Adversarial Contrastive Pre-Training and CodeT5 Performance on Syntax-Perturbed Python Tasks

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How does adversarial contrastive pre-training affect CodeT5's accuracy on syntax-perturbed Python tasks in the MBPP benchmark compared to standard fine-tuning. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Contrastive-Adversarial and Diffusion: Exploring pre-training and fine-tuning strategies for sulcal identification. Research question: How does adversarial contrastive pre-training affect CodeT5's accuracy on syntax-perturbed Python tasks in the MBPP benchmark compared to standard fine-tuning?.

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 3.3/10.

3 Results

14 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.3/10.

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
The reconstruction and contrastive learning techniques outperformed adversarial and diffusion methods in the self-superv	×	0.15
The reconstruction task achieved a multi-scale structural similarity score of 55.40% and a Hausdorff distance of 0.00 mm	×	0.02
Adversarial and reconstruction learning yielded classification scores of 0.607 and 0.594, respectively, in the multi-tas	×	0.05
Diffusion denoising learning was the most resource-intensive method in terms of memory performance and computational cos	×	0.09
Adversarial learning utilized 51.43% of the maximum GPU processing power, with an average GPU memory allocation of 97.62	×	0.05
The reconstruction task utilized 57.56% of the maximum GPU power, with an average GPU memory allocation of 95.51%, and r	×	0.03
Contrastive learning faced a memory overflow challenge with a batch number of 8, necessitating a reduction to 4, resulti	×	0.05
Diffusion denoising encountered memory overflow issues, leading to adjustments in the region of interest (ROI) size and	×	0.05
The maximum GPU power was reduced to 29.95%, and the average GPU memory allocation decreased to 55.56% for diffusion den	×	0.09
The reconstruction model and adversarial learning emerged as the optimal choices, striking a balance between computation	×	0.06
Top tuning consistently delivered an average dice score exceeding 50.00% and an average Hausdorff distance score below 2	×	0.05
Top tuning achieved over 60.00% for contrastive and reconstruction pre-training, and approximately 54% for adversarial i	×	0.11
Full tuning exhibited similar segmentation performance, surpassing 50.00% in average dice score and below 1.50 mm in ave	×	0.04
For adversarial, full tuning achieved more than 47.00% in average dice score and less than 2.80 mm in average Hausdorff	×	0.04
Decoder tuning closely aligned with full and top tuning, with slightly lower average dice score performance.	×	0.06
Low-rank adaptation (LoRA) demonstrated the least favorable results due to the high complexity of the computer vision ta	×	0.12

References

- http://arxiv.org/abs/2405.19204v1
- http://arxiv.org/abs/1901.09960v5
- http://arxiv.org/abs/2010.13337v1