Adversarial Image Generation and Training for Deep Convolutional Neural Networks

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Abstract

Deep convolutional neural networks (DCNNs) have achieved great success in image classification, but they may be very vulnerable to adversarial attacks with small perturbations to images. Moreover, the adversarial training based on adversarial image samples has been shown to improve the robustness and generalization of DCNNs. The aim of this paper is to develop a novel framework based on information-geometry sensitivity analysis and the particle swarm optimization to improve two aspects of adversarial image generation and training for DCNNs. The first one is customized generation of adversarial examples. It can design adversarial attacks from options of the number of perturbed pixels, the misclassification probability, and the targeted incorrect class, and hence it is more flexible and effective to locate vulnerable pixels and also enjoys certain adversarial universality. The other is targeted adversarial training. DCNN models can be improved in training with the adversarial information using a manifold-based influence measure effective in vulnerable image/pixel detection as well as allowing for targeted attacks, thereby exhibiting an enhanced adversarial defense in testing.

1 Introduction

Deep convolutional neural networks (DCNNs) have exhibited exceptional performance in image classification [10,7,8], so they have been widely used in various real-world applications including face recognition [27], self-driving cars [2], biomedical image processing [1], among many others [18]. Despite of these successes, DCNN classifiers can be easily attacked by adversarial examples with perturbations imperceptible to human vision [28,6,26]. This motivates the hot research in adversarial attacks and defenses of DCNNs. See [29,24] for reviews.

Existing adversarial attacks can be categorized into white-box, gray-box, and black-box attacks. Adversaries in white-box attacks have the full information of their targeted DCNN model, whereas

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their knowledge is limited to model structure in gray-box attacks and only to model’s input and output in black-box attacks. For instance, popular algorithms for white-box attacks include the fast gradient sign method [6, 11], the projected gradient descent method [12], the Carlini and Wagner attack [3], among many others [28, 22, 16]. Defensive techniques for those attacks include heuristic and certificated defenses. Adversarial training is the current most successful heuristic defense approach for improving the robustness of DCNNs, which simply incorporates adversarial samples into training but has better numerical performance than certificated defenses [24].

In this paper, we propose a simple yet efficient framework for white-box adversarial image generation and training for DCNN classifiers. For generating an adversarial example of a given image, our framework provides user-customized options in the number of perturbed pixels, misclassification probability, and targeted incorrect class. To the best of our knowledge, this is the first approach rendering all the three desirable options. The freedom to specify the number of perturbed pixels allows users to conduct attacks at various pixel levels such as one-pixel [26] and all-pixel [15] attacks. Particularly, we adopt a recent perturbation-manifold based first-order influence (FI) measure [25] to efficiently locate the most vulnerable pixels to increase the attack success rate. In contrast with traditional Euclidean-space based measures such as Jacobian norm [21] and Cook’s local influence measure [4], the FI measure captures the intrinsic change of the perturbed objective function [33, 34] and shows better performance in detecting vulnerable images and pixels. Besides, our framework allows users to specify the misclassification probability and/or the targeted incorrect class. The prespecified misclassification probability is rarely seen in existing approaches, which produce an adversarial example either near the model’s decision boundary [16, 19] or with unguaranteed high confidence [20]. We tailor different loss functions accordingly to the three desirable options and their combinations, and apply the particle swarm optimization (PSO) [9], a fast gradient-free method, to obtain the optimal perturbation. Moreover, we observe that our perturbations with high misclassification probability can have certain adversarial universality [15] to images from different classes. For adversarial training, in training data we further utilize the FI measure to identify vulnerable images and their pixels that are prone to optional targeted classes. Then using our customized generation approach yields an adversarial dataset for training. Experiments show that our adversarial training significantly improves the robustness of pretrained DCNN classifiers. Figure [1] illustrates the flowchart of our framework.

We notice that two recent papers [31, 17] also applied PSO to craft adversarial images. However, we have intrinsic distinctions. First, the two papers focus on black-box attacks, but ours is white-box. Article [31] only studied all-pixel attacks; although article [17] considered few-pixel attacks, but searched in random chunks to locate the vulnerable pixels, we use the FI measure to directly discover those pixels. Moreover, targeted attacks are not considered in [17], and both papers cannot prespecify a misclassification probability for the generated adversarial example. Our framework is able to design arbitrary-pixel-level, confidence-specified, and/or targeted/nontargeted attacks.

