

CraftRTL: High-quality Synthetic Data Generation for Verilog Code Models with Correct-by-Construction Non-Textual Representations and Targeted Code Repair

Mingjie Liu* · Yun-Da Tsai* · Wenfei Zhou · Haoxing Ren

We present **CraftRTL**, a state-of-the-art Hardware LLM designed for RTL coding. Our approach enhance data curation by generating correct-by-construction data targeting non-textual representations. Additionally, we introduce an automated framework that gathers errors from multiple model checkpoints and create targeted code repair data by error injection. We outperform prior results by 3.8%, 10.9%, 6.6% for pass@1 on VerilogEval and RTLLM.

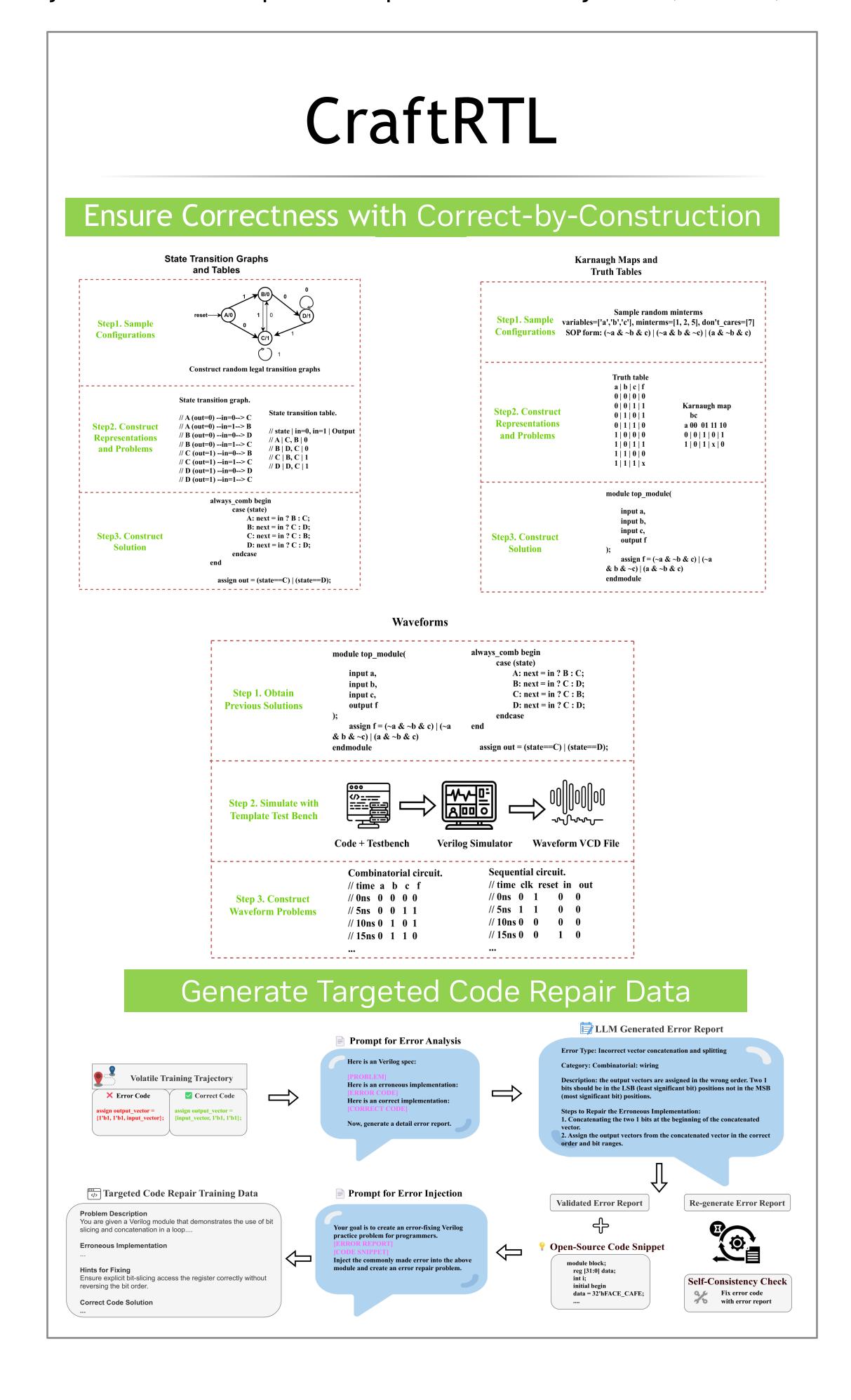
Motivation

- Challenges: Limited high-quality data, constrained capability of existing LLMs and complex verification requirements for ensuring the functional correctness.
- LLMs for RTL Generation: Reducing designer costs and efforts for completing hardware specs, code synthesis, refinement and debugging.
- Prior works on Synthetic Data Generation:
 - 1) Self-Instruct generate with in-context learning from seed examples (Wang, Yizhong, et al. 2022)
 - 2) Docu-Instruct utilize document sources from Wikipedia and textbooks to enhance diversity (Adler, Bo, et al. 2024)
 - 3) Oss-Instruct reversely generate coding problems from code snippets (Wei, Yuxiang, et al. 2023)

