Transferable Adversarial Attacks for Image and Video Object Detection

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Abstract

Adversarial examples have been demonstrated to threaten many computer vision tasks including object detection. However, the existing attacking methods for object detection have two limitations: poor transferability, which denotes that the generated adversarial examples have low success rate to attack other kinds of detection methods, and high computation cost, which means that they need more time to generate an adversarial image, and therefore are difficult to deal with the video data. To address these issues, we utilize a generative mechanism to obtain the adversarial image and video. In this way, the processing time is reduced. To enhance the transferability, we destroy the feature maps extracted from the feature network, which usually constitutes the basis of object detectors. The proposed method is based on the Generative Adversarial Network (GAN) framework, where we combine the high-level class loss and low-level feature loss to jointly train the adversarial example generator. A series of experiments conducted on PASCAL VOC and ImageNet VID datasets show that our method can efficiently generate image and video adversarial examples, and more importantly, these adversarial examples have better transferability, and thus, are able to simultaneously attack two kinds of representative object detection models: proposal based models like Faster-RCNN, and regression based models like SSD.

1. Introduction

Deep learning techniques have achieved a great success in the various computer vision tasks [25,13,19,15]. However, it is also proved that neural networks are vulnerable to the adversarial example [24]. Because of the danger, it has attracted lots of attentions. The initially involved computer vision task is image classification. For that, a variety of attacking methods have been proposed, such as FGSM [10], deepfool [18], C&W attack [3], and so on. Meanwhile, more and more methods are presented to attack other tasks. For example, Sharif, et.al [22] design the real and stealthy attacks on state-of-the-art face recognition. Wei, et.al [26] propose the sparse adversarial perturbations for video action recognition. Evtimov, et.al [8] explore the physical-world attack for road signs detection. We refer readers to [1] for the detailed threat of adversarial attacks on computer vision.

Object detection from images and videos is the fundamental task in computer vision, and thus has broad applications like automation driving, security surveillance system,
Figure 2. The overall framework of our Unified and Efficient Adversary (UEA). We formulate DAG’s high-level class loss with the proposed low-level multi-scale feature loss into GAN framework to jointly train a better generator. For the coming images or video frames, the generator is to output the corresponding adversarial images or frames to simultaneously fool the different kinds of object detectors.

etc. Compared with the image scenario, video object detection considers the temporal interactions between frames [31, 32]. In order to attack object detection, Xie, et al. [28] propose a Dense Adversary Generation (DAG) for images. They choose Faster-RCNN [21] as the threat model. DAG firstly assigns an adversarial label for each proposal region and then performs iterative gradient back-propagation to misclassify the proposals. The similar methods are also presented in [5, 10]. As we know, the current object detection models can be roughly categorized into two classes: proposal based methods and regression based methods. DAG achieves adversarial examples via manipulating the class label. The key component is a class loss, which is specially designed for misclassifying the proposals. That means DAG has poor transferability, and cannot work well on regression based detectors, where no proposals are used. In addition, DAG is an optimization method. The authors state it needs 150 to 200 iterations to meet the end for each image [28]. The high computation cost makes DAG not available for attacking video object detection, where many key frames need polluting with adversarial perturbations.

To address these issues, in this paper, we propose the Unified and Efficient Adversary (UEA) for attacking image and video object detection. “Efficient” denotes that our method is able to quickly generate the adversarial image, and thus can efficiently deal with every frame in the video data. To this end, we utilize a generative mechanism instead of the optimization procedure [28, 10]. Specifically, we formulate the problem into Generative Adversarial Network (GAN) framework like [27], and train a generator network to generate adversarial images and key frames. Because the testing step only involves the forward network, the running time is fast. As for “Unified”, it means that the proposed adversary can simultaneously attack the current two kinds of representative object detection models. We observe that both the proposal and regression based detectors utilize feature networks as their backends. For examples, Faster-RCNN and SSD [17] use the same VGG16 [23]. If we destroy the extracted features from the backend feature network, both of them will be influenced. This idea is implemented as a multi-scale feature loss in our paper, i.e., destroying the feature maps from multiple layers. In the viewpoint of DNNs’ depth, DAG’s class loss is applied on the high-level softmax layer, and feature loss is performed on the low-level backend layer. We integrate the low-level feature loss and the high-level class loss within the GAN framework to jointly enhance the transferability. When a new image or video is coming, the trained generator is to efficiently generate transferable adversarial examples. Figure 1 gives an example output by UEA, and Figure 2 lists the overall framework.

