CS189 Summer 2018

Lecture 25: Recurrent Neural Networks

Josh Tobin

Where we are in the course

- Final covers up to **yesterday's** lecture
- Today and tomorrow: advanced neural networks
- Not covered: boosting (not on the final)
- Next week: enrichment lectures (not on the final)
- Also next week: Final

How to study for the final

- Start today!
- Do as many practice problems as possible
  - Midterm problems
  - HW problems
  - Old midterm / final problems
- Go through the derivations from class
- Make sure you can re-derive things on your own
- Go to office hours and ask questions
- (Hint): make sure you understand the geometric intuition for the methods we studied. E.g., make sure you can draw a picture of what's happening

Goal for this lecture

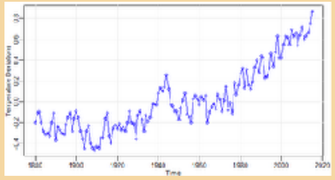
Describe a general-purpose architecture
for handling sequential data

Agenda

1. **Why recurrent neural networks (RNNs)?**
2. RNNs
3. Problem with RNNs: vanishing gradients
4. Dealing with vanishing gradients

Sequence data is everywhere

Sequence

Application	Input data	Output data
Time series forecasting	Time series 	Predicted next value

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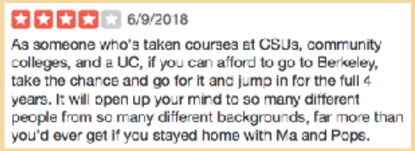
Sentiment classification	Review text 	Predicted sentiment 

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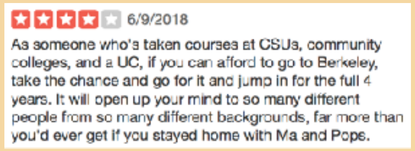
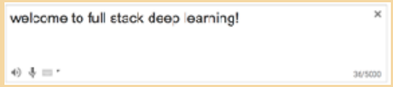
Sentiment classification	Review text 	Predicted sentiment 
Machine translation	English text 	French text 

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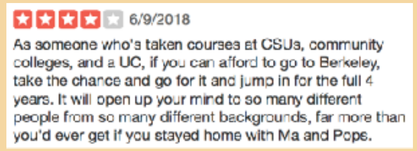
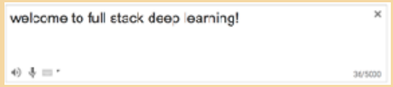
Sentiment classification	Review text 	Predicted sentiment 
Machine translation	English text 	French text 
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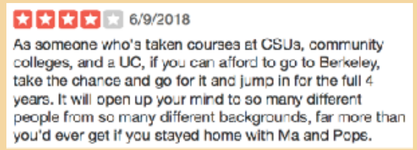
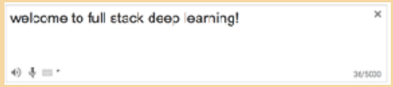
Sentiment classification	Review text 	Predicted sentiment 
Machine translation	English text 	French text 
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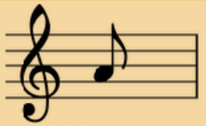
Music generation	Ø	

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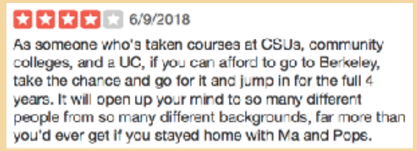
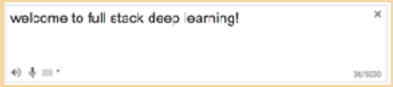
Sentiment classification	Review text 	Predicted sentiment 
Machine translation	English text 	French text 
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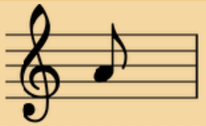
Music generation	Ø	
Image captioning	Image 	Description *“The quick brown fox jumped over the lazy dog”*

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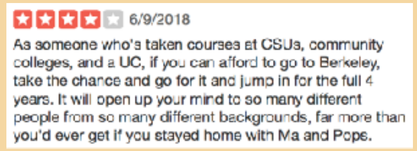
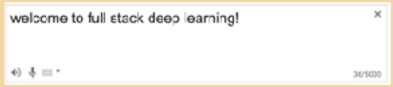
Sentiment classification	Review text 	Predicted sentiment 
Machine translation	English text 	French text 
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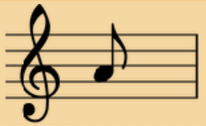
Music generation	Ø	
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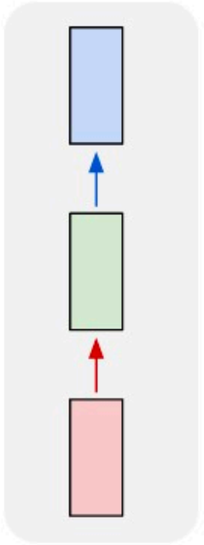
Sequence data is everywhere

- Lots of data is naturally sequential
- Sequences can form the input and/or output
- Three kinds of problems: many-to-one, one-to-many, many-to-many, none-to-many
- Even data that we don't think of temporally (like images) can be thought of as a sequence

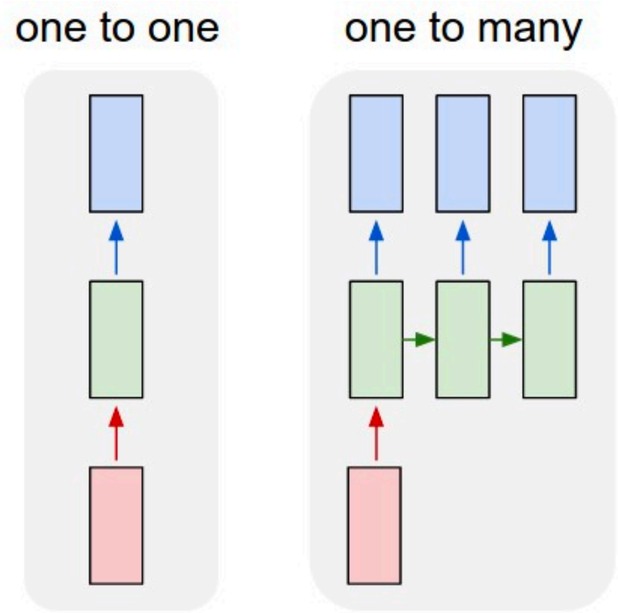
Types of sequence problems

one to one



(From http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

Types of sequence problems



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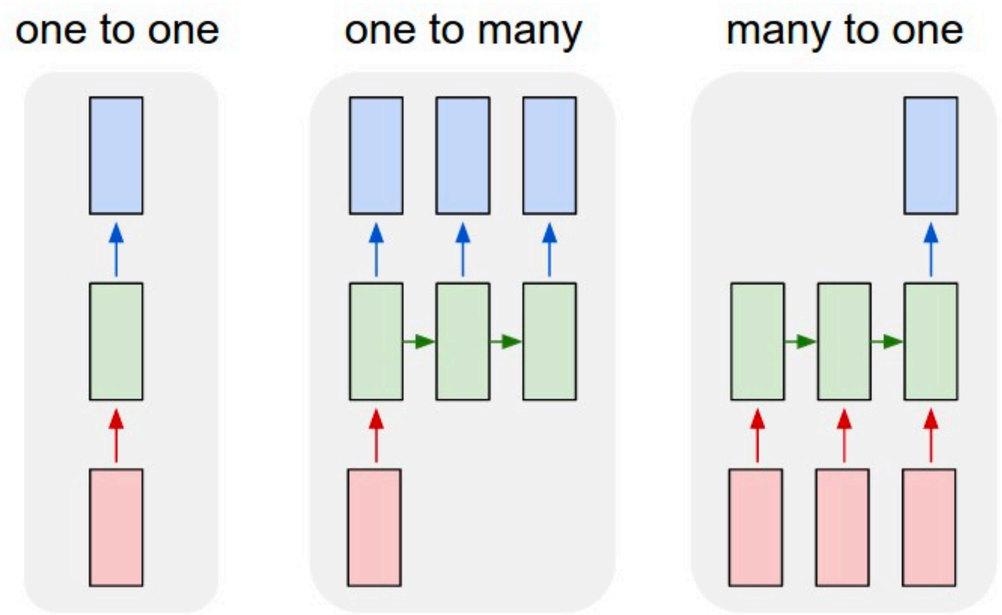

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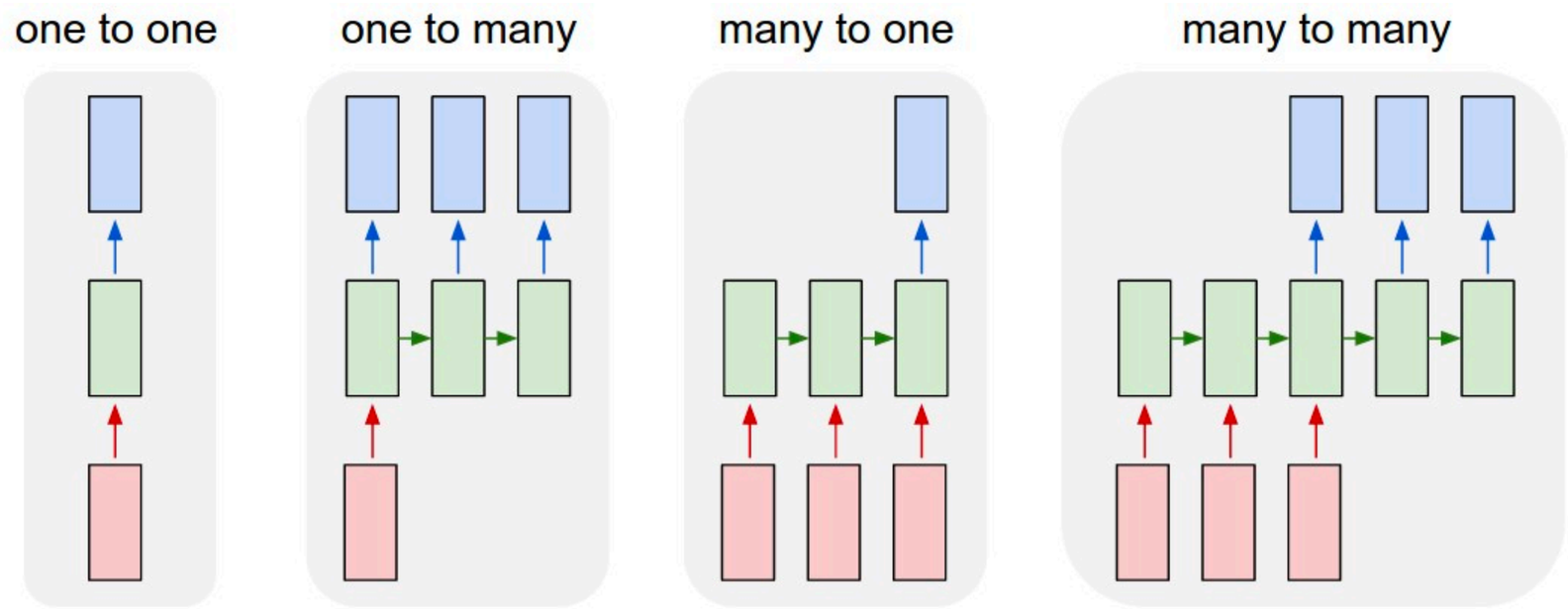

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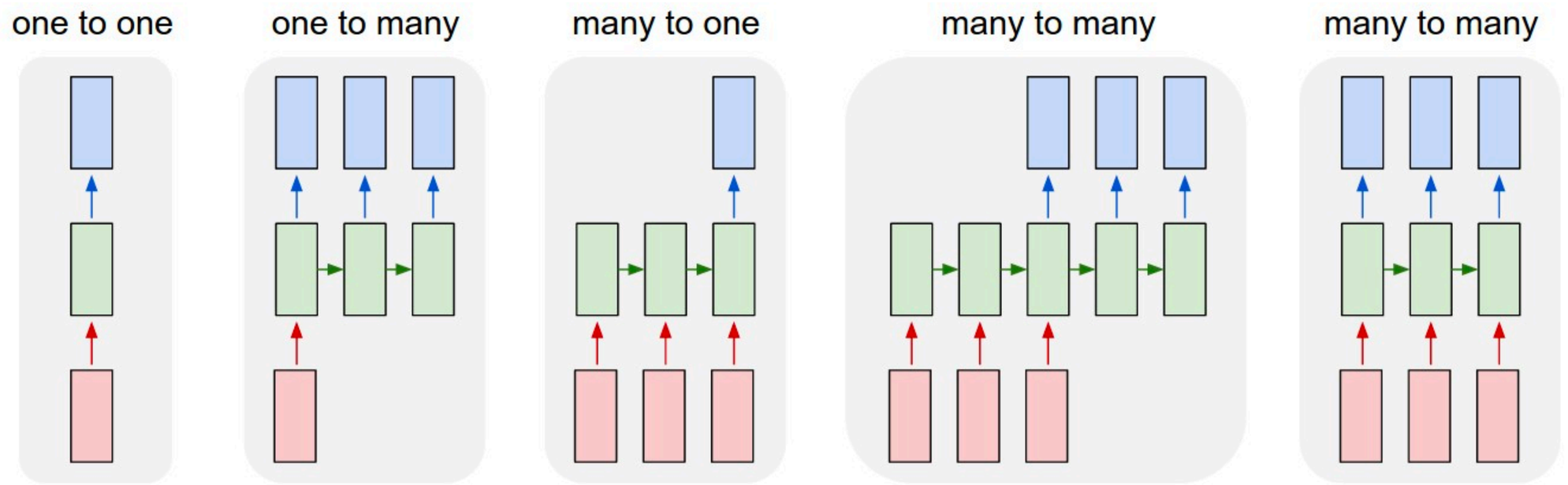

