Part 3
Lecture 2 Characterization and Monitoring

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Medical Imaging
UNIVERSITY OF TORONTO

MiDATA

Who I am…

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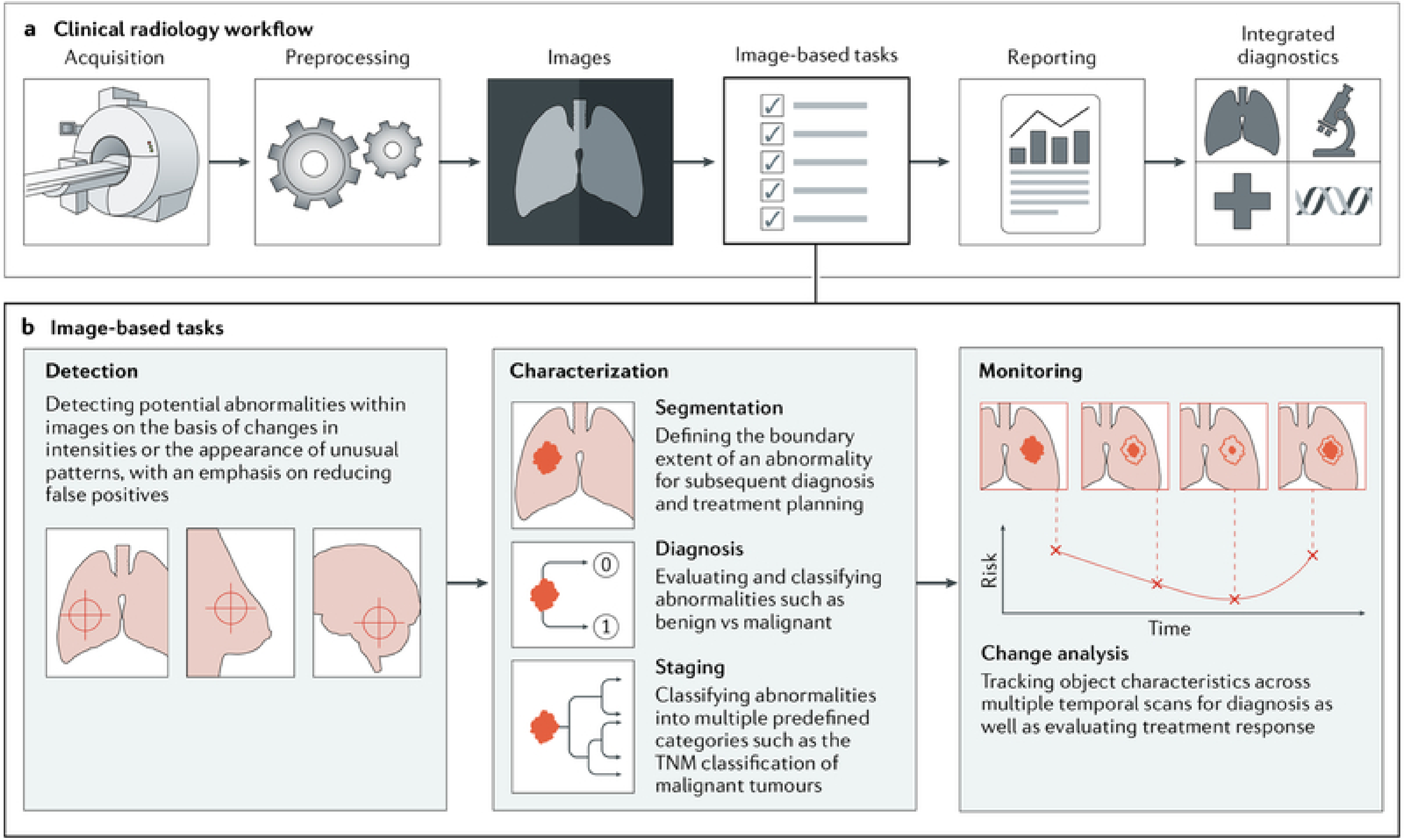
Radiology Workflow



