Recurrent Neural Networks

Scratching the Surface

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Outline

- Learning Goals
- Motivation
- Recurrent Neural Networks (RNNs)
  - Traditional RNNs
  - Long short-term memory (LSTM)
- Summary

Additional Resources

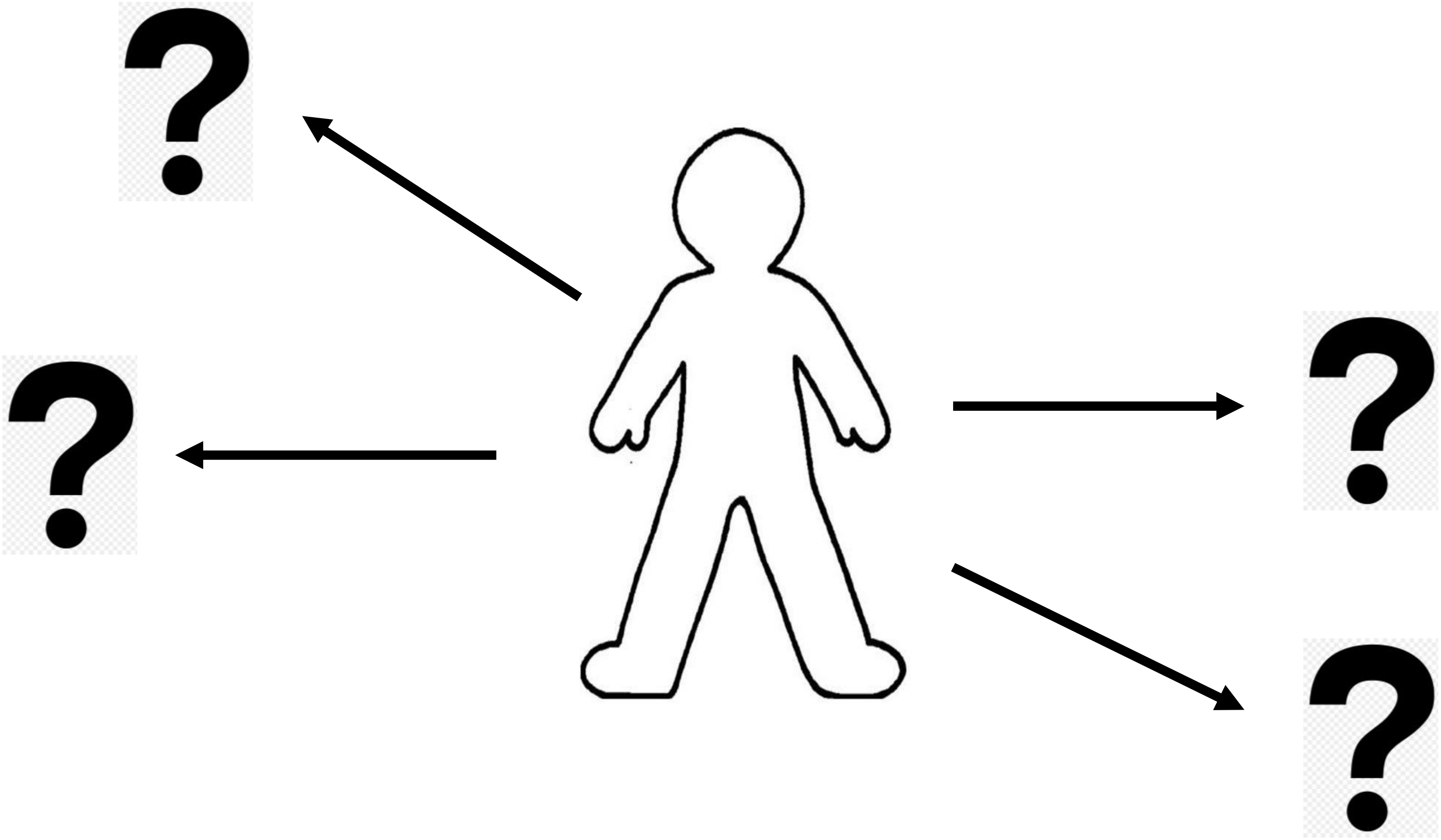
- Stanford cheatsheet:
  - https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks
- Colah’s blog:
  - https://colah.github.io/posts/2015-08-Understanding-LSTMs/
- Illustrated guide of LSTM:
  - https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

