advertorch v0.1: An Adversarial Robustness Toolbox based on PyTorch

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Abstract

advertorch is a toolbox for adversarial robustness research. It contains various implementations for attacks, defenses and robust training methods. advertorch is built on PyTorch (Paszke et al., 2017), and leverages the advantages of the dynamic computational graph to provide concise and efficient reference implementations. The code is licensed under the LGPL license and is open sourced at https://github.com/BorealisAI/advertorch.

1 Introduction

Machine learning models are vulnerable to “adversarial” perturbations (Szegedy et al., 2013; Biggio et al., 2013). They are adversarial in the sense that, after these artificially constructed perturbations are added to the inputs of the model, human observers do not change their perception, but the predictions of a model could be manipulated. Efforts of adversarial robustness research can be roughly divided into the following categories: generating strong and efficient attacks (Goodfellow et al., 2014; Carlini and Wagner, 2017; Brendel et al., 2017; Xiao et al., 2018; Dong et al., 2018); detecting adversarial examples (Metzen et al., 2017; Ma et al., 2018; Feinman et al., 2017); defending already trained models (Xu et al., 2017; Guo et al., 2017); training robust models (Kurakin et al., 2016; Madry et al., 2017; Cisse et al., 2017; Ding et al., 2018; Wong and Kolter, 2018; Mirman et al., 2018); robustness evaluation methodologies (Weng et al., 2018; Katz et al., 2017; Athalye et al., 2018); and understanding the vulnerability phenomena (Fawzi et al., 2017; Shafahi et al., 2019; Ding et al., 2019).

advertorch aims to provide researchers the tools for conducting research in all the above mentioned directions. The current version of advertorch include three of these aspects: attacks, defenses and robust training. Compared to existing adversarial robustness related toolboxes (Papernot et al., 2016a; Rauber et al., 2017), advertorch aims for

1. simple and consistent APIs for attacks and defenses;
2. concise reference implementations, utilizing the dynamic computational graphs in PyTorch; and
3. fast executions with GPU-powered PyTorch implementations, which are important for “attack-in-the-loop” algorithms, e.g. adversarial training.

In this technical report, we give an overview of the design considerations and implementations of attacks in Section 2, defenses and robust training in Section 3, and the versioning system in Section 4.
2 Attacks

`advertorch` implements various types of attacks, where `attacks/__init__.py` maintains a complete list of them. We outline some of our design considerations and choices when implementing these attacks. Specifically, we describe gradient-based attacks in Section 2.1, other attacks in Section 2.2, and the wrapper for Backward Pass Differentiable Approximation (BPDA) (Athalye et al., 2018) in Section 2.3.

2.1 Gradient-Based Attacks

`advertorch` currently implements the following gradient-based attacks:

- GradientAttack, GradientSignAttack (Goodfellow et al., 2014),
- L2BasicIterativeAttack, LinfBasicIterativeAttack (Kurakin et al., 2016),
- LinfPGDAttack, L2PGDAttack (Madry et al., 2017),
- CarliniWagnerL2Attack (Carlini and Wagner, 2017),
- LBFGSAttack (Szegedy et al., 2013),
- MomentumIterativeAttack (Dong et al., 2018),
- FastFeatureAttack (Sabour et al., 2015), and
- SpatialTransformAttack (Xiao et al., 2018).

Each of the attacks contains three core components:

- a `predict` function,
- a loss function `loss_fn`, and
- a `perturb` method.

Taking untargeted LinfPGDAttack on classifiers as the running example, `predict` is the classifier, `loss_fn` is the loss function for gradient calculation, the `perturb` method takes `x` and `y` as its arguments, where `x` is the input to be attacked, `y` is the true label of `x`. `predict(x)` contains the “logits” of the neural work. The `loss_fn` could be the cross-entropy loss function or another suitable loss function who takes `predict(x)` and `y` as its arguments.

However, the decoupling of these three core components is flexible enough to allow more versatile attacks. In general, we require the `predict` and `loss_fn` to be designed such that `loss_fn` always takes `predict(x)` and `y` as its inputs. As such, no knowledge about `predict` and `loss_fn` is required by the `perturb` method. For example, FastFeatureAttack and LinfPGDAttack share the same underlying `perturb_iterative` function, but differ in the `predict` and `loss_fn`. In FastFeatureAttack, the `predict(x)` outputs the feature representation from a specific layer, the `y` is the `guide` feature representation that we want `predict(x)` to match, and the `loss_fn` becomes the mean squared error.