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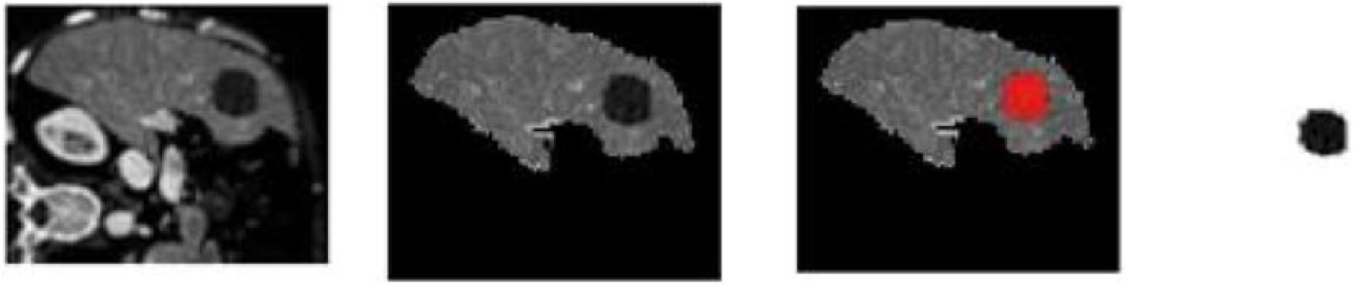
How Does Characterization Work?

- Characterization is an umbrella term referring to the segmentation, diagnosis and staging of a disease.
- These tasks are accomplished by quantifying radiological characteristics of an abnormality, such as the size, extent and internal texture.



(a) Original image **(b)** After morphological operation **(c)** Detected lesion **(d)** Segmented lesion

Why Do We Need AI for Characterization?

- While handling routine tasks of examining medical images, humans are simply not capable of accounting for more than a handful of qualitative features.
- This is exacerbated by the inevitable variability across human readers, with some performing better than others.
- It is difficult for humans to accurately predict the status of malignancy in the lung owing to the similarity between benign and malignant nodules in CT scans.

AI Can Solve That!

- Automation through AI can consider a large number of quantitative features together with their degrees of relevance while performing the task at hand in a reproducible manner every time.

- AI can automatically identify these features, and many others, while treating them as imaging biomarkers.

Segmentation and Radiology

- Segmentation finds its roots in earlier computer vision research carried out in the 1980s, with continued refinement over the past decades.

- Simpler segmentation algorithms used clustered imaging intensities to isolate different areas or utilized region growing, where regions are expanded around user-defined seed points within objects until a certain homogeneity criterion is no longer met.

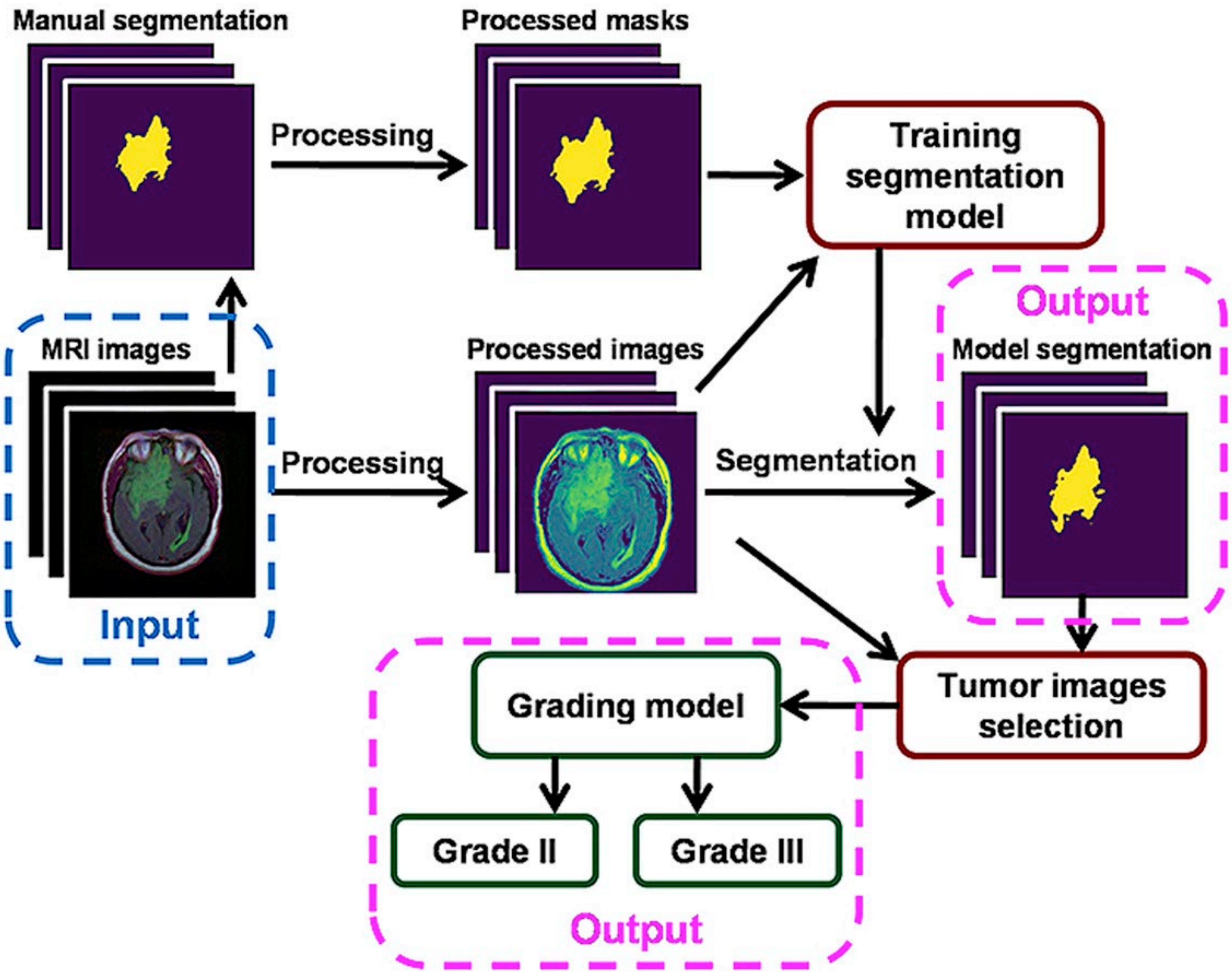
Where Are We With Segmentation?

