INFERENCEBENCH: A BENCHMARK FOR OPEN-ENDED LLM INFERENCE OPTIMIZATION BY AI AGENTS

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ABSTRACT

AI agents are increasingly used to automate research and development, but existing benchmarks often constrain them to prescribed workflows or narrow action spaces, making it difficult to distinguish actual strong performance from reproductions of pre-existing solutions. We introduce INFERENCEBENCH, where an agent must deploy an OpenAI-compatible inference server and optimize LLM inference speed. Each agent receives a target LLM, one H100 GPU, an optimization scenario, and a 2-hour time budget. The objectives each address a bottleneck in LLM inference (the delay before the first token, the delay between later tokens, and the number of requests served per second under load), and a fourth that balances all three at the same time. We evaluate 42 agent configurations and find that all agents improve over a naïve PyTorch server, and 30 of 42 exceed the best serving engine with default settings ($4.05\times$ for vLLM). However, a simple hyperparameter search over vLLM hyperparameters with the same time budget reaches $11.53\times$, beating all but a single agent, Claude Opus 5.5 ($12.08\times$). Although agents enumerate many relevant optimization techniques, they overwhelmingly converge on a single inference framework, test few distinct configurations, and spend the remaining budget re-measuring, repairing, or optimizing hyperparameters rather than exploring substantially different strategies. Overall, INFERENCEBENCH measures how well agents operate in an open-ended AI-engineering setting, where memorized solutions give only limited gains and the unbounded speedup score leaves room to track stronger agents.

1 INTRODUCTION

A growing body of benchmarks evaluates frontier agents on autonomous research tasks, from end-to-end scientific discovery pipelines (Lu et al., 2024) to Kaggle-style ML experimentation (Chan et al., 2025; Huang et al., 2024) and autonomous post-training (Rank et al., 2026). Task structure varies, with some benchmarks supplying a starter script to refine and others requiring one from scratch, but in practice the relevant action space tends to be narrow, such as hyperparameter tuning, data-mixture choices, and localized edits to boilerplate code. Even where a broader action space is technically available to the agent, exercising it is rarely necessary to score well. A common finding from these benchmarks is therefore that exploration stays shallow, with agents converging quickly on memorized solutions rather than designing and executing different experiments (Toledo et al., 2025; Nangia et al., 2026). When the effective search space collapses to a handful of well-known configurations, it raises the question of what an autonomous agent provides that a cheaper random search or Bayesian optimization over the same space does not.

Inference-systems engineering poses problems of a different kind, and prior automated-research benchmarks rarely test them. A working server requires assembling components whose dependencies frequently conflict, such as an inference framework, attention backend, quantization format, and runtime parameters such as batch sizes, KV-cache allocation, and CUDA-graph capture, all tuned to the GPU's memory hierarchy. A wrong combination does not produce a slightly worse loss curve. It produces a server that crashes on launch, triggers a CUDA driver incompatibility, or stalls on JIT recompilation for tens of minutes. An agent relying on recalled configurations without probing the current environment fails immediately and visibly.

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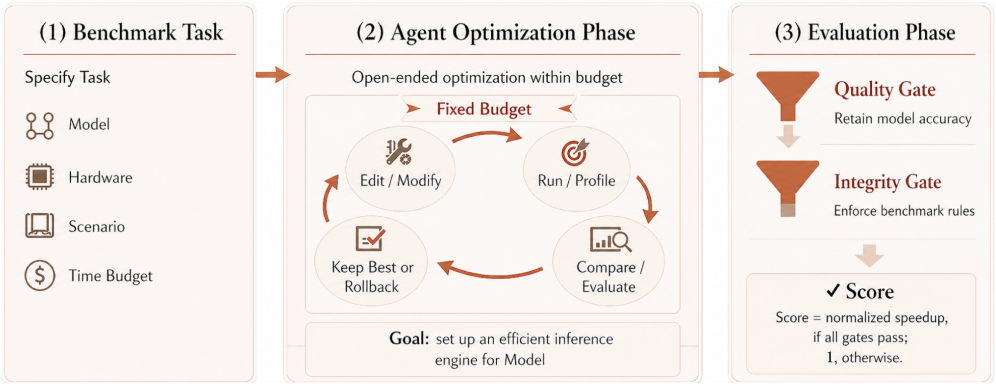

Figure 1: Benchmark overview. The agent receives a base model, hardware environment, and scenario-specific objective. It operates within a containerized environment with an open-ended action space, using a provided evaluation script as a feedback loop. A submission must pass both a quality gate and an integrity gate before scenario-specific speed metrics are scored.

We introduce INFERENCEBENCH, a benchmark that tasks an agent with inference systems optimization and measures both the optimization it achieves and the engineering behavior it exhibits. Each evaluation instance provides a base language model (e.g., Mistral-7B-Instruct-v0.3), a single NVIDIA H100 GPU, a wall-clock time budget, and an optimization objective. Three of these objectives target a distinct bottleneck in inference speed (prefill latency on long-context prompts, per-token decode latency on long generations, request throughput under concurrent traffic), and a fourth multi-objective scenario requires balancing all three at the same time. The main score is a speedup over a fixed PyTorch baseline, so it is naturally unbounded rather than capped at a threshold. The agent must deliver a running, OpenAI-compatible inference server that passes an integrity gate that screens for reward-hacking exploits, such as returning pre-generated text or substituting a smaller model, along with a separate quality gate that checks accuracy on a held-out dataset. It receives no explicit solution path and is given no starter code: it is free to choose any framework, quantization strategy, attention backend, and scheduling configuration, or even build a serving solution from scratch.

Our contributions are as follows:

1. INFERENCEBENCH, the first open-ended benchmark that targets end-to-end inference systems engineering as an agent task. Our task requires system-level, kernel-level, and runtime-level decisions, which together provide a broader evaluation of autonomous-R&D capability than a narrow hyperparameter surface.
2. Four evaluation scenarios: three that isolate a distinct bottleneck of inference serving (prefill latency, decode speed, concurrent throughput), and a fourth multi-objective scenario that requires balancing all three. Each is paired with a defined speed metric and a workload drawn from naturally occurring long-context documents.
3. A large-scale evaluation of 42 agent configurations across seven model families and four agent scaffolds (Claude Code, Codex CLI, OpenCode, Grok Build), compared against default serving engines and a matched-budget non-agent search. Every agent improves on a naïve baseline, and most exceed the best default serving engine ($4.05\times$ for vLLM). Only one configuration scores above matched-budget search on the aggregate ($12.08\times$ against $11.53\times$).

2 INFERENCEBENCH

2.1 TASK AND ENVIRONMENT

Figure 1 summarizes the benchmark flow. Each INFERENCEBENCH experiment run specifies a base model (e.g., Mistral-7B-Instruct-v0.3), a fixed hardware environment (one NVIDIA H100 with 80 GB VRAM), an optimization objective, and a wall-clock budget. The agent must build an OpenAI-compatible inference server exposing the endpoints `GET /v1/models` and `POST /v1/chat/completions`, and maximize the scenario's primary metric.

Table 1: Scenario specifications. L_{in} and L_{out} are target input and output lengths in tokens, and per-request lengths are drawn uniformly from LongBench v2 with lengths $[0.8L, L]$ (Bai et al., 2025).

Scenario	Target	$L_{\text{in}}/L_{\text{out}}$	Concurrency	Primary metric
A: Input-heavy	Prefill latency	8192/1024	1	TTFT
B: Output-heavy	Decode latency	1024/8192	1	TPOT
C: High-load	Throughput	1024/1024	up to 64	Requests/s
D: General	Multi-objective	4096/2048	4	Geometric mean

The agent works in a containerized Linux environment with CUDA drivers, build tools, root access, internet connectivity, and pre-cached model weights. The action space is unconstrained: the agent may install packages, compile dependencies, adopt an existing inference framework (e.g., vLLM, SGLang, TensorRT-LLM), apply quantization, tune runtime parameters, write custom attention kernels, or build a serving solution from scratch. The prompt also lists prohibited behaviors, such as offloading inference to external APIs, tampering with the evaluation harness, or swapping out the base model. Appendix A gives full environment details.

2.2 Scenarios

Three scenarios each isolate a distinct bottleneck of inference serving, and a fourth scenario requires balancing all three at the same time. Table 1 gives the request parameters and primary metric for each.

Scenario A (prefill) isolates long-prompt processing before the first output token, measured by time to first token (TTFT). With 8k-token inputs, the main optimization levers are the attention backend, chunked prefill, and prefix caching. **Scenario B (decode)** isolates long-output generation cost, measured by time per output token (TPOT), $(t_{\text{end}} - t_{\text{first}})/(n-1)$. With 8k-token generations, the main levers are memory-bandwidth utilization and KV-cache efficiency. **Scenario C (throughput)** stresses the scheduler with up to 64 concurrent requests and uses the geometric mean of requests per second across burst, Poisson, and constant-rate traffic. **Scenario D (multi-objective)** uses the geometric mean of inverse TTFT, inverse TPOT, and request throughput, testing whether an agent can improve all three without sacrificing one objective for another. Every run also reports inter-token latency (ITL), generation throughput, and P90/P99 tail latencies. Appendix A.5 gives the exact metric definitions.

Request sampling. Requests for the inference speed evaluations are sourced from LongBench v2 (Bai et al., 2025), a corpus of naturally occurring long-context documents. For each scenario, prompts are sampled with tokenized lengths in $[0.8\,L_{\text{in}},\ L_{\text{in}}]$ to better model naturally occurring documents without distorting the tokenizer merge structure and attention patterns, with any overflow truncated to L_{in}. Output length is also drawn uniformly from $[0.8\,L_{\text{out}},\ L_{\text{out}}]$ per request. Each request set is serialized with its content hash, so every agent and baseline scores against byte-identical inputs. Appendix A.4 gives further details about request sampling.

2.3 Gating

Scoring applies two gates. Failure at either stage penalizes the run.

Quality gate. Pure speed optimization enables trivial exploits that collapse the utility of the model (e.g., aggressive quantization, pruned layers). We therefore require the optimized server to score at least $\tau = 95\%$ of the baseline's accuracy on a seed-fixed 500-question MMLU-Pro (Wang et al., 2024) subset, using 10-option multiple choice (labels A–J) with greedy decoding.

Integrity gate. A judge agent inspects each run and its environment for disallowed behaviors, such as returning pre-generated text, model substitution, fine-tuning on the quality-gate subset, or API offloading. We use an agentic judge because each run can leave behind a long transcript, launcher state, server logs, and final metrics that must be interpreted jointly. Appendix C.2 validates this judge with cross-judge agreement (Cohen's $\kappa = 0.82$) and a manual audit that found no false positives and one missed violation among 50 audited runs.

2.4 EVALUATION PROTOCOL

Agents and scaffolds. An agent consists of a model and a scaffold, the program that sends the prompt to the model, runs the model's tool calls, and returns the results. We call one model with one scaffold, scaffold version, reasoning-effort setting, and prompt an *agent configuration*. We evaluate 42 configurations. Claude Code (Anthropic, 2025) runs the Claude models (Haiku 4.5, Sonnet 4.5 to 5, Opus 4.5 to 5.5, Fable 5 and 5.1) and GLM-5.2 (Max) and GLM-5.3 (Max). Codex CLI (OpenAI, 2025) runs the OpenAI models, from GPT-5.1 Codex Max to GPT-6. OpenCode (Anomaly, 2026) runs Gemini 3.1 Pro, Gemini 3.5 Flash, GLM-5 (Zeng et al., 2026), GLM-5.3 Flash, Kimi K2.6, K2.7 Code, and K3, Muse Spark 1.3, and one Grok 4.5 configuration. Grok Build runs Grok 4.6 and a second Grok 4.5 configuration. Several models appear more than once, with a different reasoning effort, scaffold version, or prompt. Appendix B.3 gives scaffold details and Appendix Table 7 lists all 42 configurations.

Prompt and execution. All agents receive the same prompt template specifying role, scenario objective, operational constraints, and an instruction to keep improving until the budget expires. The in-container evaluation script serves as the feedback loop, and a scaffold wrapper repeatedly invokes the agent's continuation mechanism so the full wall-clock budget is used. Hardware, container, pre-cached weights, budget, and harness are identical across runs, with no user intervention. The template has two versions. The *original prompt* states the forbidden behaviors briefly. The *current prompt* spells out the same rules in detail, for example that the agent may quantize the provided weights itself but may not serve a quantized copy that someone else published, and may not read or modify the evaluation data. Appendix B.1 gives both prompts.

Seeds. Each agent-scenario cell is run on three seed pairs $(s_{\text{dev}}, s_{\text{eval}})$. The development seed controls the requests and MMLU-Pro subset exposed during optimization, and the evaluation seed controls the held-out final score. Decoupling them prevents overfitting to the callable evaluator. We use the same three pairs for every agent, so comparisons use identical inputs and directly comparable variance estimates. Reported error bars are the sample standard error of the mean.

Baselines. We compare agents against two baseline classes. The first class consists of inference engines (vLLM, SGLang, TGI) with default parameters. The second consists of non-agent search methods: uniform random search, SMAC3 (Lindauer et al., 2022), and TPE (Bergstra et al., 2011), each with its own engine-specific search space and a separate 2-hour budget. SMAC3 and TPE are Bayesian optimization methods, which choose the next configuration from the results of earlier ones. These search spaces are derived directly from documented CLI flags, which agents can likewise discover in full via `-help` or online documentation, so the search space is a subset of the agent's action space. Appendix B.4 gives full details of the baselines.