Learning Goals

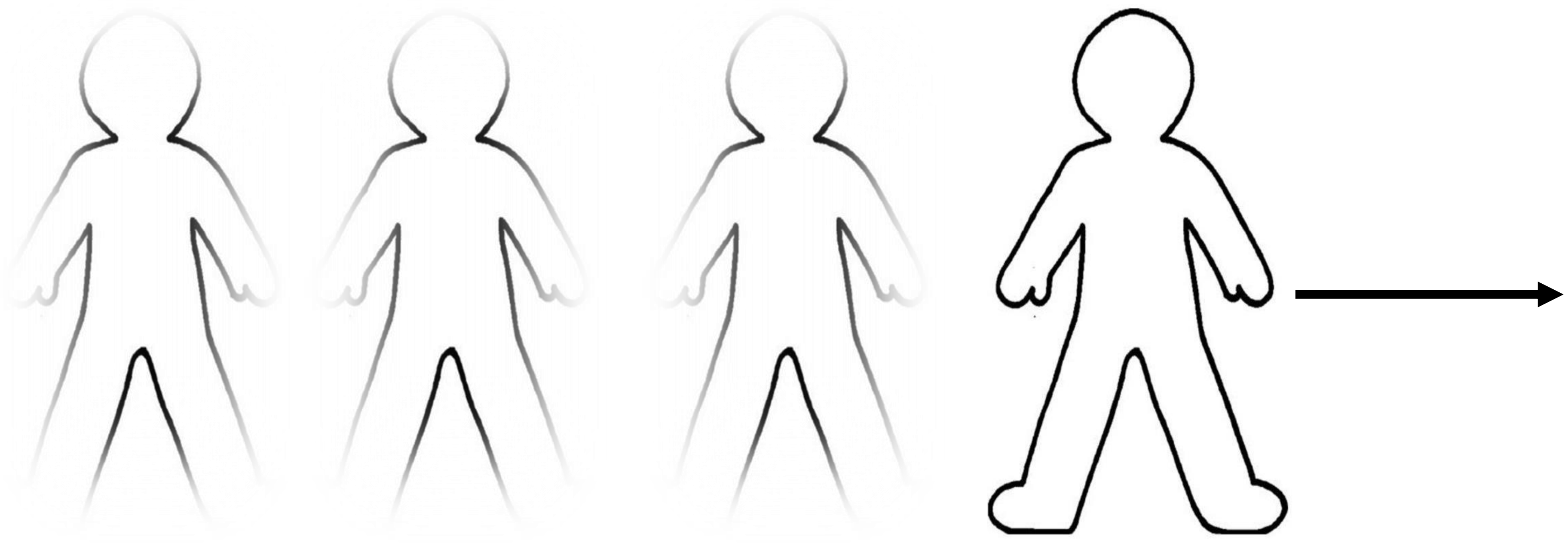
- Learn the intuition behind RNNs

- Get familiar with the most common types of RNNs (traditional and LSTM)

Where is the person going?



Where is the person going?



Motivation - Data is often sequential in nature

Steph Curry releases the ball and as it moves you know it is going to be 3 points to Golden State…

