Adversarial Robustness Toolbox v0.3.0

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Abstract

Adversarial examples and poisoning attacks have become indisputable threats to the security of modern AI systems based on deep neural networks (DNNs). The Adversarial Robustness Toolbox (ART) is a Python library designed to support researchers and developers in creating novel defence techniques, as well as in deploying practical defences of real-world AI systems. Researchers can use ART to benchmark novel defences against the state-of-the-art. For developers, the library provides interfaces which support the composition of comprehensive defence systems using individual methods as building blocks.

The Adversarial Robustness Toolbox supports machine learning models (and deep neural networks (DNNs) specifically) implemented in any of the most popular deep learning frameworks (TensorFlow, Keras, PyTorch and MXNet). Currently, the library is primarily intended to improve the adversarial robustness of visual recognition systems, however, future releases that will comprise adaptations to other data modes (such as speech, text or time series) are envisioned. The ART source code is released (https://github.com/IBM/adversarial-robustness-toolbox) under an MIT license. The release includes code examples and extensive documentation (http://adversarial-robustness-toolbox.readthedocs.io) to help researchers and developers get quickly started.

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1 Introduction

The Adversarial Robustness Toolbox (ART) is an open source Python library containing state-of-the-art adversarial attacks and defences. It has been released under an MIT license and is available at https://github.com/IBM/adversarial-robustness-toolbox. It provides standardized interfaces for classifiers using any of the most popular deep learning frameworks (TensorFlow, Keras, PyTorch). The architecture of ART makes it easy to combine various defences, e.g. adversarial training with data preprocessing and runtime detection of adversarial inputs. ART is designed both for researchers who want to run large-scale experiments for benchmarking novel attacks or defences, and for developers who want to compose and deploy comprehensive defences for real-world machine learning applications.

The purpose of this document is to provide mathematical background and implementation details for the adversarial attacks and defences implemented in ART. It is complementary to the documentation hosted on Read the Docs (http://adversarial-robustness-toolbox.readthedocs.io). In particular, it fully explains the semantics and mathematical background of all attacks and defence hyperparameters, and it highlights any custom choices in the implementation. As such, it provides a single reference for all the state-of-the-art attacks and defences implemented in ART, whereas in the past researchers and developers often had to go through the details of the original papers and compare various implementations of the same algorithm.

This document is structured as follows: Section 2 provides background and introduces mathematical notation. Section 3 gives an overview of the ART architecture and library modules. The following sections cover the different modules in detail: Section 4 introduces the classifier modules, Section 5 the evasion attacks and Section 6 the evasion defences. Section 7.1 covers detection of evasion attacks, while Section 8 detection for poisoning, and Section 9 the metrics. Finally, Section 10 describes the versioning system.

2 Background

While early work in machine learning has often assumed a closed and trusted environment, attacks against the machine learning process and resulting models have received much attention in the past years. **Adversarial machine learning** is a field that aims to protect the machine learning pipeline to ensure its safety at training, test and inference time [29, 3, 6].

The threat of evasion attacks against machine learning models at test time was first highlighted by [4]. [32] investigated specifically the vulnerability of deep neural network (DNN) models and proposed an efficient algorithm for crafting adversarial examples for such models. Since then, there has been an explosion of work on proposing more advanced adversarial attacks, on understanding the phenomenon of adversarial examples, on assessing the robustness of specific DNN architectures and learning paradigms, and on proposing as well as evaluating various defence strategies against evasion attacks.

Generally, the objective of an **evasion attack** is to modify the input to a **classifier** such that it is misclassified, while keeping the modification as small as possible. An important distinction is between **untargeted** and **targeted** attacks: If untargeted, the attacker aims for a misclassification of the modified input without any constraints on what the new class should be; if targeted, the new class is specified by the attacker. Another important distinction is between **black-box** and **white-box** attacks: in the white-box case, the attacker has full access to the architecture and parameters of the classifier. For a black-box attack, this is not the case. A typical strategy there is to use a **surrogate model** for crafting the attacks, and exploiting the **transferability** of adversarial examples that has been demonstrated among a variety of architectures (in the image classification domain, at least). Another way to approach the black-box threat model is through the use of zero-order optimization: attacks in this category are able to produce adversarial samples without accessing model gradients at all (e.g. ZOO [8]). They rely on zero-order approximations of the target model. One can also consider a wide range of **grey-box** settings in which the attacker may not have access to the classifier's parameters, but to its architecture, training algorithm or training data.

On the **adversarial defence** side, two different strategies can be considered: **model hardening** and **runtime detection** of adversarial inputs. Among the model hardening methods, a widely explored approach is to augment the training data of the classifier, e.g. by adversarial examples (so-called **adversarial training** [11, 23]) or other augmentation methods. Another approach is **input data preprocessing**, often using non-differentiable or randomized transformation [13], transformations reducing the dimensionality of the inputs [36], or transformations aiming to project inputs onto the "true" data manifold [21]. Other model hardening approaches involve special types of **regularization** during model training [31], or modifying elements of the classifier's architecture [37].

Note that **robustness metrics** are a key element to measure the vulnerability of a classifier with respect to particular attacks, and to assess the effectiveness of adversarial defences. Typically such metrics quantify the amount of perturbation that is required to cause a misclassification or, more generally, the sensitivity of model outputs with respect to changes in their inputs.

Poisoning attacks are another threat to machine learning systems executed at data collection and training time. Machine learning systems often assume that the data used for training can be trusted and fully reflects the population of interest. However, data collection and curation processes are often not fully controlled by the owner or stakeholders of the model. For example, common data sources include social media, crowdsourcing, consumer behavior and internet of the things measurements. This lack of control creates a threat of poisoning attacks where adversaries have the opportunity of manipulating the training data to significantly decrease overall performance, cause targeted misclassification or bad behavior, and insert backdoors and neural trojans [3, 27, 15, 12, 19, 20, 5, 26]. Defenses for this threat aim to detect and filter malicious training data [3, 2, 29].

Mathematical notation In the remainder of this section, we are introducing mathematical notation that will be used for the explanation of the various attacks and defence techniques in the following. Table 1 lists the key notation for quick reference.

Additionally, we will be using the following common shorthand notation for standard Python libraries in code examples:

- np for Numpy
- torch for PyTorch
- tf for TensorFlow
- k for Keras backend (keras.backend).

The notion of **classifier** will be central in the following. By $x \in \mathcal{X}$ we denote the **classifier inputs**. For most parts, we are concerned with classifier inputs that are images and hence assume the **space of classifier inputs** is $\mathcal{X} \subset \mathbb{R}^{k_1 \times k_2 \times k_3}$, where k_1 is the width, k_2 the height, and k_3 the number of color channels of the image[§]. We assume that the classifier inputs have minimum and maximum **clipping values** x_{\min} and x_{\max} , respectively, i.e. each component of x lies within the interval $[x_{\min}, x_{\max}]$. For images, this interval is typically [0, 255] in case of 8-bit pixel values, or [0, 1] if the pixel values have been normalized. For an arbitrary $x \in \mathcal{X}$, we use $\text{clip}(x, x_{\min}, x_{\max})$ to denote the input that is obtained by clipping each component of x at x_{\min} and x_{\max} , respectively. Moreover we write $\|x\|_p$ for the ℓ_p **norm** of x, and project (x, p, ϵ) for the function which returns among all x' satisfying $\|x'\|_p \le \epsilon$ the one with smallest norm $\|x - x'\|_2$. In the special case p = 2 this is equivalent to multiplying x component-wise with the minimum of 1 and $\epsilon/\|x\|_2$, and in the case $p = \infty$ equivalent to clipping each component at $\pm \epsilon$.

By $y \in \mathcal{Y}$ we denote the **classifier outputs**, which we also refer to as **labels**. We always assume the **space of classifier outputs** is $\mathcal{Y} = \{1, \dots, K\}$, i.e. there are K different classes. For most parts, we will consider classifiers based on a **logit** function $Z : \mathcal{X} \to \mathbb{R}^K$. We refer to Z(x) as the **logits** of the classifier for input x. The **class probabilities** are obtained by applying the **softmax** function,

[§]Typically $k_3 = 1$ or $k_3 = 3$ depending on whether x is a greyscale or colored image.

Notation	Description
\mathcal{X}	Space of classifier inputs
\boldsymbol{x}	Classifier input
${\mathcal X}_{\min}$	Minimum clipping value for classifier inputs
$oldsymbol{\mathcal{X}}_{ ext{max}}$	Maximum clipping value for classifier inputs
$\operatorname{clip}(x, x_{\min}, x_{\max})$	Function clipping x at x_{min} and x_{max} , respectively
$\ \mathbf{x}\ _p$	ℓ_p norm of x
$project(x, p, \epsilon)$	Function returning x' with smallest norm $ x - x' _2$ satisfying $ x' _p \le \epsilon$
${\mathcal Y}$	Space of classifier outputs (=labels)
K	Cardinality of \mathcal{Y} (note: we assume $\mathcal{Y} = \{1,, K\}$)
y	Label
Z(x)	Classifier logits (ranging in \mathbb{R}^K)
F(x)	Class probabilities (= softmax($Z(x)$))
C(x)	Classification of input x (also used to denote the classifier itself)
$\rho(x)$	Untargeted adversarial perturbation
$\psi(x,y)$	Targeted adversarial perturbation
$oldsymbol{x}_{ ext{adv}}$	Adversarial sample
$\mathcal{L}(x,y)$	Loss function
$\nabla_{\mathbf{x}} \mathcal{L}(\mathbf{x}, \mathbf{y})$	Loss gradients
$\nabla Z(x)$	Logit gradients
$\nabla F(\mathbf{x})$	Output gradients

Summary of notation.

