_{b\&w}(o_i, o_g)$, we follows the B&W framework, which defines a feature set, $\mathbf{f} = \{f_1, f_2, ...\}$, e.g., average number of commas per line, and their associated weights, $\mathbf{w} = \{w_1, w_2, ...\}$. Specifically, we first apply B&W to o_i and o_g to obtain two absolute scores. We then compute their relative difference and pass this value through a sigmoid function to map it into the range [-1,1], yielding a normalized, relative readability score. Formally,

$$R_{b\&w}(o_i, o_g) = sigmoid\left(\frac{R_{mul}(o_g) - R_{mul}(o_i)}{min(R_{mul}(o_i), R_{mul}(o_g))}\right), \quad \text{where} \quad R_{mul}(x) = \left(\sum \mathbf{f}(x) \cdot \mathbf{w}\right) \tag{8}$$

Nevertheless, certain general features, e.g., total line number, remain outside the scope of $R_{b\&w}(o_i, o_g)$. Fortunately, $R_{R2I}(o_i, o_g)$ includes these features, $\mathbf{f}$ and their associated weights $\mathbf{w}$ within its *conflicting features* and *generic features* categories. Our implementation follows the methodology established in the original research paper to generate the $R_{R2I}(o_i, o_g)$. Through renormalization of the feature-associated weights, $R_{R2I}(o_i, o_g)$ produces values within the range [-1,1], calculated using the following approach:

$$R_{R2I}(o_i, o_g) = \sum \mathbf{w} \cdot r_{elog}(\mathbf{f}(o_i) - \mathbf{f}(o_g)), \quad \text{where} \quad r_{elog}(x) = r \cdot e^{-\log_{10}(1+x)} + (1-r) \cdot \left(1 - e^{-\log_{10}(1+x)}\right) \tag{9}$$

For γ and δ in Equation (7), we allow users to adjust their values according to their specific needs.

5. Implementation

We implemented D-LIFT as a modular Python framework, using the state-of-the-art open-source decompiler, Ghidra (version 11.2).

Reinforcement learning. We train our models using the TRL library [59] (version 0.18) from Hugging-

face. During the RL, we set *num_generations* to 3, *num_iterations* to 10, *per_device_train_batch_size* to 3, *vllm_gpu_memory_utilization* to 0.7, leaving all other parameters at their default values.

Semantic check-related settings. For the `Recompiler`, we follow its default configuration by setting the maximum iteration count to 10.

For the semantics checking, we implement our semantic check framework on angr [61] (version 9.2), z3 [14] (version 4.13), and prompt [69] (verison 1.0). To reduce the training time, we set the execution timeout to 30 seconds.

D-SCORE Metric settings. We set syn_{pen} to -3, ret_{pen} to -2, and $call_{pen}$ to -1.5. For readability metric, we set γ to 0.25 and δ to 0.75 for Equation (7), which makes $R_{read}(o_i, o_g) \in (-1, 1)$. These values follow the Equation (4) and experimental observations to prevent sparse rewards [49].

6. Evaluation

We organize this section as follows:

- In Section 6.1, we describe our experimental setup, including the evaluation of the reward metric and function (i.e., D-SCORE), dataset details, and baseline model selection.
- In Section 6.2 and Section 6.3, we demonstrate how effectively D-LIFT enhances LLM-generated decompiled code via the above setup.
- In Section 6.4, we provide concrete case studies illustrating how D-LIFT refines specific decompiled snippets to improve both accuracy and readability.

6.1. Experiment Setup

In this section, we begin by evaluating D-SCORE along two dimensions, applicability and precision, in Section 6.1.1. We then describe our training/evaluation dataset in Section 6.1.2. Finally, we detail our baseline model selections and reasons behind them in Section 6.1.3.

6.1.1. D-SCORE Evaluation. We conduct experiments on a cluster node equipped with an NVIDIA A100 Tensor Core GPU (80GB of memory) [43], two 32-core AMD EPYC 7543 CPUs, and 400 GB of RAM.

Dataset. Our metric evaluation uses a dataset of 1,948 decompiled functions sourced from binaries that previous literature uses, including `coreutils` [13] (v9.5) and `util-linux` [58] (v2.41). Specifically, we first use GCC [1] to compile these projects with -O2 optimization under x86 Linux platform and then ran Ghidra [3] (version 11.2) on 578 resulting binaries and object files, yielding 5,385 unique decompiled functions (1,792 from `coreutils` and 3,593 from `util-linux`). To focus on functions with sufficient complexity and room for improvement, we then filtered this set to include only those with at least 20 lines of code and a cyclomatic complexity [41] greater than 3, leaving 1,948 (36.2%) functions (653 from `coreutils` and 1,295 from `util-linux`).

Methodology. D-SCORE contains two core components, accuracy check and readability assessment. Because its readability metric is an aggregation of two proven metrics [10], [17], our evaluation focuses on the decompiled code accuracy examination. To do this, we prompt `Qwen-Coder-2.5-3B` [6] with the above 1,948 decompiled functions and then pass each of its generated code completions, along with the corresponding original binary, through D-SCORE for scoring. We evaluate D-SCORE along two dimensions: (1) *Applicability*: The proportion of functions for which D-SCORE can successfully derive the symbolic models from the binary. (2) *Precision*: Among these analyzable functions, the fraction for which D-SCORE correctly determines that the generated code is semantically equivalent to the original.

#	Categories of Errors	Pct.
1	Underlying tool errors	43%
2	Timeout	34%
3	D-SCORE errors	14%

TABLE 1: The percentage of decompiled functions that cannot be analyzed by D-SCORE due to the listed errors.

Accuracy	0.9450
Precisions	0.9100
Recall	0.9785
F1	0.9430

TABLE 2: The accuracy, precision, recall, and F1 score of D-SCORE on the tested decompiler.

Applicability result. Our evaluation shows that out of 1,968 functions in our evaluation program set, D-SCORE can test 79.9% (1,573) of these functions, i.e., generate the symbolic models of these functions from the binary without errors. To understand the limitation, we randomly select 50 functions where D-SCORE fails and manually analyze them. Table 1 categorizes the failures encountered by D-SCORE and reports their occurrence frequency. These errors fall into three categories: (1) Errors from the underlying tool, e.g., bugs in angr or incorrect identification of function boundaries when encountering no-return calls, (2) Timeout due to the scale of a function, and (3) Internal errors of D-SCORE, e.g., unsupported floating-point instructions.

Precision result. We evaluate the precision of D-SCORE by randomly sampling 100 functions from the 1,573 that D-SCORE can analyze and manually compare each LLM-generated output against its original binary's semantics to verify whether the decision made by D-SCORE was correct. Table 2 presents our results in terms of accuracy, precision, recall, and F1 score. Our analysis uncovers that: 1 False positives occur because the memory model of D-SCORE allocates fresh memory addresses for symbolized pointers. Even when the generated code is semantically correct, the values of pointers differ from those in the original binary, causing the symbolic executor to report a spurious mismatch. (2) False negatives occur because we assume all external function calls return zero. When using a default return value in a conditional instruction, one branch will never be explored during the symbolic execution of the binary. If the LLM's output omits code for those unvisited branches, D-SCORE cannot detect the discrepancy and thus overlooks the error.

