Game Theory For Adversarial Attacks And Defenses

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Abstract

Adversarial attacks can generate adversarial inputs by applying small but intentionally worst-case perturbations to samples from the dataset, which leads to even state-of-the-art deep neural networks outputting incorrect answers with high confidence. Hence, some adversarial defense techniques are developed to improve the security and robustness of the models and avoid them being attacked. Gradually, a game-like competition between attackers and defenders formed, in which both players would attempt to play their best strategies against each other while maximizing their own payoffs. To solve the game, each player would choose an optimal strategy against the opponent based on the prediction of the opponent’s strategy choice. In this work, we are on the defensive side to apply game-theoretic approaches on defending against attacks. We use two randomization methods, random initialization and stochastic activation pruning, to create diversity of networks. Furthermore, we use one denoising technique, super resolution, to improve models’ robustness by preprocessing images before attacks. Our experimental results indicate that those three methods can effectively improve the robustness of deep-learning neural networks.

1 Introduction

1.1 Problem Description

Recently, some research works [1, 2] indicate that the deep neural networks are actually vulnerable to adversarial examples. In the image recognition and classification area, the adversarial examples refer to the the synthesized images which look identical to the original images from human view, but they will intentionally cause the classifier to make stupid mistakes, i.e., wrong recognition or classification results. The existence of such adversarial examples are great threats to using DNNs in safety intense scenarios like auto-driving, financial fraud detection, etc. When adversarial attacks are performed on training data, the learning process is misguided, resulting in an inaccurate classifier.

The topic of adversarial attacks and defenses are gaining more and more attention with the rapid development in deep neural networks. Currently both attack and defense are facing some challenges. In terms of attack, there are provable defenses targeting some attack strategies. Also, various defense methods have their strengths in tackling different attacks.

Due to the "last mover advantage" of the attacker, there seems to be no way to defend against all possible attacks. Current defense methods have different efficiency for different attacks. The proof of provable defenses only applies to a specific class of attacks.
To deal with these problems, some approaches have been investigated to protect the deep neural networks. The methods are roughly categorized as adversarial training, randomization, denoising, provable defense and so on. In this work, we use adversarial training technique firstly under white-box to form our baseline model, assuming that the attack method is already known. From this on, we explore several defense methods, and carry out some experiments on attacks to verify our assumptions. Our defense methods are: multiple initialization defense, multiple SAP-like networks, and super-resolution based adversarial defense.

1.2 Objectives and Goals

The process of adversarial attacks and defenses can be modeled as a zero-sum two-person game. More specifically, white-box attacks and defenses can be viewed as a multi-move game with perfect information.

There are two multi-move games with alternating moves by attacker and defender in our project: first, we are playing the research game of finding better attacks on current best defenses and finding better defenses against current best attacks. Second, in the process to find better attacks and defenses, we carry out experiments to play the game of the alternation of defense, attack, defense, ... on the given dataset. On the defensive side, we want to make use of the von Neumann minimax theorem [3] to the zero-sum two-person game to improve the performance of adversarial defenses under grey-box attacks.

Since there are numerous adversarial attacks defined under different metrics, and adversarial samples are still not well-understood, it is difficult to find out one defense that can effectively defend against all possible attack methods under certain situation. We are here to use game-theoretical approaches and on the defensive side to improve robustness of deep-learning models.

