

PRACTICAL MACHINE LEARNING

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# ADVERSARIAL EXAMPLES

## THIS COURSE – 4 WORKSHOPS (LECTURE+EXERCISES)

- ▶ Lecture 1 (Monday) Introduction to machine learning with neural networks and linear regression
- ▶ Lecture 2 (Tuesday) Optimisation and non-linear regression with neural networks
- ▶ Lecture 3 (Wednesday) Classification and convolutional neural networks for image classification
- ▶ Lecture 4 (Thursday) Robustness and adversarial examples to image classification problems

## WHO WE ARE



Dr Alex Booth [he/him]



Dr Linda Cremonesi [she/her]



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# ADVERSARIAL EXAMPLES

- ▶ Altering inputs (e.g. images) to neural networks so they get misclassified
- ▶ Try to do this in such a way as humans can't spot the difference



# ADVERSARIAL EXAMPLES

## ► Adding adversarial noise to images



$x$   
“panda”  
57.7% confidence

$+ .007 \times$



$\text{sign}(\nabla_x J(\theta, x, y))$   
“nematode”  
8.2% confidence

$=$



$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$   
“gibbon”  
99.3 % confidence

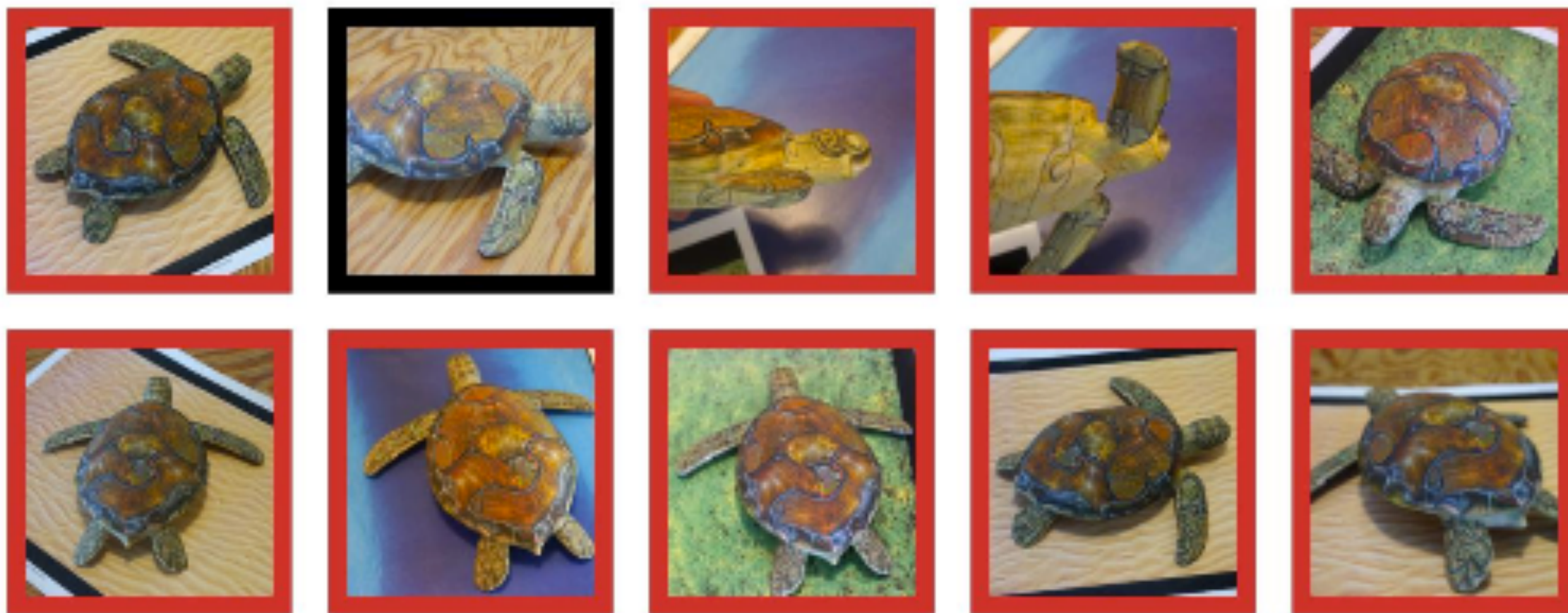
Goodfellow et al, “Explaining and Harnessing Adversarial Examples”, CoRR 1412.6572 (2014)





# ADVERSARIAL TURTLE

- ▶ 3D printed turtle that gets classified as a rifle from all angles



■ classified as turtle    ■ classified as rifle    ■ classified as other

arXiv: 1707.07397



# STOP SIGN ATTACKS

- ▶ Poster attack, 100% mis-classification







# STOP SIGN ATTACKS

- ▶ Sticker attack, 85% mis-classification



arXiv: 1707.08945





# PEDESTRIAN REMOVAL

- ▶ Noise added to remove pedestrians

(a) Image



(b) Prediction



(c) Adversarial Example



(d) Prediction





## HOW TO DO IT

- ▶ Usually during training we are updating the model weights to minimise the loss
- ▶ In adversarial attacks we increase the loss by altering the input data



## FAST GRADIENT SIGN METHOD

- ▶ Calculate the gradient of the loss function for the input image
- ▶ Either go uphill (untargeted)
- ▶ Or downhill towards target class (targeted)
- ▶ Add  $(-1)^{**}(\text{is\_targeted}) * \text{epsilon} * \text{sign}(\text{gradient})$  to each input pixel
- ▶ Implementation here: [https://github.com/cleverhans-lab/cleverhans/blob/master/cleverhans/jax/attacks/fast\\_gradient\\_method.py](https://github.com/cleverhans-lab/cleverhans/blob/master/cleverhans/jax/attacks/fast_gradient_method.py)



## YOUR TURN!

- ▶ There is a new notebook for today on GitHub
- ▶ We'll be using the `fast_gradient_method` in the `cleverhans` library





## PRE-TRAINED NETWORKS

- ▶ We're also going to be using a pre-trained neural network as the target of our attacks
- ▶ Many are available in keras, see here: <https://keras.io/api/applications/>
- ▶ Look at the time per inference step on CPU when deciding which to use!

## NOTEBOOK FOR TODAY

[https://github.com/abbeywaldron/cinvestav\\_ML\\_2024](https://github.com/abbeywaldron/cinvestav_ML_2024)