Metric Learning for Adversarial Robustness

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https://papers.nips.cc/paper/8339-metric-learning-for-adversarial-robustness.pdf

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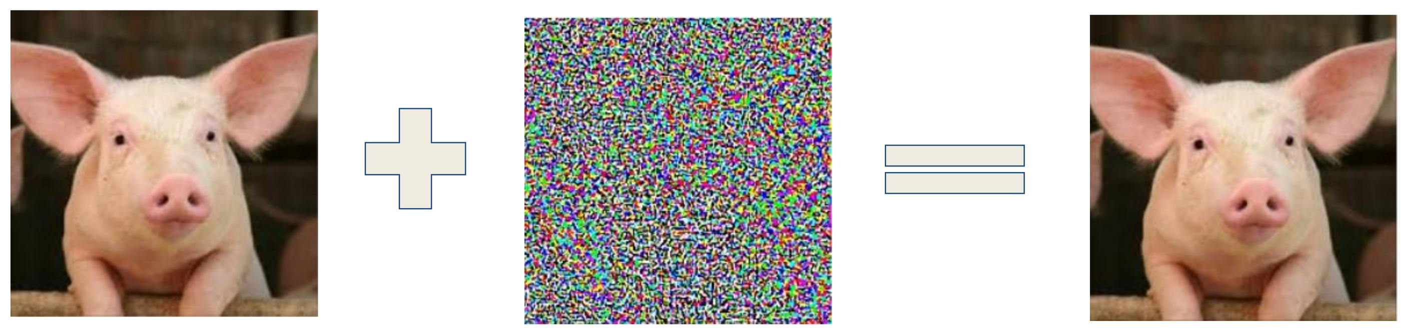
Code

Adversarial Examples

Neural networks are vulnerable under adversarial attacks.

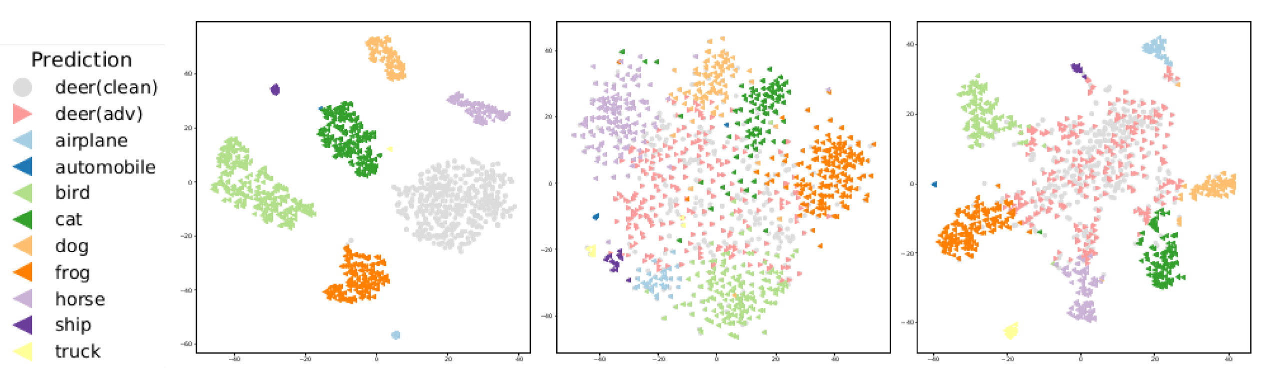


"Pig" Adversarial Noise "Airliner"

Design Motivations

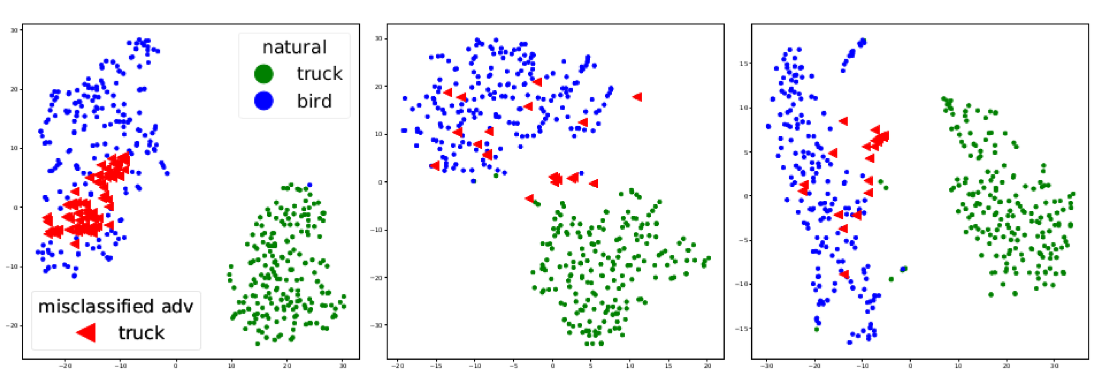
Hidden representations of DNNs under attack have not been systematically studied.

