

Defense on Image Recognition

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[Todo List](#)

[Towards Deep Learning Models Resistant to Adversarial Attacks](#)

[Contribution](#)

[Notes](#)

[Links](#)

Theoretically Principled Trade-off between Robustness and Accuracy

[Contribution](#)

[Notes](#)

[Links](#)

Unlabeled Data Improves Adversarial Robustness

[Contribution](#)

[Notes](#)

[Links](#)

Defense Against Adversarial Attacks Using Feature Scattering-based Adversarial Training

[Contribution](#)

[Notes](#)

[Links](#)

Todo List

- Muzammal Naseer, Salman Khan, and Fatih Porikli. Local gradients smoothing: Defense against localized adversarial attacks. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1300–1307. IEEE, 2019.
- Jamie Hayes. On visible adversarial perturbations & digital watermarking. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 1597–1604, 2018.
- Anish Athalye, Nicholas Carlini, and David Wagner. Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. arXiv preprint arXiv:1802.00420, 2018.
- Sven Gowal, Krishnamurthy Dvijotham, Robert Stanforth, Rudy Bunel, Chongli Qin, Jonathan Uesato, Timothy Mann, and Pushmeet Kohli. On the effectiveness of interval bound propagation for training verifiably robust models. arXiv preprint arXiv:1810.12715, 2018.
- Matthew Mirman, Timon Gehr, and Martin Vechev. Differentiable abstract interpretation for provably robust neural networks. In International Conference on Machine Learning, pp. 3575–3583, 2018.
- Alexander Levine and Soheil Feizi. Robustness certificates for sparse adversarial attacks by randomized ablation. arXiv preprint arXiv:1911.09272, 2019.
- Gotta Catch'Em All: Using HoneyPots to Catch Adversarial Attacks on Neural Networks
- Certified adversarial robustness via randomized smoothing

Towards Deep Learning Models Resistant to Adversarial Attacks

由于时间原因，该文章的笔记借鉴自“前人分享”（链接见下）。

Contribution

1. Madry.
2. 建模了对抗训练过程；
3. 使用 PGD生成的对抗样本 来做对抗训练；

Notes

1. ☆ 问题建模，**从优化的角度来看模型鲁棒性问题**。深度学习中，我们经常根据下面这个目标来训练我们的网络：即我们希望我们训练得到的模型在训练样本上的经验损失能够达到最小。

$$\min_{\theta} \rho(\theta), \text{ where } \rho(\theta) = \mathbb{E}_{(x,y) \sim \mathcal{D}} [L(\theta, x, y)]$$

但是这样的训练目标，使得模型容易受到对抗样本的攻击。故作者将对抗样本的攻击防御问题总结为以下公式，该问题原文中作者称为**鞍点问题 (saddle point problem)**，即我们希望我们训练得到的模型在训练样本**周围的**经验损失能够达到最小。

$$\min_{\theta} \rho(\theta), \text{ where } \rho(\theta) = \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[\max_{\delta \in \mathcal{S}} L(\theta, x + \delta, y) \right]$$

建模完问题以后，那么以前的对抗样本领域的工作就可以进行简单地分类：（稍微有点绕）

- 提出一个好的对抗攻击算法，来寻找使得（内层）经验损失最大化的扰动；
 - 提出一个鲁棒性好的模型，来使得（外层）最小化（内层的最大的）经验损失；
2. 文章中作者采用投影梯度下降算法 (PGD) 来生成对抗样本：（作者的代码中，在生成对抗样本之前，会添加均匀分布的随机噪声，然后再生成对抗样本）

$$x^{t+1} = \Pi_{x+\mathcal{S}} (x^t + \alpha \operatorname{sgn}(\nabla_x L(\theta, x, y)))$$

3. 实验发现：

(1) Loss 下降趋势和对抗样本算法迭代轮数的关系：无论是原始模型还是使用对抗训练得到的模型，两者使用 PGD 算法 生成对抗样本时，随着迭代轮数的上升，样本的 loss 都会上升，且到最后趋于收敛；

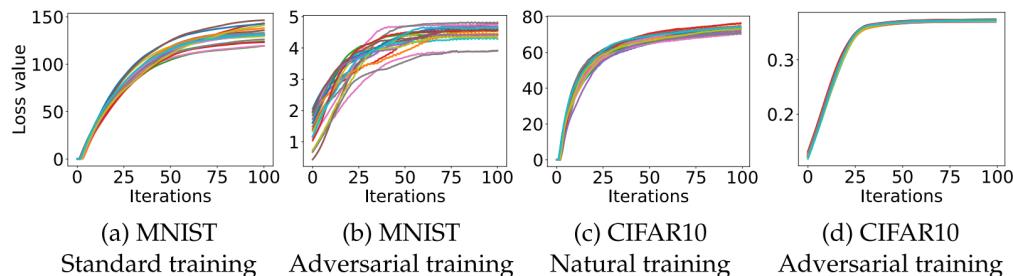


Figure 1: Cross-entropy loss values while creating an adversarial example from the MNIST and CIFAR10 evaluation datasets. The plots show how the loss evolves during 20 runs of projected gradient descent (PGD). Each run starts at a uniformly random point in the ℓ_∞ -ball around the same natural example (additional plots for different examples appear in Figure 11). The adversarial loss plateaus after a small number of iterations. The optimization trajectories and final loss values are also fairly clustered, especially on CIFAR10. Moreover, the final loss values on adversarially trained networks are significantly smaller than on their standard counterparts.

