Abstract

Though deep neural networks have achieved the state of the art performance in visual classification, recent studies have shown that they are all vulnerable to the attack of adversarial examples. In this paper, we develop improved techniques for defending against adversarial examples. First, we propose an enhanced defense technique denoted \textit{Attention and Adversarial Logit Pairing (AT+ALP)}, which encourages both attention map and logit for the pairs of examples to be similar. When being applied to clean examples and their adversarial counterparts, \textit{AT+ALP} improves accuracy on adversarial examples over adversarial training. We show that \textit{AT+ALP} can effectively increase the average activations of adversarial examples in the key area and demonstrate that it focuses on discriminate features to improve the robustness of the model. Finally, we conduct extensive experiments using a wide range of datasets and the experiment results show that our \textit{AT+ALP} achieves the state of the art defense performance. For example, on \textit{17 Flower Category Database}, under strong 200-iteration PGD gray-box and black-box attacks where prior art has 34% and 39% accuracy, our method achieves 50% and 51%. Compared with previous work, our work is evaluated under highly challenging PGD attack: the maximum perturbation $\epsilon \in \{0.25, 0.5\}$ i.e. $L_{\infty} \in \{0.25, 0.5\}$ with 10 to 200 attack iterations. To the best of our knowledge, such a strong attack has not been previously explored on a wide range of datasets.

Introduction

In recent years, deep neural networks have been extensively deployed for computer vision tasks, particularly for visual classification problems, where new algorithms have been reported to achieve even better performance than human beings (Krizhevsky, Sutskever, and Hinton 2012; He et al. 2015; Li et al. 2019a). The success of deep neural networks has led to an explosion in demand. However, recent studies have shown that they are all vulnerable to the attack of adversarial examples (Szegedy et al. 2013; Carlini and Wagner 2016; Moosavi-Dezfooli, Fawzi, and Frossard 2016; Bose and Aarabi 2018). Small and often imperceptible perturbations to the input images are sufficient to fool the most powerful deep neural networks.

In Figure 1, we visualize the spatial attention map of a flower and its corresponding adversarial image on ResNet-50 (He et al. 2015) pretrained on ImageNet (Russakovsky et al. 2015) which shows where the network focuses in order to classify the given image. Figure 1: (a) is original image and (b) is corresponding spatial attention map of ResNet-50 (He et al. 2015) pretrained on ImageNet (Russakovsky et al. 2015) which shows where the network focuses in order to classify the given image. (c) is adversarial image of (a), (d) is corresponding spatial attention map.
The contributions of this paper are summarized as follows:

- We introduce enhanced adversarial training using a technique we call **Attention and Adversarial Logit Pairing (AT+ALP)**, which encourages both attention map and logit for pairs of examples to be similar. When being applied to clean examples and their adversarial counterparts, **AT+ALP** improves accuracy on adversarial examples over adversarial training. (Araujo et al. 2019) adds random noise at training and inference time, (Xie et al. 2018) adds denoising blocks to the model to increase adversarial robustness, while neither of the above approaches focuses on the attention map.

In terms of methodologies, our work is also related to deep transfer learning and knowledge distillation problems, and the most relevant work to our study is (Zagoruyko and Komodakis 2016a; Li et al. 2019b), which constrain the $L_2$-norm of the difference between their behaviors (i.e., the feature maps of outer layer outputs in the source/target networks). Our **AT+ALP** constrains attention map and logit for pairs of clean examples and their adversarial counterparts to be similar.

**Definitions and Threat Models**

In this paper, we always assume the attacker is capable of forming attacks that consist of perturbations of limited $L_\infty$-norm. This is a simplified task chosen because it is more amenable to benchmark evaluations. We consider two different threat models characterizing amounts of information the adversary can have:

- **Gray-box Attack** We focus on defense against gray-box attacks in this paper. In a gray-back attack, the attacker knows both the original network and the defense algorithm. Only the parameters of the defense model are hidden from the attacker. This is also a standard setting assumed in many security systems and applications (Pfleeger and Pfleeger 2004).

- **Black-box Attack** The attacker has no information about the model’s architecture or parameters, and no ability to send queries to the model to gather more information.

**Methods**

**Architecture**

Figure 2 represents architecture of **Attention and Adversarial Logit Pairing (AT+ALP)**: a baseline model is adversarial trained so as, not only to make similar logits, but to also have similar spatial attention maps to those of original image and adversarial image.

