Torchattacks: A PyTorch Repository for Adversarial Attacks

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ABSTRACT

Torchattacks is a PyTorch [Paszke et al., 2019] library that contains adversarial attacks to generate adversarial examples and to verify the robustness of deep learning models. The code can be found at [https://github.com/Harry24k/adversarial-attacks-pytorch](https://github.com/Harry24k/adversarial-attacks-pytorch).

Since [Szegedy et al., 2013] found that deep learning models are vulnerable to the perturbed examples with small noises, called adversarial examples, various adversarial attacks have been continuously proposed. In this technical report, we provide a list of implemented adversarial attacks and explain the algorithms of each method.

1 Precautions

Here are some important things to check before generating adversarial examples.

- **All examples should be scaled to [0, 1].** To make it easy to use adversarial attacks, a reverse-normalization is not included in the attack process. To apply an input normalization, please add a normalization layer to the model.
- **All models should return only one vector of \((\cdot, C)\) where \(C\) is the number of classes.** Considering most models in torchvision.models return one vector of \((N, C)\), where \(N\) is the number of inputs and \(C\) is the number of classes, torchattacks also only supports limited forms of output. Please check the shape of the model’s output carefully.

2 A List of Adversarial Attacks

Adversarial attacks generate an adversarial example \(x' \in [0, 1]^n\) from an example \((x, y) \sim D\) and the model \(f\). Given a maximum perturbation \(\epsilon\) and a specific distance measure, adversarial attacks try to find a perturbation \(\delta\) in \(B(x, \epsilon)\) which denotes \(\epsilon\)-ball around an example \(x\). Usually \(L_0, L_2\) and \(L_\infty\) are used as the distance measure for \(B(x, \epsilon)\). Thus, the problem of finding an adversarial example can be formulated as follows:

\[
\max_{\delta \in B(x, \epsilon)} \ell(f(x + \delta), y) \tag{1}
\]

where \(\ell\) is a loss function. Unless specified otherwise, cross-entropy loss is used as \(\ell\).

2.1 Fast Gradient Sign Method (FGSM)

**Algorithm.** FGSM is the simplest adversarial attack proposed by [Goodfellow, Shlens, and Szegedy, 2014]. It uses one gradient of the loss \(\nabla_x \ell\) to increase \(\ell(f(x), y)\) as follows:

\[
x' = x + \epsilon \cdot \text{sgn}(\nabla_x \ell(f(x), y)) \tag{2}
\]

\(L_\infty\) is used as the distance measure.

**Implementation.**

- `model (nn.Module):` model \(f\) to attack.
- `eps (float):` maximum perturbation \(\epsilon\).
- `import torchattacks`
- `atk = torchattacks.FGSM(model, eps=8/255)`
- `adversarial_examples = atk(examples, labels)`
2.2 DeepFool

**Algorithm.** DeepFool is an adversarial attack designed to move an example to the nearest boundary (Moosavi-Dezfooli, Fawzi, and Frossard 2016). Given an output vector \( f(x) \), Moosavi-Dezfooli, Fawzi, and Frossard (2016) first defines new variables to compute the closest projection of \( x \) on the nearest boundary.

\[
f'_k = f(x)_k - f(x)_y \\
w'_k = \nabla_x f(x)_k - \nabla_x f(x)_y
\]

Here \( f(x)_k \) is the \( k \)-th value of \( f(x) \) and \( k \in [1, 2, ..., C] \) where \( C \) is the number of classes. Then, the perturbation is calculated as follows:

\[
\hat{l} = \arg\min_{k \neq y} \frac{|f'_k|}{||w'_k||_2} \\
\delta = \frac{|f'_l|}{||w'_l||_2}w'_l \\
x'_{t+1} = x'_t + \delta
\]

where \( \hat{l} \) denotes the closest hyperplane of the boundary. Instead of the maximum perturbation \( \epsilon \), DeepFool controls the strength of the attack by the number of steps. \( x'_0 = x \) and \( x'_t \) denotes the adversarial example after \( t \)-steps. \( L_2 \) is used as the distance measure.

