

Dynamic vs. Static Channel-Wise Feature Alignment in Multimodal Model Robustness

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: What is the impact of dynamic versus static channel-wise feature misalignment correction on the robustness of multimodal models when evaluated against adversarial perturbations in the MM-ReAct. 15 claims were extracted from source literature; 1 was 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: Multimodal Adversarial Defense for Vision-Language Models by Leveraging One-To-Many Relationships. Research question: What is the impact of dynamic versus static channel-wise feature misalignment correction on the robustness of multimodal models when evaluated against adversarial perturbations in the MM-ReAct benchmark?.

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. 15 claims extracted; 1 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
The study evaluates defense methods against the multimodal adversarial attack SGA with perturbation constraints of $\epsilon =$	×	0.11
FARE is an unsupervised unimodal adversarial fine-tuning scheme for CLIP that focuses on obtaining a robust CLIP vision	×	0.03
TeCoA-ITR fine-tunes all parameters using a cross-modal objective to generate adversarial images, whereas the original T	×	0.05
The models CLIP-ViT-B/16, ALBEF-14M, and BLIP w/ ViT-B were fine-tuned using MAT.	×	0.02
Adversarial images in the training process were generated via 2-step-PGD with a perturbation size of $2/255$ in l_1 -norm.	×	0.04
Adversarial texts in the training process were generated using BERT-attack with a 1-token perturbation.	×	0.05
Intra-modal augmentation enhances data points without considering image-text interactions (text \rightarrow text, image \rightarrow image).	×	0.08
Cross-modal augmentation enhances data points by leveraging the other modality (image \leftrightarrow text).	×	0.09
EDA is used as an intra-modal text augmentation technique for basic word-level edits.	×	0.02
MAT consistently achieves significantly greater robustness against multimodal attacks than the unimodal AT methods FARE	×	0.07
MAT consistently achieves significantly greater robustness against multimodal attacks than unimodal AT methods on ALBEF	×	0.08
Unimodal attacks perturb a single modality to mislead models, while multimodal attacks perturb both image and text modal	×	0.13
Multimodal attacks are significantly more effective than unimodal attacks.	×	0.11
Existing defense strategies for VL models mainly focus on vision robustness where adversarial attacks perturb only the i	✓	0.24
The proposed MAT method leverages one-to-many (1:N) image-text relationships via augmentations to enhance robustness. 4	×	0.11

References

- <http://arxiv.org/abs/2208.00428v1>
- <http://arxiv.org/abs/2405.18770v6>
- <http://arxiv.org/abs/2104.09369v1>