- In clinical cases, a higher specificity and precision are vital.
  - For instance, in clinical radiation oncology, the extents of both tumour and non-tumour tissues have to be accurately segmented for radiation treatment planning.

- Attempts at automating segmentation have made their way into the clinic, with varying degrees of success.

Challenges with Segmentation

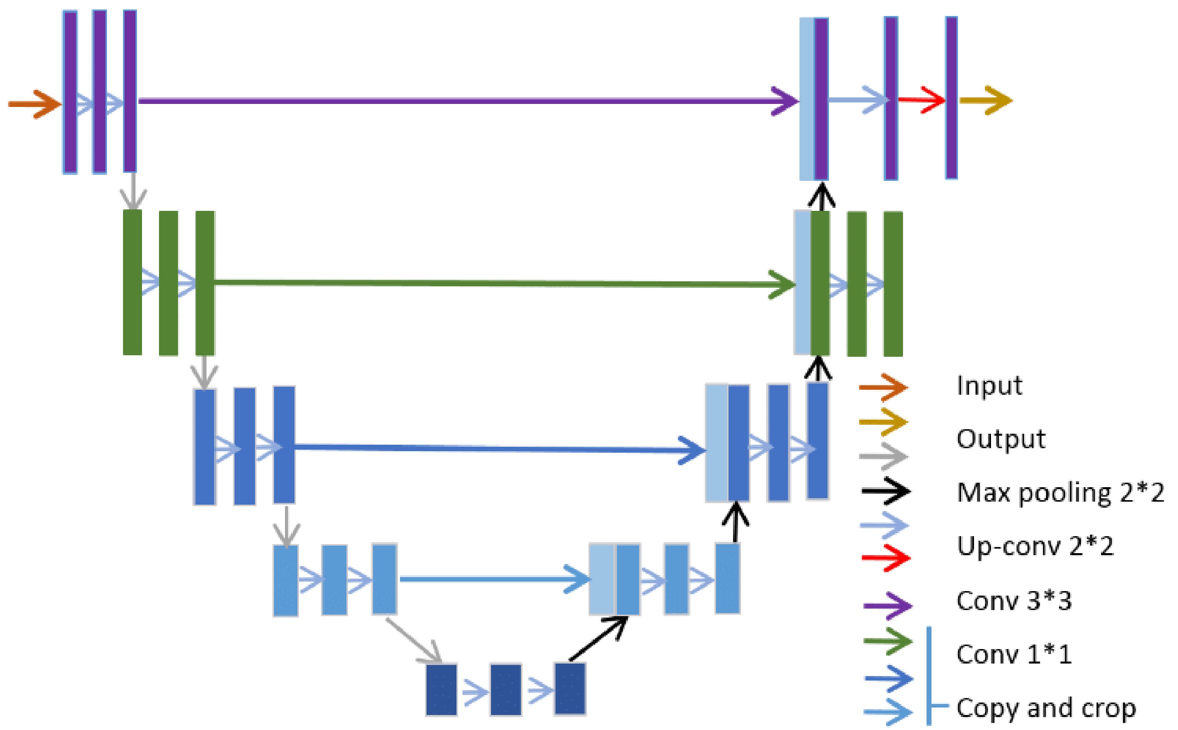
1) Variability in imaging protocols
2) Diversity of disease presentation
3) Need for high reliability