2 Literature Review

As usual DNNs, ϑ is the set of model parameters, our goal is to find the model parameters ϑ that minimize the risk \( E_{(x,y)\sim D}[L(x, y, \theta)] \). The goal of the attack model is that we want to introduce a set of tiny perturbations \( S \) which make the DNNs model misclassify the adversary sample whereas the same DNNs model can classify the normal sample correctly. The attack and defense can be described as a following saddle point problem [4]:

\[
\min_{\theta} \max_{\delta \in S} \rho(\theta), \quad \text{where} \quad \rho(\theta) = E_{(x,y)\sim D}[\max_{\delta} L(\theta, x + \delta)]
\]

The inner maximization problem corresponds to the attack problem and outer minimization problem is to find a set of parameters that have a least loss for the given attack. According to the access to the target model, attack can be divided into black-box attack and white-box attack. Under the white-box case, we can directly get the gradient information of the input point from the target model. The commonly used methods are limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS)[1], fast-gradient sign method (FGSM)[2], basic iterative method (BIM), projected gradient descent (PGD)[4], distributionally adversarial attack (DAA)[5], Carlini and Wagner (C&W) attacks[6], Jacobian-based saliency map attack (JSMA)[7], and DeepFool[8]. In the baseline process, our project focus on the attack and defense for white-box model.

Black-box means we can only get the information about the input sample and prediction result thus information about gradient cannot get directly in black-box settings. Although these methods are designed for white-box attack, they are also effective in many black-box settings[9].

Meanwhile, various defensive techniques for adversarial samples detection/classification have been proposed, including heuristic and certificated defenses[9]. Heuristic defense refers to a defense mechanism in defending specific attacks without theoretical accuracy guarantees. The representative heuristic defenses developed mainly including adversarial training, randomization-based schemes, and denoising methods.

In contrast, certified defenses can always provide certifications for their lowest accuracy under a well-defined class of adversarial attacks. The approach is to formulate an adversarial polytope and define its
upper bound using convex relaxations, which guarantees that no attack with specific limitations can surpass the certificated attack success rate. Some typical provable defensive methods are developed based on semi-definite programming, dual approach, Bayesian model and consistency. However, the actual performance of these certificated defenses is still much worse than that of the adversarial training.

3 Dataset

The CIFAR-10 dataset [10] is one of the most popular datasets for machine learning and computer vision research. The dataset is a labeled subset of 80 million tiny images. Actually, it has 60,000 32x32 color images in 10 different classes. The class tags include airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. Thus, each class has corresponding 6,000 images. Algorithms for image recognition and classification are often tested on this dataset. Since the images in the dataset are low-resolution, it is easy for researchers to train models and implement ideas quickly.

4 Evaluation metric

The accuracy we mention in this paper is the number of correct classification images dived by the number of all evaluation images. The goal of the classifier is to distinguish as much image as possible, i.e., increase accuracy. The goal of the attack side is to generate an image that the classifier cannot classify correctly, i.e., decrease the classifier’s accuracy. The goal of the defense side is to make the accuracy of the classifier not decrease too much under attack. At the same time, the defense should maintain a normal performance on the unchanged image.

5 Baseline Models

5.1 Classifier

Our group implement VGG[11] and ResNet[12] to achieve the classification task. The reason why we choose these DNNs is that they are easy to implement and take a relatively short time to train and generate attack instances. And all of them can reach around 90% accuracy on classifying the CIFAR-10 dataset[10] theoretically. The accuracy column in Table 7 shows the performance of DNNs.

5.2 Attack

The baseline methods we introduce for the attack part are Fast Gradient Sign Method (FGSM)[2], Momentum Iterative Fast Gradient Sign Method(MI-FGSM)[13], Projected Gradient Descent (PGD)[4] and Carlini and Wagner Attacks (C&W Attacks)[6]. All of these are efficient first-order adversary. The model that can effectively resist these attacks also has a certain defensive effect on other types of attacks.