6.1.2. Dataset. We begin by briefly analyzing the accuracy of the data that D-SCORE can process, and then explain how we construct our training and evaluation datasets.

#	Model Name	Synt Errs	Sem Errs	Total Errs
1	Qwen2.5-Coder-1.5B	373 (36.4%)	92 (8.98%)	465 (45.4%)
2	Qwen2.5-Coder-3B	238 (23.2%)	110 (10.7%)	348 (34.0%)
3	Llama3.2-3B	371 (36.2%)	180 (17.6%)	551 (53.8%)
4	LLM4Decompile-End-1.3B	887 (86.5%)	68 (6.63%)	955 (93.2%)

TABLE 3: Different baseline models' performance on the originally accurate (OA) decompiled code. Specifically, it shows how many functions become inaccurate *after* being processed by the baseline model (i.e., LLM without fine-tuning).

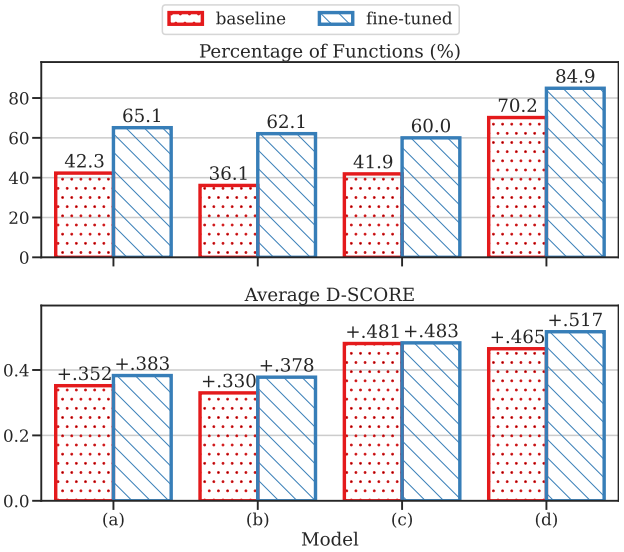
Dataset accuracy analysis. As detailed in Section 6.1.1, since D-SCORE is only able to work on 1,573 functions, we base our training and evaluation datasets on this subset. To better understand our dataset, we first analyze the score distribution from D-SCORE over these 1,573 decompiled outputs generated directly from the decompiler. Running D-SCORE on the Ghidra-generated functions allows us to partition them into two groups: originally accurate (i.e., error-free) and originally inaccurate. Of the 1,573 functions, 1,025 are classified as originally accurate (i.e., D-SCORE = 0, since $R_{read}(o_g, o_g) = 0$), while the remaining 548 fall into originally inaccurate (i.e., D-SCORE < 0), 307 exhibiting syntax errors and 241 containing semantic errors.

Training and evaluation dataset. We randomly choose 300 functions from the originally accurate group as the training data. This selection criterion is based on the fact that LLMs demonstrate a limited ability to correct decompiler-introduced inaccuracies when provided only with decompiled code, as listed in Section 6.3. To train the model, we use the following template: *"prompt": [{ "role": "system", "content": "You are a helpful assistant for improving the decompiled result from the user. The user will input the decompiled result from Ghidra. Please improve its readability while preserving its semantics. Please do not add comments. Please just output the improved code." }, { "role": "user", "content": "[original decompiled code]" } .*

We evaluate D-LIFT on the remaining 1,273 functions, which we split into two subsets: 725 functions that are **originally accurate (OA)** and 548 functions that are **originally inaccurate (OIA)**.

6.1.3. Baseline Model. Due to computational resource constraints, we restrict our LLM to fewer than 3 billion parameters. Specifically, as an RL framework, GRPO is particularly memory-intensive, since it requires simultaneous inference to generate candidate outputs and backpropagation to update model parameters, both of which consume significant GPU memory. Additionally, reward normalization in GRPO mandates generating at least two candidates per input, further increasing memory demands. In our experiments, even after using vLLM [30] with a memory-efficient setting of 0.7, we still encountered out-of-memory errors when running D-LIFT on models larger than 3 billion parameters.

Therefore, we select two code-focused LLMs, `Qwen2.5-Coder` [26] (`1.5B` and `3B` variants) and one general-purpose model, `Llama3.2-3B` [21]. We excluded the prior work `LLM4Decompile-End-1.3B` [55] from our main evaluation after observing its poor performance on our dataset. Specifically, we ask all four above models to improve our 1,025 originally accurate functions, score the outputs using D-SCORE and show the results in Table 3. Since being fine-tuned based on the model released from November 2023, `LLM4Decompile-End-1.3B` improved only 70 functions (6.8%), whereas 955 functions (93.2%) turned inaccurate. In contrast, the three newer LLMs (released around September 2024) made only 44.4% of functions inaccurate. Given this marked difference, we omit `LLM4Decompile-End-1.3B` from further analysis.



(a) Qwen2.5-Coder-1.5B (b) Qwen2.5-Coder-3B (c) Llama3.2-3B (d) All

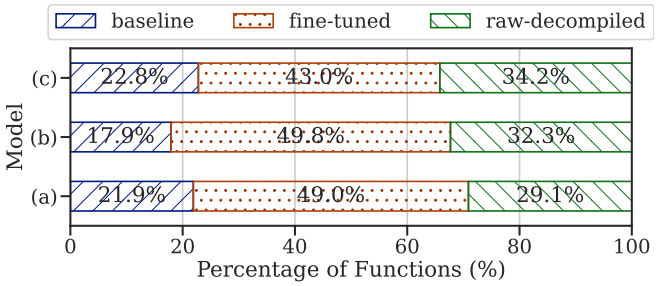
Figure 5: The performance of Different models on the OA dataset, before and after fine-tuning by D-LIFT. Specifically, it shows how many functions are improved by the model(s) compared with the original decompiled code, and these functions from D-SCORE.

6.2. D-LIFT Performance On OA

We show the evaluation of D-LIFT on originally accurate functions (OA) in two steps. In Section 6.2.1, we compare outputs from the baseline and fine-tuned models using D-SCORE. Then Section 6.2.2 analyzes the underlying reasons for the differences. Finally, in Section 6.2.3, we show how LLMs' performance is affected by the size of the training dataset.

6.2.1. Result. Figure 5 summarizes the number of original decompiled functions within the OA dataset that are improved by the baseline and fine-tuned models and their average D-SCORE. To this end, we compare the output from each model with the original decompiled code. For each model, D-LIFT improves the quality of 55.3% more functions on average, compared to the baseline LLMs. By selecting the best output among all three baseline models, 509 (70.2%) functions (avg. +0.465) show improvement, while fine-tuned models achieve improvement in 616 functions (84.9%) averaging +0.517.

