VIRGINIA TECH

Recurrent Neural Networks

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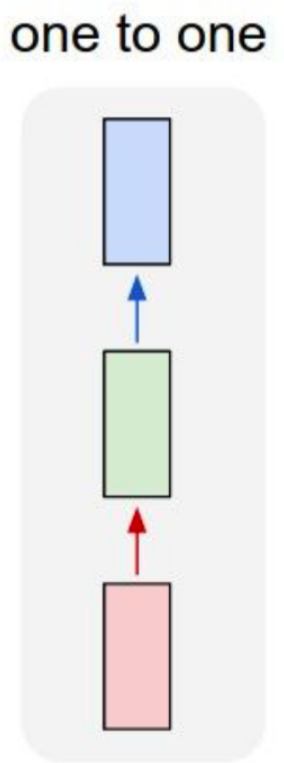
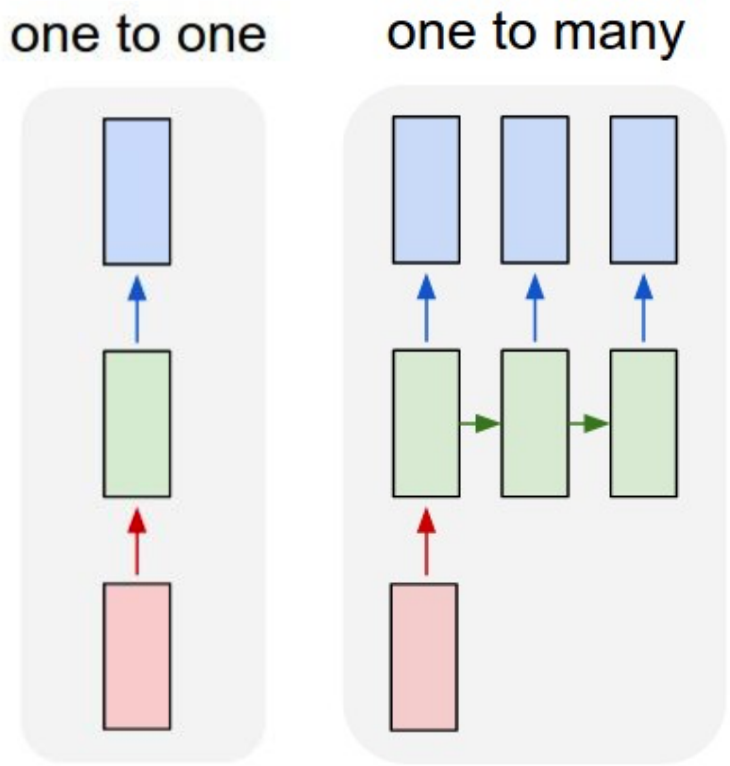
Slides adapted from Feifei Li, Justin Johnson, Serena Yeung

Recurrent Neural Networks: Process Sequences



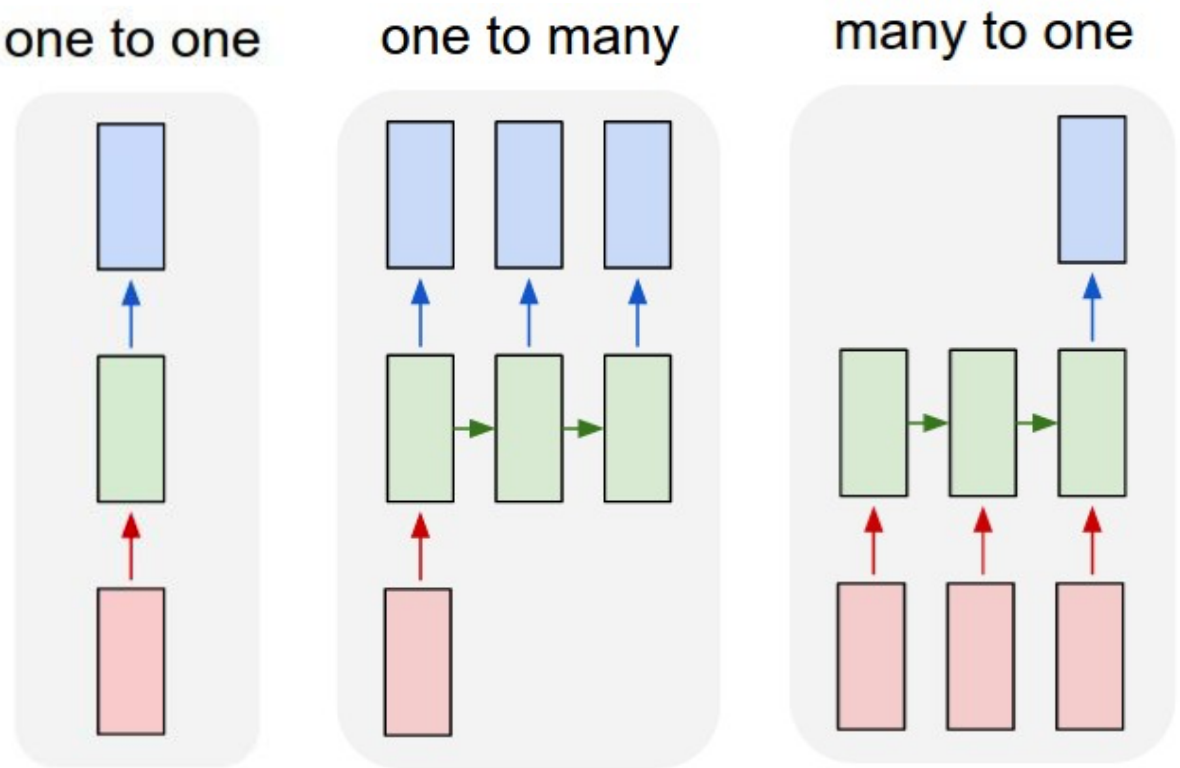
Vanilla Neural Networks
e.g., **Image Classification**
Image -> Label

Recurrent Neural Networks: Process Sequences



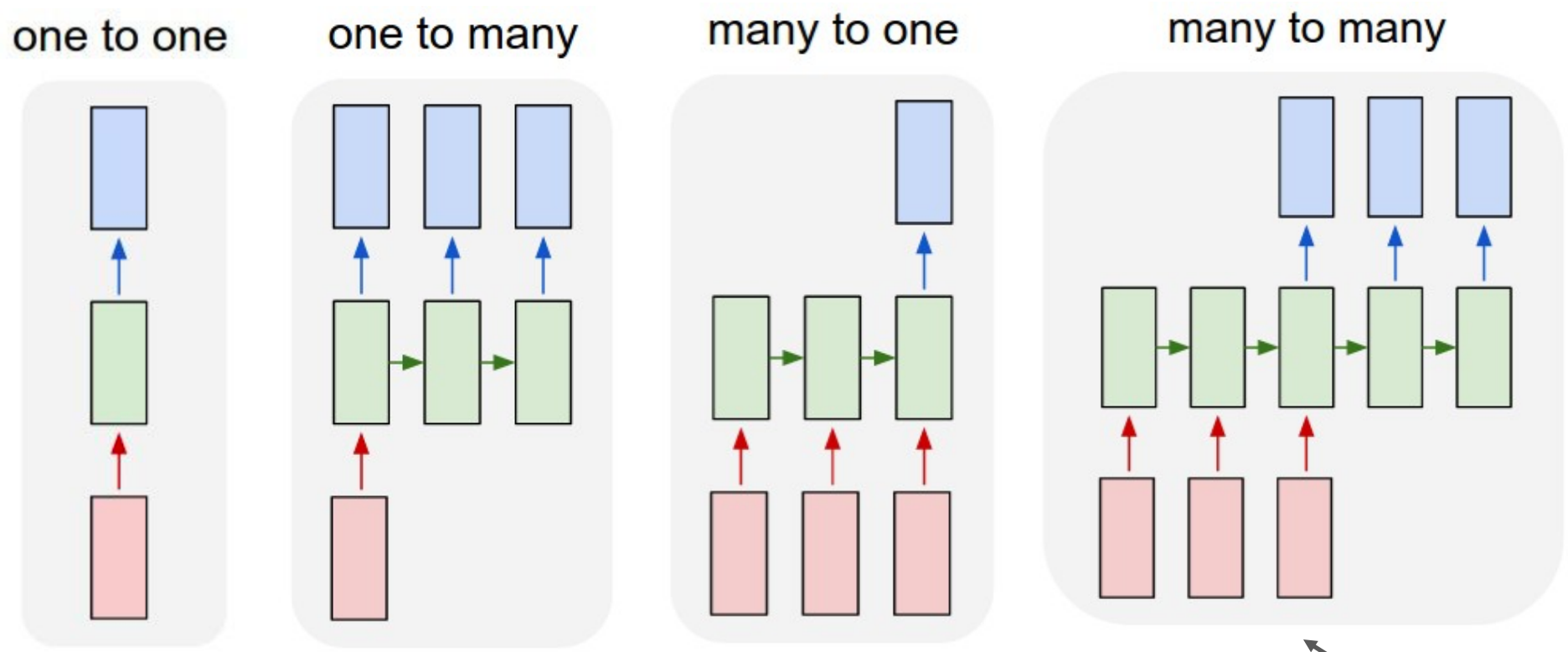
e.g., **Image Captioning**
Image -> Sequence of Words

Recurrent Neural Networks: Process Sequences



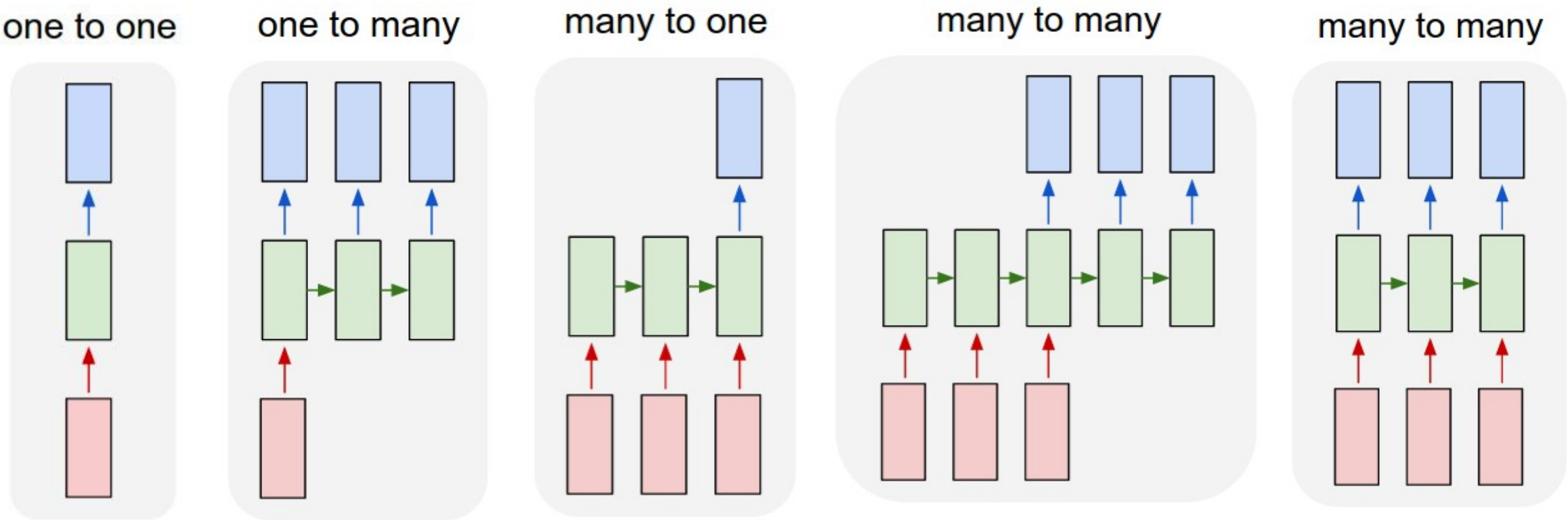
e.g., **Video/Text Classification**
Sequence of images/words -> Label