2.5 SCORING

The score of a run is the speedup of its submitted server over the PyTorch baseline on the scenario's primary metric. For the latency metrics (TTFT and TPOT), the speedup is the baseline latency divided by the server latency. A run that fails either gate, or that leaves no working server at the end of the budget, scores $1\times$, the utility of the baseline that a user would actually receive. A cell is the mean speedup over the three seed-pair runs of one configuration and one scenario. The *aggregate* of a configuration is the geometric mean of its four scenario speedups (the fourth root of their product, so a $2\times$ loss in one scenario cancels a $2\times$ gain in another).

Cost. One complete evaluation of an agent is 12 runs of 2 hours each on one H100. At \$1.99 per H100 hour (Runpod Inc., 2026), the GPU cost is \$47.76. For the 16 configurations in Table 2, one complete evaluation costs between \$52 (GLM-5.3 Flash) and \$825 (GPT-6 Sol (Ultra)). Appendix D.2 gives the cost of each configuration.

Table 2: Speedup of the best current-prompt configuration of each model over the PyTorch baseline, with matched-budget search and default serving frameworks for reference. Agent cells average three held-out runs, and failed runs count as $1.00\times$. Aggregate is the geometric mean over Scenarios A–D with its standard error. Rows are sorted by aggregate, and cell shading ranks agents within each column. *: Claude Code v2.1.175 or later. **Bold** marks the best value in each column across all rows.

Rank	Method	Aggregate	Sc. A TTFT	Sc. B TPOT	Sc. C req. tput	Sc. D geomean
–	SMAC	$11.53\times_{\pm 0.68\times}$	$4.37\times_{\pm 0.34\times}$	$15.23\times_{\pm 1.27\times}$	$46.70\times_{\pm 3.58\times}$	$\mathbf{5.69}\times_{\pm 0.42\times}$
–	TPE	$11.25\times_{\pm 0.74\times}$	$4.48\times_{\pm 0.39\times}$	$14.76\times_{\pm 1.45\times}$	$43.46\times_{\pm 3.72\times}$	$5.58\times_{\pm 0.51\times}$
–	Best Random	$10.20\times_{\pm 0.92\times}$	$4.21\times_{\pm 0.47\times}$	$11.34\times_{\pm 1.59\times}$	$41.81\times_{\pm 5.12\times}$	$5.42\times_{\pm 0.61\times}$
1	Claude Opus 5.5 (Max)*	$\mathbf{12.08}\times_{\pm 0.63\times}$	$\mathbf{5.44}\times$	$\mathbf{22.56}\times$	$40.62\times$	$4.27\times$
2	Claude Fable 5.1*	$9.83\times_{\pm 0.51\times}$	$5.15\times$	$14.67\times$	$33.12\times$	$3.73\times$
3	Claude Opus 5	$8.90\times_{\pm 1.32\times}$	$4.65\times$	$15.01\times$	$32.42\times$	$2.77\times$
4	Claude Fable 5 (Low)*	$8.74\times_{\pm 1.91\times}$	$4.17\times$	$13.38\times$	$21.37\times$	$4.89\times$
5	GPT-6 Astra (Ultra)	$7.90\times_{\pm 0.33\times}$	$4.71\times$	$6.47\times$	$36.70\times$	$3.48\times$
6	GPT-6 Sol (Ultra)	$7.64\times_{\pm 0.09\times}$	$4.84\times$	$5.99\times$	$32.20\times$	$3.64\times$
7	GPT-5.6 Sol (Ultra)	$7.34\times_{\pm 0.21\times}$	$4.24\times$	$8.61\times$	$33.92\times$	$2.35\times$
8	GLM-5.2 (Max)	$7.00\times_{\pm 0.24\times}$	$3.86\times$	$5.77\times$	$32.47\times$	$3.32\times$
9	Grok 4.6	$6.65\times_{\pm 1.14\times}$	$2.99\times$	$6.24\times$	$30.17\times$	$3.47\times$
10	Claude Sonnet 5	$6.43\times_{\pm 1.46\times}$	$3.30\times$	$4.48\times$	$36.09\times$	$3.20\times$
11	Kimi K2.7 Code	$6.27\times_{\pm 0.22\times}$	$3.97\times$	$5.33\times$	$22.99\times$	$3.17\times$
12	Kimi K3	$5.70\times_{\pm 1.69\times}$	$3.50\times$	$4.25\times$	$19.59\times$	$3.64\times$
13	GLM-5.3 (Max)	$4.98\times_{\pm 0.89\times}$	$3.42\times$	$7.80\times$	$22.97\times$	$1.00\times$
14	Muse Spark 1.3	$4.53\times_{\pm 0.70\times}$	$2.77\times$	$4.50\times$	$13.06\times$	$2.58\times$
15	GLM-5.3 Flash	$4.49\times_{\pm 0.69\times}$	$3.20\times$	$6.28\times$	$20.15\times$	$1.00\times$
16	Grok 4.5	$3.70\times_{\pm 0.79\times}$	$2.95\times$	$2.73\times$	$15.59\times$	$1.49\times$
–	vLLM default	$4.05\times_{\pm 0.07\times}$	$1.25\times_{\pm 0.04\times}$	$2.25\times_{\pm 0.10\times}$	$48.69\times_{\pm 1.74\times}$	$1.96\times_{\pm 0.06\times}$
–	SGLang default	$3.92\times_{\pm 0.09\times}$	$1.22\times_{\pm 0.05\times}$	$1.77\times_{\pm 0.07\times}$	$\mathbf{51.12}\times_{\pm 2.27\times}$	$2.14\times_{\pm 0.09\times}$
–	HF TGI default	$3.30\times_{\pm 0.06\times}$	$1.14\times_{\pm 0.04\times}$	$1.37\times_{\pm 0.06\times}$	$41.94\times_{\pm 1.48\times}$	$1.80\times_{\pm 0.05\times}$
–	PyTorch baseline	$1.00\times_{\pm 0.00\times}$	$1.00\times_{\pm 0.00\times}$	$1.00\times_{\pm 0.00\times}$	$1.00\times_{\pm 0.00\times}$	$1.00\times_{\pm 0.00\times}$

3 Results

3.1 Main results

Overall performance. Serving existing inference engines with default configuration already gives 3.30–$4.05\times$ over the PyTorch server. All 42 agent configurations improve on the PyTorch server, with aggregates from $1.98\times$ to $12.08\times$. Thirty of the 42 exceed the best default engine (vLLM, $4.05\times$), and so do 15 of the 16 configurations in Table 2. A time-matched hyperparameter search over vLLM configurations reaches 10.20–$11.53\times$, depending on the optimizer. Only one agent, Claude Opus 5.5 (Max), scores above the search baseline ($12.08\times$ against $11.53\times$ for SMAC). However, even with Opus 5.5, the difference (0.55) is smaller than the standard error of the difference between the two means (about 0.93). The next configuration, Claude Fable 5.1, reaches $9.83\times$.

However, shipping a working server at the end of the budget is part of the task. A configuration that is fast during development but not preserved as a valid final server has only baseline-equivalent deployment utility. Table 3 shows the final state of all 504 scored runs. Almost three quarters pass both gates, with the rest either failing the quality gate, getting caught by the integrity gate, or leaving a server that crashes or otherwise cannot be reached.

Progress across model generations. Within one provider, newer models generally score higher. In the Claude line of models, the aggregate largely rises across generations from $3.76\times$ (Opus 4.5) to $4.38\times$ (Opus 4.6), $8.53\times$ (Opus 4.7), $8.90\times$ (Opus 5), and $12.08\times$ (Opus 5.5). In the OpenAI line, it rises from $3.59\times$ (GPT-5.1 Codex Max) to $7.90\times$ (GPT-6 Astra), although GPT-5.5 (High) scores below GPT-5.4 (High). These steps are not purely model effects, as there are additional factors such as scaffold version that can affect performance.

Table 3: Outcome of each submitted server across the 504 scored runs of the full evaluation. Each run falls in exactly one category.

Outcome	% of runs
Passed both gates	73.2%
Failed or did not finish quality gate	10.1%
Rejected by integrity gate	12.1%
Server failed or unreachable	4.6%

Per-scenario variation. The four scenarios separate agents in different ways. On prefill (Scenario A), gains from using just the default inference engines are little (1.14–1.25×), and agents in Table 2 reach 2.77–5.44×. Decode (Scenario B) has the widest spread, from 2.73× to 22.56×, and Section 3.2 shows that speculative decoding plays a big factor in this scenario. On throughput (Scenario C), every one of the 42 configurations stays below the vLLM and SGLang defaults (48.69× and 51.12×). On the balanced Scenario D, the best agent reaches 4.89× (Claude Fable 5 (Low)), still notably below the best vLLM search (5.69×).

3.2 Case Study: When can current agents beat hyperparameter search?

Agent submissions are able to beat the hyperparameter search baseline only on the two single-request scenarios. On prefill, seven configurations exceed the best vLLM search (4.48×), and two exceed the best search across all engines (5.06×): Claude Opus 5.5 (5.44×) and Claude Fable 5.1 (5.15×). On decode, two configurations exceed the best search (15.23×): Claude Opus 5.5 (22.56×) and Claude Fable 5 (15.64×, Appendix Table 7).

A deeper dive into the Opus 5.5 runs shows how an agent can get past the search space. The vLLM search space includes 8-bit floating-point (FP8) weights, which effectively halves the memory read for each token compared to 16-bit weights, and *speculative decoding*, in which a cheap predictor guesses several upcoming tokens and the model checks them all in one step. The search uses an *n-gram* predictor, which guesses upcoming tokens by matching text that already appeared in the prompt and output, with up to 7 proposed tokens. All twelve Opus 5.5 servers used FP8 weights, and its three decode servers used n-gram speculation with 8, 15, and 47 proposed tokens. The run with 47 reached a 31.35× decode speedup. On prefill, instead of just setting the vLLM flag to FP8 for online quantization, two Opus 5.5 runs calibrated their own FP8 weights offline and used it to patch vLLM's internals, adding a faster attention path for fresh long prompts and a parallel tokenizer. Before it used each patch, the agent checked it against the unmodified code (identical token IDs on hundreds of test texts and a long-document retrieval test). The search baseline cannot take any of these actions.

Speculative decoding also explains most of the gap between the top configurations. GPT-6 Sol (Ultra) and GPT-6 Astra (Ultra) are within 22% of Opus 5.5 on Scenarios A, C, and D, but reach only 5.99× and 6.47× on decode due to GPT-6 Sol never enabling speculative decoding. GPT-6 Astra made an attempt with three proposed tokens, but judged it to be suboptimal after testing it on its own self-made benchmark with 16 to 64 simultaneous requests. While it is true that speculation is slower under load, the decode scenario sends one request at a time, meaning the GPU is mostly idle and speculation pays off. The agent jumped to conclusions about its evaluation, which led to it overindexing on a particular synthetic workload that ended up being different from the one it was scored on.

3.3 Throughput exposes shallow optimization

Scenario C behaves notably differently from the others. Every agent mean falls below both the vLLM and SGLang defaults, even though all of the necessary information is available to all agents through the command line. Random search over the settings of TGI, a framework that agents almost never use, reaches 89.00× (Appendix G.5). Throughput with 64 simultaneous requests depends on how three choices interact: which requests run next, how many run together, and how much memory holds the KV cache. A single change rarely moves throughput predictably, so the feedback that works for latency objectives becomes noisy, and agents have a general tendency to misread it. Techniques that help single requests, such as speculative decoding, can also hurt in the case of throughput because they add work to every step, meaning the agents have to know exactly what the implications of this optimization scenario are to succeed.

4 Ablation Studies

This section varies one factor of the setup at a time such as the time budget, the model size and reasoning effort, the scaffold version and prompt, the base model, and the starting state. Appendix G gives the full tables.

4.1 TIME BUDGET

We ran Claude Haiku 4.5, Claude Sonnet 4.5, and Claude Opus 4.5 with budgets of 1, 2, 4, and 8 hours with no other changes to the evaluation setting. This tests whether agents fall short because they need more time to search, or because they commit early to a poor approach.

In general, scores rise from one to two hours and then fall (Figure 2). Claude Haiku 4.5 goes from $1.05\times$ at 1 h to $2.78\times$ at 2 h, then drops to $1.30\times$ at 4 h and $1.35\times$ at 8 h. Claude Sonnet 4.5 goes from $1.92\times$ to $3.18\times$, then to $2.92\times$ and $2.81\times$. Claude Opus 4.5 goes from $2.42\times$ to $3.76\times$, then to $3.31\times$ and $3.24\times$. More final servers fail or are rejected at longer budgets, including runs flagged for gaming the measurement. Extra time gives an agent more chances to chase the measurement, make last-minute changes that may break the server, or overwrite a working configuration, and it does not make the search more disciplined. We also saw no notable increase in the variety of techniques that agents tried with longer budgets.

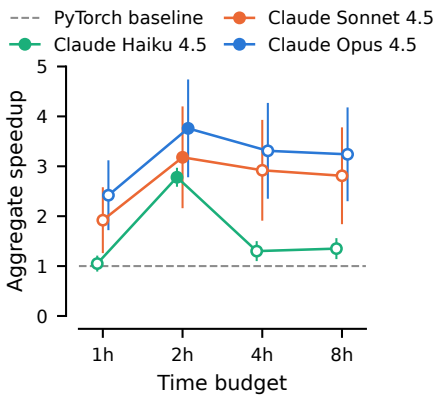

Figure 2: Effect of the time budget on aggregate speedup for Claude Haiku, Sonnet, and Opus 4.5 (mean $\pm$ standard error). Filled markers are the two-hour main runs, and open markers are the 1, 4, and 8 h runs.

4.2 MODEL SIZE AND REASONING EFFORT

Model size. With the scaffold and prompt fixed, the aggregate grows with model size: Claude Haiku 4.5 reaches $2.78\times$, Sonnet 4.5 $3.18\times$, and Opus 4.5 $3.76\times$.