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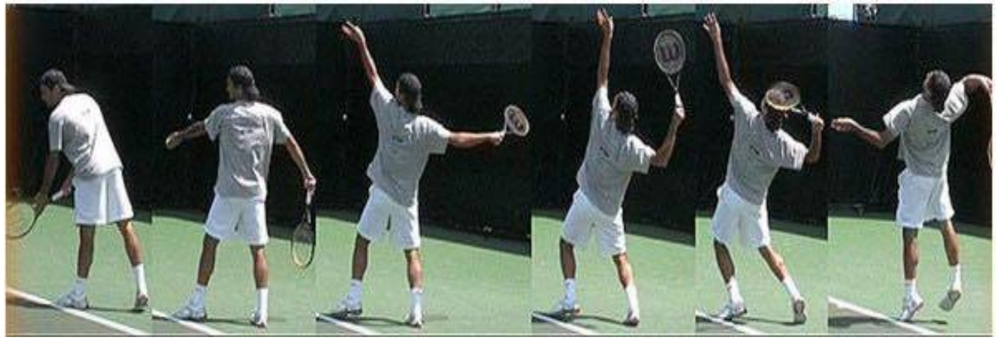

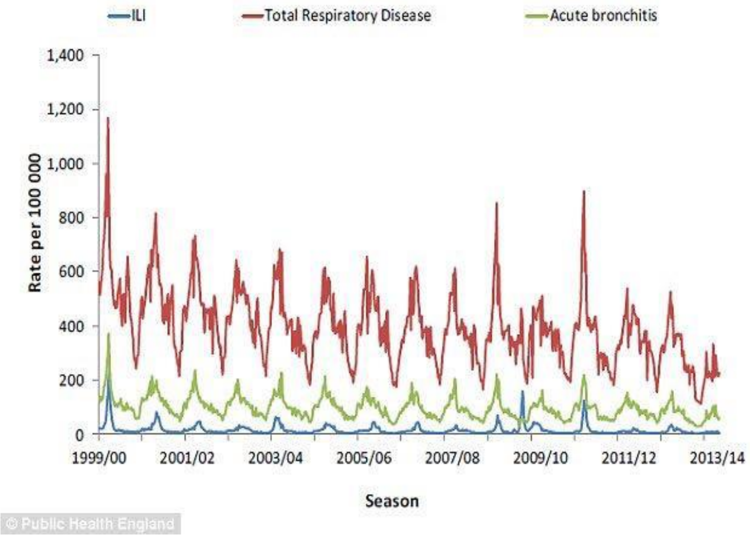

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Introduction

- Building models of sequential data is important: automatic speech recognition, machine translation, natural language, …

- Recurrent neural networks (RNNs) are a simple and general framework for this type of tasks

Introduction

`A B C A B C A B _`

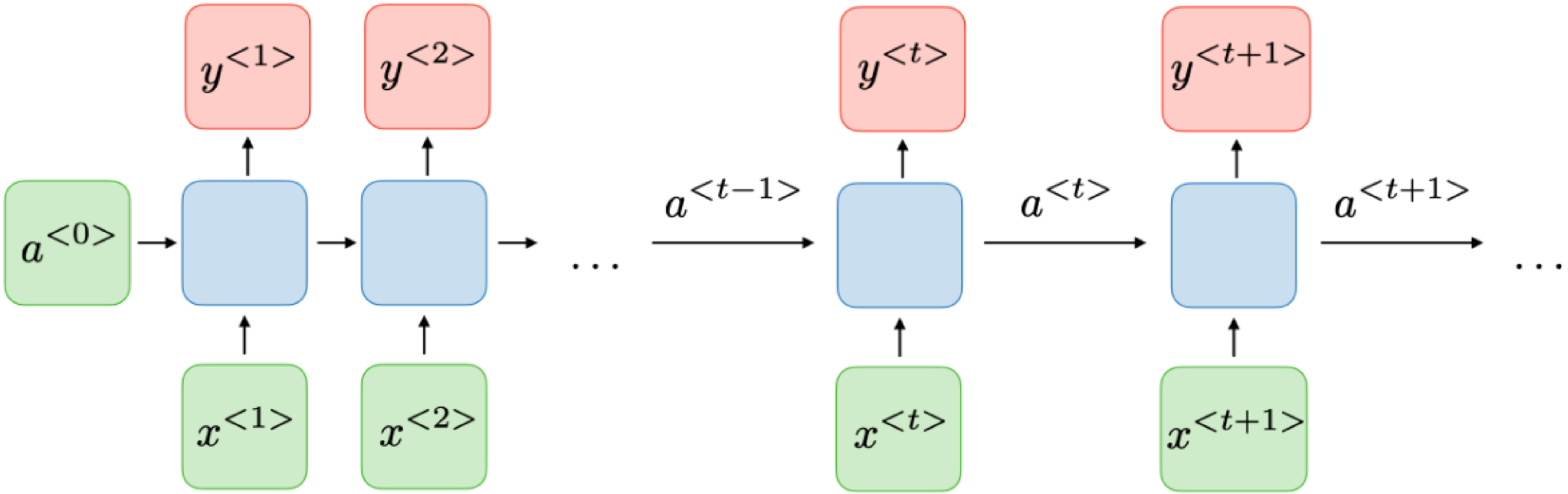
- What symbol comes next?

