COMP6248 Differentiable Programming

(and some Deep Learning)

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All credit for this slide goes to Niranjan

Data

$$\{x_n, y_n\}_{n=1}^N \qquad \{x_n\}_{n=1}^N$$

$$\{\boldsymbol{x}_n\}_{n=1}^N$$

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Function Approximator
$$\mathbf{y} = f(\mathbf{x}, \boldsymbol{\theta}) + \nu$$

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Parameter Estimation
$$E_0 = \sum_{n=1}^{N} {\{\|\boldsymbol{y}_n - f(\boldsymbol{x}_n; \boldsymbol{\theta})\|\}^2}$$

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Parameter Estimation	$E_0 = \sum_{n=1}^{N} \{ \ \mathbf{y}_n - f(\mathbf{x}_n; \boldsymbol{\theta}) \ \}^2$
Prediction	$\hat{\mathbf{y}}_{N+1} = f(\mathbf{x}_{N+1}, \hat{\boldsymbol{\theta}})$

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Prediction	$\hat{\boldsymbol{y}}_{N+1} = f(\boldsymbol{x}_{N+1}, \hat{\boldsymbol{\theta}})$
Regularisation	$E_1 = \sum_{n=1}^{N} { \ \mathbf{y}_n - f(\mathbf{x}_n; \boldsymbol{\theta}) \ }^2 + r(\ \boldsymbol{\theta} \)$

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Modelling Uncertainty	$p(\boldsymbol{\theta} \{\boldsymbol{x}_n,\boldsymbol{y}_n\}_{n=1}^N)$

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Dradiation	$\hat{\mathbf{r}} = f(\mathbf{r} + \hat{\mathbf{q}})$

 $\{x_{-}, v_{-}\}^{N}, \{x_{-}\}^{N},$

Prediction
$$\hat{\mathbf{y}}_{N+1} = t(\mathbf{x}_{N+1}, \boldsymbol{\theta})$$

Regularisation
$$E_1 = \sum_{n=1}^{N} \{ \| \mathbf{y}_n - f(\mathbf{x}_n; \boldsymbol{\theta}) \| \}^2 + r(\| \boldsymbol{\theta} \|)$$

Modelling Uncertainty
$$p(\theta | \{x_n, y_n\}_{n=1}^N)$$

Probabilistic Inference
$$\mathbb{E}[g(\theta)] = \int g(\theta) p(\theta) d\theta = \frac{1}{N_s} \sum_{n=1}^{N_s} g(\theta^{(n)})$$

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

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- Recurrent networks:

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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.

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

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

²See 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 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?

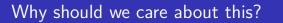
- Not necessarily!
 - Most deep learning systems are trained using first order gradient-based optimisers, but there is an active body of research on gradient-free methods.

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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.
 - 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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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