Transferability Reduced Smooth (TRS) Ensemble Training for Adversarial Transferability Attacks

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Introduction

- Trained our model adversarially on FGSM, PGD ℓ_2 norm and ℓ_∞ norm attacks, with fine-tuning
- Employed Transferability Reduced Smooth (TRS) ensemble training to combine these trainings to build a more robust model

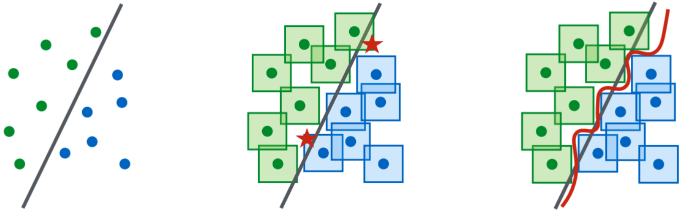


Figure 1: Illustration of standard vs. adversarial decision boundaries. [1]

Hyper-parameters for Adversarial Training

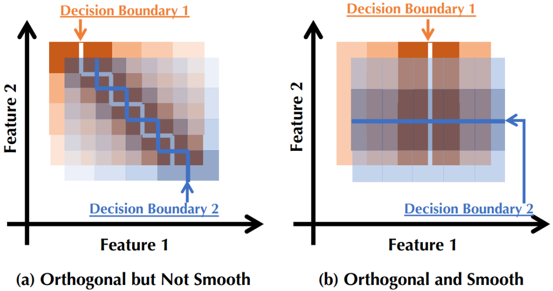
- Best adversarially trained PGD ℓ_∞ model:
  - Dynamic ϵ from 0.03 to 0.08
  - Dynamic α from 0.01 to 0.03
  - Learning rate scheduler for 50% decrease every epoch starting at lr $=$ 0.001
- Testing results:

Defensive Method	Natural Acc	PGD ℓ_∞ Acc	PGD ℓ_2 Acc
PGD ℓ_∞ Adversarial Training	41.25	37.33	41.71
TRS Ensemble Training	57.81	7.03	53.13

Table 1: Results of our defensive methods.

Ensemble Robustness via Transferability Minimization

- **Goal:** Enforce the smoothness of models to improve robustness **AND** reduce the loss gradient similarity between models to introduce global model orthogonality.



(a) Orthogonal but Not Smooth

(b) Orthogonal and Smooth

Figure 2: An illustration of the relationship between adversarial transferability, gradient orthogonality, and model smoothness [2]

TRS Ensemble Training

Reduce adversarial transferability among base models $\mathcal{F}$ and $\mathcal{G}$ by enforcing model smoothness and low loss gradient similarity **at the same time**.

- Use regularization for model smoothness and thus robustness :

$$\mathcal{L}_{\mathsf{smooth}}(\mathcal{F}, \mathcal{G}, x, \delta) = \max_{\|\hat{x}-x\|_\infty \leq \delta} (\|\nabla_{\hat{x}} \ell_{\mathcal{F}}\|_2 + \|\nabla_{\hat{x}} \ell_{\mathcal{G}}\|_2)$$

- Decrease the model loss gradient similarity by minimizing cosine similarity between loss gradient vectors $\nabla_x \ell_{\mathcal{F}}$ and $\nabla_x \ell_{\mathcal{G}}$:

$$\mathcal{L}_{\mathsf{sim}} = \left| \frac{(\nabla_x \ell_{\mathcal{F}})^\top (\nabla_x \ell_{\mathcal{G}})}{\|\nabla_x \ell_{\mathcal{F}}\|_2 \cdot \|\nabla_x \ell_{\mathcal{G}}\|_2} \right|$$

  The optimal case implies orthogonal loss gradient vectors, which ensures models learn different patterns from the data.

TRS Regularizer & Training

- **TRS Regularizer :** Increase model smoothness and diversity in learning.

$$\mathcal{L}_{\text{TRS}}(\mathcal{F}, \mathcal{G}, x, \delta) = \lambda_a \cdot \mathcal{L}_{\text{sim}} + \lambda_b \cdot \mathcal{L}_{\text{smooth}}$$

- **TRS Trainer :** Combination of the Ensemble Cross-Entropy (ECE) loss and the TRS regularizer.

$$\mathcal{L}_{\text{train}} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_{\text{CE}}(\mathcal{F}_i(x), y) + \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \mathcal{L}_{\text{TRS}}(\mathcal{F}_i, \mathcal{F}_j, x, \delta)$$

The training process focuses on making each model accurate (via ECE loss) and also on ensuring that the ensemble as a whole is robust and diverse in its learning approach (via TRS regularizer).

Conclusion & Next Steps

TRS ensures that each model is both effective on its own and contributes uniquely to the overall performance of the ensemble.

TRS ensemble training is a lightweight yet effective way to reduce adversarial transferability, and leads to more robust models.

Next steps:

- Finalize ensemble code with our adversarially trained models
- Doing adversarial training with several attack types
- *Maybe:* Test with different model architectures to improve accuracy

Publication and References

1. A. Madry, A. Makelov, L. Schmidt, D. Tsipras, A. Vladu. (2019). Towards Deep Learning Models Resistant to Adversarial Attacks. MIT. arXiv:1706.06083 [stat.ML]
2. Z. Yang, L. Li, X. Xu, S. Zuo, Q. Chen, B. Rubinstein, P. Zhou, C. Zhang, B. Li. (2021). TRS: Transferability Reduced Ensemble via Promoting Gradient Diversity and Model Smoothness. Proceedings of the 35th Conference on Neural Information Processing Systems (NeurIPS 2021). arXiv:2104.00671 [cs.LG]