`Yesterday it was Sunday, so today it must be _`

- How to predict the next word?

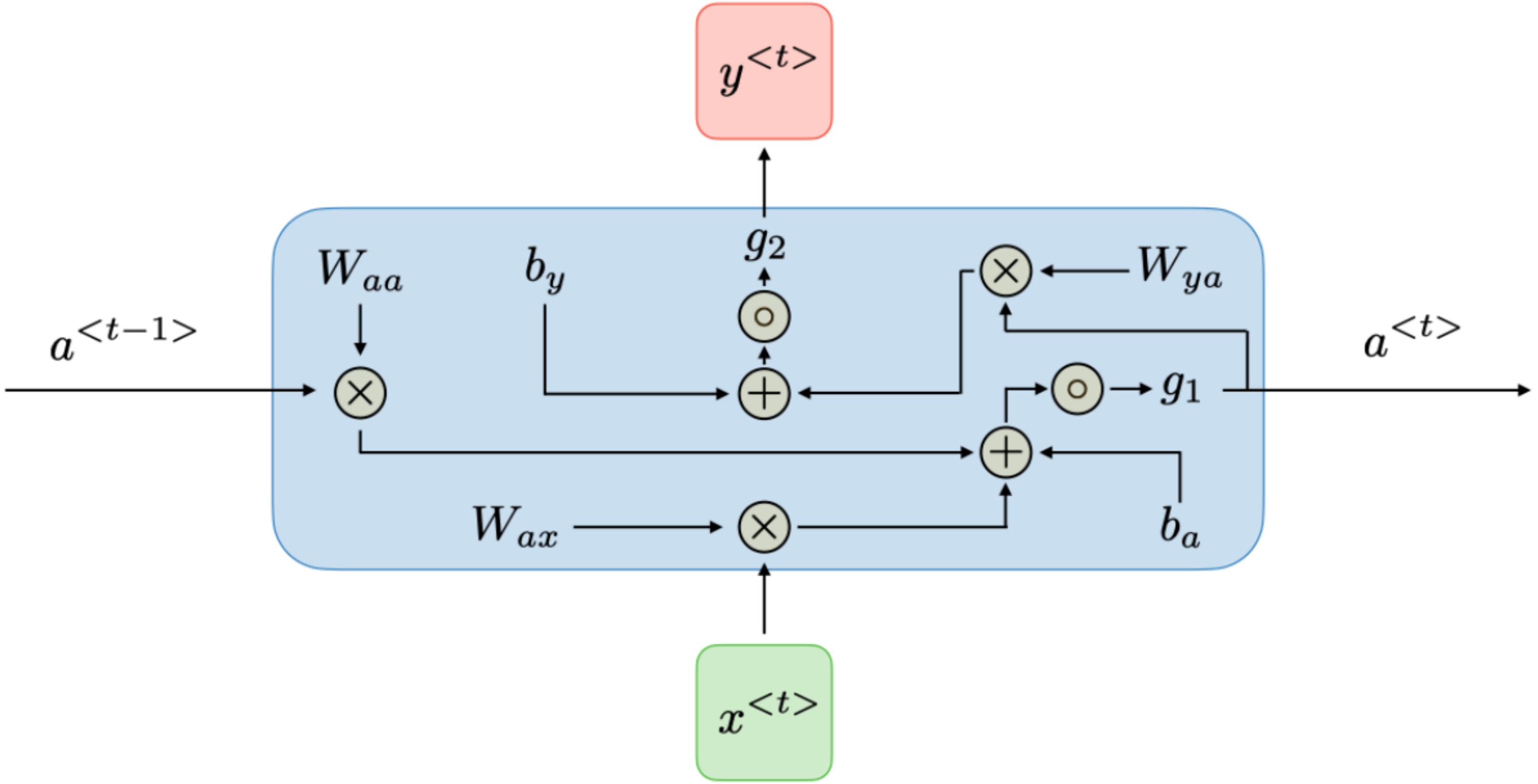
Traditional RNN

$$y^t = f(x^t, a^{t-1})$$



- RNNs can be seen as a (very deep) feedforward network with shared weights
- Model is trained using backpropagation through time

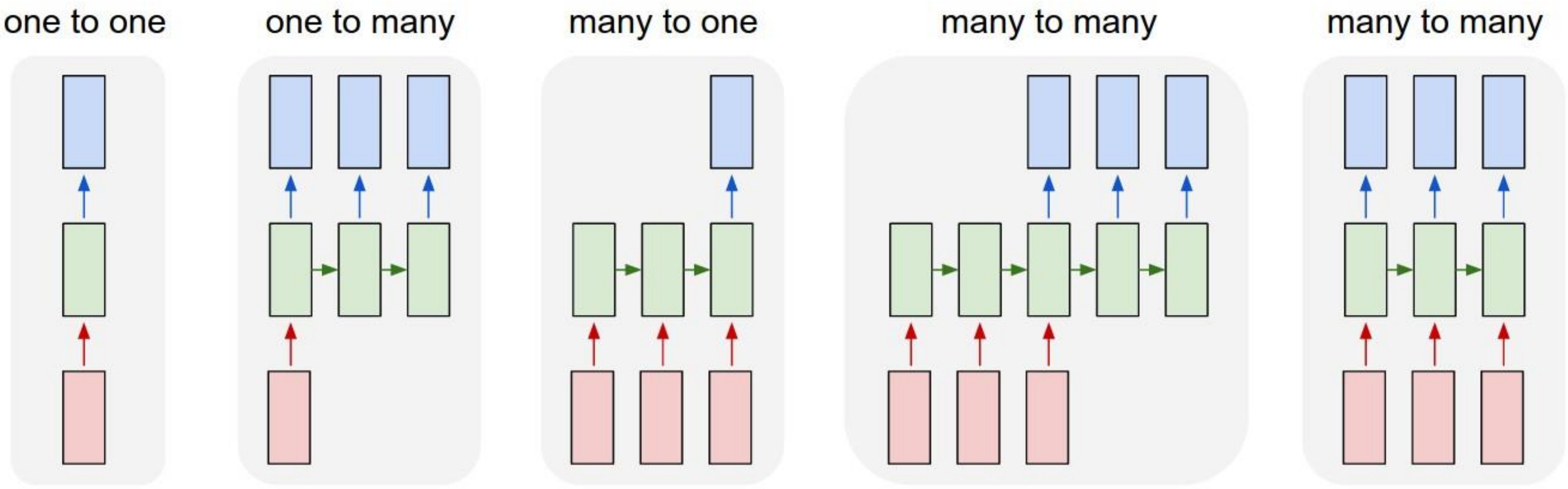
Traditional RNN



$$\boxed{a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)}$$

$$\boxed{y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)}$$

Types of RNNs



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RNNs Advantages and Disadvantages

Advantages	Disadvantages
Possibility of processing input of any length	Computation being slow
Model size not increasing with size of input	Difficulty of accessing information from a long time ago
Computations take into account historical information	Cannot consider any future input for the current state
Weights are shared across time	

Major shortcomings

- Handling of complex non-linear interactions
- Difficulties using BPTT to capture long-term dependencies exploding gradients
- Vanishing gradients

