InfraGym: Empowering LLM Agents for Real-World Computer System Optimization

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Abstract

Large language model (LLM) agents have demonstrated high potential of improving performance for complex computer system, such as cluster scheduling, network congestion control, and adaptive video streaming. However, in lack of a standard, safe, and extensible benchmarking platform, it is difficult to evaluate whether these LLM agents improve real-world system performance and by how much. We present InfraGym, an open, extensible platform where researchers can study computer system optimization with LLM agents. Our current release includes three real-world cases and supports interaction with both simulated and real environments. We benchmark multiple LLM agents on these tasks using both open-source and closed-source LLMs, and outline future directions. The code is available at https://github.com/MLSysOps/InfraGym

1 Introduction

Beyond traditional agentic applications such as game playing [1, 2] and medical assistance [3, 4], we found that Large Language Model (LLM) agents start to demonstrate great potential of optimizing complex real-world computer systems, such as load balancing [5], adaptive video streaming [6] and network congestion control [7, 8]. These systems directly affect billions of users and are critical to technology companies. For example, load balancing distributes requests across servers to avoid bottlenecks, while video streaming depends on adaptive bitrate control to maintain user experience under changing bandwidth.

The success of LLM agents in optimizing computer systems is not random. Before LLMs, Reinforcement-Learning-based (RL-based) agents are widely studied by both machine learning and system research literature [9–11]. Those RL agents can achieve high performance in controlled research environments. However, they struggle to generalize to dynamic, real-world systems [12, 13]. Further, their reliance on complex training pipelines and large datasets also limits their adoption. To understand the abilities of these RL agents, RL platforms such as Park [9] were built to standardize training and evaluation of RL agents in computer systems. In contrast, LLM-based agents can generalize to real-world systems without extra training, making it much more robust when optimizing complex real-world computer systems.

However, existing RL platforms are poorly suited for LLM agents. First, they assume structured numeric states and low-level actions (e.g., bitrate levels), while LLM agents rely on natural language descriptions. Second, RL platforms emphasize training through trial-and-error for a specific case, which limits generalization and interpretability. In contrast, LLM agents excel at inference-time adaptation, reasoning [14–16], and in-context learning [17, 18]. Third, RL platforms lack flexibility: LLM agents often need preloaded prompts [19], memory [20, 21], or tools such as web search [22] and calculators [23], none of which are supported. Thus, researchers can not plug-and-play them to benchmark agent performance with ease.

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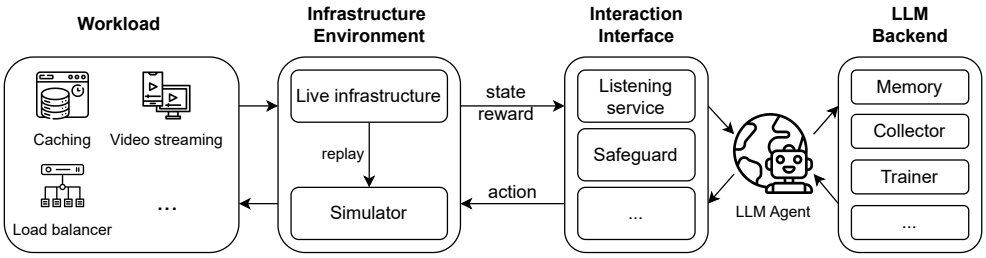


Figure 1: Overview of InfraGym. Infrastructure environments (simulated or live) send states and rewards through the interaction interface to LLM agents. Agents return actions to the interface, which validate actions before sending them to the environments. Moreover, the collector and trainer support trajectory logging and further learning.

To fill the gap, we propose to develop a new platform for building, testing, and improving LLM agents on computer system optimizations. Our design principles are as follows. First, the new system should treat natural language description as first-class input. This improves agent understanding and provides more interpretability for humans. By doing so, we open the black box of system optimizations and enable human-agent co-learning. Second, the system should pay more attention to the inference stage. Instead of training pipelines, InfraGym highlights LLMs' native abilities in reasoning, long-context processing, and tool use. Third, the platform should be highly customized. Users are able to configure the memory size, tool use, etc, to better benchmark LLM agents' ability under controlled settings.

We propose InfraGym, an open, standardized, and extensible environment with a unified interface connecting LLM agents to computer systems. First, it supports both natural language and numeric inputs and can replay traces from real-world computer systems. Second, it provides a unified interface for LLM agents to operate on simulated or production environments with ease. Meanwhile, the interface is human-readable for interpretability, validates actions for safety, and follows OpenAI Gym conventions [24] with added plug-and-play flexibility. Finally, it records agent–environment trajectories for offline analysis and reinforcement learning fine-tuning.

