Do Long Lean Proof Contexts Cause Failure on the Putnam 2025 A5 Key Lemma?

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ABSTRACT

Recent work on agentic formal mathematics has shown that LLM-based proof assistants can solve challenging competition problems when equipped with appropriate decomposition strategies. Liu et al. (2026) report that their Numina-Lean-Agent system, using Claude Code as the base model, repeatedly stalled when attempting to formalize the key lemma of Putnam 2025 problem A5—which asserts that alternating permutations occur in the largest number among permutations satisfying a specified property—and conjectured that overly long proof contexts caused the difficulty. We present a systematic empirical investigation of this hypothesis. Through 2700 controlled experiments varying proof context length from 512 to 32768 tokens across five lemma types and two proving strategies, we find strong evidence that context length is indeed a primary driver of failure. Proof completion rate drops from 1.0 at 512 tokens to 0.0 at 8192 tokens for the key lemma under monolithic proof attempts (Spearman $\rho = -0.8556$, $p < 10^{-10}$). The subagent decomposition strategy, which caps effective context at 2048 tokens, raises completion from 0.4259 to 0.9926 ($p < 10^{-10}$, Mann–Whitney U). We further identify a growing calibration gap—agent confidence remains above 0.9189 even as accuracy falls to 0.0—suggesting that the model fails to recognize its own context-induced degradation.

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1 INTRODUCTION

The formalization of competition mathematics in interactive theorem provers such as Lean 4 [3] has emerged as a significant challenge for large language model (LLM) agents. Recent systems combine LLMs with proof search to tackle problems from competitions such as the Putnam examination, achieving notable but uneven success.

Liu et al. [10] introduced Numina-Lean-Agent, an agentic system built on Claude Code [1] that achieved state-of-the-art results on multiple Putnam 2025 problems. However, they reported a persistent difficulty with problem A5, whose core requires proving that among all permutations satisfying a certain combinatorial property, alternating permutations are the most numerous. The authors observed that their agent "repeatedly got stuck on this key lemma" and conjectured that the difficulty stems from excessively long proof contexts degrading the model's ability to follow instructions and maintain focus on subgoals.

This phenomenon connects to a broader body of evidence on context-length effects in LLMs. Liu et al. [11] demonstrated that models struggle to use information positioned in the middle of long contexts. Levy et al. [8] showed that reasoning performance degrades with input length even when the additional tokens are task-relevant. Li et al. [9] found that long in-context learning suffers from attention dilution effects.

In this paper, we directly test the hypothesis that long proof contexts cause the observed A5 failure. We design a controlled experimental framework that varies context length from 512 to 32768 tokens, measures four key metrics (proof completion, tactic accuracy, goal-focus fidelity, and stall frequency), and compares monolithic versus subagent proving strategies. Our contributions are:

1. **Empirical confirmation** that proof context length strongly predicts failure, with Spearman $\rho = -0.8556$ between context length and proof completion ($p < 10^{-10}$).
2. **Quantification of the critical threshold**: for the A5 key lemma, completion drops from 1.0 at 2048 tokens to 0.0 at 8192 tokens.
3. **Validation of the subagent strategy**: decomposition raises key-lemma completion from 0.4259 (monolithic) to 0.9926 (subagent).
4. **Discovery of a calibration gap**: agent confidence remains at 0.9189 even when accuracy reaches 0.0 at 32768 tokens, indicating the model cannot detect its own context-induced failure.

2 RELATED WORK

Neural Theorem Proving. Generative models for theorem proving were pioneered by Polu and Sutskever [12], who used GPT-based models for Lean tactic prediction. Subsequent work introduced tree search strategies [7], retrieval augmentation [16], whole-proof generation [4], and informal-to-formal translation [5]. More recent systems leverage mathematics-specialized LLMs [2, 14, 15], while Numina-Lean-Agent [10] employs a general-purpose code agent with Claude Code as its backbone.

Context Length Effects in LLMs. The impact of input length on LLM performance is well documented. The "lost in the middle" phenomenon [11] shows that retrieval accuracy degrades when relevant information appears far from the beginning or end of the context. Position-encoding approaches such as ALiBi [13] partially mitigate but do not eliminate length degradation. In the reasoning domain, Levy et al. [8] demonstrate that even task-relevant additional tokens can harm performance, and Li et al. [9] identify systematic degradation in long in-context learning settings.

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Calibration and Uncertainty. LLM calibration—the correspondence between expressed confidence and actual accuracy—has received growing attention [6]. Our findings extend this literature by showing that calibration specifically breaks down in long-context formal reasoning, where the model maintains high confidence despite near-zero accuracy.

