



UC San Diego

Machine Learning for Software System / Hardware Design: Towards AI-Assisted Programming Tasks

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Towards LLM-Powered Verilog RTL Assistant: Self-Verification and Self-Correction

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* Will be presented at HotChips 2024 tutorial

Background and Motivation:

- Complexity of Traditional RTL Design
 - Describe architectures and behaviors at a granular level
- Differences between HDLs and General-Purpose PLs
 - RTL design is more complex considering timing constraints
 - RTL verification is hard considering efficiency and coverage
 - Existing code-LLMs are not tailored for RTL design

Methodology:

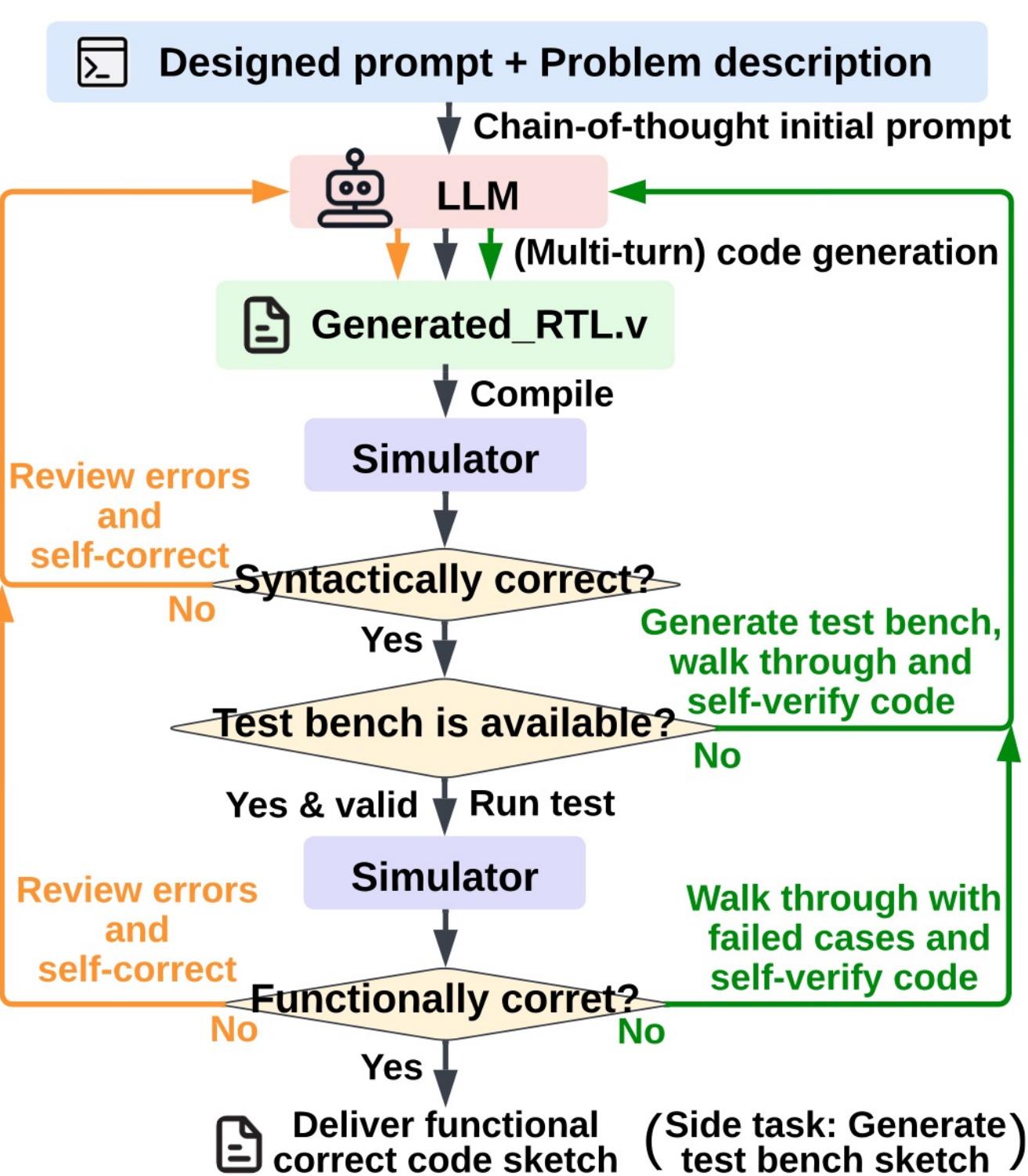
- Leverage LLMs code generation ability, iterative interaction ability, and Chain-of-thought ability
- Design prompts by mimicking human designers behavior:
 - Reason and solve the design problem step by step
 - Generate testbench with test cases, and walk through code to deductively reason the code behavior considering timing, given a certain input or a previously failed input test case
 - Based on the simulator feedback and code walk-through process, revise code, fix bugs, and meet design specifications over multiple iterations

