Applied Deep Learning

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Learning objectives of today

Goals: Introduce recurrent neural networks (RNNs) as a means to work with sequence data

- Understand the importance of sequences and the difficulty of working with them using the neural network architectures we have learned about so far
- Develop the knowledge to use basic RNNs in practice, as well as critical extensions

How will we do this?

- We start by introducing sequence data and its relevance to machine learning tasks
- We then build up the concept of recurrence underlying RNNs
- We consider limitations of standard RNNs and introduce extensions that allow for "long-term memory"
- We take a brief detour to the TensorFlow Data API that allows us to manipulate datasets effectively, which is often needed when working with RNNs

Working with sequences

The importance of sequences

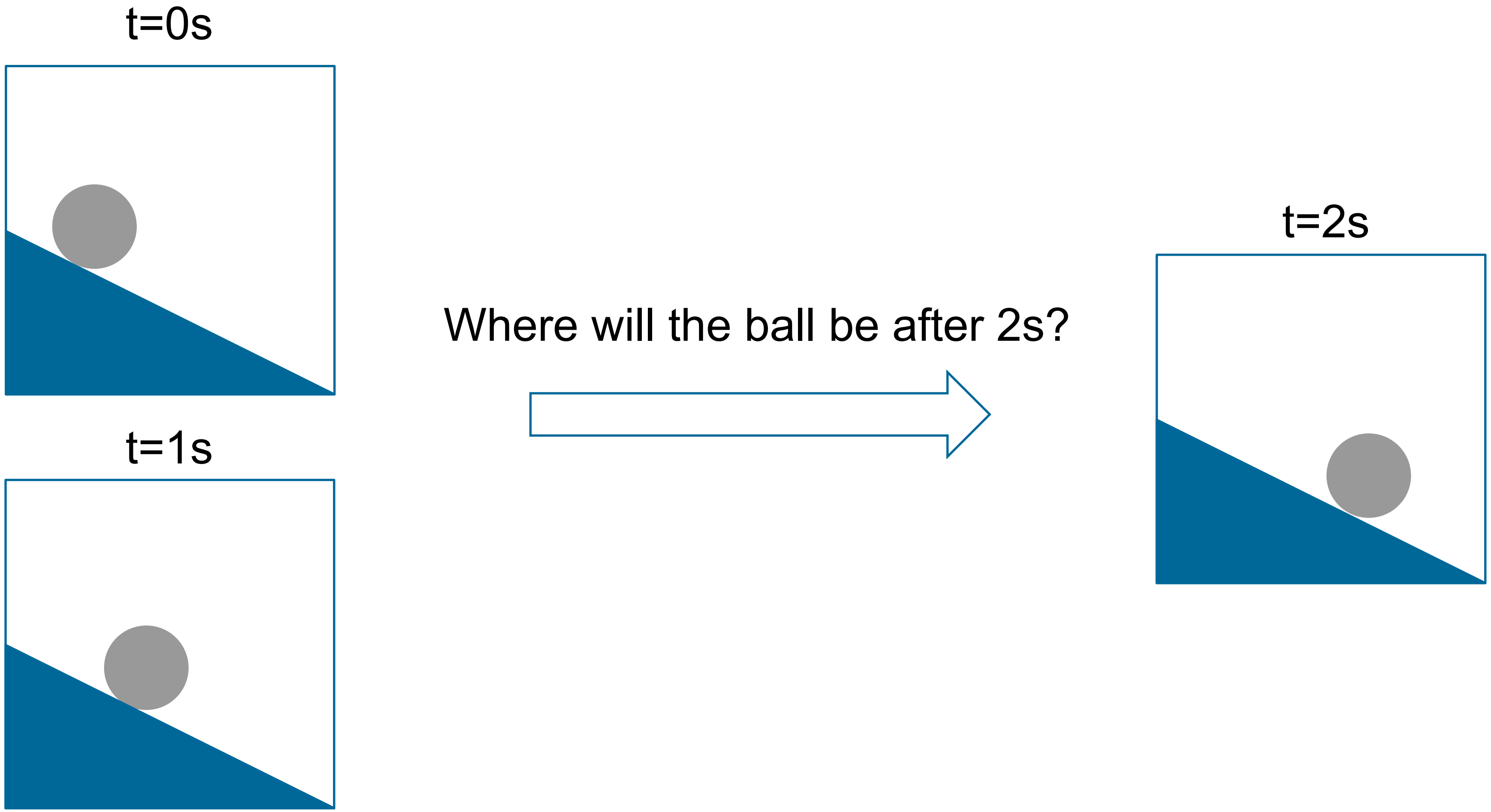
t=0s

Where will the ball be after 2s?

t=2s

?

The importance of sequences



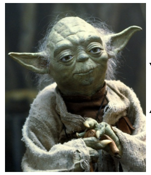
The importance of sequences

"Why do we care about sequences?"

"Why" "do" "we" "care" "about" "sequences" "?"

≠

"care" "about" "sequences" "Why" "do" "we" "?"

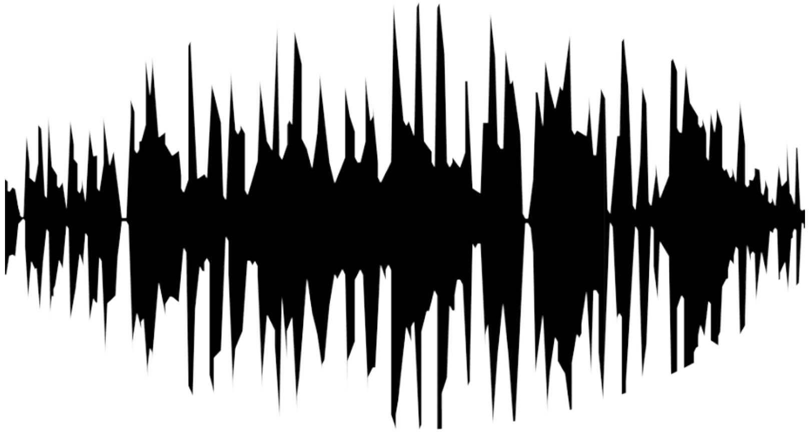
(unless you are )

Sequences

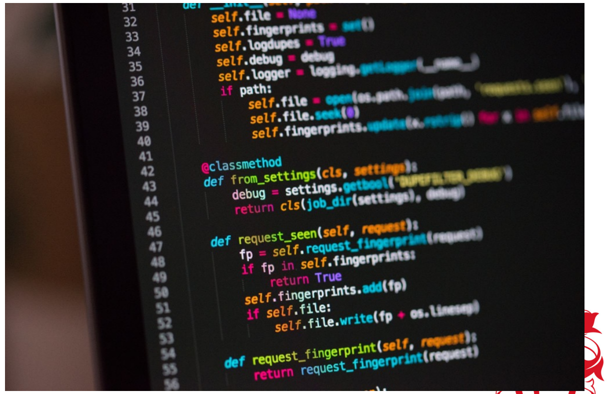
Sequences are collections of multiple elements (i.e., data points), where:

- The order matters
- Elements may be repeated
- The length is variable (and lengths of inputs and outputs don't have to match)

Sequences in real life

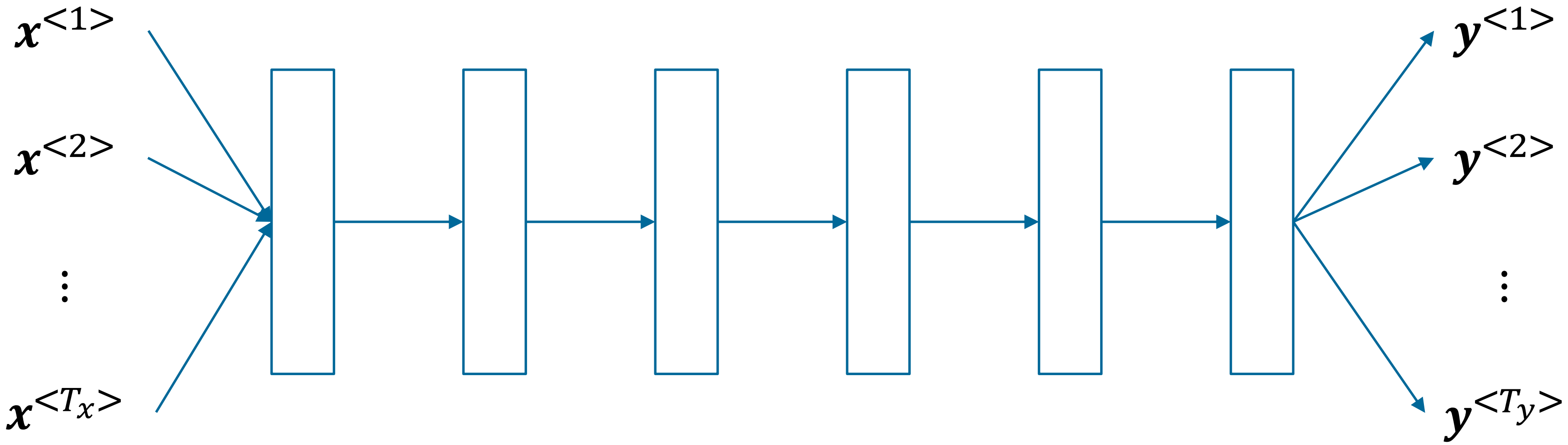


"And here I am, for all my lore, The wretched fool I was before"



Recurrence in neural networks

Why don't we do this?



