Adaptive Adversarial Logits Pairing

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Adversarial examples provide an opportunity as well as impose a challenge for understanding image classification systems. Based on the analysis of the adversarial training solution—Adversarial Logits Pairing (ALP), we observed in this work that: (1) The inference of adversarially robust model tends to rely on fewer high-contribution features compared with vulnerable ones. (2) The training target of ALP does not fit well to a noticeable part of samples, where the logits pairing loss is overemphasized and obstructs minimizing the classification loss. Motivated by these observations, we design an Adaptive Adversarial Logits Pairing (AALP) solution by modifying the training process and training target of ALP. Specifically, AALP consists of an adaptive feature optimization module with Guided Dropout to systematically pursue fewer high-contribution features, and an adaptive sample weighting module by setting sample-specific training weights to balance between logits pairing loss and classification loss. The proposed AALP solution demonstrates superior defense performance on multiple datasets with extensive experiments.

CCS Concepts: • Computing methodologies → Machine learning algorithms; Computer vision;

Additional Key Words and Phrases: Adversarial defense, adaptive, dropout

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1 INTRODUCTION

Computer Vision discipline, such as Image Classification, has made a major breakthrough in recent years. However, an adversarial attack can easily deceive these models [3, 10, 16, 21, 23, 32]. Take Image Classification as an example, Adversarial attack is a techinic that adds subtle perturbations...
that are hard for humans to detect to change output result dramatically. Recently, the adversarial attack is not limited in Image Classification problems but has been expanded to Object Detection, Face Recognition, Voice Recognition and Text Recognition [4, 8, 19, 27, 35]. Hence, it is highly needed to design such models to defend adversarial samples [7, 31].

There are three main methods for defending existing adversarial samples [1, 6, 11, 18, 20, 22, 25, 28, 29, 33, 34]: (1) Gradient masking: Hiding gradient information of images through nondifferentiable transformation methods to invalidate adversarial attack [28]. (2) Adversarial samples detecting: Preventing samples that have been attacked from being imported into the model by detecting features of adversarial samples [9]. (3) Adversarial training: Continuously adding adversarial samples into the training sets to get robust model parameters [22]. Athalye et al. [2] have released the limitations of the gradient masking methods, finding that they can still be attacked successfully by gradient simulation. In addition, adversarial samples detecting also has limitations of not being able to solve the problem of adversarial attack, which makes no contribution to the correction of the model’s fragileness. In contrast with Gradient masking and Adversarial samples detecting, adversarial training is the most effective method of improving the robustness of models.

Adversarial training was a simple training framework that aims at minimizing the cross-entropy of the original sample and adversarial sample at the same time. Under the training framework of adversarial training, Adversarial Logits Pairing (ALP) [13], which is a more strict adversarial training constraint, acts more effectively. ALP can not only constraint the cross-entropy of the original sample and adversarial sample, but can also require models to keep similar outputs between original samples and adversarial samples on logits activation. The current SOTA method TRADES [36] also uses the same idea as the ALP method, constraining the original sample and the adversarial sample to have similar representations.

When analyzing the result of models trained by ALP, we found that ALP loss had led to different effects on different samples, as in Figure 3 shows that models trained by ALP present high conference in successfully defended samples but a low conference in those failed ones. By analyzing different models with different robustness, as shown in Figure 1, we found that according to the improvement of robustness, models would show fewer high-contribution features. Hence, we think ALP still has large room to be promoted.

Based on the above findings, we propose an Adaptive Adversarial Logits Pairing training method, which greatly improves the effectiveness of adversarial training. The main contributions are as follows:

- We propose a Guided Dropout that tailors features based on feature contributions. It can prevent overfitting while improving the model’s robustness.
- We propose a method to adaptively adjust the Adversarial Logits Pairing loss.
- Our proposed method greatly improves the robustness of the model against adversarial attacks and shows excellent results on multiple datasets.

