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

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

What is Deep Learning?

Deep learning is primarily characterised by function compositions:

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

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

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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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[1] https://www.facebook.com/yann.lecun/posts/10155003011462143

[2] See our ICLR 2019 paper: https://arxiv.org/abs/1812.03928

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- 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...
    - 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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- 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 us[3] who are interested in biologically motivated models and learning methods.

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Why should we care about this?

Where did it all start & what was the motivation?

What is the objective of this module?

What will we cover in the 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