(2) Loss 分布的差异：于原始模型相比，在对抗训练得到的模型上生成对抗样本，得到的 loss 更小，更集中且没有异常值；

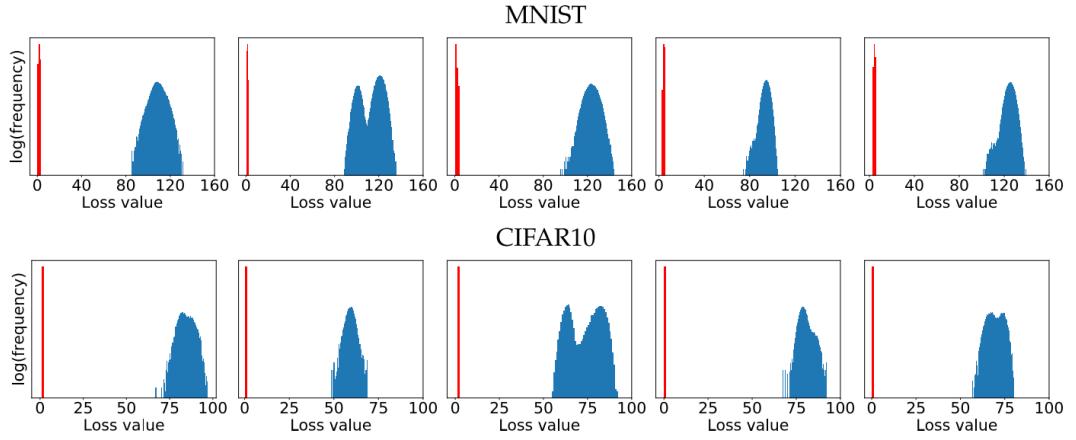


Figure 2: Values of the local maxima given by the cross-entropy loss for five examples from the MNIST and CIFAR10 evaluation datasets. For each example, we start projected gradient descent (PGD) from 10^5 uniformly random points in the ℓ_∞ -ball around the example and iterate PGD until the loss plateaus. The blue histogram corresponds to the loss on a standard network, while the red histogram corresponds to the adversarially trained counterpart. The loss is significantly smaller for the adversarially trained networks, and the final loss values are very concentrated without any outliers.

(3) 鲁棒性与模型规模的关系：相对而言，模型越复杂，鲁棒性也越好。同时，经过对抗训练的模型，在原始任务上会有一定的损失，是因为出现了如“过拟合”的现象，使得模型在测试集上面的效果并不好；

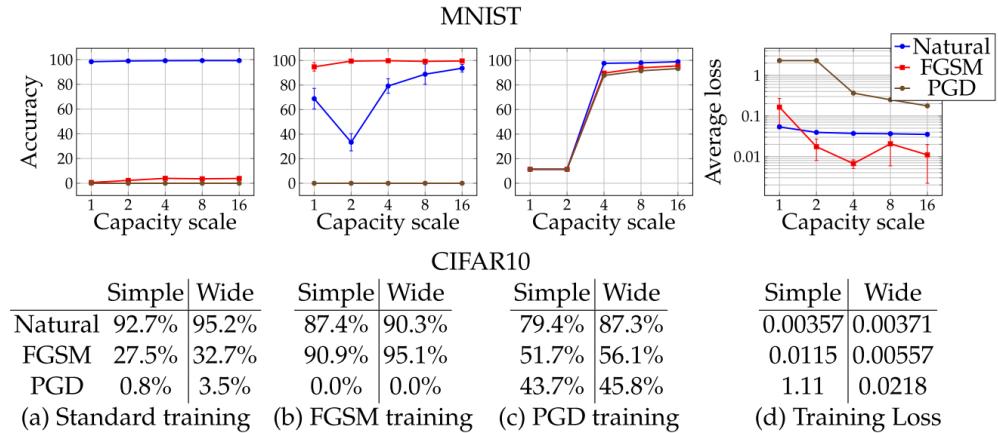


Figure 4: The effect of network capacity on the performance of the network. We trained MNIST and CIFAR10 networks of varying capacity on: (a) natural examples, (b) with FGSM-made adversarial examples, (c) with PGD-made adversarial examples. In the first three plots/tables of each dataset, we show how the standard and adversarial accuracy changes with respect to capacity for each training regime. In the final plot/table, we show the value of the cross-entropy loss on the adversarial examples the networks were trained on. This corresponds to the value of our saddle point formulation (2.1) for different sets of allowed perturbations.

(4) 范数限制的影响： l_∞ 范数比 l_2 范数成功的扰动量要小；（这个对比合理吗？）

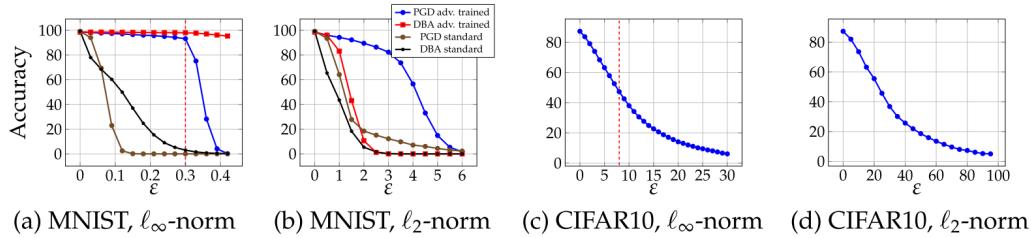


Figure 6: Performance of our adversarially trained networks against PGD adversaries of different strength. The MNIST and CIFAR10 networks were trained against $\epsilon = 0.3$ and $\epsilon = 8$ PGD ℓ_∞ adversaries respectively (the training ϵ is denoted with a red dashed lines in the ℓ_∞ plots). In the case of the MNIST adversarially trained networks, we also evaluate the performance of the Decision Boundary Attack (DBA) [4] with 2000 steps and PGD on standard and adversarially trained models. We observe that for ϵ less or equal to the value used during training, the performance is equal or better. For MNIST there is a sharp drop shortly after. Moreover, we observe that the performance of PGD on the MNIST ℓ_2 -trained networks is poor and significantly overestimates the robustness of the model. This is potentially due to the threshold filters learned by the model masking the loss gradients (the decision-based attack does not utilize gradients).

