



AI in medical imaging

Status, opportunities, pitfalls and challenges

Dr Mitra Safavi-Naeini

Principal Physicist - ANSTO

Science. Ingenuity. Sustainability.

ANSTO | We are the national nuclear science and technology agency

Operating safely for
over 60 years

Home of Australia's
landmark research
infrastructure



Lucas Heights | NSW



Main campus

Clayton | VIC



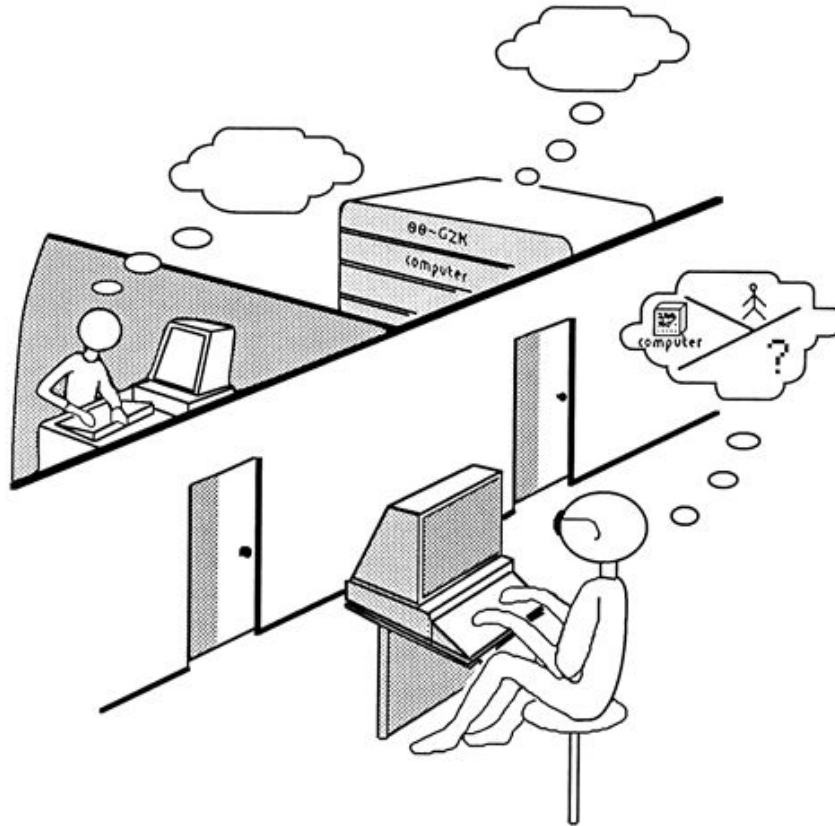
Australian Synchrotron

Camperdown | NSW



Cyclotron

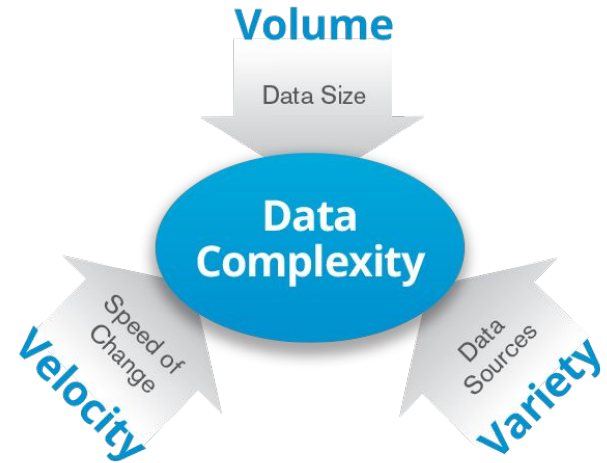
Artificial intelligence: what is intelligence?



Big Data

- Three Vs:

- Volume: Exponential increase
- Velocity: Rate at which it is produced
- Variety: Different formats with no or little structure



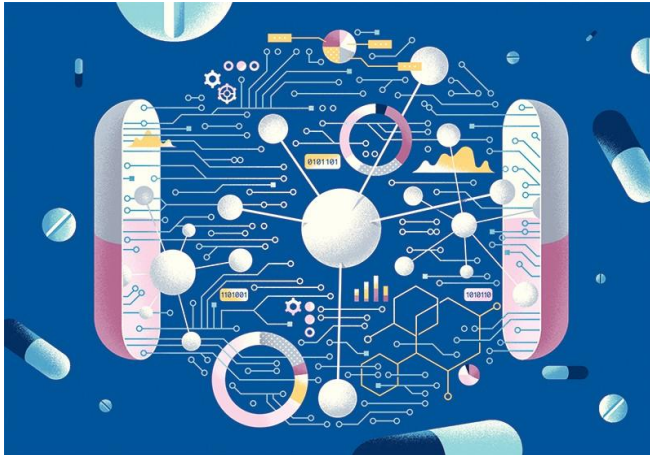
- There is an additional one that matches medical data:

- Veracity: Data might be incomplete, noisy, not meaningful, uncertain, ambiguous and inconsistent.