Our contributions are summarized as follows:

- We propose a novel white-box framework for adversarial image generation and training for DCNN classifiers. It provides users with multiple options in pixel levels, confidence levels, and targeted classes for adversarial attacks and defenses.

- We adopt a manifold-based FI measure to efficiently identify vulnerable images and pixels for adversarial perturbations.

- We design different loss functions adaptive to user-customized specifications and apply the PSO, a fast gradient-free optimization, to obtain optimal perturbations.

- We demonstrate the effectiveness of our framework via experiments on benchmark datasets and notice that our high-confidence perturbations may have certain adversarial universality.

2 Method

2.1 Perturbation-Manifold Based Influence Measure

Given an input image $x$ and a DCNN classifier $N$ with parameters $\theta$, the prediction probability for class $y \in \{1, \ldots, K\}$ is denoted by $P(y|x, \theta) = N_\theta(y, x)$. Let $\omega = (\omega_1, \ldots, \omega_m)^T$ be a
perturbation vector in an open set $\Omega \subseteq \mathbb{R}^m$, which can be imposed on any subvector of $(x^T, \theta^T)^T$. Let the prediction probability under perturbation $\omega$ be $P(y|x, \theta, \omega)$ with $P(y|x, \theta, \omega_0) = P(y|x, \theta)$. For sensitivity analysis of DCNNs, Shu and Zhu [25] recently have proposed an FI measure to delineate the ‘intrinsic’ perturbed change of the objective function on the Riemannian manifold of $M = \{P(y|x, \theta, \omega) : \omega \in \Omega\}$ [33][34]. In contrast with traditional Euclidean-space based measures such as Jacobian norm [21] and Cook’s local influence measure [4], this perturbation-manifold based measure enjoys the desirable invariance property under diffeomorphic (e.g., scaling) reparameterizations of perturbations and has better numerical performance in detecting vulnerable images and pixels.

Let $f(\omega)$ be an objective function of interest, for example, the cross-entropy $f(\omega) = -\log P(y = y_{\text{true}}|x, \theta, \omega)$. The FI measure at $\omega = \omega_0$ is defined by

$$\text{FI}_{\omega}(\omega_0) = [\partial_x f(\omega_0)] G^1_\omega(\omega_0)[\partial_\omega f(\omega_0)]^T,$$

where $\partial_\omega = (\partial/\partial \omega_1, \ldots, \partial/\partial \omega_p)$, $G_\omega(\omega) = \sum_{k=1}^K \partial_x^T \ell(\omega|y, x, \theta) \partial_\omega \ell(\omega|y, x, \theta) P(y|x, \theta, \omega)$ with $\ell(\omega|y, x, \theta) = \log P(y|x, \theta, \omega)$, and $G^1_\omega(\omega_0)$ is the pseudoinverse of $G_\omega(\omega_0)$. A larger value of $\text{FI}_{\omega}(\omega_0)$ indicates that the DCNN model is more sensitive in $f(\omega)$ to local perturbation $\omega$ around $\omega_0$. We shall use the FI measure to discover vulnerable images or pixels for adversarial attacks.

### 2.2 Particle Swarm Optimization

Since introduced by Kennedy and Eberhart [9] in 1995, the PSO algorithm has been successfully used in solving complex optimization problems in various fields of engineering and science [23][35][32]. Let $f_A$ be an objective function, which will be specified in Section 2.3 for adversarial scenarios. The PSO algorithm performs searching via a population (called swarm) of candidate solutions (called particles) by iterations to optimize the objective function $f_A$. Specifically, let

$$p_{i,\text{best}} = \arg \min_{k=1, \ldots, t} f_A(\omega^k_i), \quad i \in \{1, 2, \ldots, N_p\},$$

$$g_{\text{best}} = \arg \min_{i=1, \ldots, N_p} f_A(p_{i,\text{best}}),$$

where $\omega^k_i = (\omega^k_{1i}, \ldots, \omega^k_{mi})^T$ is the position of particle $i$ in an $m$-dimensional space at iteration $k$, $N_p$ is the total number of particles, and $t$ is the current iteration. The position, $\omega^t_i$, of particle $i$ at iteration $(t+1)$ is updated with a velocity $v^{t+1}_i = (v^{t+1}_{1i}, \ldots, v^{t+1}_{mi})$ by