Issues:

- Sequence lengths vary
- No definition of order
- Lack of parameter sharing: imagine a minute-long ECG

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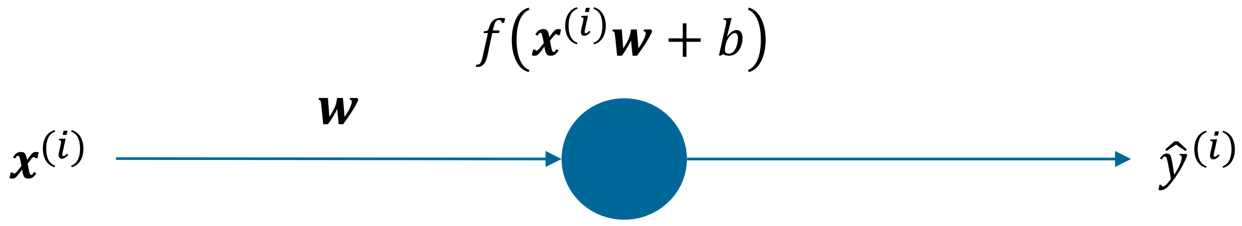
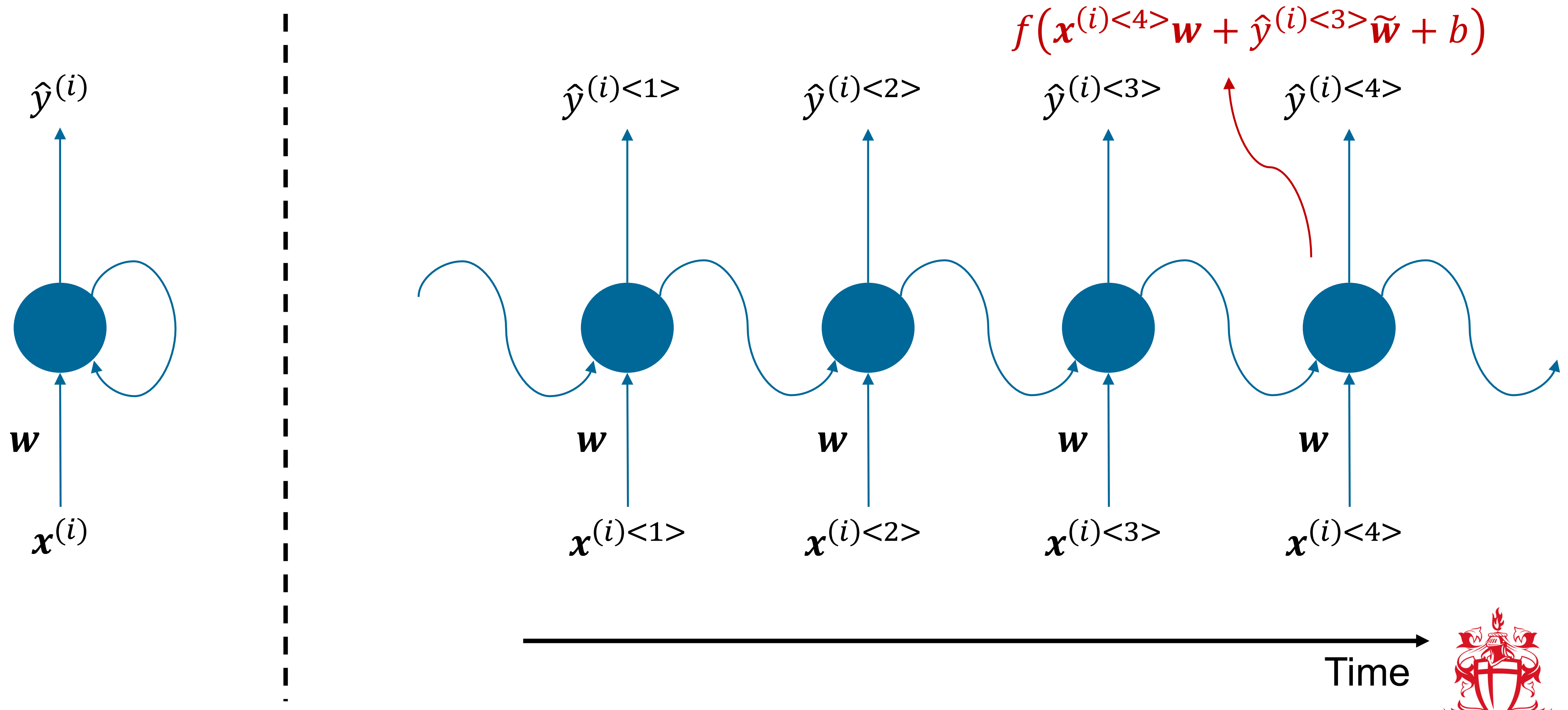
What we do instead – let's start with a single neuron

