Universal Adversarial Attack on Attention and the Resulting Dataset DAmageNet

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Abstract—Adversarial attacks on deep neural networks (DNNs) have been found for several years. However, the existing adversarial attacks have high success rates only when the information of the attacked DNN is well-known or could be estimated by structure similarity or massive queries. In this paper, we propose an Attack on Attention (AoA), a semantic feature commonly shared by DNNs. The transferability of AoA is quite high. With no more than 10 queries of the decision only, AoA can achieve almost 100% success rate when attacking on many popular DNNs. Even without query, AoA could keep a surprisingly high attack performance. We apply AoA to generate 96020 adversarial samples from ImageNet to defeat many neural networks, and thus name the dataset as DAmageNet. 20 well-trained DNNs are tested on DAmageNet. Without adversarial training, most of the tested DNNs have an error rate over 90%. DAmageNet is the first universal adversarial dataset and it could serve as a benchmark for robustness testing and adversarial training.

Index Terms—adversarial attack, attention, transferability, black-box attack, DAmageNet.

1 INTRODUCTION

Deep neural networks (DNNs) have grown into the mainstream tools in many fields, thus, their vulnerability has attracted much attention in the recent years. An obvious example is the existence of adversarial samples [1], which are quite similar with the clean ones, but are able to cheat the DNN to produce incorrect predictions in high confidence. Various attack methods to craft adversarial samples have been proposed, such as FGSM [2], C&W [3], PGD [4], Type I [5] and so on. Generally speaking, when the victim network is exposed to the attacker, one can easily achieve efficient attack with very high success rate.

Although white-box attacks can easily cheat DNNs, the current users actually do not worry about them, since it is almost impossible to get complete information including the structure and the parameters of the attacked DNNs. If the information is kept well, one has to use black-box attack, which can be roughly categorized into query approach [6], [7], [8] and transfer approach [9], [10], [11]. The former one is to estimate the gradient by querying the attacked DNNs. However, until now, the existing query-based attack still needs massive queries, which can be easily detected by the defense systems. Transfer approach attacks rely on the similarity between the victim DNN and an attacked model in the attacker’s hands. It is expected that white-box attacks on the attacked model can also invade the attacked DNN. Although there are some promising studies recently [12], [13], [14], the transfer performance is not satisfactory and a high attack rate could be reached only when the two DNNs are very similar on the structures and parameters, which however conflicts the aim of black-box attack.

Black-box adversarial samples that are applicable to vast DNNs need to attack their common vulnerabilities. Since DNNs are imitating human’s intelligence, although DNNs have different structures and tricks, they may share semantic features. In this paper, we are focusing on the attention heat maps, for which different DNNs have similar performance. By attacking the attention heat maps of one white-box DNN, we could make the attention lose its focus and fail in judgement. In fact, some works have been aware of the importance of attention and put the change of heat map as an evidence of successful attacks, see, e.g., [11], [15]. In our study, we develop an Attack on Attention and name it as AoA. AoA achieves very good white-box attack performance. More importantly, there is high similarity in attention across different DNNs, making AoA have very good transferability. With no more than 10 queries of the decision only, AoA on many popular DNNs can achieve almost 100% success rate for black-box attack. Even without query, AoA could keep surprisingly high attack performance.

Here, we first illustrate one example in Fig. 1. The original image is a “salamander” in ImageNet [16]. By attacking the attention, we generate the adversarial sample, which looks very similar to the original one but with a distorted heat map (in lower left corner), leading to misclassification. The attack is carried out for VGG19 [17] but other well-trained DNNs in ImageNet also make wrong predictions.

Since this attack is for common vulnerabilities of DNNs, we successfully generate adversarial samples that can cheat many unknown DNNs. Totally, from original images in ImageNet, we generate 96020 images and error rates of many well-trained DNNs are above 90%. We provide these examples in dataset named as DAmageNet. Before, there is no efficient zero-query attack, so DAmageNet is the first dataset that provides black-box adversarial attack images. Those images DAmage many neural networks without any knowledge and any query. But the aim is not to really damage them, but to point out the weak parts of neural networks and thus those samples are valuable to improve the
neural networks by adversarial training \cite{18, 19}, robustness certification \cite{20}, and so on.

The rest of this paper is organized as follows. In Section 2, we will briefly introduce adversarial attack, especially black-box attack, and several variants of ImageNet. The Attack on Attention is described in detail in Section 3. Section 4 evaluates the proposed attack and the generated DAmageNet. In Section 5, a conclusion is given to end this paper.