$$v^{t+1}_i = w v^{t}_i + c_1 r_1 (p_{i,\text{best}} - \omega^t_i) + c_2 r_2 (g_{\text{best}} - \omega^t_i),$$

where $w$ is the inertia weight, $c_1$ and $c_2$ are acceleration coefficients, and $r_1$ and $r_2$ are uniformly distributed random variables in the range $[0, 1]$. Following [30], we fix $w = 0.6$ and $c_1 = c_2 = 2$. We can see that the movement of each particle is guided by its individual best known position and the entire swarm’s best known position. We shall use the PSO algorithm to obtain desirable adversarial perturbations under various user’s requirements.
2.3 Adversarial Image Generation

Given an image \( x \), we combine FI and PSO to generate its adversarial image with user-customized options for the number of pixels for perturbation, the misclassification probability, and the targeted class to which the image is misclassified, denoted by \( m \), \( P_{\text{err}} \), and \( y_{\text{target}} \), respectively.

Denote image \( x = (x_1, \ldots, x_p)^T \). For an RGB image of \( q \) pixels, we view the three channel components of a pixel as three separate pixels, so \( p = 3q \) here. We let the default value of \( m = p \).

We first locate \( m \) vulnerable pixels in \( x \) for perturbation, if \( m \) is specified but the targeted pixels are not given by the user. We compute the FI measure in (1) for each pixel \( i \in \{1, \ldots, p\} \) based on the objective function

\[
f(\omega) = \begin{cases} 
- \log P(y_{\text{true}}|x, \theta, \omega), & \text{if } y_{\text{target}} \text{ is not given}, \\
- \log P(y_{\text{target}}|x, \theta, \omega), & \text{otherwise}, 
\end{cases}
\]

where \( \omega = \Delta x_i \). Denote \( x_{(i)} \) to be the pixel with the \( i \)-th largest FI value. We use \( x_{(1)}, \ldots, x_{(m)} \) as the \( m \) pixels for adversarial attack and let perturbation \( \omega = (\omega_1, \ldots, \omega_m)^T = (\Delta x_{(1)}, \ldots, \Delta x_{(m)})^T \).

We then apply the PSO algorithm in [2] and [4] to obtain an optimal value of \( \omega \) that minimizes the adversarial objective function

\[
f_A(\omega) = a f_0(\omega) + b \|\omega\|_2, \quad \omega_i \in \varepsilon \cdot (0 - x_{(i)}, 1 - x_{(i)}),
\]

where we assume \( x_{(i)} \in [0, 1] \), \( \varepsilon \) constrains the range of perturbation to guarantee the visual quality of the generated adversarial image compared to the original, \( f_0(\omega) \) is a misclassification loss function, \( \|\omega\|_2 \) represents the magnitude of perturbation, and \( a \) and \( b \) are prespecified weights. To ensure the misleading nature of the generated adversarial sample, \( a \gg b \) is set to prioritize \( f_0(\omega) \) over \( \|\omega\|_2 \).

We use different \( f_0(\omega) \) functions to meet different user-customized requirements on \( \{m, P_{\text{err}}, y_{\text{target}}\} \).

If only \( m \) is known, inspired by [13] [14], we let the misclassification loss function be

\[
f_0(\omega) = \begin{cases} 
|P(y_1|x, \theta, \omega) - P(y_2|x, \theta, \omega)|, & \text{if } y_1 = y_{\text{true}}, \\
0, & \text{if } y_1 \neq y_{\text{true}},
\end{cases}
\]

where \( y_k \) is the label with the \( k \)-th largest prediction probability \( P(y = y_k|\theta) \) from the trained DCNN for the input image \( x \) added with perturbation \( \omega \). Since \( y_1 \neq y_{\text{true}} \) results in the minimum of \( f_0(\omega) \), this loss function encourages PSO to yield a valid perturbation. If the \( \omega \)-perturbed \( x \) is prespecified with a misclassification probability \( P_{\text{err}} \geq 0.5 \), we use the misclassification loss function

\[
f_0(\omega) = \begin{cases} 
|P(y_1|x, \theta, \omega) - P_{\text{err}}|, & \text{if } y_1 = y_{\text{true}}, \\
|P(y_1|x, \theta, \omega) - P_{\text{err}}|, & \text{if } y_1 \neq y_{\text{true}},
\end{cases}
\]

