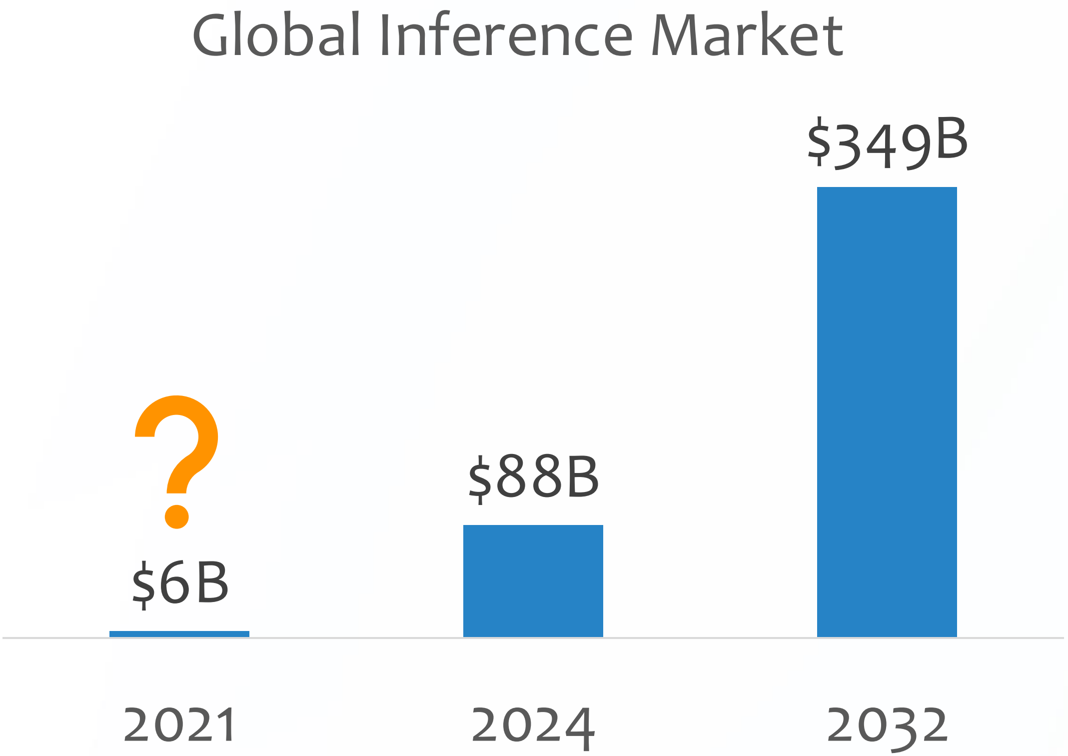
REASONING COMPILER: LLM-Guided Optimizations for Efficient Model Serving

