

Machine Learning in Medical Imaging

Machine Learning for computational sciences

UCL eResearch Symposium. 20 June 2019

David Atkinson

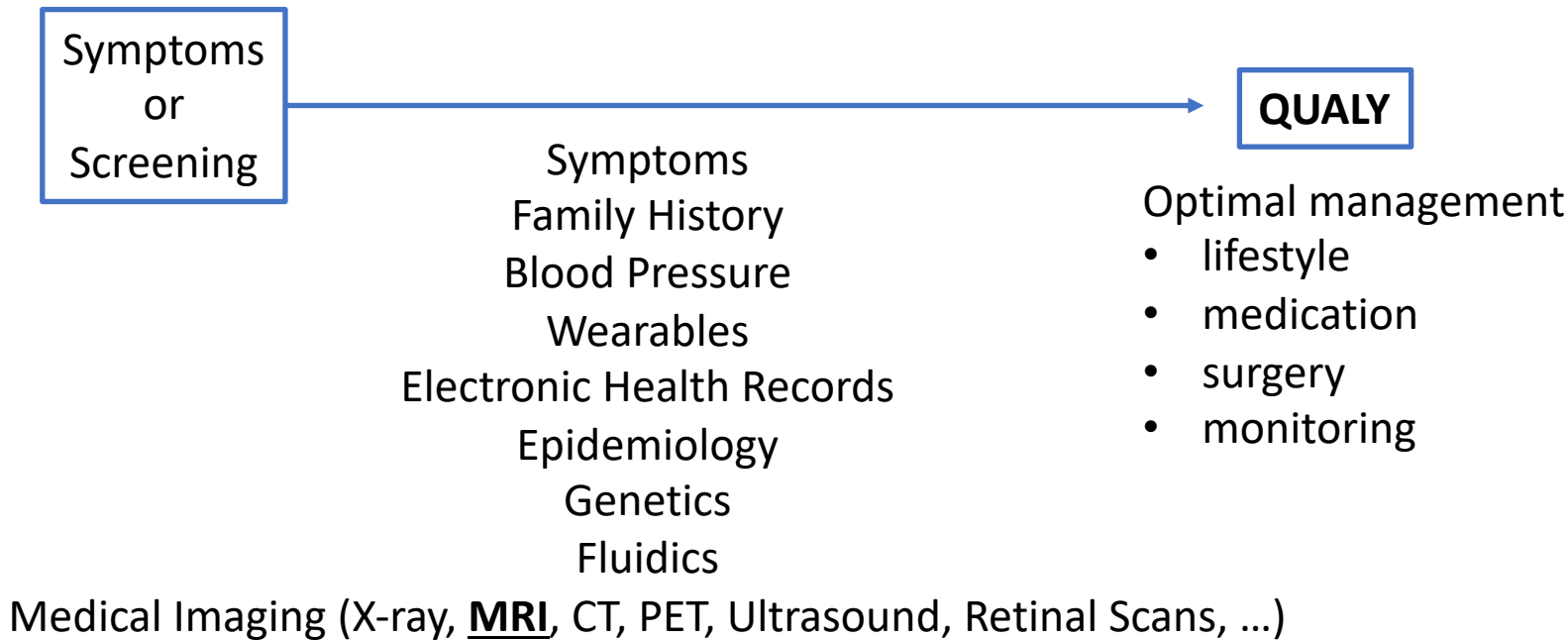
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Alan Turing Institute Fellow



The
Alan Turing
Institute

Medical Imaging in Healthcare



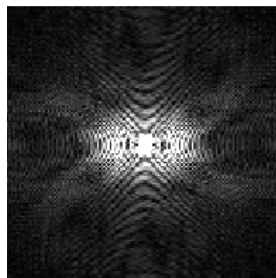
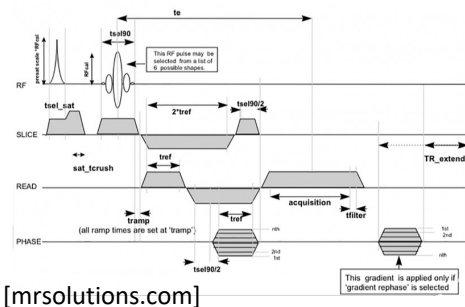
Magnetic Resonance Imaging

Acquisition

- Sequence of RF, gradients
 - many parameters
- K-space data received
- Time consuming
- Prone to artefacts

Image reconstruction

- Fourier Transform
 - (fully sampled)
- Iterative reconstructions
 - (under sampled)