 $F(x) = \operatorname{softmax}(Z(x))$, i.e. $F_i(x) = \exp(Z_i(x)) / \sum_{j \in \mathcal{Y}} \exp(Z_j(x))$ for $i \in \mathcal{Y}$. Finally, we write C(x) for the **classification** of the input x:

$$C(x) = \arg \max_{i \in \mathcal{Y}} F_i(x),$$

which, since softmax is a monotonic transformation, is equal to $\arg\max_{i\in\mathcal{Y}} Z_i(x)$. With slight abuse of notation, we often use C(x) to denote the classifier itself.

An untargeted adversarial attack is a (potentially stochastic) mapping $\rho: \mathcal{X} \to \mathcal{X}$, aiming to change the output of the classifier, i.e. $C(x+\rho(x)) \neq C(x)$, while keeping the **perturbation** $\|\rho(x)\|_p$ small with respect to a particular ℓ_p **norm** (most commonly, $p \in \{0,1,2,\infty\}$). Similarly, a **targeted adversarial attack** is a (potentially stochastic) mapping $\psi: \mathcal{X} \times \mathcal{Y} \to \mathcal{X}$, aiming to ensure the classifier outputs a specified class, i.e. $C(x+\psi(x,y))=y$, while keeping the perturbation $\|\psi(x,y)\|_p$ small. We call $x_{\text{adv}}=x+\rho(x)$ (or analogously $x_{\text{adv}}=x+\psi(x,y)$) the **adversarial sample** generated by the targeted attack ρ (untargeted attack ψ). In practice, we often consider $x_{\text{adv}}=\text{clip}(x+\rho(x),x_{\text{min}},x_{\text{max}})$ (analogously, $x_{\text{adv}}=\text{clip}(x+\psi(x,y),x_{\text{min}},x_{\text{max}})$) to ensure the adversarial samples are in the valid data range.

Finally, the following objects play an important role in the generation of adversarial samples:

- The **loss function** $\mathcal{L}: \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ that was used to train the classifier. In many cases, this is the cross-entropy loss: $\mathcal{L}(x, y) = -\log F_y(x)$.
- The **loss gradient**, i.e. the gradient $\nabla_x \mathcal{L}(x,y)$ of the classifier's loss function with respect to x.
- The class gradients, i.e. either the logit gradients $\nabla Z(x)$ or the output gradients $\nabla F(x)$ with respect to x.

3 Library Modules

The library is structured as follows:

```
art/
  _attacks/
     _attack.py
     _carlini.py
     _deepfool.py
     _fast_gradient.py
     _iterative_method.py
    \verb"_newtonfool.py"
    _saliency_map.py
    _universal_perturbation.py
     _virtual_adversarial.py
   classifiers/
     _classifier.py
     keras.py
     mxnet.py
     _pytorch.py
    _tensorflow.py
   defences/
    _adversarial_trainer.py
    _feature_squeezing.py
    <u>gaussian_augmentation.py</u>
    _label_smoothing.py
    __preprocessor.py
    _spatial_smoothing.py
  detection/
    \_detector.py
   poison_detection/
     activation_defence.py
     _clustering_analyzer.py
     _distance_analyzer.py
     ground_truth_evaluator.py
     _poison_filtering_defence.py
    _size_analyzer.py
  _metrics.py
 \_utils.py
```

The following sections each address one module of the library. The description of each library module is organized as follows: we first introduce the general concept, mathematical notation and a formal definition. We then provide a functional description of the library module. Finally, we give examples of how to use the respective functionality.

4 Classifiers

art.classifiers

This module contains the functional API allowing for the integration of classification models into the library. The API is framework-independent, and multiple machine learning backends are currently supported. The modularity of the library also allows for new frameworks to be incorporated with minimal effort. The following framework-specific classifier implementations are supported in the current version of ART:

- art.classifiers.KerasClassifier: support for the Keras [10] backend (see Section 4.2)
- art.classifiers.MXClassifier: support for MXNet [9] (detailed in Section 4.3)
- art.classifiers.PyTorchClassifier: support for PyTorch [30] (Section 4.4)
- art.classifiers.TFClassifier: implementation for TensorFlow [1] (see Section 4.5).

All these are extensions of the Classifier base class, described in the following.

4.1 The Classifier Base Class

art.classifiers.Classifier

art/classifiers/classifier.py

The Classifier abstract class provides access to the components and properties of a classifier that are required for adversarial attacks and defences. It abstracts from the actual framework in which the classifier is implemented (e.g. TensorFlow, PyTorch, etc.), and hence makes the modules for adversarial attacks and defences framework-independent. This allows for easy extension when adding support for a new framework in ART: one only has to extend the base Classifier without need of reimplementing the other modules making use of it.

The public interface of the Classifier grants access to the following properties:

- channel_index: the index of the axis containing the colour channel in the data.
- clip_values: the range of the data as a tuple (x_{\min}, x_{\max}) .
- input_shape: the shape of one input sample.
- layer_names: a list with the names of the layers in the model, ordered from input towards output. Note: this list does not include the input and output layers, only the hidden ones. The correctness of this property is not guaranteed and depends on the extent where this information can be extracted from the underlying model.
- nb_classes: the number of output classes *K*.

Additionally, each class extending Classifier has to provide the following functions:

- __init__(clip_values, channel_index, defences=None, preprocessing=(0, 1))

 Initializes the classifier with the given clip values (x_{min}, x_{max}) and defences. The preprocessing tuple of the form (substractor, divider) indicate two float values to be substracted, respectively used to divide the inputs as preprocessing operations. These will always be applied by the classifier before performing any operation on data. The default values (0, 1) correspond to no preprocessing being applied. The defences parameter is either a string or a list of strings selecting the defences to be applied from the following:
 - featsqueeze[1-8]? for feature squeezing, where the digit at the end indicates the bit depth (see Section 6.3)
 - labsmooth for label smoothing (see Section 6.4)
 - smooth for spatial smoothing (see Section 6.5).
- predict(x, logits=False) -> np.ndarray

Returns predictions of the classifier for the given inputs. If logits is False, then the class probabilities $F(\cdot)$ are returned, otherwise the class logits $Z(\cdot)$ (predictions before softmax). The shape of the returned array is (n,K) where n is the number of given samples and K the number of classes.

- class_gradient(x, label=None, logits=False) -> np.ndarray
 - Returns the gradients of the class probabilities or logits (depending on the value of the logits parameter), evaluated at the given inputs. Specifying a class label (one-hot encoded) will only compute the class gradients for the respective class. Otherwise, gradients for all classes will be computed. The shape of the returned array is of the form (n, K, I) when no label is specified, or (n, 1, I) for a given label, where I is the shape of the classifier inputs.
- loss_gradient(x, y) -> np.ndarray

Returns the loss gradient evaluated at the given inputs x and y. The labels are assumed to be one-hot encoded, i.e. the label y is encoded as the yth standard basis vector e_y . The shape of the returned array is of the form (n, I) under the above notation.

- fit(x, y, batch_size=128, nb_epochs=20) -> None

 Fits the classifier to the given data, using the provided batch size and number of epochs.

 The labels are assumed to be one-hot encoded.
- get_activations(x, layer) -> np.ndarray

Computes and returns the values of the activations (outputs) of the specified layer index for the given data x. The layer index goes from 0 to the total number of internal layers minus one. The input and output layers are not considered in the total number of available layers.

4.2 Keras Implementation

art.classifiers.KerasClassifier

art/classifiers/keras.py

This class provides support for Keras models. It differs from the base Classifier only in the signature of the constructor:

- __init__(clip_values, model, use_logits=False, channel_index=3, defences=None, preprocessing=(0, 1), input_layer=0, output_layer=0):
 - clip_values, channel_index, defences and preprocessing correspond to the parameters of the base class. channel_index should be set to 3 when using the TensorFlow backend for Keras, and 1 when using Theano.
 - model is the compiled Keras Model object.
 - use_logits should be set to True when the output of the model parameter are the logits; otherwise, probabilities as output are assumed.
 - input_layer and output_layer are two integers that allow the integration of Keras models with multiple input and outputs layers into the library. They specify the indices of the layers to be considered respectively as input and output of the classifier when computing gradients. In the case of models with only one input and output, these values do not need to be specified.

4.3 MXNet Implementation

art.classifiers.MXClassifier

art/classifiers/mxnet.py

This is the class supporting the integration of MXNet Gluon models. The constructor is as follows:

- __init__(clip_values, model, input_shape, nb_classes, optimizer=None, ctx=None, channel_index=1, defences=None, preprocessing=(0, 1)), where:
 - clip_values, channel_index, defences and preprocessing correspond to the parameters of the base class.
 - model is the mxnet.gluon.Block object containing the model.
 - input_shape is the shape of one input.
 - nb_classes is the number of classes in the model.
 - optimizer is the mxnet.gluon.Trainer used to train the classifier. This parameter is only required if fitting will be done through the Classifier interface.
 - ctx is the device on which the model runs (CPU or GPU).

4.4 PyTorch Implementation

art.classifiers.PyTorchClassifier

art/classifiers/pytorch.py

This class allows for the integration of PyTorch models. The signature of the constructor is as follows:

- __init__(clip_values, model, loss, optimizer, input_shape, nb_classes, channel_index=1, defences=None, preprocessing=(0, 1)), where:
 - clip_values, channel_index, defences and preprocessing correspond to the parameters of the base class.
 - model is the torch.nn.module object containing the model.
 - loss is the loss function for training.
 - optimizer is the optimizer used to train the classifier.
 - input_shape is the shape of one input.
 - nb_classes is the number of classes of the classifier.

