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Artificial Neural Network

Dr. Trần Vũ Hoàng

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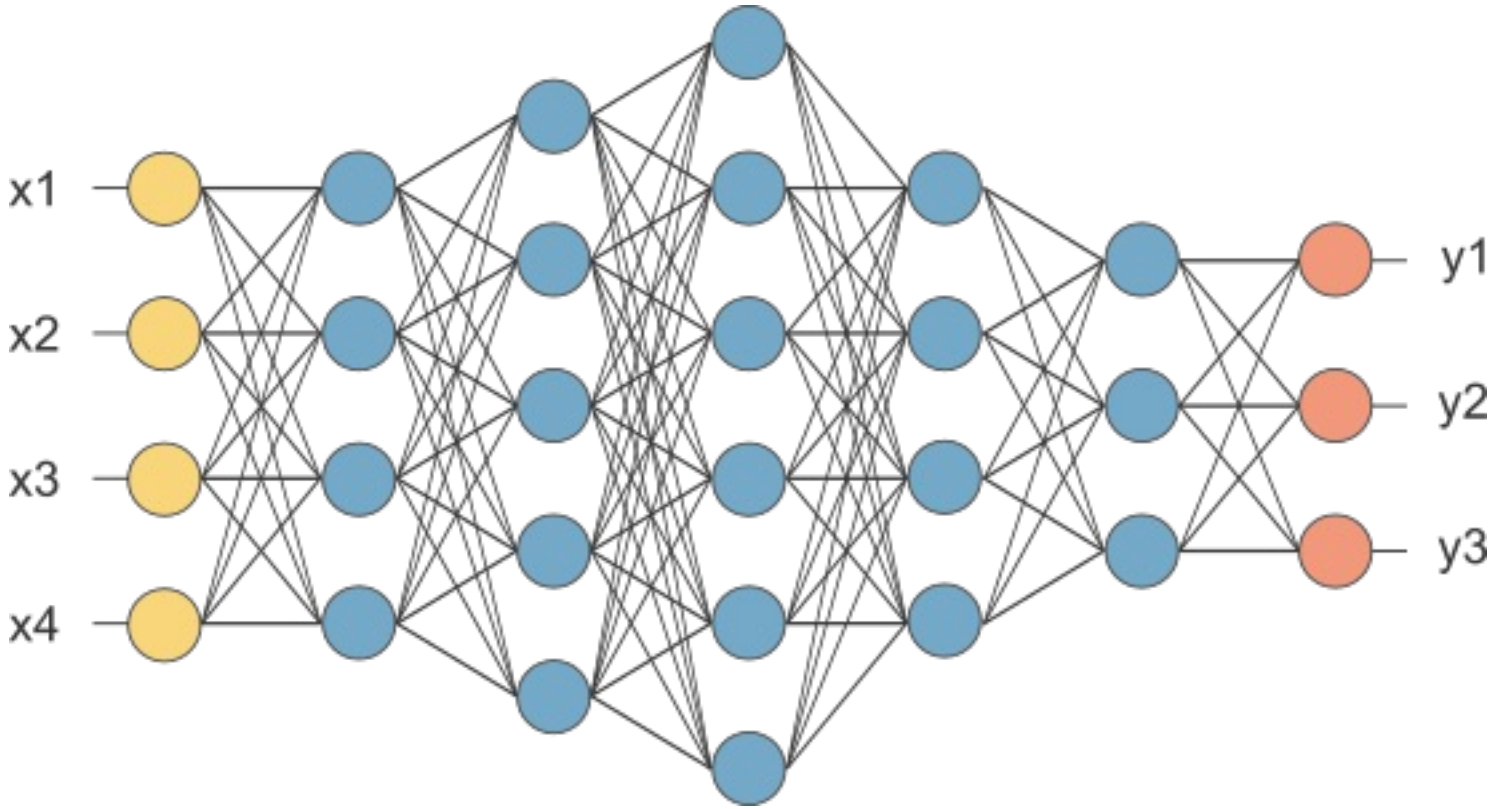
Smaller Network: RNN



This is our fully connected network. If x_1 .... x_n, n is very large and growing, this network would become too large. We now will input one x_i at a time, and re-use the same edge weights.

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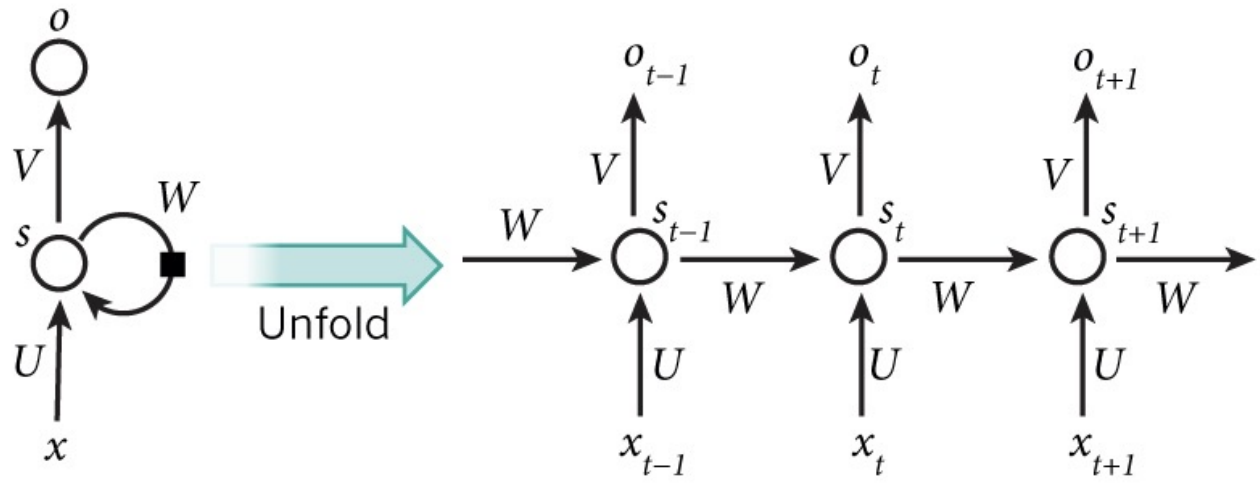
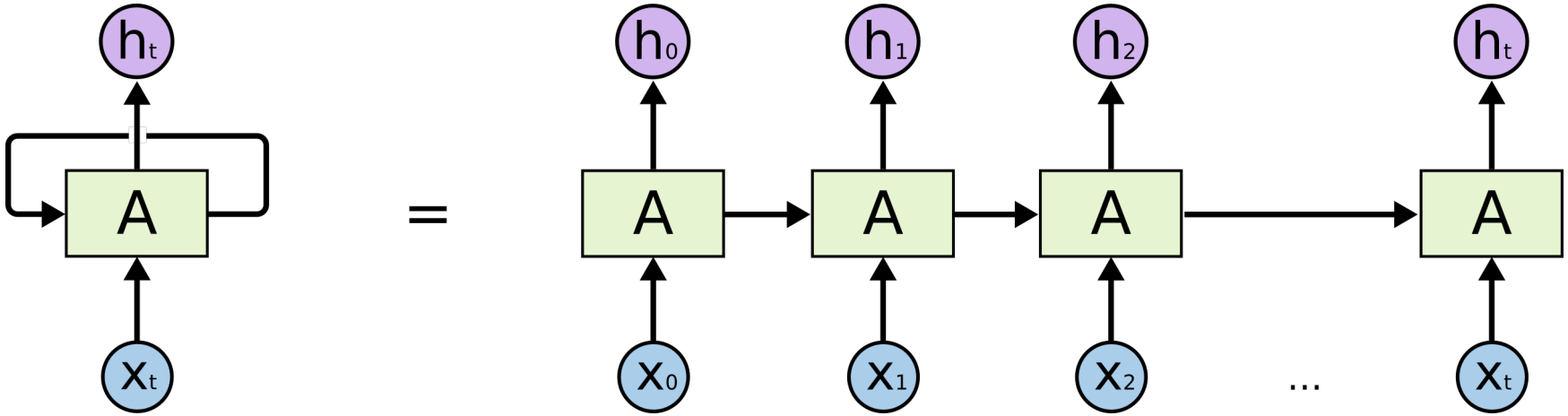
Recurrent Neural Network

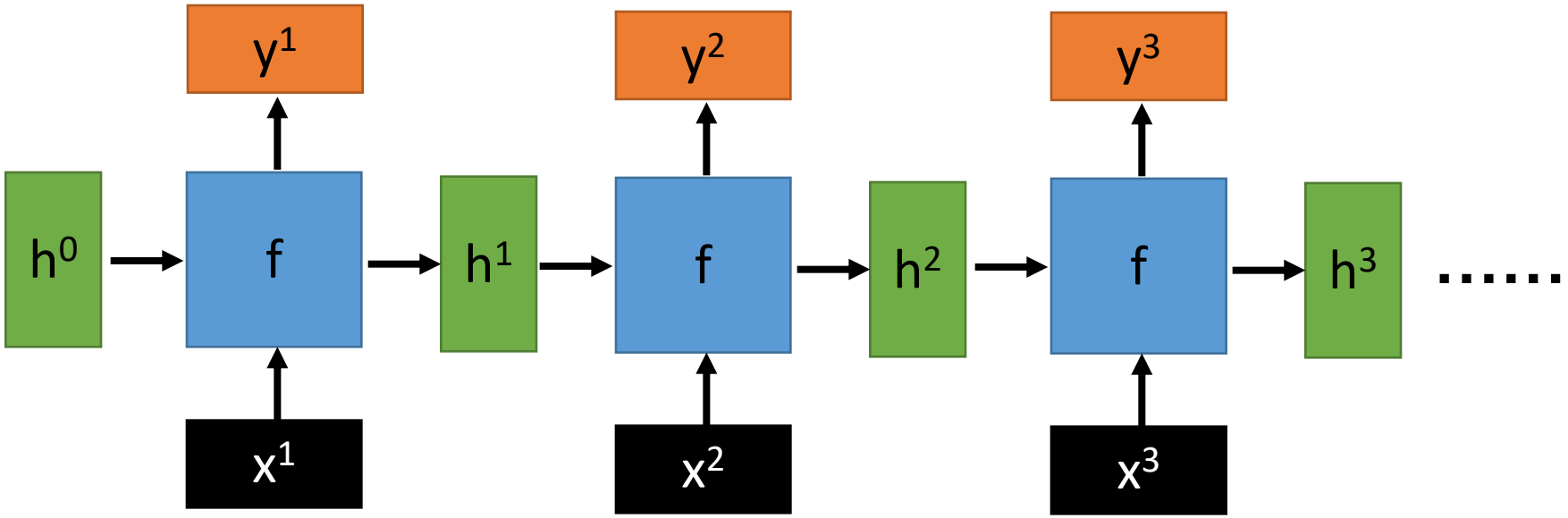




How does RNN reduce complexity?

- Given function f: h',y=f(h,x)

h and h' are vectors with the same dimension



No matter how long the input/output sequence is, we only need one function f. If f's are different, then it becomes a feedforward NN. This may be treated as another compression from fully connected network.

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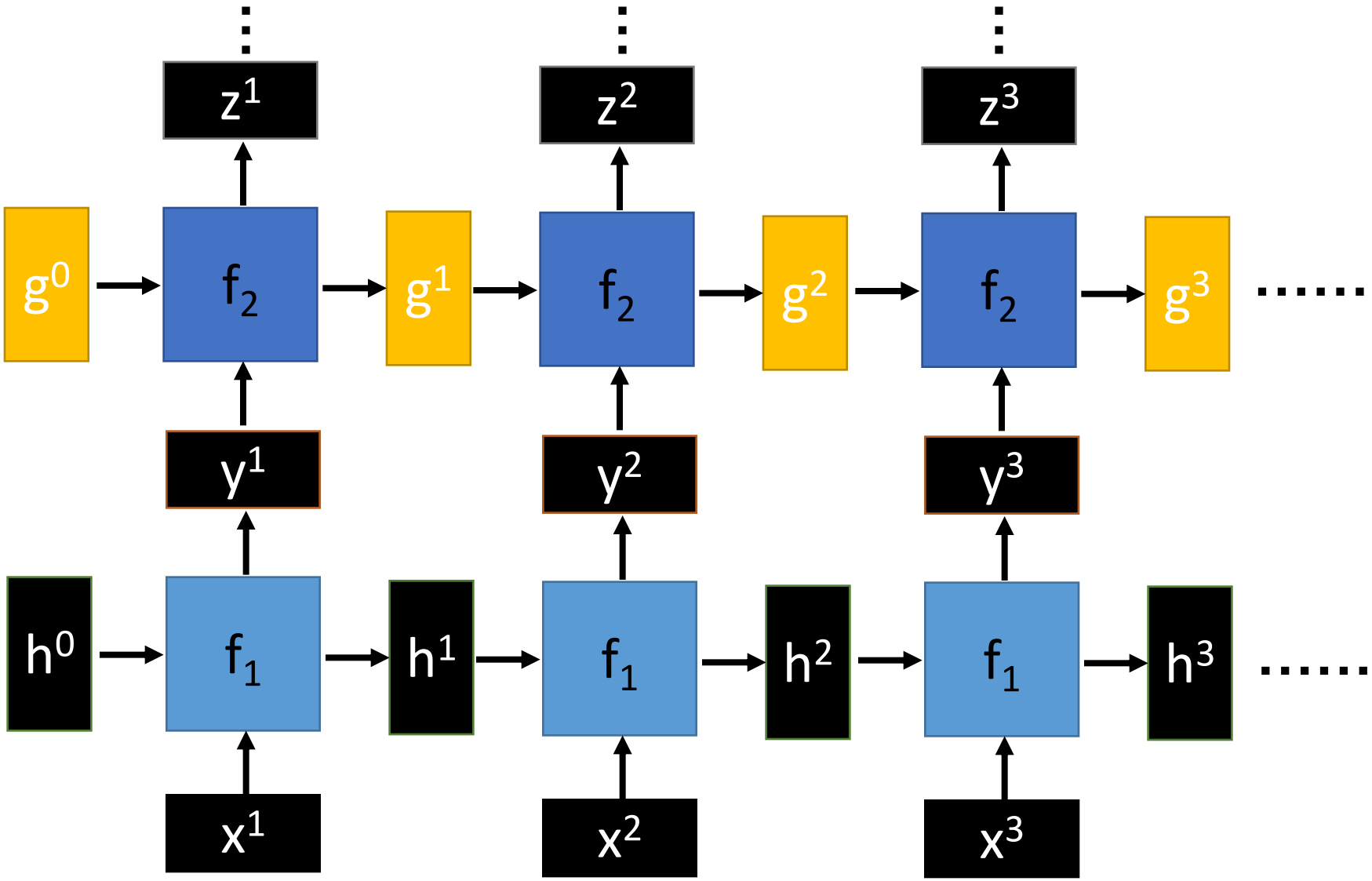
Deep RNN

$h', y = f_1(h, x),\ g', z = f_2(g, y)$ ...