**Adversarial training**

We use adversarial training with **Projected Gradient Descent (PGD)** (Madry et al. 2017) as the underlying basis for our methods:

$$\arg \min_{\theta} \mathbb{E}_{(x,y) \in \mathcal{D}_{\text{data}}} \left( \max_{\delta \in S} L(\theta, x + \delta, y) \right)$$

where $\mathcal{D}_{\text{data}}$ is the underlying training data distribution, $L(\theta, x + \delta, y)$ is a loss function at data point $x$ which has true class $y$ for a model with parameters $\theta$, and the maximization with respect to $\delta$ is approximated using PGD. In this paper, the loss is defined as:

$$L = L_{CE} + \alpha L_{ALP} + \beta L_{AT},$$

where $L_{CE}$ is cross entropy, $\alpha$ and $\beta$ are hyperparameters.
Figure 2: Schematic representation of Attention and Adversarial Logit Pairing (AT+ALP): a baseline model is trained so as, not only to make similar logits, but to also have similar spatial attention maps to those of original image and adversarial image.

**Adversarial Logit Pairing**

We also use Adversarial Logit Pairing (ALP) to encourage the logits from clean examples and their adversarial counterparts to be similar to each other. For a model that takes inputs $x$ and computes a vector of logit $z = f(x)$, logit pairing adds a loss:

$$L_{ALP} = L_a(f(x), f(x + \delta))$$

In this paper we use $L_2$ loss for $L_a$.

**Attention Map**

We use Attention Map (AT) to encourage the attention map from clean examples and their adversarial counterparts to be similar to each other. Let $I$ denote the indices of all activation layer pairs, for which we want to pay attention. Then, we can define the following total loss:

$$L_{AT} = \sum_{j \in I} \left\| \frac{Q^j_{ADV}}{||Q^j_{ADV}||_2} - \frac{Q^j_O}{||Q^j_O||_2} \right\|_p$$

Let $O, ADV$ denote clean examples and their adversarial counterparts, where $Q^j_O = \text{vec} \left( F \left( A^j_O \right) \right)$ and $Q^j_{ADV} = \text{vec} \left( F \left( A^j_{ADV} \right) \right)$ are respectively the $j$-th pair of clean examples and their adversarial counterparts attention maps in vectorized form, and $p$ refers to norm type (in the experiments we use $p = 2$).

**Experiments: Gray and Black-Box Settings**

To evaluate the effectiveness of our defense strategy, we performed a series of image-classification experiments on 17 Flower Category Database (Nilsback and Zisserman 2006), Part of ImageNet Database and Dogs-vs-Cats Database.

Following (Athalye, Carlini, and Wagner 2018; Xie et al. 2018), we assume an adversary that uses the state of the art PGD adversarial attack method.

We consider untargeted attacks when evaluating under the gray and black-box settings; untargeted attacks are also used in our adversarial training. We evaluate top-1 classification accuracy on validation images that are adversarially perturbed by the attacker. In this paper, adversarial perturbation is considered under $L_{\infty}$ norm (i.e., maximum perturbation for each pixel), with an allowed maximum value of $\epsilon$. The value of $\epsilon$ is relative to the pixel intensity scale of 256, we use $\epsilon = 64/256 = 0.25$ and $\epsilon = 128/256 = 0.5$. PGD attacker with 10 to 200 attack iterations and step size $\alpha = 1.0/256 = 0.0039$. Our baselines are ResNet-101/152. There are four groups of convolutional structures in the baseline model, group-0 extracts of low-level features, group-1 and group-2 extract of mid-level features, group-3 extracts of high-level features (Zagoruyko and Komodakis 2016b), which are described as $\text{conv}2_x, \text{conv}3_x, \text{conv}4_x$ and $\text{conv}5_x$ in (He et al. 2015)

**Image Database**

We performed a series of image-classification experiments on a wide range of datasets.

- **17 Flower Category Database** (Nilsback and Zisserman 2006) contains images of flowers belonging to 17 different categories. The images were acquired by searching the web and taking pictures. There are 80 images for each category.
Part of ImageNet Database contains images of four objects. These four objects are randomly selected from the ImageNet Database (Russakovsky et al. 2015). In this experiment, they are tench, goldfish, white shark and dog. Each object contains 1300 training images and 50 test images.

Dogs-vs-Cats Database contains 8,000 images of dogs and cats in the train dataset and 2,000 in the test val dataset.

Experimental Setup
To perform image classification, we use ResNet-101/152 that were trained on the 17 Flower Category Database, Part of ImageNet Database and Dogs-vs-Cats Database training set. We consider two different attack settings: (1) a gray-box attack setting in which the model used to generate the adversarial images is the same as the image-classification model, viz. the ResNet-101; and (2) a black-box attack setting in which the adversarial images are generated using the ResNet-152 model. The backend prediction model of gray-box and black-box is ResNet-101 with different implementations of the state-of-the-art defense methods, such as IGR (Ross and Doshi-Velez 2017), PAT (Madry et al. 2017), RAT (Araujo et al. 2019), Randomization (Xie et al. 2017), ALP (Kannan, Kurakin, and Goodfellow 2018), FD (Xie et al. 2018) and ADP (Pang et al. 2019).

