Generate High-Resolution Adversarial Samples by Identifying Effective Features

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Abstract

As the prevalence of deep learning in computer vision, adversarial samples that weaken the neural networks emerge in large numbers, revealing their deep-rooted defects. Most adversarial attacks calculate an imperceptible perturbation in image space to fool the DNNs. In this strategy, the perturbation looks like noise and thus could be mitigated. Attacks in feature space produce semantic perturbation, but they could only deal with low resolution samples. The reason lies in the great number of coupled features to express a high-resolution image. In this paper, we propose Attack by Identifying Effective Features (AIEF), which learns different weights for features to attack. Effective features, those with great weights, influence the victim model much but distort the image little, and thus are more effective for attack. By attacking mostly on them, AIEF produces high resolution adversarial samples with acceptable distortions. We demonstrate the effectiveness of AIEF by attacking on different tasks with different generative models.

1 Introduction

Deep learning methods, especially deep neural networks (DNN), have achieved extraordinary success in computer vision, natural language process and other fields in recent years [LeCun et al., 2015]. Despite its great success, the mechanism and mathematical theory of DNN have not been deeply investigated. The lack of good understanding and interpretation prevents the use of DNN in many applications with a high requirement on reliability. One evidence that DNNs are far from perfect is the existence of adversarial example, which is first proposed by [Szegedy et al., 2014] and reveals DNN’s defects by specifically customizing an image to cheat a DNN to output false decision with high confidence.

Due to the over-sensitivity of the neural networks, an adversarial sample that looks very similar to the original one is incorrectly predicted. Traditional attack in image space adds samples with semantically meaningless perturbation like noise. This noise-based attack is the main stream of adversarial attack [Goodfellow et al., 2015], [Carlini and Wagner, 2017], [Chen et al., 2018], [Su et al., 2019]. Given that, most defense methods against attack are to restrain the adversarial noise. Although noise-based attacks and the related defense methods have achieved success in understanding and strengthening DNNs, it will be more interesting to link the attack with semantic meanings, which could greatly help feature analysis [Creswell et al., 2017], [Song et al., 2018], [Tang et al., 2019]. On the contrary of noise-based attack, we call the adversarial attack with semantic meaning as feature-based attack, which reveals different information in aspects of perturbation meanings and aggression compared with noise-based attack as illustrated in Figure 1.

In the view of understanding and analyzing DNNs, feature-based attacks are more important and meaningful. However, the current feature-based attacks [Creswell et al., 2017], [Song et al., 2018] are restricted to low resolution. The reason lies in the great number of coupled features to express a high-resolution image (for noise-based attack, there is no difference between high-resolution and low-resolution attacks).

In order to fill in the blank of high-resolution feature-based attack, we propose Attack by Identifying Effective Features

Figure 1: An example for the difference between feature-based attack and noise-based attack. On top, one could observe that in noise-based attack, the change from original sample to the adversarial one has no relation to the image content. Unlike noise-based attack, the change of the feature-based attack is visible and meaningful but from the view of the oracle, e.g., human annotators, the change could not affect the decision but it indeed affects the victim DNN. They differ in mechanism so that the samples from feature-based attack are immune to defense methods for image-based attack (such as filtering).
(AIEF). AIEF first encodes the image into features by optimizing from the decoder. Then it attacks the features and simultaneously, learns the corresponding weights for perturbations of features and therefore identifies effective features for attack. Effective features, those with great learned weights, influence the victim model much but distort the image little, and thus are more effective for attack. With smaller weights, ineffective features either have a little impact on the victim model or controls crucial parts of the image, and they should be kept constant during attack. The effective features AIEF identifies by their weights are a little different from those intuitively selected by human. By attacking mostly on effective features, AIEF could generate high resolution samples (1024 or 512) for different tasks such as face verification and object classification. In numerical experiments, it has been verified that the perturbation calculated by AIEF has semantic meaning and could not be eliminated by several defense methods.

The following sections are organized as below. In Section 2, the developments of related fields in recent years are introduced. Section 3 describes Attack by Identifying Effective Features is illustrated in detail. We demonstrate experimental results on face verification and object classification in Section 4. Finally, Section 5 concludes our paper briefly.