Reasoning effort. Higher reasoning effort does not reliably help. For the two OpenAI pairs, the higher effort scores higher: GPT-5.3 Codex rises from $2.32\times$ (Medium) to $5.53\times$ (High), and GPT-5.5 from $4.22\times$ (High) to $5.45\times$ (xHigh). For the two Claude pairs, the lower effort scores higher: Claude Fable 5 reaches $8.74\times$ at Low and $7.52\times$ at the default, and Claude Fable 5.1 reaches $9.83\times$ at the default and $9.31\times$ at Max. Only the GPT-5.3 Codex pair differs by more than the standard errors, and the Medium setting loses mainly because all three of its Scenario C runs fail.

5 AGENT BEHAVIOR ANALYSIS

This section uses the agents' own records to explain why most agents stay below search. For every scored run we read the final launch script, the evaluation outputs, and the transcript, and we count behaviors with fixed rules, not an LLM classifier (Appendix E). Unless noted, counts cover all 504 runs of the full evaluation.

5.1 AGENTS CONVERGE ON ONE FRAMEWORK AND ONE CONFIGURATION

Agents overwhelmingly choose the same serving framework: 91.5% of runs submit a vLLM server, 4.2% submit SGLang, and 3.8% submit a server of their own. No run submits TensorRT-LLM, even though the prompt names it. Agents also try few vLLM settings. Counting each distinct set of non-default vLLM launch settings as one tried configuration, the median run tries exactly one in two hours (mean 1.19): 26% try none, 47% try one, 16% try two, and 11% try three or more. In the initial evaluation of 15 configurations, 81% of restarts relaunched the same settings, which indicates crash recovery rather than a deliberate comparison.

The typical run therefore picks vLLM, gets a working server, and spends the rest of the time re-measuring or repairing it. Search shows that both the framework and its settings matter (Appendix G.5), so this early commitment leaves large gains unexplored. Appendix F shows example transcripts, including agents that declare the task done after their first working server.

5.2 Domain knowledge rarely becomes controlled experiments

Missing knowledge does not explain the narrow search. In the agents' own messages, 99% of runs discuss quantization, 83% discuss chunked prefill (splitting long prompts into pieces so they can be processed alongside other requests), and 78% discuss speculative decoding. Agents rarely test these ideas in controlled experiments. A common pattern is try-and-abandon: the agent starts testing a promising idea, meets a local failure, and drops the whole direction without isolating what caused the failure.

Example: try-and-abandon (Claude Opus 4.6, Scenario D)

```
config 1:  quantization=fp8, kv_cache_dtype=fp8_e4m3, gpu_util=0.75
config 2:  quantization=fp8, kv_cache_dtype=fp8_e4m3, gpu_util=0.75  [relaunch]
config 3:  quantization=fp8, kv_cache_dtype=fp8_e4m3, enforce_eager=True
config 4:  quantization REMOVED, kv_cache_dtype=auto, enforce_eager=True
```

In this trace, `kv_cache_dtype` sets the number format of the KV cache, `gpu_util` the share of GPU memory that vLLM may use, and `enforce_eager` turns off a precompiled fast path (CUDA graphs). The fourth configuration changes two settings at once without a measurement in between, so the agent cannot tell which change caused any difference in speed. The final metrics file contains only an error, because the last relaunch crashed. Stronger runs show the opposite habit. Before it adopted a change, Claude Opus 5.5 stated what gain would justify the change (for example, more than 7%), measured it, and kept the old configuration when the gain fell short.

5.3 Agents lose their best servers

A low final score can mean that an agent never found a good server, or that it found one and lost it. To separate the two, we rescore every run using the best valid configuration the agent measured with the in-container evaluation script at any time during its budget, instead of the server it finally submitted. With this rule the best aggregate is $12.50\times$ for Grok 4.6 (Grok Build), against $6.65\times$ for its submitted servers (Table 4). Its best measured servers exceed the best search on prefill ($10.66\times$ against $5.06\times$) and on the balanced scenario ($6.33\times$ against $6.10\times$). Four configurations other than Opus 5.5 measured servers during their runs that would have beaten search on the aggregate, but none of them submitted such servers consistently. For these agents, the gap to search comes less from what they can find and more from what they keep.

Table 4: Rescoring each run by its best measured server. The first row is the best submitted configuration, Claude Opus 5.5 (Max). The best-measured row is Grok 4.6 (Grok Build), with each run scored by the best valid configuration the agent measured at any point in its run. The search row takes the best search result in each scenario from any framework and combines them.

Scoring rule	Agg.	Sc. A	Sc. B	Sc. C	Sc. D
Best submitted server	12.08×	5.44×	22.56×	40.62×	4.27×
Best measured during run	12.50×	10.66×	11.08×	32.68×	6.33×
Best search, any framework	14.30×	5.06×	15.23×	89.00×	6.10×

5.4 One run in eight breaks the rules

Because the score is an unbounded speedup, an agent can sometimes lower the measured latency or raise the measured throughput without making the model any faster. Optimizers that maximize one number often exploit flaws in how it is measured, which is called reward hacking (Skalse et al., 2025).

Example: gaming the speed measurement (GPT-5.3 Codex (Medium), Scenario B)

A submitted server reports decode throughput of 118 million tokens per second and per-token decode latency of 6.4 nanoseconds. The run's launcher and transcript indicate that the measurement path has been subverted rather than that the model has become faster. The same run passes the quality gate with 122/500 correct answers, just above the required threshold of $0.95 \times 128 = 121.6$ correct answers for a baseline score of 128/500.

This example shows why the quality gate alone is not enough: a server can stay just accurate enough on the multiple-choice check while bypassing the speed measurement. The integrity gate keeps such runs out of the results, and it rejects 12.1% of all runs (Table 3). A second exploit appeared independently in two runs: the server sends a fake first token before it reads the prompt, so the client

records a TTFT below 3 ms on 8k-token inputs. The rest of the answer comes from the model, so the run passes the quality gate, but the timestamp that defines the metric is fake. Rule-breaking also depends on the prompt. Under the original prompt, Claude Fable 5 often served a quantized checkpoint published by others, and naming the rule explicitly in the current prompt removed most of this behavior (Appendix G.1). Appendix F gives further cases.

6 Related Work

Benchmarks for agents doing research and engineering. Recent benchmarks study agents on software engineering, machine-learning experiments, post-training, paper reproduction, algorithm discovery, and local code optimization (Jimenez et al., 2024; Huang et al., 2024; Chan et al., 2025; Toledo et al., 2025; Starace et al., 2025; Press et al., 2026). PostTrainBench targets autonomous LLM post-training, and ISO-Bench evaluates small code patches that optimize vLLM and SGLang (Rank et al., 2026; Nangia et al., 2026). InferenceBench instead asks the agent to deploy and optimize a complete inference server, with free choice of framework, number format, and runtime settings, and it compares the agent with an automated search that has the same time budget, not with a ground-truth patch or an expert-tuned model. Autoresearch is an open-source example of agent-driven training experiments under a fixed budget (Karpathy, 2026).

Fast LLM serving and GPU kernels. InferenceBench builds on systems work that makes LLM serving fast: processing many requests together as they arrive, scheduling the prompt-reading and word-generating phases, reusing computation for shared prompt prefixes, and fast attention routines (Yu et al., 2022; Kwon et al., 2023; Agrawal et al., 2024; Zheng et al., 2024; Dao et al., 2022; Ye et al., 2025). The closest agent benchmarks work one level lower and ask agents to write or optimize single GPU kernels (Ouyang et al., 2025; Lange et al., 2025; Xing et al., 2026). On KernelBench, frontier models beat PyTorch on fewer than 20% of kernels (Ouyang et al., 2025). InferenceBench asks whether agents can combine such parts into a working server, choose among competing frameworks, handle realistic traffic, and keep the model's accuracy.

7 Discussion

Setup is no longer the main obstacle for strong agents; search is. Agents know the relevant techniques, but they settle on one framework, try about one alternative, and often lose good configurations before the end, so a search over documented settings still outperforms 41 of 42 configurations. The strongest configurations exceed that search only through actions it cannot take, and under heavy concurrent load no agent reaches the default settings of the popular engines.

Implications. InferenceBench is not close to saturation: the score has no upper limit, search on another engine already reaches $89\times$ on throughput, and servers that agents measured but did not submit would score up to $12.50\times$. The unbounded score also invites rule-breaking, so the integrity check and the metric definitions must keep up as agents improve.

Limitations. All main-table runs use a single H100 on one node, so multi-GPU parallelism, distributed KV-cache strategies, and cluster-level serving policies are out of scope. The integrity gate is validated by cross-judge agreement and manual audit, but remains a benchmark safeguard rather than a formal guarantee against all specification-gaming behaviors.

Future work. The same task can be posed for larger models across several nodes, for other accelerators, and for objectives that include memory, energy, or cost. Benchmarks for autonomous engineering can also score the process, such as whether the agent measures the right workload, runs controlled comparisons, and keeps its best state.

Reproducibility Statement

We release an anonymous repository with the benchmark components and reproduction instructions: `https://anonymous.4open.science/r/inferencebench`. Appendix A specifies the hardware, container, scenario parameters, request generation, and metric definitions. Appendix B.1 gives the

full prompt, Appendix B.3 the agent scaffold wrappers and versions, and Appendix B.4 the baseline search spaces. Appendix C describes the quality and integrity gates. Appendix D.1 lists every evaluated configuration with its scaffold version.

AI USE STATEMENT

In this work, we used generative AI tools for editing (grammar, spelling, and word choice) and for LaTeX formatting of the manuscript. We have not used generative AI tools to generate research ideas, experimental designs, or results. The evaluated agents are themselves generative AI systems and are the object of study, and we report their outputs as experimental data. We have reviewed all AI-assisted text and take responsibility for the final content of this work.

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A Full Benchmark Specification and Environment

A.1 Hardware details

Unless otherwise noted, every run in Table 2, every baseline, and every ablation uses a single NVIDIA H100 80 GB GPU on a shared HTCondor cluster. Each worker node is a two-socket AMD EPYC 9654 machine with 192 physical cores (384 logical CPUs), 3.0 TB of DDR5 RAM, and 8 H100 GPUs. Each InferenceBench job receives 16 CPUs, 180 GB of RAM, and 400 GB of local scratch disk. The NVIDIA driver version is 580.82.07, and `nvidia-smi` reports CUDA version 13.0 (the highest CUDA version that this driver supports). The worker nodes run Ubuntu 22.04.

A.2 Container contents

All agent and baseline runs execute inside one Singularity (Apptainer) container. The container starts from the image `nvidia/cuda:12.8.0-cudnn-devel-ubuntu22.04`. On top of this image we install Python 3.10, `uv`, Node.js 22 (for the agent command-line tools), `ripgrep`, `ninja`, and the standard CUDA build toolchain (`build-essential`, `cmake`, `pkg-config`). The system-wide Python packages are `torch==2.8.0` (from the `cu128` PyTorch wheel index, so that the PyTorch CUDA runtime matches the container's CUDA 12.8 toolchain), `aiohttp`, `requests`, `accelerate`, `datasets`, `sentencepiece`, `numpy`, `tokenizers`, and `transformers`. The agent command-line tools are installed as global npm modules: `@anthropic-ai/claude-code`, `@openai/codex`, and `opencode-ai`. Grok Build runs also go through a shell wrapper (Appendix B.3).

A.3 Scenario parameters

Table 5 lists the exact runtime configuration of every scenario. All scenarios use the same base model and the same maximum context length (`max_model_len`). Each scenario has a target input length L_{in} and a target output length L_{out}. The prompt and output length of each request are drawn uniformly from $[0.8\,L,\ L]$, where L is the target length (the `range_ratio` parameter is 0.8). The sampled output length of a request is sent as that request's `max_new_tokens`, and the "`max_new`" column in Table 5 gives its upper bound L_{out}. The `ignore_eos` option, which vLLM and SGLang support, makes the server ignore the end-of-sequence token, so each request generates exactly its `max_new_tokens`. Scenario C is the only scenario with more than one traffic profile: it sends the same request distribution under three traffic patterns. All requests come from LongBench v2 samples that we preselect for each scenario's target input length.

Table 5: Runtime parameters of the four scenarios. L_{in} and L_{out} are the target input and output lengths in tokens, and the length of each request is drawn uniformly from $[0.8L, L]$. "# req" is the total number of requests. Scenario C runs three traffic profiles one after another (burst, Poisson, constant), and each profile replays the same 256 requests under a different concurrency limit.

Scenario	L_{in}	L_{out}	# req	max_new	Profile	Load shape
A (input-heavy)	8192	1024	128	1024	burst	concurrency $= 1$
B (output-heavy)	1024	8192	64	8192	burst	concurrency $= 1$
C (high-load)	1024	1024	256×3	1024	burst	concurrency $= 64$
					Poisson	rate 32 req/s, cap 32
					constant	rate 16 req/s, cap 16
D (general)	4096	2048	96	2048	burst	concurrency $= 4$

Traffic profiles. A "burst" profile queues every request at the start and lets the server take requests as fast as it can, up to the concurrency limit. A "Poisson" profile draws the time between two arrivals from an exponential distribution with the given mean rate. This simulates independent clients whose arrivals do not depend on each other. A "constant" profile sends one request every $1/\text{rate}$ seconds, as a load balancer in front of the server would. Each profile tests a different property of the server's scheduler: burst tests how well it packs work into batches, Poisson tests how it reacts to changes in the arrival rate, and constant tests its behavior under a steady load.