In summary, this paper has the following contributions:

- We propose the Unified and Efficient Adversary (UEA) for attacking image and video detection. UEA is the first attacking method that can not only efficiently deal with both image and video data, but also simultaneously fool the proposal based detectors and regression based detectors.

- We propose a multi-scale feature loss to enhance the transferability of current attacking methods for object detection. Furthermore, we formulate the high-level class loss and low-level feature loss within GAN framework to jointly train a better generator.

The rest of this paper is organized as follows. In Section 2, we briefly review the related work. We present the proposed Unified and Efficient Adversary framework in Sec-
tion 3. Section 4 reports all experimental results. Finally, we summarize the conclusion in Section 5.

2. Related Work

The related work comes from two aspects: image and video object detection based on deep learning and adversarial attack for object detection.

2.1. Image and Video Object Detection

Object detection is an area where deep learning has shown its great power. Currently, the dominant object detection models can be roughly categorized two classes: proposal based models and regression based models. The former class typically contains R-CNN [9], Faster-RCNN [21], Mask-RCNN [11], etc. This kind of methods use a two-step procedure. They firstly detect many proposal regions, and then classify them to output the final detected results. The latter class is represented by YOLO [20] and SSD [17]. They regard the detection task as the regression process, and directly predict the coordinates of bounding boxes. Because region proposals are omitted, these methods are more efficient. Compared with the image scenario, video object detection incorporates temporal interactions between adjacent frames in the procedure. They usually apply the existing image detector on the selected key frames, and then propagate the bounding boxes via temporal interactions [31] [22] [4] [30]. Therefore, image object detection forms the basis of the video object detection. In this paper, we try to present an unified method that can attack both the image and video object detection models.

2.2. Adversarial Attack for Object Detection

Currently, adversarial attacks for the object detection are rare. The first method is proposed by [28], named DAG. They firstly assign an adversarial label for each proposal region and then perform iterative gradient back-propagation to misclassify the proposals. DAG is based on the optimization, and is time consuming, it needs many iterations to accomplish an adversarial image. [5] [16] also present the similar idea. In addition, [2] tries to attack the face detector. But their threat model is also based on proposal based detectors (specifically Faster-RCNN). The same points of these works lie in the attacks versus proposal based object detectors, and usage of the optimization manner. Up to now, there is no any method that aims at attacking the regression based detectors. And of course, an unified adversary, which can simultaneously attack proposal based and regression based detectors, is absent. In this paper, we try to fill in this gap, and present an unified method that can attack both the detectors. Table 1 shows the difference between ours and the existing attacking methods.

| Methods | Image | Video | Proposal | Regression |
|---------|-------|-------|----------|------------|
| [2]     | ✓     | ✓     | ✓        | ✓          |
| [5]     | ✓     | ✓     | ✓        | ✓          |
| [16]    | ✓     | ✓     | ✓        | ✓          |
| [28]    | ✓     | ✓     | ✓        | ✓          |
| Ours    | ✓     | ✓     | ✓        | ✓          |

3. Methodology

In this section, we introduce the details of the proposed Unified and Efficient Adversary (UEA).