Recurrent Neural Networks: Process Sequences



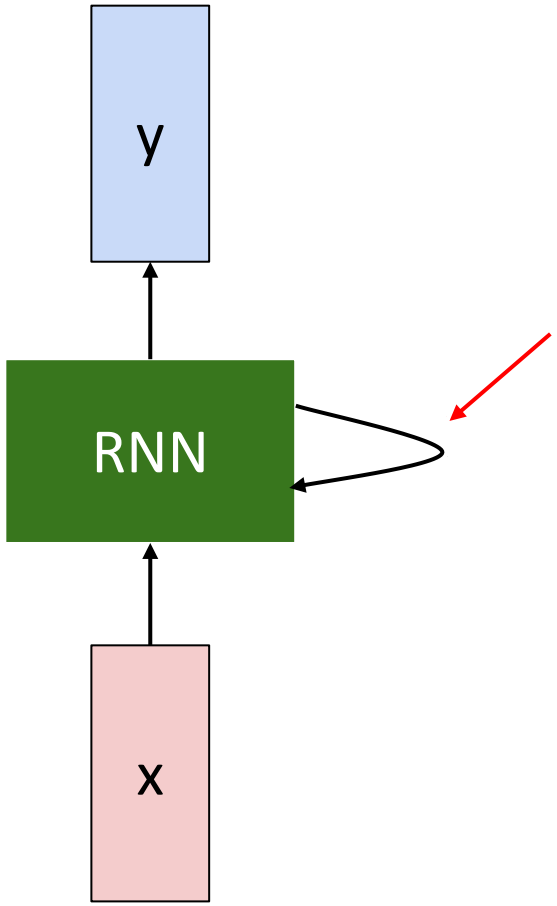
e.g., **Machine Translation**
Sequence of words -> Sequence of words

Recurrent Neural Networks: Process Sequences

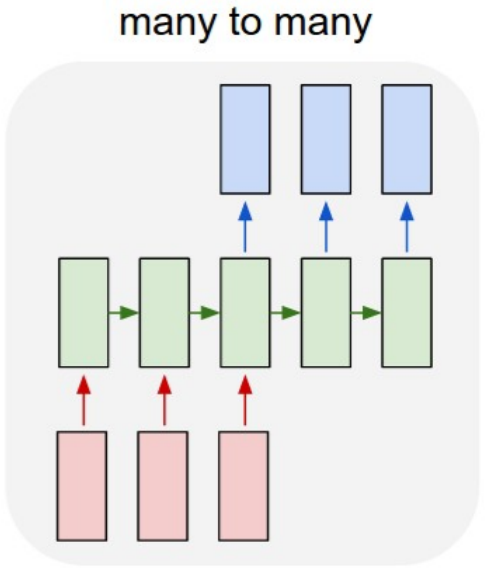


e.g., **Per-frame Video Classification**
Sequence of images -> Sequence of labels

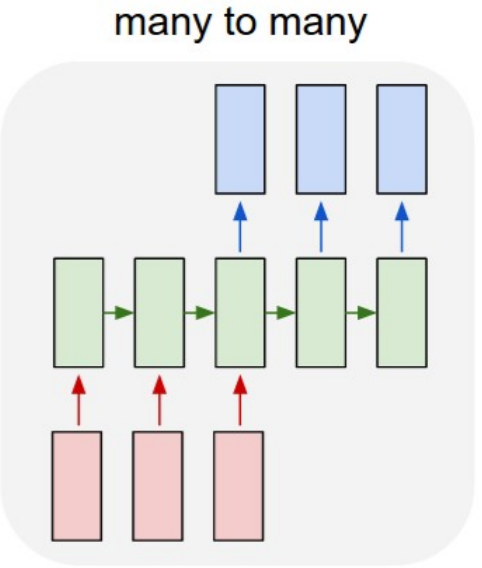
Recurrent Neural Networks

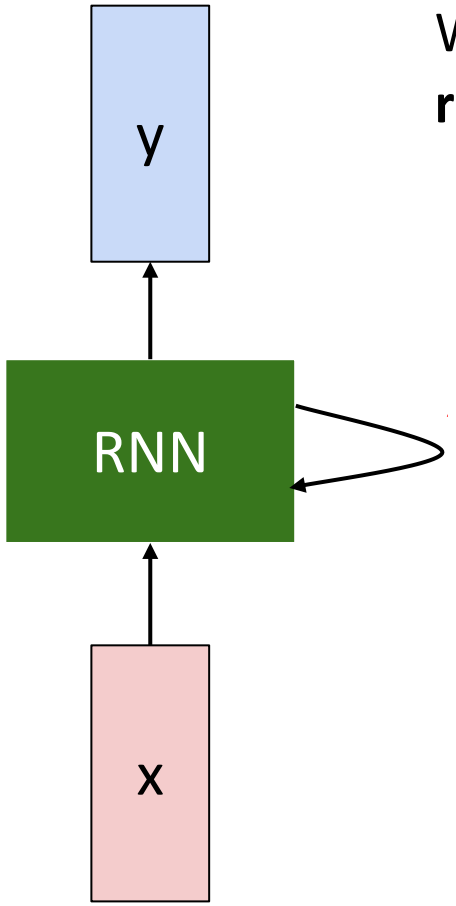


Key idea: RNNs have an "internal state" that is updated as a sequence is processed



Recurrent Neural Networks





We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

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

new state

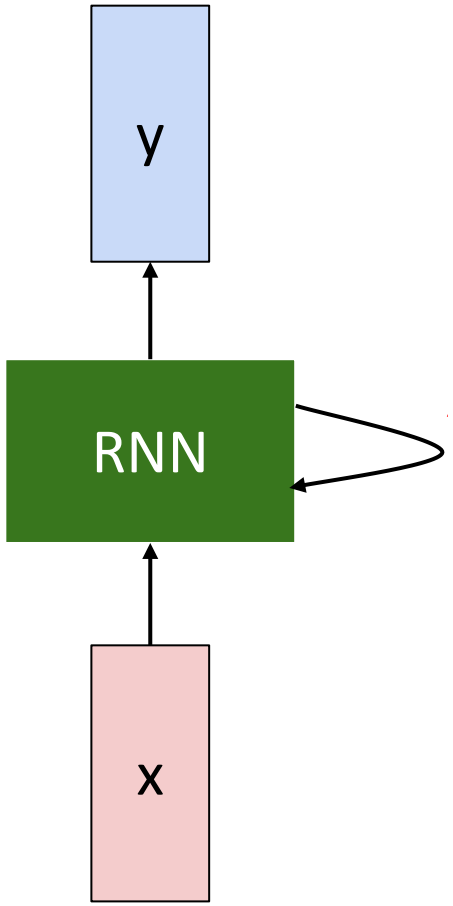
some function with parameters W

old state

input vector at some time step

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

(Vanilla) Recurrent Neural Networks



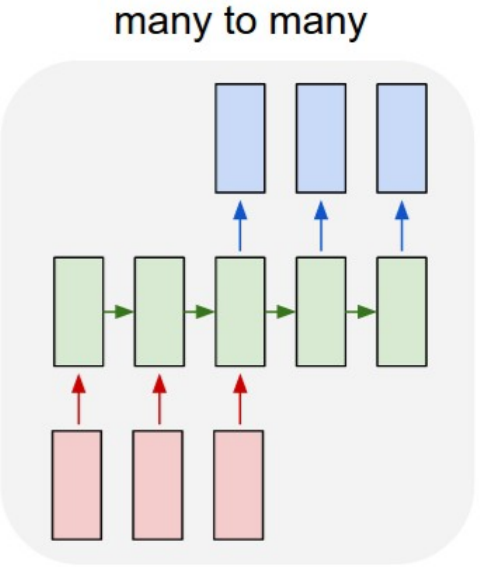
The state consists of a single *"hidden"* vector **h**:

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

(also bias term)

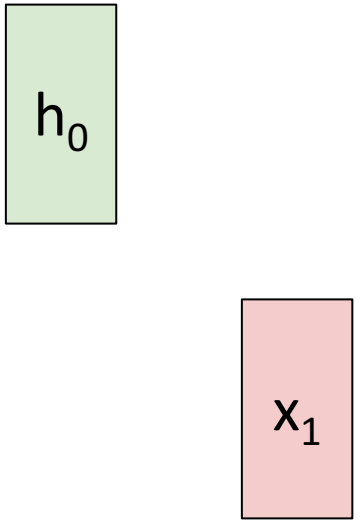
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$



RNN Computational Graph

Initial hidden state
Either set to all 0,
or learn it



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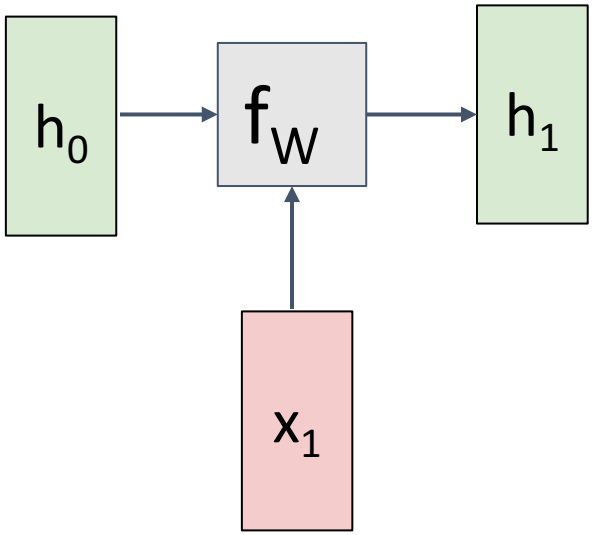

