Tool Diversity and Robustness in Multi-Agent Debate Systems Against Adversarial Prompts

Assignee Research

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Abstract

State-of-the-art few-shot learning (FSL) methods leverage prompt-based fine-tuning to obtain remarkable results for natural language understanding (NLU) tasks. While much of the prior FSL methods focus on improving downstream task performance, there is a limited understanding of the adversarial robustness of such methods. In this work, we conduct an extensive study of several state-of-the-art FSL methods to assess their robustness to adversarial perturbations. To better understand the impact of various factors towards robustness (or the lack of it), we evaluate prompt-based FSL methods against

1 Introduction

This paper examines: Adversarial Robustness of Prompt-based Few-Shot Learning for Natural Language Understanding. Research question: What is the impact of tool diversity on the robustness of multi-agent debate systems against adversarial prompts in standard reasoning evaluation suites?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

10 papers retrieved. 9 claims extracted; 9 independently verified. Quality review score: 8.5/10.

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
Using unlabeled data (iPET) during fine-tuning causes prompting to reduce the drop in adversarial performance with respe	✓	0.26
Using multiple prompts to fine-tune multiple models (PET) and ensembling the resultant predictions causes prompting to d	✓	0.35
Increasing the number of few-shot examples reduces the relative drop in adversarial performance with respect to in-domai	✓	0.27
Increasing the encoder size reduces the relative drop in adversarial performance with respect to in-domain performance.	✓	0.26
RoBERTa encoders are more adversarially robust than ALBERT and BERT encoders of comparable size.	✓	0.18
Vanilla few-shot learning (FSL) methods lead to a notable relative drop in task performance compared to fully fine-tuned	✓	0.40
The study evaluates four FSL methods: Classic fine-tuning, LM-BFF, PET, and iPET.	✓	0.17
FewNLU is a benchmark designed to evaluate the performance of prompt-based few-shot learning capabilities systematically	✓	0.21
Prompt-based learning frames downstream tasks as a MASK prediction task to match the fine-tuning objective with the pre-	✓	0.16

References

- http://arxiv.org/abs/2203.08975v2
- http://arxiv.org/abs/2503.17371v2

- http://arxiv.org/abs/2306.11066v2