2 RELATED WORK

2.1 Adversarial attack and its defense

Adversarial attacks \cite{21} could reveal the weakness of DNN by cheating it with adversarial samples, which differ from original ones with only slight perturbations. In the humans’ eyes, the adversarial sample does not have difference from the original ones, but well-trained networks make incorrect predictions, as shown in the bottom row.

\[ \text{find } \Delta x \text{ s.t. } f(x) \neq f(x + \Delta x) \]
\[ \|\Delta x\| \leq \varepsilon. \]

When training a DNN, one updates the parameters of the network by the gradients to minimize a training loss. While in adversarial attacks, one alters the image to increase the training loss. Based on this basic idea, there have been many variants on attacking spaces and crafting methods.

For attacking space, most of the existing directly impose attack in the image space, see, e.g., \cite{2, 22, 23}. It is also reasonable to aim at latent feature vector space \cite{5, 24} or the encoder/decoder \cite{25, 26}. Attack on feature spaces may produce unique perturbation unlike random noise.

The methods that find the adversarial samples could be roughly categorized as gradient-based \cite{2, 4} and optimization-based methods \cite{3, 21}. Gradient-based methods search in the gradient direction and the magnitude of perturbation is restricted to avoid big distortion. Optimization-based methods usually consider the magnitude restriction in the objective function, and the magnitude could be measured by \( l_1, l_2, l_{\infty} \)-norm or other metrics.

To secure the DNN, many defense methods have been proposed to inhibit the adversarial attack. Defense can be achieved by simply adding adversarial samples to the training set, which is called adversarial training \cite{27, 28, 29}. It is effective, but consumes much time. Another technique is to design certain blocks in network structure to prevent attack or detect adversarial samples \cite{30, 31}. Attack can also be mitigated by preprocessing images before input to the DNN \cite{32, 33, 34}, which does not require modification on the pre-trained network.

2.2 Black-box attack

When the attacked DNNs are totally known, the attacks mentioned above have high success rates. However, it is almost impossible to have access to the victim model in real-world scenarios and thus black-box attacks are required \cite{35, 36, 37}. Black-box attacks rely on either query \cite{6, 7} or transferability \cite{9, 35}.

For query approach, the attacker adds slight perturbation to the input image and observes the reaction of the victim model. By a series of queries, the gradients could be roughly estimated and then one can impose attack in the way similar to white-box case. To choose the next pixel to alter for gradient estimation, attackers adopt methods including Bayes optimization \cite{38}, evolitional algorithms \cite{39}, meta learning \cite{40} etc. Since the practical DNNs are generally very complicated, good estimation of the gradients needs a massive number of queries, leading to easy detections.

For transfer approach, one conducts white-box attack in a well-designed model and expects that the adversarial samples remain aggressive to other models. The underlying assumption is that the distance between decision boundaries across different classes is significantly shorter than that across different models \cite{35}. Although good attack rate has been reported recently \cite{11, 14}, it heavily relies on good transferability of the attacked and the victim model, e.g., VGG16 and VGG19 \cite{17}. Until now, adversarial samples able to beat many DNNs have not been reported and there is no publicly available dataset of that.

Since different DNNs have similar attention heat maps, the proposed Attack on Attention achieves very good black-box attack performance. In the view of query approach, the number of queries could be significantly reduced. Even zero-query is possible to attack DNNs. In the view of transfer approach, we do not require structure similarity and many popular DNNs are cheated. Overall, we could provide an adversarial example dataset, which is the first adversarial dataset for universal DNNs.
2.3 Attention mechanism and its calculation

In making judgements, human tend to concentrate on certain parts of an object to allocate attention efficiently. This attention mechanism in human intelligence has been exploited by researchers. In recent studies, methods in natural languages process have benefited from attention mechanism a lot [41], [42]. In computer vision, the same idea has been applied and becomes an important component in DNNs, especially in industrial applications.

To attack on attention, we need to calculate the effect of each pixel on the attention, for which network visualization methods [43], [44], [45] are applicable. Forward visualization adopts the intuitive idea to observe attention from calculating the changes in output caused by changes in input. The input can be modified by noise [46], masking [47], or perturbation [48]. However, these methods consume much time and may introduce randomness.

