Using Feature Alignment Can Improve Clean Average Precision and Adversarial Robustness in Object Detection

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ABSTRACT

The 2D object detection in clean images has been a well-studied topic, but its vulnerability against adversarial attack is still worrying. Existing work \([1]\) has improved robustness of object detectors by adversarial training, at the same time, the average precision (AP) on clean images drops significantly. In this paper, we propose that using feature alignment of intermediate layer can improve clean AP and robustness in object detection. Further, on the basis of adversarial training, we present two feature alignment modules: Knowledge-Distilled Feature Alignment (KDFA) module and Self-Supervised Feature Alignment (SSFA) module, which can guide the network to generate more effective features. We conduct extensive experiments on PASCAL VOC and MS-COCO datasets to verify the effectiveness of our proposed approach. The code of our experiments is available at https://github.com/grispeut/Feature-Alignment.git.

Index Terms—deep learning, object detection, adversarial robustness, adversarial training

1. INTRODUCTION

It is a long-standing problem that deep learning models are easily attacked. Studies have shown that both classification models and detection models are easily defeated by adversarial disturbances \([2,3,4,5]\). In order to improve robustness of deep learning models, the mainstream method is based on adversarial training \([3,7]\). Adversarial training is to solve a two-level optimization problem. The inner loop is a maximization problem that maximizes the proxy loss to generate adversarial samples. The outer loop is a minimization problem that minimizes the loss to train the parameters of models.

On the basis of adversarial training, some researchers promote adversarial robustness from the perspective of generating adversarial samples, such as reusing gradient information to generate adversarial samples \([8]\), FGSM with random initialization \([9]\) and constructing adversarial samples in an unsupervised manner \([10]\). Some researchers also optimize the minimization problem of outer loop to increase robustness, such as adding a self-supervised branch to the classification network, which uses the output of the penultimate layer as the input of this branch and predicts the rotation angle of the picture \([11]\), or adding the regularization term GradAlign to prevent catastrophic overfitting \([12]\), or applying self-supervised comparative representation learning to adversarial training \([13]\).

The above-mentioned methods have been verified on classifiers and benchmark datasets, but few works have extended their methods to object detection task. The reason may be that the object detector is more complicated, which leading to higher training costs, and some methods are not suitable for direct migration to the adversarial training of object detection, such as FGSM with random initialization using cyclic learning rate to accelerate the convergence speed \([2]\), the self-supervised branch to predict rotation \([11]\), and GradAlign which needs to create calculation graph of the gradient of input \([12]\), resulting in the batch size should be reduced under limited graphics memory. Nevertheless, the discovery of catastrophic overfitting phenomenon \([9,12]\) and the combining unsupervised or self-supervised learning with adversarial training \([10,13]\) are still instructive for object detection task.

For the robustness of detector, Zhang et al. \([1]\) propose to take object detection as multi-task learning and use task oriented domain to generate adversarial samples. They conduct experiments on a variety of one-stage detectors and the experiments show that their method can improve robustness of models. However, we find that the clean AP drops significantly (about 25 points on PASCAL VOC), while the robustness against attack is improved. In our experiments, we find that the clean AP and robustness are really difficult to obtain at the same time. Therefore, we hope to improve robustness on the basis of reducing the drop of clean AP.

In this paper, we are devoted to better balance clean AP and robustness. Considering that detectors have more layers than classifiers, there are additional location branches and feature fusion modules such as feature pyramid modules \([14]\). Therefore, in the face of a deeper and more complex detection network, we propose feature alignment approach, which...
Adversarial training is proposed by Goodfellow et al. [3], and module. Finally, we introduce evaluation methods of clean ment in intermediate layer and introduce our KDFA and SSFA training. Then we analyze the advantage of feature align- [21] and two-stage detector FASTER-RCNN-FPN [14].

Compared with self-supervised representation learning, prior features of feature alignment not only come from siamese networks, but also from teacher networks. So feature alignment is a more general concept.

The contribution of this paper includes two aspects: i) we propose to guide the output of middle layer to strengthen adversarial training in object detection, and provide two feature alignment methods based on knowledge distillation and self-supervised learning; ii) on PASCAL VOC and MS-COCO datasets, our approach obtains higher clean AP and robust- ness than existing works across one-stage detector YOLO-V3 [21] and two-stage detector FASTER-RCNN-FPN [14].