2 DATA ANALYSIS AND MOTIVATION

The Adversarial Logits Pairing is currently the most classic adversarial training method that constrains the activation layer. The Adversarial Logits Pairing consists of two constraints, among which classification loss is used to constrain the correct classification of the model, and ALP loss constrains the original sample and the adversarial sample to guarantee a similar output. ALP loss [13] is defined as follows:

\[
ALP \text{ loss} = ||\text{Logits}_{clean} - \text{Logits}_{adv}||_2^2.
\]
where Logits\textsubscript{clean} and Logits\textsubscript{adv} refer to the activation value of the original sample in the Logits layer and the activation value of the adversarial sample in the Logits layer, respectively.

We want to explore the mechanism of the ALP method and find a general method for improving adversarial training from the perspectives of the training process and the training target. The data analysis part intends to solve the following two problems:

- How does the ALP method affect the model features after training?
- Is the training target of the ALP method applicable to all samples?

In this section, we define the PGD \cite{madry2017towards} as the adversarial attack, and the attack configuration is as follows: On the MNIST dataset: \(\varepsilon = 0.3\), attack step size = 0.01, iteration = 40; SVHN dataset \cite{natciak2021advprop}: \(\varepsilon = 12\text{pix}\), attack step size = 3pix, iteration = 10; CIFAR dataset \cite{goodfellow2014explaining}: \(\varepsilon = 8\text{pix}\), attack step size = 2pix, iteration = 7.

### 2.1 Feature Analysis

Although the Adversarial Logits Pairing performs well, its mechanism is still unclear. The original author only simply used ALP as an extension of adversarial training, but did not analyze in-depth how this extension improved the effect of adversarial training.

We use first-order Taylor expansion to further derive the formula of ALP and give a more intuitive form, through which, we can intuitively see how ALP improves adversarial training. We define \(f(\cdot)\) as a function to obtain the activation of the Logits layer of the neural network, so ALP can be rewritten as

\[
\text{ALP loss} = (f(x_{adv}) - f(x))^T (f(x_{adv}) - f(x))
= (f(x + \Delta x) - f(x))^T (f(x + \Delta x) - f(x))
= (f(x) + \frac{\partial f(x)}{\partial x} \Delta x - f(x))^T (f(x) + \frac{\partial f(x)}{\partial x} \Delta x - f(x))
\]

where \(\Delta x\) is adversarial perturbations, adversarial perturbations can be approximated as

\[
\Delta x = \alpha \frac{\partial \text{Loss}}{\partial f(x)}.
\]

So, ALP loss can be further expressed as

\[
\text{ALP loss} = \alpha^2 \left( \frac{\partial f(x)}{\partial x} \frac{\partial \text{Loss}}{\partial f(x)} \right)^T \left( \frac{\partial f(x)}{\partial x} \frac{\partial \text{Loss}}{\partial f(x)} \right)
\]

The rewritten ALP loss is mainly composed of \(\frac{\partial \text{Loss}}{\partial f(x)}\) and \(\frac{\partial f(x)}{\partial x}\). Constraining ALP loss means that the product of \(\frac{\partial \text{Loss}}{\partial f(x)}\) and \(\frac{\partial f(x)}{\partial x}\) becomes smaller. The expression of \(\frac{\partial \text{Loss}}{\partial f(x)}\) is very similar to the Grad-CAM algorithm. Constraint \(\frac{\partial \text{Loss}}{\partial f(x)}\) can be understood as reducing high-contribution features. \(\frac{\partial f(x)}{\partial x}\) can be understood as the gradient of the Logits layer to the input image, and constraint \(\frac{\partial f(x)}{\partial x}\) means to make the input gradient smoother.
Fig. 1. Distribution histogram of the feature contribution of different training algorithms. COM represents general training; ADV represents adversarial training; ALP represents adversarial logits pairing training. The horizontal axis represents feature contribution, and the vertical axis represents frequency.

We want to further quantify the impact of feature contributions on the robustness of the model, so we define the value of $C$ as the contribution of the feature to the training target,

$$C = \text{mean} \left( \text{abs} \left( \frac{\partial \text{Loss}}{\partial A_{fc}} \right) \right),$$

where $\text{mean}(\cdot)$ represents the average function, $\text{abs}(\cdot)$ represents the absolute value function, and $A_{fc}$ refers to the activation value of the layer before the Logits layer. Because the output of the Logits layer contains class information, we choose the activation value of the previous layer of the Logits layer to calculate the feature contribution.