Manual segmentation
Processing
Processed masks
Training segmentation model
MRI images
Processed images
Output
Model segmentation
Processing
Segmentation
Input
Grading model
Tumor images selection
Grade II
Grade III
Output

U-net

- ❑ Convolutional networks for biomedical image segmentation
- ❑ Specifically designed for medical images
- ❑ Multiple radiographic characteristics are also employed in subsequent diagnosis tasks

Architecture of U-net



Deep Learning and Segmentation

- Magnetic resonance imaging can provide non-invasive detailed images of the brain.
- Automatic tumor segmentation and grading are beneficial for treatment planning.
- Deep learning using U-net shows promise for automatic brain tumor segmentation.
- Transfer learning using Vgg16 can be used for grading gliomas of brain tumors.
- Tumor segmentation, detection, and grading are essential tools for clinical use.

Applications

- Applications of probabilistic atlases include segmenting brain MRI for locating diffuse low-grade glioma, prostate MRI for volume estimation and head and neck CT for radiotherapy treatment planning, to name a few.

- Recently proposed deep learning architectures for segmentation include fully convolutional networks, which are networks comprising convolutional layers only, that output segmentation probability maps across entire images.

Biomarkers and Segmentation

- Within the initial segmentation step, while non-diseased organs can be segmented with relative ease, identifying the extent of diseased tissue is potentially orders of magnitude more challenging.

- Typical practices of tumour segmentation within clinical radiology today are often limited to high-level metrics such as the largest in plane diameter.

- Biomarkers could be used to predict malignancy likelihood among other clinical end points including risk assessment, differential diagnosis, prognosis and response to treatment.

Example Biomarker: PI-RADS for Prostate Cancer

- PI-RADS: Prostate Imaging – Reporting and Data System
- PI-RADS promotes standardization for prostate multiparametric magnetic resonance imaging (mpMRI)
- The PROMIS trial has recently published its findings confirming a role for multiparametric MRI in the diagnostic pathway of patients with suspected prostate cancer
- Sensitivity of 0.74 and specificity of 0.88 for prostate cancer detection using PI-RADS
- This may allow 27% of patients to avoid a primary biopsy

Where Are We Going?

- A second generation of algorithms saw the incorporation of statistical learning and optimization methods to improve segmentation precision, such as the watershed algorithm, where images are transformed into topological maps with intensities representing heights.

- More advanced systems incorporate previous knowledge into the solution space, as in the use of a probabilistic atlas — often an attractive option when objects are ill-defined in terms of their pixel intensities.

Monitoring

- Disease monitoring is essential for diagnosis as well as for evaluation of treatment response.

- The workflow involves an image registration preprocess where the diseased tissue is aligned across multiple scans, followed by an evaluation of simple metrics on them using predefined protocols — which is very similar to diagnosis tasks on single time-point images.

