Adversarial Robustness of Graph Convolutional Networks and Transformers in Code Dependency Graph Imputation

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does the adversarial robustness of graph convolutional networks compare to transformer-based architectures for code generation dependency graph imputation, as measured by BLEU scores under. Following the success in advancing natural language processing and understanding, transformers are expected to bring revolutionary changes to computer vision. This work provides a comprehensive study on the robustness of vision transformers (ViTs) against adversarial. 12 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: On the Adversarial Robustness of Vision Transformers. Research question: How does the adversarial robustness of graph convolutional networks compare to transformer-based architectures for code generation dependency graph imputation, as measured by BLEU scores under adversarial perturbations?.

2 Methodology

Systematic literature search across multiple databases yielded 11 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

11 papers retrieved. 12 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
ViTs are more robust to high-frequency perturbations than CNNs.	✓	0.20
CNNs learn more low-level features compared with ViTs.	×	0.08
ViT feature maps become noisier when ResNet features are introduced (ViT-B/16-Res).	×	0.03
ViT feature maps become noisier when neighboring tokens are aggregated into one token recursively (T2T-ViT-24).	×	0.03
ViT variants that introduce non-transformer modules (e.g., ResNet blocks and T2T blocks) diminish the model's original a	×	0.12
Hybrid ViTs (e.g., ResViTs and T2T-ViTs) exhibit inferior adversarial robustness against high-frequency perturbations co	×	0.15
ViTs pay less attention to high-frequency patterns in images compared to CNNs.	✓	0.16
Under High-pass filtered PGD attack with epsilon 0.001, the ResNet-based hybrid model achieves 62.9% Robust Accuracy whi	×	0.06
Under High-pass filtered PGD attack with epsilon 0.1, the ResNet-based hybrid model drops to 3.3% Robust Accuracy.	×	0.05
SAM-ViT maintains a Robust Accuracy of 0.3560 under High-pass attack conditions where other DeiT variants drop below 0.2	×	0.02
Swin-L/4 achieves a Clean Accuracy of 84.2%.	×	0.01
Under adversarial attack with epsilon 0.005, Swin-L/4 retains 11.1% accuracy while Deit-B/16 retains 6.0% accuracy.	×	0.04

References

- http://arxiv.org/abs/2603.11099v1
- http://arxiv.org/abs/1905.01907v2
- http://arxiv.org/abs/2103.15670v3