LLM4Decompile: Decompiling Binary Code with Large Language Models

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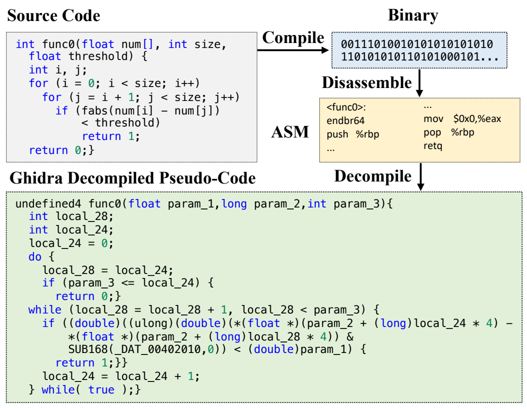
Abstract

Decompilation aims to convert binary code to high-level source code, but traditional tools like Ghidra often produce results that are difficult to read and execute. Motivated by the advancements in Large Language Models (LLMs), we propose LLM4Decompile, the first and largest open-source LLM series (1.3B to 33B) trained to decompile binary code. We optimize the LLM training process and introduce the LLM4Decompile-End models to decompile binary directly. The resulting models significantly outperform GPT-4o and Ghidra on the HumanEval and ExeBench benchmarks over 100% in terms of re-executability rate. Additionally, we improve the standard refinement approach to fine-tune the LLM4Decompile-Ref models, enabling them to effectively refine the decompiled code from Ghidra and achieve a further 16.2% improvement over the LLM4Decompile-End. LLM4Decompile[1] demonstrates the potential of LLMs to revolutionize binary code decompilation, delivering remarkable improvements in readability and executability while complementing conventional tools for optimal results.

1 Introduction

Decompilation, the reverse process of converting machine code or binary code into a high-level programming language, facilitates various reverse engineering tasks such as vulnerability identification, malware research, and legacy software migration (Brumley et al., 2013; Katz et al., 2018; Hosseini and Dolan-Gavitt, 2022; Xu et al., 2023; Armengol-Estapé et al., 2023; Jiang et al., 2023; Wong et al., 2023; Hu et al., 2024). Decompilation is challenging due to the loss of information inherent in the compilation process, particularly finer details such as variable names (Lacomis et al., 2019)



```
int func0(float num[], int size,
  float threshold) {
  int i, j;
  for (i = 0; i < size; i++)
    for (j = i + 1; j < size; j++)
      if (fabs(num[i] - num[j])
          < threshold)
          return 1;
  return 0;}
```

```
0011101001010101010101010
110101010110101000101...
```

```
<func0>:              ...
endbr64               mov   $0x0,%eax
push  %rbp            pop   %rbp
...                   retq
```

```
undefined4 func0(float param_1,long param_2,int param_3){
  int local_28;
  int local_24;
  local_24 = 0;
  do {
    local_28 = local_24;
    if (param_3 <= local_24) {
      return 0;}
  while (local_28 = local_28 + 1, local_28 < param_3) {
    if ((double)((ulong)(double)(*(float *)(param_2 + (long)local_24 * 4) -
        *(float *)(param_2 + (long)local_28 * 4)) &
        SUB168(_DAT_00402010,0)) < (double)param_1) {
      return 1;}}
    local_24 = local_24 + 1;
  } while( true );}
```

Figure 1: Illustration of compiling source code to binary, disassembling binary to assembly code (ASM), and decompiling ASM to pseudo-code with Ghidra. The pseudo-code is hard to read and not executable.

and fundamental structures like loops and conditionals (Wei et al., 2007). To address these challenges, numerous tools have been developed for decompilation, with Ghidra (Ghidra, 2024a) and IDA Pro (Hex-Rays, 2024) being the most commonly used. Although these tools have the capability to revert binary code to high-level pseudo-code, the outputs often lack readability and re-executability (Liu and Wang, 2020a; Wang et al., 2017), which are essential for applications like legacy software migration and security instrumentation tasks (Wong et al., 2023; Dinesh et al., 2020).

Figure 1 illustrates the transformation from the source C code to a binary file, assembly code (ASM), and pseudo-code decompiled from Ghidra. In this pseudo-code, the original nested `for` structure is replaced with a less intuitive combination of a `do-while` loop inside another `while` loop. Furthermore, array indexing like `num[i]` is decompiled into complicated pointer arithmetic such as `*(float *)(param_2 + (long)local_24 * 4)`. The decompiled output also exhibits syntactical errors, with the function return type being converted to `undefined4`. Overall, traditional decompilation tools often strip away the syntactic clarity provided

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[1]`https://github.com/albertan017/LLM4Decompile`

by high-level languages and do not ensure the correctness of syntax, posing significant challenges even for skilled developers to reconstruct the algorithmic logic (Wong et al., 2023; Hu et al., 2024).

Recent advancements in Large Language Models (LLMs) have greatly improved the process of decompiling code. There are two primary approaches to LLM-based decompilation—*Refined-Decompile* and *End2end-Decompile*. In particular, *Refined-Decompile* prompts LLMs to refine the results from traditional decompilation tools (Hu et al., 2024; Wong et al., 2023; Xu et al., 2023). However, LLMs are primarily optimized for high-level programming languages and may not be as effective with binary data. *End2end-Decompile* fine-tunes LLMs to decompile binaries directly. Nevertheless, previous open-source applications of this approach were limited by the use of smaller models with only around 200 million parameters and restricted training corpus (Hosseini and Dolan-Gavitt, 2022; Armengol-Estapé et al., 2023; Jiang et al., 2023), In contrast, utilizing larger models trained on broader datasets has proven to substantially improve the performance (Hoffmann et al., 2024; Kaplan et al., 2020; Rozière et al., 2023; OpenAI, 2023).

To address the limitations of previous studies, we propose LLM4Decompile, the first and largest open-source LLM series with sizes ranging from 1.3B to 33B parameters specifically trained to decompile binary code. To the best of our knowledge, there's no previous study attempts to improve the capability of LLM-based decompilation in such depth or incorporate such large-scale LLMs. Based on the *End2end-Decompile* approach, we introduce three critical steps: data augmentation, data cleaning, and two-stage training, to optimize the LLM training process and introduce the LLM4Decompile-End models to decompile binary directly. Specifically, our LLM4Decompile-End-6.7B model demonstrates a successful decompilation rate of 45.4% on HumanEval (Chen et al., 2021) and 18.0% on ExeBench (Armengol-Estapé et al., 2022), far exceeding Ghidra (Ghidra, 2024a) or GPT-4o (OpenAI, 2023) by over 100%. Additionally, we improve the *Refined-Decompile* strategy by examining the efficiency of Ghidra's decompilation process, augmenting and filtering data to fine-tune the LLM4Decompile-Ref models, which excel at refining Ghidra's output. Experiments suggest a higher performance ceiling for the enhanced *Refined-Decompile* approach, with 16.2% improvement over LLM4Decompile-End. Additionally, we assess the risks associated with the potential misuse of our model under obfuscation conditions commonly used in software protection. Our findings indicate that neither our approach nor Ghidra can effectively decompile obfuscated code, mitigating concerns about unauthorized use for infringement of intellectual property.

