DAFAR: Defending against Adversaries by Feedback-Autoencoder Reconstruction

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Abstract—Deep learning has shown impressive performance on challenging perceptual tasks and has been widely used in software to provide intelligent services. However, researchers found deep neural networks vulnerable to adversarial examples. Since then, many methods are proposed to defend against adversaries in inputs, but they are either attack-dependent or shown to be ineffective with new attacks. And most of existing techniques have complicated structures or mechanisms that cause prohibitively high overhead or latency, impractical to apply on real software. We propose DAFAR, a feedback framework that allows deep learning models to detect/purify adversarial examples in high effectiveness and universality, with low area and time overhead. DAFAR has a simple structure, containing a victim model, a plug-in feedback network, and a detector. The key idea is to import the high-level features from the victim model’s feature extraction layers into the feedback network to reconstruct the input. This data stream forms a feedback autoencoder. For strong attacks, it transforms the imperceptible attack on the victim model into the obvious reconstruction-error attack on the feedback autoencoder directly, which is much easier to detect; for weak attacks, the reformation process destroys the structure of adversarial examples. Experiments are conducted on MNIST and CIFAR-10 data-sets, showing that DAFAR is effective against popular and arguably most advanced attacks without losing performance on legitimate samples, with high effectiveness and universality across attack methods and parameters.

Index Terms—Adversarial example, deep neural network, autoencoder, deep learning

1 INTRODUCTION

Deep learning system plays an increasingly important role in people’s everyday life in recent years. However, researchers found deep neural networks (DNNs) to be vulnerable to adversarial examples by applying specially crafted perturbations imperceptible to humans on the original samples \[1\], \[2\], \[3\], \[4\], \[5\], \[6\]. The adversarial examples can cause deep learning models to give a wrong classification, which cast a great threat on modern deep learning systems. With the widespread application of deep learning technology in software, adversarial examples also cause nonnegligible harm to the reliability and dependability of software in real world (e.g., cell-phone camera attack \[7\], attack on Autonomous Vehicles \[8\], and cyberspace attack \[9\]).

With advanced adversarial attack methods continuing appearing, researches of defense against adversarial examples also have lots of breakthroughs \[10\], \[11\], \[12\], \[13\], \[14\], \[15\]. However, most defense methods either target specific attacks or were shown to be ineffective with new attacks. Some defense methods only focus on properties of specific attack but ignore common properties of adversarial examples (e.g., adversarial training \[16\] and adversary detector \[17\], \[18\]), leading to attack-dependence. Other defense methods with relatively high universality are often easily broken down by strong attack (e.g., Gradient Masking \[12\]. Input Transformation \[13\] and MagNet \[10\]). Furthermore, most of these existing techniques have complicated structures or mechanisms, which adds them prohibitively high area, time or energy overhead, making them impractical to apply on real software.

We propose DAFAR\(^1\), shown in Figure 1, the first autogenous hybrid defense method to defend against adversarial examples. Besides the victim network, DAFAR only contains a feedback network and a detector that can optionally be an anomaly detector. The feature extraction layers of the victim network and the feedback network constitute a feedback autoencoder. Namely, the victim network and the feedback autoencoder share the feature extraction layers, i.e. encoder, and also share the interference introduced by possible adversarial perturbations in high-level feature space. The encoder first extracts high-level features of the input sample, and then pass them to the feedback network. The feedback network reconstruct the sample from these features, and the detector compares the difference between the input sample and its reconstruction, to judge whether the input is adversarial. If so, DAFAR will discard this sample; if not, the reconstruction will be put back into the victim network to be classified instead of the original input. Relying on feedback reconstruction, the discard data flow and the feedback loop data flow constitute the autogenous hybrid defense.

DAFAR has four significant advantages. First, the architecture and mechanism are simple and effortless. DAFAR only contains a feedback network and a detector besides the victim network, and the feedback network can be transformed from the byproduct of victim network’s pre-training due to its decoder-basis \[19\], \[20\], \[21\]. And there are only one feedback loop and one error comparison besides the normal classification data flow. Second, it does not modify the victim network, for the feedback network is a plug-

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\(^1\) DAFAR is the abbreviation for Defending against Adversaries by Feedback-Autoencoder Reconstruction.

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in structure, and the detector is an independent part, so it can be used to protect a wide range of neural networks. Third, DAFAR’s victim network, feedback network, and the optional anomaly detector are trained on normal samples, without prior knowledge of attack techniques, so DAFAR is attack-independent. Forth, with its autogenous-hybrid-defense strategy, DAFAR achieves considerable defense effectiveness against adversarial examples at whether very low or high attack intensities.

