

# LogiCoT: Logical Chain-of-Thought Instruction Tuning

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## Abstract

Generative Pre-trained Transformer 4 (GPT-4) demonstrates impressive chain-of-thought reasoning ability. Recent work on self-instruction tuning, such as Alpaca, has focused on enhancing the general proficiency of models. These instructions enable the model to achieve performance comparable to GPT-3.5 on general tasks like open-domain text generation and paraphrasing. However, they fall short of helping the model handle complex reasoning tasks. To bridge the gap, this paper presents LogiCoT, a new instruction-tuning dataset for **Logical Chain-of-Thought** reasoning with GPT-4. We elaborate on the process of harvesting instructions for prompting GPT-4 to generate chain-of-thought rationales. LogiCoT serves as an instruction set for teaching models of logical reasoning and elicits general reasoning skills.

## 1 Introduction

Instruction tuning Large Language Models (LLMs) has become a popular paradigm for Natural Language Processing (NLP) in recent years (Ouyang et al., 2022; Sun et al., 2022). A prominent line of research is the development of OpenAI’s ChatGPT and GPT-4 (OpenAI, 2023). LLMs demonstrate multi-step chain-of-thought (CoT) reasoning ability with proper prompting (Kojima et al., 2022; Huang and Chang, 2022). CoT instruction tuning has drawn attention for its potential to encourage complex, step-by-step reasoning. For example, Wei et al. (2023) and Kojima et al. (2022) have demonstrated the ability of LLMs to generate a coherent sequence of reasoning steps leading to the final answer through CoT prompting. Moreover, ChatGPT and GPT-4 have shown remarkable zero-shot complex reasoning abilities on several logical reasoning datasets (Liu et al., 2023a).

Yet, developing such proprietary models as GPT-4 and ChatGPT often necessitates intensive data

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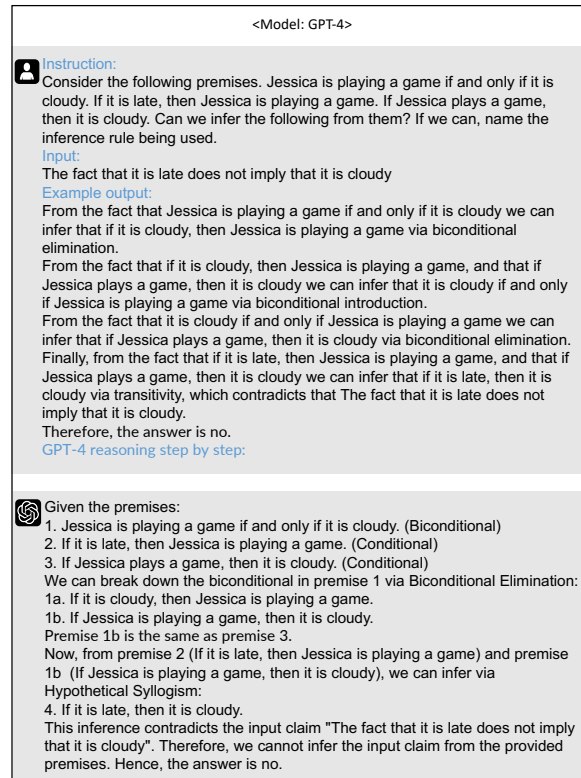


Figure 1: A showcase of using GPT-4 and existing inference data to generate CoT rationales for logical reasoning.

and instruction engineering, a process that has, thus far, been largely kept private. Recent research endeavours have begun to explore the distillation of the instruction data using self-instruct techniques (Wang et al., 2022; Peng et al., 2023), where GPT-3 or GPT-4 are used to generate instruction-following examples. This technique represents a promising avenue for reducing the human labour involved in instruction tuning, offering a more economical way to produce community models trained with instructional data. A paradigmatic example is the pipeline by Wang et al. (2022) for cultivating instruction data, where initial instructions are authored by humans, and LLMs are then used to extend this instruction data. This pipeline has been used to produce multiple open-sourced, instruction-tuned