Enhancing Reasoning in Language Models Through Chain-of-Thought Prompting

Abstract

This research paper presents an innovative approach to improving the reasoning capabilities of large pre-trained language models (LMs) through a technique known as chain-of-thought prompting. By feeding models examples that demonstrate step-by-step reasoning processes, the study shows significant enhancements in the models' abilities to tackle complex tasks in arithmetic reasoning, commonsense reasoning, and symbolic reasoning. Experiments conducted on three large language models, including the PaLM 540B model, demonstrate record-breaking performance on benchmarks such as the GSM8K math word problem, showcasing the potential of chain-of-thought prompting to revolutionize how LMs handle reasoning tasks.

Introduction and Background

The paper begins by acknowledging the advancements in language model performance and efficiency due to increased model sizes, as discussed in works by Kaplan et al. (2020) and Brown et al. (2020). However, it also highlights the limitations identified by Rae et al., indicating that simply scaling up model size is insufficient for excelling in complex reasoning areas. This sets the stage for the introduction of chain-of-thought prompting as a method to address these challenges by enhancing the reasoning abilities of LMs.

Chain-of-Thought Prompting Methodology

Chain-of-thought prompting is described as a technique that encourages models to break down problems into a series of natural language reasoning steps before arriving at a final answer. This approach mimics human problem-solving strategies, particularly for complex questions requiring multi-step reasoning. By guiding LMs through a thought process similar to that of humans, the technique aims to make the reasoning explicit and easier to follow, thereby improving the models' problem-solving capabilities.

Experimental Setup and Results

The research involved comparing the effectiveness of standard few-shot prompting and chain-of-thought prompting across multiple datasets, including GSM8K, SVAMP, ASDiv, AQuA, and MAWPS. The findings revealed that chain-of-thought prompting significantly outperformed standard prompting methods, especially in models with over 100 billion parameters. Notably, the PaLM 540B model achieved unprecedented success on the GSM8K math word problem benchmark, surpassing even a specially adjusted GPT-3 model. Additionally, the study explored the robustness of this prompting technique across different annotators and styles, finding it effective not only in arithmetic reasoning but also in commonsense and symbolic reasoning tasks. This suggests a broad applicability of the method beyond specific domains, potentially aiding in out-of-domain generalization for various reasoning tasks.

Discussion and Limitations

While the paper reports substantial improvements in reasoning tasks through chain-of-thought prompting, it also acknowledges certain limitations. These include questions around the nature of " reasoning" as performed by LMs and the cost implications of scaling up models. The paper calls for future research to explore other prompting methods and ways to improve the factual accuracy of model generations.

Conclusion

This research highlights the significant potential of chain-of-thought prompting in enhancing the reasoning capabilities of large language models. By demonstrating improved performance across a range of complex tasks, the study not only sets new benchmarks but also opens up avenues for further exploration into the applicability and optimization of this method. The findings contribute valuable insights into how LMs can be better prompted to perform complex reasoning, marking a step forward in the development of more intelligent and versatile AI systems.