Our main contributions are:

- We summarize four principles to achieve ideal adversarial example defense effectiveness (Section 3): 1) assume no specific knowledge of attack techniques; 2) for strong attack, detect it; 3) for weak attack, purify it; 4) use a hybrid of detection and purification.
- Based on the four principles, we design DAFAR, a semi-supervised-trained framework, to defend against adversarial examples in an autogenous-hybrid-defense manner, in high effectiveness and universality (Section 4).
- Using some representative DNN models and popular datasets, we demonstrate that DAFAR can effectively defend against the adversarial examples generated by different up-to-date attack techniques with a better performance and simpler mechanism than other representative defense methods (Section 5).

2 Background

2.1 Deep Learning

Deep learning is a type of machine learning methods based on deep neural networks (DNNs) [22], which makes information systems to learn knowledge without explicit programming and extract useful features from raw data. Deep learning models play an increasingly important role in modern life. They are used in image classification [23, 24], financial analysis [25], disease diagnosis [26], speech recognition [27] and information security [28, 29].

Several popular network structures are used in daily life and research widely: LeNet [30], AlexNet [31], VGGNet [32], GoogLeNet [33] and ResNet [34]. Attackers usually generate adversarial examples against these baseline architectures [35].

2.2 Adversarial Examples

Adversarial examples are original clean samples with specially crafted small perturbations, often barely recognizable by humans, but able to misguide the classifier. Since the discovery of adversarial examples for neural networks in [1], researchers have developed several methods to generate adversarial examples, such as fast gradient sign method (FGSM) [2], Carlini and Wagner Attacks (CW) [4], Jacobian-based Saliency Map Attack (JSMA) [3], and Projected Gradient Descent (PGD) [5]. We will use these four up-to-date attack techniques to craft adversarial examples in our experiments later.

2.3 Defense Methods

Adversarial example defense can be categorized into two types: Only Detection methods and Complete Defense methods [36]. And recently some research combined these two ideas, which we call Hybrid Defense. In this section we briefly summarize some representative defense methods in these three categories separately.

Only Detection is meant to recognize potentially adversarial examples in input to reject them in any further processing. Only-binary-classifier method [17] simply trains a supervised binary classifier on normal and adversarial samples to classify them. MagNet [10] contains an autoencoder-based anomaly detector to detect adversaries with large reconstruction errors and a probability-divergence-based detector to handle small ones. Feature Squeezing [11] detects adversarial examples by comparing a DNN model’s prediction on the original input with that on squeezed inputs. These methods are either attack-dependent or easily cheated by low-intensity attacks, where DAFAR shows a better performance.

Complete Defense aims at enabling the victim network to achieve its original goal on the adversarial examples, e.g. a classifier predicting labels of adversarial examples with acceptable accuracy [36]. Adversarial training techniques [16] train a more robust model by including adversarial information in training process. Gradient Masking techniques [12] leverage distillation training techniques [37] and hide the gradient between the pre-softmax layer (logits) and softmax outputs to defend against gradient-based attacks. Input Transformation techniques [13] like image denoising reduce the model sensitivity to small input changes by transforming the inputs, relieving or changing the input changes, destroying the structure of adversarial example because of its low robustness. Generative Model Methods [38, 39] find a close output to a given image which does not contain the adversarial changes using a generative model like DefenseGAN [38]. These methods either lose effectiveness in some cases or are easily broken by high-intensity attacks, which is exactly what DAFAR is good at.

Hybrid Defense combines the advantages of Only Detection and Complete Defense, that detection methods are highly effective against high-intensity attacks and purification methods are good.
at handling low-intensity attacks. To achieve hybrid defense, MagNet \[10\] attaches an autoencoder-based reformer to denoise low-intensity adversarial examples, while Feature Squeezing \[11\] combines the method of \textit{adversarial training}. Although they perform well in experiments, they have complicated structures or cumbersome mechanisms due to the addition of external defense methods to achieve hybrid defense, which makes them prohibitively impractical. In contrast, DAFAR does not require any external structures or methods to form hybrid defense. That is why DAFAR is an \textit{autogenous hybrid defense} method, which guarantees the simple structure and effortless mechanism of DAFAR.

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3.1 Motivation and Goal

Despite the considerable research effort expended towards defending against adversarial examples, scientific literature still lacks universal and effective methods to defend against adversarial examples.

