A Mask-Based Adversarial Defense Scheme

Weizhen Xu, Chenyi Zhang, Fangzhen Zhao and Liangda Fang
Jinan University

Abstract

Adversarial attacks hamper the functionality and accuracy of Deep Neural Networks (DNNs) by meddling with subtle perturbations to their inputs. In this work, we propose a new Mask-based Adversarial Defense scheme (MAD) for DNNs to mitigate the negative effect from adversarial attacks. To be precise, our method promotes the robustness of a DNN by randomly masking a portion of potential adversarial images, and as a result, the output of the DNN becomes more tolerant to minor input perturbations. Compared with existing adversarial defense techniques, our method does not need any additional denoising structure, nor any change to a DNN’s design. We have tested this approach on a collection of DNN models for a variety of data sets, and the experimental results confirm that the proposed method can effectively improve the defense abilities of the DNNs against all of the tested adversarial attack methods. In certain scenarios, the DNN models trained with MAD have improved classification accuracy by as much as 90% compared to the original models that are given adversarial inputs.

1 Introduction

Deep Neural Networks (DNNs) have achieved great success in the past decade in research areas such as image classification, natural language processing, and data analytics, with a variety of application domains like banking, financial services and insurance, IT & Telecom, manufacturing, and healthcare etc. [Report, 2020]. However, researchers have discovered that it is possible to introduce human imperceptible perturbations to inputs of a DNN in a certain way that induces incorrect or misleading outputs from the DNN at the choice of an adversary [Szegedy et al., 2014; Goodfellow et al., 2015; Papernot et al., 2016a]. As of today, the bulk of the existing defense approaches can be roughly grouped in two categories, i.e., they either focus on the detection of adversarial inputs (e.g., [Ma et al., 2018; Cohen et al., 2020; Xu et al., 2018]), or to take steps to strengthen DNNs (e.g., [Meng and Chen, 2017; Madry et al., 2018; Mustafa et al., 2019]), making them more robust to withstand perturbations on inputs.

In this paper, we follow the latter path by enhancing robustness in the decision procedure of DNNs. Again, there exist a rich class of works in the school of adversarial defense. Some early works propose adversarial training which applies adversarial inputs together with clean inputs at the time of training, in order to reduce the effectiveness of adversarial samples on DNNs [Madry et al., 2018; Lee et al., 2020], or distillation [Papernot et al., 2016b] which trains a model to reduce the magnitude of gradients against adversarial attacks. Other approaches boost robustness of DNNs by redesigning training methods [Mustafa et al., 2019], or apply filtering mechanisms that “correct” the adversarial inputs through autoencoder-based structures [Meng and Chen, 2017; Salman et al., 2020]. Motivated by a recent paper [He et al., 2021] which restores missing pixels of an image, we devise a new adversarial defense scheme called a Mask-based Adversarial Defense training method (MAD) for DNNs that classify images. In addition, we believe that such a mechanism may also be applicable to improve DNN robustness in other scenarios. Firstly, we have the following observations.

- Information density is often low in images, as missing patches from an image can often be mostly recovered by a neural network structure [He et al., 2021] or by a human brain (as you look at something through a fence).
Adversarial attacks on images usually introduce a minor perturbation to inputs, which may be reduced or cancelled by (randomly) covering part of the image.

In this approach, we split an image into grids of pre-defined size (e.g., $4 \times 4$), and randomly mask each grid with a given probability (e.g., 75%) into a default value (e.g., the black value in RGB for those masked pixels) to generate training samples. After the training, we also apply masking to images at the test stage (for the classification task), as illustrated in Fig. 1. Given an (unmasked) image, the test process is to be repeated a number of times, which makes a better chance of filtering out malicious perturbations, and the final decision is then defined as the most-voted class taking into account the outputs for all randomly masked inputs.

**Contribution.** In this work, we introduce a new adversarial defence method MAD which applies masking at both the training phase and the test phase. This approach enjoys the following properties.