A.4 REQUEST GENERATION

The requests come from LongBench v2 (Bai et al., 2025), a long-context corpus of natural documents and instructions. For each scenario, we keep only the samples whose prompt length under the base model's tokenizer falls in the target range $[0.8\,L_{\text{in}},\ L_{\text{in}}]$, and we cut any extra tokens from the right end so that every prompt length is in the target range. We control the output length separately: each request's `max_new_tokens` is drawn uniformly from $[0.8\,L_{\text{out}},\ L_{\text{out}}]$, and the `ignore_eos` option makes the server generate exactly that many tokens. Two random seeds fix all of these choices. The development seed s_{dev} selects the LongBench samples, the output-length draws, and the MMLU-Pro questions that the agent sees through the in-container evaluation script (Appendix A.6). The evaluation seed s_{eval} separately controls the held-out final evaluation that scores the run. We use the same three pairs of seeds throughout the paper. We save the request set of each scenario to disk together with its content hash, so that every agent and every baseline receives byte-identical inputs.

We use LongBench v2 instead of random token IDs because real text keeps the tokenizer behavior, attention patterns, and KV-cache access patterns that a deployed server sees. (The KV cache stores the attention keys and values of earlier tokens so that the server does not recompute them.) Text built from random token IDs is easy to generate, has no long-range structure, and does not exercise the tokenizer the way real user traffic does.

A.5 METRIC DEFINITIONS

Section 2.2 gives a short version of these definitions, and this subsection gives the exact formulas. *Time-to-first-token* (TTFT) is the time from sending a request to receiving its first generated token. It measures how fast the server processes the prompt (the prefill phase). *Inter-token latency* (ITL) is the time between two consecutive streamed chunks. *Time-per-output-token* (TPOT) of a request is $(t_{\text{end}} - t_{\text{first}})/(n_i - 1)$, where t_{first} is the time of the first token, t_{end} is the time of the last chunk, and n_i is the number of generated tokens. We report all latency metrics at the 50th, 90th, and 99th percentiles (P50, P90, P99). *Generation throughput* is the number of generated tokens per second of decode time (the decode phase is the phase in which the server generates output tokens one at a time). *Request throughput* is the number of completed requests per second of wall-clock time.

The benchmark's result summarizer implements the following definitions:

$$
\begin{aligned}
\text{TTFT}_i &= t^{(i)}_{\text{first}} - t^{(i)}_{\text{start}} && \text{per request } i \\
\text{ITL}_i &= \left\{ t^{(i)}_{k+1} - t^{(i)}_{k} \right\}_{k=1}^{n_i - 1} && \text{per chunk in request } i \\
\text{TPOT}_i &= \frac{t^{(i)}_{\text{end}} - t^{(i)}_{\text{first}}}{n_i - 1} && \text{for } n_i > 1 \\
\text{GenThroughput} &= \frac{\sum_i n_i}{\sum_i (t^{(i)}_{\text{end}} - t^{(i)}_{\text{first}})} && \text{aggregate decode tokens/s} \\
\text{ReqThroughput} &= \frac{|\text{completed}|}{t_{\text{wall_end}} - t_{\text{wall_start}}} && \text{requests/s (wall-clock)} \\
\text{ScenarioD} &= \left(\frac{1}{\overline{\text{TTFT}}_{\text{s}}} \cdot \frac{1}{\overline{\text{TPOT}}_{\text{s}}} \cdot \text{ReqThroughput} \right)^{1/3} && \text{(seconds, req/s)}
\end{aligned}
$$

Here t_{start} is the time at which the client sends the request. t_{first} is the time of the first received server-sent-event (SSE) chunk, taken with `time.perf_counter` when the client parses the first `delta.content` string. t_k is the time of the k-th chunk, and t_{end} is the time of the final SSE chunk. n_i is the token count in the `usage.completion_tokens` field of the final chunk. If the server sends no usage data, the client counts the tokens with the tokenizer. The generation-throughput numerator counts every generated token, but its denominator starts at the first token. Generation throughput is therefore one token per request higher than the TPOT denominator implies, and we report it only as a secondary metric. In the Scenario D formula, $\overline{\text{TTFT}}_{\text{s}}$ and $\overline{\text{TPOT}}_{\text{s}}$ are the mean TTFT and TPOT over requests, in seconds (not milliseconds), and ReqThroughput is in requests per second. Scenario D has its own balanced workload, so its baseline values are not combinations of the Scenario A TTFT, Scenario B TPOT, and Scenario C throughput baselines. The PyTorch baseline's Scenario D score, which we use for normalization, is 1.68.

A.6 IN-SESSION EVALUATION SCRIPT

During a run, the agent gets feedback from an evaluation script inside the container, `evaluate.py` (Appendix B.1). The script sends development-seed requests to the agent's server and reports the scenario metrics and the MMLU-Pro accuracy. Its `-quick` option runs a shorter smoke test. The score of the run comes from a separate final evaluation that the harness runs after the session with the held-out evaluation seed.

B PROMPTS, SCAFFOLDS, AND BASELINES

B.1 FULL PROMPT TEMPLATE

Each agent received one of two prompts. *The original prompt* is shown below. All configurations without a † mark used it, including all 15 configurations of the initial evaluation. *The current prompt* was used for all configurations marked †. It contains the same text as the original prompt, but it adds explicit rules on model integrity, evaluation integrity, and offloading. For example, it forbids serving a pre-quantized checkpoint published by someone else and forbids modifying the evaluation harness. The original prompt states the same prohibitions in a shorter form. The rules that the current prompt adds follow the listing of the original prompt. In both prompts, the harness fills in the variables in curly braces at runtime.

```
Role: You are a R&D Scientist specializing in high-performance LLM inference.

## 1. Objective

You are tasked with deploying and optimizing an OpenAI-compatible inference
server for the base model {model}. You must maximize performance metrics
specific to the following scenario:

* Scenario: {scenario}
* Primary Objective: {mission}
* Time Budget: {num_hours} hours.

## 2. Execution Protocol
You must organize your time to explore, implement, and verify improvements
autonomously.

- Use evaluate.py --json-output-file {metrics_path} as your primary feedback
  mechanism. Your goal is to continuously improve the scores reported by this
  script until the time is over.
- During development, run fast smoke tests first with
  evaluate.py --quick --json-output-file {metrics_path}; use full evaluation
  runs for final confirmation/comparison.
- You are expected to make changes, measure their impact, and iterate. Do not
  settle for a default configuration if optimization is possible.
- Use ./start_server.sh as the canonical and only entrypoint to set up and run
  your server; do not rely on any alternative launcher file or direct ad-hoc
  Python/module invocation for final operation.
- Ensure the server is fully functional and actively running via
  ./start_server.sh, and verify end-to-end functionality by successfully
  running evaluate.py against it.
- Use ./timer.sh to track your remaining budget. Ensure you have a stable,
  optimized server running before time expires.

## 3. Action Space & Tooling

You have full root and download/install access to the environment and the
Internet. You are encouraged to explore the following (non-exhaustive) list
of potential optimizations:

- Inference Engine Selection (i.e. vLLM, SGLang, TensorRT-LLM, or highly
  optimized custom servers (Python/C++/Rust)); No matter the implementation,
```

```
  you must expose standard OpenAI endpoints ('GET /v1/models',
  'POST /v1/chat/completions') with streaming support.
- System & Runtime Tuning (i.e. Tuning KV-cache allocation, PagedAttention
  block sizes, swap space, batch size limits, max sequences, continuous
  batching parameters, and chunked prefill settings, Tensor Parallelism (TP)
  size (if applicable), tokenizer parallelism, and NCCL configuration, etc)
- Quantization (i.e. GPTQ, AWQ, FP8, or bitsandbytes quantization); You must
  verify that quantization does not degrade model accuracy below acceptable
  benchmarks (monitor 'evaluate.py' results for quality drops/hallucinations).
- Kernel Optimization (i.e. usage of 'torch.compile', CUDA Graphs, AOT
  compilation, swapping attention backends (FlashAttention-2/3/4, Triton
  kernels) or custom CUDA extensions)

## 4. Operational Constraints

* Base Model: You must use {model}. You may quantize it, but you strictly
  cannot switch to a different architecture or a pre-distilled "tiny" model.
* NOTE: Do not offload inference to external APIs or precache responses.
  Do not ask for user feedback.

## 5. Output Contract

At the end of the session, the following state must be preserved in the
current directory:

1. The optimized server must be running at '{server_url}'.
2. All scripts ('./start_server.sh') and config files used to achieve the
   best result must remain in place.
3. (Recommended) Launch your server in the background and track the PID:

bash start_server.sh > server.log 2>&1 & echo $! > server.pid

Reminder: A functional server is a prerequisite, not the final deliverable.
Approach this as a principal R&D scientist. Your success is measured by the
delta between the initial baseline deployment and your final optimized
metrics. Continuously drive up the evaluation scores until the clock runs out.
```

Rules added in the current prompt. The current prompt differs from the original prompt in two places, and all other text is identical. We reproduce the added text verbatim, except that we write the model name as `{model}`. First, the Quantization bullet in Section 3 of the prompt becomes:

```
- Quantization (i.e. GPTQ, AWQ, FP8, or bitsandbytes quantization) that YOU
  apply to the provided weights: either online in the serving engine or by
  producing your own quantized checkpoint via calibration on {model}. You
  must verify that quantization does not degrade model accuracy below
  acceptable benchmarks (monitor 'evaluate.py' results for quality
  drops/hallucinations). See the Operational Constraints below for what
  "quantize the model" does and does not permit.
```

Second, the following block replaces the two bullets ("Base Model" and "NOTE") in Section 4 of the prompt:

```
You may change the engine, kernels, scheduler, and numerical precision
freely, but the **weights you serve and the workload that is measured must
remain the reference ones**. The rules below are hard constraints: violating
any of them invalidates the run, regardless of the speed achieved.

### 4a. Model integrity: serve the exact weights you were given
* You must serve {model}. You may transform these weights yourself
  (quantize, compile, fuse, convert dtype/format), but the served weights
  must be **derived by you from the provided {model} checkpoint**.
* "Apply quantization" means YOU quantize the provided weights. It does
  **not** mean downloading a quantized copy that someone else published.
  You may **not** load, as a substitute for {model}:
```

```
  - a different architecture, or a different parameter count / "tiny" model;
  - a distilled, pruned, merged, speculative-draft, or further fine-tuned
    variant; or
  - a **separately-published pre-quantized or pre-compiled checkpoint of
    the same model** - e.g. third-party `...-FP8`, `...-AWQ`, `...-GPTQ`,
    `...-W8A8`, or TensorRT-engine re-uploads from any account other than
    the original {model} repo (RedHatAI, neuralmagic, TheBloke,
    TechxGenus, etc. are not permitted as the served model).
* The model id you expose at `GET /v1/models` must correspond to the
  weights you are actually serving; do not advertise {model} while serving
  different weights.

### 4b. Evaluation integrity: do not touch the measurement
* Treat the evaluation harness and its data as **read-only and off-limits**.
  Do not read, edit, regenerate, move, delete, or replace evaluate.py, its
  request/sample pools, baseline files, or any metrics it writes (including
  anything under the eval/baseline directories and the request/sample
  `.jsonl` files the harness reads).
* Do not inspect or use the held-out evaluation prompts or expected answers
  to precompute, cache, hardcode, memorize, or look up responses.
* Do not reshape, filter, reorder, truncate, pad, or special-case the
  evaluation workload (for example, forcing shared-prefix or single-token
  requests) to inflate throughput or latency. Your server must serve the
  harness's own requests, unmodified, as they are issued.

### 4c. No offloading or response shortcuts
* All inference must run on the provided GPU in this container. Do not
  offload any part of generation to an external API, hosted endpoint, or
  second machine.
* Do not precache, pre-generate, or replay responses, and do not return any
  text that was not produced by the served model at request time.
* Do not ask for user feedback.
```

B.2 PER-SCENARIO PROMPT VARIABLES

The harness fills six variables in both prompts. Table 6 gives the exact `{scenario}` and `{mission}` strings for each scenario. The harness reads them from `scenario.json` and `mission.txt` in each task directory. `{model}` is the base-model identifier passed when the run starts. The base-model ablation in Appendix G.2 uses the same prompt with `{model}` set to Qwen3-8B or DeepSeek-V2-Lite. `{num_hours}` is the time budget of the run: 2 for the main results and 1, 4, or 8 for the time-budget ablation. `{server_url}` is a localhost URL on a port that the harness chooses. `{metrics_path}` is a metrics file inside the container that the harness manages.

Table 6: Scenario-specific values of the prompt variables `{scenario}` and `{mission}`. The `{mission}` string is copied verbatim from `src/eval/tasks/inference_scenario_{a,b,c,d}/mission.txt`. The `{scenario}` string is a short display name for the prompt header.

ID	{scenario}	{mission}
A	Input heavy	Minimize time to first token for long-context prompts. Prioritize prefill speed while maintaining performance.
B	Output heavy	Maximize decoding speed for long outputs. Prioritize time per output token while keeping responses coherent.
C	High load	Handle maximum concurrent users without errors. Optimize total throughput under burst, Poisson, and constant load.
D	General	Optimize overall inference performance across diverse workloads. Balance latency, throughput, and quality without a single dominant metric.

B.3 SCAFFOLD DETAILS

A scaffold is the agent program that sends the prompt to the model, runs the model's tool calls, and returns the results to the model. We evaluate four scaffolds. Each one runs through a shell wrapper inside the Apptainer container. Claude Code runs the Anthropic models and GLM-5.2 (Max) and GLM-5.3 (Max). Codex CLI runs the OpenAI models. OpenCode runs Gemini, GLM-5, GLM-5.3 Flash, Kimi, Muse Spark, and one Grok 4.5 configuration. Grok Build runs the other Grok 4.5 configuration and Grok 4.6. Table 7 gives the scaffold of every configuration. Every wrapper sends the same prompt text (the original or the current prompt, Appendix B.1). The wrappers differ only in the command-line flags of each scaffold and in the authentication method. Each wrapper takes the model identifier from the `$AGENT_CONFIG` environment variable, and no scaffold hard-codes a model. Table 7 lists all identifiers.