3.1. Problem Definition

Given an image \( I \), our goal is to generate its corresponding adversarial image \( \hat{I} \). We hope that \( \hat{I} \) can attack the object detector \( D_t \). For a ground-truth object \((B_i, C_i)\) on \( I \), where \( B_i \) is the bounding box, and \( C_i \) is the label. Suppose the object detector \( D_t \) succeeds to detect this object and outputs \((\hat{b}_i, \hat{c}_i)\), where the IoU between \( B_i \) and \( \hat{b}_i \) is more than 0.5, and \( C_i = \hat{c}_i \). We let \((\hat{b}_i, \hat{c}_i)\) denote the detected result of this object on the adversarial image \( \hat{I} \) (Note that \( \hat{b}_i \) may be empty, which represents \( D_t \) doesn’t detect this object). If the IoU between \( b_i \) and \( \hat{b}_i \) is less than 0.5 or \( \hat{c}_i \neq C_i \), we can say the object detector \( D_t \) is successfully attacked or fooled. In order to roundly measure the performance of attacking methods, we will compute the mAP metric on the entire dataset, and check the mAP drop after attacks. For videos, we regard the key frames in a video as images, and perform the same operation above. We expect the adversarial video can also fool the state-of-the-art video detection models. The \( D_t \) is based on proposals or regression.

3.2. Unified and Efficient Adversary

In this section, we introduce the technical details of UEA. Overall, we utilize a generative mechanism to accomplish this task. Specifically, we formulate our problem into the conditional GAN framework. The objective of the conditional GAN can be expressed as:

\[
\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_I[\log D(I)] + \mathbb{E}_{\hat{I}}[\log (1 - G(\hat{I}))],
\]

(1)

where \( G \) is the generator to compute adversarial examples, and \( D \) is the discriminator to distinguish the adversarial examples from the clean images. Because adversarial examples are defined as close as possible with original examples [24], we input the original images (or frames) and adversarial images (or frames) to the discriminator to compute GAN loss in Eq. (1). In addition, a \( L_2 \) loss between the clean images (or frames) and adversarial images (or frames) is applied to measure their similarity:

\[
\mathcal{L}_{L_2}(G) = \mathbb{E}_I[||I - G(I)||_2].
\]

(2)
After training the generator based on GAN framework, we use this generator to generate adversarial examples for testing images and videos. The adversarial examples are then fed into the state-of-the-art object detectors to accomplish the attacking task.

### 3.3. Network Architecture

Essentially, the adversarial example generation can be formulated into an image-to-image translation problem. The clean images or frames are input, and the adversarial images or frames are output. Therefore, we can refer to the training manner of pix2pix [12]. In this paper, we utilize the network architecture in [27] for ImageNet images, that is the first framework to generate adversarial examples using a pix2pix adversarial generative network. The generator is an encoder-decoder network with 19 components. The discriminator is similar to ResNet-32 for CIFAR-10 and MNIST [27]. Please refer to [27] for the detailed structure of the generator and discriminator.

### 3.4. Loss Functions

To simultaneously attack the current two kinds of object detectors, we need additional loss functions on the basis of Eq. (1) and Eq. (2). To fool Faster-RCNN detector, DAG [28] uses a misclassify loss to make the predictions of all proposal regions go wrong. We here also integrate this loss. The class loss function is defined as follows:

\[ L_{DAG}(G) = \mathbb{E}_I[\sum_{n=1}^{N} [f_{l_n}(X, t_n) - f_{\hat{l}_n}(X, t_n)]] \]

where \( X \) is the extracted feature map from the feature network of Faster-RCNN on \( I \), and \( \tau = \{t_1, t_2, ..., t_N\} \) is the set of all proposal regions on \( X \). The symbol \( t_n \) is the \( n \)-th proposal region from the Region Proposal Network (RPN). \( l_n \) is the ground-truth label of \( t_n \), and \( \hat{l}_n \) is the wrong label randomly sampled from other incorrect classes. \( f_{l_n}(X, t_n) \in \mathbb{R}^C \) denotes the classification score vector (before softmax normalization) on the \( n \)-th recognition proposal region of \( X \). We see that Eq. (3) can find adversarial perturbations to make adversarial examples go beyond the classification boundary. In the experiments, we restrict 2000 proposals, and pick those with more than 0.7 score.

DAG loss function is specially designed for attacking Faster-RCNN, therefore its transferability to other kinds of models is weak. To address this issue, we propose the following multi-scale feature loss:

\[ L_{Fca}(G) = \mathbb{E}_I[\sum_{m=1}^{M} ||X_m - R_m||_2], \]

where \( X_m \) is the extracted feature map in the \( m \)-th layer of the feature network. \( R_m \) is a randomly generated feature map, and its size is the same with \( X_m \). Eq. (4) enforces the random permutation of feature maps. In the experiments, we choose the Relu layer after conv3-3 and the Relu layer after conv4-2 in VGG16 to destroy their feature maps.