- Our method seems easily applicable to many existing DNNs. Compared with other adversarial defense methods, we do not need special treatment to the structures of DNNs, redesign of loss functions, or any (autoencoder-based) input filtering.
- The randomized masking at both the training phase and the test phase yields our method more resistant to adaptive white-box adversarial attacks.
- The experiment on a variety of models (LeNet, VGG and ResNet) has shown the effectiveness of our methods with a significant improvement in defense (up to 93% precision gain) when facing various adversarial samples, compared to the models without MAD.

## 2 Related Work

Since we work on an adversarial defense scheme, we conduct a brief overview to the mechanism of adversarial attacks and various types of adversarial defense works.

### 2.1 Adversarial attack

In general, an adversarial attack method generates tiny perturbations that are applied to clean inputs, making them incorrectly classified by a DNN. Some of the earliest methods include box-constrained L-BFGS [Szegedy et al., 2014], Fast gradient sign method (FGSM) [Goodfellow et al., 2015] and Jacobian-based Saliency Map Attack (JSMA) [Papernot et al., 2016b]. Perhaps the most widely used attack method is FGSM, which is also included in our experiment. FGSM generates a perturbation for an image by computing the following:

$$
\delta = \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y))
$$

(1)

where $L(\cdot)$ is the loss function used for neural network training which calculates the difference between label $y$ and the output produced from input $x$ for the DNN with parameter $\theta$. The direction of movement is obtained by the gradient of loss and constant $\epsilon$ which restricts the norm of perturbation. Basic iterative method (BIM) [Kurakin et al., 2017] and projected gradient descent (PGD) [Madry et al., 2018] are the iteration and extension of FGSM to obtain better attack effect, respectively.

The other advanced adversarial attack methods used in our experiments are DeepFool [Moosavi-Dezfooli et al., 2016] and CW [Carlini and Wagner, 2017]. DeepFool computes an approximation of a minimal perturbation according to the DNN model’s decision boundary. In detail, given an image, DeepFool iteratively computes a small perturbation, taking into account the linearized boundary of region that contains the current perturbed image, thus it can be shown that DeepFool is able to compute a smaller perturbation than FGSM while keeping similar successful attack ratios. Carlini and Wagner introduce adversarial attack methods that make quasi-imperceptible perturbations by restricting $l_0$, $l_2$ and $l_\infty$ norms. The CW attack not only breaks some of the well accepted adversarial defense methods such as defensive distillation [Papernot et al., 2016a], but also achieves remarkable transferability, in the sense that it can also be used for black box attacks when the parameters of a model is unknown.

### 2.2 Adversarial defense

Adversarial defense aims to counter the adversarial effect and to make DNNs achieve performance on adversarial samples close to results on clean samples. Existing approaches can be roughly classified as (1) use of additional denoising structures before the DNN, and (2) enforcing the DNN to become more robust against adversarial attacks.

**Additional denoising structures.** MagNet [Meng and Chen, 2017] is a framework consisting of a detector that rejects adversarial samples that are far away the normal input manifolds and a reformer that finds the closest normal input if the adversarial input is not far from the manifolds. A similar approach is HGD [Liao et al., 2018] which applies high-level representation guided denoiser, so that it can be designed as a defense model that transforms adversarial inputs to easy-to-classify inputs. Defense-GAN [Samangouei et al., 2018] tries to model the distribution of clean images, and it can find a close output to an adversarial image which does not contain the adversarial changes. Denoised smoothing [Salman et al., 2020] prepends a custom-trained denoiser to a DNN and uses randomized smoothing for training the combination which enforces a non-linear Lipschitz property. PixelDefend [Song et al., 2018] approximates the training distribution using a PixelCNN model and purifies images towards higher probability areas of the training distribution. Compared with our method, all these approaches introduce additional network structures which help to remove adversarial noise from inputs at the cost of increasing the number of parameters of the working model. In our experiment, we also empirically show that MAD outperforms MagNet and Denoised smoothing in most of the test cases.

