Sequence Modeling by RNNs

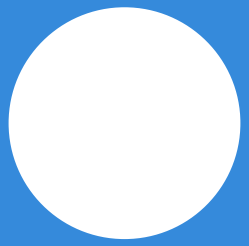
textbook: Deep Learning, An MIT Press book

http://www.deeplearningbook.org/

slides by: Ava Soleimany, MIT

MIT EECS

Given an image of a ball,
can you predict where it will go next?



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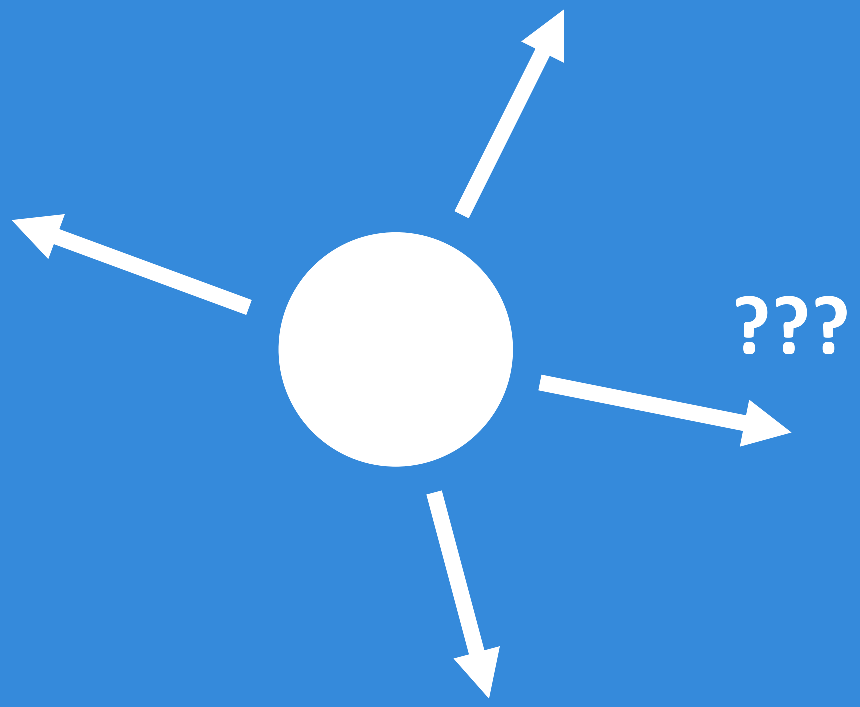

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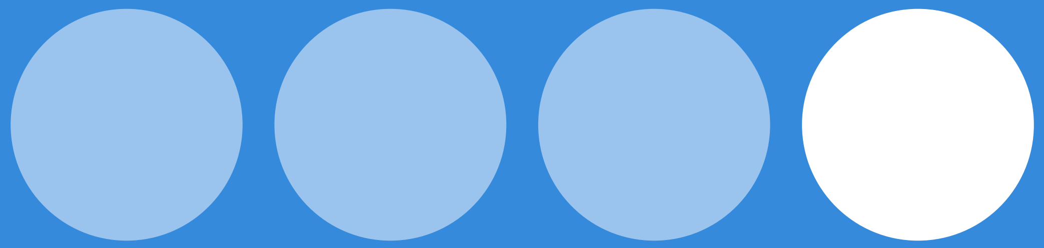

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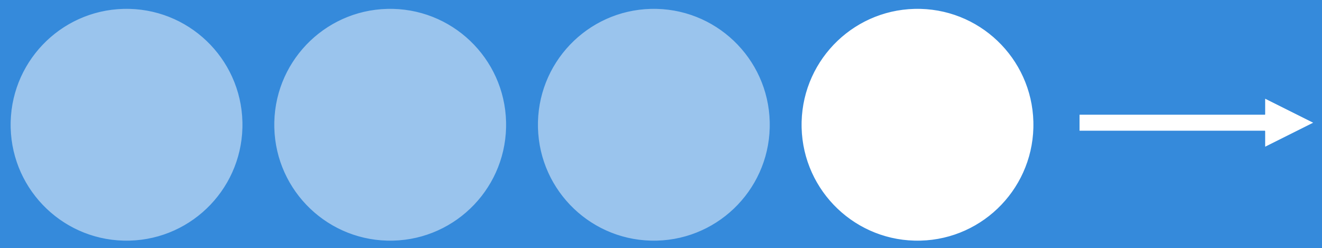

Sequences in the wild

Audio

Sequences in the wild

Introduction to Deep Learning

Text

A Sequence Modeling Problem: Predict the Next Word

A sequence modeling problem: predict the next word

"This morning I took my cat for a walk."

Adapted from H. Suresh, 6.S191 2018

A sequence modeling problem: predict the next word

"This morning I took my cat for a walk."

given these words

Adapted from H. Suresh, 6.S191 2018

A sequence modeling problem: predict the next word

"This morning I took my cat for a walk."

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Idea #1: use a fixed window

"This morning I took my cat for a walk."

given these two words

predict the next word

Adapted from H. Suresh, 6.S191 2018

Idea #1: use a fixed window

"This morning I took my cat for a walk."

given these two words

predict the next word

One-hot feature encoding: tells us what each word is

[1 0 0 0 0 0 1 0 0 0]

for a

prediction

Adapted from H. Suresh, 6.S191 2018

Problem #1: can't model long-term dependencies

"**Sweden** is where I grew up, but I now live in **Berlin**. I speak fluent ___."

We need information from **the distant past** to accurately predict the correct word.

Adapted from H. Suresh, 6.S191 2018

Idea #2: use entire sequence as set of counts

"This morning I took my cat for a"

↓

"bag of words"

[0 1 0 0 1 0 0 ... 0 0 1 1 0 0 0 1]

↓

prediction

Adapted from H. Suresh, 6.S191 2018

Problem #2: counts don't preserve order

The food was good, not bad at all.

vs.

The food was bad, not good at all.

Adapted from H. Suresh, 6.S191 2018

Idea #3: use a really big fixed window

"This morning I took my cat for a walk."

given these words

predict the next word

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

morning I took this cat

↓

prediction

Adapted from H. Suresh, 6.S191 2018

Problem #3: no parameter sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

Adapted from H. Suresh, 6.S191 2018

Problem #3: no parameter sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

[0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 ...]

this morning

Adapted from H. Suresh, 6.S191 2018

Problem #3: no parameter sharing

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

this morning took the cat

Each of these inputs has a **separate parameter:**

[0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 ...]

this morning

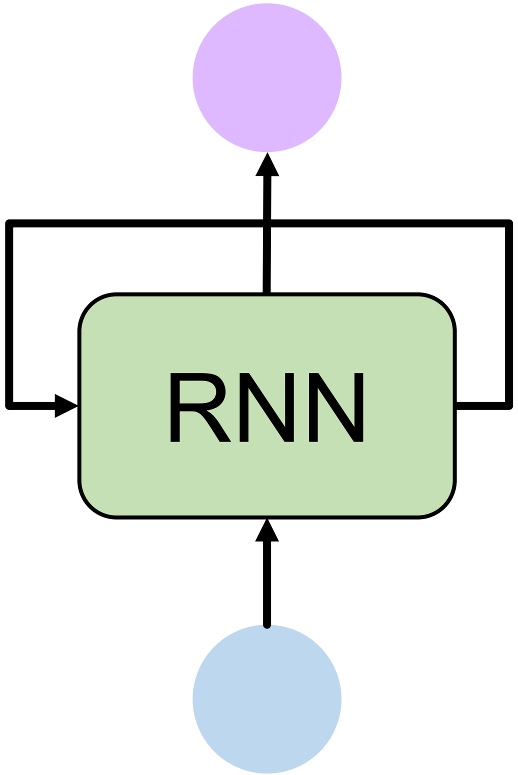
Things we learn about the sequence **won't transfer** if they appear **elsewhere** in the sequence.

Adapted from H. Suresh, 6.S191 2018

Sequence modeling: design criteria

To model sequences, we need to:

1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**
4. **Share parameters** across the sequence

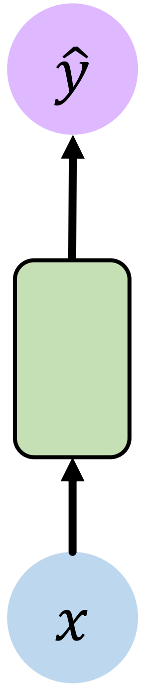


Today: **Recurrent Neural Networks (RNNs)** as an approach to sequence modeling problems

Adapted from H. Suresh, 6.S191 2018

Recurrent Neural Networks (RNNs)

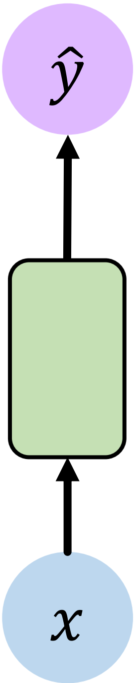
Standard feed-forward neural network



One to One
"Vanilla" neural network

[1]

Recurrent neural networks: sequence modeling



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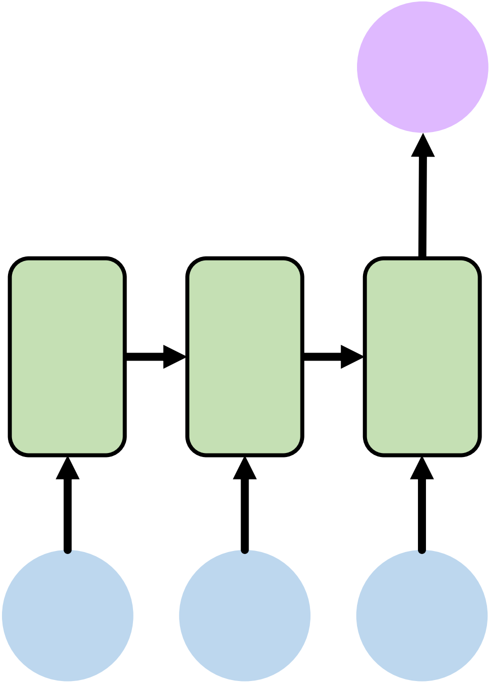
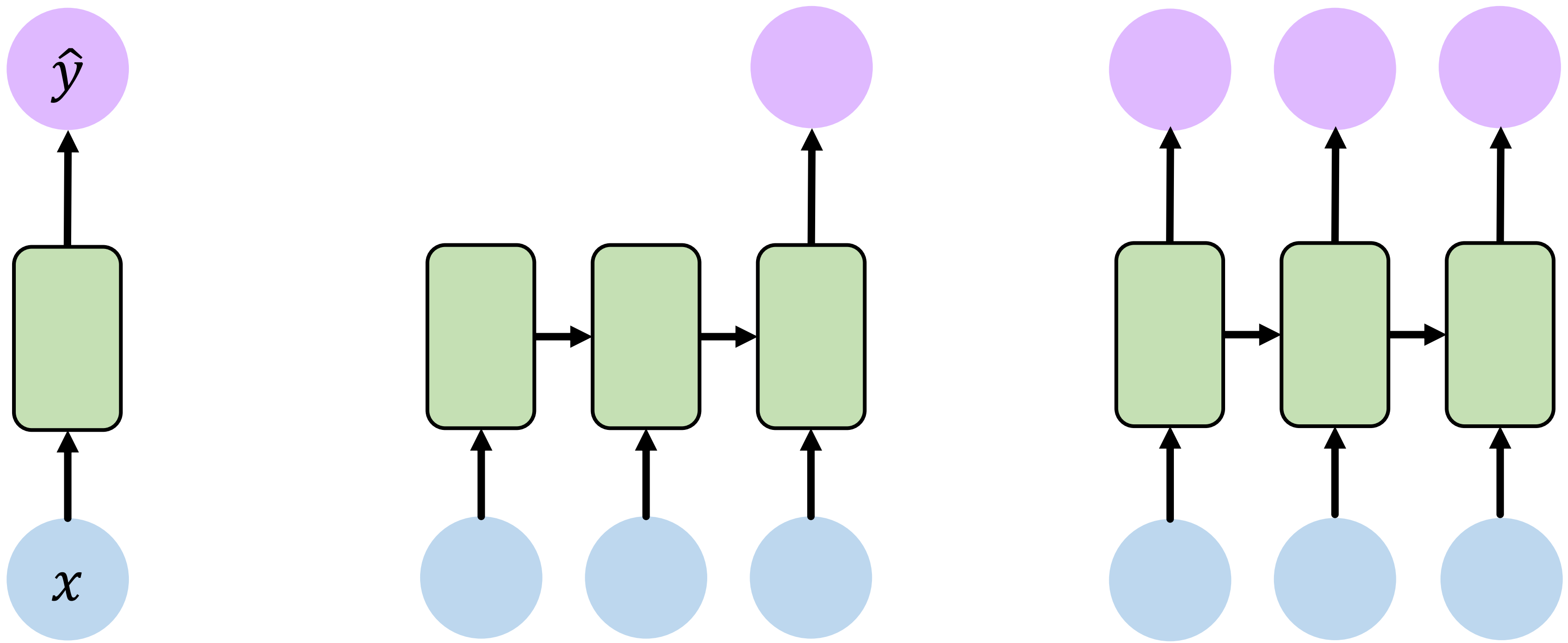


Many to One
Sentiment Classification

[1]

Recurrent neural networks: sequence modeling



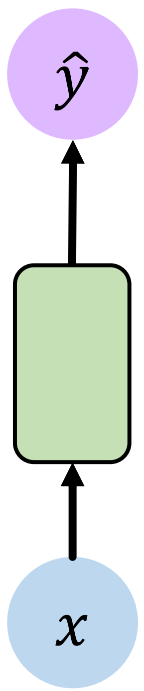
One to One
"Vanilla" neural network

Many to One
Sentiment Classification

Many to Many
Music Generation

[1]

Recurrent neural networks: sequence modeling



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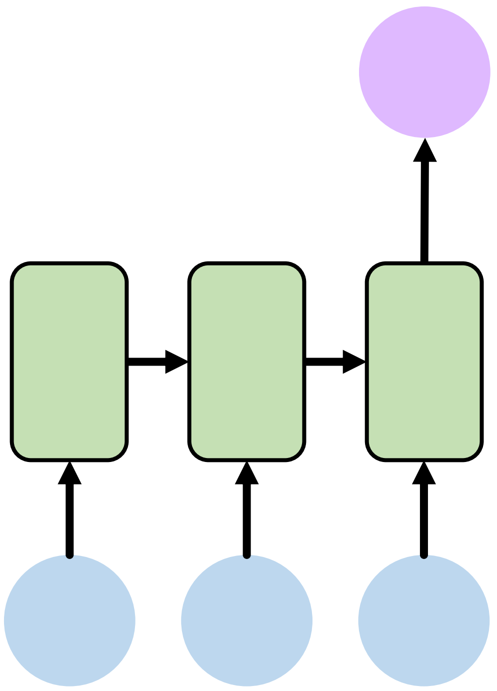
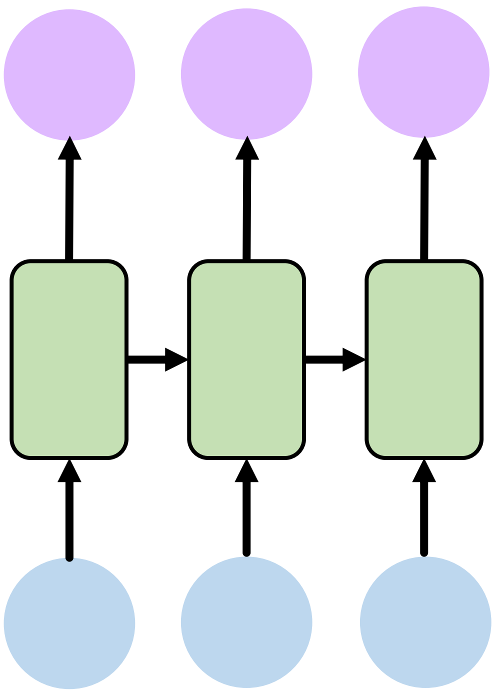


