Recurrent Neural Networks

Machine Learning Decal

Hosted by Machine Learning at Berkeley

ML@B

Agenda

Motivation

Basic Recurrent Layers

Long Short-Term Memory

Demo: Language Modeling

RNNs vs CNNs

Questions

Motivation

Time Series Tasks

ML@B

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- **Image Captioning**: Write a caption for a particular image

Image Captioning

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Music Composition

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Play

Using Regular Neural Networks

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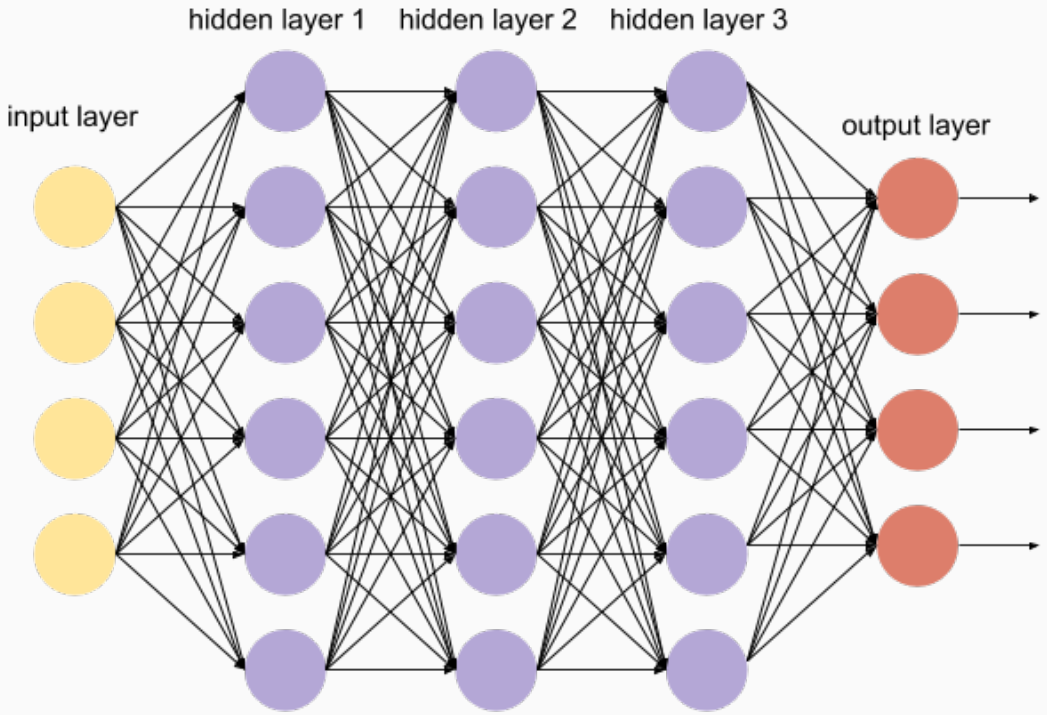

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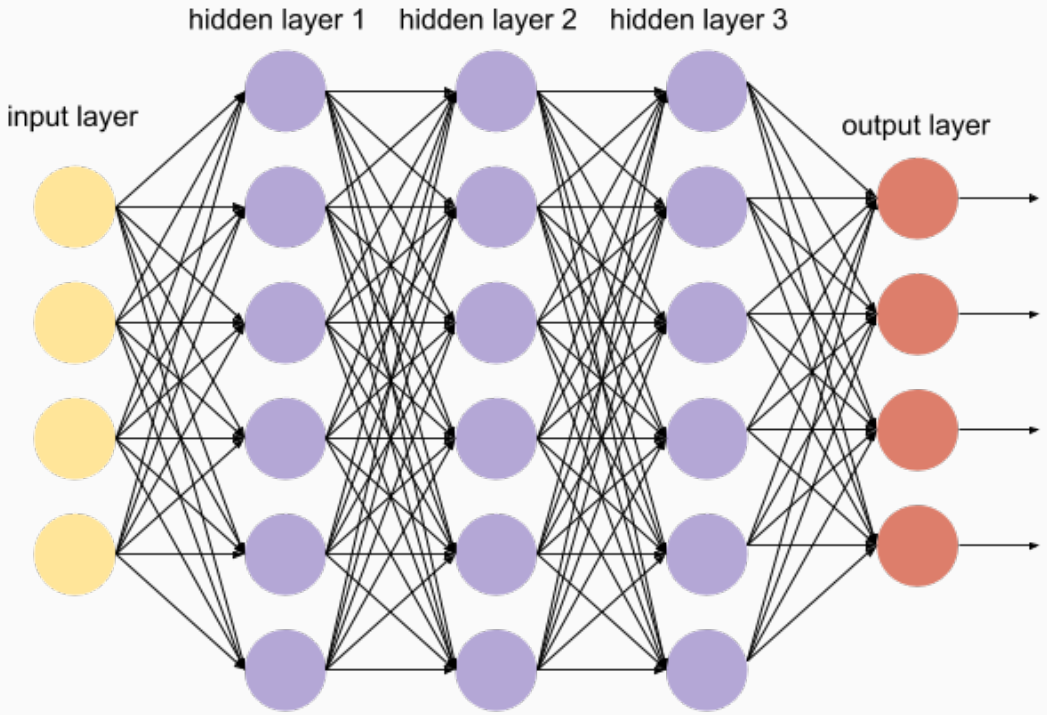
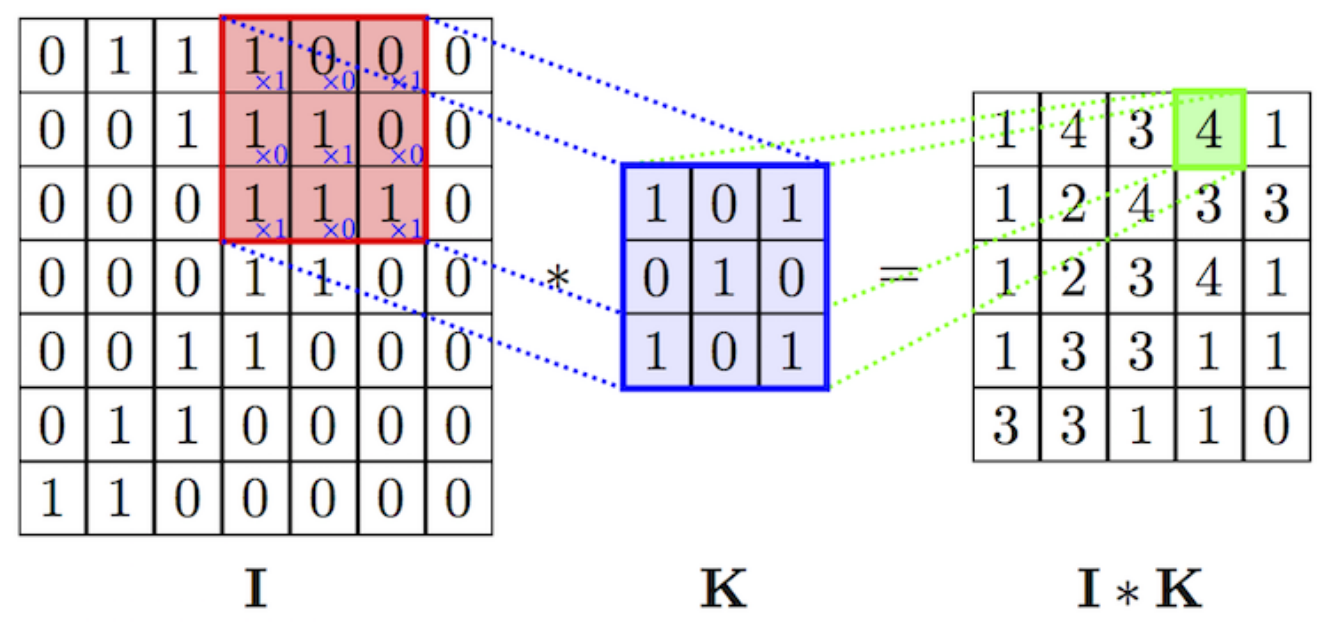


How could we train a standard neural network to perform this task? What are some issues that can arise?

