# COMP6248 Differentiable Programming

(and some Deep Learning)

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All credit for this slide goes to Niranjan

Data

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Sequence Modelling 
$$\mathbf{x}_n = f(\mathbf{x}_{n-1}, \boldsymbol{\theta})$$

#### What is Deep Learning?

Deep learning is primarily characterised by function compositions:

- Feedforward networks:  $\mathbf{y} = f(g(\mathbf{x}, \theta_g), \theta_f)$ 
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In the early days the focus of deep learning was on learning functions for classification. Nowadays the functions are much more general in their inputs and outputs.

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<sup>&</sup>lt;sup>1</sup>https://www.facebook.com/yann.lecun/posts/10155003011462143

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  - The implication is that we need to be able to compute gradients with respect to the parameters of these functional blocks. We'll start explore this in detail next week...
  - The idea of Differentiable Programming also opens up interesting possibilities:
    - The functional blocks don't need to be direct functions in a mathematical sense; more generally they can be algorithms.
    - What if the functional block we're learning parameters for is itself an algorithm that optimises the parameters of an internal algorithm using a gradient based optimiser?!<sup>2</sup>

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# Is all Deep Learning Differentiable Programming?

- Not necessarily!
  - Most deep learning systems are trained using first order gradient-based optimisers, but there is an active body of research on gradient-free methods.

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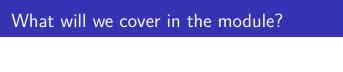
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  - Most deep learning systems are trained using first order gradient-based optimisers, but there is an active body of research on gradient-free methods.
  - There is an increasing interest in methods that use different styles of learning, such as Hebbian learning, within deep networks. More broadly there are a number of us<sup>3</sup> who are interested in biologically motivated models and learning methods.

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What is the objective of this module?



How is this module going to be delivered?

# Lecture & lab session plan

What do we expect you already know?

# What might you already know?

#### Assessment Structure

#### Assessment Timetable

# The Main Assignment

The ICLR Reproducibility Challenge