Purifying Adversarial Perturbation with Adversarially Trained Auto-encoders

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Abstract

Machine learning models are vulnerable to adversarial examples. Iterative adversarial training has shown promising results against strong white-box attacks. However, adversarial training is very expensive, and every time a model needs to be protected, such expensive training scheme needs to be performed. In this paper, we propose to apply iterative adversarial training scheme to an external auto-encoder, which once trained can be used to protect other models directly. We empirically show that our model outperforms other purifying-based methods against white-box attacks, and transfers well to directly protect other base models with different architectures.

1 Introduction

Deep neural models have shown tremendous success in recent years in many machine learning tasks. However, like other machine learning models, researchers have found neural models are vulnerable to adversarial attacks, where small perturbation of input flips the model’s output with high confidence.

Many defense techniques have been proposed, but have achieved limited success on white-box attacks. Early approaches such as [23, 20, 17] only defend against black-box attacks and/or oblivious attacks [5], where attackers are not aware of the presence of defense. On the contrary, white-box attackers have full knowledge of both the base model and the defense. To defend against such strong white-box attacks, researchers tried to hide the input gradients that are used by first-order attackers. Such techniques include making some operations in the model non-differentiable [4, 10, 18], adding stochastic to the gradients [8, 33], and exploring gradients vanishing/exploding [27]. However, these techniques can be side-stepped by approximating the true gradients [3], and as a result provided little robustness to white-box attacks.

The most successful defense against white-box attacks is iterative adversarial training [19, 14]. Adversarial training [9] is a defense technique that augments training data with adversarially generated examples. Madry et al. [19] showed that when applying adversarial training in an iterative manner, the model can achieve state-of-the-art defense against white-box attacks.

However, iterative adversarial training introduces significant computational overhead, as it generates adversarial examples on-the-fly in every training iteration. Depending on the attack algorithm used, the overhead is typically 10-30x, and it is hard for the technique to scale to ImageNet [14, 29]. In addition, iterative adversarial training achieves robustness through modifying the parameters of the base classifier under protection. In other words, the robustness is embedded inside the model,
and cannot be easily transferred to other models. Every time a model needs to be protected, such expensive training scheme needs to be performed.

On the other hand, some approaches do not modify the base model, but purify the input. Representative approaches include DefenseGAN [25], MagNet [20] and several others [26, 11, 27, 17]. We call such approaches the purifying-based methods. Since the data domain does not change after purification, such models, once trained, can be directly used to protect different base models. We refer such property as “transferability” or “generalizability” in this paper, and use the two terms interchangeably. However, current purifying-based approaches have shown limited success in white-box attack. For example, MagNet [20] and HGD [17] has been shown to provide no white-box security [6, 2]. And it has been shown PixelDefend [27] and DefenseGAN [25] could be bypassed by simple gradient approximation of the vanished gradients [3].

In this paper, we study the possibility to combine the robustness of iterative adversarial training with the generalizability of purifying-based approaches. In particular, we propose to apply iterative adversarial training scheme to train only an external auto-encoder instead of the underlying base model. The auto-encoder is trained to perform two functionalities at the same time. On one hand, it should not modify clean input so that clean images can still be classified correctly by the model; on the other hand, the auto-encoder is trained with adversarial examples in iterative manner, such that it removes the adversarial perturbation before feeding inputs to the base classifier, even against strong white-box attacks.

We empirically evaluate the robustness of our model against three threat models on MNIST and CIFAR10 dataset, and show state-of-the-art white-box robustness compared with other purifying-based methods. We also demonstrate the transferability of our approach by showing that, the auto-encoder trained on one model performs well when plugged in other models with different architectures. To further improve the transferability of the model, we propose to apply ensemble training across multiple base models, and show empirically improved performance.