Table 1: Pass rate (%) comparison of RTL code generators on VerilogEval [16] and RTLLM [17] benchmarks.

Model Type	Evaluated Model	VerilogEval-Machine			VerilogEval-Human			RTLLM ⁵ pass@5	
		pass@1	pass@5	pass@10	pass@1	pass@5	pass@10	Syntax(%)	Func(%)
Open-Source Model	CodeGen-16B [20]	5.00	9.00	13.9	0.90	4.10	7.25	72.4	6.90
	CodeGen-Verilog-16B [28]	44.0	52.6	59.2	30.3	43.9	49.6	86.2	24.1
Closed-Source Model	ChipNeMo-13B [15] ^T	43.4	N/A	N/A	22.4	N/A	N/A	N/A	N/A
	ChipNeMo-70B [15] ^T	53.8	N/A	N/A	27.6	N/A	N/A	N/A	N/A
	verilog-sft-16B [16] ^T	46.2	67.3	73.7	28.8	45.9	52.8	N/A	N/A
	Claude-3 [4]	55.3	63.8	69.4	34.4	48.3	53.4	93.1	55.2
	GPT-3.5	46.7	69.1	74.1	26.7	45.8	51.7	89.7	37.9
	GPT-4	60.0	70.6	73.5	43.5	55.8	58.9	100	65.5
VeriAssist	Ours + Claude-3 Improvement (Δ)*	63.8	70.4	78.4	41.6	55.5	62.5	96.6	65.5
	Ours + GPT-3.5 Improvement (Δ)*	55.3	76.5	80.1	34.4	51.3	58.9	93.1	48.3
	Ours + GPT-4 Improvement (Δ)*	67.5	78.3	83.2	50.5	62.8	69.2	100	75.9
Ablation Study	Self-Verification + GPT-4	63.8	73.2	78.4	48.3	58.9	64.7	96.6	69.0
	Self-Correction + GPT-4	62.5	72.2	77.2	47.1	58.9	66.0	100	69.0

Takeaways:

- VeriAssist suggests accurate code sketch, testbench with test cases
- VeriAssist reduces human intervention and improves productivity
- The proposed process of generating test benches, and self-code walk-throughs significantly improves the correctness of RTL code



Evaluation:

- Metrics: syntax pass rate, functionality pass rate, PPA, pass@k: a problem is considered solved if any of the k samples pass the unit tests.
- VeriAssist suggests high-quality RTL code with an average pass@5 score of 72.3% and comparable PPA, along with corresponding test benches.