Results and Discussion
Here, we first present results with AT+ALP on 17 Flower Category Database. Compared with previous work, (Kannan, Kurakin, and Goodfellow 2018) was evaluated under 10-iteration PGD attack and $\epsilon = 0.0625$, our work are evaluated under highly challenging PGD attack: the maximum perturbation $\epsilon \in \{0.25, 0.5\}$, i.e., $L_\infty \in \{0.25, 0.5\}$ with 10 to 200 attack iterations. The bigger the value of $\epsilon$, the
Table 1: Defense against gray-box and black-box attacks on 17 Flower Category Database, Part of ImageNet Database and Dogs-vs-Cats Database. The adversarial perturbation were produced using PGD with step size $\alpha = 1.0/256 = 0.0039$ and 200 attack iterations. As shown in this table, AT+ALP got the highest Top-1 Accuracy on all these database.

| 17 Flower Category Database | Gray-Box $\epsilon = L_\infty$ | Black-Box $\epsilon = L_\infty$ |
|-----------------------------|-------------------------------|-------------------------------|
| No Defence                  | 0 0                           | 15 10                         |
| IGR(Ross and Doshi-Velez 2017) | 10 3                          | 17 10                         |
| PAT(Madry et al. 2017)      | 55 34                         | 57 39                         |
| RAT(Araujo et al. 2019)     | 54 30                         | 57 32                         |
| Randomization(Xie et al. 2017) | 12 6                        | 27 16                         |
| ALP(Kannan, Kurakin, and Goodfellow 2018) | 47 23 | 49 25 |
| FD(Xie et al. 2018)         | 33 10                         | 33 10                         |
| ADP(Pang et al. 2019)       | 22 8                          | 23 8                          |
| Our AT                      | 41 24                         | 45 29                         |
| Our AT+ALP                  | 68 50                         | 70 51                         |

| Part of ImageNet Database | Gray-Box $\epsilon = L_\infty$ | Black-Box $\epsilon = L_\infty$ |
|----------------------------|-------------------------------|-------------------------------|
| No Defence                  | 2 3                           | 52 50                         |
| IGR(Ross and Doshi-Velez 2017) | 32 32                     | 34 34                         |
| PAT(Madry et al. 2017)      | 76 76                         | 77 77                         |
| RAT(Araujo et al. 2019)     | 76 76                         | 77 76                         |
| Randomization(Xie et al. 2017) | 40 41                     | 62 59                         |
| ALP(Kannan, Kurakin, and Goodfellow 2018) | 54 54 | 55 55 |
| FD(Xie et al. 2018)         | 60 61                         | 61 61                         |
| ADP(Pang et al. 2019)       | 42 44                         | 43 44                         |
| Our AT                      | 76 76                         | 77 76                         |
| Our AT+ALP                  | 82 82                         | 82 82                         |

| Dogs-vs-Cats Database       | Gray-Box $\epsilon = L_\infty$ | Black-Box $\epsilon = L_\infty$ |
|----------------------------|-------------------------------|-------------------------------|
| No Defence                  | 1 1                           | 52 53                         |
| IGR(Ross and Doshi-Velez 2017) | 57 60                     | 51 52                         |
| PAT(Madry et al. 2017)      | 51 51                         | 52 52                         |
| RAT(Araujo et al. 2019)     | 49 49                         | 50 50                         |
| Randomization(Xie et al. 2017) | 10 8                       | 55 54                         |
| ALP(Kannan, Kurakin, and Goodfellow 2018) | 57 56 | 57 57 |
| FD(Xie et al. 2018)         | 57 57                         | 57 57                         |
| ADP(Pang et al. 2019)       | 50 50                         | 50 50                         |
| Our AT                      | 50 50                         | 50 50                         |
| Our AT+ALP                  | 67 67                         | 71 71                         |
Figure 4: Activation attention maps for defense against gray-box PGD attacks ($\epsilon = 0.25$) on 17 Flower Category Database. (a) is original image and (b) is corresponding adversarial image. (c) and (d) are activation attention maps of baseline model for original image and adversarial image. (e)-(f) are activation attention maps of ALP, AT and AT+ALP for adversarial image. Group-0 to group-3 represent the activation attention maps of four groups of convolutional structures in the baseline model, group-0 extracts of low-level features, group-1 and group-2 extract of mid-level features, group-3 extracts of high-level features (Zagoruyko and Komodakis 2016b). It can be clearly found that group-0 of AT + ALP can extract the outline and texture of flowers more accurately, and group-3 has a higher level of activation on the whole flower, compared with other defense methods, only it makes accurate prediction.

bigger the disturbance, the more significant the adversarial image effect is. To the best of our knowledge, such a strong attack has not been previously explored on a wide range of datasets. As shown in Figure 3 that our AT+ALP outperform the state-of-the-art in adversarial robustness against highly challenging gray-box and black-box PGD attacks. For example, under strong 200-iteration PGD gray-box and black-box attacks where prior art has 34% and 39% accuracy, our method achieves 50% and 51%.