In summary, our contributions are as follows:

- We introduce the LLM4Decompile series, the first and largest open-source LLMs (ranging from 1.3B to 33B parameters) fine-tuned on 15 billion tokens for decompilation.

- We optimize the LLM training process and introduce LLM4Decompile-End models, which set a new performance standard of direct binary decompilation, significantly surpassing GPT-4o and Ghidra by over 100% in terms of re-executability on the HumanEval and ExeBench benchmarks.

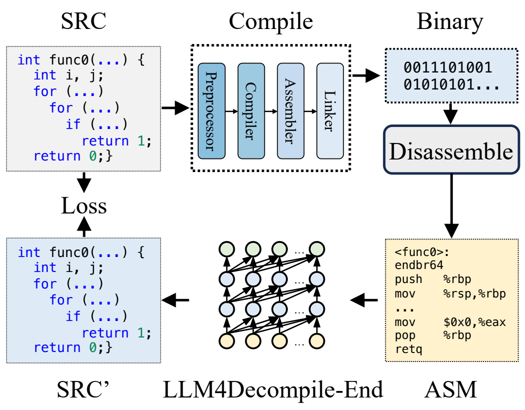
- We improve the *Refined-Decompile* approach to fine-tune the LLM4Decompile-Ref models, enabling them to effectively refine the decompiled results from Ghidra and achieve further 16.2% re-executability enhancements over LLM4Decompile-End.

2 Related Work

The practice of reversing executable binaries to their source code form, known as decompilation, has been researched for decades (Miecznikowski and Hendren, 2002; Nolan, 2012; Katz et al., 2019). Traditional decompilation relies on analyzing the control and data flows of program (Brumley et al., 2013), and employing pattern matching, as seen in tools like Hex-Rays Ida pro (Hex-Rays, 2024) and Ghidra (Ghidra, 2024a). These systems attempt to identify patterns within a program's control-flow graph (CFG) that corresponding to standard programming constructs such as conditional statements or loops. However, the output from such decompilation processes tends to be a source-code-like representation of assembly code, including direct translations of variables to registers, use of gotos, and other low-level operations instead of the original high-level language constructs. This output, while often functionally similar to the original code, is difficult to understand and may not be re-executable (Liu and Wang, 2020b; Wong et al., 2023). Drawing inspiration from neural machine translation, researchers have reformulated decompilation as a translation exercise, converting machine-level instructions into readable source code (Katz et al., 2019). Initial attempts in this area utilized recurrent neural networks (RNNs) (Katz et al., 2018) for decompilation, complemented by error-correction techniques to enhance the outcomes.

Motivated by the success of Large Language Models (Li et al., 2023; Rozière et al., 2023; Guo et al., 2024), researchers have employed LLMs for decompilation, primarily through two approaches—*Refined-Decompile* and *End2end-Decompile*. In particular, *Refined-Decompile* prompts the LLMs to refine results from traditional decompilation tools like Ghidra or IDA Pro. For instance, DeGPT (Hu et al., 2024) enhances Ghidra's readability by reducing cognitive load by 24.4%, while DecGPT (Wong et al., 2023) increases IDA Pro's re-executability rate to over 75% by integrating error messages into its refinement process. These approaches, however, largely ignore the fact that LLMs are designed primarily for high-level programming languages (Li et al., 2023; Rozière et al., 2023; Guo et al., 2024), and their effectiveness with binary files is not well-established. *End2end-Decompile*, on the other hand, fine-tunes LLMs to decompile binaries directly. Early open-source models like BTC (Hosseini and Dolan-Gavitt, 2022) and recent development Slade (Armengol-Estapé et al., 2023) adopt the language model with around 200 million parameters (Lewis et al., 2020a) to fine-tune for decompilation. While Nova (Jiang et al., 2023), which is not open-sourced, develops a binary LLM with 1 billion parameters and fine-tunes it for decompilation. Consequently, the largest open-source model in this domain is limited to 200M. Whereas utilizing larger models trained on broader datasets has proven to substantially improve the performance (Hoffmann et al., 2024; Kaplan et al., 2020; Rozière et al., 2023).

Therefore, our objective is to present the first and most extensive open-source LLM4Decompile series, aiming at comprehensively advancing the decompilation capability of LLMs. Initially, we optimize the *End2end-Decompile* approach to train the LLM4Decompile-End, demonstrating its effectiveness in directly decompiling binary files. Subsequently, we enhance the *Refined-Decompile* frameworks to integrate LLMs with Ghidra, augmenting traditional tools for optimal effectiveness.



```
int func0(...) {
  int i, j;
  for (...)
    for (...)
      if (...)
        return 1;
  return 0;}
```

```
0011101001
01010101...
```

```
<func0>:
endbr64
push   %rbp
mov    %rsp,%rbp
...
mov    $0x0,%eax
pop    %rbp
retq
```

```
int func0(...) {
  int i, j;
  for (...)
    for (...)
      if (...)
        return 1;
  return 0;}
```

Figure 2: *End2end-Decompile* framework. The source code (SRC) is compiled to binary, disassembled to assembly instructions (ASM), and decompiled by LLM4Decompile to generate SRC'. Loss is computed between SRC and SRC' for training.

3 LLM4Decompile

First, we introduce our strategy for optimizing LLM training to directly decompile binaries, the resulting models are named as LLM4Decompile-End. Following this, we detail our efforts for enhancing the *Refined-Decompile* approach, the corresponding fine-tuned models are referred to as LLM4Decompile-Ref, which can effectively refine the decompiled results from Ghidra.

3.1 LLM4Decompile-End

In this section, we describe the general *End2end-Decompile* framework, and present details on our strategy to optimize the training of LLM4Decompile-End models.

3.1.1 The End2End-Decompile Framework

Figure 2 illustrates the *End2end-Decompile* framework from compilation to decompilation processes. During compilation, the Preprocessor processes the source code (SRC) to eliminate comments and expand macros or includes. The cleaned code is then forwarded to the Compiler, which converts it into assembly code (ASM). This ASM is transformed into binary code (0s and 1s) by the Assembler. The Linker finalizes the process by linking function calls to create an executable file. Decompilation, on the other hand, involves converting binary code back into a source file. LLMs, being trained on text, lack the ability to process binary data directly. Therefore, binaries must be disassembled by `Objdump` into assembly language (ASM) first. It should be noted that binary and disassembled ASM are equivalent, they can be interconverted, and thus we refer to them interchangeably. Finally, the loss is computed between the decompiled code and source code to guide the training.