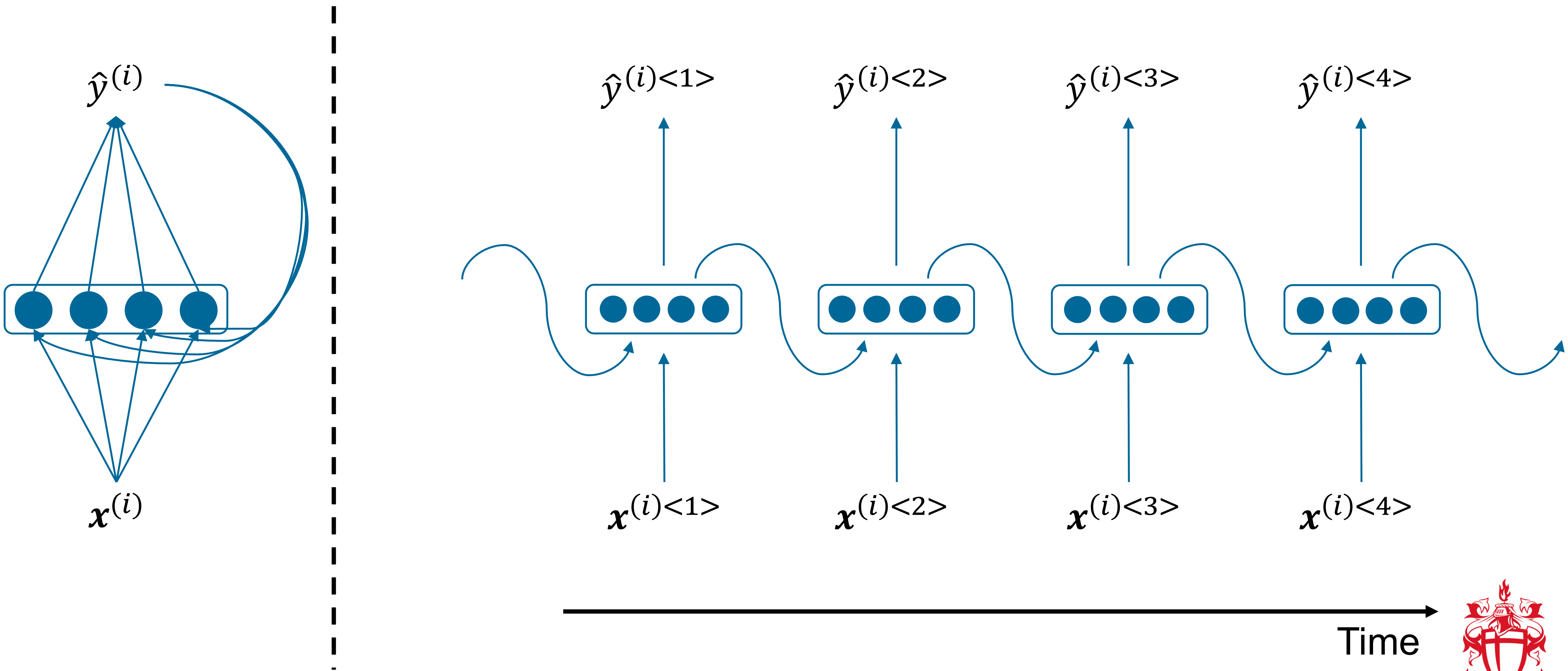


A recurrent neuron

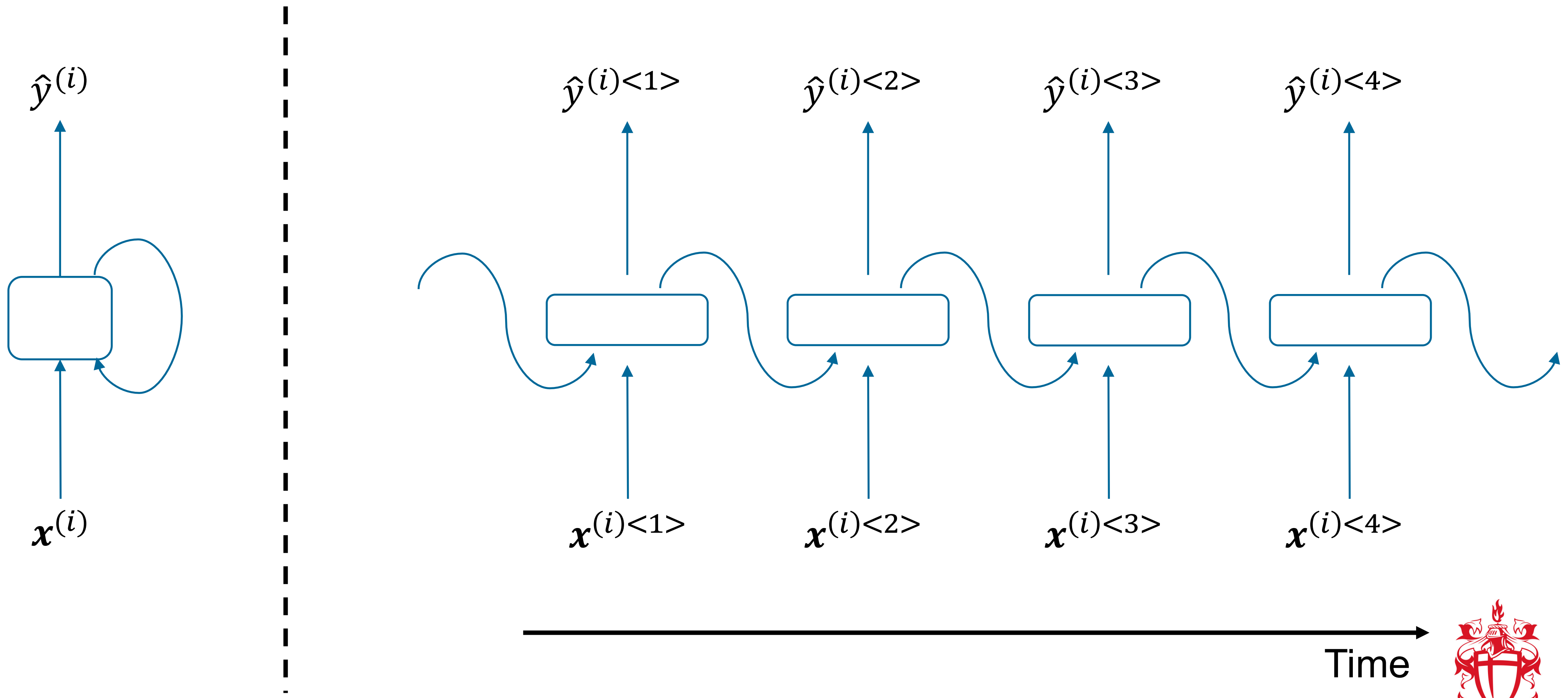


Let’s see a recurrent neuron in practice

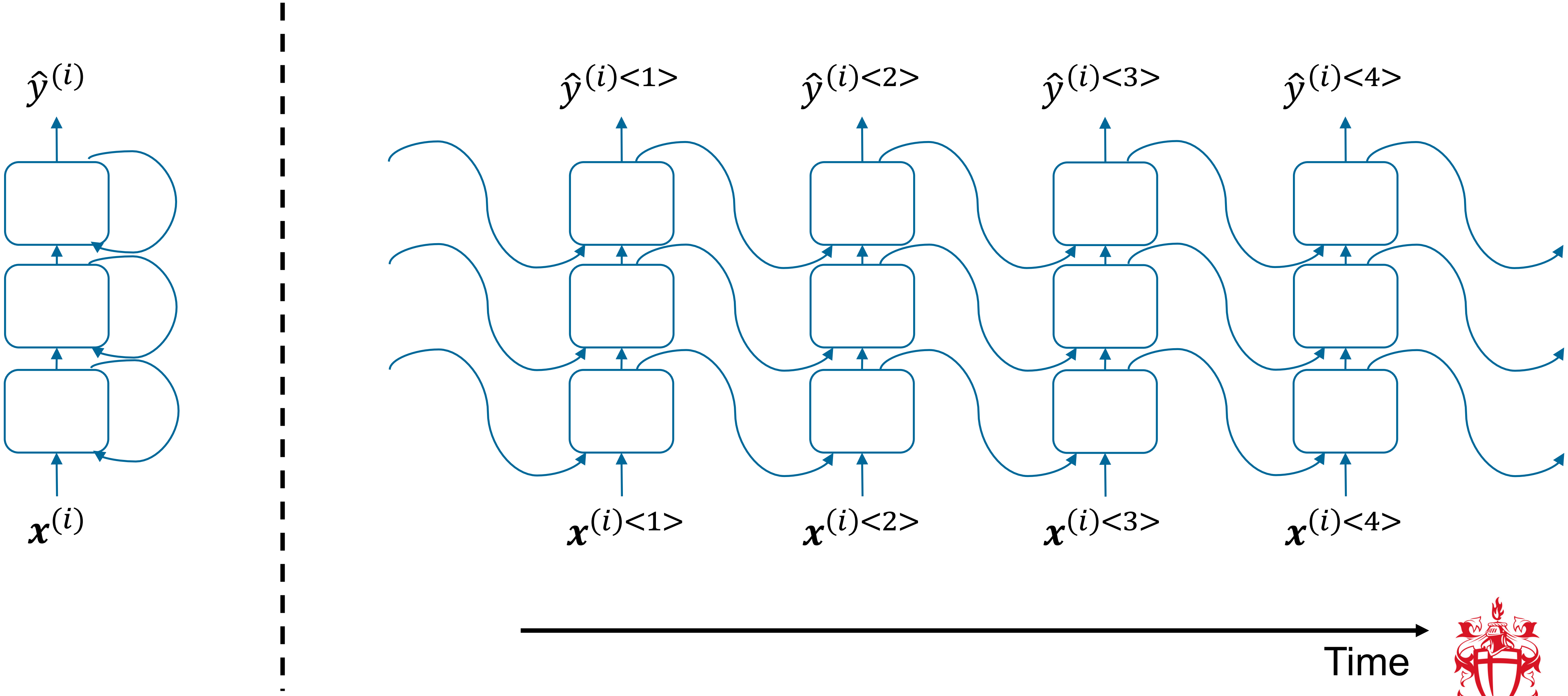
Layers of recurrent neurons – a recurrent neural network (RNN)