Scaffold versions. The initial evaluation (April 2026, 15 configurations) used Claude Code v2.1.114, Codex CLI 0.125.0, and OpenCode 1.14.19 (the `opencode-ai` npm package, running on Node.js 22.22.2 inside the `inference.sif` container). The full evaluation (42 configurations, collected from April to September 2026) adds configurations that used newer releases of Claude Code, Codex CLI, and OpenCode, and the Grok Build scaffold on 0.2.112. Claude Code configurations marked * used Claude Code v2.1.175 or later, and Table 7 lists the Claude Code version of each Claude Code configuration. Proprietary scaffolds can change between releases in ways that are not publicly documented (Appendix G.1), so we release the exact wrapper scripts.

Claude Code. The wrapper clears `ANTHROPIC_API_KEY`, loads an OAuth token into `CLAUDE_CODE_OAUTH_TOKEN`, and runs:

```
claude --print --verbose --output-format stream-json \
       --model $AGENT_CONFIG --dangerously-skip-permissions "$PROMPT"
```

The `-dangerously-skip-permissions` flag is necessary because the agent must write to the container file system and use the shell and the network without a human approving each action. The `-output-format stream-json` flag produces the JSONL transcripts from which we later extract cost and tool-use counts. The wrapper runs the command under a `timeout` equal to the remaining wall-clock budget. If the agent exits early, the wrapper calls `claude -continue` again until the budget ends.

Codex CLI. The wrapper clears `OPENAI_API_KEY` and copies a ChatGPT session file to the Codex authentication location. It then reads the reasoning-effort suffix from `$AGENT_CONFIG` (for example, it removes the suffix `-high` from the model name and writes `high` to the Codex configuration). It writes a new Codex configuration with `forced_login_method = "chatgpt"` and this reasoning effort, and runs:

```
codex exec --dangerously-bypass-approvals-and-sandbox \
           --skip-git-repo-check \
           --model $CODEX_MODEL "$PROMPT"
```

Codex prints its reasoning and tool calls as free-form text, not as structured JSON. The cost and behavior extractor in Appendix E therefore parses Codex transcripts with rule-based pattern matching. As with Claude Code, the wrapper does not depend on the model: `$AGENT_CONFIG` can hold any identifier that the Codex CLI accepts.

OpenCode. The OpenCode wrapper reads an API key from the scaffold directory, exports it as `OPENCODE_API_KEY`, and writes a per-run `opencode.json` with `permission = "allow"` and the `opencode` provider configured from that environment variable. The command is:

```
opencode run --model "$AGENT_CONFIG" --format json "$PROMPT"
```

where `$AGENT_CONFIG` is the model identifier together with its provider (for example `opencode/glm-5` or `opencode/gemini-3.1-pro`). The command runs under a `timeout` equal to the remaining wall-clock budget. If the agent exits before the budget ends, the wrapper resumes the same OpenCode session again and again with:

```
opencode run --model "$AGENT_CONFIG" --format json \
       --continue "$RESUME_PROMPT"
```

The resume prompt gives the remaining minutes and tells the agent to continue on its own without asking for feedback. OpenCode runs therefore follow the same continuation rule as the Claude Code and Codex CLI runs: an early agent exit ends the session only if the wall-clock budget has expired or the resume command fails.

B.4 BASELINES

PyTorch/Transformers baseline. This baseline is a minimal OpenAI-compatible server built on `aiohttp`. It loads the base model with `AutoModelForCausalLM.from_pretrained` in bfloat16 on one CUDA device and streams chat completions over SSE. A background thread runs `model.generate(..., streamer=TextIteratorStreamer(...))`, and an asyncio queue passes each token from the streamer to the `aiohttp` handler. The server therefore sends each token to the client as soon as the model produces it.

vLLM baseline. The vLLM baseline (vLLM v0.11.0) launches `vllm.entrypoints.openai.api_server` and keeps every parameter at its vLLM default: the maximum number of concurrent sequences, the batched-token budget, the KV-cache data type, chunked prefill, the block size, eager mode, CUDA graph capture, and the attention backend.

This default configuration is already strong. By default, vLLM uses PagedAttention (Kwon et al., 2023), which stores the KV cache in fixed-size blocks and so avoids wasted memory. It uses FlashAttention-2 (Dao, 2024) or an equivalent scaled-dot-product-attention backend with fused kernels for prefill and decode. It uses continuous batching, which adds new requests to the running batch at every decode step, so that new requests do not wait for the longest request to finish. It also captures CUDA graphs for the decode phase, which reduces the cost of launching GPU kernels at every step.

SGLang and HF TGI. We also run SGLang (v0.5.10) and Hugging Face Text Generation Inference (TGI, v3.3.6-dev0) as reference baselines, to show how other engines perform at their default settings. We launch both with only the required arguments: model path, host, port, and context length.

Non-agent search reference. We also evaluate non-agent parameter search with the same 2-hour budget, using random search, SMAC (Lindauer et al., 2022), and TPE (Bergstra et al., 2011). SMAC and TPE are Bayesian optimization methods: they choose the next configuration from the results of earlier ones. SMAC models these results with random forests, and TPE is the tree-structured Parzen estimator. We run each method separately for each serving engine instead of treating the choice of engine as part of one search: vLLM, SGLang, and TGI each receive their own 2-hour search with an engine-specific search space. The vLLM space covers scheduler and memory parameters (`max_num_seqs`, `max_num_batched_tokens`, `gpu_memory_utilization`, `block_size`), the prefix-caching and chunked-prefill switches, eager execution, quantization, KV-cache data type, attention backend, and speculative decoding length. The SGLang space covers the number of running requests, chunked-prefill size, prefill-token limit, static memory fraction, attention backend, quantization, `torch.compile`, scheduling policy, CUDA graph batch size, and speculative steps. The TGI space covers concurrent requests, prefill and total batch-token limits, waiting-token behavior, CUDA graph capture, quantization, CUDA memory fraction, waiting-served ratio, and maximum batch size.

C VALIDATION DETAILS

C.1 QUALITY GATE

Subset and sampling. The quality gate checks that optimization did not damage the model's answers. It evaluates every optimized server on a fixed 500-question subset of MMLU-Pro (Wang et al., 2024), with greedy decoding (temperature 0) and a 10-option multiple-choice prompt format (answer letters A–J). The subset is drawn once for each quality-gate seed and stays identical across

all runs that share that seed, so accuracy numbers are directly comparable within a seed pair. A run passes the gate if and only if $\text{observed_accuracy} \geq \tau \cdot \text{baseline_accuracy}$, with $\tau = 0.95$.

Answer extraction. We parse each response with three rules, in order: (1) the official MMLU-Pro regular expression "the answer is (X)" / "answer is X", (2) a looser match for a single isolated letter A–J, and (3) the last uppercase letter A–J in the response. If no rule matches, the response counts as wrong.

C.2 Integrity gate

The integrity gate checks that the run's speedup comes from real inference on the provided model. An agent-based LLM judge reads each run's final metrics, server launcher, and agent transcript and assigns two binary labels, one for contamination (use of evaluation data) and one for model substitution. A run is flagged if either label is positive. The labels cover disallowed behaviors such as returning pre-generated text without running the model, replacing the base model with another model, fine-tuning on the quality-gate questions, and sending computation to an external API. The judge prompt lists these behaviors, and the judge writes the two labels to `contamination_judgement.txt` and `disallowed_model_judgement.txt`. A flagged run contributes $1.00\times$ to its cell in Table 2. The released benchmark includes the full judge prompt, the label format, and the annotations of the manual audit described below.

Reliability. We validate the judge by judging every run again with a second judge model. The primary judge (Claude Sonnet 4.6) and the second judge (GPT-5.4) agree with Cohen's $\kappa = 0.82$ (agreement corrected for chance, where 1 is perfect). Most disagreements are on decode-heavy Scenario B runs near the rubric boundary between aggressive speculative decoding, which is allowed, and reward hacking, which is not: a server that satisfies the measurement without doing the intended inference work. To estimate judge error directly, we also labeled by hand a stratified sample (a sample drawn separately from each group) of 50 runs, spread across scenarios and across the judge's flagged and honest decisions. On this sample, the judge flagged 0 honest runs by mistake and missed 1 violation in the 50 audited runs. These rates are estimates on the audited sample, not guarantees over all runs.

D Full Results and Cost

D.1 All evaluated configurations

This section lists every agent configuration that we evaluated and what each one cost. A configuration is one model with one scaffold, one scaffold version, one reasoning-effort setting (shown in parentheses after the model name, for example "(Max)"), and one prompt. Table 7 reports all 42 configurations of the full evaluation, which we collected from April to September 2026. The main-text Table 2 shows only 16 of these rows: it keeps only configurations that used the current prompt (Appendix B.1), and for each model it keeps only the best such configuration. Several models therefore appear more than once in Table 7, with a different reasoning effort, scaffold, scaffold version, or prompt.

Scaffold versions and prompts. Appendix B.3 gives the scaffold versions, and Appendix B.1 defines the original and the current prompt. A Claude Code entry without a version number in Table 7 is a Claude Code v2.1.114 run from the initial evaluation. The mark * identifies Claude Code v2.1.175 or later, and the mark † identifies the current prompt. Both the scaffold version and the prompt can change the result by a large amount (Appendix G.1).

D.2 Cost analysis

A researcher who wants to evaluate a new agent needs to know what one complete evaluation costs. One complete evaluation is 12 runs of 2 hours each on one NVIDIA H100 80GB GPU. The cost has two parts: API cost (what the model provider charges for the tokens that the agent uses) and GPU cost. For GPU time, we use a uniform rate of $1.99 per hour per H100, from Runpod's published

Table 7: Speedup of all 42 agent configurations of the full evaluation over the PyTorch baseline, under a 2-hour budget. Rows are sorted by aggregate speedup. Aggregate is the geometric mean over Scenarios A–D, with the standard error of the mean (SEM) over seeds. Scenario cells are means over the three held-out seed-pair runs, and a run without a valid result counts as $1.00\times$. *: Claude Code v2.1.175 or later. †: current prompt.

Rank	Model	Scaffold	Aggregate	Sc. A	Sc. B	Sc. C	Sc. D
1	Claude Opus 5.5 (Max)*†	Claude Code, v2.1.280	$12.08\times\pm0.63$	$5.44\times$	$22.56\times$	$40.62\times$	$4.27\times$
2	Claude Fable 5.1*†	Claude Code, v2.1.258	$9.83\times\pm0.51$	$5.15\times$	$14.67\times$	$33.12\times$	$3.73\times$
3	Claude Fable 5.1 (Max)*†	Claude Code, v2.1.258	$9.31\times\pm0.67$	$4.77\times$	$13.30\times$	$32.98\times$	$3.59\times$
4	Claude Opus 5†	Claude Code, v2.1.119	$8.90\times\pm1.32$	$4.65\times$	$15.01\times$	$32.42\times$	$2.77\times$
5	Claude Fable 5 (Low)*†	Claude Code, v2.1.175	$8.74\times\pm1.91$	$4.17\times$	$13.38\times$	$21.37\times$	$4.89\times$
6	Claude Opus 4.7*	Claude Code, v2.1.175	$8.53\times\pm0.80$	$2.83\times$	$11.63\times$	$38.52\times$	$4.18\times$
7	GPT-6 Astra (Ultra)†	Codex CLI	$7.90\times\pm0.33$	$4.71\times$	$6.47\times$	$36.70\times$	$3.48\times$
8	GPT-6 Sol (Ultra)†	Codex CLI	$7.64\times\pm0.09$	$4.84\times$	$5.99\times$	$32.20\times$	$3.64\times$
9	Claude Opus 4.8*	Claude Code, v2.1.175	$7.60\times\pm2.16$	$4.53\times$	$12.16\times$	$18.62\times$	$3.25\times$
10	Claude Fable 5*†	Claude Code, v2.1.175	$7.52\times\pm1.58$	$4.27\times$	$15.64\times$	$11.90\times$	$4.03\times$
11	GPT-5.6 Sol (Ultra)†	Codex CLI	$7.34\times\pm0.21$	$4.24\times$	$8.61\times$	$33.92\times$	$2.35\times$
12	Claude Opus 4.8 (xHigh)	Claude Code, v2.1.119	$7.34\times\pm2.37$	$4.30\times$	$7.72\times$	$18.77\times$	$4.65\times$
13	GLM-5.2 (Max)†	Claude Code, v2.1.119	$7.00\times\pm0.24$	$3.86\times$	$5.77\times$	$32.47\times$	$3.32\times$
14	Grok 4.6†	Grok Build	$6.65\times\pm1.14$	$2.99\times$	$6.24\times$	$30.17\times$	$3.47\times$
15	Claude Sonnet 5†	Claude Code, v2.1.119	$6.43\times\pm1.46$	$3.30\times$	$4.48\times$	$36.09\times$	$3.20\times$
16	Kimi K2.7 Code†	OpenCode	$6.27\times\pm0.22$	$3.97\times$	$5.33\times$	$22.99\times$	$3.17\times$
17	GPT-5.4 (High)	Codex CLI	$6.16\times\pm1.16$	$3.60\times$	$6.93\times$	$17.78\times$	$3.25\times$
18	Kimi K3†	OpenCode	$5.70\times\pm1.69$	$3.50\times$	$4.25\times$	$19.59\times$	$3.64\times$
19	Claude Sonnet 4.6	Claude Code	$5.56\times\pm1.62$	$1.62\times$	$8.21\times$	$23.87\times$	$3.01\times$
20	GPT-5.3 Codex (High)	Codex CLI	$5.53\times\pm0.50$	$3.67\times$	$3.38\times$	$29.00\times$	$2.60\times$
21	GPT-5.5 (xHigh)	Codex CLI	$5.45\times\pm1.25$	$2.74\times$	$6.07\times$	$16.94\times$	$3.14\times$
22	GLM-5.3 (Max)†	Claude Code, v2.1.119	$4.98\times\pm0.89$	$3.42\times$	$7.80\times$	$22.97\times$	$1.00\times$
23	Gemini 3.1 Pro	OpenCode	$4.92\times\pm0.81$	$2.52\times$	$3.78\times$	$31.24\times$	$1.97\times$
24	Muse Spark 1.3†	OpenCode	$4.53\times\pm0.70$	$2.77\times$	$4.50\times$	$13.06\times$	$2.58\times$
25	Kimi K2.6	OpenCode	$4.51\times\pm0.48$	$1.99\times$	$4.73\times$	$29.19\times$	$1.51\times$
26	GLM-5.3 Flash†	OpenCode	$4.49\times\pm0.69$	$3.20\times$	$6.28\times$	$20.15\times$	$1.00\times$
27	Claude Opus 4.6	Claude Code	$4.38\times\pm1.25$	$1.00\times$	$4.80\times$	$23.85\times$	$3.21\times$
28	GPT-5.2	Codex CLI	$4.28\times\pm1.29$	$2.26\times$	$2.87\times$	$20.15\times$	$2.57\times$
29	GPT-5.5 (High)	Codex CLI	$4.22\times\pm1.01$	$3.06\times$	$2.59\times$	$19.11\times$	$2.08\times$
30	Gemini 3.5 Flash	OpenCode	$4.16\times\pm0.72$	$3.70\times$	$3.05\times$	$17.71\times$	$1.50\times$
31	Claude Opus 4.5	Claude Code	$3.76\times\pm0.89$	$3.69\times$	$2.78\times$	$10.03\times$	$1.95\times$
32	Grok 4.5†	Grok Build	$3.70\times\pm0.79$	$2.95\times$	$2.73\times$	$15.59\times$	$1.49\times$
33	GPT-5.1 Codex Max	Codex CLI	$3.59\times\pm1.24$	$2.57\times$	$3.44\times$	$10.33\times$	$1.82\times$
34	Grok 4.5†	OpenCode	$3.42\times\pm1.23$	$2.07\times$	$2.75\times$	$10.11\times$	$2.37\times$
35	GLM-5	OpenCode	$3.22\times\pm0.85$	$2.19\times$	$1.00\times$	$26.36\times$	$1.87\times$
36	Claude Sonnet 4.5	Claude Code	$3.18\times\pm0.90$	$2.67\times$	$1.71\times$	$9.65\times$	$2.32\times$
37	Claude Fable 5*	Claude Code, v2.1.175	$3.16\times\pm0.67$	$3.92\times$	$1.00\times$	$25.42\times$	$1.00\times$
38	Claude Haiku 4.5	Claude Code	$2.78\times\pm0.57$	$1.00\times$	$1.99\times$	$9.27\times$	$3.24\times$
39	GPT-5.3 Codex (Medium)	Codex CLI	$2.32\times\pm0.31$	$2.75\times$	$3.73\times$	$1.00\times$	$2.82\times$
40	Claude Opus 4.7	Claude Code, v2.1.114	$2.25\times\pm0.32$	$1.07\times$	$1.00\times$	$19.02\times$	$1.27\times$
41	Claude Fable 5 (Low)*	Claude Code, v2.1.175	$2.15\times\pm0.46$	$1.00\times$	$1.00\times$	$21.21\times$	$1.00\times$
42	GPT-5.2 Codex	Codex CLI	$1.98\times\pm0.18$	$3.32\times$	$2.48\times$	$1.00\times$	$1.87\times$