**DNN model Enhancement.** In this category, adversarial training [Madry et al., 2018] and defensive distillation [Papernot et al., 2016a] are among the early successful approaches. In particular, adversarial training introduces adversarial samples at the training stage to enhance resistance against attacks. Defensive distillation transfers one DNN to another with the same functionality but less sensitive
to input perturbations. However, both adversarial training
and defensive distillation require substantially more training
cost. Introducing randomized variation to inputs and network pa-
rameters at the time of training as been discussed in [Podevin
et al., 2019; Gu and Rigazio, 2015]. Parseval networks [Cisse
et al., 2017] limits the Lipschitz constant of linear, con-
volutional and aggregation layers in the network to be smaller
than 1, making these layers tight frames. PCL [Mustafa et al.,
2019] separates the hidden feature of different categories by
designing a new loss function and bypass network, so as to
increase the difficulty of adversarial attacks and achieve the
effect of adversarial defense. Since the existing DNN mod-
els are already being optimized regarding performance (e.g.,
network neural search (NAS) [Zoph and Le, 2016] technol-
y is widely used to find neural networks structure with bet-
ter performance), the modification of DNN structures may
introduce human bias, resulting in unpredictable performance
degradation. In contrast, our approach MAD does not require
 any change to network structure or loss function design.

3 Mask-based adversarial defense

In this paper we focus on DNNs that classify images. For-
 formally, a DNN is a function \( f_\theta \) which maps \( X \subseteq \mathbb{R}^d \) to \( Y \),
where \( \theta \) represents values for the network parameters that
are determined at training, \( d \) is the dimension of the input space.
\( X \) is the input space for images and \( Y \) is a finite set of classes
or labels to be returned from \( f_\theta \). An adversarial input can be
written as \( x' = x + \delta \) with \( x \) a clean input and \(|\delta||_p < \varepsilon, \)
such that \( f_\theta(x) \neq f_\theta(x') \), where \(|\delta||_p \) is the \( p \) norm of the
perturbation \( \delta \) and \( \varepsilon > 0 \) is of negligible size, making \( x \) and
\( x' \) in the same class to a human being.

3.1 Training a classifier for masked images

A natural approach to counter an adversarial input \( x' \) is to
reduce the effect of perturbation \( \delta \). Given \( \delta \) combined with
the pixels of a natural image \( x \), masking part of \( x' \) would poten-
tially reduce the adversarial effect of \( \delta \). Fortunately, such
a masking operation which “covers” parts of an image does
not necessarily make the classification job more difficult for
DNNs. Since natural images are heavy in spatial information
redundancy, as shown in [He et al., 2021], in which missing
pixels of an image can be reconstructed by the state-of-the-
art MAE model even though a large amount of input pixels
are masked\(^1\). Since the task of classification is to be

\( \tau : \mathbb{R}^d \times C \rightarrow \mathbb{R}^d \) a masking operator, where \( C \) is a
pre-defined set which has its cardinality depending on the
number of grids that cover the input. For example, masking
a \( 4 \times 4 \) image by using \( 2 \times 2 \) grids gives \( 2^4 = 16 \) possible
ways of masking (2 possibilities for each grid), so that in this
case one may set \(|C| = 16\). (The extreme case is that all grids
are masked, but this hardly happen as we are to explain in
our experiment.) Suppose the original classifier \( f_\theta \) is trained
with sample set \( Z \), we use sample set \( Z \times C \) to retrain the

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
$\# \text{ tests}$ & 1 & 3 & 5 & 7 \\
\hline
precision & 75.89 & 81.78 & 82.50 & 82.97 \\
\hline
\end{tabular}
\caption{The precision of retrained model for $3/4$ masked images from CIFAR-10 with multiple tests}
\end{table}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure.png}
\caption{An experiment showing weakened effect of partially removed adversarial vectors generated from CIFAR-10 samples on the accuracy of a VGG16 network.}
\end{figure}

\footnotetext[1]{Our human brains possess similar power of recognizing (or even reconstructing) a partially masked object.}

\(^1\)Our human brains possess similar power of recognizing (or even reconstructing) a partially masked object.