To achieve ideal effectiveness for adversary defense, DefenseGAN, MagNet, and Feature Squeezing provide preliminary examples. We advocate four principles to achieve ideal defense effectiveness.

1) Instead of assuming knowledge of the specific process for generating the adversarial examples, find intrinsic common properties among all adversarial examples across attack methods and parameters, such as pixel perturbation, label changing, and feature space interference. This principle will lead to attack-independent detection and defense.

2) For detection methods, first amplify the difference between normal sample and adversarial example as much as possible, use comparable features to express their difference, and detect adversarial examples according to that difference. Do not operate on raw pixel values. This principle will lead to high detection accuracy, especially on high-intensity attack.

3) For purification methods, destroy the structure of adversarial examples by finding a close legitimate sample to the adversarial example in manifold, or transforming the adversarial image. Specially crafted adversarial perturbations are usually not robust, especially those generated from weak attacks. Even tiny changes can destroy the attack effect. This principle will lead to effective defense on low-intensity and low-robust attack.

4) Use a hybrid of detection and purification to achieve the ideal defense effect within the full range of attack intensity.

Our goal is to design an adversary defense framework based on the above four principles, which can achieve high effectiveness as well as universality across attack methods and parameters, with relatively low area and time overhead. To do so, we propose DAFAR to defend deep learning models against adversarial examples in an autogenous-hybrid-defense manner, based on common properties of adversarial examples, i.e., feature space interference. We carry out empirical experiments to demonstrate the rationale of our ideas. We also conduct experiments to evaluate DAFAR by comparing it with several representative and state-of-the-art adversary defense methods.

3.2 Threat Model

As done in many prior works \[40, 41, 42, 43\], we give three threat models in this paper:

1) A \textit{Black-box Adversary} generates adversarial examples without the knowledge of the victim model (i.e., the training methods, the model architecture and parameters) and the defense method.

2) A \textit{Gray-box Adversary} generates adversarial examples with the knowledge of unsecured victim model but is not aware that the defense method is in place.

3) A \textit{White-box Adversary} generates adversarial examples with the full knowledge of victim model and the defense method (i.e., the training methods, the model architecture and parameters, the defense structure, parameters and mechanism). It is also often called adaptive attack or defense-aware attack.

We mainly consider the \textit{Gray-box Adversary} in our design and experiments, because in actual software application scenarios, due to confidentiality and product packaging, it is difficult for attackers to get all the information about the victim model and its defenses. And because of the independent plug-in property of the feedback network and the detector, they can be easily disassembled or installed from the victim model without affecting its performance, so they are not regarded as a part of the threat model.

3.3 Datasets

In this paper we consider two datasets used throughout the existing work in this field.

The \textit{MNIST} dataset \[44\] consists of 70,000 28 × 28 greyscale images of handwritten digits from 0 to 9. Our CNN achieves 99.14\% accuracy on this dataset.

The \textit{CIFAR-10} dataset \[45\] consists of 60,000 32 × 32 color images of ten different objects (e.g., horse, airplane, etc). This dataset is substantially more difficult. For representativeness, we use a common DNN architecture as the victim model. It achieves an 86.17\% accuracy, which is at the normal level.

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4.1 High-level Feature Interference

![Fig. 2. 2-D sample space. The red curve is the boundary of the manifold of the task. The green points and blue points are separately in two categories, while the gray points are adversarial examples.](image-url)
Whether gradient-based or optimization-based attacks mislead the classifier by adding specially crafted small perturbations to clean samples. Deep learning models determine the label of a sample by extract the high-level features of the sample at deep layers [22]. There are two cases how adversarial examples mislead a classifier [10]:

1) The original sample is far from the boundary of the manifold of the task, shown as the green point 1 in Figure 2. Adversarial perturbations significantly interfere in the feature extraction process, namely, strong attack, inducing huge disturbance into high-level features extracted, leading to unexpected change of feature semantics, ultimately causing the classifier to mis-classify, shown as the gray point 2 in Figure 2.

2) The original sample is close to the boundary of the manifold, shown as the green point 3 in Figure 2. Although adversarial perturbations just slightly interfere in the feature space, namely, weak attack, the classification easily changes because of its original low confidence, shown as the gray point 4 in Figure 2.