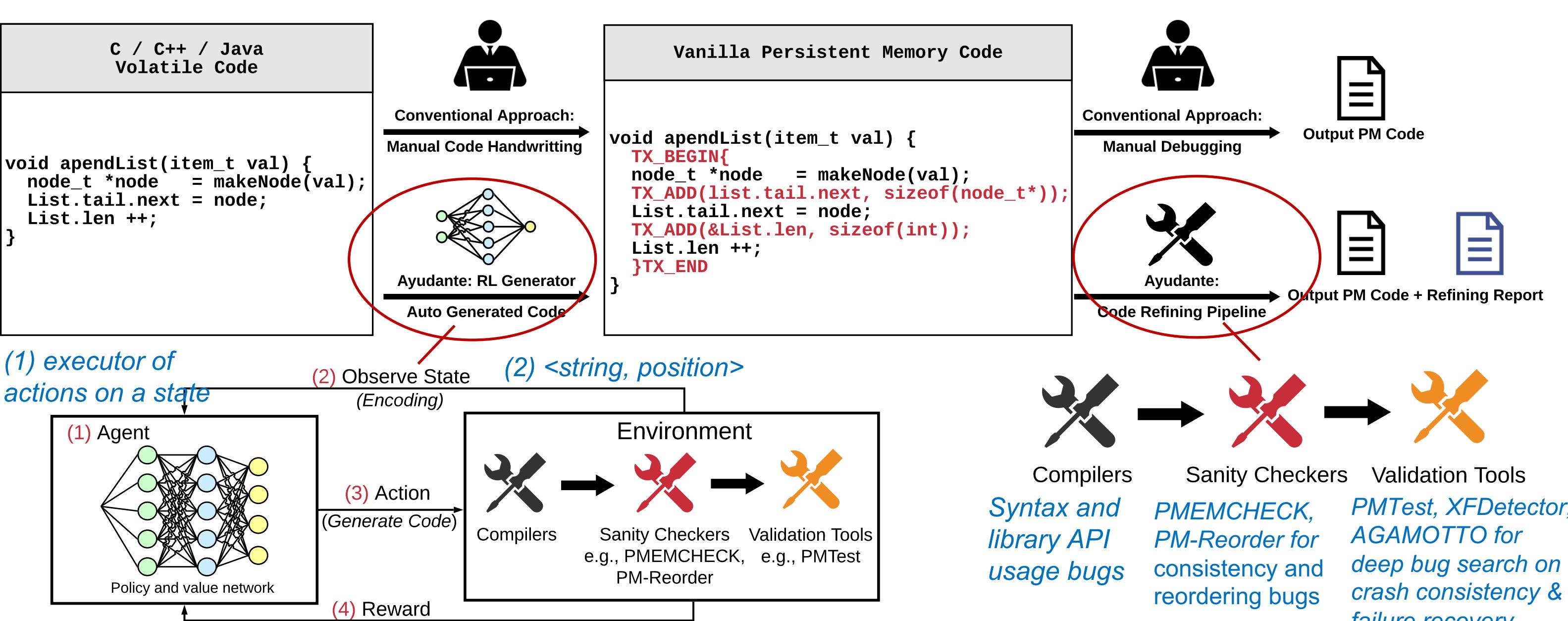
Ayudante: A Deep Reinforcement Learning Approach to Assist Persistent Memory Programming

Hanxian Huang, Zixuan Wang, Juno Kim, Steven Swanson, Jishen Zhao
 University of California San Diego

Background and Motivation:

- Persistent Memory (PM)
 - Comparable performance of DRAM + Persistence property of storage Persistent Memory (PM)
- PM-aware programming
 - Adopt PM library to maintain crash consistency and recover failure
- Challenges in PM-aware programming
 - Non-trivial labor effort, error-prone
 - Require detailed PM programming knowledge

Methodology:



An example of generated code:

```
1 int64_t Queue::pop() {
2     int64_t ret = 0;
3     auto pool = pmem::obj::pool_by_vptr(this);
4     obj::transaction::run(pool, [this, &ret] {
5         if (head == nullptr)
6             throw std::runtime_error("Empty queue");
7         ret = head->value;
8         auto n = head->next;
9         obj::delete_persistent<Node>(head);
10        head = n;
11        if (head == nullptr) tail = nullptr;
12    });
13    return ret;
}
```

(Navigation Action → Edit Action)

- Ayudante can assist with sophisticated PM-programming tasks through efficient PM code generation and code refining
- Ayudante improves the accessibility of domain-specific programming
- More insights: Monte Carlo tree-search (search efficiency); knowledge transferable among PLs; validation tools are critical

Selected Publications:

- "Multi-modal Learning for WebAssembly Reverse Engineering", Hanxian Huang, Jishen Zhao. In the Proceedings of ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA), 2024
- "Fasor: A Fast Tensor Program Optimization Framework for Efficient DNN Deployment", Hanxian Huang, Xin Chen, Jishen Zhao. In the Proceedings of the International Conference on Supercomputing (ICS), 2024
- "Q-gym: An Equality Saturation Framework for DNN Inference Exploiting Weight Repetition", Cheng Fu, Hanxian Huang, Bram Wasti, Chris Cummins, Riyad Baghdadi, Jim Hazelwood, Yuandong Tian, Jishen Zhao, and Hugh Leather. In the Proceedings of the International Conference on Parallel Architectures and Compilation Techniques (PACT), 2022
- "Ayudante: A Deep Reinforcement Learning Approach to Assist Persistent Memory Programming", Hanxian Huang, Zixuan Wang, Juno Kim, Steven Swanson, and Jishen Zhao. In the Proceedings of USENIX Annual Technical Conference (USENIX ATC), 2021
- "Towards LLM-Powered Verilog RTL Code Assistant: Self-Correction and Self-Verification", Hanxian Huang, Zhenghan Lin, Zixuan Wang, Xin Chen, Ke Ding, and Jishen Zhao. Under Review
- "Neural WebAssembly Comprehension: A Transferable WebAssembly Learning for Generalized Analysis Tasks", Hanxian Huang, Jishen Zhao. Under Review

Fasor: A Fast Tensor Program Optimization Framework for Efficient DNN Deployment

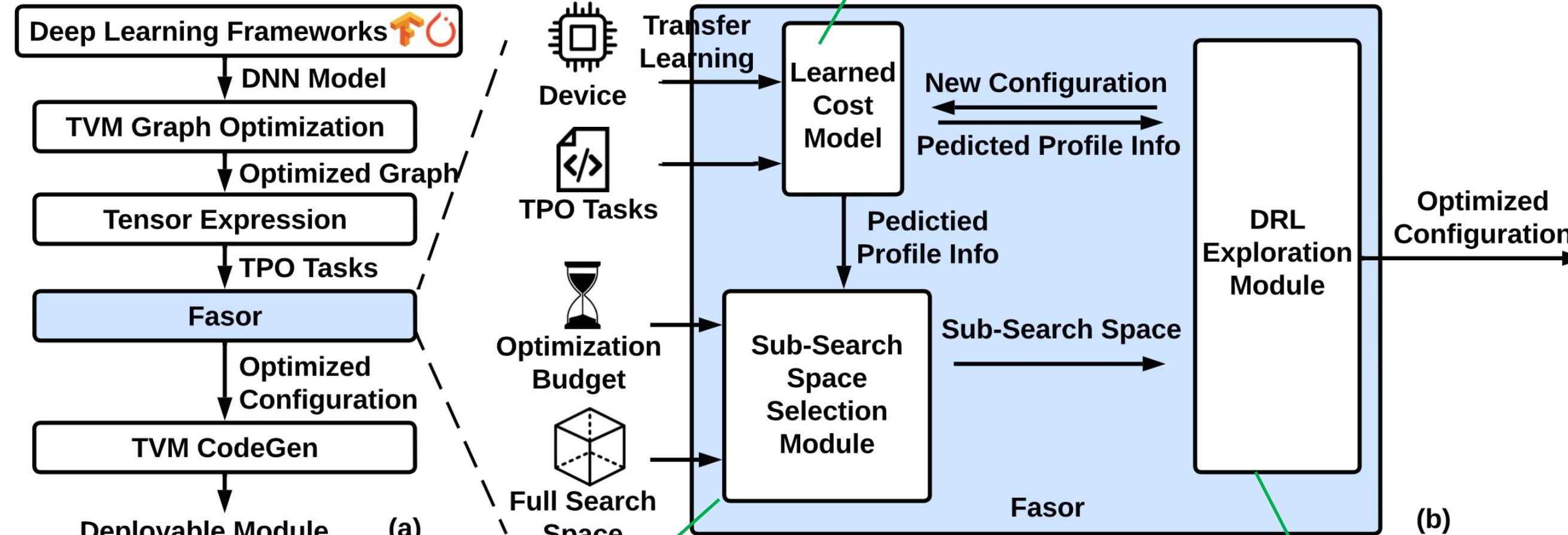
Hanxian Huang¹, Xin Chen², Jishen Zhao¹
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Background and Motivation:

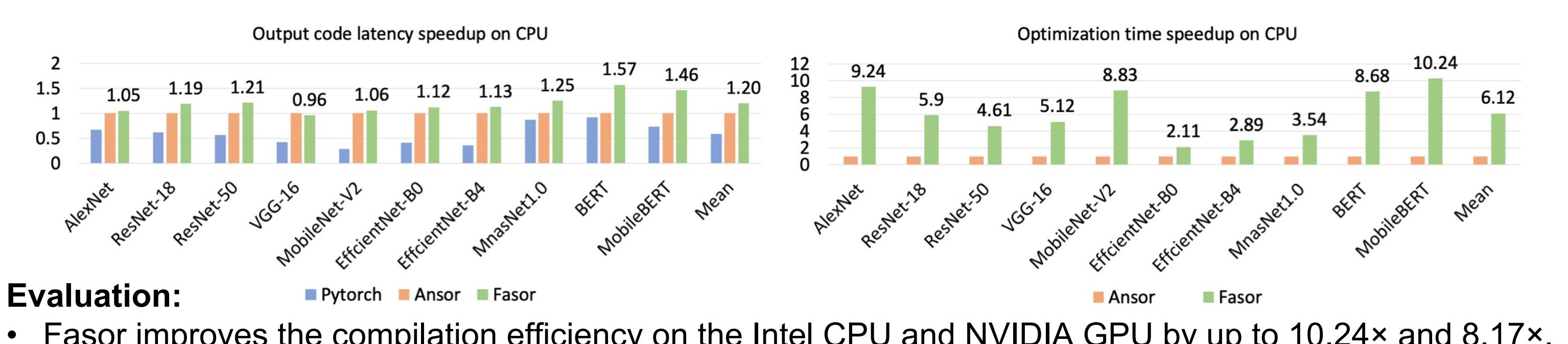
- DNN deployment is becoming a bottleneck in DNN delivery
- Two inefficiencies in tensor program optimization:
 - Cost model training or transferring inefficiency, involving costly on-device measurement
 - Search sampling inefficiency, overlooking the potential of reusing pre-tuned schedules

Methodology:

- Hardware-transferable cost model
 - (1) task feature: kernel/input/output shapes, serialized schedule configurations
 - (2) hardware feature: hardware specifications
 - (3) a small calibration dataset with tasks that contribute distinct hardware-specific knowledge



Stage1: Exploiting Pre-tuned Schedule as Search Start Point
 Stage2: Fast DRL Search. (Roofline model guided reward)