**Implementation.**

- model (nn.Module): model \( f \) to attack.
- steps (int): number of steps.
- import torchattacks
  atk = torchattacks.DeepFool(model, step=3)
  adversarial_examples = atk(examples, labels)

We note that DeepFool needs enough time to generate an adversarial example because it requires \( \nabla_x f(x)_k \) instead of \( \nabla_x \ell \). To calculate \( \nabla_x f(x)_k \), we are forced to split the batch into individual examples on PyTorch, which leads a computational time penalty.

2.3 Basic Iterative Method (BIM)

**Algorithm.** BIM (or iterative-FGSM) is an iterative adversarial attack proposed by Kurakin, Goodfellow, and Bengio (2016). It uses multiple gradients to generate the adversarial example. To find the best perturbation, Kurakin, Goodfellow, and Bengio (2016) define a step size \( \alpha \) smaller than \( \epsilon \). The formula is as follows:

\[
x'_{t+1} = \text{clip}_{(x, \epsilon)} \{x'_t + \alpha \cdot \text{sgn}(\nabla_{x'} \ell(f(x'_t), y))\}
\]

where \( \text{clip}_{(x, \epsilon)} \{x'\} \) denotes \( \min(\max(x', x - \epsilon), x + \epsilon) \). \( x'_0 = x \) and \( x'_t \) denotes the adversarial example after \( t \)-steps. \( L_\infty \) is used as the distance measure.

**Implementation.**

- model (nn.Module): model \( f \) to attack.
- eps (float): maximum perturbation \( \epsilon \).
- alpha (float): step size \( \alpha \).
- steps (int): number of steps.
- import torchattacks
  atk = torchattacks.BIM(model, eps=4/255, alpha=1/255, steps=4)
  adversarial_examples = atk(examples, labels)
2.4 CW

Algorithm. [Carlini and Wagner (2017)] proposed the alternative formulation for constructing adversarial examples. Using \( \tanh(x) \in [-1, 1]^n \), it performs optimization on \( \tanh \) space.

\[
\begin{align*}
    w' &= \min_w \frac{1}{2} (\tanh(w) + 1) - x \|_2^2 + c \cdot g\left(\frac{1}{2} (\tanh(w) + 1)\right) \\
    x' &= \frac{1}{2} (\tanh(w') + 1)
\end{align*}
\]

where \( g(x) = \max(f(x), y) - \max_{x \neq y} f(x), -\kappa \) and \( c \) is a hyperparameter. The larger \( c \), the stronger adversarial example will produced. [Carlini and Wagner (2017)] use Adam [Kingma and Ba (2014)] as an optimizer to minimize the above objective function. Here \( \kappa \) is a confidence to encourage an adversarial example \( x' \) classified as a wrong label, because the optimizer will reduce \( f(x)_y - \max_{x \neq y} f(x)_i \) until it is equal to the \( -\kappa \). To change the attack into the targeted mode with the target class \( y' \), \( g(x) = \max(\max_{x \neq y'} f(x)_i - f(x)_y', -\kappa) \) should be the objective function to generate an adversarial example closer to \( y' \). \( L_2 \) is used as the distance measure.

Implementation.

- model (\( nn.Module \)): model \( f \) to attack.
- \( c \) (float): hyperparameter \( c \).
- kappa (float): the confidence \( \kappa \).
- lr (float): learning rate of Adam.
- steps (int): number of optimization steps.
- import torchattacks
  atm = torchattacks.CW(model, c=1, kappa=0, steps=100, lr=0.01)
adversarial_examples = atm(examples, labels)

In the original paper [Carlini and Wagner (2017)], a binary search for \( c \) is adopted to generate most successful adversarial examples. However, because it costs too much time, it is excluded in the implementation. In addition, early stopping is used when the objective value in the previous 10th step is lower than the current objective value.