In summary, we make the following contributions:

- We propose a novel purifying-based method to protect neural models against adversarial examples. In particular, we apply iterative adversarial training to external auto-encoders. We empirically show that our method outperforms other purifying-based method on strong white-box attacks.
- We show that our trained auto-encoder on one base model can be used directly to protect other base models with high accuracy, achieving model transferability. We further propose to apply ensemble training across different base models, and empirically show the performance boost on model transferability.

2 Background

2.1 Model and notations

We assume the pre-trained base model is an m-class classifier in the form of neural networks. Following the notation used in the literature [7, 19], let \( F_\theta(x) = y \) be an m-class neural network classifier that accepts an n-dimensional image input \( x \in \mathbb{R}^n \), and produces \( y \in [0, 1]^m \) as the probability of prediction. The output \( y \) is computed using the softmax function to ensure \( \sum y_i = 1 \). The input \( x \) is classified as \( C(x) = \arg \max_i y_i \). The model parameter \( \theta \) is trained to minimize some loss \( L(\theta; x, y) \), typically the cross-entropy loss, i.e. \( L(\theta; x, y) = H(F_\theta(x), y) \).

2.2 Adversarial attacks

An adversarial example of \( x \) for the model \( F(x) \) is \( x' \) that is similar to \( x \) in some distance measure \( D(x, x') \), such that \( C(x') \neq C(x) \). The difference \( \delta = x' - x \) is called adversarial perturbation.

**Fast Gradient Sign Method (FGSM)** Given an image \( x \) and its corresponding true label \( y \), the FGSM attack [9] computes the adversarial example as:

\[
x' = x + \epsilon \cdot \text{sign}(\nabla_x L(\theta; x, y))
\] (1)
where $\epsilon$ is a small constant denoting the amount of perturbation. FGSM is designed to be very fast to generate proof-of-concept adversarial examples.

**Projected Gradient Descent (PGD)** Also known as Basic Iterative Method (BIM) or Iterative FGSM (FGSM$^k$) [14, 19], PGD is a more powerful, multi-step variant of FGSM. In each iteration, the input is projected to be in the valid range [0,1] and within allowed perturbation range $S$. Formally,

$$x_{t+1} = \text{Proj}_{x + S}(x_t + \epsilon \cdot \text{sign}(\nabla_{x_t} L(\theta; x_t, y)))$$  \hspace{1cm} (2)

The Randomized Fast Gradient Sign Method (RAND+FGSM) [29] is the one iteration special case of PGD, and thus is strictly weaker than PGD. In particular, PGD has been suggested to be the universal first-order $\ell_\infty$-bounded attack [19].

**Carlini-Wagner (CW) $\ell_2$ attack** CW $\ell_2$ attack [7] is an optimization based technique as opposed to the above gradient sign methods. The optimization problem is formulated as:

$$\min_{\delta} \|\delta\|_2 + c \cdot f(x + \delta) \quad \text{s.t.} \quad x + \delta \in [0, 1]^n$$  \hspace{1cm} (3)

where $f$ is a function specially designed such that $f(x') < 0$ if and only if $C(x') = t$, with $t$ being the target adversarial class label. This optimization approach is shown to be much stronger than gradient-based ones, but with the price of computational overhead due to the optimization steps.

### 2.3 Iterative adversarial training

The idea of iterative adversarial training [19, 14] is to train the classifier with adversarial examples generated by some attacks during the training process. Formally, iterative adversarial training is formulated as a min-max optimization problem:

$$\min_{\theta} \mathbb{E}_{(x, y) \in \chi} \left[ \max_{\delta \in S} L(\theta; x + \delta, y) \right]$$  \hspace{1cm} (4)

where $\chi$ is the data distribution, $S \in \mathbb{R}^n$ is some allowed perturbations, typically set to $\ell_\infty$-ball in the literature of adversarial training due to runtime efficiency of performing FGSM and PGD.

### 2.4 Threat Model

Following terminology in the literature [22, 5], we consider the following threat models based on how much information the attacker has access to.

- **black-box attack**: the attacker knows neither the model nor the defense [22]. The attacker is allowed to query the model (with defense in place) for the outputs of given inputs, collect data, and train a substitute model, and perform attack on the substitute model to generate adversarial examples. These adversarial examples are then tested on the black-box model.

