



# Adversarial Label Flips

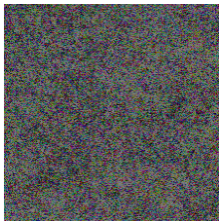
Matthias Dellago & Maximilian Samsinger

A short recap

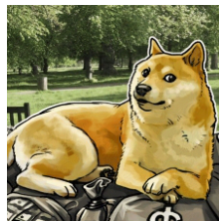
# Adversarial attack



+ €



=



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

		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.

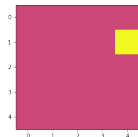
Some simple theory

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

# Quantifying Difference ( $\epsilon$ )

$L^0$ -Norm

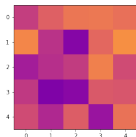
Number of  
different pixels



Change very few  
pixels maximally

$L^1$ -Norm

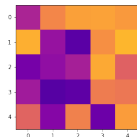
Sum of  
all differences



Minimise sum

$L^2$ -Norm

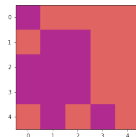
Sum of the *square*  
of all differences



Minimise sum  
of squares

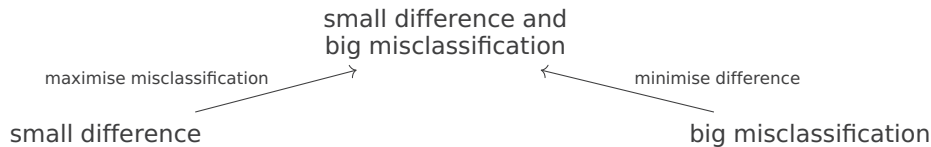
$L^\infty$ -Norm

Maximum of  
all differences



Change all  
pixels equally

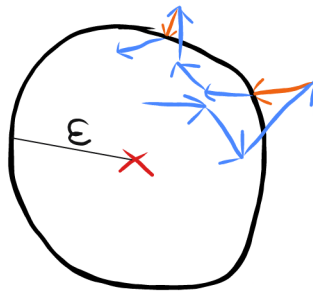
# Two Different Approaches





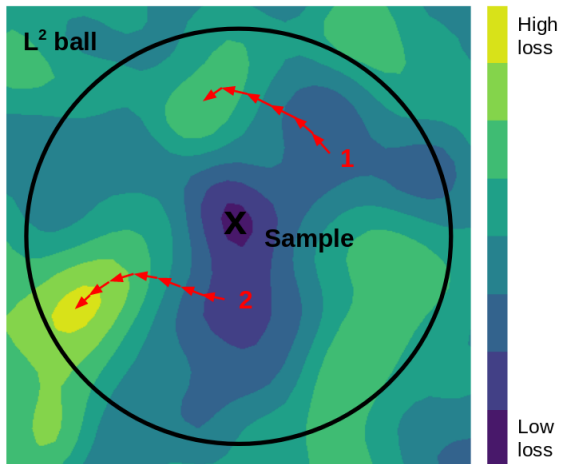
# Projected Gradient Decent

- 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](https://towardsdatascience.com), 2019

# Carlini-Wagner-Attack

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

Problem: Non-linearity of constraint makes optimisation 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.

→ minimise: difference - "how misclassified is x?"\*  
i.e. minimise difference while maximising misclassification.

Apply Adam optimisation.

\*loss function

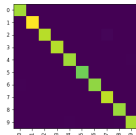
Towards Evaluating the Robustness of Neural Networks, Nicholas Carlini and David Wagner, IEEE, 2017

# Code

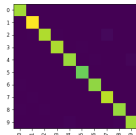
# Results

# MNIST, $L^\infty$ -PGD

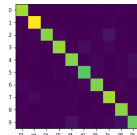
$\epsilon = 0.01$



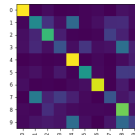
$\epsilon = 0.02$



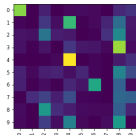
$\epsilon = 0.05$



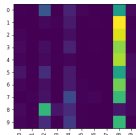
$\epsilon = 0.1$



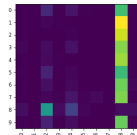
$\epsilon = 0.2$



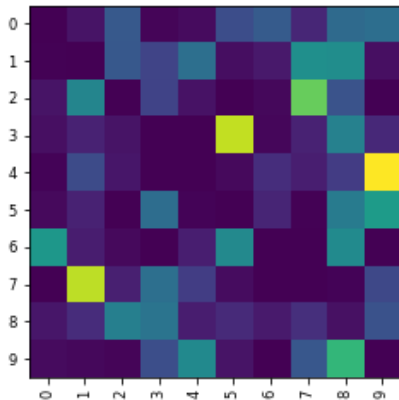
$\epsilon = 0.5$



$\epsilon = 1$



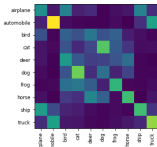
# MNIST, $L^2$ -Carlini-Wagner-Attack



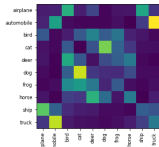


# CIFAR-10, $L^\infty$ -PGD

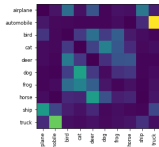
$\epsilon = 0.01$



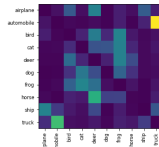
$\epsilon = 0.02$



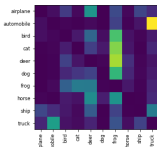
$\epsilon = 0.05$



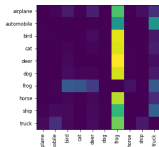
$\epsilon = 0.1$



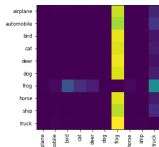
$\epsilon = 0.2$



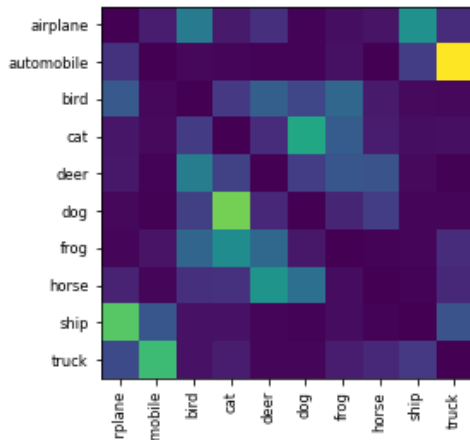
$\epsilon = 0.5$



$\epsilon = 1$



# 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



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# References II



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