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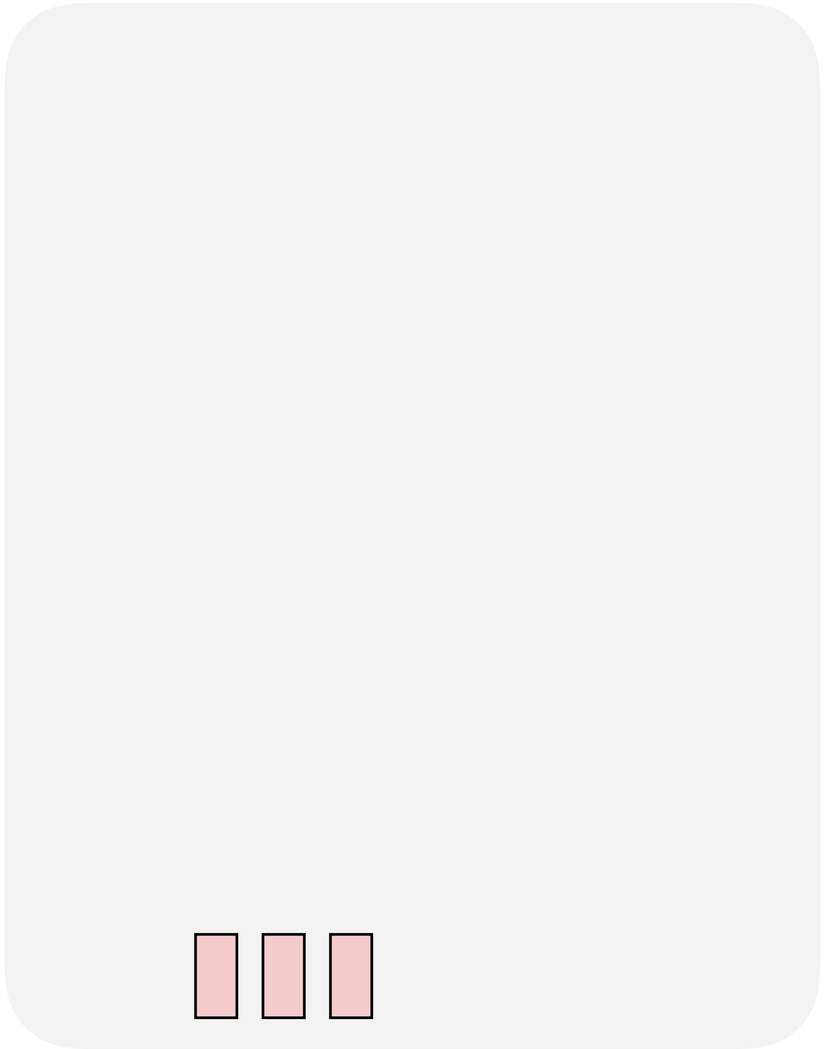
Why not use feedforward networks?

many to many



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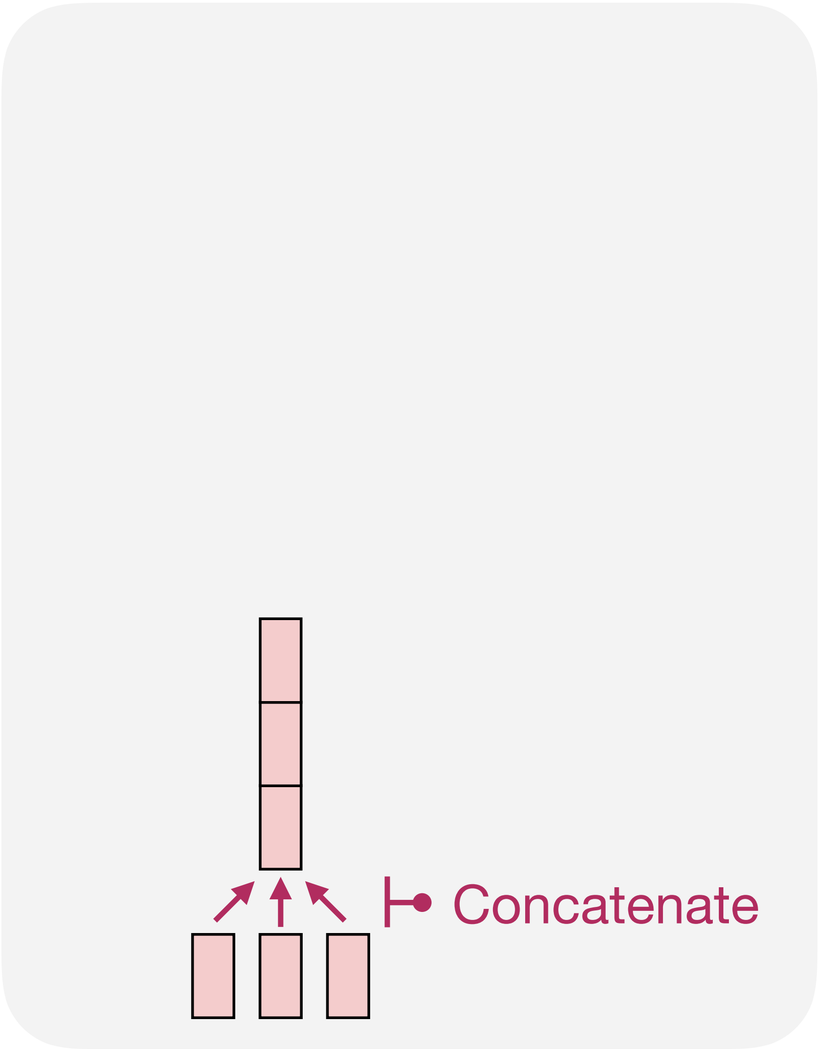

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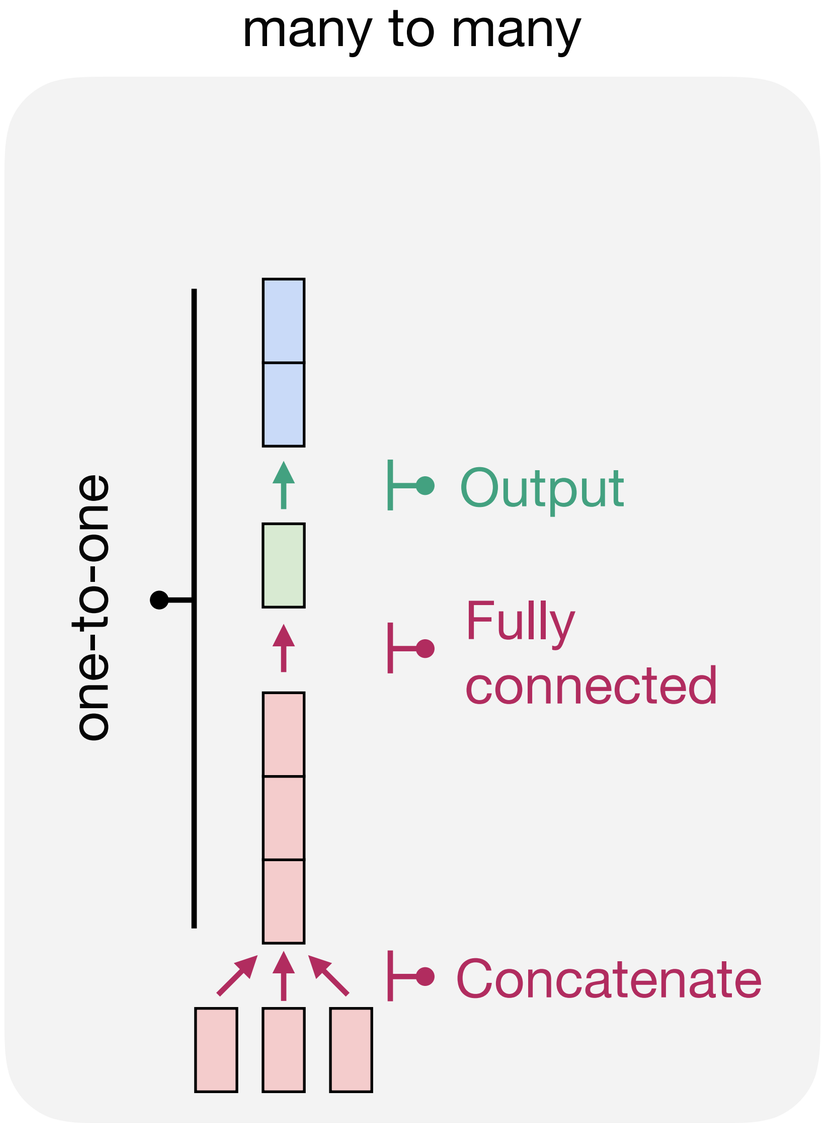

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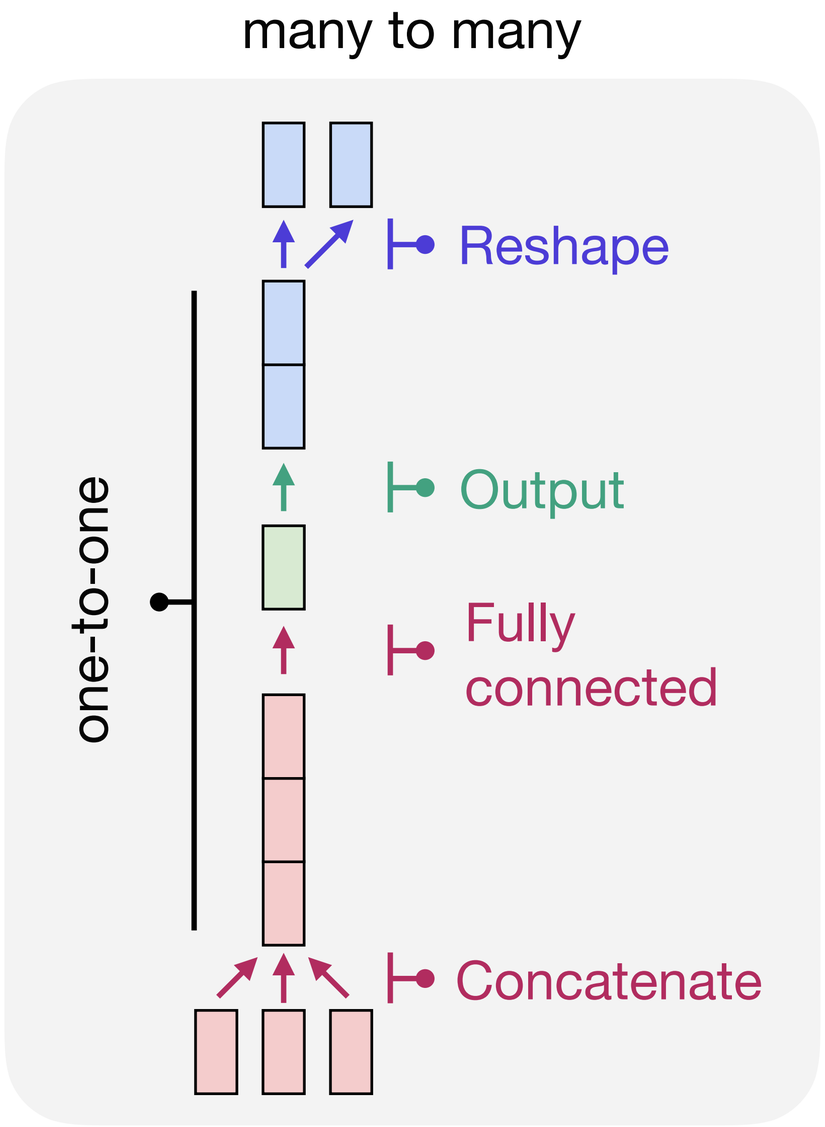
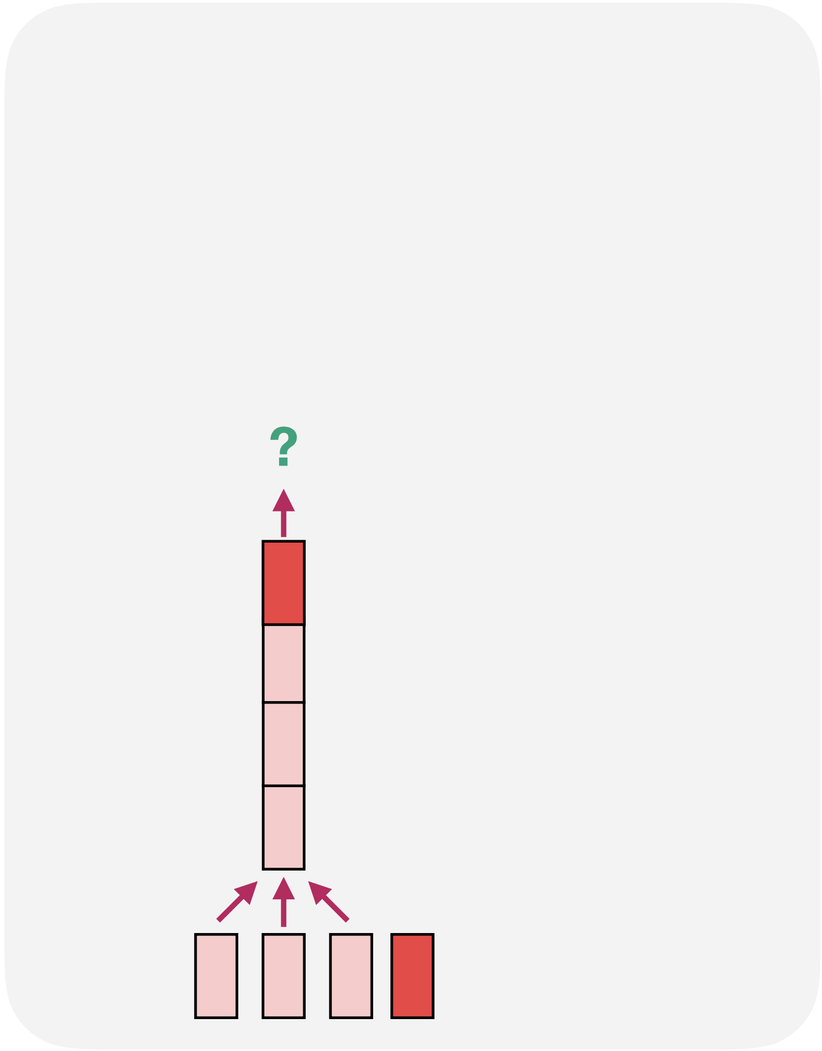