Many to One
Sentiment Classification

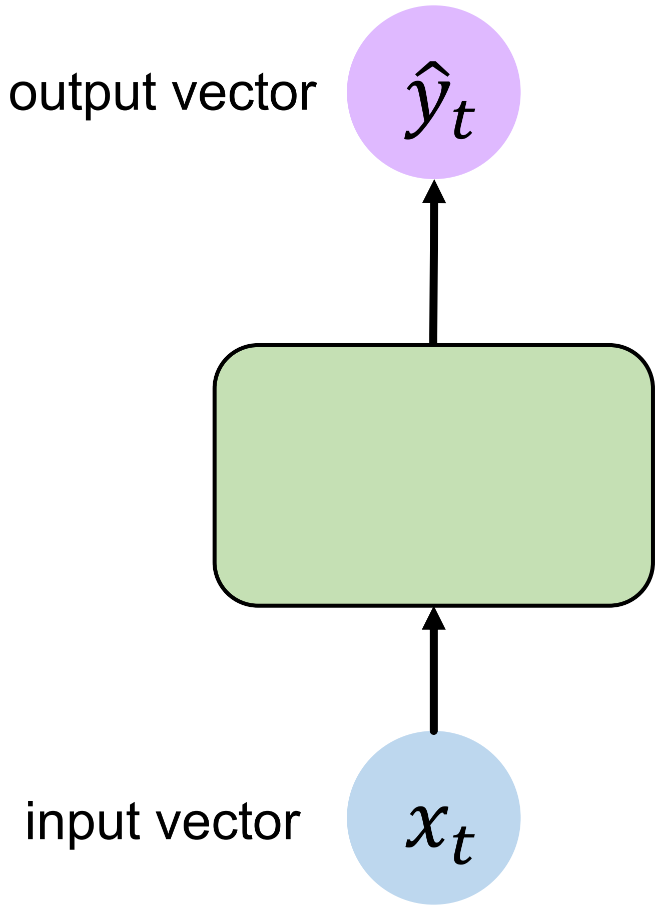


Many to Many
Music Generation

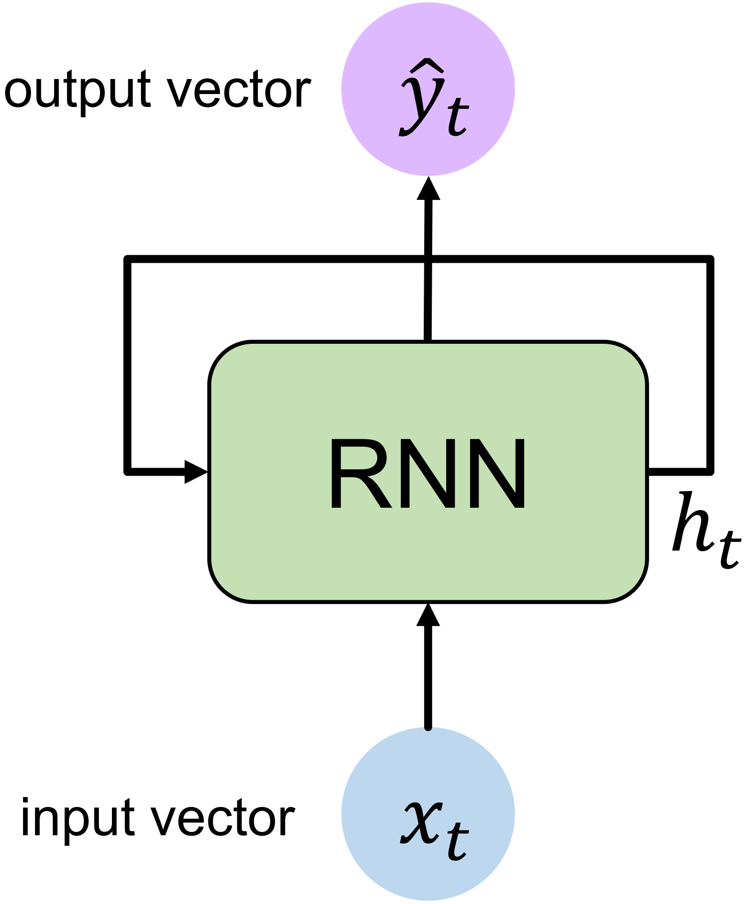
… and many other architectures and applications

[1]

A standard "vanilla" neural network

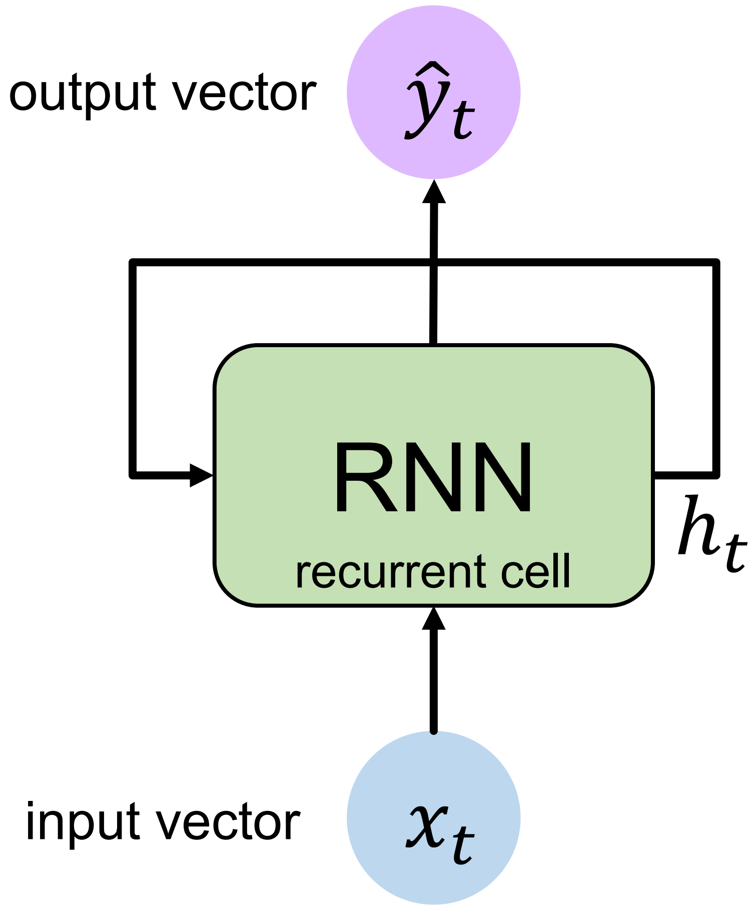


A recurrent neural network (RNN)



[2]

A recurrent neural network (RNN)



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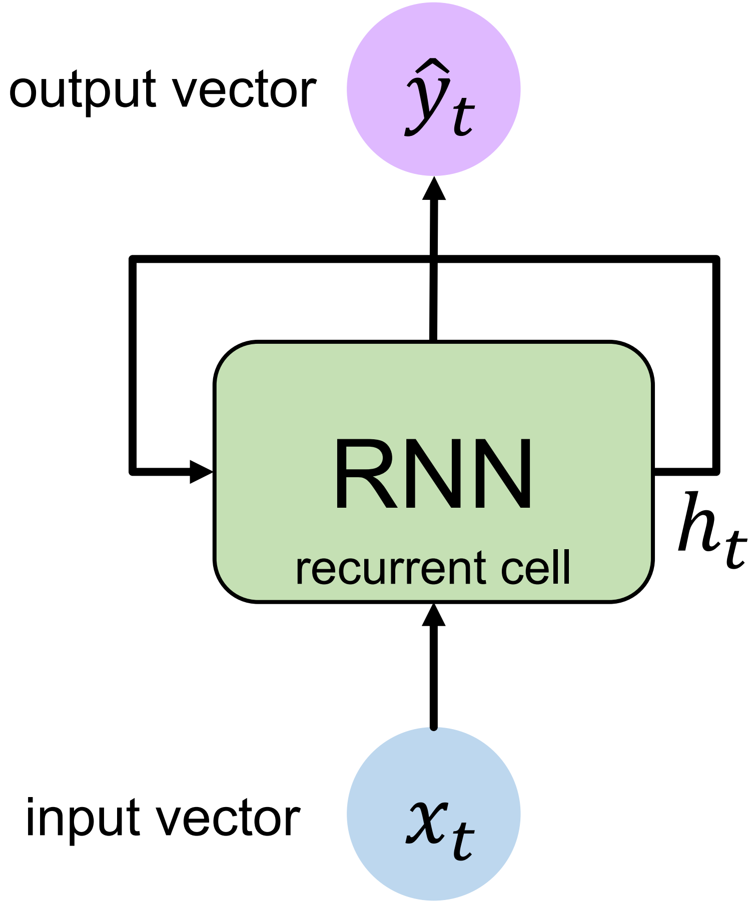
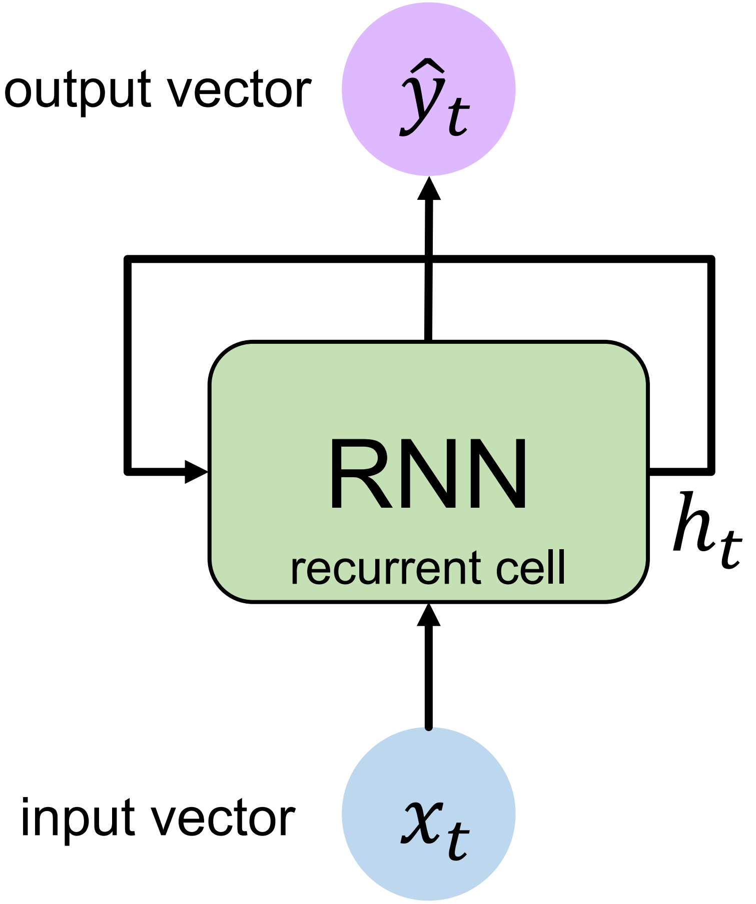


Apply a **recurrence relation** at every time step to process a sequence:

A recurrent neural network (RNN)



Apply a **recurrence relation** at every time step to process a sequence:

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

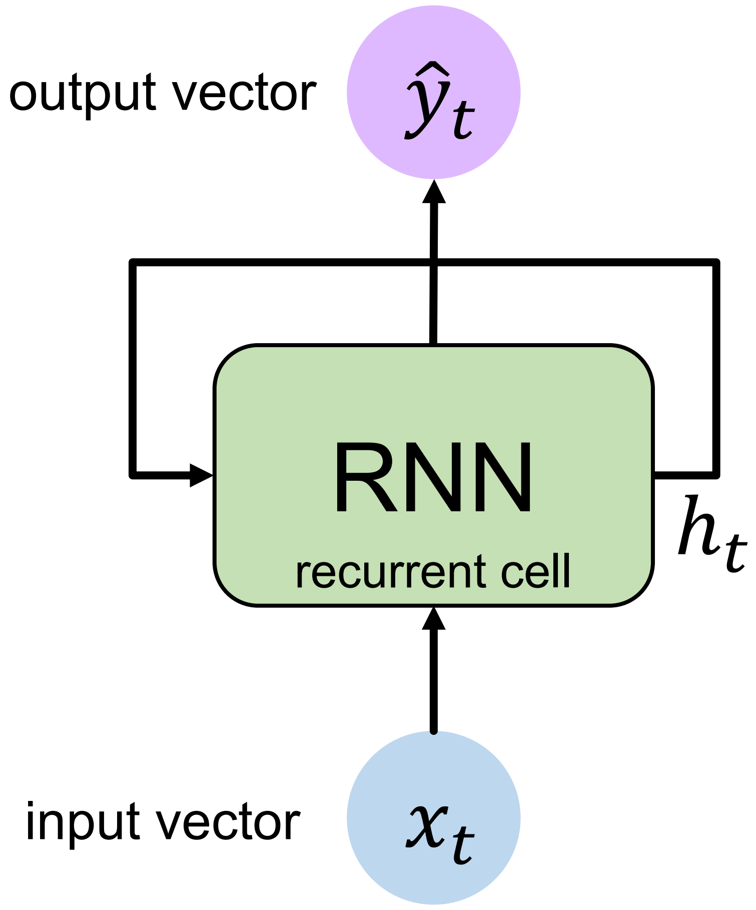
cell state

function parameterized by W

old state

input vector at time step *t*

A recurrent neural network (RNN)



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$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