NETFLIX



alexa



UB A Machine Learning Success Story

Pioneering work on Postal Automation at UB

- Handwriting recognition for postal automation
- Saving hundreds of millions of dollars in labor costs for the US Postal Service
- Over 95% of US letter mail sorted without manual intervention
- Technology licensed to Australia Post and UK's Royal Mail

Mail Transport Hardware (Processing/Sorting)

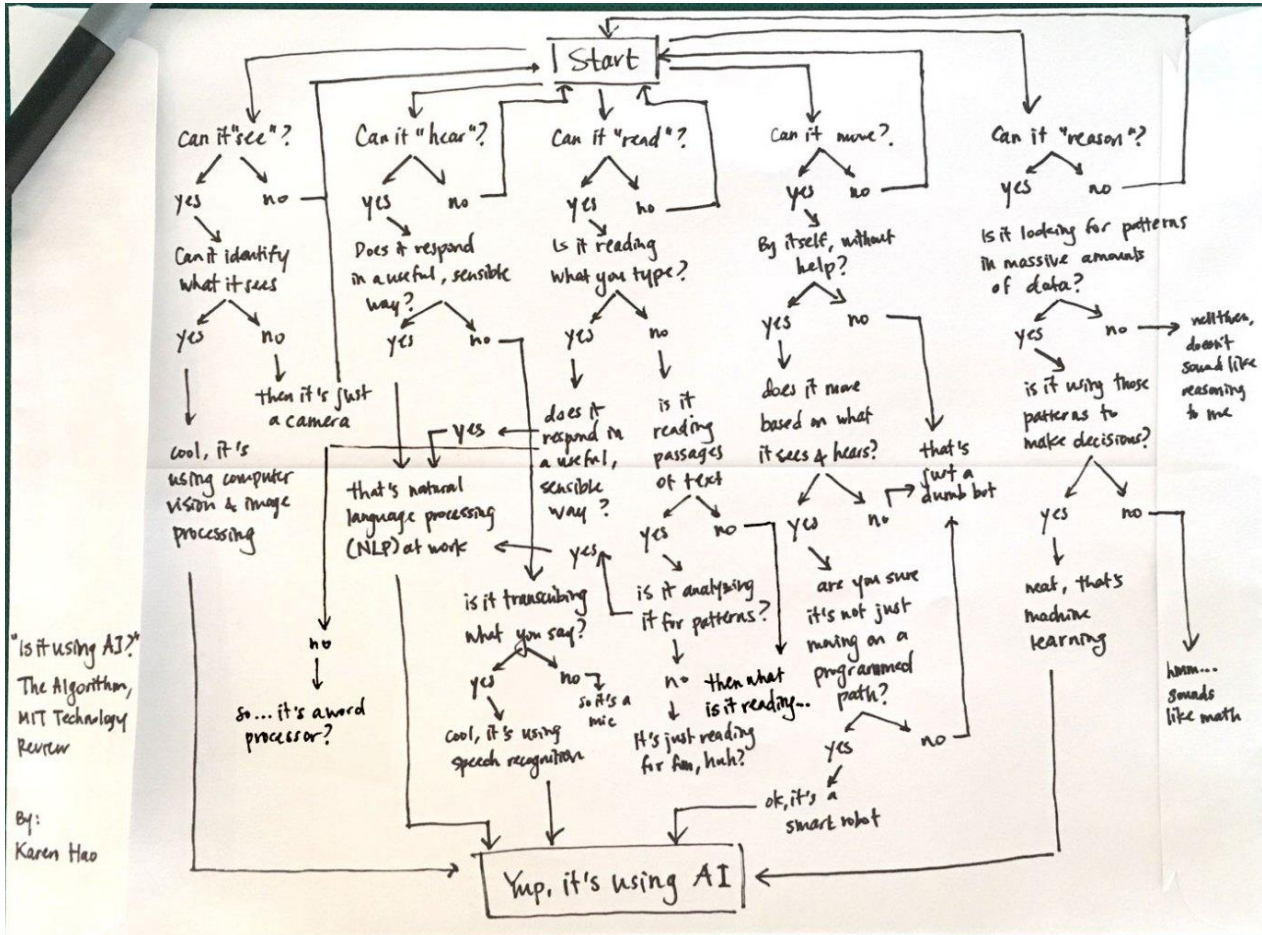
Automated Handwritten Address Interpretation

Remote Computer Reader (RCR) Software

"A lexicon driven approach to handwritten word recognition for real-time applications",
IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No. 4, pp. 366-379, 1997

SIEMENS **POST** UNITED STATES POSTAL SERVICE Royal Mail LOCKHEED MARTIN

Is it AI?



"Is it using AI?"
The Algorithm,
MIT Technology
Review

By:
Karen Hao

Yep, it's using AI

What is machine learning?

- All useful programs “learn” something
- Learning is improving at a task (set of skills) with experience
 - Experience = Data
 - The more data the better
 - However, more data requires more computational power and storage

“Field of study that gives computers the ability to learn without being explicitly programmed.” ~Arthur Samuel (1959)