We calculate the contribution of the previous layer of Logits after convergence in the SVHN dataset and Cifar10 dataset. As the robustness of the COM, ADV, and ALP algorithms increases in turn, it can be seen from Figure 1 that as the robustness increases, the model shows fewer high-contribution features.

For feature analysis, GradCAM [26] is a commonly used tool, which can visualize the contribution of features. GradCAM provides the activation map with the gradients and activations of the models:

$$\text{Grad CAM} = \text{relu} \left( \frac{\partial \text{Loss}_c}{\partial A_i} \ast A_i \right),$$

where $\text{relu}(\cdot)$ represents the relu function, $\text{Loss}_c$ represents the classification loss of the model for category $c$, and $A_i$ refers to the activation value of the layer $i$.

We visualize the adversarial sample's activation maps of the three methods: general training, adversarial training, and ALP training in Figure 2. It can be seen from the figure that as the robustness of the model increases, the areas strongly related to the model gradually decrease.

The difference in the activation maps and the distributions can prove:

- Robust model features have the distribution characteristics of few high-contribution.
- Strongly related areas during training are also areas of greater concern for neural networks.

The changes in the activation maps and the distributions of contribution show a high degree of consistency. The fewer high-contribution features cause the model to focus on the most critical areas in the image. Thereby the model reducing the impact of other areas on the model output after being attacked by adversarial samples.
This phenomenon inspires us to make the model focus more on the most important part of the image during the training process to improve the robustness of the model.

2.2 Sample Optimization Analysis

In the previous section, we find that the robust model presents the distribution characteristics of fewer high-contribution features. The high contribution feature will bring strong confidence, and ALP is a typical multi-loss collaborative method, which is prone to cause interactions among losses. So, we want to know whether the fewer high-contribution feature distribution will affect the confidence of the model.

We choose the ALP model and find that the samples mainly present two states in the three data sets of MNIST, SVHN, and Cifar10. One type of successfully defended samples, proves the ALP model’s validity in the defense of the adversarial sample with equal high confidence as with the original samples, while the other type of failed defended samples is generally accompanied by lower confidence. The two types of samples are shown in Figure 3.

As for the original intention of adversarial defense and ALP, we want to avoid the phenomenon, which the original sample is correctly classified and the adversarial sample is incorrectly classified. We define a type of sample with correct classification of the original sample but wrong classification of the adversarial sample as the Inconsistent Set. Similarly, all correctly classified samples are defined as Consistent Set. For Inconsistent Set samples obviously violating the ALP training target, we want to explore why such samples fail to be defended by the ALP model.

Because ALP focuses more on the constraints of confidence score, we decide to observe the confidence score in the Inconsistent Set and use the samples in the Consistent Set to compare to explore the characteristics of the samples that failed to defend. We separately count the clean sample’s ground-truth confidence, adversarial sample’s ground-truth confidence, classification loss, and ALP loss of the two types of samples in the test set, as shown in Table 1.
Fig. 3. On the top is a class of data with correct classification of the original and adversarial samples, on the bottom is a class of data with correct classification of the original samples but wrong classification of adversarial samples, the first row of each group of figures is the original sample, the second row is the adversarial sample, green bar is the confidence score of the ground truth, and the red bar is the confidence score of the attack target class.

Table 1. Confidence Score, Classification Loss, and ALP Loss Before and After the Adversarial Attack in Inconsistent Set and Consistent Set

| Data Set | AvgProb$_{clean}$ | AvgProb$_{adv}$ | Classification loss | ALP loss  |
|----------|-------------------|-----------------|---------------------|-----------|
| MNIST    |                   |                 |                     |           |
| Consistent Set | 94.61%  | 92.58%  | 0.3262              | 0.1443    |
| Inconsistent Set | 60.94%  | 21.87%  | 4.1833              | 2.2442    |
| SVHN     |                   |                 |                     |           |
| Consistent Set | 86.25%  | 52.37%  | 5.1866              | 0.9199    |
| Inconsistent Set | 54.61%  | 11.22%  | 7.0301              | 3.0740    |
| Cifar10  |                   |                 |                     |           |
| Consistent Set | 89.53%  | 69.81%  | 2.0889              | 0.5236    |
| Inconsistent Set | 59.88%  | 14.34%  | 6.2318              | 2.7438    |

The above data analysis shows that the following differences exist between Inconsistent Set and Consistent Set:

- Consistent Set’s clean sample average confidence and adversarial sample average confidence are much higher than that of Inconsistent Set.
- Inconsistent Set’s classification loss and ALP loss are much higher than that of Consistent Set.
- The percentage of ALP loss taking over total loss in Consistent Set is less than that in Inconsistent Set.