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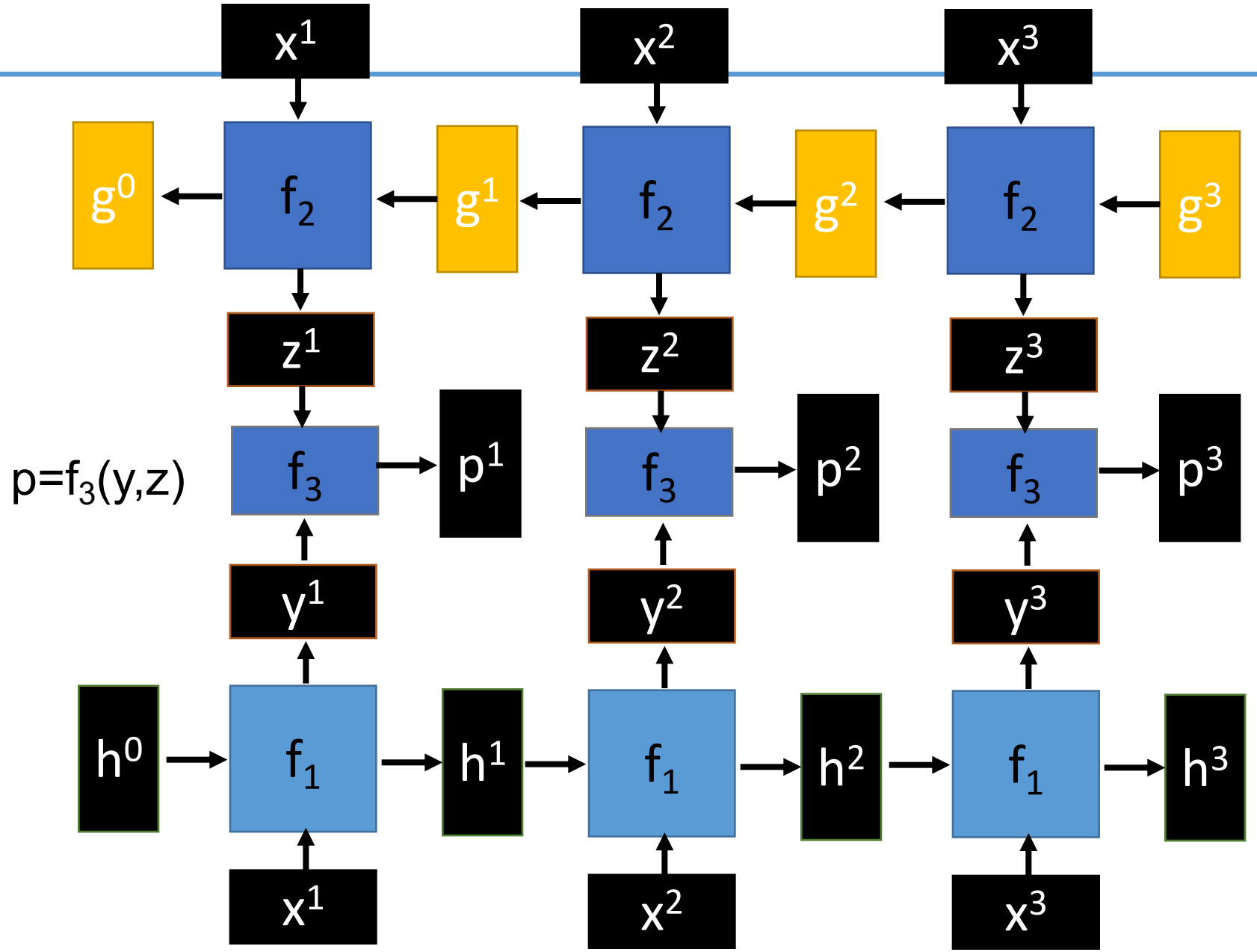
Bidirectional RNN

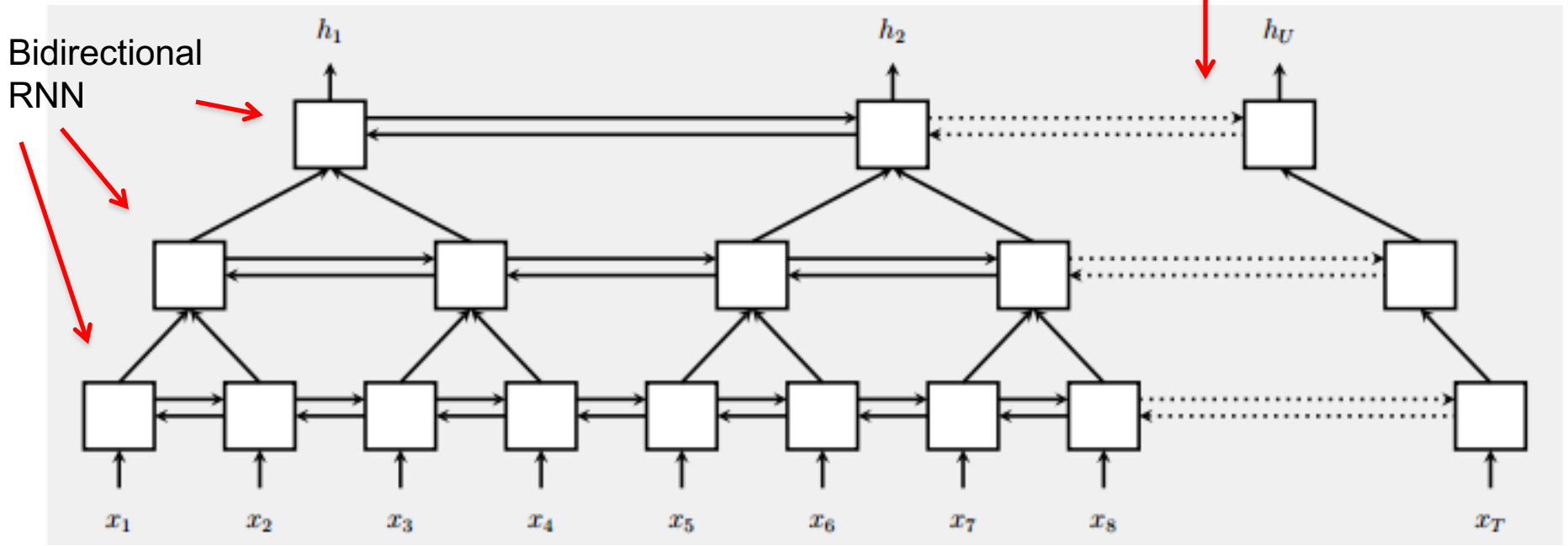
$y,h=f_1(x,h)$ $z,g=f_2(g,x)$



Pyramid RNN

Significantly speed up training

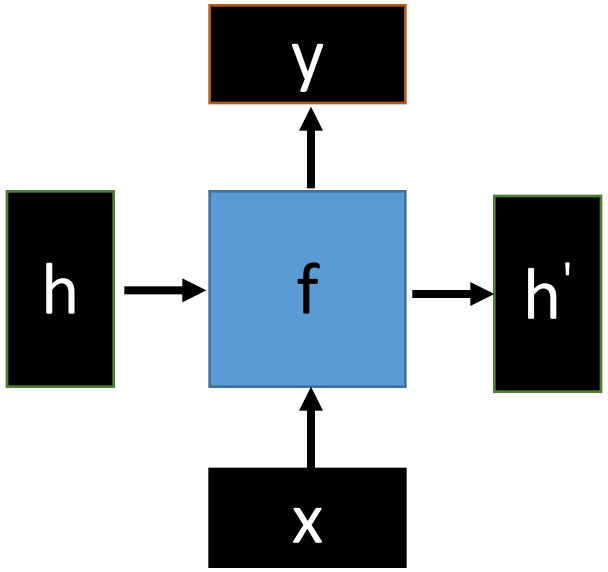
- Reducing the number of time steps



W. Chan, N. Jaitly, Q. Le and O. Vinyals, "Listen, attend and spell: A neural network for large vocabulary conversational speech recognition," ICASSP, 2016

Naïve RNN

- Given function f: h',y=f(h,x)



$$h' = \sigma(W^h h + W^i x)$$

$$y = \sigma(W^o h')$$

softmax

Note, y is computed from h'

We have ignored the bias

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Problems with naive RNN

- When dealing with a time series, it tends to forget old information. When there is a distant relationship of unknown length, we wish to have a "memory" to it.
- Vanishing gradient problem.

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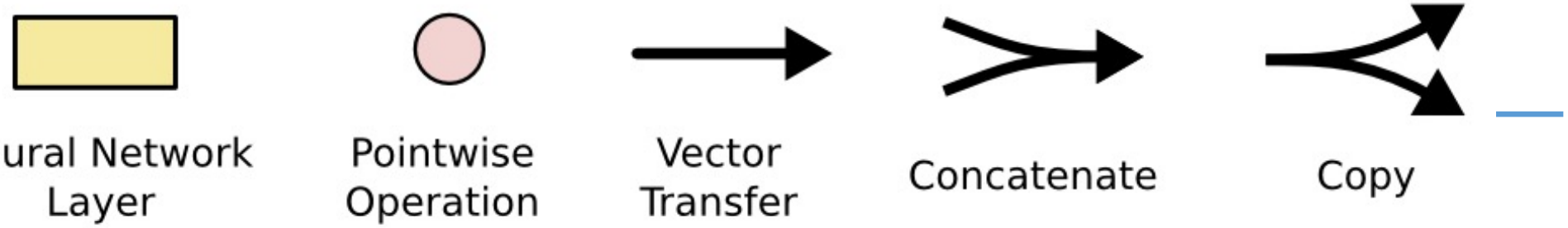
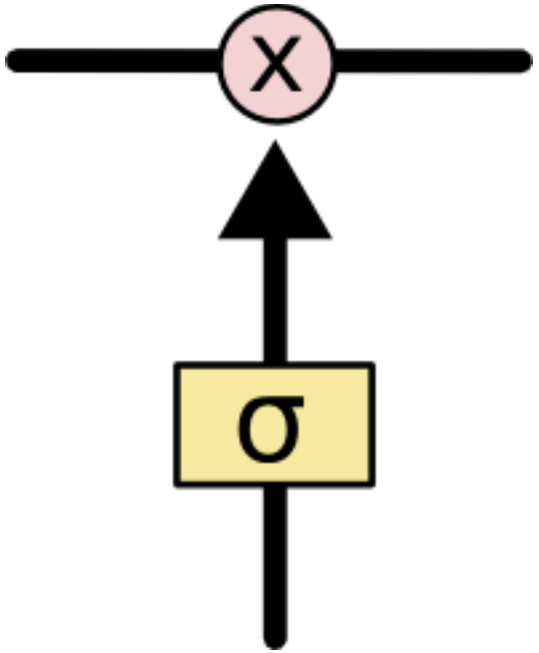
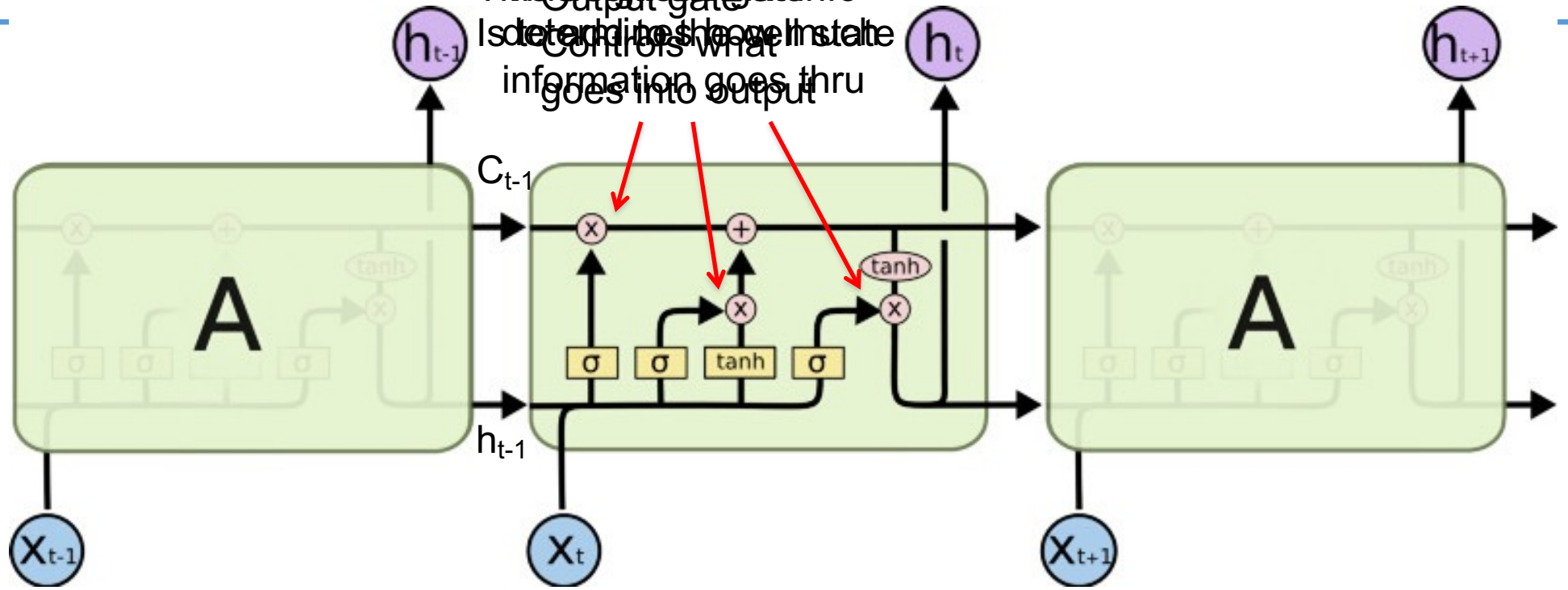




The sigmoid layer outputs numbers between 0-1 determine how much each component should be let through. Pink X gate is point-wise multiplication.