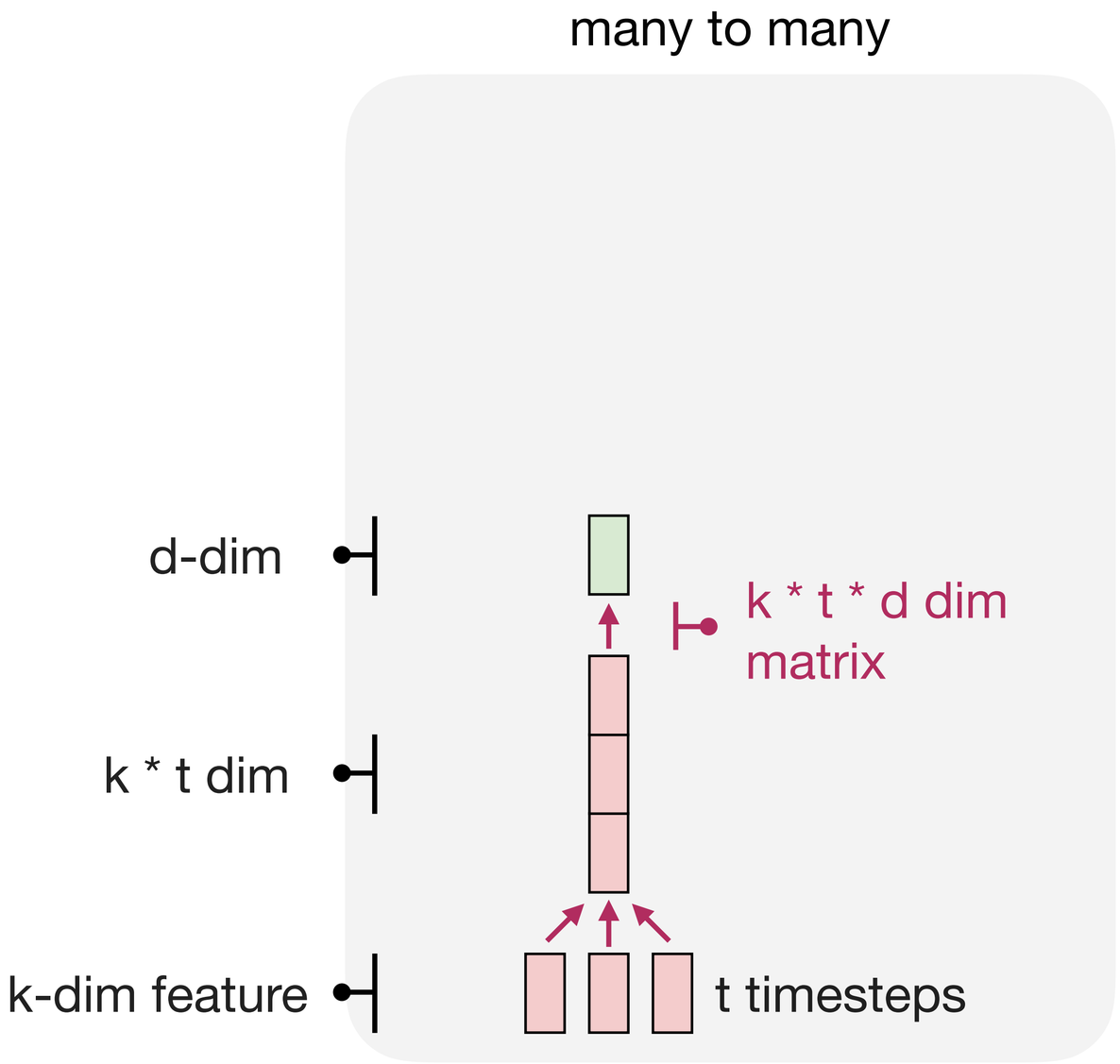
Problem 1: variable length inputs

many to many



Can deal with this by padding all sequences to the max length, but…

Problem 2: memory scaling



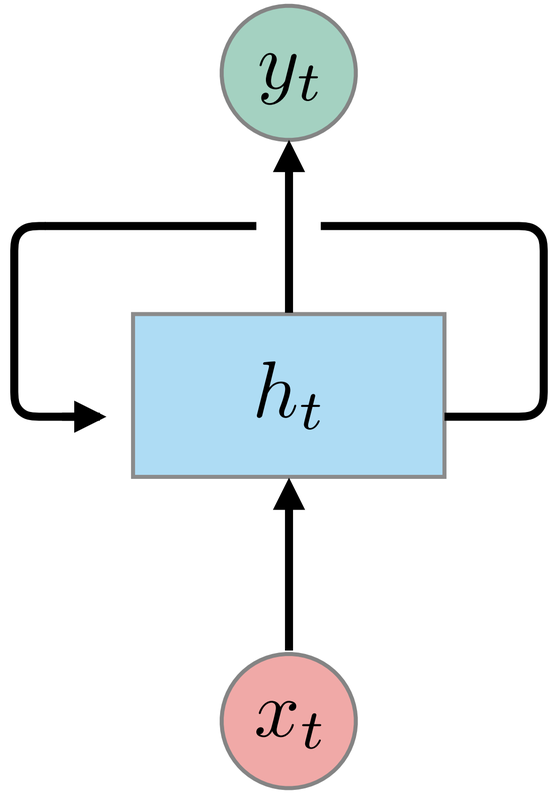
Memory requirement scales linearly in number of timesteps

Agenda

1. Why recurrent neural networks (RNNs)?
2. **RNNs**
3. Problem with RNNs: vanishing gradients
4. Dealing with vanishing gradients

Core idea of RNNs

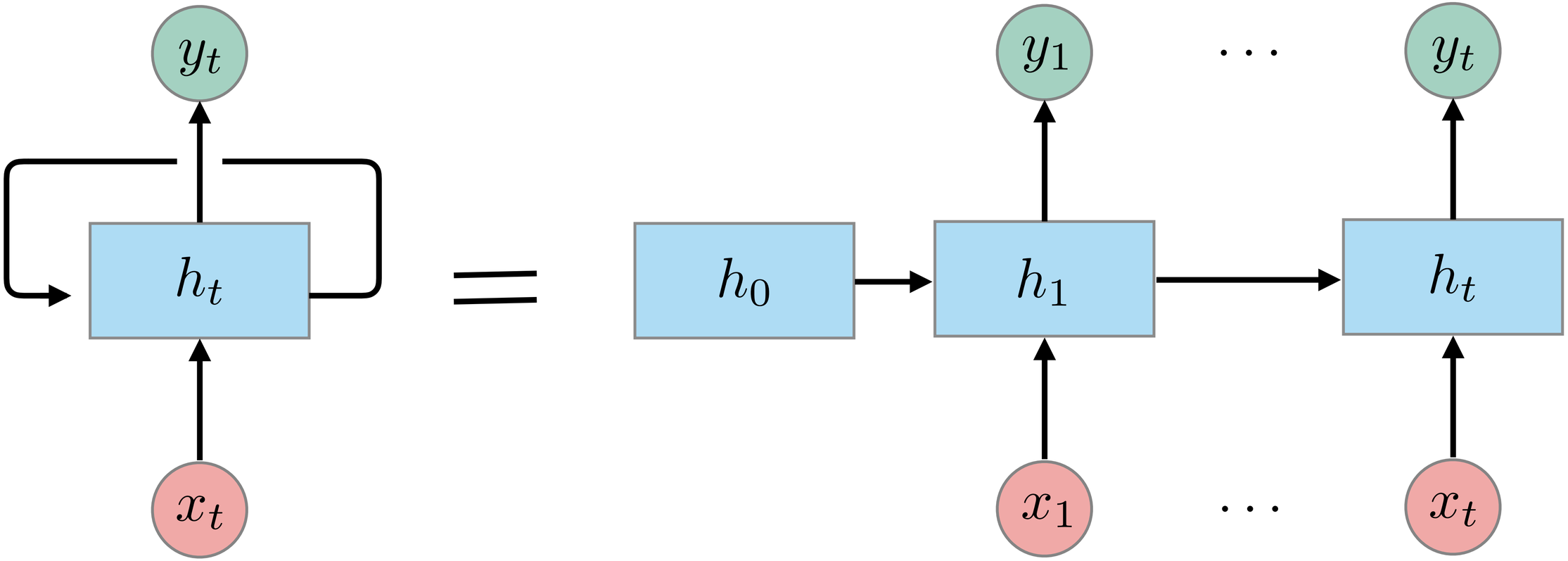
Stateful computation



$$y_t, h_t = f(x_t, h_{t-1})$$

Core idea of RNNs

Stateful computation



$$y_t, h_t = f(x_t, h_{t-1})$$

The RNN in code

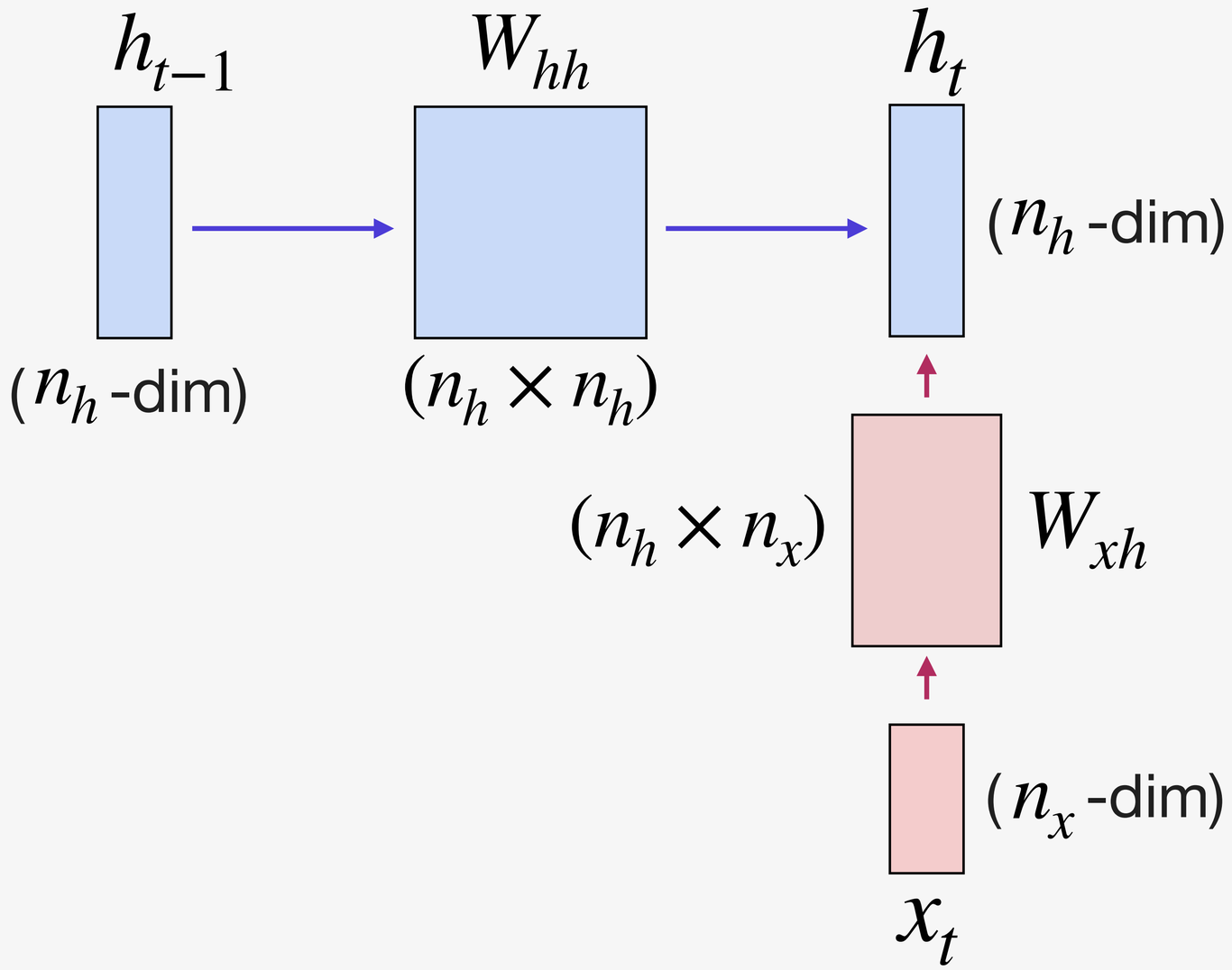
```
class RNN:
    # ...
    def compute_next_h(self, x):
        # Simplest hidden state computation. Will get fancier later.
        h = np.tanh(self.W_hh.dot(self.h) + self.W_xh.dot(x))
        return h

    def step(self, x):
        # Update the hidden state
        self.h = self.compute_next_h(x)
        # Compute the output vector
        y = self.W_hy.dot(self.h)
        return y
```

