Introduction

Admin

1. Course web page: `https://github.com/sje30/dl2022`
2. Office hour: Monday 1-2pm.
3. One assignment to be set at end of term.
4. Key reference placed in paperpile:
   `https://paperpile.com/shared/pb4w0p`.

Online learning

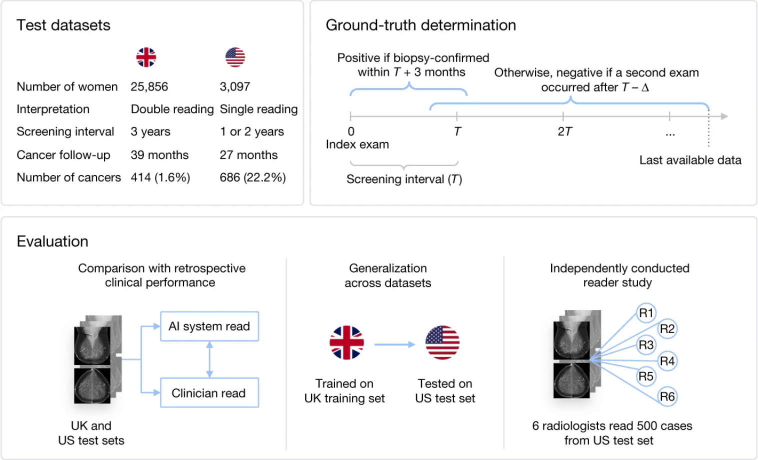
- Lectures Mon and Thurs to be available on Teams channel.
- MPhil Comp Biology students will also get small group exercise classes with Max Niroomand.

Example of deep learning/1

McKinney et al (2020). International evaluation of an AI system for breast cancer screening.

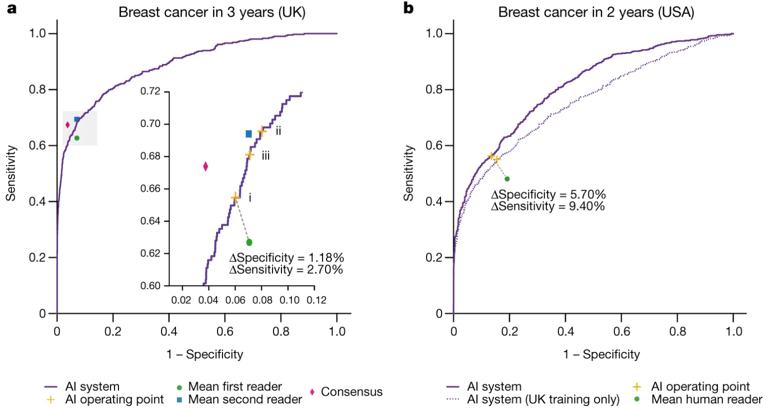
42 million scans/year in UK and US.

Figure 1:



Example of deep learning/2

McKinney et al (2020). International evaluation of an AI system for breast cancer screening. See figure 2:



Sensitivity: test correctly identifies patients with the disease; **specificity**: test correctly identifies patients without the disease.

`https://ebn.bmj.com/content/23/1/2`

System performs better than first reader; "no worse" than second reader,

What is deep learning?

What do these terms mean and how might they interact with each?

- Machine learning (applied statistics)
- Deep learning
- Artificial Intelligence
- Neural modelling

Classification

Input vectors $\mathbf{x}$ associated with output vectors $\mathbf{y}$.
Learn mapping: $\mathbf{x} \Rightarrow \mathbf{y}$.
Generalise to data not seen during learning. (“Training set” vs “test set” and also “validation set”).

Approaches to classification

1. Logistic regression (binary outputs). Applied Statistics.
2. Naive Bayes. Machine Learning / probablistic modelling.
3. Multi-layer perceptron. Neural networks part I.
4. Support vector machines. Kernel methods.
5. Decision Trees and Forests.
6. Neural networks part II.

Prediction vs understanding

- Why build a deep network vs another classifier?
- Performance: want something better than currently available?
- Understanding: want to understand how it works? Or how the brain works?

Looking for general introduction to machine learning?

An Introduction to statistical learning with applications in R.
`http://statlearning.com`
James, Witten, Hastie and Tibshirani.

Key references

1. Artificial Intelligence Engines (Stone). If you like the book, please review it on Amazon. `https://jim-stone.staff.shef.ac.uk/AIEngines/`
2. ITILA (David Mackay).
3. Deep learning (Goodfellow et al.).
4. Theoretical Neuroscience (Dayan and Abbott).
5. Deep learning with R (Chollet and Allaire). “Clone” of Deep Learning with Python (Chollet).
6. Key papers will be highlighted at end of each section.

What's to cover in the first week?

1. Introduction to neuroscience
2. Single neuron models
3. Perceptron
4. Background reading: chapters 1–2 of Stone.

Looking further ahead

1. Backpropagation
2. Hopfield networks
3. Dimensionality reduction
4. Convolutional networks
5. Recurrent neural networks [??]
6. Practical aspects: coding in Flux.jl / PyTorch
7. Advanced topics: GANs, GNNs, Transformers

Key reading: Mckinney et al 2020. Stone (chapters 1–2).