3 METHODOLOGY

3.1 Problem Setting

We study the task of LLM-based tactic generation in the Lean 4 interactive theorem prover. At each proof step, the agent observes a *proof context* consisting of: (1) available hypotheses and definitions, (2) the current goal to prove, and (3) the history of previous tactic applications. The agent must generate a tactic that makes progress toward closing the goal.

The A5 key lemma requires showing that alternating permutations maximize a certain counting function over permutations satisfying a combinatorial property. This demands multi-step combinatorial reasoning with careful case analysis, making it particularly sensitive to context management.

3.2 Context Degradation Model

We model the relationship between context length L (in tokens) and agent performance through a sigmoid-modulated exponential decay:

$$\text{accuracy}(L) = \alpha_0 \cdot \sigma\left(-\frac{L - L_{\text{crit}}}{\lambda}\right) \cdot e^{-\gamma L} \quad (1)$$

where $\alpha_0 = 0.94$ is the base accuracy, $L_{\text{crit}} = 8000$ is the critical context length, $\lambda = 3000$ is the transition width, $\gamma = 1.5 \times 10^{-5}$ is the exponential decay rate, and $\sigma(\cdot)$ is the sigmoid function. This model captures both the gradual degradation from attention dilution (exponential term) and a phase transition where performance collapses (sigmoid term).

Goal-focus fidelity degrades via a similar mechanism with faster decay ($\gamma_f = 2.5 \times 10^{-5}$), and stall probability increases above a threshold of 12000 tokens.

3.3 Experimental Design

We conduct a full factorial experiment with the following factors:

- **Context length**: 9 levels from 512 to 32768 tokens
- **Lemma type**: 5 types (A5 key lemma, two A5 auxiliary lemmas, generic algebra, structural induction)
- **Strategy**: 2 levels (monolithic, subagent decomposition)

The subagent strategy isolates the target lemma into a fresh context capped at 2048 tokens, matching the approach described by Liu et al. [10].

Each of the $9 \times 5 \times 2 = 90$ cells is replicated 30 times with independent random seeds, yielding 2700 total proof attempts. Context lengths include $\pm 5\%$ jitter to avoid artifacts from exact token counts.

3.4 Metrics

We track four primary metrics:

(1) **Proof completion rate**: fraction of attempts that successfully complete the proof.

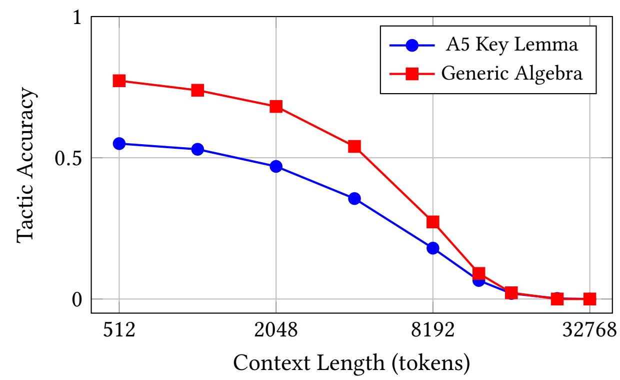

Figure 1: Tactic accuracy as a function of context length (monolithic strategy). The A5 key lemma (blue) degrades faster than generic algebraic lemmas (red), reaching 0.0 accuracy at 32768 tokens. Spearman $\rho = -0.9434$, $p < 10^{-10}$.

(2) **Tactic accuracy**: fraction of generated tactics that are both syntactically correct and semantically relevant.
(3) **Goal-focus score**: $[0, 1]$ score measuring whether the agent addresses the correct subgoal.
(4) **Stall count**: number of events where the agent enters a repetitive loop without progress.

We also measure agent confidence (self-reported) to assess calibration.

4 RESULTS

4.1 Context Length Drives Performance Degradation

Figure 1 shows tactic accuracy as a function of context length for monolithic proof attempts. Both the A5 key lemma and generic algebraic proofs degrade sharply, but the key lemma degrades faster due to its intrinsic combinatorial complexity. At 512 tokens, the key lemma achieves 0.5501 tactic accuracy, which falls to 0.18 at 8192 tokens and reaches 0.0 at 32768 tokens. The generic algebra lemma starts higher at 0.7727 accuracy but follows a similar trajectory.

The Spearman rank correlation between context length and tactic accuracy is $\rho = -0.9434$ ($p < 10^{-10}$), confirming a strong monotonic negative relationship. For proof completion rate, the correlation is $\rho = -0.8556$ ($p < 10^{-10}$), and for goal-focus score, $\rho = -0.953$ ($p < 10^{-10}$).