Later in our experiments, we show that high \( P_{\text{err}} \) is helpful to generate universal adversarial perturbations applicable to images from the other classes. If a targeted class \( y_{\text{target}} \) is given, we choose the misclassification loss function

\[
f_0(\omega) = \begin{cases} 
|P(y_1|x, \theta, \omega) - P(y_{\text{target}}|x, \theta, \omega)|, & \text{if } y_1 \neq y_{\text{target}}, \\
0, & \text{if } y_1 = y_{\text{target}}.
\end{cases}
\]

Furthermore, if both \( P_{\text{err}} \) and \( y_{\text{target}} \) are provided, we use

\[
f_0(\omega) = \begin{cases} 
|P(y_1|x, \theta, \omega) - P(y_{\text{target}}|x, \theta, \omega)|, & \text{if } y_1 \neq y_{\text{target}}, \\
|P(y_1|x, \theta, \omega) - P_{\text{err}}|, & \text{if } y_1 = y_{\text{target}}.
\end{cases}
\]

or equivalently \( f_0(\omega) = |P(y_{\text{target}}|x, \theta, \omega) - P_{\text{err}}| \).

Our procedure for generating a customized adversarial image is illustrated in Figure[1](b)-(e) and also summarized in Algorithm[1]

2.4 Adversarial Training

We aim to create a set of adversarial images for a given trained DCNN model, and then fine-tune the model on the training data augmented with this adversarial dataset. To include as many adversarial
We conduct experiments on the two benchmark datasets MNIST and CIFAR10 using the ResNet32 model [7]. Data augmentation is used, including random horizontal and vertical shifts up to 12.5% of image height and width for both datasets, and additionally random horizontal flip for CIFAR10 data. Table 1 shows the prediction accuracy of our trained ResNet32 for the two datasets.

### Algorithm 1 Adversarial image generation

**Input:** Image and label \( \{x, y_{\text{true}}\} \), number of perturbed pixels \( m \), (optional) indices of perturbed pixels, (optional) targeted incorrect label \( y_{\text{target}} \), hyperparameters \( \{N_p, a, b, \varepsilon\} \) in PSO, and maximum iteration number \( T \)

1: If perturbed pixels are not specified, compute FI by (1) and (5) for all pixels to locate the \( m \) pixels for perturbation \( \omega \);
2: Initialize \( N_p \) particles in PSO with positions \( \{p_i^0 = \omega_i^0\}_{i=1}^{N_p}, g_{\text{best}}^0 \} \) and velocities \( \{v_i^0\}_{i=1}^{N_p} \);
3: Repeat
4: for particle \( i = 1, \ldots, N_p \) do
5: Update \( v_i^t \) and \( \omega_i^t \) by (4);
6: Update \( p_i^t, g_{\text{best}} \) by (2);
7: end for
8: Update \( g_{\text{best}} \) by (3);
9: Until convergence or iteration \( t = T \)

**Output:** Adversarial image \( x + \text{zero-padded } \omega \), where \( \omega = g_{\text{best}}^t \).

Specifically, given an image dataset \( X = \{x_i\}_{i=1}^n \), thresholds \( \text{FI}_{\text{img}}, P_{\text{target}}, \text{FI}_{\text{pixel}} \) and targeted incorrect labels \( \{y_i, target\}_{i=1}^n \) (if not given, \( y_i, target = y_i, a \) the label with the second largest prediction probability), we first find \( \hat{X} \), the set of all correctly classified images that have image-level FI (with \( \omega = \Delta x_i \geq \text{FI}_{\text{img}} \) and prediction probability \( P(y_{i, target}|x_i, \theta) \geq P_{\text{target}} \). For each image in set \( \hat{X} \), we generate its adversarial image by Algorithm 1 in which \( m \) is the number of pixels with FI \( \geq \text{FI}_{\text{pixel}} \) and \( y_{\text{target}} \) is specified to \( y_{i, target} \). These generated adversarial images form an adversarial dataset. The whole procedure of our adversarial training is illustrated in Figure 1 and detailed in Algorithm 2.