FGSM[2] is an one-step attack algorithm, which only updates along the direction of gradient of adversary loss once. The formula of FGSM[2] can be described as follow:

$$x' = x + \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y)) \quad (2)$$

MI-FGSM[13] is an iterative version of FGSM[2] with the momentum term to remember the previous iterations’ gradients. In each iteration, the update is as follows:

$$x'_{t+1} = \text{Clip}\{x'_t + \alpha \cdot \text{sign}(g_{t+1})\} \quad (3)$$

Where the gradient is updated with a momentum term:

$$g_{t+1} = \xi \cdot g_t + \nabla_x J(\theta, x'_t, y) / ||\nabla_x J(\theta, x'_t, y)||_1 \quad (4)$$

PGD[4] is also an iterative attack method. It projects the adversarial samples learned into the $\epsilon$-L$\infty$ neighbor of the benign samples at each time.

$$x^{t+1} = \text{Proj}(x' + \alpha \cdot \text{sign}(\nabla_x L(\theta, x, y))) \quad (5)$$
C&W Attacks[6] are optimization-based adversarial attacks that can generate adversarial samples of different norms. They have the optimization objective as follows:

$$\min_\delta D(x, x + \delta) + c \cdot f(x + \delta) \text{ subject to } x + \delta \in [0, 1]$$  (6)

Where $\delta$ is the adversarial perturbation, $D$ is the distance metric, which can be $L_0$, $L_2$ or $L_\infty$, and $f(x + \delta)$ is the customized adversarial loss.

For the first round of baseline implementation, we have implemented white-box FGSM attack[2] based on several different classifiers. We use the same network to classify the original images, and to generate attack instances, then we try to classify attack instances. The result of FGSM[2] can be found in Table 7. The accuracy of DNNs drops to about 10-20% under FGSM attack[2]. However, the total white-box setting is too ideal for the attacker. Also, in order to effectively evaluate our defense methods, we need to utilize multiple attacks. Therefore, we have conducted multiple gray-box attack experiments, which are described in 5.2.1.

### 5.2.1 Gray-box Attacks

In the real world, models are often inaccessible to attackers, so white-box attack might be too ideal. Given our task to attack and defend on the CIFAR-10 dataset[10], we can evaluate our attack and defense effectiveness in a somewhat gray-box setting: the training dataset is given, the attacker doesn’t know the structure of the target model; the defender doesn’t know the surrogate classifier the attacker is using. Given this realistic background, we can generate tables to record the result of attacks on different classifiers, and tables to record the result of defenders defending against attacks. This kind of experiments will help us understand the transferability of attacks and defenses. If the transferability of attacks is poor, it’s possible for us to generate a good defense by combining a set of diverse networks, which is a way to utilize the von Neumann mixed strategy [3].

Given that the images in the CIFAR-10 dataset[10] are of low-resolution (32x32 pixel colored images), and after the transformation, the values in the images are of 0 mean and 1 standard deviation, we deliberately constrain the $s$ of each attach to be 0.03 in the following experiments. This means that we constrain the $L_\infty$ norm of the adversarial perturbation to be less than 0.03. In the experiments, we re-implement the FGSM attack[2] and the MI-FGSM attack[13]. We use the Adversarial Robustness Toolbox (ART)[14] v1.5 for PGD[4] and C&W attacks[6] (here we use the $L_\infty$ C&W attack[6] to stay consistency).

In the result tables 1, 2, 3, 4, columns represent classifiers to evaluate the attack samples, rows represent the models that generate the adversarial samples. Records on the diagonal are the accuracies of the white-box attack, and others are of gray-box attacks.

According to the results, we can see that under our settings, the overall transferability of adversarial samples across models of different architectures is not very well, compared to the effectiveness of white-box attacks. Even with the best gray-box attack PGD [4], the accuracy drop from the ordinary samples to adversarial samples is only 7-20%. These experiments have shown us an opportunity to utilize multiple networks of different architectures to generate a good defense.

To further prove the reliability of the opportunity, we have conducted some experiments with the attack generated from multiple models. The idea of the experiments comes from the ensemble attack scheme[13] which won the first places in the non-targeted adversarial attack and targeted adversarial attack competitions (black-box setting) at the 2017 Neural Information Processing Systems (NIPS) conference. In our experiments, the gradient is the average gradient from 3 models, and the gray-box attack result is validated on the only one model that is not involved in the gradient generation. From the result table 5, we can see that the accuracy drop from the ordinary samples to adversarial samples is 10-20%, which successfully adds persuasiveness of the opportunity explained above.