Links

- 论文链接: [Madry A, Makelov A, Schmidt L, et al. Towards deep learning models resistant to adversarial attacks\[J\]. arXiv preprint arXiv:1706.06083, 2017.](https://arxiv.org/abs/1706.06083)
- 论文代码 - mnist: https://github.com/MadryLab/mnist_challenge
- 论文代码 - cifar10: https://github.com/MadryLab/cifar10_challenge

从代码上来看，作者提供的模型的输入是 $32 * 32 * 3$ 大小的，这样经过压缩的输入维度，是否导致了对抗样本算法难以实现呢？或者说生成对抗样本的过程能否利用一下这个特点？

- 论文模型: https://github.com/MadryLab/cifar10_challenge
- 前人分享: <https://zhuanlan.zhihu.com/p/45684812>

Theoretically Principled Trade-off between Robustness and Accuracy

Contribution

1. Trades.
2. 从理论上证明了成功率和鲁棒性 对于分类问题来说是一个权衡利弊的问题；（虽然我并不太关注这个证明）
3. 在理论的基础上，提出了新的对抗训练的损失函数；

Notes

1. 文章思想：（证明部分直接忽略不看）
 - (1) 文章整体的思想如下图，即为在保证模型分类准确的前提下，希望模型的边界能够离这些真实的样本远一些：

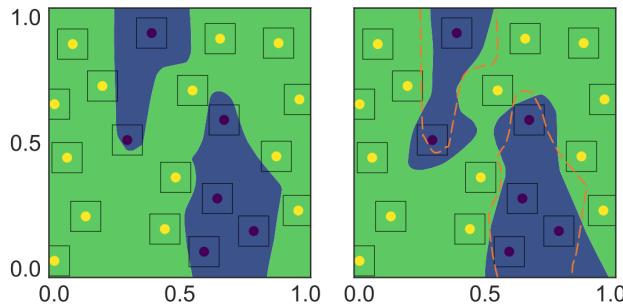


Figure 1: **Left figure:** decision boundary learned by natural training method. **Right figure:** decision boundary learned by our adversarial training method, where the orange dotted line represents the decision boundary in the left figure. It shows that both methods achieve zero natural training error, while our adversarial training method achieves better robust training error than the natural training method.

(2) 文章中提到了鲁棒误差 (Robust Error)、自然误差 (Natural Error) 和边界误差 (Boundary Error) :

- 鲁棒误差:

$$\mathcal{R}_{\text{rob}}(f) := \mathbb{E}_{(\mathbf{X}, Y) \sim \mathcal{D}} \mathbf{1}\{\exists \mathbf{X}' \in \mathbb{B}(\mathbf{X}, \epsilon) \text{ s.t. } f(\mathbf{X}')Y \leq 0\}$$

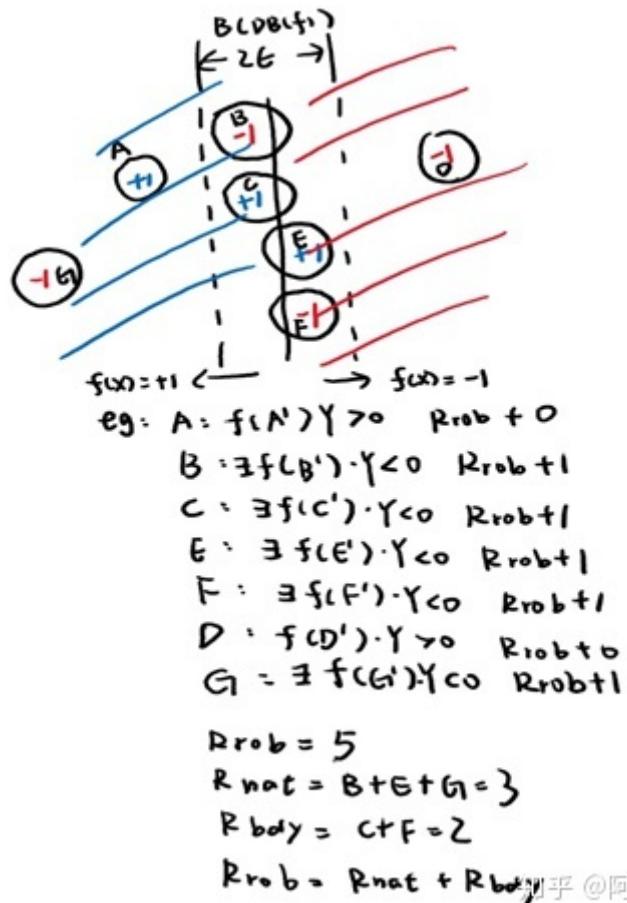
- 自然误差: $\mathcal{R}_{\text{nat}}(f) := \mathbb{E}_{(\mathbf{X}, Y) \sim \mathcal{D}} \mathbf{1}\{f(\mathbf{X})Y \leq 0\}$

- 边界误差:

$$\mathcal{R}_{\text{bdy}}(f) := \mathbb{E}_{(\mathbf{X}, Y) \sim \mathcal{D}} \mathbf{1}\{\mathbf{X} \in \mathbb{B}(\text{DB}(f), \epsilon), f(\mathbf{X})Y > 0\}$$

- 三者关系: $\mathcal{R}_{\text{rob}}(f) = \mathcal{R}_{\text{nat}}(f) + \mathcal{R}_{\text{bdy}}(f)$

理解起来有点困难，借鉴前人分享的图（[链接见下](#)）：



画个示意图：假设中间是决策边界，A点~G点是x，外面的圈圈是给定的扰动，虚线是决策边界的边界。

2. 最优化问题：

$$\min_f \mathbb{E} \left\{ \underbrace{\phi(f(\mathbf{X})Y)}_{\text{for accuracy}} + \underbrace{\max_{\mathbf{X}' \in \mathbb{B}(\mathbf{X}, \epsilon)} \phi(f(\mathbf{X})f(\mathbf{X}')/\lambda)}_{\text{regularization for robustness}} \right\}$$

左半部分用来保证模型的**准确性**，而右半部分则用来保证模型的**鲁棒性**；上式其实表述的是一个二分类的问题，对于多分类问题，作者修改上式为：

$$\min_f \mathbb{E} \left\{ \mathcal{L}(f(\mathbf{X}), \mathbf{Y}) + \max_{\mathbf{X}' \in \mathbb{B}(\mathbf{X}, \epsilon)} \mathcal{L}(f(\mathbf{X}), f(\mathbf{X}'))/\lambda \right\}$$

