Report on the Research Paper: "Distillation: Smaller Models Can Be Powerful Too" by [Authors]

Abstract
This research paper presents DeepSeek-R1, a model designed to parallel the performance of OpenAI's o1-1217 in reasoning tasks. The authors introduce an array of models, including DeepSeek-R1-Zero, DeepSeek-R1, and multiple distilled models ranging from 1.5 billion to 70 billion parameters, derived from DeepSeek-R1. The study explores reinforcement learning (RL) methodologies, particularly focusing on self-evolution of large language models (LLMs) through unsupervised RL, and examines the distillation process to create efficient smaller models that retain the reasoning prowess of larger counterparts. Introduction to DeepSeek-R1 Models

The research highlights the open-sourcing of various models, including DeepSeek-R1 and its distilled variants, to aid the research community. The focus is on advancing reasoning abilities in LLMs via reinforcement learning without relying on extensive supervised datasets. The GRPO (Generalized Policy Optimization) framework by Shao et al. (2024) is utilized to bolster the reasoning capabilities, demonstrating that the reinforcement learning paradigm can significantly enhance model performance.

DeepSeek-R1-Zero: Reinforcement Learning on the Base Model

Reinforcement Learning Algorithm

The paper outlines a reinforcement learning approach applied to foundational models, detailing the specific algorithms and novel techniques adapted for the base model. Reward Modeling

An essential component is the reward modeling mechanism, which structures and computes rewards within the RL framework, providing feedback that influences the model's learning trajectory and decision-making processes. Distilled Model Evaluation

This section elaborates on the evaluation of distilled models, which are simplified yet efficient versions of larger models, retaining most predictive performance. The evaluation metrics include accuracy, computational efficiency, and cost analysis. Discussion: Model Distillation vs. Reinforcement Learning

The authors compare model distillation with reinforcement learning, discussing the strengths and limitations of each. While distillation transfers the knowledge of complex models to simpler ones, RL equips agents to learn decision-making through rewards, showcasing applications where these methodologies can complement each other. Methodology

GRPO Objective

GRPO is presented as an efficient RL algorithm, substituting the traditional critic model with a group score-based baseline, optimizing the policy by maximizing expected rewards while minimizing KL divergence from a reference policy. Training and Performance of DeepSeek-R1-Zero

DeepSeek-R1-Zero employs a rule-based reward system, enhancing the model's reasoning capabilities without supervised fine-tuning. The template structure guides the model's learning, significantly improving its scoring on benchmarks like AIME 2024. Self-Evolution and "Aha Moments"

The model exhibits self-evolution, autonomously refining its reasoning strategies, illustrated by "aha moments" where it revisits problem-solving approaches, emphasizing the efficacy of RL in fostering sophisticated reasoning skills. DeepSeek-R1: Cold Start Reinforcement Learning

DeepSeek-R1 introduces a cold start method, using minimal high-quality data to kickstart training. The pipeline integrates this data with reasoning-oriented RL, rejection sampling, and supervised fine-tuning, achieving remarkable performance improvements. Experimental Results

The paper showcases the success of the DeepSeek-R1 model and its distilled variants across numerous benchmarks. Notably, the 14B distilled model surpasses the QwQ-32B-Preview model, and larger distilled models set new records in reasoning benchmarks. Conclusion: Distillation and Future Directions

Distillation has proven to be an effective technique to retain reasoning capabilities in smaller models, although large-scale RL remains crucial for achieving peak performance. The paper acknowledges challenges such as readability and language inconsistencies, proposing future efforts to enhance general capabilities, language consistency, and optimization for specific tasks like software engineering. Overall, the study presents significant advancements in model reasoning through innovative applications of RL and distillation, providing a robust framework for future research and development in machine learning.