Different architectures certainly provide diversity in the set of models. From the experiments, we assume that increasing diversity in a set of models can help the whole set of models defend against adversarial samples. However, in the real world, the attacker may know what architecture the classifier is using. This is another gray-box attack scenario: the attacker knows the architecture of the model, but doesn’t have access to the parameters. We have carried out some experiments to see if models with different initializations and of the same architecture can provide enough diversity to defend against attacks. In these experiments, we use multiple Resnet20 models with different initializations. The un-attacked original accuracies of the models are around 85%. From the result table 6, we can see
that our assumption is somewhat correct: models with different initializations can provide diversity to defend against attacks. We have tried to generate a defense method by utilizing the diversity from different initializations, which is described in 6.1.

5.3 Defense

On the defense side, adversarial training is one of the most successful intuitive defense methods used to improve the robustness of a neural network. We train the model with augmented dataset produced by adversarial examples.

Using PGD to train[4] a robust network adversarially can improve the robustness of CNNs and ResNets[12] against several typical first-order attacks under both black-box and white-box settings.

To defend FGSM-generated attacks, we use training dataset including both benign and FGSM-generated adversarial samples[15]. Using a hyper parameter $c$ to balance the accuracy on benign and adversarial samples, the proposed adversarial objective can be formulated as follows:

$$\tilde{J}(\theta, x, y) = cJ(\theta, x, y) + (1 - c)J(\theta, x + \epsilon \cdot sign[\nabla_x J(\theta, x, y)], y)$$  \hspace{1cm} (7)

We choose $c = 0.5$ to ensure that the Network after adversarial training will also keep a high accuracy on unchanged images. The adversarial training result in Table 7 using two different algorithms. RenNet50 applies a white-box defense as shown below in algorithm 1. Whereas ResNet18 and ResNet20 use grey-box defense as shown in algorithm 2. Obviously, white-box defense perform better in the current condition. But white-box requires more information about the attack network.

Table 3: Accuracies of baseline classifiers on PGD[4] adversarial samples

| Attack | Classifier | VGG16 % | ResNet18 | ResNet20 | ResNet50 |
|--------|------------|---------|----------|----------|----------|
| VGG16  | 16.66     | 83.21   | 77.81    | 81.24    |
| ResNet18 | 82.03     | 32.36   | 77.69    | 78.82    |
| ResNet20 | 84.92     | 85.17   | 3.77     | 80.44    |
| ResNet50 | 81.90     | 81.42   | 69.48    | 20.30    |
Table 4: Accuracies of baseline classifiers on C&W[6] adversarial samples

| Attack | VGG16 % | ResNet18 % | ResNet20 % | ResNet50 % |
|--------|---------|------------|------------|------------|
| VGG16  | 19.58   | 88.52      | 88.41      | 88.44      |
| ResNet18| 89.75   | 33.98      | 88.09      | 87.42      |
| ResNet20| 91.42   | 89.85      | 3.53       | 89.00      |
| ResNet50| 90.02   | 88.23      | 86.68      | 22.09      |

Table 5: Accuracies of baseline classifiers on adversarial samples generated from 3 other models

| Attack | VGG16 % | ResNet18 % | ResNet20 % | ResNet50 % |
|--------|---------|------------|------------|------------|
| FGSM   | 81.68   | 81.48      | 71.05      | 78.31      |
| MI-FGSM| 81.81   | 82.28      | 74.83      | 78.92      |

Algorithm 1: White-box adversarial training

Data: original dataset, Attack instance

1. generate attack instance using FGSM;
2. initialize Network;
3. for epoch ∈ {1, ..., epochs} do
   4. loss1 ← loss on original dataset;
   5. loss2 ← loss on attack instance;
   6. loss = loss1 + loss2;
   7. update parameter based on loss;
4. end

Algorithm 2: Grey-box adversarial training

Data: original dataset

1. initialize Network;
2. for epoch ∈ {1, ..., epochs} do
   3. loss1 ← loss on original dataset;
   4. generate attack from current model;
   5. loss2 ← loss on attack;
   6. loss ← loss1 + loss2;
   7. update parameter based on loss;
8. end

From our experiments, the adversarial training on FGSM-generated attack instance improves the performance significantly. And complicated network with high accuracy on the original image is more robust facing the FGSM attack.

