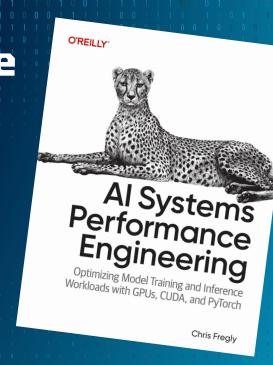


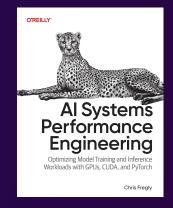
Dynamic & Adaptive Inference Tuning (Reinforcement Learning & Other Methods)



By Chris Fregly

Why focus on inference tuning?

Faster time-to-response



Better end-user experience

Serve more users with same hardware

GPU cost savings (\$\$\$ => \$)

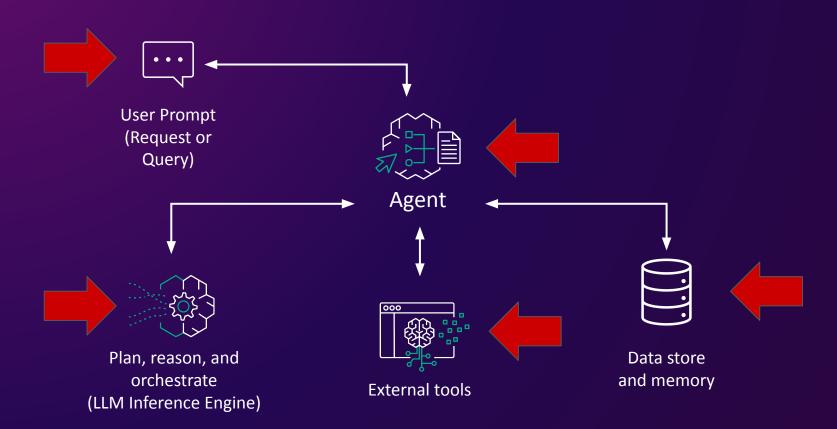
"Mechanical sympathy"

Original reference: Race car driver, Jackie Stewart, who was famously aware of the inner workings his race car.

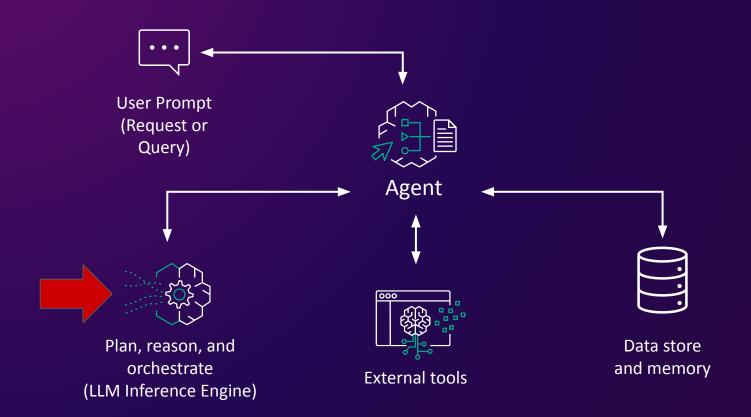
-- Martin Thompson (https://mechanical-sympathy.blogspot.com)

Today's computing reference: Co-designing software and algorithms hand-in-hand with hardware capabilities to maximize performance.

Where are the bottlenecks?



Where are the bottlenecks that I will cover today?



Agenda

1 Dynamic and Adaptive Al System Optimizations

RL Agents for Production Systems Tuning and Operations

AI-Assisted Kernel and System Tuning

Dynamic and Adaptive Al System Optimizations

Adaptive Parallelism Switching

=>

Dynamic Precision Changes

Adaptive Batching and Scheduling (Chunked Prefill configuration, etc.)

