cleverhans v2.0.0: an adversarial machine learning library

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Abstract

`cleverhans` is a software library that provides standardized reference implementations of *adversarial example* construction techniques and *adversarial training*. The library may be used to develop more robust machine learning models and to provide standardized benchmarks of models' performance in the adversarial setting. Benchmarks constructed without a standardized implementation of adversarial example construction are not comparable to each other, because a good result may indicate a robust model or it may merely indicate a weak implementation of the adversarial example construction procedure.

This technical report is structured as follows. Section 1 provides an overview of adversarial examples in machine learning and of the `cleverhans` software. Section 2 presents the core functionalities of the library: namely

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the attacks based on adversarial examples and defenses to improve the robustness of machine learning models to these attacks. Section 3 describes how to report benchmark results using the library. Section 4 describes the versioning system.

1 Introduction

Adversarial examples are inputs crafted by making slight perturbations to legitimate inputs with the intent of misleading machine learning models [8]. The perturbations are designed to be small in magnitude, such that a human observer would not have difficulty processing the resulting input. In many cases, the perturbation required to deceive a machine learning model is so small that a human being may not be able to perceive that anything has changed, or even so small that an 8-bit representation of the input values does not capture the perturbation used to fool a model that accepts 32-bit inputs. We invite readers unfamiliar with the concept to the detailed presentation in [8, 4, 7, 2]. Although completely effective defenses have yet to be proposed, the most successful to date is adversarial training [8, 4]. Different sources of adversarial examples used in the training process can make adversarial training more effective; as of this writing, to the best of our knowledge, the most effective version of adversarial training on ImageNet is ensemble adversarial training [10] and the most effective version on MNIST is the basic iterative method [5] applied to randomly chosen starting points [6].

The `cleverhans` library provides reference implementations of the attacks, which are intended for use for two purposes. First, machine learning developers may construct robust models by using adversarial training, which requires the construction of adversarial examples during the training procedure. Second, we encourage researchers who report the accuracy of their models in the adversarial setting to use the standardized reference implementation provided by `cleverhans`. Without a standard reference implementation, different benchmarks are not comparable—a benchmark reporting high accuracy might indicate a more robust model, but it might also indicate the use of a weaker attack implementation. By using `cleverhans`, researchers can be assured that a high accuracy on a benchmark corresponds to a robust model.

Implemented in TensorFlow [1], `cleverhans` is designed as a tool to help developers add defenses against adversarial examples to their models and benchmark the robustness of their models to adversarial examples. The interface for `cleverhans` is designed to accept models implemented using any model framework (such as Keras [3]) or implemented without any specific model abstraction.

The `cleverhans` library is a collaboration is free, open-source software, licensed under the MIT license. The project is available online through GitHub[1]. The main communication channel for developers of the library is a mailing list, whose discussions are publicly available online[2].

[1] `https://github.com/openaicleverhans`
[2] `https://groups.google.com/group/cleverhans-dev`

2 Core functionalities

The library's package is organized by modules. The most important modules are:

- `attacks`: contains the `Attack` class, defining the interface used by all CleverHans attacks, as well as implementations of several specific attacks.
- `model`: contains the `Model` class, which is a very lightweight class defining a simple interface that models should implement in order to be compatible with `Attack`. CleverHans includes a `Model` implementation for Keras `Sequential` models and examples of `Model` implementations for TensorFlow models that are not implemented using any modeling framework library.

In the following, we describe some of the research results behind the implementations made in `cleverhans`.

2.1 Attacks

Adversarial example crafting algorithms implemented in `cleverhans` take a model, and an input, and return the corresponding adversarial example. Here are the algorithms currently implemented in the `attacks` module.

2.1.1 Fast Gradient Sign Method

The fast gradient sign method (FGSM) was introduced by Goodfellow et al. [4]. The intuition behind the attack is to linearize the cost function J used to train a model f around the neighborhood of the training point $\vec{x}$ that the adversary wants to force the misclassification of. The resulting adversarial example $\vec{x}^*$ corresponding to input $\vec{x}$ is computed as follows:

$$\vec{x}^* \leftarrow x + \varepsilon \cdot \nabla_{\vec{x}} J(f, \theta, \vec{x}) \tag{1}$$

where ε is a parameter controlling the magnitude of the perturbation introduced. Larger values increase the likelihood that $\vec{x}^*$ will be misclassified by f, but make the perturbation easier to detect by a human.

The fast gradient sign method is available by calling `attacks.fgsm()` The implementation defines the necessary graph elements and returns a tensor, which once evaluated holds the value of the adversarial example corresponding to the input provided. The implementation is parameterized by the parameter ε introduced above. It is possible to configure the method to clip adversarial examples so that they are constrained to be part of the expected input domain range.