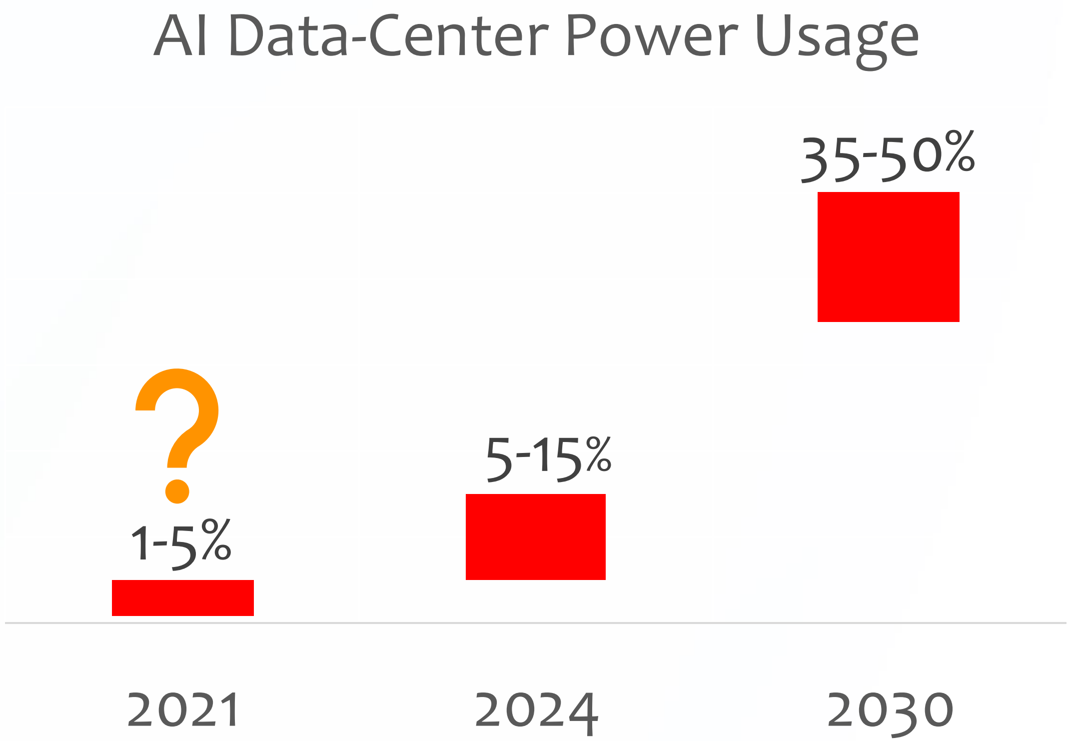
Annabelle Sujun Tang, **Christopher Priebe, Rohan Mahapatra, Lianhui Qin, Hadi Esmaeilzadeh**

Alternative Computing Technologies (ACT) Lab
University of California, San Diego

NEURAL INFORMATION PROCESSING SYSTEMS

The Shift towards Model Serving





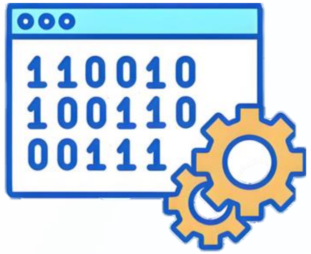
Global AI Inference Market is projected to grow at a CAGR of 18.91% over 2025-2032.

Source: Yahoo Finance

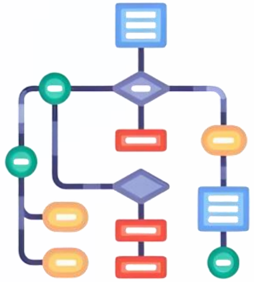
AI-oriented IaaS will more than double in 2025–2026; inference is the demand driver.