Finally, our full objective can be expressed as:

\[ L = L_{GAN} + \alpha L_{L_2} + \beta L_{DAG} + \epsilon L_{Fca}, \]

where \( \alpha, \beta, \epsilon \) are the relative importance of each objective. We set \( \alpha = 0.05, \beta = 1 \). For \( \epsilon \), we set 0.00002 and 0.00004 for the selected two layers, respectively. \( G \) and \( D \) are obtained by solving the minmax game \( \arg\min_{G} \max_{D} L \). To optimize our networks under Eq. (5), we follow the standard approach from [12]. We use minibatch SGD and apply the Adam solver [13]. The best weights are obtained after 6 epochs. At the inference time, we run the generator net in exactly the same manner as during the training phase.

### 4. Experiments

#### 4.1. Datasets

**Image Detection** In order to train the adversarial generator in UEA, we use the training dataset of PASCAL VOC 2007. Thus, there are totally 5011 images. They are categorized into 20 classes. In testing phase, we use the PASCAL VOC 2007 testing set [2] with 4952 images.

**Video Detection** For video detection, we use ImageNet VID dataset[1]. There are 759 video snippets for training set, and 138 for testing set. The frame rate is 25 or 30 fps for most snippets. There are 30 object categories, which are a subset of the categories in the ImageNet dataset.

#### 4.2. Metrics

We will evaluate UEA from three aspects: attacking performance against object detectors; perceptibility of generating adversarial examples; the generating time for adversarial examples. Specifically, we choose the following three evaluation metrics:

**Fooling Rate** to test the fooling rate of different attacking methods, we use the drop versus mAP metric (mean Average Precision). The mAP is usually to evaluate the recognition accuracy of object detectors both for image and video data. If the adversary is strong, detectors will achieve a lower mAP on adversarial examples than clean examples. The reducing error can be used to measure the attacking methods.

**Perceptibility** because adversarial examples are expected to be close with clean examples, we hope the generated adversarial examples are imperceptible. Here we use PSNR (Peak Signal to Noise Ratio) and SSIM (Structural Similarity Index) to give the quantitative measure about the quality of adversarial examples.

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[1] http://visionweb1.cs.unc.edu/ILSVRC2017/download-videos-1p39.php
Time: to tackle with video data, the time for generating adversarial examples is important. In the experiments, we report the processing time for each image (frame) versus different attacking methods.

4.3. Threat Models

Image Detection In this setting, our goal is to simultaneously attack the proposal based detectors and regression based detectors. We select two representative methods: Faster-RCNN and SSD300. There are a lot of implementation codes for them. Here we use the Simple Faster-RCNN\footnote{https://github.com/chenyuntc/simple-faster-rcnn-pytorch} and torchCV SSD300\footnote{https://github.com/kuangliu/torchcv}. We retrain their models on PASCAL VOC training datasets. Specifically, Faster-RCNN is trained on the PASCAL VOC 2007 training dataset, and tested on the PASCAL VOC 2007 testing set. The detection accuracy (mAP) reaches 0.70. SSD300 is trained on the hybrid dataset consisting of PASCAL VOC 2007 and 2012 training set, and tested on the PASCAL VOC 2007 testing set. The detection accuracy (mAP) reaches 0.68.

Video Detection As mentioned previously, the current video detection methods are based on image detection. They usually perform image detection on key frames, and then propagate the results to other frames \cite{31,32,4,30}. However, as shown in \cite{32}, the recognition accuracy of these efficient methods cannot even outperform the simple dense detection method, that densely runs the image recognition on each frame in a video. In \cite{31}, although their method beats dense detection method, they cost more time. If they reduce the processing time, the accuracy also falls below the dense detection. Therefore, we choose the dense detection method as the thread model. We think if the dense detection method is successfully attacked, the efficient methods will also fail.