4.5 TensorFlow Implementation

art.classifiers.TFClassifier

art/classifiers/tensorflow.py

The TFClassifier provides a wrapper around TensorFlow models allowing to integrate them under the Classifier API. Its __init_ function takes the following parameters:

- __init__(clip_values, input_ph, logits, output_ph=None, train=None, loss=None, learning=None, sess=None, channel_index=3, defences=None, preprocessing=(0, 1)), where:
 - clip_values, channel_index, defences and preprocessing correspond to the parameters of the base class.
 - input_ph: The input placeholder of the model.
 - logits: The logits layer.
 - output_ph: The label placeholder.
 - train: The symbolic training objective.
 - loss: The symbolic loss function.
 - learning: The placeholder to indicate if the model is training.
 - sess: The TensorFlow session.

Note that many of these parameters are only required when training a TensorFlow classifier through ART. When using a ready-trained model, only clip_values, input_ph, output_ph, logits and sess are required.

5 Attacks

art.attacks

This module contains all the attack methods supported by the library. These require access to a Classifier object, which is the target of the attack. By using the framework-independent API to access the targeted model, the attack implementation becomes agnostic to the framework used for training the model. It is thus easy to implement new attacks in the library.

The following attacks are currently implemented in ART:

- art.attacks.FastGradientMethod: Fast Gradient Sign Method (FGSM) [11], presented in Section 5.2
- art.attacks.BasicIterativeMethod: Basic Iterative Method (BIM) [18], detailed in Section 5.3
- art.attacks.SaliencyMapMethod: Jacobian Saliency Map Attack (JSMA) [28], see Section 5.4

- art.attacks.CarliniL2Method: Carlini & Wagner attack [7], see Section 5.5
- art.attacks.DeepFool: DeepFool [24], see Section 5.6
- art.attacks.UniversalPerturbation: Universal Perturbation [25], see Section 5.7
- art.attacks.NewtonFool: NewtonFool [16], see Section 5.8
- art.attacks.VirtualAdversarialMethod: Virtual Adversarial Method [23], detailed in Section 5.9

We now describe the base class behind all attack implementations.

5.1 The Attack Base Class

art.attacks.Attack

art/attacks/attack.py

ART has an abstract class Attack in the art.attacks.attack module which implements a common interface for any of the particular attacks implemented in the library. The class has an attribute classifier, an instance of the Classifier class, which is the classifier C(x) that the attack aims at. Moreover, the class has the following public methods:

- __init__(classifier)
 Initializes the attack with the given classifier.
- generate(x, **kwargs) -> np.ndarray

 Applies the attack to the given input x, using any attack-specific parameters provided in the

 **kwargs dictionary. The parameters provided in the dictionary are also set in the attack
 attributes. Returns the perturbed inputs in an np.ndarray which has the same shape as x.
- set_params(**kwargs) -> bool
 Initializes attack-specific hyper-parameters provided in the **kwargs dictionary; returns "True" if the hyper-parameters were valid and the initialization successful, "False" otherwise.

5.2 FGSM

art.attacks.FastGradientMethod

art/attacks/fast_gradient.py

The Fast Gradient Sign Method (FGSM) [11] works both in targeted and untargeted settings, and aims at controlling either the ℓ_1 , ℓ_2 or ℓ_∞ norm of the adversarial perturbation. In the targeted case and for the ℓ_∞ norm, the adversarial perturbation generated by the FGSM attack is given by

$$\psi(x,y) = -\epsilon \cdot \operatorname{sign}(\nabla_x \mathcal{L}(x,y))$$

where $\epsilon > 0$ is the **attack strength** and y is the target class specified by the attacker. The adversarial sample is given by

$$x_{\text{adv}} = \text{clip}(x + \psi(x, y), x_{\text{min}}, x_{\text{max}}).$$

Intuitively, the attack transforms the input x to reduce the classifier's loss when classifying it as y. For the ℓ_p norms with p=1,2, the adversarial perturbation is calculated as

$$\psi(x,y) = \epsilon \cdot \frac{\nabla_x \mathcal{L}(x,y)}{\|\nabla_x \mathcal{L}(x,y)\|_p}.$$

Note that "Sign" in the attack name "FGSM" refers to the specific calculation for the ℓ_∞ norm (for which the attack was originally introduced). Sometimes the modified attacks for the ℓ_1 and ℓ_2

norms are referred to as "Fast Gradient Methods" (FGM), nevertheless we will also refer to them as FGSM for simplicity. The untargeted version of the FGSM attack is devised as

$$\rho(\mathbf{x}) = -\psi(\mathbf{x}, C(\mathbf{x})),\tag{1}$$

i.e. the input x is transformed to increase the classifier's loss when continuing to classify it as C(x).

ART also implements an extension of the FGSM attack, in which the **minimum perturbation** is determined for which $C(x_{\text{adv}}) \neq C(x)$. This modification takes as input two extra floating-point parameters: ϵ_{step} and ϵ_{max} . It sequentially performs the standard FGSM attack with strength $\epsilon = k \cdot \epsilon_{\text{step}}$ for $k = 1, 2, \ldots$ until either the attack is successful (and the resulting adversarial sample x_{adv} is returned), or $k \cdot \epsilon_{\text{step}} > \epsilon_{\text{max}}$, in which case the attack has failed.

The main advantage of FGSM is that it is very efficient to compute: only one gradient evaluation is required, and the attack can be applied straight-forward to a batch of inputs. This makes the FGSM (or variants thereof) a popular choice for adversarial training (see Section 6.1) in which a large number of adversarial samples needs to be generated.

The strength of the FGSM attack depends on the choice of the parameter ϵ . If ϵ is too small, then $C(x_{adv})$ might not differ from C(x). On the other hand, the norm $||x - x_{adv}||_p$ grows linearly with ϵ . When choosing ϵ , it is particularly important to consider the actual data range $[x_{min}, x_{max}]$.

Implementation details The FastGradientMethod class has the following attributes:

- norm: The norm p of the adversarial perturbation (must be either np.inf, 1 or 2).
- eps: The attack strength ϵ (must be greater than 0).
- targeted: Indicating whether the attack is targeted (True) or untargeted (False).

The functions in the class take the following form:

- __init__(classifier, norm=np.inf, eps=0.3, targeted=False)
 Initializes an FGSM attack instance.
- generate(x, **kwargs) -> np.ndarray

Applies the attack to the given input x. The function accepts the same parameters as '_init_', but has two additional parameters:

- y: An np.ndarray containing labels for the inputs x in one-hot encoding. If the attack is targeted, y is required and specifies the target classes. If the attack is untargeted, y is optional and overwrites the C(x) argument in (1). Note that it is not advisable to provide true labels in the untargeted case, as this may lead to the so-called **label leaking** effect [18].
- minimal: True if the minimal perturbation should be computed. In that case, also eps_step for the step size and eps_max for the maximum perturbation should be provided (default values are 0.1 and 1.0, respectively).

5.3 Basic Iterative Method

 $\verb"art.attacks.BasicIterativeMethod"$

art/attacks/iterative_method.py

The Basic Iterative Method (BIM) [18] is a straightforward extension of FGSM that applies the attack multiple times, iteratively. This attack differs from FGSM in that it is targeted towards the least likely class for a given sample, i.e. the class for which the model outputs the lowest score. Like in the case of FGSM, BIM is limited by a total attack budget ϵ , and it has an additional parameter ϵ_{step} determining the step size at each iteration. At each step, the result of the attack is projected back onto the ϵ -size ball centered around the original input. The attack is originally designed for L_{∞} norm perturbations, but can easily be extended to other norms.

Implementation details The BasicIterativeMethod class has the following specific parameters:

- norm: The norm p of the adversarial perturbation (must be either np.inf, 1 or 2).
- eps: The attack strength ϵ (must be greater than 0).
- eps_step: The step size ϵ_{step} to be taken at each iteration.

The functions in the class follow the Attack API. The previous parameters can be set either in __init__ or when calling the generate function.

5.4 JSMA

art.attacks.SaliencyMapMethod

art/attacks/saliency_map.py

The Jacobian-based Saliency Map Attack (JSMA) [28] is a targeted attack which aims at controlling the ℓ_0 norm, i.e. the number of components of x that are being modified when crafting the adversarial sample $x_{\rm adv}$. The attack iteratively modifies individual components of x until either the targeted misclassification is achieved or the total number of modified components exceeds a specified budget.

Details are outlined in Algorithm 1. To simplify notation, we let N denote the total number of components of x and refer to individual components using subscripts: x_i for $i=1,\ldots,N$. The key step is the computation of the saliency map (line 4), which is outlined in Algorithm 2. Essentially, the saliency map determines the components i_{\max} , j_{\max} of x to be modified next based on how much this would increase the probability $F_y(x)$ of the target class y (captured in the sum of partial derivatives α), and decrease the sum of probabilities over all other classes (captured in the sum of partial derivatives β). In particular, line 4 in Algorithm 2 ensures that α is positive, β is negative and $|\alpha \cdot \beta|$ is maximal over all pairs in the search space. Considering pairs instead of individual components is motivated by the observation that this increases the chances of satisfying the conditions $\alpha > 0$ and $\beta < 0$ ([28], page 9). In our implementation of the saliency map, we exploit that β can be expressed as

$$\beta = -\left(\frac{\partial F_y(x)}{\partial x_i} + \frac{\partial F_y(x)}{\partial x_j}\right)$$

(due to $\sum_{k \in \mathcal{Y} \setminus \{y\}} F_k(x) = 1 - F_y(x)$), and thus i, j are the two largest components of $\nabla F_y(x)$.