Source: Gartner

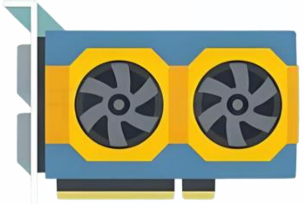
The Triangle of Improvement



Compiler

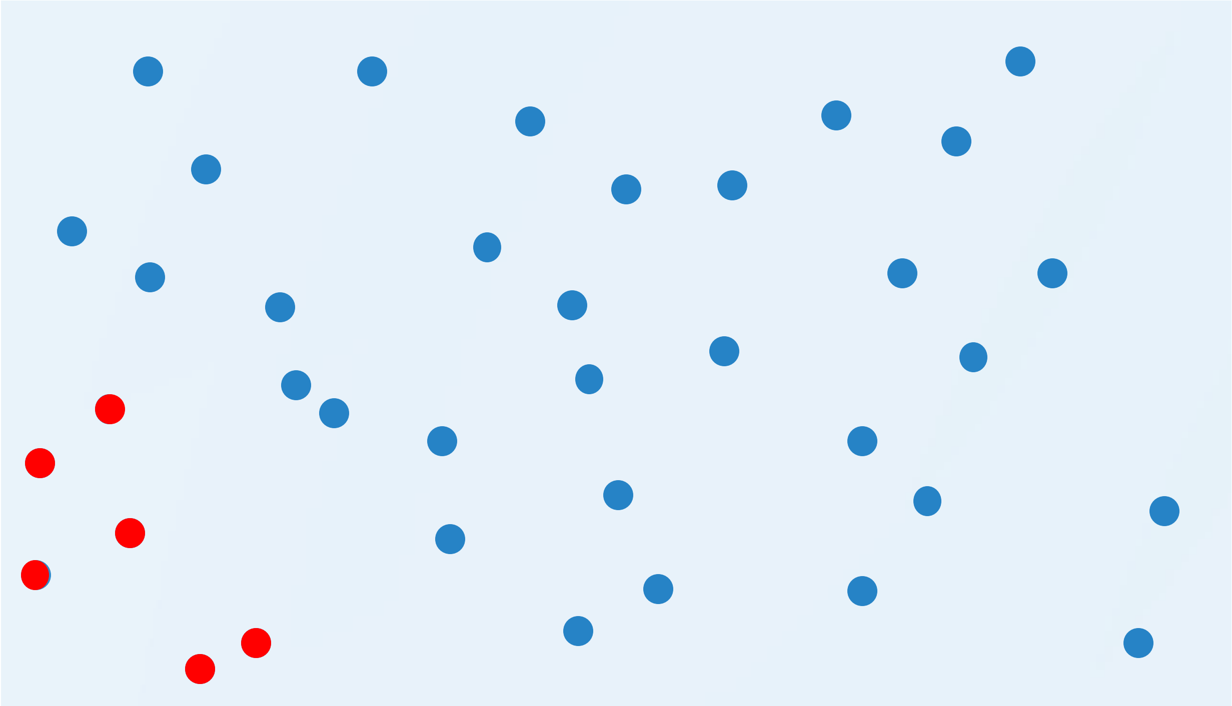


Algorithm



Hardware

Category I: Rule-Based Compiler Optimizations



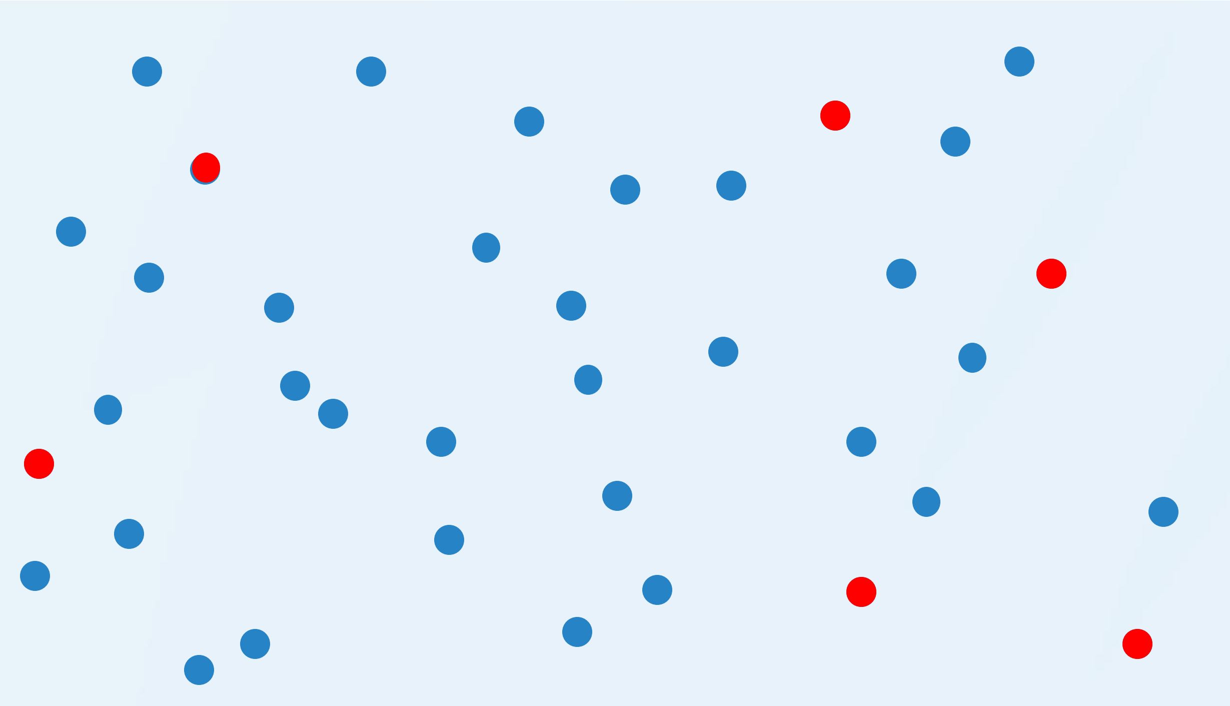
Relies on hand-tuning or domain-specific heuristics