2.1.2 Jacobian-based Saliency Map Approach

The Jacobian-based saliency map approach (JSMA) was introduced by Papernot et al. [7]. The method iteratively perturbs features of the input that have large adversarial saliency scores. Intuitively, this score reflects the adversarial goal of taking a sample away from its source class towards a chosen target class.

First, the adversary computes the Jacobian of the model and evaluates it in the current input: this returns a matrix $\left[\frac{\partial f_j}{\partial x_i}(\vec{x})\right]_{i,j}$ where component (i, j) is the derivative of class j with respect to input feature i. To compute the adversarial saliency map, the adversary then computes the following for each input feature i:

$$S(\vec{x}, t)[i] = \begin{cases} 0 \text{ if } \frac{\partial f_t(\vec{x})}{\partial \vec{x}_i} < 0 \text{ or } \sum_{j \neq t} \frac{\partial f_j(\vec{x})}{\partial \vec{x}_i} > 0 \\ \left(\frac{\partial f_t(\vec{x})}{\partial \vec{x}_i}\right) \left| \sum_{j \neq t} \frac{\partial f_j(\vec{x})}{\partial \vec{x}_i} \right| \text{ otherwise} \end{cases} \tag{2}$$

where t is the target class that the adversary wants the machine learning model to assign. The adversary then selects the input feature i with the largest saliency score $S(\vec{x}, t)[i]$ and increases its value[3]. The process is repeated until misclassification in the target class is achieved or the maximum number of perturbed features has been reached.

In `cleverhans`, the Jacobian-based saliency map approach may be called with `attacks.jsma()`. The implementation returns the adversarial example directly, as well as whether the target class was achieved or not, and how many input features were perturbed.

2.2 Defenses

The intuition behind defenses against adversarial examples is to make the model smoother by limiting its sensitivity to small perturbations of its inputs (and therefore making adversarial examples harder to craft). Since all defenses currently proposed modify the learning algorithm used to train the model, we implement them in the modules of `cleverhans` that contain the functions used to train models. In module `utils_tf`, the following defenses are implemented.

2.2.1 Adversarial training

The intuition behind adversarial training [8, 4] is to inject adversarial examples during training to improve the generalization of the machine learning model. To achieve this effect, the training function `tf_model_train()` implemented in module `utils_tf` can be given the tensor definition for an adversarial example: e.g., the one returned by the method described in Section 2.1.1. When such a tensor is given, the training algorithm modifies the loss function used to optimize the model parameters: it is in that case defined as the average between the loss for predictions on legitimate inputs and the loss for predictions made on adversarial examples. The remainder of the training algorithm is left unchanged.

[3] In the original paper and the `cleverhans` implementation, input features are selected by pairs using the same heuristic.

3 Reporting Benchmark Results

This section provides instructions for how to preprare and report benchmark results.

When comparing against previously published benchmarks, it is best to to use the same version of `cleverhans` as was used to produce the previous benchmarks. This minimizes the possibility that an undetected change in behavior between versions could cause a difference in the output of the benchmark results.

When reporting new results that are not directly compared to previous work, it is best to use the most recent versioned release of `cleverhans`.

In all cases, it is important to report the version number of `cleverhans`.

In addition to this information, one should also report which attack methods were used, and the values of any configuration parameters used for these attacks.

For example, you might report "We benchmarked the robustness of our method to adversarial attack using v2.0.0 of CleverHans (Papernot et al. 2017). On a test set modified by `fgsm` with `eps` of 0.3, we obtained a test set accuracy of 97.9%."

The library does not provide specific test datasets or data preprocessing. End users are responsible for appropriately preparing the data in their specific application areas, and for reporting sufficient information about the data preprocessing and model family to make benchmarks appropriately comparable.

4 Versioning

Because one of the goals of `cleverhans` is to provide a basis for reproducible benchmarks, it is important that the version numbers provide useful information. The library uses semantic versioning,[4] meaning that version numbers take the form of MAJOR.MINOR.PATCH.

The PATCH number increments whenever backwards-compatible bug fixes are made. For the purpose of this library, a bug is not considered backwards-compatible if it changes the results of a benchmark test. The MINOR number increments whenever new features are added in a backwards-compatible manner. The MAJOR number increments whenever an interface changes.

Any time a bug in CleverHans affects the accuracy of any performance number reported as a benchmark result, we consider fixing the bug to constitute an API change (to the interface mapping from the specification of a benchmark experiment to the reported performance) and increment the MAJOR version number when we make the next release. For this reason, when writing academic articles, it is important to compare CleverHans benchmark results that were produced with the same MAJOR version number. Release notes accompanying each revision indicate whether an increment to the MAJOR number invalidates earlier benchmark results or not.

Release notes for each version are available at `https://github.com/tensorflow/cleverhans/releases`

[4] `http://semver.org/`

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