其中 $\mathcal{L}(\cdot, \cdot)$ 为交叉熵损失函数；

3. 训练方法：

Algorithm 1 Adversarial training by TRADES

```

1: Input: Step sizes  $\eta_1$  and  $\eta_2$ , batch size  $m$ , number of iterations  $K$  in inner optimization, network
   architecture parametrized by  $\theta$ 
2: Output: Robust network  $f_\theta$ 
3: Randomly initialize network  $f_\theta$ , or initialize network with pre-trained configuration
4: repeat
5:   Read mini-batch  $B = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}$  from training set
6:   for  $i = 1, \dots, m$  (in parallel) do
7:      $\mathbf{x}'_i \leftarrow \mathbf{x}_i + 0.001 \cdot \mathcal{N}(\mathbf{0}, \mathbf{I})$ , where  $\mathcal{N}(\mathbf{0}, \mathbf{I})$  is the Gaussian distribution with zero mean and identity
       variance
8:     for  $k = 1, \dots, K$  do
9:        $\mathbf{x}'_i \leftarrow \Pi_{\mathbb{B}(\mathbf{x}_i, \epsilon)}(\eta_1 \text{sign}(\nabla_{\mathbf{x}'_i} \mathcal{L}(f_\theta(\mathbf{x}_i), f_\theta(\mathbf{x}'_i))) + \mathbf{x}'_i)$ , where  $\Pi$  is the projection operator
10:    end for
11:   end for
12:    $\theta \leftarrow \theta - \eta_2 \sum_{i=1}^m \nabla_\theta [\mathcal{L}(f_\theta(\mathbf{x}_i), \mathbf{y}_i) + \mathcal{L}(f_\theta(\mathbf{x}_i), f_\theta(\mathbf{x}'_i))/\lambda]/m$ 
13: until training converged

```

首先在样本上面添加高斯随机噪声 ([cifar10-challenge](#) 中用的是均匀分布随机噪声)，然后再利用 PGD 生成对抗样本 (这里希望对抗样本的概率分布和原始概率分布能够尽可能的不同)，最后微调模型。

4. 实验：

(0) 实验评估：使用两个成功率来评估方法的好坏，为了说明实验方法即保证较高的成功率，又有很好的鲁棒性，我们应该希望实验得到的数据 \mathcal{A}_{rob} and \mathcal{A}_{nat} 都比较大；

$$\begin{aligned}\mathcal{A}_{rob}(f) &= 1 - \mathcal{R}_{rob}(f) \\ \mathcal{A}_{nat}(f) &= 1 - \mathcal{R}_{nat}(f)\end{aligned}$$

(1) 参数 λ 的作用：

- 参数设置：

MNIST setup. We use the CNN which has two convolutional layers, followed by two fully-connected layers. The output size of the last layer is 10. We set perturbation $\epsilon = 0.1$, perturbation step size $\eta_1 = 0.01$, number of iterations $K = 20$, learning rate $\eta_2 = 0.01$, batch size $m = 128$, and run 50 epochs on the training dataset. To evaluate the robust error, we apply FGSM^k (white-box) attack with 40 iterations and 0.005 step size. The results are in Table 4.

CIFAR10 setup. We apply ResNet-18 [HZRS16] for classification. The output size of the last layer is 10. We set perturbation $\epsilon = 0.031$, perturbation step size $\eta_1 = 0.007$, number of iterations $K = 10$, learning rate $\eta_2 = 0.1$, batch size $m = 128$, and run 100 epochs on the training dataset. To evaluate the robust error, we apply FGSM^k (white-box) attack with 20 iterations and the step size is 0.003. The results are in Table 4.

- 实验结果：在 MNIST 上面对原始分类成功率的影响不大，但是对 CIFAR10 的影响还是比较大的。所以后面的实验中，作者分别使用 $\lambda = 1$ or $\lambda = 6$ ，分别保证成功率和鲁棒性；

Table 4: Sensitivity of regularization hyperparameter λ on MNIST and CIFAR10 datasets.

$1/\lambda$	MNIST		CIFAR10	
	$\mathcal{A}_{\text{rob}}(f) (\%)$	$\mathcal{A}_{\text{nat}}(f) (\%)$	$\mathcal{A}_{\text{rob}}(f) (\%)$	$\mathcal{A}_{\text{nat}}(f) (\%)$
0.1	91.09 \pm 0.0385	99.41 \pm 0.0235	26.53 \pm 1.1698	91.31 \pm 0.0579
0.2	92.18 \pm 0.0450	99.38 \pm 0.0094	37.71 \pm 0.6743	89.56 \pm 0.2154
0.4	93.21 \pm 0.0660	99.35 \pm 0.0082	41.50 \pm 0.3376	87.91 \pm 0.2944
0.6	93.87 \pm 0.0464	99.33 \pm 0.0141	43.37 \pm 0.2706	87.50 \pm 0.1621
0.8	94.32 \pm 0.0492	99.31 \pm 0.0205	44.17 \pm 0.2834	87.11 \pm 0.2123
1.0	94.75 \pm 0.0712	99.28 \pm 0.0125	44.68 \pm 0.3088	87.01 \pm 0.2819
2.0	95.45 \pm 0.0883	99.29 \pm 0.0262	48.22 \pm 0.0740	85.22 \pm 0.0543
3.0	95.57 \pm 0.0262	99.24 \pm 0.0216	49.67 \pm 0.3179	83.82 \pm 0.4050
4.0	95.65 \pm 0.0340	99.16 \pm 0.0205	50.25 \pm 0.1883	82.90 \pm 0.2217
5.0	95.65 \pm 0.1851	99.16 \pm 0.0403	50.64 \pm 0.3336	81.72 \pm 0.0286

(2) 横向对比 - 白盒攻击:

- 参数设置:

MNIST setup. We use the CNN architecture in [CW17] with four convolutional layers, followed by three fully-connected layers. We set perturbation $\epsilon = 0.3$, perturbation step size $\eta_1 = 0.01$, number of iterations $K = 40$, learning rate $\eta_2 = 0.01$, batch size $m = 128$, and run 100 epochs on the training dataset.

CIFAR10 setup. We use the same neural network architecture as [MMS⁺18], i.e., the wide residual network WRN-34-10 [ZK16]. We set perturbation $\epsilon = 0.031$, perturbation step size $\eta_1 = 0.007$, number of iterations $K = 10$, learning rate $\eta_2 = 0.1$, batch size $m = 128$, and run 100 epochs on the training dataset.

in [ZSLG16, KGB17, RDV17] on the CIFAR10 dataset as they are also regularization based methods. For MNIST dataset, we apply FGSM^k (white-box) attack with 40 iterations and the step size is 0.01. For CIFAR10 dataset, we apply FGSM^k (white-box) attack with 20 iterations and the step size is 0.003, under which the

- 实验结果:

Table 5: Comparisons of TRADES with prior defense models under white-box attacks.

