Advbox: a toolbox to generate adversarial examples that fool neural networks

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Abstract

In recent years, neural networks have been extensively deployed for computer vision tasks, particularly visual classification problems, where new algorithms reported to achieve or even surpass the human performance. Recent studies have shown that they are all vulnerable to the attack of adversarial examples. Small and often imperceptible perturbations to the input images are sufficient to fool the most powerful neural networks. *Advbox* is a toolbox to generate adversarial examples that fool neural networks in PaddlePaddle, PyTorch, Caffe2, MxNet, Keras, TensorFlow and it can benchmark the robustness of machine learning models. Compared to previous work, our platform supports black box attacks on Machine-Learning-as-a-service, as well as more attack scenarios, such as Face Recognition Attack, Stealth T-shirt, and Deepfake Face Detect. The code is licensed under the Apache 2.0 license and is openly available at https://github.com/advboxes/AdvBox.

1 Introduction

Deep learning (DL) has made significant progress in a wide domain of machine learning (ML): image classification [Krizhevsky *et al.*, 2012; Simonyan and Zisserman, 2014; He *et al.*, 2016], object detection [Redmon *et al.*, 2016; Redmon and Farhadi, 2017], speech recognition [Graves *et al.*, 2013; Amodei *et al.*, 2016], language translation [Sutskever *et al.*, 2014; Bahdanau *et al.*, 2014], voice synthesis [Oord *et al.*, 2016; Shen *et al.*, 2018].

Szegedy et al. first generated small perturbations on the images for the image classification problem and fooled state-of-the-art deep neural networks with high probability [Szegedy *et al.*, 2013]. These misclassified samples were named as *Adversarial Examples*. A large number of attack algorithms have been proposed, such as FGSM [Goodfellow *et al.*, 2014], BIM [Kurakin *et al.*, 2016], DeepFool [Moosavi-Dezfooli *et al.*, 2016], JSMA [Papernot *et al.*, 2016b], CW [Carlini and Wagner, 2017], PGD [Madry *et al.*, 2017a].

The scope of researchers' attacks has also gradually extended from the field of computer vision [Fischer *et al.*, 2017; Xie *et al.*, 2017; Wang *et al.*, 2019a; Jia *et al.*, 2020] to the field of natural language processing [Ebrahimi *et al.*, 2017; Li *et al.*, 2018; Gao *et al.*, 2018] and speech [Carlini and Wagner, 2018; Qin *et al.*, 2019; Yakura and Sakuma, 2019].

Success of ML algorithms has led to an explosion in demand. To further broaden and simplify the use of ML algorithms, cloud-based services offered by Amazon, Google, Microsoft, Clarifai and other public cloud companies have developed ML-as-a-service tools. Thus, users and companies can readily benefit from ML applications without having to train or host their own models[Hosseini *et al.*, 2017b]. For example, Google introduced the Cloud Vision API for image analysis. A demonstration website has been also launched, where for any selected image, the API outputs the image labels, identifies and reads the texts contained in the image and detects the faces within the image. It also determines how likely is that the image contains inappropriate contents, including adult, spoof, medical, or violence contents. Unlike common attacks against web applications, such as SQL injection and XSS, there are very special attack methods for machine learning applications, e.g., *Adversarial Attack*. Obviously, neither public cloud companies nor traditional security companies pay much attention to these new attacks and defenses[Goodman and Hao, 2020; Goodman and Wei, 2019; Li *et al.*, 2019; Goodman *et al.*, 2019b; Goodman *et al.*, 2019a; Goodman and Hao, 2019; Goodman, 2020; Goodman *et al.*, 2018].

In this paper, we will focus on adversarial example attack, defense and detection methods based on our AdvBox. Our key items covered:

- The basic principles and implementation ideas.
- Adversarial example attack, defense and detection methods.
- Black box attacks on Machine-Learning-as-a-service.
- More attack scenarios, such as Face Recognition Attack, Stealth T-shirt, and Deepfake Face Detect.

2 Related Work

Currently, several attack/defense platforms have been proposed, like Cleverhans [Papernot *et al.*, 2016a], FoolBox [Rauber *et al.*, 2017], ART [Nicolae *et al.*, 2018], DEEPSEC [Ling *et al.*, 2019], etc. For a detailed comparison, see the Table 1.

Table 1: Comparison of different adversarial attack/defense platforms. "$\surd$" means "support".

	Cleverhans	FoolBox	ART	DEEPSEC	Our
Tensorflow[Abadi *et al.*, 2016]	$\surd$	$\surd$	$\surd$		$\surd$
PyTorch[Paszke *et al.*, 2019]	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
MxNet[Chen *et al.*, 2015]		$\surd$	$\surd$		$\surd$
PaddlePaddle[1]					$\surd$
Adversarial Attack	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Adversarial Defense	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Robustness Evaluation		$\surd$	$\surd$	$\surd$	$\surd$
Adversarial Detection		$\surd$	$\surd$	$\surd$	$\surd$
Attack on ML-as-a-service					$\surd$
Actual attack scenario					$\surd$

3 Adversarial Attack

3.1 Problem Formulation

The function of a pre-trained classification model F, e.g. an image classification or image detection model, is mapping from input set to the label set. For a clean image example O, it is correctly classified by F to ground truth label $y \in Y$, where Y including $\{1, 2, \ldots, k\}$ is a label set of k classes. An attacker aims at adding small perturbations in O to generate adversarial example ADV, so that $F(ADV) \neq F(O)$, where $D(ADV, O) < \epsilon$, D captures the semantic similarity between ADV and O, ϵ is a threshold to limit the size of perturbations. For computer vision, D usually stands for Perturbation Measurement.

