PixelDefend: Leveraging Generative Models to Understand and Defend against Adversarial Examples

Yang Song[1], Taesup Kim[2], Sebastian Nowozin[3], Stefano Ermon[1], Nate Kushman[3]

[1]Stanford University, [2]Université de Montréal, [3]Microsoft Research

ABSTRACT

- We show that generative models can be used for detecting adversarially perturbed images and observe that most adversarial examples lie in low probability regions.
- We introduce a novel family of methods for defending against adversarial attacks based on the idea of purification.
- We show that a defensive technique from this family, PixelDefend, can achieve state-of-the-art results on a large number of attacking techniques, improving the accuracy against the strongest adversary on the CIFAR-10 dataset from 32% to 70%.

ADVERSARIAL EXAMPLES

State-of-the-art classifiers can be fooled by adding quasi-imperceptible noise.

Figure 1: Various attacks of an image from CIFAR-10. The text above shows the attacking methods while the text below shows the predicted labels (of a ResNet).

NEURAL DENSITY MODELS

PixelCNN a convolutional neural network that factorizes $p(X)$ using the product rule

$$p(X) = \prod_{i=1}^{n} p(x_i \mid x_{1:(i-1)}),$$

where the pixel dependencies are in raster scan order.

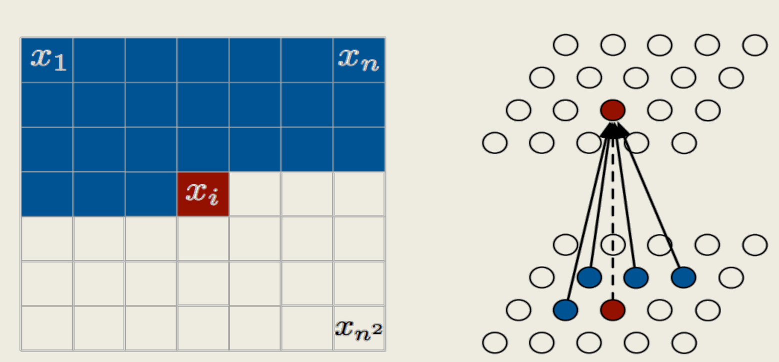

Figure 2: PixelCNN.

Figure 3: Sampled images for Fashion-MNIST and CIFAR-10. Above red line are real images. Below read line are PixelCNN samples.

DETECTING ADVERSARIAL EXAMPLES

Observation: The PixelCNN density of an adversarial example is usually significantly lower than that of an clean example. Therefore, $p(X)$ *can be used as a test statistic to detect adversarial examples.*

Statistical test: Given an input $X' \sim q(X)$ and training images $X_1, X_2, \cdots, X_N \sim p_t(X)$. The null hypothesis is $H_0: p_t(X) = q(X)$ while the alternative is $H_1: p_t(X) \neq q(X)$. The p-value is computed as

$$\text{p-value} = \frac{1}{N+1}\left(\sum_{i=1}^{N} \mathbb{I}\left[p(X_i) \leq p(X')\right] + 1\right)$$

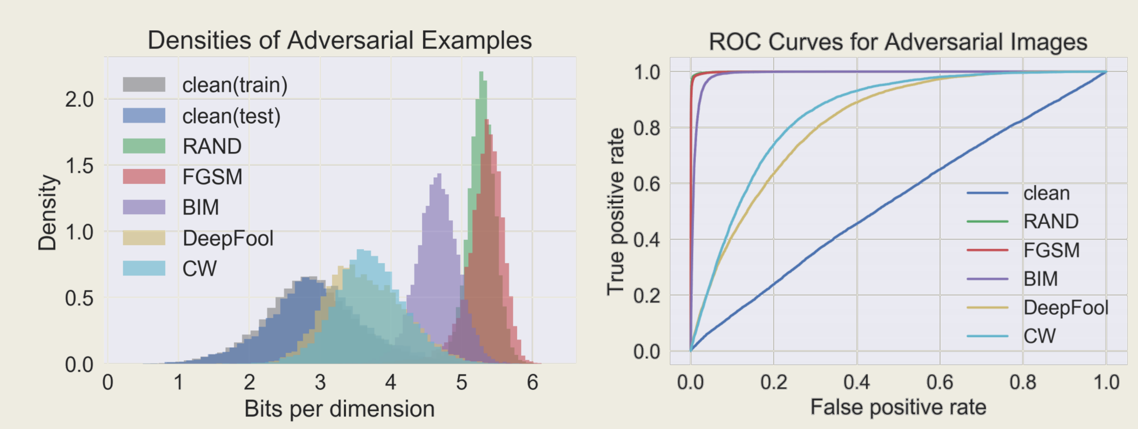

Figure 4: (Left) Likelihoods of different adversarial examples. (Right) ROC curves for detecting various attacks.

