

COMP6248 Differentiable Programming

(and some Deep Learning)

Kate Farrahi and Jonathon Hare

Vision, Learning and Control
University of Southampton

Machine Learning - A Recap

All credit for this slide goes to Niranjan

Data

$$\{\mathbf{x}_n, \mathbf{y}_n\}_{n=1}^N \quad \{\mathbf{x}_n\}_{n=1}^N$$

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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: $\mathbf{y} = f(g(\mathbf{x}, \boldsymbol{\theta}_g), \boldsymbol{\theta}_f)$
 - Often with relatively simple functions (e.g. $f(\mathbf{x}, \boldsymbol{\theta}_f) = \sigma(\mathbf{x}^\top \boldsymbol{\theta}_f)$)

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 $\mathbf{y}_t = f(\mathbf{y}_{t-1}, \mathbf{x}_t, \boldsymbol{\theta}) = f(f(\mathbf{y}_{t-2}, \mathbf{x}_{t-1}, \boldsymbol{\theta}), \boldsymbol{\theta}) = \dots$

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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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- Differentiable programming is a term coined by Yann Lecun¹ to describe a superset of Deep Learning.

¹<https://www.facebook.com/yann.lecun/posts/10155003011462143>

²See our ICLR 2019 paper: <https://arxiv.org/abs/1812.03928>

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- Differentiable programming is a term coined by Yann Lecun¹ to describe a superset of Deep Learning.
- Captures the idea that computer programs can be constructed of parameterised functional blocks in which the parameters are learned using some form of gradient-based optimisation.

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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...

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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?!²

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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.

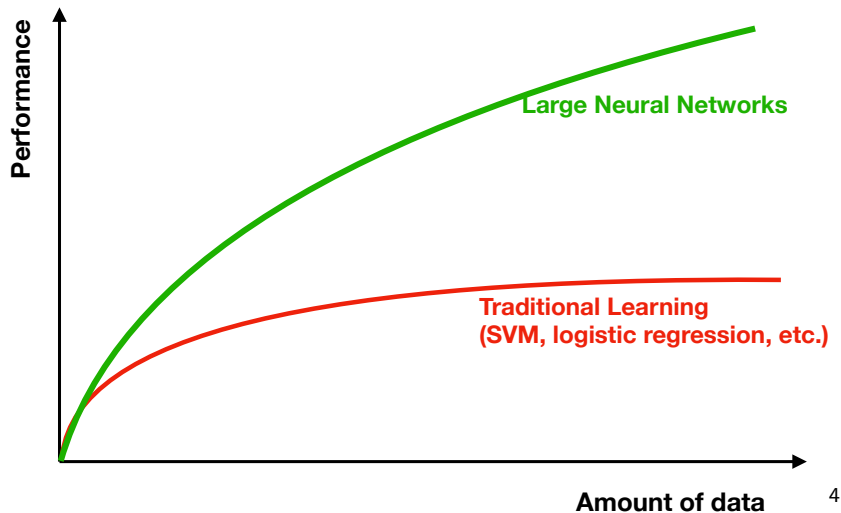
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 - Most deep learning systems are trained using first order gradient-based optimisers, but there is an active body of research on gradient-free methods.
 - There is an increasing interest in methods that use different styles of learning, such as Hebbian learning, within deep networks. More broadly there are a number of us³ who are interested in biologically motivated models and learning methods.

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Why should we care about this?



⁴Reference: Andrew Ng

Where did it all start & what was the motivation?

What is the objective of this module?

- 1 To gain an in-depth theoretical and practical understanding of modern deep neural networks and their applications.
- 2 Understand the underlying mathematical and algorithmic principles of deep learning
- 3 Understand the key factors that have made deep learning successful for various applications
- 4 Apply existing deep learning models to real datasets
- 5 Gain facility in working with deep learning libraries in order to create and evaluate network architectures
- 6 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?

- 1 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?

- ① COMP3206 or COMP3223 or COMP6229 or COMP6245
- ② Fundamentals of Linear Algebra, Probability and Statistics, Calculus
- ③ Programming in Python

Assessment Structure

- ① Lab work 40%
- ② Final project 40%
- ③ 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`