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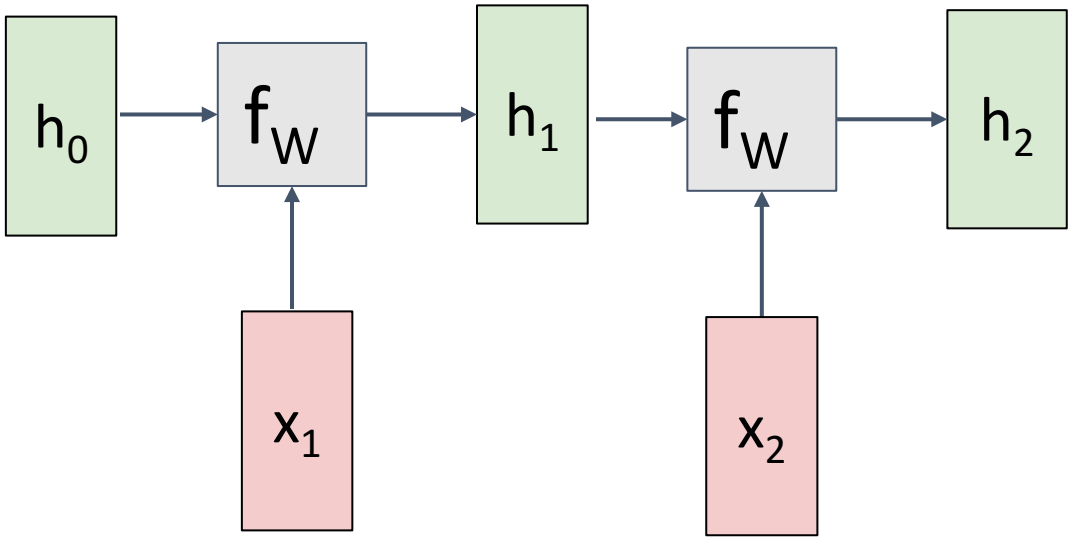

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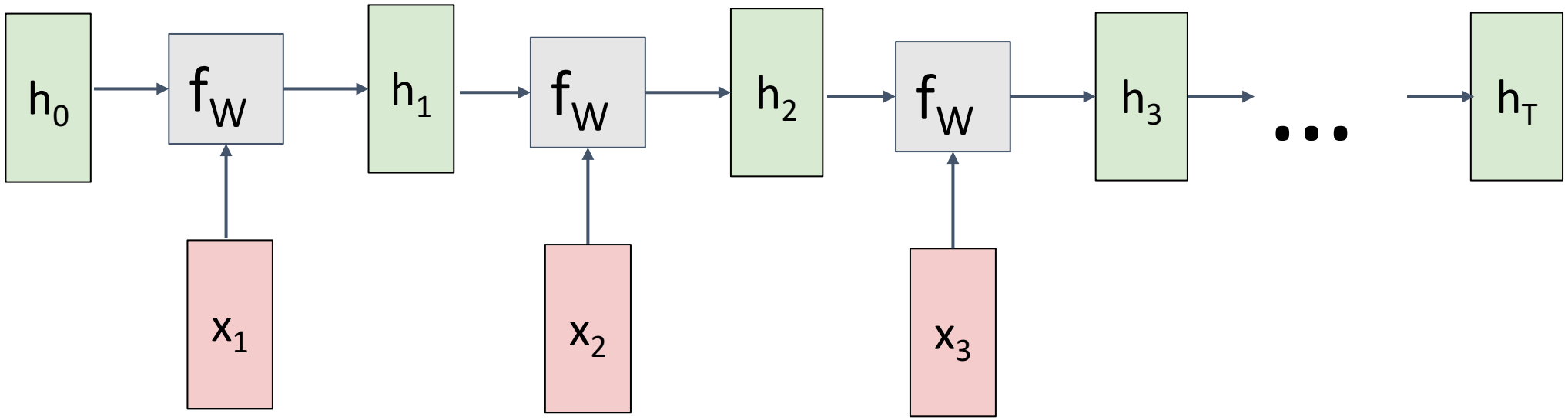
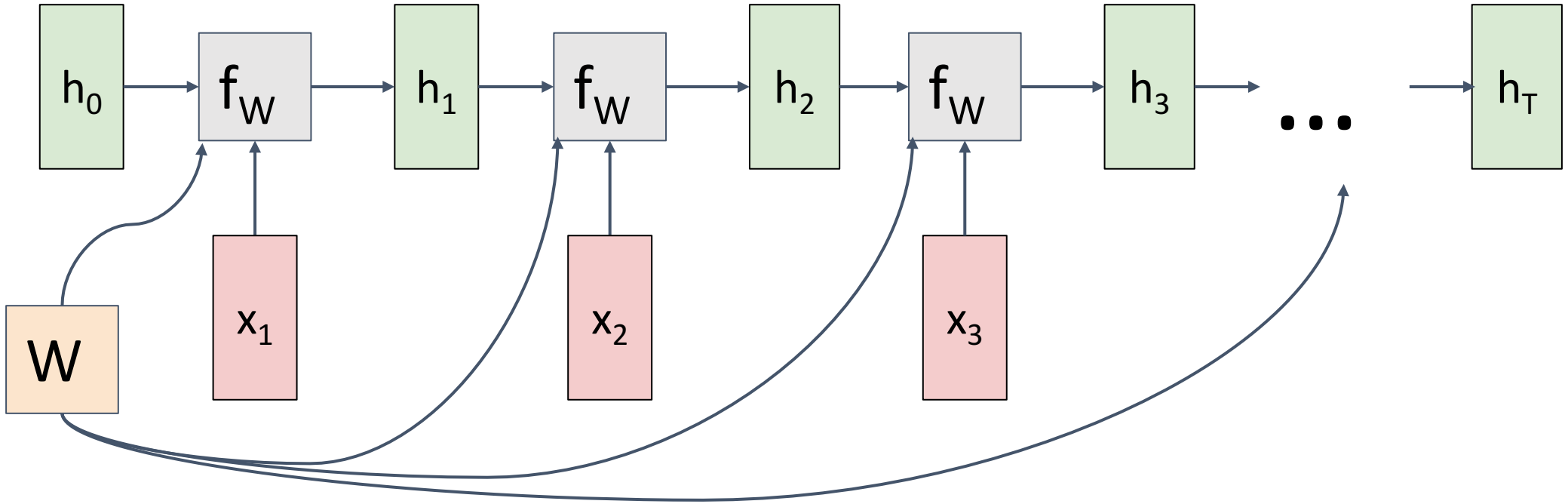


RNN Computational Graph

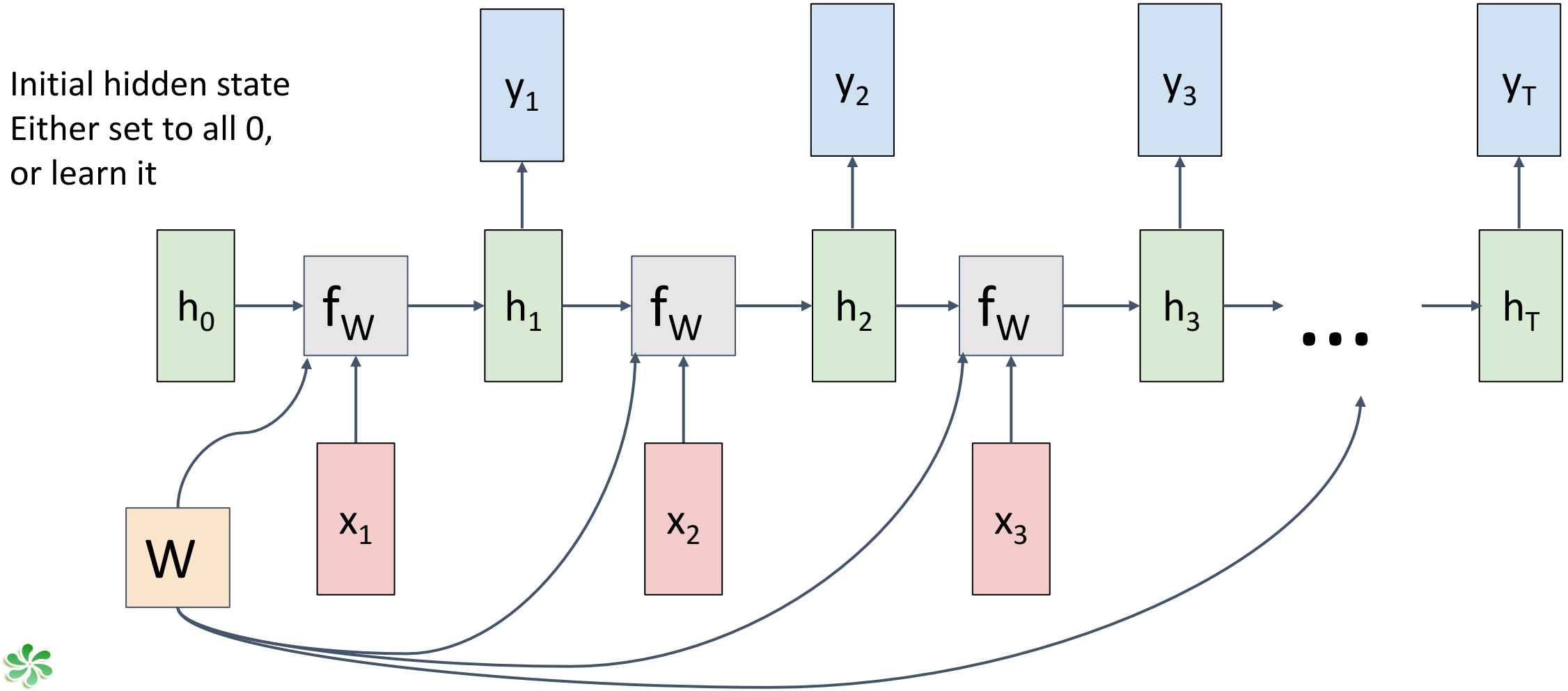
Re-use the same weight matrix at every time-step

Initial hidden state
Either set to all 0,
or learn it



RNN Computational Graph (Many to Many)