2. OUR APPROACH

In this section, we first revisit the basic form of adversarial training. Then we analyze the advantage of feature alignment in intermediate layer and introduce our KDFA and SSFA module. Finally, we introduce evaluation methods of clean AP and robustness.

2.1. Adversarial Training

Adversarial training is proposed by Goodfellow et al. [3], and can be formulated as follows:

\[
\min_ \theta \sum_i ((1- \alpha) \ast \max_{\delta \in \Delta} \ell (f_\theta (x_i + \delta) , y_i) 
+ \alpha \ast \ell (f_\theta (x_i) , y_i))
\]

where \( f, \theta, \ell \) denote the deep learning model, parameters of model and proxy loss function, and \( x_i, y_i, \delta, \Delta \) are the clean sample, the label of sample, disturbances added to clean sample and the upper bound of disturbances.

2.2. Feature Alignment of Middle Layer

Reviewing the Spectral Analysis of Unstability proposed by Szegedy et al. [2], the unstability of network can be expressed by the Lipschitz constant of each layer, which can be formulated as follows:

\[
\| f(x) - f(x + \delta) \| \leq \prod_{k=1}^{M} L_k \| \delta \| \\
\| f_{\text{mid}}(x) - f_{\text{mid}}(x + \delta) \| \leq \prod_{k=1}^{K} L_k \| \delta \|
\]

where \( L_k \) is the the upper Lipschitz constant of layer \( k \), and \( f_{\text{mid}}(x) \) denotes the output of middle layer. In this paper, the last layer of backbone is set as the \( M \)th layer.

By imposing constraints, \( f_{\text{mid}}(x + \delta) \) can be approximately equal to \( f_{\text{mid}}(x) \) or \( f_{\text{mid}}(x + \delta) \), where \( f_t \) denotes the teacher network. We define the process of guiding \( f_{\text{mid}}(x + \delta) \) equal to another prior features as feature alignment. Feature alignment can reduce the unstability of network before \( M \)th layer, thereby reducing the probability of adversarial examples. In addition, the alignment can guide the learning of the network before \( M \)th layer to generate more effective features, and effective features are conducive to the learning of the network after \( M \)th layer.

The structure of feature alignment is shown in Fig. 1. KDFA is the case that guiding \( f_{\text{mid}}(x + \delta) \) equals to \( f_{\text{mid}}(x) \). We use the detector trained on the clean dataset as the teacher network, of which feature representation outputted by the middle layer on the clean data can be a good prior knowledge. SSFA is the case that guiding \( f_{\text{mid}}(x + \delta) \) equals to \( f_{\text{mid}}(x) \), which uses the prior knowledge that clean pictures and their corresponding adversarial examples should have the same feature representation. In addition, considering for each sample, the dimension of output feature is \( W \ast H \ast C \), which is a high-dimensional feature representation, and the feature may be noisy or redundant. In our work, we project such a high-dimensional feature into a low-dimensional manifold. Specifically, we use average-pooling as the feature projection operator, so the low-dimensional manifold is a \( C \)-dimensional feature. Then feature alignment is achieved by maximizing their feature similarity in the middle layer. Inspired by the idea of stop-grad in SimSiam [20], when calculating the feature representation of the clean picture in student network, we do not keep the calculation graph.

Adversarial training with feature alignment can be formulated as follows:
Table 1. Evaluation results on PASCAL VOC. FPN is FASTER-RCNN-FPN. YOLO is YOLO-V3. AT is vanilla adversarial training. TOD is using task oriented domain in adversarial training. FA is using SSFA + KDFA.