To better quantify the improvements brought by fine-tuning, we compared the output of each fine-tuned model



(a) Qwen2.5-Coder-1.5B (b) Qwen2.5-Coder-3B (c) Llama3.2-3B

Figure 6: Overall performance of D-LIFT on the OA dataset. This chart shows, for each function, which source, baseline LLM, fine-tuned LLM, or original decompiler achieves the highest D-SCORE score and reports the percentage of functions in each category.

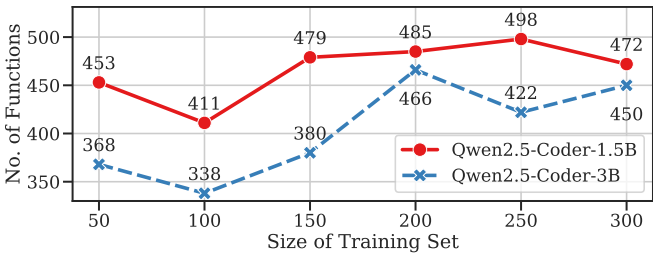


Figure 7: This table shows how many functions from the OA dataset scored higher (y-axis) after being processed by the fine-tuned LLMs with different sizes of the training sets (x-axis), compared to the original decompiled code under D-SCORE.

against its corresponding baseline and the original decompiled output. To do this, for each function, we select the version with the highest D-SCORE score among the three and show the result in Figure 6. Specifically, for `Qwen2.5-Coder-1.5B`, fine-tuned output is best for 355 (49.0 %) functions (avg. +0.399), baseline LLM for 159 (21.9 %) functions (avg. +0.419). For `Qwen2.5-Coder-3B`, fine-tuned output is best for 361 (49.8%) functions (avg. +0.402) and baseline LLM for 130 (17.9%) functions (avg. +0.398). For `Llama3.2-3B`, fine-tuned output is best for 312 (43.0%) functions (avg. +0.523) and baseline LLM for 165 (22.8%) functions (avg. +0.561). Moreover, by taking the best output among all six LLMs and the original decompiled code, 625 (86.2 %) functions showed improvement (average +0.585), while only 100 functions remained unimproved. The above result shows that D-LIFT helps the fine-tuned LLMs dominate their performance in generating high-quality decompiled code.

6.2.2. Findings. To better understand D-LIFT's influence on LLM performance, we conducted an additional analysis by directly comparing the fine-tuned output and the baseline model output. Specifically, we analyze how D-LIFT modifies function performance through two distinct categories: improvements, where fine-tuned models successfully resolve issues present in baseline outputs, and regressions, where previously error-free baseline functions develop new problems following the fine-tuning process. Based on it, we classify these changes into six categories: syntax fixes, semantic fixes, syntax regressions, semantic regressions, readability improvements, and readability regressions. Table 4 reports the number of functions falling into each category. These results show that D-LIFT achieves considerable accuracy enhancements for the majority of models, with regression instances remaining at acceptably low levels.

To investigate the root causes of both improvements and regressions, we randomly selected 50 functions from each group (i.e., those that improved and those that regressed) and performed a manual code review. Our findings, summarized in Table 5, show that fine-tuning corrects five main categories of errors: (1) Missing instructions, e.g., missing goto labels, variable declarations, and value assignments. (2) Incorrect brackets in conditional expressions, e.g., missing parentheses in if statements or misplacement leading to incorrect pointer dereference. (3) Incorrect variable naming and casting, e.g., using *mode_t* when only *__mode_t* is defined. (4) Unwanted instruction insertions, e.g., duplicate goto labels and unwanted function calls. (5) Incorrect literal value. e.g., constant values are inconsistencies with the original values. However, fine-tuning also introduces regressions in three areas: (1) Missing instructions. (2) Incorrect brackets in conditional expressions. (3) Unwanted instruction insertions. We provide more representative examples of the enhancements that D-LIFT enables in Section 6.4.

Summary: When the original decompiled code does not have syntax or semantic error, D-LIFT yields substantial improvement over the baseline, in both the number of functions improved and their average D-SCORE.

6.2.3. Training Efficiency. To determine the optimal training set size, we select our best-performing LLM, i.e., `Qwen2.5-Coder`, to evaluate LLM performance with training sets of 50, 100, 150, 200, 250, and 300 functions. Figure 7 shows how many functions from the OA dataset scored higher after being processed by the fine-tuned LLM, compared to the original decompiled code under D-SCORE. As shown, the performance stabilizes once the training set reaches around 200 to 300 functions.

6.3. D-LIFT Performance On OIA

We show the evaluation of D-LIFT on originally inaccurate functions (OIA) in two steps. First, in Section 6.3.1, we use D-SCORE to compare outputs from the baseline and fine-tuned models. Then, in Section 6.3.2, we analyze the underlying reasons for these observed scores.

6.3.1. Result. Table 6 summarizes, for both baseline and fine-tuned models, how many functions achieve a higher D-SCORE than the original decompiled output and the average score improvement for those functions.

Both the baseline model and the models that are fine-tuned with 300 instances struggle with improving the original inaccurate functions. By taking the best output among all six LLMs and the original decompiled code, only 44 functions

#	Model Name	Improvements				Regressions			
		Syntax	Semantic	Readability	Total	Syntax	Semantic	Readability	Total
1	Qwen2.5-Coder-1.5B	135	18	202	355	25	2	132	159
2	Qwen2.5-Coder-3B	88	17	256	361	12	2	116	130
3	Llama3.2-3B	116	38	114	268	19	9	150	178

TABLE 4: This table shows how many functions get improved and regressed by D-LIFT. This comparison happens between the output of the fine-tuned model and the baseline model, where the improvement refers to the function get higher score from the fine-tuned model and the regression refers to the function get higher score from the baseline model.

Performance	Error Type	No. Func
Improvement	Missing instruction	24
	Incorrect brackets	12
	Incorrect variable naming and casting	5
	Unwanted instruction insertions	7
	Incorrect literal value	2
Degradation	Missing instruction	14
	Incorrect brackets	24
	Unwanted instruction insertions	12

TABLE 5: This table shows the root causes of both improvements and regressions caused by D-LIFT, where the result is concluded by manually reviewing randomly selected 100 functions.

#	Model Name	No. of Func	Avg. D-S.
1	Qwen2.5-Coder-1.5B-baseline	8 (1.48%)	-0.591
2	Qwen2.5-Coder-3B-baseline	12 (2.23%)	-0.936
3	Llama3.2-3B-baseline	14 (2.6%)	-0.614
4	All baseline models	31 (5.66%)	-1.170
5	Qwen2.5-Coder-1.5B-fine-tuned	6 (1.12%)	+0.113
6	Qwen2.5-Coder-3B-fine-tuned	9 (1.67%)	-0.396
7	Llama3.2-3B-fine-tuned	8 (1.49%)	-0.243
8	All fine-tuned models	19 (3.47%)	-0.469

[1] "No. of Func" shows how many functions were improved and the percentage relative to the total functions.
[2] "Avg. D-S." is the average D-SCORE difference (improved vs. raw decompiled).