Revisiting CNNs



Recall from last time how convolutional neural networks take advantage of spatial locality in images to learn more efficiently

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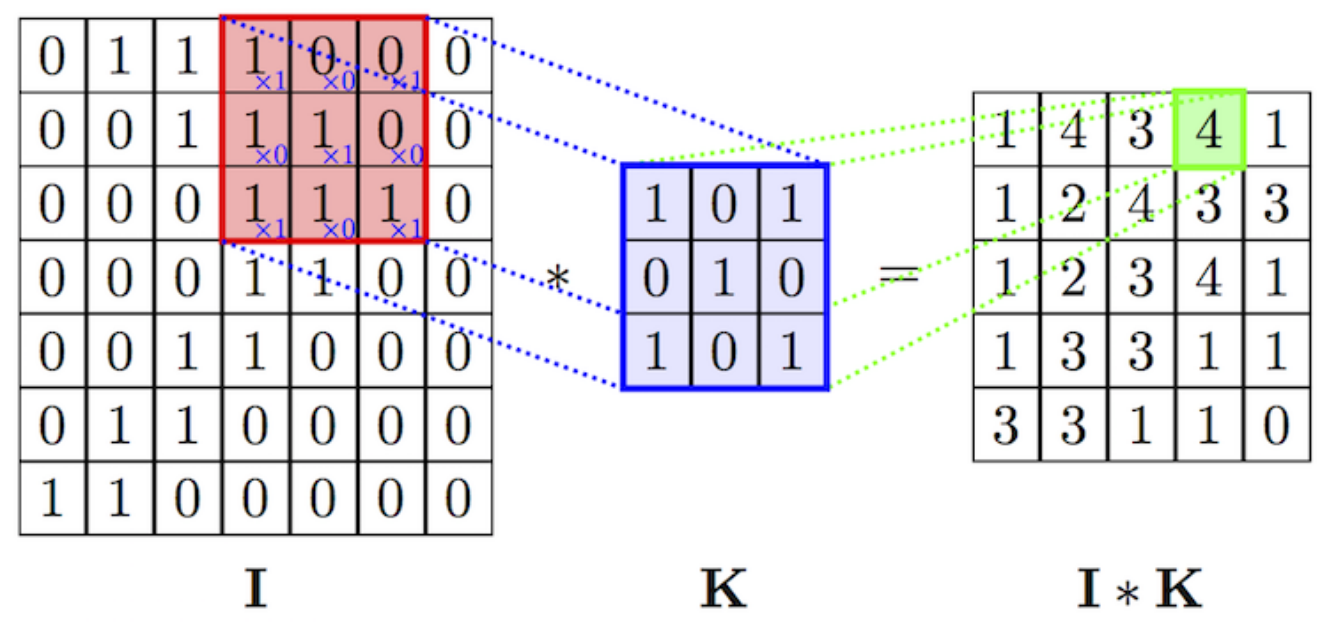

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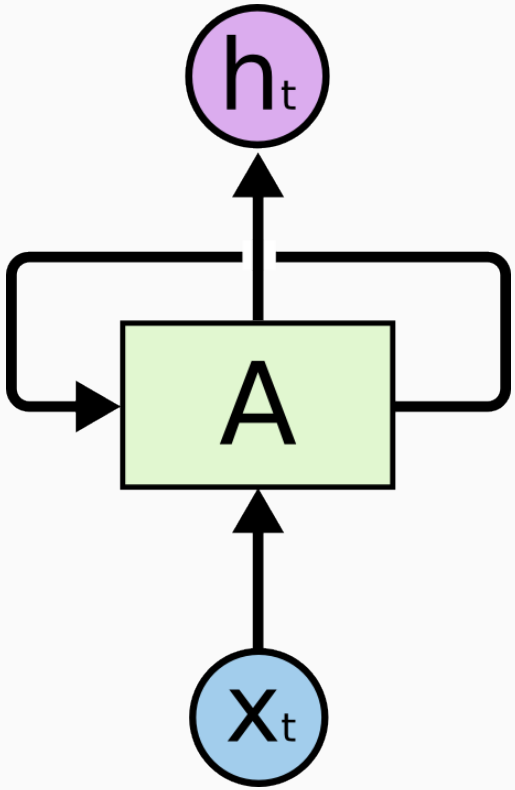
How can we exploit common structure in time series tasks?

Basic Recurrent Layers

Adding Recurrence



Key idea: not only do we give the layer the input, but also the previous output of the same layer!

Unrolling the RNN

We can **unroll** this recurrent layer to get a better sense of how it works over time.