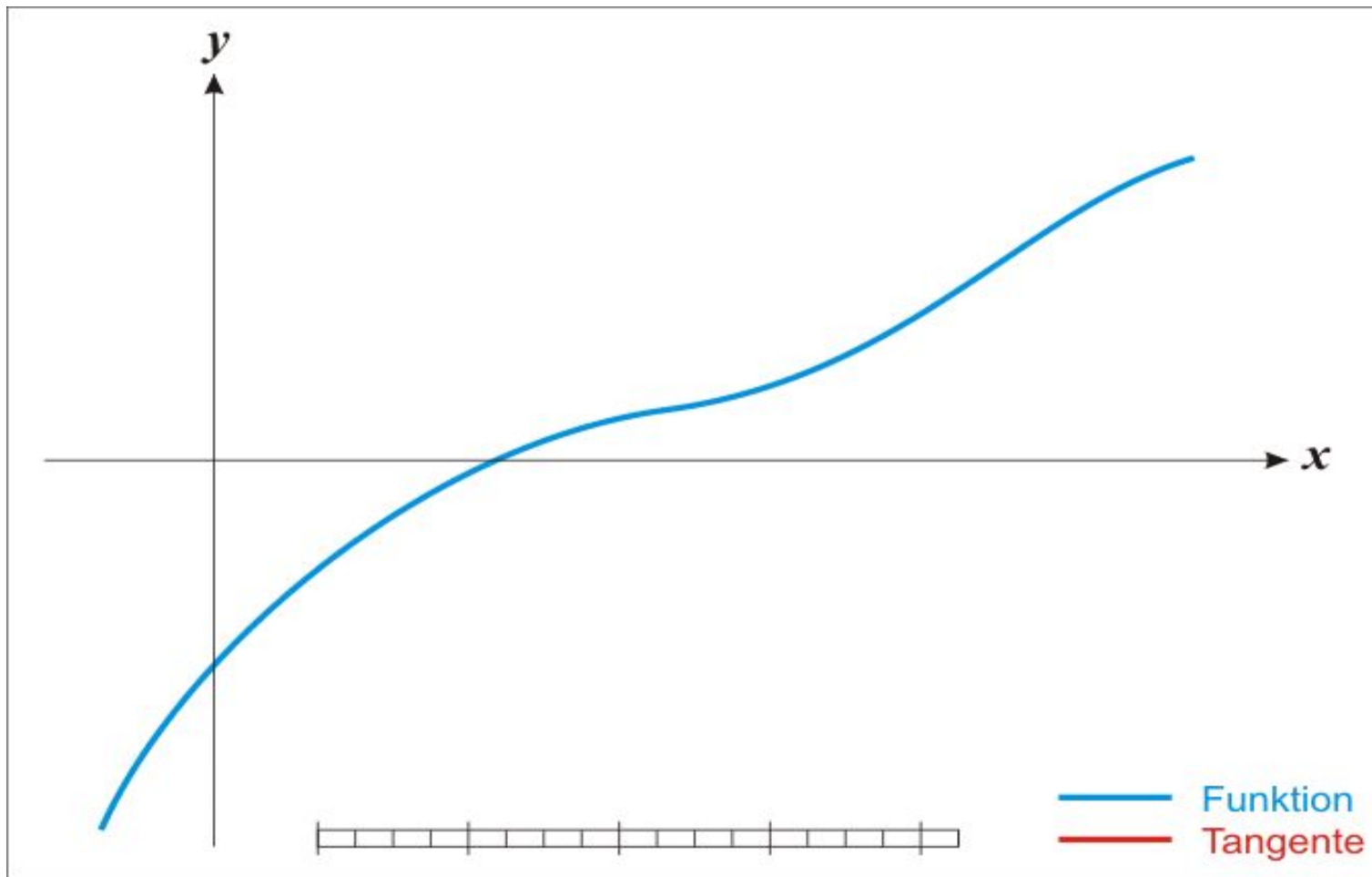
What is machine learning?