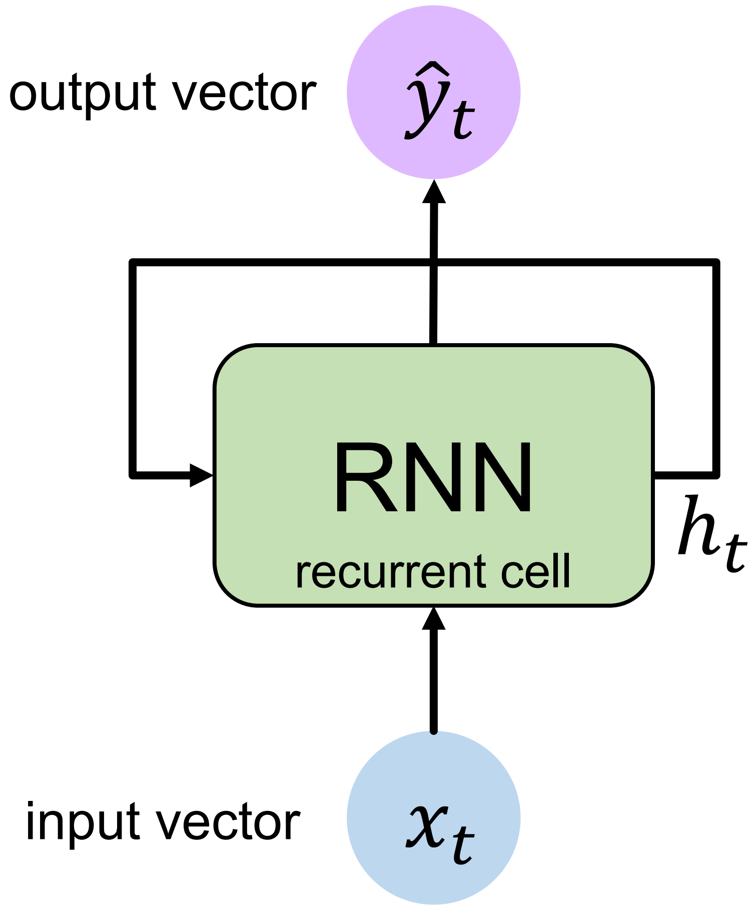
function parameterized by W

old state

input vector at time step *t*

Note: the same function and set of parameters are used at every time step

RNN state update and output



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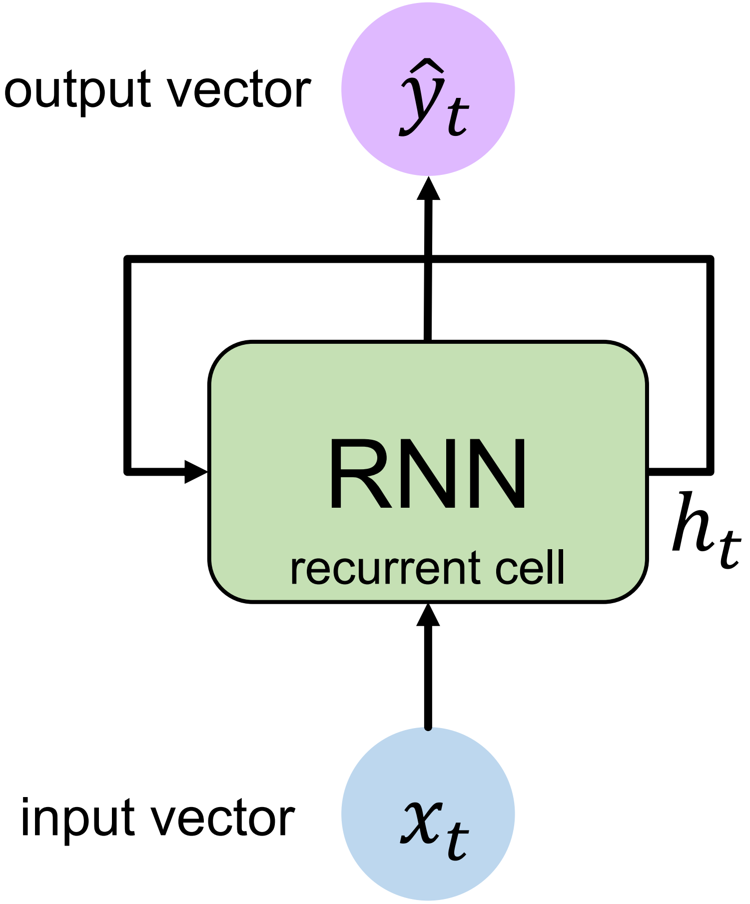
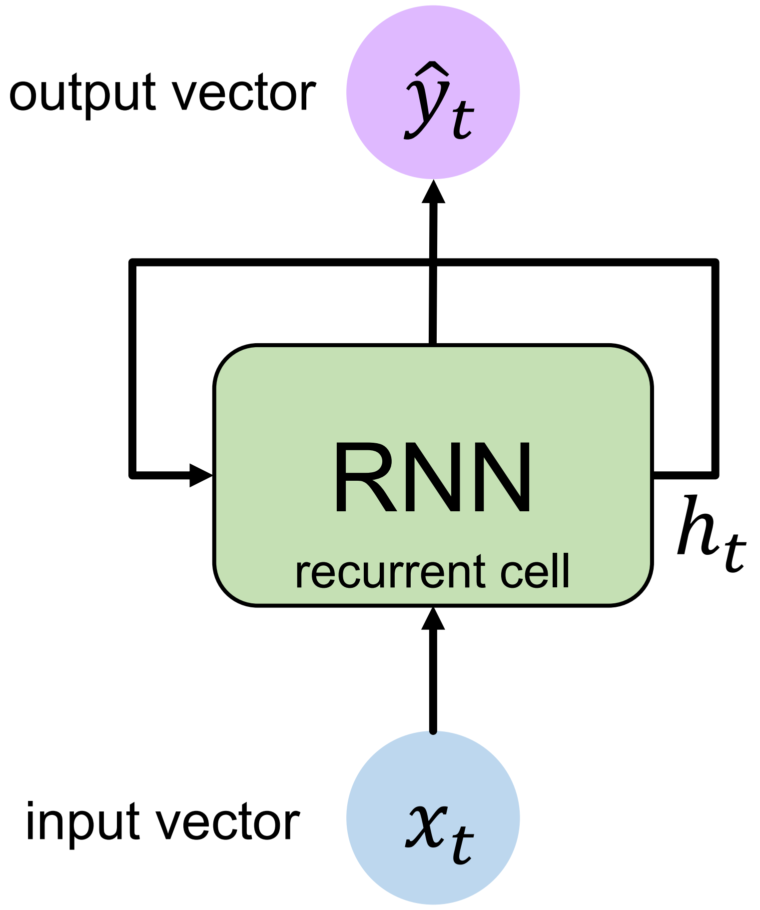


Input Vector

RNN state update and output

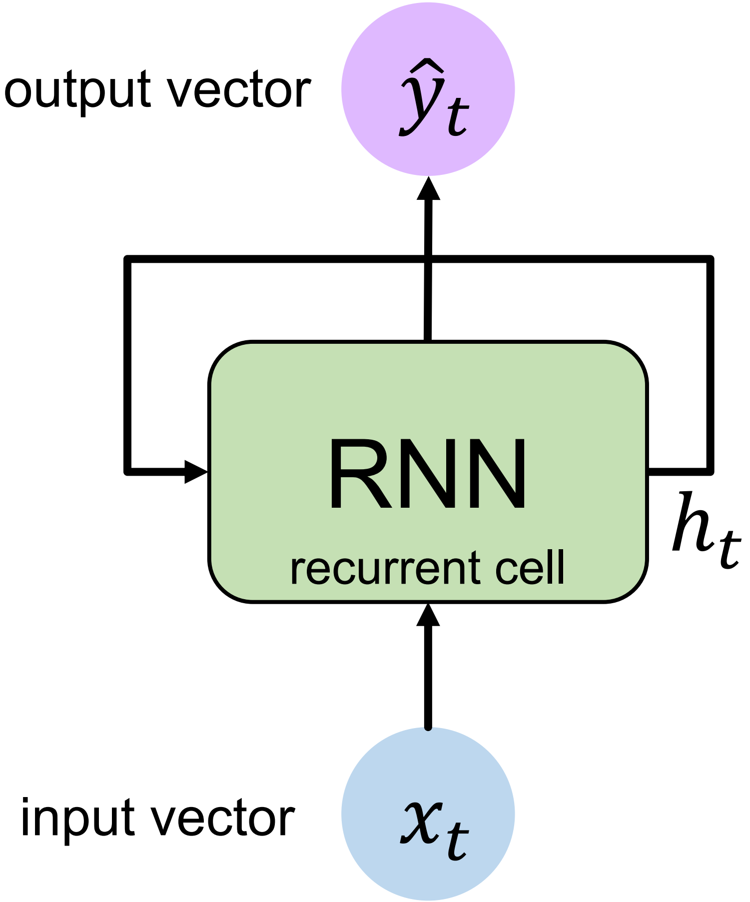


Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{\boldsymbol{hh}} h_{t-1} + \boldsymbol{W}_{\boldsymbol{xh}} x_t)$$

Input Vector

RNN state update and output



Output Vector

$$\hat{y}_t = \boldsymbol{W}_{\boldsymbol{hy}} h_t$$

Update Hidden State

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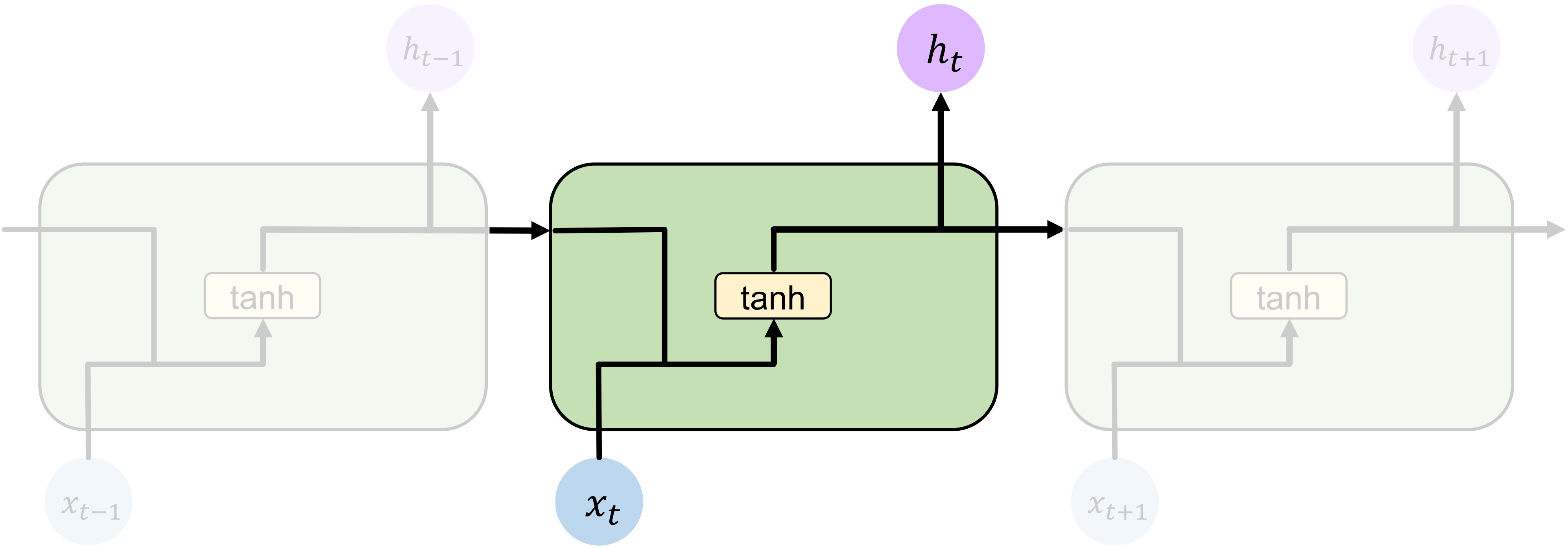
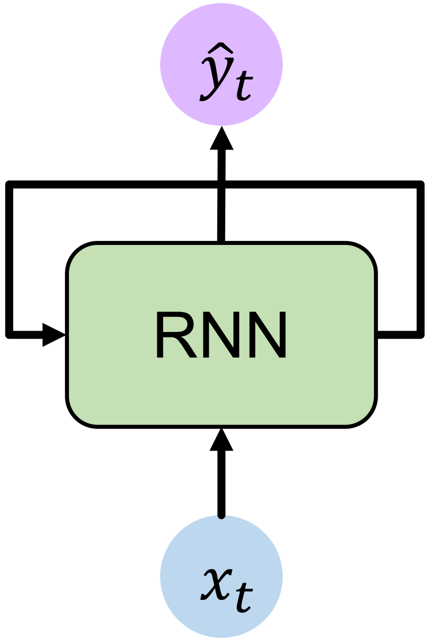
Input Vector

RNN state update and output



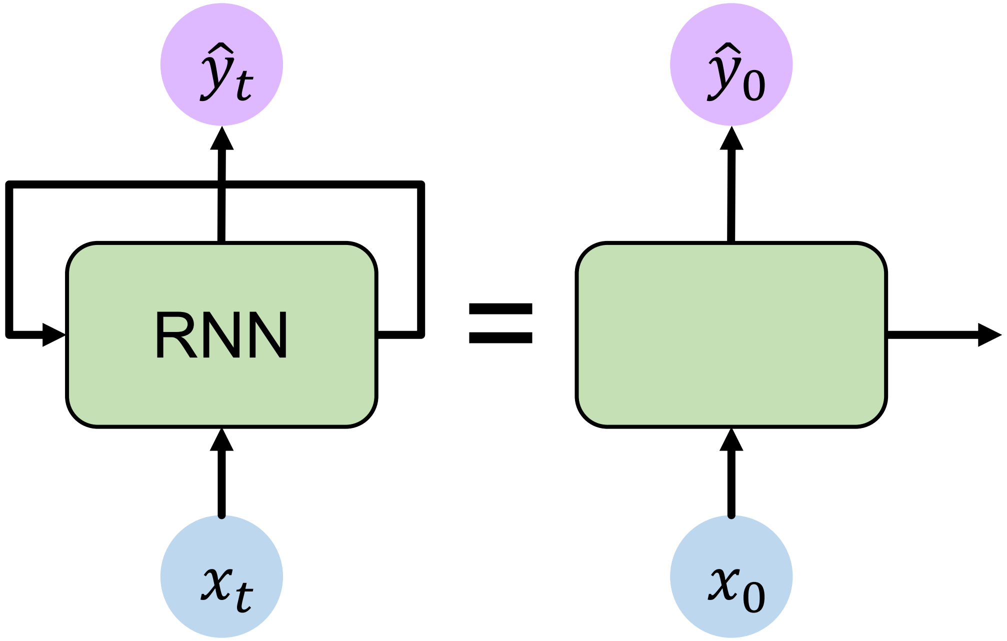
[2]