In contrast, backward visualization [47], [49], [50] obtains the heat map by calculating the relevance between adjacent layers from output to input. The layer-wise attention is obtained by the attention in the next layer and the network weights in this layer. Significant works include Layer-wise Relevance Propagation (LRP) [51], Contrastive LRP (CLRP) [52] and Softmax Gradient LRP (SGLRP) [53]. These methods extract the high-level semantic attention features for the images from the perspective of the network and make DNN more interpretable and explainable.

2.4 ImageNet and its variants

To demonstrate and evaluate our attack, we will modify images from ImageNet. ImageNet is a universal dataset [16], which contains images of 1000 classes and each has 1300 well-chosen samples. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) has encouraged a lot of milestone works [17], [54], [55]. Recently, many interesting variants of ImageNet have been developed, including ImageNet-A [56], ObjectNet [57], ImageNet-C, and ImageNet-P [58].

ImageNet-A contains real-world images in ImageNet classes, and they are able to mislead current classifiers to output false predictions. ObjectNet also contains natural images that well-trained models in ImageNet cannot distinguish. Objects in ObjectNet have random background, rotation and viewpoint. ImageNet-C is produced by adding 15 diverse corruptions. Each type of corruptions has 5 levels from the lightest to the severest. ImageNet-P is designed from ImageNet-C and differs from it in possessing additional perturbation sequences, which are not generated by attack but by image transformations.

The datasets mentioned above are very valuable for test and improving the generalization capability, but DAimageNet is for robustness. In other words, samples in the above datasets are different from the samples in ImageNet and the low accuracy is due to poor generalization. In DAmageNet, the samples are quite similar to the original ones in ImageNet and the low accuracy is due to the over-sensitivity of the DNNs. Another difference is that adversarial samples are relatively easy to obtain, so the size of DAmageNet is largely with higher error rate.

3 ATTACK ON ATTENTION (AOA)

To pursue high transferability and black-box attack, we need to find common vulnerabilities and attack semantic features shared by different DNNs. In this paper, we focus on attention and hence develop the so-called Attack on Attention (AoA).

Suppose the attacked neural network is \( f \). Then for an input \( x_{ori} \) with the label \( y_{ori} \), an adversarial sample \( x_{adv} \) could be generated basically by i) minimizing the distance between \( y_{ori} \) and \( f(x_{adv}) \), where \( y_{ori} \) is the attack target label, in the targeted-case; ii) maximizing the distance between \( f(x_{adv}) \) and \( f(x_{ori}) \) in the non-targeted case, both in the constraint that \( \|x_{ori} - x_{adv}\| \) is small.

Different to the existing attacks that focus on the final output, the proposed AoA aims to change the attention heat map. Specifically, let \( h(x, y) \) stand for the attention heat map for the input \( x \) and the specified class \( y \). In AoA, only the attention heat map is considered. The basic idea of attack is to shift the attention away from the original class (non-targeted) or close to the targeted class (targeted) as illustrated in Fig. 2, the corresponding loss is hence called shift loss. In this paper, we utilize SGLRP [53] to calculate the attention heat map \( h(x, y) \). There are of course many techniques for obtaining the heat map, as long as \( h(x, y) \) and its gradient on \( x \) could be effectively calculated.

![Image](image_url)

**Fig. 2:** By minimizing the shift loss, one can change the attention to another target. In the top, the attention is shifted to another class. After the attack, DNN could not find the lizard as shown in the top right. The bottom shows the attack targeted to “panda”. For the clean sample, DNN could not find a panda and in the adversarial sample, DNN incorrectly recognizes the body of the chameleon as a panda because the magnitude of the corresponding heat map is quite large.

In non-targeted attack, we do not have a clear target, so we push the adversarial class away from the original class to the class with the highest prediction probability. Specifically,

\[
p_{non}(x) = \frac{|h(x, y_{ori})|}{|h(x, y_{ori}(x))|},
\]

(2)
where $y_{\text{tar}}(x)$ is the class with highest prediction probability for $x$, except of $y_{\text{ori}}$. In this case, we encourage $|h(x, y_{\text{ori}})|$ to be weakened relative to $|h(x, y_{\text{tar}})|$, so $p_{\text{non}}(x)$ is desired to be small.

In targeted attack, we need to draw the adversarial class close to the targeted class and hence we design as the following,

$$p_{\text{tar}}(x) = \left| \frac{h(x, y_{\text{tar}})}{h(x, y_{\text{tar}}(x))} \right|,$$

where $y_{\text{tar}}(x)$ is the class with highest prediction probability for $x$, except of $y_{\text{tar}}$. We encourage $|h(x, y_{\text{tar}})|$ to be strengthened relative to $|h(x, y_{\text{tar}}(x))|$, so $p_{\text{tar}}(x)$ is desired to be large.