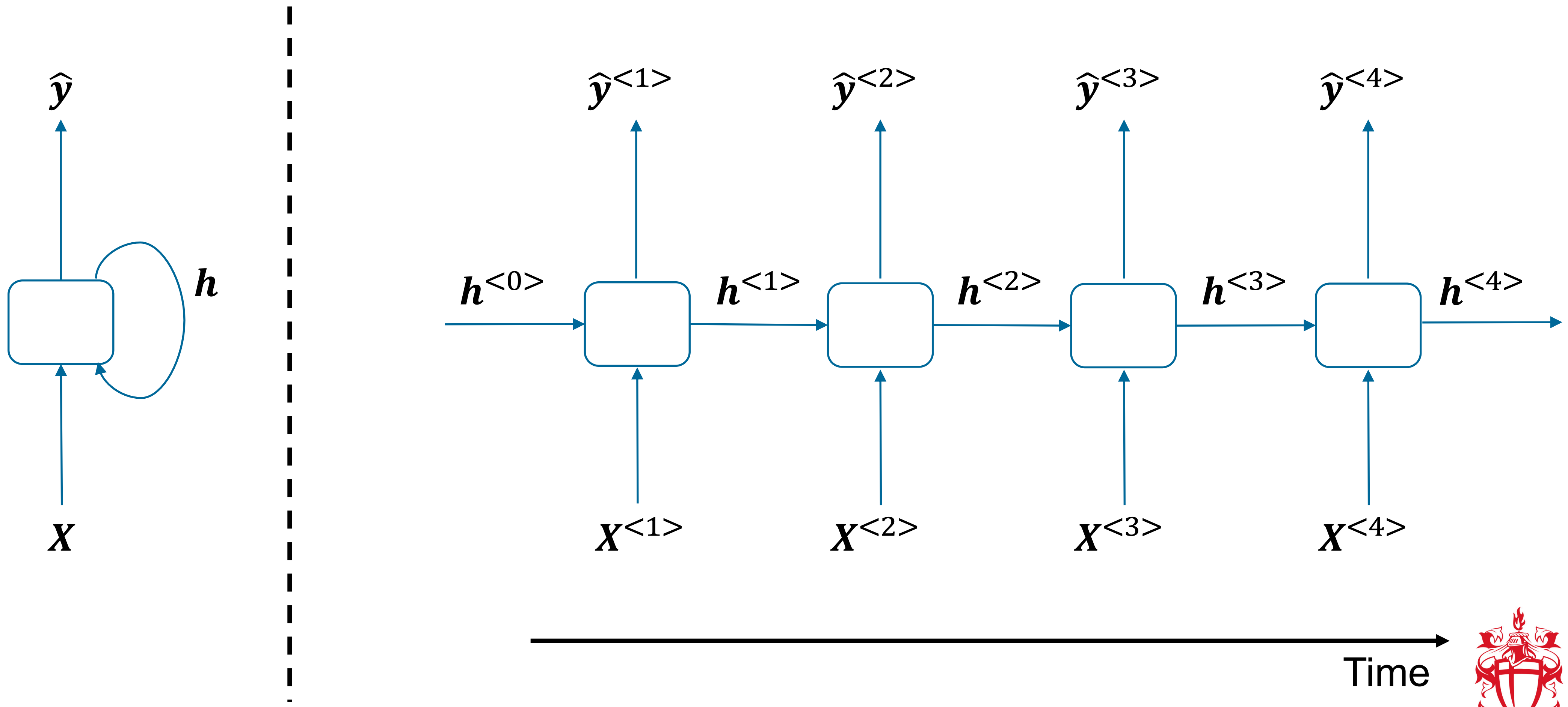
Layers of recurrent neurons – a recurrent neural network (RNN)



Deep RNNs



Representing RNNs and memory more generally



Let’s see more complex recurrent networks

The issues with training RNNs

Problem 1 – vanishing and exploding gradients

- In principle, same as with other networks

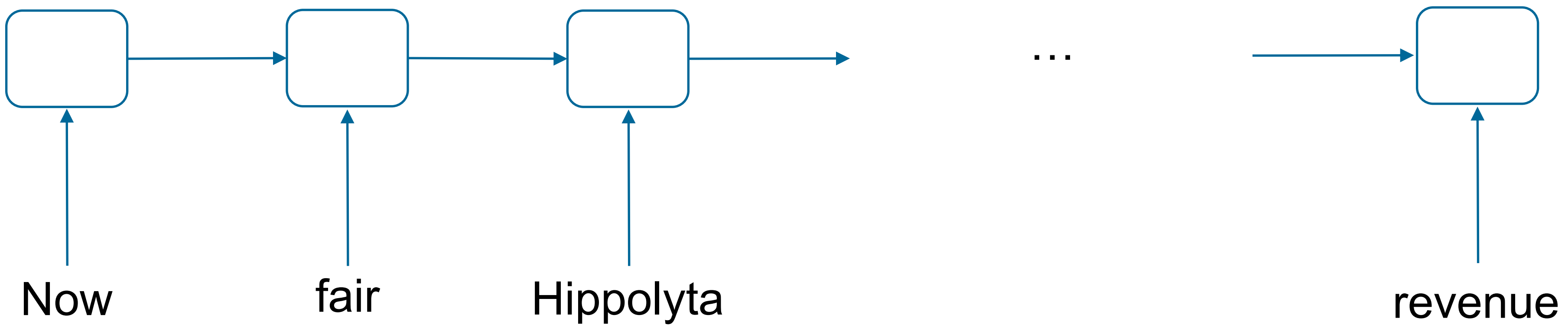
- Before, we mostly focused on vanishing gradients
  → use of non-saturating activation functions such as ReLU

- With RNNs, exploding gradients become more of a problem
  - Same weights used for different time steps can lead to self-reinforcing increases of gradients

  → We frequently use saturating activation functions, such as tanh, or other methods such as gradient clipping

Problem 2 – memory issues

- Vanishing gradients are still a problem (sometimes even more so than in other networks):



- This is essentially a very very deep neural network!
  - Some information is lost at each time step

- After just a few time steps, there is virtually no more information about the first input

When memory loss can be a problem

The BA students, which had been working for days on end, was finally done with their projects.