RNNs: computational graph across time

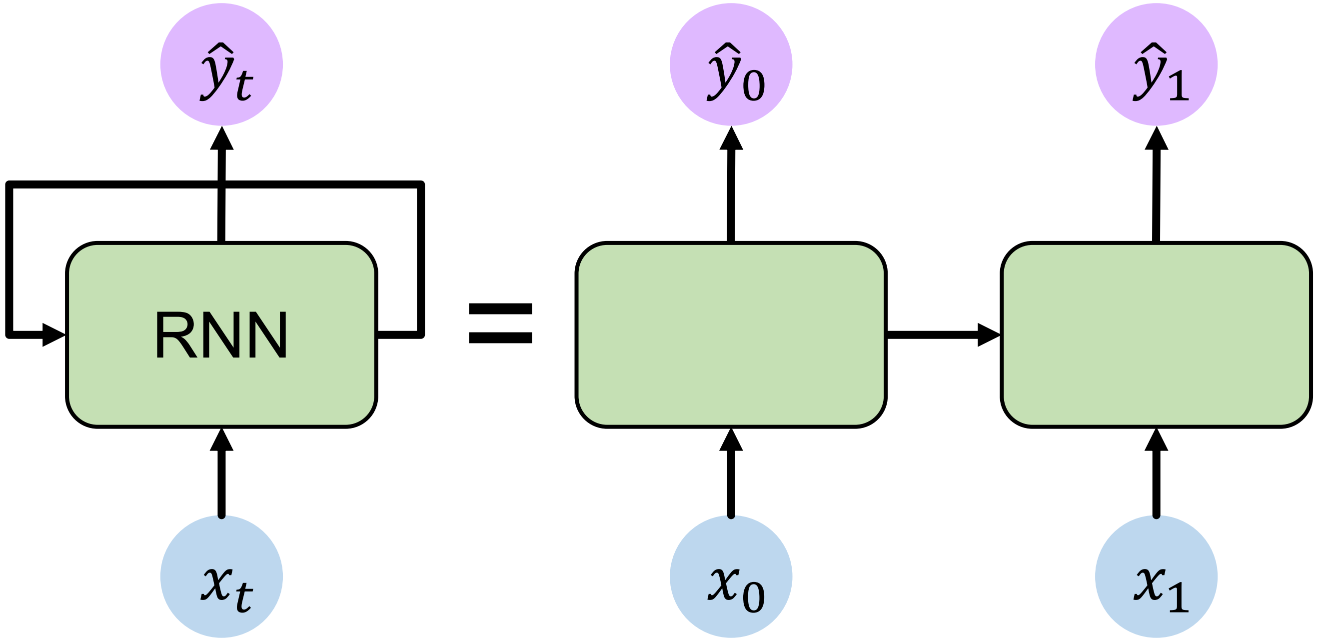


$=$ Represent as computational graph unrolled across time

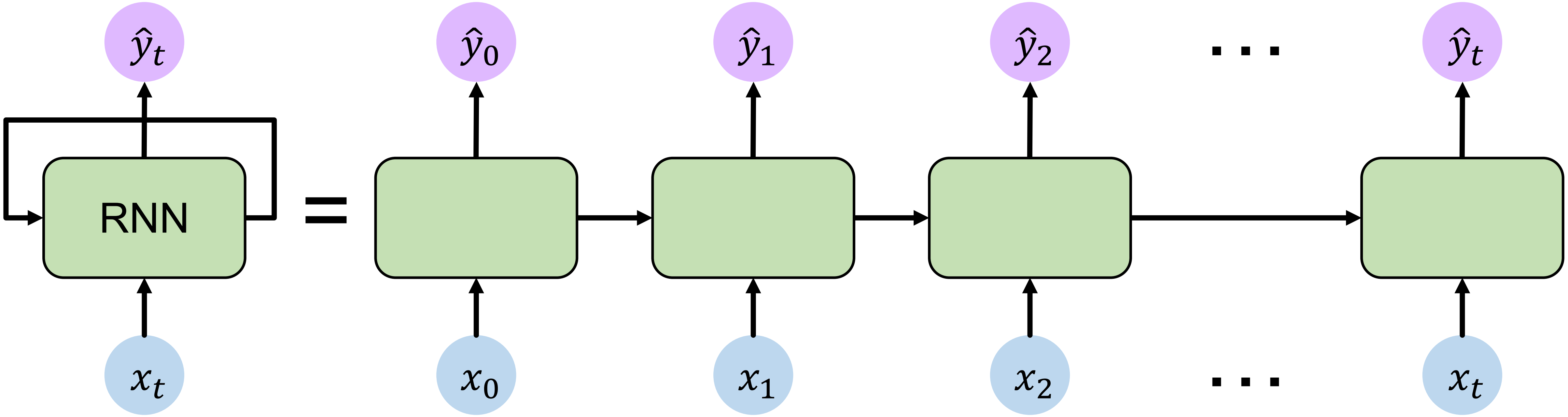
RNNs: computational graph across time



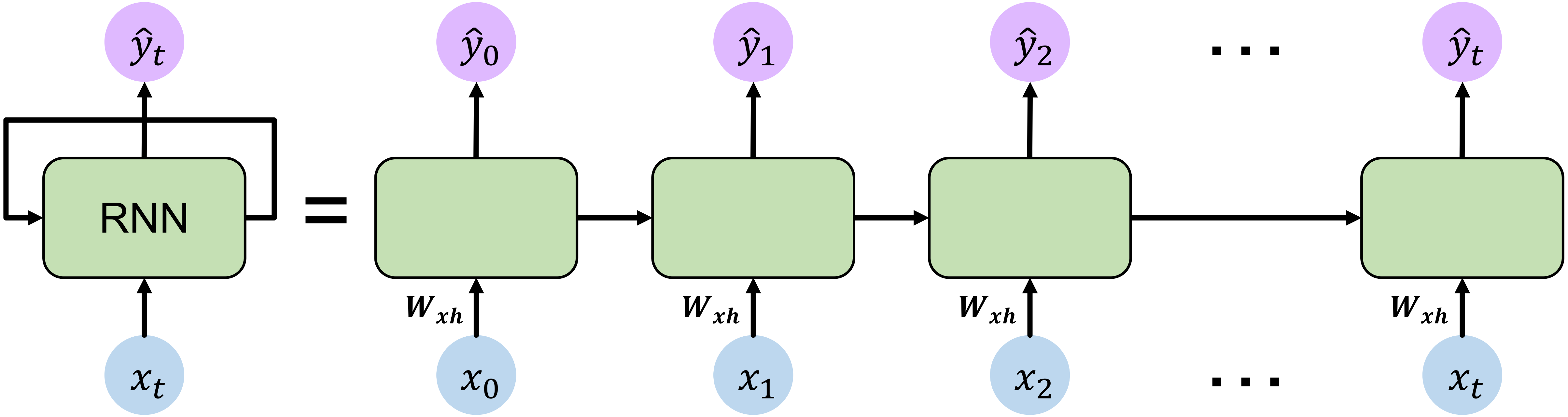
RNNs: computational graph across time



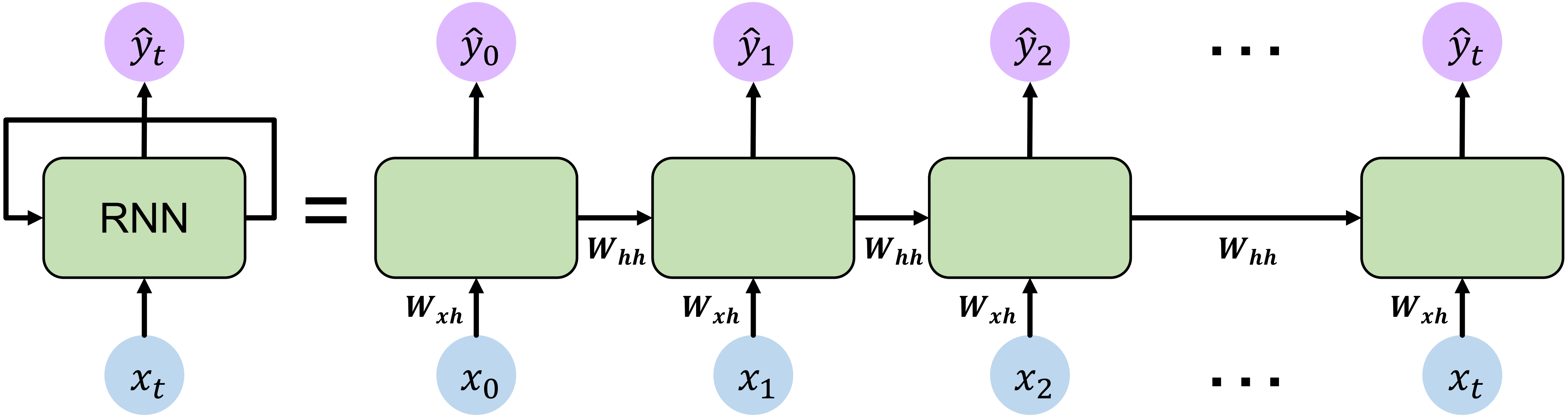
RNNs: computational graph across time



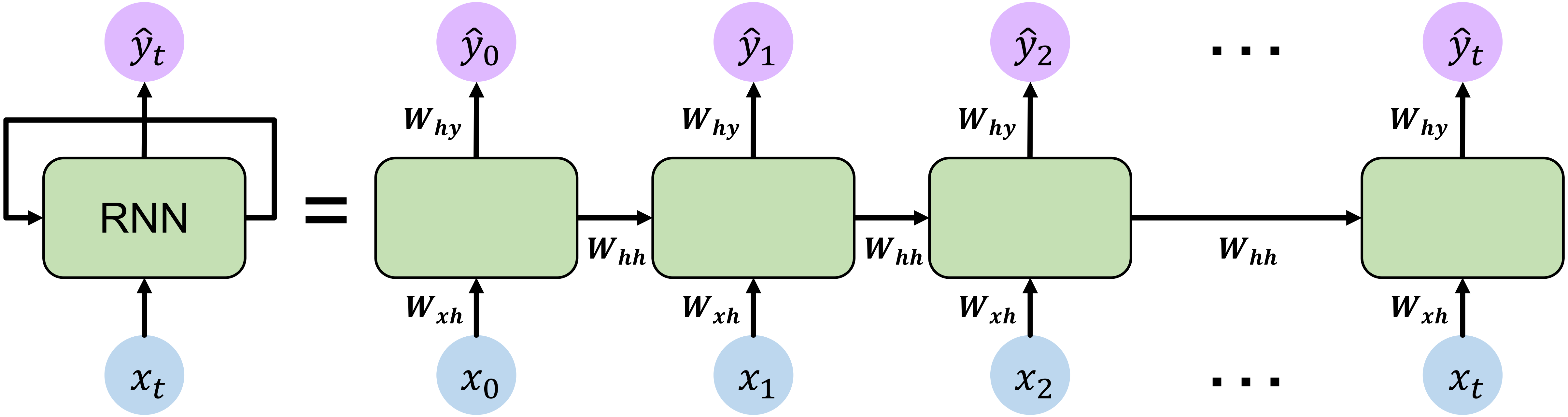
RNNs: computational graph across time



RNNs: computational graph across time

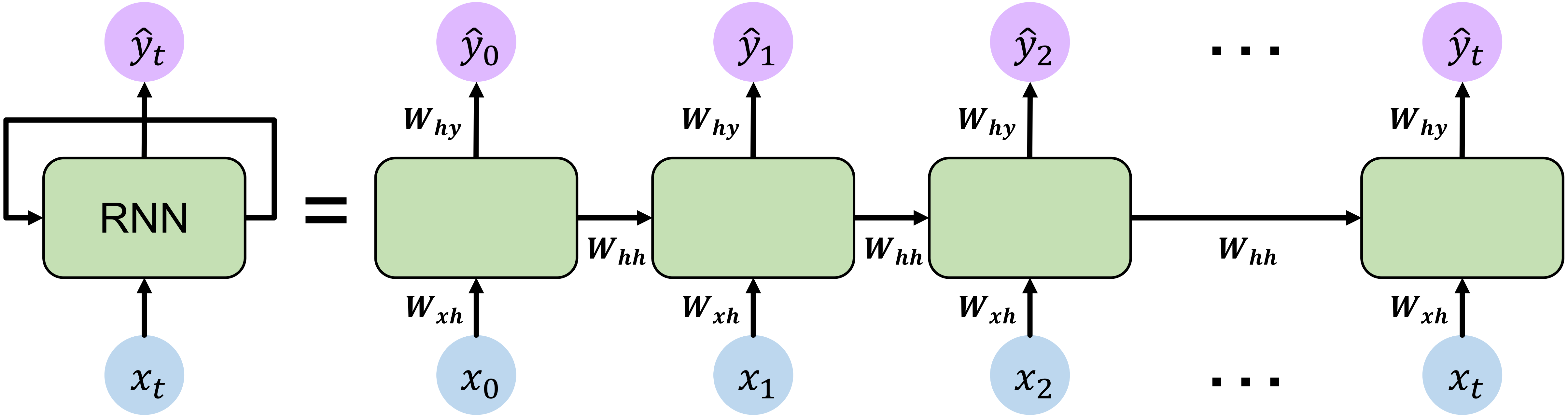


RNNs: computational graph across time



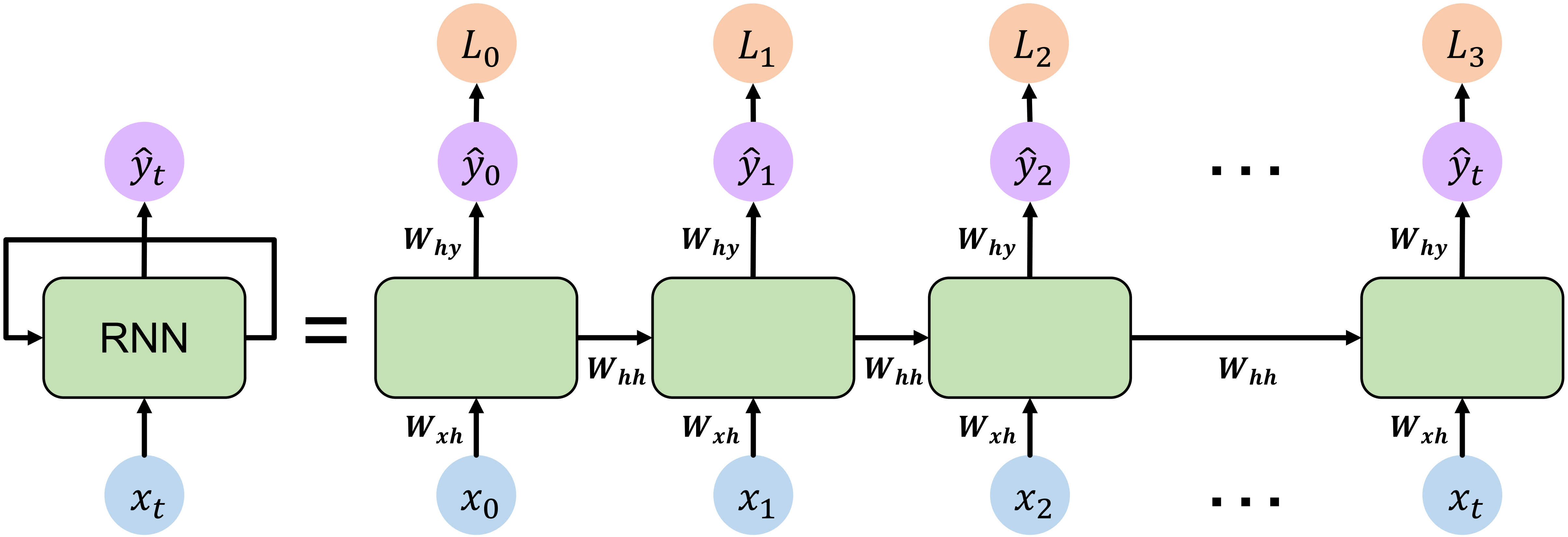