Line 9 in Algorithm 1 applies the perturbations to the components determined by the saliency map. The set Ω_{search} keeps track of all the components that still can be modified (i.e. the clipping value x_{max} has not been exceeded), and Ω_{modified} of all the components that have been modified at least once. The algorithm terminates if the attack has succeeded (i.e. C(x) = y), the number of modified components has exhausted the budget (i.e. $|\Omega_{\text{modified}}| > |\gamma \cdot N|$), less than 2 components can still be modified (i.e. $|\Omega_{\text{search}}| < 2$), or the saliency map returns the saliency score $s_{\text{max}} = -\infty$ (indicating it hasn't succeeded in determining components satisfying the conditions in line 4 of Algorithm 2).

Two final comments on the JSMA method:

- Algorithms 1 and 2 describe the method for positive values of the input parameter θ , resulting in perturbations where the components of x are increased while crafting x_{adv} . In principle, it is possible to also use negative values for θ . In fact, the experiments in [28] (Section IV D) suggest that using a negative θ results in perturbations that are harder to detect by the human eye[¶]. The implementation in ART supports both positive and negative θ , however note that for negative θ the following changes apply:
 - In Algorithm 1, line 2: change the condition $x_i \neq x_{max}$ to $x_i \neq x_{min}$.
 - In Algorithm 1, line 10: change the condition $x_k \neq x_{max}$ to $x_k \neq x_{min}$.

[¶]Which however might be specific to the MNIST data set that was used in those experiments.

Algorithm 1 JSMA method

x: Input to be adversarially perturbed

Input:

```
y: Target label \theta: Amount of perturbation per step and feature (assumed to be positive; see discussion in
```

text) γ : Maximum fraction of features to be perturbed (between 0 and 1)

```
1: \Omega_{\text{modified}} \leftarrow \emptyset
  2: \Omega_{\text{search}} \leftarrow \{i \in \{1, \dots, N\} : x_i \neq x_{\text{max}}\}
  3: while C(x) \neq y and |\Omega_{\text{search}}| > 1 do
             (s_{\max}, i, j) \leftarrow \text{saliency} \max(x, y, \Omega_{\text{search}})
  5:
             \Omega_{\text{modified}} \leftarrow \Omega_{\text{modified}} \cup \{i, j\}
             if s_{	ext{\tiny max}} = -\infty or |\Omega_{	ext{\tiny modified}}| > \lfloor \gamma \cdot N \rfloor then
  6:
                  break
  7:
             end if
  8:
             x_i \leftarrow \text{clip}(x_i + \theta, x_{\min}, x_{\max}), x_j \leftarrow \text{clip}(x_j + \theta, x_{\min}, x_{\max})
  9:
 10:
             \Omega_{\text{search}} \leftarrow \Omega_{\text{search}} \setminus \{k \in \{i, j\} : x_k = x_{\text{max}}\}
 11: end while
12: x_{\text{adv}} \leftarrow x
Output:
```

Adversarial sample x_{adv} .

- In Algorithm 2, line 4: change the conditions $\alpha > 0$ and $\beta < 0$ to $\alpha < 0$ and $\beta > 0$, respectively.
- While Algorithm 2 outlines the computation of the saliency map based on the partial derivates of the classifier probabilities F(x), one can, in principle, consider the partial derivates of the classifier logits Z(x) instead. As discussed in [7], it appears that both variants have been implemented and used in practice. The current implementation in ART uses the partial derivates of the classifier probabilities which, as explained above, can be performed particularly efficiently.

Implementation details The SaliencyMapMethod class has the following attributes:

- theta: Amount of perturbation θ per step and component (can be positive or negative).
- gamma: Maximum fraction of components γ to be perturbed (must be > 0 and ≤ 1).

The functions in the class take the following form:

- __init__(classifier, theta=0.1, gamma=1)
 Initializes a JSMA attack instance.
- generate(x, **kwargs) -> np.ndarray

Applies the attack to the given input x. The function accepts the same parameters as __init__, but has one additional parameter:

- y, which is an np.ndarray containing the target labels, one-hot encoded. If not provided, target labels will be sampled uniformly from $\mathcal{Y} \setminus \{C(x)\}$.

5.5 Carlini & Wagner attack

```
art.attacks.CarliniL2Method
```

art/attacks/carlini.py

The Carlini & Wagner (C&W) attack [7] is a targeted attack which aims to minimize the ℓ_2 norm of adversarial perturbations $^{||}$. Below we will discuss how to perform untargeted C&W

¹¹ Also ℓ_0 and ℓ_∞ versions of the C&W attack exist; they build upon the ℓ_2 attack.

Algorithm 2 JSMA saliency_map

Input:

x: Input to be adversarially perturbed y: Target label

 Ω_{search} : Set of indices of x to be explored.

- 1: $s_{\max} \leftarrow -\infty$, $i_{\max} \leftarrow \text{None}$, $j_{\max} \leftarrow \text{None}$
- 2: **for** each subset $\{i,j\} \subset \Omega_{\text{search}}$ with i < j **do**
- Compute

$$\alpha = \frac{\partial F_y(x)}{\partial x_i} + \frac{\partial F_y(x)}{\partial x_j}, \ \beta = \sum_{k \in \mathcal{Y} \setminus \{y\}} \left(\frac{\partial F_k(x)}{\partial x_i} + \frac{\partial F_k(x)}{\partial x_j} \right).$$

- if $\alpha > 0$ and $\beta < 0$ and $|\alpha \cdot \beta| > s_{max}$ then
- $s_{\max} \leftarrow |\alpha \cdot \beta|, i_{\max} \leftarrow i, j_{\max} \leftarrow j$ end if 5:
- 7: end for

Output:

Maximum saliency score and selected components (s_{max} , i_{max} , j_{max}).

attacks. For a fixed input x, a target label y and a confidence parameter $\kappa \geq 0$, consider the objective function

$$L(c, x') := \|x' - x\|_2^2 + c \cdot \ell(x')$$
 (2)

where

$$\ell(\mathbf{x}') = \max \Big(\max \{ Z_i(\mathbf{x}') : i \in \mathcal{Y} \setminus \{y\} \} - Z_y(\mathbf{x}') + \kappa, 0 \Big).$$
 (3)

Note that $\ell(x') = 0$ if and only if C(x') = y and the logit $Z_y(x')$ exceeds any other logit $Z_i(x')$ by at least κ , thus relating to the classifier's confidence in the output C(x'). The C&W attack aims at finding the smallest c for which the x' minimizing L(x',c) is such that $\ell(x')=0$. This can be regarded as the optimal trade-off between achieving the adversarial target while keeping the adversarial perturbation $\|x'-x\|_2^2$ as small as possible. In the ART implementation, binary search is used for finding such *c*.

Details are outlined in Algorithm 3. Note that, in lines 1-2, the components of x are mapped from $[x_{\min}, x_{\max}]$ onto \mathbb{R} , which is the space in which the adversarial sample is created. Working in $\mathbb R$ avoids the need for clipping x during the process. The output x_{adv} is transformed back to the $[x_{\min}, x_{\max}]$ range in lines 15-16. Algorithm 3 relies on two helper functions:

- minimize_objective (line 7): this function aims at minimizing the objective function (2) for the given value of c. In the ART implementation, the minimization is performed using Stochastic Gradient Descent (SGD) with decayed learning rate; the minimization is aborted if a specified number of iterations is exceeded.* During the minimization, among all samples x' for which $\ell(x') = 0$, the one with the smallest norm $||x' - x||_2^2$ is retained and returned at the end of the minimization.
- update (line 12): this function updates the parameters c_{lower}, c, c_{double} used in the binary search. Specifically, if an adversarial sample with $\ell(x_{\text{new}}) = 0$ was found for the previous value of c, then c_{lower} remains unchanged, c is set to $(c + c_{\text{lower}})/2$ and c_{double} is set to False. If $\ell(x_{\text{new}}) \neq 0$, then c_{lower} is set to c, and c is either set to $2 \cdot c$ (if c_{double} is True) or to $c + (c - c_{\text{lower}})/2$ (if c_{double} is False). The binary search is abandoned if c exceeds the upper bound c_{upper} (line 6).

^{*}The original implementation in [7] used the Adam optimizer for the minimization problem and implemented an additional stopping criterion.

[†]This is a slight simplification of the original implementation in [7].

The **untargeted** version of the C&W attack aims at changing the original classification, i.e. constructing an adversarial sample x_{adv} with the only constraint that $C(x_{\text{adv}}) \neq C(x)$. The only difference in the algorithm is that the objective function (3) is modified as follows:

$$\ell(\mathbf{x}') = \max \left(Z_y(\mathbf{x}') - \max \left\{ Z_i(\mathbf{x}') : i \in \mathcal{Y} \setminus \{y\} \right\} + \kappa, 0 \right)$$
(4)

where y is the original label of x (or the prediction C(x) thereof). Thus, $\ell(x') = 0$ if and only if there exists a label $i \in \mathcal{Y} \setminus \{y\}$ such that the logit $Z_i(x)$ exceeds the logit $Z_y(x)$ by at least κ .