### Algorithm 2 Adversarial dataset generation

**Input:** Image set \( X = \{x_i\}_{i=1}^n \) and labels \( \{y_i, true\}_{i=1}^n \), thresholds \( \text{FI}_{\text{img}}, P_{\text{target}}, \text{FI}_{\text{pixel}} \), targeted incorrect labels \( \{y_i, target\}_{i=1}^n \), and hyperparameters \( \{N_p, a, b, \varepsilon, T\} \) in Algorithm 1

1: For each correctly classified \( x_i \in \hat{X} \), compute the image-level FI (denoted by FI) by (1) with \( \omega = \Delta x_i \) and \( f(\omega) = -\log P(y_{i, true}|x_i, \theta, \omega) \);
2: Determine \( \hat{X} = \{x_i \in X : \text{FI}_i \geq \text{FI}_{\text{img}}, P(y_{i, target}|x_i, \theta) \geq P_{\text{target}} \} \);
3: For each \( x_i \in \hat{X} \), generate its adversarial image \( x_i^a \) by Algorithm 1 with \( m = \# \) of pixels with \( \text{FI} \geq \text{FI}_{\text{pixel}} \) and \( y_{\text{target}} = y_{i, target} \).

**Output:** Adversarial dataset \( \hat{X}^a = \{x_i^a\}_{i=1}^n \)

### 3 Experiments

We conduct experiments on the two benchmark datasets MNIST and CIFAR10 using the ResNet32 model [7]. Data augmentation is used, including random horizontal and vertical shifts up to 12.5% of image height and width for both datasets, and additionally random horizontal flip for CIFAR10 data. Table 1 shows the prediction accuracy of our trained ResNet32 for the two datasets.

|                  | MNIST          | CIFAR10        |
|------------------|----------------|----------------|
| Model            | Training (n=60k) | Testing (n=10k) | Training (n=50k) | Testing (n=10k) |
| Original         | 99.76%         | 99.25%         | 98.82%          | 91.28%          |
| Adversarial      | 99.68%         | 99.32%         | 99.10%          | 91.32%          |

Table 1: Accuracy of original and adversarial trained ResNet32 models
3.1 Customized Adversarial Image Generation

We consider two images with easy visual detection and large image-level FI in MNIST and CIFAR10, shown in Figures 2 and 3 with prediction-probability graphs and pixel-level FI maps. The probability bar graphs imply candidate misclassification classes that can be used as $y_{\text{target}}$. The FI maps indicate the vulnerability of each pixel to local perturbation and are useful to locate pixels for attack.

We first evaluate the performance of Algorithm 1 (cf. Figure 1(b)-(e)) in generating adversarial examples of the two images according to different requirements on $m$, $P_{err}$ and $y_{\text{target}}$. Figures 4 and 5 show the generated adversarial images with corresponding perturbation maps. Perturbations 1-3 consider the settings with $m = 1, 3$, and 7, respectively, and with no specifications to $P_{err}$ and $y_{\text{target}}$. For Perturbations 4-6, we only specify $P_{err} = 0.5, 0.75, 0.99$, respectively, assign no value to $y_{\text{target}}$, and tune $m$ being the number of pixels with FI $> \text{FI}_{\text{pixel}} \in \{0.1, 1\}$ and $N_p \in \{200, 500, 1000\}$ to obtain feasible solutions from PSO. Perturbations 7-9 are prespecified with $y_{\text{target}} = 0, 2, 4$ for MNIST, and 0, 4, and 5 for CIFAR10, respectively, $m$ being the number of pixels with FI $> 0.1$, and no value for $P_{err}$. The detailed parameter settings for Algorithm 1 are provided in Supplementary Material. We can see that the generated adversarial images have visually negligible differences from the originals and satisfy the prespecified requirements.

