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1. Introduction

In recent years, Large Language Models (LLMs) have been undergoing rapid iteration and evolution (Anthropic, 2024; Google, 2024; OpenAI, 2024a), progressively diminishing the gap towards Artificial General Intelligence (AGI).

Recently, post-training has emerged as an important component of the full training pipeline. It has been shown to enhance accuracy on reasoning tasks, align with social values, and adapt to user preferences, all while requiring relatively minimal computational resources against pre-training. In the context of reasoning capabilities, OpenAI's o1 (OpenAI, 2024b) series models were the first to introduce inference-time scaling by increasing the length of the Chain-of-Thought reasoning process. This approach has achieved significant improvements in various reasoning tasks, such as mathematics, coding, and scientific reasoning. However, the challenge of effective test-time scaling remains an open question for the research community. Several prior works have explored various approaches, including process-based reward models (Lightman et al., 2023; Uesato et al., 2022; Wang et al., 2023), reinforcement learning (Kumar et al., 2024), and search algorithms such as Monte Carlo Tree Search and Beam Search (Feng et al., 2024; Trinh et al., 2024; Xin et al., 2024). However, none of these methods has achieved general reasoning performance comparable to OpenAI's o1 series models.

In this paper, we take the first step toward improving language model reasoning capabilities using pure reinforcement learning (RL). Our goal is to explore the potential of LLMs to develop reasoning capabilities without any supervised data, focusing on their self-evolution through a pure RL process. Specifically, we use DeepSeek-V3-Base as the base model and employ GRPO (Shao et al., 2024) as the RL framework to improve model performance in reasoning. During training, DeepSeek-R1-Zero naturally emerged with numerous powerful and interesting reasoning behaviors. After thousands of RL steps, DeepSeek-R1-Zero exhibits super performance on reasoning benchmarks. For instance, the pass@1 score on AIME 2024 increases from 15.6% to 71.0%, and with majority voting, the score further improves to 86.7%, matching the performance of OpenAI-o1-0912.

However, DeepSeek-R1-Zero encounters challenges such as poor readability, and language mixing. To address these issues and further enhance reasoning performance, we introduce DeepSeek-R1, which incorporates a small amount of cold-start data and a multi-stage training pipeline. Specifically, we begin by collecting thousands of cold-start data to fine-tune the DeepSeek-V3-Base model. Following this, we perform reasoning-oriented RL like DeepSeek-R1-Zero. Upon nearing convergence in the RL process, we create new SFT data through rejection sampling on the RL checkpoint, combined with supervised data from DeepSeek-V3 in domains such as writing, factual QA, and self-cognition, and then retrain the DeepSeek-V3-Base model. After fine-tuning with the new data, the checkpoint undergoes an additional RL process, taking into account prompts from all scenarios. After these steps, we obtained a checkpoint referred to as DeepSeek-R1, which achieves performance on par with OpenAI-o1-1217.

We further explore distillation from DeepSeek-R1 to smaller dense models. Using Qwen2.5-32B (Qwen, 2024b) as the base model, direct distillation from DeepSeek-R1 outperforms applying RL on it. This demonstrates that the reasoning patterns discovered by larger base models are crucial for improving reasoning capabilities. We open-source the distilled Qwen and Llama (Dubey et al., 2024) series. Notably, our distilled 14B model outperforms state-of-the-art open-source QwQ-32B-Preview (Qwen, 2024a) by a large margin, and the distilled 32B and 70B models set a new record on the reasoning benchmarks among dense models.