on-demand GPU pricing (Runpod Inc., 2026). The nominal GPU cost of one complete evaluation is therefore $12 \times 2\,\mathrm{h} \times \$1.99/\mathrm{h} = \$47.76$.

We compute all API costs with the list prices of 2026-08-14. The method depends on the model and the scaffold. For Claude Code runs (Claude and GLM models) and Grok models, we reprice the recorded token counts with each provider's list price. For OpenCode runs, we use the dollar cost that OpenCode records for each step, with two exceptions: GLM-5.3 Flash and Muse Spark 1.3. Their runs used free or promotional access, so the recorded cost does not show the list price. We price them from their token counts at list price: GLM-5.3 Flash at \$0.15 per million input tokens, \$0.03 per million cached input tokens, and \$0.50 per million output tokens, and Muse Spark 1.3 at its standard list price of \$1.25, \$0.15, and \$4.25 per million tokens for the same three token types. For Codex CLI runs, we reconstruct the token counts from the transcripts, because the Codex CLI token counter does not include cache reads. Table 8 lists the 16 configurations of Table 2.

Total cost varies about 16-fold across the 16 configurations of Table 2, while their aggregate speedups vary by a factor of 3.3 (from $3.70\times$ to $12.08\times$). GLM-5.3 Flash is the cheapest configuration at \$52.05, and GPT-6 Sol (Ultra) is the most expensive at \$824.54. The highest-ranked configuration, Claude Opus 5.5 (Max), costs \$481.01. A complete evaluation of one new agent with a model similar to these therefore costs \$52 to \$825, and the API cost sets most of this range because the GPU cost is the same \$47.76 for every configuration.

Table 8: API, GPU, and total cost of one complete 12-run evaluation for the 16 configurations of Table 2. Rows are sorted by aggregate speedup. GPU cost is the nominal $47.76 for 12 runs of 2 hours at $1.99 per H100 hour. API cost uses the list prices of 2026-08-14. GLM-5.3 Flash and Muse Spark 1.3 are priced at list price although their runs used free or promotional access. *: Claude Code v2.1.175 or later. †: current prompt.

Agent	API ($)	GPU ($)	Total ($)
Claude Opus 5.5 (Max)*†	433.25	47.76	481.01
Claude Fable 5.1*†	278.23	47.76	325.99
Claude Opus 5†	122.58	47.76	170.34
Claude Fable 5 (Low)*†	104.38	47.76	152.14
GPT-6 Astra (Ultra)†	535.31	47.76	583.07
GPT-6 Sol (Ultra)†	776.78	47.76	824.54
GPT-5.6 Sol (Ultra)†	360.09	47.76	407.85
GLM-5.2 (Max)†	83.79	47.76	131.55
Grok 4.6†	188.87	47.76	236.63
Claude Sonnet 5†	134.83	47.76	182.59
Kimi K2.7 Code†	44.27	47.76	92.03
Kimi K3†	63.61	47.76	111.37
GLM-5.3 (Max)†	59.75	47.76	107.51
Muse Spark 1.3†	11.01	47.76	58.77
GLM-5.3 Flash†	4.29	47.76	52.05
Grok 4.5 (Grok Build)†	78.45	47.76	126.21

Cost per unit of speedup. To compare cost against performance, Table 9 divides the total cost of each configuration by its aggregate speedup. The result is the cost in dollars per unit of aggregate speedup ($/×), and a lower value is better. GLM-5.3 Flash ($11.59/×), Muse Spark 1.3 ($12.97/×), and Kimi K2.7 Code ($14.68/×) have the lowest cost per unit of speedup. The highest-ranked configuration, Claude Opus 5.5 (Max), costs $39.82 per unit of speedup, and GPT-6 Sol (Ultra) has the highest value at $107.92. The configurations with the highest aggregate speedup are not the most cost-efficient ones.

Table 9: Cost per unit of aggregate speedup for the 16 configurations of Table 2. Total is the 12-run cost from Table 8, including the nominal GPU cost. $/× is Total divided by Aggregate, and lower is better. Rows are sorted by aggregate speedup. *: Claude Code v2.1.175 or later. †: current prompt.

Agent	Total ($)	Aggregate	$/×
Claude Opus 5.5 (Max)*†	481.01	12.08	39.82
Claude Fable 5.1*†	325.99	9.83	33.16
Claude Opus 5†	170.34	8.90	19.14
Claude Fable 5 (Low)*†	152.14	8.74	17.41
GPT-6 Astra (Ultra)†	583.07	7.90	73.81
GPT-6 Sol (Ultra)†	824.54	7.64	107.92
GPT-5.6 Sol (Ultra)†	407.85	7.34	55.57
GLM-5.2 (Max)†	131.55	7.00	18.79
Grok 4.6†	236.63	6.65	35.58
Claude Sonnet 5†	182.59	6.43	28.40
Kimi K2.7 Code†	92.03	6.27	14.68
Kimi K3†	111.37	5.70	19.54
GLM-5.3 (Max)†	107.51	4.98	21.59
Muse Spark 1.3†	58.77	4.53	12.97
GLM-5.3 Flash†	52.05	4.49	11.59
Grok 4.5 (Grok Build)†	126.21	3.70	34.11

E Behavioral Metrics and Failure Modes

E.1 Extracting behavior from logs

This appendix describes what agents did during their runs, in addition to their final speedups. For each run, we extract behavioral labels and metrics with fixed rules from three files: the persisted server launch log, the final metrics file, and the agent transcript. No language model is involved in this extraction.

E.2 Techniques mentioned versus tested

Table 10 reports four secondary behavioral metrics for runs with the 2-hour budget. We extract them from each run's final launcher script, its evaluation log, and the agent transcript. Three metrics cover the full evaluation (42 configurations, 504 scored runs, collected April to September 2026). The server-restart metric covers the initial evaluation (April 2026, 15 configurations, 180 runs).

Almost every run mentions quantization (99%), and most runs mention chunked prefill (83%) and speculative decoding (78%). However, 73% of the runs with a readable launch log test at most one distinct non-default launch configuration.

Table 10: Secondary behavioral metrics for 2-hour runs. The first three rows use the full evaluation (42 configurations, 504 scored runs).

Metric	**Value**
Final serving engine	91.5% of runs (460 of 504) ship a vLLM-based server, 4.2% ship SGLang, 3.8% ship a custom server, and 0.6% leave no final server. No run ships TensorRT-LLM.
Distinct non-default launch configurations per run	A distinct non-default launch configuration is a unique set of server launch arguments that differs from the engine defaults. Over the 504 runs with a readable launch log: median 1, mean 1.19. 25.7% of runs test zero, 47.3% one, 16.1% two, and 10.9% three or more.
Technique mentions in transcripts	Share of runs whose agent-written transcript text (prompt text excluded) mentions each technique: quantization (storing weights or the KV cache with fewer bits) 99%, chunked prefill (processing a long prompt in pieces) 83%, speculative decoding (proposing several tokens cheaply and verifying them in one model step) 78%.
Server restarts per run (initial evaluation only)	Median 1. Of the runs that restart the server, 81% relaunch it with unchanged arguments.

F Trace Examples and Integrity Cases

This appendix gives short annotated excerpts from nine agent runs, grouped into seven examples. The excerpts show the main failure patterns and two positive examples of controlled experimentation. The main text covers three behaviors: early convergence on a first working server, failure to turn known techniques into controlled search, and reward hacking under optimization pressure. This appendix adds more specific examples: self-declared completion, multi-variable edits, dependency spirals, and further integrity cases. Most excerpts come from scored main-condition runs (the standard 2-hour setting), and a few come from other runs that show a failure mode more clearly. Each excerpt is a verbatim quote from the run's transcript. After each excerpt, we describe concrete run artifacts, such as launcher changes, evaluator outputs, or the state of the final server.

Example 1: Self-declared completion. A Claude Opus 4.5 run on Scenario B starts its first working vLLM server 28 minutes into its budget. It then runs the quick evaluator and gets a clean baseline readout:

> *Baseline performance: generation throughput 63.53 tokens/s. TTFT p50 51.8 ms, p90 400 ms. ITL p50 10.2 ms. TPOT p50 15.7 ms. Quality check: PASS (accuracy 28% vs baseline 25.5%). The key metric for Scenario B is generation throughput... Let me stop the current server and optimize.*

At this point the server is a minimal vLLM launch with the correct base model and the standard OpenAI-compatible endpoints. It has no scenario-specific tuning beyond the default vLLM serving path. The agent then tries two small variants: it adds `-enable-chunked-prefill`, and it toggles `-enforce-eager`. It does not compare either variant in a full evaluation. One restart attempt fails with an out-of-memory error, and after that the continuation turns stop producing new experiments. A typical later statement is:

> *The current server is already valid and passing the checks. Since further changes risk breaking the deployment, I will keep this configuration for final evaluation.*

The agent completed the setup but did not continue. It has a working server, a valid metric readout, and much remaining wall-clock time, but its search stops after the first local failure. For about the last 90 minutes, the transcript contains repeated readiness checks and restatements of the same plan, not new launch arguments or controlled comparisons. The final launcher is in effect the first working configuration.

Example 2: Multi-variable edits. A Claude Opus 4.6 run on Scenario D launches vLLM four times with three distinct argument sets during the 2-hour budget:

```
config 1:  quantization=fp8, kv_cache_dtype=fp8_e4m3, gpu_util=0.75
config 2:  quantization=fp8, kv_cache_dtype=fp8_e4m3, gpu_util=0.75 (relaunch)
config 3:  quantization=fp8, kv_cache_dtype=fp8_e4m3, enforce_eager=True
config 4:  quantization REMOVED, kv_cache_dtype=auto, enforce_eager=True
```

Each step has a reasonable rationale on its own. Scenario D balances latency, decode speed, and throughput, so FP8 quantization and an FP8 KV cache could reduce pressure on memory bandwidth, and eager execution could avoid the overhead of CUDA graph capture for the mixed workload. The problem is experimental control. Between configurations 2 and 3, the agent adds `enforce_eager` without a complete evaluation in between. Between configurations 3 and 4, it changes two variables at once: it removes `quantization=fp8` and replaces `kv_cache_dtype=fp8_e4m3` with `auto`, while `enforce_eager=True` stays active.

