Adversarial Label Flips
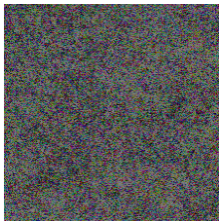
Matthias Dellago & Maximilian Samsinger

A short recap
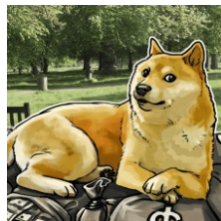
Adversarial attack

Husky
(42.82% confidence)

$+ \epsilon$

Noise (PGD-40)
50x amplified

$=$

Handkerchief
(99.999988% confidence)

Source: `ctf.codes`, circa 2021

What we want to do

Confusion Matrix

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

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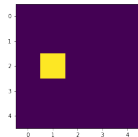
Some simple theory

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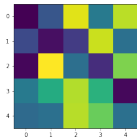But what is "similar"?

Quantifying Difference (ϵ)

L^0-Norm	L^1-Norm	L^2-Norm	L^∞-Norm
Number of different pixels	Sum of all differences	Sum of the *square* of all differences	Maximum of all differences
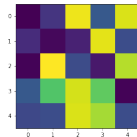
Change very few pixels maximally	Minimise sum	Minimise sum of squares	Change all pixels equally
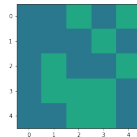
Two Different Approaches

small difference and
big misclassification

maximise misclassification   minimise difference

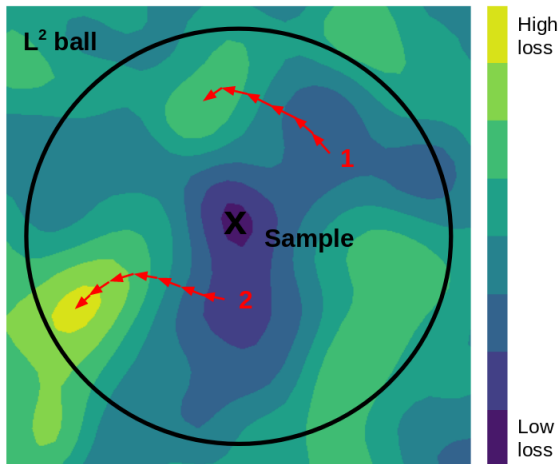small difference   big misclassification
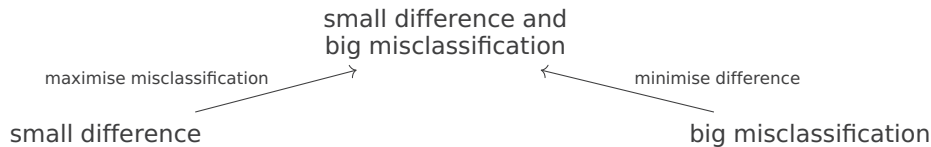
Projected Gradient Decent

1. Pick spot in epsilon ball
2. Iterate gradient decent
3. If leaving ball, project back onto surface
4. Repeat to convergence
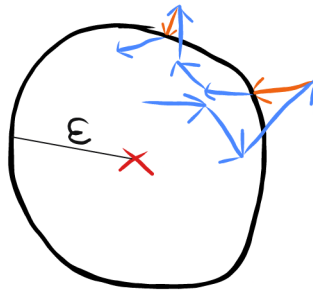
Towards Deep Learning Models Resistant to Adversarial Attacks, Aleksander Madry et al., arXiv, 2019

Projected Gradient Decent

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

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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
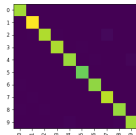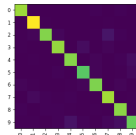
Code

Results

MNIST, L^∞-PGD
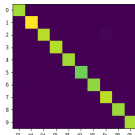
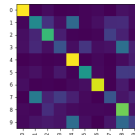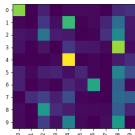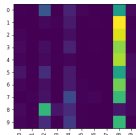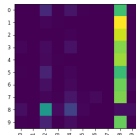# MNIST, L^2-Carlini-Wagner-Attack
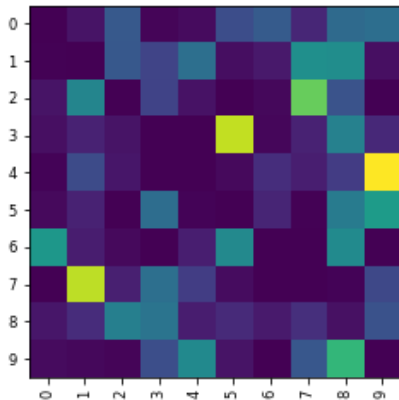
CIFAR-10, L^∞-PGD
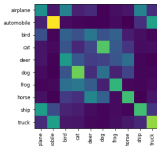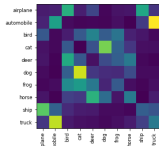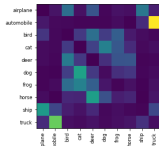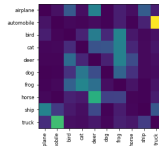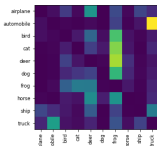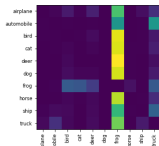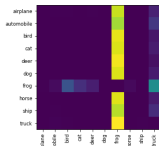
CIFAR-10, L^0-Brendel-Bethge-Attack

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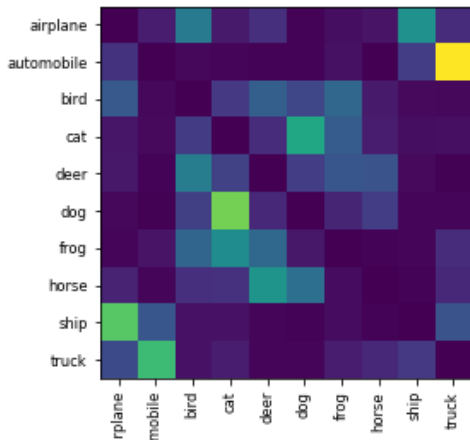
Tentative Findings

Small $\epsilon \rightarrow$ symmetric confusion matrix

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

References I

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

📄 Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy.
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📄 Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu.
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arXiv preprint arXiv:1706.06083, 2017.

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2009.