Algorithm 3 Carlini & Wagner's ℓ₂ attack (targeted)

```
Input:
       x: Input to be adversarially perturbed
       y: Target label
       \gamma: constant to avoid over-/underflow in (arc)tanh computations
       c_{\text{init}}: initialization of the binary search constant
       c_{upper}: upper bound for the binary search constant
       b_{\text{steps}}: number of binary search steps to be performed
   1: \mathbf{x} \leftarrow (\mathbf{x} - \mathbf{x}_{\min}) / (\mathbf{x}_{\max} - \mathbf{x}_{\min})
  2: \mathbf{x} \leftarrow \operatorname{arctanh}(((2 \cdot \mathbf{x}) - 1) \cdot \gamma)
  3: x_{\text{adv}} \leftarrow x
  4: c_{\text{lower}} \leftarrow 0, c \leftarrow c_{\text{init}}, c_{\text{double}} \leftarrow \text{True}
  5: l_{\min} \leftarrow \infty
  6: while b_{\text{steps}} > 0 and c < c_{\text{upper}} do
           x_{\text{new}} \leftarrow \texttt{minimize\_objective}(c)
           if \ell(x_{\text{new}}) = 0 and ||x_{\text{new}} - x||_2^2 < l_{\text{min}} then
                l_{\min} \leftarrow ||x_{\text{new}} - x||_2^2
  9:
                \pmb{x}_{\text{adv}} \leftarrow \pmb{x}_{\text{new}}
 10:
 11:
            (c_{\text{lower}}, c, c_{\text{double}}) \leftarrow \text{update}(c, c_{\text{double}}, \ell(x_{\text{new}}))
 12:
            b_{\text{steps}} \leftarrow b_{\text{steps}} - 1
 13:
 14: end while
 15: \mathbf{x}_{\text{adv}} \leftarrow (\tanh(\mathbf{x}_{\text{adv}})/\gamma + 1)/2
16: \mathbf{x}_{adv} \leftarrow \mathbf{x}_{adv} \cdot (\mathbf{x}_{max} - \mathbf{x}_{min}) + \mathbf{x}_{mir}
Output:
```

Implementation details The C&W attack is implemented in the CarliniL2Method class, with the following attributes:

- confidence: κ value to be used in Objective (3).
- targeted: Specifies whether the attack should be targeted (True) or not (False).
- learning_rate: SGD learning rate to be used in minimize_objective (line 7).
- decay: SGD decay factor to be used in minimize_objective.
- max_iter: Maximum number of SGD iterations to be used in minimize_objective.
- binary_search_steps: Number b_{steps} of binary search steps.
- initial_const: Initial value c_{init} of the binary search variable c.

The signatures of the functions are:

Adversarial sample x_{adv} .

• __init__(classifier, confidence=5, targeted=True, learning_rate=1e-4, binary_search_steps=25, max_iter=1000, initial_const=1e-4, decay=0)
Initialize a C&W attack with the given parameters.

- generate(x, **kwargs) -> np.ndarray
 - Applies the attack to the given input x. The function accepts the same parameters as __init__, and an additional parameter:
 - y, which is an np.ndarray containing labels (one-hot encoded). In the case of a targeted attack, y is required and specifies the target labels. In the case of an untargeted attack, y is optional (if not provided, C(x) will be used); as commented earlier for the FGSM attack, it is advised not to provide the true labels for untargeted attacks in order to avoid label leaking.

If binary_search_steps is large, then the algorithm is not very sensitive to the value of initial_const. The default value initial_const=1e-4 is suggested in [7]. Note that the values $\gamma = 0.999999$. and $c_{upper} = 10e10$ in Algorithm 3 are hardcoded with the same values used by the authors of the method.

5.6 DeepFool

art.attacks.DeepFool

art/attacks/deepfool.py

DeepFool [24] is an untargeted attack which aims, for a given input x, to find the nearest decision boundary in ℓ_2 norm[‡]. Implementation details are provided in Algorithm 4. The basic idea is to project the input onto the nearest decision boundary; since the decision boundaries are non-linear, this is done iteratively. DeepFool often results in adversarial samples that lie exactly on a decision boundary; in order to push the samples over the boundaries and thus change their classification, the final adversarial perturbation $x_{adv} - x$ is multiplied by a factor $1 + \epsilon$ (see line 8).

Algorithm 4 DeepFool attack

Input:

x: Input to be adversarially perturbed

 i_{max} : Maximum number of projection steps

 ϵ : Overshoot parameter (must be ≥ 0)

- 1: $\mathbf{x}_{\text{adv}} \leftarrow \mathbf{x}$
- 2: $i \leftarrow 0$
- 3: while $i < i_{\text{max}}$ and $C(x) = C(x_{\text{adv}})$ do
- Compute

$$l \leftarrow \underset{k \in \mathcal{Y} \setminus \{C(x)\}}{\operatorname{arg\,min}} \frac{\left| Z_k(x_{\text{adv}}) - Z_{C(x)}(x_{\text{adv}}) \right|}{\left\| \nabla Z_k(x_{\text{adv}}) - \nabla Z_{C(x)}(x_{\text{adv}}) \right\|_2}, \tag{5}$$

$$\boldsymbol{x}_{\text{adv}} \leftarrow \boldsymbol{x}_{\text{adv}} + \frac{\left| Z_{l}(\boldsymbol{x}_{\text{adv}}) - Z_{C(\boldsymbol{x})}(\boldsymbol{x}_{\text{adv}}) \right|}{\left\| \nabla Z_{l}(\boldsymbol{x}_{\text{adv}}) - \nabla Z_{C(\boldsymbol{x})}(\boldsymbol{x}_{\text{adv}}) \right\|_{2}^{2}} \cdot \left(\nabla Z_{l}(\boldsymbol{x}_{\text{adv}}) - \nabla Z_{C(\boldsymbol{x})}(\boldsymbol{x}_{\text{adv}}) \right). \tag{6}$$

- 5: $x_{\text{adv}} \leftarrow \text{clip}(x_{\text{adv}}, x_{\text{min}}, x_{\text{max}})$ 6: $i \leftarrow i + 1$
- 7: end while
- 8: $x_{\text{adv}} \leftarrow \text{clip}(x + (1 + \epsilon) \cdot (x_{\text{adv}} x), x_{\text{min}}, x_{\text{max}})$

Output:

Adversarial sample x_{adv} .

Implementation details The DeepFool class has two attributes:

• max_iter: Maximum number of projection steps i_{\max} to be undertaken.

[‡]While [24] also explains how to adapt the algorithm to minimize the ℓ_1 or ℓ_∞ norms of adversarial perturbations by modifying the expressions in (5)-(6), this is currently not implemented in ART.

• overshoot: Overshoot parameter ϵ (must be ≥ 0).

The class functions implement the Attack API in the following:

- __init__(classifier, max_iter=100) Initialize a DeepFool attack with the given parameters.
- generate(x, **kwargs) -> np.ndarray Apply the attack to x. The same parameters as for __init__ can be specified at this point.

Universal Adversarial Perturbations

```
art.attacks.UniversalPerturbation
                                             art/attacks/universal_perturbation.py
```

Universal adversarial perturbations [25] are a special type of untargeted attacks, aiming to create a constant perturbation ρ that successfuly alters the classification of a specified fraction of inputs. The universal perturbation is crafted using a given untargeted attack $ho(\cdot)$. Essentially, as long as the target fooling rate has not been achieved or the maximum number of iterations has not been reached, the algorithm iteratively adjusts the universal perturbation by adding refinements which help to perturb additional samples from the input set; after each iteration, the universal perturbation is projected into the ℓ_p ball with radius ϵ in order to control the attack strength. Details are provided in Algorithm 5.

Algorithm 5 Universal Adversarial Perturbation

```
Input:
```

```
X: Set of inputs to be used for constructing the universal adversarial perturbation
     \rho(\cdot): Adversarial attack to be used
     \delta: Attack failure tolerance (1 – \delta is the target fooling rate)
     \epsilon: Attack step size
     p: Norm of the adversarial perturbation
     i_{\text{max}}: Maximum number of iterations
 1: \rho \leftarrow 0
 2: r_{\text{fool}} \leftarrow 0
 3: i \leftarrow 0
 4: while r_{\text{fool}} < 1 - \delta and i < i_{\text{max}} do
        for x \in X in random order do
           if C(x + \rho) = C(x) then
 6:
 7:
               x_{\text{adv}} \leftarrow x + \rho(x + \rho)
               if C(x_{adv}) \neq C(x) then
 8:
 9:
                  \rho \leftarrow \operatorname{project}(x_{\operatorname{adv}} - x + \rho, p, \epsilon)
               end if
10:
11:
           end if
        end for
12:
        r_{\text{fool}} \leftarrow \frac{1}{|X|} \sum_{x \in X} \mathbb{I}(C(x) \neq C(x + \rho))
        i \leftarrow i + 1
15: end while
Output:
     Adversarial samples x_{\text{adv}} = x + \rho for x \in X.
```

Implementation details The UniversalPerturbation class has the following attributes:

• attacker: A string representing which attack ρ should be used in Algorithm 5. The following attacks are supported: carlini (Carlini & Wagner attack), deepfool (DeepFool), fgsm (Fast Gradient Sign Method), jsma (JSMA), newtonfool (NewtonFool) and vat (Virtual Adversarial Method).

- attacker_params: A dictionary with attack-specific parameters that will be passed onto the selected attacker. If this parameter is not specified, the default values for the chosen attack are used.
- delta: Attack failure tolerance δ (must lie in [0,1]).
- max_iter: Maximum number of iterations i_{max} .
- eps: Attack step size ϵ .
- norm: Norm *p* of the adversarial perturbation (must be either np.inf, 1 or 2).

The class functions implement the Attack API as follows:

• __init__(classifier, attacker='deepfool', attacker_params=None, delta=0.2, max_iter=20, eps=10.0, norm=np.inf)

Initialize a Universal Perturbation attack with the given parameters.

• generate(x, **kwargs) -> np.ndarray
Apply the attack to x. The same parameters as for __init__ can be specified at this point.

5.8 NewtonFool

art.attacks.NewtonFool

art/attacks/newtonfool.py

NewtonFool [16] is an untargeted attack that tries to decrease the probability $F_y(x)$ of the original class y = C(x) by performing gradient descent. The step size δ is determined adaptively in Equation (7): when $F_y(x_{adv})$ is larger than 1/K (recall K is the number of classes in \mathcal{Y}), which is the case as long as $C(x_{adv}) = y$, then the second term will dominate; once $F_y(x_{adv})$ approaches or falls below 1/K, the first term will dominate. The tuning parameter η determines how aggressively the gradient descent attempts to minimize the probability of class y. The method is described in detail in Algorithm 6.