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Adding long-term memory

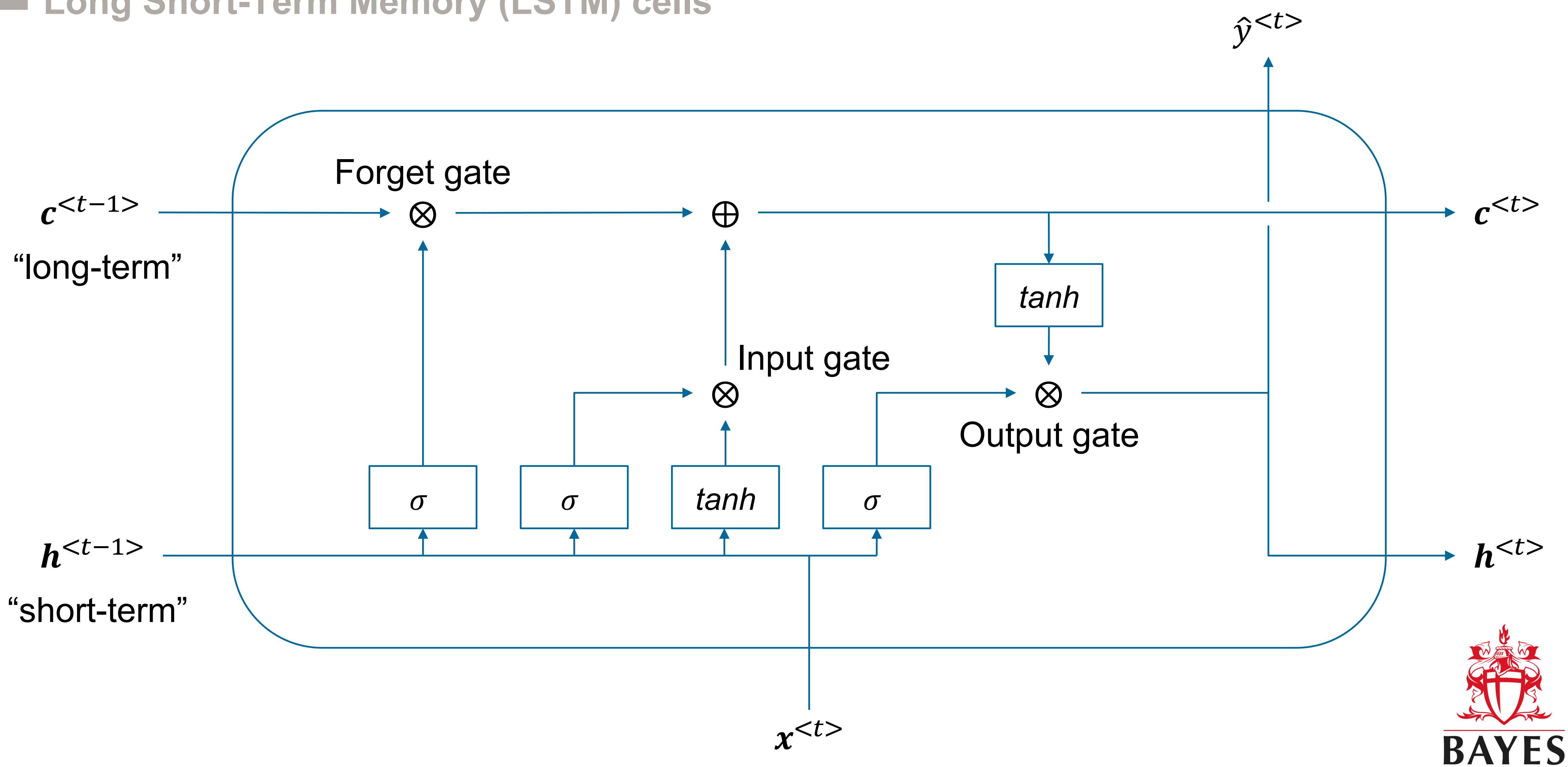
General idea

- Knowledge acquired so far as a state that is managed

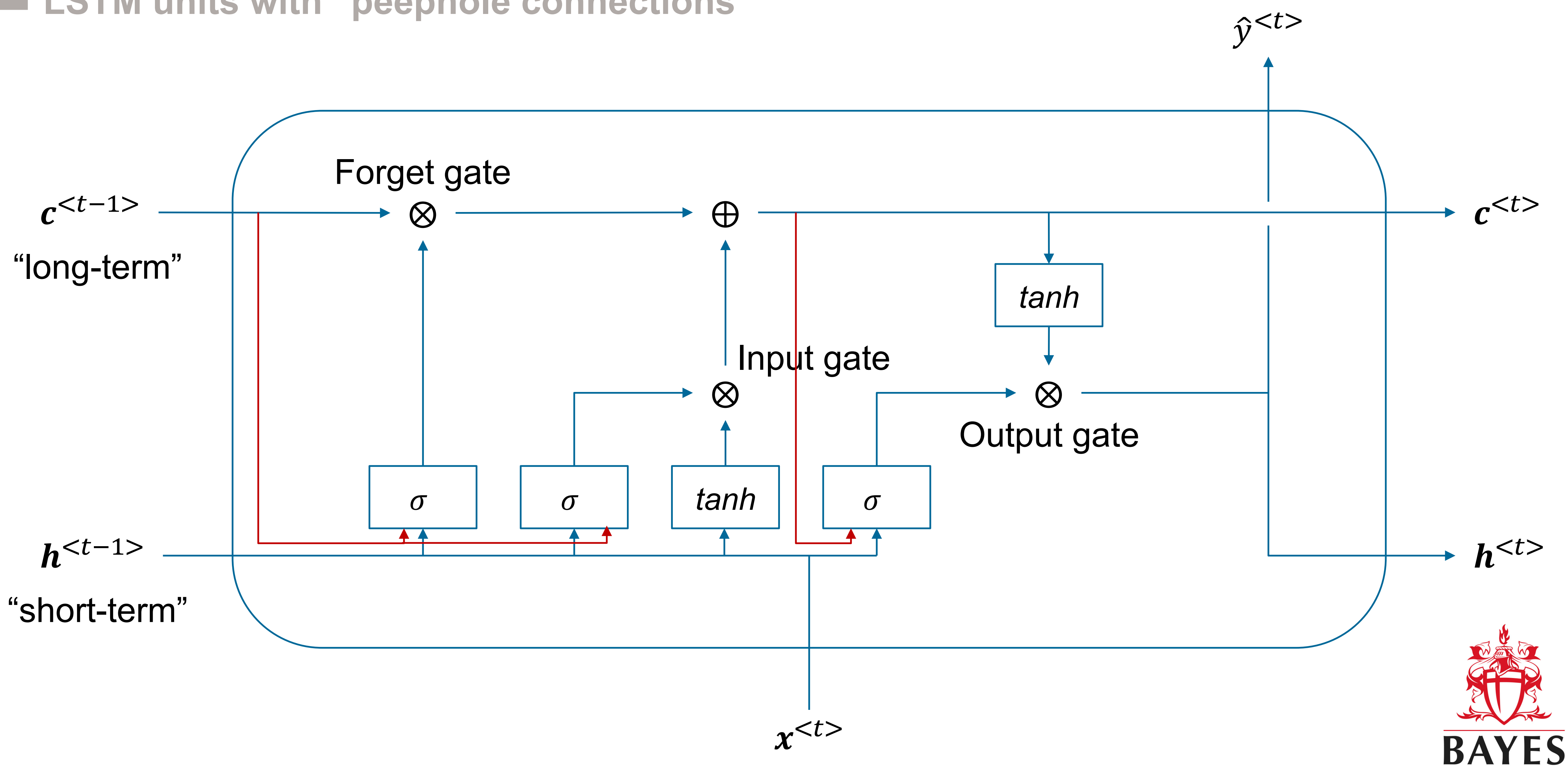
- Use “gates” to add or remove information in each recurrent unit
  - Remove information that is no longer relevant
  - Selectively add information from current input that will be relevant later down the line