\subsection*{3.2 Mitigating adversarial attacks}

In our next step, we investigate how the new model trained
for masked images can be used to boost defense against ad-
versarial inputs. Given an adversarial input $x' = x + \delta$, the new model produces $f_\theta'(\tau(x + \delta, c))$. Let $\delta' = \tau(x + \delta, c) - \tau(x, c)$, which is the actual perturbation on the input to $f_\theta'$, it is obvious that we have $||\delta'||_p \leq ||\delta||_p$ for any $p$, since only unmasked pixels of $x$ are affected by $\delta$. As an example, suppose $3/4$ of the input pixels are masked, the expected $\ell_1$ norm of $\delta'$ is only about $1/4$ in size of the $\ell_1$ norm of the original perturbation $\delta$.

In order to measure how much effect of adversarial inputs is weakened by masking, we conduct another preliminary study by randomly removing part of the perturbation vector $\delta$ from an adversarial input. We train a VGG16 network on CIFAR-10 data set using the conventional method. Then adversarial samples are generated from clean samples, from which we obtain a perturbation vector by taking the difference between an adversarial input and its corresponding clean image. These vectors are then randomly masked before adding back to the clean images to form a set of weakened attack samples. The relationship between network accuracy and the proportion of the remaining adversarial disturbance is shown in Figure 2 where $100\%$ remaining adversarial disturbance represents strength of the original adversarial inputs, and $20\%$ remaining represents the adversarial inputs with $80\%$ of the perturbation dimensions removed. In particular, we find that the CW attack is more sensitive to this perturbation removal operation, which may be due to that CW generates perturbations with higher relevance. For most other attacks, we find that removing at least $60\%$ of the perturbation (i.e., $40\%$ of the attack remaining) is required to deliver significant improvement regarding classification accuracy.

In general, there is often a trade-off between the strength of defense and the degree of accuracy. As shown in Table 2 of our experiment in the next section, after fixing a network structure, increasing the percentage of covered pixels (at both the training and test phases) often results in a stronger defense against most of the tested adversarial attacks, but with less accurate classification results on benign (clean) inputs. For example, given the first FGSM attack with perturbation degree $15$ and mask rate of $1/3$ yields a model with defense accuracy of $70.17\%$ on adversarial samples, which is less effective compared to the $85.3\%$ accuracy when each grid has a $4/5$ probability of being masked. However, the $4/5$-masked-model only has $76.14\%$ accuracy on benign images, while the $1/3$-masked-model has $85.31\%$ accuracy.

4 Experiment

The experiments are based on TensorFlow 2.6 and completed on a server running Ubuntu 18.04LTS with a NVIDIA GeForce RTX 3090 GPU. The Adam optimizer is used in the training phase with learning rate $0.001$. Foolbox [Rauber et al., 2017] is used to generate adversarial samples for the test set. We choose three popular DNN models (LeNet with MNIST [Lecun et al., 1998], VGG16 [Simonyan and Zisserman, 2015] with CIFAR-10 [Krizhevsky and Hinton, 2009] and ResNet18 [He et al., 2016] with SVHN [Netzer et al., 2011]). In order to achieve a classification accuracy close to its corresponding DNN model on benign (clean) images, a MAD model is tested with 20 randomly masked images transformed from a given image, followed by taking the most favored class of all 20 tests as the output.

