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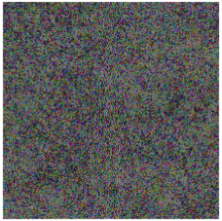
Adversarial Label Flips

Matthias Dellago & Maximilian Samsinger

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

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.

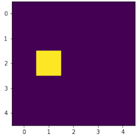
Some simple theory

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

Quantifying Changes

L^0-Norm

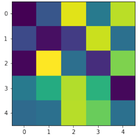
Number of
pixels changed



Perturb one
pixel maximally

L^1-Norm

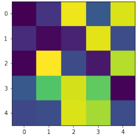
Sum of
all changes



Minimise sum

L^2-Norm

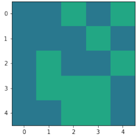
Sum of the *square*
of all changes



Minimise sum
of squares

L^∞-Norm

Maximum of
all changes



Perturb all
pixels equally

Two Different Approaches

small displacement and
big misclassification

maximise misclassification

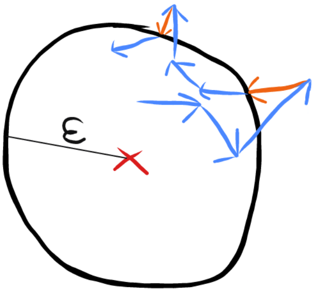
minimise displacement

small displacement

big misclassification

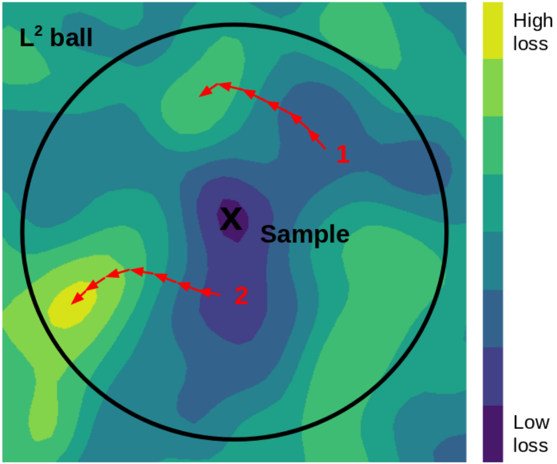
Projected Gradient Decent

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



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 disance while always staying in "misclassification territory".

Problem: Nonlinearity of constraint makes for bad optimisation properties.

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: distance - "how misclassified is x?"*

i.e. minimise distance while maximising misclassification.

*loss function

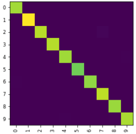
Towards Evaluating the Robustness of Neural Networks, Nicholas Carlini and David Wagner, IEEE, 2017

Code

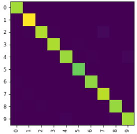
Results

MNIST, L^{∞}-PGD

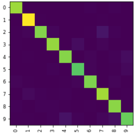
$\epsilon = 0.01$



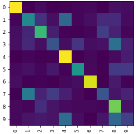
$\epsilon = 0.02$



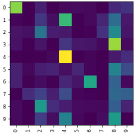
$\epsilon = 0.05$



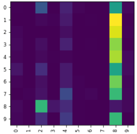
$\epsilon = 0.1$



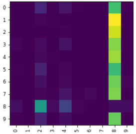
$\epsilon = 0.2$



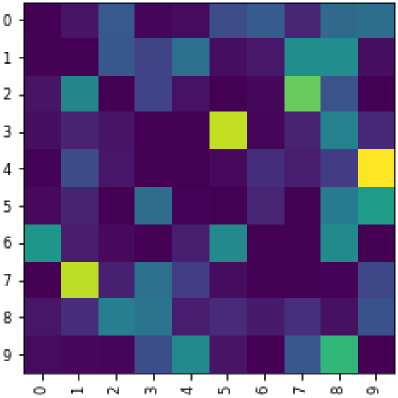
$\epsilon = 0.5$



$\epsilon = 1$

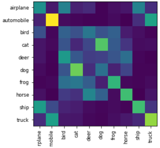


MNIST, L^2-Carlini-Wagner-Attack

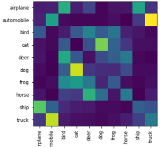


CIFAR-10, L^{∞}-PGD

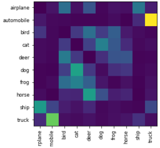
$\epsilon = 0.01$



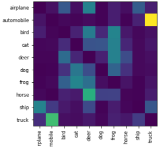
$\epsilon = 0.02$



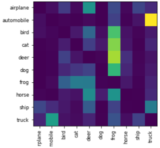
$\epsilon = 0.05$



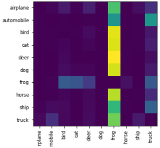
$\epsilon = 0.1$



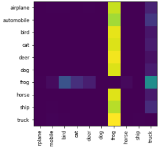
$\epsilon = 0.2$



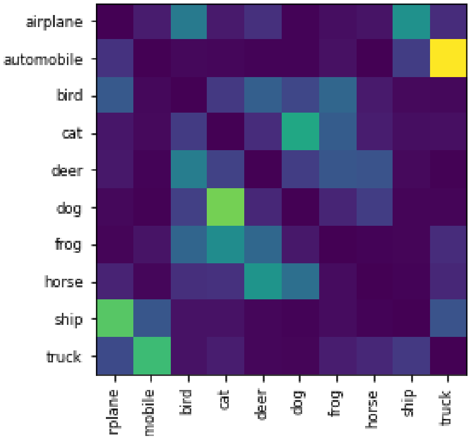
$\epsilon = 0.5$



$\epsilon = 1$



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



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