Differentiate your Objective

COMP6258 Differentiable Programming and Deep Learning

Jonathon Hare and Antonia Marcu

Vision, Learning and Control
University of Southampton

What do Differentiable Programming and Deep Learning give us?

Machine Learning - A Recap

All credit for this slide goes to Niranjan

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

What is Deep Learning?

Deep learning is primarily characterised by function compositions:

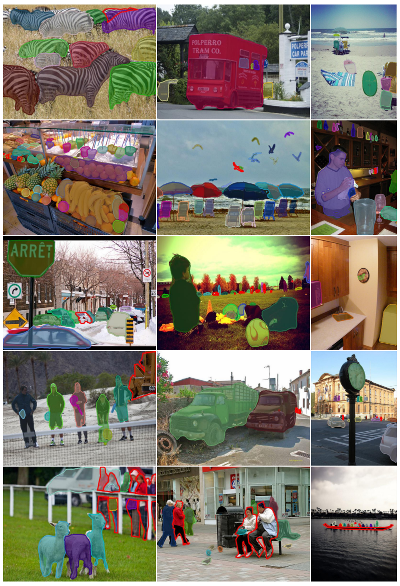
- Feedforward networks: $\boldsymbol{y} = f(g(\boldsymbol{x}, \boldsymbol{\theta}_g), \boldsymbol{\theta}_{\boldsymbol{f}})$
  - Often with relatively simple functions (e.g. $f(\boldsymbol{x}, \boldsymbol{\theta}_f) = \sigma(\boldsymbol{x}^\top \boldsymbol{\theta}_f)$)
- Recurrent networks:
  $\boldsymbol{y}_t = f(\boldsymbol{y}_{t-1}, \boldsymbol{x}_t, \boldsymbol{\theta}) = f(f(\boldsymbol{y}_{t-2}, \boldsymbol{x}_{t-1}, \boldsymbol{\theta}), \boldsymbol{x}_t, \boldsymbol{\theta}) = \dots$

What is Differentiable Programming?

- Captures the idea that computer programs can be partially learned rather than fully programmed by humans.
- The program is made of functions with optimisable parameters.
- So we need to be able to compute gradients with respect to the parameters of these functional blocks.
- 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?![1]

[1] See our ICLR 2019 paper: https://arxiv.org/abs/1812.03928 and NeurIPS 2019 paper: https://arxiv.org/abs/1906.06565

Success stories - Object detection and segmentation



Pinheiro, Pedro O., et al. "Learning to refine object segments." European Conference on Computer Vision. Springer, 2016.

Success stories - Image generation

Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015).