Algorithm 6 NewtonFool attack

Input:

- *x*: Input to be adversarially perturbed
- η : Strength of adversarial perturbations

 i_{max} : Maximum number of iterations

- 1: $y \leftarrow C(x), x_{adv} \leftarrow x, i \leftarrow 0$
- 2: while $i < i_{max}$ do
- 3: Compute

$$\delta \leftarrow \min \left\{ \eta \cdot \|\mathbf{x}\|_{2} \cdot \|\nabla F_{y}(\mathbf{x}_{adv})\|, F_{y}(\mathbf{x}_{adv}) - 1/K \right\},$$

$$d \leftarrow -\frac{\delta \cdot \nabla F_{y}(\mathbf{x}_{adv})}{\|\nabla F_{y}(\mathbf{x}_{adv})\|_{2}^{2}}$$

$$(7)$$

- 4: $x_{\text{adv}} \leftarrow \text{clip}(x_{\text{adv}} + d, x_{\text{min}}, x_{\text{max}})$
- 5: $i \leftarrow i + 1$
- 6: end while

Output:

Adversarial sample x_{adv} .

Implementation details The NewtonFool class has the following attributes:

- eta: Strength of adversarial perturbations η .
- max_iter: Maximum number of iterations i_{max} .

The class functions implement the Attack API as follows:

- __init__(classifier, max_iter=100, eta=0.01)
 Initialize NewtonFool with the given parameters.
- generate(x, **kwargs) -> np.ndarray
 Apply the attack to x. The same parameters as for __init__ can be specified at this point.

5.9 Virtual Adversarial Method

```
art.attacks.VirtualAdversarialMethod art/attacks/virtual_adversarial.py
```

The Virtual Adversarial Method [22] is not intended to create adversarial samples resulting in misclassification, but rather samples that, if included in the training set for adversarial training, result in local distributional smoothness of the trained model. We use N to denote the total number of components of classifier inputs and assume, for sake of convenience, that $\mathcal{X} = \mathbb{R}^N$. By $N(\mathbf{0}, \mathbf{I}_N)$ we denote a random sample of the N-dimensional standard normal distribution, and by e_i the ith standard basis vector of dimension N. The key idea behind the algorithm is to construct a perturbation d with ℓ_2 unit norm maximizing the Kullback-Leibler (KL) divergence $\mathrm{KL}[F(x)\|F(x+d)]$. In Algorithm 7 this is done iteratively via gradient ascent along finite differences (line 9). The final adversarial example x_{adv} is constructed by adding $\epsilon \cdot d$ to the original input x (line 14), where ϵ is the perturbation strength parameter provided by the user.

Algorithm 7 Virtual Adversarial Method with finite differences

```
Input:
```

```
x: Input to be adversarially perturbed
      \epsilon: Perturbation strength
      \xi: Finite differences width
      i_{\text{max}}: Maximum number of iterations
  1: d \leftarrow N(0, I_N)
 2: d \leftarrow d/\|d\|_2
 3: i \leftarrow 0
 4: while i < i_{max} do
         \kappa_1 \leftarrow \text{KL}[F(x) || F(x+d)]
         d_{\text{new}} \leftarrow d
 6:
         for i = 1, 2, ..., N do
 7:
              \kappa_2 \leftarrow \text{KL}[F(x) || F(x + d + \xi \cdot e_i)]
 8:
              d_{\text{new}} \leftarrow d_{\text{new}} + (\kappa_2 - \kappa_1)/\xi \cdot e_i
 9:
          end for
10:
          d \leftarrow d_{\text{new}}
11:
         d \leftarrow d/\|d\|_2
12:
13: end while
14: \mathbf{x}_{\text{adv}} \leftarrow \text{clip}(\mathbf{x} + \boldsymbol{\epsilon} \cdot \boldsymbol{d}, \mathbf{x}_{\min}, \mathbf{x}_{\max})
Output:
      Adversarial sample x_{adv}.
```

 $\textbf{Implementation details} \quad \textbf{The VirtualAdversarialMethod class has the following attributes:} \\$

- eps: Strength of adversarial perturbations ϵ .
- finite_diff: Finite differences width ξ .
- max_iter: Maximum number of iterations i_{max} .

The following functions are accessible to users:

- __init__(classifier, max_iter=1, finite_diff=1e-6, eps=0.1)

 Initialize an instance of the virtual vdversarial perturbation generator for Virtual Adversarial Training.
- generate(x, **kwargs) -> np.ndarray
 Compute the perturbation on x. The **kwargs dictionary allows the

Compute the perturbation on x. The **kwargs dictionary allows the user to overwrite any of the attack parameters, which will be set in the class attributes. Returns an array containing the adversarially perturbed sample(s).

6 Defences

art.defences

There is a plethora of methods for defending against evasion attacks which can roughly be categorized as follows:

Model hardening refers to techniques resulting in a new classifier with better robustness properties than the original one with respect to some given metrics.

Data preprocessing techniques achieve higher robustness by using transformations of the classifier inputs and labels, respectively, at test and/or training time.

Runtime detection of adversarial samples by extending the original classifier with a detector in order to check whether a given input is adversarial or not.

The following defences are currently implemented in ART:

- art.defences.AdversarialTrainer: adversarial training, a method for model hardening (see Section 6.1).
- art.defences.FeatureSqueezing: feature squeezing, a defence based on input data preprocessing (see Section 6.3)
- art.defences.LabelSmoothing: label smoothing, a defence based on processing the labels before model training (described in Section 6.4).
- art.defences.SpatialSmoothing: spatial smoothing, a defence based on input data preprocessing (see Section 6.5).
- art.defences.GaussianAugmentation: data augmentation based on Gaussian noise, meant to reinforce the structure of the model (described in Section 6.6).

6.1 Adversarial Training

art.defences.AdversarialTrainer

art/defences/adversarial_trainer.py

The idea of adversarial training [11] is to improve the robustness of the classifier C(x) by including adversarial samples in the training set. A special case of adversarial training is virtual adversarial training [23] where the adversarial samples are generated by the Virtual Adversarial Method (see Section 5.9).

The ART implementation of adversarial training incorporates the original protocol, as well as ensemble adversarial training [33], training fully on adversarial data and other common setups. If multiple attacks are specified, they are rotated for each batch. If the specified attacks have as target a different model that the one being trained, then the attack is transferred. A ratio parameter determines how many of the clean samples in each batch are replaced with their adversarial counterpart. When the attack targets the current classifier, only successful adversarial samples are used.

Implementation details The AdversarialTrainer class has the following public functions:

- __init__(classifier, attacks, ratio=.5),
 - The parameters of the constructor are the following:
 - classifier: The classifier C(x) to be hardened by adversarial training.
 - attacks: Attack or list of attacks to be used for adversarial training. These are instances
 of the 'Attack' class.
 - ratio: The proportion of samples in each batch to be replaced with their adversarial counterparts. Setting this value to 1 allows to train only on adversarial samples.

Each instance of the class Attack (corresponding to $\rho_i(x)$ in the notation above), has an attribute classifier with the classifier the attack aims at, corresponding to $C_i(x)$ in the notation above.

• fit(x, y, batch_size=128, nb_epochs=20) -> None

Method for training the hardened classifier. x and y are the original training inputs and labels, respectively. The method applies the adversarial attacks specified in the attacks parameter of $_init_$ to obtain the enhanced training set as explained above. Then the fit function of the classifier specified in the class attribute classifier is called with the enhanced training set as input. The hardened classifier is trained with the given batch size for as many epochs as specified. After calling this function, the classifier attribute of the class contains the hardened classifier C(x).

predict(x, **kwargs) -> np.ndarray
 Calls the predict function of the hardened classifier C(x), passing on the dictionary of arguments **kwargs).

6.2 The Data Preprocessor Base class

art.defences.Preprocessor

art/defences/preprocessor.py

The abstract class Preprocessor provides a unified interface for all data preprocessing transformations to be used as defences. The class has the following public methods:

- fit(x, y=None, **kwargs): Fit the transformations with the given data and parameters (where applicable).
- _call_(x, y=None): Applies the transformations to the provided labels and/or inputs and returns the transformed data.
- is_fitted: Check whether the transformations have been fitted (where applicable).

Feature squeezing, label smoothing, spatial smoothing and Gaussian data augmentation are all data preprocessing techniques. Their implementation is based on the Preprocessor abstract class. We describe them individually in the following sections.

6.3 Feature Squeezing

$\verb"art.defences.FeatureSqueezing"$

art/defences/feature_squeezing.py

Feature squeezing [36] reduces the precision of the components of x by encoding them on a smaller number of bits. In the case of images, one can think of feature squeezing as reducing the common 8-bit pixel values to b bits where b < 8. Formally, assuming that the components of x all lie within [0,1] (which would have been obtained, e.g., by dividing 8-bit pixel values by 255) and given the desired **bit depth** b, feature squeezing applies the following transformation component-wise:

$$x \leftarrow |x \cdot (2^b - 1)|/(2^b - 1).$$
 (8)

Future implementations of this method will support arbitrary data ranges of the components of r

Implementation details The FeatureSqueezing class is an extension of the Preprocessor base class. Since feature squeezing does not require any model fitting for the data transformations, is_fitted always returns True, and the fit function does not have any effect. We now describe the functions and parameters specific to this class:

- __init__(bit_depth=8)
 - bit_depth: The bit depth *b* on which to encode features.
- _call_(x, y=None, bit_depth=None) -> np.ndarray

As feature squeezing only works on the inputs x, providing labels y to this function does not have any effect. The bit_depth parameter has the same meaning as in the constructor. Calling this method returns the squeezed inputs x.