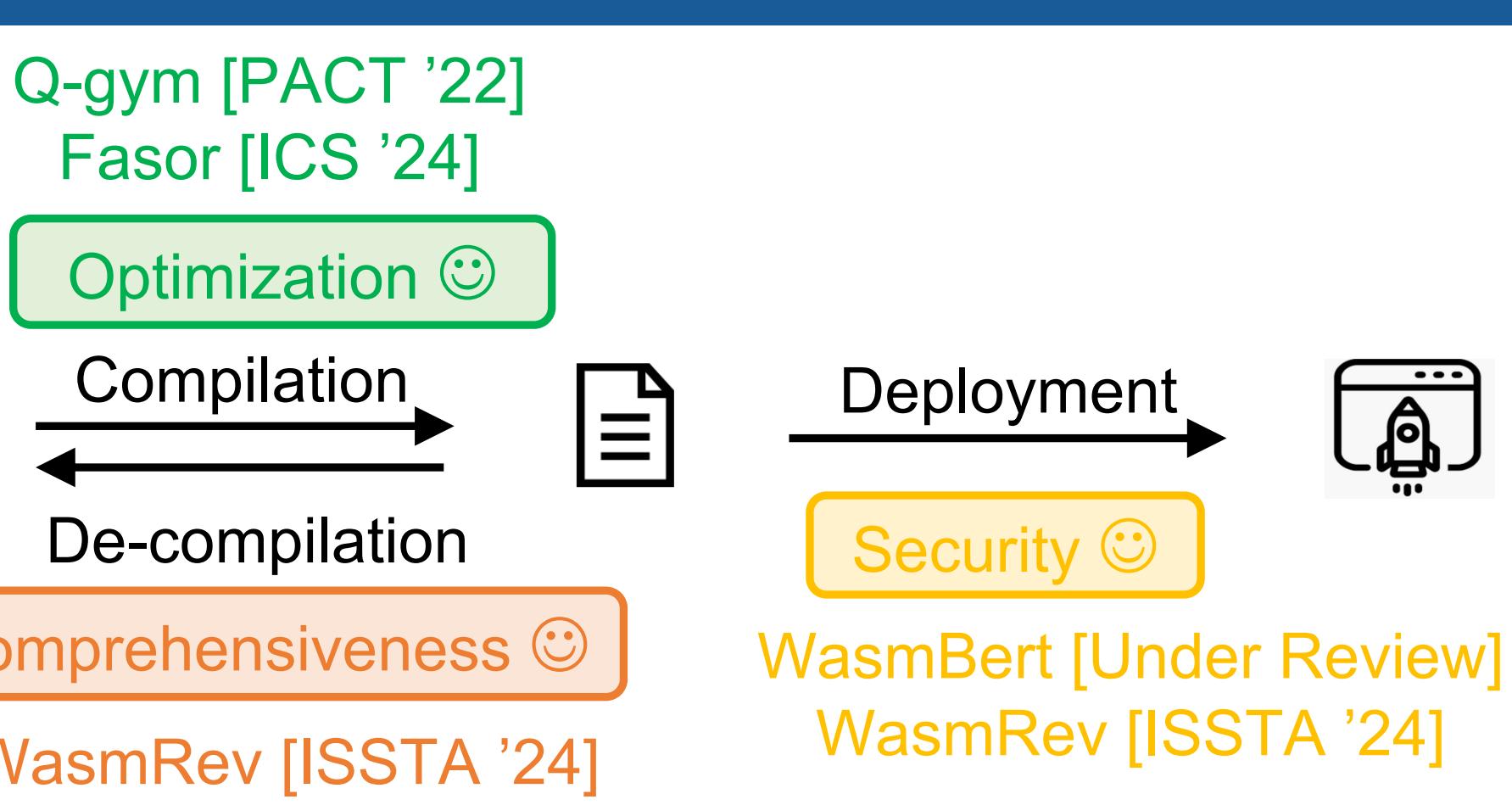
Evaluation:

- Fasor improves the compilation efficiency on the Intel CPU and NVIDIA GPU by up to 10.24x and 8.17x.
- Fasor delivers better or equal output code latency performance with 1.22x average speedup.
- Fasor effectively solves the cost model measurement (81%↓) and search (73%↓) inefficiencies.

Takeaways:

- Fasor provides a high-accurate hardware-transferable cost model that helps with configuration searching
- Fasor exploits tensor program similarity and introduces roofline model guidance achieve a faster and better configuration searching