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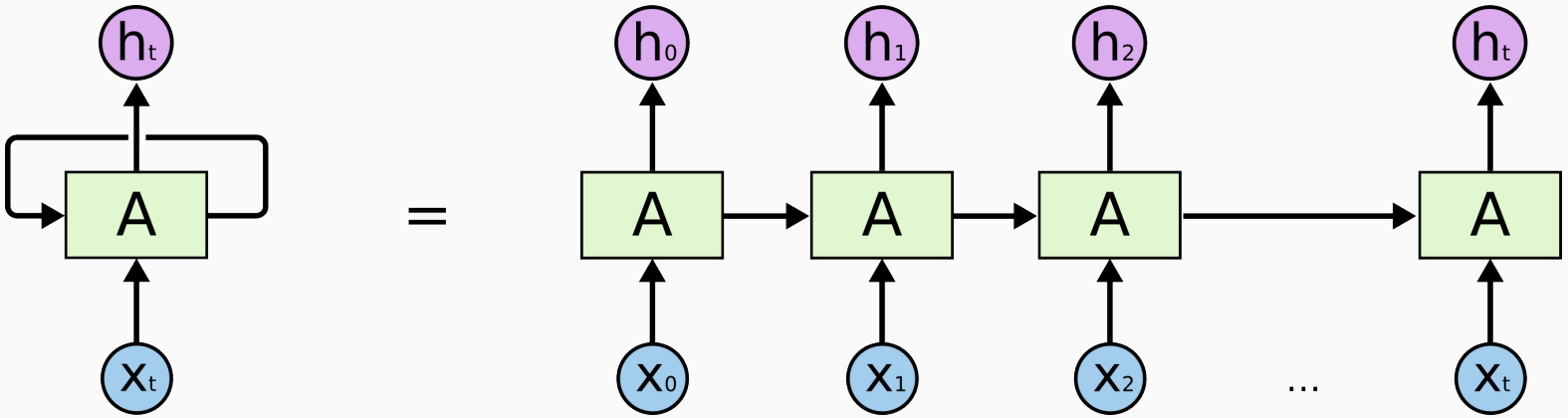
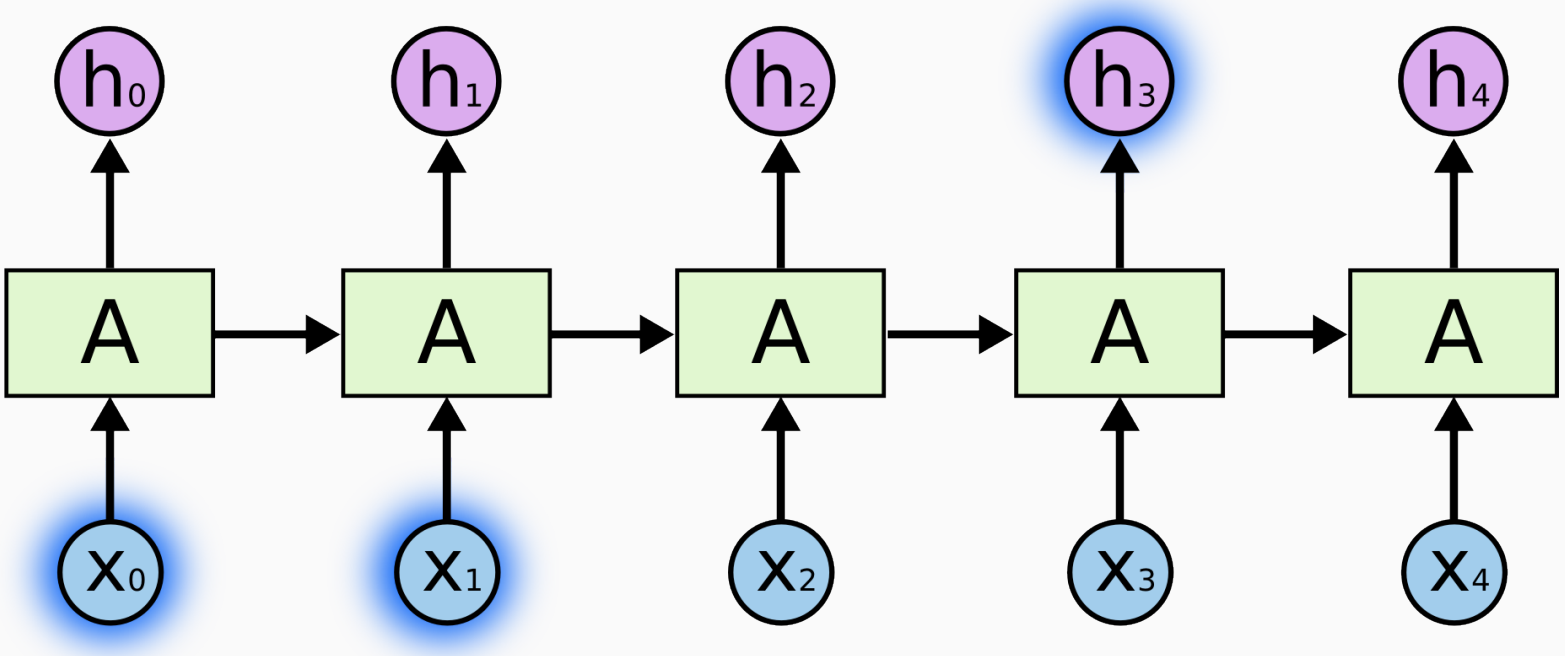


RNN Output

The output at any particular timestep now depends on all the inputs up to that timestep!



Types of RNN Layers

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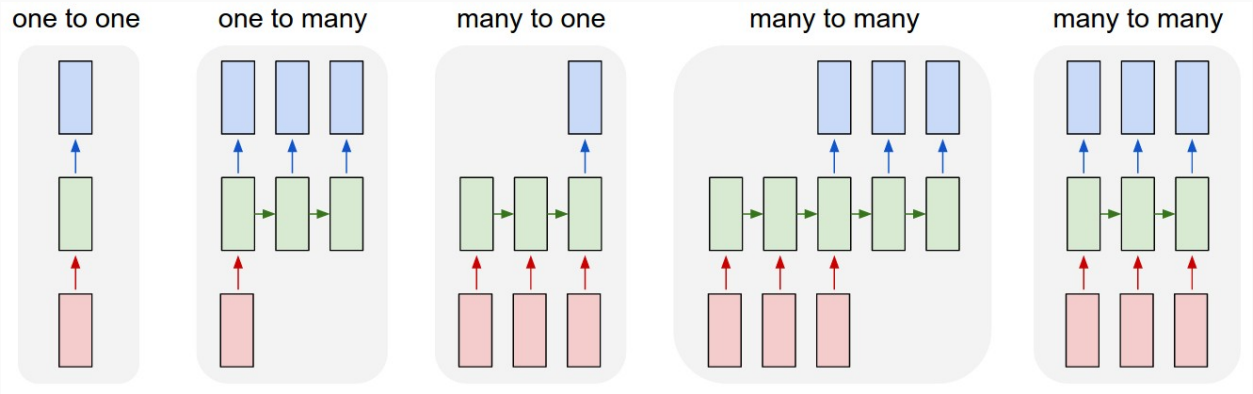

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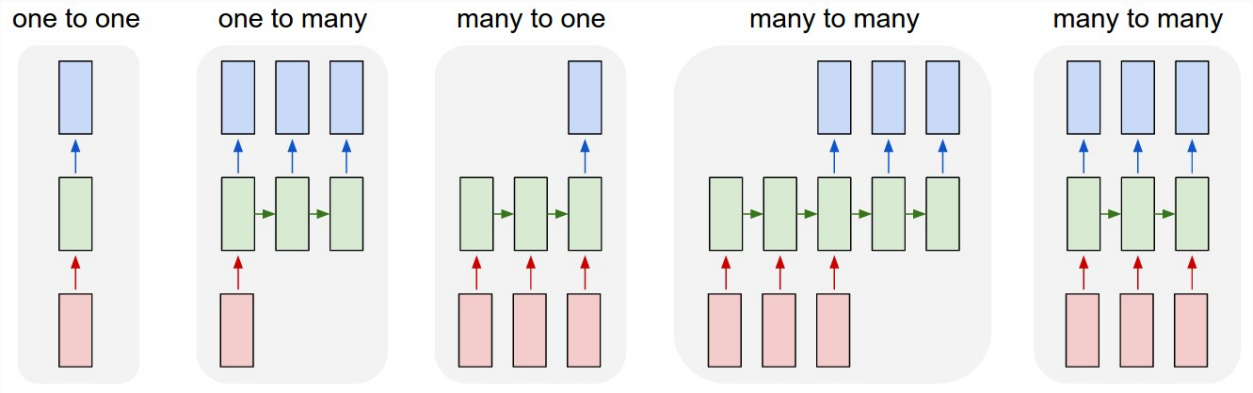