- Output based on the state and the input

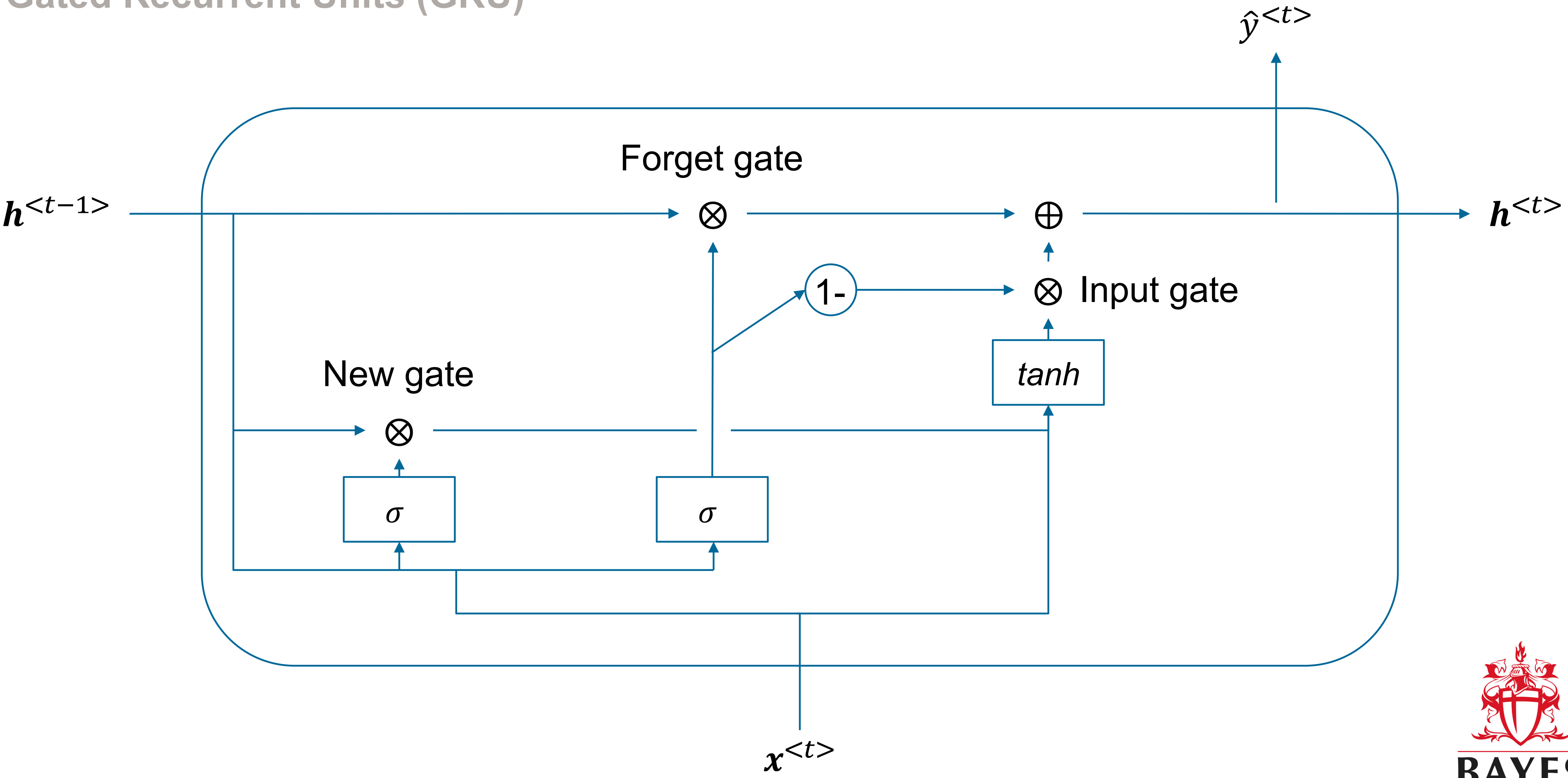
Long Short-Term Memory (LSTM) cells



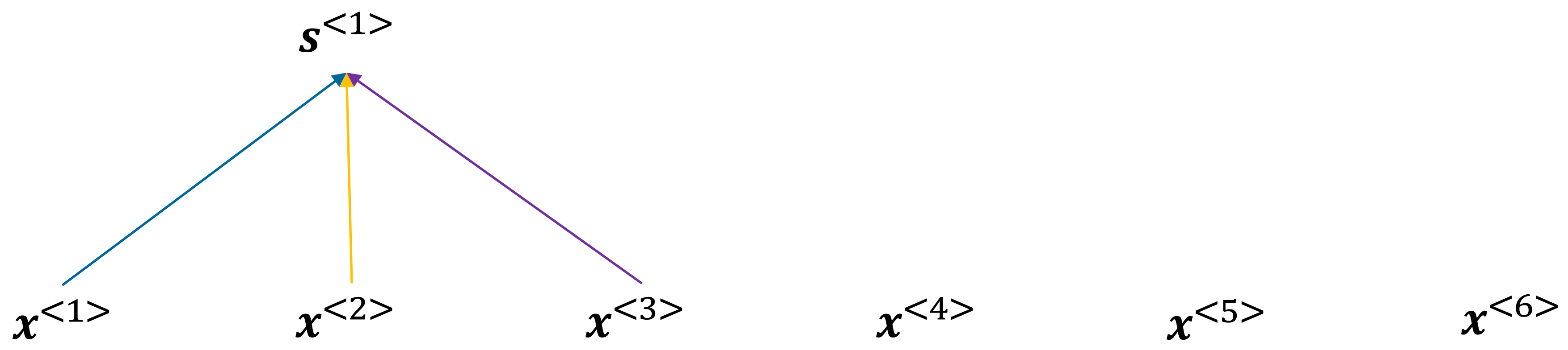
LSTM units with “peephole connections”



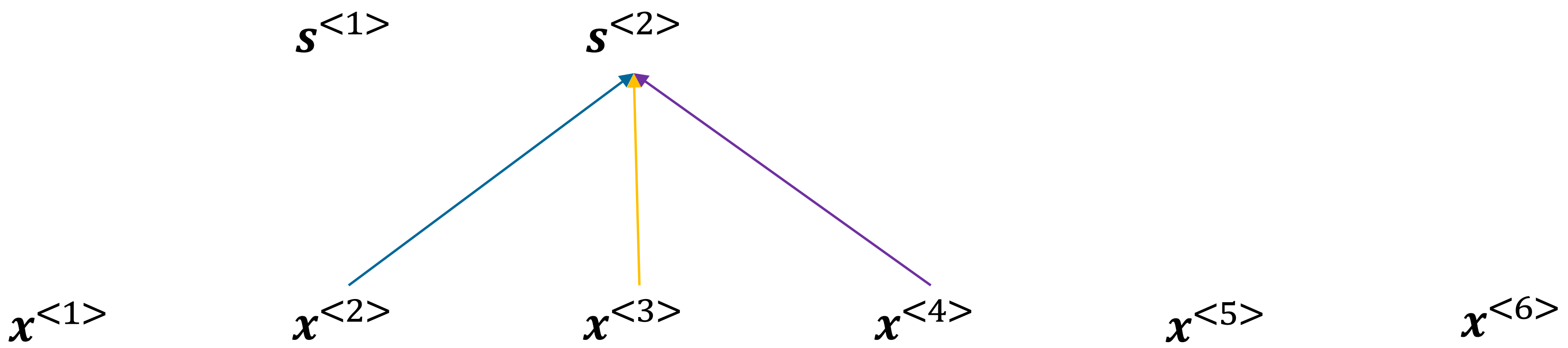
Gated Recurrent Units (GRU)