- Representations from the same class are mistakenly classified to different classes.



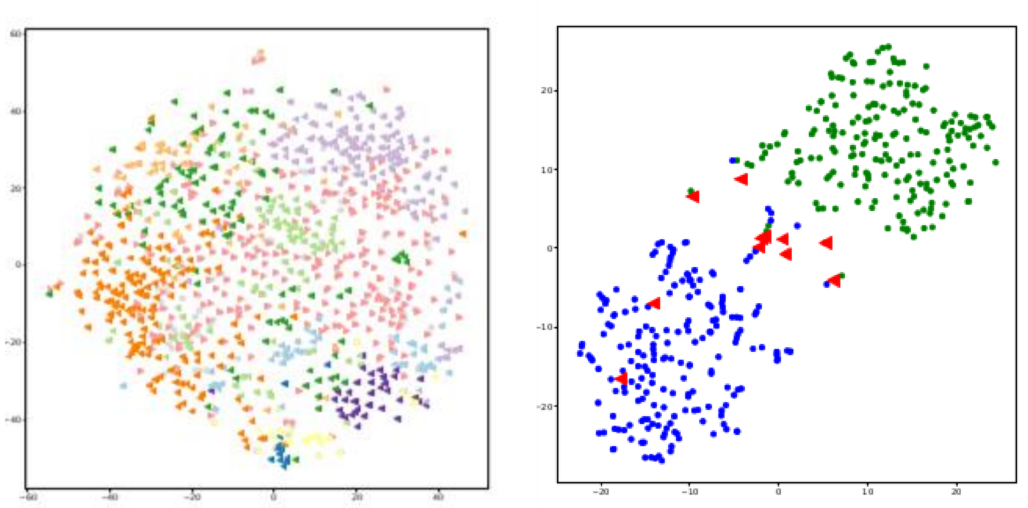
(a) UM (b) AT (c) ALP

- Representations of the adversarial examples are shifted inside the false class.



(a) UM (b) AT (c) ALP

After TLA training



(d) TLA (d) TLA

- The examples from the same class are clustered together.
- The adversarial examples are separated from the corresponding false class by a margin.

Methodology

Triplet Loss

- Pull the representations of the same class together
- Push the representations of different classes away up to a margin
- Anchor $x_a^{(i)}$ and positive $x_p^{(i)}$ are from the same class, negative $x_n^{(i)}$ is from a different class

$$\sum_i^N \mathcal{L}_{trip}(\mathbf{x}_a^{(i)}, \mathbf{x}_p^{(i)}, \mathbf{x}_n^{(i)}) = \sum_i^N [D(h(\mathbf{x}_a^{(i)}), h(\mathbf{x}_p^{(i)})) - D(h(\mathbf{x}_a^{(i)}), h(\mathbf{x}_n^{(i)})) + \alpha]_+$$

Triplet Loss for Adversarial Robustness (TLA)

$$\mathcal{L}_{all} = \sum_i^N \mathcal{L}_{ce}(f(\mathbf{x}_a'^{(i)}), y^{(i)}) + \lambda_1 \mathcal{L}_{trip}(h(\mathbf{x}_a'^{(i)})), h(\mathbf{x}_p^{(i)}), h(\mathbf{x}_n^{(i)})) + \lambda_2 \mathcal{L}_{norm}$$