- **oblivious attack**: the attacker has access to the full base classification model, including architecture and parameters. But the attacker does not know the presence of the defense, thus adversarial examples are only generated for the base model.

- **white-box attack**: the attacker has full access to the base model as well as the defense, including all architectures and parameters. The adversarial examples are generated against the model with defense in place.

We remark that in the literature there has been inconsistent usage of oblivious and white-box threat models. Many papers report only oblivious attack results while claiming white-box ones. As suggested by the literature, white-box attacks are much stronger and more realistic threat model than oblivious attacks [5].
3 Approach

Given a classifier model $F_\theta(x)$, we add an auto-encoder $AE_\phi(x)$ to preprocess the input before classifying it. Thus the full model is

$$M_{\theta, \phi}(x) = F_\theta(AE_\phi(x))$$  \hspace{1cm} (5)

Let $x$ denote the clean image, $x + \delta$ denote the adversarial image with perturbation $\delta$. Instead of minimizing adversarial loss over the classifier model parameter $\theta$ as was done in Eq. 4 in this paper, we assume that the classifier model $F_\theta(x)$ has been pre-trained with clean images and $\theta$ is fixed, and we train only the auto-encoder parameter $\phi$ with the following adversarial objective:

$$\min_{\phi} \mathbb{E}_{(x,y) \in \chi} \left[ \max_{\delta \in \mathcal{S}} L(\theta; AE_\phi(x + \delta), y) \right]$$  \hspace{1cm} (6)

It turns out training only on this adversarial objective may lead to decrease of clean image accuracy. Thus, we propose to combine the adversarial objective with the reconstruction error of clean image and train the auto-encoder parameter $\phi$ with the following objective:

$$\min_{\phi} \mathbb{E}_{(x,y) \in \chi} \left[ \max_{\delta \in \mathcal{S}} L(\theta; AE_\phi(x + \delta), y) + \lambda D(AE_\phi(x), x) \right]$$  \hspace{1cm} (7)

where $D$ is some distance metric, in particular cross-entropy is used in our experiment. $\lambda \geq 0$ is a hyper parameter to trade-off the two error terms.

3.1 Auto-encoder architecture

Auto-encoder is originally proposed as denoiser [31, 32]. It consists of an encoder and a decoder. Typical auto-encoders have a bottleneck layer in the middle that is much lower dimensional than the input, so that only useful information is retained after training. The training objective is the reconstruction error between encoder’s input and decoder’s output under Gaussian noise. When applying in image domain, encoder and decoder are typically stacked convolutional layers.

For more challenging datasets, the bottleneck layer causes the denoised image to be blur, and as a consequence the model experiences a significant drop in classification accuracy on clean images. This creates an upper limit on the defense performance against adversarial inputs. Inspired by previous work by Liao et al. [17], we use U-net [24] as the auto-encoder architecture to solve this problem. U-net was originally proposed for image segmentation tasks. It adds lateral connections from encoder layers to their corresponding decoder layers. This way, the fine-level details of the image are retained, which helps dramatically with the fidelity of the auto-encoder.

3.2 Ensemble training across models

The optimization in Eq. 7 has the base model in place. A natural idea to increase its generalizability is to train the model on multiple base models. Based on this insight, we propose to apply ensemble training to the auto-encoder across different base models. Such ensemble training acts as a regularizer, so that the auto-encoder generalizes across models. Formally, given a list of base models $F_1, \ldots, F_k$ with loss term $L_1, \ldots, L_k$, we optimize the following problem:

$$\min_{\phi} \sum_{i=1}^k \mathbb{E}_{(x,y) \in \chi} \left[ \max_{\delta \in \mathcal{S}} L_i(\theta_i; AE_\phi(x + \delta), y) + \lambda D(AE_\phi(x), x) \right]$$  \hspace{1cm} (8)