RNNs: computational graph across time

Re-use the **same weight matrices** at every time step

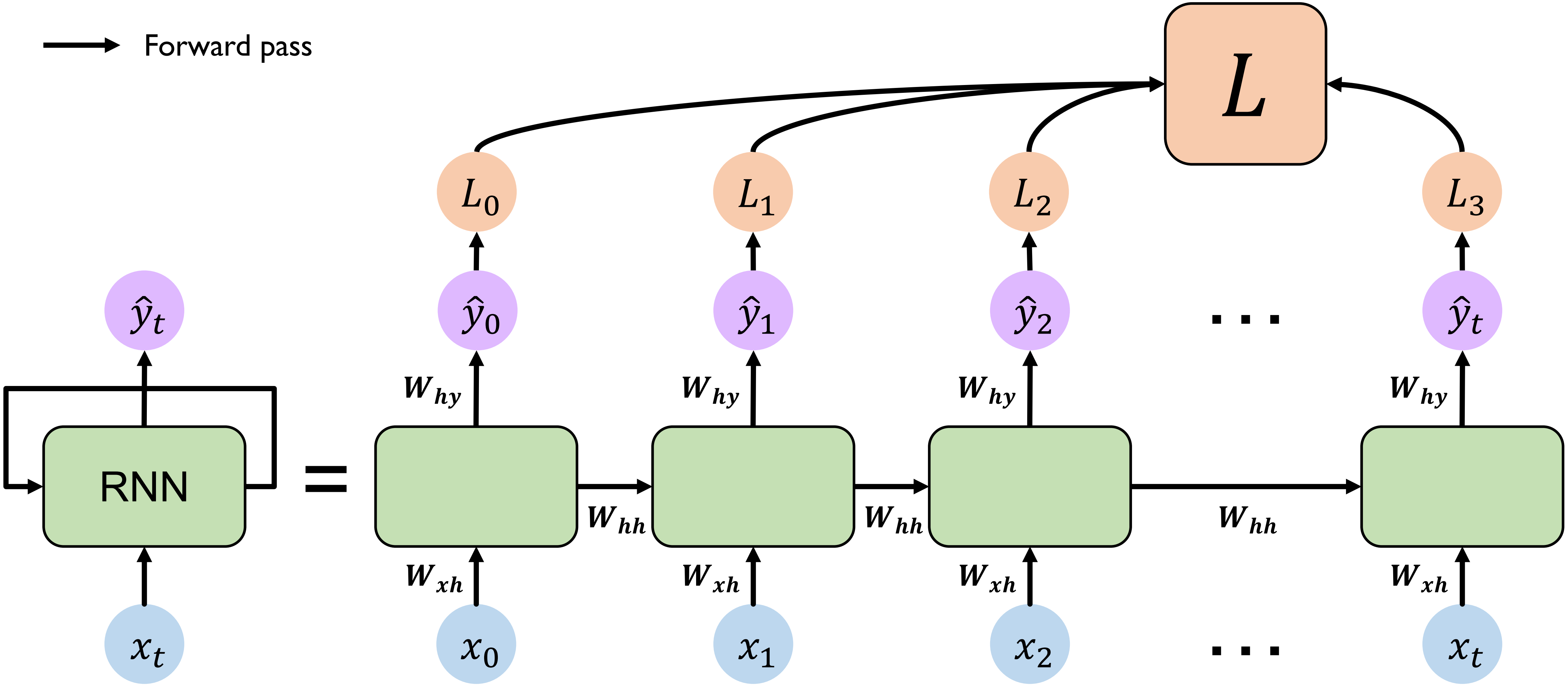


RNNs: computational graph across time

Forward pass

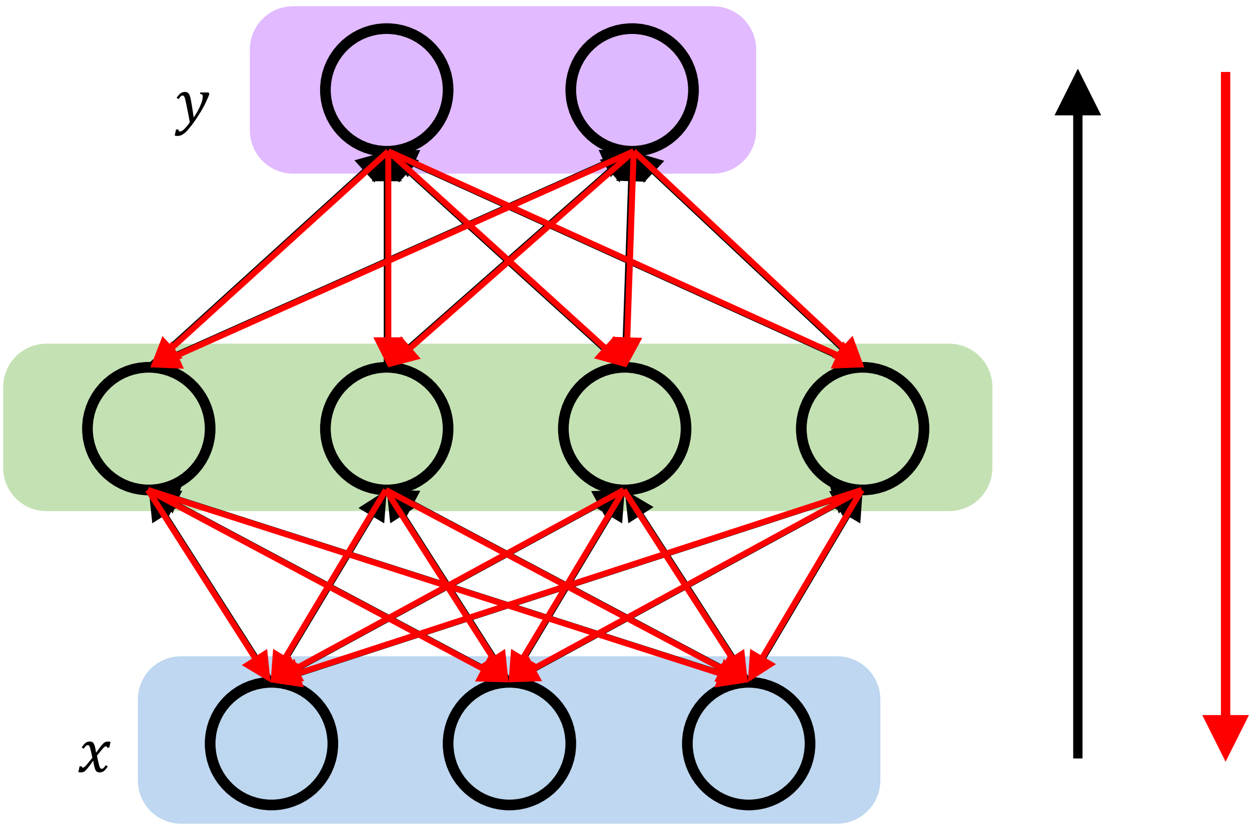


RNNs: computational graph across time



Backpropagation Through Time (BPTT)

Recall: backpropagation in feed forward models

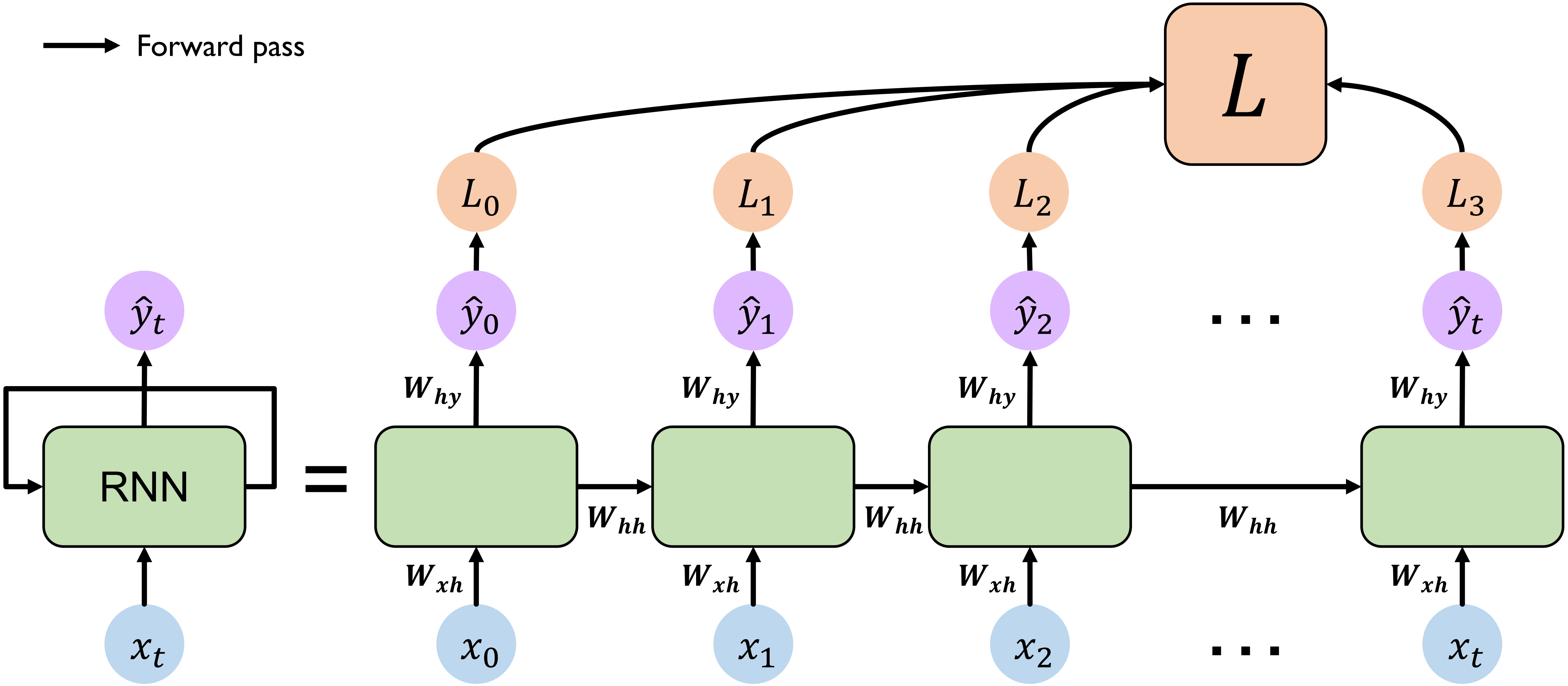


Backpropagation algorithm:

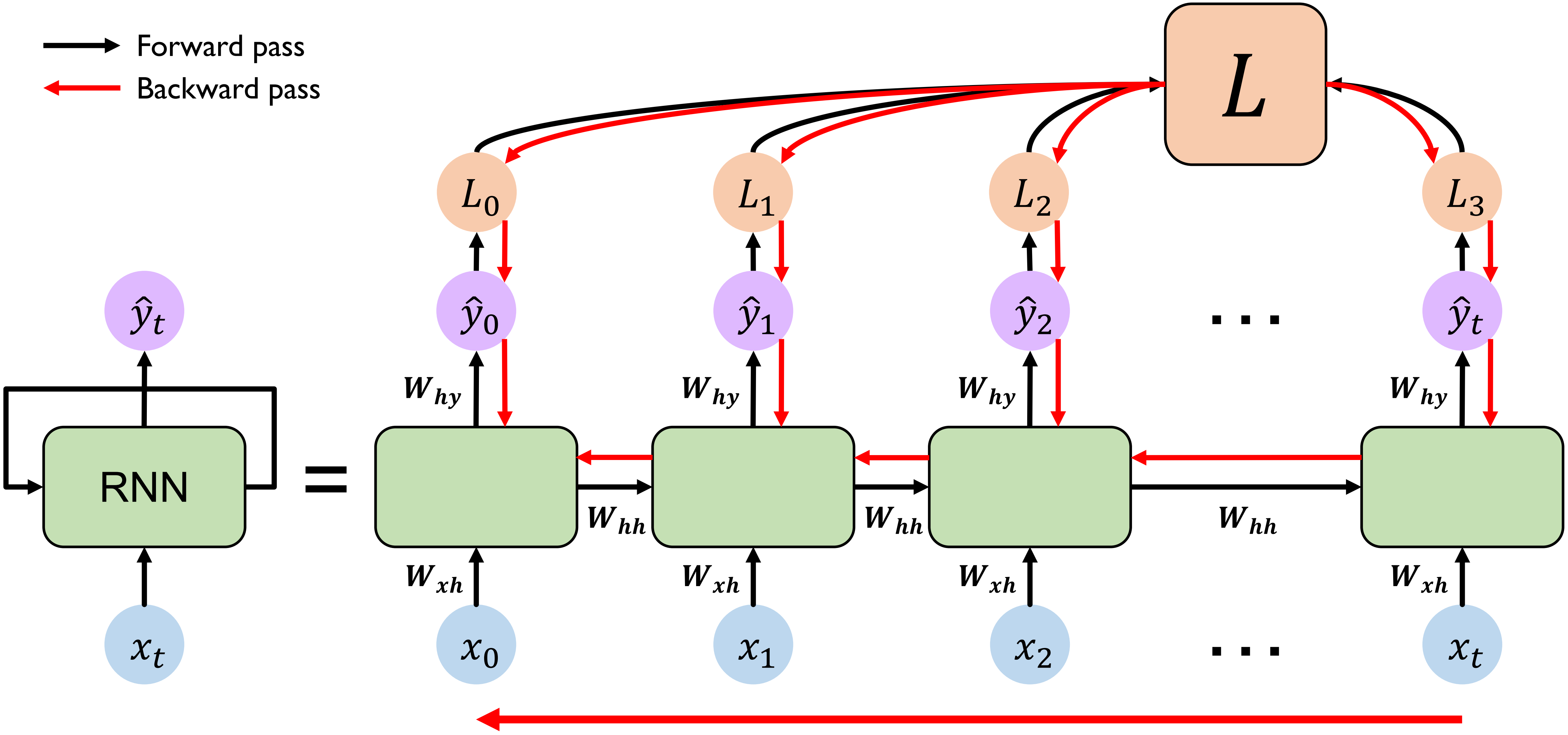
1. Take the derivative (gradient) of the loss with respect to each parameter
2. Shift parameters in order to minimize loss

[3]