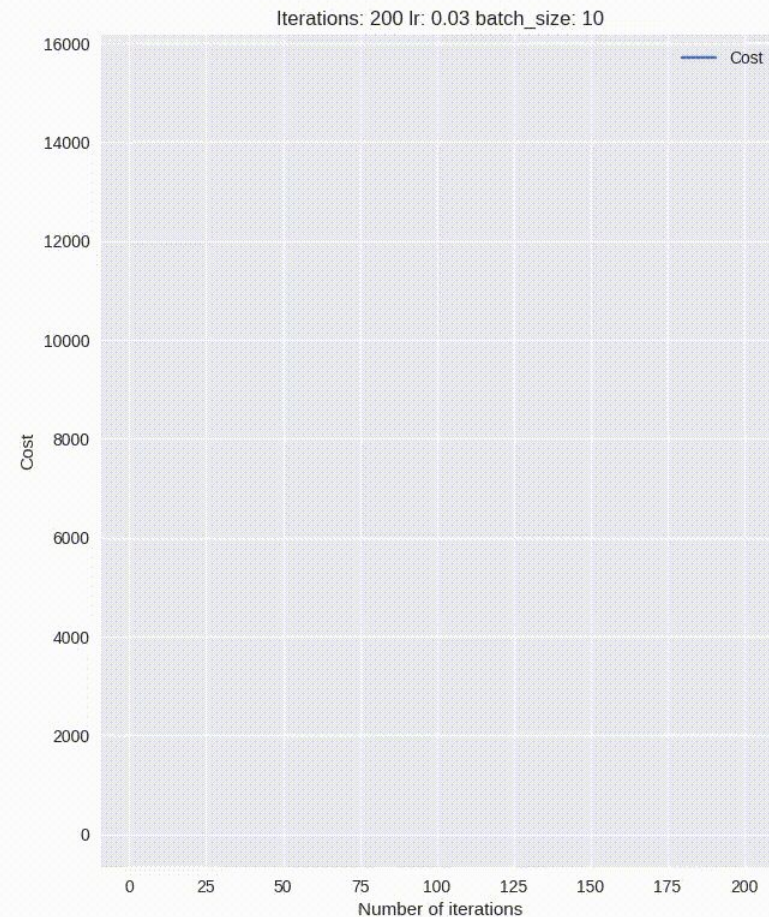
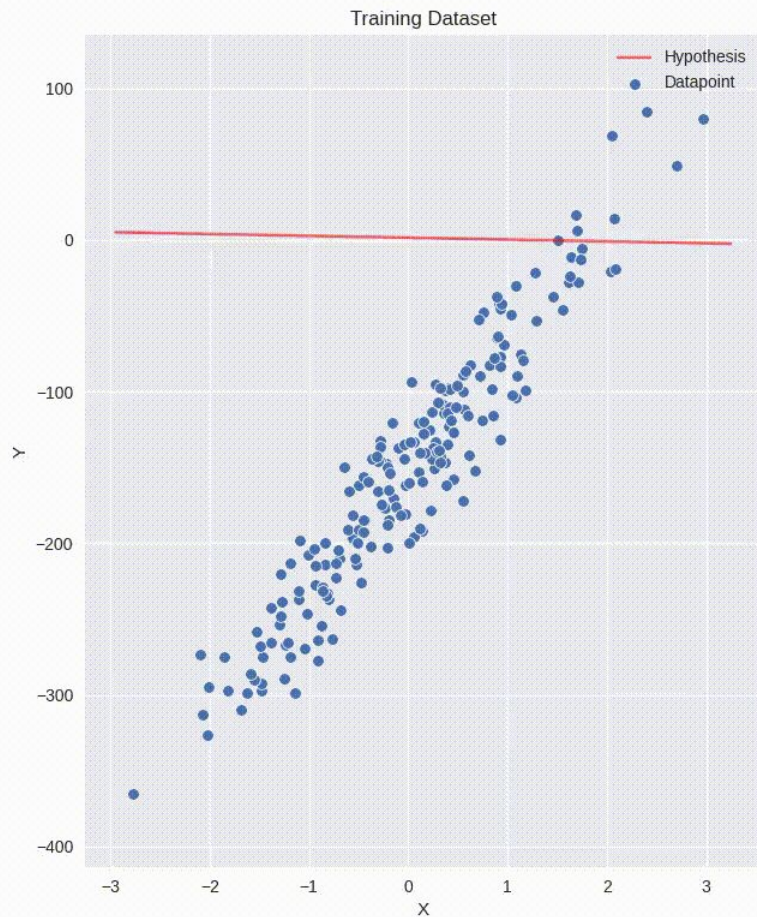
Conventional programming



Example: Newton-Raphson method

$$x_1 = x_0 - f(x_0)/f'(x_0)$$





Source: <https://github.com/Gautam-J/Machine-Learning>

What is machine learning?

Conventional programming



Machine Learning

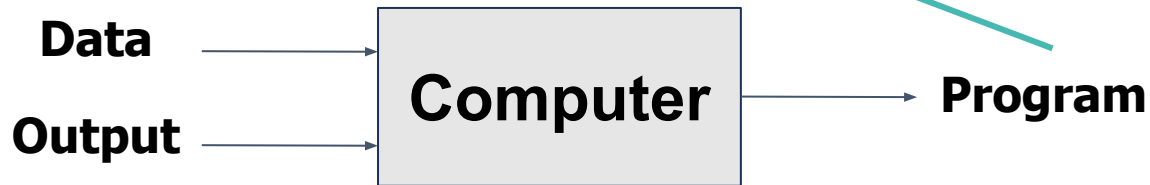


What is machine learning?