2.5 R+FGSM

Algorithm. To avoid gradient masking effect [Papernot et al. (2016), Tramèr et al. (2017)] added a random initialization before computing the gradient.

\[
\begin{align*}
    x'_0 &= x + \alpha \cdot \text{sgn}(\mathcal{N}(0^n, \Gamma^n)) \\
    x'_{t+1} &= \text{clip}(x, \epsilon)\{x'_t + (\epsilon - \alpha) \cdot \text{sgn}(\nabla x'_t \ell(f(x'_t), y))\}
\end{align*}
\]

where \( \text{clip}(x, \epsilon) \) denotes \( \min(\max(x', x - \epsilon), x + \epsilon) \) and \( \mathcal{N}(0^n, \Gamma^n) \) is a normal distribution. \( x'_t \) denotes the adversarial example after \( t \)-steps and \( \alpha \) denotes a step size. \( L_\infty \) is used as the distance measure.

Implementation.

- model (\( nn.Module \)): model \( f \) to attack.
- eps (float): maximum perturbation \( \epsilon \).
- alpha (float): step size \( \alpha \).
- steps (int): number of steps.
- import torchattacks
  atm = torchattacks.RFGSM(model, eps=8/255, alpha=4/255, steps=2)
adversarial_examples = atm(examples, labels)

2.6 Projected Gradient Descent (PGD)

Algorithm. To produce a more powerful adversarial example, [Madry et al. (2017)] proposed a method projecting the adversarial perturbation to \( \epsilon \)-ball around an example. Furthermore, before calculating the gradient, a uniformly randomized noise is added to the original example.

\[
\begin{align*}
    x'_0 &= x + \mathcal{U}(-\epsilon, \epsilon) \\
    x'_{t+1} &= \Pi_{B(x, \epsilon)}\{x'_t + \alpha \cdot \text{sgn}(\nabla x'_t \ell(f(x'_t), y))\}
\end{align*}
\]
where $\Pi_{B(x, \epsilon)}$ refers the projection to $B(x, \epsilon)$ and $U$ is a uniform distribution. $x'_t$ denotes the adversarial example after $t$-steps and $\alpha$ denotes a step size. $L_{\infty}$ is used as the distance measure.

**Implementation.**

- model (`nn.Module`): model $f$ to attack.
- eps (`float`): maximum perturbation $\epsilon$.
- alpha (`float`): step size $\alpha$.
- steps (`int`): number of steps.
- random_start (`bool`): True for using a uniformly randomized noise.
- import torchattacks
  atk = torchattacks.PGD(model, eps=8/255, alpha=4/255, steps=2, random_start=False)
  adversarial_examples = atk(examples, labels)

2.7 Averaged PGD (APGD)

**Algorithm.** To attack randomized models, [Athalye et al. (2018)] suggested Expectation over Transformation (EOT) to compute the gradient over the expected transformation to the input. For instance, to estimate stronger gradient of the Bayesian neural network including Adv-BNN [Liu et al. 2018], [Zimmermann (2019)] proposed averaged PGD (APGD) as follows:

$$x'_{t+1} = \Pi_{B(x, \epsilon)} \{ x'_t + \alpha \cdot \text{sgn}(\mathbb{E}[\nabla x'_t \ell(f(x'_t), y)]) \}$$  \hspace{1cm} (9)

where $f$ is a randomized model which implies $f$ outputs a different value each forward propagation even if same input is given. $x'_t$ denotes the adversarial example after $t$-steps and $\alpha$ denotes a step size. APGD uses $\frac{1}{m} \sum_i \nabla x'_t \ell(f(x'_t), y)$ as an approximation of $\mathbb{E}[\nabla x'_t \ell(f(x'_t), y)]$. $L_{\infty}$ is used as the distance measure.

**Implementation.**

- model (`nn.Module`): model $f$ to attack.
- eps (`float`): maximum perturbation $\epsilon$.
- alpha (`float`): step size $\alpha$.
- steps (`int`): number of steps.
- sampling (`int`): number of models to estimate the mean gradient $m$.
- import torchattacks
  atk = torchattacks.APGD(model, eps=8/255, alpha=4/255, steps=2, sampling=10)
  adversarial_examples = atk(examples, labels)