Inference Traffic Pattern	Recommended Parallelism	Rationale
Many short requests (<256 tokens, high QPS)	Data Parallel / Replica Scaling	Minimizes inter-GPU communications, each GPU runs replicas handling independent requests (assuming the model fits into a single GPU's memory)
Few long requests (≥8k tokens, low concurrency)	Pipeline Parallelism (with micro-batches)	Reduces per-request latency by splitting layers across GPUs
Mixed load (short + some long)	Hybrid Dynamic (auto-switching)	Runs small chats on single GPUs, pipelines long ones to meet latency SLAs
Extremely large model (>1 GPU memory)	Tensor + Pipeline Hybrid	Required to fit model; balances compute and memory across both dimensions
MoE model inference (sparse expert selection)	Expert Parallelism	Distributes individual experts across GPUs; each request only invokes a subset of experts, reducing per-device memory and compute load

Adjustable Speculative Decoding and KV-Cache Prefetching Configuration (Draft Model)

Occupancy-Aware CUDA Kernel Launch Parameters

Hot-Swappable CUDA Kernel Implementations

RL Agents for Production Systems Tuning and Operations

RL-based, Adaptive System Tuning

=>

Action 1: choose parallelism mode: single, TP, PP, and hybrid

Action 2: choose precision: full FP8 versus mixing FP8 and FP4

Action 3: adjust batch size or batch-waiting time

Action 4: enable or disable cache compression

Action 5: enable or disable speculative decoding

Action 6: select a smaller draft model for speculative decoding

Action 7: select a larger draft model for speculative decoding

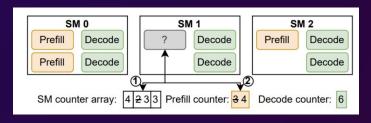
Action 8: enable or disable speculative ky prefetching

Congestion-Aware Disaggregated Prefill-Decode Request Routing

RL Agent for Real-Time Monitoring, Ops, and Issue Resolution

RL-based Mixture-of-Experts (MoE) Expert Routing

GPU-aware Prefill-Decode Kernel Placement =>



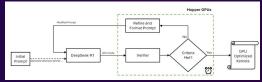
Al-Assisted Kernel and System Tuning

Alpha Tensor Project (Google DeepMind). Rediscovered Strassen's sub-quadratic GEMM algorithm. Optimized CUDA kernel (better than NVIDIA).



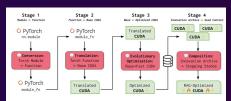
Optimize Attention CUDA kernel (NVIDIA). Used DeepSeek-R1 reasoning model to

create optimized Attention CUDA kernel implementation.

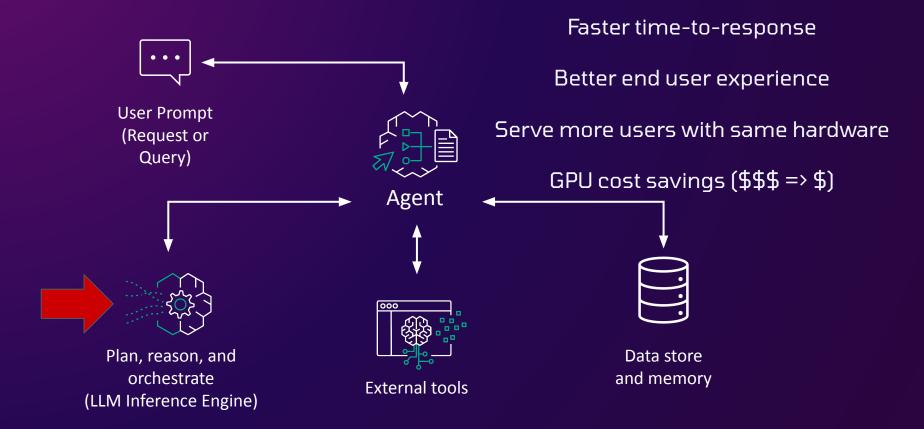


"AI CUDA Engineer" (Sakana.ai). Evolutionary strategies to iteratively refind CUDA

kernel code. Optimized CUDA kernel (5x NVIDIA performance). Also, was able to process 230 of 250 primitive PyTorch ops.



Embrace Adaptive, Al-Assisted System Optimizations





Thank You!

Dynamic & Adaptive Inference Tuning (Reinforcement Learning & Other Methods)



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