- Encode the input sequence and out a new sequence



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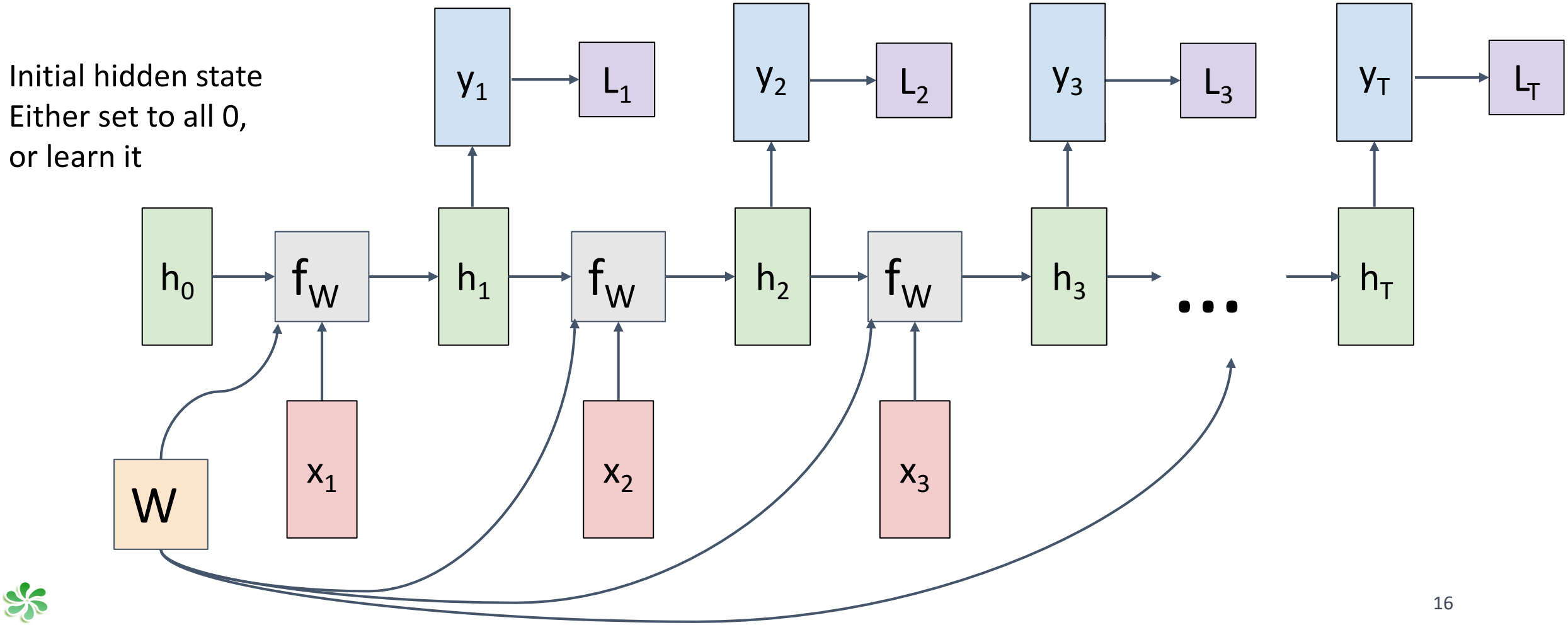
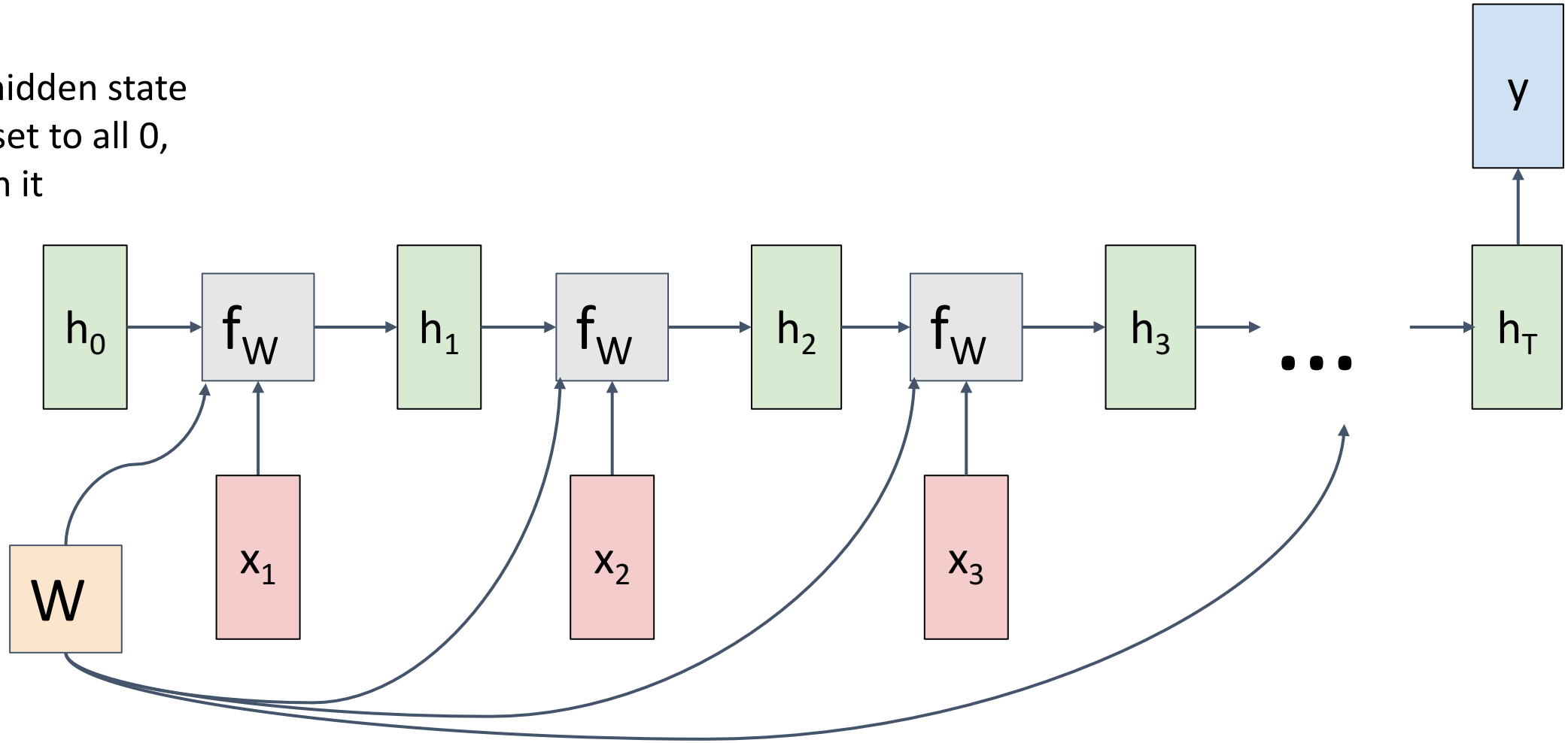


RNN Computational Graph (Many to One)

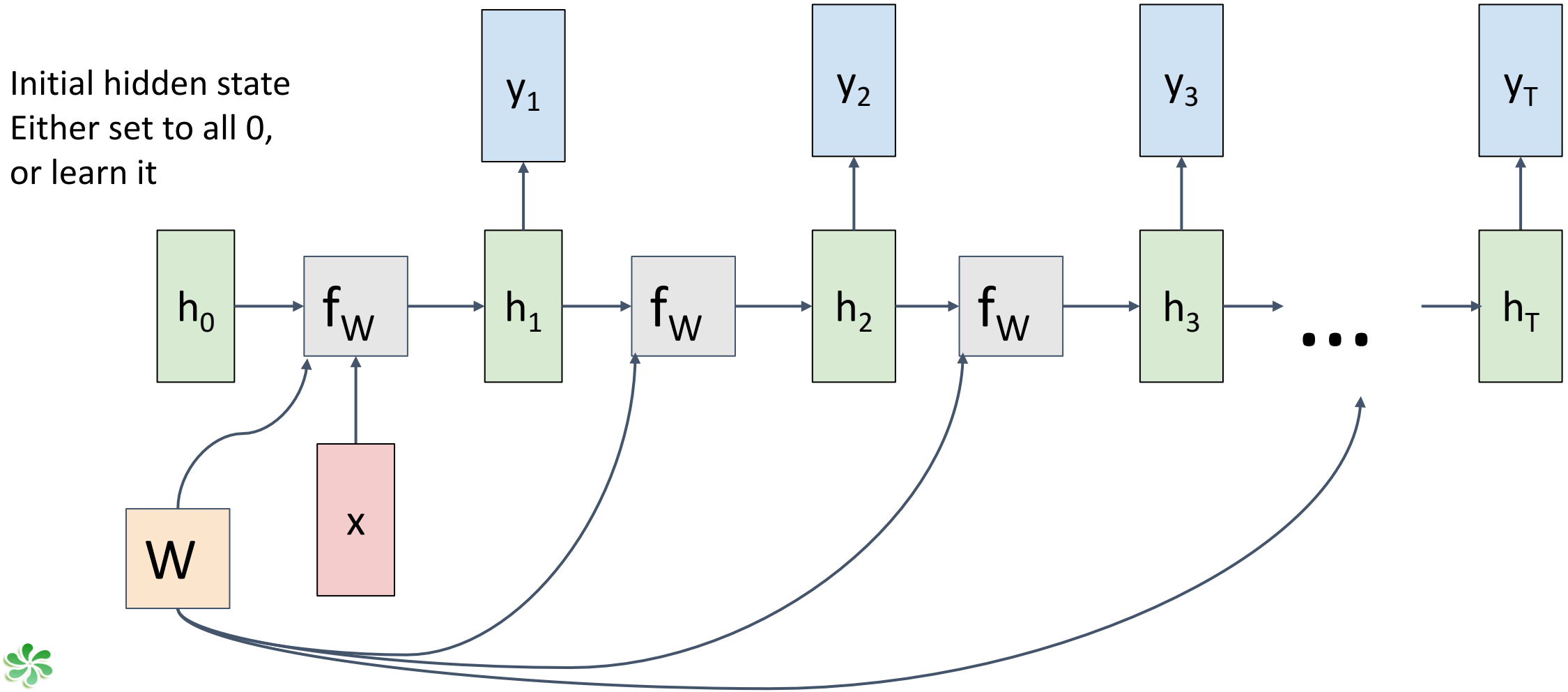
- Encode the input sequence but output a single vector

Initial hidden state
Either set to all 0,
or learn it



RNN Computational Graph (One to Many)

- Take in a single input vector but produce an output sequence

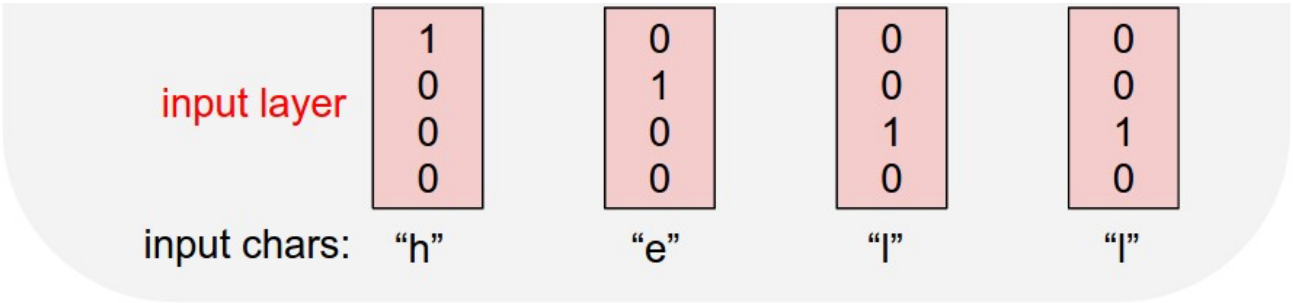


Example: Character-level Language Modeling

Given Characters 1, 2, …, t,
model predicts character t+1

Training sequence: ”hello”

Vocabulary: [h, e, l, o]