Defense	Defense type	Under which attack	Dataset	Distance	$\mathcal{A}_{\text{nat}}(f)$	$\mathcal{A}_{\text{rob}}(f)$
[BRRG18]	gradient mask	[ACW18]	CIFAR10	0.031 (ℓ_∞)	-	0%
[MLW ⁺ 18]	gradient mask	[ACW18]	CIFAR10	0.031 (ℓ_∞)	-	5%
[DAL ⁺ 18]	gradient mask	[ACW18]	CIFAR10	0.031 (ℓ_∞)	-	0%
[SKN ⁺ 18]	gradient mask	[ACW18]	CIFAR10	0.031 (ℓ_∞)	-	9%
[NKM17]	gradient mask	[ACW18]	CIFAR10	0.015 (ℓ_∞)	-	15%
[WSMK18]	robust opt.	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	27.07%	23.54%
[MMS ⁺ 18]	robust opt.	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	87.30%	47.04%
[ZSLG16]	regularization	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	94.64%	0.15%
[KGB17]	regularization	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	85.25%	45.89%
[RDV17]	regularization	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	95.34%	0%
TRADES (1/ λ = 1)	regularization	FGSM ^{1,000} (PGD)	CIFAR10	0.031 (ℓ_∞)	88.64%	48.90%
TRADES (1/ λ = 6)	regularization	FGSM ^{1,000} (PGD)	CIFAR10	0.031 (ℓ_∞)	84.92%	56.43%
TRADES (1/ λ = 1)	regularization	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	88.64%	49.14%
TRADES (1/ λ = 6)	regularization	FGSM ²⁰ (PGD)	CIFAR10	0.031 (ℓ_∞)	84.92%	56.61%
TRADES (1/ λ = 1)	regularization	DeepFool (ℓ_∞)	CIFAR10	0.031 (ℓ_∞)	88.64%	59.10%
TRADES (1/ λ = 6)	regularization	DeepFool (ℓ_∞)	CIFAR10	0.031 (ℓ_∞)	84.92%	61.38%
TRADES (1/ λ = 1)	regularization	LBFGSAttack	CIFAR10	0.031 (ℓ_∞)	88.64%	84.41%
TRADES (1/ λ = 6)	regularization	LBFGSAttack	CIFAR10	0.031 (ℓ_∞)	84.92%	81.58%
TRADES (1/ λ = 1)	regularization	MI-FGSM	CIFAR10	0.031 (ℓ_∞)	88.64%	51.26%
TRADES (1/ λ = 6)	regularization	MI-FGSM	CIFAR10	0.031 (ℓ_∞)	84.92%	57.95%
TRADES (1/ λ = 1)	regularization	C&W	CIFAR10	0.031 (ℓ_∞)	88.64%	84.03%
TRADES (1/ λ = 6)	regularization	C&W	CIFAR10	0.031 (ℓ_∞)	84.92%	81.24%
[SKC18]	gradient mask	[ACW18]	MNIST	0.005 (ℓ_2)	-	55%
[MMS ⁺ 18]	robust opt.	FGSM ⁴⁰ (PGD)	MNIST	0.3 (ℓ_∞)	99.36%	96.01%
TRADES (1/ λ = 6)	regularization	FGSM ^{1,000} (PGD)	MNIST	0.3 (ℓ_∞)	99.48%	95.60%
TRADES (1/ λ = 6)	regularization	FGSM ⁴⁰ (PGD)	MNIST	0.3 (ℓ_∞)	99.48%	96.07%
TRADES (1/ λ = 6)	regularization	C&W	MNIST	0.005 (ℓ_2)	99.48%	99.46%

(3) 横向对比 - 黑盒攻击:

- 参数设置:

MNIST setup. We use the CNN architecture in [CW17] with four convolutional layers, followed by three fully-connected layers. We set perturbation $\epsilon = 0.3$, perturbation step size $\eta_1 = 0.01$, number of iterations $K = 40$, learning rate $\eta_2 = 0.01$, batch size $m = 128$, and run 100 epochs on the training dataset.

CIFAR10 setup. We use the same neural network architecture as [MMS⁺18], i.e., the wide residual network WRN-34-10 [ZK16]. We set perturbation $\epsilon = 0.031$, perturbation step size $\eta_1 = 0.007$, number of iterations $K = 10$, learning rate $\eta_2 = 0.1$, batch size $m = 128$, and run 100 epochs on the training dataset.

For both datasets, we use FGSM^k (black-box) method to attack various defense models. For MNIST dataset, we set perturbation $\epsilon = 0.3$ and apply FGSM^k (black-box) attack with 40 iterations and the step size is 0.01. For CIFAR10 dataset, we set $\epsilon = 0.031$ and apply FGSM^k (black-box) attack with 20 iterations and the step size is 0.003. Note that the setup is the same as the setup specified in Section 5.3.1. We summarize our

- 实验结果：

Table 6: Comparisons of TRADES with prior defenses under black-box FGSM⁴⁰ attack on the MNIST dataset. The models inside parentheses are source models which provide gradients to adversarial attackers. We provide the average cross-entropy loss value $\mathcal{L}(f(\mathbf{X}), \mathbf{Y})$ of each defense model in the bracket. The defense model ‘Madry’ is the same model as in the antepenultimate line of Table 5. The defense model ‘TRADES’ is the same model as in the penultimate line of Table 5.

Defense Model	Robust Accuracy $\mathcal{A}_{\text{rob}}(f)$
Madry	97.43% [0.0078484] (Natural)
TRADES	97.63% [0.0075324] (Natural)
Madry	97.38% [0.0084962] (Ours)
TRADES	97.66% [0.0073532] (Madry)

Table 7: Comparisons of TRADES with prior defenses under black-box FGSM²⁰ attack on the CIFAR10 dataset. The models inside parentheses are source models which provide gradients to adversarial attackers. We provide the average cross-entropy loss value of each defense model in the bracket. The defense model ‘Madry’ is implemented based on [MMS⁺18], and the defense model ‘TRADES’ is the same model as in the 11th line of Table 5.