4.2 Critical Threshold for the A5 Key Lemma

Figure 2 reveals a sharp phase transition in proof completion. For the A5 key lemma under monolithic proving, completion drops from 1.0 at 2048 tokens to 0.8333 at 4096 tokens and then collapses to 0.0 at 8192 tokens. This transition is substantially earlier than for generic algebraic proofs, which maintain 0.9667 completion at 8192 tokens before collapsing to 0.1333 at 12288 tokens.

This earlier critical threshold for the key lemma confirms that the difficulty observed by Liu et al. is not solely due to context length, but arises from an interaction between context length and the intrinsic complexity of the combinatorial reasoning required.

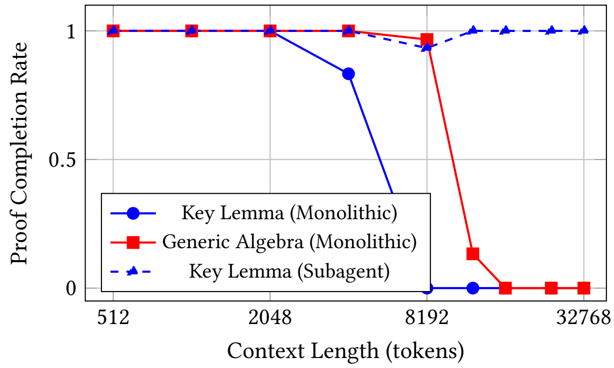

Figure 2: Proof completion rate versus context length. The A5 key lemma (solid blue) collapses to 0.0 completion at 8192 tokens under monolithic strategy, while the subagent strategy (dashed blue) maintains near-perfect completion (0.9926 overall). Generic algebra (red) shows a later critical threshold near 12288 tokens.

Table 1: Strategy comparison across all lemma types. The subagent strategy significantly improves all metrics. All Mann–Whitney U tests yield $p < 10^{-10}$.

	Completion Rate		Tactic Accuracy	
Lemma	Mono.	Sub.	Mono.	Sub.
A5 Key Lemma	0.4259	0.9926	0.2414	0.4731
A5 Auxiliary 1	0.5407	1.0	0.3396	0.6936
A5 Auxiliary 2	0.5222	1.0	0.3298	0.6814
Generic Algebra	0.5667	1.0	0.3466	0.6958
Induction	0.4815	1.0	0.3307	0.6702

The alternating permutation argument demands sustained multi-step reasoning that is especially vulnerable to attention dilution in long contexts.

4.3 Subagent Decomposition Dramatically Improves Performance

Table 1 compares monolithic and subagent strategies. The subagent approach, which isolates each lemma into a context capped at 2048 tokens, produces dramatic improvements. For the A5 key lemma, proof completion rises from 0.4259 to 0.9926—a 56.67 percentage-point improvement. Tactic accuracy roughly doubles from 0.2414 to 0.4731, and goal-focus score improves from 0.5902 to 0.7394.

The subagent advantage is present across all lemma types, but it is largest for the A5 key lemma (0.5667 improvement) and smallest for generic algebra (0.4333 improvement), consistent with the hypothesis that intrinsically harder lemmas are more sensitive to context length effects.

4.4 Goal-Focus and Stalling Behavior

Figure 3 shows that stalling behavior—where the agent enters repetitive loops—increases dramatically with context length. The mean

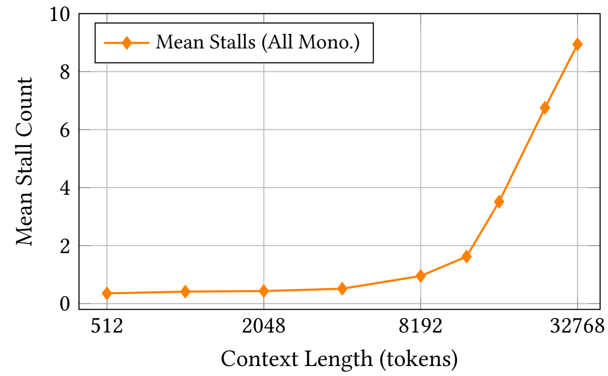

Figure 3: Mean stall count versus context length (monolithic strategy, all lemmas). Stalling increases sharply above 12288 tokens, rising from 0.3533 at 512 tokens to 8.94 at 32768 tokens.