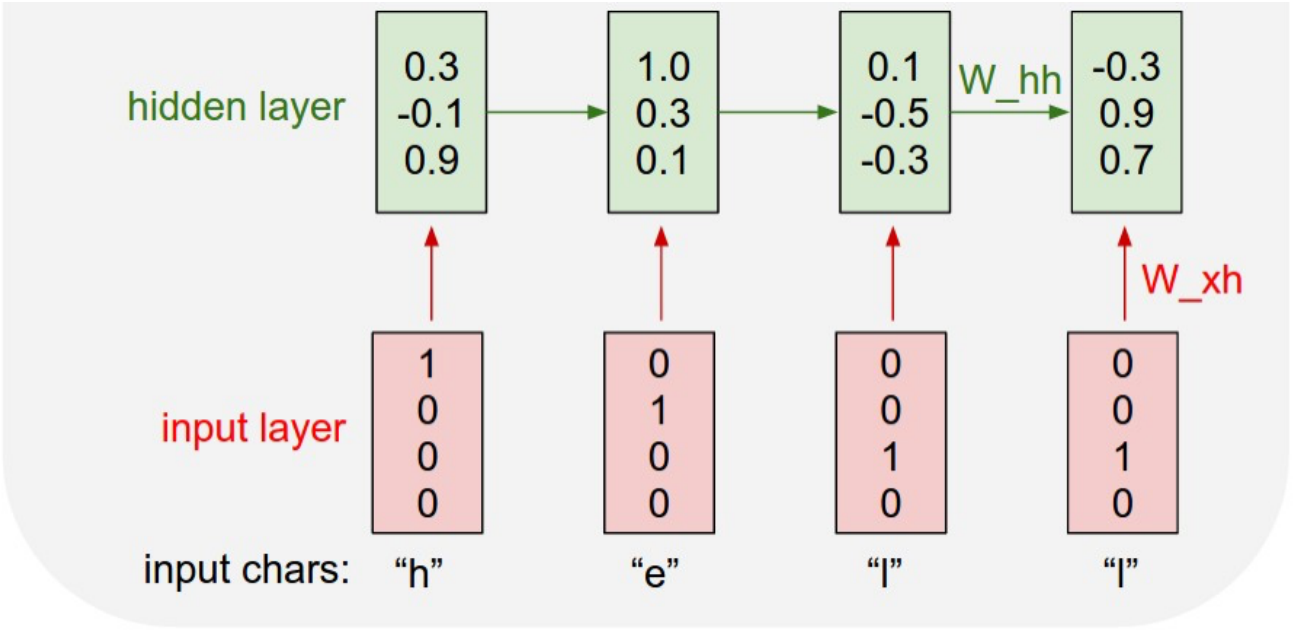
Example: Character-level Language Modeling

Given Characters 1, 2, …, t,
model predicts character t+1

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

Training sequence: ”hello”

Vocabulary: [h, e, l, o]



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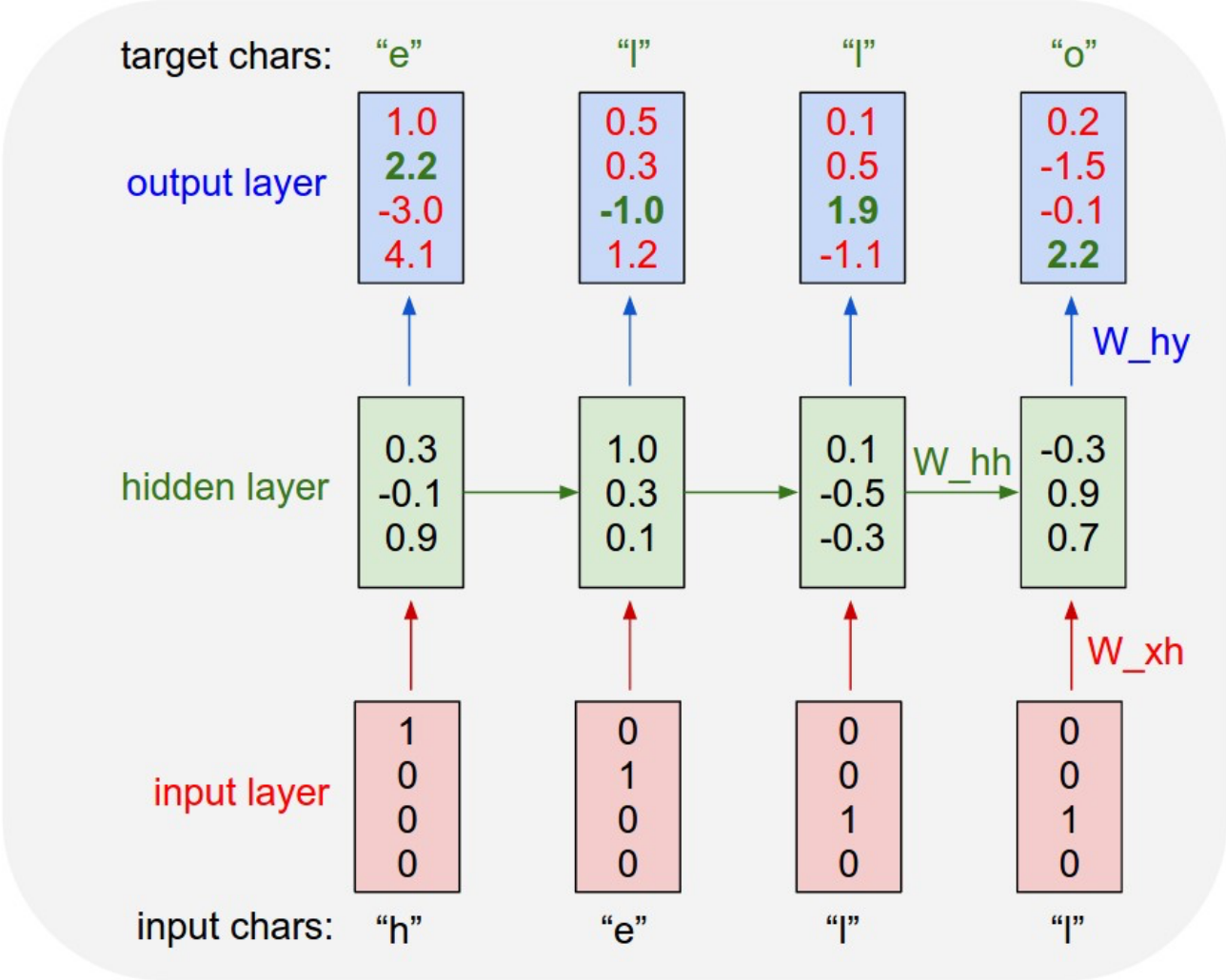


Example: Character-level Language Modeling

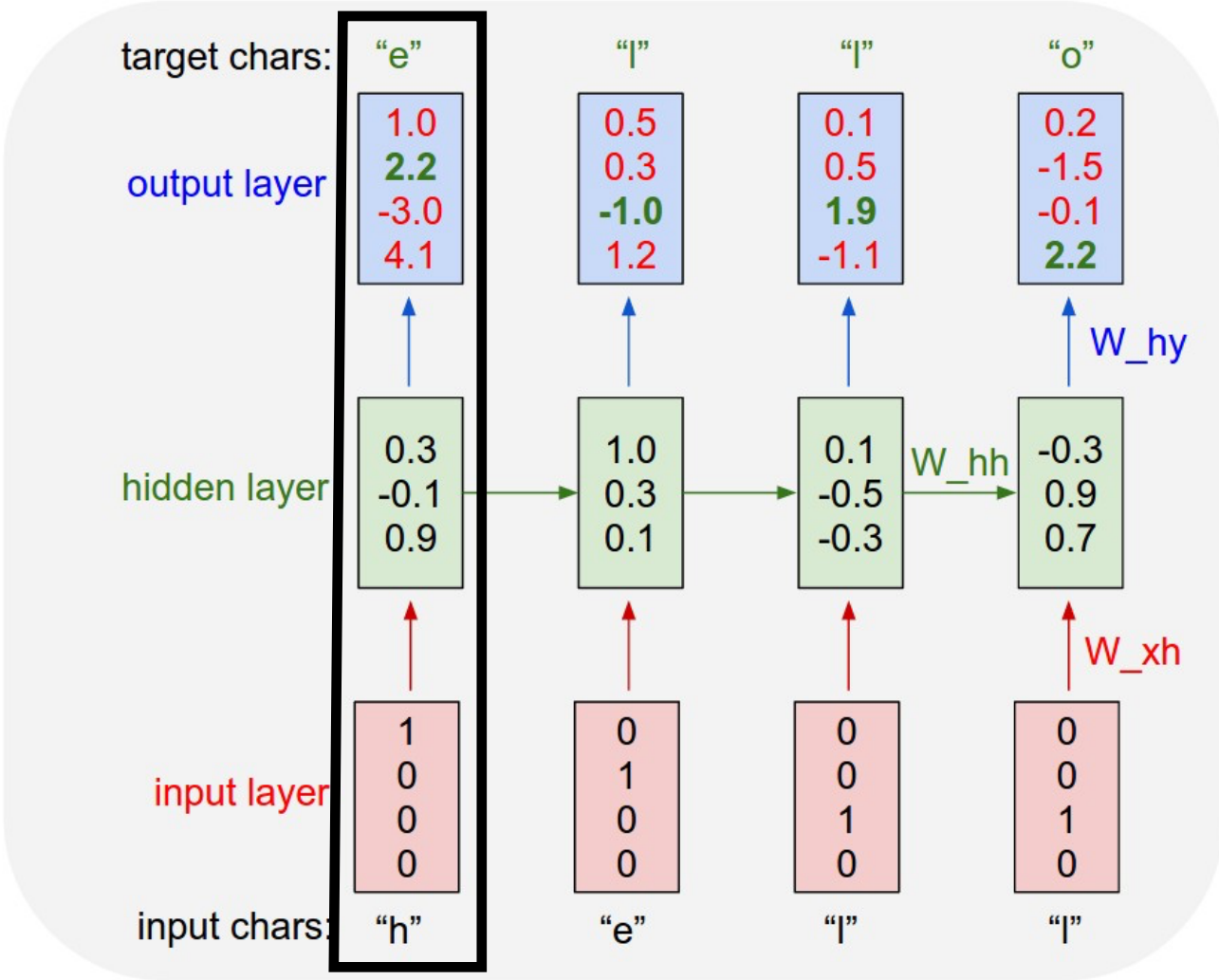
Given “h”, predict “e”

Given Characters 1, 2, …, t,
model predicts character t+1

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

Training sequence: ”hello”

Vocabulary: [h, e, l, o]