RNNs: backpropagation through time

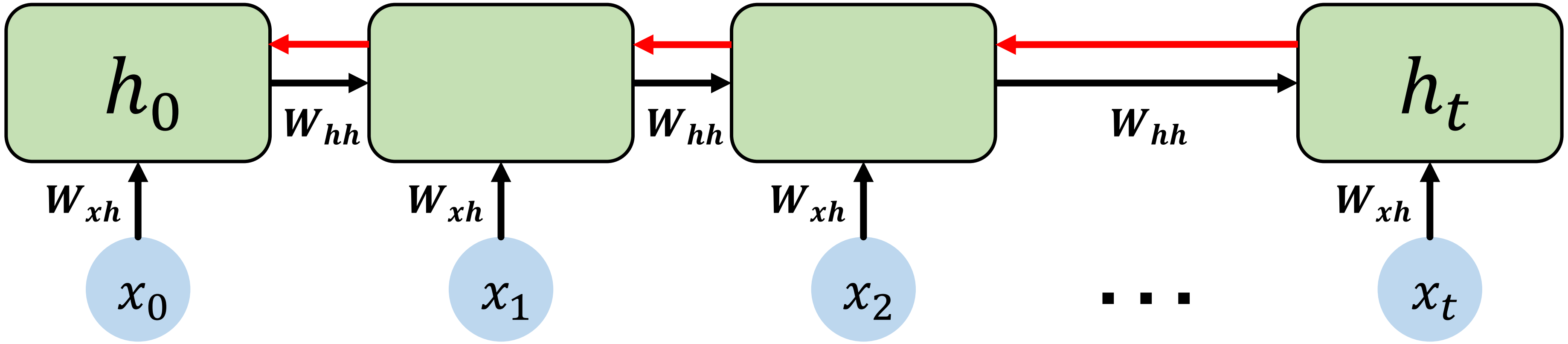


RNNs: backpropagation through time



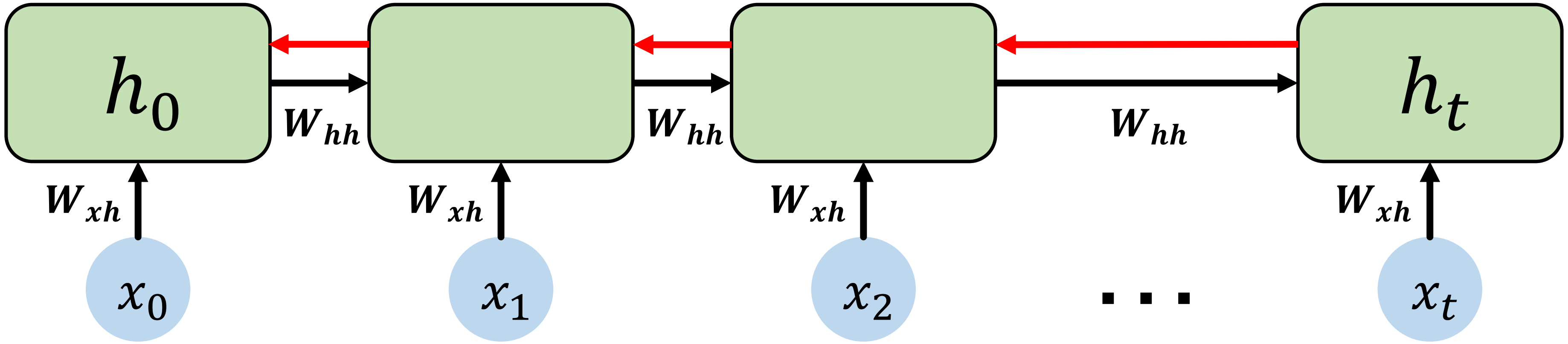
[4]

Standard RNN gradient flow



[1]

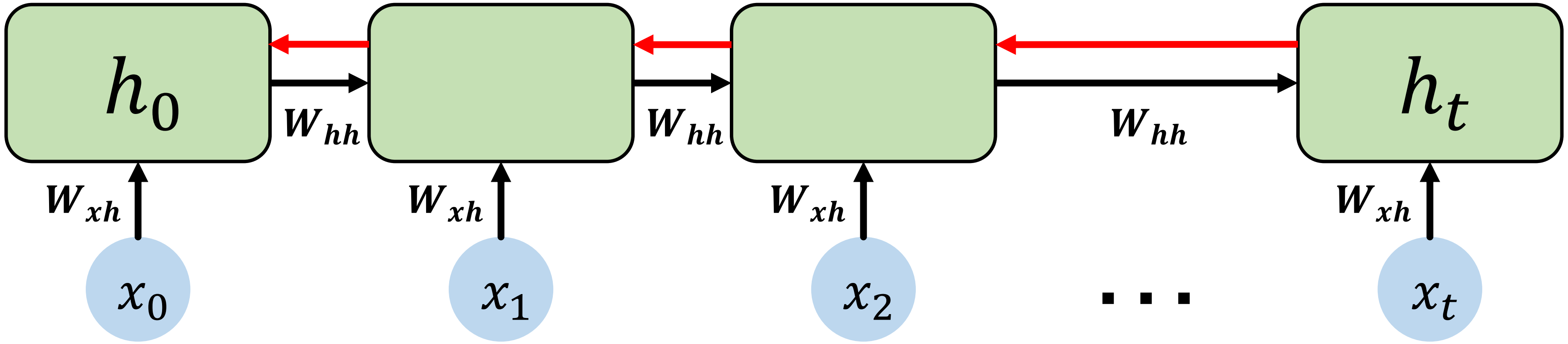
Standard RNN gradient flow



Computing the gradient wrt h_0 involves **many factors of** W_{hh} (and repeated f'!)

[1]

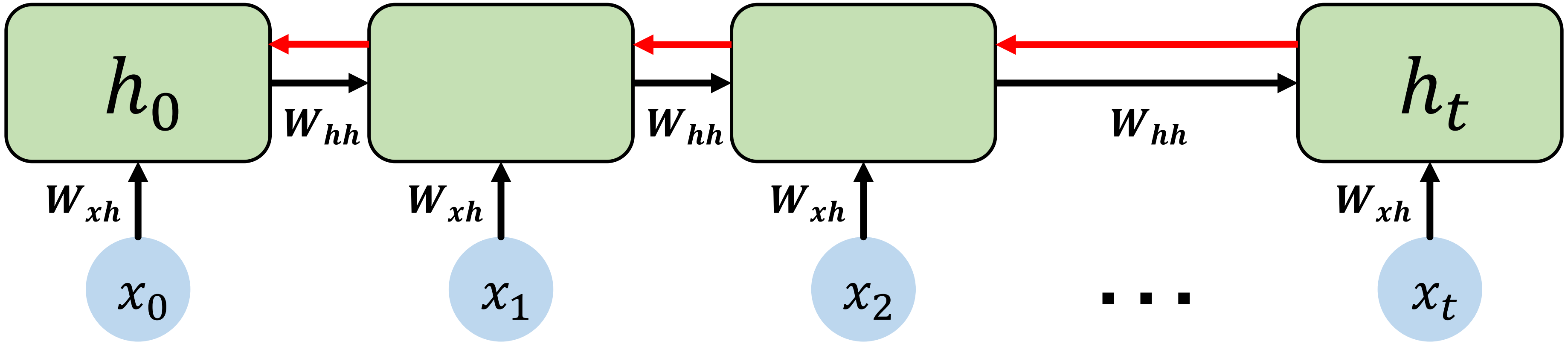
Standard RNN gradient flow: exploding gradients



Computing the gradient wrt h_0 involves **many factors of W_{hh}** (and repeated f'!)

Many values > 1:
exploding gradients

Standard RNN gradient flow: exploding gradients



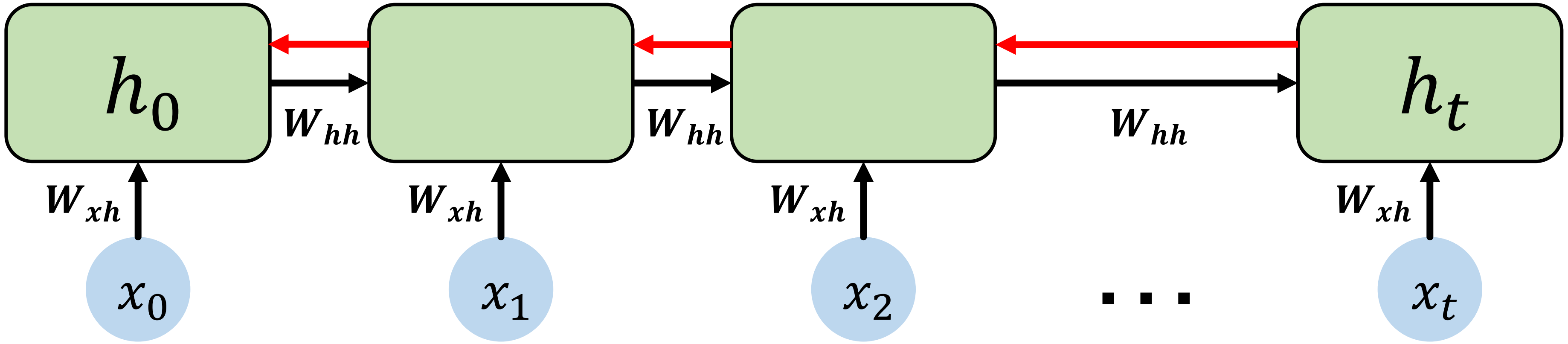
Computing the gradient wrt h_0 involves **many factors of W_{hh}** (and repeated f'!)

Many values > 1:
exploding gradients

Gradient clipping to
scale big gradients

[1]

Standard RNN gradient flow: vanishing gradients



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Many values < 1:
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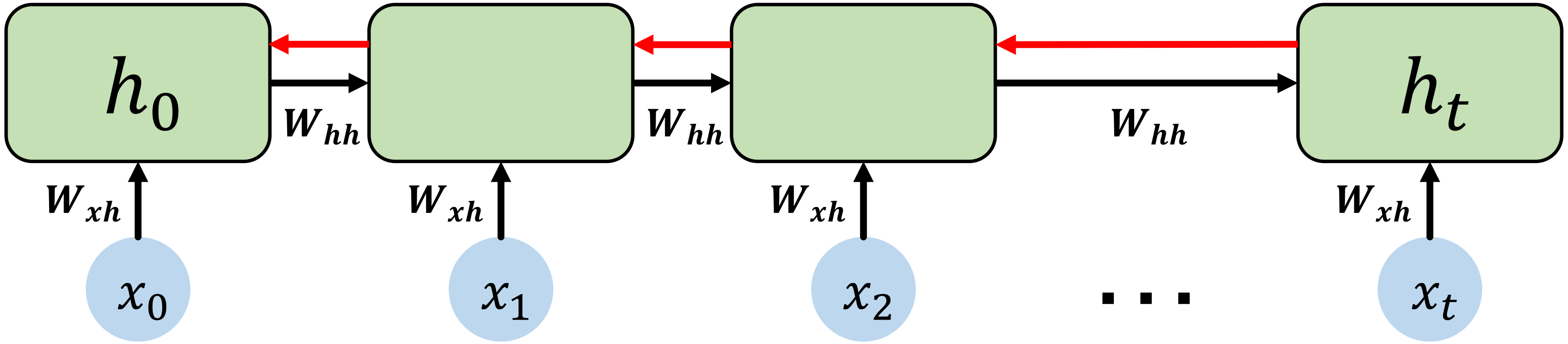

Computing the gradient wrt h_0 involves **many factors of W_{hh}** (and repeated f'!)

Many values > 1:
exploding gradients

Gradient clipping to scale big gradients

Many values < 1:
vanishing gradients

1. Activation function
2. Weight initialization
3. Network architecture

[1]

The problem of long-term dependencies

Why are vanishing gradients a problem?

The problem of long-term dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

The problem of long-term dependencies

Why are vanishing gradients a problem?

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↓

Errors due to further back time steps
have smaller and smaller gradients

The problem of long-term dependencies

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Bias network to capture short-term dependencies

The problem of long-term dependencies

"The clouds are in the ___"

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Bias network to capture short-term dependencies

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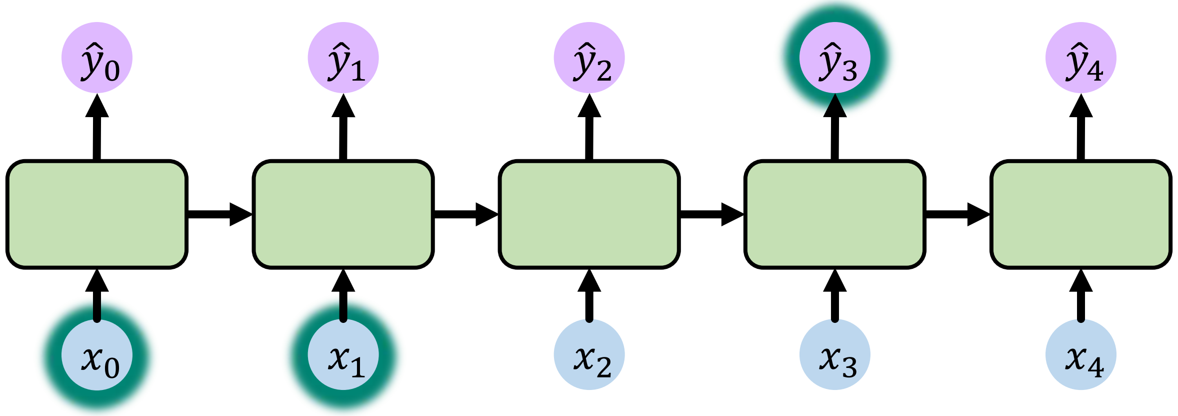
Bias parameters to capture short-term dependencies

"The clouds are in the ___"



The problem of long-term dependencies

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Bias parameters to capture short-term dependencies

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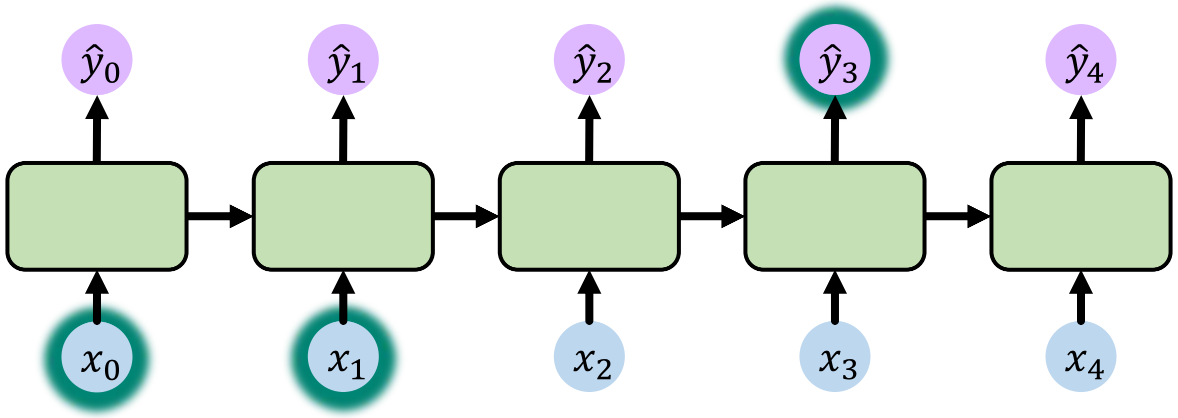


"I grew up in France, … and I I speak fluent___ "

The problem of long-term dependencies

Why are vanishing gradients a problem?