LSTM



Forget gate

input gate

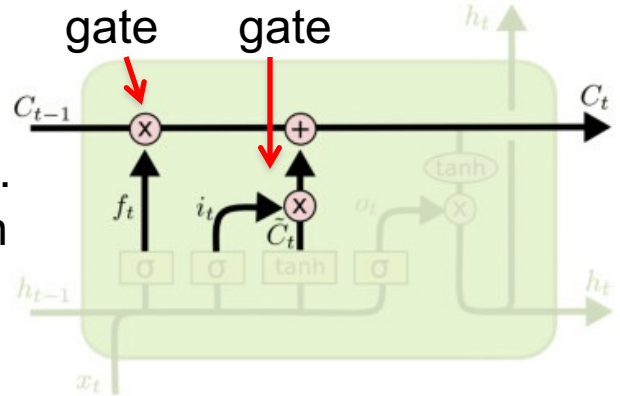
The core idea is this cell state C_t, it is changed slowly, with only minor linear interactions. It is very easy for information to flow along it unchanged.

Why sigmoid or tanh:

Sigmoid: 0,1 gating as switch.

Vanishing gradient problem in LSTM is handled already.

ReLU replaces tanh ok?



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

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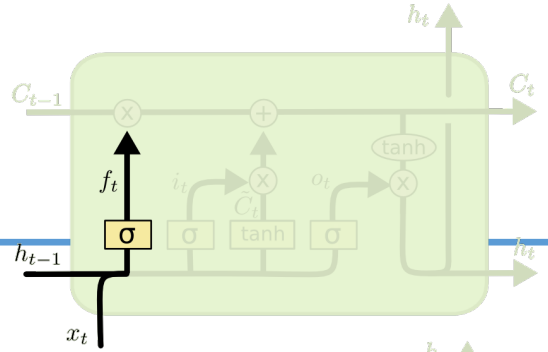
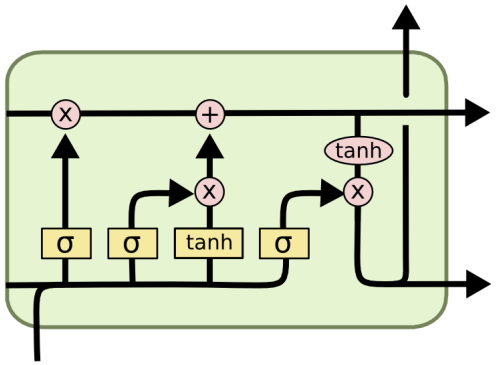
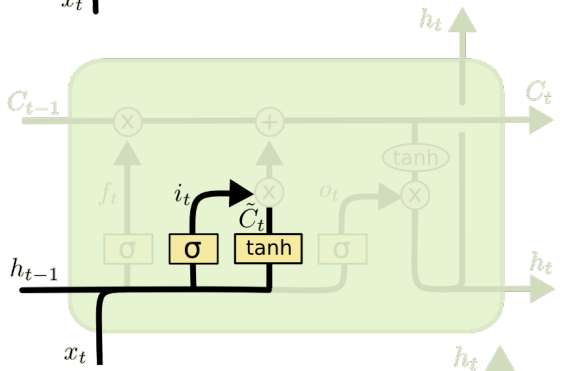


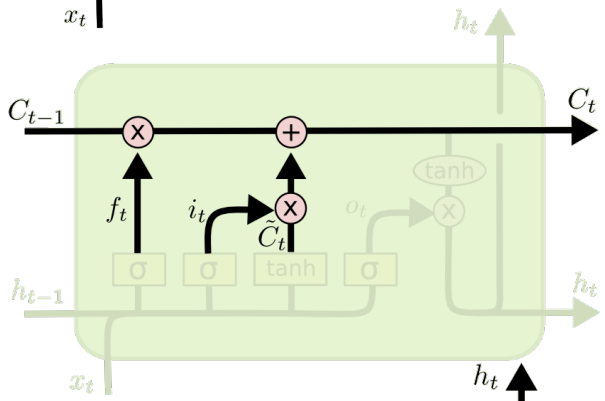
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$





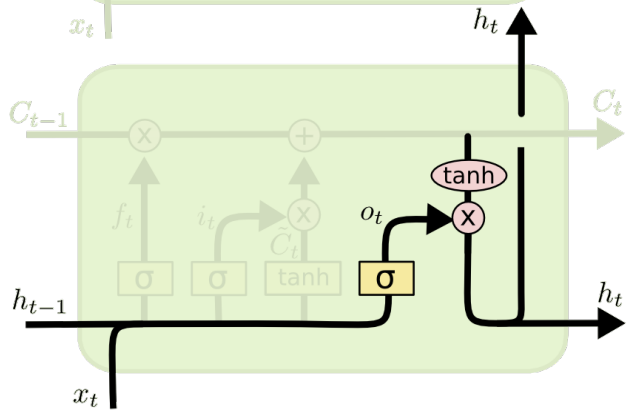
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

i_t decides what component is to be updated.
C'$_t$ provides change contents



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

Updating the cell state



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

Decide what part of the cell state to output

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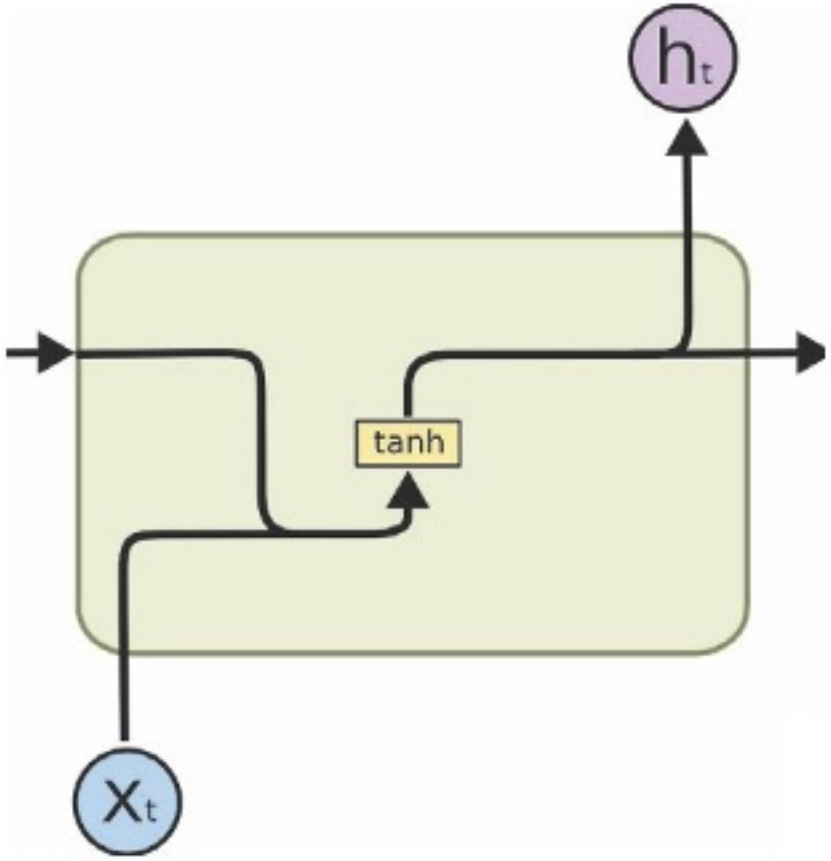
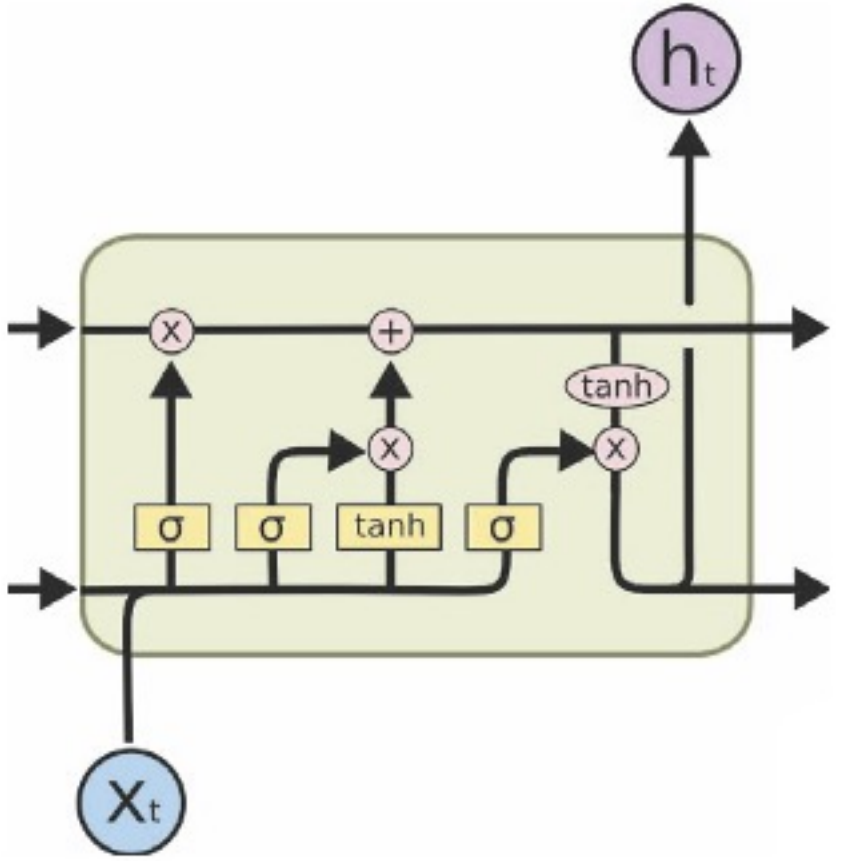
RNN vs LSTM

