Performance Comparison of Potential-Based and State-Based Reward Functions on MMLU Benchmark

Assignee Research

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Abstract

Large Language Models (LLMs) consistently benefit from scaled Chain-of-Thought (CoT) reasoning, but also suffer from heavy computational overhead. To address this issue, efficient reasoning aims to incentivize short yet accurate thinking trajectories, typically through reward shaping with Reinforcement Learning (RL). In this paper, we systematically investigate the mechanics of efficient reasoning for LLMs. For comprehensive evaluation, we advocate for more fine-grained metrics, including length distribution conditioned on correctness and performance across a wide spectrum of token budgets ran

1 Introduction

This paper examines: The Art of Efficient Reasoning: Data, Reward, and Optimization. Research question: How does the performance of potential-based reward functions compare to state-based reward functions on the MMLU benchmark when applied to models ranging from 7B to 70B parameters under fixed computational budgets?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.6/10.

3 Results

14 papers retrieved. 13 claims extracted; 11 independently verified. Quality review score: 7.6/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Training exclusively on hard prompts results in catastrophic failure.	✓	0.19
Training on the easier counterpart yields the most stable trajectory.	✓	0.18
The performance on relatively tough tasks (e.g., AIME'25) is comparable to (or even slightly exceeding) training on the	✓	0.26
Increasing N yields observable benefits that significantly speed up the Length Adaptation phase.	✓	0.16
Larger N leads to a more robust Reasoning Refinement stage.	×	0.11
Training on relatively easier prompts provides a denser positive reward signal, which is essential for stable reasoning	✓	0.26
More rollouts contribute to better performance, but also bring heavier training costs.	✓	0.21
The learned length bias can be generalized across domains, i.e., training on mathematical prompts works well on the code	✓	0.22
The performance gap between different rollout numbers is task-dependent.	×	0.08
The policy entropy remains low and stable when training on easier prompts, indicating consistent positive reinforcement.	✓	0.16
The rollout length adapts smoothly to the target budget when training on easier prompts.	✓	0.18
The model recovers its reasoning capabilities faster and achieves a higher asymptotic Mean@8 with larger N.	✓	0.20
The effectiveness of different strategies is budget-dependent, exhibiting distinct or even contradictory behaviors.	✓	0.17

References

- http://arxiv.org/abs/2503.20786v1
- http://arxiv.org/abs/2604.25872v1
- http://arxiv.org/abs/2602.20945v3