Note that any instance of the Classifier class which has feature squeezing as one of their defences will automatically apply this operation when the fit or predict functions are called. The next example shows how to activate this defence when creating a classifier object from a Keras model:

```
In [1]: from keras.models import load_model

model = load_model('keras_model.h5')
classifier = KerasClassifier((0, 1), model, defences='featsqueeze5')
```

Applying feature squeezing to data without using a classifier would be done as follows:

6.4 Label Smoothing

```
art.defences.LabelSmoothing
```

art/defences/label_smoothing.py

Label smoothing [34] modifies the labels y during model training: instead of using one-hot encoding, where y is represented by the standard basis vector $y = e_y$, the following representation is used:

$$y_i \leftarrow \begin{cases} y_{\text{max}} & \text{if } i = y \\ (1 - y_{\text{max}})/(K - 1) & \text{otherwise,} \end{cases}$$

where $y_{\text{max}} \in [0,1]$ is a parameter specified by the user. The label representation y is thus "smoothed" in the sense that the difference between its maximum and minimum components is reduced and its entropy increased. The motivation behind this approach is that it might help reducing gradients that an adversary could exploit in the construction of adversarial samples.

Implementation details Same as feature squeezing, label smoothing does not require any model fitting, hence is_fitted is always True, and the fit function is a dummy. Its LabelSmoothing class specific functions are:

- __init__(max_value=.9)
 - max_value: Represents y_{max} in the notation above.

• _call_(x, y, max_value=0.9) -> (np.ndarray, np.ndarray)

This function expects one-hot encoded labels in y and returns the unmodified inputs x along with the smoothed labels. max_value can be specified directly when calling the method instead of the constructor.

Note that any instance of the Classifier class which has label smoothing activated in the defences will automatically apply it when the fit function is called. One can initiaze this defence when creating a classifier as follows:

```
In [1]: from keras.models import load_model
    model = load_model('keras_model.h5')
    classifier = KerasClassifier((0, 1), model, defences='label_smooth')
```

Label smoothing can be used directly to preprocess the dataset as follows:

6.5 Spatial Smoothing

```
art.defences.SpatialSmoothing
```

art/defences/spatial_smoothing.py

Spatial smoothing [36] is a defence specifically designed for images. It attempts to filter out adversarial signals using local spatial smoothing. Let x_{ijk} denote the components of x. Recall that i indexes width, j height and k the color channel. Given a **window size** w, the component x_{ijk} is replaced by a median-filtered version:

```
x_{ijk} \leftarrow \text{median}\{x_{i'i'k}: i - \lfloor w/2 \rfloor \le i' \le i + \lceil w/2 \rceil - 1, j - \lfloor w/2 \rfloor \le j' \le j + \lceil w/2 \rceil - 1\},
```

where features at the borders are reflected where needed:

- $x_{ijk} = x_{(1-i),i,k}$ for i = 0, -1, ...
- $x_{(k_1+i),j,k} = x_{(k_1+1-i),j,k}$ for i = 1, 2, ...

and analogously for j. Note that the local spatial smoothing is applied separately in each color channel k.

Implementation details Same as for the previous two defences, is_fitted is always True, and the fit function does not have any effect. The signatures of functions in the SpatialSmoothing class are:

- __init__(window_size=3)
 - window_size: The window size w.
- _call_(self, x, y=None, window_size=None) -> np.ndarray

 This method only requires inputs x and returns them with spatial smoothing applied.

Note that any instance of the Classifier class which has spatial smoothing as one of their defences will automatically apply it when the predict function is called. The next example shows how to initialize a classifier with spatial smoothing.

6.6 Gaussian Data Augmentation

```
art.defences.GaussianAugmentation art/defences/gaussian_augmentation.py
```

Gaussian data augmentation [37] is a standard data augmentation technique in computer vision that has also been used to improve the robustness of a model to adversarial attacks. This method augments a dataset with copies of the original samples to which Gaussian noise has been added. An important advantage of this defence is its independence from the attack strategy. Its usage is mostly intended for the augmentation of the training set.

Implementation details The GaussianAugmentation class extends the Preprocessor abstract class. Applying this method does not require training, thus the fit function is a dummy. The functions supported by this class are:

- __init__(sigma=1., ratio=1.), where:
 - sigma: The standard deviation of the Gaussian noise to be added to the samples.
 - ratio: The augmentation ratio, i.e. how many adversarial samples to generate for each original sample. A ratio of 1 will double the size of the dataset.
- _call_(x, y=None, sigma=None, ratio=None) -> (np.ndarray, np.ndarray)

 Notice that the labels y are not required, as the method does not apply any preprocessing to them. If provided, they will be returned as the second object in the tuple; otherwise, a single object containing the augmented version of x is returned. The other parameters are the same as for the constructor.

The following example shows how to use GaussianAugmentation. Notice that the size of the dataset doubles after processing. aug_x contains all the original samples and their Gaussian augmented copy. The order of the labels in aux_y corresponds to that of aug_x.

7 Evasion Detection

```
art.detection
```

This module fills the purpose of providing runtime detection methods for adversarial samples. Currently, the library implements two types of detectors:

- art.detection.BinaryInputDetector: a detector based on opposing clean and adversarial data at the input level (see Section 7.2).
- art.detection.BinaryActivationDetector a detector built based on the activation values produced by a neural network classifier at a given internal layer (see Section 7.3).

The previous methods implement the API provided in the Detector base class, that we describe in the follwing.

7.1 The Detector Base Class

art.detection.Detector

art/detection/detector.py

The Detector abstract class provides a unified interface for all runtime adversarial detection methods. The class has the following public methods:

- fit(x, y=None, **kwargs) -> None
 Fit the detector with the given data and parameters (where applicable).
- _call_(x) -> np.ndarray
 Applies detection to the provided inputs and returns binary decisions for each input sample.
- is_fitted

 Check whether the detector has been fitted (where applicable).

7.2 Binary Detector Based on Inputs

art.detection.BinaryInputDetector

art/detection/detector.py

This method builds a binary classifier, where the labels represent the fact the a given input is adversarial (label 1) or not (label 0). The detector is fit with a mix of clean and adversarial data; following this step, it is ready to detect adversarial inputs.

Implementation details The BinaryInputDetector implements the Detector abstract class. Its constructor takes the following parameters:

• __init__(detector), where detector is a Classifier object and represents the architecture that will be trained for detection.

7.3 Binary Detector Based on Activations

 $\verb"art.poison_detection.BinaryActivationDetector"$

art/detection/detector.py

This method builds a binary classifier, where the labels represent the fact the a given input is adversarial (label 1) or not (label 0). The activations detector is different from the previous one in that it uses as inputs for training the values of the activations of a different classifier. Only activations from one layer that is specified are used.

Implementation details The BinaryActivationDetector implements the Detector abstract class. The method is initialized with the following parameters:

- __init__(classifier, detector, layer), where:
 - classifier is a trained Classifier object; its activation values will be used for training the detector.
 - detector is a Classifier object and represents the architecture that will be trained for detection.
 - layer represents the layer indice or layer name to be used for computing the activations of classifier.

8 Poisoning Detection

art.poison_detection

Data used to train machine learning models are often collected from potentially untrustworthy sources. This is particularly true for crowdsourced data (e.g. Amazon Mechanical Turk), social media data, and data collected from user behavior (e.g. customer satisfaction ratings, purchasing history, user traffic). Adversaries can craft inputs to modify the decision boundaries of machine learning models to misclassify inputs or to reduce model performance.

As part of targeted misclassification attacks, recent work has shown that adversaries can generate "backdoors" or "trojans" into machine learning models by inserting malicious data into the training set [12]. The resulting model performs very well on the intended training and testing data, but behaves badly on specific attacker-chosen inputs. As an example, it has been demonstrated that a network trained to identify street signs has strong performance on standard inputs, but identifies stop signs as speed limit signs when a special sticker is added to the stop sign. This backdoor provides adversaries a method for ensuring that any stop sign is misclassified simply by placing a sticker on it. Unlike adversarial samples that require specific, complex noise to be added to an image, backdoor triggers can be quite simple and can be easily applied to an image - as easily as adding a sticker to a sign or modifying a pixel.

ART provides filtering defences to detect poison this type of attacks.

8.1 The PoisonFilteringDefence Base Class

 $\verb|art.poison_detection.PoisonFilteringDefence art/poison_detection/poison_filtering_defence.py| \\$

The abstract class PoisonFilteringDefence defines an interface for the detection of poison when the training data is available. This class takes a model and its corresponding training data and indentifies the set of data points that are suspected of being poisonous. The functions supported by this class are:

- __init__(self, classifier, x_train, y_train, verbose=True), where:
 - classifier: corresponds to the trained model evaluated for poison
 - x_train: is the training data (features) used to train 'classifier'.
 - y_train: corresponds to the set of labels associate with x_train.
 - verbose: bool, 'True' prints information about the analysis, by default it is set to 'True'.
- detect_poison(self, **kwargs) -> 'list'
 Here, kwargs are defence-specific parameters used by child classes. This function returns a 'list' with items identified as poison.
- evaluate_defence(self, is_clean, **kwargs) -> JSON object
 If ground truth is known, this function returns a confusion matrix in the form of a JSON object. The parameters of this function are:
 - is_clean: 1-D array where is_clean[i]=1 means x_train[i] is clean and is_clean[i]=0 that it is poisonous.
 - kwargs: are defence-specific parameters used by child classes.

