Combating Adversaries with Anti-Adversaries

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Abstract

Deep neural networks are vulnerable to small input perturbations known as adversarial attacks. Inspired by the fact that these adversaries are constructed by iteratively minimizing the confidence of a network for the true class label, we propose the anti-adversary layer, aimed at countering this effect. In particular, our layer generates an input perturbation in the opposite direction of the adversarial one, and feeds the classifier a perturbed version of the input. Our approach is training-free and theoretically supported. We verify the effectiveness of our approach by combining our layer with both nominally and robustly trained models, and conduct large scale experiments from black-box to adaptive attacks on CIFAR10, CIFAR100 and ImageNet. Our anti-adversary layer significantly enhances model robustness while coming at no cost on clean accuracy.

1. Introduction

Deep Neural Networks (DNNs) are vulnerable to small input perturbations known as adversarial attacks [11, 23]. While there has been interest in training DNNs that are robust to adversarial attacks, assessing a defense’s robustness remains an elusive task. This difficulty is related to: (i) Model robustness varies with the information the attacker is assumed to know, e.g., training data, gradients, logits, etc.—dichotomously categorizing adversaries as black- or white-box. Consequently, this categorization imposes difficulties for comparing defenses tailored to specific types of adversaries. For instance, some defenses crafted for white-box attacks were later broken by black-box attacks [4, 20]. (ii) In addition, empirically-evaluated robustness can be overestimated if weaker efforts are invested in adaptively constructing attacks [6, 24]. The lack of reliable assessments is responsible for false senses of security, as presumably-strong defenses against white-box attacks were subsequently broken by carefully-crafted adaptive attacks [2]. The few defenses standing the test of time require costly training and degrade clean-sample performance [25]. Even worse, while most defenses are designed to resist white-box attacks, fewer efforts have been invested into resisting black-box attacks, which are more practical [5], e.g., public APIs (IBM Watson, Microsoft Azure, etc.) may not disclose information about their models’ inner workings.

In this work, we propose a simple, generic, training-free layer that robustifies both nominally and robustly trained DNNs. Given a base classifier \( f : \mathbb{R}^n \rightarrow \mathcal{Y} \), which maps \( \mathbb{R}^n \) to labels in set \( \mathcal{Y} \), and an input \( x \), our layer constructs a data- and model-dependent perturbation \( \gamma \) in the anti-adversary direction, i.e., the direction maximizing the classifier’s confidence on the pseudo-label \( f(x) \) (illustrated in Figure 1). The new sample \((x + \gamma)\) is then fed to \( f \) in lieu of \( x \). We dub this approach the anti-adversary classifier \( g \). We conduct an extensive robustness assessment of our layer on several datasets and under black-box, white-box, and adaptive attacks, and find across-the-board improvements in robustness over all base classifiers \( f \).

1.1. Related Work

Given the security concerns that adversarial vulnerability brings, a stream of works built models that both accu-
2. Methodology

Motivation. Adversary directions maximize a loss function w.r.t. the input, i.e. move input $x$ closer to the decision boundary, thereby minimizing the confidence on the predicted label. In this work, we leverage this and prepend a layer to a trained model to generate a new input $(x + \gamma)$, which moves $x$ away from the decision boundary, thus hindering the capacity of adversaries to tailor attacks.

Preliminaries and Notation. We use $f_\theta : \mathbb{R}^n \rightarrow \mathcal{P}(Y)$ to denote a classifier, e.g. a DNN parameterized by $\theta$, where $\mathcal{P}(Y)$ is the probability simplex over the set $Y = \{1, 2, \ldots, k\}$ of $k$ labels. For input $x$, an attacker constructs a small perturbation $\delta$ (e.g. $\|\delta\|_p \leq \epsilon$) such that $\arg\max_i f_\theta(x + \delta) \neq y$, where $y$ is $x$’s true label. One approach to construct $\delta$ is by solving the following constrained problem with a loss function $L$:

$$\max_{\delta} L(f_\theta(x + \delta), y) \text{ s.t. } \|\delta\|_p \leq \epsilon. \quad (1)$$

Depending on the information about $f_\theta$ accessible by the attacker when solving (1), the adversary can generally be categorized into one of three types. (i) Black-box: Only function evaluations $f_\theta$ are available. (ii) White-box: Only $f_\theta$ and $\nabla_x f_\theta$ are accessible, with no other intermediate layer information available to the attacker. (iii) Adaptive: The attacker has full knowledge about the classifier $f_\theta$, including the $\theta$, intermediate-layer gradients, training data, etc.

Anti-Adversary Layer. Analogous to constructing an adversary by solving (1), we propose to prepend a layer that perturbs the input to maximize the classifier’s prediction’s confidence at an input, hence the term anti-adversary. Formally, given classifier $f_\theta$, our anti-adversary classifier $g$ (prepending an anti-adversary layer to $f_\theta$) is:

$$g(x) = f_\theta(x + \gamma),$$

$$\text{s.t. } \gamma = \arg\min_{\zeta} L(f_\theta(x + \zeta), \hat{y}(x)), \quad (2)$$

where $\hat{y}(x) = \arg\max_i f_\theta(x)$ is the predicted label. Note our proposed anti-adversary $g$ is agnostic to the choice of $f_\theta$. Moreover, it does not require retraining $f_\theta$, unlike previous works [5, 28] that add random input perturbations, hurting clean accuracy. This is because correctly-classified instances, i.e. instances where $y = \arg\max_i f_\theta(x)$, will also be, by construction, classified correctly by $g$. Thus, our layer only increases the confidence of $f_\theta(x)$’s top prediction. We illustrate our approach in Figure 2. Finally, our layer solves Problem (2) with $K$ signed gradient descent iterations, zero initialization, where $L$ is the cross-entropy loss. Algorithm 1 summarizes $g$’s forward pass.