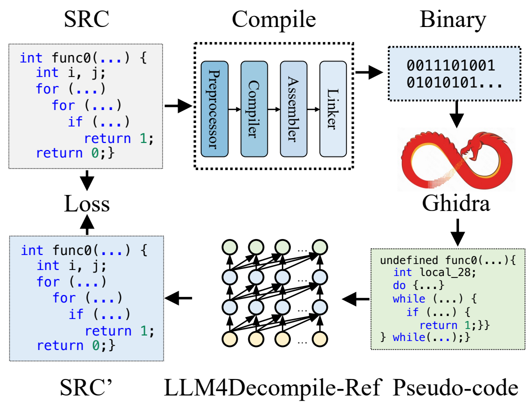
3.1.2 Optimize LLM4Decompile-End

We optimize the training of LLM4Decompile-End Models through three key steps: 1) augmenting the training corpus, 2) improving the quality of the data, 3) and incorporating two-state training.

Training Corpus. As indicated by the Scaling-Law (Hoffmann et al., 2024; Kaplan et al., 2020), the effectiveness of an LLM heavily relies on the size of the training corpus. Consequently, our initial step in training optimization involves incorporating a large training corpus. We construct asm-source pairs based on ExeBench (Armengol-Estapé et al., 2022), which is the largest public collection of five million C functions. To further expand the training data, we consider the compilation optimization states frequently used by developers. The compilation optimization involves techniques like eliminating redundant instructions, better register allocation, and loop transformations (Muchnick, 1997), which perfectly acts as data augmentation for decompilation. The key optimization levels are O0 (default, no optimization) to O3 (aggressive optimizations). We compile the source code into all four stages, i.e., O0, O1, O2, and O3, and pair each of them with the source code.

Data Quality. Data quality is critical in training an effective model (Li et al., 2023). Therefore, our second step is to clean our training set. We follow the guidelines of StarCoder (Li et al., 2023) by computing MinHash (Broder, 2000) for the code and utilizing Locally Sensitive Hashing (LSH) to remove duplicates. We also exclude samples that are less than 10 tokens.

Two-Stage Training. Our final step for training optimization aims to educate the model with binary knowledge, and includes two-stage training. In the first stage, we train the model with a large corpus of compilable but not linkable (executable) data. Note that it's significantly easier to extract C code that is compilable but not linkable (da Silva et al., 2021; Armengol-Estapé et al., 2022). Such not-executable binary object code will closely resemble its executable version except it lacks linked addresses for external symbols. Therefore, in the first stage, we use the extensive compilable codes to ground our model in binary knowledge. In the second stage, we refine the model using executable code to ensure its practical applicability. We also conduct an ablation study for the two-stage training in Section 4.1.2. Comparison between compilable and executable data is detailed in Appendix B.



```
int func0(...) {
  int i, j;
  for (...)
    for (...)
      if (...)
        return 1;
  return 0;}
```

```
undefined func0(...){
  int local_28;
  do {...}
  while (...) {
    if (...) {
      return 1;}}
} while(...);}
```

Figure 3: *Refined-Decompile* framework. It differs from *End2end-Decompile* (Figure 2) only in the LLM's input, which is pseudo-code decompiled from Ghidra.

3.2 LLM4Decompile-Ref

We now examine how the conventional decompilation tool, Ghidra, can be significantly improved by integrating it with LLMs. Note that our approach aims at refining entire outputs from Ghidra, offering a broader strategy than merely recovering names or types (Nitin et al., 2021; Xu et al., 2024). We begin by detailing the general *Refined-Decompile* framework, and discuss our strategy to enhance Ghidra's output by LLM4Decompile-Ref.

3.2.1 The Refined-Decompile Framework

The *Refined-Decompile* approach is shown in Figure 3. This approach differs from that in Figure 2 only in terms of the LLM's input, which in the case of *Refined-Decompile* comes from Ghidra's decompilation output. Specifically, Ghidra is used to decompile the binary, and then the LLM is fine-tuned to enhance Ghidra's output. While Ghidra produces high-level pseudo-code that may suffer from readability issues and syntax errors, it effectively preserves the underlying logic. Refining this pseudo-code significantly mitigates the challenges associated with understanding the obscure ASM.

3.2.2 Refine Ghidra by LLM4Decompile-Ref

Decompiling using Ghidra. Decompiling the executable code with Ghidra (Figure 3) is time-consuming due to the complex nature of the executables in ExeBench, which include numerous external functions and IO wrappers. Ghidra Headless (Ghidra, 2024b) requires 2 seconds per sample using 128-core multiprocessing. Given such a high computational load, and the high similarities between non-executable and executable binaries, we choose to decompile the non-executable files using Ghidra. This choice significantly reduces the time to 0.2 seconds per sample, enabling us to efficiently gather large amounts of training data.

Optimization Strategies. Similar to Section 3.1.2, we augment our dataset by compiling with optimization levels O0, O1, O2, and O3. We further filter the dataset using LSH to remove duplicates. As shown in Figure 1, Ghidra often generates overly long pseudo-code. Consequently, we filter out any samples that exceed the maximum length accepted by our model.

4 Experiments

In this section, we discuss the experimental setups and results for LLM4Decompile-End and LLM4Decompile-Ref respectively.

4.1 LLM4Decompile-End

4.1.1 Experimental Setups

Training Data. As discussed in Section 3.1.2, we construct asm-source pairs based on compilable and executable datasets from ExeBench (Armengol-Estapé et al., 2022), where we only consider the decompilation of GCC (Stallman et al., 2003) compiled C function under x86 Linux platform. After filtering, our refined compilable training dataset includes 7.2 million samples, containing roughly 7 billion tokens. Our executable training dataset includes 1.6 million samples, containing roughly 572 million tokens. To train the model, we use the following template: `# This is the assembly code: [ASM code] # What is the source code? [source code]`, where `[ASM code]` corresponds to the disassembled assembly code from the binary, and `[source code]` is the original C function. Note that the template choice does not impact the performance, since we fine-tune the model to produce the source code.

Evaluation Benchmarks and Metrics. To evaluate the models, we introduce HumanEval (Chen et al., 2021) and ExeBench (Armengol-Estapé et al., 2022) benchmarks. HumanEval is the leading benchmark for code generation assessment and includes 164 programming challenges with accompanying Python solutions and assertions. We converted these Python solutions and assertions into C, making sure that they can be compiled with the GCC compiler using standard C libraries (Free Software Foundation, 2024) and pass all the assertions, and name it HumanEval-Decompile. ExeBench consists of 5000 real-world C functions taken from GitHub with IO examples. Note that the HumanEval-Decompile consists of individual functions that depend only on the standard C library. In contrast, ExeBench includes functions extracted from real-world projects with user-defined structures and functions[2].

As for the evaluation metrics, we follow previous work to calculate the re-executability rate (Armengol-Estapé et al., 2023; Wong et al., 2023). During evaluation, the C source code is first compiled into a binary, then disassembled into assembly code, and fed into the decompilation system to be reconstructed back into C code. This decompiled C code is then combined with the assertions to check if it can successfully execute and pass those assertions.

