

FVEL: Interactive Formal Verification Environment with Large Language Models via Theorem Proving

Xiaohan Lin<sup>\*1,</sup> Qingxing Cao<sup>\*1</sup>, Yinya Huang<sup>\*2</sup>, Haiming Wang<sup>\*3</sup>, Jianqiao Lu<sup>4</sup>, Zhengying Liu<sup>5</sup>, Linqi Song<sup>2</sup>, Xiaodan Liang<sup>1,6</sup>

<sup>1</sup>Shenzhen Campus of Sun Yat-sen University, <sup>2</sup>City University of Hong Kong, <sup>3</sup>Sun Yat-sen University, <sup>4</sup>The University of Hong Kong <sup>5</sup>Huawei Noah's Ark Lab <sup>6</sup>DarkMatter AI Research



Motivation:

- Formal verification\* has witnessed growing significance with emerging program synthesis by the evolving large language models.
- Current formal verification mainly resorts to **symbolic verifiers** or **hand-craft rules**, resulting in limitations for **extensive and flexible** verification.
- To utilizes the LLMs' ability of theorem proving for **rigorous and interactive** formal verification.

Contributions:

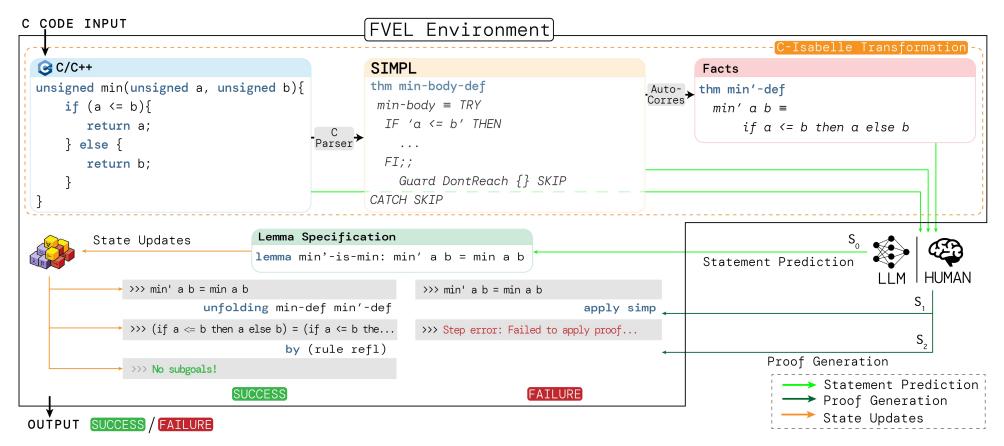
- FVEL: an interactive formal verification environment with LLMs.
- FVELer: a large-scale verification dataset with 758 theories, 29,304 lemmas, and 201,498 proof steps in total that contain deep dependencies.
- The fine-tuned LLMs with FVELer outperform on Code2Inv and SV-Comp datasets, and successfully verify translated Python code.

<sup>\*</sup> Formal verification is the process of mathematically checking that a system's behavior satisfies a given property.



FVEL provides an interactive environment with LLMs that leverage rigorous theorem-proving processes:

- 1. Transforms the input C code into facts, and then provides the facts to the LLM.
- 2. The LLM **generates a lemma in Isabelle** (a formal system for theorem proving) as a formal description of the code specification;
- 3. The LLM generates proof steps with feedbacks from Isabelle;
- 4. The output is a binary result indicating the success or failure of the verification.

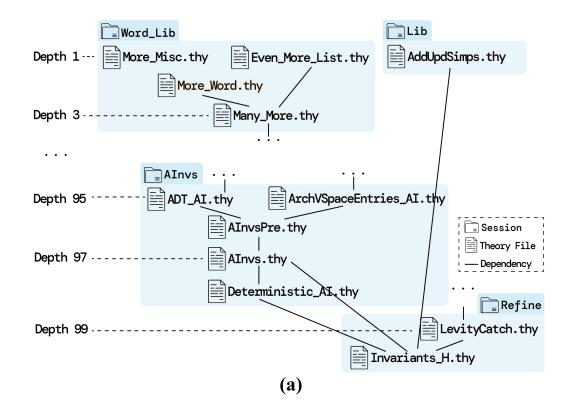




FVELer has two main components:

1. **Theories dependencies** (Figure a). A resource for dependencies among theories, lemmas, and C code specified by SeL4 (a micro-kernel operating system) verification.