Conventional programming



Machine Learning

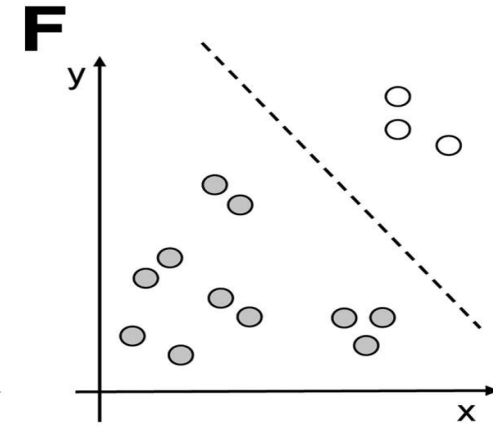
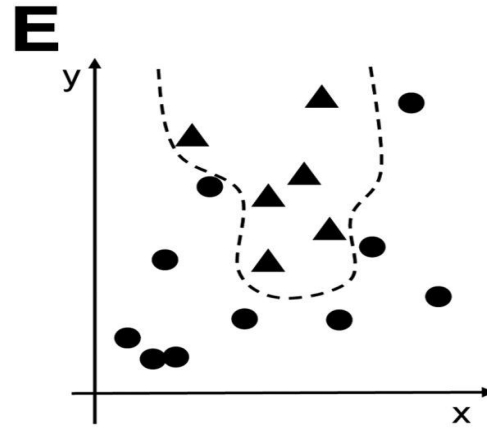
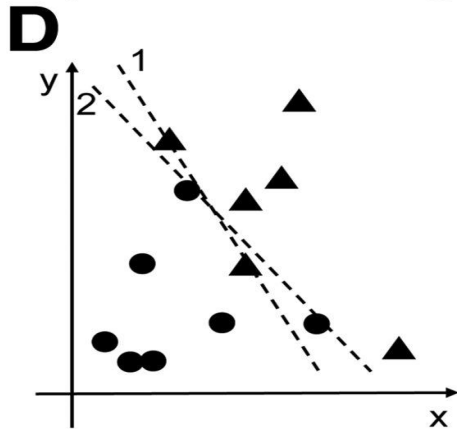
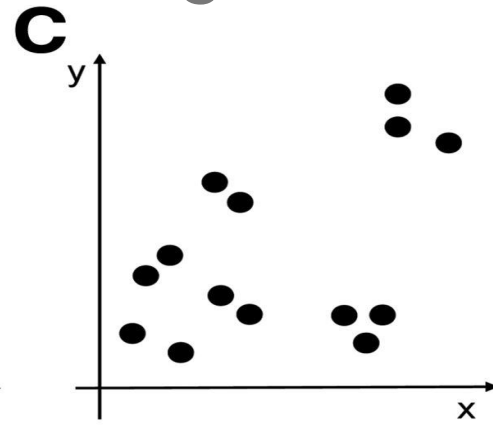
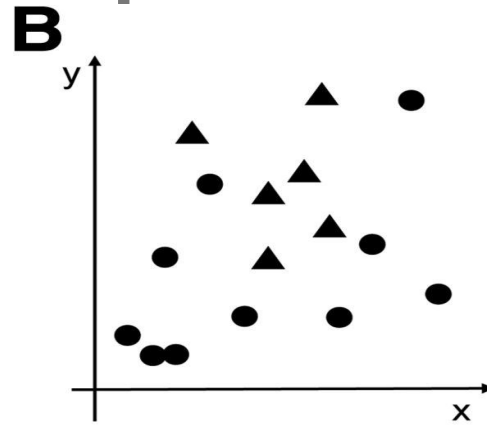
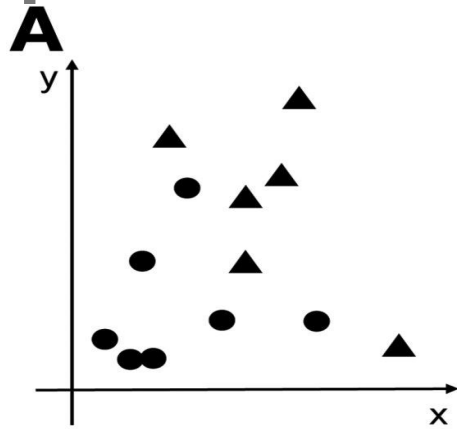


Basic paradigm

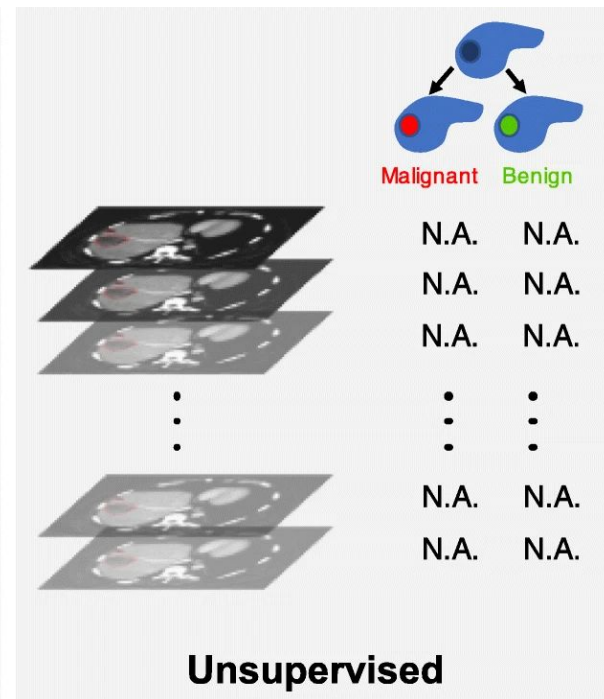
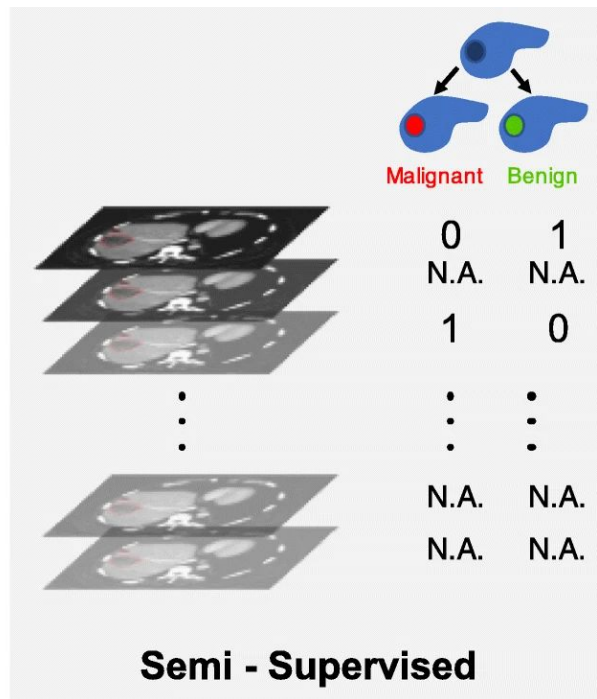
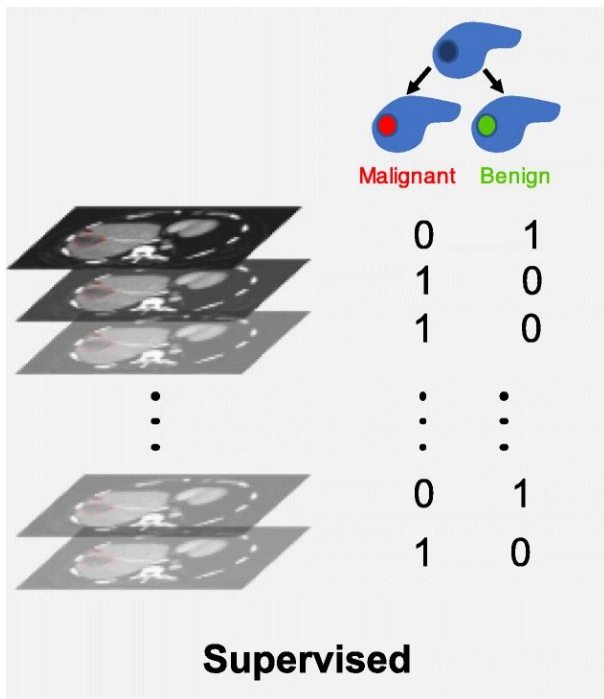
- Observe a set of examples:
training data
- Infer something about the underlying model:
inference engine
- Use inference to make predictions about unseen data:
test data