4 Experiment

We implement the model using Tensorflow [1] and Cleverhans [21] framework. Our source code will be freely available, and is attached in the supplementary material for a preview. The experiment is performed on a single RTX 2080Ti graphic card.
4.1 Experiment setup

**Dataset and Model architecture** We apply our approach to MNIST [15] and CIFAR10 [13] dataset. MNIST consists of a training set of 60,000 and testing set of 10,000 28x28x1 images of handwritten digits with 10 classes. CIFAR10 contains a training set of 50,000 and testing set of 10,000 32x32x3 RGB images of objects with 10 classes. The pixel value is normalized into [0,1] by dividing 255. During training, 10% of training data is hold out as validation data. All tests are evaluated on testing data.

For MNIST, we use a simple CNN as base model with four convolutional layers, containing 32,32,64,64 channels, all with 3x3 filters. The architecture detail is depicted as model X in Table 2. This model achieves 99.6% accuracy on clean data. We use a simple auto-encoder model where the encoder consists of two convolutional blocks, each with a 32 channel, 3x3 convolutional layer, a batch normalization layer, a ReLU activation layer, and a 2x2 max pooling layer. The decoder consists of two convolutional blocks as well, each with a 32-channel 3x3 convolutional layer, a ReLU activation layer, and a 2x2 up sampling layer. The output goes through one last convolutional layer of 3 channels activated by sigmoid function to ensure that the decoded image is in valid range [0,1], and the shape is the same as input.

For CIFAR10, we use a standard ResNetV2 with 29 convolutional layers. We apply standard data augmentation, including random crops and flips as were done in [19]. This network achieves 89% on clean test images. The U-net [24] described in Sec 3.1 is used as the auto-encoder architecture. Specifically, the encoder contains 5 convolutional layers, with channel size 32,64,128,256,512 and 3x3 kernel filters. The decoder consists of 5 convolutional layers with channel size 256,128,64,32,3 and 3x3 kernels. There are residual connections to stack the layer in the encoder onto the corresponding layer in the decoder. The final decoded image is produced by a sigmoid activation function to produce valid image in range [0,1].

**Training Details** We train the auto-encoder using the combined adversarial loss and clean image reconstruction loss in Eq. 7. For MNIST, λ is set to 0, because the reconstruction term is not necessary for the model to reach high accuracy on clean image. For CIFAR10, λ is set to 1. During iterative adversarial training, we use PGD to generate adversarial examples. For MNIST model, we use 40 iterations of PGD with step size 0.01 and a maximum distortion of 0.3. For CIFAR10, we uses 10 iterations of PGD with step size 2/255 maximum distortion 8/255.

All models are trained using Adam optimizer with learning rate of 1e-3 and learning rate decay of a factor of 0.5 when the validation loss does not improve over 4 epochs. Training early stops if the validation loss does not improve over 10 epochs, and the best model is restored. It typically takes 30 to 50 epochs to train a model. We observe consistent performance during development, and report results for a single run.

**Threat model** We evaluate attacks in all three kinds of threat models. As a recap, the white-box attack is applied to the entire model (CNN with auto-encoder in place), and the oblivious attack is applied to CNN model only, and the generated adversarial examples are used to attack the model with defense. For black-box attack, we follows [22] and train a substitute model using the 150 holdout data samples in testing dataset as a seed, and query our entire model (CNN with Auto-encoder) as the black-box model for 6 epochs. Then, we apply attack on the substitute model in a white-box manner, and test the resulting adversarial examples on the black-box model. We test different models as the substitute model, and do not find statistically significant difference, thus we report one result where the substitute model has the same architecture as the black-box model.

**Applied attacks** We evaluate both \( l_\infty \)-bounded attacks (FGSM and PGD) and \( l_2 \)-bounded attacks (CW \( l_2 \)). For FGSM, we set the distortion to be \( \epsilon = 0.3 \) for MNIST and \( \epsilon = 8/255 \) for CIFAR10. For PGD, we use the same attack parameters as those used during training. We do not present the CW \( l_\infty \) attack, as the PGD has been shown to be a universal first-order \( l_\infty \)-bounded attack.