TABLE 6: Different models' performance on the OIA dataset, before and after fine-tuning by D-LIFT. Specifically, it shows how many functions are improved by the model(s) compared with the raw decompiled code and these functions' score from D-SCORE

showed improvement (average -0.759), while 504 functions remained unimproved (average -2.50).

6.3.2. Findings. To investigate why LLMs perform poorly on the OIA dataset, we randomly select 50 functions, where 25 are successfully improved by any LLMs (including baseline LLMs and fine-tuned LLMs) and 25 are not improved by LLMs, and manually analyze the underlying factors.

For the 25 functions where LLMs achieve improvements, surprisingly, we observed a consistent pattern: each involved variables declared as `undefined [16]`, a 16-byte type with unknown signedness. The LLMs typically converted the variables with these opaque declarations into fixed-length arrays and updated member accesses accordingly. For instance, we observe that the declaration changed from `undefined [16] auVar1;` to an array, `ulong auVar1[2]` and this variable's first eight-byte assignment is modified from `auVar1._0_8_ = 0;` to `auVar1[0] = 0;`. Although these transformations sometimes introduce subtle semantic inaccuracies, they consistently eliminate syntax errors, resulting in higher D-SCORE.

For the 25 functions where LLMs fail to achieve any improvements, we find three main causes: (1) Syntax errors due to undefined function pointer types. In 13 cases, errors stem from unresolved function pointer types like `(code *)puVar3[4]`. (2) Syntax errors from unsolvable type patterns. In 7 cases, issues arise from constructs like `CONCAT31((int3)XX)`, where the type `int3` is not well-formed. (3) Semantic errors from uninitialized global variables. In 5 cases, the decompiled code fails to initialize global variables to the correct value.

Summary: When the original decompiled code contains syntax or semantic errors, neither baseline LLMs nor our fine-tuned models can deliver real improvements, indicating the importance of the decompiler front-end and limitations of current LLMs.

6.4. Case Study

In this section, we present several illustrative cases that demonstrate how D-LIFT effectively improves the quality of decompiled code generated by the LLM without fine-tuning. Specifically, we show how D-LIFT fixes syntax errors introduced by the LLM in Section 6.4.1, fixes semantic errors introduced by the LLM in Section 6.4.2, and improves the readability in Section 6.4.3.

6.4.1. Syntax Error Fixes.

Fixing Incorrect Variable Casting and Refactor Loop. Figure 8 illustrates how D-LIFT enhances the output of `Qwen2.5-Coder-3B` model for the decompiled snippet of the `uuid_copy` function (`util-linux`).

Specifically, this function simply copies 16 bytes from the second parameter (`src`) to the first (`dst`). Since the decompiler cannot reconstruct the original struct or pointer types for the two input parameters, it falls back to manual pointer casting these parameters to byte pointers and uses pointer offsetting by (`lVar1`) to copy each byte (see line 8 of the original decompiled output). Meanwhile, the decompiler also uses a `do-while` loop that checks `lVar1 != 0x10`, rather than the more natural `for (i = 0; i < 16; i++)` construct. When the baseline LLM refactors the loop, though it successfully rewrites it as a `for` with `i < 16`, it mistakenly applies the array subscript operator to the input parameters of type `long`, leading to the compiler error. D-LIFT, however, fine-tunes the model to insert the correct byte-pointer casts and maintain the `for` with `i < 16`, which eliminates the syntax error while yielding a more readable, semantically faithful implementation. As a result, D-LIFT improves the D-SCORE from -3.000 to +0.8887.

Source:

```
void uuid_copy(uuid_t dst,
     const uuid_t src)
{
 unsigned char *cp1;
 const unsigned char *cp2;
 int i;

 for (i=0, cp1 = dst, cp2
      = src; i < 16; i++)
 *cp1++ = *cp2++;
}
```

Original Decompiler:

```
void uuid_copy (long
     param_1,long param_2)

{
 long lVar1;

 lVar1 = 0;
 do {
 *(undefined *) (param_1 +
      lVar1) = *(undefined
      *)(param_2 + lVar1);
  lVar1 = lVar1 + 1;
 } while (lVar1 != 0x10);
 return;
}
```

Baseline model:

```
void uuid_copy (long
     dest, long src)
{
 long i;

 for (i = 0; i < 16;
      i++)
 {
  dest[i] = src[i];
 }
}
```

Fine-tuned model:

```
void uuid_copy(long dest,
     long src)
{
 long i;

 for (i = 0;i < 0x10; i++)
 {
 *(unsigned char *)(dest +
      i) = *(unsigned char
      *)(src + i);
 }
}
```

Figure 8: This code snippet shows how D-LIFT helps `Qwen2.5-Coder-3B` enhance its ability to generate more readable code while correcting the syntax error *"error: subscripted value is neither array nor pointer nor vector"* that appears at line 7 of the baseline output.

Source:

```
if(!tb ||
     !tb->colors_wanted ||
     tb->format !=
     SCOLS_FMT_HUMAN)
 return NULL;
...
 tb->cur_color = color;
```

Original decompiler:

```
if (param_1 == 0) {
 return;
}
if ((*(byte *)(param_1 +
     0x140) & 2) == 0) {
 return;
}
if (*(int *)(param_1 + 0x108)
     != 0) {
 return;
}
...
*(char **)(param_1 + 0x120) =
     param_3;
```

Baseline model:

```
if (!param_1) return;
if (!(*(byte*)(param_1 +
     0x140) & 2)) return;
if (*(int*)(param_1 +
     0x108)!= 0) return;
...
*(char **)param_1 + 0x120 =
     param_3;
```

Fine-tuned model:

```
if (param_1 == 0) return;
if (((*(byte *)(param_1 +
     0x140) & 2) == 0) ||
     (*(int *)(param_1 +
     0x108)!= 0)) return;
...
*(char **)(param_1 + 0x120)
     = param_3;
```

Figure 9: This code snippet shows how D-LIFT helps `Qwen2.5-Coder-1.5B` enhance its ability to generate more readable code while correcting the syntax error *"error: lvalue required as left operand of assignment."* that appears at line 5 of the baseline output.

Fixing Missing Parentheses and Consolidate Conditionals. Figure 9 demonstrates another example about how D-LIFT corrects the syntax errors while enhancing readability in the decompiled `fputs_color_cell_close` (`util-linux`).

Specifically, for inaccuracy, line 5 in baseline `Qwen2.5-Coder-1.5B` model output lacks the necessary parentheses around the assignment target, resulting in the compilation error, *lvalue required as left operand of assignment*. Regarding readability, the original source code combines three checks with two `or` expressions (line 1). The original decompiled output, however, expands this into three separate `if` statements. For the output from the baseline model, though it removes redundant braces, it still uses three `if` blocks. Our fine-tuned model not only adds the necessary parentheses in line 4 but also merges the second and third checks into one consolidated if statement in line 2, mirroring the source code's succinct logic. As a result, D-LIFT raises the D-SCORE for this function from –3.000 to +1.275.