Training dataset → Inference Engine → Test dataset

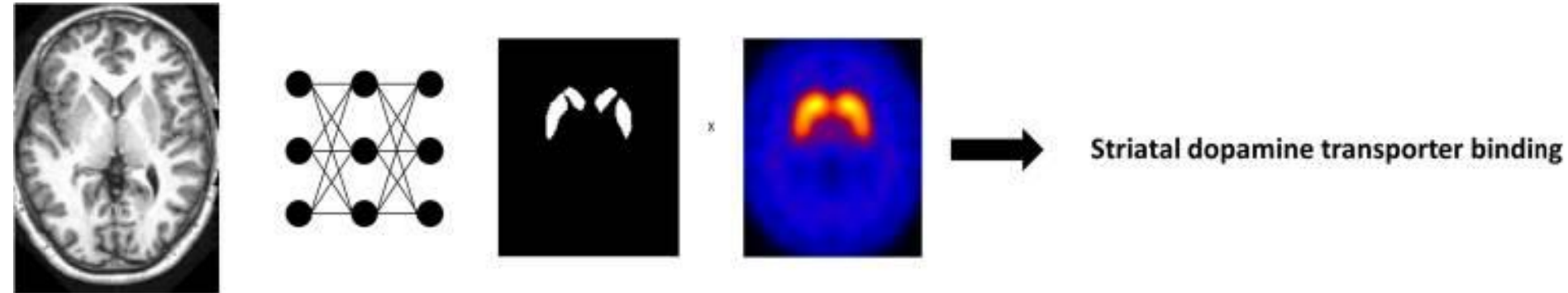
Supervised vs unsupervised learning



Supervised, semi-supervised, unsupervised learning



Example: segmentation and quantification



Status: what works?

- New Image reconstruction methods
- Quality assessment algorithms
- Triaging of cases to find similar patient data and diagnostic classification
- Lesion and disease detection and classification
- Segmentation, identification and feature extraction (radiomics) and quantification



What are the challenges? What is on the horizon?

- Diversification of learning for prognosis and predictive information.
- Building trust and reliability in the models
- Labelling the unlabelled image-data using unsupervised learning.
- Fairness and bias mitigation and understanding the limits of our algorithms.

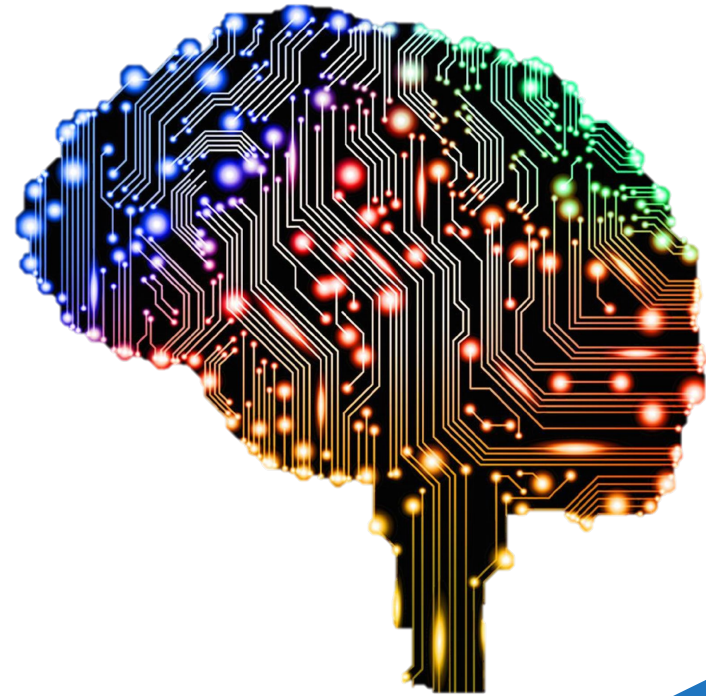


Garbage in - garbage out!

