



Adversarial Label Flips

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A short recap

Adversarial attack



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Husky (42.82% confidence)

Noise (PGD-40) 50x amplified Handkerchief (99.999988% confidence)

Source: ctf.codes, circa 2021

What we want

Confusion Matrix

Adversarial Example of a

Categorised as

Dog	Cat	Plane
0.0	?	?
?	0.0	?
?	?	0.0

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

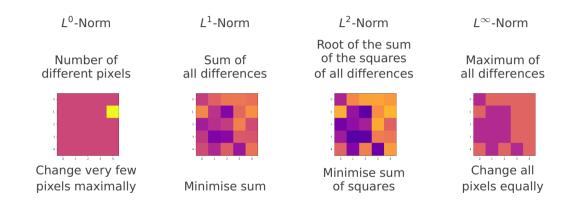
Dog

Cat Plane

Some simple theory

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

Quantifying Difference (ϵ)

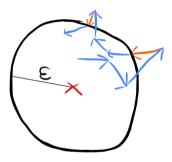


Two Different Approaches



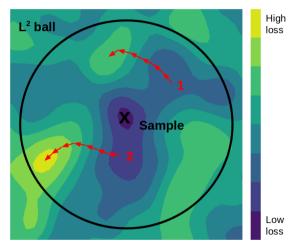
Projected Gradient Decent

- Pick spot in epsilon ball around target
- 2 Iterate gradient decent
- If leaving ball, project back onto surface
- 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 region".

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.

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

Apply Adam optimisation.

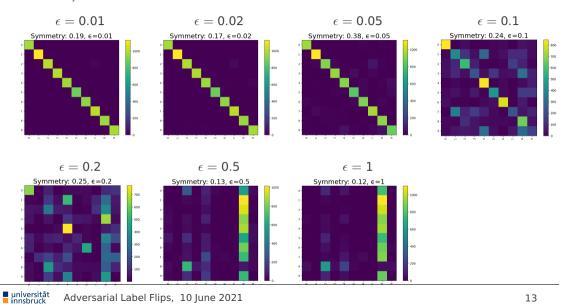
*loss function

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

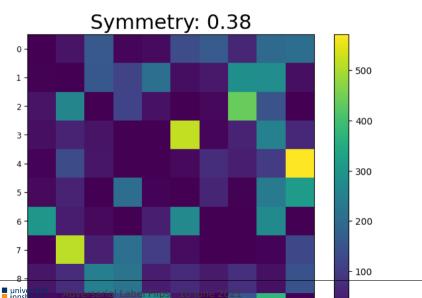
Code

Results

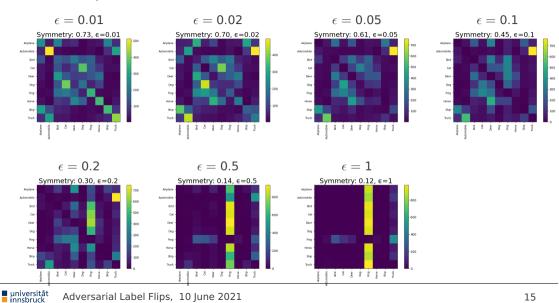
MNIST, L^{∞} -PGD



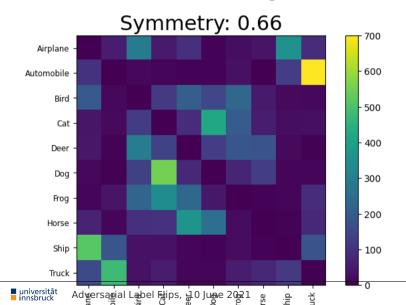
MNIST, L²-Carlini-Wagner-Attack



CIFAR-10, L^{∞} -PGD



CIFAR-10, L⁰-Brendel-Bethge-Attack



Tentative Findings

Small $\epsilon \to \text{symmetric confusion matrix}$

Large $\epsilon \to \text{strong attractor classes}$ ("8" and "frog")

References I