6 Our Methods

6.1 Multiple Initialization Defense

When training the neuron networks, what we do is to find the local minimum of the loss function. So even if the same networks will not guarantee to reach the same local minimum with different initialization. And this can partially explains that why the adversarial attack in gray-box settings is much harder than white-box. With different networks of different initialization, the attacker can only succeed in a small part of networks. Thus we can utilize this to protect our networks.

In our experiments, we initialized the networks for 100 times with different random seeds. Thus, for each given image, we have 100 predictions. The final results will combine these 100 predictions and make the final decision. In our proposed model, we use majority vote among the 100 predictions to estimate the final results.

During the experiments, we found that with the increase of training epoch, the attack can more easily succeed, because networks with different initialization tend to reach similar local minimum after more epochs of training. Finally we choose 10 epoch as the final epoch number, because we can increase the accuracy of network when facing attack without hurting the capacity of recognizing normal image.

Table 6: Accuracies of Resnet20 classifiers with different initializations on adversarial samples

| Attack | FGSM % | MI-FGSM | PGD % | C&W % |
|--------|--------|---------|-------|-------|
| White-box | 37.16  | 31.03   | 26.62 | 29.17 |
| Different initializations | 76.70  | 81.77   | 73.72 | 81.97 |
Table 7: Accuracy of baseline classifier on original image

| DNNs   | Accuracy | White-box FGSM attack ($\alpha=0.05$) | Adversarial training |
|--------|----------|---------------------------------------|----------------------|
| VGG16  | 92.22%   | 19.42%                                | -                    |
| ResNet18 | 88.86%  | 13.26%                                | 42.80%               |
| ResNet20 | 91.6%    | 19.28%                                | 47.32%               |
| ResNet50 | 91.81%   | 24.77%                                | 63.89%               |

6.2 Multiple SAP-like networks

In addition to using random initialization of networks to create diversity, which is computationally expensive as whole training processes are required to generate the models, we build multiple Stochastic Activation Pruning [16] (SAP)-like networks to increase diversities among networks by stochastic pruning activation and to minimize computation consumption by sharing the same weights and bias with the pretrained model. Stochastic activation pruning should make sense as a method of creating diverse networks post hoc from a single pretrained network. It should work even better with multiple pretrained networks. We have applied SAP to the dense model, resnet18, hoping to generate multiple SAP-like post networks, which would perform better than randomly initializing resnet18 multiple times.

SAP is similar to the dropout technique. The idea of SAP is to stochastic drop out nodes in each layer during forward propagation. However, there is a crucial difference: SAP is more likely to sample activation that are high in absolute value, whereas dropout samples each activation with the same probability. Because of this difference, SAP, unlike dropout, can be applied post-hoc to pretrained models without significantly decreasing the accuracy of the model.

The properties of SAP that makes it powerful are: (1) It can be applied to an already trained network and takes much less computation than retraining; (2) It enables random generation of an arbitrarily large set of distinct networks with different random seeds; (3) It is done after the input datum D is presented, giving you last move advantage; (4) You can test the diversity of the networks specifically evaluated on datum D. The approach flow is as shown in the Algorithm 3.