Struggle to generate functionally correct data

Our Contributions:

- We develop correct-by-construction datasets targeting non-textual representations, improving model understanding and generation capabilities.
- We have developed an automated system that collects errors from various model checkpoints and injects these into code to create targeted code repair datasets..
- CraftRTL-15B surpasses previous state-of-theart results by achieving higher pass@1 rates on VerilogEval-Machine, VerilogEval-Human, and RTLLM benchmarks.



Experimental Results

- 1									
ı				VerilogEval (L			iu et al., 2023b)		
ı	Type	Model	Size	Machine (%)			Human (%)		
ı				pass@1	pass@5	pass@10	pass@1	pass@5	pass@10
	Foundational	Llama-3.1	8B	48.7	67.3	74.1	26.9	37.8	44.2
		Llama-3.1	405B	67.3	75.1	76.9	53.8	61.0	62.8
	Models	Nemotron-4	340B	53.0	60.3	62.2	43.1	48.3	50.0
	Wiodels	GPT-3.5-turbo	-	58.0	74.0	77.6	31.2	44.1	47.4
		GPT-4o	-	65.9	71.4	72.7	57.1	63.9	66.7
	Code Models	CodeLlama	7B	43.1	47.1	47.7	18.2	22.7	24.3
		CodeQwen	7B	46.5	54.9	56.4	22.5	26.1	28.0
		Starcoder2	15B	68.7	82.3	88.5	37.7	50.6	57.2
		DeepSeek-Coder	6.7B	52.2	55.4	56.8	30.2	33.9	34.9
		DeepSeek-Coder-V2	16B	67.4	78.3	81.8	46.9	55.9	58.9
		DeepSeek-Coder-V2	236B	68.2	74.1	76.2	56.4	62.2	66.0
	RTLCoder	Mistral	7B	62.5	72.2	76.6	36.7	45.5	49.2
	(Liu et al., 2023c)	DeepSeek-Coder	7B	61.2	76.5	81.8	41.6	50.1	53.4
	BetterV (Pei et al., 2024)	CodeLlama	7B	64.2	75.4	79.1	40.9	50.0	53.3
		DeepSeek-Coder	6.7B	67.8	79.1	84.0	45.9	53.3	57.6
		CodeQwen	7B	68.1	79.4	84.5	46.1	53.7	58.2
ı	CodeV (Zhao et al., 2024)	CodeLlama	7B	78.1	86.0	88.5	45.2	59.5	63.8
		DeepSeek-Coder	6.7B	77.9	88.6	90.7	52.7	62.5	67.3
		CodeQwen	7B	77.6	88.2	90.7	53.2	65.1	68.5
	OriGen (Cui et al., 2024)	DeepSeek-Coder	6.7B	74.1	82.4	85.7	7 54.4 60.1		64.2
	Oues	CodeLlama	7B	78.1	85.5	87.8	63.1	67.8	69.7
	Ours	DeepSeek-Coder	6.7B	77.8	85.5	88.1	65.4	70.0	72.1
	SDG-CC-Repair	Starcoder2	15B	81.9	86.9	88.1	68.0	72.4	74.6

Main Experiment: Pass-rates of recent large language models and the proposed CraftRTL. Pass@1 = #passed case/#total case. We report the best pass@k score among temperature {0.2, 0.8}.

-1		verilogEval		KILLMIVI.I		vernogevar		KILLWI VI.I
	Model	Machine	Human	Func	Model	Machine	Human	Func
П		pass@1 (%)		pass@5 (%)		pass@1 (%)		pass@5 (%)
П	Starcoder2-15B	68.7	37.7	37.6	SDG-CC	73.9	62.0	62.8
П	SDG (80.1k)	75.2	54.7	62.1	SDG-CC-Repair	81.9	68.0	65.8
П	SDG-CC (108.6k)	73.9	62.0	62.8	w/o self-consistency	75.3	63.3	63.7
	SDG-CC-Repair (110.0k)	81.9	68.0	65.8	w/o error report	76.9	59.6	59.4

Ablation Study: Pass-rate (%) from the ablation study evaluating the effectiveness of various synthetic data groups and framework components.