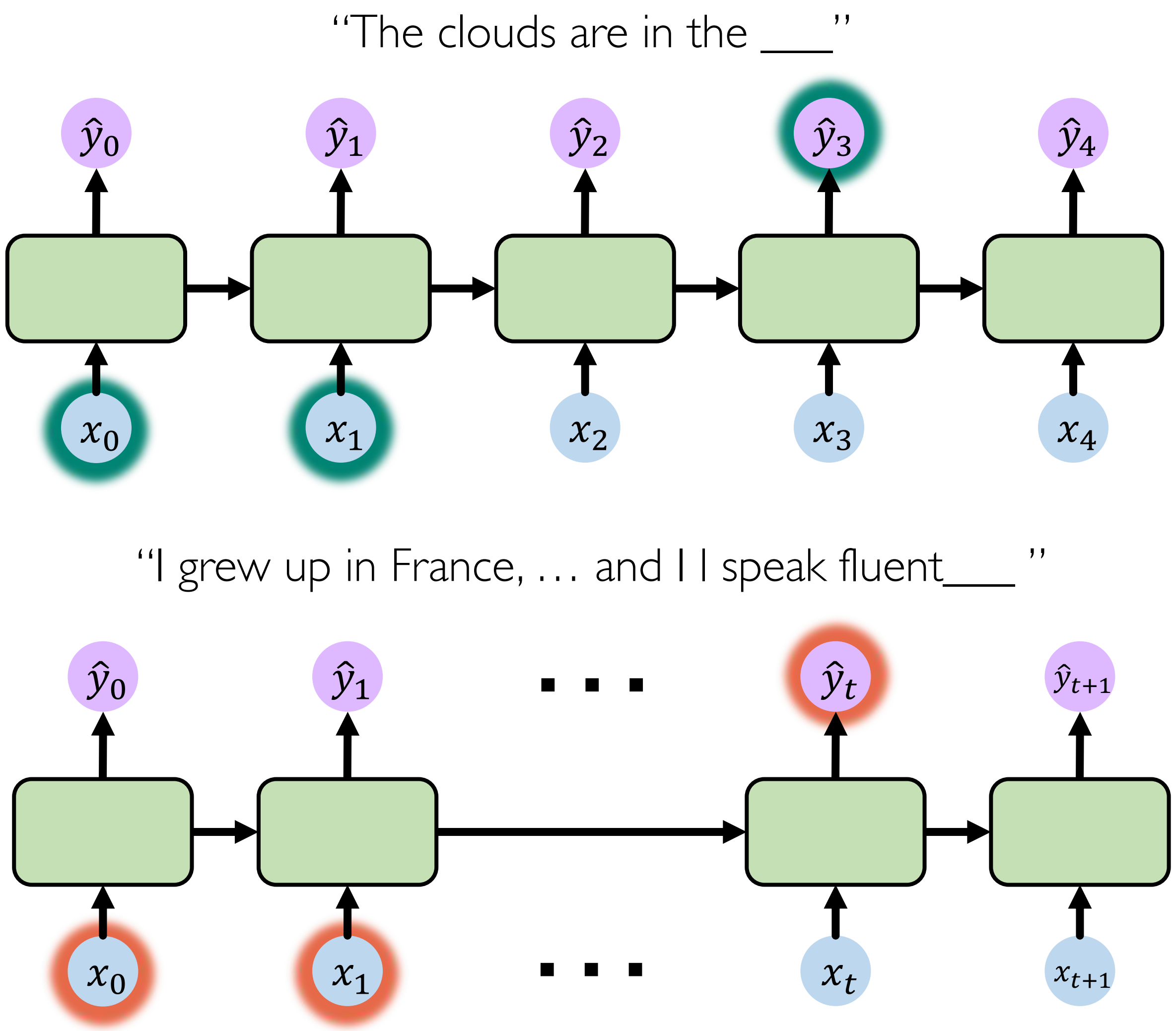
Multiply many **small numbers** together

↓

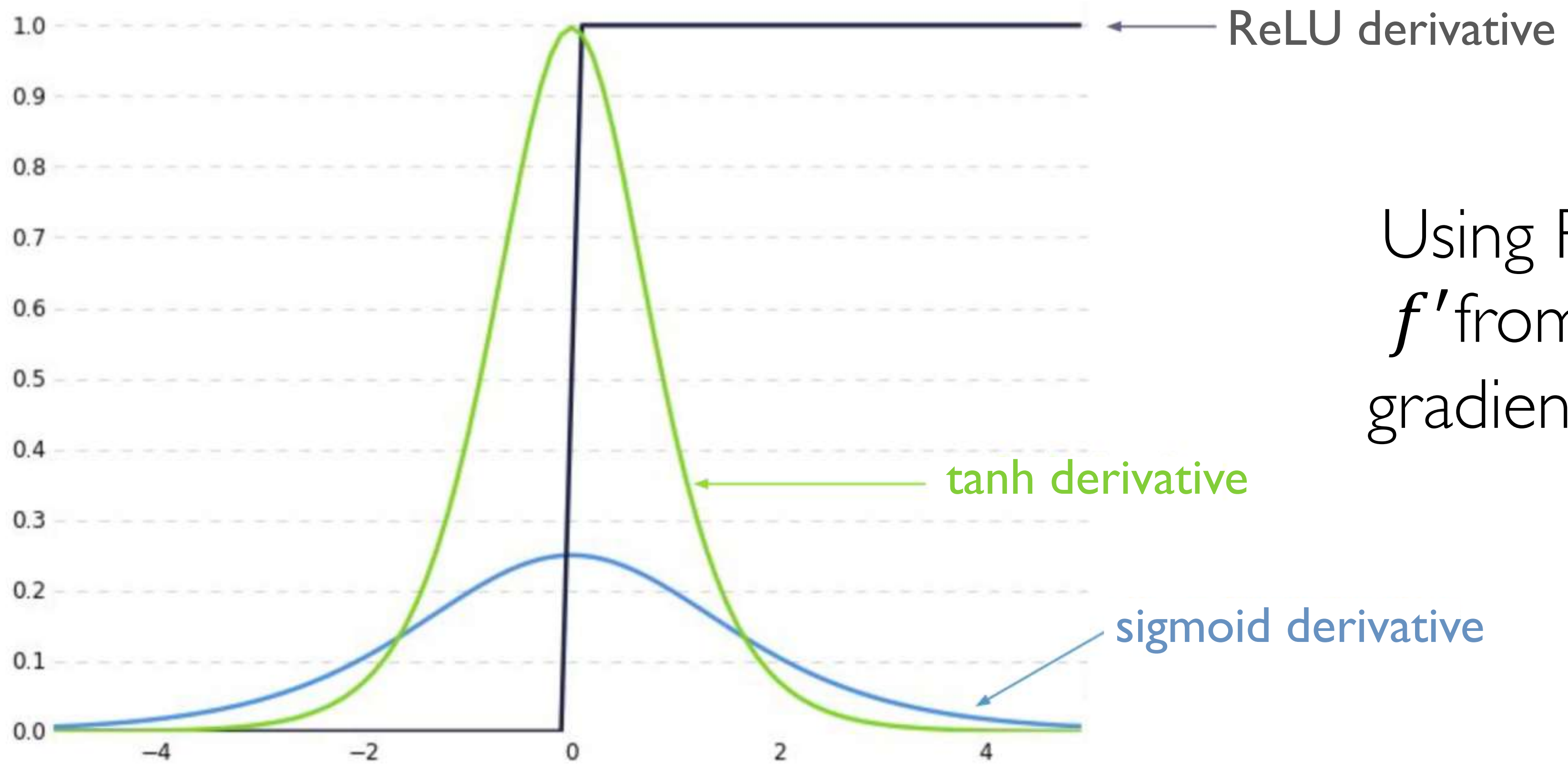
Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies



Trick #1: activation functions



Using ReLU prevents f' from shrinking the gradients when $x > 0$

Adapted from H. Suresh, 6.S191 2018

Trick #2: parameter initialization

Initialize **weights** to identity matrix

Initialize **biases** to zero

$$I_n = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}$$

This helps prevent the weights from shrinking to zero.

Adapted from H. Suresh, 6.S191 2018

Solution #3: gated cells

Idea: use a more **complex recurrent unit with gates** to control what information is passed through

gated cell

LSTM, GRU, etc.

Adapted from H. Suresh, 6.S191 2018

Solution #3: gated cells

Idea: use a more **complex recurrent unit with gates** to control what information is passed through

gated cell

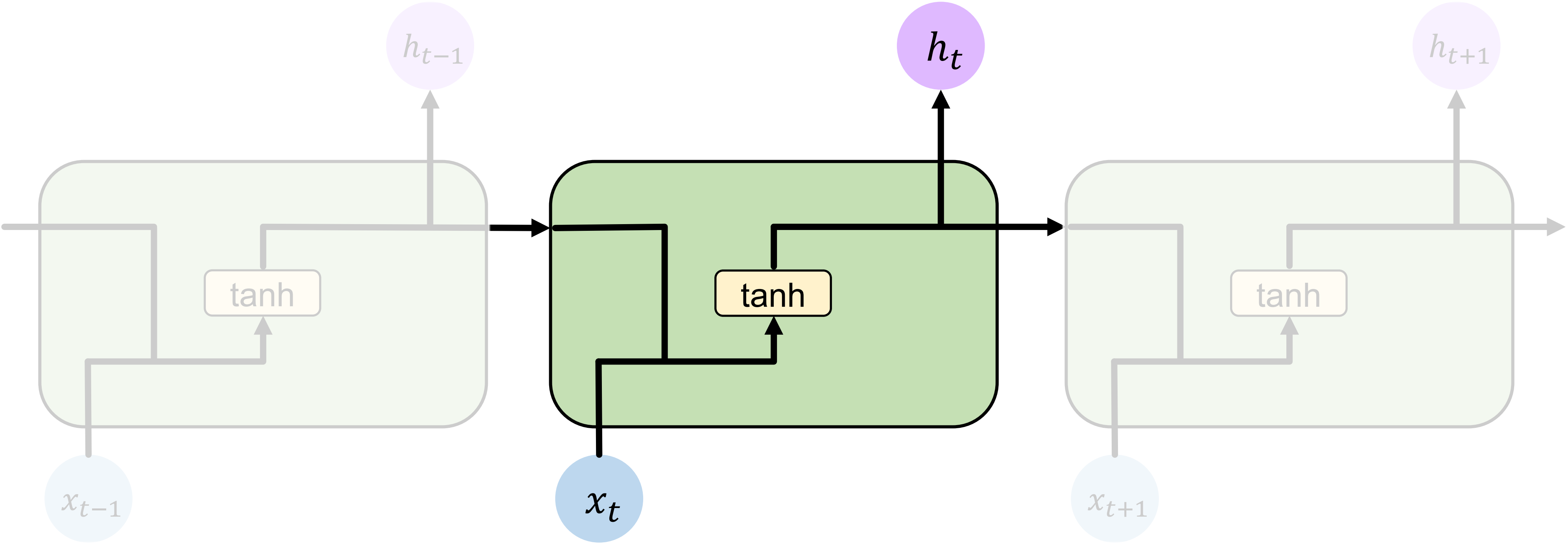
LSTM, GRU, etc.

Long Short Term Memory (LSTMs) networks rely on a gated cell to track information throughout many time steps.

Adapted from H. Suresh, 6.S191 2018

Standard RNN

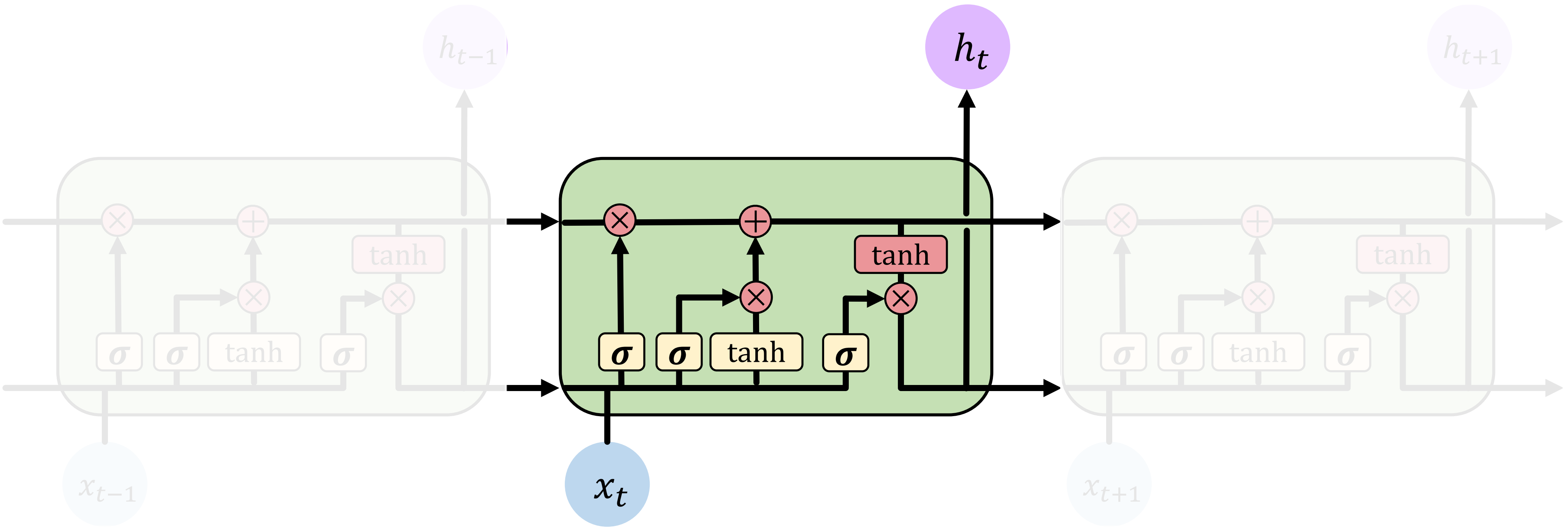
In a standard RNN, repeating modules contain a **simple computation node**



[2]

Long Short Term Memory (LSTMs)

LSTM repeating modules contain **interacting layers** that **control information flow**

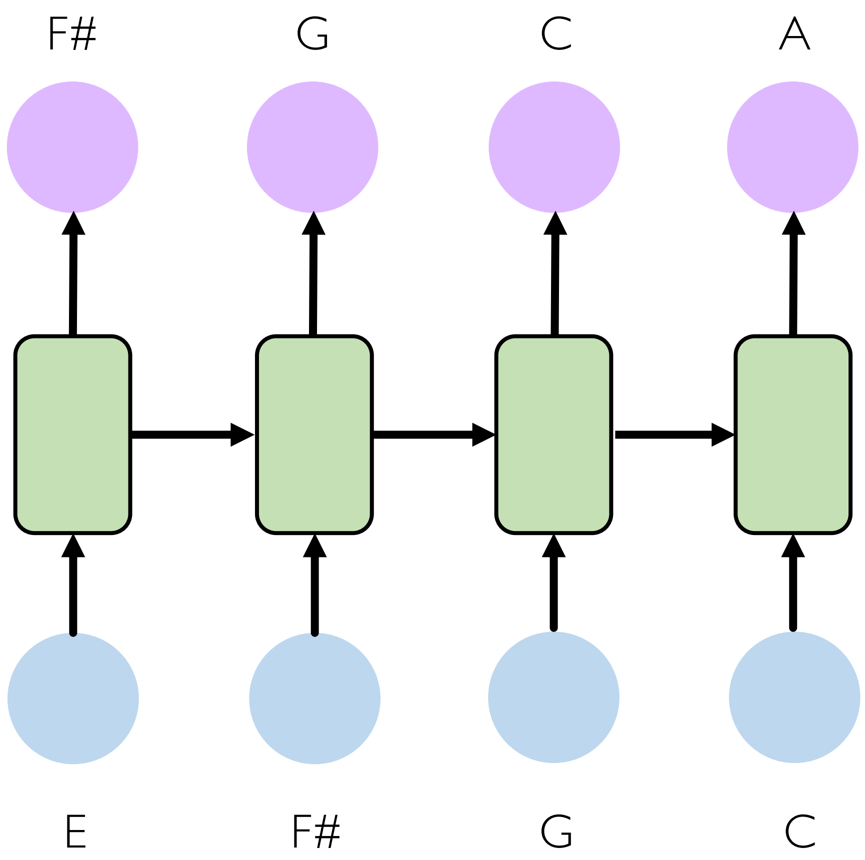


LSTM cells are able to track information throughout many timesteps

Hochreiter & Schmidhuber, 1997 [2, 5]