Learning

- Declarative knowledge (memorising)
 - Accumulation of individual facts
 - Limitations: Storage capacity and observation time

- Imperative knowledge (generalisation)
 - Deduce new facts from old facts
 - Limitation: accuracy of deduction process (assuming that past can predict the future)



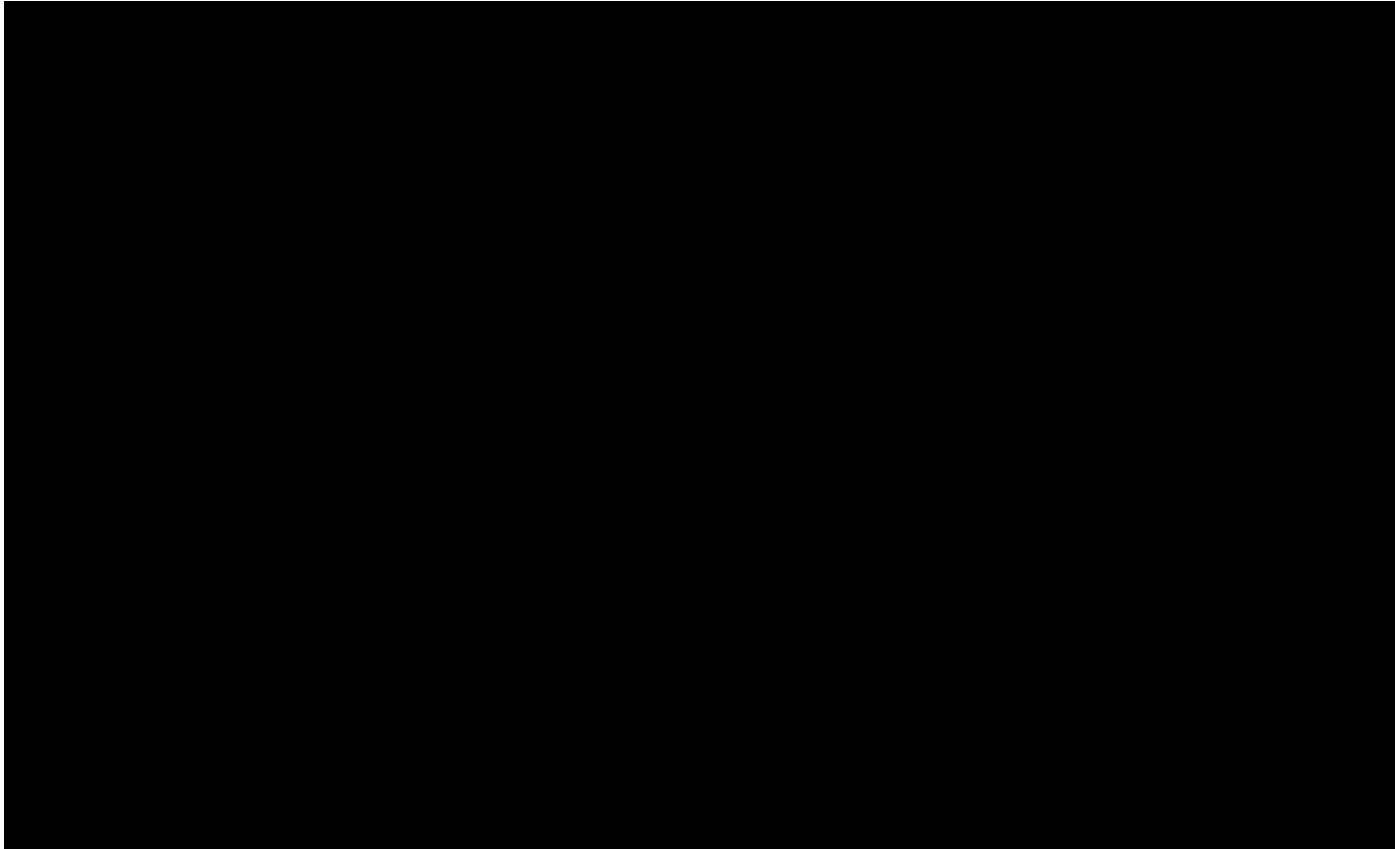
Demonstration: Brain tumour segmentation

- This is an example from Matlab, using the Deep Learning toolbox.
- The first and most important part of any ML solution is training data
- This example uses segmented MRI brain images from the BraTS data set from the Medical Segmentation decathlon (<http://medicaldecathlon.com/>)

Training data

- The data set includes 750 MRI images of brains with tumours, 484 of which have been manually labelled as **tumour** or **background**. These are what we will use.
- Image dimensions: **240 (h) x 240 (w) x 155 (d) x 4** (scan modality)
- Labelled images are divided into three subsets:
 - **Training** (400) - to train the neural network
 - **Validation** (29) - to monitor over/underfitting during training
 - **Testing** (55) - to evaluate the performance of the trained network

MRI image sample



Preprocessing and preparation of training data

- Volume and label images are converted from NIFTI to Matlab binary format
- To reduce the memory and processing burden, the images are cropped to remove non-brain regions
- 16 132x132x132 subsets ('patches') of each image are randomly selected as training samples
- Patches are **normalised** - so we don't have to do this later during training (faster to just do it once)

Constructing the network

- We will use U-Net, an encoder/decoder convolutional neural network (CNN) which is widely used for image segmentation
- A default 3D U-Net network is constructed; input dimension is the patch size (132x132x132x4) and output dimension is 44x44x44x2 (due to the use of 'valid' style padding on each patch - no zero-padding is used)
- The input and output layers are modified from defaults
 - Input layer does not need to do normalisation (already done during preprocessing)
 - Output layer is changed to a `dicePixelClassificationLayer` for better segmentation of small tumour regions