4.4. Results on Image Detection

4.4.1 Comparisons with State-of-the-art Methods

The current state-of-the-art attacking method for image detection is DAG. Therefore, we use DAG as our compared method. For that, we generate adversarial image using DAG and UEA, respectively, and then perform the same Faster-RCNN (FR) and SSD300 (SSD) on the adversarial examples to observe the accuracy drop (compared with the accuracy on clean images). Meanwhile, we also check the quality (SSIM) of generated adversarial images and the generating time (Time). The comparison results are reported in Table 2.

From the table, we see: (1) Both DAG and UEA work well versus Faster-RCNN detector. They achieve the same 0.65 accuracy drop (0.70-0.05). This is expected because DAG and UEA formulate the same class loss of Eq. (3) into their methods, and Eq. (3) is specially designed for Faster-RCNN. That means DAG and UEA perform the white-box attack against Faster-RCNN. (2) DAG cannot attack SSD detector, the accuracy drop is only 0.04 (0.68-0.64). As a contrast, UEA obtains a 0.40 accuracy drop (0.68-0.28), which is 10 times larger than DAG. This is also interpretable because DAG is an optimization method, the generated adversarial images are overfitting to attack Faster-RCNN, and thus cannot transfer to attack other detectors. Instead, UEA integrates a feature loss to destroy the shared feature networks between Faster-RCNN and SSD. The feature loss enhances the transferability of UEA to other kinds of detectors. In the experiments, we take SSD as the example to verify UEA. Theoretically, UEA is able to attack a large class of object detectors, because the majority of object detectors use the feature network. (3) As for the generating time of adversarial examples, UEA is almost 1000 times faster than DAG (0.01 vs 9.3). The efficiency is helpful to tackle with video data for UEA. Even for the video with 100 frames, UEA will only costs one second to pollute all the frames, and generates an adversarial video to fool video object detectors. (4) The SSIM of DAG is better than UEA. However, we give a comparison of the adversarial examples of DAG and UEA in Figure 3. We see that their appearances are similar, and cannot be distinguished by human beings.

### Table 2. The comparison results between DAG and UEA versus three aspects.

| Methods | FR | SSD | SSIM | Time(s) |
|---------|----|-----|------|---------|
| Clean Images | 0.70 | 0.68 | 1.00 | \   |
| DAG     | 0.05 | 0.64 | 0.98 | 9.3    |
| UEA     | 0.05 | 0.28 | 0.81 | 0.01   |

Figure 3. Comparisons of adversarial images generated by DAG and UEA. The first row is output by DAG and the second row is output by UEA. We see that although SSIM values in Table 2 have the difference, their appearances are similar, and cannot be distinguished by human beings.

4.4.2 Ablation Study of UEA

Now we look into the ablation study of UEA. As introduced in Section 3, UEA utilizes two key loss functions in the training phase. The first is class loss, i.e., Eq. (3), and the second is multi-scale feature loss, i.e., Eq. (4). We study the
function of each loss, and report the results in Table 3.

Table 3. The ablation study of UEA under different settings.

| Methods     | FR  | SSD | PSNR | SSIM |
|-------------|-----|-----|------|------|
| Class Loss  | 0.09| 0.48| 33.34| 0.90 |
| Feature Loss| 0.03| 0.17| 28.83| 0.75 |
| Hybrid Loss | 0.05| 0.28| 30.08| 0.81 |

In Table 3, “Class Loss” denotes the absence of “Feature Loss” in UEA and vice versa. “Hybrid Loss” is the full version of UEA with both “Class Loss” and “Feature Loss”. From the table, we see “Class Loss” has the weakest attacking ability both for Faster-RNN and SSD300, while the quality of their adversarial examples is the best (33.34 for PSNR, and 0.90 for SSIM). On the contrary, “Feature Loss” shows the strongest attacking ability with the low-quality adversarial examples. UEA reaches a balance between the attacking ability and quality of adversarial examples. These results demonstrate that hybrid the high-level class loss and low-level feature loss is a reasonable choice for attacking object detector. The ablation study of UEA for each category recognition is also given in Figure 4.