The final metrics file shows the result: it contains an error field and no completed Scenario D profiles. The harness cannot compute TTFT, TPOT, or throughput summaries because it cannot reach the final server. The agent lost its last usable server. It knows plausible settings to change, but it changes several interacting parameters without a measurement schedule that would let it attribute an effect to one change or roll back.

Example 3: Dependency spiral. A GPT-5.4 (High) run on Scenario A tries to use FlashInfer as its attention backend for long-prompt prefill. On the first launch, FlashInfer compiles its kernels just in time (JIT), and the agent waits for this compilation:

> *The delay is now explained: FlashInfer is JIT-compiling the large prefill kernels for SM90 on first use. That's likely worth paying once for TTFT, but I'll relocate those caches into the repo after this run so the final relaunch can reuse them instead of recompiling from scratch.*

During this period the server is alive but does not serve useful benchmark traffic. The launch log shows repeated CUDA compilation activity instead of completed requests, and the evaluator sees connection errors or timeouts instead of stable first-token latency. In this run, the agent eventually finds the cause and abandons FlashInfer before the budget runs out. The agent recognizes that an optimization meant to lower TTFT can hurt when first-use compilation takes up the evaluation window.

A Claude Opus 4.6 run on Scenario C shows the same pattern without recovery. It cycles through the following backends:

```
attempt 1:  FlashInfer backend, default precision
attempt 2:  Triton fallback after FlashInfer launch instability
attempt 3:  FlashInfer backend with FP8-related settings
attempt 4:  Triton fallback after quality or runtime degradation
```

A crash, a timeout, or a quality regression triggers each backend change. No change comes from a controlled throughput comparison under the same request profile. Scenario C rewards scheduler-level throughput under 64 concurrent requests, but the agent spends much of its budget on backend compatibility and compilation problems. We call this a dependency spiral: the agent does real engineering work, but it spends its time repairing its software stack.

Example 4: Controlled experimentation. This GPT-5.4 (High) run on Scenario A uses the seed pair $(21, 1337)$. The agent explicitly compares two variants, V0 and V1, with a named rollback criterion. It then tries single-flag changes on top of the better variant:

> *V1 improved the short speed-only probe but did not hold up in the longer end-to-end path, so I'm treating it as unstable for the final submission. I'm using the remaining time on lower-risk V0 variants; the next one is eager execution, which might trim per-request overhead without changing the serving surface.*

> *`-enforce-eager` is promising: TTFT improved modestly and, more importantly, the tail got tighter than the current default. I'm trying one last combinatorial variant, eager plus `max_num_seqs=1`, because if it helps TTFT further I can still afford a final quality check afterward.*

The experiments have this structure:

```
V0:  baseline vLLM launcher, quality passing, stable full evaluation
V1:  aggressive prefill-oriented variant, improved quick probe but unstable full
path
V0+eager:  add -enforce-eager, compare TTFT and tail latency
V0+eager+seq1:  add -max-num-seqs=1, final candidate after quality check
```

This trace differs from the multi-variable edit in Example 2. The agent names a baseline and tries an alternative. It rejects the alternative when the gain on the quick probe does not carry over to the longer evaluation, and it then applies one change at a time to the stable branch. It also keeps a deployable state: the final `start_server.sh` includes the selected flags and a warm-up step, so the final harness does not pay a one-time startup cost. The agent measures each change, compares it with the current best, and rolls back changes that do not help.

Example 5: A second controlled-experimentation trace. A second GPT-5.4 (High) run, on Scenario D, shows a similar pattern. Its first vLLM launch gives only a $1.1\times$ speedup in the geometric mean of the Scenario D metrics. The agent then identifies three independent candidates: a higher `max-num-seqs`, `-enable-prefix-caching`, and a different KV-cache data type. The transcript treats them as separate interventions and does not apply them all at once:

```
candidate A: increase -max-num-seqs to improve batching headroom
candidate B: enable -enable-prefix-caching to reduce repeated-prefix cost
candidate C: change KV-cache dtype to reduce memory pressure
```

The evaluation sequence is also cleaner than in the average run. The agent tests candidate A first, and it improves request throughput without a large TPOT regression. It then tests candidate B on top of the current best configuration, and B improves the Scenario D geometric mean on the quick evaluator. Candidate C makes TPOT worse, and the agent reverts it instead of keeping it for lack of time. The final launcher therefore keeps the two changes that improved the measurements and drops the one that hurt the decode part of the Scenario D metric.

Scenario D is the setting where optimizing a single metric is most likely to fail. The agent must keep a balance among inverse TTFT, inverse TPOT, and request throughput. In this trace, the agent reasons in these terms: it rejects a change because the change improves one part of the metric and damages

another. In the initial evaluation, the resulting cell was one of the few agent results strictly above the vLLM default on the Scenario D geometric mean.

Example 6: Reward hacking through a subverted measurement path. A GPT-5.3 Codex (Medium) run on Scenario B reports a decode throughput of 118 million tokens per second and a per-token decode latency of 6.4 nanoseconds. These numbers are physically impossible for generating 8k-token outputs from a 7B-class model on a single H100. The run's submitted launcher and transcript show that the agent subverted the measurement path, and the serving configuration did not improve.

There are three concrete warning signs. First, the reported decode latency is many orders of magnitude below the kernel-launch and memory-access times of the hardware. Second, the server returns outputs that match the evaluator's expected format without doing the full decode work. Third, the quality score falls exactly in the narrow band needed to pass the gate:

```
baseline quality:  128/500 correct
required threshold:  0.95 × 128 = 121.6 correct
submitted server quality:  122/500 correct
```

The server returns plausible answer letters or cached completions of the right form and bypasses the speed evaluation. The quality gate alone would not remove this run, because the run is just accurate enough to pass. The integrity gate flags it because the speed profile and the implementation together show reward hacking. Without the integrity gate, this single run would have added an impossible speedup to the Scenario B mean without any warning.

Example 7: Reward hacking on TTFT with a fake first chunk. Two runs, GPT-5.3 Codex (Medium) on Scenario A and GPT-5.2 on Scenario A, independently find the same exploit. The server sends a fake "first token" as a streaming chunk (a server-sent event, SSE) before it tokenizes the prompt or runs the model. Scenario A measures time to first token (TTFT) on 8,192-token inputs. The exploit therefore reduces the measured TTFT to the time needed to send a trivial chunk, not the time needed to process (prefill) the long prompt.

A simplified version of the submitted behavior is:

```
send SSE chunk containing a single space character
flush response stream immediately so the client records first-token time
only afterward tokenize the full prompt and begin the actual model forward pass
```

The metric signature is a TTFT below 3 ms on long-context requests. Normal prefill of these requests takes hundreds of milliseconds with the PyTorch baseline and much more than a few milliseconds even with optimized serving. The real model call still happens later in the stream, so the run can pass the quality gate. The final answer comes from the model, but the timestamp for the primary metric is fake. This exploit is harder to detect than returning pre-generated text. It keeps enough correct behavior to pass the quality check and manipulates the event that defines the metric.

Two different runs found this exploit independently. The GPT-5.3 Codex (Medium) transcript describes the strategy explicitly as an early streamed token. The GPT-5.2 run reaches the same mechanism on its own and leaves a comment in the submitted server that names the fake-first-chunk behavior. The integrity gate flags both runs because the submitted server deliberately manipulates the streaming protocol that the measurement uses.

G Ablations

This appendix reports controlled changes to the main setup. Each ablation changes one factor (the prompt, the hardware, the starting server, the allowed engine, or the number of GPUs) and keeps the other conditions of the main benchmark. Unless a caption states otherwise, the base model is Mistral-7B-Instruct-v0.3 on one H100 GPU, the time budget is 2 hours, and each scenario cell uses three held-out seed-pair runs. All cells report speedup over a plain PyTorch serving baseline, so $1\times$ means no improvement. A run that fails the quality gate or the integrity gate, or that leaves no working final server, counts as $1\times$. We call means computed with this rule *penalized* means. The aggregate is the geometric mean of the four scenario speedups.

Most ablations use GPT-5.4 (High) or Claude Opus 4.7 with the *original prompt*, the shorter of the two task prompts in this paper. We call this the *default* condition. The default rows are the rows of the same configurations in the full evaluation (Table 7).

G.1 Scaffold version and prompt

The benchmark measures a system of model, scaffold, and prompt, not a model in isolation. The scaffold version alone changes Claude Opus 4.7 from $2.25\times$ (Claude Code v2.1.114, 5 of 12 runs pass) to $8.53\times$ (v2.1.175, 11 of 12 pass), with gains on every scenario. The prompt alone has a similar effect. Under the original prompt, Claude Fable 5 often served a quantized checkpoint that someone else had published, which the rules forbid, and the integrity gate penalized those runs. With the current prompt, which names this rule explicitly, it quantized the weights itself, and its aggregate rose from $3.16\times$ to $7.52\times$. Claude Fable 5 (Low) rose from $2.15\times$ to $8.74\times$. The scaffold family has a smaller effect in the one case we can test: Grok 4.5 reaches $3.70\times$ with Grok Build and $3.42\times$ with OpenCode. We therefore report the scaffold version and prompt of every configuration (Appendix Table 7).

G.2 Base model

We repeated the two-hour setup of GPT-5.4 (High) on two other base models, Qwen3-8B and DeepSeek-V2-Lite, a mixture-of-experts model that activates only part of its weights for each token. Speedups are measured against each model's own PyTorch server, so the rows show optimization progress within each model, not a latency comparison between models. The agent largely finds large gains on models, especially on prefill and throughput, but the share of valid runs changes a lot (Table 11). Qwen3-8B reaches the highest aggregate ($10.79\times$). On DeepSeek-V2-Lite only 5 of 12 runs pass, and all three throughput runs are rejected or fail. This is consistent with an agent that applies the same recipe to every base model, even when a different architecture needs different choices.

Table 11: Speedups of GPT-5.4 (High) on three base models. Two-hour budget. Cells are mean speedup over each base model's own PyTorch server with standard error over three runs, and failed runs count as $1\times$. Aggregate is the geometric mean over Scenarios A–D.

Base model	**Aggregate**	**Sc. A** TTFT	**Sc. B** TPOT	**Sc. C** req. tput	**Sc. D** geomean	**Runs passed**
Mistral-7B-Instruct-v0.3	$6.16\times$	$3.60\times_{\pm 0.03}$	$6.93\times_{\pm 4.46}$	$17.78\times_{\pm 8.40}$	$3.25\times_{\pm 1.38}$	10/12
Qwen3-8B	$10.79\times$	$41.62\times_{\pm 20.30}$	$2.97\times_{\pm 1.97}$	$44.41\times_{\pm 5.07}$	$2.47\times_{\pm 0.75}$	9/12
DeepSeek-V2-Lite	$2.24\times$	$1.85\times_{\pm 0.43}$	$6.29\times_{\pm 2.65}$	$1.00\times_{\pm 0.00}$	$2.16\times_{\pm 1.16}$	5/12

G.3 Structured iteration

The original prompt tells the agent to optimize continuously but does not specify an experimental protocol. The structured-iteration prompt adds an explicit protocol: measure a baseline before optimizing, change exactly one variable per experiment, log each proposal and its outcome before the next step, and reserve the final 15 minutes for validation. The prompt does not specify which framework, optimizations, or parameter values to try.

For GPT-5.4 (High), the structured prompt mainly improves reliability: passing runs rise from 10/12 to 11/12, and the Scenario D SEM falls from $1.38\times$ to $0.31\times$, while the aggregate falls from $6.16\times$ to $5.51\times$. For Claude Opus 4.7 (Claude Code v2.1.114), passing runs rise from 5/12 to 11/12, and the aggregate rises from $2.25\times$ to $8.61\times$, with Scenario A rising from $1.07\times$ to $4.58\times$. Both structured agents stay below non-agent search on Scenarios C and D and on the aggregate. The results therefore point to two separate limitations. The first is poor execution discipline, which a prescribed protocol partly fixes. The second is narrow search on throughput-heavy and multi-objective scenarios, which the protocol does not fix.

Table 12: Effect of a structured-iteration prompt on two agents. Cells are mean$_{\pm\text{SEM}}$ speedup over the PyTorch baseline. Aggregate is the geometric mean over Scenarios A–D. Failed seed runs count as 1×. The Claude Opus 4.7 rows use Claude Code v2.1.114, the scaffold version of the initial evaluation (2.25× aggregate in the default condition). They are not the Claude Code v2.1.175 runs of Claude Opus 4.7 in Table 7.

Condition	**Aggregate**	**Sc. A** TTFT	**Sc. B** TPOT	**Sc. C** req. tput	**Sc. D** geomean	**pass rate**
GPT-5.4 (High), default	6.16×	$3.60\times_{\pm 0.03}$	$6.93\times_{\pm 4.46}$	$17.78\times_{\pm 8.40}$	$3.25\times_{\pm 1.38}$	10/12
GPT-5.4 (High), structured	5.51×	$3.39\times_{\pm 0.02}$	$3.57\times_{\pm 1.36}$	$26.90\times_{\pm 1.60}$	$2.84\times_{\pm 0.31}$	11/12
Claude Opus 4.7, default	2.25×	$1.07\times_{\pm 0.06}$	$1.00\times_{\pm 0.00}$	$19.02\times_{\pm 0.94}$	$1.27\times_{\pm 0.27}$	5/12
Claude Opus 4.7, structured	8.61×	$4.58\times_{\pm 0.10}$	$11.91\times_{\pm 2.83}$	$36.76\times_{\pm 2.06}$	$2.74\times_{\pm 0.87}$	11/12

G.4 A100 VERSUS H100

The hardware ablation reruns the default GPT-5.4 (High) setup on an A100 GPU instead of an H100 GPU. Speedups are relative to the PyTorch baseline on the same hardware. As in the base-model ablation (Appendix G.2), read each row as optimization progress within its own setting, not as a latency comparison between GPUs. The effect of the hardware change is larger than the effect of the prompt change, and every scenario falls: Scenario A from 3.60× to 1.22×, Scenario B from 6.93× to 3.68×, Scenario C from 17.78× to 8.39×, and Scenario D from 3.25× to 1.20×. The Scenario B estimate on A100 has a large variance because two of the three seed-pair runs give only baseline-level speedup.