6.4.2. Semantic Error Fixes.

Fixing Incorrect Literal Value and Extract Functional Variable. Figure 10 shows how the decompiled code snippet from the `fdisk_delete_all_partitions` function (`util-linux`) is improved by correcting the semantic errors while enhancing the readability.

Semantically, the baseline `Qwen2.5-Coder-3B` output mistakenly returns the decimal constant `-65538` (lines 8 and 11), which equates to `0xfffefffe` rather than the intended `0xfffffffea`. Our fine-tuned model fixes this by emitting `return 0xfffffffea;` at lines 9 and 12, restoring correct behavior. For readability, our fine-tuned model makes two key improvements. First, it removes a redundant `if-else` construct (original decompiled code line 14) and replaces it with a direct `return 0xfffffffea` without an `else` condition added (fine-tuned model output line 12), yielding a control flow structure that more closely mirrors the original source. Second, it extracts the repeated expression `*(long *)(*(long *)(param_1 + 0x180) + 0x30)` (fine-tuned model output line 14), into a named variable, reducing duplicated usage (original decompiled code line 15 and line 23). As a result, D-LIFT raises this function's D-SCORE from –2.000 to +0.625.

6.4.3. Readability Improvement.

Arithmetic Operators & Boolean Expression Simplification. Figure 11 illustrates how D-LIFT enhances readability by simplifying both arithmetic operators and Boolean expressions.

Specifically, the source code, extracted from `strv_length` function (`util-linux`), contains 38 non-blank characters. Ghidra's original decompilation, however, leaves all operators unsimplified, expanding

Source:

```
int fdisk_delete_all_partitions (struct fdisk_context *cxt)
{
 size_t i;
 int rc = 0;

 if (!cxt || !cxt->label)
  return -EINVAL;

 for (i = 0; i < cxt->label->nparts_max; i++) {

  if (!fdisk_is_partition_used(cxt, i))
   continue;
  rc = fdisk_delete_partition(cxt, i);
  if (rc)
   break;
 }

 return rc;
}
```

Original decompiler:

```
undefined8 fdisk_delete_all_partitions(long param_1)

{
 int iVar1;
 undefined8 uVar2;
 ulong uVar3;

 if (param_1 == 0) {
  return 0xffffffea;
 }
 if (*(long *)(param_1 + 0x180) == 0) {
  uVar2 = 0xffffffea;
 }
 else {
  uVar3 = 0;
  if (*(long *)(*(long *)(param_1 + 0x180) + 0x30)!= 0) {
   do {
    iVar1 = fdisk_is_partition_used(param_1,uVar3);
    if ((iVar1 != 0) && (uVar2 =
         fdisk_delete_partition(param_1,uVar3), (int)uVar2
         != 0)) {
     return uVar2;
    }
    uVar3 = uVar3 + 1;
   } while (uVar3 < *(ulong *)(*(long *)(param_1 + 0x180) +
       0x30));
  }
  uVar2 = 0;
 }
 return uVar2;
}
```

Baseline model:

```
int fdisk_delete_all_partitions(long param_1) {
 int iVar1;
 long lVar2;
 long lVar3;
 long lVar4;

 if (param_1 == 0) {
  return -65538; // Equivalent to 0xffffffea
 }
 if (*(long *)(param_1 + 0x180) == 0) {
  return -65538; // Equivalent to 0xffffffea
 }
 lVar2 = 0;
 if (*(long *)(*(long *)(param_1 + 0x180) + 0x30)!= 0) {
  do {
   iVar1 = fdisk_is_partition_used(param_1, lVar2);
   if ((iVar1!= 0) && (lVar3 =
        fdisk_delete_partition(param_1, lVar2),
        (int)lVar3!= 0)) {
     return lVar3;
     // Return error code if partition deletion fails
   }
   lVar2 = lVar2 + 1;
  } while (lVar2 < *(ulong *)(*(long *)(param_1 + 0x180) +
      0x30));
 }
 return 0; // Return success
}
```

Fine-tuned model:

```
int fdisk_delete_all_partitions(long param_1) {
 int iVar1;
 long lVar2;
 long lVar3;
 long lVar4;
 long lVar5;

 if (param_1 == 0) {
  return 0xffffffea;
 }
 if (*(long *)(param_1 + 0x180) == 0) {
  return 0xffffffea;
 }
 lVar2 = *(long *)(*(long *)(param_1 + 0x180) + 0x30);
 if (lVar2!= 0) {
  lVar3 = 0;
  do {
   iVar1 = fdisk_is_partition_used(param_1, lVar3);
   if ((iVar1!= 0) && (lVar5 =
        fdisk_delete_partition(param_1, lVar3),(int)lVar5!=
        0)) {
    return lVar5;
   }
   lVar3 = lVar3 + 1;
  } while (lVar3 < lVar2);
 }
 return 0;
}
```

Figure 10: This code snippet shows how D-LIFT helps `Qwen2.5-Coder-3B` enhance its ability to generate more readable code while correcting the semantic error. Specifically, the return value `-65538` at line 8 and line 11 of the baseline output is not the same as `0xffffffea`.

the snippet to 138 non-blank characters. The baseline `Qwen2.5-Coder-1.5B` model makes marginal improvements, reducing 11 characters in code by simplifying one Boolean expression in lines 6 and 7 of the baseline model output. In contrast, our fine-tuned model systematically rewrites both arithmetic and logical operations, bringing a total of 29 non-blank character reductions while preserving semantics. Consequently, D-LIFT boosts this function's D-SCORE from +0.605 to +0.790.

7. Discussion

Applicability. As illustrated in Section 6.3.2, D-LIFT performs poorly when the decompiler front-end fails to produce

Source:

```
if (!l)
 return 0;

for (; *l; l++)
 n++;

return n;
```

Original decompiler:

```
if (param_1 == (long *)0x0) {
 return 0;
}
if (*param_1 != 0) {
 do {
  param_1 = param_1 + 1;
  iVar1 = iVar1 + 1;
  } while (*param_1 != 0);
 return iVar1;
}
return 0;
```

Baseline model:

```
if (param_1 == NULL) {
 return 0;
}
if (*param_1!= 0) {
 do {
  param_1 = param_1 + 1;
  iVar1++;
 } while (*param_1!= 0);
 return iVar1;
}
return 0;
```

Fine-tuned model:

```
if (!param_1) {
 return 0;
}
if (*param_1) {
 do {
  param_1++;
  iVar1++;
 } while (*param_1);
 return iVar1;
}
return 0;
```

Figure 11: This code snippet shows how D-LIFT helps `Qwen2.5-Coder-3B` enhance its ability to generate more readable code by reducing 29 characters while preserving the accuracy.

accurate code. Moreover, because D-LIFT relies on function-level decompiled output, it cannot help if the decompiler is unable to process the binary. Hence, D-LIFT performs poorly in addressing internal decompiler issues, such as bugs that cause decompiler crashes or persistent decompilation challenges, including the identification of function boundaries and indirect calls.