2 Related Work

2.1 Noise-based attack

Adversarial attack, when first proposed [Szegedy et al., 2014], was solved as an optimization problem in image space, which consumes much time. To output samples more effectively, [Goodfellow et al., 2015] developed Fast Gradient Sign Method (FGSM) to compute adversarial perturbation, and it works well in even one step. [Carlini and Wagner, 2017] proposed C&W to restrict $l_0$, $l_2$ and $l_{\infty}$, which serves as an overwhelming attacking method for defensive distillation. [Chen et al., 2018] formulated the process of attacking DNNs as an elastic-net regularized optimization problem. Interestingly, [Su et al., 2019] adopted generic algorithm to achieve one-pixel attack, which alters only one pixel in the image to cheat the DNN.

2.2 Defense methods for attack

To defend noise-based attacks, various methods are broadly proposed. The direct way to improve network’s robustness is to retrain it in an adversarial way [Ganin et al., 2016] [Shrivastava et al., 2017]. The second method is to fundamentally modify the network structure [Xie et al., 2019]. The last technique, the easiest one to implement, is to take a further step to eliminate the adversarial noise before input as the case in [Liu et al., 2019] [Xie et al., 2018], [Prakash et al., 2018]. Despite their success in noise-based attack, they tend to fail faced with feature-based attack.

2.3 Feature-based attack

Different from noise-based attacks, feature-based attacks are recently proposed. [Creswell et al., 2017] changed the framework of variational autoencoder to calculate additive and multiplicative perturbation. This attack alters latent feature vectors in a minimum degree so output of the classifier remains the same, but the decoded images belong to different classes. [Song et al., 2018] used AC-GAN to construct unrestricted adversarial samples in low resolution. Since it uses the auxiliary classifier (AC) as an oracle to guarantee that the samples remain in the same class in view of human, AC must be for the same task as the victim network. New AC-GANs have to be trained for new tasks and tasks beyond classification could not be achieved. In [Tang et al., 2019], Type I attack was discussed compared to the traditional Type II attack. Type I attack cheats the classifiers with significant changes, but the output of victim model remains unchanged. It demonstrates high resolution samples for Type I attack, but we provide Type II ones that look similar to original ones.

2.4 Generative models in attack

To realize adversarial attack in feature space, a decoder to generate image from latent feature space is required. The thriving of the generative model contributes greatly to the growing of feature-based attack. Variational autoencoder (VAE) [Kingma and Welling, 2014] and generative adversarial network (GAN) [Goodfellow et al., 2014] are two mainstream approaches. As for their usage in attack, feature-based one tends to use VAE since the distribution in latent space is constrained to standard normal. But the image VAE generates is vague with blurry edge compared to GAN. In our work, we implement AIEF on the latest StyleGAN [Karras et al., 2019] with 1024*1024 output and BigGAN [Brock et al., 2019] with 512*512 output. AIEF can also be applied to other GAN structure readily.

2.5 Explain the adversarial attack

Given the threat of adversarial attack, many researches provide explanations for them. [Dong et al., 2019], [Zhang and Zhu, 2019] found that the attack influences the attention of DNNs, which may account for the aggression of adversarial samples. Another thriving topic is to study the boundary of attack’s threat and therefore certify the robustness of DNNs [Cohen et al., 2019], [Salman et al., 2019]. By this way, the degree of aggression or robustness could be theoretically calculated. [Ilyas et al., 2019] interpreted adversarial samples as a result of learning from non-robust features, which are defined in image space and disentangled from robust ones by optimization in encoding. They are falsely exploited by DNNs to increase accuracy, which reveals their poor generalization. Differently, our effective features are defined in latent space and identified during adversarial attack, which are effective for attack and reveal the over-sensitivity of DNNs.

3 Attack by Identifying Effective Features

In this section, we would describe and analyse AIEF in detail. The loss functions for attack and identifying effective features are first introduced. Then, procedures of AIEF are illustrated. We would lastly identify effective features and analyse how they influence the attack.