Model Configurations. The LLM4Decompile uses the same architecture as DeepSeek-Coder (Guo et al., 2024) and we initialize our models with the corresponding DeepSeek-Coder checkpoints. We employ Sequence-to-sequence prediction (S2S), which is the training objective adopted in most neural machine translation models that aim to predict the output given the input sequence. As illustrated in Equation 1, it minimizes the negative log likelihood for the source code tokens $x_i, ..., x_j$:

$$\mathcal{L} = -\sum_i \log P_i(x_i, ..., x_j | x_1, ..., x_{i-1}; \theta) \quad (1)$$

Where the loss is calculated only for the output sequence $x_i ... x_j$, or the source code.

Baselines. We selected two key baselines for comparison. First, GPT-4o (OpenAI, 2023) represents the most capable LLMs, providing an upper bound on LLM performance. Second, DeepSeek-Coder (Guo et al., 2024) is selected as the current SOTA open-source Code LLM. It represents the forefront of publicly available models specifically tailored for coding tasks. While recent work

[2]Exebench provides comparison of the test set against the GitHub population using nine distinct code complexity metrics, confirming that the characteristics of the testing functions are aligned with functions in larger real-world projects.

Model/Benchmark	HumanEval-Decompile					ExeBench				
	O0	O1	O2	O3	AVG	O0	O1	O2	O3	AVG
DeepSeek-Coder-6.7B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GPT-4o	30.49	11.59	10.37	11.59	16.01	4.43	3.28	3.97	3.43	3.78
LLM4Decompile-End-1.3B	47.20	20.61	21.22	20.24	27.32	17.86	13.62	13.20	13.28	14.49
LLM4Decompile-End-6.7B	**68.05**	**39.51**	**36.71**	**37.20**	**45.37**	**22.89**	**16.60**	**16.18**	**16.25**	**17.98**
LLM4Decompile-End-33B	51.68	25.56	24.15	24.75	31.54	18.86	14.65	13.96	14.11	15.40

Table 1: Main comparison of *End2end-Decompile* approaches for re-executability rates on evaluation benchmarks.

Model/Benchmark	HumanEval-Decompile					ExeBench				
	O0	O1	O2	O3	AVG	O0	O1	O2	O3	AVG
Compilable-1.3B	42.68	16.46	16.46	17.07	23.17	5.68	4.46	4.16	4.43	4.68
Compilable-6.7B	**51.83**	**33.54**	**32.32**	**32.32**	**37.50**	7.52	6.49	6.71	6.60	6.83
Executable-1.3B	19.51	12.80	12.80	11.59	14.18	21.94	19.46	19.31	19.50	20.05
Executable-6.7B	37.20	18.29	22.56	17.07	23.78	**29.38**	**25.98**	**25.91**	**25.49**	**26.69**

Table 2: Ablation study on training dataset. The "Compilable" models are trained on 7.2M non-executable functions, while the "Executable" models are trained on 1.6M executable functions.

Slade (Armengol-Estapé et al., 2023) fine-tunes language model for decompilation, it relies on intermediate compiler outputs, specifically, the *.s files. In practice, however, such intermediate files are rarely released by developers. Therefore, we focus on a more realistic approach, and consider decompilation only from the binaries, for further discussions please refer to Appendix B.

Implementation. We use the DeepSeek-Coder models obtained from Hugging Face (Wolf et al., 2019). We train our models using LLaMA-Factory library (Zheng et al., 2024). For 1.3B and 6.7B models, we set a $batch\ size = 2048$ and $learning\ rate = 2e{-}5$ and train the models for 2 epochs (15B tokens). Experiments are performed on NVIDIA A100-80GB GPU clusters. Fine-tuning the 1.3B and 6.7B LLM4Decompile-End takes 12 and 61 days on $8 \times A100$ respectively. Limited by the resources, for the 33B model we only train for 200M tokens. For evaluation, we use the *vllm* (Kwon et al., 2023) to accelerate the generation (decompilation) process. We employ greedy decoding to minimize randomness.

4.1.2 Experimental Results

Main Results. Table 1 presents the re-executability rate under different optimization states for our studied models. The base version of DeepSeek-Coder-33B is unable to accurately decompile binaries. It could generate code that seemed correct but failed to retain the original program semantics. GPT-4o shows notable decompilation skills; it's capable to decompile non-optimized (O0) code with a success rate of 30.5%, though the rate significantly decreases to about 11% for optimized codes (O1-O3). The LLM4Decompile-End models, on the other hand, demonstrate excellent decompilation abilities. The 1.3B version successfully decompiles and retains the program semantics in 27.3% of cases on average, whereas the 6.7B version has a success rate of 45.4%. This improvement underscores the advantages of using larger models to capture a program's semantics more effectively. While attempting to fine-tune the 33B model, we encountered substantial challenges related to the high communication loads, which significantly slowed the training process and restricted us to using only 200M tokens (Section 4.1.1). Despite this limitation, the 33B model still outperforms the 1.3B model, reaffirming the importance of scaling up the model size.

Ablation Study. As discussed in Section 4.1.1, our training data comprises two distinct sets: 7.2 million compilable functions (non-executable) and 1.6M executable functions. We conducted an ablation study using these datasets, and the results are displayed in Table 2. Here, "Compilable" denotes the model trained solely on compilable data, while "Executable" indicates models trained exclusively on executable data. Notably, the binary object from compilable functions lacks links to

Model/Metrics	Re-executability Rate					Edit Similarity				
	O0	O1	O2	O3	AVG	O0	O1	O2	O3	AVG
LLM4Decompile-End-6.7B	68.05	39.51	36.71	37.20	45.37	15.57	12.92	12.93	12.69	13.53
Ghidra										
Base	34.76	16.46	15.24	14.02	20.12	6.99	6.13	6.19	5.47	6.20
+GPT-4o	46.95	34.15	28.66	31.10	35.22	6.60	5.63	5.67	4.99	5.72
+LLM4Decompile-Ref-1.3B	68.90	37.20	40.85	37.20	46.04	15.17	13.25	12.92	12.67	13.50
+LLM4Decompile-Ref-6.7B	74.39	46.95	47.56	42.07	52.74	**15.59**	13.53	13.42	12.73	13.82
+LLM4Decompile-Ref-33B*	70.73	47.56	43.90	41.46	50.91	15.40	**13.79**	**13.63**	**13.07**	**13.97**
+LLM4Decompile-Ref-22B*	**80.49**	**58.54**	**59.76**	**57.93**	**64.18**	15.19	**14.04**	13.58	**13.40**	13.85

Table 3: Main comparison of *Refined-Decompile* approaches for re-executability rate and Edit Similarity on HumanEval-Decompile benchmark. "+GPT-4o" refers to enhance the Ghidra results with GPT-4o, "+LLM4Decompile-Ref" means refining Ghidra results with the fine-tuned LLM4Decompile-Ref models. Note that the 33B model was trained using only 200M tokens, which is just 10% of the tokens used for the 1.3B/6.7B/22B model. For the 22B model, Please refer to Appendix D.

function calls, which is similar in text distribution to the HumanEval-Decompile data, consisting of single functions dependent only on standard C libraries. Consequently, the 6.7B model trained only on compilable data successfully decompiled 37.5% of HumanEval-Decompile functions, but only 6.8% on ExeBench, which features real functions with extensive user-defined functions. On the other hand, the 6.7B model trained solely on executable data achieved a 26.7% re-executability rate on the ExeBench test set but faced challenges with single functions, with only a 23.8% success rate on HumanEval-Decompile due to the smaller size of the training corpus. Limited by the space, we present further analysis in Appendix C.