2. Lemmas from theories with their Isabelle proof states (Figure b), which support step-wise proving process in Isabelle.



lemma word_div_eq_1_iff: "n div m = 1 ↔						
$n \ge m \land unat n < 2 * unat (m :: 'a ::$						
len word)"						
<pre>apply (simp only: word_arith_nat_defs)</pre>						
<pre>apply (simp flip: unat_div)</pre>						
done						
 FVELER Extraction						
,FVELER Data						
<b>lemma</b> word_div_eq_1_iff: "n div m = 1 $\leftrightarrow$						
n ≥ m ∧ unat n < 2 * unat (m :: 'a ::						
len word)"						
>>> (n div m = 1) = (m $\leq$ n $\land$ unat n $<$ 2 $*$ unat m)						
<pre>apply (simp only: word_arith_nat_defs)</pre>						
<pre>&gt;&gt;&gt; (take_bit LENGTH('a) (unat n div unat m) = take_bit LENGTH('a) (Suc 0)) = (unat n div unat m = Suc 0)</pre>						
<pre>apply (simp flip: unat_div)</pre>						
>>> proof (prove) goal: No subgoals!						
done						
>>> No subgoals!						
(b)						



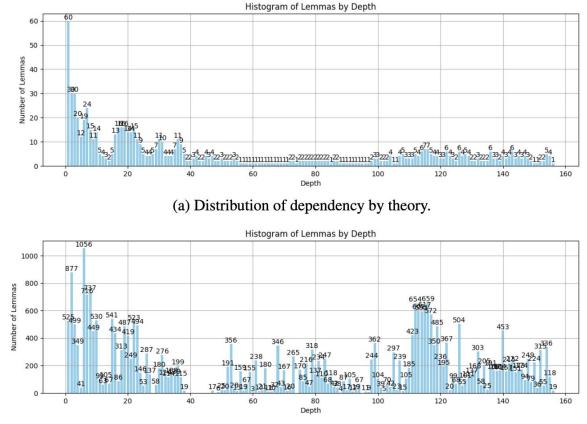
FVELer contains **758 theories**, **29,304 lemmas**, **and 201,498 proof steps**. We randomly split FVELer according to lemmas. Lemmas in the "test-hard set" are in higher depths in the dependency relationship.

	Total	Train	Val	Test	Test-Hard
▷ Theory					
Number of Theories	758	-	-	_	-
Average depth*	-	73.687	73.732	73.958	31.476
Maximum depth	156	156	155	155	115
⊳ Lemma					
Number of Lemmas	29,304	26,192	1,145	1,115	852
⊳ Proof Step					
Number of proof steps**	201,498	181,887	6,931	8,036	4,644
Average proof steps	-	6.944	6.053	7.207	5.450
Maximum proof steps	963	963	188	574	107

Table 1: FVELER Statistics. A *theory* is a .thy file in seL4 that contains multiple *lemmas*. Each *lemma* has multiple *proof steps*. The train/val/test/test-hard data split is based on *lemmas*.

\* Depth: Degree of the theory dependency graph by import relationship.

\*\* Proof step: A single step in Isabelle producing a valid statement for interaction."



(b) Distribution of dependency by lemma.



FVELer fine-tuned Llama3-8B solves 17.39% (69 $\rightarrow$ 81) more problems, and Mistral-7B 12% (75 $\rightarrow$ 84) more problems in SV-COMP dataset.

For Python code verification, the fine-tuned LLMs are able to verify more Python code with translation to C code.

Table 2: Result on formal verification task. FT: Fine-tuned.						
Model	Code2Inv (#=133)	SV-COMP-47 (#=47)	SV-COMP (#=1,000)			
▷ Symbolic Solver						
UAUTOMIZER [10]	92	1	374			
ESBMC [6]	68	1	358			
▷ LLM-based Solver						
Lemur-GPT-3.5-turbo [40]	103	14	-			
Lemur-GPT-4 [40]	107	25	-			
Mistral-7B [14]	37	10	75			
Mistral-7B-FT	40	14	84			
Llama3-8B <sup>4</sup>	46	11	69			
Llama3-8B-FT	46	16	81			

## Table 4: Result on Python (Translated to C) Code Verification.

# Verified
35/93
42/93
38/93
43/93

Please refer to our paper for more analyses and implement details.



## Thank you for listening!

Contact: linxh55@mail2.sysu.edu.cn