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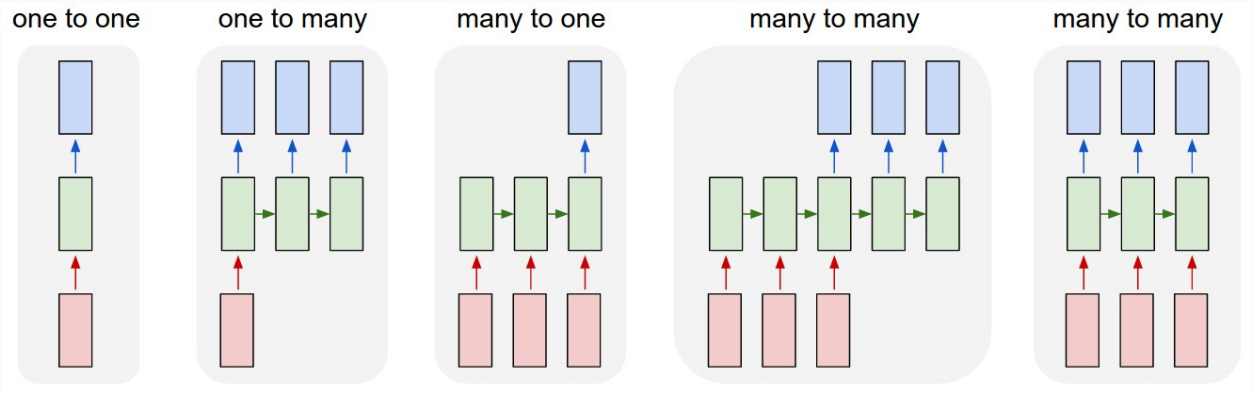

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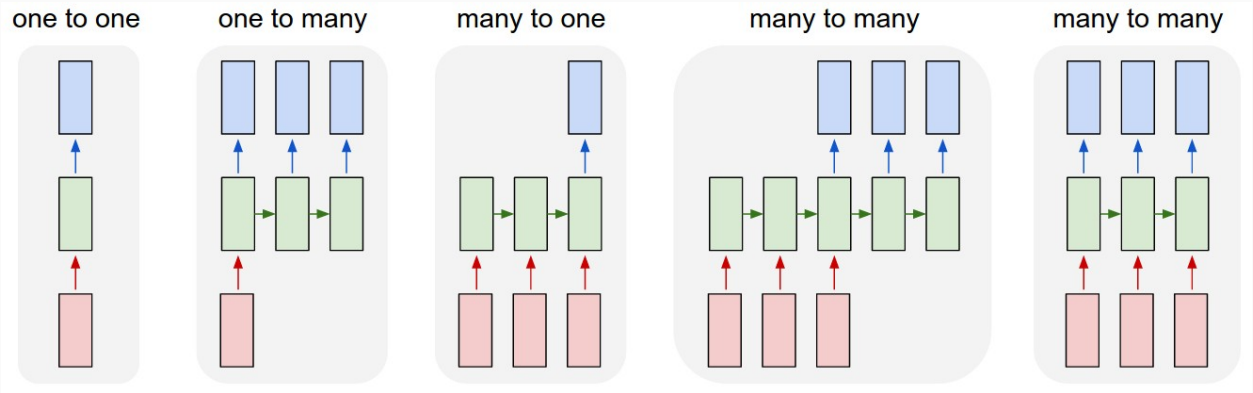

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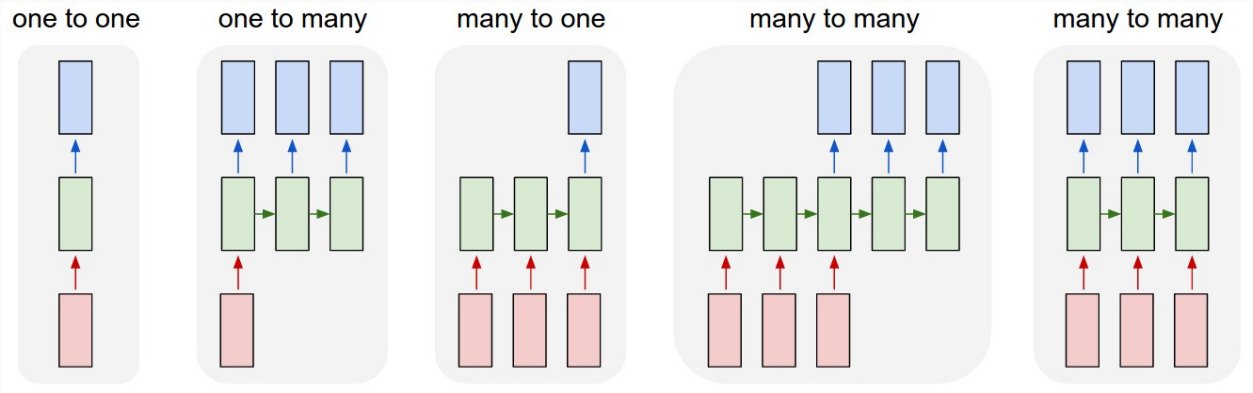

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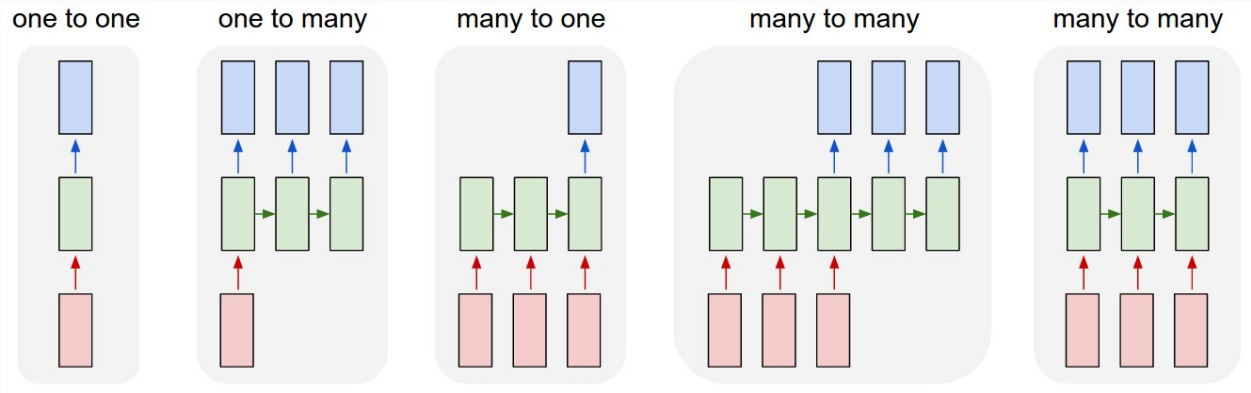

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- **Many-to-many (type 1)**: Machine Translation
- **Many-to-many (type 2)**: Video Classification by Frame

