Adversarial Training and Chain-of-Thought Prompting for CodeT5 Reasoning Accuracy

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: What is the impact of combining adversarial training with chain-of-thought prompting on the reasoning accuracy of CodeT5 when solving complex algorithmic tasks in the HumanEval dataset. 13 claims were extracted from source literature; 2 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Prompt Selection and Augmentation for Few Examples Code Generation in Large Language Model and its Application in Robotics Control. Research question: What is the impact of combining adversarial training with chain-of-thought prompting on the reasoning accuracy of CodeT5 when solving complex algorithmic tasks in the HumanEval dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.5/10.

3 Results

16 papers retrieved. 13 claims extracted; 2 independently verified. Quality review score: 4.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
In simulated tabletop environments, the proposed algorithm achieves a 3.4% increase in successful task completions compa	✓	0.21
In simulated tabletop environments, the proposed algorithm decreases the number of examples used by over 70% compared to	✓	0.19
The GSM8K dataset consists of 1310 question-answer pairs excluding examples in the prompts.	×	0.03
The SVAMP dataset consists of 1000 question-answer pairs excluding examples in the prompts.	×	0.03
A subset of 200 Q&A pairs from the GSM8K training set was used to finetune weights.	×	0.03
Using Gemini Pro on the GSM8K dataset, the proposed algorithm achieved an accuracy of 76.9%, compared to 76.6% for the s	×	0.02
Using Gemini Pro on the GSM8K dataset, the proposed algorithm reduced the number of examples from 9 to 3.98.	×	0.06
Using Gemini Pro on the SVAMP dataset, the proposed algorithm achieved an accuracy of 86.7%, compared to 85.7% for the s	×	0.02
Using Gemini Pro on the SVAMP dataset, the proposed algorithm reduced the number of examples from 7 to 3.26.	×	0.06
Using GPT-3.5-turbo-instruct on the GSM8K dataset, the proposed algorithm achieved an accuracy of 74.1%, compared to 73.	×	0.02
Using GPT-3.5-turbo-instruct on the SVAMP dataset, the proposed algorithm achieved an accuracy of 77.5%, compared to 77.	×	0.02
Using GPT-3.5-turbo-instruct on the SVAMP dataset, the proposed algorithm reduced the number of examples from 7 to 3.26.	×	0.05
Bayesian Optimization was chosen for finetuning weights due to the expensive inferencing nature of LLMs.	×	0.03

References

- http://arxiv.org/abs/2410.03595v1

- http://arxiv.org/abs/2403.12999v1
- http://arxiv.org/abs/2007.08428v4