For \( l_2 \)-bounded attack, we use the untargeted CW \( l_2 \) attack with learning rate 0.2 and max iteration 1000. We remark that previously, adversarial training is only evaluated on \( l_\infty \)-bounded attacks [19]. That’s because adversarial training used \( l_\infty \) attacks during training, and thus only claims \( l_\infty \) security. In this evaluation, we show that models trained with \( l_\infty \) attacks can also provide substantial robustness against CW \( l_2 \) attack, though only for simple MNIST dataset.
Table 1: MNIST accuracy results on three threat models.

| Attacks | No def | oblivious | black-box | white-box (left: purifying-based) |
|---------|--------|-----------|-----------|-----------------------------------|
|         |        | AdvAE | AdvAE | AdvAE | HGD | DefGAN | It-Adv-train |
| No attack | 99.6 |         |         | 99.1 | 98.3 | 92.2 | 99.5 |
| FGSM $\ell_{\infty}$ | 41.1 | 96.5 | 96.8 | **96.9** | 57.1 | 87.8 | **98.0** |
| PGD $\ell_{\infty}$ | 1.6 | 97.1 | 97.6 | **94.8** | 1.3 | 44.0 | **97.2** |
| CW $\ell_{2}$ | 0.0 | 96.6 | 97.3 | **82.7** | 0.0 | 36.5 | **93.0** |

For each attack, we perform adversarial perturbation on 1000 random samples from testing dataset, and report the model accuracy on these adversarial examples.

### 4.2 Models in comparison

We compare our model (denoted as AdvAE) with three representative models, HGD, DefenseGAN, and iterative adversarial training (denoted It-Adv-train). We compare with DefenseGAN [25] because it is the best-performing purifying-based technique against white-box attacks in practice. We choose to compare with HGD [17] for two reasons. First, it is closely related to our approach, thus the comparison can clearly show the advantage of applying iterative training scheme. Second, it acts as a representative of approaches which claim only oblivious attack security but not white-box one, and we show they provide little white-box robustness. It-Adv-train is not a purifying-based method, but since our technique also builds atop this technique, we compare the performance to see if applying adversarial training on part of the model can achieve similar robustness. We omit other earlier approaches such as MagNet [20] and PixelDefend [27], because they have been shown to perform worse [25], and does not provide white-box security [3, 6].

When performing white-box attacks on DefenseGAN, we follow the BPDA algorithm suggested by Athalye et al. [3] to approximate the vanished gradients. In particular, we directly set the gradient of the “projection step” of DefenseGAN to 1 during back-propagation when calculating the input gradient. We train GAN for 200,000 iterations. The DefenseGAN projection step is performed with gradient descent iteration $L=200$ and random restart $R=10$, as was evaluated in the original paper.

### 4.3 MNIST results

The MNIST experiment results against three threat models are shown in Table 1. The CNN model achieves 99.6% accuracy on clean data. As a baseline, when no defense is applied, the model is very vulnerable against all attacks. By comparison, the oblivious results of AdvAE show that adding our auto-encoder can indeed protect the model very well without modifying the model itself. The black-box accuracy does not drop, showing that our model does not suffer from adversarial examples transferred from substitute models.

For white-box results, compared to HGD which also features an external denoiser, we show that, by applying iterative adversarial training scheme instead of a single adversarial training step, we can tremendously boost the white-box security, from 1.3% accuracy to 94.8% for PGD attack and from 0% to 82.7% for CW $\ell_{2}$ attack. We show that DefenseGAN performs poorly under BPDA attack, with 44.0% and 36.5% accuracy against PGD and CW $\ell_{2}$, respectively. Thus, we claim ours as the new state-of-the-art purifying-based model against white-box attacks. Comparing with It-Adv-train, AdvAE performs worse but still comparable. This is as expected, because AdvAE restricts itself by not modifying the base model. This result shows that AdvAE successfully introduces the white-box robustness from It-Adv-train into purifying-based approaches.