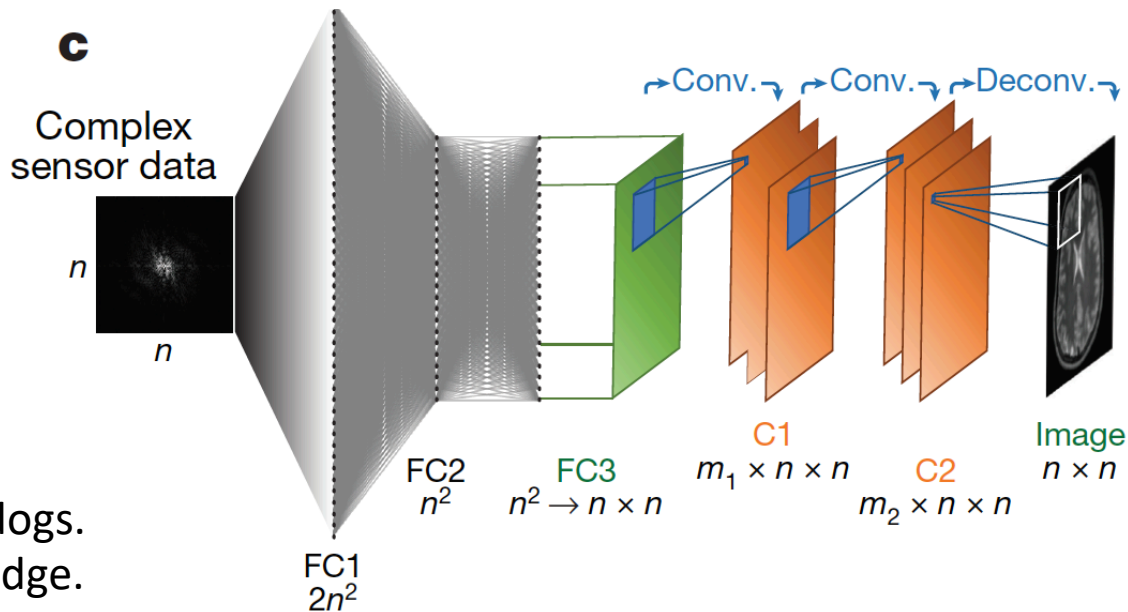


Machine Learning Strengths

- Convolutional Neural Networks
 - Suited to images (computer vision, self-driving cars...).
- NNs as universal function approximators.
 - Reconstruction is a 'function'.
- Learn from data
 - Avoid 'hand-crafted' algorithms.
- Reinforcement Learning
 - potential for 'move 37' leaps in sequence design.
- Inference is Fast

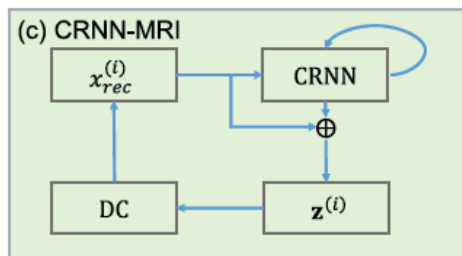
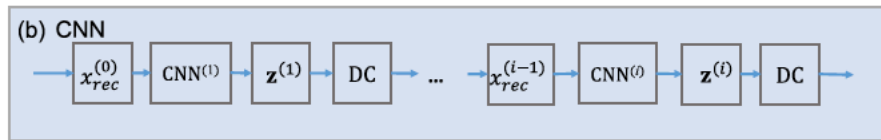
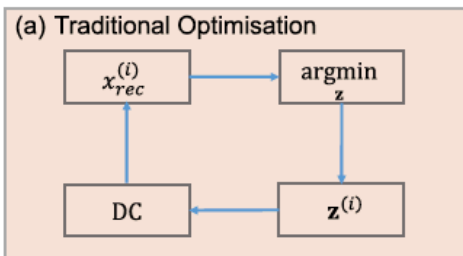
AUTOMAP

MR reconstruction

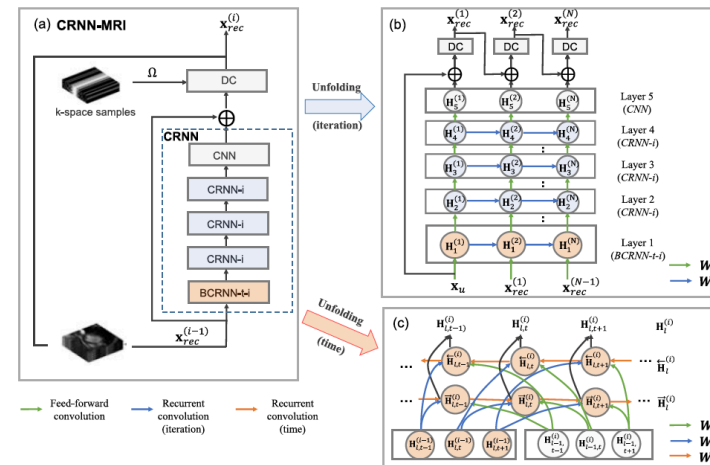


- Trained on cats and dogs.
- Little domain knowledge.
- Learnt FT!
- Large - hard to scale
- FAST

Iterative Reconstruction as a Network



- Unroll iterations as a network.
- Uses domain knowledge
- Uses CNNs with feed forward links as appropriate
- Better explainability?
- Feels ‘hand-crafted’ again ...



Potential Discovery Tool

Pulse sequences have very many parameters and permutations.

Design trade-offs based in-part on experience and intuition.

Physics is known (Maxwell's and Bloch equations).

Design a 'game score' and use reinforcement learning to find a faster/better strategy?

Discussion Themes

How to use AI to enhance, rather than replace, computational models

- Selectively replace: “data” parts of models, e.g. regularization parameters, de-noising steps, hand-crafted filters.
 - Iterative unrolling example.
- Train against human quality scores to learn to quantify image artefacts?

Balancing 1st principles approaches vs using machine learning

- AUTOMAP “wasteful”, but fast and generalizable?
- ‘move 37’ uses 1st principles (game rules / physics) but might teach us new strategies.

How to promote the application of novel theoretical mathematical models to research challenges

- Flip ‘Kaggle’ challenges to encourage 1st principles approaches?



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Thanks