universität innsbruck

Adversarial Label Flips

Related work presentation

Matthias Dellago & Maximilian Samsinger

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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Fast gradient sign method

Modify an input image x, with respective label y,

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

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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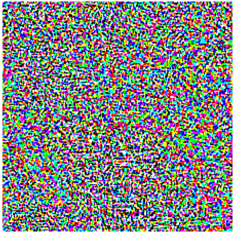
using the loss function J.

[1] Intriguing properties of neural networks, 2014
[3] Towards deep learning models resistant to adversarial attacks, 2018

Fast gradient sign method

$+\ \epsilon$



$=$

Panda

(57.7% confidence)

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

Gibbon

(99.3% confidence)

[2] Explaining and harnessing adversarial examples, 2014

What we want to do

Confusion Matrix

Adversarial Example of a — Categorised as

	Dog	Cat	Plane
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

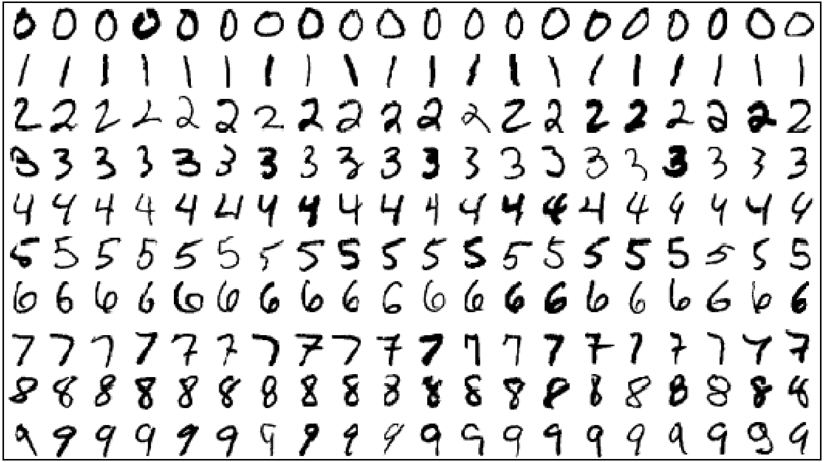
Projected Gradient Descent (PGD) attack for different `epsilons`.

```
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

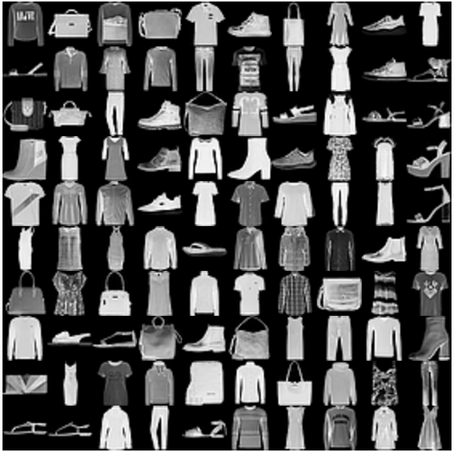
Datasets

MNIST [5]



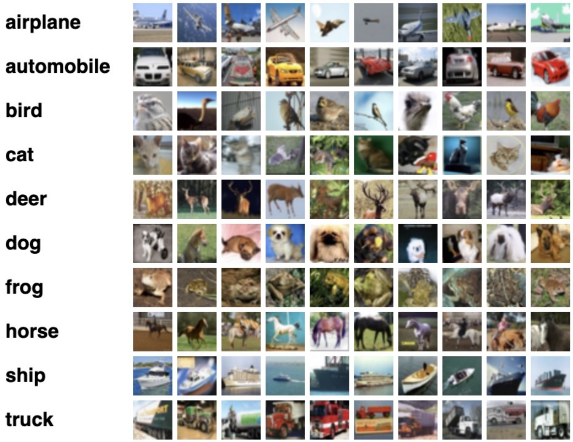
The MNIST database of handwritten digit images for machine learning research, 2012

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

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  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.
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  Towards deep learning models resistant to adversarial attacks.
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  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.

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2009.