8.2 Poisoning Filter Using Activation Clustering Against Backdoor Attacks

art.poison_detection.ActivationDefence

art/poison_detection/activation_defence.py

The Activation Clustering defence detects poisonous data crafted to insert backdoors into neural networks. For this purpose, the defence takes the data used to train the provided classifier and analyses the differences in how a neural network decides on the classification of each data point in the training set. Concretely, each sample in the training set is classified and the activations of the

last hidden layer are retained. These activations are segmented according to their labels. For each activation segment, the dimensionality is reduced, and then a clustering algorithm is applied. Experimental results suggest that poisonous and legitimate data separate into distinct clusters, akin to the way in which different areas of the brain light up on scans when subjected to different stimuli. Then each resulting cluster is analyzed for poison according to different heuristics, for example cluster size, cluster cohesiveness, among others. Analysts can also manually review the results. After poisonous data is identified, the model needs to be repaired accordingly.

Implementation details The ActivationDefence class extends the PoisonFilteringDefence abstract class. Hence, it uses its constructor:

- __init__(self, classifier, x_train, y_train, verbose=True), where:
 - classifier: corresponds to the trained model evaluated for poison
 - x_train: is the training data (features) used to train 'classifier'.
 - y_train: corresponds to the set of labels associate with x_train.
 - verbose: bool, 'True' prints information about the analysis, by default it is set to 'True'.
- detect_poison(self, **kwargs) -> 'list'
 The activation defense allows to set up the following parameters:
 - clustering_method: clustering algorithm to be used. Currently 'KMeans' is the only method supported.
 - n_clusters: number of clusters to find. This value needs to be greater or equal to one.
 - reduce: method used to reduce dimensionality of the activations. Supported methods include 'PCA', 'FastICA' and 'TSNE'.
 - ndims: number dimensions to be reduced.
 - cluster_analysis: heuristic to automatically determine if a cluster contains poisonous data. Supported methods include 'smaller' and 'distance'. The 'smaller' method defines as poisonous the cluster with less number of data points, while the 'distance' heuristic uses the distance between the clusters.

When an ActivationDefence is instantiated, the following parameters are used by default: Dimensionality reduction is set to 'PCA'. The clustering method is set to 'K-means' and the number of clusters to two. The default dimensionality reduction technique is 'PCA' and the heuristic to analyze the cluster is 'smaller' which assigns as poisonous the smaller cluster.

• evaluate_defence(self, is_clean) -> JSON object

If ground truth is known, this function returns a confusion matrix in the form of a JSON object. Here, is_clean: 1-D array where is_clean[i]=1 means x_train[i] is clean and is_clean[i]=0 that it is poisonous.

The following example shows how to use ActivationDefence.

Finally, it is possible to take the clusters generated by the defense and inspect them manually.

9 Metrics

art.metrics

For assessing the **robustness** of a classifier against adversarial attacks, possible **metrics** are: the average minimal perturbation that is required to get an input misclassified; the average sensitivity of the model's loss function with respect to changes in the inputs; the average sensitivity of the model's logits with respect to changes in the inputs, e.g. based on Lipschitz constants in the neighborhood of sample inputs. The art.metrics module implements several metrics to assess the robustness respectively vulnerability of a given classifier, either generally or with respect to specific attacks:

- Empirical robustness (see Section 9.1)
- Loss sensitivity (see Section 9.2)
- CLEVER score (see Section 9.3).

9.1 Empirical Robustness

art.metrics.empirical_robustness

art/metrics.py

Empirical robustness assesses the robustness of a given classifier with respect to a specific attack and test data set. It is equivalent to the average minimal perturbation that the attacker needs to introduce for a successful attack, as introduced in [24]. Given a trained classifier C(x), an untargeted attack $\rho(x)$ and test data samples $X = (x_1, ..., x_n)$, let I be the subset of indices $i \in \{1, ..., n\}$ for which $C(\rho(x_i)) \neq C(x_i)$, i.e. for which the attack was successful. Then the empirical robustness (ER) is defined as:

$$ER(C, \rho, X) = \frac{1}{|I|} \sum_{i \in I} \frac{\|\rho(x_i) - x_i\|_p}{\|x_i\|_p}.$$

Here p is the norm used in the creation of the adversarial samples (if applicable); the default value is p = 2.

Implementation details The method for calculating the empirical robustness has the following signature:

empirical_robustness(classifier, x, attack_name, attack_params=None) -> float.

It returns the empirical robustness value as defined above. The input parameters are as follows:

- classifier: The classifier C(x) to be assessed.
- x: An np.ndarray with the test data X.
- attack_name: A string specifying the attack ρ to be used. Currently, the only supported attack is 'fgsm' (Fast Gradient Sign Method, see Section 5.2).
- attack_params: A dictionary with attack-specific parameters. If the attack has a norm attribute, then this is used as the p in the calculation above; otherwise the standard Euclidean distance is used (p = 2).

9.2 Loss Sensitivity

art.metrics.loss_sensitivity

art/metrics.py

Local loss sensitivity aims to quantify the smoothness of a model by estimating its Lipschitz continuity constant, which measures the largest variation of a function under a small change in its input: the smaller the value, the smoother the function. This measure is estimated based on

the gradients of the classifier logits, as considered e.g. in [17]. It is thus an attack-independent measure offering insight on the properties of the model.

Given a classifier C(x) and a test set $X = (x_1, ..., x_n)$, the loss sensitivity (LS) is defined as follows:

$$LS(C, X, \mathbf{y}) = \frac{1}{n} \sum_{i=1}^{n} \|\nabla \mathcal{L}(x_i, y_i)\|_2.$$

Implementation details The method for calculating the loss sensitivity has the signature that follows and returns the loss sensitivity as defined above.

loss_sensitivity(classifier, x, y) -> float, where:

- classifier is the classifier C(x) to be assessed
- x is an np.ndarray with the test data X
- y is an np.ndarray with the one-hot encoded labels of X.

9.3 CLEVER

art.metrics.clever_u
art.metrics.clever_t art/metrics.py

The Cross Lipschitz Extreme Value for nEtwork Robustness metric (CLEVER) [35] estimates, for a given input x and ℓ_p norm, a lower bound γ for the minimal perturbation that is required to change the classification of x, i.e. $||x - x'||_p < \gamma$ implies C(x) = C(x') (see Corollary 3.2.2 in [35]). The derivation of γ is based on a Lipschitz constant for the gradients of the classifier's logits in an ℓ_p -ball with radius R around x. Since in general there is no closed-form expression or upper bound for this constant[‡], the CLEVER algorithm uses an estimate based on extreme value theory.

Algorithm 8 outlines the calculation of the CLEVER metric for targeted attacks: given a target class y, the score γ is constructed such that $C(x') \neq y$ as long as $\|x - x'\|_p < \gamma$. Below we discuss how to adapt the algorithm to the untargeted case. A key step in the algorithm is outlined in lines 5-6 where the norm of gradient differences is evaluated at points randomly sampled from the uniform distribution on the ℓ_p -ball with radius R around x. The set S_{\max} collects the maximum norms from n_{batch} batches of size n_{sample} each (line 8), and $\hat{\mu}$ is the MLE of the location parameter μ of a reverse Weibull distribution given the realizations in S. The final CLEVER score is calculated in line 11. Note that it is bounded by the radius R of the ℓ_p -ball, as for any larger perturbations the estimated Lipschitz constant might not apply.

The CLEVER score for **untargeted attacks** is simply obtained by taking the minimum CLEVER score for targeted attacks over all classes $y \in \mathcal{Y}$ with $y \neq C(x)$.

Implementation details The method for calculating the CLEVER score for targeted attacks has the following signature:

clever_t(classifier, x, target_class, nb_batches, batch_size, radius, norm,
c_init=1, pool_factor=10) -> float.

Consider its parameters:

- classifier, x and target_class are respectively the classifier C(x), the input x and the target class y for which the CLEVER score is to be calculated.
- nb_batches and batch_size are the number of batches n_{batch} and batch size n_{sample} respectively.
- radius is the radius *R*.
- norm is the perturbation norm p.

[‡]Closed-form expressions for special types of classifier are derived in [14], which is the first work considering Lipschitz bounds for deriving formal guarantees of classifiers robustness against adversarial inputs.

Algorithm 8 CLEVER score for targeted attack

```
Input:
```

```
x: Input for which to calculate the CLEVER score
     y: Target class
     n_{\text{batch}}: Number of batches over each of which the maximum gradient is computed
     n_{\text{sample}}: Number of samples per batch
     p: Perturbation norm
     R: Maximum \ell_p norm of perturbations considered in the CLEVER score
 1: S_{\text{max}} \leftarrow \{\}
 2: q \leftarrow p/(p-1)
 3: for i = 1, ..., n_{\text{batch}} do
        for j = 1, \ldots, n_{\text{sample}} do
           x_i \leftarrow B_p(x, R)
 5:
           b_j' \leftarrow \|\nabla Z_{C(x)}(x_i) - \nabla Z_y(x_j)\|_q
 6:
 7:
        S_{\max} \leftarrow S_{\max} \cup \{\max_i b_i\}
 9: end for
10: \hat{\mu} \leftarrow \text{MLE}_{\text{Weibull}}(S_{\text{max}})
11: \gamma \leftarrow \min\{(Z_{C(x)}(x) - Z_y(x))/\hat{\mu}, R\}
Output:
     CLEVER score \gamma.
```

- c_init is a hyper-parameter for the MLE computation in line 10 (which is using the weibull_min function from scipy.stats).
- pool_factor is an integer factor according to which a pool of pool_factor $\times n_{\text{sample}}$ random samples from the ℓ_p -ball with radius R and center x is created and (re-)used in lines 5-6 for computational efficiency purposes.

The method clever_u for calculating the CLEVER score of untargeted attacks has the same signature as clever_t except that it doesn't take the target_class parameter.

10 Versioning

The library uses semantic versioning*, meaning that version numbers take the form of MA-JOR.MINOR.PATCH. Given such a version number, we increment the

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

Consistent benchmark results can be obtained with ART under constant MAJOR.MINOR versions. Please report these when publishing experiments.

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^{*}https://semver.org

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