In the first case, adversarial perturbations significantly interfere in the feature space. Formally, given \( f(\cdot) \) as the victim classifier, \( E(\cdot) \) as feature extraction layers of \( f \), \( F(\cdot) \) as the output layers of \( f \), \( x \) as a normal sample, and \( x' \) as an adversarial sample of \( x \), the process that \( x' \) misguides \( f \) can be described as

\[
\delta(E(x), E(x')) \gg \delta(x, x')
\]

\[
F(E(x')) \neq F(E(x))
\]

where \( \delta(a, b) \) means the difference between \( a \) and \( b \) for a given distance function \( \delta(\cdot, \cdot) \). We will demonstrate the high-level feature interference caused by adversary in Section 5.2.1 with experiments.

In the second case, adversarial perturbations just slightly interfere in the feature space, so the process that \( x' \) misguides \( f \) can be described as

\[
\delta(E(x), E(x')) \approx 0
\]

\[
F(E(x')) \neq F(E(x))
\]

4.2 Reconstruction Errors

In Formula 1, when encountering relatively strong attacks, we find an inequality, \( \delta(E(x), E(x')) \gg \delta(x, x') \), corresponding to Principle 2, that to detect adversarial examples with high accuracy, the amplification of the difference between normal sample and adversarial example is necessary.

What we have when detecting are an input sample \( x \), deep neural network \( f \) and high-level features \( E(x) \). According to [19], [46], [47], an autoencoder reconstructs a sample using the features extracted by its encoder (feature extraction layers). If the features extracted by encoder are disturbed, the decoded output will present a significant reconstruction error. This significant reconstruction error, or called reconstruction distance between the reconstructed sample and the original sample is exactly what we want, according to Principle 2. So we can add a feedback decoder \( D(\cdot) \) to the feature extraction layers \( E(\cdot) \) of victim network, to reconstruct the high-level features \( E(x) \) to a reconstruction \( D(E(x)) \). The victim network \( E(\cdot) \) and the feedback network \( D(\cdot) \) constitute a feedback autoencoder \( D(E(\cdot)) \). This structure transforms the attack on the victim network (imperceptible perturbations) into an obvious attack on the feedback autoencoder (reconstruction error) directly, because the feedback autoencoder and the victim network share the interference introduced by possible adversarial perturbations in high-level feature space as they share the feature extraction layers. After appropriate training, the normal samples will be reconstructed perfectly with small reconstruction errors, while the adversarial ones that attack the victim network will present significant reconstruction errors because they attack the feedback autoencoder as well. Formally we can give a description by

\[
\delta(x', D(E(x'))) \gg \delta(x, D(E(x)))
\]

where \( \delta(x, D(E(x))) \) is the reconstruction distance of sample \( x \), which can be described as

\[
\delta(x, D(E(x))) = \|x - D(E(x))\|_p
\]

In this way we greatly amplify the difference between a normal sample and an adversarial example. By detecting the difference, we can detect adversarial examples with higher accuracy. Moreover, since the amplification is based on the common properties among all adversarial examples, according to Principle 2, this method is attack-independent. In other words, DAFAR is able to detect adversarial examples with high accuracy and universality. More formally, we describe detection process of DAFAR by

\[
O(x) = F(E(x)) \wedge C(\delta(x, D(E(x))))
\]

where \( C(\cdot) \) is the detector that judges a sample whether legitimate or adversarial by the reconstruction errors, which can optionally be an anomaly detector.

Compared to the anomaly detector of MagNet, DAFAR detects the disturbance caused by adversarial examples in the victim network fully, for it directly changes the attack on victim network to the attack on the feedback autoencoder, through shared feature extraction layers.

4.3 Purification by Reconstruction

In Formula 2, when encountering very weak attacks, the high-level feature disturbance is so small that the feedback process cannot generate large enough reconstruction errors to be detected. However, the feedback autoencoder is also a generative model, so it has a high probability to find a close legitimate sample to the weak adversarial example in manifold, just as Defense-GAN [38]. Formally, the generative defense process can be described by

\[
\delta(x, D(E(x'))) \approx 0
\]

\[
F(D(E(x')))) \approx F(E(x))
\]

In aspect of adversarial examples’ robustness to explain it, because adversarial perturbations are crafted by machine learning methods, most adversarial examples, especially weak ones, have poor robustness. Although the reconstruction process tries to make the reconstructed sample close to the original sample, there will always be changes in the pixel value, which will destroy the structure of the adversarial perturbations and make the adversarial perturbations invalid.