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ML@B

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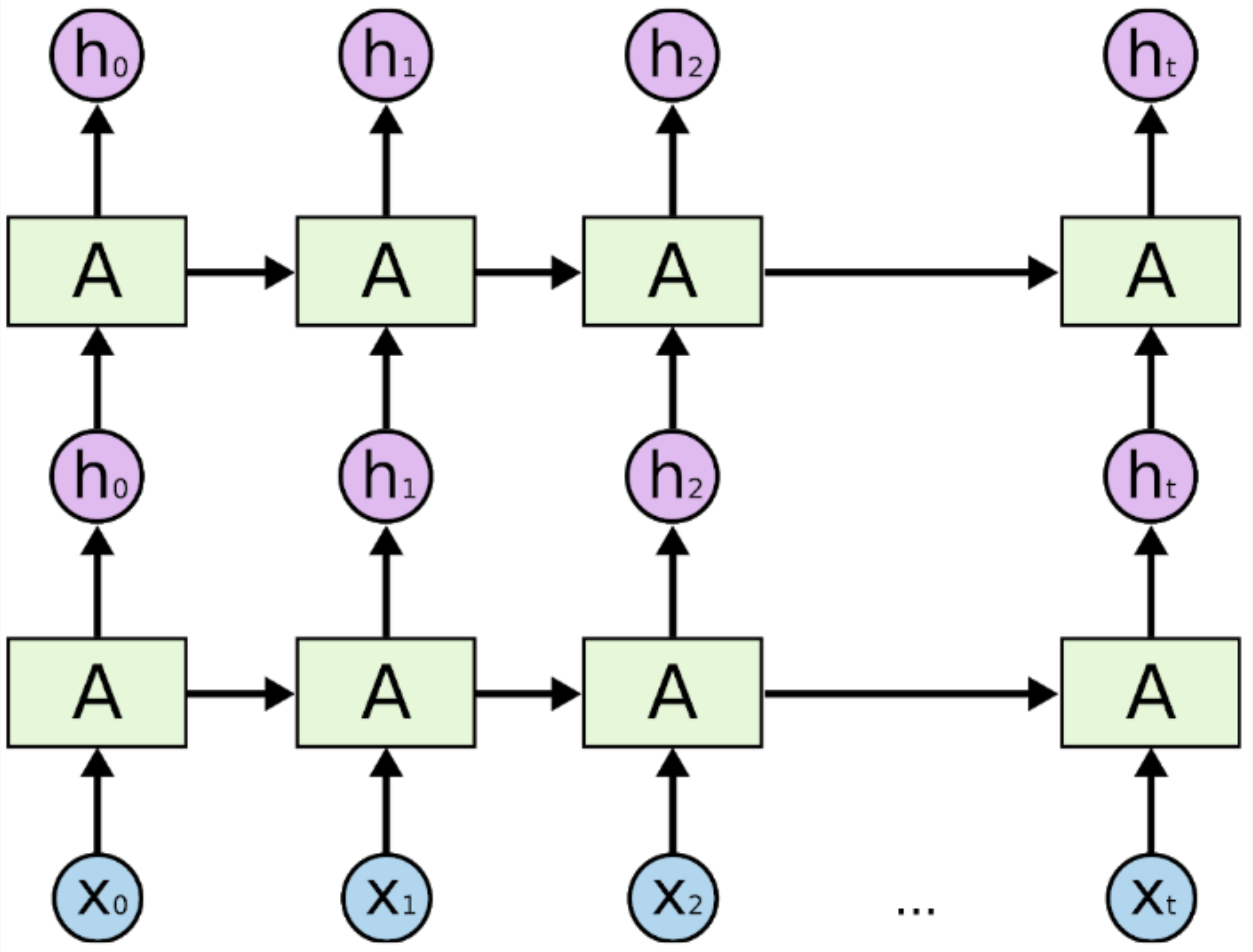
- We use a tanh activation so that values within the hidden layer don't explode over long time periods

Multi-layer RNNs

Note: We can stack multiple recurrent layers, just like fully connected NNs and CNNs!



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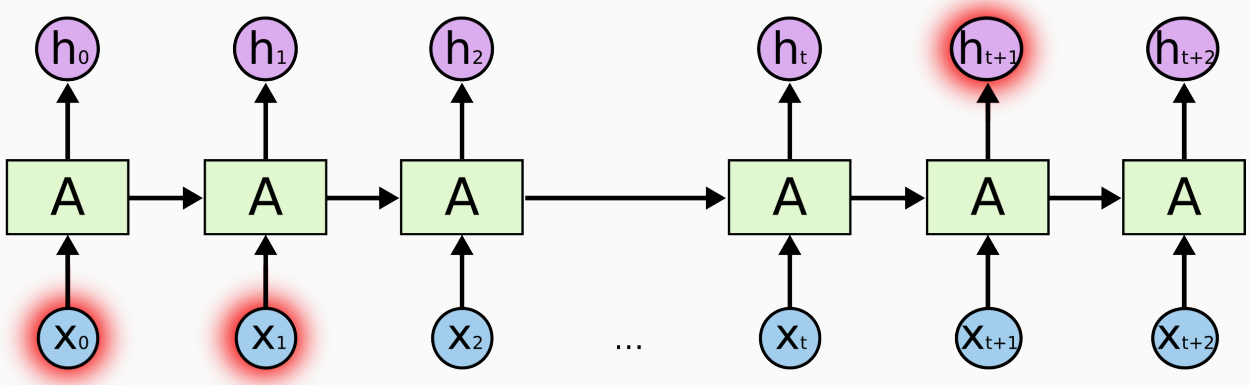

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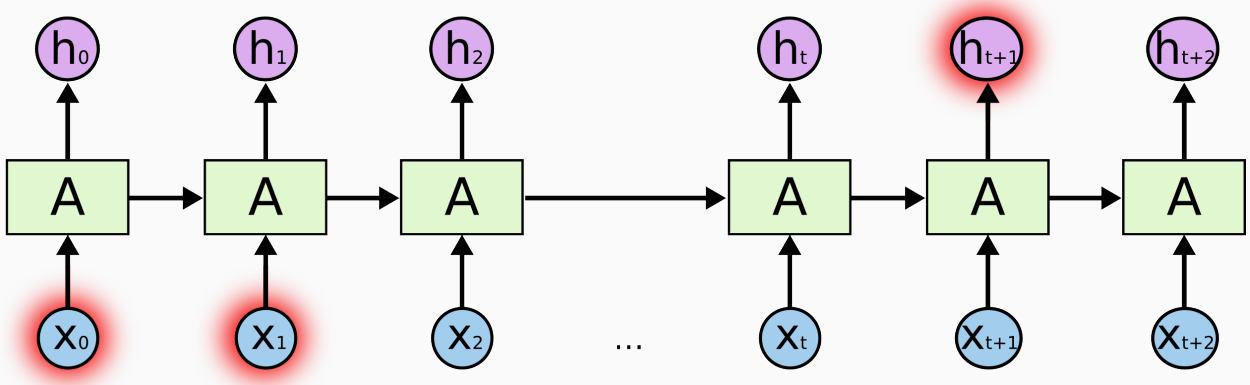

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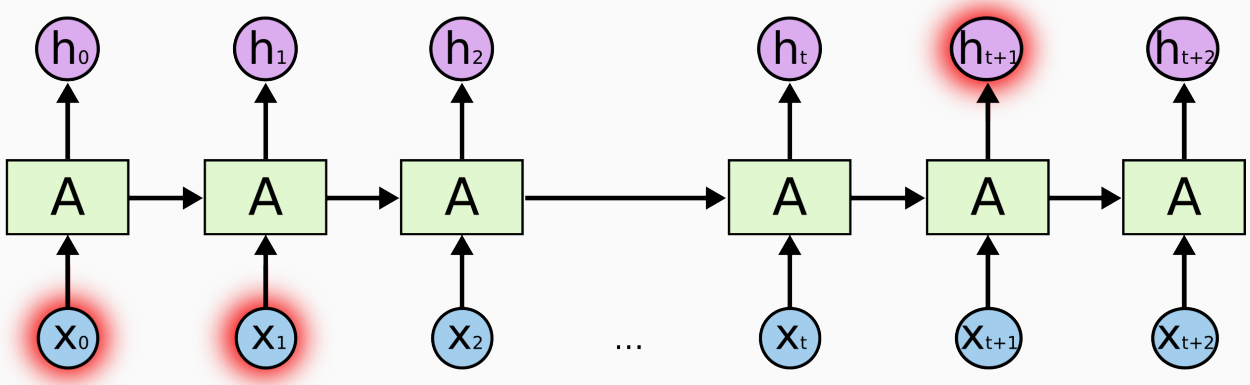

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- For very long dependencies, these gradients approach zero!