Vanishing gradients

- As we propagate the gradients back in time, usually their magnitude quickly decreases: this is called “vanishing gradient problem”

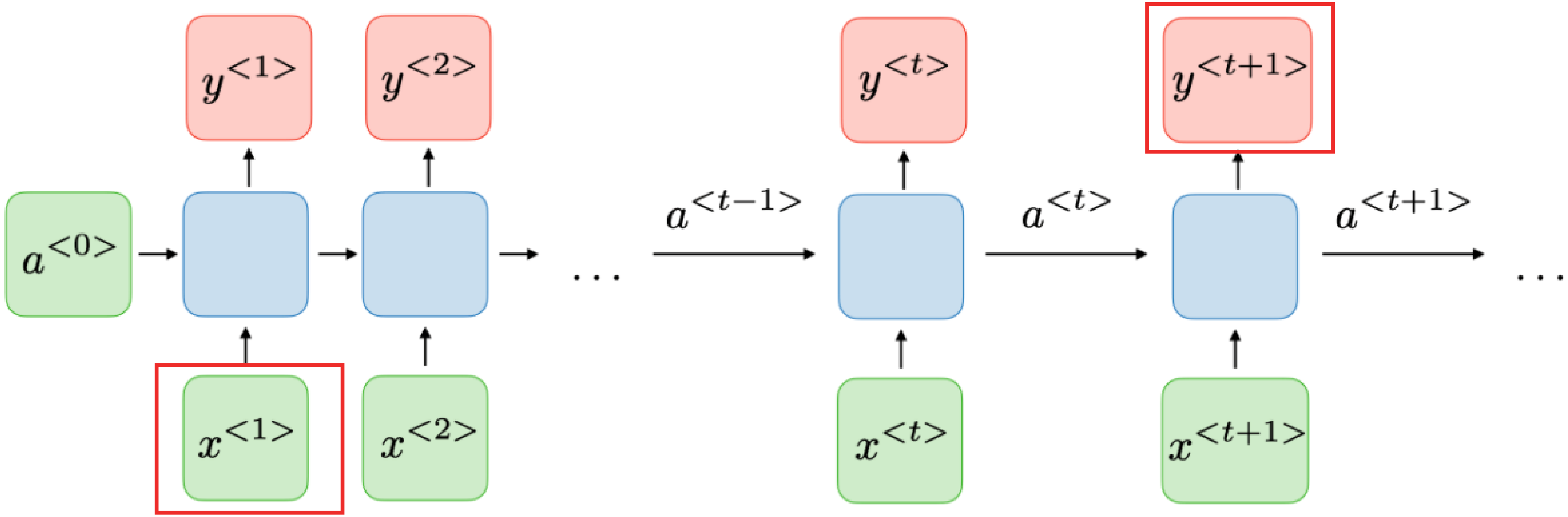
- In practice this means that learning long term dependencies in data is difficult for simple RNN architecture

- Special RNN architectures address this problem:
  - *Exponential trace memory* (Jordan 1987, Mozer 1989)
  - *Long Short-term Memory* (Hochreiter & Schmidhuber, 1997))

Exploding gradients

- Sometimes, the gradients start to increase exponentially during backpropagation through the recurrent weights
- Happens rarely, but the effect can be catastrophic: huge gradients will lead to big change of weights, and thus destroy what has been learned so far
- One of the main reasons why RNNs were supposed to be unstable
- Simple solution: clip or normalize values of the gradients to avoid huge changes of weights

The Problem of Long-Term Dependencies



"In theory, RNNs are absolutely capable of handling such "long-term dependencies." A human could carefully pick parameters for them to solve toy problems of this form. Sadly, in practice, RNNs don't seem to be able to learn them."

