Robustness Comparison of CodeT5 and JaCoText Under Adversarial Docstring Perturbations

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: How does the robustness of CodeT5 and JaCoText compare when evaluated on adversarial docstring perturbations across different programming languages in the MBPP benchmark. 15 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: A Deep Dive into Adversarial Robustness in Zero-Shot Learning. Research question: How does the robustness of CodeT5 and JaCoText compare when evaluated on adversarial docstring perturbations across different programming languages in the MBPP benchmark?.

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 3.5/10.

3 Results

16 papers retrieved. 15 claims extracted; 1 independently verified. Quality review score: 3.5/10.

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
The Caltech-UCSD-Birds 200-2011 (CUB) dataset contains 200 classes, 312 attributes, and a total of 11,788 images.	×	0.02
The SUN dataset contains 717 classes, 102 attributes, and a total of 14,340 images.	×	0.03
The Animals with Attributes 2 (AWA2) dataset contains 50 classes, 85 attributes, and a total of 37,322 images.	×	0.02
The experiments use the data splits proposed in reference [57] for both Zero-Shot Learning (ZSL) and Generalized Zero-Sh	✓	0.20
Zero-Shot Learning (ZSL) evaluation uses standard per-class top-1 accuracy.	×	0.14
Generalized Zero-Shot Learning (GZSL) evaluation computes harmonic scores using per-class top-1 accuracy values for seen	×	0.12
The defense method noted in reference [62] is inherently more effective against l0-norm attacks.	×	0.02
Under FGSM attack with epsilon 0.001 on the CUB dataset, the original model's Zero-Shot top-1 accuracy is 54.5%.	×	0.06
Under FGSM attack with epsilon 0.001 on the CUB dataset, the original model's Generalized Zero-Shot unseen accuracy is 2	×	0.06
Under FGSM attack with epsilon 0.1 on the CUB dataset, the original model's Zero-Shot top-1 accuracy drops to 15.2%.	×	0.06
The experiments merge a ResNet-101 feature extractor with the ALE model to make the computational graph end-to-end diffe	×	0.05
To reproduce ALE results, the feature extractor is frozen and only the ALE model is trained for each dataset.	×	0.02
The experiments were implemented using PyTorch.	×	0.03
The Attribute-label embedding (ALE) model is formulated as F(x, y; W) = θ(x)W^T φ(y), where θ(x) represents visual embed	×	0.03
The study selects the ALE model because it is a label-embedding model shown to be stable and competitive in modern bench	×	0.07

References

- http://arxiv.org/abs/2103.15670v3
- http://arxiv.org/abs/2008.07651v1
- http://arxiv.org/abs/2007.08428v4