4.4 DAFAR Structure

We discuss the detailed structure and workflow of DAFAR in this section, which is shown in Figure 3.
As we mentioned above, DAFAR distinguishes adversarial examples by detecting significant reconstruction distance. We use an anomaly detection autoencoder as the decoder, shown as $C(\cdot)$ in Figure 3. Autoencoder is often used in anomaly detection [48, 49, 50]. In most cases, the number of adversarial examples is much less than normal samples, so adversarial examples are an anomaly. However, since the difference between normal samples and adversarial examples is very small, directly applying anomaly detection autoencoder to adversary detection is not recommended. Yet in our case, we have greatly amplified the difference between adversarial examples and normal samples by feedback autoencoder, in the form of reconstruction errors. So it is reasonable to use anomaly detection autoencoder as our final detector. To this end, we use image subtraction $(a - b$ in Figure 3) as reconstruction errors. Given $E_{\text{train}},$ as the the training set only containing reconstruction errors of normal samples, and $\delta$ as the reconstruction errors of a normal sample in $E_{\text{train}},$ we train the detector $C(\cdot)$ by minimizing mean squared error loss in a semi supervised learning manner

$$J_C (E_{\text{train}}) = \frac{1}{\#E_{\text{train}}} \cdot \sum_{\delta \in E_{\text{train}}} ||\delta - C(\delta)||_2$$

After training, the detector $C(\cdot)$ will reconstruct normal data well, while failing to do so for anomaly data which the detector $C(\cdot)$ has not encountered. The detector $C(\cdot)$ does not tell us whether a reconstruction error belongs to an adversarial example or not directly. It only gives us a reconstruction distance between its input and output, which is used as anomaly score. Input with high anomaly score is considered to be an anomaly. In order to define whether an anomaly score is high or low, a threshold $\alpha$ is needed. We set the 99.7% confidence interval’s right edge calculated from anomaly scores of all normal samples in training set as $\alpha$ for MNIST, and 95% for CIFAR-10. Given $\bar{x}$ as the average score, $\sigma$ as the standard deviation and $n$ as the number of normal samples in training set, then $\alpha$ is

$$\alpha = \bar{x} + z \cdot \frac{\sigma}{n}, \quad z = 2, 3$$

For other datasets, people can set the threshold with an appropriate confidence interval according to real needs, in the same manner as MNIST and CIFAR-10 here.

However, note that the anomaly detector here is optional in order to reduce area and time overhead when actually used in software. Because instead of using the anomaly detector, we can directly calculate the $L_2$ distance of reconstruction errors and use the same threshold as mentioned above to detect adversaries. Although the detection accuracy may be reduced, because DAFAR is a autogenous hybrid defense method and there is the feedback purification afterwards, discarding the detector has only small influence on the final defense effect, which we will show in our experiments later. But if pursuing the most effective defense, we recommend adding this anomaly detector.

5 Experiments

5.1 Network Structure

In this section we describe network structures used in our experiments.

Victim network. We choose common network structures as victim networks, which face the adversarial attacks directly, shown in Table 1. Though we have mentioned the encoder of feedback autoencoder is the feature extraction layers of victim network, actually the encoder does not have to include all feature extraction
layers. It can be just several former layers, according to real needs. In other words, we can determine the layers to capture high-level features (i.e., feedback positions) according to what trade-off we want to make between training overhead and detection effectiveness.

### MNIST $\mathcal{T}_M$ and CIFAR-10 $\mathcal{T}_C$

| Encoder $\mathcal{E}_M$ | Encoder $\mathcal{E}_C$ |
|-------------------------|-------------------------|
| Conv.ReLU 3 x 3 x 32   | Conv.ReLU 3 x 3 x 96    |
| Conv.ReLU 3 x 3 x 32   | Conv.ReLU 3 x 3 x 96    |
| MaxPool 2 x 2          | Conv.ReLU 3 x 3 x 96    |
| Conv.ReLU 3 x 3 x 64   | Conv.ReLU 3 x 3 x 96    |
| Conv.ReLU 3 x 3 x 64   | Conv.ReLU 3 x 3 x 96    |
| MaxPool 2 x 2          | Conv.ReLU 3 x 3 x 96    |
| Output $\mathcal{F}_M$  | Output $\mathcal{F}_C$  |
| LinearReLU 200         | Conv.ReLU 3 x 3 x 192   |
| LinearReLU 200         | Conv.ReLU 3 x 3 x 192   |
| Softmax 10             | ConvReLU 3 x 3 x 192    |