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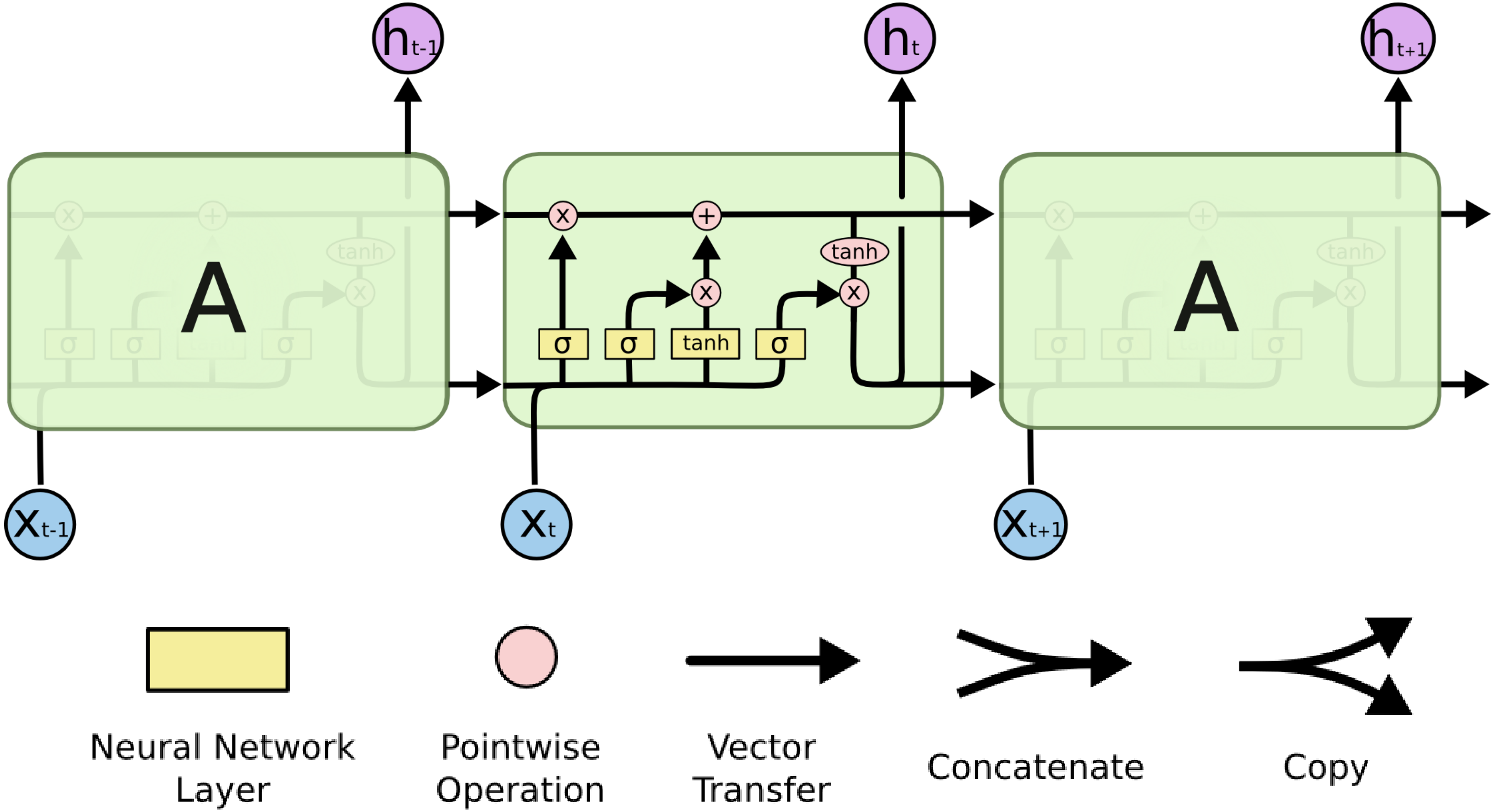
Long Short-Term Memory (LSTM)

- LSTM is a type of RNN capable of learning long-term dependencies



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Summary

- RNNs are capable of handling sequences of arbitrary lengths
- Traditional RNNs are not capable in practice to model long-term dependencies in data
- The LSTM model allows you to model these long-term dependencies
- More details in the tutorials…

Thank you!