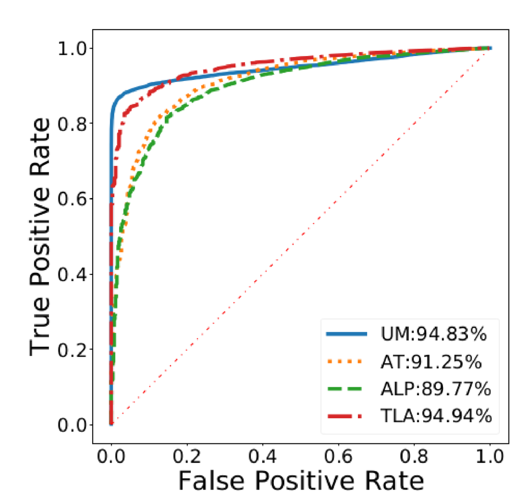
Semi-hard negative example retrieval

- Negative examples randomly sampled from another class are too easy.
- Retrieving the closest examples from the total training set is slow and too hard as a negative example.
- We propose to retrieve the closest negative example from a mini-batch of training data.

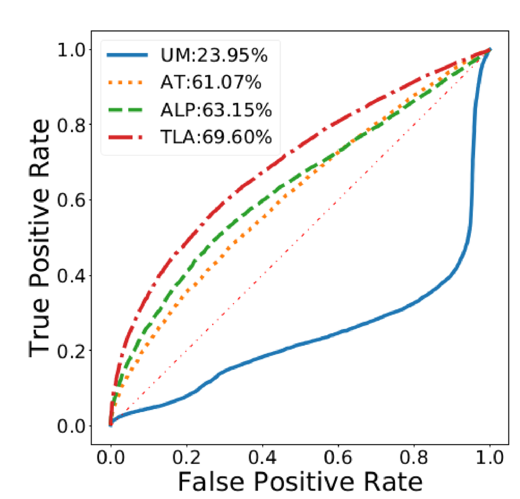
- We propose to regularize the distorted representation under attack with metric learning, to produce more robust classifier.
- Our method, TLA, produces desirable internal representation that improves adversarial robust accuracy and misclassification detection efficiency.