**TABLE 1** Structures of victim networks.

**Decoder/Feedback network.** The structures of decoders are often the reverse of their encoders, shown in Table 2. But they can be modified according to real needs, such as transforming from the byproduct network in unsupervised pre training.

| MNIST $\mathcal{D}_M$ | CIFAR-10 $\mathcal{D}_C$ |
|-----------------------|--------------------------|
| MaxUnpool 2 x 2       | MaxUnpool 2 x 2          |
| ConvTranspose.ReLU 3 x 3 x 64 | ConvTranspose.ReLU 3 x 3 x 192 |
| ConvTranspose.ReLU 3 x 3 x 32 | ConvTranspose.ReLU 3 x 3 x 96 |
| MaxPool 2 x 2         | MaxUnpool 2 x 2          |
| ConvTranspose.ReLU 3 x 3 x 32 | ConvTranspose.ReLU 3 x 3 x 96 |
| ConvTranspose.Tanh 3 x 3 x 1  | ConvTranspose.ReLU 3 x 3 x 96 |

**TABLE 2** Structures of decoders.

**Detector.** Detectors are simple 5-layer fully connected autoencoders for MNIST and CIFAR-10, shown in Table 3. Note that we did not carefully craft the structure of the detectors, for the input patterns are very simple. But the experimental results later are outstanding, showing the effectiveness of DAFAR.

| MNIST $\mathcal{C}_M$ | CIFAR-10 $\mathcal{C}_C$ |
|-----------------------|--------------------------|
| Linear.ReLU 256       | Linear.ReLU 512          |
| Linear.ReLU 32        | Linear.ReLU 64           |
| Linear.ReLU 256       | Linear.ReLU 512          |
| Linear.Tanh 784       | Linear.Tanh 3072         |

**TABLE 3** Structures of detectors

5.2 **Reconstruction Error: How Does DAFAR Detect?**

In this section we conduct experiments to characterize the phenomenon of reconstruction errors in DAFAR structure, to explain how DAFAR detects.

5.2.1 **High-level Feature Interference**

As we discussed in Section 4.1, whether gradient-based or optimization-based attacks induce huge disturbance into high-level features, leading to unexpected changes of feature semantics. In order to show high-level feature interference caused by adversarial perturbations, we carry out experiments by extracting high-level features of adversarial examples and their original normal samples from deep layers of victim network and calculating distance between them. We compare the result with the distance between high-level features of samples added same-intensity Gaussian noise and that of their original samples in Table 4.

| Perturbations | Gaussian (0, 0.3) | PGSM 0.3 | PGD 0.2 |
|---------------|-------------------|----------|---------|
| $L_2$ distance| 36.13             | 109.64   | 96.44   |

**TABLE 4** Average high-level features $L_2$ distance between samples with certain perturbations and their original samples, of 1000 samples in MNIST test set.

Clearly adversarial perturbations cause a much bigger interference to high-level features of a sample. Here we can draw an observation.

**Observation 1.** Adversarial perturbations induce huge disturbance into high-level features extracted by deep layers of victim network.

5.2.2 **Reconstruction Errors**

The interference in adversarial examples’ high-level features will lead to big reconstruction errors, as we discussed in Section 4.2. In this section we will give more details on characterizations of reconstruction errors.

Figure 4 shows the significant difference between the reconstruction errors of normal samples and that of adversarial examples clearly. To quantitatively characterize how reconstruction errors distribute with attack methods and intensities, we calculate the reconstruction distance of normal samples and adversarial examples across different attack methods and intensities in the form of $L_2$ distance. The results are shown in Figure 5.

Here we can draw three observations.

**Observation 2.** Difference of reconstruction errors between normal and adversarial samples is significant in two aspects: 1)
reconstruction errors of normal and adversarial samples show very different patterns; 2) reconstruction errors in the form of $L_2$ shows distinctively separated concentrations across attack intensities.

**Observation 3.** Though the difference is clear, there is no fixing reconstruction-error threshold to perfectly divide normal samples and adversarial examples, especially at low attack intensity.

**Observation 4.** Difference of reconstruction errors between adversarial examples and normal samples increases with attack intensities.

5.2.3 Anomaly Score

As we discussed in Section 4.4.3 detector needs a threshold to tell whether an input is an anomaly, so there should be a clear dividing line of anomaly score between normal inputs and anomalies. We train a detector in semi supervised manner on clean samples’ reconstruction errors. Then we input clean samples and adversarial examples across different attack methods and intensities to calculate their anomaly scores. Figure 6 shows how anomaly scores distribute with attack methods and intensities. Here we draw two important observations.