### 4.4 MNIST transferability results

In this section, we evaluate whether auto-encoders trained on one model can be used to protect other models, i.e. transferability. In addition to the CNN we used in previous experiment (denoted as model $X$), we evaluate 4 alternative models that were used in [25], denoted model A,B,C,D. The

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1This result is different from the performance reported in original DefenseGAN paper, because we apply BPDA attack [3] to approximate the vanished gradient.
Table 2: Alternative model architectures. Each convolutional layer is activated by ReLU.

| X            | A            | B            | C            | D            |
|--------------|--------------|--------------|--------------|--------------|
| Conv(32,3x3,1) | Conv(64,5x5,1) | Dropout(0.2) | Conv(128,3x3,1) | FC(200)      |
| Conv(32,3x3,1)+MaxPool | Conv(64,8x8,2) | Conv(64,3x3,2) | Dropout(0.5) | FC(200)      |
| Conv(64,3x3,1) | Dropout(0.25) | Conv(128,6x6,2) | Dropout(0.25) | FC(200)      |
| Conv(64,3x3,1)+MaxPool | Conv(128,5x5,1) | FC(128)      | Dropout(0.5) | FC(10)+Softmax |
| FC(200)+Dropout(0.5) | FC(10)+Softmax | FC(10)+Softmax | FC(10)+Softmax | FC(10)+Softmax |

Table 3: MNIST accuracy results on model transfer and ensemble against white-box attacks. X/A means auto-encoder is trained on model X, but used on model A. [XAB] / C means auto-encoder is ensemble trained on three model X,A,B, and evaluated on model C.

| Attacks | Transfer | Ensemble |
|---------|----------|----------|
|         | X/X | X/A | X/B | X/C | X/D | {XAB}/A | {XAB}/B | {XAB}/C | {XAB}/D |
| No attack | 99.1 | 98.1 | 96.8 | 96.5 | 79.7 | 99.0 | 99.1 | 97.9 | 95.0 |
| FGSM $\ell_\infty$ | 96.9 | 93.1 | 92.1 | 93.1 | 73.8 | 97.1 | 95.8 | 94.7 | 88.5 |
| PGD $\ell_\infty$ | 94.8 | 90.7 | 88.2 | 90.9 | 71.8 | 95.7 | 93.8 | 93.4 | 85.4 |
| CW $\ell_2$ | 82.7 | 76.9 | 71.7 | 77.9 | 50.2 | 85.0 | 81.8 | 81.2 | 69.7 |

The architecture of the all models used is shown in Table 2. There is a ReLU activation layer after each convolutional layer. All base models are pre-trained with clean images. For transfer experiment, we train our auto-encoder on model X, and evaluate on model A,B,C,D. We also evaluate the ensemble training. In particular, the auto-encoder is trained using Eq. 8 on model X,A,B, and tested on model A,B,C,D.

The results are shown in Table 3. In the left half of Table 3 we can see the trained auto-encoders can transfer to protect other models very well. The accuracy decreases up to 11% when transferring from model X to model A,B,C. However, the accuracy drops 20-30% when transferring from model X to model D. This is reasonable considering there is a large architecture change from CNN to FC-only network. In the right half of Table 3 we show the ensemble training across different CNN models. In all cases, the ensemble boosted the transferability by a large margin, for example, although not trained on model C, performance of “XAB/C” against all attacks is considerably better than that of “X/C”. Interestingly, the auto-encoder trained on X,A,B can work very well on model D despite the dramatic change of model architecture.

4.5 CIFAR10 results

We observe the accuracy drop on clean data on AdvAE as well as It-Adv-train. This shows the trade-off of robustness and accuracy, which is also discussed by several recent papers [28, 29]. We didn’t compare with DefenseGAN on CIFAR10, as DefenseGAN does not claim robustness against CIFAR10. We leave the transferability experiment of models on CIFAR10 as a future work, because CIFAR10 requires much more complicated models such as DenseNet and ResNet. Transferability between these models is a challenging research topic.