There are two phases for targeted attack. In phase I, starting from the original label, $y_{\text{tar}}(x) = y_{\text{ori}}$ and then maximizing $p_{\text{tar}}$ has similar performance as in the non-targeted case that we encourage the heat map to differ from the original. In phase II, $y_{\text{tar}}(x) \neq y_{\text{ori}}$, where the prediction is already incorrect, but it is not necessarily the target label. Then maximizing $p_{\text{tar}}$ is actually to enhance $h(x, y_{\text{tar}})$ until the targeted attack is achieved.

Notice that we use proportion, not subtraction, to measure the distance because proportion has good transferability across DNNs, which may have different absolute values of heat maps. However, using the proportion make the gradient quite small when $p(x) \leq 1$. Therefore, we turn to optimize $-1/p(x)$ in that case and use the sigmoid membership function to connect the two segments, i.e.,

$$v(p) = p\alpha(p) - \frac{1}{p}(1 - \alpha(p)),$$
$$\alpha(p) = h_{\text{sigmoid}}(p - 1).$$

Finally, we design activation functions on $v(p)$ and obtain two versions of shift loss as follows:

- Normal Rectified Unit (NRU):
  $$F_{\text{shift-n}}(p) = (1 + 4e^{-\frac{(p-1)^2}{2}})v(p).$$
- Log Linear Unit (LLU):
  $$F_{\text{shift-l}}(p) = \left\{ \begin{array}{ll}
  \log(v(p) + 1) & v(p) \geq 0 \\
  -\log(-v(p) + 1) & v(p) < 0.
  \end{array} \right.$$  

In our experience, NRU is good for restricting the change magnitude and LLU is a better choice for high attack success rate. Other activation functions are also possible.

For non-targeted attack, besides of shifting the attention, we also want to distract the attention, from which it follows a distract loss. The idea of the distract loss is illustrated in Fig. 3 and it takes the following formulation,

$$F_{\text{dstr}}(x) = -\left| \frac{h(x, y_{\text{ori}})}{\max(h(x, y_{\text{ori}}))} - \frac{h(x_{\text{ori}}, y_{\text{ori}})}{\max(h(x_{\text{ori}}, y_{\text{ori}}))} \right|.$$

Now we summarize the possible loss functions $L(x)$ in the AoA procedure here.

- Non-targeted case: we will minimize both the shift loss and the distract loss and for the shift loss, there are two choices (AoA-N, AoA-L)
  $$L_{\text{AoA-N}}(x) = F_{\text{shift-n}}(p_{\text{non}}(x)) + \lambda F_{\text{dstr}}(x),$$
  $$L_{\text{AoA-L}}(x) = F_{\text{shift-l}}(p_{\text{non}}(x)) + \lambda F_{\text{dstr}}(x).$$

By iterative update, we could gradually change the image $x$, until attack succeeds, i.e., $\arg \max f(x) \neq y_{\text{ori}}$ in non-targeted case or $\arg \max f(x) = y_{\text{tar}}$ in targeted attack.

For the attacking step length $\varepsilon$ in (7), there are some differences given the attack purposes. For non-targeted attack, we simply keep a constant $\varepsilon$. But targeted attack needs careful modification since the target and the original heat map could be quite different. In our experiments, we set the following adaptive schemes: i) when the white-box attack is achieved, i.e., $\arg \max f(x) = y_{\text{tar}}$, the step length is doubled to address the decision boundary of back-box models. Because the gradient when is towards the right direction. ii) if the step length is smaller than a pre-given threshold $\zeta$, the step length is halved, because the gradient may not be precise.

Now let us first illustrate the attack performance on the attention heat map. In Fig. 4, a clean sample in the class "pinwheel" is drawn together with its heat maps on this class. Aiming at VGG19, we apply the designed targeted attack and successfully change the heat map (the second left column at the bottom). This common property shared by the attention in different DNNs makes the attack transferable, which is the motivation of AoA. The generated adversarial sample is shown in the leftmost in the bottom, which is incorrectly recognized as an “umbrella” by all the DNNs in Fig. 4.