**Basic settings for adversarial attack and defense.** We leave the parameters of all adversarial attack methods as default, except for the perturbation degree $\epsilon$, which is given along with the “Attack method” in the tables. Note that for all experiments in this paper, adversarial samples are generated only from benign images that are correctly classified by the DNNs to be attacked. The adversarial methods also take into account the parameters of the MAD model (in which sense they are white-box attacks). The generated adversarial samples aim to lower the accuracy of the MAD model without masking being applied, e.g., the FGSM L1 with $\epsilon = 10$ attack results in a $44.12\%$ accuracy. When multiple randomized masking is applied at testing, the accuracy of the MAD model becomes $68.94\%$ (with $24.82\%$ improvement) facing the same adversarial samples.

**On the mask rate and grid size.** The effectiveness of MAD also depends on two critical hyperparameters. The mask rate is a constant which is used as the probability for a grid to be masked at the training phase as well as test phase. As mentioned before, a larger mask rate potentially remove more perturbation (which means better defense) at the cost of less usable information for the classifier, which may lead to worse accuracy on clean images.

We carry out an experiment on a selection of mask rates
The grid size is another hyperparameter to be determined before the main experiment. Intuitively, a larger grid size allows better continuity of information on average that is preserved in a masked image, examples illustrated in Figure 3. Table 4 presents the preliminary experimental results on a VGG model with CIFAR-10 data set for a selection of grid size values in the masking operation at the time of training and testing, respectively. Given images in CIFAR-10 are of size 32 × 32, we try a number of combinations for values that divide 32, and again, we do not claim that we are able to find an optimal setting in such an experiment. If we focus on the three columns where 8 × 8 grids are used for training, the results seem to suggest that using a larger grid in the test phase produces a better classification accuracy on benign data.

### Table 2: Defense of different mask rates with the grid size of 8 × 8 for the training phase and 4 × 4 for test phase, on a VGG16 model with CIFAR-10 data set

| Attack method | Attack Defense Improvement |
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Table 4: Defense effects of different grid sizes with mask rate of 3/4 on VGG16 and CIFAR-10.

| Training Test | Benign | 4 × 4 | 4 × 4 | 8 × 8 | 8 × 8 | 8 × 8 | 8 × 8 |
|---------------|--------|------|------|------|------|------|------|
|               | LeNet l = 0.15 | 86.61% | 83.84% | 85.34% | 82.63% | 75.68% |
| FGSN | L1 = 0.20 | 83.20% | 79.39% | 82.74% | 79.25% | 71.72% |
| FGSN L2 | 0.03 | 89.54% | 87.13% | 86.17% | 84.62% | 79.84% |
| FGSN L2 | 0.04 | 86.63% | 83.41% | 85.34% | 81.89% | 73.11% |
| FGSN L1 = 0.01 | 86.10% | 82.11% | 84.42% | 81.05% | 73.63% |
| FGSN Linf | 0.02 | 73.64% | 67.07% | 73.93% | 68.77% | 59.87% |
| BIM L1 = 10 | 89.21% | 85.66% | 87.64% | 84.71% | 75.67% |
| BIM L1 = 15 | 84.62% | 79.36% | 86.61% | 80.96% | 65.50% |
| BIM L2 = 0.3 | 87.52% | 83.55% | 86.12% | 83.21% | 71.88% |
| BIM L2 = 0.4 | 83.64% | 80.76% | 85.50% | 80.88% | 65.82% |
| BIM Linf = 0.01 | 86.60% | 81.86% | 86.47% | 81.80% | 68.67% |
| BIM Linf = 0.015 | 81.26% | 72.97% | 83.62% | 77.06% | 56.05% |
| PGD L1 = 15 | 88.99% | 84.76% | 85.34% | 81.89% | 75.11% |
| PGD L1 = 20 | 85.78% | 80.08% | 86.23% | 83.48% | 71.13% |
| PGD L2 = 0.3 | 90.35% | 87.03% | 88.07% | 86.42% | 78.77% |
| PGD L2 = 0.4 | 88.01% | 83.48% | 87.20% | 84.45% | 74.79% |
| PGD Linf = 0.01 | 88.64% | 84.05% | 86.61% | 84.78% | 73.89% |
| PGD Linf = 0.015 | 84.57% | 77.20% | 84.46% | 81.45% | 65.54% |
| CW L2 = 1 | 94.78% | 95.25% | 89.53% | 91.28% | 93.94% |
| DeepFool L2 = 0.6 | 88.54% | 87.10% | 85.03% | 84.20% | 80.31% |
| DeepFool L2 = 0.8 | 85.73% | 82.75% | 82.65% | 81.99% | 75.53% |
| DeepFool Linf = 0.01 | 90.33% | 88.21% | 85.42% | 85.23% | 80.42% |
| DeepFool Linf = 0.015 | 86.03% | 82.66% | 82.16% | 80.44% | 74.92% |

