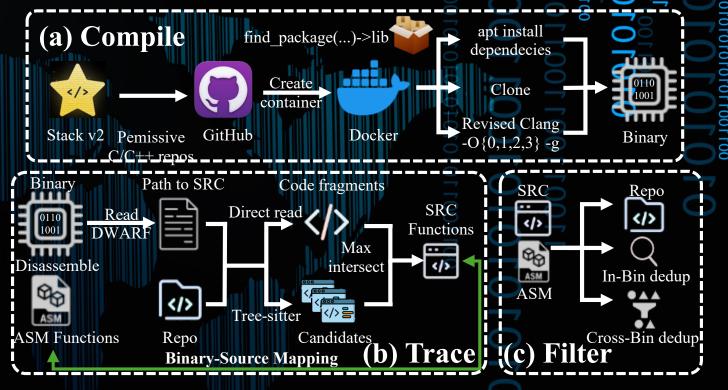


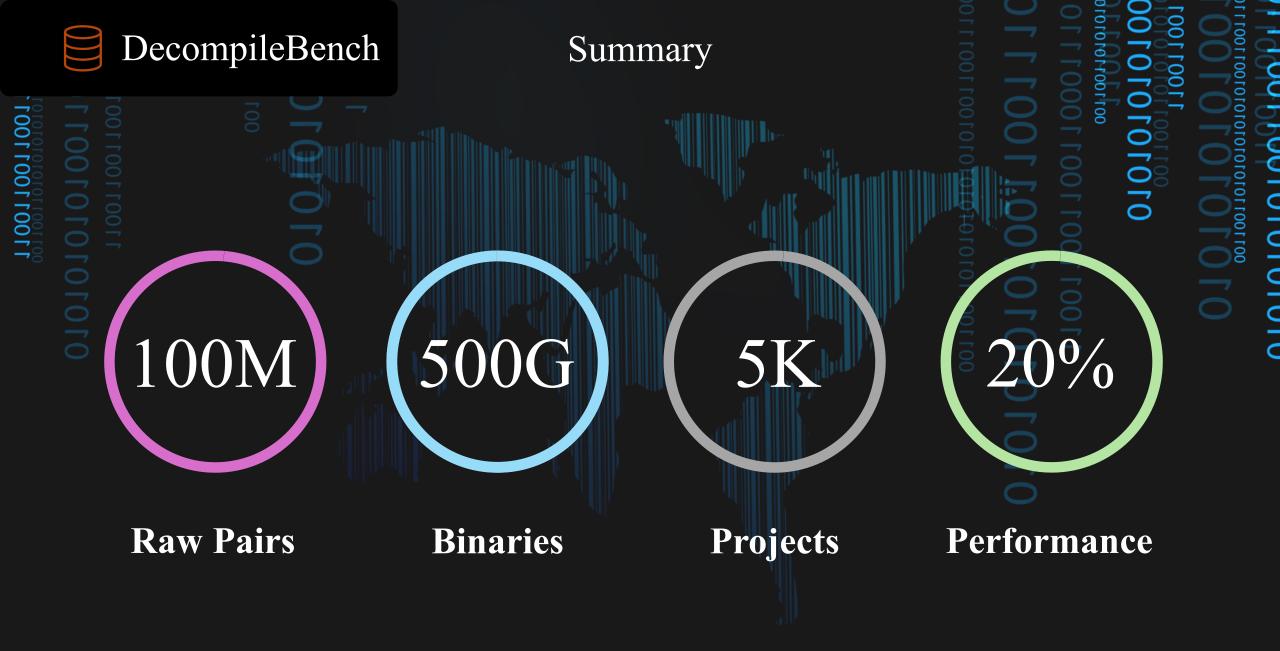
Million-Scale Binary-Source Function
Pairs for Real-World Binary Decompilation

Hanzhuo Tan



First and largest binary-source dataset, 2M pairs condensed from 100M

Evaluation set: Github2025 (least data leakage)



# DecompileBench

### Previous Work

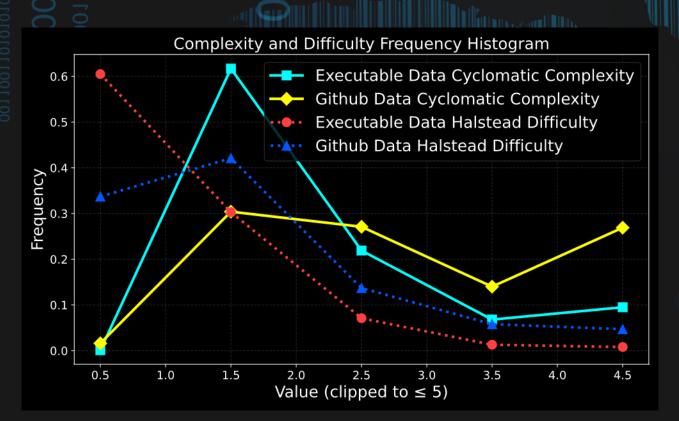
Category	Code Contest	Synthetic					
Benchmarks	Decompile-Dataset [26] HumanEval-Decompile [11]	AnghaBench [27] ExeBench [28] CSMith [48]					
Samples	<pre>int func0(float num [], int size, float threshold){ int i, j for (i = 0; i &lt; size; i++)   for () if ()} </pre>	<pre>struct of _device{int dummy; }; struct device {int dummy; }; struct device* bus _find _device    (int /*&lt;&lt;&lt; orphan*/ *,); int /*&lt;&lt;&lt; orphan*/;}</pre> <pre>b</pre>					
Category	Fragment-Level	Real-World Function-Level					
Benchmarks	Dire[9] Dirty [29] Resym [10] Assemblage [30]	CodeCMR [53] Idioms [54] <b>Decompile-Bench</b>					
Samples	source code       rva       func         return J();       0x00004320       46         return t->size();       0x00001A80       55         column++;       0x000034F0       58         if (lookahead &0x0000B050       c	Game::Game(std::size_t grid_width, std::size_t grid_height) : snake(grid_width, grid_height), snake2(grid_width, grid_height), engine(dev()), { snake.setPosition()}					



We need more real data

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### Why not synthetic data?