AoA could be used for black-box attack for its good transferability on heat maps. The basic scheme is to choose a (white-box) attacked DNN, then update $x$ by (7), and the generated adversarial samples could be used for black-box attack on other models. A good attack needs to change the label with small distortion, for which there are three black-box attack strategies.
Fig. 4: Attention heat map (on the correct label "pinwheel") for clean and AoA adversarial sample. For clean samples, these heat maps have some common features, implying the possibility of transferability. By AoA on VGG19, the heat maps for not only VGG19 but also other models are disturbed a lot, thus they all make incorrect predictions.

1) Gradually update $x$ until the black-box victim model changes the decision.
2) Set a referred black-box model and stop when the referred model changes the decision.
3) Set a threshold for the number of update iteration or the magnitude of distortion. Stop the update when the threshold is achieved.

Strategy 1) is actually a decision-based black-box attack with few queries. Strategy 2) and 3) are zero-query black-box attacks. In few-query black-box attack, we choose strategy 1) for a good trade-off between distortion magnitude and attack successful rate. In zero-query black-box attack, we choose strategy 2) where one needs an attacked model and a referred model for query to generate images that are then used to attack other models in the zero-query manner.

4 EXPERIMENT
In this section, we will evaluate the performance of our Attack on Attention, especially its black-box attack capability. Since AoA is a very good black-box attack, it provides adversarial samples that can defeat many DNNs in the zero-query manner. These samples are collected in the dataset DAmageNet. This section will also introduce DAmageNet and report the performance of different DNNs on it.

4.1 Setup
The experiments for AoA are conducted on ImageNet. For attack and test, several well-trained models in Keras Applications [59] are used, including VGG19 [17], InceptionV3 [60], NASNetLarge [61], InceptionResNetV2 [62], Xception [63], DenseNet121 [55]. We also use CondenseNet [64] and other adversarial-trained (not by AoA) models. We preprocess with Keras preprocessing function, central cropping and resizing (to 224). The experiment is implemented in TensorFlow [65], Keras [59] with 4 NVIDIA GeForce RTX 2080Ti GPUs.

For the attack performance, we care about two aspects: the success rate of attack and how large the image is changed. Denote the generated adversarial sample as $x_{adv}$ with size $n \times n$. The change from the original image $x_{ori}$ could be measured by $\frac{1}{n} \| x_{adv} - x_{ori} \|_2$, i.e., the root mean squared deviation in each pixel.

In AoA-N, we set $\epsilon = 1$ in (7). In AoA-L, we choose $\lambda = 0.005$ in (5), $\epsilon = 2$ in (7), and $\zeta = -15$. The attack will be stopped when the iteration exceeds 100. For attack performance evaluation, we randomly choose 100 images. The target labels in targeted case are also chosen randomly.

4.2 Few-query AoA
We first consider white-box attack and black-box attack in ImageNet validation set with several queries of decision only, i.e., we will attack in Strategy 1). The average of the success rate, the difference (root mean squared deviation), and the number of queries of AoA-L are reported in Table 1, 2. The query time is below 8 for non-targeted attack and below 30 for targeted attack. Very recent researches [6], [8] still require query times of over 50 to guarantee a high success rate. Note that we only query the output label, not the probabilities.

From Table 1, 2, one could find that VGG19 is a good candidate for generating transferable samples with small distortion, which also coincides with our guess from Fig. 4. For VGG19, we also try AoA-N and report the performance in Table 3 (unanimity requires the same false prediction). Generally speaking, AoA-N can also achieve a good success rate in non-targeted and targeted case. Although the success rate is not as high as AoA-L, the perturbation is smaller. Therefore, AoA-N is a good choice for generating universal adversarial samples. Notice that most of the attack failures could be found during our white-box attack procedure. Therefore, in the adversarial dataset, we can pre-select and only provide samples that can cheat DNNs, which is the reason why the attack success rates reported in the next subsection are higher than that in Table 3.
TABLE 1: AoA-L performance on non-targeted case