2.8 PGD in TRADES (TPGD)

**Algorithm.** [Zhang et al. (2019)] proposed a new adversarial training method called TRADES to increase robustness of the model based on the theoretical analysis. In TRADES, the adversarial example is generated by PGD with KL-divergence loss $\ell_{KL}$ as follows:

$$x'_0 = x + 0.001 \cdot \mathcal{N}(0^n, \Gamma^n)$$
$$x'_{t+1} = \Pi_{B(x, \epsilon)} \{ x'_t + \alpha \cdot \text{sgn}(\nabla x'_t \ell_{KL}(f_\theta(x), f_\theta(x'_t))) \}$$  \hspace{1cm} (10)

where $\Pi_{B(x, \epsilon)}$ refers the projection to $B(x, \epsilon)$ and $\mathcal{N}(0^n, \Gamma^n)$ is a normal distribution. $x'_t$ denotes the adversarial example after $t$-steps and $\alpha$ denotes a step size. $L_{\infty}$ is used as the distance measure.

**Implementation.**

- model (`nn.Module`): model $f$ to attack.
- eps (`float`): maximum perturbation $\epsilon$.
- alpha (`float`): step size $\alpha$.
- steps (`int`): number of steps.
- import torchattacks
  atk = torchattacks.TPGD(model, eps=8/255, alpha=4/255, steps=2, sampling=10)
  adversarial_examples = atk(examples, labels)
2.9 FGSM in fast adversarial training (FFGSM)

**Algorithm.** In fast adversarial training [Wong, Rice, and Kolter 2020], a uniform randomization $U(-\epsilon, \epsilon)$ is used instead of $\text{sgn}(N(0^n, I^n))$ in R+FGSM. Furthermore, for the first time, a step size $\alpha$ is set to a larger value than $\epsilon$.

\[
x'_0 = x + U(-\epsilon, \epsilon) \\
x' = \Pi_{B(x, \epsilon)} \{x'_0 + \alpha \cdot \text{sgn}(\nabla_x \ell(f(x'_0), y)) \}
\]

(11)

where $\Pi_{B(x, \epsilon)}$ refers the projection to $B(x, \epsilon)$. $L_\infty$ is used as the distance measure.

**Implementation.**

- `model (nn.Module)`: model $f$ to attack.
- `eps (float)`: maximum perturbation $\epsilon$.
- `alpha (float)`: step size $\alpha$.
- `import torchattacks`
  
  ```python
  atk = torchattacks.FFGSM(model, eps=8/255, alpha=10/255)
  adversarial_examples = atk(examples, labels)
  ```

3 Useful methods

All adversarial attacks in `torchattacks` are subclasses of `torchattacks.attacks.Attack`. In this section, we provide inherited methods from `torchattacks.attacks.Attack` to help users generate and reuse adversarial examples made by `torchattacks`.

**set_attack_mode** (mode). Through this method, users can decide the attack mode.

- `mode (str)`:
  - 'original' (DEFAULT).
  - 'targeted' - Use input labels as targeted labels.
  - 'least_likely' - Use least likely labels as targeted labels.
- `import torchattacks`
  
  ```python
  atk = torchattacks.PGD(model, eps=8/255, alpha=2/255, steps=7)
  atk.set_attack_mode('targeted')
  ```

**set_return_type** (type). Through this method, users can decide whether to output adversarial examples as int or float.

- `type (str)`:
  - 'int' for converting adversarial images to integer type.
  - 'float' for converting adversarial images to float type.
- `import torchattacks`
  
  ```python
  atk = torchattacks.PGD(model, eps=8/255, alpha=2/255, steps=7)
  atk.set_return_type('int')
  ```

**save** (file_name, data_loader, accuracy). Through this method, users can save adversarial examples from given `torch.utils.data.DataLoader`.

- `file_name (str)`: save path.
- `data_loader (torch.utils.data.DataLoader)`: set of the original images and labels to make adversarial images.
- `accuracy (bool)`: True for printing accumulated accuracy.
- `import torchattacks`
  
  ```python
  atk = torchattacks.PGD(model, eps=8/255, alpha=2/255, steps=7)
  atk.save(file_name="PGD.pt", data_loader=test_loader, accuracy=True)
  adv_images, adv_labels = torch.load("PGD.pt")
  ```

References

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