Often overfit to a specific workload or hardware target

+ **Relatively Fast**

- *Cannot explore the entirety of search spaces*

Category II: Stochastic Search for Compilation



+ **Find Higher Quality Optimized Programs**
– **Sample Inefficient**
– **Cannot leverage context and interdependence**

STOKE (Stochastic Super Optimization) [ASPLOS '13]

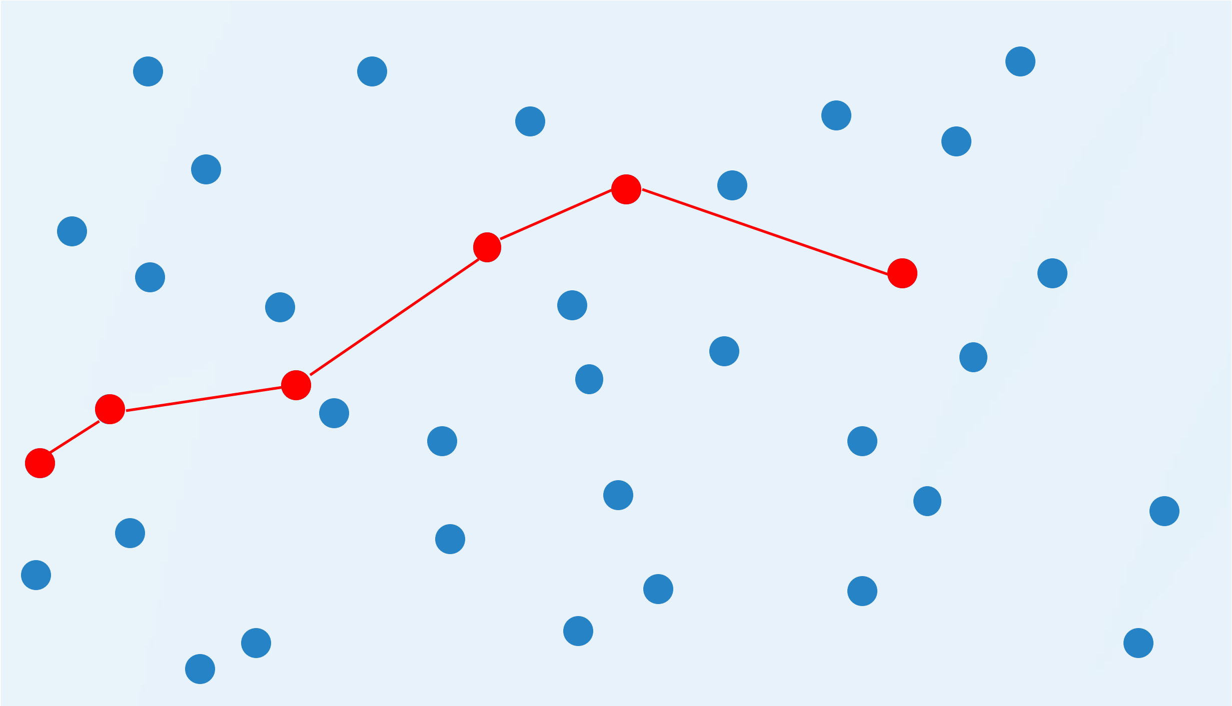
- Markov Chain Monte Carlo (MCMC)
- High quality programs often lie in regions separated by low-probability paths