3.2 Perturbation Measurement

l_p measures the magnitude of perturbation by p-norm distance:

$$\|x\|_p = \left(\sum_{i=1}^{n} \|x_i\|^p \right)^{\frac{1}{p}} \tag{1}$$

l_0, l_2, l_∞ are three commonly used l_p metrics. l_0 counts the number of pixels changed in the adversarial examples; l_2 measures the Euclidean distance between the adversarial example and the original sample; l_∞ denotes the maximum change for all pixels in adversarial examples.

4 AdvBox

4.1 Overview

Advbox is a toolbox to generate adversarial examples that fool neural networks in PaddlePaddle, PyTorch, Caffe2, MxNet, Keras, TensorFlow and it can benchmark the robustness of machine learning models.

4.2 Structure

Advbox is based on Python[2] and uses object-oriented programming.

Attack Class

Advbox implements several popular adversarial attacks which search adversarial examples. Each attack method uses a distance measure(L1, L2, etc.) to quantify the size of adversarial perturbations. Advbox is easy to craft adversarial example as some attack methods could perform internal hyperparameter tuning to find the minimum perturbation. The code is implemented as $advbox.attack$.

Model Class

Advbox implements interfaces to Tensorflow[Abadi *et al.*, 2016], PyTorch[Paszke *et al.*, 2019], MxNet[Chen *et al.*, 2015], and PaddlePaddle[3]. Additionally, other deep learning framworks such as TensorFlow can also be defined and employed. The module is use to compute predictions and gradients for given inputs in a specific framework.

AdvBox also supports GraphPipe[4], which shields the underlying deep learning platform. Users can conduct black box attack on model files generated by Caffe2[5], CNTK[6], MATLAB[7] and Chainer[8] platforms. The code is implemented as $advbox.model$.

Adversary Class

Adversary contains the original object, the target and the adversarial examples. It provides the misclassification as the criterion to accept a adversarial example. The code is implemented as $advbox.adversary$.

4.3 Adversarial Attack

Advbox supports 6 attack algorithms:

- **FGSM[Goodfellow *et al.*, 2014]**
- **BIM[Kurakin *et al.*, 2016]**
- **DeepFool[Moosavi-Dezfooli *et al.*, 2016]**
- **JSMA[Papernot *et al.*, 2016b]**
- **CW[Carlini and Wagner, 2017]**

[2]https://www.python.org/

[3]https://github.com/paddlepaddle/paddle

[4]https://github.com/oracle/graphpipe

[5]https://caffe2.ai/

[6]https://docs.microsoft.com/en-us/cognitive-toolkit/

[7]https://www.mathworks.com/products/deep-learning.html

[8]https://chainer.org/

(a) Labeled as "Bill Gates" (b) Labeled as "Michael Jordan" (c) Labeled as "Michael Jordan"

Figure 1: Robustness of our Stealth T-shirt.

- **PGD[Madry *et al.*, 2017a]**

The code is implemented as $advbox.attack$. JSMA are often used as a baseline l_0 attack algorithm. CW are often used as a baseline l_2 attack algorithm. FGSM and PGD are often used as a baseline l_∞ attack algorithm.

4.4 Adversarial Attack Mitigation

Advbox supports 6 defense algorithms:

- **Feature Squeezing[Xu *et al.*, 2017]**
- **Spatial Smoothing[Xu *et al.*, 2017]**
- **Label Smoothing[Xu *et al.*, 2017]**
- **Gaussian Augmentation[Zantedeschi *et al.*, 2017]**
- **Adversarial Training[Madry *et al.*, 2017b]**
- **Thermometer Encoding[Buckman *et al.*, 2018]**

The code is implemented as $advbox.defense$. Adversarial Training is often used as a baseline defense algorithm.

4.5 Robustness Evaluation Test

We independently developed a sub-project *Perceptron*[9] to evaluate the robustness of the model. Perceptron is a robustness benchmark for computer vision DNN models. It supports both image classification and object detection models as AdvBox, as well as cloud APIs. Perceptron is designed to be agnostic to the deep learning frameworks the models are built on.