Defense Model	Robust Accuracy $\mathcal{A}_{\text{rob}}(f)$
Madry	84.39% [0.0519784] (Natural)
TRADES	87.60% [0.0380258] (Natural)
Madry	66.00% [0.1252672] (Ours)
TRADES	70.14% [0.0885364] (Madry)

Links

- 论文链接：[Zhang H, Yu Y, Jiao J, et al. Theoretically principled trade-off between robustness and accuracy\[C\]//International Conference on Machine Learning, PMLR, 2019: 7472-7482.](#)
- 论文代码：<https://github.com/yaodongyu/TRADES>
- 前人分享：<https://zhuanlan.zhihu.com/p/337989683>

Unlabeled Data Improves Adversarial Robustness

Contribution

1. RST.
2. 在 [TRADES](#) 的基础上修改了损失函数，添加了无标签数据；
3. 文章给我的感觉是，就是利用更多数据来训练网络，不过这个数据可以是无标签的数据，这样的话就不需要进行大量的认为标注；

Notes

1. 训练方法：（证明部分直接忽略不看）

Meta-Algorithm 1 Robust self-training

Input: Labeled data $(x_1, y_1, \dots, x_n, y_n)$ and unlabeled data $(\tilde{x}_1, \dots, \tilde{x}_{\tilde{n}})$

Parameters: Standard loss L_{standard} , robust loss L_{robust} and unlabeled weight w

- 1: Learn $\hat{\theta}_{\text{intermediate}}$ by minimizing $\sum_{i=1}^n L_{\text{standard}}(\theta, x_i, y_i)$
 - 2: Generate pseudo-labels $\tilde{y}_i = f_{\hat{\theta}_{\text{intermediate}}}(\tilde{x}_i)$ for $i = 1, 2, \dots, \tilde{n}$
 - 3: Learn $\hat{\theta}_{\text{final}}$ by minimizing $\sum_{i=1}^n L_{\text{robust}}(\theta, x_i, y_i) + w \sum_{i=1}^{\tilde{n}} L_{\text{robust}}(\theta, \tilde{x}_i, \tilde{y}_i)$
-

- 首先使用有标签数据训练网络，这里使用 standard loss 为：

$$L_{\text{standard}}(\theta, x, y) = -\log p_{\theta}(y | x)$$

- 使用训练好的网络，标记无标签的数据；
- 使用有标签和“自标签”的数据继续训练网络，这里使用 robust loss 为：

$$L_{\text{robust}}(\theta, x, y) = L_{\text{standard}}(\theta, x, y) + \beta L_{\text{reg}}(\theta, x),$$

$$\text{where } L_{\text{reg}}(\theta, x) := \max_{x' \in \mathcal{B}_\epsilon^p(x)} D_{\text{KL}}(p_\theta(\cdot | x) \| p_\theta(\cdot | x'))$$

这里又到了经典的如何拟合 $L_{\text{reg}}(\theta, x)$ 项（因为寻找邻域内的最大值太困难），作者提出了两种方法：

- **Adversarial Training**: 使用 PGD 获取邻域最大值

$$L_{\text{reg}}^{\text{adv}}(\theta, x) := D_{\text{KL}}(p_\theta(\cdot | x) \| p_\theta(\cdot | x'_{\text{PG}}[x]))$$

- **Stability Training**: 使用 高斯分布 采样邻域的值

$$L_{\text{reg}}^{\text{stab}}(\theta, x) := \mathbb{E}_{x' \sim \mathcal{N}(x, \sigma^2 I)} D_{\text{KL}}(p_\theta(\cdot | x) \| p_\theta(\cdot | x'))$$

使用 Stability Training 的网络在测试的时候也做了改变，**模型输出的是高斯分布 采样邻域中的可能性最大的分类**

$$g_\theta(x) := \underset{y \in \mathcal{Y}}{\operatorname{argmax}} q_\theta(y | x), \text{ where } q_\theta(y | x) := \mathbb{P}_{x' \sim \mathcal{N}(x, \sigma^2 I)}(f_\theta(x') = y)$$

2. 实验：

(0) 实验参数：

- 数据集：大致意思就是从 **80M的CIFAR10-TINY** 中为每个类挑选出 50K 张图片组成一个 500K 大小的无标签数据集；

To obtain unlabeled data distributed similarly to the CIFAR-10 images, we use the **80 Million Tiny Images (80M-TI)** dataset [46], of which CIFAR-10 is a manually labeled subset. However, most images in 80M-TI do not correspond to CIFAR-10 image categories. To select relevant images, we train an 11-way classifier to distinguish CIFAR-10 classes and an 11th “non-CIFAR-10” class using a Wide ResNet 28-10 model [54] (the same as in our experiments below). For each class, we select additional 50K images from 80M-TI using the trained model’s predicted scores²—this is our 500K images unlabeled which we add to the 50K CIFAR-10 training set when performing RST. We provide a detailed description of the data sourcing process in Appendix B.6.

- 模型 & 训练参数：

Architecture. We use a Wide ResNet 28-10 architecture, as in [29] and similarly to [56], who use a 34-10 variant.

Robust self-training. We set the regularization weight $\beta = 6$ as in [56]. We implicitly set the unlabeled data weight to $w = 50K/500K = 0.1$ by composing every batch from equal parts labeled and unlabeled data.

Adversarial self-training. We compute x_{PG} exactly as in [56], with step size 0.007, 10 iterations and $\epsilon = 8/255$.

Stability training. We set the additive noise variance to $\sigma = 0.25$. We perform the certification using the randomized smoothing protocol described in [9], with parameters $N_0 = 100$, $N = 10^4$, $\alpha = 10^{-3}$ and noise variance $\sigma = 0.25$.

- (1) 经验性防御 (heuristic defense) : 主要关注 L_∞ 攻击；(☆ 针对作者提供的这种方法，作者还自己对 PGD 做了修改以达到最好的攻击成功率，这一点在做攻击的时候可以借鉴一下。)

Model	PG _{Madry}	PG _{TRADES}	PG _{Ours}	CW [7]	Best attack		No attack
RST _{adv} (50K+500K)	63.1	63.1	62.5	64.9	62.5 ± 0.1		89.7 ± 0.1
TRADES [56]	55.8	56.6	55.4	65.0	55.4		84.9
Adv. pre-training [18]	57.4	58.2	57.7	-	57.4 [†]		87.1
Madry et al. [29]	45.8	-	-	47.8	45.8		87.3
Standard self-training	-	0.3	0	-	0		96.4

Table 1: **Heuristic defense.** CIFAR-10 test accuracy under different optimization-based ℓ_∞ attacks of magnitude $\epsilon = 8/255$. Robust self-training (RST) with 500K unlabeled Tiny Images outperforms the state-of-the-art robust models in terms of robustness as well as standard accuracy (no attack). Standard self-training with the same data does not provide robustness. \dagger : A projected gradient attack with 1K restarts reduces the accuracy of this model to 52.9%, evaluated on 10% of the test set [18].