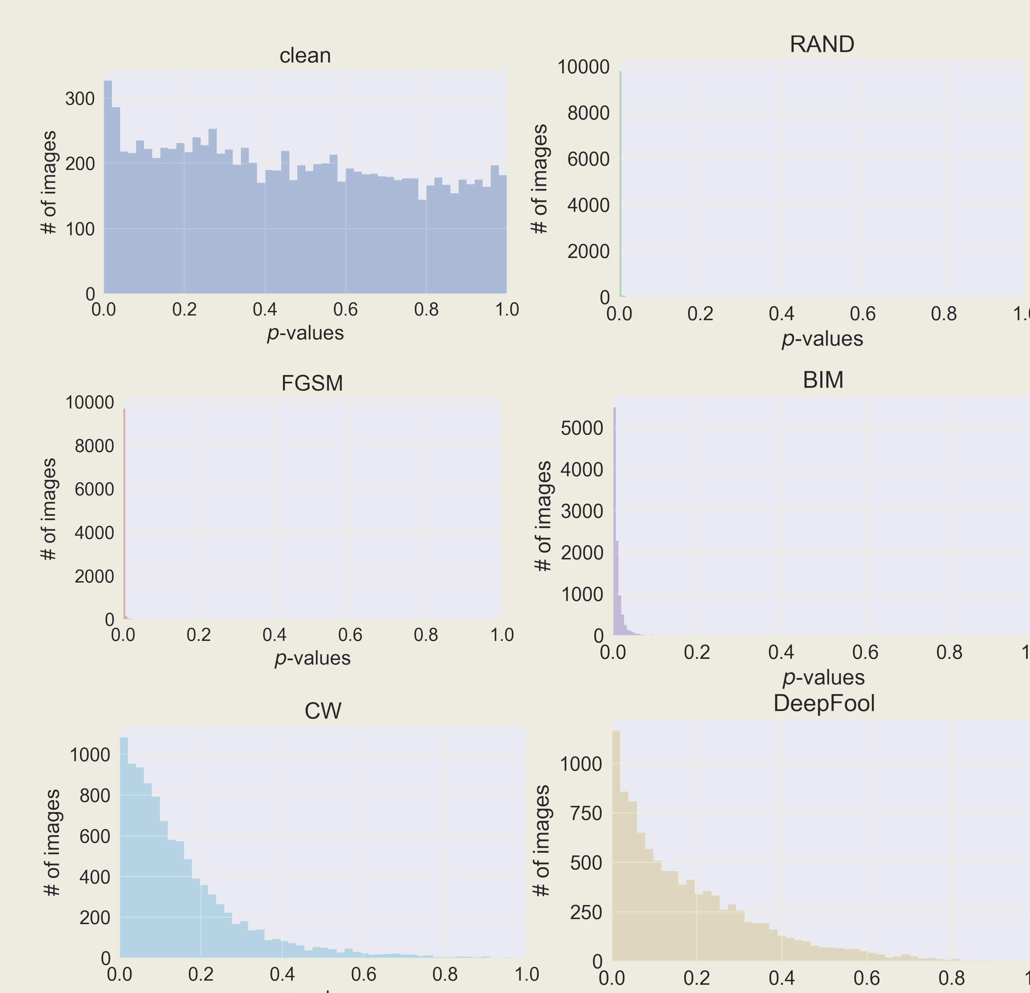

Figure 5: Distributions of p-values for different attacks.

PIXELDEFEND

Intuition: The harm of adversarial examples might be reduced if they can be modified to have higher likelihood.

Algorithm 1 PixelDefend

Input: Image $\mathbf{X}$, Defense parameter ϵ_{defend}, Pre-trained PixelCNN model p_{CNN}
Output: Purified Image $\mathbf{X}^*$

```
X* ← X
for each row i do
    for each column j do
        for each channel k do
            x ← X[i, j, k]
            Set feasible range R ← [max(x − ε_defend, 0), min(x + ε_defend, 255)]
            Compute the 256-way softmax p_CNN(X*).
            Update X*[i, j, k] ← arg max_{z∈R} p_CNN[i, j, k, z]
        end for
    end for
end for
```

EXPERIMENTS

Table 1: **Fashion MNIST** ($\epsilon_{\text{attack}} = 8/25$, $\epsilon_{\text{defend}} = 32$)