Long Short-Term Memory

Introducting LSTMs

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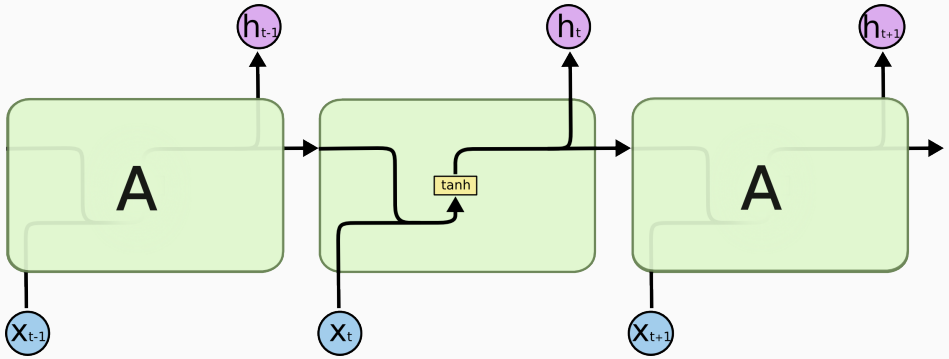
- Long-term memory, when talking about ML algorithms, are the learned parameters of the model, since they are held indefinitely once trained.
- The hidden states in RNNs are short-term memory, since they last only for the current prediction and are then cleared,
- LSTMs allow for the short-term memory of RNNs to be held for much longer than the basic RNN cell.

Introducting LSTMs

We go from this



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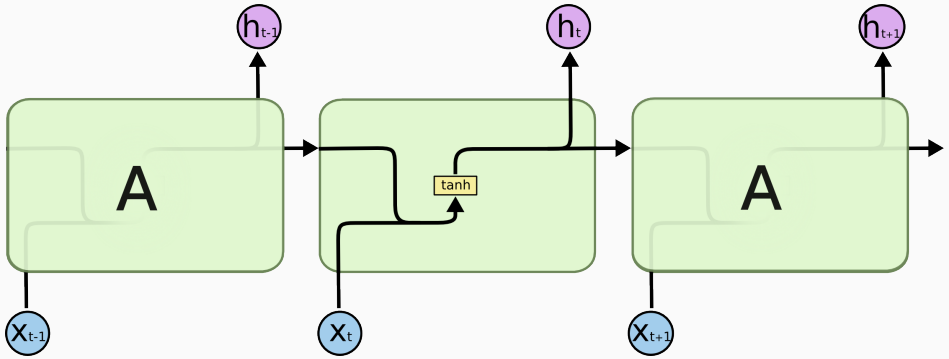

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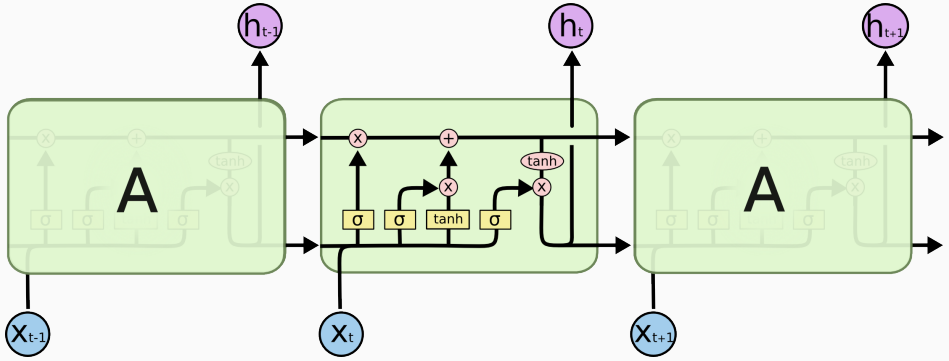

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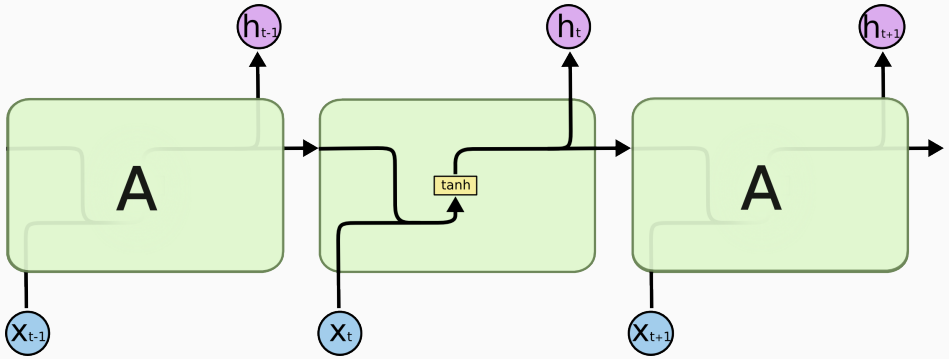

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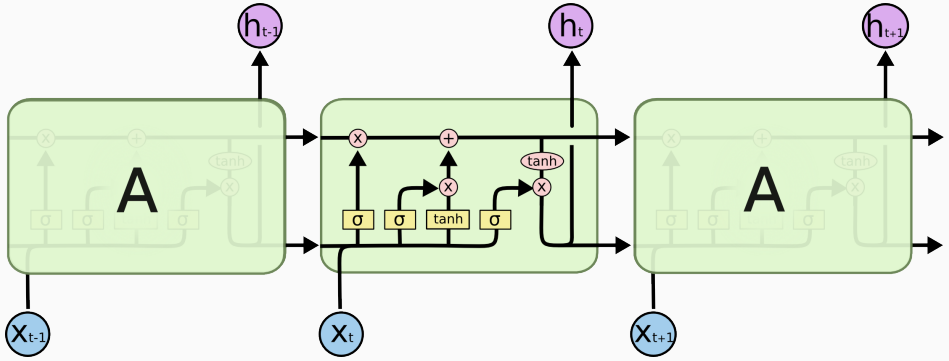
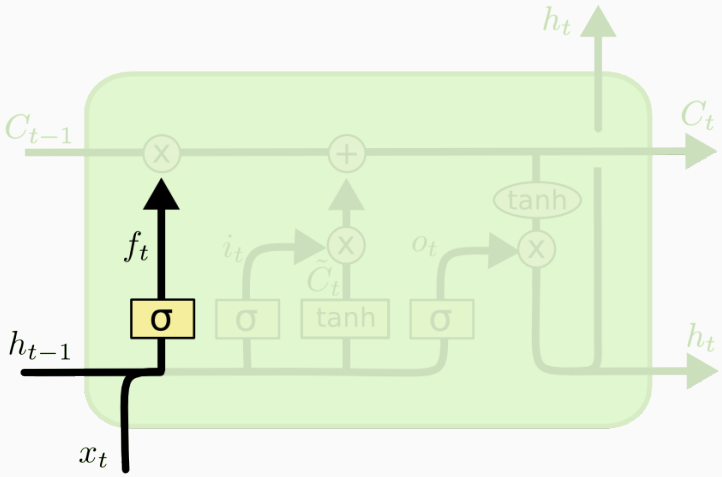


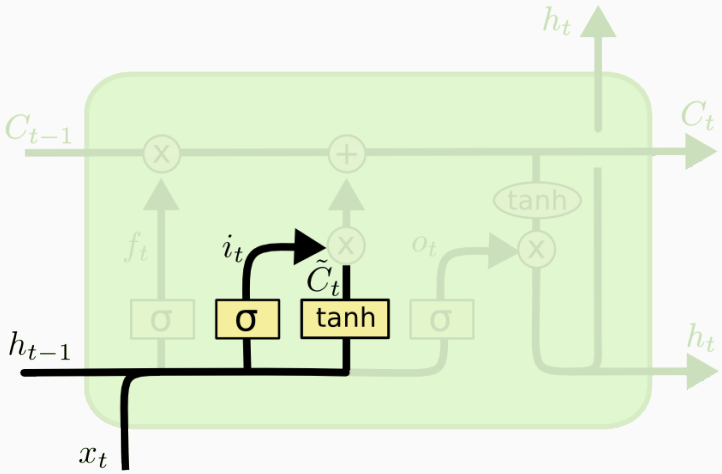
Let's break it down...