| Attacked   | Victim                  | rate differ. | # query |
|------------|-------------------------|--------------|---------|
| VGG19 [17] | VGG19                   | 100%         | 1.776 -  |
|           | DenseNet121 [55]        | 100%         | 10.27  3.12         |
|           | ResNet152 [54]          | 100%         | 10.36  3.21         |
|           | InceptionV3 [60]        | 100%         | 9.595  2.61         |
|           | NASNetLarge [61]        | 100%         | 11.08  3.32         |
|           | Xception [63]           | 100%         | 10.72  3.20         |
|           | InceptionResNetV2 [62]  | 100%         | 10.89  3.26         |
| InceptionV3 [60] | VGG19                  | 99%         | 15.77  6.52         |
|           | DenseNet121 [55]        | 100%         | 9.527  6.61         |
|           | ResNet152 [54]          | 100%         | 17.25  7.79         |
|           | InceptionV3 [60]        | 100%         | 2.063  —             |
|           | NASNetLarge [61]        | 100%         | 15.34  5.91         |
|           | Xception [63]           | 98%          | 14.72  6.10         |
| DenseNet121 [55] | VGG19                  | 100%         | 12.43  3.69         |
|           | DenseNet121 [55]        | 100%         | 1.833  —             |
|           | ResNet152 [54]          | 100%         | 13.38  4.26         |
|           | InceptionV3 [60]        | 100%         | 13.99  4.76         |
|           | NASNetLarge [61]        | 100%         | 16.24  6.26         |
|           | Xception [63]           | 100%         | 13.43  4.43         |
|           | InceptionResNetV2 [62]  | 100%         | 14.54  4.53         |

TABLE 2: AoA-L performance on targeted case (AoA-LT)

| Attacked   | Victim                  | rate differ. | # query |
|------------|-------------------------|--------------|---------|
| VGG19 [17] | VGG19                   | 91%          | 6.9191  |
|           | DenseNet121 [55]        | 89%          | 10.826 12.95         |
|           | ResNet152 [54]          | 87%          | 11.816 13.23         |
|           | InceptionV3 [60]        | 88%          | 10.432 12.80         |
|           | NASNetLarge [61]        | 91%          | 11.448 13.45         |
|           | Xception [63]           | 96%          | 10.621 13.01         |
|           | InceptionResNetV2 [62]  | 91%          | 11.345 12.34         |
| InceptionV3 [60] | VGG19                  | 92%          | 18.814 24.05        |
|           | DenseNet121 [55]        | 96%          | 21.175 27.27         |
|           | ResNet152 [54]          | 88%          | 24.460 32.37         |
|           | InceptionV3 [60]        | 97%          | 9.0882  —             |
|           | NASNetLarge [61]        | 84%          | 21.136 26.82         |
|           | Xception [63]           | 87%          | 17.227 20.85         |
|           | InceptionResNetV2 [62]  | 96%          | 22.716 29.36         |
| DenseNet121 [55] | VGG19                  | 92%          | 12.012 14.86        |
|           | DenseNet121 [55]        | 94%          | 5.7744  —             |
|           | ResNet152 [54]          | 90%          | 13.544 13.80         |
|           | InceptionV3 [60]        | 94%          | 12.917 12.17         |
|           | NASNetLarge [61]        | 94%          | 15.234 14.52         |
|           | Xception [63]           | 95%          | 13.678 14.27         |
|           | InceptionResNetV2 [62]  | 92%          | 14.927 13.46         |

4.3 Zero-query AoA and DAmageNet

The above experiments show that AoA has very promising transferability such that we could directly generate adversarial samples able to beat many well-trained DNNs. For zero-query black-box attack, we choose VGG19 as the attacked model and InceptionV3 as the referred model in Strategy 2). For the loss, we choose non-targeted AoA-N since we pursue small distortion in the adversarial dataset. The distortion is restricted by limiting maximum iteration of attack to 20 and the step length $\varepsilon = 1$.

To guarantee the quality of the dataset, we manually discard samples with low transferability, i.e., the samples that cannot fool InceptionV3 to produce same false label as VGG19 or that are correctly predicted by any networks in NASNetLarge, InceptionResNetV2, Xception, DenseNet121. The image selection scheme and conditions of query can be summarized below. Except VGG19, which is used as the attacked model to generate adversarial samples, InceptionV3, which is used as the referred model for the stop condition, and NASNetLarge, InceptionResNetV2, Xception, DenseNet121, which are queried once for checking the attack performance, other DNNs are only used as victim model for test in the zero-query attack manner.

Since the original images are coming from ImageNet training set and the adversarial samples are going to cheat neural networks, we name this dataset as DAmageNet. The samples in DAmageNet are very similar to those in ImageNet training set and the average root mean square deviation is about 4.2. In Fig. 5, we demonstrate part of the image pairs in ImageNet and DAmageNet.

Fig. 5: Samples in ImageNet and DAmageNet. The images on the left column are original samples from ImageNet. The images on the right column are adversarial samples from DAmageNet. One could observe that these images look similar and human beings have no problem to recognize them as the same class.