In the data analysis of Consistent Set and Inconsistent Set, we reckon that Inconsistent Set has an adverse effect on the training target of adversarial training, so we decide to observe the differences between Inconsistent Set and Consistent Set during the entire ALP training process.

We record the ALP loss value of the model for each sample of the test set after the end of each epoch in the training process and divide the samples into Consistent Set and Inconsistent Set.
Adaptive Adversarial Logits Pairing

Fig. 4. ALP loss value changes of Inconsistent Set and Consistent Set with the increase of training times.

according to the situation of the model convergence. Then, we print the average ALP loss of each epoch of Consistent Set and Inconsistent Set, as shown in Figure 4.

It can be seen from the figure that during an ALP training process, the ALP loss of Consistent Set gradually decreases, and the robustness gradually increases under the constraint of ALP loss. The ALP loss of Inconsistent Set is gradually increasing. Obviously, the constraint of ALP loss is too strong for Inconsistent Set, which affects the convergence of such samples.

Therefore, although the ALP algorithm plays a certain role in defense, it does not have a good enough training target, which hampers the overall defense effect of the model. This phenomenon inspired us to design an ALP loss that can treat Consistent Set and Inconsistent Set differently to achieve a better training effect.

3 METHOD

In this section, we will solve the problems in the ALP method from two perspectives: (1) For optimizing the training process, we want to give the model a higher priority to train high-contribution features. (2) To alleviate the negative impact of the ALP loss on Inconsistent Samples at the training target, we want to design an adaptive loss that can coordinate different samples. The overall framework is shown in Figure 5.

3.1 Adaptive Feature Optimization

According to the data analysis, reducing high-contribution features will help the model improve robustness. This phenomenon motivates us to design an algorithm that is intended to train high-contribution features.

In terms of model structure, the dropout layer is the most suitable model structure to achieve this demand. The initial design of dropout is to solve the over-fitting phenomenon of the model [30]. By randomly cutting the model features, the quality of the model features and the generalization of the model are improved. In recent years, many algorithms have improved the performance of the model by controlling the cutting process of the dropout layer, such as combining attention with dropout [5]. Therefore, we want to combine dropout and feature contribution to make the dropout layer conform to certain rules for feature cutting, so that the models have fewer high-contribution features, thereby improving the robustness of the model.

We use the characteristics of the dropout layer to selectively tailor the neural network. By keeping the highly contributed features and cutting the weakly contributed features, we force the model to focus on the highly contributed features during the training process. Specifically, in forwarding propagation, we first calculate the contribution scores between each neuron in the previous layer of the Logits layer, retaining the first 50% of neurons and discarding the remaining 50% of neurons. Then, we update the parameters of the model after trimming to realize Guided Dropout.
We combine the expansion of ALP loss in Equation (4) and the GradCAM algorithm to define $R_{loss}$ to measure feature contribution:

$$R_{loss} = mean\left(abs\left(\frac{\partial Loss}{\partial A_{fc}} * A_{fc}\right)\right), \quad (7)$$

where $A_{fc}$ represents the activation value of the previous layer of Logits, $abs(\cdot)$ represents the absolute value function, and $mean(\cdot)$ represents the average function. The resulting $R_{loss}$ is a vector with the same shape as $A_{fc}$, which stores the contribution scores of each feature of the $A_{fc}$ layer with the current round of data:

$$Guided\ Dropout = R_{loss} \geq middle(R_{loss}), \quad (8)$$

where $middle(\cdot)$ represents the median function. We want to keep the high-contribution features in the training process to continue training so that the contribution of those features can be reduced. After making comparison in Equation (8), we define that the part of $R_{loss}$ greater than the median is 1, and the part less than the median is 0. Then the vector is regarded as the mask of the dropout, to realize the Guided Dropout.