4.2 LLM4Decompile-Ref

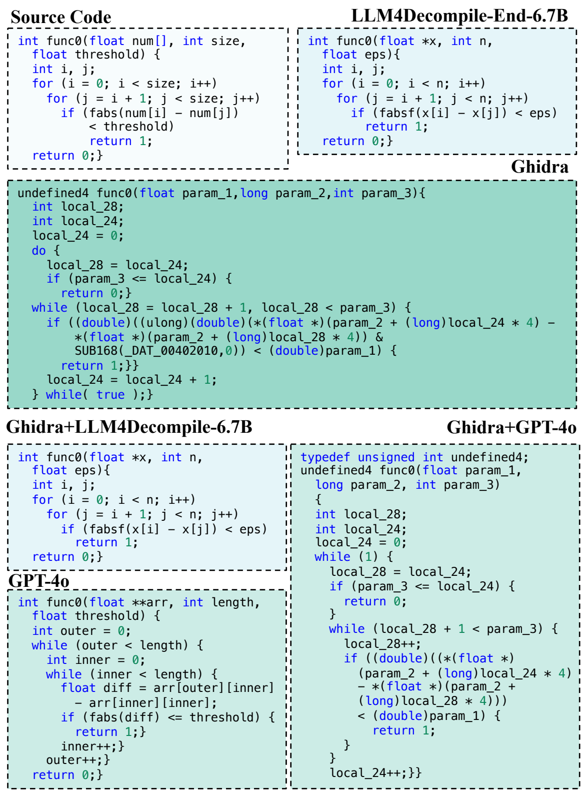
4.2.1 Experimental Setups

Experimental Datasets. The training data is constructed using ExeBench, with Ghidra Headless (Ghidra, 2024b) employed to decompile the binary object file. Due to constraints in computational resources, only 400K functions each with optimization levels from O0 to O3 (1.6M samples, 1B tokens) are used for training and the evaluation is conducted on HumanEval-Decompile. The models are trained using the same template described in Section 4.1.1. In addition, following previous work (Hosseini and Dolan-Gavitt, 2022; Armengol-Estapé et al., 2023), we access the readability of decompiled results in terms of Edit Similarity score.

Implementation. Configuration settings for the model are consistent with those in Section 4.1.1. For the 1.3B and 6.7B models, the fine-tuning process involves **2B tokens** in 2 epochs, and requires 2 and 8 days respectively on $8 \times A100$. Limited by the resource, for 33B model we only train for **200M tokens**. For evaluation, we first access the re-executability rate of Ghidra to establish a baseline. Subsequently, GPT-4o is used to enhance Ghidra's decompilation result with the prompt, `Generate linux compilable C/C++ code of the main and other functions in the supplied snippet without using goto, fix any missing headers. Do not explain anything.`, following DecGPT (Wong et al., 2023). Finally, we use LLM4Decompile-Ref models to refine the Ghidra's output.

4.2.2 Experimental Results

The results for the baselines and *Refined-Decompile* approaches are summarized in Table 3. For the pseudo-code decompiled by Ghidra, which is not optimized for re-execution, only an average of 20.1% of them pass the test cases. GPT-4o assists in refining this pseudo-code and enhancing its quality. The LLM4Decompile-Ref models offer substantial improvements over Ghidra's outputs, with the 6.7B model yielding a 160% increase in re-executability. Similar to the discussion in Section 4.1.2, the 33B model outperforms the 1.3B model even though it used considerably less training data. And it achieves performance that is only 3.6% below the 6.7B model, which benefited from ten times more training data. When compared to LLM4Decompile-End-6.7B, the LLM4Decompile-Ref-6.7B model, though trained on just 10% of the data in LLM4Decompile-Ref models, shows a 16.2% performance increase, suggesting a greater potential for the *Refined-Decompile* approach. We present further analysis in Appendix D.


Source Code

```
int func0(float num[], int size,
  float threshold) {
  int i, j;
  for (i = 0; i < size; i++)
    for (j = i + 1; j < size; j++)
      if (fabs(num[i] - num[j])
          < threshold)
          return 1;
  return 0;}
```

LLM4Decompile-End-6.7B

```
int func0(float *x, int n,
  float eps){
  int i, j;
  for (i = 0; i < n; i++)
    for (j = i + 1; j < n; j++)
      if (fabsf(x[i] - x[j]) < eps)
        return 1;
  return 0;}
```

Ghidra

```
undefined4 func0(float param_1,long param_2,int param_3){
  int local_28;
  int local_24;
  local_24 = 0;
  do {
    local_28 = local_24;
    if (param_3 <= local_24) {
      return 0;}
  while (local_28 = local_28 + 1, local_28 < param_3) {
    if ((double)((ulong)(double)(*(float *)(param_2 + (long)local_24 * 4) -
        *(float *)(param_2 + (long)local_28 * 4)) &
        SUB168(_DAT_00402010,0)) < (double)param_1) {
      return 1;}}
    local_24 = local_24 + 1;
  } while( true );}
```

Ghidra+LLM4Decompile-6.7B

```
int func0(float *x, int n,
  float eps){
  int i, j;
  for (i = 0; i < n; i++)
    for (j = i + 1; j < n; j++)
      if (fabsf(x[i] - x[j]) < eps)
        return 1;
  return 0;}
```

GPT-4o

```
int func0(float **arr, int length,
  float threshold) {
  int outer = 0;
  while (outer < length) {
    int inner = 0;
    while (inner < length) {
      float diff = arr[outer][inner]
        - arr[inner][inner];
      if (fabs(diff) <= threshold) {
        return 1;}
      inner++;}
    outer++;}
  return 0;}
```

Ghidra+GPT-4o

```
typedef unsigned int undefined4;
undefined4 func0(float param_1,
  long param_2, int param_3)
  {
  int local_28;
  int local_24;
  local_24 = 0;
  while (1) {
    local_28 = local_24;
    if (param_3 <= local_24) {
      return 0;
    }
    while (local_28 + 1 < param_3) {
      local_28++;
      if ((double)((*(float *)
        (param_2 + (long)local_24 * 4)
        - *(float *)(param_2 +
        (long)local_28 * 4)))
        < (double)param_1) {
          return 1;
      }
    }
    local_24++;}}
```

Figure 4: Decompilation results of different approaches. GPT-4o output is plausible yet fail to recover the array dimension (incorrect 2D array `arr[outer][inner]`). Ghidra's pseudo-code is notably less readable as discussed in Figure 1. GPT-refined Ghidra result (Ghidra+GPT-4o) marginally enhances readability but fails to correctly render `for` loops and array indexing. Conversely, LLM4Decompile-End and LLM4Decompile-Ref produce accurate and easy-to-read outputs.