#### Cyclomatic Complexity (CC) Equation: CC=E-N+2

E = number of edges in the control flow graph

N = number of nodes

P = number of connected components (usually

1 for a single program)

### Halstead Difficulty (D)

**Equation:** 
$$D = \frac{\eta_1}{2} \times \frac{N_1}{\eta_2}$$

 $\eta_1$ = the number of distinct operators (+-\*/)

 $\eta_2$ = the number of distinct operands (variables)

 $N_1$ = the total number of operators

 $N_2$ = the total number of operands



We need more real data



## DecompileBench

## Compile-Trace-Filter (CTF)

## Compile

1.Patch Clang driver and invocation logic to force our desired -O{0,1,2,3} and -g flags 2.parse CMakeLists.txt for find\_package(...), query GPT for the correct install commands

3.Leverage Docker to isolate install environment

#### Algorithm 1 Pairing Binary Functions with Source Functions

```
Input: Binary project B, source project S
```

Output: Map M, containing the mapping between each binary function in B to a source function

- 1: **for all** binary function  $f_b$  in B **do**
- 2: Extract DWARF information in  $f_b$  to obtain corresponding source-code lines; group them as func\_segment
- 3: Candidates  $\leftarrow \emptyset$
- for all source line  $\ell$  in func\_segment do
- Use Tree-sitter on S to extract the complete source function  $f_s$  containing  $\ell$
- 6: Candidates  $\leftarrow$  Candidates  $\cup \{f_s\}$
- 7: end for

#### 8:

$$f_s^* \leftarrow \arg\max_{f_s \in \text{Candidates}} |\text{func\_segment} \cap \text{Lines}(f_s)|$$

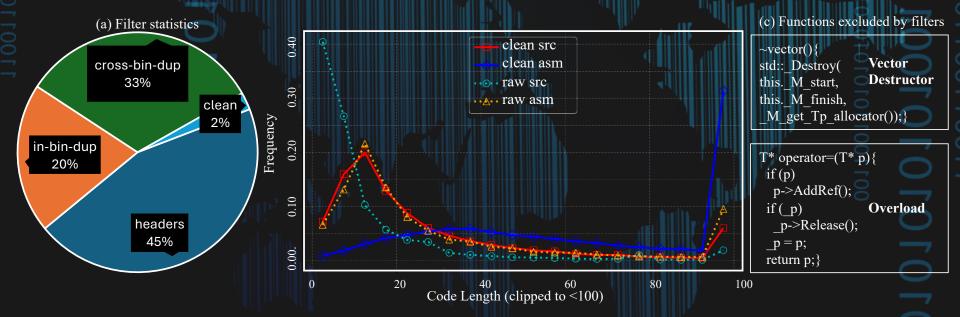
- 9:  $M[f_b] \leftarrow f_s^*$
- 10: **end for**
- 11: return M

#### Filter

Trace

- 1.Project-scope filter. Remove any source function not in the target repository. E.g., get() and set()
- 2.In-binary deduplicator. Several functions within one binary claim the same source function
- 3. Cross-binary deduplicator. Apply MinHash-LSH to eliminate near-duplicate

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- 1.DecompileBench retains only 2% of the raw data (two million functions out of 100M)
- 2. Removing codes from header files or duplicates eliminates the vast majority (40% of all raw data) of short snippets (under five lines)
- 3. The project-scope filter mostly discards trivial helpers (e.g., get()), constructors, and destructors from system or dependency headers. In-binary duplicates stem from template instantiation.

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Re-Executability Rates	HumanEval				MBPP O				00	
	O0	<b>O</b> 1	O2	O3	AVG	O0	<b>O</b> 1	O2 <u></u>	O3	AVG
LLM4Decompile-End	26.22	12.81	14.03	13.42	16.22	29.16	16.99	17.92	18.07	20.54
+Exebench	$-26.\overline{22}$	13.89	<u> 13.11</u>	$1\bar{3}.\bar{8}9$	16.78	-27.16	17.66	18.74	$-17.\overline{25}$	-20.20
+Decompile-Bench-raw	24.70	13.41	13.11	12.20	15.86	26.49	16.48	15.40	14.32	18.17
+Decompile-Bench	33.23	18.60	16.47	15.24	20.89	35.06	21.56	22.80	20.28	24.93

- 1. LLM4Decompile-End is trained on ExeBench and additional training from the same source does not provide further benefit
- 2. Model trained on Decompile-Bench-raw (no filter), the low-quality nature leads to 2.2% and 11.4% re-executability **decline** against to the base model
- 3. Clean and compact data from Decompile-Bench significantly improves the re-executablility of the base model for **over 20%**