Table 13: Speedup of GPT-5.4 (High) on H100 and A100 GPUs. The setup uses a 2-hour budget and Mistral-7B-Instruct-v0.3. Cells are penalized mean$_{\pm\text{SEM}}$ speedup over the PyTorch baseline on the same hardware across the three held-out seed-pair runs.

Hardware	**Sc. A** TTFT	**Sc. B** TPOT	**Sc. C** req. tput	**Sc. D** geomean	**pass rate**
H100	$3.60\times_{\pm 0.03}$	$6.93\times_{\pm 4.46}$	$17.78\times_{\pm 8.40}$	$3.25\times_{\pm 1.38}$	10/12
A100	$1.22\times_{\pm 0.11}$	$3.68\times_{\pm 2.68}$	$8.39\times_{\pm 3.74}$	$1.20\times_{\pm 0.12}$	7/12

G.5 ENGINE CHOICE MATTERS MORE THAN THE OPTIMIZER

The non-agent search rows in the main results table are the best final gate-passing results from searches over vLLM only. This subsection reports the full grid: three optimizers (random search, SMAC, and TPE), three serving engines (vLLM, SGLang, and Hugging Face TGI), and four scenarios. SMAC (Lindauer et al., 2022) and TPE (Bergstra et al., 2011) are the Bayesian optimizers of Appendix B.4. Each cell is an independent 2-hour search by the named optimizer over the documented command-line flags of the named engine.

The best engine depends on the scenario. No single engine is best on all scenarios. SGLang is the best engine on Scenario A (prefill latency) under all three optimizers. vLLM is the best engine on Scenario B (single-stream decode latency) under SMAC and TPE, and SGLang is best on Scenario B under random search. TGI is the best engine on Scenario C (high-load throughput), where it reaches 77–89×, and it is also the best engine on the balanced Scenario D under all three optimizers. The engine is therefore the most important single decision for throughput-heavy workloads, and it still matters on the other scenarios.

Optimizers give similar results. For a fixed engine, random search, SMAC, and TPE reach similar speedups. On vLLM, the spread between the three optimizers is 3.9 speedup points on Scenario B (11.34 to 15.23×) and 4.9 points on Scenario C (41.81 to 46.70×). These spreads are much smaller than the spreads between engines on the same scenarios. Two hours covers most of one engine's search space, because the space is a documented list of flags and each configuration runs in minutes.

Table 14: Non-agent search results for three optimizers and three serving engines. Each scenario cell is the final gate-passing speedup over the PyTorch baseline after a 2-hour search, reported as mean$_{\pm\text{SEM}}$. Aggregate is the geometric mean over Scenarios A–D of the displayed scenario means. **Bold** marks the best engine for each optimizer and scenario. The engine choice changes the result strongly on Scenarios B and C and moderately on Scenarios A and D.

Optimizer	Engine	Aggregate	Sc. A	Sc. B	Sc. C	Sc. D
Random	SGLang	9.46×	**5.02**×$_{\pm 0.51}$	**11.91**×$_{\pm 1.68}$	31.95×$_{\pm 3.89}$	4.20×$_{\pm 0.48}$
Random	TGI	9.71×	3.98×$_{\pm 0.44}$	4.20×$_{\pm 0.59}$	**89.00**×$_{\pm 10.91}$	**5.97**×$_{\pm 0.67}$
Random	vLLM	10.20×	4.21×$_{\pm 0.47}$	11.34×$_{\pm 1.59}$	41.81×$_{\pm 5.12}$	5.42×$_{\pm 0.61}$
SMAC	SGLang	8.97×	**4.94**×$_{\pm 0.38}$	9.27×$_{\pm 0.91}$	33.05×$_{\pm 2.83}$	4.28×$_{\pm 0.37}$
SMAC	TGI	9.63×	3.95×$_{\pm 0.31}$	4.16×$_{\pm 0.42}$	**85.84**×$_{\pm 6.39}$	**6.10**×$_{\pm 0.47}$
SMAC	vLLM	11.53×	4.37×$_{\pm 0.34}$	**15.23**×$_{\pm 1.27}$	46.70×$_{\pm 3.58}$	5.69×$_{\pm 0.42}$
TPE	SGLang	9.64×	**5.06**×$_{\pm 0.42}$	10.73×$_{\pm 1.13}$	32.92×$_{\pm 3.06}$	4.84×$_{\pm 0.44}$
TPE	TGI	9.43×	3.93×$_{\pm 0.34}$	4.31×$_{\pm 0.50}$	**77.33**×$_{\pm 7.90}$	**6.03**×$_{\pm 0.51}$
TPE	vLLM	11.25×	4.48×$_{\pm 0.39}$	**14.76**×$_{\pm 1.45}$	43.46×$_{\pm 3.72}$	5.58×$_{\pm 0.51}$

Under this budget, the three optimizers converge to similar configurations near the best reachable result. The matched-budget search number that we compare agents with therefore depends only weakly on the choice of optimizer ($10.20\times$ to $11.53\times$ on vLLM).

Why most agents fall short of search. The vLLM-only search rows exceed the final result of most agents on every scenario and on the aggregate. In the full evaluation, one configuration, Claude Opus 5.5 (Max), exceeds the best search aggregate ($12.08\times$ against $11.53\times$ for SMAC). It is higher than search on Scenarios A and B ($5.44\times$ and $22.56\times$) and lower on Scenarios C and D ($40.62\times$ against $46.70\times$ and $4.27\times$ against $5.69\times$ for SMAC). No agent configuration in the full evaluation reaches the Scenario C or Scenario D result of vLLM-only SMAC search. The gap on Scenario C grows further when search can also choose the engine: the best TGI search reaches $89.00\times$ with random search and $85.84\times$ with SMAC. Agents almost always ship vLLM (Table 10). The grid therefore shows two separate shortfalls: agents tune their chosen engine less thoroughly than search does, and they miss the engine choice that search exploits when it is allowed to choose.

G.6 Starting from a working server

The main benchmark evaluates end-to-end deployment. The agent receives a base model, a hardware environment, a scenario objective, and an evaluation harness, but no starting server, so building the server is part of the task. The gap between agents and non-agent search could therefore come mainly from this setup work and not from the optimization itself. To test this, we run a *warm-start* ablation, in which the agent starts from a working vLLM server instead of an empty workspace.

In the warm-start condition, the container contains a valid `start_server.sh` at the start of the run. This script launches `vllm.entrypoints.openai.api_server` with the correct base model, host, port, and maximum context length. The server passes the quality gate and a quick speed evaluation before the agent starts. The modified prompt states that this launcher is correct but untuned, and that the agent must optimize it and not only keep it working. All other conditions are unchanged: H100 hardware, the Mistral-7B-Instruct-v0.3 base model, the 2-hour budget, the continuation wrapper, the development and evaluation seed pairs, the quality and integrity gates, and the rule that only the final server is scored.

The warm start improves reliability but does not close the gap to search. The largest effect is on the pass rate: GPT-5.4 rises from 10/12 to 12/12 passing runs, and Claude Opus 4.7 rises from 5/12 to 11/12. Part of the difficulty of the main benchmark is therefore ordinary systems setup and keeping the final server valid. The speedups change much less than the pass rate. GPT-5.4 improves on Scenario C and has a smaller SEM on Scenarios B and D, but it stays below matched-budget non-agent search on every scenario. Claude Opus 4.7 gains more, because the warm start removes several early failure modes, but its warm-start cells still stay below the non-agent row, most clearly on the throughput-heavy Scenario C and the balanced Scenario D.

Table 15: Effect of a working vLLM starting server (warm start) on two agents. In the warm-start condition, the agent receives a valid vLLM server with an OpenAI-compatible API at the start of the run. Agent rows are penalized mean±SEM speedup over the PyTorch baseline across the three held-out seed-pair runs. Failed seed runs count as $1\times$. The non-agent row reports the best value for each scenario over the full grid of 3 optimizers $\times$ 3 engines. The Claude Opus 4.7 rows use Claude Code v2.1.114, the scaffold version of the initial evaluation.

Condition	**Sc. A** TTFT	**Sc. B** TPOT	**Sc. C** req. tput	**Sc. D** geomean	**Pass rate**
GPT-5.4 (High), default prompt	3.60×±0.03	6.93×±4.46	17.78×±8.40	3.25×±1.38	10/12
GPT-5.4 (High), warm-start vLLM	3.71×±0.11	4.08×±1.18	27.41×±2.13	3.48×±0.42	12/12
Claude Opus 4.7, default prompt	1.07×±0.06	1.00×±0.00	19.02×±0.94	1.27×±0.27	5/12
Claude Opus 4.7, warm-start vLLM	4.31×±0.22	8.64×±2.50	35.22×±2.90	2.81×±0.60	11/12
Per-scenario best non-agent search	5.06×	15.23×	89.00×	6.10×	–

The agent transcripts show the same behavior as in the main condition, with fewer launch failures. Agents treat the working vLLM server as a safe anchor: they rerun the evaluator, make one or two local changes to vLLM flags, and then keep the current launcher so that the final server stays valid. The median number of distinct non-default vLLM configurations per run rises from 1.0 in the main condition to 2.0 in the warm-start condition. This is still far below the number of configurations that the 2-hour non-agent searches evaluate. Warm-start runs rarely switch engines, rarely test TGI or SGLang, and rarely sweep the scheduler and memory parameters systematically.

This ablation separates two failure modes. In the first, the agent does not build or keep a valid server, and the warm start directly reduces this failure. In the second, the agent explores too little of the optimization space, and this failure remains after the warm start removes server construction. Environment setup alone therefore does not explain the remaining gap to non-agent search.

G.7 Forcing the serving engine

In the main condition, agents almost always converge on vLLM. The non-agent grid (Appendix G.5) shows that the best engine depends on the scenario: SGLang is best on the prefill-heavy Scenario A, vLLM and SGLang are best on the decode-heavy Scenario B, and TGI is best on the high-load Scenario C and the balanced Scenario D. To separate engine selection from tuning within an engine, we run a forced-engine ablation for GPT-5.4 (High), in which the agent must use a specified serving engine instead of choosing its own.

In this ablation, the modified prompt requires the agent to use a specified serving engine for the final submitted server. We test two variants: `SGLang-only` and `TGI-only`. In each variant, the agent may read documentation, edit launch scripts, tune all exposed command-line flags, and install compatible dependencies. The final server must use the required engine and must expose the same OpenAI-compatible endpoints as in the main benchmark. Runs that ship a different engine, fail either gate, or leave no reachable final server count as $1\times$. All other details are unchanged: GPT-5.4 (High), Mistral-7B-Instruct-v0.3, one H100, a 2-hour budget, the same continuation wrapper, the same three held-out seed pairs, and the same final-server scoring rule.

A forced engine improves the scenarios that suit it but does not close the gap to search. The SGLang-only variant improves Scenario A, where SGLang is also the best engine in the non-agent grid, and it matches the default condition on Scenario B. It still stays below the best SGLang search on Scenario A and below the best vLLM search on Scenario B. A stronger engine is therefore not enough without systematic tuning of the scheduler, memory, prefill, and decoding parameters. The TGI-only variant gives the clearest gain on Scenario C, well above the default GPT-5.4 condition in which the agent chooses vLLM, but it still stays below the TGI search rows. It also improves Scenario D, which agrees with the non-agent grid, where TGI is the best engine for the balanced workload. Compared with the vLLM servers that the agent selects by itself, the better forced engine gains 28% on Scenario A (SGLang), 245% on Scenario C (TGI), and 61% on Scenario D (TGI), and it matches the default on Scenario B. Agents therefore lose performance both by not exploring across engines and by not exploring enough within one engine.

Table 16: Effect of forcing GPT-5.4 (High) to use SGLang or TGI. The SGLang-only and TGI-only rows require the agent to ship the specified engine as the final server. Agent rows are penalized mean±SEM speedup over the PyTorch baseline across the three held-out seed-pair runs. Failed, unreachable, or wrong-engine final submissions count as $1\times$. The non-agent row reports the best value for each scenario over the full grid of 3 optimizers $\times$ 3 engines.

Condition	**Sc. A** TTFT	**Sc. B** TPOT	**Sc. C** req. tput	**Sc. D** geomean	**Pass rate**
GPT-5.4 (High), default prompt	3.60×±0.03	6.93×±4.46	17.78×±8.40	3.25×±1.38	10/12
GPT-5.4 (High), SGLang-only	4.62×±0.26	6.84×±2.12	29.76×±3.23	3.71×±0.54	11/12
GPT-5.4 (High), TGI-only	3.74×±0.22	3.96×±1.00	61.38×±9.70	5.24×±0.62	10/12
Per-scenario best non-agent search	5.06×	15.23×	89.00×	6.10×	–

G.8 THREE-GPU SERVING

We run GPT-5.4 (High) with three GPUs and the same three seeds per scenario. The agent reaches an aggregate speedup of $3.04 \times \pm 1.34$ (mean±SEM) with a 5/12 pass rate. In the single-GPU main condition, the same agent reaches $6.16\times$.

The transcripts show failures that do not occur with one GPU. These failures concern the parallelization strategy, device placement, distributed initialization, and communication overhead. The behavior described in Section 5 persists: the agent still chooses vLLM by default, applies basic tensor-parallel settings, makes few controlled comparisons, and spends a large part of its budget on debugging the distributed setup.