NETWORK	TRAINING TECHNIQUE	CLEAN	RAND	FGSM	BIM	DEEP FOOL	CW	STRONGEST ATTACK
ResNet	Normal	**93/93**	89/71	38/24	00/00	06/06	20/01	00/00
VGG	Normal	92/92	91/87	73/58	36/08	49/14	43/23	36/08
ResNet	Adversarial FGSM	**93/93**	**92**/89	85/85	51/00	63/07	67/21	51/00
	Adversarial BIM	92/91	**92/91**	84/79	76/63	82/72	81/70	76/63
	Label Smoothing	**93/93**	91/76	73/45	16/00	29/06	33/14	16/00
	Feature Squeezing	84/84	84/70	70/28	56/25	83/83	83/83	56/25
	Adversarial FGSM + Feature Squeezing	88/88	87/82	80/77	70/46	86/82	84/85	70/46
ResNet	Normal + ***PixelDefend***	88/88	88/89	85/74	83/76	87/87	87/87	83/74
VGG	Normal + ***PixelDefend***	89/89	89/89	87/82	85/83	88/88	88/88	85/82
ResNet	Adversarial FGSM + ***PixelDefend***	90/89	91/90	**88**/82	**85**/76	**90**/88	**89/88**	**85**/76
	Adversarial FGSM +***Adaptive PixelDefend***	91/91	91/**91**	**88/88**	**85/84**	89/**90**	**89**/84	**85/84**

Table 2: **CIFAR-10** ($\epsilon_{\text{attack}} = 2/8/16$, $\epsilon_{\text{defend}} = 16$)

NETWORK	TRAINING TECHNIQUE	CLEAN	RAND	FGSM	BIM	DEEP FOOL	CW	STRONGEST ATTACK
ResNet	Normal	**92/92/92**	**92**/87/76	33/15/11	10/00/00	12/06/06	07/00/00	07/00/00
VGG	Normal	89/89/89	89/88/80	60/46/30	44/02/00	57/25/11	37/00/00	37/00/00
ResNet	Adversarial FGSM	91/91/91	90/**88**/84	**88/91/91**	24/07/00	45/00/00	20/00/07	20/00/00
	Adversarial BIM	87/87/87	87/87/86	80/52/34	74/32/06	79/48/25	76/42/08	74/32/06
	Label Smoothing	**92/92/92**	91/**88**/77	73/54/28	59/08/01	56/20/10	30/02/02	30/02/01
	Feature Squeezing	84/84/84	83/82/76	31/20/18	13/00/00	75/75/75	78/78/78	13/00/00
	Adversarial FGSM + Feature Squeezing	86/86/86	85/84/81	73/67/55	55/02/00	**85/85/85**	83/83/83	55/02/00
ResNet	Normal + ***PixelDefend***	85/85/88	82/83/84	73/46/24	71/46/25	80/80/80	78/78/78	71/46/24
VGG	Normal + ***PixelDefend***	82/82/82	82/82/84	80/62/52	80/61/48	81/76/76	81/79/79	80/61/48
ResNet	Adversarial FGSM + ***PixelDefend***	88/88/86	86/86/**87**	81/68/67	**81**/69/**56**	**85/85/85**	**84/84/84**	**81**/69/**56**
	Adversarial FGSM + ***Adaptive PixelDefend***	90/90/90	86/87/**87**	81/70/67	**81/70/56**	82/81/82	81/80/81	**81/70/56**

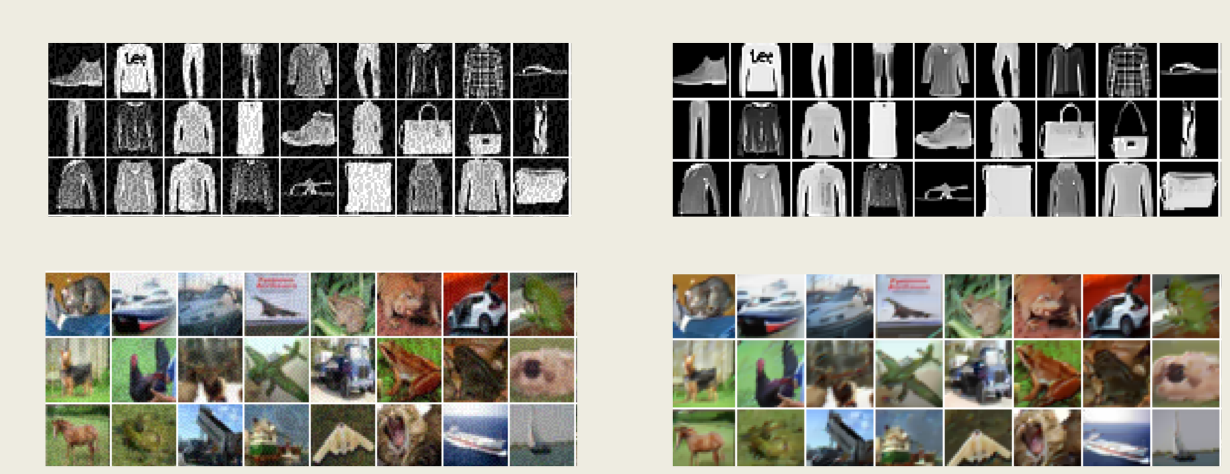

Figure 6: Adversarial images (left) and purified images after PixelDefend (right).