We evaluate agents powered by three LLMs (GPT4 [25], Gemini [26], and Qwen3 [27]) across three representative environments: video streaming, caching, and load balancing. Results show the great potential of LLM agents in reducing cost and improving resource utilization while also discussing their limitations. We open-sourced InfraGym and plan to expand it with more environments and agents to foster community-driven research: https://github.com/MLSysOps/InfraGym.

2 The InfraGym Design

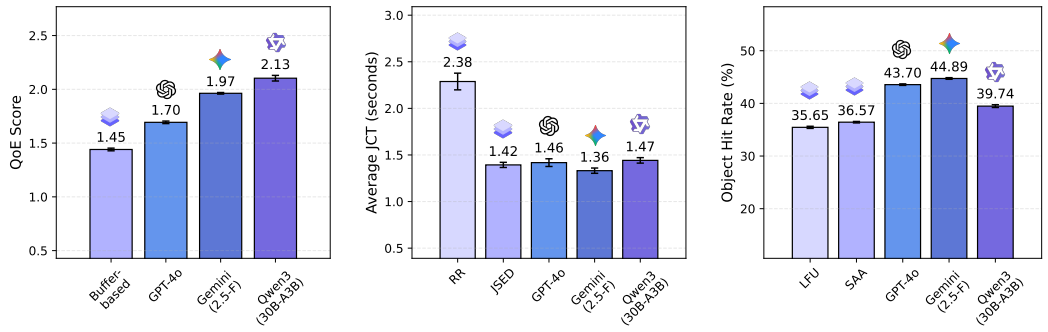
This section describes InfraGym's architecture (Figure 1). Computer environments send states and rewards to LLM agents for decision-making. Between them, InfraGym defines an interaction interface that translates raw, unstructured data into a structured observation space with optional natural language descriptions. This translation helps agents interpret environment changes and plan actions. The interface also safeguards real systems by blocking risky [28] or invalid actions [29]. In addition, InfraGym provides a collector and trainer to support continuous learning and adaptation.

```python
import infragym
from infragym import Agent

# Create a load balancing environment
env = infragym.make('load_balance',
                    num_server=3,
                    max_episode_steps=1000,
                    reward_scale=1.0)
# Init the env
obs, info = env.reset()
# Define the Agent
agent = Agent(obs['task_description'],
              obs['available_actions'])
# Agent-env interaction loop
While True:
  server_index = agent.action(obs['text_observation'])
  obs, reward, done, truncated, info = env.step(1)
# Close the env
env.close()
```

Figure 2: Example Interface of InfraGym

Infrastructure environment. InfraGym supports both simulated and live environments, each with its own states, actions, and reward functions. Simulated environments can be used in two ways: replaying real-world traces to reproduce historical events, or generating synthetic data to explore edge cases. Live environments allow direct interaction with production systems. To integrate with them, users need to follow our standards and examples to define their own wrappers.



(a) Video streaming QoE (Higher the better)

(b) Load balancing average JCT (Lower the better)

(c) Caching hit rate (Higher the better)

Figure 3: Benchmark results on InfraGym. LLM agents outperform rule-based baselines in video streaming, load balancing, and caching, showing both effectiveness and variability across LLMs.

Interaction interface. This component serves two purposes. First, it receives raw RPC requests (states and rewards) from environments and converts them into structured observations [30]. Users may choose to attach natural language descriptions as shown in Figure 2, which improve agent comprehension, or omit them to test agents' ability to interpret raw data and reduce inference latency. Second, the interface validates actions from agents and returns executable commands via RPC. This design ensures safe, seamless integration of diverse environments and agents.

LLM backend. The backend includes three components: agents, a collector, and a trainer. Users can implement agents backed by different LLMs using a unified template, enabling fast prototyping of prompts and workflows. We adopt LangGraph [31] as the agent backend. The collector, built with Langfuse [32], records trajectories of agent–environment interactions for analysis and future training. Finally, a trainer wrapper built on the Verl framework [33] supports reinforcement learning to further improve agent performance [34].

3 Benchmark Studies

We evaluate InfraGym on three representative infrastructure tasks: adaptive bitrate (ABR) streaming, caching, and load balancing. These tasks reflect core challenges in computer system optimization, including maintaining user quality of experience, reducing latency, and balancing system resources.

Experimental settings. We compare three LLM agents: GPT-4o [25], Gemini-2.5-Flash [26], and Qwen3-30B (without reasoning mode) [27], against rule-based baselines. Each experiment is repeated ten times with different seeds. For ABR and load balancing, we use simulated environments with 50 warm-up steps followed by 200 test steps. For caching, we evaluate on a real-world trace with 200 warm-up steps and 1000 test steps.