**Observation 5.** The distribution of anomaly scores is approximately normal, so we assume that the score follows a normal distribution. We set the 99.7% confidence interval’s right edge of normal samples’ anomaly scores for MNIST and 95% for CIFAR-10 as the threshold to distinguish normal and adversarial samples, as discussed in Section 4.4.3. We show the score threshold of MNIST and CIFAR-10 in Table 5, and also show in Figure 6.

| Dataset | Score threshold |
|---------|-----------------|
| MNIST   | 23.533          |
| CIFAR-10| 230.143         |

**TABLE 5** Score threshold of MNIST and CIFAR-10.

**Observation 6.** Detector further magnifies the difference between normal and adversarial samples. There is a clear dividing line of anomaly score between normal input and anomaly, which means it is reasonable to determine a threshold to tell whether an input is an anomaly.

We hypothesize that detector’s secondary amplification effect is introduced by two reasons: 1) reconstruction distances of adversarial examples with large intensities are much bigger than that of normal samples, which detector can easily distinguish; 2) even if the reconstruction-distance difference between normal and adversarial samples is not that much, their reconstruction errors show very different patterns as shown in Figure 4 which detector can refer to.

5.3 Evaluation of Detection

In this section we evaluate the accuracy and universality of DAFAR in detecting adversarial examples using FGSM, JSMA, CW$_2$ and PGD across different attack intensities, and compare the results with only-binary-classifier method, detection system of MagNet and Feature Squeezing. For FGSM, PGD and CW$_2$, we used the implementation of Cleverhans [51]. For JSMA, we use authors’ open source implementation [3].

In principle, DAFAR shows a better performance of accuracy than MagNet, and Feature Squeezing, especially in low attack intensities, and the same level of universality as MagNet and Feature Squeezing across attack methods, which is much better than only-binary-classifier method.

5.3.1 Detection Accuracy and Universality across Intensities

In this section we evaluate DAFAR’s adversary-detection accuracy and universality across different attack intensities, separately on MNIST and CIFAR-10, using FGSM attack across different attack intensities.

**MNIST.** We train a victim network in DAFAR method on MNIST and achieve an accuracy of 99.24% on the test set, which is close to the state of the art. We test the adversary detection accuracy of each method on test sets only containing FGSM adversarial examples across different attack intensities. The results are shown in Figure 7. Here we can draw some conclusions.

**Effect on normal examples.** The victim network trained in DAFAR method achieves an accuracy of 99.24%, and the detector of DAFAR shows a false positive rate of only 0.16%, which means DAFAR does not affect victim network’s accuracy.

**Effect on adversarial examples.** DAFAR detects MNIST adversarial examples in an accuracy of 100% across all attack intensities, as shown in Figure 7, higher than other three methods especially in low attack intensities, showing the best detection accuracy and universality. Because DAFAR can eliminate all
In this section we evaluate DAFAR’s detection accuracy and universality across different attack methods, separately on MNIST and CIFAR-10, using FGSM, JSMA, CW, and PGD.

**MNIST.** We test the adversary detection accuracy of each method on MNIST test sets containing adversarial examples across different attack methods. Figure 8 shows the results, which provides evidence that DAFAR has the same level of universality across different attack methods as detection system of MagNet and Feature Squeezing, much better than only-binary-classifier method.

**CIFAR-10.** We test the adversary detection accuracy of each method on CIFAR-10 test sets containing adversarial examples across different attack methods. The results are shown in Figure 8 which give the same conclusion as MNIST’s.

For all parts in DAFAR are trained in semi supervised way or only on clean samples, theoretically DAFAR has outstanding universality across attack methods, which is strongly proved by our experimental results. Note that DAFAR detection alone can achieve that considerable defense effect.
the attack intensity is low, which will make sense in DAFAR’s autogenous hybrid defense. Furthermore, when the attack intensity is 0, namely, the input normal samples, although there is one more feedback loop than the original classification data stream, the classification accuracy is 99.04%, very close to the original 99.14%. Therefore, the additional feedback reconstruction loop of DAFAR purification will not affect the performance of the victim model on legitimate samples.

5.5 Evaluation of Autogenous Hybrid Defense

Though DAFAR detection shows a relatively good performance, it still does not achieve ideal detection accuracy at very low attack intensities when encountering complex data-sets. There are two ways to approach ideal defense effectiveness. First, train DAFAR in more appropriate parameters, network architectures and training methods, to compress anomaly score interval of normal samples (i.e., the blue peaks in Figure 9) as much as possible until the interval converges to 0, which is the ideal condition, but very difficult to achieve. Second, find a way to deal specifically with adversarial examples with low attack intensity.