LSTMs: The Forget Gate



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

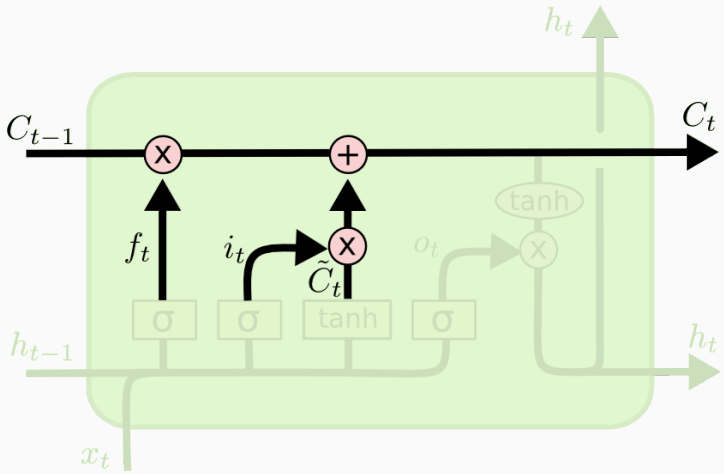
LSTMs: The Remember Gate



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

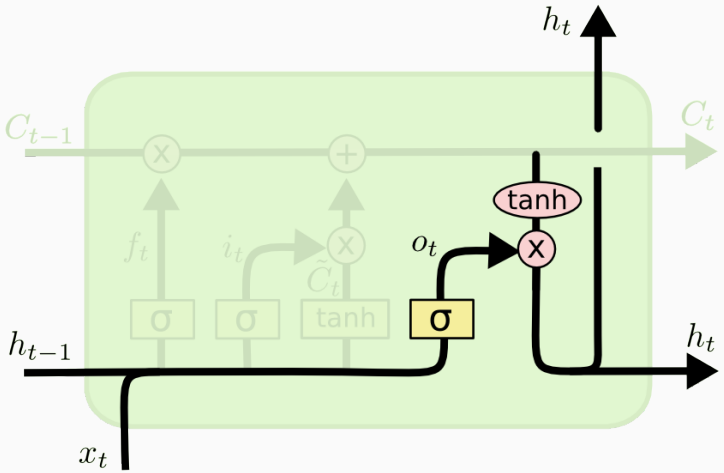
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTMs: Updating the Cell State



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

LSTMs: Updating the Hidden State



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Demo: Language Modeling

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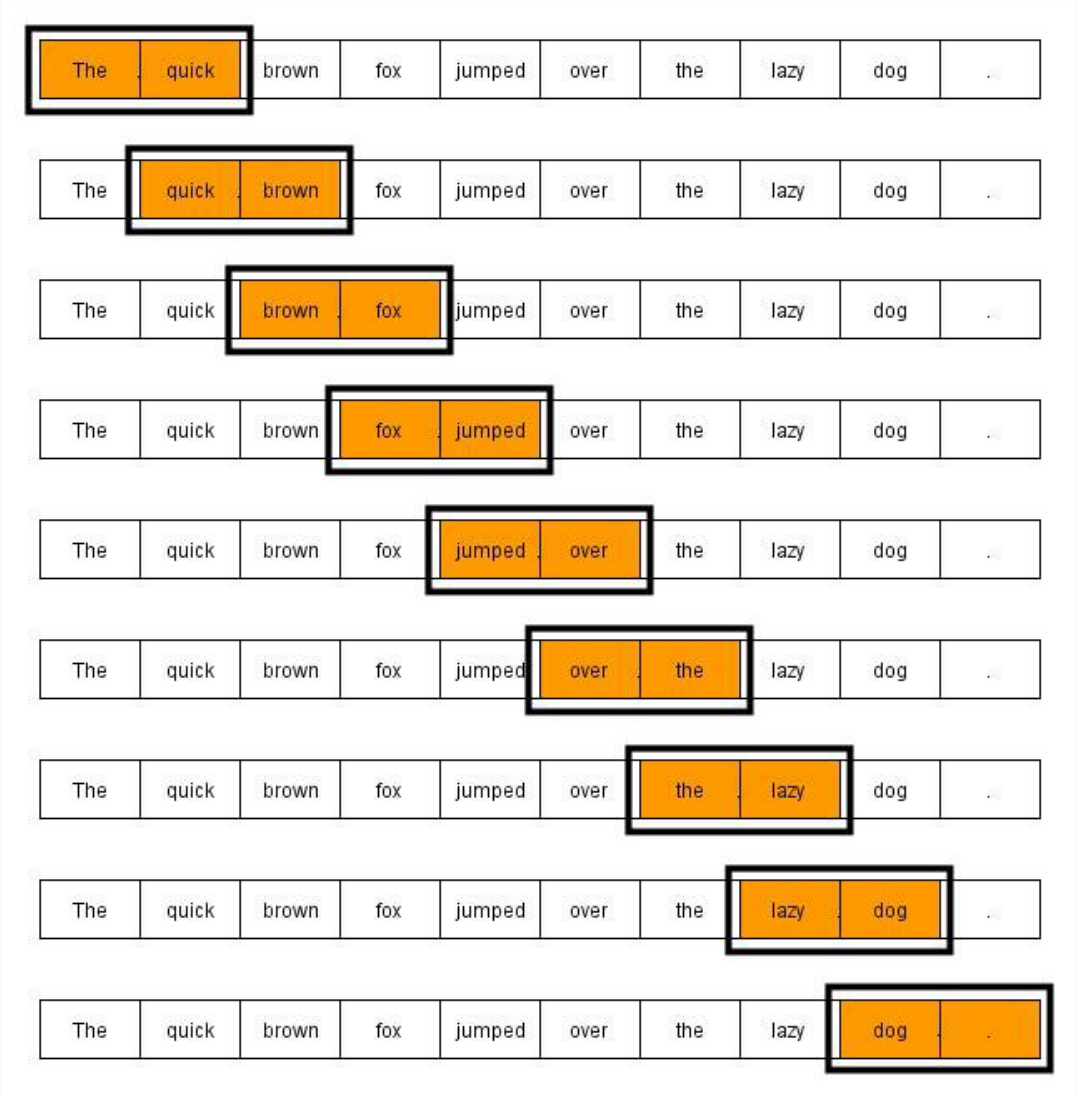
- We can train an RNN to perform language modeling by giving previous words/letters as input, and outputting the next word/letter

