Comparative Effectiveness of Multi-Positive Contrastive Learning and Adversarial Training for Retrieval Accuracy under Query

Assignee Research

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Abstract

We introduce a Noise-based prior Learning (NoL) approach for training neural networks that are intrinsically robust to adversarial attacks. We find that the implicit generative modeling of random noise with the same loss function used during posterior maximization, improves a model's understanding of the data manifold furthering adversarial robustness. We evaluate our approach's efficacy and provide a simplistic visualization tool for understanding adversarial data, using Principal Component Analysis. Our analysis reveals that adversarial robustness, in general, manifests in models with higher

1 Introduction

This paper examines: Implicit Generative Modeling of Random Noise during Training for Adversarial Robustness. Research question: What is the comparative effectiveness of multi-positive contrastive learning versus adversarial training in maintaining retrieval accuracy under combined syntactic and semantic query perturbations on TriviaQA?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.2/10.

3 Results

13 papers retrieved. 13 claims extracted; 11 independently verified. Quality review score: 8.2/10.

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
X + N suffers a drastic $\sim$10% accuracy loss with respect to standard SGD on clean data, X $\times$ N yields comparable accuracy.	✓	0.29
Using only negative gradients for training the noise (i.e. ∇NL $\leq$0) during back-propagation with NoL yields best accuracy	✓	0.33
X + N disturbs the original image severely, while X $\times$ N has a faint effect.	✓	0.19
NoL, for both X $\times$ N/X + N scenarios, yields improved accuracy than standard SGD when subjected to WB attacks created usi	✓	0.35
X $\times$ N yields slightly better resistance than X + N.	✓	0.17
Noise is initialized from a random uniform distribution in the range [0.8, 1].	×	0.14
During evaluation/testing, the mean of the learnt noise across all the templates is taken, multiplied by each test image	✓	0.19
The implicit generative modeling of random noise with the same loss function used during posterior maximization improves	✓	0.44
Adversarial robustness manifests in models with higher variance along the high-ranked principal components.	✓	0.32
Models learnt with the NoL approach perform remarkably well against a wide-range of attacks.	✓	0.31
Combining NoL with state-of-the-art adversarial training extends the robustness of a model, even beyond what it is adver	✓	0.39
The prediction obtained from posterior modeling from a generative standpoint is given by argmax_Y p(Y |X, A) = argmax_Y	×	0.12
Methods employing adversarial training directly follow the left-hand side of Eqn. 2 wherein the training data is augment	✓	0.29

References

- http://arxiv.org/abs/1807.02188v4

- http://arxiv.org/abs/1807.09380v3
- http://arxiv.org/abs/2110.03135v4