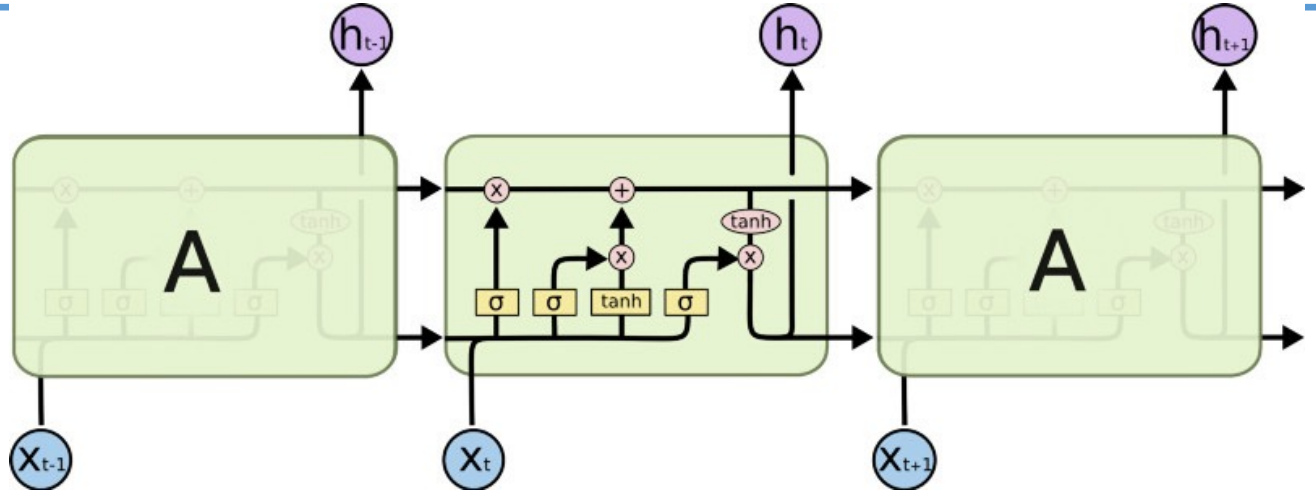


(a) RNN

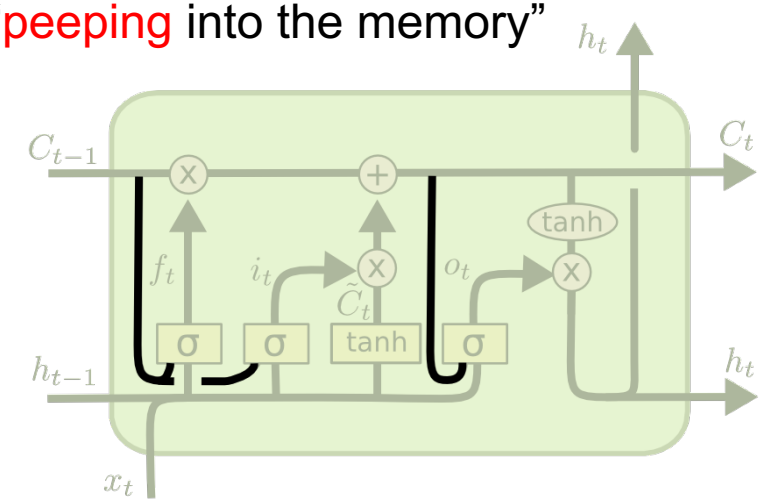


(b) LSTM

Peephole LSTM

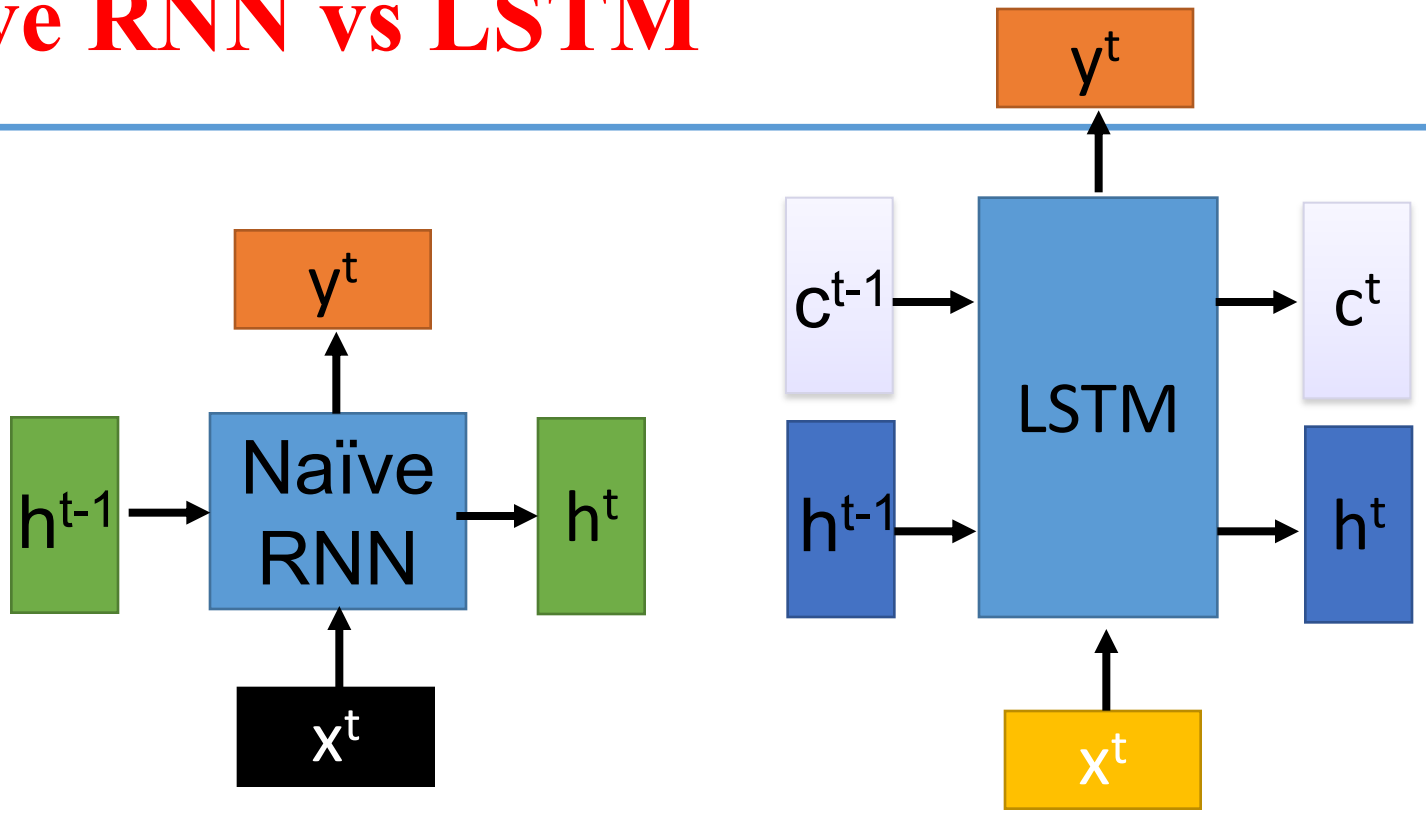


Allows “peeping into the memory”



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Naïve RNN vs LSTM



c changes slowly ➡ c^t is c^{t-1} added by something

h changes faster ➡ h^t and h^{t-1} can be very different

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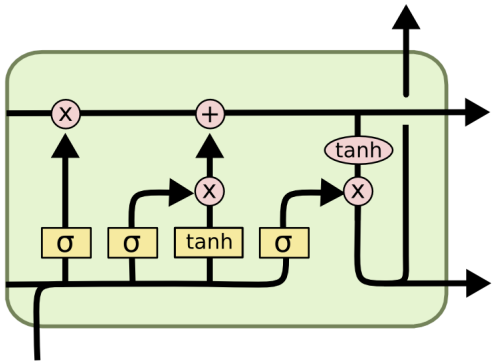

These 4 matrix computation should be done concurrently.

$$z = \tanh\left(W \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

c^{t-1}

$$z^i = \sigma\left(W^i \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

Controls forget gate

Controls input gate

Updating information

Controls Output gate

$$z^f = \sigma\left(W^f \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

z^f z^i z z^o

h^{t-1} x^t

$$z^o = \sigma\left(W^o \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

Information flow of LSTM

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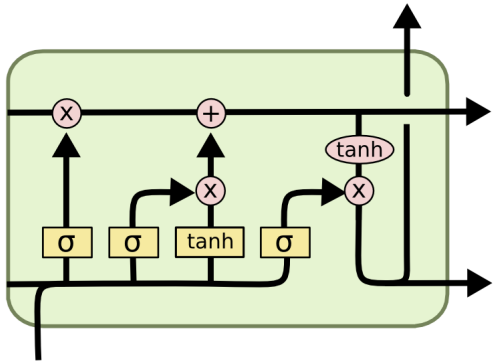

x^t

z =tanh(W h^{t-1})

c^{t-1}

diagonal

"peephole"

z^o z^f z^i obtained by the same way

z^f z^i z z^o

h^{t-1} x^t

Information flow of LSTM

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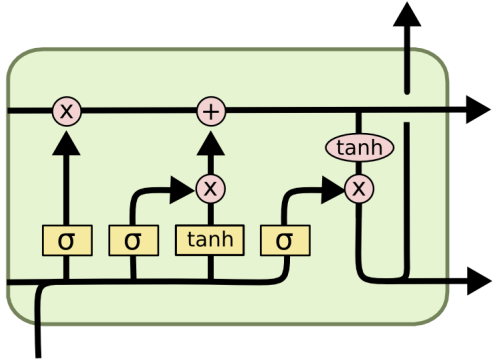
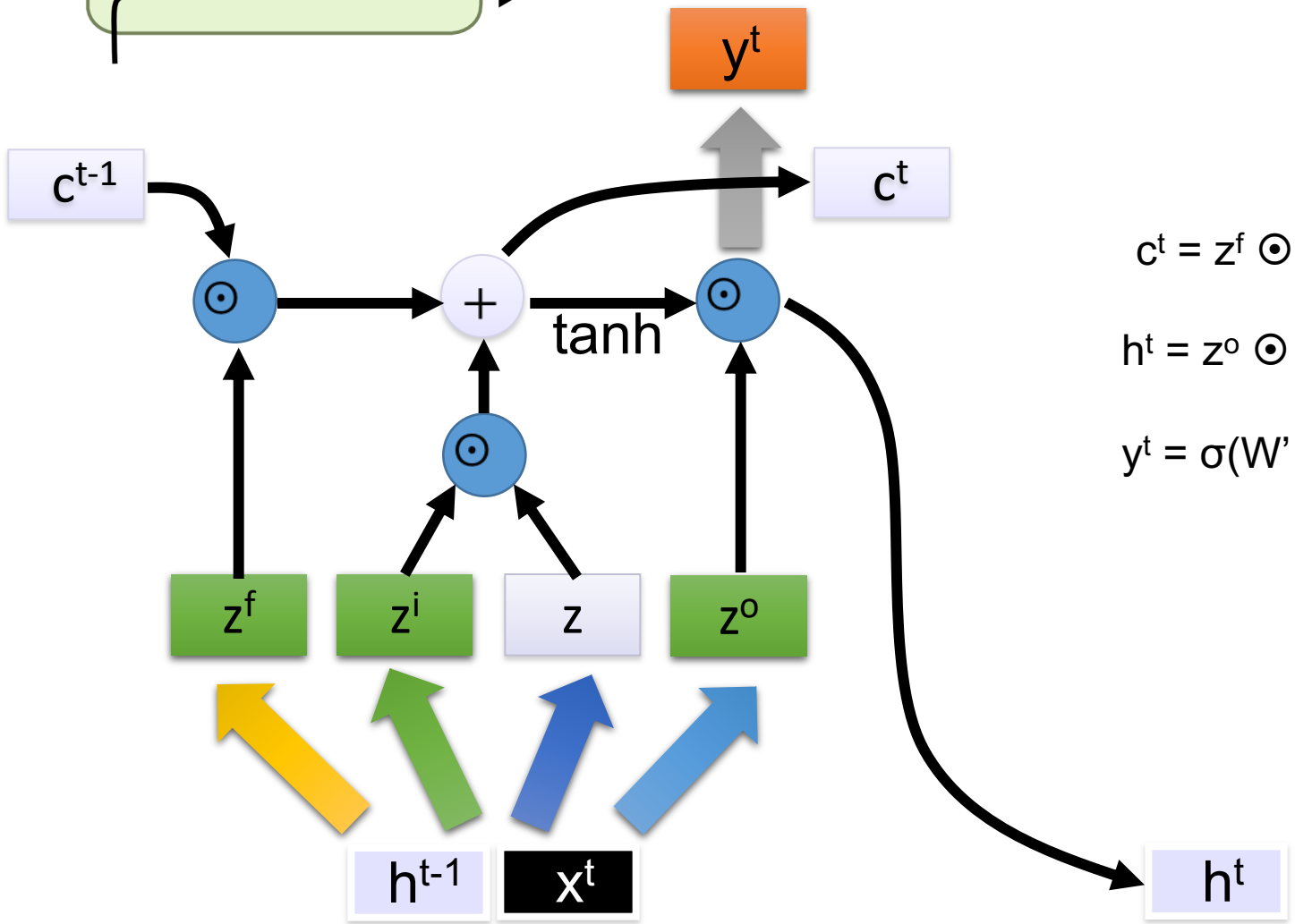


⊙ Element-wise multiply



$c^t = z^f \odot c^{t-1} + z^i \odot z$

$h^t = z^o \odot \tanh(c^t)$

$y^t = \sigma(W' h^t)$

Information flow of LSTM

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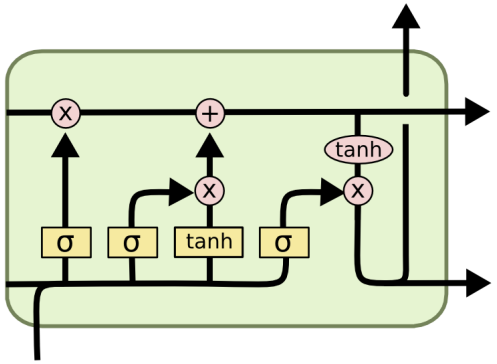
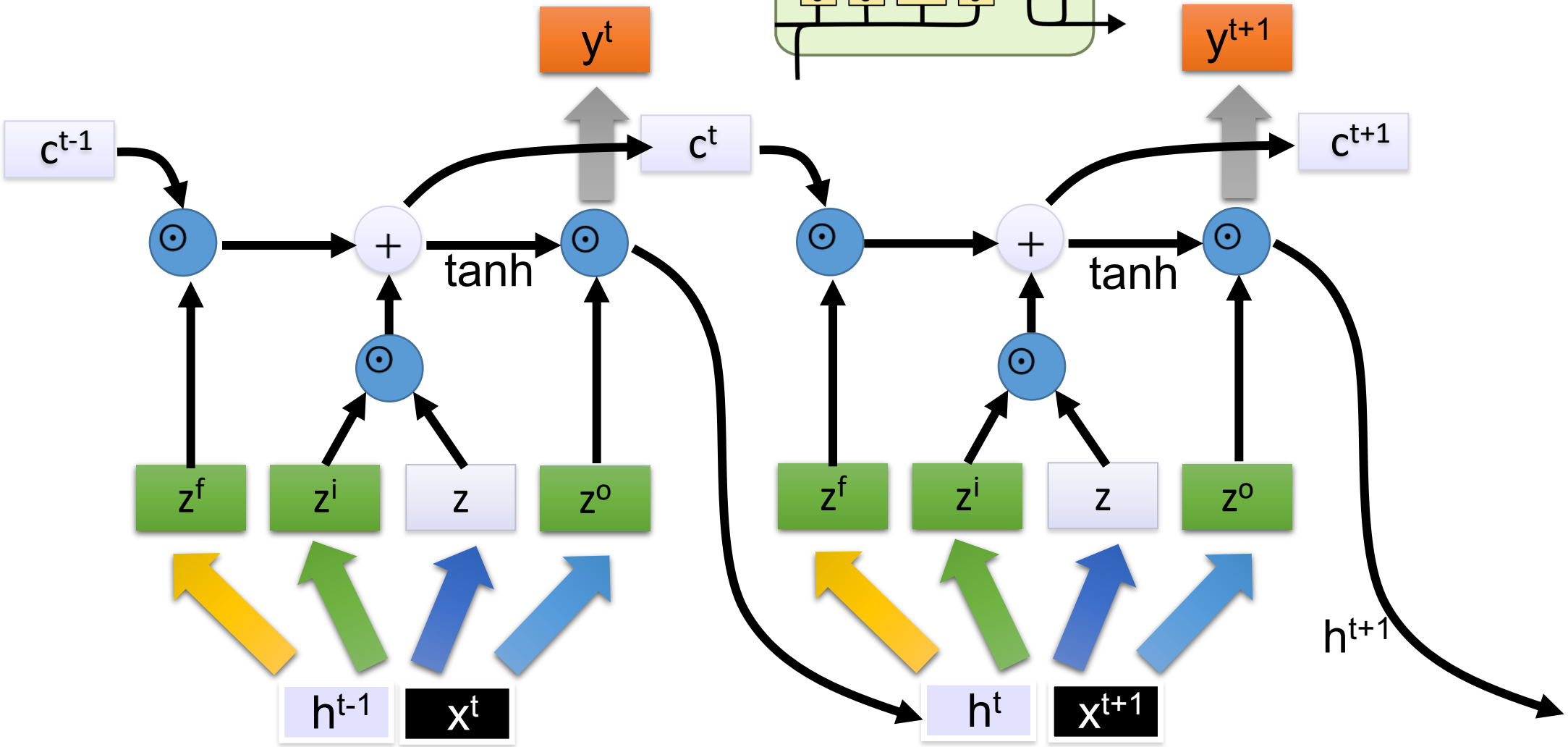
LSTM information flow

