



Adversarial Label Flips

Related work presentation

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Standard sources on adversarial examples

Adversarial examples [1]

Deep neural networks are vulnerable to adversarial perturbations!

[1] Intriguing properties of neural networks, 2013

[2] Explaining and harnessing adversarial examples, 2014

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Deep neural networks are vulnerable to adversarial perturbations!

Fast gradient sign method [2]

Even worse: Adversarial examples generalize over multiple datasets and architectures. Even cheap attacks like FGSM can work.

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Even worse: Adversarial examples generalize over multiple datasets and architectures. Even cheap attacks like FGSM can work.

Fast gradient sign method

Modify an input image x , with respective label y ,

$$x + \epsilon \operatorname{sign}(\nabla_x J(\theta, x, y)).$$

using the loss function J .

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Projected gradient descent [3]

Strong and cheap attacks therefore exist: Projected gradient descent (PGD) iteratively computes FGSM.

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[1] Intriguing properties of neural networks, 2014

[3] Towards deep learning models resistant to adversarial attacks, 2018

Fast gradient sign method



The diagram illustrates the Fast Gradient Sign Method (FGSM). It shows a sequence of three images: a panda, a noisy gradient image, and a gibbon. The panda image is on the left, followed by a plus sign, a small epsilon symbol, a noisy gradient image, an equals sign, and the gibbon image on the right. Below the panda image is the text "Panda (57.7% confidence)". Below the noisy gradient image is the text $\text{sign}(\nabla_x J(\theta, x, y))$. Below the gibbon image is the text "Gibbon (99.3% confidence)".

Panda
(57.7% confidence)

$\text{sign}(\nabla_x J(\theta, x, y))$

Gibbon
(99.3% confidence)

[2] Explaining and harnessing adversarial examples, 2014

What we want to do

Confusion Matrix

		Categorised as		
		Dog	Cat	Plane
Adversarial Example of a	Dog	0.0	?	?
	Cat	?	0.0	?
	Plane	?	?	0.0

How many modified dogs get classified as cats vs as planes? etc.

Case study

Foolbox

A suit of attacks is available with FoolBox! [4]

[4] Foolbox: A python toolbox to benchmark the robustness of machine learning models, 2017

Foolbox

A suit of attacks is available with FoolBox! [4]

Foolbox

- Over 40 different attacks.
- Available in PyTorch, TensorFlow and JAX.
- Easy to work with.

[4] Foolbox: A python toolbox to benchmark the robustness of machine learning models, 2017

Foolbox

Projected Gradient Descent (PGD) attack for different `epsilons`.

[4] Foolbox: A python toolbox to benchmark the robustness of machine learning models, 2017

Foolbox

Projected Gradient Descent (PGD) attack for different epsilons.

```
import foolbox as fb

model = ...
fmodel = fb.PyTorchModel(model, bounds=(0, 1))

attack = fb.attacks.LinfPGD()
epsilons = [0.0, 0.001, 0.01, 0.03, 0.1, 0.3, 0.5, 1.0]
_, advs, success = attack(fmodel, images, labels, epsilons=epsilons)
```

[4] Foolbox: A python toolbox to benchmark the robustness of machine learning models, 2017

Datasets

MNIST [5]



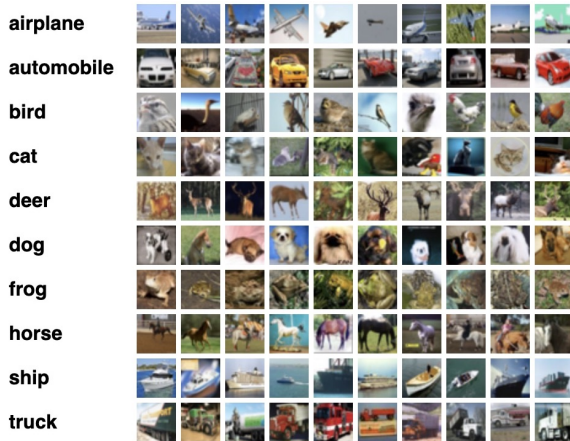
The MNIST database of handwritten digit images for machine learning research, 2012

Fashion-MNIST [6]



Fashion-MNIST: A novel image dataset for benchmarking machine learning algorithms, 2017

CIFAR-10 [7]



Learning multiple layers of features from tiny images, 2009

References I



Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus.

Intriguing properties of neural networks.

In International Conference on Learning Representations (ICLR), 2014.



Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy.

Explaining and harnessing adversarial examples.

arXiv preprint arXiv:1412.6572, 2014.



Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu.

Towards deep learning models resistant to adversarial attacks.

arXiv preprint arXiv:1706.06083, 2017.

References II



Jonas Rauber, Wieland Brendel, and Matthias Bethge.
Foolbox: A python toolbox to benchmark the robustness of
machine learning models.
arXiv preprint arXiv:1707.04131, 2017.



Li Deng.
The mnist database of handwritten digit images for machine
learning research [best of the web].
IEEE Signal Processing Magazine, 29(6):141–142, 2012.



Han Xiao, Kashif Rasul, and Roland Vollgraf.
Fashion-mnist: a novel image dataset for benchmarking machine
learning algorithms.
arXiv preprint arXiv:1708.07747, 2017.

References III



Alex Krizhevsky, Geoffrey Hinton, et al.
Learning multiple layers of features from tiny images.
2009.