Underlying tools. Since D-LIFT employs D-helix, it inherits the limitations of D-helix, including missing support for floating point instructions, missing support for double pointers (due to the memory model), and missing support for large binaries because of timeouts.

External function calls. For external function calls, D-SCORE differs from `D-helix`'s approach of modeling return values as the sum of the least significant bytes of its arguments; Instead, D-SCORE counts the number of calls. This simplification can be problematic when a function's return value affects control flow. By default, we assign zero (0) as the return value of every external function call, which may prevent exploration of branches that require nonzero return values. Nevertheless, accurately determining whether an external call yields a meaningful return itself is an open challenge [34]. We leave the more precise modeling of external function calls as future work.

8. Related Work

Regarding LLM-based decompiled-code enhancement, several approaches have been proposed. Besides LLM4Decompiler [55], researchers have also proposed DecGPT [63], which focuses on making decompiled code more recompilable. Nevertheless, this approach does not provide any method to handle the semantic errors, e.g., hallucination errors, introduced by the LLM. To the best of our knowledge, DeGPT [25] is the only existing work that attempts to validate the accuracy of LLM-generated decompiled code. DeGPT introduces MSSC, a static analysis framework that assigns random values to inputs and observes the resulting changes in symbolic values in both the decompiled code and the LLM-generated code, aiming to detect discrepancies and identify inaccuracies. However, this method has notable drawbacks. For instance, MSSC does not recompile the code; it cannot detect syntax errors. Meanwhile, by testing with random inputs, the validation result can be inconsistent across runs.

Fine-tuning LLM to generate better quality code is not new. PPOcoder [54] uses structural differences, measured via Data Flow Graphs (DFGs) and Abstract Syntax Trees (ASTs) between the source code and generated code, as its reward signal, to improve the performance of LLM in multiple code generation tasks. StepCoder, CodeRL, and Palit [15], [32], [45] utilize compiler and unit tests as feedback for reinforcement learning. Nevertheless, all the above approaches accept only one unique ground truth, which makes them inappropriate in the decompilation scenario.

Researchers have also investigated the use of symbolic execution tools to validate the semantics of LLM-generated code. Taneja [56] applies Alive2 [39] on the vectorized code generated by LLM to verify its semantic correctness. Similarly, Wang [62] integrates Alive2 into a compiler's translation-validation pipeline to ensure semantic fidelity. Nevertheless, since Alive2 is primarily designed to detect bugs, such as undefined behaviors, arising from compiler optimizations, it may miss decompiler-specific errors.

Regarding the code readability metric, subsequent studies have been proposed based on B&W framework. Specifically, researchers [23], [42], [47], [51], [57] have shifted toward the broader concept of code comprehensibility, which extends readability by also considering elements beyond the code itself, such as associated documentation, during evaluation. However, because these metrics assume the presence of comments and external documentation, features that decompiled code typically lacks, they are not well suited for assessing decompiled output.

9. Conclusion

We design D-LIFT, an automatic decompilation pipeline with an LLM-based back-end that is fine-tuned using reinforcement learning to improve the quality of the decompiled code, adhering to the principle of *preserving accuracy while improving readability*. We propose D-SCORE, an integrated scoring mechanism designed specifically for decompilation recovery tasks. We implement D-LIFT based on Ghidra and fine-tune three LLMs, and achieve significant decompiled code improvement for widely used benchmark functions. Compared to the baseline LLMs, on average, our fine-

tuned LLMs improve the quality of 55.3% more functions. Moreover, for functions that are accurately decompiled, when choosing the best output among the baseline model, the fine-tuned model (i.e., D-LIFT), and the original decompiled code, we find that on average, 47.3% of the top-scoring functions come from D-LIFT, whereas only 20.9% come from the baseline model.

Ethics Statement

We note that our found bugs do not pose an immediate threat to users or developers since they mainly affect the accuracy of LLM-generated code.

We acknowledge the use of Chat-GPT [44] and Claude-AI [4] solely as a paraphrasing aid to improve clarity and readability; at no point did we allow it to generate new content, ideas, or arguments. All substantive work and original insights remain entirely our own.

References

[1] Free Software Foundation. Gcc. https://gcc.gnu.org/.

[2] Hex-Rays SA. Hex rays decompiler. https://hex-rays.com/decompiler/.

[3] National Security Agency. Ghidra. https://ghidra-sre.org/.

[4] Anthropic. Claude AI (Claude 3, May 2025 version). https://claude.ai, 2025. Large language model. Accessed: 2025-06-04.

[5] Avast Software. RetDec: A retargetable machine-code decompiler. https://retdec.com/.

[6] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenhang Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, K. Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Yu Bowen, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xing Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. Qwen technical report. *ArXiv*, abs/2309.16609, 2023.

[7] Zion Leonahenahe Basque, Ati Priya Bajaj, Wil Gibbs, Jude O'Kain, Derron Miao, Tiffany Bao, Adam Doupé, Yan Shoshitaishvili, and Ruoyu Wang. Ahoy SAILR! there is no need to DREAM of c: A Compiler-Aware structuring algorithm for binary decompilation. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 361–378, Philadelphia, PA, August 2024. USENIX Association.

[8] David Brumley, JongHyup Lee, Edward J Schwartz, and Maverick Woo. Native x86 decompilation using {Semantics-Preserving} structural analysis and iterative {Control-Flow} structuring. In *22nd USENIX Security Symposium (USENIX Security 13)*, pages 353–368, 2013.

[9] Kevin Burk, Fabio Pagani, Christopher Kruegel, and Giovanni Vigna. Decomperson: How humans decompile and what we can learn from it. In *31st USENIX Security Symposium (USENIX Security 22)*, pages 2765–2782, Boston, MA, August 2022. USENIX Association.

[10] Raymond P.L. Buse and Westley R. Weimer. Learning a metric for code readability. *IEEE Transactions on Software Engineering*, 36(4):546–558, 2010.

[11] Ying Cao, Runze Zhang, Ruigang Liang, and Kai Chen. Evaluating the effectiveness of decompilers. In *Proceedings of the 33rd ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA 2024, page 491–502, New York, NY, USA, 2024. Association for Computing Machinery.

[12] Qibin Chen, Jeremy Lacomis, Edward J. Schwartz, Claire Le Goues, Graham Neubig, and Bogdan Vasilescu. Augmenting decompiler output with learned variable names and types. In *31st USENIX Security Symposium (USENIX Security 22)*, pages 4327–4343, Boston, MA, August 2022. USENIX Association.

[13] coreutils. coreutils. http://git.savannah.gnu.org/gitweb/?p=coreutils.git.

[14] Leonardo De Moura and Nikolaj Bjørner. Z3: An efficient smt solver. In *Proceedings of the Theory and Practice of Software, 14th International Conference on Tools and Algorithms for the Construction and Analysis of Systems*, TACAS'08/ETAPS'08, page 337–340, Berlin, Heidelberg, 2008. Springer-Verlag.