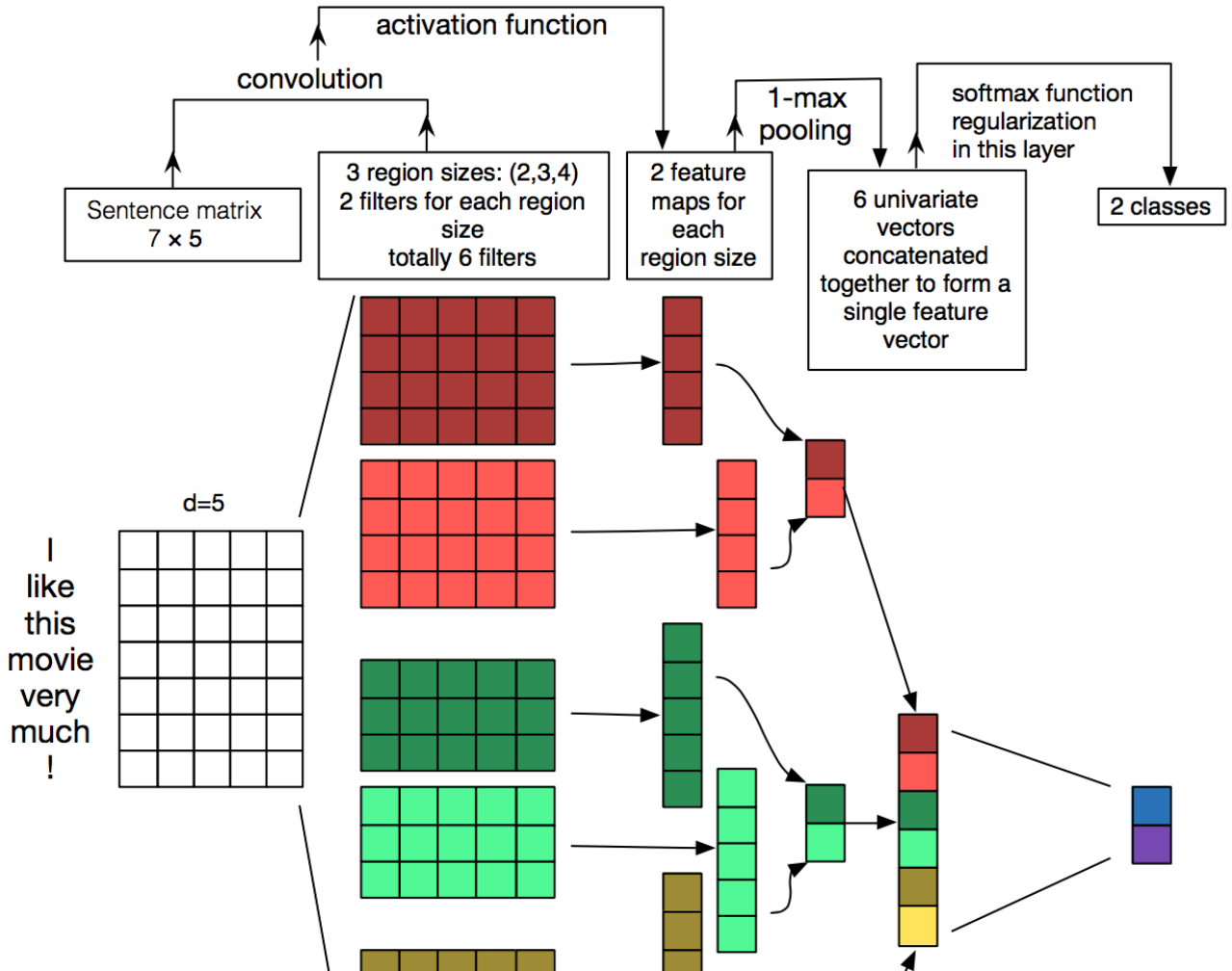
Using a Sliding Window for Input



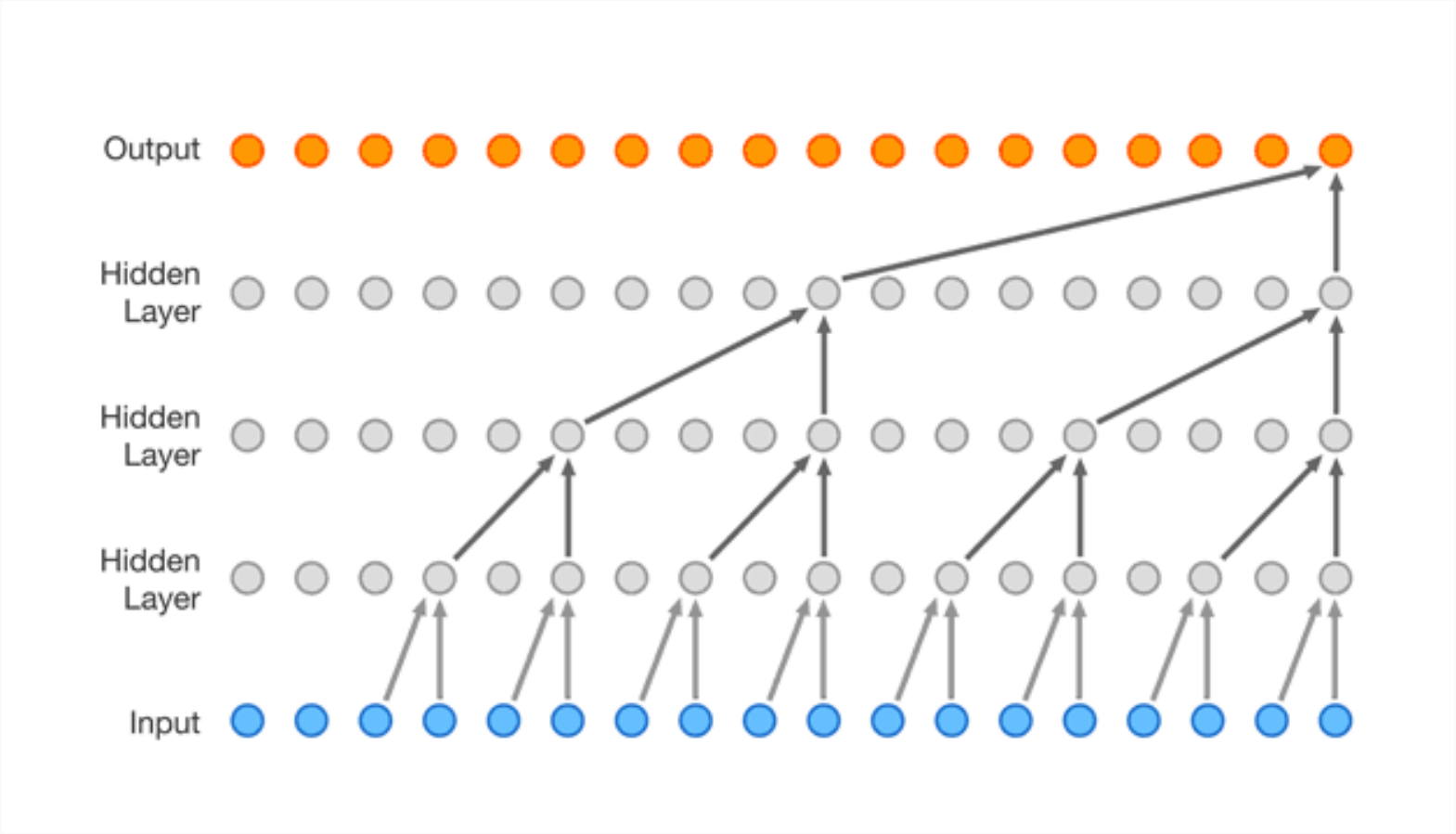
RNNs vs CNNs

Comparings RNNs and CNNs

Oftentimes, you can use CNNs to perform the same tasks as RNNs with equal or better results



Wavenet



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