An analysis of readability across different methods is also conducted and presented in Table 3 with illustrative examples presented in Figure 4. For text similarity, all decompiled outputs diverge from the original source code, with Edit Similarity ranging from 5.7% to 14.0%, primarily because the compilation process removes variable names and optimizes the logic structure. Ghidra generates pseudo-code that is particularly less readable with 6.2% Edit Similarity on average. Interestingly, with refinement from GPT (Ghidra+GPT-4o), there is a marginal decrease in Edit Similarity. GPT assists in refining type errors like `undefined4` and `ulong` (Figure 4). However, it struggles to accurately reconstruct `for` loops and array indexing. In contrast, both LLM4Decompile-End and LLM4Decompile-Ref generate outputs that are more aligned with the format of the source code and easier to comprehend.

To summarize, domain-specific fine-tuning is crucial for enhancing re-executability and readability of decompilation outputs.

We further employed GPT-4o to evaluate readability (Wang et al., 2023; Liu et al., 2023). Specifically, we guide GPT to assess syntax similarity (variables, loops, conditions) and structural integrity (logic flow, structure) using a structured template. We then summarize readability with a score from 1 (Poor) to 5 (Excellent), based on detailed comparisons between original and decompiled code. The template is available on our GitHub repository[3]. Table 4 summarizes our readability assessments on HumanEval-Decompile across various models and optimization levels.

Optimization Level	O0	O1	O2	O3	AVG
GPT-4o	2.8171	2.3537	2.2927	2.311	2.4436
Ghidra	2.9756	2.4085	2.5183	2.3841	2.5716
LLM4Decompile-End-6.7B	4.0732	3.4634	3.4024	3.2378	3.5442

Table 4: Evaluation by GPT-4o on the readability of decompiled results from various methods.

Compared with the results in Table 3, it indicates that Edit Similarity (ES) follows a trend similar to GPT evaluation. Although ES is mathematically based, its values can be difficult to interpret. For instance, a 15 ES score obtained by LLM4Decompile model may seem low, yet the decompiled function and the source code are highly aligned. In contrast, GPT evaluation, which measures readability conceptually, is more intuitive. A score of 4 on the GPT scale suggests that the decompiled code is nearly identical to the original. Nonetheless, these scores are derived from GPT's "subjective" judgments. Combining insights from both ES and GPT-Eval could lead to a more thorough assessment of code readability.

5 Obfuscation Discussion

The process of decompilation aims at revealing the source code from binaries distributed by developers, presenting a potential threat to the protection of intellectual property. To resolve the ethical concerns, this section accesses the risks of the possible misuse of our decompilation models.

In software development, engineers typically implement obfuscation techniques before releasing binary files to the public (Lachaux et al., 2021; Junod et al., 2015). This is done to protect the

[3]https://github.com/albertan017/LLM4Decompile/blob/main/samples/readability_template.txt

Model/Obfuscation	Control Flow Flattening					Bogus Control Flow				
	O0	O1	O2	O3	AVG	O0	O1	O2	O3	AVG
LLM4Decompile-End-6.7B	4.27	4.88	4.88	3.05	4.27	9.76	7.32	7.93	9.76	8.69
Ghidra	12.20	6.71	6.10	6.71	7.93	6.10	4.27	3.05	4.27	4.42
+LLM4Decompile-Ref-6.7B	6.71	3.66	4.88	5.49	5.19	15.85	14.02	8.54	7.93	11.59

Table 5: Re-executability rates of different approaches on the HumanEval-Decompile benchmark under obfuscations. Compared to Table 3, the decompilation success rates significantly drop for over 70%.

software from unauthorized analysis or modification. In our study, we focus on two fundamental obfuscation techniques as suggested in Obfuscator-LLVM (Junod et al., 2015): Control Flow Flattening (CFF) and Bogus Control Flow (BCF). These techniques are designed to disguise the true logic of the software, thereby making decompilation more challenging to protect the software's intellectual property. We present the details of these two techniques in the Appendix E.

Results summarized in Table 5 demonstrate that basic conventional obfuscation techniques are sufficient to prevent both Ghidra and LLM4Decompile from decoding obfuscated binaries. For example, the decompilation success rate for the most advanced model, LLM4Decompile-Ref-6.7B, drops significantly for 90.2% (0.5274 to 0.0519) under CFF and 78.0% (0.5274 to 0.1159) under BCF. Considering the industry standard of employing several complex obfuscation methods prior to software release, experimental results in Table 5 mitigate the concerns about unauthorized use for infringement of intellectual property.

6 Conclusions

We propose LLM4Decompile, the first and largest open-source LLM series with sizes ranging from 1.3B to 33B trained to decompile binary code. Based on the *End2end-Decompile* approach, we optimize the LLM training process and introduce the LLM4Decompile-End models to decompile binary directly. The resulting 6.7B model shows a decompilation accuracy of 45.4% on HumanEval and 18.0% on ExeBench, surpassing existing tools like Ghidra and GPT-4o over 100%. Additionally, we improve the *Refined-Decompile* strategy to fine-tune the LLM4Decompile-Ref models, which excel at refining the Ghidra's output, with 16.2% improvement over LLM4Decompile-End. Finally, we conduct obfuscation experiments and address concerns regarding the misuse of LLM4Decompile models for infringement of intellectual property.

Limitations

The scope of this research is limited to the compilation and decompilation of C language targeting the x86 platform. While we are confident that the methodologies developed here could be easily adapted to other programming languages and platforms, these potential extensions have been reserved for future investigation. Furthermore, Our research is limited by financial constraints, with a budget equivalent to using $8 \times A100$ GPUs for one year, which includes all trials and iterations. As a result, we have only managed to fully fine-tune models up to 6.7B, and conducted initial explorations on the 33B models with a small dataset, leaving the exploration of 70B and larger models to future studies. Nonetheless, our preliminary tests confirm the potential advantages of scaling up model sizes and suggest a promising direction for future decompilation research into larger models.

Ethic Statement

We have evaluated the risks of the possible misuse of our decompilation models in Section 5. Basic obfuscation methods such as Control Flow Flattening and Bogus Control Flow have been empirically tested and proven to protect against unauthorized decompilation by both traditional tools like Ghidra and advanced models like LLM4Decompile. This built-in limitation ensures that while LLM4Decompile is a powerful tool for legitimate uses, it does not facilitate the infringement of intellectual property.