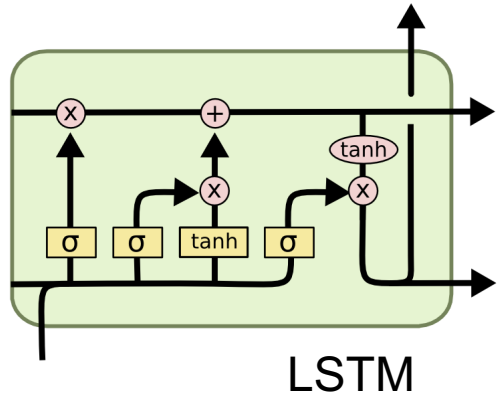




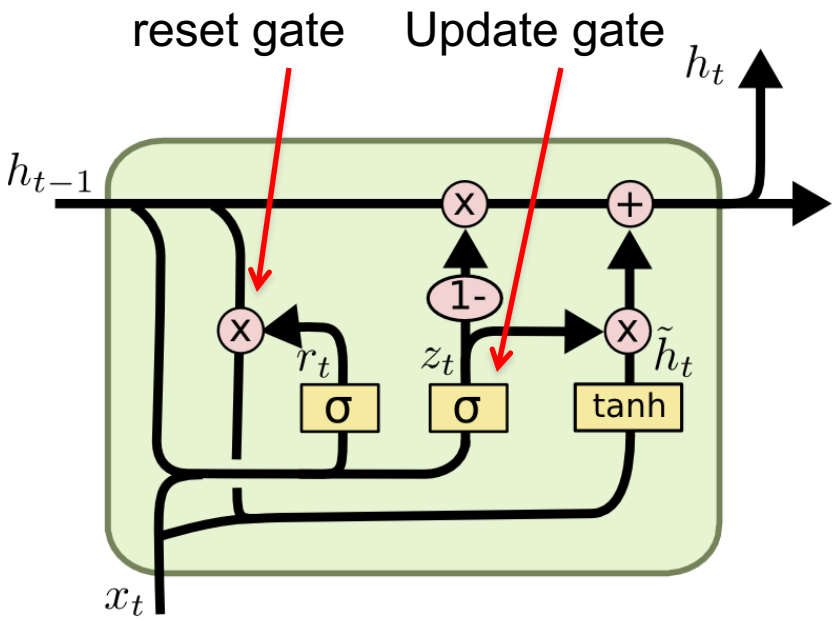
Information flow of LSTM

GRU – gated recurrent unit

(more compression)



LSTM



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

It combines the forget and input into a single update gate.
It also merges the cell state and hidden state. This is simpler than LSTM. There are many other variants too.

X,*: element-wise multiply

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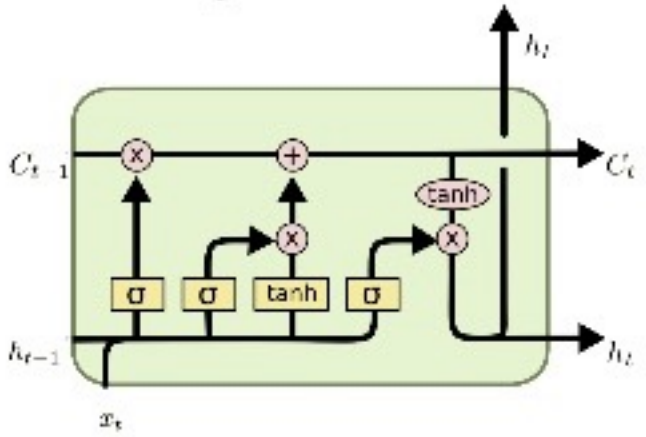
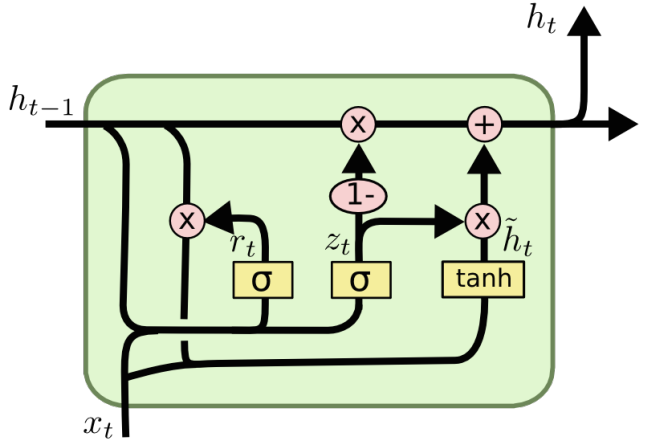
LSTM and GRU

- LSTM [Hochreiter&Schmidhuber97]



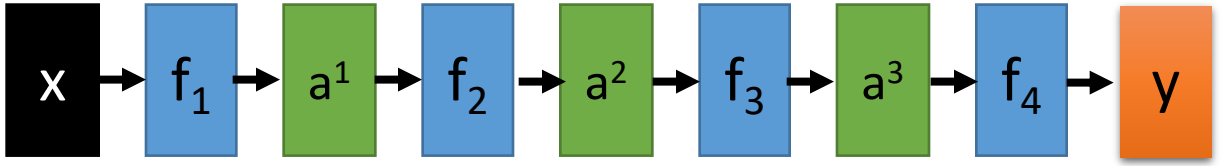
- GRU [Cho+14]



GRUs also takes x_t and h_{t-1} as inputs. They perform some calculations and then pass along h_t. What makes them different from LSTMs is that GRUs don't need the cell layer to pass values along. The calculations within each iteration insure that the h_t values being passed along either retain a high amount of old information or are jump-started with a high amount of new information.