Training hyperparameters

- The main training hyperparameters of interest (and suggested values):
 - Use the **adam** optimiser (popular choice for segmentation)
 - Specify which data you are using for validation, and how often to validate (e.g. every 400 iterations)
 - Maximum number of training epochs (passes through all training data - e.g. 50)
 - Initial learning rate (0.0005), mode of decrease ('piecewise') and rate of decrease ($\times 0.95$ every 5 epochs)
 - MiniBatchSize - make larger if you have more GPU memory (but you might be better off with larger patch size)

Training

- This is the easy part - one line of code!

```
[net, info] = trainNetwork (dsTrain, lgraph, options);
```

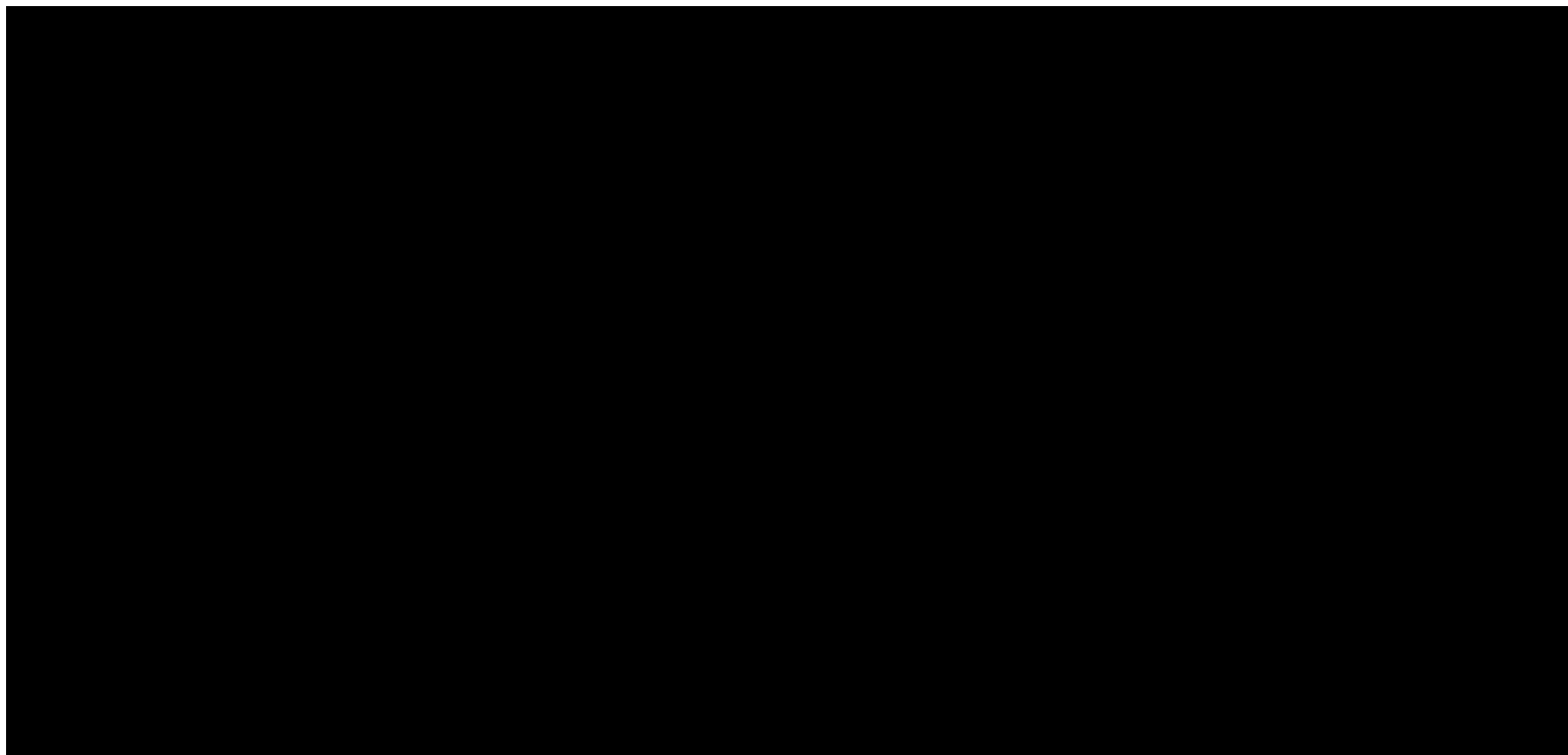
- **lgraph** is the network, **dsTrain** is our training datastore and **options** are our training options
- Important: save the resulting network **net** for future use
- it will be about 60 MB
- Takes roughly 30 hours to train on a powerful GPU/CPU system - *much* slower without a GPU

Applying the trained network

- Since the input size of the network is smaller than the dimension of the training data, we step through the input image size with a stride equal to the output patch size, and extract patches equal to the input patch size.
- Each patch is segmented:

```
patchSeg = semanticseg (patch, net);
```
- The resulting segmented patches are then stitched back together and the final image is cropped to the original size

Ground truth (L) and segmented (R)



Performance

- The network performs very well. Results for testing data show that:
 - ~98% of the network-classified voxels agree with the ground truth (true positive + true negative)
 - Jaccard score is $> 95\%$ for all evaluated images
 - Dice similarity score $> 99.9\%$ for background and $> 95\%$ for tumour
- The approach can be generalised to other image segmentation problems

Code

Original example:

<https://au.mathworks.com/help/vision/ug/segment-3d-brain-tumor-using-deep-learning.html>

Commented code:

Thank you



Email Address: mitras@ansto.gov.au