Example: Character-level Language Modeling

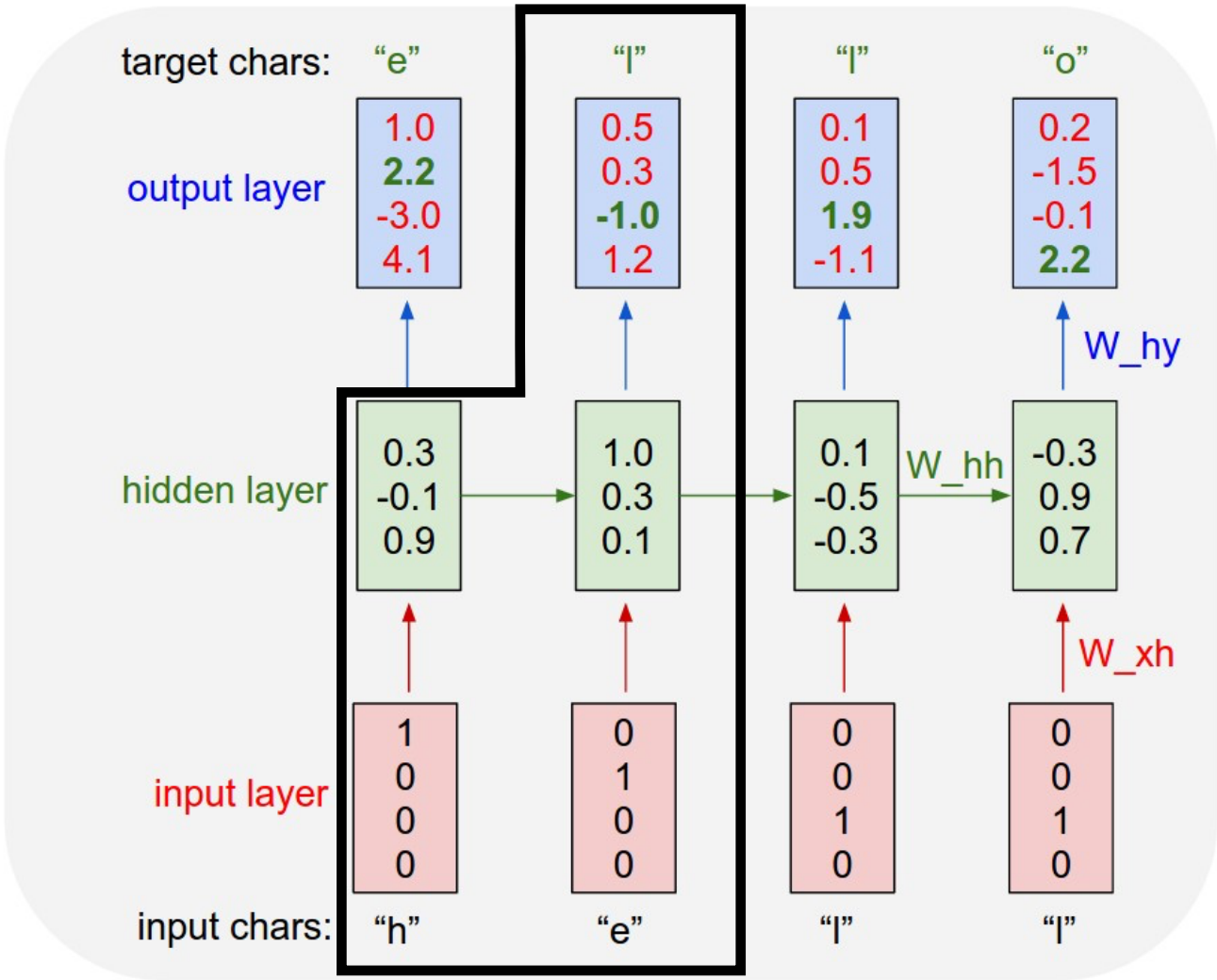
Given "he", predict "l"

Given Characters 1, 2, …, t,
model predicts character t+1

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

Training sequence: "hello"

Vocabulary: [h, e, l, o]



Example: Character-level Language Modeling

Given "hel", predict "l"

Given Characters 1, 2, …, t,
model predicts character t+1

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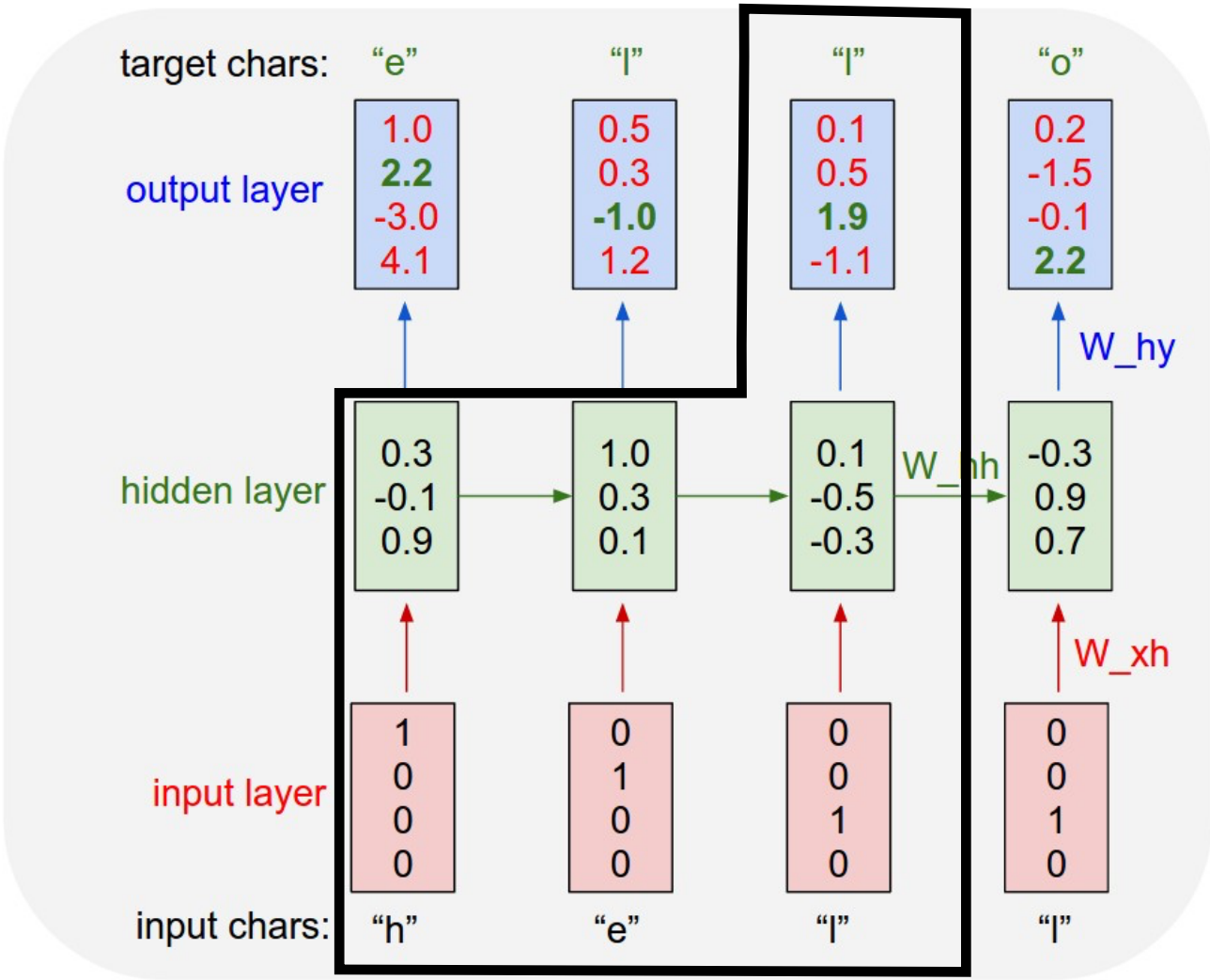
Training sequence: "hello"

Vocabulary: [h, e, l, o]



Example: Character-level Language Modeling

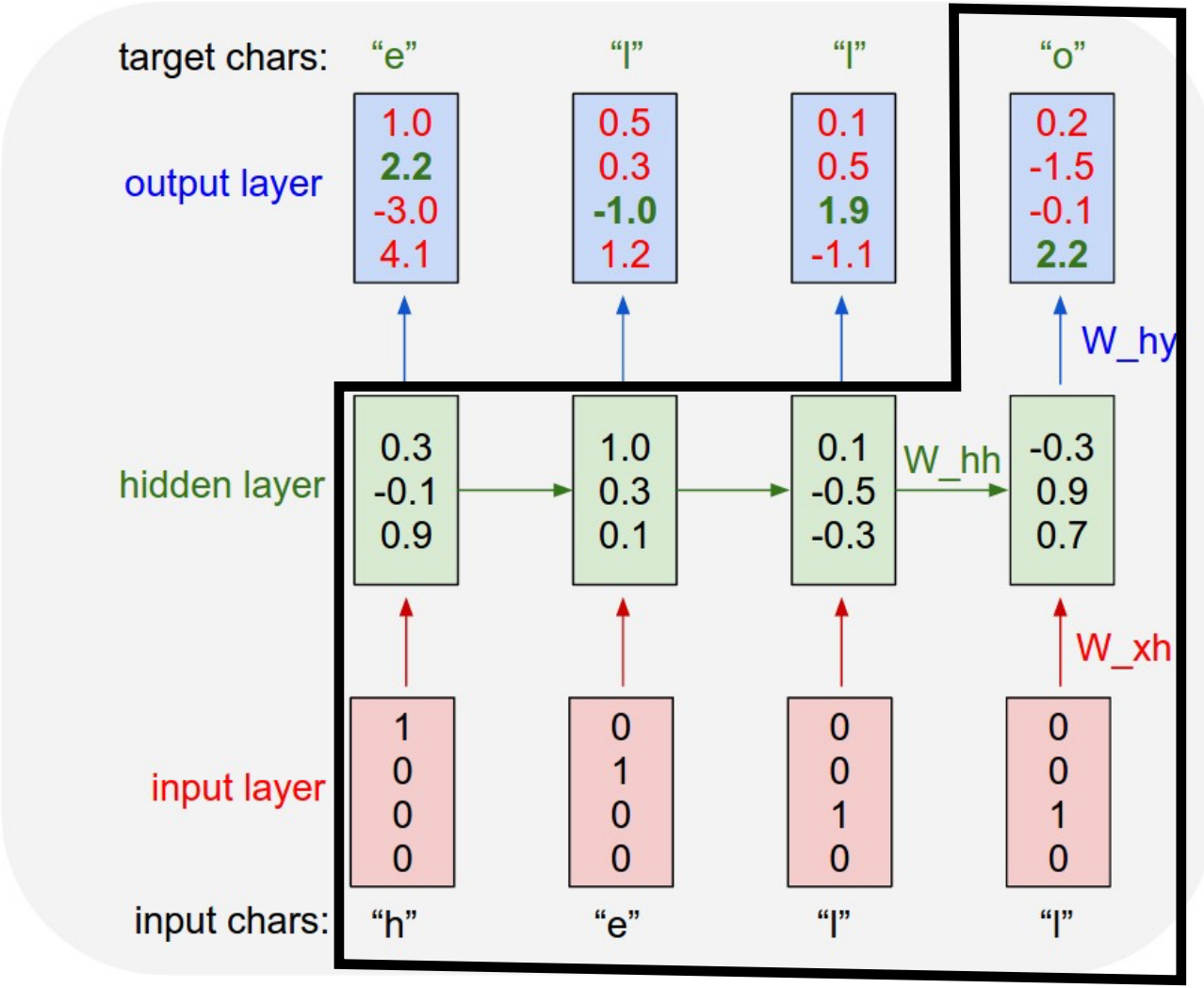
Given "hell", predict "o"

Given Characters 1, 2, …, t,
model predicts character t+1

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

Training sequence: "hello"

Vocabulary: [h, e, l, o]