(*Adapted from* http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

A look at compute_next_h

```
def compute_next_h(self, x):
```



n_h = dim of the RNN

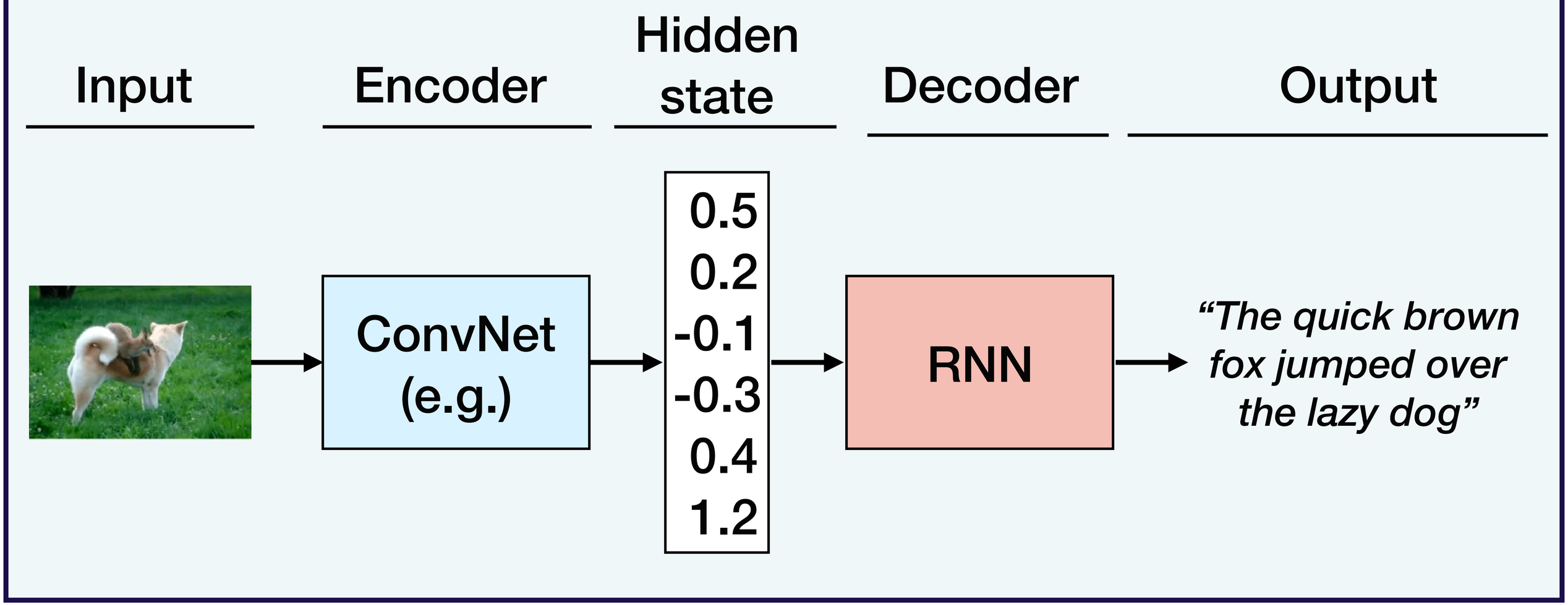
Using RNNs for many-to-one problems

- Prediction is based on the output of the RNN *last timestep*
- Reset the hidden state at the beginning of each sequence

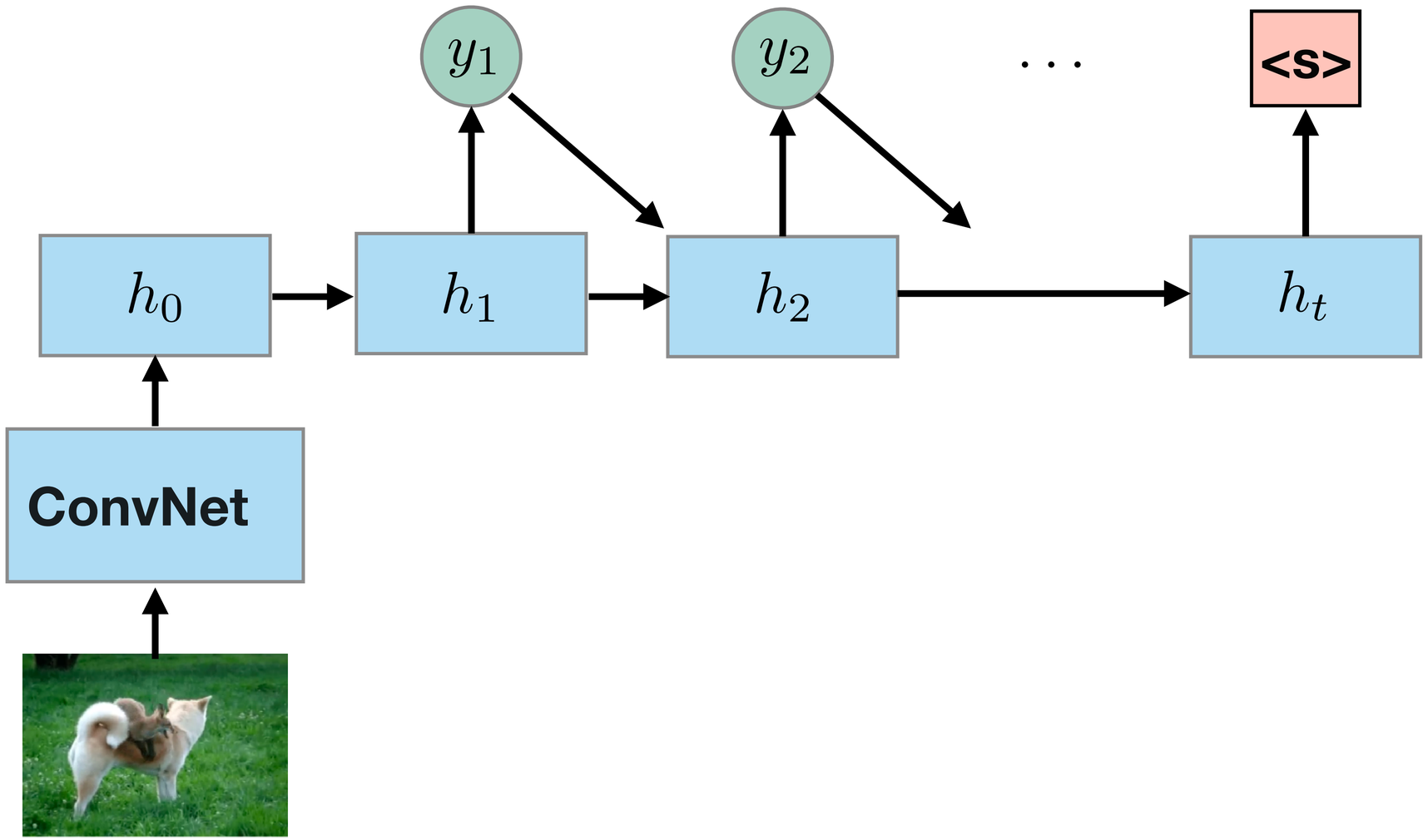
```
X, y = data # X.shape == (100, 7), y.shape == (1,)
T = X.shape[0]
rnn = RNN()
rnn.h.fill(0.0)
for i in range(T-1):
    RNN.step(x[i])
y_hat = RNN.step(x[-1])
```