In the experiments, we used adversarially trained network resnet18 as the base network. We sampled nodes to keep for each activation map with probabilities proportional to the magnitude of their activation. Activation values of dropped nodes are all set to zeros, while other surviving nodes are multiplied by a scale-up factor as a hyperparameter to preserve the dynamic range of the activations in each layer. To obtain better performance, the following things should be taken into account: (1) Number of nodes retained for each layer, such that the model can not only keep its accuracy close to the original model but also be distinct from the original one. (2) Scale-up factor, modify the simple factor to a more complicated formula based on the probabilities to make SAP networks work better.

Algorithm 3: Stochastic Activation Pruning (SAP)

Data: Input datum $x$, neural network with $n$ layers, with $i^{th}$ layer having weight matrix $W_i$, non-linearity $i$ and number of samples to be drawn $r^i$  

Result: New activation map

1. Calculate activation vector for layer $i$, $h^i \leftarrow \phi^i (W^i h^{i-1})$;
2. Normalize activations on to the simplex with multinomial probability distribution,
   
   $p_j^i \leftarrow \frac{(h_j^i)}{\sum_{k=1}^{a^i} (h_k^i)}; \forall j \in \{1, \ldots, a^i\}$;

3. Draw a set of indices of activations to be kept and prune the left based on the distribution;
4. Scale up survived activations, $(h_j^i) \frac{h_j^i}{1-(1-p_j^i)}$.

6.3 Super Resolution based Adversarial Defense

Compared with modifying the defense classifier, another way is to transform the input attack samples into the clean images, i.e., removing the adversarial noise. We implement an effective image
restoration approach inspired by the previous works [17–19], which has a strong defense mechanism to mitigate the perturbations of adversarial images. Generally, a deep network is learned to map off-the-manifold adversarial images onto the natural clean image manifold, which makes the classifier able to classify them correctly. The advantages of this approach is that it not only improves the robustness against adversarial attacks, but also enhances image quality and performs well on clean images. Besides, this method does not need to know whether the input image is natural or perturbed beforehand.

The approach consists of two steps. For the first process, we apply the wavelet denoising operation to suppress the addition noises. And then super resolution is utilized to enhance the whole image and remove the noise patterns.

The approach flow is as shown in the Algorithm 4. To start, we mitigate the effect of adversarial noise by using the soft wavelet denoising. And next, we utilize deep super resolution as the mapping strategy to transform the images from low-resolution adversarial manifolds to high-resolution natural space, as well as enhancing the image visual quality. As illustrated, this kind of method tends to minimize the adversarial perturbation effects while avoiding degrading on clean natural images.

Algorithm 4: Defense Against Adversarial Attacks with Wavelet Denoising and Super Resolution

| Data: perturbed adversarial image $x_{adv}$ | Result: denoised image $x_d = D(x_{adv})$, super resolved image $x_s = S(x_d)$ |
|-------------------------------------------|--------------------------------------------------|
| 1 Convert the RGB image into YCbCr space; | 2 Convert the image into wavelet domain using the discrete wavelet transform; |
| 3 Remove noisy wavelet coefficients using soft thresholding; | 4 Invert shrunken wavelet coefficients using Inverse Wavelet Transform; |
| 5 Revert the image back into RGM domain; | 6 Map adversarial images to clean image manifold using deep super resolution network $S$; |
| 7 Input recovered images to classification model for prediction. |

7 Experiments

7.1 Result of Multiple initialization Defense

The table 8 shows the result of multiple initialization defense. Dev acc is the mean accuracy of 100 classifiers of development dataset. MV acc is the results from the majority vote of the 100 prediction of development dataset. Average attack acc is the mean accuracy of 100 classifiers of generating attack image. MV when attack is the results from the majority vote of the 100 prediction of attack image.

It’s intuitive that the accuracy will increase after we increase the training epoch. At the same time, like I mentioned before, the accuracy on the attack image decrease when we train more epoch. This is kind of like generalization v.s. overfitting. As we increase the training epoch, the classifier will capture some slight noise that human-being cannot detect.