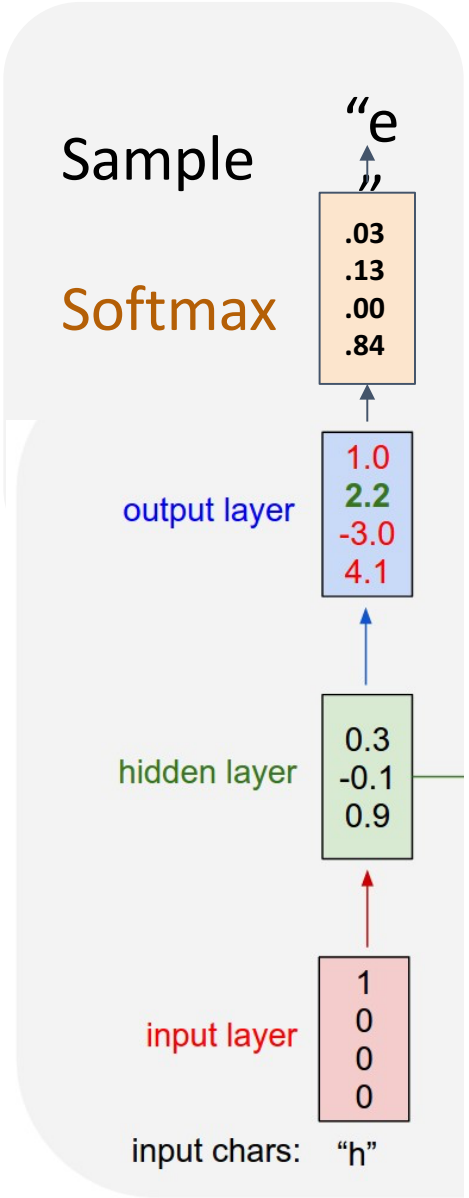


Example: Character-level Language Modeling

At test-time, **generate** new text: sample characters one at a time, feed back to model

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

Vocabulary: [h, e, l, o]



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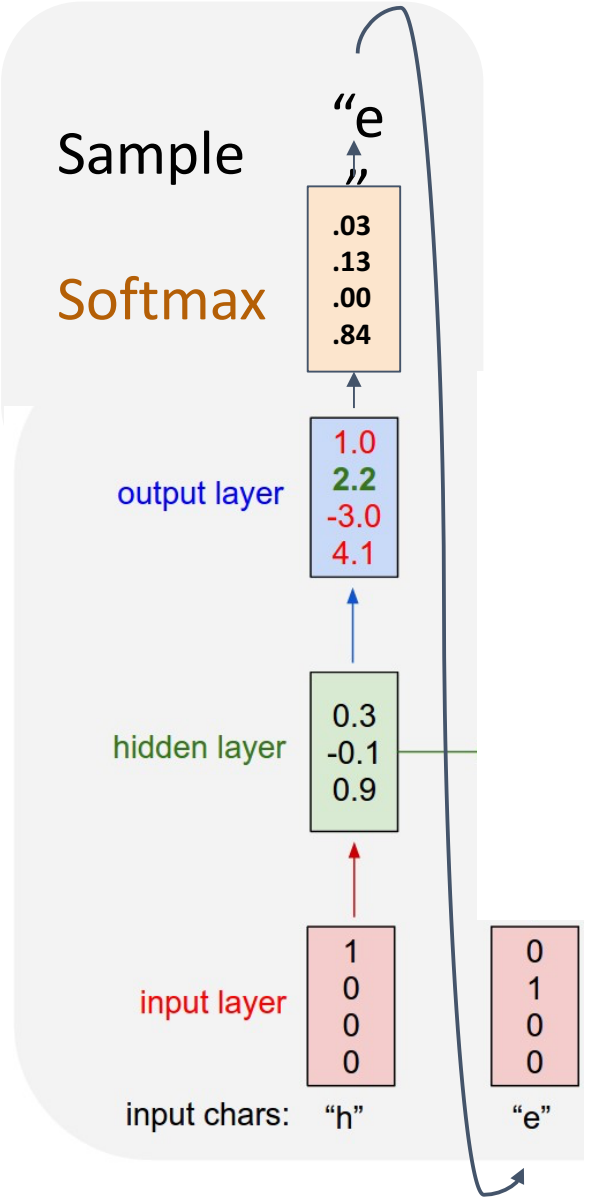

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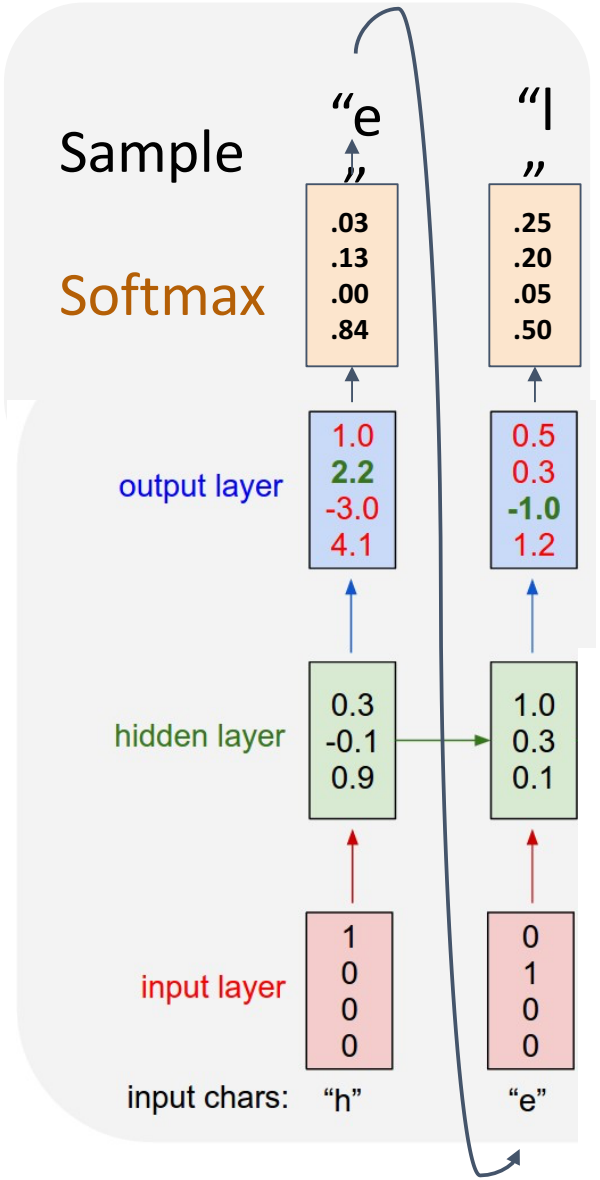

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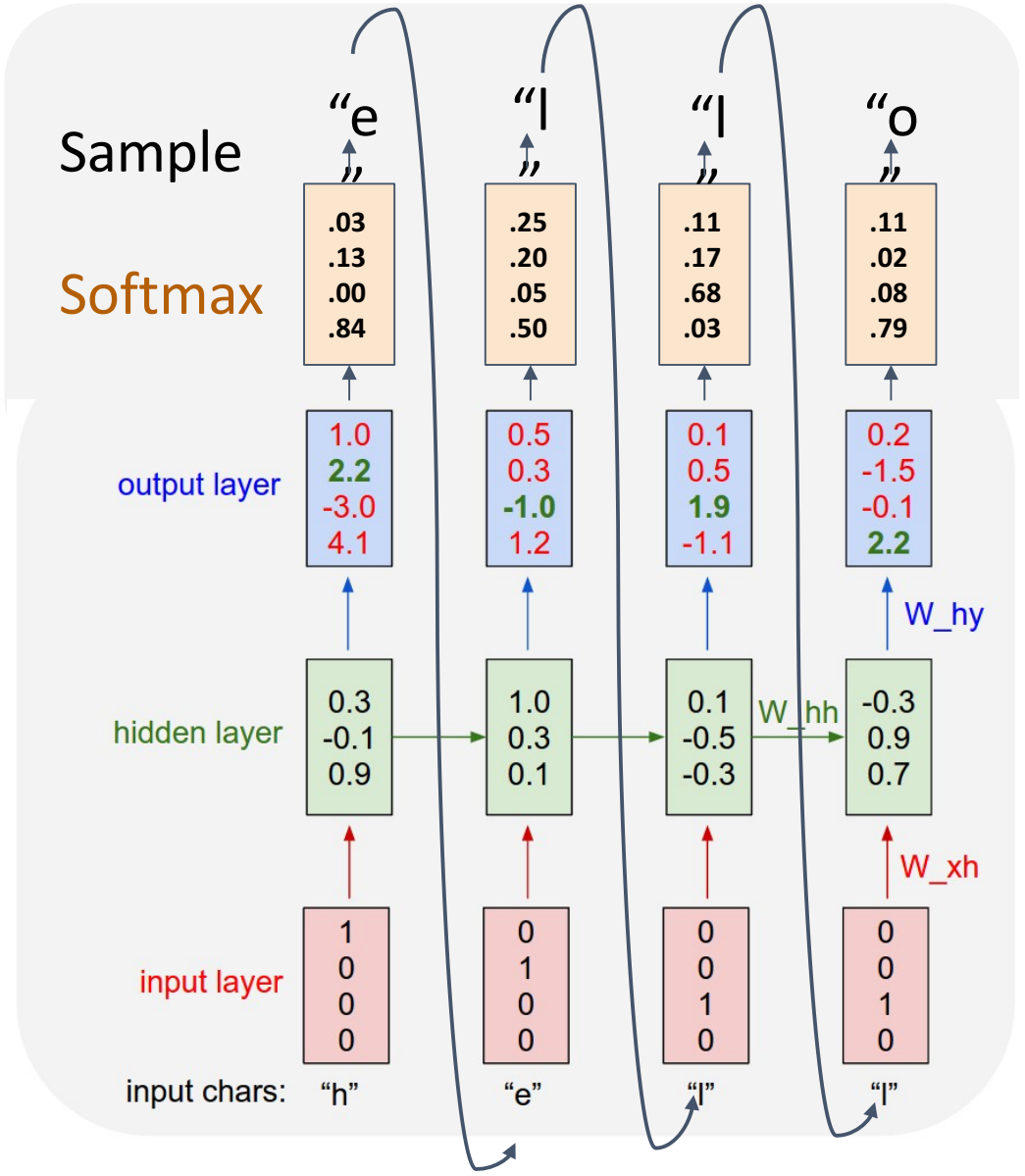
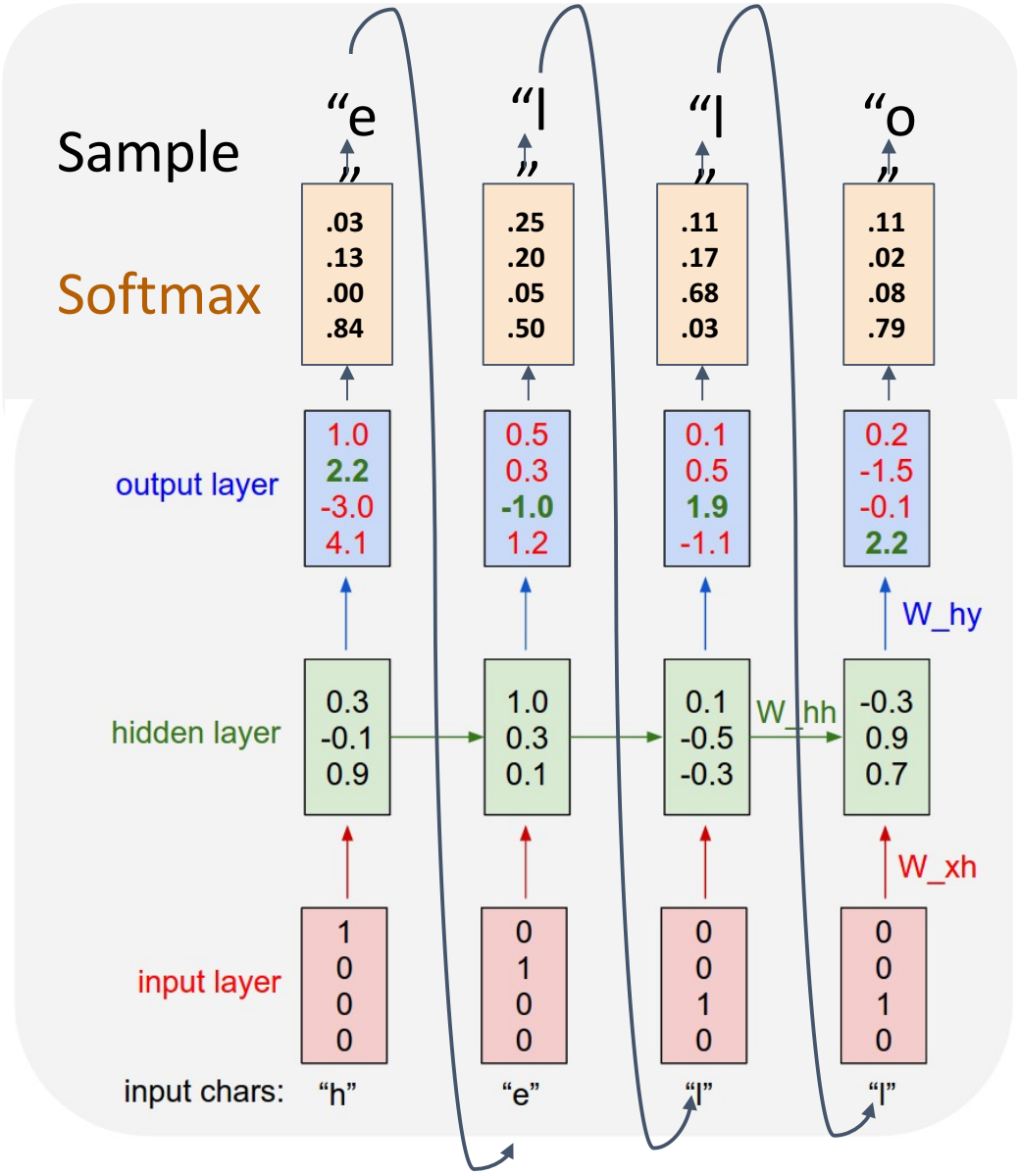