3.1 Method

The intuitive idea for attack is to change the output of the victim network while keeping image perturbation small. However, direct imposing these two purposes on feature space
may result to an unacceptable image distortion. This phenomenon is even more prominent for high resolution images because of the great number of features to express a high-resolution image. For example, 20 latent features would be enough to represent a 28×28 gray-scale digit number in VAE, but a 1024×1024×3 image requires 18×512 features to express in StyleGAN. Manually selecting features to attack is also impractical because they are coupled in most cases. To achieve high-resolution attack, we propose Attack by Identifying Effective Features (AIEF) as in Figure 2.

In AIEF, the key idea is to learn different weights, denoted as $\sigma_i$, for different feature perturbations $\Delta z_i$. The weights correspond to the effectiveness of the features in attack and therefore serve as the basis for feature identification. $\sigma$ is normalized by its sum before multiplied with the feature perturbation $\Delta z$ in the element-wise way. The overall strategy to generate adversarial samples is

$$x = \text{dec} \left( z + \frac{\sigma}{\sum_{i=1}^n \sigma_i} \cdot \Delta z \right),$$

(1)

where $x$ is the adversarial sample, $z$ is the original features need to be obtained by encoding from the decoder $\text{dec}$.

The procedure could be divided into encoding and attacking. To conduct feature-based attack, one should first encode the sample into latent space. Rather than training a new encoder, we conduct this process by optimizing $L_{\text{img}}$, which does not consume much time. After encoding, the corresponding $z$ for the original images is obtained and fixed in the following steps.

In attacking, we optimize $L_{\text{pred}}$ on $\Delta z$ for fooling the victim network as other methods do. Differently, we also periodically optimize $L_{\text{img}}$ to modify $\sigma$, the corresponding weights for the perturbation in latent space. After several iterations, effective features with larger weights are identified.

The crucial scheme is to optimize $\Delta z$ for false prediction and optimize $\sigma$ for an acceptable image distortion separately. The former loss $L_{\text{pred}}$ is specified for different tasks and $L_{\text{img}}$ is defined in pixel-wise absolute difference. They are expressed as

$$L_{\text{pred}} = L(f, x),$$
$$L_{\text{img}} = |x - x_{\text{ori}}|,$$

(2)

where $x_{\text{ori}}$ stands for the original clean sample.

As summarized in Algorithm 1, the encoding before attack is also done easily with no additional encoder. In attacking, $\sigma$ truly serves as weights given that magnitude of $\Delta z$ is relatively similar. The features with great weights are called effective features for attack. AIEF selects them as good candidates for attack, which means changes in them influence the prediction of the victim model a lot, but do not distort the decoded image much. In contrast, features with small weights are ineffective features. Modifications on them are either unnecessary for false prediction or dangerous for large distortion.

According to the weights learned during the attack, one could then abandon the $\Delta z_i$ for ineffective features in pursuit of a smaller distortion but also maintain good attack performance. Analysis on this feature identification would be thoroughly illustrated in the next subsection.

### 3.2 Analysis

We study the weights distribution and their affects by taking StyleGAN [Karras et al., 2019] as the decoder, and FaceNet [Schroff et al., 2015] as the victim model. Here, we study about whether the feature weights reflect their real influence.
in attack and how features with different weights influence the attack. All Results are demonstrated in Figure 3 and we would illustrate it in the remaining section.

StyleGAN has a hierarchy of features from crucial to superficial ones, which respectively control key or irrelevant parts of the image as specified in the structure. We adopt this setting in StyleGAN for analysing the hierarchy of effective features identified in AIEF. The weights are generally plotted at top of Figure 3, from which one could find that superficial features are most effective for attack. The reason is that most superficial features have little influence on the prediction of victim network while the crucial features impose an unacceptable impact on the image.

To further study how features with different weights affect the image and attack, we set the feature perturbations $\Delta z_i$ to 0 for a proportion of features with the smallest weight (most ineffective features) to conduct feature selection. Except them, the perturbations for the remaining feature are still functional. We denote the ratio of the remaining functional features as $R$. $R = 0$ gives original samples since all perturbations of features are set to 0. Those samples are shown on the leftmost column in Figure 3. To evaluate on the attack, other samples are matched with the clean sample by FaceNet. An image is considered as an adversarial sample if it is not matched with the original one. The attack would succeed just if a small proportion of feature perturbations (for effective features) are functional, which indicates the necessity to learn different weights for different features.