[15] Shihan Dou, Yan Liu, Haoxiang Jia, Limao Xiong, Enyu Zhou, Wei Shen, Junjie Shan, Caishuang Huang, Xiao Wang, Xiaoran Fan, et al. Stepcoder: Improve code generation with reinforcement learning from compiler feedback. *arXiv preprint arXiv:2402.01391*, 2024.

[16] Luke Dramko, Jeremy Lacomis, Edward J. Schwartz, Bogdan Vasilescu, and Claire Le Goues. A taxonomy of c decompiler fidelity issues. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 379–396, Philadelphia, PA, August 2024. USENIX Association.

[17] Haeun Eom, Dohee Kim, Sori Lim, Hyungjoon Koo, and Sungjae Hwang. R2i: A relative readability metric for decompiled code. *Proc. ACM Softw. Eng.*, 1(FSE), July 2024.

[18] Cheng Fu, Huili Chen, Haolan Liu, Xinyun Chen, Yuandong Tian, Farinaz Koushanfar, and Jishen Zhao. *Coda: an end-to-end neural program decompiler*. Curran Associates Inc., Red Hook, NY, USA, 2019.

[19] GitHub and OpenAI. Github copilot. https://github.com/features/copilot, 2021. Available at https://github.com/features/copilot.

[20] Google. Gemini Code Assist. https://developers.google.com/gemini-code-assist, 2025. Accessed: 2025-06-04.

[21] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, and Abhishek Kadian et al. The llama 3 herd of models, 2024.

[22] HyungSeok Han, JeongOh Kyea, Yonghwi Jin, Jinoh Kang, Brian Pak, and Insu Yun. Queryx: Symbolic query on decompiled code for finding bugs in cots binaries. In *2023 IEEE Symposium on Security and Privacy (SP)*, pages 3279–3295, 2023.

[23] Gustaf Holst and Felix Dobslaw. On the importance and shortcomings of code readability metrics: A case study on reactive programming, 2021.

[24] Jingcheng Hu, Yinmin Zhang, Qi Han, Daxin Jiang, Xiangyu Zhang, and Heung-Yeung Shum. Open-reasoner-zero: An open source approach to scaling up reinforcement learning on the base model, 2025.

[25] Peiwei Hu, Ruigang Liang, and Kai Chen. Degpt: Optimizing decompiler output with llm. *Proceedings 2024 Network and Distributed System Security Symposium*, 2024.

[26] Binyuan Hui, Jian Yang, Zeyu Cui, Jiaxi Yang, Dayiheng Liu, Lei Zhang, Tianyu Liu, Jiajun Zhang, Bowen Yu, Kai Dang, An Yang, Rui Men, Fei Huang, Shanghaoran Quan, Xingzhang Ren, Xuancheng Ren, Jingren Zhou, and Junyang Lin. Qwen2.5-coder technical report. *ArXiv*, abs/2409.12186, 2024.

[27] Juyong Jiang, Fan Wang, Jiasi Shen, Sungju Kim, and Sunghun Kim. A survey on large language models for code generation, 2024.

[28] Linxi Jiang, Xin Jin, and Zhiqiang Lin. Beyond classification: Inferring function names in stripped binaries via domain adapted llms. *Proceedings of the 2025 on ACM SIGSAC Conference on Computer and Communications Security*, 2025.

[29] Omer Katz, Yuval Olshaker, Yoav Goldberg, and Eran Yahav. Towards neural decompilation. *ArXiv*, abs/1905.08325, 2019.

[30] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention, 2023.

[31] LaurieWired. Ghidramcp: Mcp server for ghidra. https://github.com/LaurieWired/GhidraMCP, 2025. Accessed: 2025-06-04.

[32] Hung Le, Yue Wang, Akhilesh Deepak Gotmare, Silvio Savarese, and Steven Chu Hong Hoi. Coderl: Mastering code generation through pretrained models and deep reinforcement learning. *Advances in Neural Information Processing Systems*, 35:21314–21328, 2022.

[33] JongHyup Lee, Thanassis Avgerinos, and David Brumley. TIE: principled reverse engineering of types in binary programs. In *Proceedings of the Network and Distributed System Security Symposium, NDSS 2011, San Diego, California, USA, 6th February - 9th February 2011*. The Internet Society, 2011.

[34] Yan Lin and Debin Gao. When function signature recovery meets compiler optimization. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 36–52, 2021.

[35] Zhiqiang Lin, X. Zhang, and Dongyan Xu. Automatic reverse engineering of data structures from binary execution. In *Network and Distributed System Security Symposium*, 2010.

[36] Yiheng Liu, Hao He, Tianle Han, Xu Zhang, Mengyuan Liu, Jiaming Tian, Yutong Zhang, Jiaqi Wang, Xiaohui Gao, Tianyang Zhong, Yi Pan, Shaochen Xu, Zihao Wu, Zhengliang Liu, Xin Zhang, Shu Zhang, Xintao Hu, Tuo Zhang, Ning Qiang, Tianming Liu, and Bao Ge. Understanding llms: A comprehensive overview from training to inference, 2024.

[37] Zhibo Liu and Shuai Wang. How far we have come: testing decompilation correctness of c decompilers. In *Proceedings of the 29th ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA 2020, page 475–487, New York, NY, USA, 2020. Association for Computing Machinery.

[38] Zichen Liu, Changyu Chen, Wenjun Li, Penghui Qi, Tianyu Pang, Chao Du, Wee Sun Lee, and Min Lin. Understanding r1-zero-like training: A critical perspective, 2025.

[39] Nuno P. Lopes, Juneyoung Lee, Chung-Kil Hur, Zhengyang Liu, and John Regehr. Alive2: bounded translation validation for llvm. In *Proceedings of the 42nd ACM SIGPLAN International Conference on Programming Language Design and Implementation*, PLDI 2021, page 65–79, New York, NY, USA, 2021. Association for Computing Machinery.

[40] Alessandro Mantovani, Luca Compagna, Yan Shoshitaishvili, and Davide Balzarotti. The convergence of source code and binary vulnerability discovery – a case study. In *Proceedings of the 2022 ACM on Asia Conference on Computer and Communications Security*, ASIA CCS '22, page 602–615, New York, NY, USA, 2022. Association for Computing Machinery.

[41] Thomas J. McCabe. A complexity measure. *IEEE Transactions on Software Engineering*, SE-2(4):308–320, 1976.

[42] Marvin Muñoz Barón, Marvin Wyrich, and Stefan Wagner. An empirical validation of cognitive complexity as a measure of source code understandability. In *Proceedings of the 14th ACM / IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM)*, ESEM '20, New York, NY, USA, 2020. Association for Computing Machinery.

[43] NVIDIA. NVIDIA Data Center Deep Learning Product Performance AI Inference. *NVIDIA Developer*.

[44] OpenAI. ChatGPT (May 2025 version). https://chat.openai.com, 2025. Large language model. Accessed: 2025-06-04.

