Differentiate your Objective

VLC = ∭ Vision Learning Control dVdLdC

COMP6258 Differentiable Programming and Deep Learning

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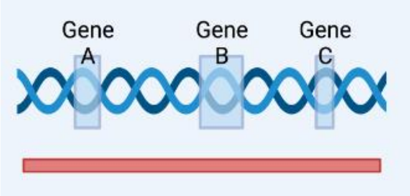
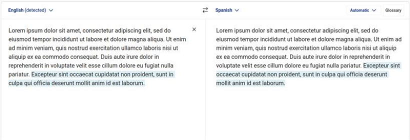
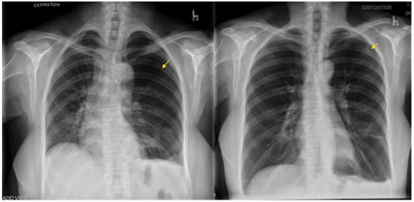
Vision, Learning and Control
University of Southampton

What do Differentiable Programming and Deep Learning give us?







Machine Learning - A Recap

All credit for this slide goes to Niranjan

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

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

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- Captures the idea that computer programs can be partially learned rather than fully programmed by humans.

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- 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]

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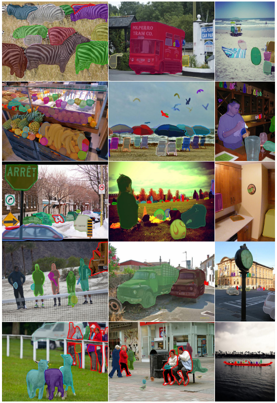
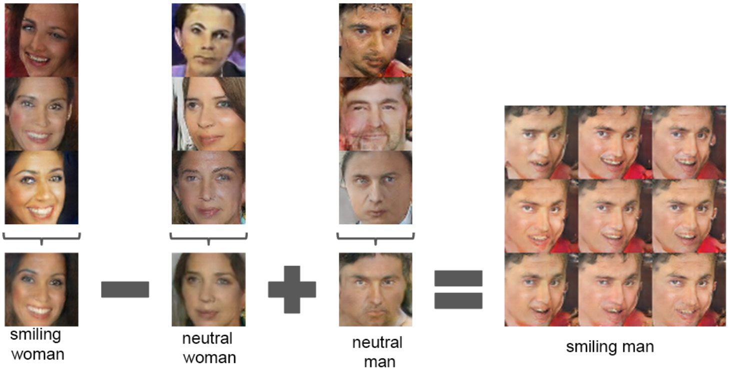
Success stories - Object detection and segmentation



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

GPT-4

Prompt:
Translate the following Irish text to English:
"Bhí mé ag siúl sa choill nuair a chuala mé ceol álainn ón adharc."

Output (With LLM Integration):
I was walking in the forest when I heard beautiful music from the horn.
Output (Traditional MT):
I was in the wood when I heard nice sound from the horn.

Lyu, C., Du, Z., Xu, J., Duan, Y., Wu, M., Lynn, T., Aji, A.F., Wong, D.F., Liu, S. and Wang, L., 2023. A Paradigm Shift: The Future of Machine Translation Lies with Large Language Models. LREC-COLING 2024

Why should we care about this?

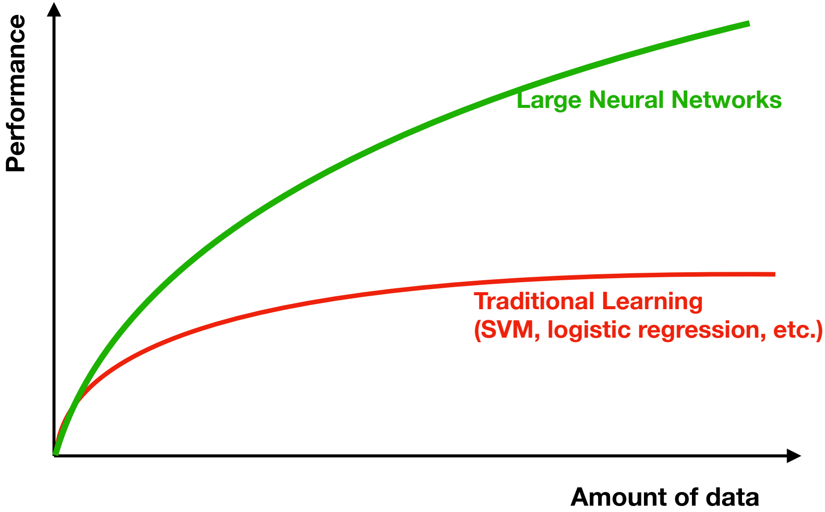


Image courtesy of Andrew Ng

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- ...allows for **bigger/deeper/more complex models**
- ...models that can **learn the features**
- and these can have far **greater performance**

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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- Apply deep learning methods to real datasets.
- Learn how to train models using deep learning libraries.
- Think critically about upcoming research in deep learning.

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!

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  - 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 & both of us.
  - 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)

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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

- 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 COMP6258 Reproducibility Challenge

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