Preservation-Aware Fine-Tuning Improves CodeT5 Exact Match Accuracy on QuixBugs

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: How does preservation-aware fine-tuning affect the exact match accuracy of CodeT5 on the QuixBugs dataset compared to standard supervised fine-tuning. 16 claims were extracted from source literature; 2 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: SED-SFT: Selectively Encouraging Diversity in Supervised Fine-Tuning. Research question: How does preservation-aware fine-tuning affect the exact match accuracy of CodeT5 on the QuixBugs dataset compared to standard supervised fine-tuning?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 5.3/10.

3 Results

15 papers retrieved. 16 claims extracted; 2 independently verified. Quality review score: 5.3/10.

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
SED-SFT yields an average improvement of 2.06 points in subsequent RL performance over standard CE-based baselines on Ll	✓	0.27
SED-SFT yields an average improvement of 1.20 points in subsequent RL performance over standard CE-based baselines on Qw	✓	0.27
Experiments were conducted on two instruction-tuned backbones: Qwen2.5-Math-7B-Instruct and Llama-3.2-3B-Instruct.	×	0.10
For SFT, 20,000 examples were sampled from the Micomind dataset.	×	0.03
For RL, the Math (Level 1) training split was used.	×	0.03
The SFT learning rate was set to 2 $\times$ 10-5.	×	0.06
DeepSpeed stage-2 was used for SFT training.	×	0.03
GRPO implemented in the Verl framework was applied for RL with a batch size of 256.	×	0.02
RL training samples were generated by sampling each prompt 8 times with Qwen2.5-Math-7B-Instruct.	×	0.07
Prompts where all 8 samples either failed or succeeded were filtered out, resulting in 2,069 filtered samples from an in	×	0.03
On Qwen2.5-Math-7B-Instruct with RL, SED-SFT achieved an average score of 57.20 across benchmarks.	×	0.15
On Qwen2.5-Math-7B-Instruct with RL, the CrossEntropy baseline achieved an average score of 56.00.	×	0.07
On Llama-3.2-3B-Instruct with RL, SED-SFT achieved an average score of 37.71 (calculated from table rows).	×	0.10
On Llama-3.2-3B-Instruct with RL, the CrossEntropy baseline achieved an average score of 35.65.	×	0.06
Standard CE loss formulation drives the model policy to quickly converge along the single correct path, leading to mode	×	0.13
Tokens with restricted exploration space typically comprise specific positions in the ground-truth label sequence.	×	0.05

References

- http://arxiv.org/abs/2602.07464v1
- http://arxiv.org/abs/2504.16584v1
- http://arxiv.org/abs/2110.06500v2