Effectiveness. Across all three tasks, LLM agents consistently outperform rule-based baselines as shown in Figure 3, highlighting their ability to adapt to dynamic system conditions. In video streaming, they deliver higher quality-of-experience scores, with Qwen3-30B achieving the best result (2.13) compared to the buffer-based baseline (1.45). We hypothesize that this advantage comes from the model's smaller size: while larger models sometimes "overthink" and hallucinate in simple decision tasks, Qwen3-30B produces more direct and stable responses, which is beneficial for ABR control. In load balancing, all LLMs reduce average job completion time, with Gemini-2.5-Flash performing best at 1.36 s versus 2.38 s for round robin. In caching, LLM agents also surpass rule-based methods such as Least Frequently Used (LFU) and Size-Aware Admission (SAA), with Gemini-2.5-Flash

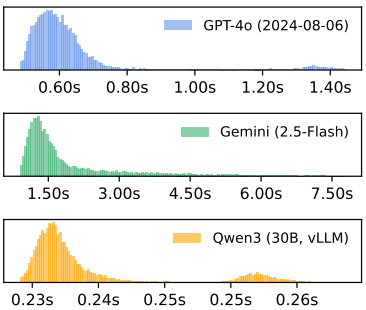


Figure 4: LLM agent latency distributions.

reaching a 44.9% hit rate compared to 35–37% for rules. These results confirm that LLM agents can generalize across different infrastructure problems, though the performance gap among models suggests opportunities to further improve robustness and efficiency.

Efficiency. Figure 4 shows the latency distribution of the three LLMs when applied to load balancing. Qwen3-30B, deployed with vLLM, achieves the lowest and most stable latency (0.23–0.26 s). GPT-4o exhibits moderate latency (0.6–1.4 s), striking a balance between responsiveness and reasoning quality. Gemini-2.5-Flash, while achieving high effectiveness, incurs the highest latency (1.5–7.5 s), limiting its suitability for latency-sensitive environments. These results reveal a trade-off between capability and efficiency, pointing to future work on hybrid strategies that combine fast small models with powerful large ones.

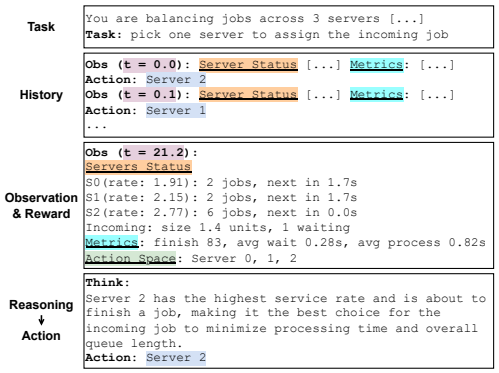


Figure 5: InfraGym case study

Cast study. Beyond performance, InfraGym enables interpretability by exposing how LLM agents reason and act. Figure 5 shows a load balancing example where the agent explains its choice of server in natural language, making the decision process transparent. Unlike RL agents, which often act as black boxes, LLM agents provide step-by-step rationales that help researchers debug, trust, and refine their behavior. InfraGym's interface supports this human–agent co-evolution, allowing users to understand mistakes, adjust prompts or rules, and iteratively improve agent policies.

4 Related Work

We review two lines of related work: LLM agents for computer system optimization, and gym-style environments for benchmarking.

LLM agents for computer system. Recent studies applied LLM agents to computer systems. One line of work [5] uses the ReAct framework for multi-objective HPC job scheduling, where LLM agents improved throughput, wait time, and fairness over FIFO and Google OR-Tools by leveraging adaptive reasoning. Other work [7, 8] explored congestion control with LLM agents, showing promising results, while NetLLM [6] unified several network optimization tasks under a single LLM framework. Unlike these task-specific efforts, InfraGym provides an open, extensible platform for both LLM and infrastructure researchers to benchmark and improve agents across diverse optimization problems.

Gym environments. Open gym environments are crucial for benchmarking and refining LLM agents. ML-Gym [35] and ML-Dojo [36] standardize machine learning tasks for evaluating ML engineering agents. SWE-Gym [37] builds software development environments for training software engineering agents. AgentGym [38] extends evaluation to interactive domains such as the web and games. In contrast, InfraGym focuses on computer systems, which pose distinct challenges: dynamic, distributed workloads and strict requirements for reliability and efficiency.

5 Conclusion

We presented InfraGym, an open platform for studying LLM agents in infrastructure optimization. InfraGym provides three key features: support for simulated and live environments, a flexible LLM backend, and a unified interaction interface. We benchmarked four LLM agents on three representative tasks, highlighting both their promise and current limitations. Despite encouraging results, InfraGym also exposes challenges of LLM agents: cost, latency, and stability. Large models often incur high inference costs and response delays, making them less suitable for latency-sensitive systems. Their decisions can also be inconsistent, raising robustness concerns. Looking ahead, we will extend InfraGym with more environments and agents, and explore hybrid strategies that combine fast small models with powerful large ones. We invite the community to build on our open-source release https://github.com/MLSysOps/InfraGym.

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