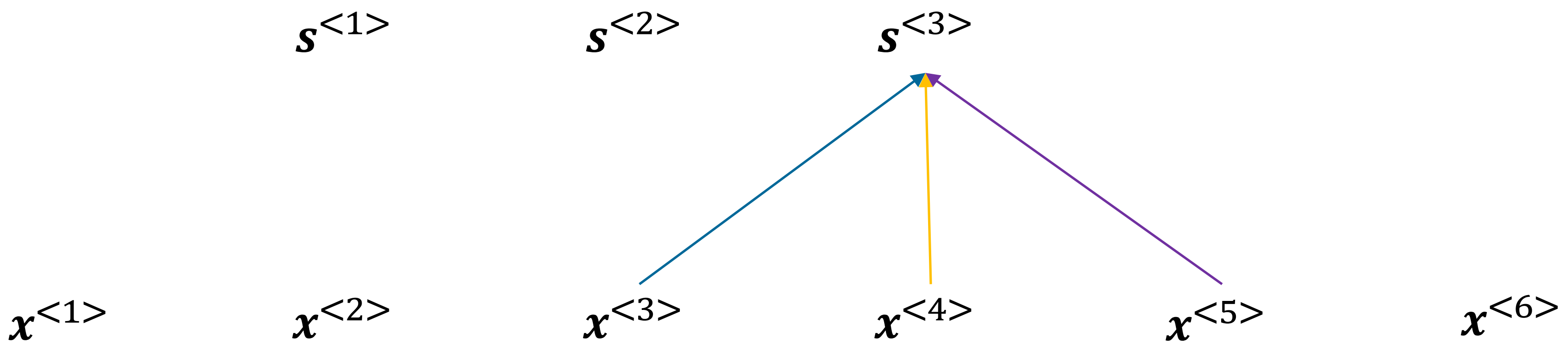
1D convolutional layers



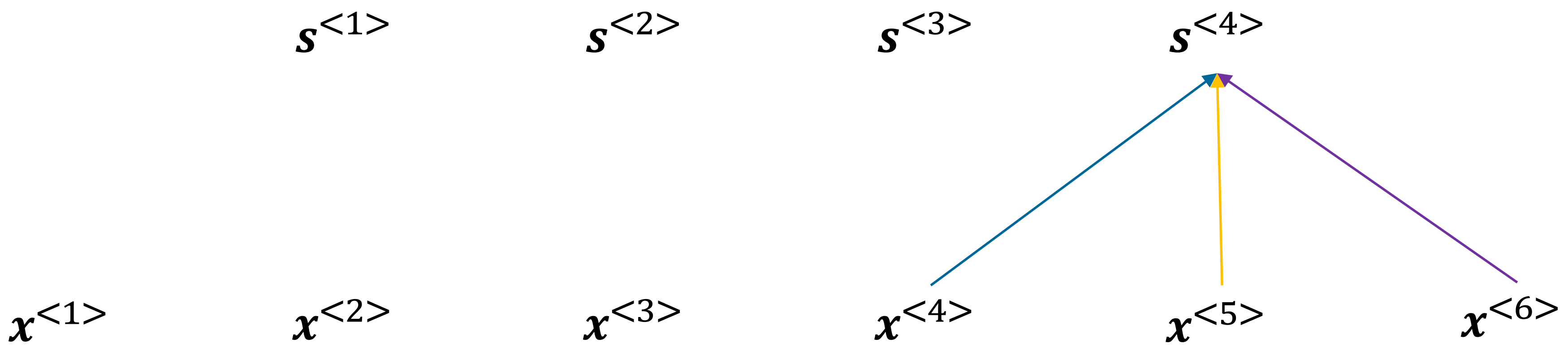
1D convolutional layers



1D convolutional layers



1D convolutional layers



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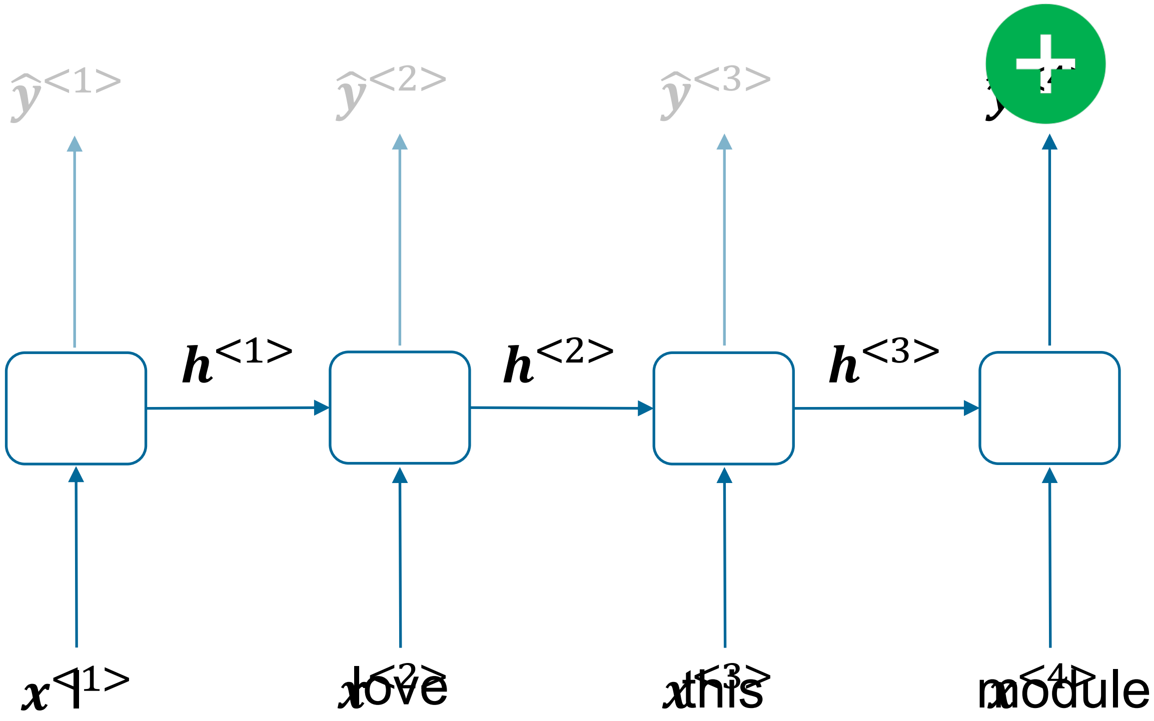
Long-term memory in practice

RNN variants and their applications

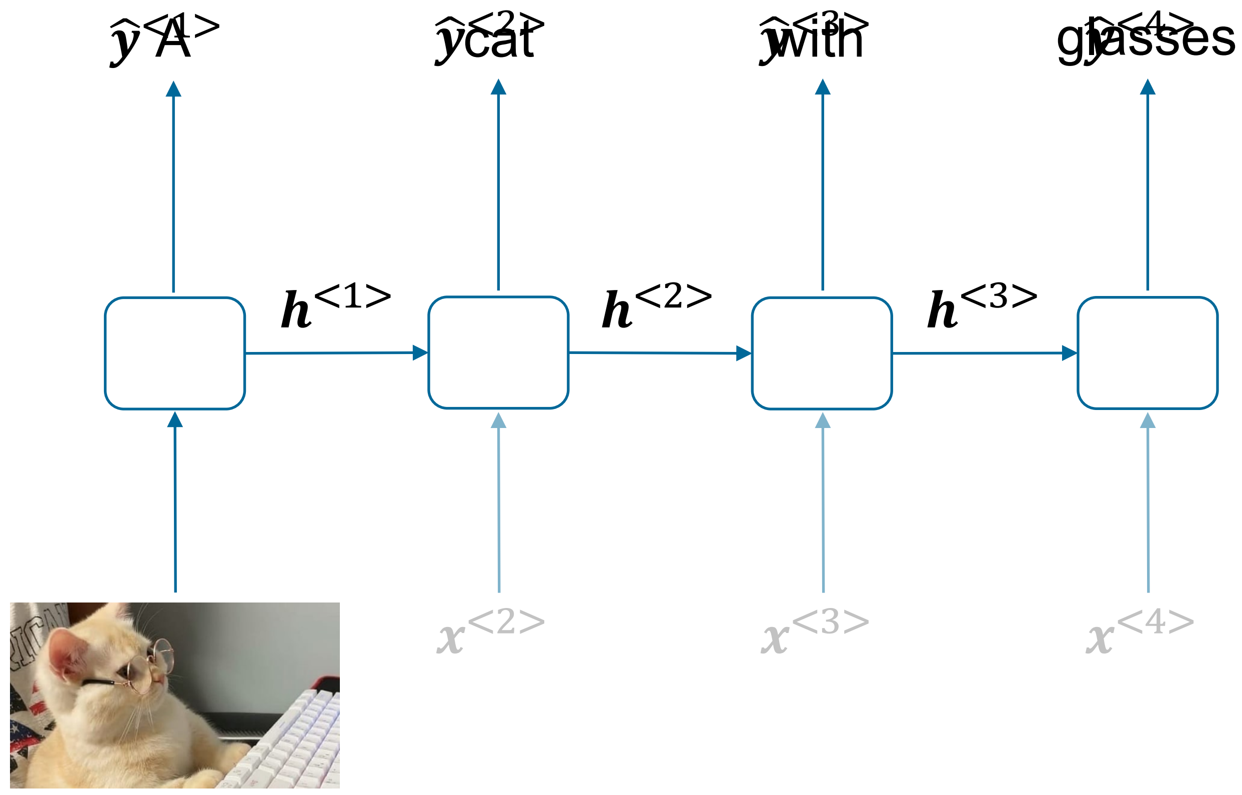
Sequence-to-vector networks



For example:

- Video activity recognition
- DNA sequence probing
- Sentiment classification

Vector-to-sequence networks



For example:

- Text generation
- Music generation
- Image captions

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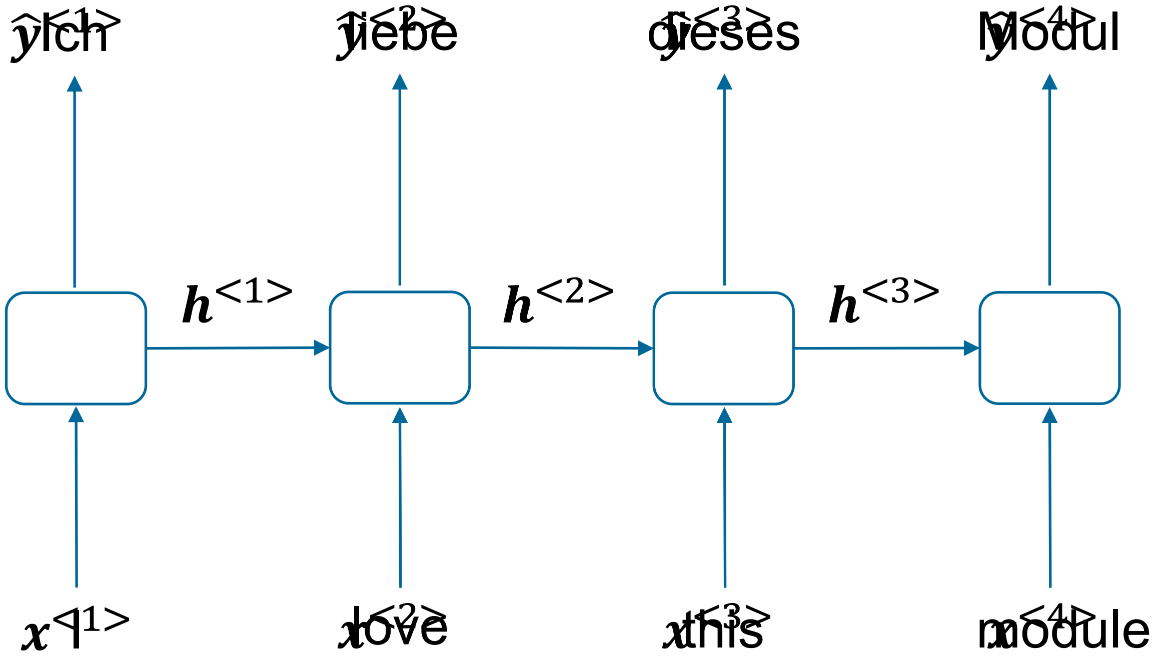
Sequence-to-sequence networks