Table 5: Comparison of effects of different adversarial defense methods on VGG16 and CIFAR-10.

| Attack method | MagNet | Denoised smoothing | Parseval networks | PCL | MAD |
|---------------|--------|--------------------|-------------------|-----|-----|
| Benign | 82.32% | 79.72% | 83.47% | 82.65% |
| FGSN L1 = 0.15 | 67.41% | 81.97% | 43.26% | 74.94% |
| FGSN L1 = 0.20 | 65.68% | 76.50% | 33.11% | 70.53% |
| FGSN L2 = 0.03 | 72.15% | 85.88% | 52.41% | 79.54% |
| FGSN L2 = 0.04 | 69.75% | 81.70% | 42.69% | 75.32% |
| FGSN Linf = 0.01 | 57.81% | 82.83% | 44.22% | 75.56% |
| FGSN Linf = 0.02 | 44.98% | 65.25% | 20.75% | 62.72% |
| BIM L1 = 10 | 66.56% | 80.11% | 45.23% | 64.03% |
| BIM L1 = 15 | 62.63% | 68.58% | 26.22% | 48.03% |
| BIM L2 = 0.3 | 67.63% | 77.36% | 38.57% | 61.26% |
| BIM L2 = 0.4 | 65.73% | 66.06% | 24.96% | 48.34% |
| BIM Linf = 0.01 | 51.34% | 75.51% | 29.55% | 59.83% |
| BIM Linf = 0.015 | 42.84% | 62.41% | 13.52% | 43.31% |
| PGD L1 = 15 | 67.08% | 79.83% | 37.84% | 66.63% |
| PGD L1 = 20 | 64.66% | 72.81% | 24.64% | 53.18% |
| PGD L2 = 0.3 | 71.98% | 84.65% | 48.20% | 70.68% |
| PGD L2 = 0.4 | 69.44% | 79.17% | 35.14% | 66.70% |
| PGD Linf = 0.01 | 56.92% | 81.17% | 36.89% | 72.22% |
| PGD Linf = 0.015 | 47.79% | 70.74% | 19.35% | 54.74% |
| DeepFool L2 = 0.6 | 92.58% | 99.74% | 43.42% | 89.48% |
| DeepFool L2 = 0.8 | 63.84% | 65.04% | 34.10% | 49.95% |
| DeepFool Linf = 0.01 | 62.79% | 81.43% | 30.49% | 58.80% |
| DeepFool Linf = 0.015 | 54.26% | 71.68% | 9.49% | 53.28% |

Table 6: Performance comparison of different detection methods on VGG16 and CIFAR-10.

5 Conclusion

In this paper, we have proposed a new model-based adversarial defense method called MAD, and have conducted extensive experiments showing that our method provides an effective defense against a variety of adversarial attacks.

Moreover, since the attack algorithms are allowed to have access to the parameters of MAD, our defense seems to provide a way to withstand adaptive white-box attacks, as the randomized masking technique may enforce attackers to consider an attack space of size exponential to the number of grids required to cover the input. We plan to study detailed measurement of this effect on adaptive white-box adversarial attack methods in our future work.
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