RNN Applications

Example task: music generation



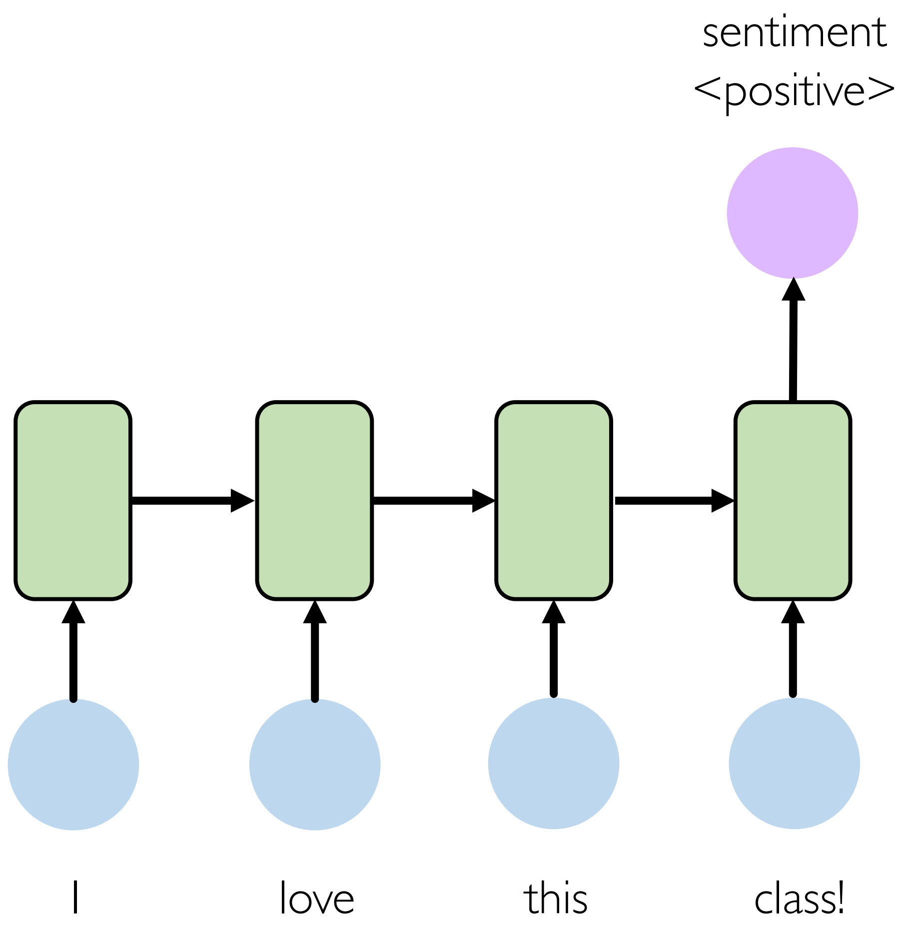
Input: sheet music

Output: next character in sheet music

Adapted from H. Suresh, 6.S191 2018

[6]

Example task: sentiment classification



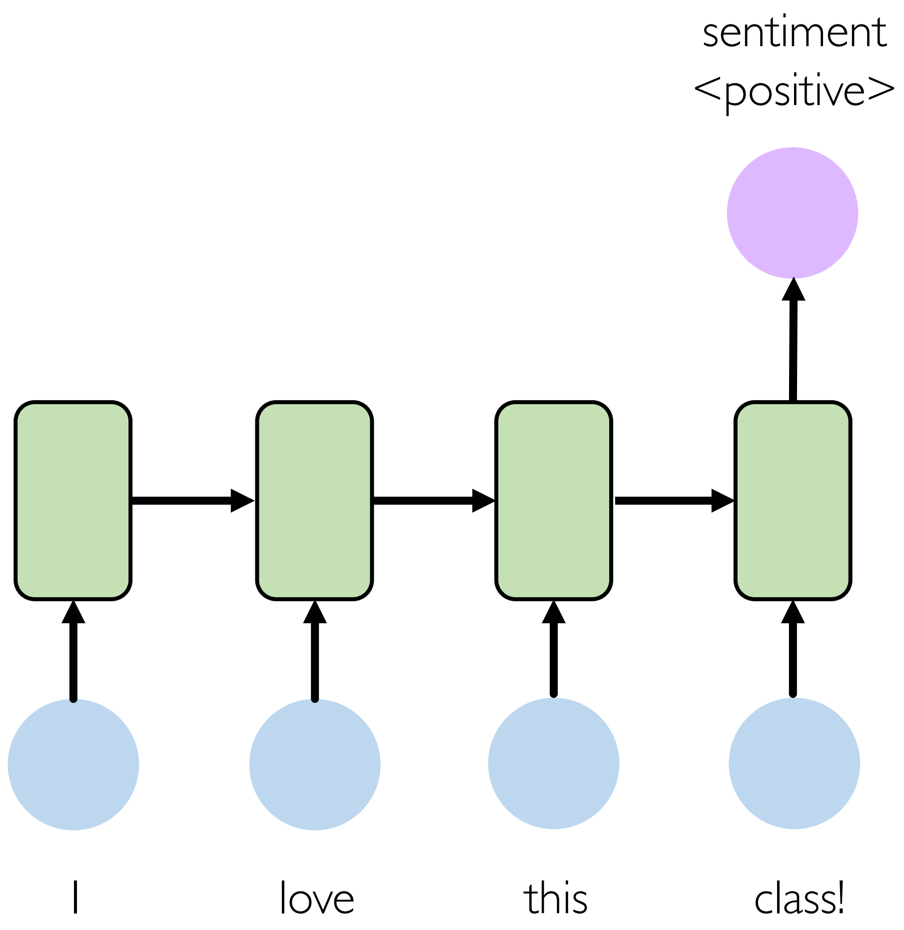
Input: sequence of words

Output: probability of having positive sentiment

Adapted from H. Suresh, 6.S191 2018

[7]

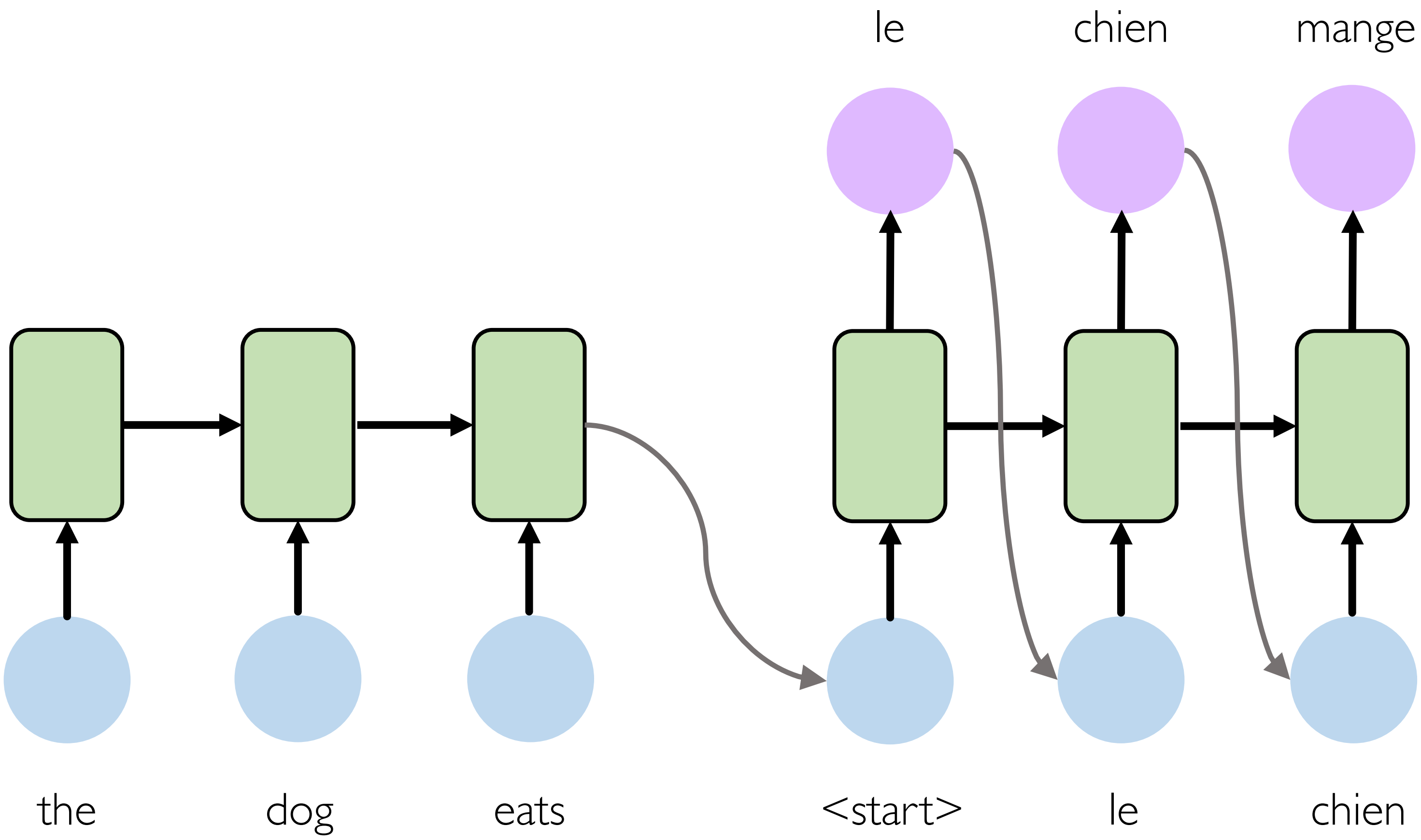
Example task: sentiment classification



Tweet sentiment classification

Adapted from H. Suresh, 6.S191 2018

Example task: machine translation

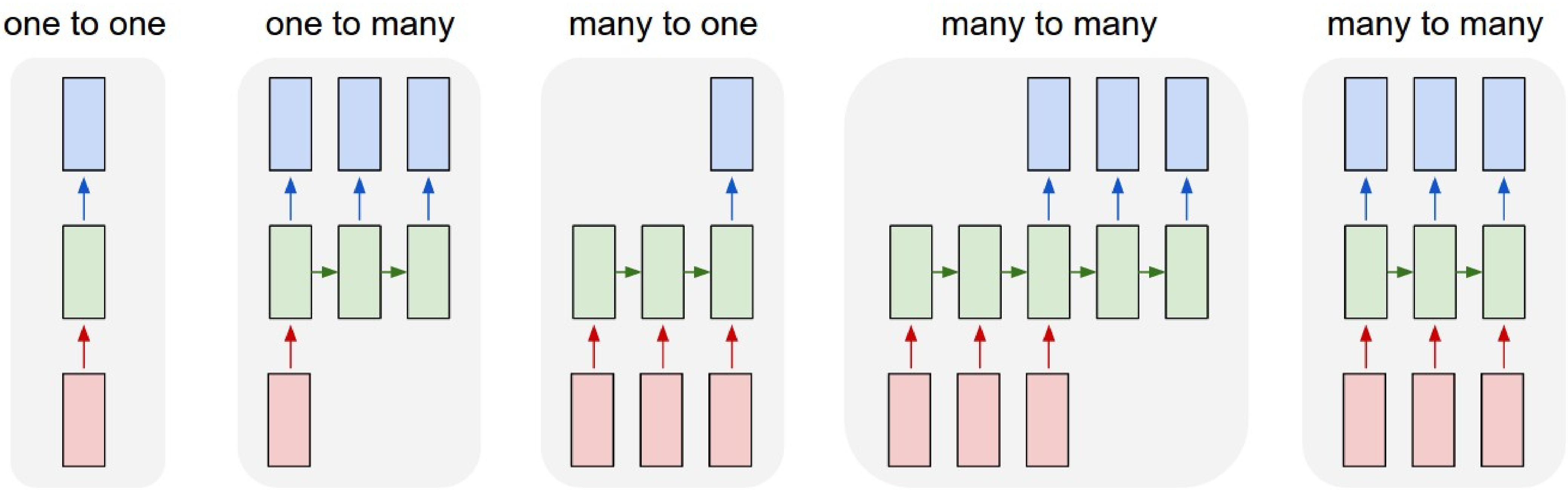


Encoder (English) **Decoder (French)**

Adapted from H. Suresh, 6.S191 2018

[8,9]

Different designs



res: Andrej Karpathy

Different designs

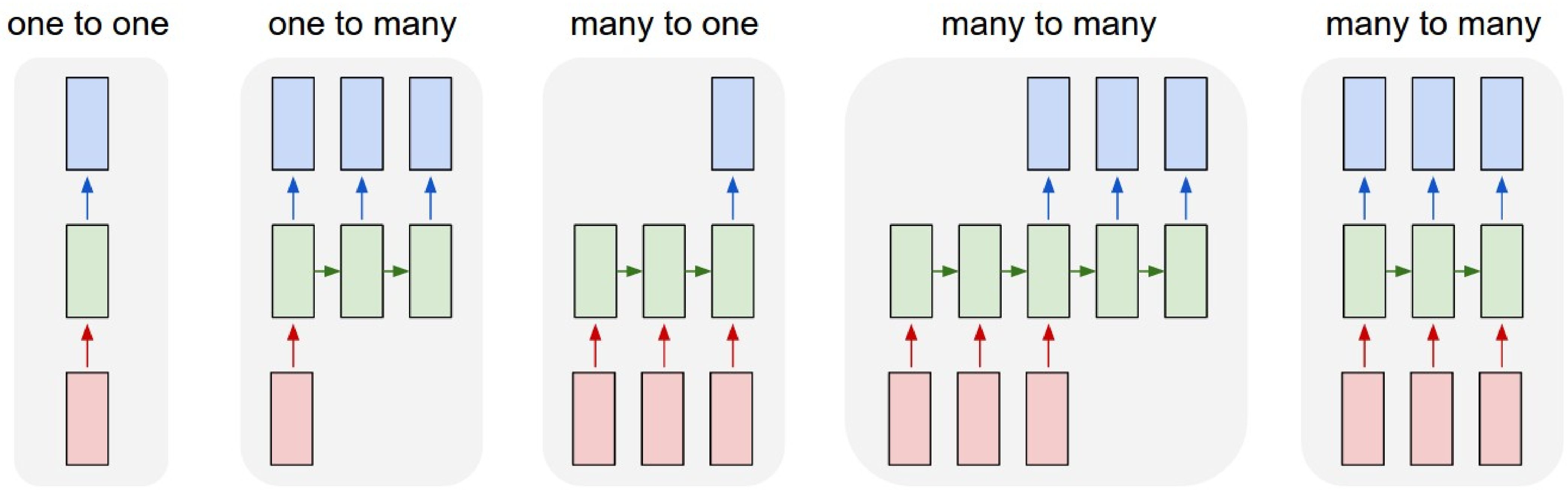


image captioning

sentiment analysis

machine translation

video classification

res: Andrej Karpathy

Recurrent neural networks (RNNs)

1. RNNs are well suited for sequence modeling tasks
2. Model sequences via a recurrence relation
3. Training RNNs with backpropagation through time
4. Models for caption generation, classification, machine translation