In practical applications in the industry, software developers typically employ a series of complex obfuscation methods before releasing their software. This practice adds an additional layer of security and intellectual property protection against decompilation. LLM4Decompile's design and intended use respect these measures, ensuring that it serves as an aid in legal and ethical scenarios, such as understanding legacy code or enhancing cybersecurity defenses, rather than undermining them.

The development and deployment of LLM4Decompile are guided by strict ethical standards. The model is primarily intended for use in scenarios where permission has been granted or where the software is not protected by copyright. This includes academic research, debugging, learning, and situations where companies seek to recover lost source code of their own software.

Acknowledgments

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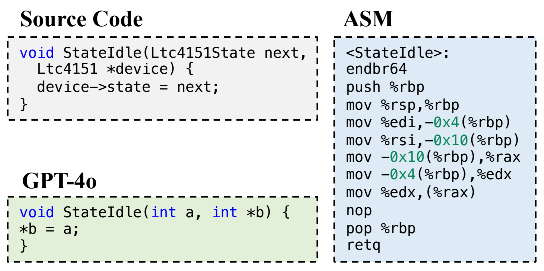
A ExeBench Setups

For every sample in ExeBench's executable splits, assembly code from *.s file—a compiler's intermediate output as discussed in Section 3.1 and Figure 1—is required to compile the sample into a binary. The specific compilation settings and processing details, however, are not provided by their authors. Consequently, we choose to compile the code in a standard way and manage to compile only half of the samples. This leaves us with 443K out of 797K samples for the executable training set and 2621 out of 5000 samples for the executable test set. Accordingly, we train our model on the 443K samples and conduct the re-executability evaluation on these 2621 samples, the results are shown in Table 1.

The researchers from Slade (Armengol-Estapé et al., 2023), who also developed ExeBench (Armengol-Estapé et al., 2022), have published their decompilation findings on ExeBench. They chose to decompile the intermediate output, or assembly code from *.s file, directly without further compilation into binaries, where in practice, such intermediate output is rarely released by software developers. Their reported results, as seen in Table 6, show a significant difference from ours. Their version of ChatGPT achieved a re-executability rate of 22.2% and an edit similarity of 44.0% under O0 optimization. On the other hand, our GPT-4o model only reached a 4.4% re-executability rate and a 7.9% edit similarity. The approach taken by Slade involves settings not commonly available in practical decompilation scenarios, which explains why their results vary significantly from ours. We adhere to a more realistic setting, decompiling



Source Code

```
void StateIdle(Ltc4151State next,
  Ltc4151 *device) {
  device->state = next;
}
```

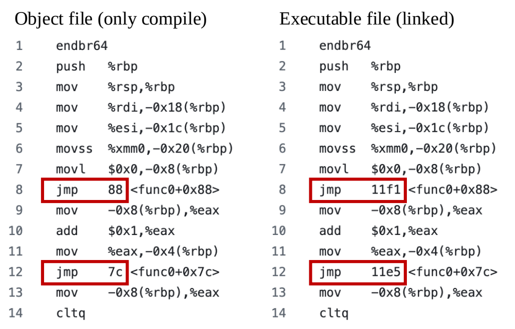
ASM

```
<StateIdle>:
endbr64
push %rbp
mov %rsp,%rbp
mov %edi,-0x4(%rbp)
mov %rsi,-0x10(%rbp)
mov -0x10(%rbp),%rax
mov -0x4(%rbp),%edx
mov %edx,(%rax)
nop
pop %rbp
retq
```

GPT-4o

```
void StateIdle(int a, int *b) {
*b = a;
}
```

Figure 5: Decompilation results of GPT-4o on ExeBench test case.



Object file (only compile)

```
endbr64
push   %rbp
mov    %rsp,%rbp
mov    %rdi,-0x18(%rbp)
mov    %esi,-0x1c(%rbp)
movss  %xmm0,-0x20(%rbp)
movl   $0x0,-0x8(%rbp)
jmp    88 <func0+0x88>
mov    -0x8(%rbp),%eax
add    $0x1,%eax
mov    %eax,-0x4(%rbp)
jmp    7c <func0+0x7c>
mov    -0x8(%rbp),%eax
cltq
```

Executable file (linked)

```
endbr64
push   %rbp
mov    %rsp,%rbp
mov    %rdi,-0x18(%rbp)
mov    %esi,-0x1c(%rbp)
movss  %xmm0,-0x20(%rbp)
movl   $0x0,-0x8(%rbp)
jmp    11f1 <func0+0x88>
mov    -0x8(%rbp),%eax
add    $0x1,%eax
mov    %eax,-0x4(%rbp)
jmp    11e5 <func0+0x7c>
mov    -0x8(%rbp),%eax
cltq
```

Figure 6: Compilable data and Executable data.

binary files based solely on their intrinsic data, without any external information.

Model/Metrics	Re-executability		Edit Similarity	
Optimization Level	O0	O3	O0	O3
Slade	59.5	52.2	71.0	60.0
ChatGPT	22.2	13.6	44.0	34.0
GPT-4o(ours)	4.4	3.4	7.9	6.6

Table 6: Re-executability and Edit Similarity on Exebench.

To further illustrate our settings, Figure 5 offers an example where the source function includes specific user-defined types like `Ltc4151State`, `Ltc4151`, and `device`. However, these types are completely lost after compilation, i.e., no information related to these user-definitions can be found in the binary (disassembled ASM code). Consequently, GPT-4o is unable to reconstruct these types based purely on the ASM (the realistic setting), but converting them to default types `int` or `pointer`, producing non-executable code. This issue was pervasive across the ExeBench test set, leading to the failure of GPT-4o models in decompiling the ExeBench samples in a realistic setting.

B Compilable and Executable Binary

The statistics of training and testing datasets is summarized in the Table 7. We also present an example to illustrate the difference between these two datasets.

Dataset/Code	ASM	SRC
Train-Executable	205.08	119.35
Test-Exebench	280.27	162.68
Train-Compilable	711.89	241.16
Test-Decompile-Eval	808.07	186.84

Table 7: Statistics of training and testing set.

As shown in Figure 6, the primary distinction between a compilable binary and an executable binary is the handling of function operation addresses. In a compilable file, the address for a jump operation is placeholder, representing only a relative offset within the function. Conversely, in an executable file, this jump operation address is resolved during the linking process, pointing directly to the specific memory location where the code will execute.

C Further Analysis of LLM4Decompile-End

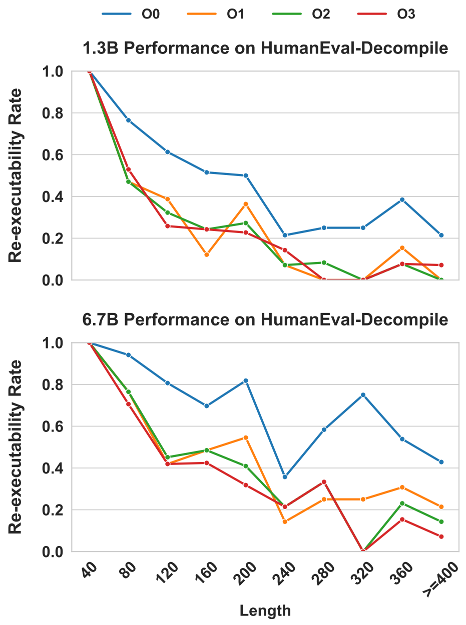


Figure 7: Re-executability rate with the growth of input length. The 6.7B model is more robust against input length.