| model performance | trained with PGD-1 | trained with PGD-2 | trained with PGD-3 |
|-------------------|-------------------|-------------------|-------------------|
|                   | clean AP | advAP | acAP   | clean AP | advAP | acAP   | clean AP | advAP | acAP   |
| FPN               |          |       |        |          |       |        |          |       |        |
| AT [8]            | 0.834   | 0.074 | 0.454  | 0.824   | 0.236 | 0.530  | 0.822   | 0.137 | 0.480  |
| TOD [11]          | 0.833   | 0.106 | 0.470  | 0.828   | 0.247 | 0.538  | 0.821   | 0.173 | 0.497  |
| ours (K DFA)      | 0.838   | 0.143 | 0.467  | 0.828   | 0.273 | 0.551  | 0.823   | 0.217 | 0.520  |
| ours (SSFA)       | 0.838   | 0.103 | 0.400  | 0.829   | 0.246 | 0.548  | 0.824   | 0.190 | 0.507  |
| ours (FA)         | 0.834   | 0.166 | 0.495  | 0.832   | 0.286 | 0.559  | 0.825   | 0.260 | 0.543  |
| YOLO              |          |       |        |          |       |        |          |       |        |
| AT [8]            | 0.724   | 0.201 | 0.463  | 0.665   | 0.217 | 0.441  | 0.604   | 0.201 | 0.403  |
| TOD [11]          | 0.702   | 0.208 | 0.455  | 0.659   | 0.228 | 0.444  | 0.581   | 0.206 | 0.394  |
| ours (K DFA)      | 0.739   | 0.217 | 0.478  | 0.702   | 0.240 | 0.471  | 0.672   | 0.240 | 0.456  |
| ours (SSFA)       | 0.730   | 0.189 | 0.460  | 0.693   | 0.221 | 0.457  | 0.653   | 0.223 | 0.438  |
| ours (FA)         | 0.745   | 0.217 | 0.481  | 0.712   | 0.241 | 0.477  | 0.677   | 0.241 | 0.459  |

Fig. 2. Model performance trained with PGD-1 under different $\alpha$ and $\varepsilon$. (a) is the performance on clean dataset, and (b) is the performance under PGD-1 attack with 0.03 budget. Y-P is YOLO-V3 on PASCAL VOC and Y-M is YOLO-V3 on MS-COCO. F-P is FASTER-RCNN-FPN on PASCAL VOC.

2.3. PGD attack

In order to verify our approach, we use the powerful attack PGD [7] to test the robustness of detector. The k-step PGD (PGD-k) can be formulated as follows:

$$
\min_{\theta} \sum_{i} (1 - \alpha) * \max_{\delta \in \Delta} \ell(f_{\theta}(x_{i} + \delta), y_{i}) + \alpha * \ell(f_{\theta}(x_{i}), y_{i}) + \beta * (1 - \cos_{sim}(f_{mid}(x_{i} + \delta), f_{mid}(x_{i}))) + \gamma * (1 - \cos_{sim}(f_{mid}(x_{i} + \delta), f_{l}(x_{i})))
$$

(3)

where $\cos_{sim}$ denotes cos similarity, which can be expressed as $\cos_{sim}(x, y) = x^T y / \|x\| \|y\|$.

2.3. Results on PASCAL VOC and MS-COCO

Determine the basic form of adversarial training. We conduct experiments with different $\alpha$ and $\varepsilon$ in vanilla adversarial training (without feature alignment). The results trained with PGD-1 are shown in Fig[2]. It can be observed that smaller $\varepsilon$ can achieve better result on clean AP and advAP when $\alpha = 0$. It may be due to the catastrophic overfitting phenomenon, when large $\varepsilon$ is used in PGD-1 training. We think this is the reason that clean AP drops significantly after adver-
model performance | clean AP | advAP | acAP  
---|---|---|---
standard | **0.545** | 0.065 | 0.305 
AT [3] | 0.49 | 0.089 | 0.290 
TOD [1] | 0.488 | 0.088 | 0.288 
ours | K DFA | 0.506 | 0.110 | 0.308 
| SSFA | 0.499 | 0.103 | 0.301 
| FA | **0.510** | **0.120** | **0.315** 

Table 2. YOLO-V3 trained with PGD-1 on MS-COCO

3.3. Feature visualization

To better understand the effect of feature alignment, we visualize the feature of $M$th layer of FASTER-RCNN-FPN with Grad-CAM [22]. Visualization of test examples under PGD-1 attack ($\varepsilon = 0.03$) is shown as Fig.3. It is observed that adversarial training can help to reduce FP and FN than standard training. Our approach can further reduce FN, FP and increase confidence of TP than vanilla adversarial training and using task oriented domain. In feature visualization results, we find that feature alignment can generate more effective features, which focus more on objects.

4. CONCLUSIONS

In this paper, we present a new approach feature alignment to strengthen adversarial training by guiding output of intermediate feature layer, and propose two feature alignment modules based on knowledge distillation and self-supervised learning, which can help to generate more effective features. On PASCAL VOC and MS-COCO, our approach obtains better performance than existing works. However, there is still a large performance gap between adversarial samples and clean samples. The future work will include experiments on different $M$th layers and more detectors, and explore the balance between different feature alignment modules and adversarial training.
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