Perceptron provides different attack and evaluation approaches:

- **CW[Carlini and Wagner, 2017]**
- **Gaussian Noise[Hosseini *et al.*, 2017a]**
- **Uniform Noise[Hosseini *et al.*, 2017a]**
- **Pepper Noise[Hosseini *et al.*, 2017a]**
- **Gaussian Blurs[Goodman, 2020; Yuan *et al.*, 2019]**
- **Brightness[Goodman *et al.*, 2019b; Yuan *et al.*, 2019]**
- **Rotations[Engstrom *et al.*, 2017]**
- **Bad Weather[Narasimhan and Nayar, 2000]**

[9]https://github.com/advboxes/perceptron-benchmark

5 Attack scenario

Compared to previous work[Abadi *et al.*, 2016; Rauber *et al.*, 2017; Nicolae *et al.*, 2018; Ling *et al.*, 2019], our platform supports more attack scenarios, such as Face Recognition Attack, Stealth T-shirt, and Deepfake Face Detect.

5.1 Scenario 1: Face Recognition Attack

We chose a pre-trained FaceNet[Schroff *et al.*, 2015] model that is a state-of-the-art and widely used face recognition system as our white box attacked model. We used gradient-based attacks methods and modify its loss function using FaceNet embedding distance.

As shown in Fig. 1, Fig. (a) and Fig. (b) can be correctly identified, but Fig. (c) is incorrectly identified.

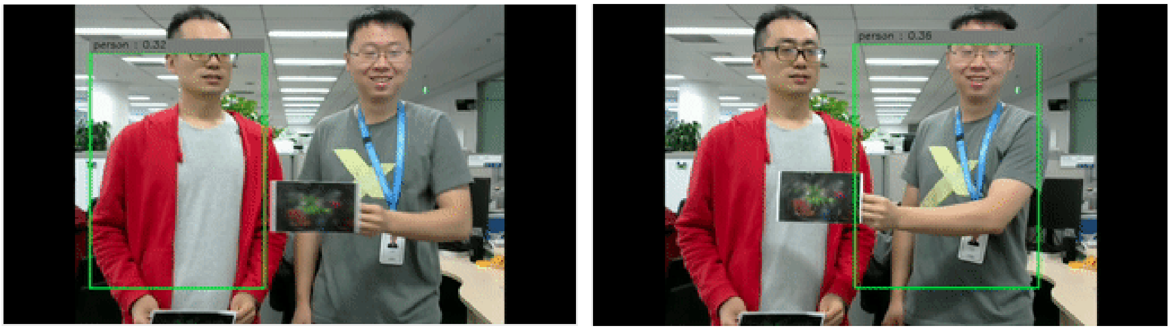
5.2 Scenario 2: Stealth T-shirt

On Defcon China[Goodman *et al.*, 2019a], we demonstrated T-shirts that can disappear under smart cameras. We open source the programs and deployment methods of smart cameras for demonstration.

To raise people's awareness of techniques that can deceive deep learning models, we designed this "Stealth T-shirt" with the adversarial pattern to fool an object detector. The T-shirt is capable of hiding a person who wears it from an open-source object detector. By wearing it and showing the adversarial pattern in front of a camera and its object detector behind it, the person who wears it disappears, whereas the person who doesn't wear the T-shirt is still under object detector detection.

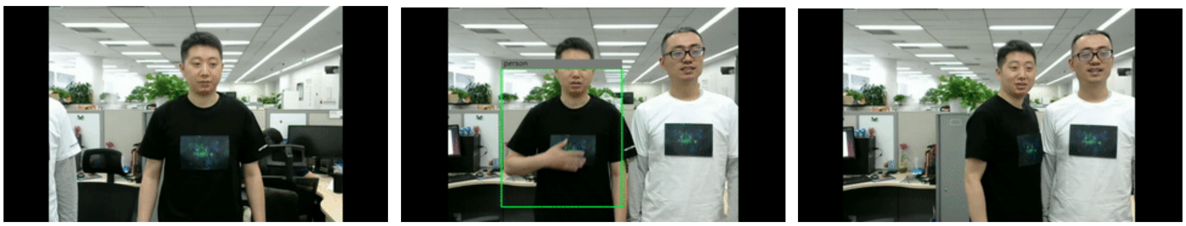
When the smart camera recognizes a human body in the video, it uses a green box to mark the range of the human body. Assume that the black piece of paper in the Fig. 2 is part of the T-shirt. As shown in Fig. (a), the black piece of paper covered the gray man, but did not cover the man in red. The man in red was identified, and the man in gray was not identified. As shown in Fig. (b), the black piece of paper blocked the man in red, and the man in gray was not covered. The man in gray was identified, and the man in red was not identified.

As shown in the Fig. 3, unlike the previous work[Thys *et al.*, 2019; Xu *et al.*, 2019], the picture we need to print in the T-shirt is smaller, facing the distortion, folding, turning, the attack effect is more robust.



(a) (b)

Figure 2: Screenshots to demonstrate our Stealth T-shirt.



(a) Normal (b) Occlusion (c) Turning

Figure 3: Robustness of our Stealth T-shirt.

5.3 Scenario 3: Deepfake Face Detect

We have opened the Deepfake detection capability for free, and you can remotely call our cloud detection detection api by using the Python script we provide. Details of our related work can refer to the conference[Wang *et al.*, 2019c; Wang *et al.*, 2019b].

Acknowledgement

Thanks to every code submitter. Thanks to everyone who uses or cites *AdvBox* in their papers.

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