The CIFAR10 experiment results are shown in Table 4. As a baseline, the undefended model has poor accuracy on all attacks, while AdvAE performs well against all attacks in oblivious and black-
box attacks. For white-box attacks, we observe similar pattern as MNIST results for $\ell_\infty$-bounded attacks, the FGSM and PGD attacks. In particular, AdvAE achieves 50.8% and 43.6% accuracy against FGSM and PGD attack, respectively. This is on-par with the performance of It-Adv-train performing on the underlying CNN model, showing again the validity of applying adversarial training on-demand to only the auto-encoder. Lastly, in contrary to MNIST dataset, results on CW $\ell_2$-bounded attack suggest that iterative adversarial training in general (and hence our AdvAE model) does not offer additional white-box security against the $\ell_2$-bounded attack on more challenging dataset like CIFAR10.

5 Related work

Our work builds upon iterative adversarial training. Adversarial training [9] protects a model against adversarial perturbation by augmenting training data with adversarial examples. Original adversarial training generates the adversarial examples once before training. As a result the trained model is still vulnerable to white-box attacks. Iterative adversarial training [14, 19] generates adversarial examples during each iteration of training, and is shown to be successful against white-box attacks. However, such iterative training scheme introduces much computational overhead. To make things worse, current adversarial training cannot protect a pre-trained models without modifying it, thus such computational overhead needs to be paid whenever a model needs to be hardened. Ensemble adversarial training [29] augments the training data with adversarial examples generated on other pre-trained models. Like adversarial training, this technique trains the base classifier, thus cannot be transferred to protect other models. Feature denoising [34] also uses adversarial training to enhance white-box robustness. But they integrate denoise blocks between the convolutional layers in the base model, and thus is model specific and lack of transferability.

There has been a line of work of purifying-based approach where the defense mechanism purifies the adversarial examples into benign ones, without modifying the underlying models being protected. One kind of such work is by adding denoisers, e.g. MagNet [20] and HGD [17]. However, as shown by [6, 3], none of them achieve white-box security. In particular, HGD by Liao et al. [17] is very similar to us, in the sense that they also add auto-encoders that are trained using adversarial examples. However, same as original adversarial training, the adversarial examples are pre-generated against the base model. As a result, the model is still vulnerable to white-box attacks [2]. Defense-VAE [16] uses VAE instead of denoising auto-encoders. Same as HGD, Defense-VAE pre-generates adversarial examples, and does not claim white-box security, but oblivious one.

Another kind of purifying-based approach builds upon generative models [25, 12, 27]. These approaches train a generative model $G$ for the clean data distribution, and purify an adversarial example $x$ by finding the closest data point to $x$ on the generator’s manifold $G(z)$. However, such models suffer from white-box attack in two perspectives. First, as shown by previous work [3, 12], the adversarial examples exist on the generator’s manifold, and thus the underlying principle of these approaches has been shown to provide 0% accuracy against white-box attacks [3]. Second, note that the white-box robustness of these approaches comes from the generator manifold projection step, where an optimization loop caused the gradients to vanish. However, this can be simply bypassed by BPDA algorithm [3] that approximates the vanished gradient as 1, as it is supposed to be identity mapping. Such gradient approximation has been shown to reduce the white-box accuracy significantly [3]. Ilyas et al. [12] proposed to further robustify the generative models through adversarial training on the base classifier. This is different from our objective, where we do not wish to modify the underlying classifier.

6 Conclusion

In this paper, we propose a novel purifying-based defense approach that applies iterative adversarial training to auto-encoders to protect neural models against adversarial examples without modifying the base models. We empirically show that our proposed method is the state-of-the-art purifying-based approach against white-box attacks. Additionally, we show that our auto-encoders can be directly applied to protect other models very well, and ensemble training further boost the transferability.
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