Figure 7 illustrates that the re-executability rate decreases as the input length increases, and there is a marked decline in performance at higher levels of code optimization, highlighting the difficulties in decompiling long and highly optimized sequences. Importantly, the performance difference between the 1.3B and 6.7B models showcased in the figure emphasizes the advantages of larger models in such

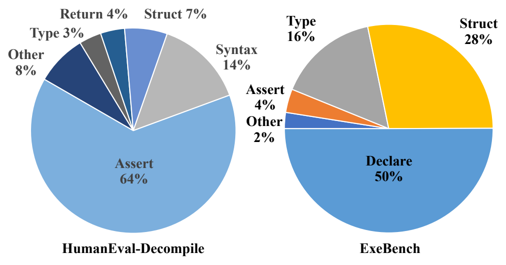


Figure 8: Types of errors identified in the two benchmarks: LLM4Decomile-End-6.7B faces issues with logical errors in HumanEval-Decompile and user-defined components in ExeBench.

tasks. Larger models, with their expanded computational resources and deeper learning capabilities, are inherently better at resolving the challenges posed by complex decompilations.

The error analysis presented in Figure 8 for LLM4Decompile-End-6.7B indicates that logical errors are prevalent in the HumanEval-Decompile scenarios, with 64% of errors due to assertions that the decompiled codes do not pass. In the ExeBench dataset, which features real functions with user-defined structures and types, the major challenges are related to reclaiming these user-specific components. Where 50% of the errors come from undeclared functions, and 28% from improper use of structures. Given that these user-defined details are typically lost during the compilation process, reconstructing them can be particularly challenging. Integrating techniques like Retrieval Augmented Generation (Lewis et al., 2020b) might supplement the decompilation process with necessary external information.

D Data Quality, Volume and Model

Data Quality In this project, we intentionally limited our data preprocessing to classical techniques such as filtering short texts and removing duplicates. This approach was chosen to establish a fair baseline model for decompilation that minimizes potential biases, aiming to provide a broad, unrefined baseline model that reflects diverse scenarios. We acknowledge that selective data removal, specifically excluding data incompatible with standard C libraries (Free Software Foundation, 2024), can enhance performance, as evidenced in Table 8 with Decompile-Eval, which only relies on standard C libraries. While refining the dataset can lead to improved performance, our primary goal in this study was to set a foundational baseline for the community. We believe this baseline can serve as a starting point encouraging future research to refine and expand.

Models	Re-executability Rate				
Optimization Level	O0	O1	O2	O3	AVG
Compilable-6.7B	51.83	33.54	32.32	32.32	37.50
+Executable (2B tokens)	68.05	39.51	36.71	37.20	45.37
+Exe w. Standard C (100M tokens)	71.80	42.68	41.31	41.46	49.31

Table 8: Performance improves when training data (+Exe w. Standard C) closely resembles the testing set patterns.

Data Volume We have summarized the relationship between performance and training epochs (2B token in one epoch) for the LLM4Decompile-Ref-1.3B model in Table 9. From this, it is clear that a single epoch serves as a strong baseline, while two epochs optimize performance. Additional epochs tend to lead to overfitting and diminished results.

Epoch	O0	O1	O2	O3	Avg
1	67.68	41.46	41.46	35.37	46.49
2	68.29	40.85	40.85	37.20	46.80
3	62.80	37.80	36.59	29.88	41.77
4	51.22	32.93	27.44	26.22	34.45

Table 9: Performance of LLM4Decompile-Ref-1.3B on HumanEval-Decompile w.r.t. different training epochs.

Moreover, we have included results from the 6.7B model to address scaling issues and provided comparison with the 1.3B and 33B models in Table 10. Notably, the 6.7B model achieves comparable performance to the 1.3B model with only 20% of the data, and the 33B model reaches similar outcomes to the 6.7B with just 10% of the data, although these ratios may differ with varying datasets.

Size	epoch	O0	O1	O2	O3	Avg
1.3B	1.0	67.68	41.46	41.46	35.37	46.49
6.7B	0.05	55.49	31.71	34.76	30.49	38.11
6.7B	0.1	57.93	36.74	32.77	32.01	39.86
6.7B	0.2	65.85	37.80	40.24	34.76	44.66
6.7B	0.5	65.55	45.73	43.29	43.75	49.58
6.7B	1.0	72.56	45.73	43.90	42.68	51.22
33B	0.1	70.73	47.56	43.90	41.46	50.91

Table 10: Performance of LLM4Decompile-Ref models on HumanEval-Decompile w.r.t. different training epochs.

Our findings suggest that model scaling can significantly enhance performance when the training data is adequately large (100M tokens), but repetitive training risks overfitting after a few epochs.

Model Choosing the right base model for decompilation training significantly influences performance. Our first choice, Deepseek-Coder-6.7B, delivered an encouraging average re-executability rate of 52.74% on the HumanEval-Decompile benchmark. Conversely, LLM-Compiler-7B (Cummins et al., 2024), trained to compile source code into LLVM IR (Lattner and Adve, 2004)—the opposite of decompilation—served as a more effective foundation, enhancing performance by 3.5% compared to Deepseek-Coder-6.7B. Additionally, Yi-Coder-9B (01-AI, 2024), introduced in September 2024 as the current state-of-the-art model, markedly improved decompilation training results by 23.1%. Furthermore, CodeStral-22B (Mistral-AI, 2024), benefiting from its larger architecture, provided a 21.7% improvement over smaller models.

Model/Opt. Level	O0	O1	O2	O3	AVG
DeepSeek-Coder-6.7B	74.39	46.95	47.56	42.07	52.74
LLM-Compiler-7B	72.56	51.83	48.78	45.12	54.57
Yi-Coder-9B	79.27	**62.20**	**61.59**	56.71	**64.94**
CodeStral-22B	**80.49**	58.54	59.76	**57.93**	64.18

Table 11: Comparison of re-executability rates for base models in the LLM4Decompile-Ref series.

E Obfuscation Techniques

We provide the details of two classic obfuscation techniques suggested in Obfuscator-LLVM (Junod et al., 2015).

Control Flow Flattening. It enhances the security of software by transforming its straightforward, hierarchical control flow into a more complex, flattened structure. The workflow involves breaking a function into basic blocks, arranging these blocks at the same level, and encapsulating them within a switch statement inside a loop.

Bogus Control Flow. It modifies a function's execution sequence by inserting an additional basic block prior to the existing one. This added block includes an opaque predicate, followed by a conditional jump that leads back to the original block. Additionally, the original basic block is polluted with randomly selected, meaningless instructions.