We analyze the reason why the Guided Dropout module works. We believe that high-contribution features will have higher $l_2$ loss due to their larger weight in the fully connected layer. When they are trained separately, $l_2$ loss will restrict their weight to decrease, thus achieving our goal of reducing the number of high-contribution features.

### 3.2 Adaptive Sample Weighting

As analyzed above, the ALP loss does not have a good effect on all samples. In the process of the ALP loss restraining the Inconsistent Samples, we find the normal convergence is sometimes affected. So, we propose a training method called Adaptive ALP loss to adaptively control the ALP loss weight of different samples in the training process. According to the experimental results in the previous section, it is noted that the Inconsistent Set has a large impact and the confidence of the Inconsistent Set is low. To weaken the negative impact of ALP loss, we propose to use the confidence score to weight ALP loss. We first calculate the confidence scores of the original samples and set these confidence scores as the ALP loss weight of the samples in the training round. Adaptive ALP loss can effectively distinguish the Consistent Samples and the Inconsistent Samples, reduce the ALP loss weight of the Inconsistent Samples, and better help against training convergence. At the same time, adaptive ALP loss will overall reduce the negative impact of ALP loss during the entire training process, allowing the model to converge faster:

$$Adaptive\ ALP\ loss = Probs_{clean} * ALP\ loss, \quad (9)$$

where $Probs_{clean}$ denotes the clean sample’s confidence score of the ground-truth.
Table 2. Comparison of Defense Performance with Madry, Kannan, and Others under Different Adversarial Attack Methods on Multi Datasets

| DataSet | Method      | Clean | FGSM  | PGD10 | PGD20 | PGD40 | PGD100 | CW10 | CW20 | CW40 | CW100 |
|---------|-------------|-------|-------|-------|-------|-------|--------|------|------|------|-------|
| MNIST   | RAW         | 99.18%| 7.72% | 0.49% | 0.54% | 0.64% | 0.53%  | 0.0% | 0.0% | 0.0% | 0.0%  |
|         | Madry adv   | 99.00%| 96.92%| 95.69%| 95.52%| 94.14%| 92.49% | 95.85%| 95.78%|      |       |
|         | Kannan ALP  | 98.77%| 97.68%| 96.66%| 96.58%| 96.37%| 94.50% | 96.96%| 97.07%| 96.73%| 96.16%|
|         | TRADES      | 98.48%| 98.34%| 96.90%| 96.68%| 96.35%| 95.35% | 97.09%| 97.09%| 96.96%| 95.76%|
|         | AALP        | 98.16%| 98.17%| 97.13%| 97.04%| 97.04%| 97.04% | 97.04%| 97.04%| 97.04%| 97.04%|
|         | AALP_{sw}   | 98.16%| 97.77%| 97.05%| 96.82%| 96.66%| 95.87% | 97.18%| 97.15%| 96.87%| 96.76%|
|         | AALP        | 98.49%| 98.19%| 97.22%| 97.13%| 97.13%| 96.32% | 97.28%| 97.34%| 97.26%| 96.89%|

| SVHN    | RAW         | 95.37%| 8.85% | 2.23% | 2.22% | 2.25% | 2.17%  | 0.83%| 0.76%| 0.71% | 0.66%  |
|         | Madry adv   | 86.41%| 48.53%| 31.51%| 27.44%| 25.02%| 38.41% | 35.32%| 33.93%| 33.04%|        |
|         | Kannan ALP  | 85.28%| 53.47%| 40.05%| 36.55%| 35.07%| 34.15% | 44.82%| 42.48%| 41.52%| 40.86% |
|         | TRADES      | 84.05%| 61.14%| 42.71%| 40.42%| 39.46%| 38.78% | 46.77%| 44.83%| 44.00%| 43.54% |
|         | AALP_{dd}   | 86.23%| 59.18%| 44.05%| 42.57%| 42.27%| 41.23% | 46.47%| 44.96%| 44.51%| 44.05% |
|         | AALP_{sw}   | 84.66%| 62.83%| 44.30%| 40.99%| 40.99%| 39.94% | 47.78%| 45.87%| 44.68%| 43.80% |
|         | AALP        | 84.13%| 57.67%| 45.05%| 43.35%| 42.60%| 42.18% | 47.92%| 47.08%| 46.77%| 46.57% |