Table 8: Accuracy of different number of taring epoch Epochs

| Epochs | Dev acc | MV acc | Average attack acc | MV when attack |
|--------|---------|--------|--------------------|----------------|
| 4      | 71.54%  | 80.90% | 64.07%             | 73.69          |
| 10     | 81.31%  | 88.65% | 64.29%             | 71.95          |
| 15     | 83.90%  | 90.67% | 63.65%             | 69.79          |
| 20     | 85.70%  | 91.90% | 63.26%             | 68.99          |
| 30     | 87.43%  | 92.61% | 63.97%             | 69.67          |

7.2 Result of Multiple SAP-like networks Defense

The table 9 shows the result of SAP-like models defense. The SAP-like model here applied formula in the Algorithm 3 as scale-up factor and added SAP layer in the last two convolution layers after
activation layers. Dev acc is the test accuracy of test dataset. Average attack acc is the mean accuracy of 50 random SAP-like networks of attack instances generated from white-box resnet18 FGSM attack with perturbation magnitude epsilon equals to 0.05.

There is a trade-off between creating networks’ diversity to make them more random and robust enough when being attacked and keeping their accuracy at a relative high level. From experiments, we know sampling ratio around 1.0, which means to draw samples with a hundred percentage of each activation map will lead models to a better performance.

Table 9: Accuracy of different Sampling Ratio of SAP models

| Sampling Ratio | Dev acc | Average attack acc |
|----------------|---------|--------------------|
| No SAP         | 86.11%  | 15.64              |
| 0.5            | 85.81%  | 9.08               |
| 1.0            | 86.09%  | 28.2               |
| 1.5            | 86.31%  | 27.7               |

7.3 Results of Super Resolution based Adversarial Defense

The Table 10 shows the experiment results of our improved super resolution based adversarial defense towards different white box attacks in the CIFAR-10 dataset. We choose the ResNet-20 as the baseline classifier. Attack methods include FGSM, I-FGSM, MI-FGSM and PGD. s denotes the perturbation size for attack samples. The AdvTrain refers to the common adversarial training. We can observe from the table that our improved super resolution based adversarial defense brings incremental performance gain compared with the adversarial training, which is due to the reason that super resolution networks can negate the effect of adversarial noise in a way.

Table 10: Accuracy of the super resolution based adversarial defense method on white-box attacks in the CIFAR-10 dataset. (%)

| Attacks | Parameter | Baseline | AdvTrain | SR-AdvTrain |
|---------|-----------|----------|----------|-------------|
| No Attack | -         | 91.2     | -        | -           |
| FGSM    | s = 0.02  | 36.9     | 44.1     | 48.8        |
| FGSM    | s = 0.03  | 25.2     | 37.8     | 42.3        |
| I-FGSM  | s = 0.02  | 6.4      | 8.3      | 10.5        |
| MI-FGSM | s = 0.02  | 7.6      | 9.7      | 13.1        |
| PGD     | s = 0.02  | 6.1      | 8.2      | 10.4        |

8 Conclusion and Future Work

Our gray-box attack experiments have shown us an opportunity to utilize diverse networks to generate a good defense. Our proposed multiple initialization method can protect our network from attack effectively.

Experiments on SAP-like networks also indicated that we have already found a combination of parameters that makes SAP layers work. Future work can follow the ideas to use the developed SAP-like network to generate multiple networks for each attack image, such that the attacker will be unable to know detailed parameters of the networks, which makes attacks less effective.

The image restoration method based on wavelet denoising and super resolution, which maps the off-the-manifold adversarial images back to the clean natural manifold, proves to be effective against the adversarial samples while retaining the classification accuracy on natural images. The addition of adversarial noise could be removed in a way by the super resolution scheme through the experiments conducted. In the future work, we consider to combine more advanced denoising methods dealing with different kinds of adversarial noises to recover images for classification.

For the future work, we can combine SAP and random initialization to further increase randomness and diversity of the network.
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