Table 1 shows Main Result of our work: under strong 200-iteration PGD gray-box and black-box attacks, our AT+ALP outperform the state-of-the-art in adversarial robustness on all these databases.

We visualized activation attention maps for defense against PGD attacks. Baseline model is ResNet-101 (He et al. 2015), which is pre-trained on ImageNet (Rusakovsky et al. 2015) and fine-tuned on 17 Flower Category Database (Nilsback and Zisserman 2006), group-0 to group-3 represent the activation attention maps of four groups of convolutional structures in the baseline model, i.e., $conv_{2,x}$, $conv_{3,x}$, $conv_{4,x}$ and $conv_{5,x}$ of ResNet-101, group-0 extracts of low-level features, group-1 and group-2 extract of mid-level features, group-3 extracts of high-level features (Zagoruyko and Komodakis 2016b). We found from Figure 4 that group-0 of AT + ALP can extract the outline and texture of flowers more accurately, and group-3 has a higher level of activation on the whole flower, compared with other defense methods, only AT + ALP makes accu-
Table 2: Comparing average activations on discriminate parts of 17 Flower Category Database for different defense methods. In addition, we included new statistical results of activations on part locations of 17 Flower Category Database supporting the above qualitative cases. The 17 Flower Category Database defined discriminative parts of flowers. So for each image, we got several key regions which are very important to discriminate its category. Using all testing examples of 17 Flower Category Database, we calculated normalized activations on these key regions of these different defense methods. As shown in this table, AT+ALP got the highest average activations on those key regions, demonstrating that AT+ALP focused on more discriminate features for flowers recognition.

| Defense | Black-Box | Gray-Box |
|---------|-----------|----------|
| $\epsilon = L_\infty$ | 0.25 0.5 | 0.25 0.5 |
| No Defense | 0.41 0.41 | 0.21 0.21 |
| ALP (Kannan, Kurakin, and Goodfellow 2018) | 0.16 0.16 | 0.15 0.15 |
| IGR (Ross and Doshi-Velez 2017) | 0.37 0.37 | 0.33 0.33 |
| PAT (Madry et al. 2017) | 0.42 0.42 | 0.44 0.44 |
| RAT (Araujo et al. 2019) | 0.40 0.40 | 0.41 0.41 |
| Our AT | 0.55 0.54 | 0.56 0.56 |
| **Our AT+ALP** | **0.98 0.98** | **0.96 0.96** |

We compared average activations on discriminate parts of 17 Flower Category Database for different defense methods. 17 Flower Category Database defined discriminative parts of flowers. So for each image, we got several key regions which are very important to discriminate its category. Using all testing examples of 17 Flower Category Database, we calculated normalized activations on these key regions of these different defense methods. As shown in Table 2, AT+ALP got the highest average activations on those key regions, demonstrating that AT+ALP focused on more discriminate features for flowers recognition.

**Conclusion**

In this paper, we introduced enhanced defense using a technique we called Attention and Adversarial Logit Pairing (AT+ALP), a method that encouraged both attention map and logit for pairs of examples to be similar. When being applied to clean examples and their adversarial counterparts, AT+ALP improved accuracy on adversarial examples over adversarial training. Our AT+ALP achieves the state of the art defense on a wide range of datasets against PGD gray-box and black-box attacks. Compared with other defense methods, our AT+ALP is simple and effective, without modifying the model structure, and without adding additional image preprocessing steps.

Figure 5: (a) is original image and (b) is corresponding discriminative parts. 17 Flower Category Database defined discriminative parts of flowers. So for each image, we got several key regions which are very important to discriminate its category.

Figure 6: Comparison of loss landscapes. Loss plots are generated by varying the input to the models, starting from an original input image chosen from the test set. We see that ALP and AT sometimes induces decreased loss near the input locally, and gives a “bumpier” optimization landscape, our AT+ALP has better robustness. The $z$ axis represents the loss. If $x$ is the original input, then we plot the loss varying along the space determined by two vectors: $r_1 = sign(\nabla_x f(x))$ and $r_2 \sim Rademacher(0.5)$. We thus plot the following function: $z = loss(x \cdot r_1 + y \cdot r_2)$. 
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