4.4.3 Qualitative Comparisons

We give some qualitative comparisons between DAG and UEA. Figure 5 lists five such examples. From the figure, we see both Faster-RCNN and SSD300 work well on the clean images, and detect the correct bounding boxes and labels. For DAG, it succeeds to attack Faster-RCNN (see the sixth row where Faster-RCNN doesn’t detect any object on two images and predicts wrong labels on three images). However, SSD300 still works well on the adversarial examples generated by DAG (see the third row). For UEA, Faster-RCNN cannot detect any bounding box on the adversarial examples, and SSD300 detects two wrong objects besides the zero detection on three images. More results of UEA can be found in Figure 6.

To better show the intrinsic mechanism of UEA, we visualize the feature maps extracted from adversarial examples via DAG and UEA, respectively. Because Faster-RCNN and SSD300 utilize the same VGG16 as their feature net-
In this section, we report the results on video object detection. We here use the ImageNet VID dataset. As discussed in section 4.3, we attack the dense frame detection methods. Specifically, we train Faster-RCNN and SSD300 on ImageNet VID dataset, and then run the detectors on each frame in the testing video. We believe that if the dense frame detection method can be successfully attacked, other efficient methods will be also fooled. Figure 10 reports the qualitative attacking results versus “airplane”, “bird”, and “horse and person”. Similarly, UEA simultaneously fools Faster-RCNN and SSD300. More results can be found in https://sites.google.com/view/ueaattack/home.

Table 4 shows the quantitative attacking performance of UEA on ImageNet VID. Specifically, we train Faster-RCNN and SSD300 on the training set of ImageNet VID, and run the trained detectors on the testing set to obtain the original mAP performance. In addition, we use UEA to generate the corresponding adversarial videos for the testing set of ImageNet VID, and then run the same detectors. The mAP drop is used to measure the attacking performance. In Table 4, we see UEA achieves 0.40 mAP drop for Faster-RCNN, and 0.39 mAP drop for SSD300, which shows the effectiveness of UEA.

We here use the VGG16 based Faster-RCNN and SSD300. [32] shows that if we use ResNet 101 as the backbone network, and replace Faster-RCNN with FCN [6] as the object detector, the original mAP will reach 0.73. Because this paper aims at measuring the attacking ability of UEA, rather than the detecting performance, the mAP drop is the key metric, rather than mAP. Therefore, we here don’t use ResNet 101+FCN. Similarly, we also don’t use the SSD500, although it has better detection than SSD300. The current mAP drop has verified the powerful attacking ability of UEA both against the proposal based detector (Faster-RCNN) and regression based detector (SSD300). We believe that if we use the advanced object detectors, the mAP drop will also improve.

Table 4. The attacking performance of UEA on video detection.

| Methods     | Faster-RCNN | SSD300 | SSIM  |
|-------------|-------------|--------|-------|
| Clean Videos| 0.43        | 0.50   | 1.00  |
| UEA         | 0.03        | 0.11   | 0.82  |
| mAP drop    | 0.40        | 0.39   | 0.18  |

In Figure 9 we list the comparison mAP performance for each category recognition. Readers can have a clear observation for the mAP drop for each class on ImageNet VID.

5. Conclusion

In this paper, we proposed the Unified and Efficient Adversary (UEA). UEA was able to efficiently generate adversarial examples, and its processing time was 1000 times
Clean frames  Faster-RCNN on clean frames  SSD300 on clean frames  Faster-RCNN on adversarial frames output by UEA  SSD300 on adversarial frames output by UEA

VID verified the effectiveness and efficiency of UEA. Experiments conducted on PASCAL VOC and ImageNet (we chose Faster-RCNN and SSD300 in the experiments). Tack the current two kinds of representative object detectors existing attacking methods, and thus, it could meanwhile at.

More importantly, UEA had better transferability than the current attacking methods. Therefore, UEA could deal with not only image data, but also video data. More importantly, UEA had better transferability than the existing attacking methods, and thus, it could meanwhile attack the current two kinds of representative object detectors (we chose Faster-RCNN and SSD300 in the experiments). Experiments conducted on PASCAL VOC and ImageNet VID verified the effectiveness and efficiency of UEA.

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Figure 10. Three qualitative results about the attacks versus video object detection. You can see that more clearly in the large version.
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