| Cifar10 | RAW         | 90.51%| 14.24%| 5.93% | 5.80% | 5.97% | 6.04%  | 1.92%| 1.88%| 1.73%| 1.33%  |
|         | Madry adv   | 83.36%| 63.28%| 49.29%| 45.25%| 44.83%| 44.72% | 46.20%| 45.16%| 44.76%| 44.65% |
|         | Kannan ALP  | 82.80%| 64.96%| 52.79%| 49.04%| 48.81%| 48.60% | 52.81%| 52.13%| 51.79%| 51.65% |
|         | TRADES      | 82.73%| 64.17%| 53.47%| 52.52%| 52.38%| 52.29% | 59.74%| 58.91%| 58.71%| 58.66% |
|         | AALP_{dd}   | 80.50%| 65.00%| 54.78%| 51.69%| 51.51%| 51.40% | 59.00%| 58.45%| 58.31%| 58.23% |
|         | AALP_{sw}   | 82.37%| 65.69%| 53.96%| 50.25%| 49.91%| 49.74% | 53.35%| 52.51%| 52.33%| 52.12% |
|         | AALP        | 80.45%| 65.42%| 55.23%| 52.59%| 52.41%| 52.38% | 60.00%| 59.47%| 59.34%| 59.30% |

The overall loss is calculated as follows:

$$\text{Total loss} = C\text{lassification Loss} + \alpha \times \text{Adaptive ALP loss},$$

where $\alpha$ is the weight of the Adaptive ALP loss.

4 EXPERIMENT

In the experimental part, we want to verify whether we have reached the designed goals of the algorithm: whether AALP loss treats the Consistent and Inconsistent Sets differently, and whether the Guided Dropout reduces the contribution of the high-contribution features. At the same time, we show the adversarial defense effect and analyze the parameter selection.

4.1 Experimental Setting

The Adaptive ALP experiment was carried out on three datasets and models, i.e., LeNet [17] trained based on MNIST dataset, ResNet9 [12] trained based on SVHN dataset, and ResNet32 trained based on Cifar10 dataset. MNIST basic configuration: Backbone network is LeNet. We use Adam optimization [14] and make lr = 0.0001. PGD40 is used to create the adversarial samples and attack step size is 0.01, $\epsilon = 0.3$. SVHN basic configuration: backbone network is ResNet9. We use Adam optimization and make lr = 0.0001. We select PGD10 to generate the adversarial samples and attack step size is 3pix, $\epsilon = 8$pix. The basic configuration of Cifar10: Backbone network is ResNet32. We use Adam optimization and make lr = 0.0001. We select PGD7 to generate the adversarial samples and attack step size is 2pix, $\epsilon = 8$pix.

4.2 Performance on Adversarial Defense

We conduct a defense effect test on three datasets, comparing Madry’s adversarial training algorithm, Kannan’s ALP algorithm and Zhang’s TRADES algorithm. We choose FGSM, PGDX, and CWX (X represents the number of iterations) as the comparative attack algorithms.
4.3 Parameter Analysis

The algorithm we propose has one main parameter that can be adjusted, namely, $\alpha$, which controls the loss ratio. We selected the SVHN dataset for parameter analysis.

In Figure 6, the change of $\alpha$ has obvious effects on defense. When we increase $\alpha$, it will obviously improve the defense effect, but it will also lose the clean classification accuracy, so we choose the final result $\alpha = 1.0$, which is better for the overall result.

4.4 Fewer High-contribution Features

In the previous data analysis, we found that models with stronger robustness usually have fewer high-contribution features, and these high-contribution features are usually concentrated in the parts that are crucial for classification.

In Figure 7, we also add the feature contribution of the AALP model to the comparison and find that the model trained by the AALP algorithm has more characteristics of fewer high-contribution features.

In Figure 8, we compare the three defense algorithms ADV, ALP, and AALP and their differences in the activation map, finding that the model trained by the AALP algorithm is more willing to focus on the parts that are important for classification.
Adaptive Adversarial Logits Pairing

Fig. 7. Distribution histogram of the feature contribution of different training algorithms. COM represents general training; ADV represents adversarial training; ALP represents adversarial logits pairing training; AALP represents adaptive adversarial logits pairing training. The horizontal axis represents feature contribution, and the vertical axis represents frequency.