For the decoded image, one could observe the slight changes in the middle of Figure 3. As $R$ gradually increases, the decoded sample gradually grows aggressive and crosses the decision boundary at some point. In this period, effective features work and the sample quickly becomes an adversarial one. As $R$ continues to increase, influence of ineffective features reveals. The resulting additional slight changes focus on the most superficial features, i.e., blurriness and light, and the most crucial features, i.e., expression and facial features, which corresponds to previous analysis about the hierarchy of ineffective features.

Note that we choose StyleGAN here because it expresses a high-resolution image with hierarchy features as specified in its structure. This property provides basis of analysing the hierarchy of feature that AIEF identifies. AIEF could also be applied to any generative models other than StyleGAN, i.e., BigGAN [Brock et al., 2019] as shown in the next section.

4 Experiment

In this section, we implement AIEF on StyleGAN (trained on CelebA-HQ [Karras et al., 2017]) and BigGAN (trained on ImageNet [Deng et al., 2009]) to generate adversarial samples. We set the parameters in Algorithm 1 as encoding loss threshold $\epsilon = 3.5$, maximum attack iteration $m = 100$, optimization proportion $p = 2$ for experiments below. Adam optimizer [Kingma and Ba, 2015] with $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$ is used.

We use well-trained victim models including FaceNet [Schroff et al., 2015], ResNet152 [He et al., 2016], DenseNet121 [Huang et al., 2017] and VGG19 [Simonyan and Zisserman, 2015] implemented in TensorFlow [Abadi et al., 2015] or PyTorch [Paszke et al., 2019]. 4 NVIDIA GeForce RTX 2080Ti GPUs are used for computation.

It could be seen that AIEF is capable of feature-based high-resolution attack for different tasks and these adversarial samples are immune to several defense methods.

4.1 AIEF on face verification

We first report the results of experiments on face verification, which is relatively harder to attack. For the classification task, the victim network could be fooled to produce any decision other than the correct one. However, in face verification, the embedding features of two images are extracted and matched in distance. In this case, only feature extraction procedure could be attacked. A common practice to attack on face verification is to fool network not to match two different images of one person. Compared to that, we implement AIEF in a more challenging scenario where adversarial sample has to fool the victim not to match it with the original one.

We take the synthesis network in StyleGAN (1024*1024 output, trained on CelebA-HQ) as the decoder and FaceNet as the victim model. StyleGAN has 18*512 features, on which we conduct AIEF. We use the FaceNet pre-trained on CelebA, which has 99.05% accuracy on LFW [Huang et al., 2008] dataset. The same face alignment, pre-whitening, and pre-processing operations are conducted as in [Schroff et al., 2015]. We specify the prediction loss in face verification as

$$L(f_{face}, x) = h_{ReLU}(1.6 - D_{face}(x, x_{ori})).$$

(3)

$D_{face}$ is calculated in the way FaceNet specified (below 1.242 for matching). It induces $D_{face}$ to grow larger but saturates.
when it is too large (exceeds 1.6). Adam learning rate is 0.2 for $L_{img}$ and 0.005 for $L_{prd}$. The analysis in the last section share the same setting, but here, we show the numerical and image results for massive experiments.

The adversarial samples produced by AIEF are demonstrated in Figure 4. One could observe that they differ from the original samples only in a small semantic perturbation. But FaceNet does not match them as the same person, and outputs large distances far larger than the threshold.