Using RNNs for <one/many> to many problems

Encoder-decoder architectures

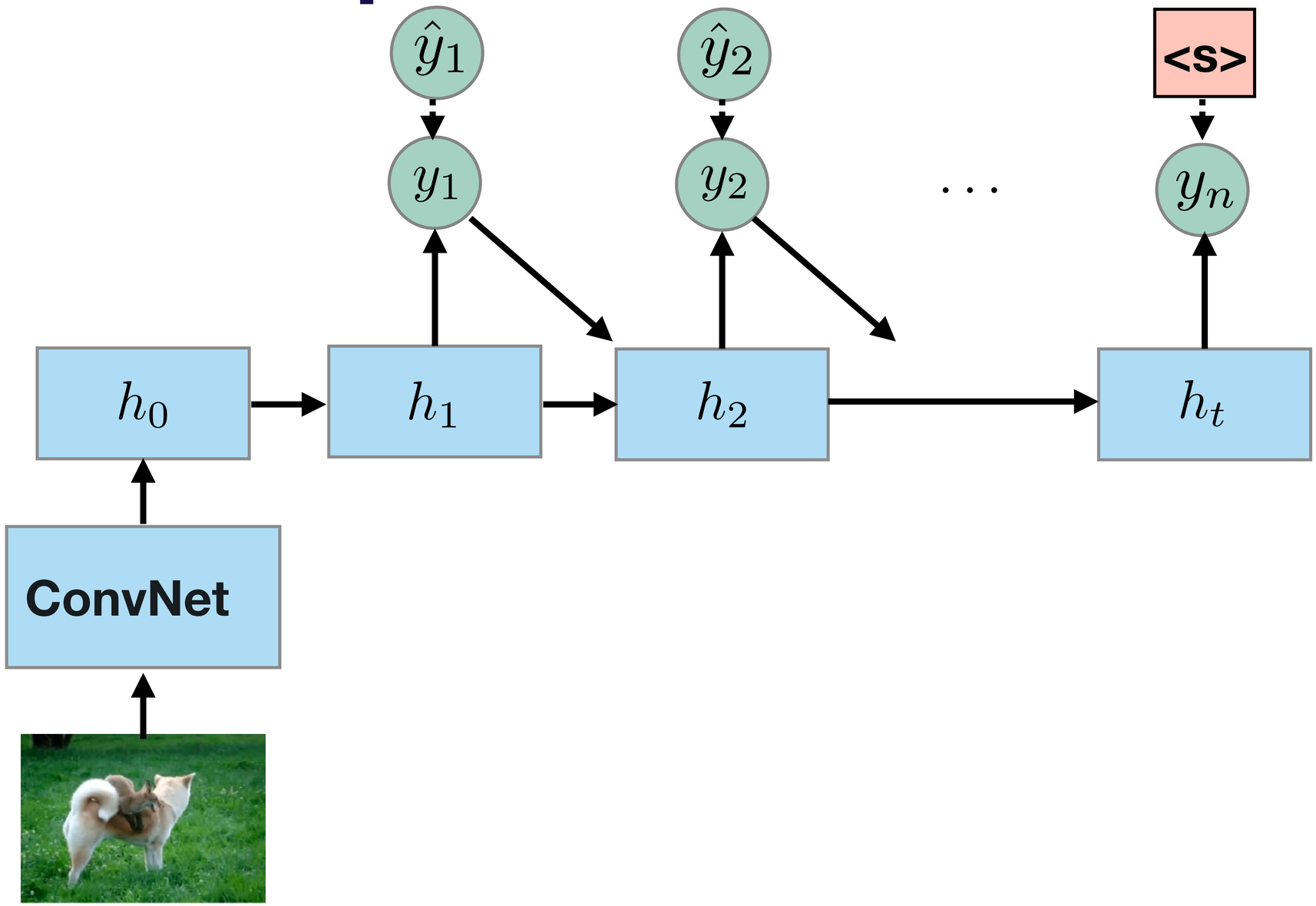


Stop characters



Special character that tells the network to stop generating

Sequence loss functions

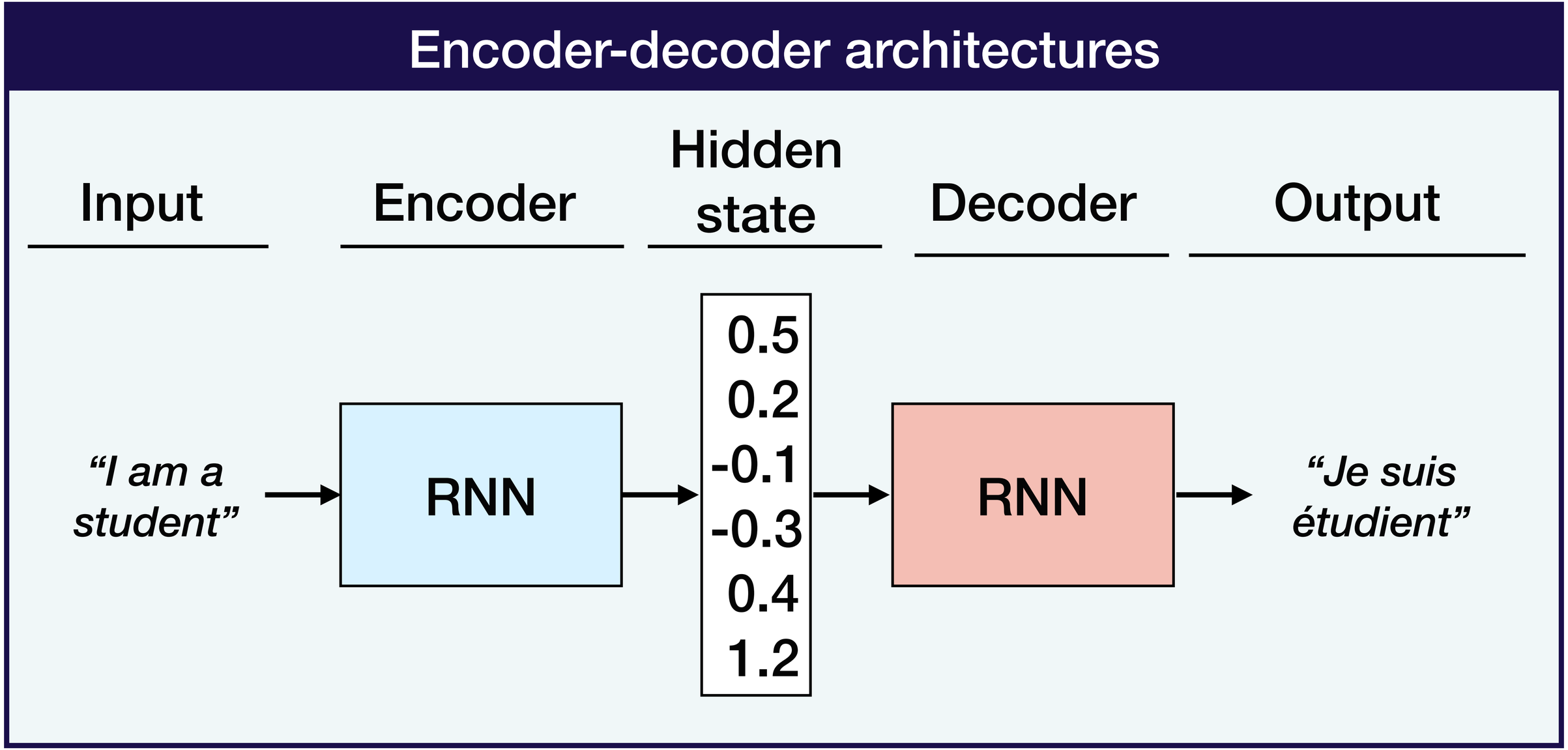


Sum of cross-entropy losses on *all* ground-truth terms from the sequence

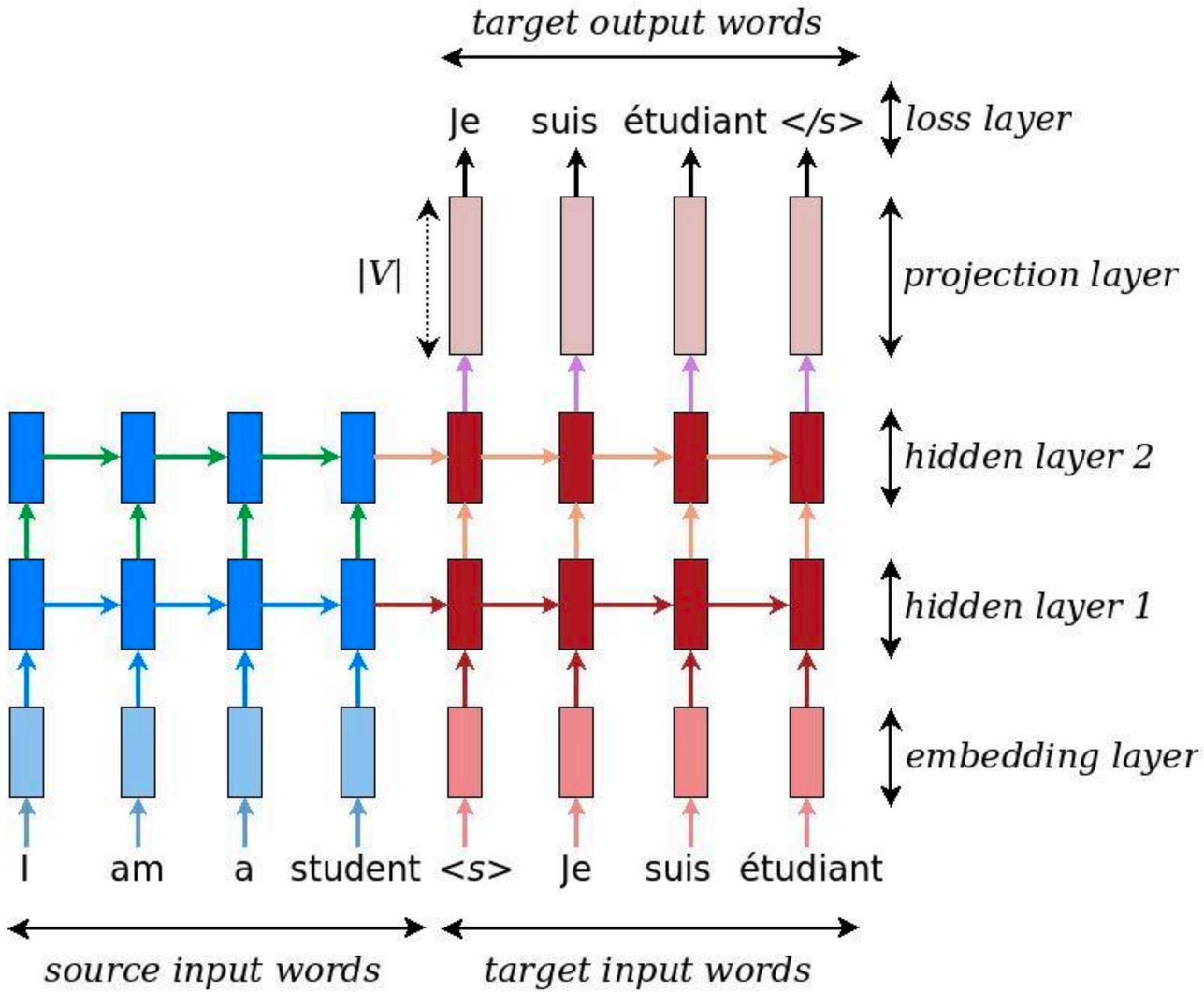
Using RNNs for one to many problems (in code)

```
output_dim = y.shape[0]
encoder = CNN(output_dim)
decoder = RNN()
hidden_state = encoder(image)
decoder.h = hidden_state
outputs = []
output = 0
while output != STOP_CHARACTER:
    output = decoder.step(output)
    outputs.append(output)
```

Using RNNs for <one/many> to many problems



Using RNNs for many->many problems



Using RNNs for many->many problems (in code)

```
encoder = RNN()
decoder = RNN()
output = 0
while output != STOP_CHARACTER:
    output = encoder.step(output)

decoder.h = encoder.h
outputs = []
output = 0
while output != STOP_CHARACTER:
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```
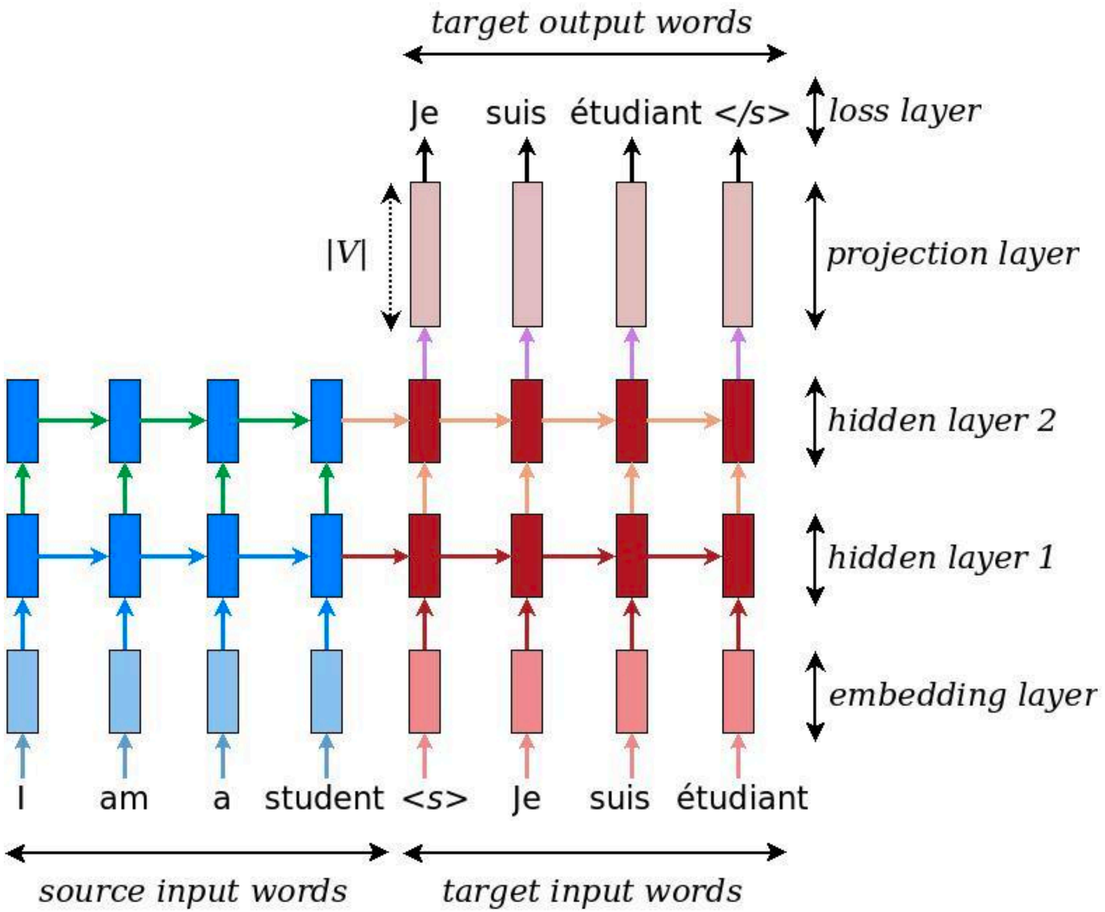
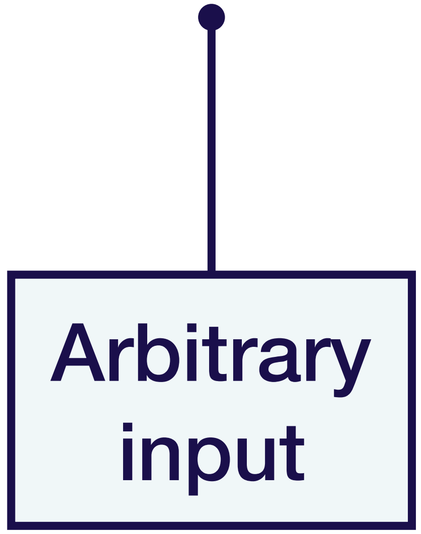

Deep learning with RNNs