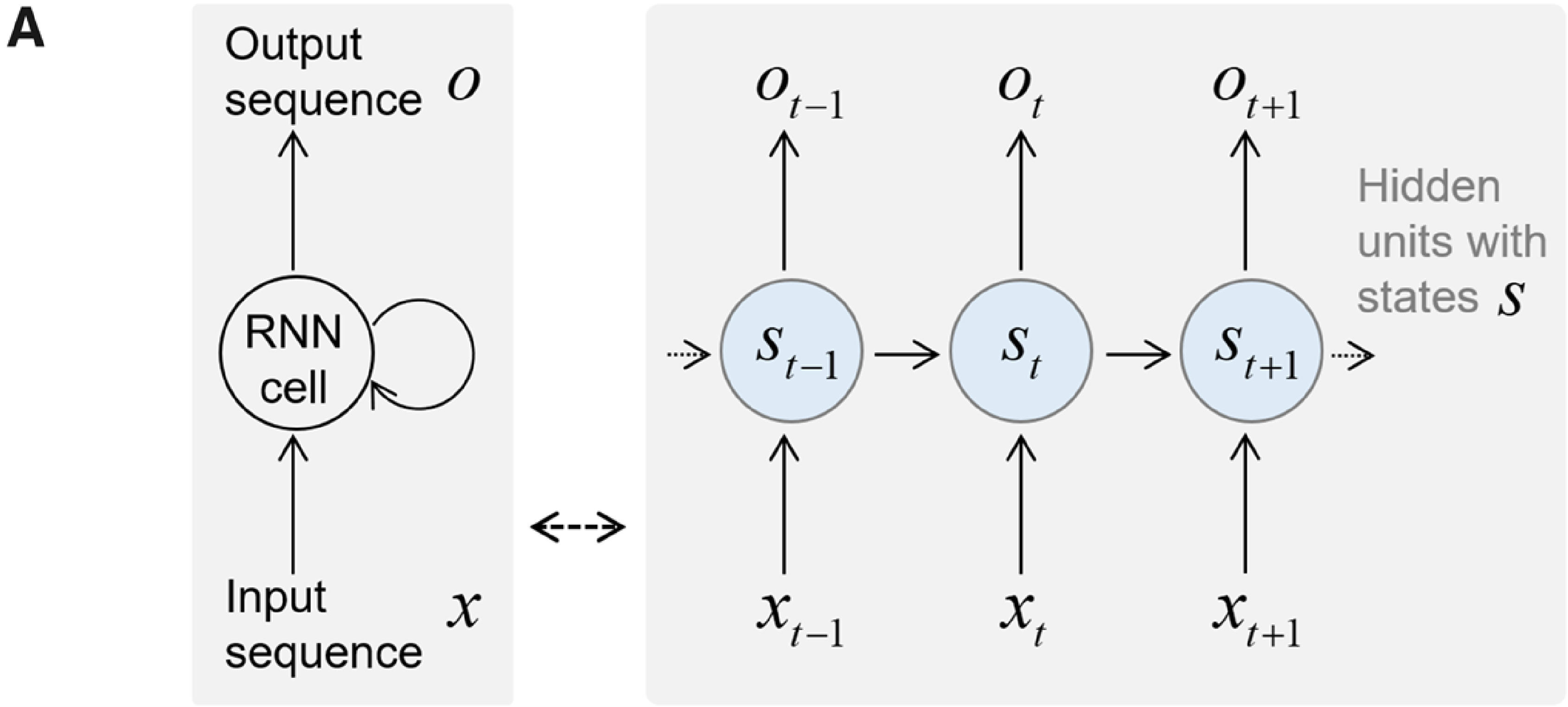
  - With computer-aided change analysis based on deep learning, feature engineering is eliminated and a joint data representation can be learned.

  - Deep learning architectures, such as recurrent neural networks, are very well suited for such temporal sequence data formats and are expected to find ample applications in monitoring tasks

Recurrent Neural Network (RNN)

- RNN can evaluate an input sequence in a manner that, at a certain point of the sequence, responses to earlier parts of the sequence are taken into account as well
- Reflected by a given set of weighting parameters, an RNN trained to detect an infection might have a stronger response to a high white blood cell count if measurements of white blood cells, C-reactive protein, and procalcitonin were low at an earlier time point.
    - Because the evaluation results of previous sequence elements are taken into account at each step of a sequence, it is said that RNNs possess a ‘memory’.

How RNNs Work



RNN vs CNN?

Convolutional Neural Network

- Feed Forward
- Size of input and output remain fixed
- Spatial data (ie. Medical Images)

Recurring Neural Network

- Recurring
- Size of input and output may vary
- Temporal or Sequential data

Do RNN's have any use cases in Radiology or Medical Imaging?

End of Lecture 2

Next up Part 4 Lecture 1: How to critically review AI/ML publications