More generally, `y` could be any targets of the adversarial perturbation, `predict(x)` can output more complex data structures, as long as the `loss_fn` can take them as its inputs. For example, we might want to generate one perturbation that fools both model A’s classification result and model B’s feature representation at the same time. In this case, we just need to make `y` and `predict(x)` to be tuples of labels and features, and modify the `loss_fn` accordingly. There is no need to modify the original perturbation implementation.
2.2 Other Attacks

Besides gradient-based attacks, the current version of advertorch also implements
- SinglePixelAttack, LocalSearchAttack (Narodytska and Kasiviswanathan, 2016), and
- JacobianSaliencyMapAttack (Papernot et al., 2016b).

2.3 BPDA Wrapper

The Backward Pass Differentiable Approximation (Athalye et al., 2018) is an attack technique that enhances gradient-based attacks, when attacking defended models who have non-differentiable or gradient-obfuscating components. Specifically, let \( y = f(x) \) be a classifier, and let \( \hat{x} = d(x) \) be a preprocessing based defense module that takes the original input \( x \) and preprocesses it to be \( \hat{x} \). When \( d(\cdot) \) is non-differentiable or gradient-obfuscating, gradient-based attacks will be ineffective on the defended model \( f(\hat{x}) \), since \( \nabla_x(f(d(x))) \) is either unavailable or uninformative. BPDA solves this problem by replacing the backward pass of \( d(\cdot) \), \( \frac{\partial d}{\partial x} \), with the backward pass of another function \( g(\cdot) \), \( \frac{\partial g}{\partial x} \).

In advertorch, we implement BPDAWrapper that allows convenient backward pass replacements. With BPDAWrapper, one can either
- specify \( g(\cdot) \), the forward pass function that is used create the backward pass replacement, \( \frac{\partial g}{\partial x} \),
  or
- directly specify the backward pass replacement \( \frac{\partial g}{\partial x} \).

To give a concrete example, let defense be the defense module \( d(x) \) that preprocesses the input.
\[
defense_{\text{withbpda}} = \text{BPDAWrapper}(\text{defense}, \text{forwardsub=lambda x: x})
\]
directly returns a defense module with the same forward pass, but having its backward pass replaced with the backward pass of \( \text{forwardsub} \), which is specified as the identity function by the function \( \lambda x: x \). This specific backward pass replacement is also known as the straight-through gradient estimator (Bengio et al., 2013).

3 Defenses and Robust Training

Preprocessing-based Defenses: The current version implements a few preprocessing based defenses including
- JPEGFilter (Dziugaite et al., 2016),
- BitSqueezing, MedianSmoothing2D (Xu et al., 2017), and
- linear filters including ConvSmoothing2D, AverageSmoothing2D, and GaussianSmoothing2D.

These defenses are all implemented as PyTorch modules which can be easily combined on the fly, thanks to the dynamic computation graph nature of PyTorch.

Robust Training: Adversarially augmented training (Kurakin et al., 2016; Madry et al., 2017; Ding et al., 2018) and provably robust training (Wong and Kolter, 2018; Mirman et al., 2018; Gowal et al., 2018) have been shown to be the most effective methods against worst-case perturbations. Currently, these training algorithms are not standardized yet, and usually have different variations that

\[1\text{We will keep expanding this list over time.}\]
are difficult to be modularized. Therefore, our plan is to provide reference implementations of representative training algorithms in the folder `advertorch_examples`. The current version includes an example, `tutorial_train_mnist.py`, implementing Madry et al. adversarial training on the MNIST dataset.

4 Versioning and Reporting Benchmark Results

`advertorch` follows Semantic Versioning 2.0.0 (Preston-Werner, 2013), where the version number takes the MAJOR.MINOR.PATCH format. Given such a version number, quoting from Preston-Werner (2013), we increment the:

1. MAJOR version when we make incompatible API changes,
2. MINOR version when we add functionality in a backwards-compatible manner, and
3. PATCH version when we make backwards-compatible bug fixes.

When benchmark reporting results from `advertorch`, the authors should report the MAJOR.MINOR version number and detailed hyperparameters. For example, when performing untargeted LinfPGDAttack, the following hyperparameters shall be reported: the loss function, the maximum perturbation magnitude, the number of iterations, the step size, and whether the attack is randomly initialized.

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