Example: Character-level Language Modeling

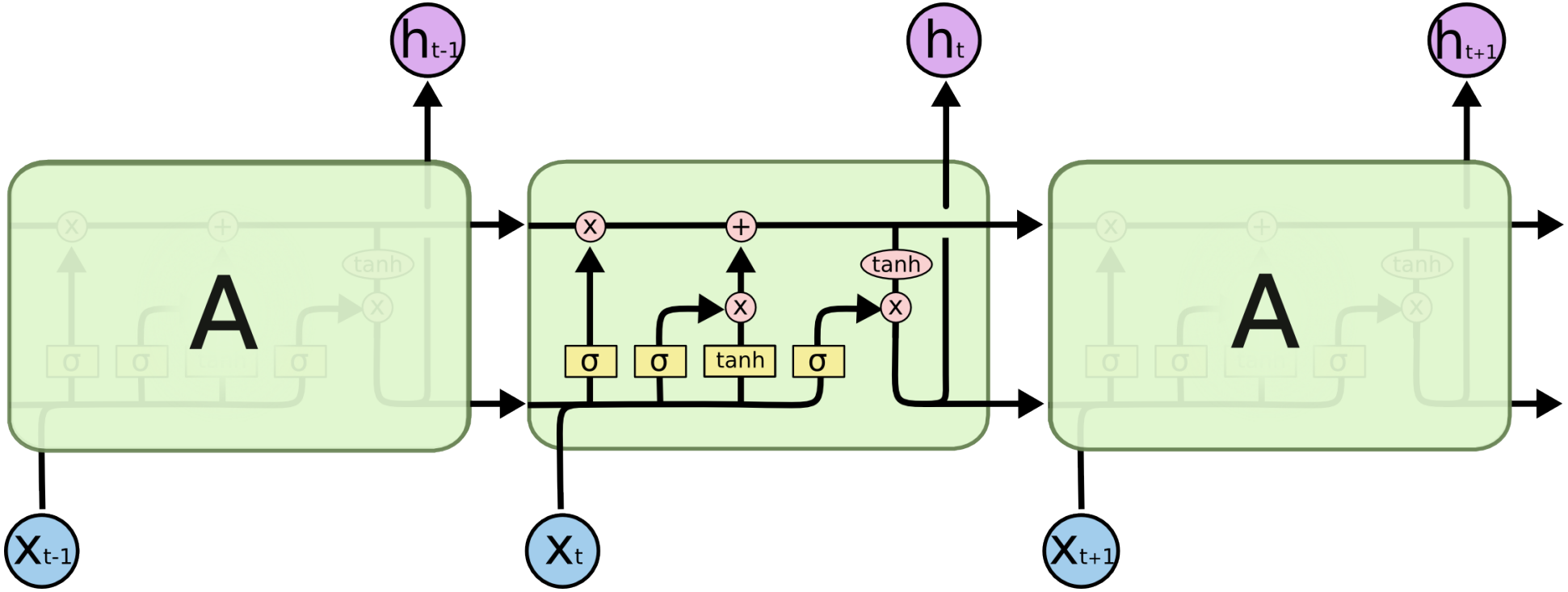
So far: encode inputs
as **one-hot-vector**

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{14} \\ w_{31} & w_{32} & w_{33} & w_{14} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} w_{11} \\ w_{21} \\ w_{31} \end{bmatrix}$$

Matrix multiply with a one-hot vector just extracts a column from the weight matrix. Often extract this into a separate **embedding** layer



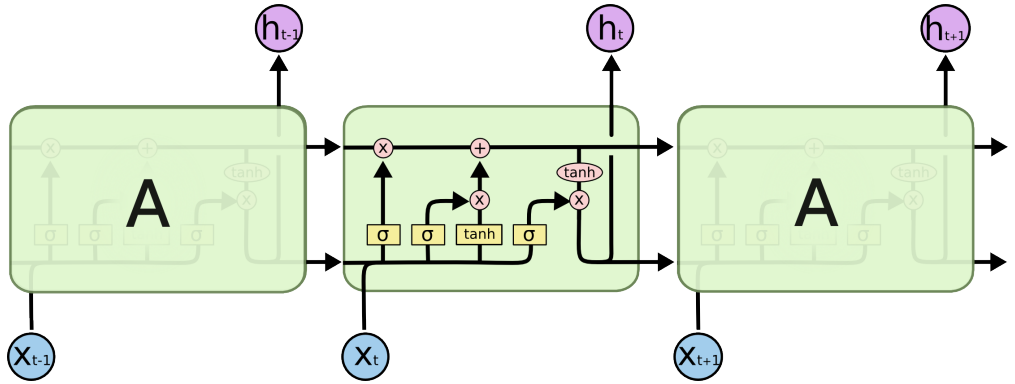
Long Short Term Memory (LSTM)



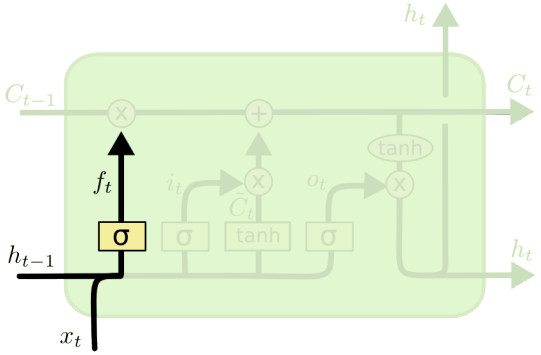
https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Hochreiter and Schmidhuber, “Long Short Term Memory”, Neural Computation

Gate Functions in Long Short Term Memory (LSTM)



1. Forget Gate: How much information to be forgot from the cell

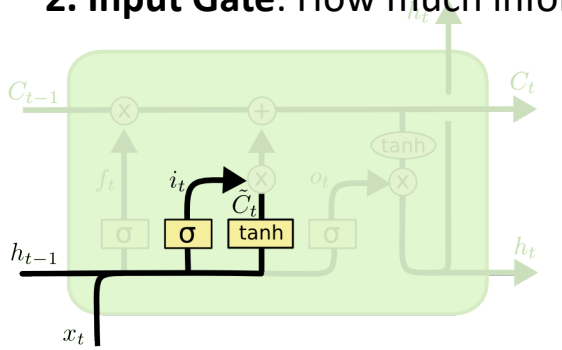


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

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

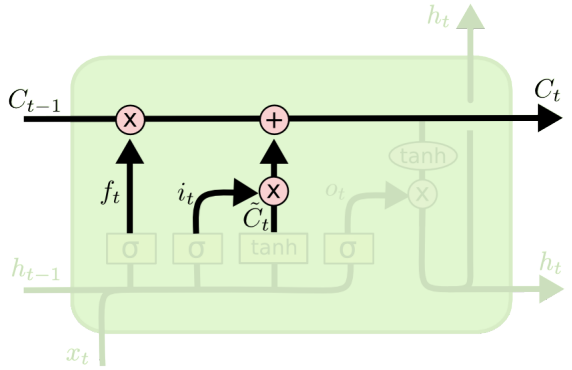
Hochreiter and Schmidhuber, "Long Short Term Memory", Neural Computation

2. Input Gate: How much information to be put into the cell



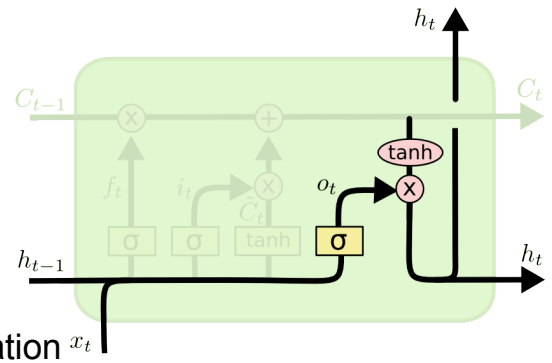
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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



3. Update the Cell

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



4. Output Gate: What to be output from the Cell

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

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

Applications of Recurrent Neural Networks

- Named Entity Recognition
  - Recognize all entity names from a given sentence
  - Given a sentence, use RNN, e.g., LSTM, to encode each token and obtain a hidden representation, then classify it into a particular category, e.g., organization (ORG), person (PER), location (LOC), other (O)