(2) 证明性防御 (certified defense) : 同时关注 L_∞ 和 L_2 攻击;

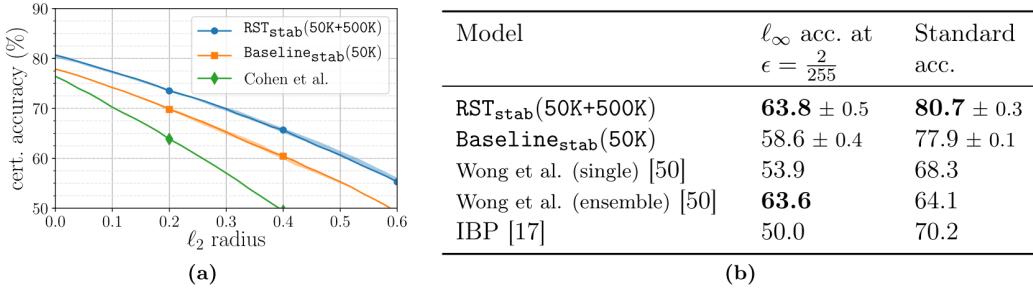


Figure 1: **Certified defense.** Guaranteed CIFAR-10 test accuracy under all ℓ_2 and ℓ_∞ attacks. Stability-based robust self-training with 500K unlabeled Tiny Images ($\text{RST}_{\text{stab}}(50K+500K)$) outperforms stability training with only labeled data ($\text{Baseline}_{\text{stab}}(50K)$). (a) Accuracy vs. ℓ_2 radius, certified via randomized smoothing [9]. Shaded regions indicate variation across 3 runs. Accuracy at ℓ_2 radius 0.435 implies accuracy at ℓ_∞ radius $2/255$. (b) The implied ℓ_∞ certified accuracy is comparable to the state-of-the-art in methods that directly target ℓ_∞ robustness.

(3) SVHN (Street View House Numbers) 实验: 实验的结果表明, 数据的标签对于模型的鲁棒性影响并不大; (我这里比较好奇的是, 在 SVHN 这个任务上作者提出的方法并没有优于 $\text{Baseline}_{\text{adv}}(604K)$ 的效果)

Model	PG _{Ours}	No attack
Baseline _{adv} (73K)	75.3 ± 0.4	94.7 ± 0.2
RST _{adv} (73K+531K)	86.0 ± 0.1	97.1 ± 0.1
Baseline _{adv} (604K)	86.4 ± 0.2	97.5 ± 0.1

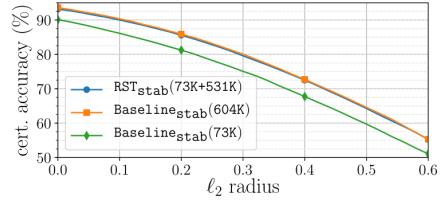


Figure 2: SVHN test accuracy for robust training without the extra data, with unlabeled extra (self-training), and with the labeled extra data. Left: Adversarial training and accuracies under ℓ_∞ attack with $\epsilon = 4/255$. Right: Stability training and certified ℓ_2 accuracies as a function of perturbation radius. Most of the gains from extra data comes from the unlabeled inputs.

Links

- 论文链接: [Carmon Y, Raghunathan A, Schmidt L, et al. Unlabeled data improves adversarial robustness\[J\]. arXiv preprint arXiv:1905.13736, 2019.](#)
- 论文代码: <https://github.com/yaircarmon/semisup-adv>

Defense Against Adversarial Attacks Using Feature Scattering-based Adversarial Training

Contribution

1. 使用 Wasserstein Distance 来生成对抗样本;

Notes

1. Background:

(1) Adversarial Training, 可以被形式化为 $\min - \max$ 问题:

$$\min_{\theta} \left[\max_{x' \in \mathcal{S}_x} \mathcal{L}(x', y; \theta) \right]$$

其中内层最大值经常用对抗样本生成来近似, 如使用单步的 *FGSM* 算法, 或者是多步的 *PGD* 算法 (算法第一次迭代时首先会添加上一个随机噪声, 然后再迭代生成对抗样本), *PGD* 算法公式如下:

$$x^{t+1} = \mathcal{P}_{\mathcal{S}_x}(x^t + \alpha \cdot \text{sign}(\nabla_x \mathcal{L}(x^t, y; \theta)))$$

(2) 对抗训练的问题:

- 标签泄露 (Label Leaking) : 生成的对抗扰动本身和目标类别是密切相关的, 导致训练好的模型看到测试集的对抗扰动便知道目标分类, 而与原始的图片无关;
- 梯度隐藏 (Gradient Masking) : 指的是训练后的模型学习到了尽可能生成一些无用的梯度 (这个和我想象中的“梯度隐藏”的概念不同, 从作者的解释来看是模型学习到了这种生成无用梯度的能力, 可能是我没有真正理解这个含义, 因为我感觉即使是梯度隐藏也是可以起到防御对抗攻击的效果的);

2. 最优运输理论 (Optimal Transport Theory)

(1) 参考链接:

- [【数学】Wasserstein Distance](#)
- [机器学习工具 \(二\) Notes of Optimal Transport](#)
- [令人拍案叫绝的Wasserstein GAN](#)

(2) Wasserstein Distance的优点: Wasserstein距离相比KL散度、JS散度的优越性在于, 即便两个分布没有重叠, Wasserstein距离仍然能够反映它们的远近

3. 训练方法:

Algorithm 1 Feature Scattering-based Adversarial Training

Input: dataset S , training epochs K , batch size n , learning rate γ , budget ϵ , attack iterations T
for $k = 1$ to K **do**

for random batch $\{x_i, y_i\}_{i=1}^n \sim S$ **do**
 initialization: $\mu = \sum_i u_i \delta_{x_i}$, $\nu = \sum_i v_i \delta_{x'_i}$, $x'_i \sim B(x_i, \epsilon)$
 feature scattering (maximizing feature matching distance \mathcal{D} w.r.t. ν):
 for $t = 1$ to T **do**
 $\cdot x'_i \leftarrow \mathcal{P}_{\mathcal{S}_x}(x'_i + \epsilon \cdot \text{sign}(\nabla_{x'_i} \mathcal{D}(\mu, \nu))) \quad \forall i = 1, \dots, n$, $\nu = \sum_i v_i \delta_{x'_i}$
 end for
 adversarial training (updating model parameters):
 $\cdot \theta \leftarrow \theta - \gamma \cdot \frac{1}{n} \sum_{i=1}^n \nabla_{\theta} \mathcal{L}(x'_i, y_i; \theta)$
 end for
 end for
 end for
 Output: model parameter θ .