![Figure 4: AIEF on face verification. The first column is the original clean samples. AIEF generates semantic perturbation in the second column. The adversarial samples in the third column are not matched with the original ones with a FaceNet distance of 1.59, 1.59, 1.61, 1.65 respectively. (below 1.242 for matching)](image)

Table 1: Performance on AIEF for Face Verification

| $D_{face}$ | RMSD |
|-----------|------|
| AIEF | PGD | AIEF | PGD |
| $R = 0.3$ | 0.923 | — | 8.1463 | — |
| $R = 0.5$ | 1.295 | — | 9.8953 | — |
| $R = 0.7$ | 1.543 | — | 10.358 | — |
| $R = 1.0$ | 1.620 | 1.633 | 12.962 | 1.3161 |
| $R = 1.0$ (JPEG) | 1.617 | 0.992 | 13.201 | 2.7112 |
| $R = 1.0$ (Random) | 1.487 | 0.329 | 41.315 | 40.216 |
| $R = 1.0$ (Pixel) | 1.566 | 0.351 | 14.733 | 10.156 |

We generate 1000 adversarial samples to evaluate AIEF. Besides the FaceNet distance $D_{face}$, we also care about the image perturbation in root mean square deviation (RMSD), calculated by $\frac{1}{n} \| x - x_{ori} \|^2_2$ for a $n \times n$ image. The average numerical results are shown in Table 1. In the first three rows, we vary the proportion of functional feature perturbation $R$. That is, we only allow $R * 100\%$ most effective features to be modified. One would find that most samples become adversarial ones when $R > 0.5$, which means only about 50% features are required to be modified for a success attack.

For the last four rows, we set $R = 1$ to modify all features and compare the results with PGD [Madry et al., 2018], the strongest noise-based attack, in face of defense methods including JPEG compression [Liu et al., 2019], random padding and resizing [Xie et al., 2018] (large distortion is from the black padding), pixel deflection [Prakash et al., 2018]. The attack iteration for PGD is also $m = 100$ and its step length is 1. The results reveal that AIEF could mislead FaceNet to produce samples that fool it to make extreme false prediction ($D_{face}$ over 1.6). The semantic perturbation leads to a relatively large RMSD, but it has no impact on the crucial parts of the image, so it is acceptable with no violation of the principle for attack. Noise-based attack could fool FaceNet but their aggression could be mitigated by several defense methods. But AIEF, which is based on features and produce non-noise perturbations, could bypass those defense methods.

### 4.2 AIEF on object classification

In this section, we put AIEF on another GAN structure for a different task. Specifically, we take BigGAN (512*512 output, trained on ImageNet) as the decoder, ResNet152, DenseNet121 and VGG19 as the victim model and conduct AIEF on object classification. BigGAN has 128-D feature input in the latent space, but the feature has no hierarchy as StyleGAN. BigGAN could generate high resolution images with high fidelity for a specified class in ImageNet. The officially public pre-trained model is capable of generating 4 classes of images, so we could only attack image in these classes.

The prediction loss is specified as the output probability in the original correct class as

$$L(y_{ori}, x) = f_{obj}^{y_{ori}}(x)$$  \hspace{1cm} (4)

where $y_{ori}$ is the original class ID. Adam learning rate is 0.01 for $L_{img}$ and 0.1 for $L_{prd}$. We do not use the traditional MSE or CrossEntropy training loss because attack aims for an incorrect decision, not an incorrect output distribution. The generated adversarial samples are shown in Figure 5. Also, AIEF cheats various networks by producing semantic perturbations and fools ResNet152 to predict on a completely irrelevant class. The adversarial samples differ from the original ones in background or shape, but the object remains in the same class. Numerically, the overall success rate is higher than 95% for three victim networks and the distortion is in the same magnitude as face verification. However, here we could not provide the success rate over the whole ImageNet, since BigGAN is only capable of generating images in four ImageNet classes.
5 Conclusion

Traditional noise-based attack could not generate samples with semantic perturbation, which however, is the strength of feature-based attack. Current feature-based attacks are restricted in low resolution because of the great number of coupled features to express a high-resolution image. In this paper, we address this issue by learning the weights for different features and are the first to conduct high resolution attack. In the proposed Attack by Identifying Effective Features (AIEF), effective features for attack are automatically learned and identified during attack. Although they account for less than 50% of the features, effective features have a significant influence on fooling the victim network with an acceptable distortion. Accordingly, one could select a proportion of the most effective features to attack for a trade-off between attack result and image distortion. By conducting experiments on StyleGAN for face recognition and BigGAN for object classification, we demonstrate that AIEF could be applied to different generative models and attack on various tasks.

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