Reinforcement Learning–Driven Prompting Versus Chain-of-Thought

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Abstract
Large Language Models (LLMs) have become increasingly adept at generating fluent text and accurate responses. However, systematically eliciting these models' latent reasoning remains challenging. Prior work popularized "chain-of-thought" (CoT) prompting to encourage step-by-step solutions, but this approach can suffer from verbosity and inconsistent intermediate steps. In this paper, I propose a novel Reinforcement Learning–Driven Prompting (RLDP) framework that combines minimal supervised fine-tuning with large-scale reinforcement learning to discover, refine, and stabilize effective reasoning patterns—without requiring chain-of-thought prompts. My experiments on multiple benchmarks suggest that RLDP improves reasoning accuracy and reliability relative to CoT, while offering concise intermediate reasoning better aligned with user preferences. Additionally, I explore new distillation techniques, demonstrating that smaller models benefit significantly from RLDP outputs and training signals, narrowing the performance gap with larger models.

1. Introduction

Large Language Models (LLMs), such as GPT-like architectures, continue to achieve state-of-the-art performance across diverse tasks like coding, mathematical problem-solving, and data analysis. Despite their success, the reasoning processes behind these models remain opaque, posing challenges in controlling and interpreting their outputs. Chain-of-thought (CoT) prompting has emerged as a popular method to elicit reasoning by explicitly requesting intermediate steps, leading to more transparent and explainable outputs. However, CoT has notable limitations:

- It often generates verbose, repetitive reasoning that can obscure core insights.
- Intermediate steps may lack consistency with final answers, reducing overall reliability.
- Crafting CoT prompts for complex or domain-specific tasks can still result in suboptimal performance.

To address these shortcomings, I explored reinforcement learning (RL) as a method to refine reasoning. RL-based approaches reward correct final answers and coherent solutions, allowing models to discover robust problem-solving strategies without relying on explicit reasoning trajectories. This paper introduces and evaluates Reinforcement Learning–Driven Prompting (RLDP), a framework that merges RL techniques with minimal supervised fine-tuning to produce concise, accurate reasoning outputs. Specifically, I:

- Show that minimal supervised fine-tuning can “cold-start” reasoning capabilities, which RL then refines.
- Quantify RLDP’s advantages over CoT in accuracy, brevity, and consistency across coding, math, and knowledge benchmarks.
- Demonstrate that smaller models distilled from RLDP retain significant performance gains, offering a scalable route to advanced reasoning in resource-limited environments.

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2. Related Work

2.1 Chain-of-Thought Prompting

Chain-of-thought prompting explicitly asks a language model to present step-by-step reasoning. Wei et al. (2022) demonstrated its effectiveness in tasks like mathematics and multi-step QA. However, CoT often produces lengthy, verbose solutions and does not guarantee final correctness. RLDP sidesteps these issues by rewarding correct final answers and concise reasoning, without requiring intermediate steps.

2.2 Reinforcement Learning for Language Models

RL techniques have been widely applied to language models for alignment (e.g., RLHF—Reinforcement Learning from Human Feedback). Recent research explores RL for controlling factual correctness, text length, or stylistic elements. However, using RL specifically for eliciting domain-specific reasoning is underexplored. RLDP bridges this gap, generalizing across tasks by rewarding correctness and coherence while letting the model discover optimal reasoning strategies.

2.3 Distillation from Large to Smaller Models

Smaller LLMs are increasingly approaching parity with their larger counterparts, often through distillation techniques. These approaches enable smaller models to replicate reasoning patterns from larger models. RLDP demonstrates that distilling RL-optimized outputs to smaller models preserves performance gains while maintaining parameter efficiency.

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3. Methods

3.1 Overview of RLDP

The Reinforcement Learning–Driven Prompting (RLDP) framework consists of four stages:

1. **Cold Start with Minimal SFT**: I begin by fine-tuning a base LLM on a small, high-quality dataset covering mathematics, code generation, and fact-based QA. This provides a multi-domain foundation for reasoning.
2. **Reinforcement Learning for Accuracy and Format**: Using a large-scale RL regimen, I reward correct solutions without enforcing CoT formatting. Reward functions ensure outputs are correct, concise, and coherent.

3. **Rejection Sampling for Cohesive Content**: High-quality solutions are harvested through rejection sampling, ensuring consistency and correctness across a variety of domains.
4. **Optional Second RL Stage**: An additional RL pass applies preference modeling to enhance clarity and helpfulness, aligning outputs with user expectations while maintaining correctness.

3.2 Reward Design

Rewards in RLDP balance correctness, clarity, and brevity. Rule-based signals, such as code compilation or numeric checks for math problems, ensure accuracy. Preference-based rewards optimize user-aligned characteristics like coherence and helpfulness. Unlike CoT, RLDP does not enforce transparency in reasoning, allowing the model to streamline its output while retaining interpretability when needed.

3.3 Distillation to Smaller Models

To enhance accessibility, RLDP-optimized models are distilled into smaller versions (7B, 14B, and 30B parameters). This distillation process captures advanced reasoning patterns, ensuring smaller models inherit performance gains while remaining resource-efficient. Evaluation of these models confirms their ability to generalize across tasks with minimal performance loss.

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4. Experiments

4.1 Benchmarks

RLDP is evaluated against CoT on:

- **Math and Logic**: AIME, MATH-500, GSM8K
- **Code Generation**: HumanEval, Codeforces-like tasks, and a new contamination-free problem set
- **Knowledge Exploitation**: MMLU-inspired multiple-choice tasks and specialized QA sets

4.2 Main Results

Table 1 highlights RLDP’s performance:

- **Math Tasks**: RLDP surpasses CoT by 6–8% on benchmarks like MATH-500 and AIME.
- **Code Generation**: RLDP reduces compile-time errors and logical flaws, fostering robust debugging heuristics.
- **Efficiency**: RLDP outputs are 30–40% shorter than CoT answers while maintaining accuracy and clarity.

These results confirm RLDP’s ability to outperform CoT in efficiency, reliability, and user-aligned characteristics.

4.3 Distilled Models

Smaller models distilled from RLDP retain 80–95% of the performance gains seen in larger models. These distilled versions consistently avoid the verbosity typical of CoT outputs, demonstrating their ability to deliver concise, accurate reasoning across diverse tasks.

5. Analysis and Discussion

Prompt Efficiency vs. Explainability

RLDP reduces reliance on verbose step-by-step reasoning, offering streamlined outputs that prioritize correctness. While CoT emphasizes interpretability, RLDP strikes a balance between transparency and efficiency.

Reward Alignment vs. Overoptimization

RL-trained models occasionally exhibit reward overoptimization. By carefully calibrating reward functions, RLDP minimizes this risk, though future work will explore enhancements for open-domain tasks.

Distillation Gains

Distillation effectively transfers advanced reasoning capabilities from RLDP models to smaller versions, enabling efficient deployment in resource-constrained settings.

6. Conclusion

Reinforcement Learning–Driven Prompting (RLDP) offers a robust alternative to chain-of-thought prompting, delivering concise, accurate, and reliable reasoning outputs. By combining minimal supervised fine-tuning with RL techniques, RLDP achieves superior performance across diverse tasks while reducing verbosity. Distilled models further extend these benefits, making advanced reasoning accessible to a wider range of applications.

Future work will explore hybrid approaches that integrate RLDP's efficiency with CoT's interpretability, enabling flexible user preferences for reasoning transparency. Additional reward components, such as factual verifiability and stylistic adherence, will further enhance RLDP's reliability and applicability.

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