```
rnn = RNN()
y_1 = rnn.step(x)
y_2 = rnn.step(y_1)
y_3 = rnn.step(y_2)
y = RNN.step(y_3)
```

RNNs describe programs

$$y_t, h_t = f(x_t, h_{t-1})$$



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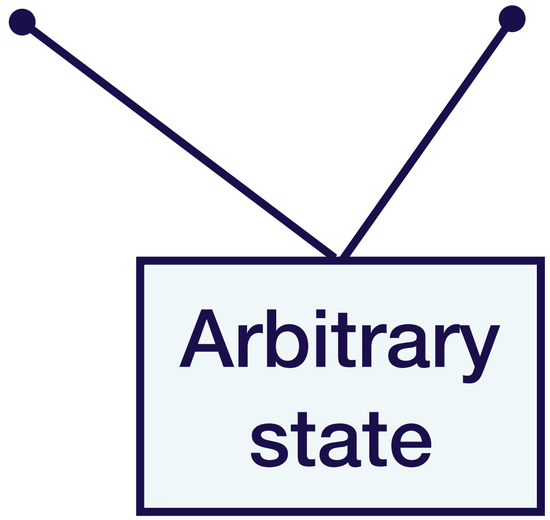

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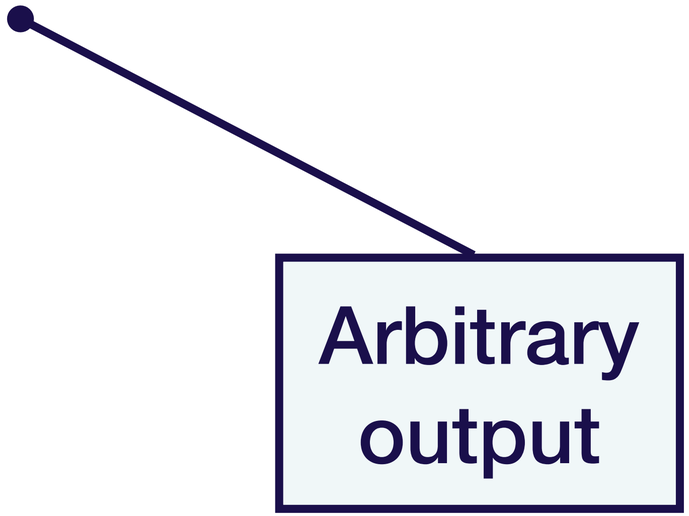


RNNs describe programs

$$y_t, h_t = f(x_t, h_{t-1})$$

Fact: RNNs are Turing complete
(i.e., you can model any program
with an arbitrarily large RNN)

http://binds.cs.umass.edu/papers/1995_Siegelmann_Science.pdf

Agenda

1. Why recurrent neural networks (RNNs)?
2. RNNs
3. **Problem with RNNs: vanishing gradients**
4. Dealing with vanishing gradients

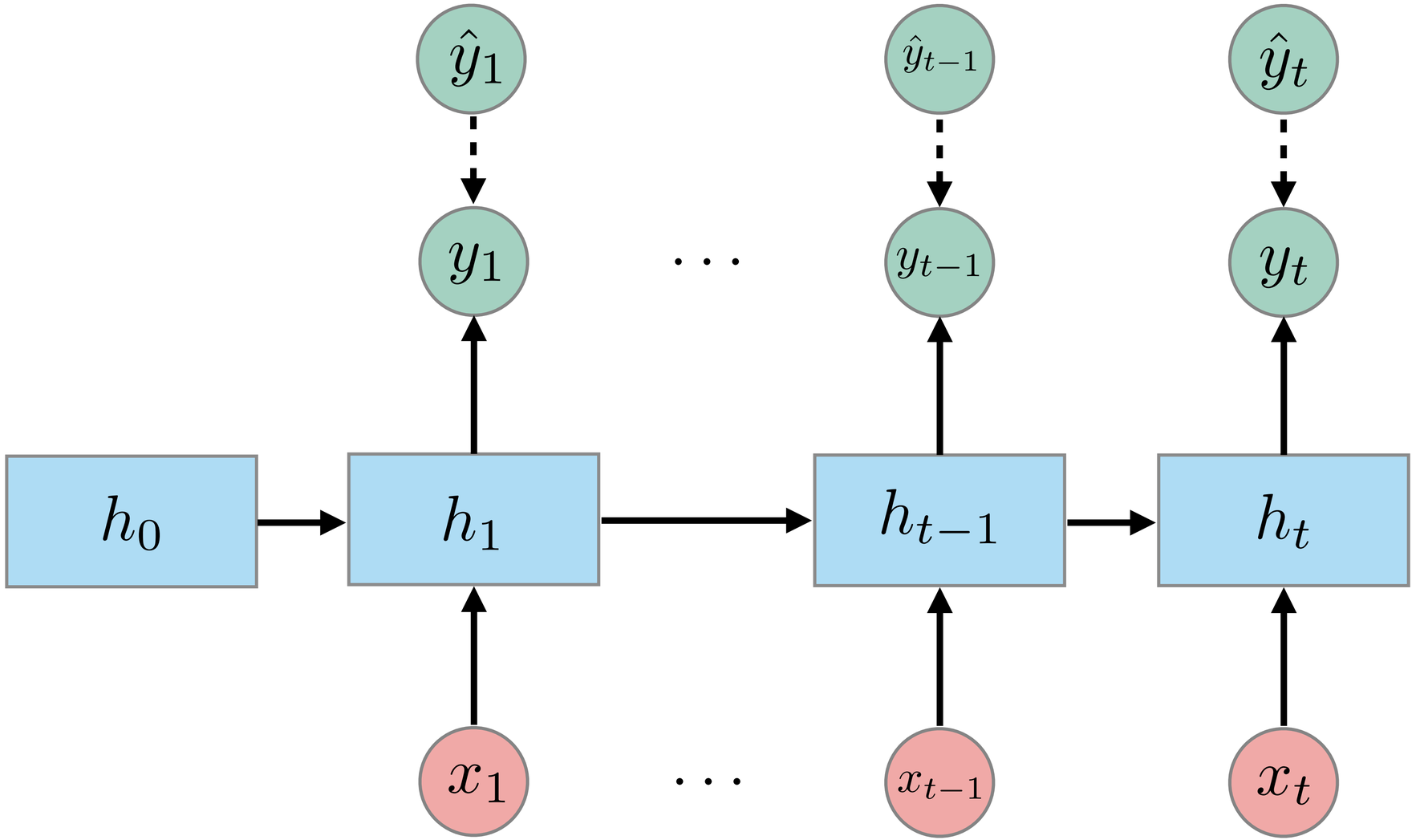
RNN Desiderata

- Goal: handle sequences
- In particular, long sequences (where linear scaling is an issue)
- Connect events from the past to outcomes in the future
  - i.e., *Long-term dependencies*
  - e.g., remember the name of a character from the first sentence

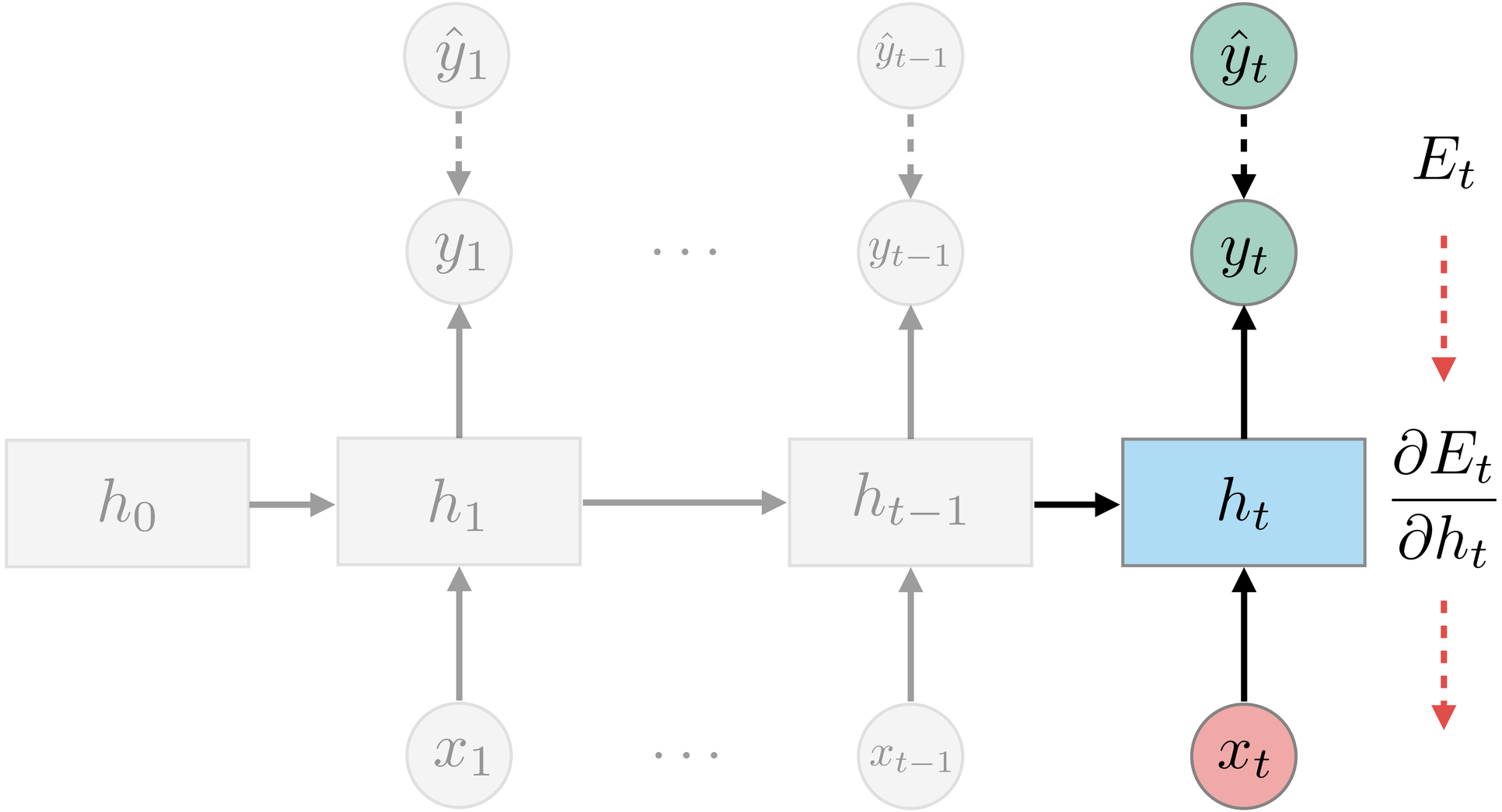
Vanilla RNNs: the reality

- Can’t handle more than 10-20 timesteps
- Longer-term dependencies get lost
- Why? ***Vanishing gradients***

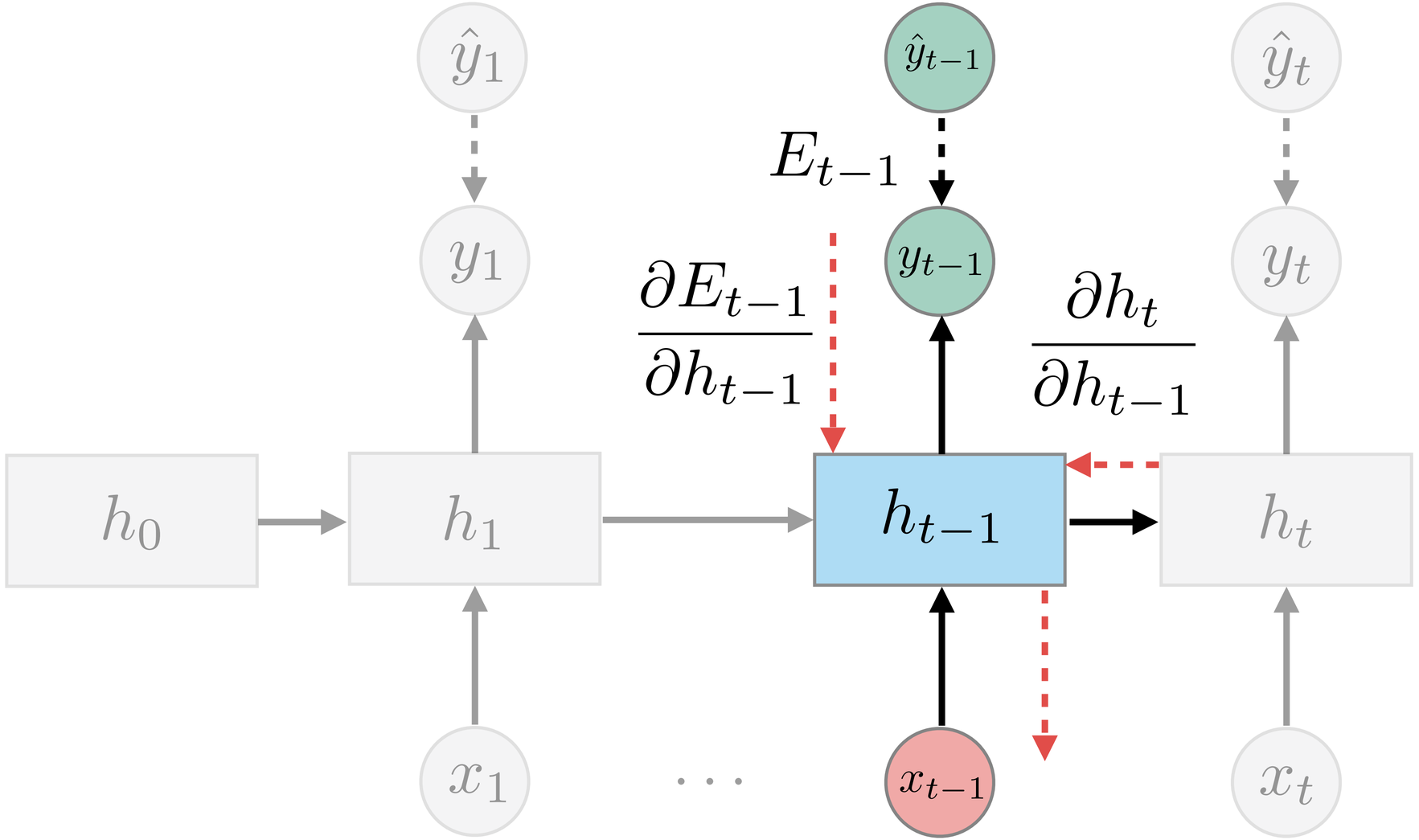
Gradients in RNNs: backpropogation through time



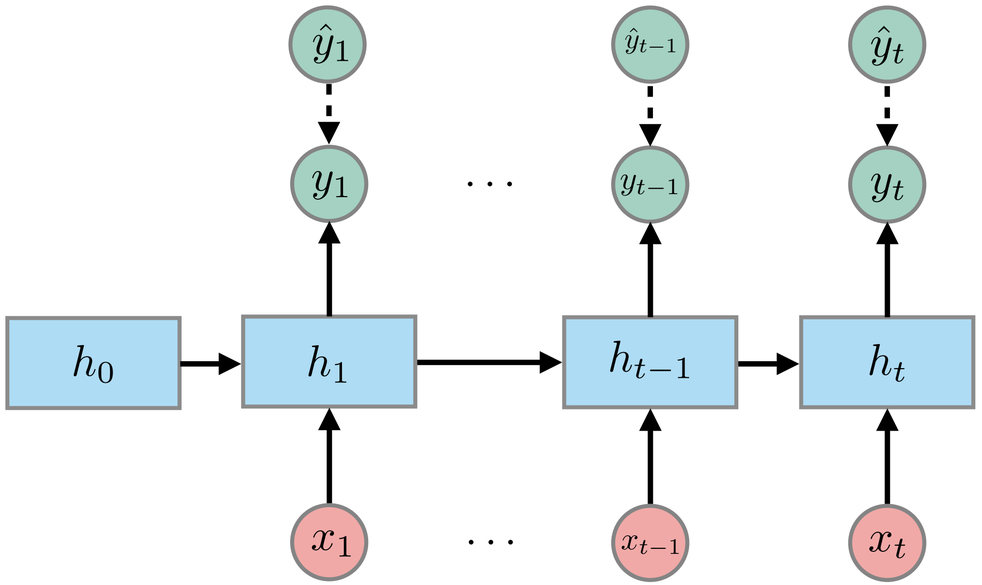
Gradients in RNNs: backpropogation through time



Gradients in RNNs: backpropogation through time



Gradients in RNNs: backpropogation through time



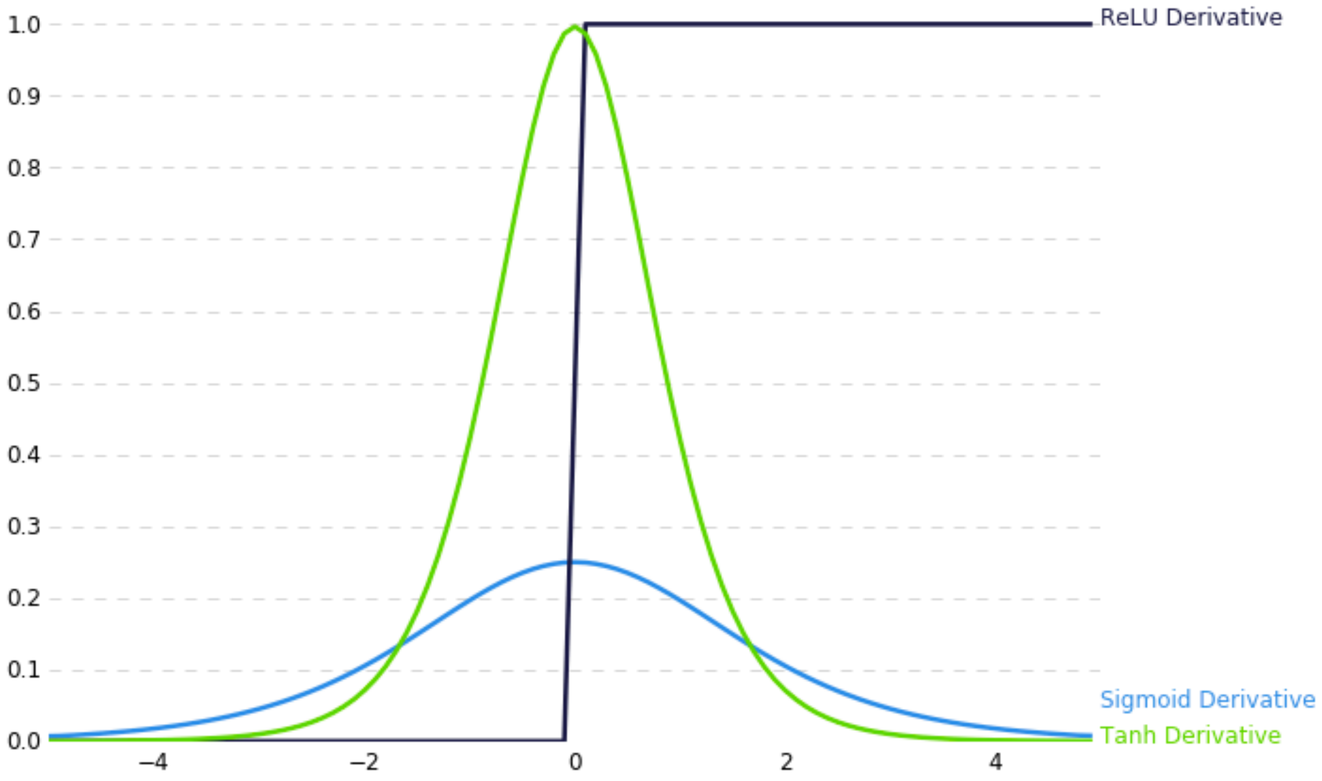
$\frac{\partial E_t}{\partial W_{hh}}$ depends on each $\frac{\partial h_j}{\partial h_{j-1}}$

Recall $h_j = \tanh(W_{hh}h_{j-1} + W_{xh}x_j)$

So each $\frac{\partial h_j}{\partial h_{j-1}}$ introduces a $\tanh'$

Back to vanishing gradients

Derivatives of common activation functions



- sigmoid and tanh have derivatives << 1 near saturation
- At each step magnitude of gradients tends to decrease
- After enough steps gradients are too small
- (ReLU RNNs often have the opposite problem - exploding gradients)

Agenda

1. Why recurrent neural networks (RNNs)?
2. RNNs
3. Problem with RNNs: vanishing gradients
4. **Dealing with vanishing gradients**

Intro to LSTMs

Recall vanilla RNNs

