Differentiate your Objective

VLC = ∭ Vision Learning Control dVdLdC

COMP6258 Differentiable Programming and Deep Learning

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

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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 Lecun[1] to describe a superset of Deep Learning.

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

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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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    - There's a lot of recent research that computes biological proxies for gradients though!
  - This course will primarily focus on differentiable methods, but we'll look at how relaxations can be made to make non-differentiable operators learnable with gradient-based optimisers.

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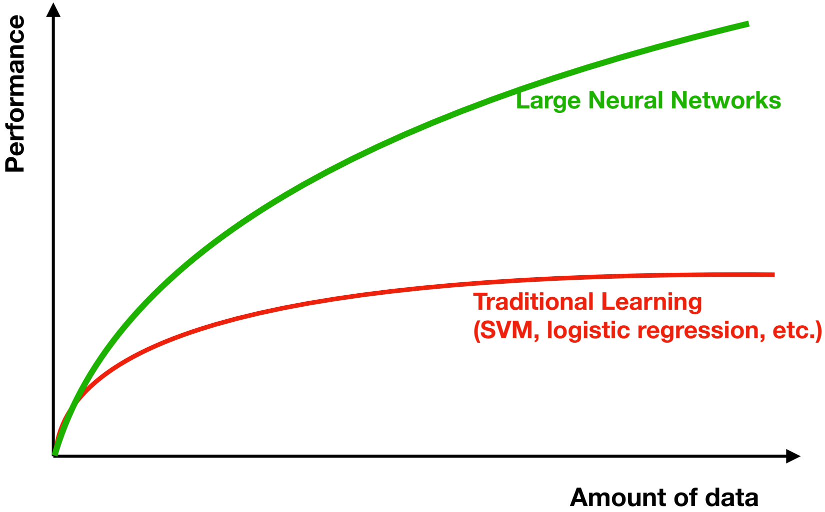
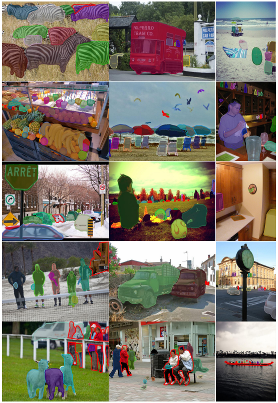
Why should we care about this?



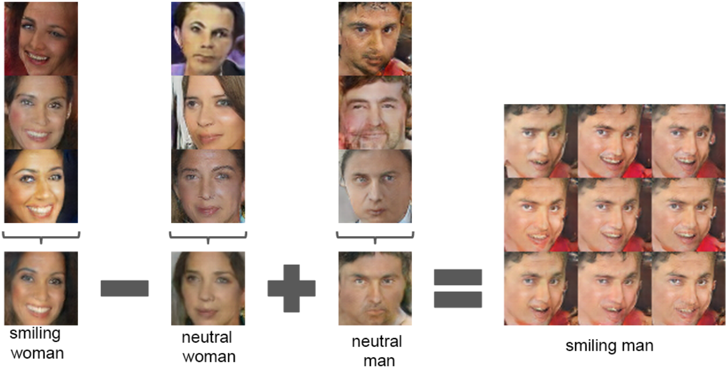
Reference: Andrew Ng

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).

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.

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- 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.

How is this module going to be delivered?

- Lectures (3 per week)
  - 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 a little room for some flexibility later in the course on topics - tell us what you're interested in!

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  - Lectures will be face to face, but also recorded for the website.

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- Labs (1x 2 hour session per week for 8 weeks + additional help sessions)
  - 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 in the cloud).
  - Labs are in-person (25/1007) with a team of PhD student demonstrators & myself*.
  - 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	10/02/23	Introducing PyTorch
Lab 2	17/02/23	Automatic Differentiation
Lab 3	24/02/23	Optimisation
Lab 4	03/03/23	NNs with PyTorch and Torchbearer
Lab 5	10/03/23	CNNs with PyTorch and Torchbearer
Lab 6	17/03/23	Transfer Learning
Lab 7	24/03/23	RNNs, Sequence Prediction and Embeddings
	Break	
Lab 8	28/04/23	Deep Generative Models

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- Programming in Python

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- 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

- Lab work 40% - Handin in week 10 (3rd May, 4PM)
- Final project 40% - Handin in week 12 (17th May, 4PM) (+ interim handin in week 5)
- Online quizzes 20% - Planned for week 6 (8th Mar) and week 10 (3rd May)

The Main Assignment

The ICLR Reproducibility Challenge

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