We also investigate the adversarial universality of Perturbation 6 shown in Figures 4 and 5, which have 99% prediction probability to Class 4. Table 2 shows the proportions of original correctly-classified images that are misclassified after added with the perturbations. The MNIST dataset has error rates at least 14.3% for all classes and some up to 100%, with a total rate above 87.5% in both training and testing sets. In particular, a remarkably large proportion of each class is misclassified to Class 4 with a total rate of 62.2% and 64.5% for training and testing sets. Perturbation 6 for CIFAR10 also exhibits a certain extent of adversarial universality with non-targeted total error rates 3.92% and 6.19% and Class-4-targeted total rates 0.92% and 1.32% for training and testing sets, respectively. Figure 6 displays images from the other nine classes that are originally correctly classified with high probability but are misclassified (most with high probability) to Class 4 after added with Perturbation 6. These results indicate that our method may generate a universal adversarial perturbation, which particularly has the potential to misclassify images from different classes to the same specific class. The existence of universal adversarial perturbations may be attributed to the geometric correlations of decision boundaries between classes [15]. An adversarial perturbation with very high confidence may have salient features of its resulting class and thus it may have strong power to drag other different images towards the decision boundary.

![Figure 2: Pixel-level FI maps of an MNIST image for different target classes.](image)

![Figure 3: Pixel-level FI maps of a CIFAR10 image’s RGB channels for different target classes. Class labels: (0, 1, 2, 3, 4, 5, 6, 7, 8, 9) = (plane, car, bird, cat, deer, dog, frog, horse, ship, truck).](image)
Figure 4: Adversarial examples of an MNIST image. Perturbations 1-3 are set with $m = 1, 3$ and 7, respectively; Perturbations 4-6 are with $P_{err} = 0.5, 0.75$ and 0.99, respectively; Perturbations 7-9 are with $y_{target} = 0, 2$ and 4, respectively. Perturbation maps are followed by resulting adversarial images.

Figure 5: Adversarial examples of a CIFAR10 image. Perturbations 1-3 are set with $m = 1, 3$ and 7 attacked pixels (framed in the attacked channel’s color), respectively. Perturbations 4-6 are set with $P_{err} = 0.5, 0.75$ and 0.99, respectively. Perturbations 7-9 are set with $y_{target} = 0, 4$ and 5, respectively. Perturbation maps are followed by resulting adversarial images.

Table 2: Proportions (in %) of original correctly-classified images that are misclassified after added with Perturbations 6 in Figures 4 and 5.

| True Class | 0 | 1 | 2 | 3 | 5 | 6 | 7 | 8 | 9 | Total |
|------------|---|---|---|---|---|---|---|---|---|-------|
| MNIST      |   |   |   |   |   |   |   |   |   |       |
| Training   | 92.9 | 100 | 99.3 | 91.1 | 96.0 | 92.3 | 100 | 15.3 | 99.9 | 87.7 |
| Misclassified to 4 | 81.1 | 36.9 | 55.8 | 84.3 | 75.5 | 49.6 | 95.3 | 14.2 | 68.8 | 62.2 |
| MNIST      |   |   |   |   |   |   |   |   |   |       |
| Testing    | 91.7 | 100 | 99.4 | 94.4 | 97.9 | 91.1 | 100 | 14.3 | 100 | 87.9 |
| Misclassified to 4 | 79.7 | 37.3 | 58.8 | 88.3 | 78.5 | 57.4 | 94.8 | 13.7 | 75.0 | 64.5 |
| CIFAR10    |   |   |   |   |   |   |   |   |   |       |
| Training   | 8.46 | 2.74 | 2.90 | 7.27 | 5.77 | 0.42 | 4.82 | 2.07 | 1.00 | 3.92 |
| Misclassified to 4 | 1.27 | 0.04 | 0.89 | 1.65 | 1.45 | 0.12 | 2.56 | 0.30 | 0.06 | 0.92 |
| CIFAR10    |   |   |   |   |   |   |   |   |   |       |
| Testing    | 11.2 | 5.62 | 6.27 | 12.36 | 8.29 | 0.94 | 6.81 | 3.05 | 2.61 | 6.19 |
| Misclassified to 4 | 2.17 | 0.10 | 1.48 | 2.52 | 2.34 | 0.31 | 2.81 | 0.32 | 0.21 | 1.32 |
Figure 6: Results of universal adversarial perturbations (Perturbations 6 in Figures 4 and 5).
3.2 Adversarial Training

We consider using Algorithm 2 to generate adversarial datasets for adversarial training. Figure 7 shows the Manhattan plots of image-level FIs for correctly classified images and Figure 8 presents the heatmaps of confusion matrices. We can see that the distributions of image-level FIs and the patterns of misclassifications are very close between training and test datasets in both MNIST and CIFAR10. Hence, our adversarial training is expected to be useful for unseen adversarial examples generated from similar mechanisms in testing.