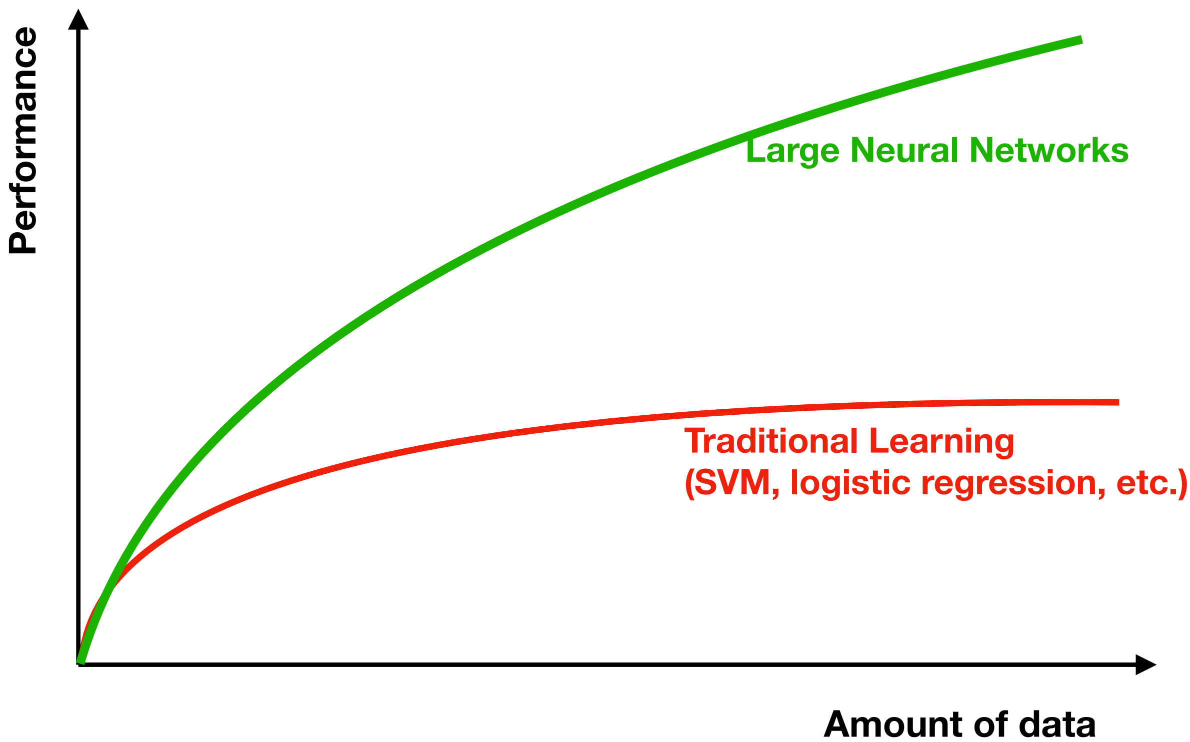
Success stories - Translation

ENGLISH TEXT
The reason Boeing are doing this is to cram more seats in to make their plane more competitive with our products," said Kevin Keniston, head of passenger comfort at Europe's Airbus.

TRANSLATED TO FRENCH
La raison pour laquelle Boeing fait cela est de creer plus de sieges pour rendre son avion plus competitif avec nos produits", a declare Kevin Keniston, chef du confort des passagers chez Airbus.

Wu, Yonghui, et al. "Google's neural machine translation system: Bridging the gap between human and machine translation." arXiv preprint arXiv:1609.08144 (2016).

Why should we care about this?



Reference: Andrew Ng

What is the objective of this module?

A word of warning: This is not a module about how to apply someone else's deep network architecture to a task, or how to train existing models!

You will learn some of that along the way of course, but the real objective is for you to graduate knowing how to understand, critique and implement new and recent research papers on deep learning and associated topics.

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 differentiable programming 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.
- Have a technical and mathematical grounding that enables you to understand the field as it rapidly evolves.
- Find out about some of the research going on here!

How is this module going to be delivered?

- Lectures (3 per week except when we have seminars)
  - Note: We are refreshing some material from last year, but the website may have old links.
  - You need to read the suggested papers/links before the lectures!
  - There is maybe a little room for some flexibility later in the course on topics - tell us what you're interested in!
  - Lectures will be face to face, but also recorded for the website when possible (do not rely on this!).

How is this module going to be delivered?

- Seminars (4)
  - We'll look at a particular paper, papers or ideas in some detail and have an open discussion
  - You'll need to prepare in advance & be ready to ask questions and share your thoughts
  - Not recorded, but contents examinable in the quizzes

How is this module going to be delivered?

- Labs (1x 2 hour session per week for 8 weeks + additional help sessions if required)
  - Labs consist of a number of Juypter notebooks you will work though.
    - You'll be using PyTorch as the primary framework, with Torchbearer to help out.
    - You will need to utilise GPU-compute for the later labs (we provide Google Colab links so you can use NVidia K80s or newer in the cloud).
  - Labs are in-person (Zepler L3) with a team of PhD student demonstrators & myself and/or Antonia.
  - Please ask lots of questions and use this time to get help on the labs and coursework.
  - After each lab you will have to do a follow-up problem-sheet exercise that will be marked.

What will we cover in the module?

`https://ecs-vlc.github.io/COMP6258/`

Lab session plan

Lab	Date	Topic
Lab 1	31/01/25	Introducing PyTorch
Lab 2	07/02/25	Automatic Differentiation
Lab 3	14/02/25	Optimisation
Lab 4	21/02/25	NNs with PyTorch and Torchbearer
Lab 5	28/02/25	CNNs with PyTorch and Torchbearer
Lab 6	07/03/25	Transfer Learning
Lab 7	14/03/25	RNNs, Sequence Prediction and Embeddings
Lab 8	21/03/25	Deep Generative Models
Lab 9	28/03/25	(catch-up/questions)

What do we expect you already know?

- COMP3223 or COMP6245 (fundamentals of statistical learning, MLPs, gradient descent, how to train and evaluate learning machines, supervised-vs-unsupervised)
- Fundamentals of:
  - Matrix Algebra (matrix-matrix, matrix-vector and matrix-scalar operations, inverse, determinant, rank, Eigendecomposition, SVD);
  - Probability & Statistics (1st-order summary statistics, simple continous and discrete probability distributions, expected values, etc); and,
  - Multivariable Calculus (partial differentiation, chain-rule).
- Programming in Python

What might you already know?

- How to use a deep learning framework (Keras, Tensorflow, PyTorch)?
- How to train an existing model architecture using a GPU?
- How to perform transfer learning?
- How to perform differentiable sampling of a Multivariate Normal Distribution?

Assessment Structure

- Interim project plan - Handin in week 5 (26th Feb, 4PM)
- Lab work 40% - Handin in week 11 (7th May, 4PM)
- Online quizzes 20% - Planned for week 6 (5th March) and week 12 (14th May)
- Final project 40% - Handin in week 12 (16th May, 4PM)

The Main Assignment

The ICLR Reproducibility Challenge

https://ecs-vlc.github.io/COMP6258/coursework.html