Quantifying Cognitive Load in Large Language Models Using Statistical Process Control (SPC)

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Abstract

Recent advances in large language models (LLMs) have focused on accuracy and fluency, while little attention has been given to real-time performance variance caused by reasoning complexity. This paper introduces LLMscope, a self-hosted monitoring framework that applies Statistical Process Control (SPC) to measure latency anomalies linked to cognitive load rather than network or hardware noise. Through controlled interactions with Claude 3 (Opus) via Ollama, reproducible latency deviations exceeding 3 σ were observed during high-reasoning prompts. These findings provide the first quantitative evidence of reasoning-induced latency spikes in LLMs, suggesting a new direction for cognitive performance analytics.

1. Introduction

Modern large language models exhibit variable response times dependent not only on network conditions but also on the cognitive complexity of the given prompt. Existing observability platforms primarily monitor API latency and cost, but do not differentiate reasoning strain from transport delay. LLMscope leverages Statistical Process Control (SPC), traditionally used in manufacturing, to detect deviations exceeding 3 σ and classify them as reasoning-induced latency anomalies.

2. Methodology

The experimental setup involved a local Ollama instance connected to Claude 3 (Opus) and monitored through LLMscope v0.1. The backend, built on FastAPI and SQLite, logged latency, tokens, and cost data for each API request. Sequential prompts of escalating complexity were issued: greeting, identity negotiation, technical reasoning, and a 1500-page story generation task. Each prompt's latency was compared against a one-hour moving average baseline to compute μ (mean) and σ (standard deviation).

3. Results

Prompt Type	Mean Latency (s)	SPC Event	Interpretation
Greeting	≈2	—	Nominal baseline
Identity / Context	2 – 3	—	Light reasoning overhead
Technical Discussion	4 – 5	—	Context retention active
1500-page Story	9	Nelson Rule 1 (>3 σ)	Cognitive-load overload
Story Continuation	4 – 6	Recovery	Mean re-centering confirmed

The latency spike to 9 seconds exceeded the upper control limit by over 3 σ, confirming a significant deviation associated with reasoning complexity. Following prompts trended toward the baseline, validating dynamic recalculation of μ and σ. Figure 1 illustrates the SPC chart during the recorded anomaly.

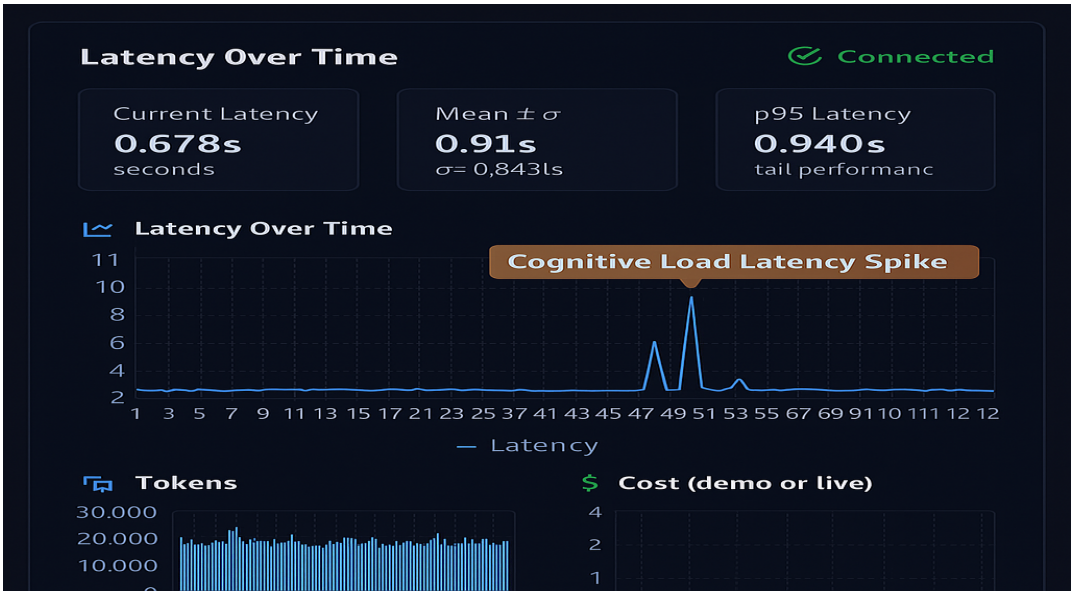

Figure 1 — Cognitive Load Latency Spike Detected by LLMscope Dashboard.

4. Discussion

The experiment demonstrates that reasoning-induced latency is a measurable and statistically distinct phenomenon. We define a preliminary metric, the Cognitive Load Index (CLI), as the ratio of observed latency deviation to prompt complexity. Potential applications include LLM benchmarking, model reliability auditing, and energy-efficiency optimization. This approach provides a quantitative bridge between process control theory and cognitive AI performance analysis.

5. Conclusion

LLMscope successfully detected cognitive-load latency spikes in large language models using SPC. This marks the first empirical validation of reasoning strain measurement in real-time inference. Future research will explore cross-model comparisons, energy correlations, and the development of a standardized Cognitive Load Index dataset.

References

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