[45] Indranil Palit and Tushar Sharma. Generating refactored code accurately using reinforcement learning. *arXiv preprint arXiv:2412.18035*, 2024.

[46] Rangeet Pan, Ali Reza Ibrahimzada, Rahul Krishna, Divya Sankar, Lambert Pouguem Wassi, Michele Merler, Boris Sobolev, Raju Pavuluri, Saurabh Sinha, and Reyhaneh Jabbarvand. Lost in translation: A study of bugs introduced by large language models while translating code. In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*, ICSE '24, page 1–13. ACM, April 2024.

[47] Daryl Posnett, Abram Hindle, and Premkumar Devanbu. A simpler model of software readability. In *Proceedings of the 8th Working Conference on Mining Software Repositories*, MSR '11, page 73–82, New York, NY, USA, 2011. Association for Computing Machinery.

[48] Pemma Reiter, Hui Jun Tay, Westley Weimer, Adam Doupé, Ruoyu Wang, and Stephanie Forrest. Automatically mitigating vulnerabilities in binary programs via partially recompilable decompilation. *IEEE Transactions on Dependable and Secure Computing*, 22:2270–2282, 2022.

[49] Martin Riedmiller, Roland Hafner, Thomas Lampe, Michael Neunert, Jonas Degrave, Tom Wiele, Vlad Mnih, Nicolas Heess, and Jost Tobias Springenberg. Learning by playing solving sparse reward tasks from scratch. In *International conference on machine learning*, pages 4344–4353. PMLR, 2018.

[50] Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Romain Sauvestre, Tal Remez, Jérémy Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. Code llama: Open foundation models for code, 2023. Accessed: 2025-06-04.

[51] Simone Scalabrino, Mario Linares-Vásquez, Rocco Oliveto, and Denys Poshyvanyk. A comprehensive model for code readability. *J. Softw. Evol. Process*, 30(6), June 2018.

[52] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms, 2017.

[53] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models, 2024.

[54] Parshin Shojaee, Aneesh Jain, Sindhu Tipirneni, and Chandan K Reddy. Execution-based code generation using deep reinforcement learning. *arXiv preprint arXiv:2301.13816*, 2023.

[55] Hanzhuo Tan, Qi Luo, Jing Li, and Yuqun Zhang. Llm4decompile: Decompiling binary code with large language models. In *Conference on Empirical Methods in Natural Language Processing*, 2024.

[56] Jubi Taneja, Avery Laird, Cong Yan, Madan Musuvathi, and Shuvendu K Lahiri. Llm-vectorizer: Llm-based verified loop vectorizer. *arXiv preprint arXiv:2406.04693*, 2024.

[57] Asher Trockman, Keenen Cates, Mark Mozina, Tuan Nguyen, Christian Kästner, and Bogdan Vasilescu. "automatically assessing code understandability" reanalyzed: combined metrics matter. In *Proceedings of the 15th International Conference on Mining Software Repositories*, MSR '18, page 314–318, New York, NY, USA, 2018. Association for Computing Machinery.

[58] util-linux. util-linux. https://github.com/util-linux/util-linux.

[59] Leandro von Werra, Younes Belkada, Lewis Tunstall, Edward Beeching, Tristan Thrush, Nathan Lambert, Shengyi Huang, Kashif Rasul, and Quentin Gallouédec. TRL: Transformer Reinforcement Learning.

[60] Daniel Votipka, Seth Rabin, Kristopher Micinski, Jeffrey S. Foster, and Michelle L. Mazurek. An observational investigation of reverse Engineers' processes. In *29th USENIX Security Symposium (USENIX Security 20)*, pages 1875–1892. USENIX Association, August 2020.

[61] Fish Wang and Yan Shoshitaishvili. Angr - the next generation of binary analysis. In *2017 IEEE Cybersecurity Development (SecDev)*, pages 8–9, 2017.

[62] Yanzhao Wang and Fei Xie. Enhancing translation validation of compiler transformations with large language models, 2024.

[63] Wai Kin Wong, Huaijin Wang, Zongjie Li, Zhibo Liu, Shuai Wang, Qiyi Tang, Sen Nie, and Shi Wu. Refining decompiled c code with large language models. *ArXiv*, abs/2310.06530, 2023.

[64] Danning Xie, Zhuo Zhang, Nan Jiang, Xiangzhe Xu, Lin Tan, and Xiangyu Zhang. Resym: Harnessing llms to recover variable and data structure symbols from stripped binaries. In *Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security*, CCS '24, page 4554–4568, New York, NY, USA, 2024. Association for Computing Machinery.

[65] Xiangzhe Xu, Zhuo Zhang, Zian Su, Ziyang Huang, Shiwei Feng, Yapeng Ye, Nan Jiang, Danning Xie, Siyuan Cheng, Lin Tan, and Xiangyu Zhang. Unleashing the power of generative model in recovering variable names from stripped binary. 01 2025.

[66] Khaled Yakdan, Sergej Dechand, Elmar Gerhards-Padilla, and Matthew Smith. Helping johnny to analyze malware: A usability-optimized decompiler and malware analysis user study. In *IEEE Symposium on Security and Privacy, SP 2016, San Jose, CA, USA, May 22-26, 2016*, pages 158–177. IEEE Computer Society, 2016.

[67] Khaled Yakdan, Sebastian Eschweiler, Elmar Gerhards-Padilla, and Matthew Smith. No more gotos: Decompilation using pattern-independent control-flow structuring and semantic-preserving transformations. In *22nd Annual Network and Distributed System Security Symposium, NDSS 2015, San Diego, California, USA, February 8-11, 2015*. The Internet Society, 2015.

[68] Zao Yang and Stefan Nagy. Bin2wrong: a unified fuzzing framework for uncovering semantic errors in binary-to-c decompilers. August 2025.

[69] Tuba Yavuz and Ken (Yihang) Bai. Analyzing system software components using api model guided symbolic execution. *Journal of Automated Software Engineering*, 2020.

[70] Zhuo Zhang, Yapeng Ye, Wei You, Guanhong Tao, Wen-chuan Lee, Yonghwi Kwon, Yousra Aafer, and Xiangyu Zhang. Osprey: Recovery of variable and data structure via probabilistic analysis for stripped binary. In *2021 IEEE Symposium on Security and Privacy (SP)*, pages 813–832, 2021.

[71] Chang Zhu, Ziyang Li, Anton Xue, Ati Priya Bajaj, Wil Gibbs, Yibo Liu, Rajeev Alur, Tiffany Bao, Hanjun Dai, Adam Doupé, Mayur Naik, Yan Shoshitaishvili, Ruoyu Wang, and Aravind Machiry. TYGR: Type inference on stripped binaries using graph neural networks. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 4283–4300, Philadelphia, PA, August 2024. USENIX Association.

[72] Muqi Zou, Arslan Khan, Ruoyu Wu, Han Gao, Antonio Bianchi, and Dave (Jing) Tian. D-Helix: A generic decompiler testing framework using symbolic differentiation. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 397–414, Philadelphia, PA, August 2024. USENIX Association.

Appendix