```
class RNN:
    # ...
    def compute_next_h(self, x):
        # Simplest hidden state computation. Will get fancier later.
        h = np.tanh(self.W_hh.dot(self.h) + self.W_xh.dot(x))
        return h

    def step(self, x):
        # ...
```

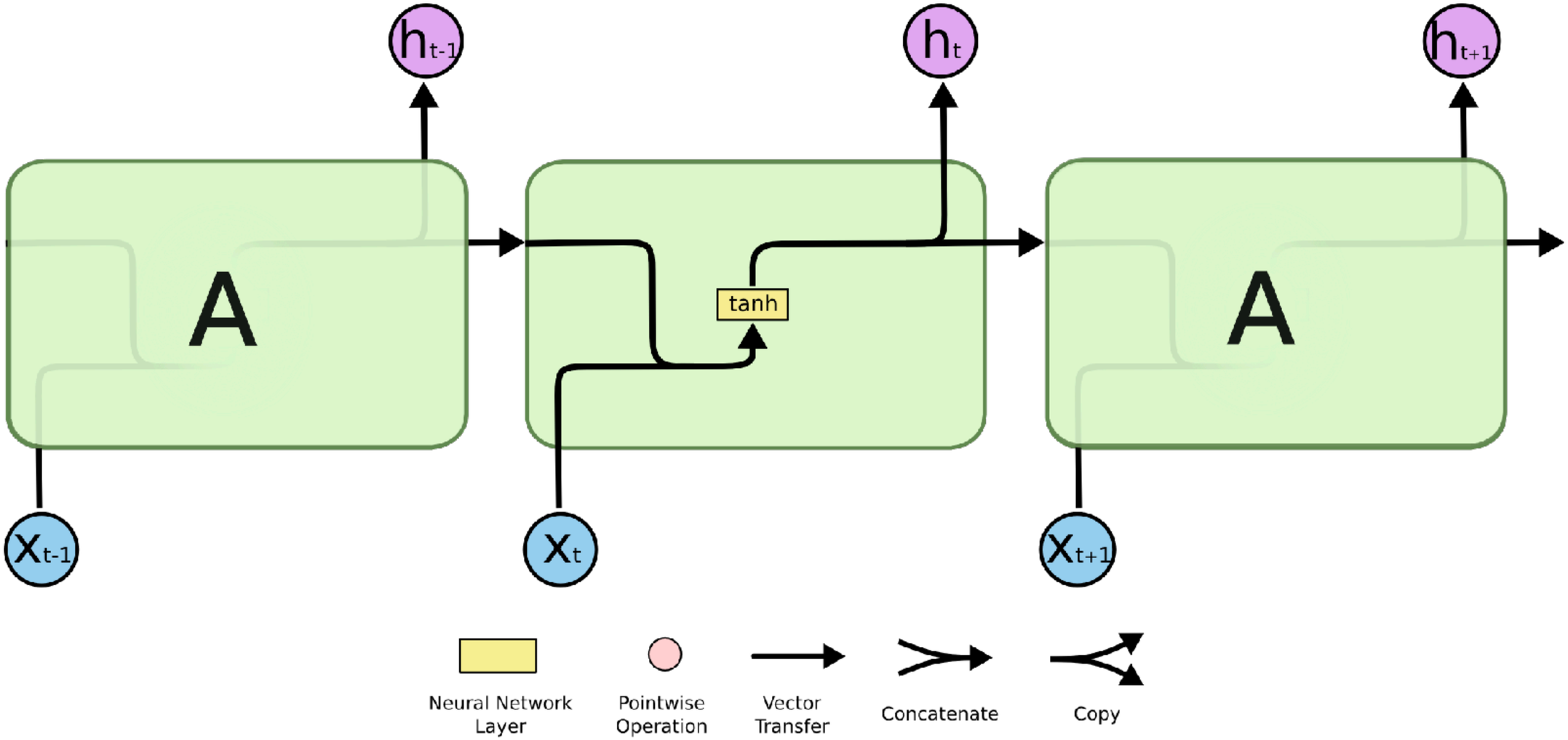
Intro to LSTMs

Idea: use a compute_next_h that preserves gradients