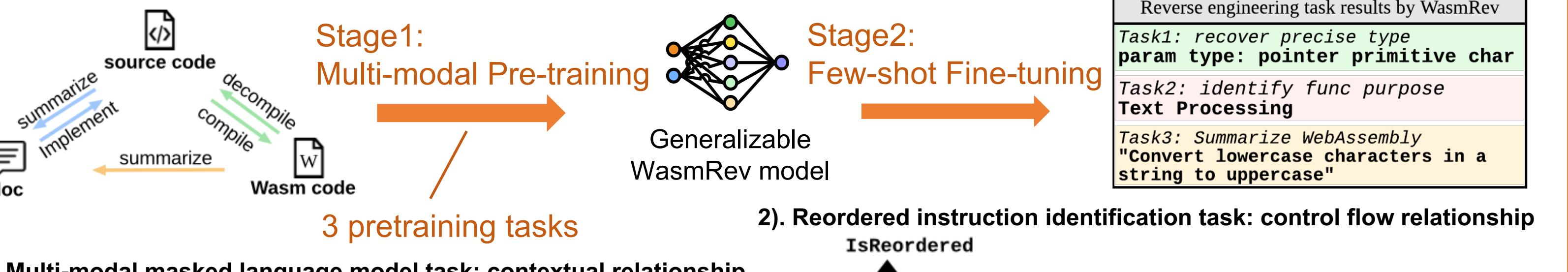
Overview



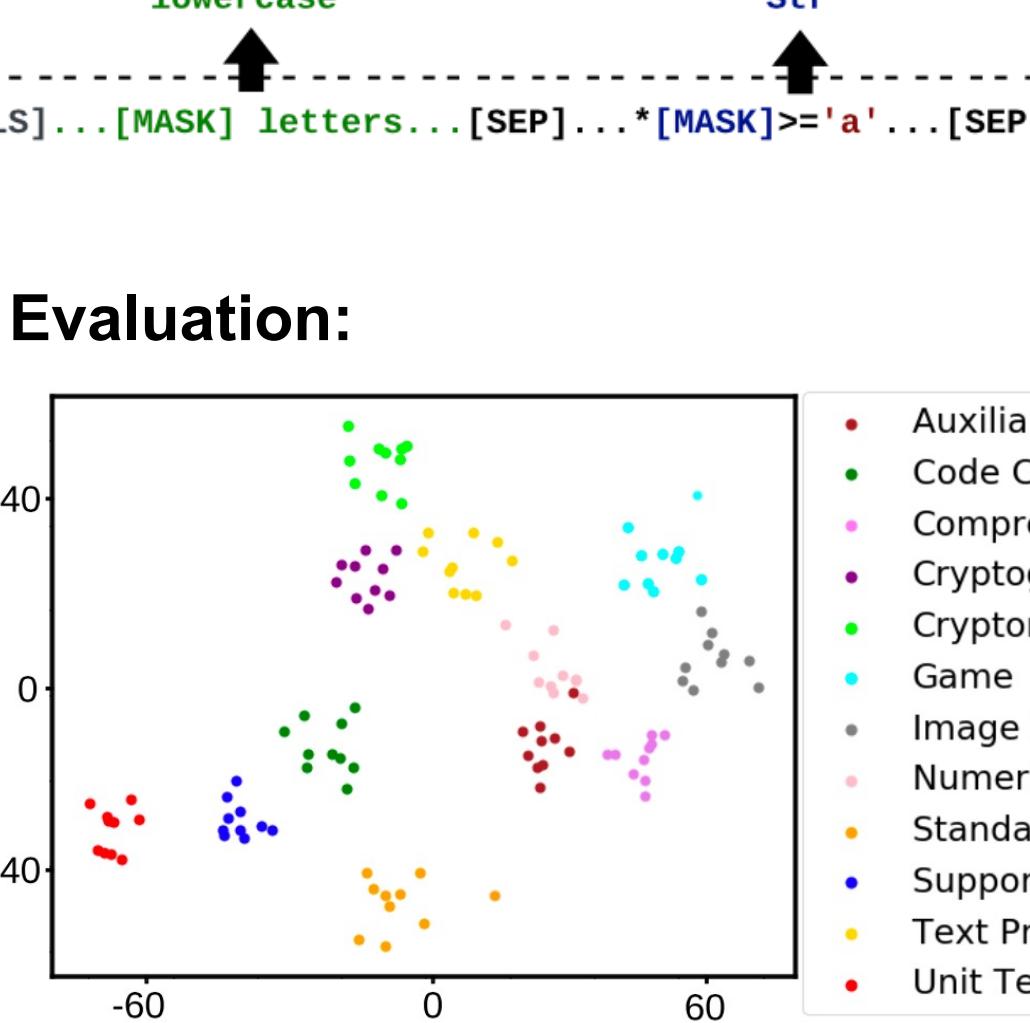
Background and Motivation:

- WebAssembly (Wasm)
 - A novel assembly-like bytecode format; compiled from source code in high-level languages (e.g., C/C++, Rust); stack machine architecture
- WebAssembly code comprehension is necessary
 - Many (malicious) Wasm modules are distributed through third-party services
 - Enabling debugging, checking vulnerabilities and maintenance
- Challenges in WebAssembly comprehension
 - Lacking high-level information, e.g., limited data types
 - Tracking stack behavior is cumbersome and error-prone

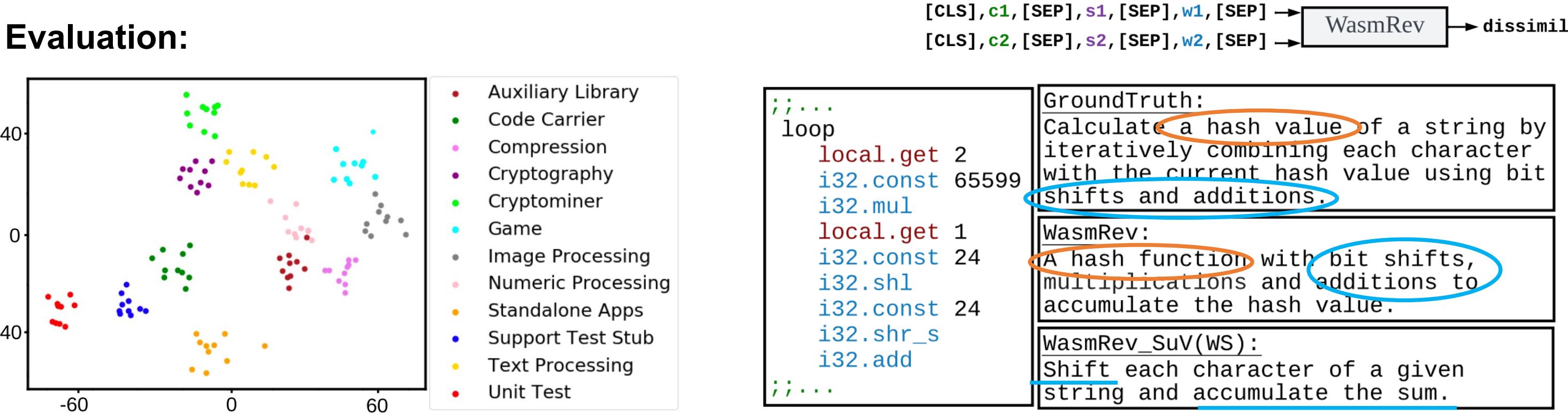
Methodology:



1. Multi-modal masked language model task: contextual relationship



Evaluation:



A case study of WS.

- WasmRev assists WebAssembly comprehension by providing high-level semantics
- WasmRev relieves the burden of both WebAssembly users and tool developers
- WasmRev is data-efficient and transferable to new tasks

Takeaways:

Task	Parameter Type Prediction	Return Type Prediction
Type Language	L_{SW}	L_{SW}
Type Prefix Score	L_{SW}	L_{SW}
Top-1 Acc	44.5%	18.6%
Top-5 Acc	75.2%	27.1%
Top-50 Acc	90.0%	40.6%
Top-100 Acc	95.0%	46.0%
Top-1000 Acc	98.0%	50.7%
Top-10000 Acc	99.0%	50.7%
Top-100000 Acc	99.5%	50.7%
Top-1000000 Acc	99.8%	50.7%
Top-10000000 Acc	99.9%	50.7%
Top-100000000 Acc	99.95%	50.7%
Top-1000000000 Acc	99.99%	50.7%
Top-10000000000 Acc	99.995%	50.7%
Top-100000000000 Acc	99.999%	50.7%
Top-1000000000000 Acc	99.9995%	50.7%
Top-10000000000000 Acc	99.9999%	50.7%
Top-100000000000000 Acc	99.99995%	50.7%
Top-1000000000000000 Acc	99.99999%	50.7%
Top-10000000000000000 Acc	99.999995%	50.7%
Top-100000000000000000 Acc	99.999999%	50.7%
Top-1000000000000000000 Acc	99.9999995%	50.7%
Top-10000000000000000000 Acc	99.9999999%	50.7%
Top-100000000000000000000 Acc</		