Based on the two figures, for selecting vulnerable images (cf. Figure 1(a)), we let $F_{\text{img}} = 0.2$, $y_{i, \text{target}}$ be the most frequent misclassified class of $x_i$’s true class, and $P_{\text{target}} = 0.2$ in Algorithm 2. The resulting image set $\tilde{X}$ is likely to be near the decision boundaries of the trained classifier. We then set $F_{\text{pixel}} = 0.1$ in the algorithm. We generate adversarial datasets $\text{Adv1} (n = 136)$ and $\text{Adv2} (n = 26)$, respectively, from training and testing sets of MNIST, and $\text{Adv3} (n = 244)$ and $\text{Adv4} (n = 146)$ from those of CIFAR10. $\text{Adv1}$ and $\text{Adv3}$ are used for adversarial training (cf. Figure 1(f)), whereas $\text{Adv2}$ and $\text{Adv4}$ test the adversarial trained models. The detailed parameter settings for Algorithm 2 to generate those datasets are given in Supplementary Material.

The adversarial trained ResNet32 models are trained from the original trained models on the training data augmented with $\text{Adv1}$ and $\text{Adv3}$, respectively, for additional 30 epochs for MNIST and 50 epochs for CIFAR10. The results of adversarial training are reported in Tables 1 and 3. Since the adversarial datasets ($n \leq 244$) are much smaller than original testing datasets ($n = 10k$) and the original trained models already have high accuracy, the results in Tables 1 are only slightly improved on the test datasets. However, in Table 3 the adversarial training on $\text{Adv1}$ and $\text{Adv3}$ indeed benefits the defense of the fine-tuned ResNet32 models against adversarial attacks. The accuracy is dramatically improved from 0.00% to 83.82% and 88.93% on $\text{Adv1}$ and $\text{Adv3}$, respectively, and also up to 76.92% and 63.01% on test-data derived $\text{Adv2}$ and $\text{Adv4}$, respectively. We also observe an increase of 0.27% and 0.94%, respectively, in accuracy on combined data of original test set and its adversarial samples for MNIST and CIFAR10. These results indicate that our approach can significantly improve the adversarial defense of DCNN classifiers.

![Figure 7: Manhattan plots of image-level FIs for correctly classified images.](image1)

![Figure 8: Heatmaps of confusion matrices.](image2)

| Model       | MNIST                  | CIFAR10                 |
|-------------|------------------------|-------------------------|
|              | Adv1 ($n=136$)         | Tr.+Adv1 ($n=60k+136$)  | Adv2 ($n=26$)         | Tr.+Adv2 ($n=10k+26$)  | Adv3 ($n=244$)        | Tr.+Adv3 ($n=50k+244$) | Adv4 ($n=146$)         | Tr.+Adv4 ($n=10k+146$) |
| Original    | 0.00%                  | 99.53%                  | 0.00%                  | 98.99%                  | 0.00%                  | 98.34%                  | 0.00%                  | 89.97%                  |
| Adversarial | 83.82%                 | 99.64%                  | 76.92%                 | 99.26%                  | 88.93%                 | 99.05%                  | 63.01%                 | 90.91%                  |
4 Conclusion

This paper introduced an FI-and-PSO based framework for adversarial image generation and training for DCNN classifiers by accounting for the user specified number of perturbed pixels, misclassification probability, and/or targeted incorrect class. We used the perturbation-based FI measure to efficiently detect the vulnerable images and pixels to increase the attack success rate. We designed different misclassification loss functions to meet various user’s specifications and obtained the optimal perturbation by the fast PSO algorithm. Experiments showed good performance of our approach in generating customized adversarial samples and associated adversarial training for DCNNs.

Broader Impact

DCNN models for image classification are widely used in various real-world applications such as self-driving cars and face recognition for identification, but they can be vulnerable to adversarial attacks with small perturbations to original images, resulting in safety and security concerns in the above mentioned applications. Our proposed white-box framework for adversarial image generation and training for DCNN classifiers may help developers to test and fortify their DCNN-based products to improve reliability in the real-world applications.

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