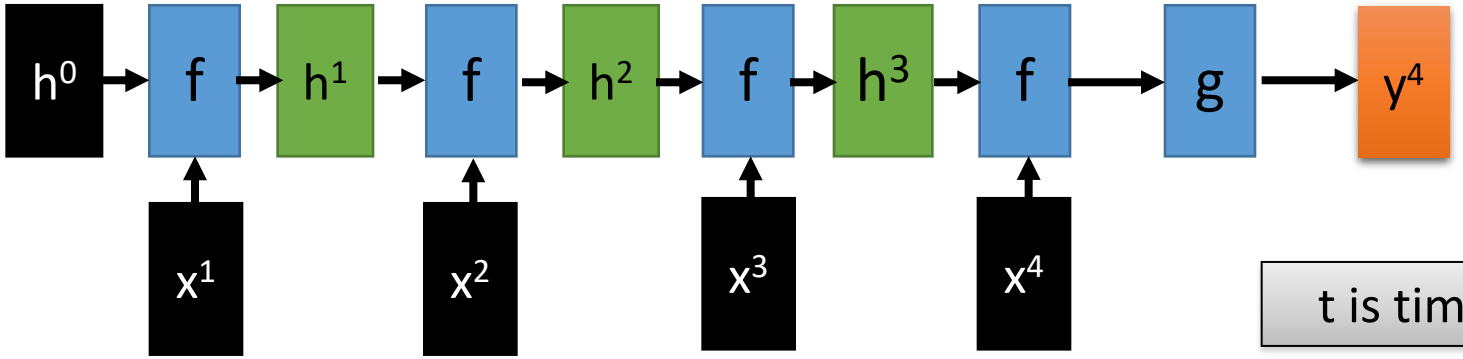
Feed-forward vs Recurrent Network

1. Feedforward network does not have input at each step
2. Feedforward network has different parameters for each layer



t is layer

$a^t = f_t(a^{t-1}) = \sigma(W^t a^{t-1} + b^t)$



t is time step

$a^t = f(a^{t-1}, x^t) = \sigma(W^h a^{t-1} + W^i x^t + b^i)$

GRU → Highway Network

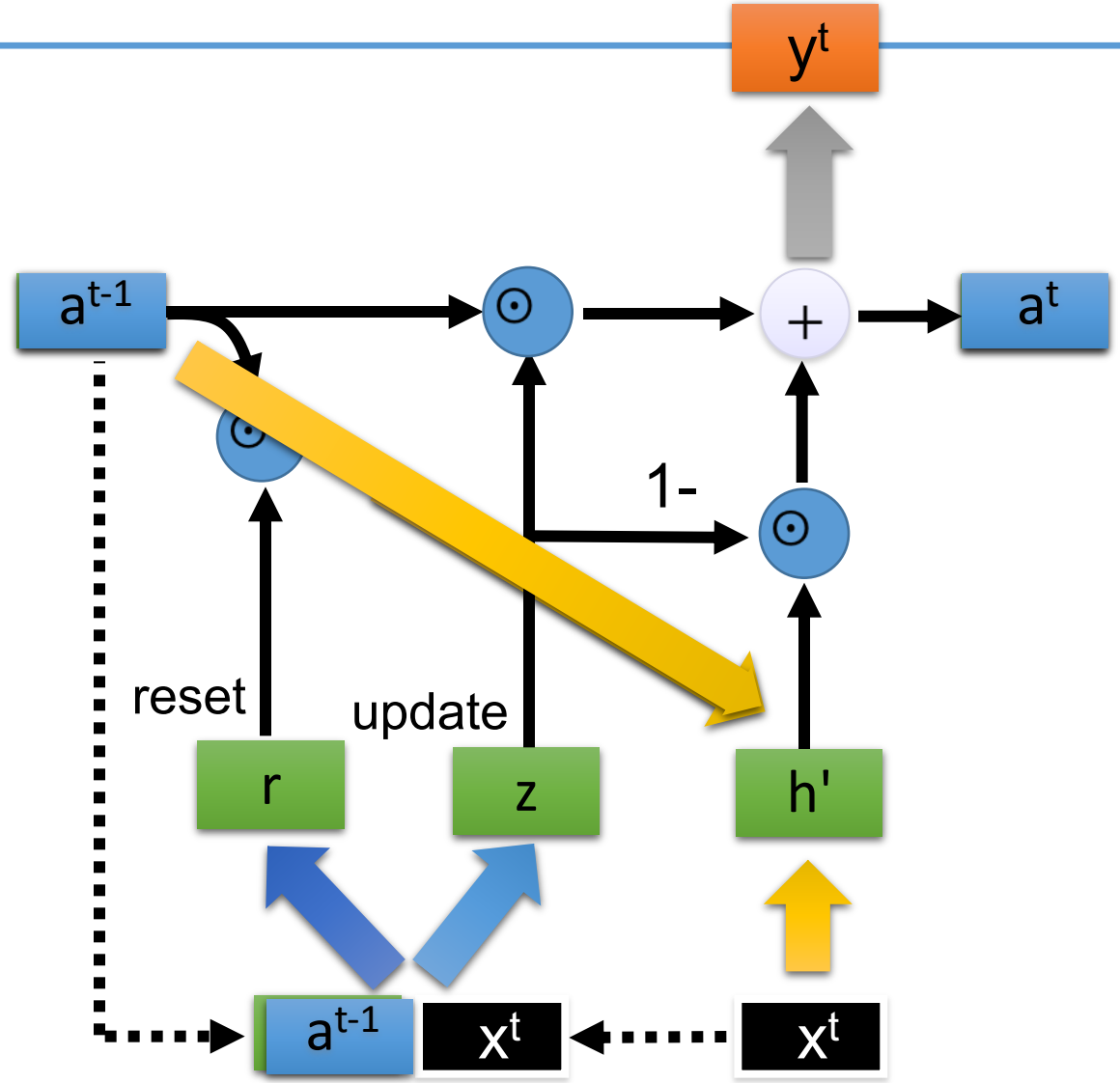
No input x^t at each step

No output y^t at each step

a^{t-1} is the output of the (t-1)-th layer

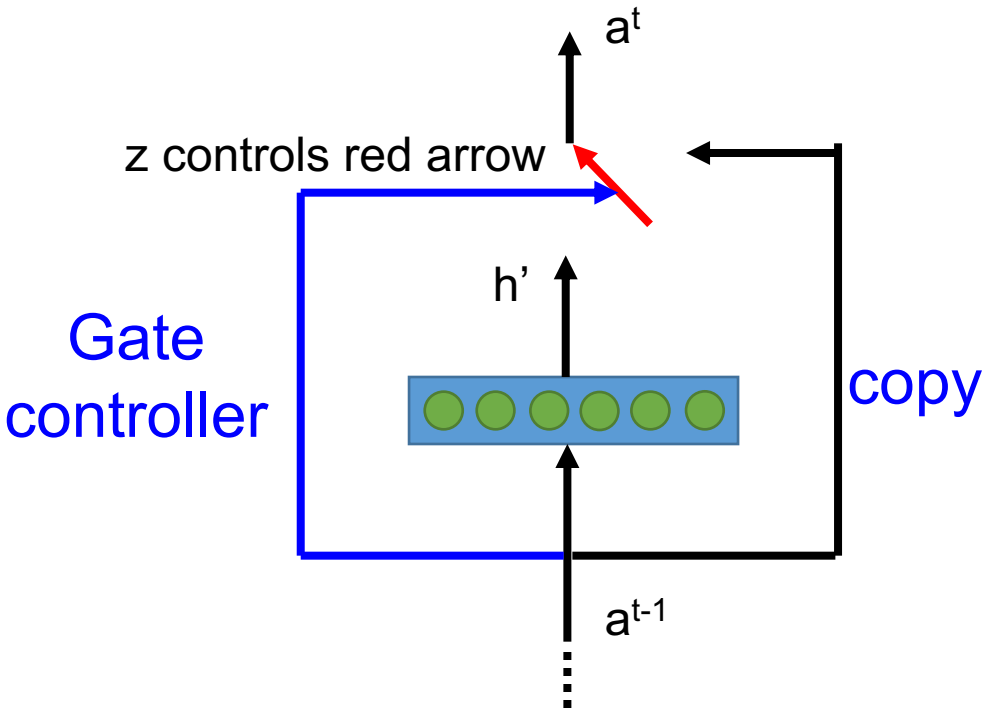
a^t is the output of the t-th layer

No reset gate



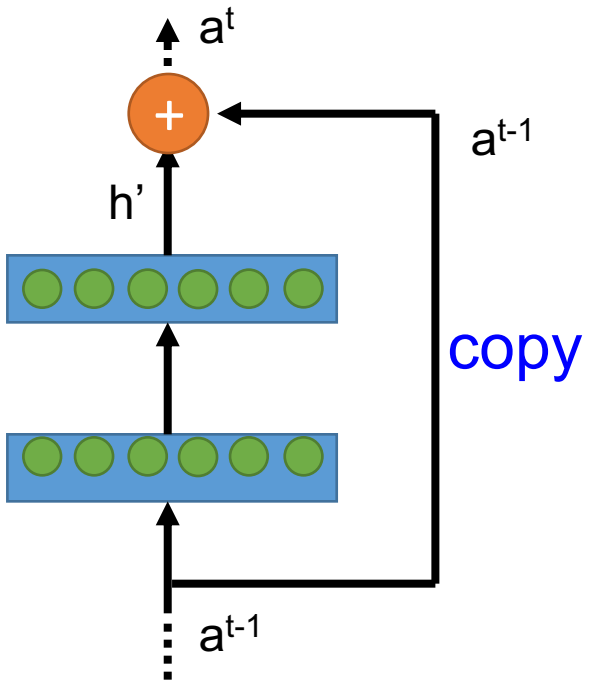
Highway Network

- **Highway Network**



Training Very Deep Networks
https://arxiv.org/pdf/1507.06228v2.pdf

- **Residual Network**



Deep Residual Learning for Image Recognition
http://arxiv.org/abs/1512.03385

$h' = \sigma(Wa^{t-1})$

$z = \sigma(W'a^{t-1})$

$a^t = z \odot a^{t-1} + (1-z) \odot h'$

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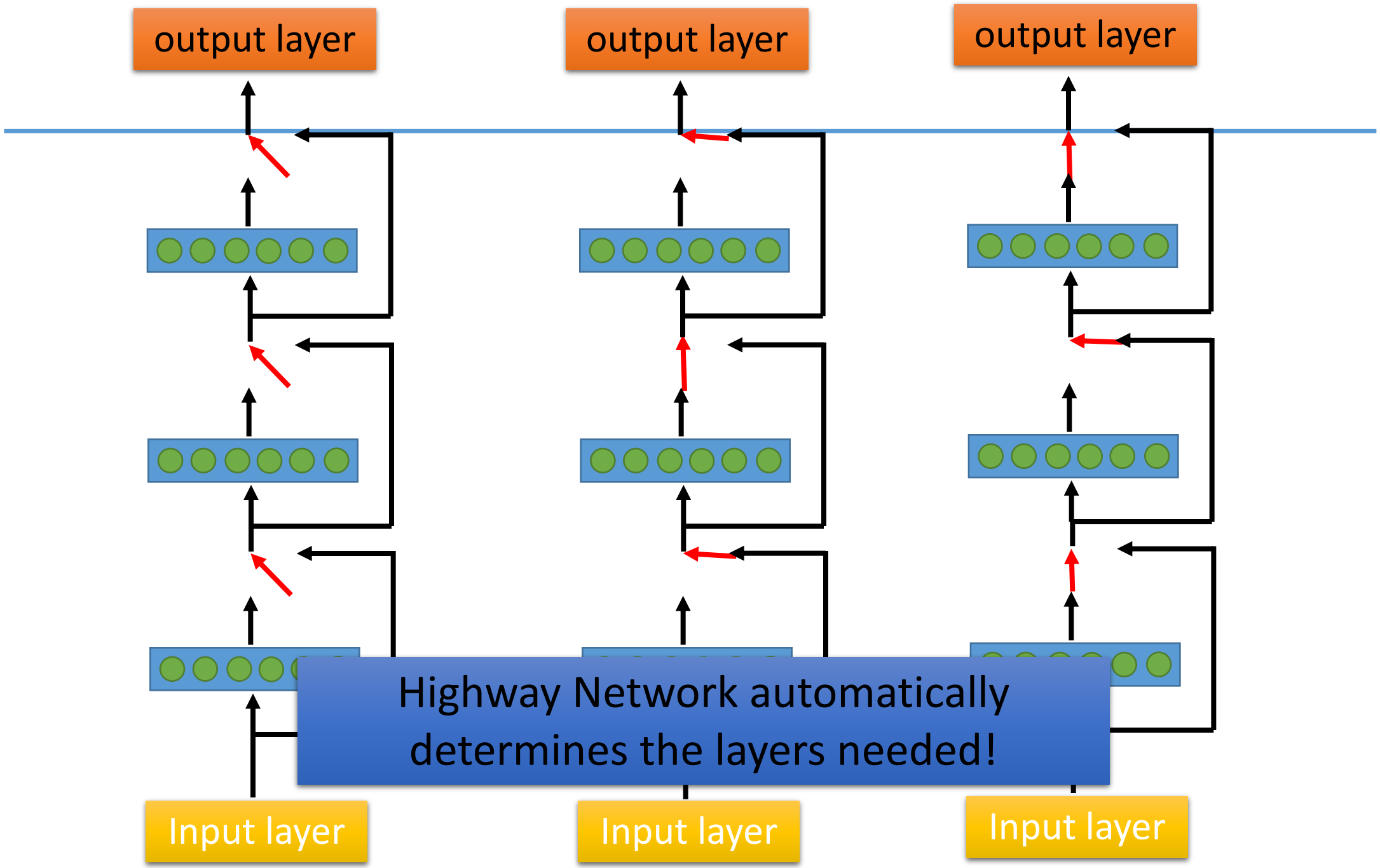
output layer
output layer
output layer
Highway Network automatically determines the layers needed!
Input layer
Input layer
Input layer

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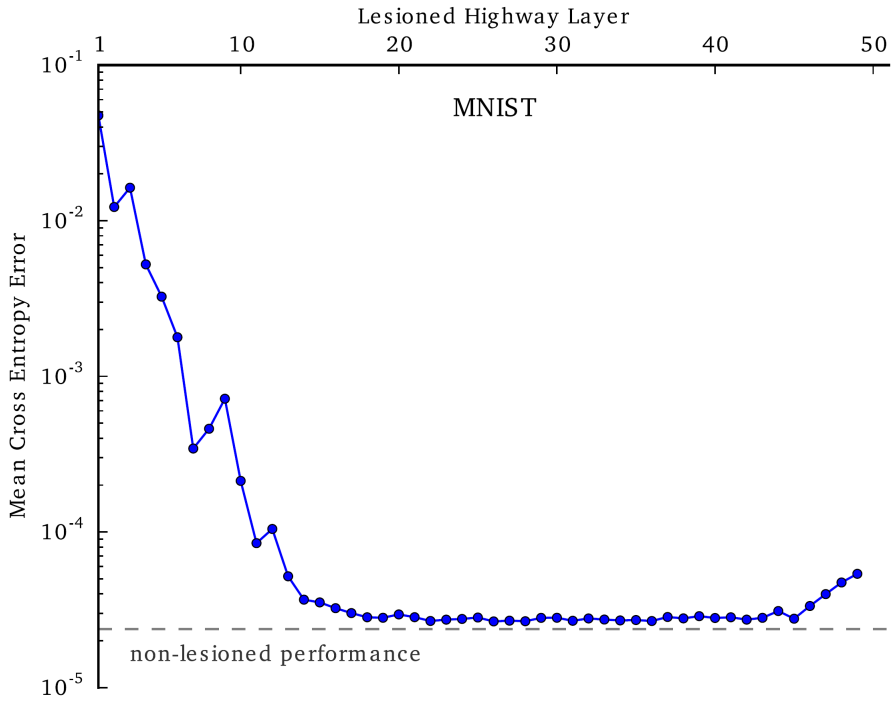
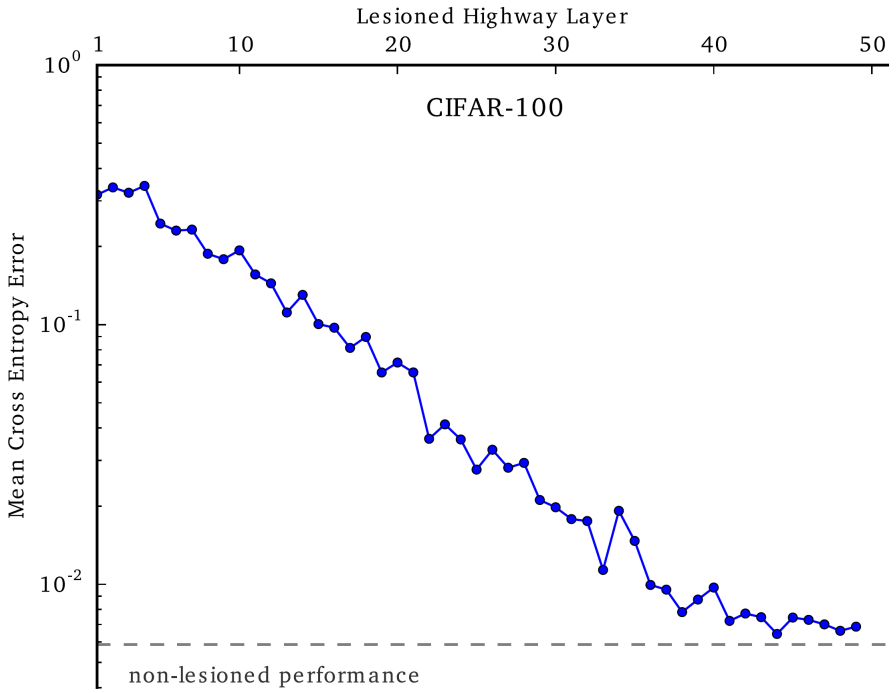
Highway Network Experiments





