# 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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  - 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?

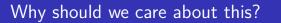
- Not necessarily!
  - Most deep learning systems are trained using first order gradient-based optimisers, but there is an active body of research on gradient-free methods.

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- 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.
  - 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?

- To gain an in-depth theoretical and practical understanding of modern deep neural networks and their applications.
- Understand the underlying mathematical and algorithmic principles of deep learning
- Understand the key factors that have made deep learning successful for various applications
- Apply existing deep learning models to real datasets
- Gain facility in working with deep learning libraries in order to create and evaluate network architectures
- Critically appraise the merits and shortcomings of model architectures on specific problems

#### What will we cover in the module?

http://comp6248.ecs.soton.ac.uk/

#### How is this module going to be delivered?

Reading material before the lectures

## Lab session plan

Lab	Date	Topic
Lab 1	05/02/19	Introducing PyTorch
Lab 2	12/02/19	Automatic Differentiation
Lab 3	19/02/19	Optimisation
Lab 4	26/02/19	NNs with PyTorch and Torchbearer
Lab 5	05/03/19	CNNs with PyTorch and Torchbearer
Lab 6	12/03/19	Transfer Learning
Lab 7	19/03/19	RNNs, Sequence Prediction and Embeddings
Lab 8	26/03/19	Deep Generative Models
	Break	
Lab 9	30/04/19	Coursework Help and Advice
Lab 10	30/04/19	Coursework Help and Advice
Lab 11	30/04/19	Coursework Help and Advice

#### What do we expect you already know?

- COMP3206 or COMP3223 or COMP6229 or COMP6245
- Fundamentals of Linear Algebra, Probability and Statistics, Calculus
- Programming in Python

#### Assessment Structure

- 1 Lab work 40%
- Final project 40%
- In-class tests 20%

#### Assessment Timetable

Assessment	Date	Time
Labs 1-3	22/02/19	16:00
Coursework Team Information	27/02/19	16:00
In - class Test 1	01/03/19	midnight
Labs 4-6	15/03/19	16:00
In - class Test 2	29/03/19	midnight
Labs 7-8	03/05/19	16:00
Final Coursework Submission	15/05/19	16:00

# The Main Assignment

The ICLR Reproducibility Challenge

http://comp6248.ecs.soton.ac.uk/coursework.html