Fortunately, according to Principle 4, and as we discussed in Section 4.3, DAFAR’s feedback autoencoder can be also used as a generative model, which is good at handling low-intensity adversaries. And as we obtained from experiments in Section 5.4, DAFAR purification indeed shows considerable effectiveness when attack intensity is low. So we compose DAFAR detection and purification to form an autogenous hybrid defense. To evaluate this structure, we carry out experiments on data-sets derived from CIFAR-10 by conducting PGD attacks on CIFAR-10 samples that can be correctly classified by the victim model. In these data-sets, the ratio of adversarial examples and normal samples is 1 : 1. We show the results in Figure 10. The classification accuracies of DAFAR Hybrid across all attack intensities are near 100%, higher than all the other methods, presenting ideal defense effectiveness and low side effect. Even without the anomaly detector, DAFAR still shows considerable effectiveness.

5.6 Evaluation of Practicality

To defend software mounted with deep learning system against adversarial examples, the defense method should be flexible, area-efficient, low-latency and low-cost, while guaranteeing a high defense effectiveness. However, almost all existing adversarial example defense methods fail to meet these requirements. They either have complicated structure or mechanism that cause prohibitively high overhead and latency, or the defense effect is not good enough, or the installation and implementation costs a lot, preventing them from being practically applied in actual software. Nevertheless, DAFAR is excellent in all three aspects. To evaluate the practicality of DAFAR, referring to previous experiments, we comprehensively compare the defense effect (DE), defense universality (DU), number of extra parameters (# P. Namely, area overhead), extra dataflow length (L. Namely, latency), implementation operations (IO. Namely, flexibility), and cost of DAFAR with other representative defense methods in Table 6. So far, DAFAR is the most suitable adversarial example defense method for software, especially mobile device software, which have high demand for low memory footprint and low latency.

6 Conclusion

DAFAR is the first autogenous hybrid defense method that helps deep learning models to defend against adversarial examples effectively and efficiently. Besides the victim network, DAFAR only contains a plug-in feedback network and an optional anomaly detector. DAFAR imports the high-level features from the victim model’s feature extraction layers into the feedback network to reconstruct the input. Namely, the feature extraction layers of the victim network and the feedback network constitute a feedback autoencoder. For strong attacks, DAFAR transforms the imperceptible attack on the victim model into the obvious reconstruction-error attack on the feedback autoencoder directly, which is much easier to detect; for weak attacks, the reformation process destroys the structure of adversarial examples. Considering all parts in DAFAR are trained on normal samples or in semi supervised way, DAFAR is attack-independent. Our experiments explain DAFAR’s work mechanisms and show DAFAR can defend against state-of-the-art attacks in high effectiveness and universality, with low overhead. We compare DAFAR with seven representative defense methods and derive the conclusion: so far, DAFAR is the most lightweight, effective and universal adversarial example defense method for the security and reliability of software mounted with deep learning systems.

2. Given that the number of parameters of the victim network is \( n \).
| Method | DE  | DU  | # P  | L  | IO | Cost |
|--------|-----|-----|------|----|----|------|
| DAFAR without Anomaly Detector | High | High | $\frac{n}{T}$ | $n$ | None | Low |
| DAFAR with Anomaly Detector | High | High | $\frac{n}{2}$ | $2n$ | Train the anomaly detector on reconstruction errors | Low |
| MagNet Hybrid | Middle | High | $>2n$ | $2n$ | Train autoencoders on normal samples, choose $T$ | High |
| Feature Squeezing Hybrid | Middle | Middle | 0 | 2n | choose squeezing patterns, adversarial training | High |
| Denoising Autoencoder | Middle | Middle | $n$ | $n$ | Train an autoencoder | Middle |
| Defense-GAN | Middle | High | 2n | $n$ | Train a GAN | High |
| Adversarial Training | Middle | Low | 0 | 0 | Generate Adversarial Examples, Retraining | High |
| Binary Classifier | High | Low | $n$ | $n$ | Generate Adversarial Examples, Train a binary classifier | Low |
| Binary Filter | Low | Middle | 0 | 0 | Design the Filter | Low |

**TABLE 6**
Comparison of practicality between DAFAR and other representative defense methods.

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