TVM [OSDI '18], Ansor [OSDI '20], FlexTensor [ASPLOS '20], Tensor Comprehensions [arXiv '18]

- Genetic Algorithm
- Simulated Annealing

REASONING COMPILER

Context-Informed, Guided, Structured Search



+ **Find Higher Quality Optimized Programs**
+ **Sample Efficient**

Leaps from fully stochastic to structured optimizations

Models optimization as Markov Decision Process

Uses Monte Carlo Tree Search (MCTS) as a planner

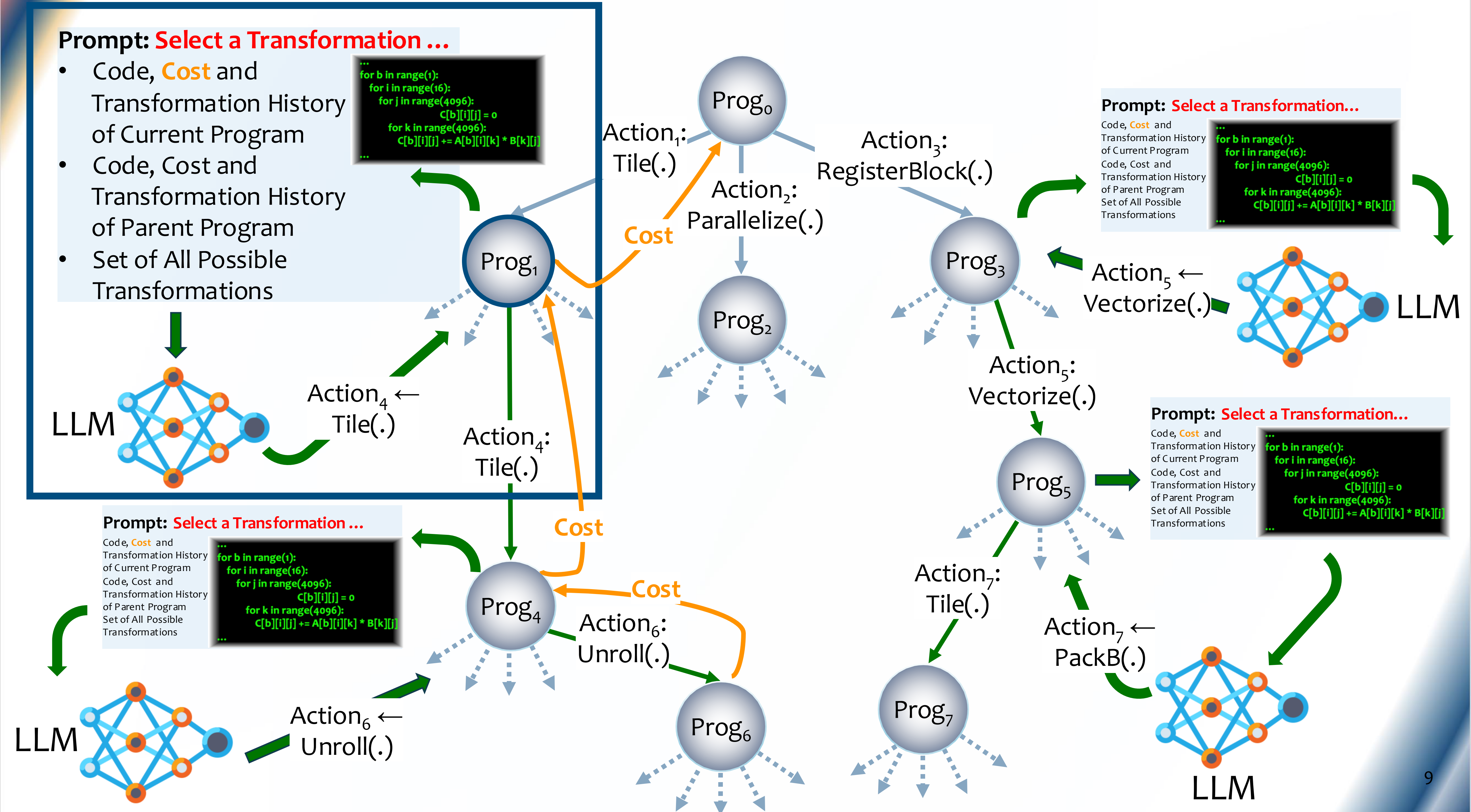
Utilizes LLM reasoning as a guide for Monte-Carlo Tree Search

Can LLM reasoning, without retraining, guide context-sensitive compiler optimizations?