```
class LSTM(RNN):
    # ...
    def compute_next_h(self, x):
        h = lstm(x, self.h)
        # or gru(x, self.h), etc.
        return h
    # ...
```

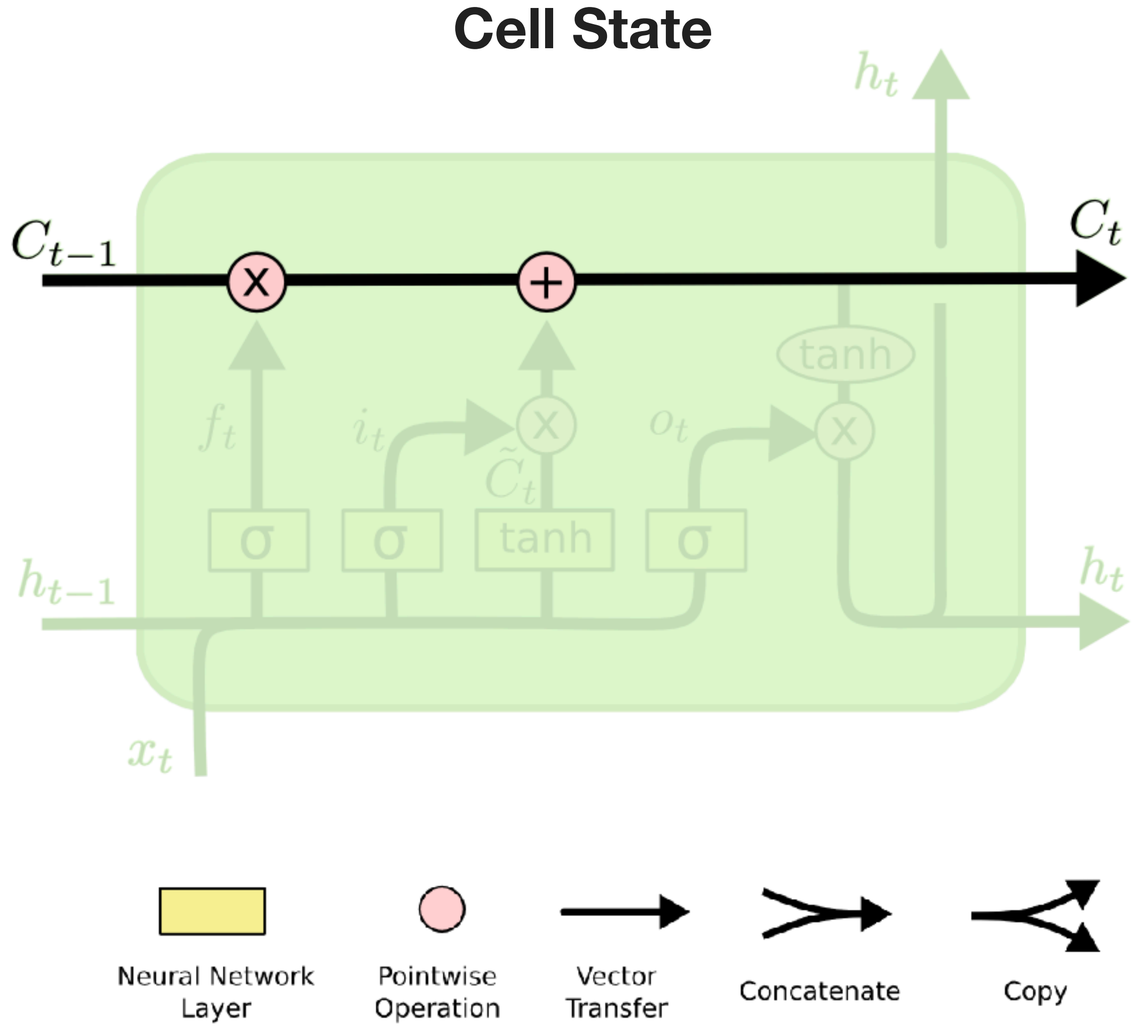
For more info, see http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Visualization of vanilla RNNs



From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

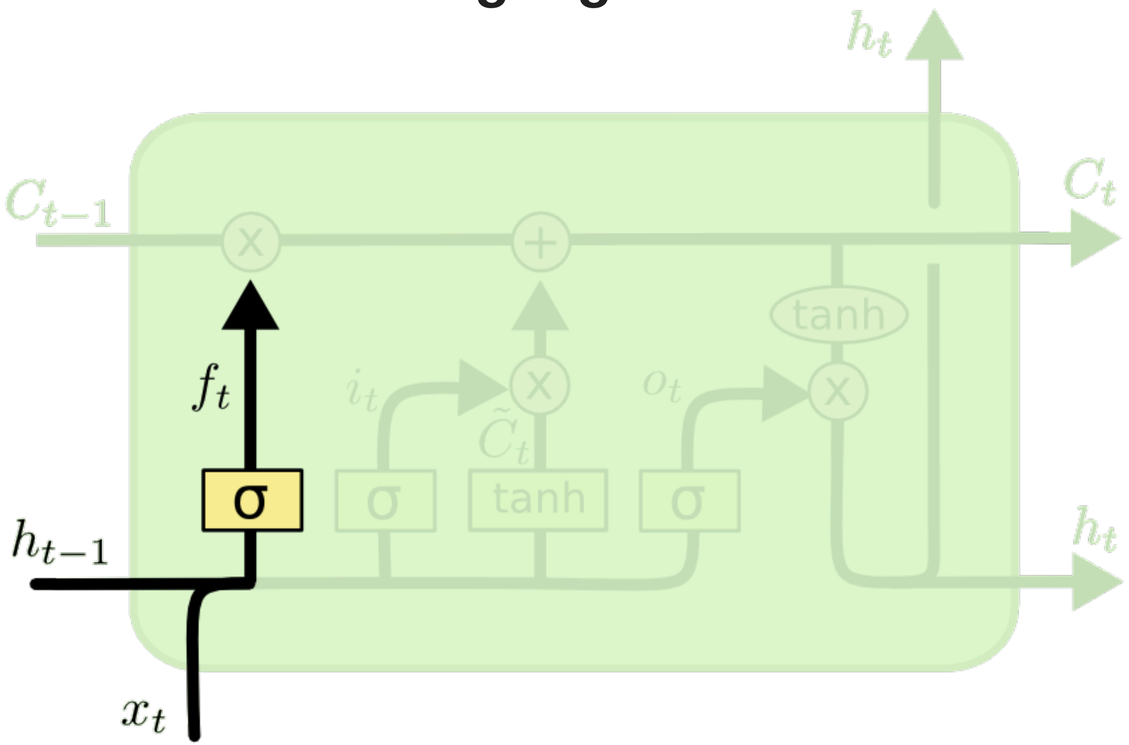
Building up to LSTMs



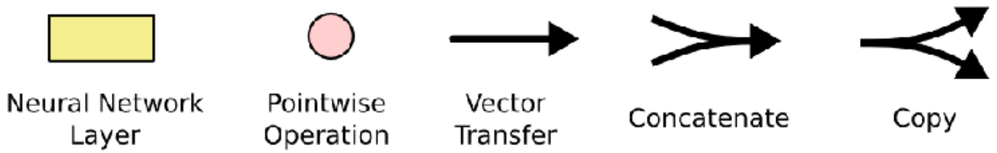
From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Building up to LSTMs

Forget gate



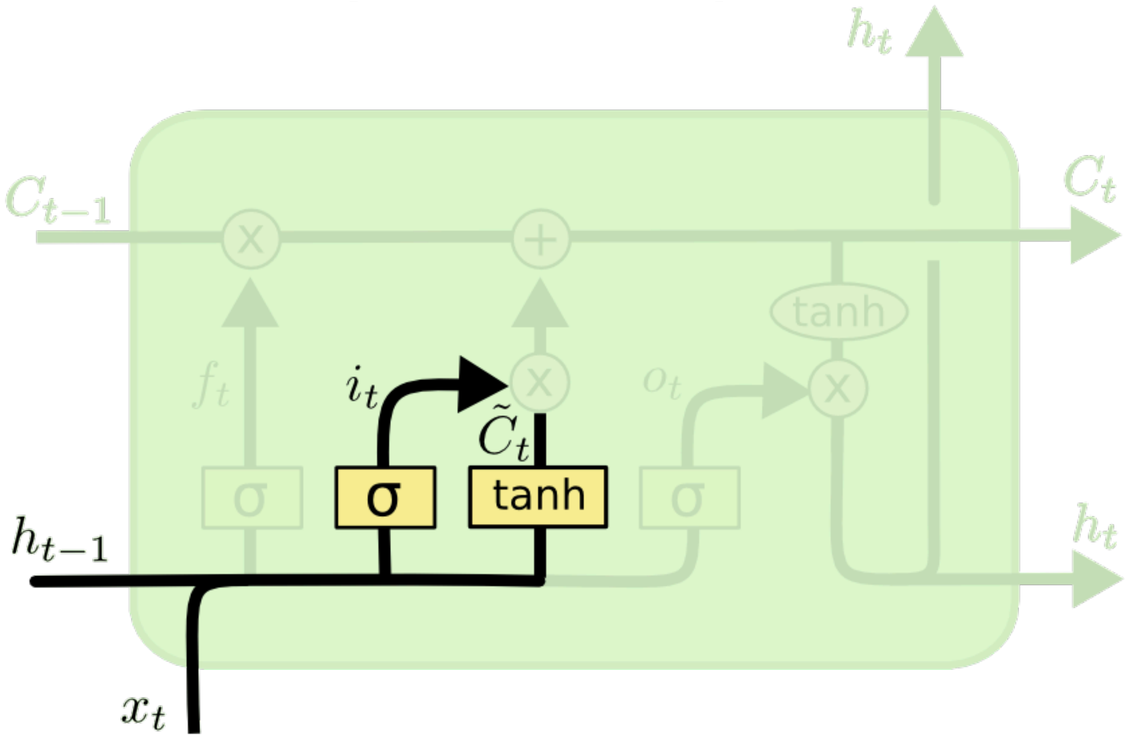
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$



From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

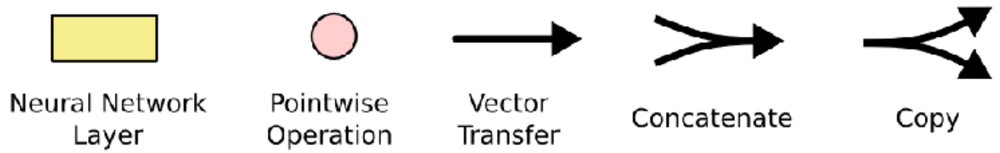
Building up to LSTMs

Proposed state update



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

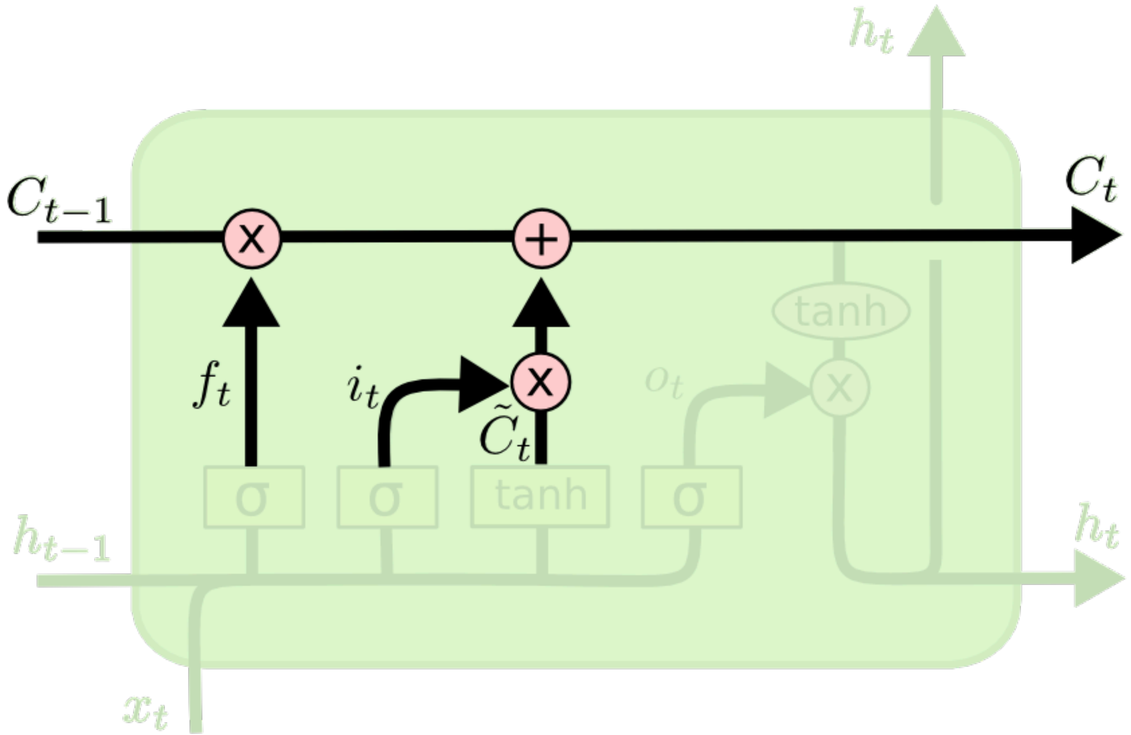
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$



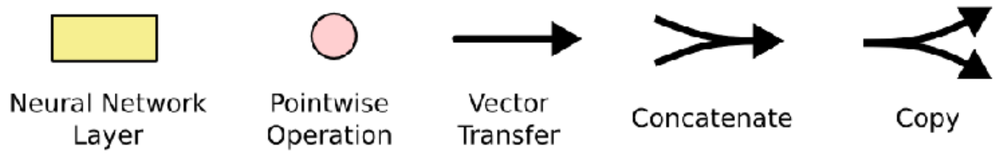
From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Building up to LSTMs

Update the state



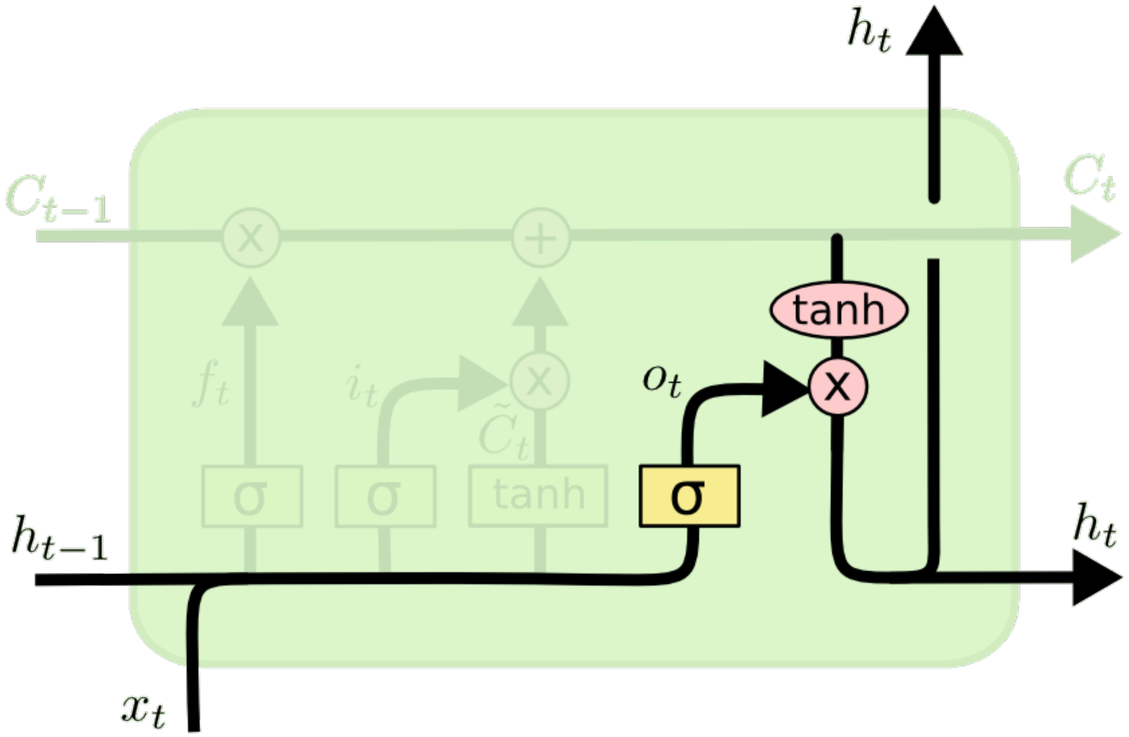
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$



From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

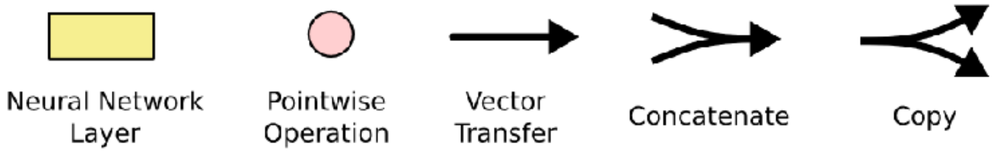
Building up to LSTMs

Decide what to output



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

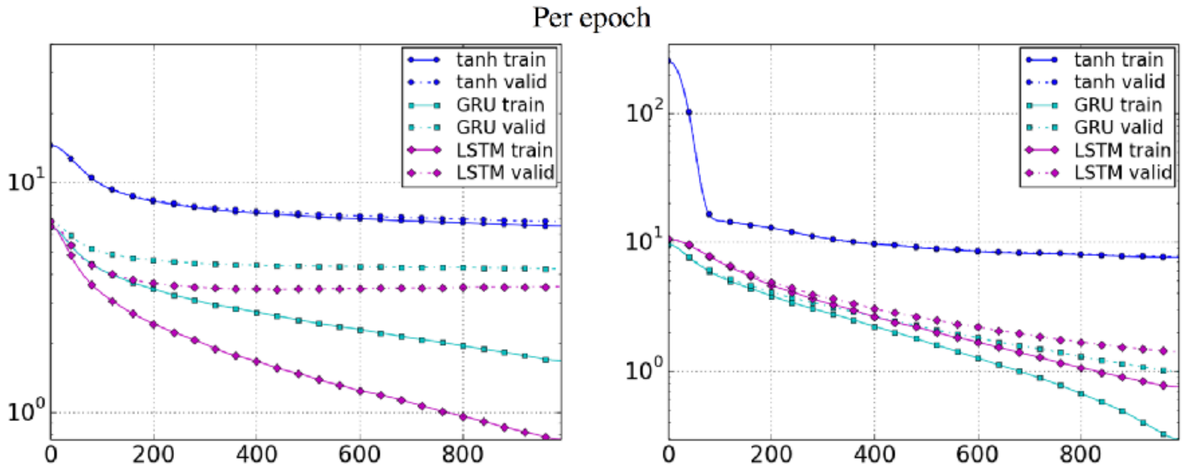
$$h_t = o_t * \tanh\left(C_t\right)$$



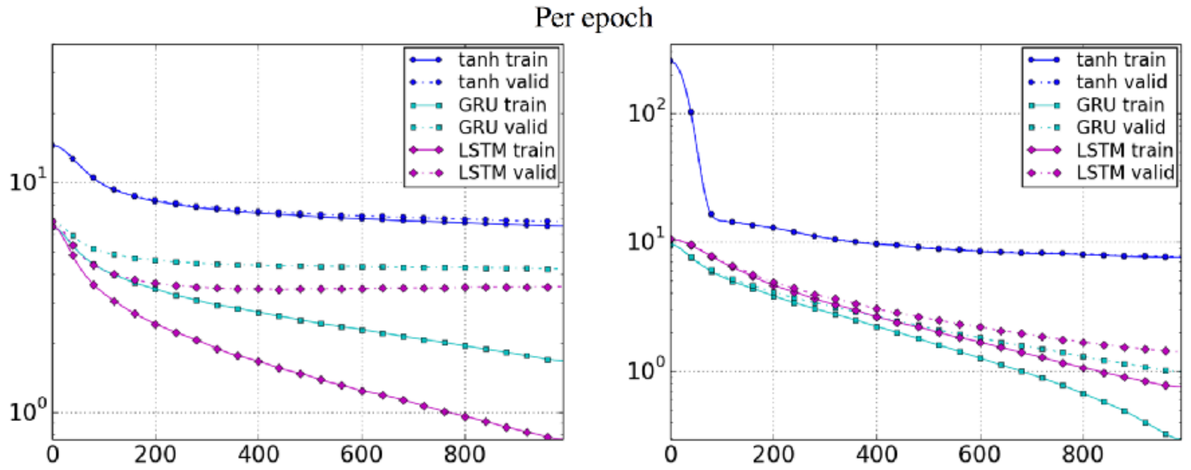
From http://colah.github.io/posts/2015-08-Understanding-LSTMs/

How well do LSTMs work?

Music modeling



Speech signal modeling



Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling (Chung et al.)

What about GRUs, etc?

LSTM: A Search Space Odyssey
Greff, et al.

- 9 LSTM variants (including GRU)
- 3 datasets
- **Conclusion:** Hard to beat regular LSTM

An Empirical Exploration of Recurrent Neural Network Architectures
(Jozefowicz, Zaremba, Sutskever)

- 10,000 architectures
- 3 datasets
- **Conclusion:** GRUs > LSTMs. Some architectures better than GRU (but only slightly)

What about GRUs, etc?

My advice

- LSTMs work well for most tasks
- May also try GRUs if LSTMs are not performing well
- Not usually worth considering other LSTM variants

Other ways of dealing with vanishing/exploding gradients

- Identity initialization & ReLU
- Gradient clipping
- Skip connections
- Leaky connections
- Attention
- Explicit memory networks
  (e.g., Neural Turing Machines)

Conclusion

- Encoder / decoder architectures can model arbitrary (one-to-many, many-to-one, and many-to-many) sequence problems
- Combined with LSTMs, great default option for tasks with sequential data

Where to learn more?

- Andrej Karpathy's blog post on RNNs:
  http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Chris Olah's blogpost on LSTMs:
  http://colah.github.io/posts/2015-08-Understanding-LSTMs/