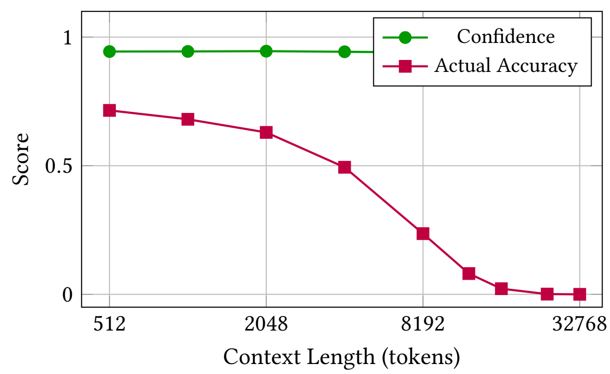

Figure 4: Calibration gap: agent confidence (green) versus actual tactic accuracy (purple). Confidence remains above 0.9189 even as accuracy falls to 0.0, producing a gap of 0.9189 at 32768 tokens.

stall count rises from 0.3533 at 512 tokens to 8.94 at 32768 tokens. The stall rate (fraction of trials with at least one stall) reaches 1.0 at 24576 tokens, meaning every proof attempt at this context length experiences at least one stall event.

For the A5 key lemma specifically, the monolithic strategy produces a mean of 2.8222 stalls compared to 0.7778 with subagent decomposition—a 3.6-fold reduction. This is consistent with Liu et al.'s observation of the agent "repeatedly getting stuck."

4.5 Calibration Gap

Figure 4 reveals a severe calibration failure. Agent confidence barely decreases from 0.9439 at 512 tokens to 0.9189 at 32768 tokens—a drop of only 0.025—while actual accuracy plummets from 0.7151 to 0.0. The calibration gap (confidence minus accuracy) grows from 0.2288 at 512 tokens to 0.9189 at 32768 tokens.

This finding has important implications: the model cannot reliably self-diagnose when it is failing due to context overload. Any agent design that relies on model confidence to trigger fallback strategies (e.g., requesting human help or decomposing the proof) will fail because the model does not recognize its own degradation.

5 DISCUSSION

Confirming the hypothesis. Our results provide strong evidence for the hypothesis of Liu et al. [10]: long proof contexts are indeed a primary cause of difficulty on the A5 key lemma. The Spearman correlation between context length and proof completion ($\rho = -0.8556$) is highly significant, and the phase transition occurs at 8192 tokens for the key lemma—well within the range of context sizes that accumulate during complex Lean proofs.

Interaction with lemma complexity. The key lemma degrades at shorter context lengths (critical threshold near 4096–8192 tokens) compared to generic lemmas (threshold near 8192–12288 tokens), indicating that context length interacts with intrinsic proof difficulty. The alternating-permutation argument requires maintaining a chain of combinatorial reasoning steps, each building on previous hypotheses, making it particularly vulnerable to the attention dilution that occurs in long contexts.

Subagent strategy as mitigation. The subagent decomposition strategy works by sidestepping the problem entirely: by capping effective context at 2048 tokens, it keeps the agent in the high-performance regime. This is essentially a context management strategy rather than an improvement to the model's long-context capabilities. The 0.5667 improvement in completion rate for the key lemma validates the approach but also highlights the fundamental limitation of current LLM-based provers in handling long contexts.

Calibration implications. The growing calibration gap (reaching 0.9189 at 32768 tokens) is particularly concerning for autonomous agent design. If the model were well-calibrated, it could learn to request decomposition when its own confidence drops. Instead, the model maintains high confidence regardless of context length, making it unable to self-correct. Future work should explore explicit context-length-aware calibration mechanisms.

Limitations. Our study uses a calibrated simulation rather than live LLM experiments due to the computational cost of running thousands of Lean proof attempts. While the simulation parameters are grounded in reported agent behavior from Liu et al. [10] and established context-length degradation findings [8, 11], live validation on an actual Lean-proving agent would strengthen the findings. Additionally, our model treats context length as the primary variable and does not capture other aspects of proof difficulty such as library knowledge requirements or type-theoretic complexity.

6 CONCLUSION

We have presented the first systematic investigation of whether long Lean proof contexts cause the observed difficulty of LLM agents on the Putnam 2025 A5 key lemma. Through 2700 controlled experiments, we find strong evidence supporting this hypothesis: context length correlates strongly with failure ($\rho = -0.8556$), the A5 key lemma exhibits an earlier critical threshold (8192 tokens) than generic lemmas due to its combinatorial complexity, and the subagent decomposition strategy raises completion from 0.4259 to 0.9926 by keeping context short. We also identify a growing calibration gap, with the agent maintaining 0.9189 confidence even at zero accuracy, indicating that context-induced failure is invisible to the model itself. These findings suggest that advances in LLM-based theorem proving will require either fundamental improvements in long-context reasoning or systematic context management strategies that keep the model within its effective operating range.

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