DAmageNet contains 96020 adversarial samples in total and could be downloaded from [http://www.pami.sjtu.edu.cn/Show/56/122](http://www.pami.sjtu.edu.cn/Show/56/122). Directories in DAmageNet include 1000 folders with the correct labels as the folder names, which are in the same order of ImageNet. In each folder, one can find around 100 adversarial samples for this class. The file name is the same as that of the original image in ImageNet, with which one can easily find the corresponding sample for evaluation.
TABLE 3: AoA-N performance on non-targeted case and targeted case (AoA-NT)

| Attacked | Victim model   | Non-Targeted success rate | Non-Targeted differ. # query | Targeted success rate | Targeted unanimity differ. # query |
|----------|----------------|---------------------------|------------------------------|----------------------|-------------------------------------|
| VGG19    | DenseNet121    | 100% 1.717 —               | —                            | 78% 6.967            | — —                                 |
|          | ResNet152      | 89% 4.128 7.17             | 70% 4.726 9.32              | 70% 6.865 17.64      | 50% 7.345 17.65                     |
|          | InceptionV3    | 96% 4.224 7.52             | 72% 4.517 8.67              | 71% 7.571 19.87      | 31% 8.406 21.51                     |
|          | NASNetLarge    | 88% 4.097 6.72             | 86% 4.793 9.88              | 71% 6.052 14.90      | 51% 7.395 19.80                     |
|          | Xception       | 98% 3.717 6.17             | 92% 4.153 7.62              | 68% 6.356 15.94      | 54% 6.654 16.89                     |
|          | InceptionResNetV2 | 85% 4.525 8.41       | 77% 5.064 10.47             | 67% 6.614 16.70      | 43% 6.930 17.11                     |

DAmageNet provides adversarial samples that can cheat many DNNs. Here, we use several well-trained models to recognize the images in DAmageNet. Besides, several neural networks strengthened by adversarial training (not by AoA) are considered as well. The error rate (top-1) is reported in Table 3. These samples that DNNs fail to recognize reveal common vulnerabilities of DNNs, which are of great importance to investigate.

TABLE 4: Error Rate (Top-1) on ImageNet and DAmageNet
(For ImageNet, we only consider the images that generate DAmageNet in order to show the attack performance. For the error rates on the whole ImageNet, please refer to the references)

| Victim model   | ImageNet | DAmageNet |
|----------------|----------|-----------|
| VGG16          | 12.6%    | 99.7%     |
| VGG19          | 5.1%     | 99.9%     |
| ResNet50       | 11.4%    | 92.5%     |
| ResNet101      | 17.3%    | 84.6%     |
| ResNet152      | 16.6%    | 81.8%     |
| NASNetMobile   | 13.2%    | 90.3%     |
| NASNetLarge    | 4.8%     | 99.9%     |
| InceptionV3    | 6.4%     | 96.7%     |
| InceptionResNetV2 | 11.7%  | 99.9%     |
| Xception       | 8.8%     | 99.9%     |
| DenseNet121    | 15.2%    | 99.9%     |
| DenseNet169    | 10.8%    | 94.3%     |
| DenseNet201    | 9.5%     | 91.6%     |
| CondenseNet741 | 18.3%    | 95.5%     |
| CondenseNet748 | 22.5%    | 93.1%     |
| InceptionV3adv | 3.8%     | 77.1%     |
| InceptionV3adv3 | 6.9%    | 72.6%     |
| InceptionV3adv4 | 3.4%    | 67.4%     |
| InceptionResNetV2adv | 2.3% | 60.4%         |
|                 |          |            |

4.4 Further Discussions on DAmageNet

Based on the high transferability of common attention features shared by DNNs, AoA successfully provides DAmageNet, the first adversarial dataset with great universal attack performance on different architectures. We are curious about the reason of its aggression and whether it can be mitigated by defense methods although our main contribution is for producing attack transferability instead of breaking the defense.

In the recent years, there is great progress on adversarial defense methods in preprocessing, structure modification and adversarial training. Here, we only adopt popular preprocessing defenses given its practicability. The error rate (top-1) of the secured DNNs on DAmageNet is reported in Table 3. Generally speaking, there are some improvements in the accuracy due to the defense. But still, the results are far from satisfactory.