Problem Statement – Neural Code Optimization

```
Self-Attention Layer of Llama-3-8B
…
…
for b in range(1):
    for i in range(16):
        for j in range(4096):
            C[b][i][j] = 0
            for k in range(4096):
                C[b][i][j] += A[b][i][k] * B[k][j]
…
…
```

Tile
    Tile size for each loop
Parallelize
    Axis, Policy
Vectorize
    Width
Unroll
    Factor
PackB
    k-panel size, j-panel Size
Prefetch
    Target, Distance
RegisterBlock
    m-register Tile Size,
    n-register Tile Size
…



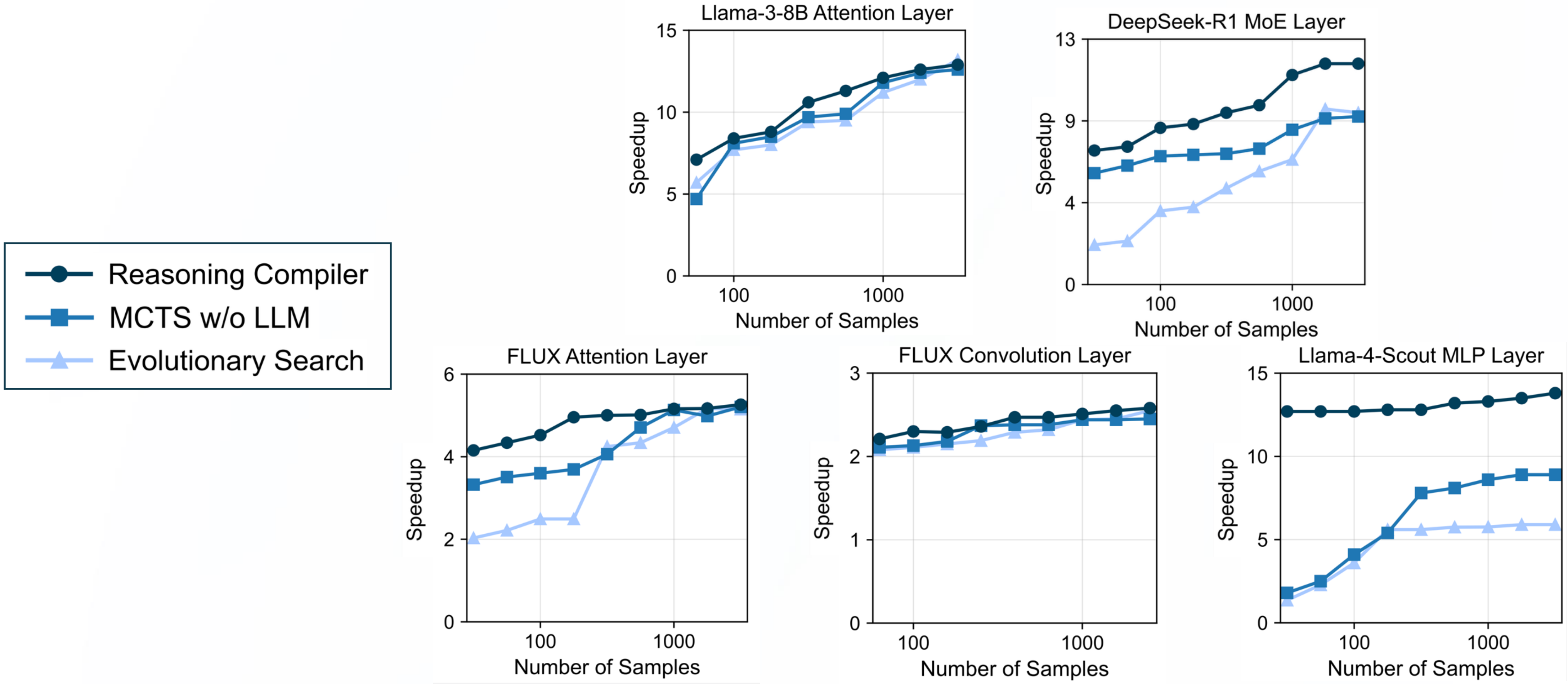
Prompt: Select a Transformation ...
Code, Cost and Transformation History of Current Program
Code, Cost and Transformation History of Parent Program
Set of All Possible Transformations
for b in range(1):
for i in range(16):
for j in range(4096):
C[b][i][j] = 0
for k in range(4096):
C[b][i][j] += A[b][i][k] * B[k][j]
LLM
Prog$_0$
Prog$_1$
Prog$_2$
Prog$_3$
Prog$_4$
Prog$_5$
Prog$_6$
Prog$_7$
Action$_1$: Tile(.)
Action$_2$: Parallelize(.)
Action$_3$: RegisterBlock(.)
Action$_4$: Tile(.)
Action$_4$ ← Tile(.)
Action$_5$: Vectorize(.)
Action$_5$ ← Vectorize(.)
Action$_6$: Unroll(.)
Action$_6$ ← Unroll(.)
Action$_7$: Tile(.)
Action$_7$ ← PackB(.)
Cost