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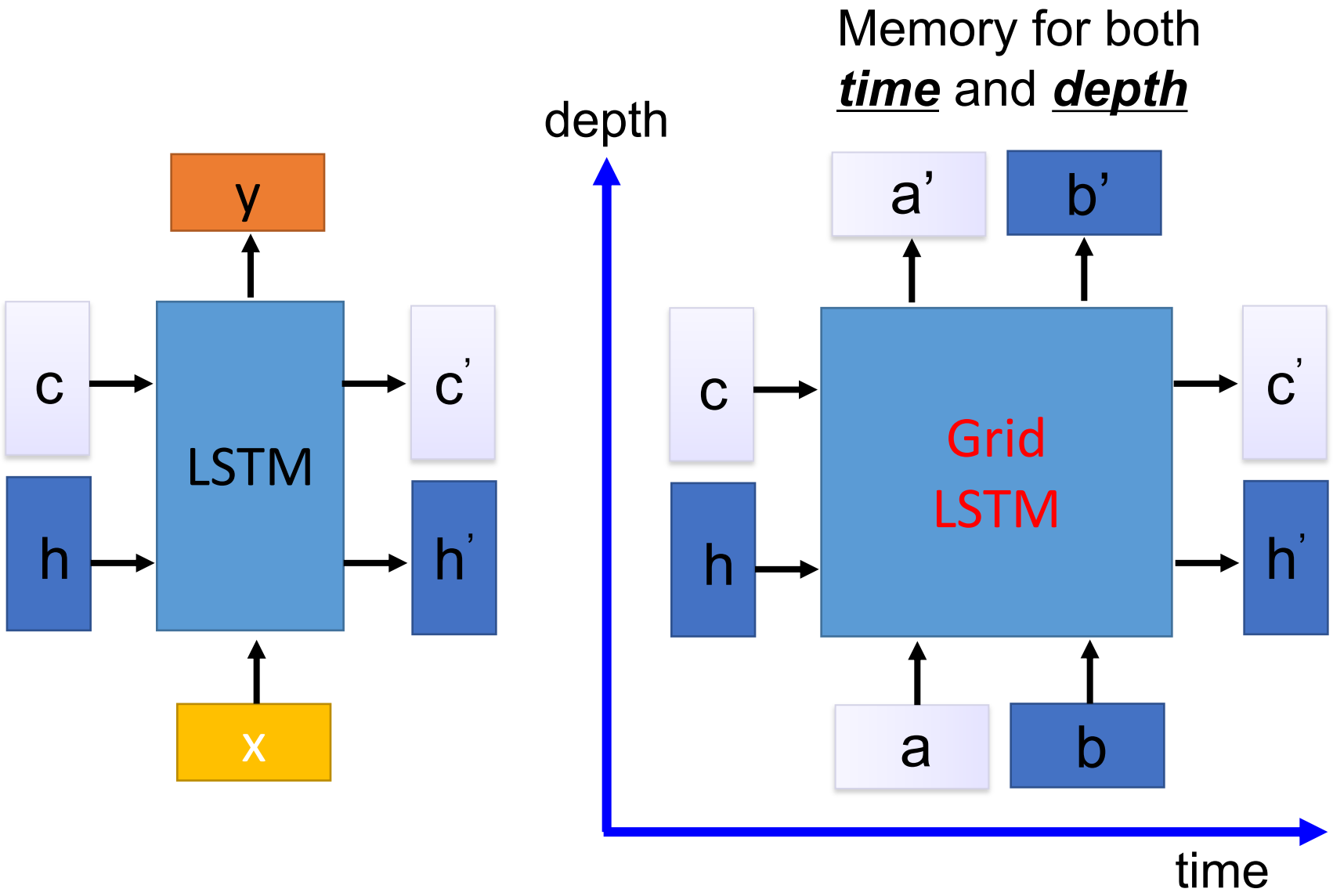
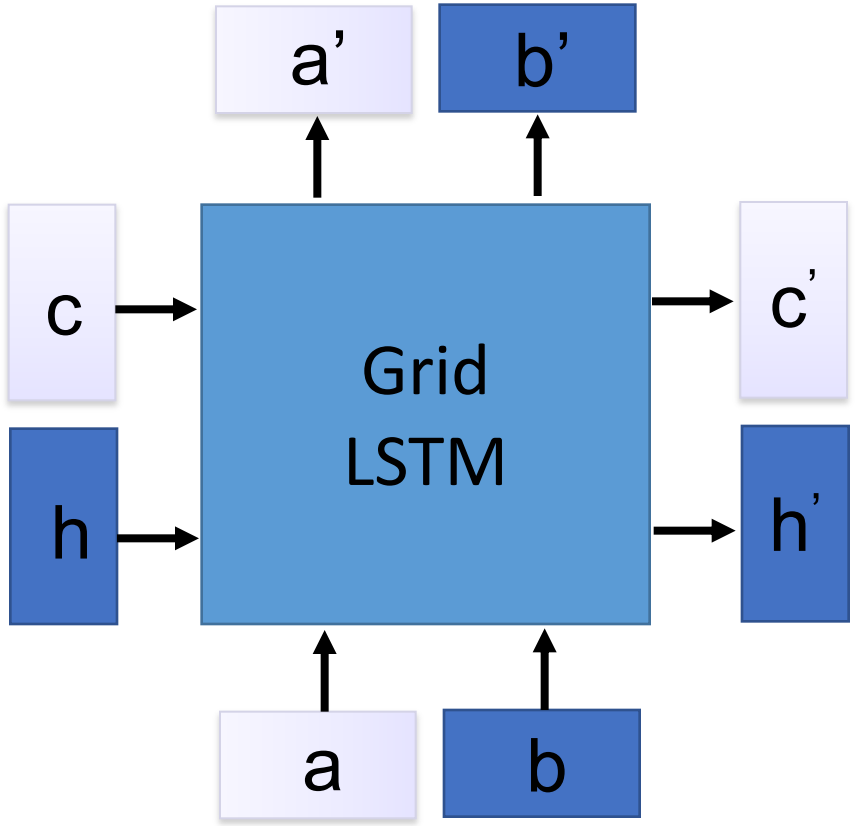
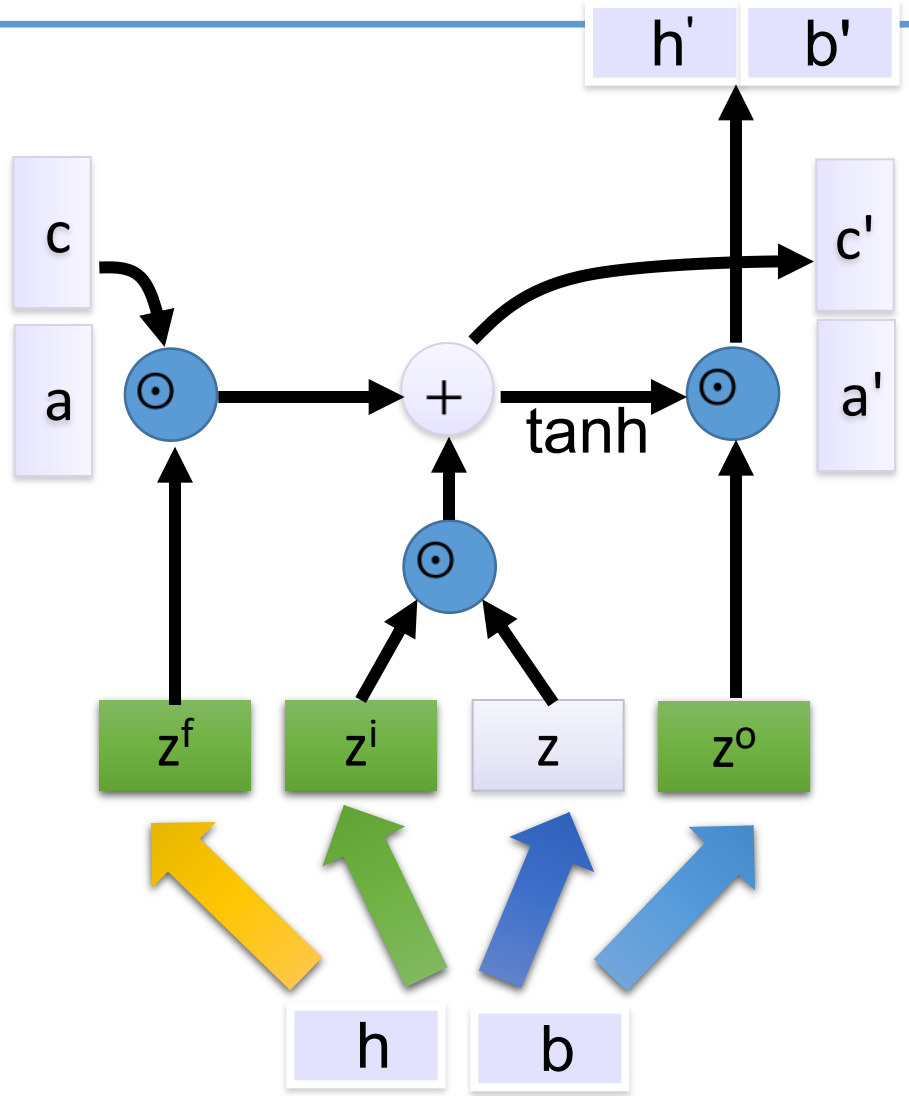
Grid LSTM



Grid LSTM

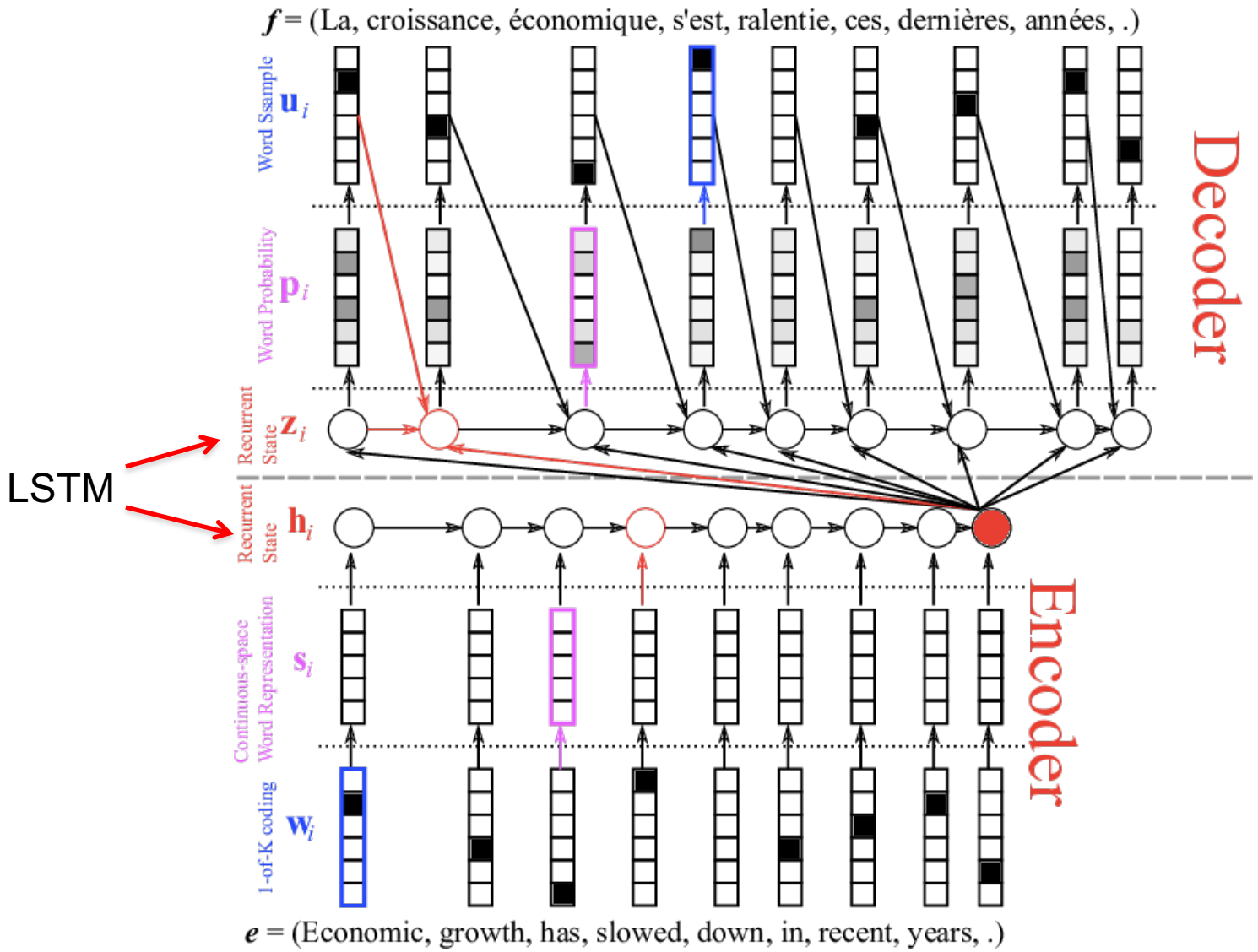




You can generalize this to 3D, and more.

Applications of LSTM / RNN

Neural machine translation



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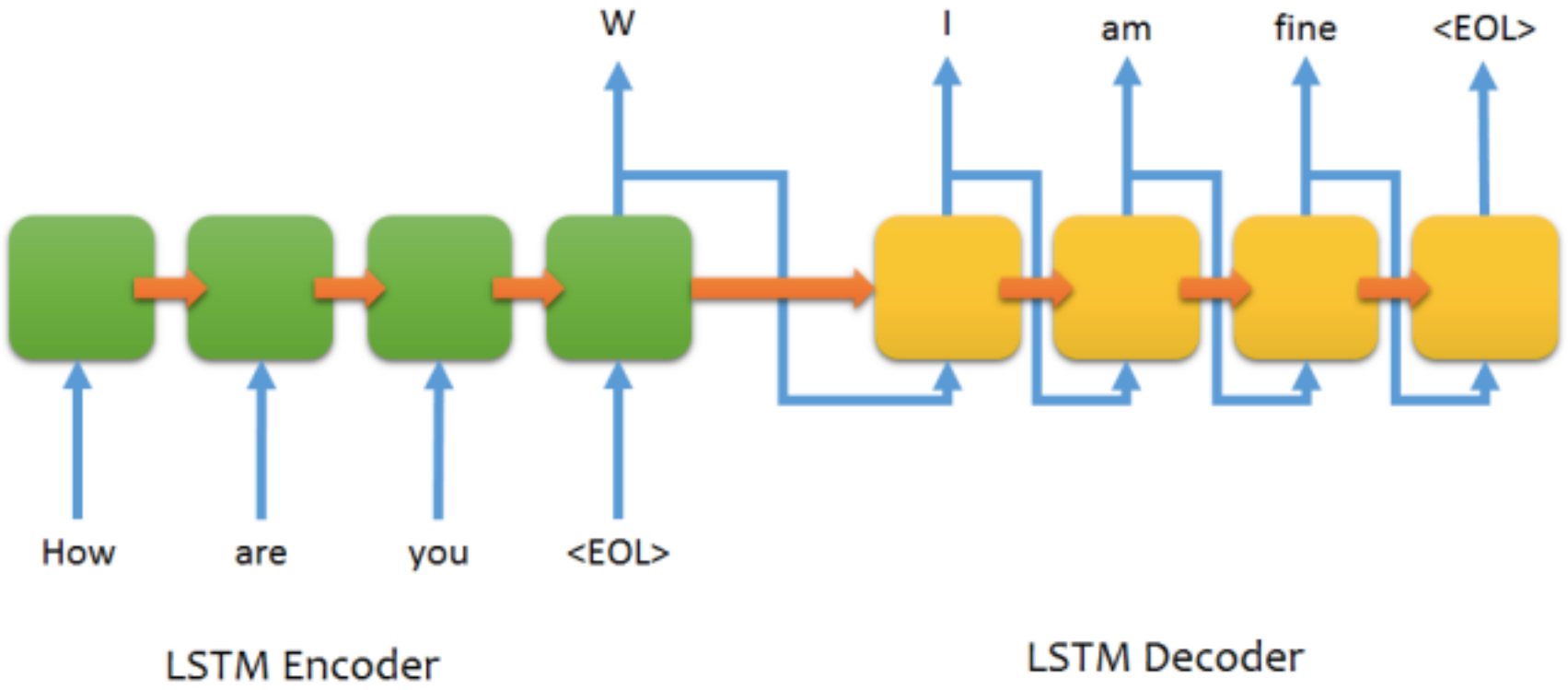
Sequence to sequence chat model