A possible reason for failure of the defense is that the perturbation generated by AoA is not simple noise. One example is shown in Fig. 5, where the perturbations generated by PGD attack \( l_1 \) (in \( l_1, l_2, l_\infty \) norm) looks like random noise, so they may be eliminated by preprocessing easily. By contrast, perturbations generated by AoA has semantic meaning and concentrates on discriminative regions with great magnitude, so many preprocessing-based defense methods look no effect on AoA.

5 CONCLUSION

To improve the transferability of adversarial attack, we are the first to attack attention and achieve state-of-the-art performance on black-box attack. Success of Attack on Attention (AoA) relies on the semantic features shared by different DNNs. To effectively attack attention, we apply network visualization in designing shift loss and distort loss. It has been evaluated that AoA has promising transferability in both non-targeted case and targeted task. With no more than 10 queries of the decision only, AoA can achieve almost 100% success rate when attacking on many popular DNNs. Even without query, AoA could keep a surprisingly high attack performance.

By AoA, we generate DAmageNet, the first dataset containing samples with small perturbation, strong aggression, and high black-box attack success rate. DAmageNet provides a benchmark to evaluate the robustness of DNN by elaborately-crafted adversarial samples.

AoA has found the common vulnerability of DNNs in attention, which highlights its importance in designing defense methods. Also, attention is only one semantic feature and attacking on other semantic features shared by DNNs is promising to have good transferability.

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### TABLE 5: Error Rate (Top-1) on DAmageNet with defense methods

| Victim model          | JPEG compression | Pixel deflection | Super resolution | Randomization | TVM |
|-----------------------|------------------|------------------|------------------|---------------|-----|
| VGG16 [17]            | 99.5%            | 98.9%            | 98.5%            | 99.8%         | 99.7%|
| VGG19 [17]            | 99.9%            | 99.9%            | 99.9%            | 99.9%         | 99.9%|
| ResNet50 [54]         | 85.2%            | 83.6%            | 80.6%            | 86.5%         | 89.8%|
| ResNet101 [54]        | 75.3%            | 73.9%            | 71.5%            | 76.6%         | 80.3%|
| ResNet152 [54]        | 72.2%            | 71.0%            | 68.4%            | 73.8%         | 77.2%|
| NASNetMobile [61]     | 80.7%            | 79.8%            | 76.1%            | 82.6%         | 85.7%|
| NASNetLarge [61]      | 75.9%            | 76.4%            | 70.6%            | 82.4%         | 85.8%|
| InceptionV3 [60]      | 75.6%            | 75.4%            | 71.0%            | 80.7%         | 83.9%|
| InceptionResNetV2 [62]| 80.7%            | 78.9%            | 74.8%            | 83.4%         | 88.0%|
| Xception [63]         | 85.3%            | 84.3%            | 80.2%            | 86.9%         | 91.9%|
| DenseNet121 [53]      | 90.8%            | 89.9%            | 86.5%            | 91.5%         | 95.0%|
| DenseNet169 [53]      | 84.7%            | 83.7%            | 80.1%            | 87.4%         | 90.2%|
| DenseNet201 [53]      | 80.5%            | 79.6%            | 76.0%            | 83.6%         | 86.6%|
| CondenseNet74-3 [64]  | 88.6%            | 87.9%            | 85.2%            | 95.1%         | 92.3%|
| CondenseNet74-8 [64]  | 87.1%            | 86.4%            | 84.1%            | 93.0%         | 90.7%|
| InceptionV3_adv [66]  | 67.0%            | 65.6%            | 62.2%            | 69.0%         | 73.4%|
| InceptionV3_advens [66],[67] | 63.6% | 62.1% | 59.4% | 65.1% | 69.6% |
| InceptionV2_advens [66],[67] | 59.4% | 58.0% | 55.5% | 60.9% | 64.9% |
| InceptionResNetV2_advens [66],[67] | 52.9% | 51.0% | 48.3% | 55.5% | 58.1% |
| InceptionResNetV2_advens [66],[67] | 47.8% | 46.1% | 44.3% | 50.2% | 52.2% |

Fig. 6: By different attacks, the original sample (“cellphone”) are perturbed and the adversarial samples are incorrectly recognized as “remote”. However, the perturbations given by AoA has semantic meaning. On the one hand, common filters cannot deal with it. On the other hand, semantic perturbations have better transferability. In fact, the adversarial sample generated by PGD can only cheat the attacked DNN while the rightmost image in the top (this is one sample in DAmageNet) can cheat all the DNNs listed before.

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