Results

Effect of TLA on mis-classification detection: ROC Curve



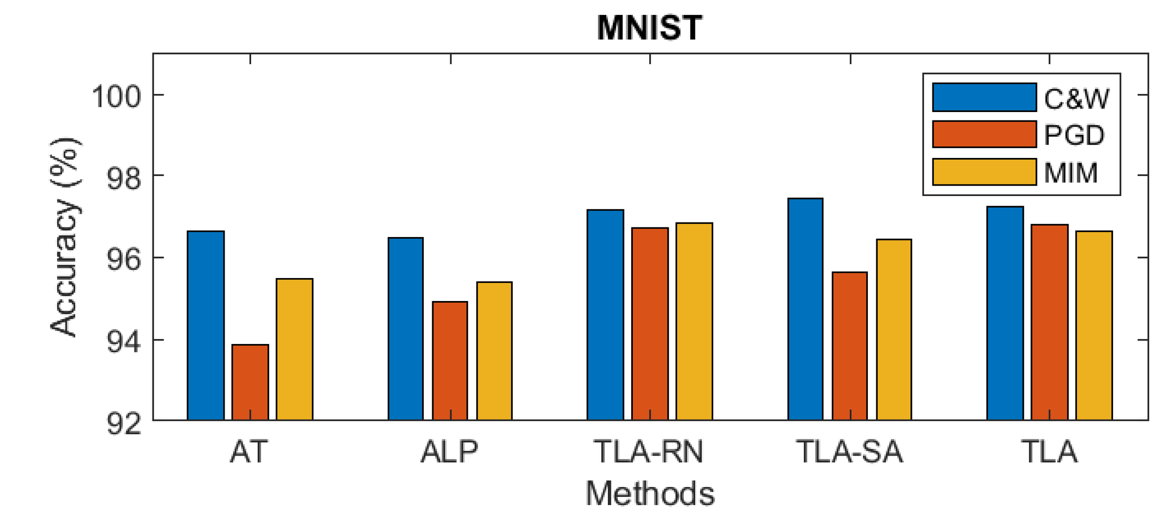
(a) MNIST



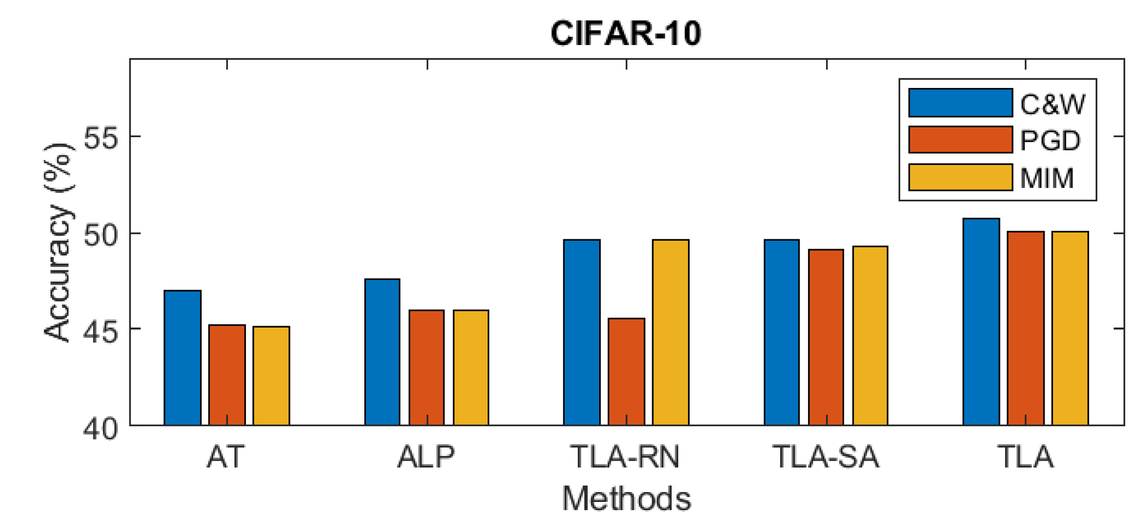
(b) CIFAR-10

- PGD attack under larger perturbation norm bound compared with training time
- TLA Improves the **AUC** score for detection by
  - **3.69%** on MNIST
  - **6.46%** on CIFAR-10.

Effect of TLA on classification accuracy under attacks

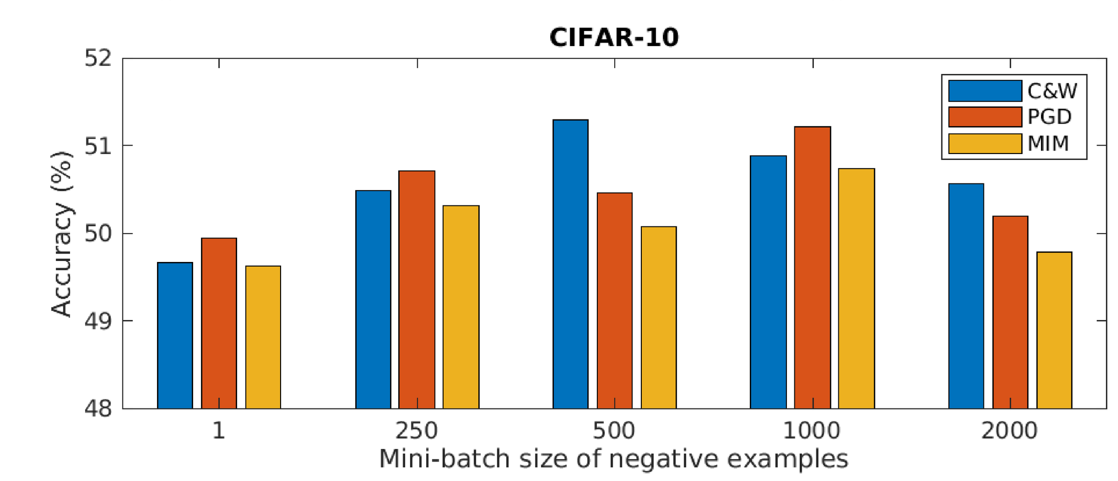


- With 2000 steps of PGD
- Improve the accuracy by
  - **1.86%** compared with Adversarial Logit Pairing
  - **2.92%** compared with Adversarial Training.



- With 400 steps of PGD
- Improve the accuracy by
  - **4.05%** compared with Adversarial Logit Pairing
  - **4.82%** compared with Adversarial Training.

Semi-hard negative example retrieval using mini-batch



- By choosing the proper mini-batch size, performance is improved by up to **1.64%**

Nearest Neighbors Retrieval Using Learned Metric