我的理解:

- 简单的来看, 作者提出的方法和已有的方法的不同之处在于使用了 Wasserstein Distance 作为生成对抗样本时的损失函数;
- 思考一下, 变换了这个损失函数的作用有可能那么大么? 从 Wasserstein Distance 自身的有点来看, 它的优点主要是体现在两个分布没有重叠时, 还能够有效地指导网络训练。所以从对抗样本的生成角度来看, Wasserstein Distance 对于较大扰动时的对抗样本生成是更加有效的, 因为此时两个样本的解码概率分布可能已经差异十分

大了，用 KL 散度并不能更好地指导生成对抗样本；**概括一下，能够指导生成更多样化的对抗样本，从而更好地进行对抗训练；**

- 再思考一下，这篇文章作者一直是从 feature 这个角度来说的，其实我一直不太明白作者这样说有什么意义，但是我们揣测一下的话，因为在利用 Wasserstein Distance 生成对抗样本的时候，其实是要利用到一整个batch的样本来调整扰动的，这也是这个方法和前面方法的不同之处；**概括一下，用到了batch来生成对抗样本；**

方法示意图：

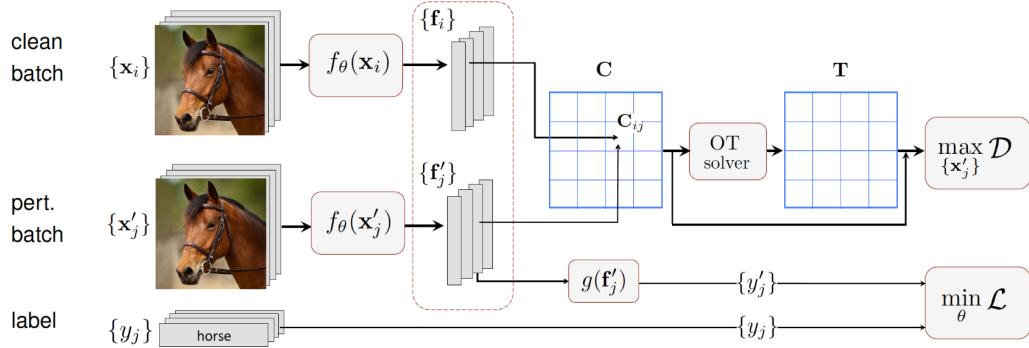


Figure 1: **Feature Scattering-based Adversarial Training Pipeline.** The adversarial perturbations are generated collectively by feature scattering, *i.e.*, maximizing the feature matching distance between the clean samples $\{x_i\}$ and the perturbed samples $\{x'_j\}$. The model parameters are updated by minimizing the cross-entropy loss using the perturbed images $\{x'_j\}$ as the training samples.

4. 实验：

(0) 实验参数：

- 数据集 & 基准方法：

We conduct extensive experiments across several **benchmark datasets** including CIFAR10 [31], CIFAR100 [31] and SVHN [42]. We use Wide ResNet (WRN-28-10) [68] as the network structure following [36]. We compare the performance of the proposed method with a number of baseline methods, including: *i*) the model trained with standard approach using clean images (**Standard**) [31], *ii*) PGD-based approach from Madry *et al.* (**Madry**) [36], which is one of the most effective defense method [2], *iii*) another recent method performs adversarial training with both image and label adversarial perturbations (**Bilateral**) [61]. For training, the learning rate η is 0.1 for CIFAR and 0.01 for SVHN.

- 测试参数：

and Sinkhorn algorithm [12] with regularization of 0.01 is used. For testing, model robustness is evaluated by approximately computing an upper bound of robustness on the test set, by measuring the accuracy of the model under different adversarial attacks, including white-box FGSM [24], PGD [36], CW [8] (CW-loss [8] within the PGD framework) attacks and variants of black-box attacks.

(1) 白盒攻击结果：

Models	Clean	Accuracy under White-box Attack ($\epsilon = 8$)								
		FGSM	PGD10	PGD20	PGD40	PGD100	CW10	CW20	CW40	CW100
Standard	95.6	36.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Madry	85.7	54.9	45.1	44.9	44.8	44.8	45.9	45.7	45.6	45.4
Bilateral	91.2	70.7	—	57.5	—	55.2	—	56.2	—	53.8
Proposed	90.0	78.4	70.9	70.5	70.3	68.6	62.6	62.4	62.1	60.6

Table 1: Accuracy comparison of the **Proposed** approach with **Standard**, **Madry** [36] and **Bilateral** [61] methods on CIFAR10 under different threat models.

Models	Clean	White-box Attack ($\epsilon=8$)				Models	Clean	White-box Attack ($\epsilon=8$)				
		FGSM	PGD20	PGD100	CW20			FGSM	PGD20	PGD100	CW20	CW100
Standard	97.2	53.0	0.3	0.1	0.3	0.1	Standard	79.0	10.0	0.0	0.0	0.0
Madry	93.9	68.4	47.9	46.0	48.7	47.3	Madry	59.9	28.5	22.6	22.3	23.2
Bilateral	94.1	69.8	53.9	50.3	—	48.9	Bilateral	68.2	60.8	26.7	25.3	—
Proposed	96.2	83.5	62.9	52.0	61.3	50.8	Proposed	73.9	61.0	47.2	46.2	34.6

Table 2: Accuracy comparison on (a) SVHN and (b) CIFAR100.

Links

- 论文链接: [Zhang H, Wang J. Defense against adversarial attacks using feature scattering-based adversarial training\[J\]. arXiv preprint arXiv:1907.10764, 2019.](#)
- 论文代码: <https://github.com/Haichao-Zhang/FeatureScatter>