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Adversarial Label Flips

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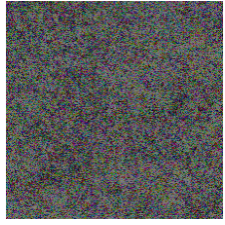
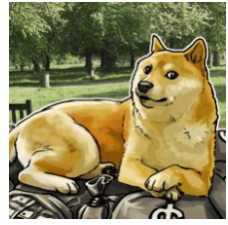
A short recap

Adversarial attack

$+ \epsilon$



$=$



Husky
(42.82% confidence)

Noise (PGD-40)
50x amplified

Handkerchief
(99.999988% confidence)

Source: `ctf.codes`, circa 2021

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.

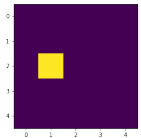
Some simple theory

We want similar images that are classified differently.
But what is "similar"?

Quantifying Difference

L^0-Norm

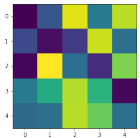
Number of different pixels



Change very few pixels maximally

L^1-Norm

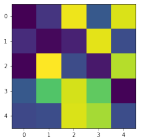
Sum of all differences



Minimise sum

L^2-Norm

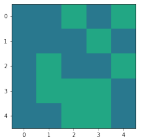
Sum of the *square* of all differences



Minimise sum of squares

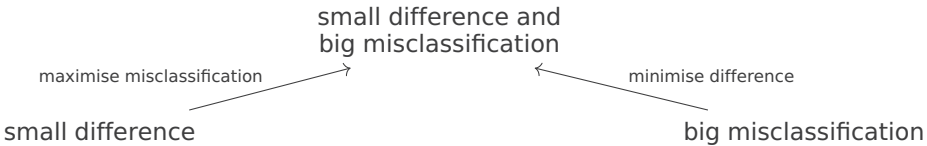
L^∞-Norm

Maximum of all differences



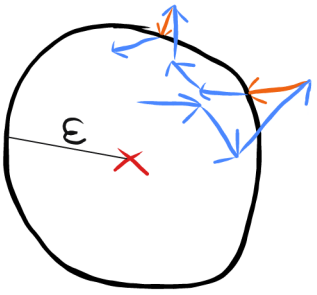
Change all pixels equally

Two Different Approaches



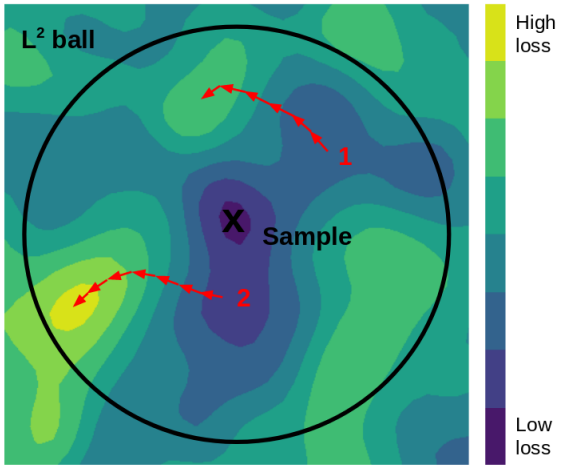
Projected Gradient Decent

1. Pick spot in epsilon ball
2. Iterate gradient decent
3. If leaving ball, project back onto surface
4. Repeat to convergence



Towards Deep Learning Models Resistant to Adversarial Attacks, Aleksander Madry et al., arXiv, 2019

Projected Gradient Decent



Know your enemy, Oscar Knagg, towardsdatascience.com, 2019

Carlini-Wagner-Attack

Original approach: minimise difference while always staying in "misclassification territory".

Problem: Non-linearity of constraint makes optimimisation difficult.

Towards Evaluating the Robustness of Neural Networks, Nicholas Carlini and David Wagner, IEEE, 2017

Carlini-Wagner-Attack

Solution: Pack constraint into the function that is optimised.

$\rightarrow$ minimise: difference - "how misclassified is x?"*

i.e. minimise difference while maximising misclassification.

Apply Adam optimisation.

*loss function

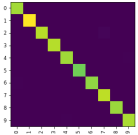
Towards Evaluating the Robustness of Neural Networks, Nicholas Carlini and David Wagner, IEEE, 2017

Code

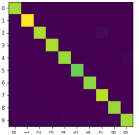
Results

MNIST, L^∞-PGD

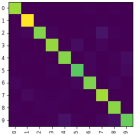
$\epsilon = 0.01$



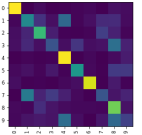
$\epsilon = 0.02$



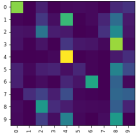
$\epsilon = 0.05$



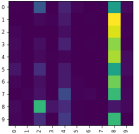
$\epsilon = 0.1$



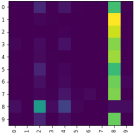
$\epsilon = 0.2$



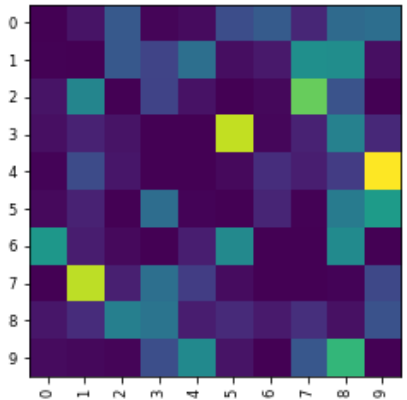
$\epsilon = 0.5$



$\epsilon = 1$

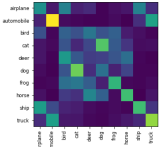


MNIST, L^2-Carlini-Wagner-Attack

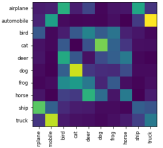


CIFAR-10, L^∞-PGD

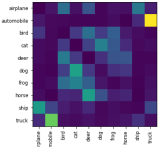
$\epsilon = 0.01$



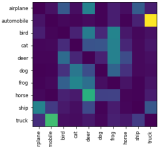
$\epsilon = 0.02$



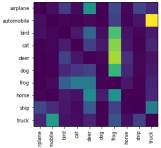
$\epsilon = 0.05$



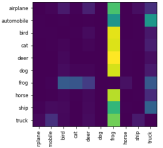
$\epsilon = 0.1$



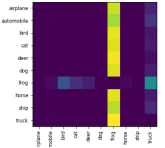
$\epsilon = 0.2$



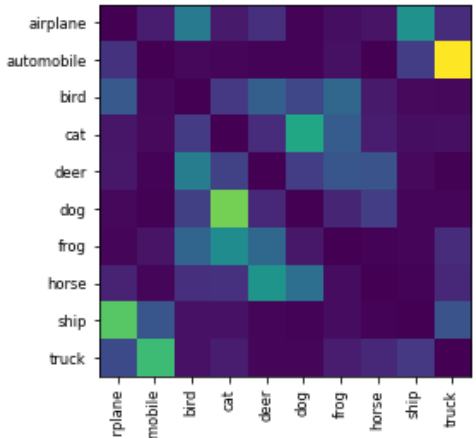
$\epsilon = 0.5$



$\epsilon = 1$



CIFAR-10, L^0-Brendel-Bethge-Attack



Tentative Findings

Small $\epsilon \rightarrow$ symmetric confusion matrix

Large $\epsilon \rightarrow$ strong attractor classes ("8" and "frog")

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.