

Vendi-RAG Diversity-Weight Effects on FLAN-T5-xl Performance in Adversarial NLI Benchmarks

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How does the diversity-weight parameter in Vendi-RAG impact FLAN-T5-xl accuracy and F1-score on the ANLI and HANS adversarial benchmarks. 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. 8 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: Adversarial Robustness of Prompt-based Few-Shot Learning for Natural Language Understanding. Research question: How does the diversity-weight parameter in Vendi-RAG impact FLAN-T5-xl accuracy and F1-score on the ANLI and HANS adversarial benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 14 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

14 papers retrieved. 8 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
Using unlabeled data (iPET) during fine-tuning causes prompting to reduce the drop in adversarial performance with respect to in-domain performance.	×	0.12
Using multiple prompts to fine-tune multiple models (PET) and ensembling the resultant predictions causes prompting to reduce the drop in adversarial performance with respect to in-domain performance.	×	0.12
Increasing the number of few-shot examples reduces the relative drop in adversarial performance with respect to in-domain performance.	✓	0.17
Increasing the encoder size reduces the relative drop in adversarial performance with respect to in-domain performance.	×	0.08
RoBERTa encoders are more adversarially robust than ALBERT and BERT encoders of comparable size.	×	0.06
Vanilla few-shot learning (FSL) methods lead to a notable relative drop in task performance compared to fully fine-tuned methods.	✓	0.42
The study evaluates four FSL methods: Classic fine-tuning, LM-BFF, PET, and iPET.	×	0.11
FewNLU is a benchmark designed to evaluate the performance of prompt-based few-shot learning capabilities systematically.	×	0.15

References

- <http://arxiv.org/abs/2008.06239v2>
- <http://arxiv.org/abs/2502.11228v2>
- <http://arxiv.org/abs/2306.11066v2>