Benchmarks

- Self-Attention Layer from Llama-3-8B
- Mixture-of-Experts Layer from DeepSeek-R1
- Self-Attention Layer from FLUX (Stable Diffusion)
- Convolution Layer from FLUX (Stable Diffusion)
- MLP Layer from Llama-4-Scout
- End-to-End Llama-3-8B

- Amazon Graviton2
- AMD EPYC 7R13
- Apple M2 Pro
- Intel Core i9
- Intel Xeon E3

Higher Speed with Fewer Samples



Across all 25 platform-operator pairs, REASONING COMPILER achieves 5.0× speedup with 5.8× fewer samples: 10.8× improvement in sample efficiency over Evolutionary Search.

Consistent End-To-End Improvements

Hardware Platforms	Evolutionary Search		Reasoning Compiler		Improvement	
	# Samples	Speedup	# Samples	Speedup	Sample Reduction	Sample Efficiency Gain
Amazon Graviton2	4,560	3.7×	1,440	5.1×	3.2×	4.4×
AMD EPYC 7R13	410	2.0×	140	2.2×	2.9×	3.2×
Apple M2 Pro	4,820	2.2×	1,770	3.9×	2.7×	4.8×
Intel Core i9	3,800	2.2×	720	4.9×	5.3×	11.8×
Intel Xeon E3	4,640	5.0×	670	5.0×	6.9×	6.9×
Geomean	–	**2.8×**	–	**4.0×**	**3.9×**	**5.6×**

For Llama-3-8B, REASONING COMPILER achieves 4.0× speedup using 3.9× fewer samples achieving 5.6× sample efficiency over Evolutionary Search

REASONING COMPILER
Structured, Sample-Efficient Search

REASONING COMPILER represents an effective leap from stochastic search to LLM-guided, structured planning for compiler optimizations.

REASONING COMPILER formulates optimizations as a sequential, context-aware planning process, pairing LLM-generated proposals with MCTS.

REASONING COMPILER's sample efficiency lowers serving cost, reduces energy, improves system responsiveness, and accelerates training cycles.

The same LLM that guides compilation can accelerate its own inference, creating a virtuous, self-optimizing cycle.

Paper

https://arxiv.org/abs/2506.01374

Github

https://github.com/Anna-Bele/LLM_MCTS_Search

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Contact: Annabelle Sujun Tang, sujun@ucsd.edu