Table 3. Cooperation between Guided Dropout and Other Algorithms

|       | Clean | PGD10 | CW10 |
|-------|-------|-------|------|
| Raw   | 95.57%| 2.23% | 0.0% |
| Raw+gd| 94.36%| 3.17% | 0.04%|
| ADV   | 86.41%| 31.51%| 24.03%|
| ADV+gd| 95.07%| 35.34%| 34.51%|
| ALP   | 85.28%| 40.05%| 31.17%|
| AALP  | 86.23%| 44.05%| 37.57%|

At the same time, we also observe changes in the distribution of features throughout the AALP training process. We train an AALP model and save a model every 10,000 steps. We record the feature distribution of each storage point and the activation map of the model under the storage point to obtain Figures 9 and 10:

It can be seen that as the training progresses, the distribution of model features gradually shows a less and less high-contribution trends, and the activation map is also increasingly focused on the key information of the picture.

We also want to test whether Guided Dropout can play a role in other training methods. We use the ResNet9 to train on the SVHN dataset, add the Guided Dropout module to general training and adversarial training (ADV), and observe its working effect. The results can be seen in Table 3.

From the data, it can be conducted that the addition of Guided Dropout has played a huge role in defending the adversarial samples. After adding the Guided Dropout module, the ADV model and ALP model have significantly improved the defense of PGD and CW algorithms. The ADV model has also significantly improved the classification of clean samples. However, Guided Dropout does not seem to work for general training. It makes the accuracy of clean samples slightly lower. Although the defense adversarial samples have improved, they are of little availability.

4.5 Changes of Consistent Set and Inconsistent Set

We compare the changes in the Consistent Set and the Inconsistent Set of the model and the changes in the number of samples of these two types after using the AALP method. We set the clean sample’s confidence scores to the x-axis and the adversarial sample’s confidence scores to
Fig. 8. Changes of activation maps of adversarial samples in the different training methods (from top to bottom: activation maps for general training, adversarial training, ALP method, and AALP method).

Fig. 9. Changes of feature distributions in the process of training AALP.

the y-axis to show the changes of the samples in the entire test set. In Figure 11, the blue sample points are Consistent Samples, and the red sample points are Inconsistent Samples.

Through the comparison of the three datasets, it can be found that the sample points of the model trained by AALP tend to be distributed on the straight line $y = x$. It shows that adversarial
attack has a lower impact on the output of the AALP model’s confidence, and the AALP model has stronger robustness.

Then, we compare the changes in the proportion of the Inconsistent Samples in the three datasets.

It can be seen from Table 4 that under the AALP algorithm, the number of the consistent samples in all three datasets has increased, and the robustness of the model has also been significantly enhanced.
Table 4. Consistent Set Samples Proportion Changes after Using the AALP Method

|                  | ALP Consistent Samples | AALP Consistent Samples |
|------------------|------------------------|-------------------------|
| MNIST            | 94.91%                 | 96.03%                  |
| SVHN             | 30.89%                 | 36.58%                  |
| Cifar10          | 41.61%                 | 43.78%                  |

Fig. 12. ALP and AALP training methods convergence speed comparison.

We trained two MNIST models, one with the ALP method applied; the other with the AALP method applied. We record the loss changes of the test set, and the accuracy of clean samples and adversarial samples during the training of the two models.

In Figure 12, it can be seen that the AALP algorithm, compared with ALP, has better effects on both convergence and defense.

At the same time, the proposed algorithm solves the problem of ALP loss constraints on different samples; it also reduces the side effects of ALP loss during the training process, accelerates the entire training process, and greatly improves the efficiency of ALP training.

5 CONCLUSIONS

This work analyzes problems qualitatively and quantitatively in the ALP method: (1) the robust model should reduce the high-contribution features, and (2) the ALP training target cannot fit all samples. Therefore, we proposed the AALP method, improved the ALP method from the training process and training target, and analyzed the AALP method qualitatively and quantitatively. In the future, we plan to continue to explore the reasons behind the relationship between feature contributions and robustness and better apply this method to adversarial defense or other computer vision tasks.

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