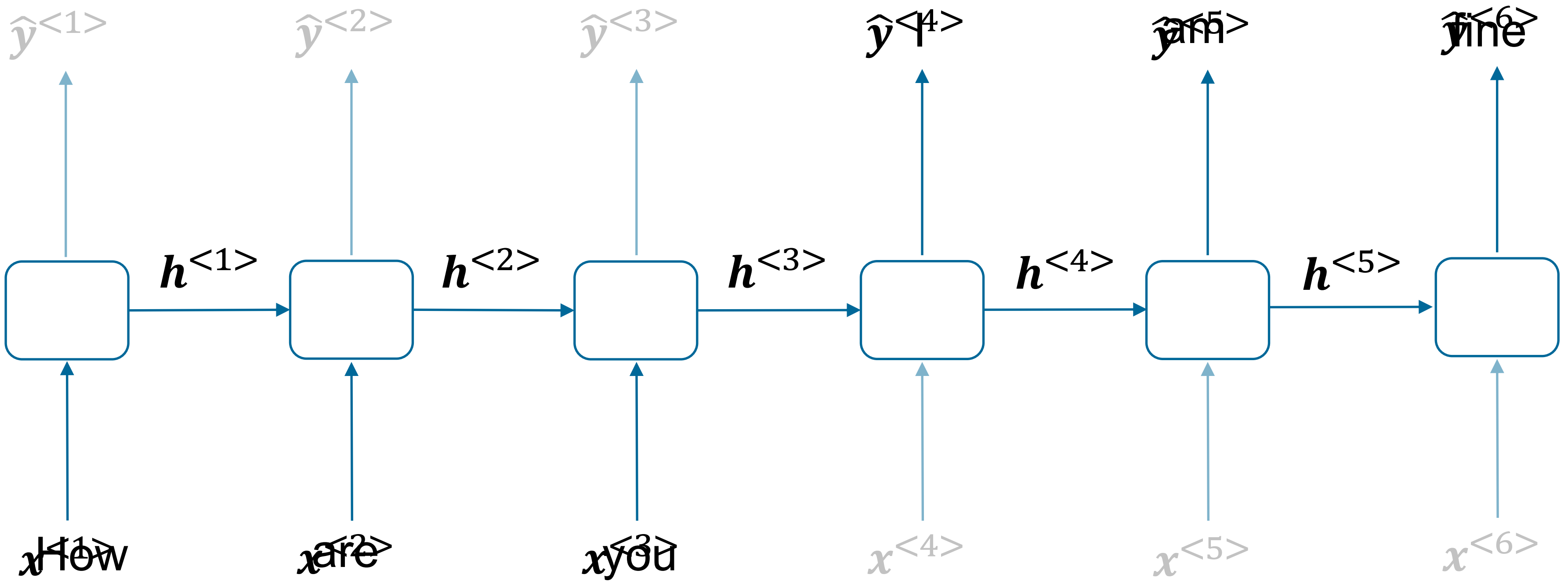


For example:

- Speech recognition
- Price predictions
- Translations

Let's use a sequence-to-sequence network to forecast multiple time steps ahead

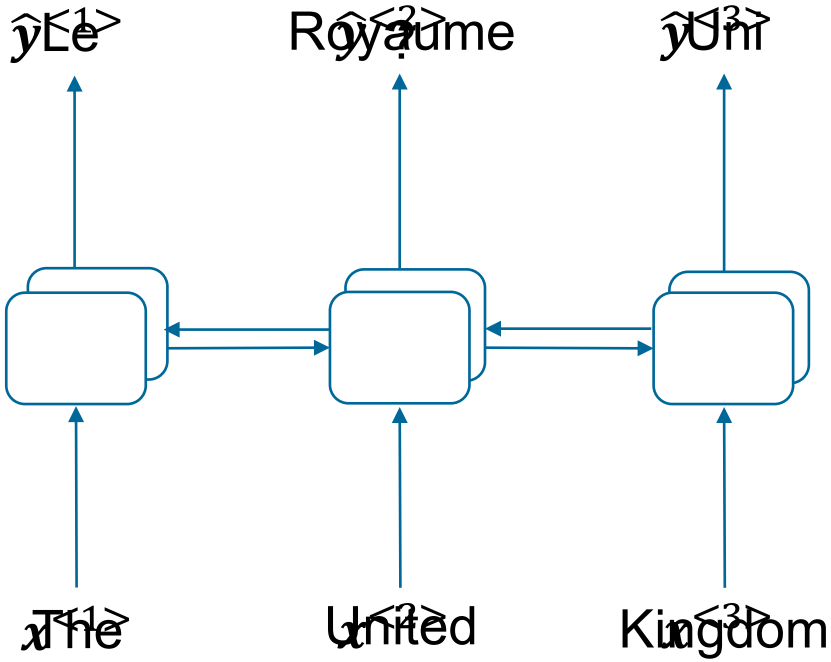
Encoder-decoder networks



For example:

- Translations
- Dialogue

Bidirectional RNNs – looking into the future



For example:

- All sorts of NLP
- Also, in combination with the previous

Data handling with TensorFlow

The data problem with deep learning

Complex data preprocessing

Instead of a “normal” dataset, work with TensorFlow’s Data API

The TensorFlow Data API

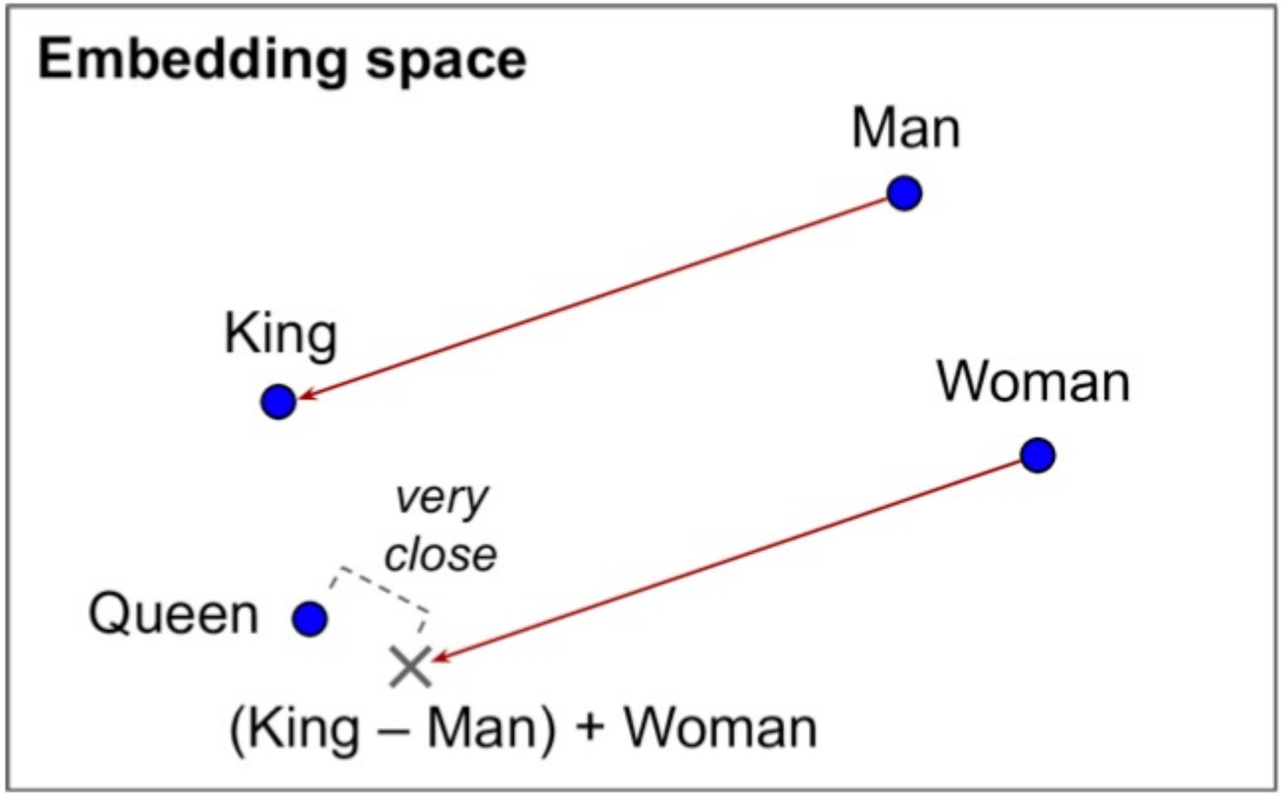
- Go through part 2 of the notebook "*ADL_Week 9_Recturrent Neural Networks.ipynb*"

- We introduce some of the key functionalities of the TensorFlow Data API

- This is useful for models in general, but it is particularly important for RNNs, since we need to do a lot of data manipulation

Creating music with RNNs – time permitting

A note on embeddings



Let's take a look: https://projector.tensorflow.org

Source: Géron

Let’s be creative

- Go through part 3 of the notebook “*ADL_Week 9_Recturrent Neural Networks.ipynb*”

- We develop a model that learns to predict chorales written by Joghann Sebastian Bach… and can create new ones in the same style!

- In principle, this is an extension of what we have learned so far about RNNs. However, there are a few details on data wrangling that make it an important exercise

See you next week!

Sources

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