3. Experiments

We validate the effectiveness of our anti-adversary classifier $g$ by evaluating robustness against various adversaries. (i) We compare $f_\theta$’s robustness with our anti-adversary classifier $g$ against black-box attacks (Bandits [15], NES [14] and Square [1]) both when $f_\theta$ is nominally and robustly trained. We observe significant robustness improvements over $f_\theta$ with virtually no drop in clean accuracy, while also outperforming the recently-proposed SND [5] defense. (ii) We experiment in the white-box setting with AutoAttack [9] (with APGD, ADLR [9], and FAB [8]), when $f_\theta$ is trained robustly with ImageNet-Pre [13] and AWP [27]. In all experiments, we do not retrain $f_\theta$ after prepending our layer.
3.1. Robustness under Black-Box Attacks

We measure black-box robustness gains when prepend-
ing our layer to classifiers. This setting is interesting for commercial APIs that only provide model predictions and
so can only be targeted with black-box adversaries.

**Robustness of Nominally-Trained $f_\theta$.** We experiment with ResNet18 [12] on CIFAR10 [16] and ResNet50 on ImageNet [17]. We compare the clean and robust accuracies of $f_\theta$ against SND [5], and our anti-adversary classifier. We conduct 10k queries of two black-box attacks, Bandits and NES, and set $\alpha = 0.01$ in Algorithm 1. Following SND [5], we evaluate on 1000 and 500 instances of CIFAR10 and ImageNet, respectively, and report results in Table 1.

As shown in Table 1, nominally trained models are brittle: while clean accuracies on CIFAR10 and ImageNet are 93.7% and 79.2%, respectively, these drop to 4.8% and 21% under black-box attacks. Moreover, while SND improves robustness, i.e. to 25.5% and 60.2% on CIFAR10 and ImageNet, our proposed anti-adversary outperforms SND across attacks and datasets. For instance, on ImageNet we outperform SND by 1.2% and 5.8% for Bandits and NES, respectively, while not hurting clean accuracy.

**Robustness of Robustly-Trained $f_\theta$.** The previous section showed our anti-adversary layer improves black-box robustness of a nominally-trained $f_\theta$. Here, we investigate if our layer can also improve robustness when $f_\theta$ is robustly trained. We thus study black-box robustness of our anti-adversary layer with two state-of-the-art robustly trained $f_\theta$ (IN-Pret and AWP) on CIFAR10 and CIFAR100. We report robust accuracy for 1000 instances under Bandits and NES attacks. For the more efficient Square attack, we report robust accuracy on the full test set.

In Table 2, we report the black-box robust accuracies on CIFAR10 and CIFAR100. Confirming previous observations, prepending our anti-adversary layer to $f_\theta$ does not hurt clean accuracy. More importantly, although $f_\theta$ is robustly trained, our anti-adversary layer can still boost robustness by an impressive $\sim 15\%$. For instance, even for the highest worst-case robust accuracy on CIFAR10 (AWP’s 66.18%), the anti-adversary improves robustness by 14.53%, reaching 80.71%. Similarly, for CIFAR100 our layer improves the worst-case black-box robustness of AWP by 11.7%. Overall, our layer consistently improves black-box robustness against all attacks and for all robust training methods $f_\theta$ on both CIFAR10 and CIFAR100.

3.2. Robustness under White-Box Attacks

In this setting, the attacker (1) only accesses the classifier’s outputs and gradients. Note that the attacker ignores the classifier’s inner workings and training specifications. While this setup is less realistic than the black-box setting, it is an interesting measure of robustness by providing more information to the attacker, which is related to why most prior works report performance in this category by computing accuracy under PGD [19] or AutoAttack, such as [29].

We prepend our anti-adversary layer to robustly trained classifiers $f_\theta$ and assess robustness on CIFAR10 and CIFAR100. We report robust accuracy against three white-box attacks, namely APGD, ADLR and AutoAttack (AA) on CIFAR10 and CIFAR100.

Table 2. Black-box attacks on robust models equipped with Anti-Adv. We report clean (%) and robust accuracies against Bandits, NES and Square attack on CIFAR10 and CIFAR100. Bold values indicate highest accuracy in each experiment. Our layer provides across-the-board improvements on robustness against all attacks, without affecting clean accuracy.

|          | Clean | Bandits | NES | Square |
|----------|-------|---------|-----|--------|
| CIFAR10  |       |         |     |        |
| ImageNet-Pre + Anti-Adv | 88.7 | 68.4 | 78.1 | 62.4 |
| AWP + Anti-Adv | 88.5 | 71.5 | 80.1 | 66.2 |
| CIFAR100 |       |         |     |        |
| ImageNet-Pre + Anti-Adv | 59.0 | 40.6 | 47.7 | 34.6 |
| AWP + Anti-Adv | 59.4 | 39.8 | 47.3 | 34.7 |

Table 3. White-box attacks on robust models equipped with Anti-Adv. We report clean and robust accuracies against APGD, ADLR, and AutoAttack (AA) on CIFAR10 and CIFAR100.

|          | Clean | APGD | ADLR | AA |
|----------|-------|------|------|----|
| CIFAR10  |       |      |      |    |
| ImageNet-Pre + Anti-Adv | 87.11 | 57.65 | 55.32 | 55.31 |
| AWP + Anti-Adv | 88.25 | 63.81 | 60.53 | 60.53 |
| CIFAR100 |       |      |      |    |
| ImageNet-Pre + Anti-Adv | 59.37 | 33.45 | 29.03 | 28.96 |
| AWP + Anti-Adv | 60.38 | 33.56 | 29.16 | 29.15 |
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