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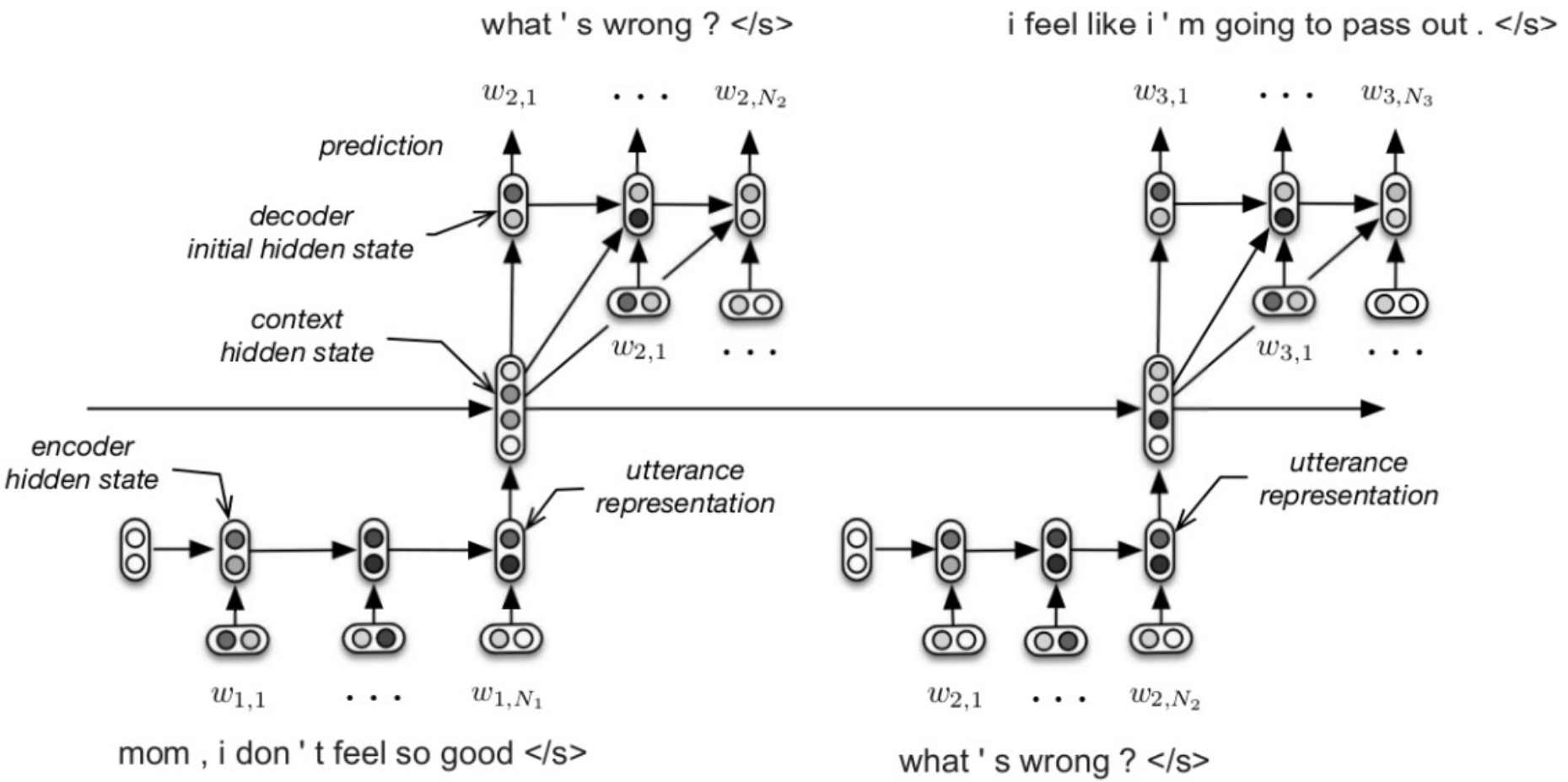
Chat with context



Serban, Iulian V., Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau, 2015 "Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models.

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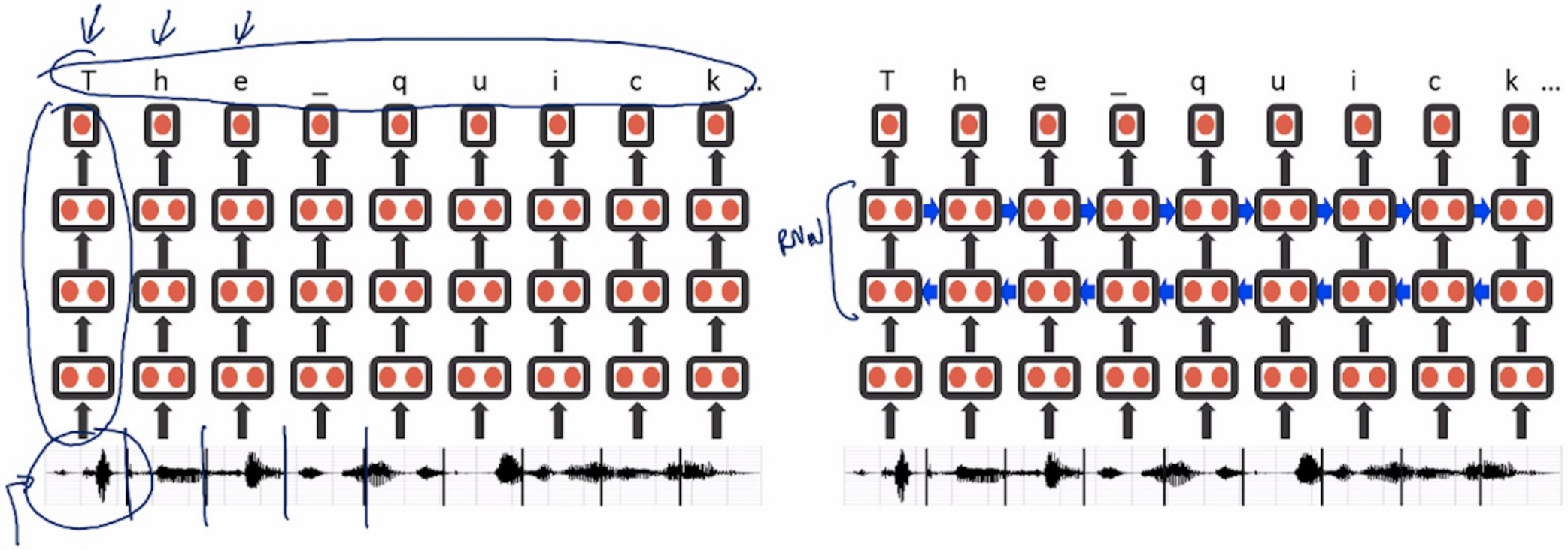
Baidu's speech recognition using RNN

Speech recognition example (Deep Speech)



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Attention

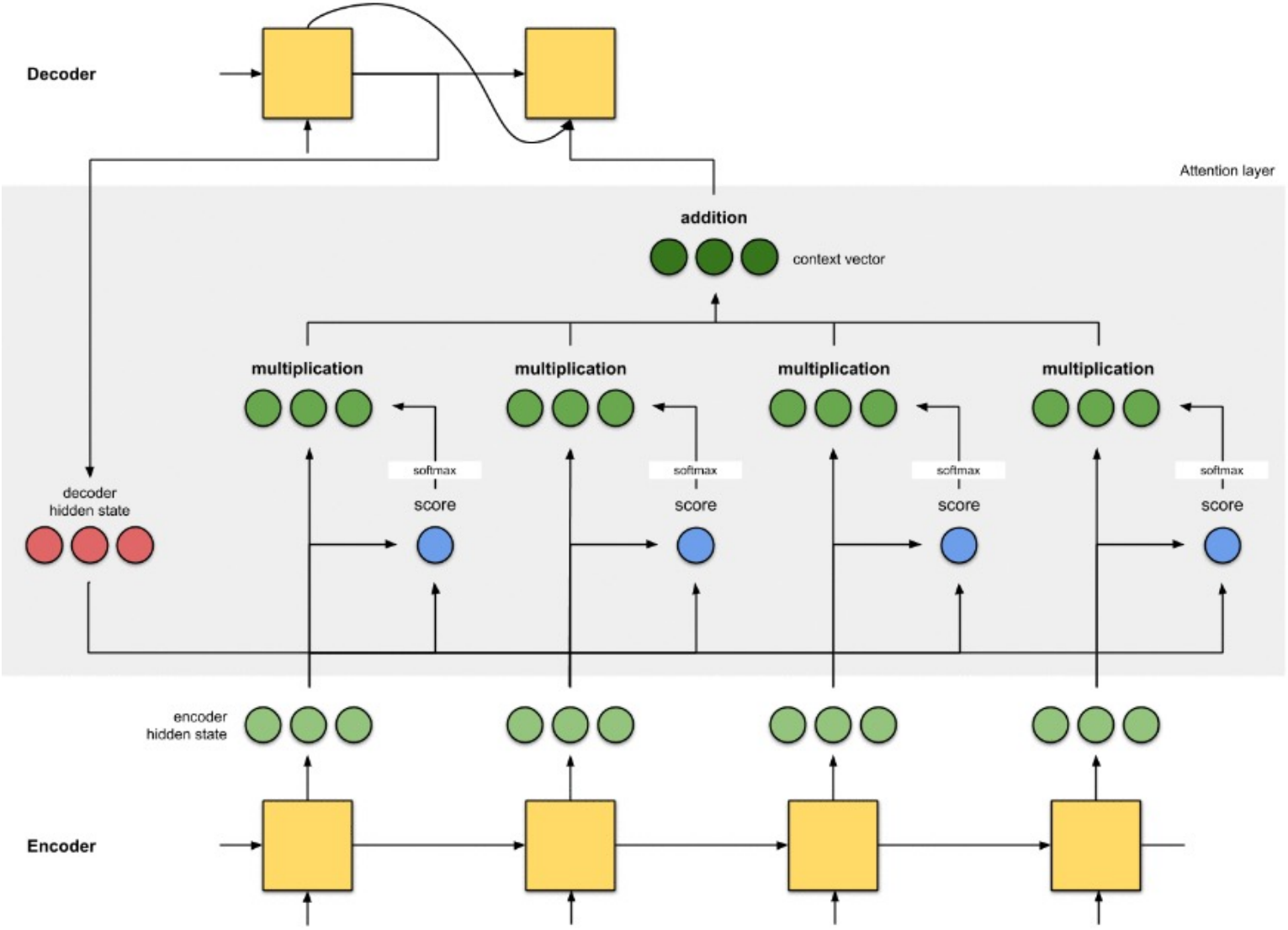

Image caption generation using attention

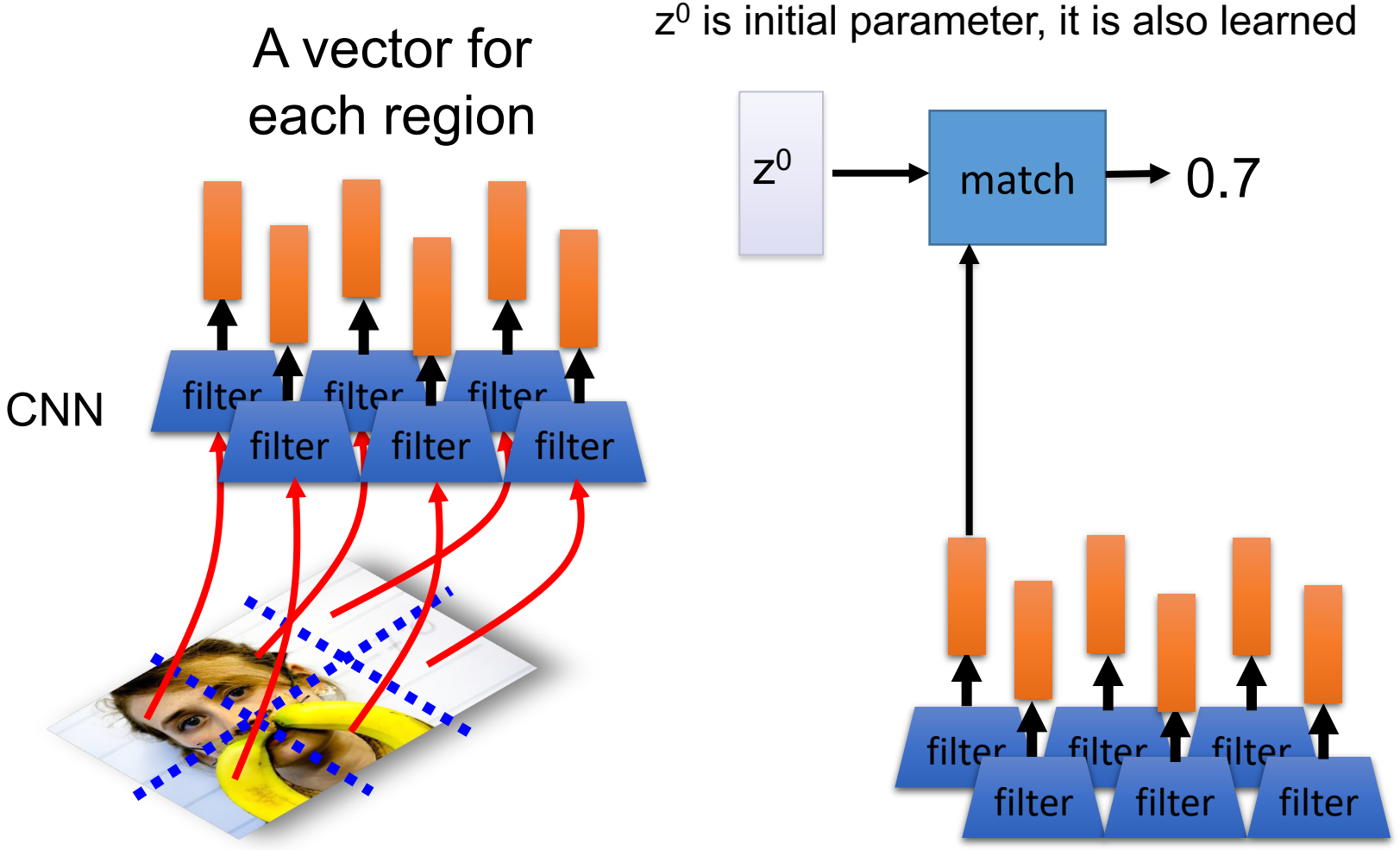

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Image caption generation using attention

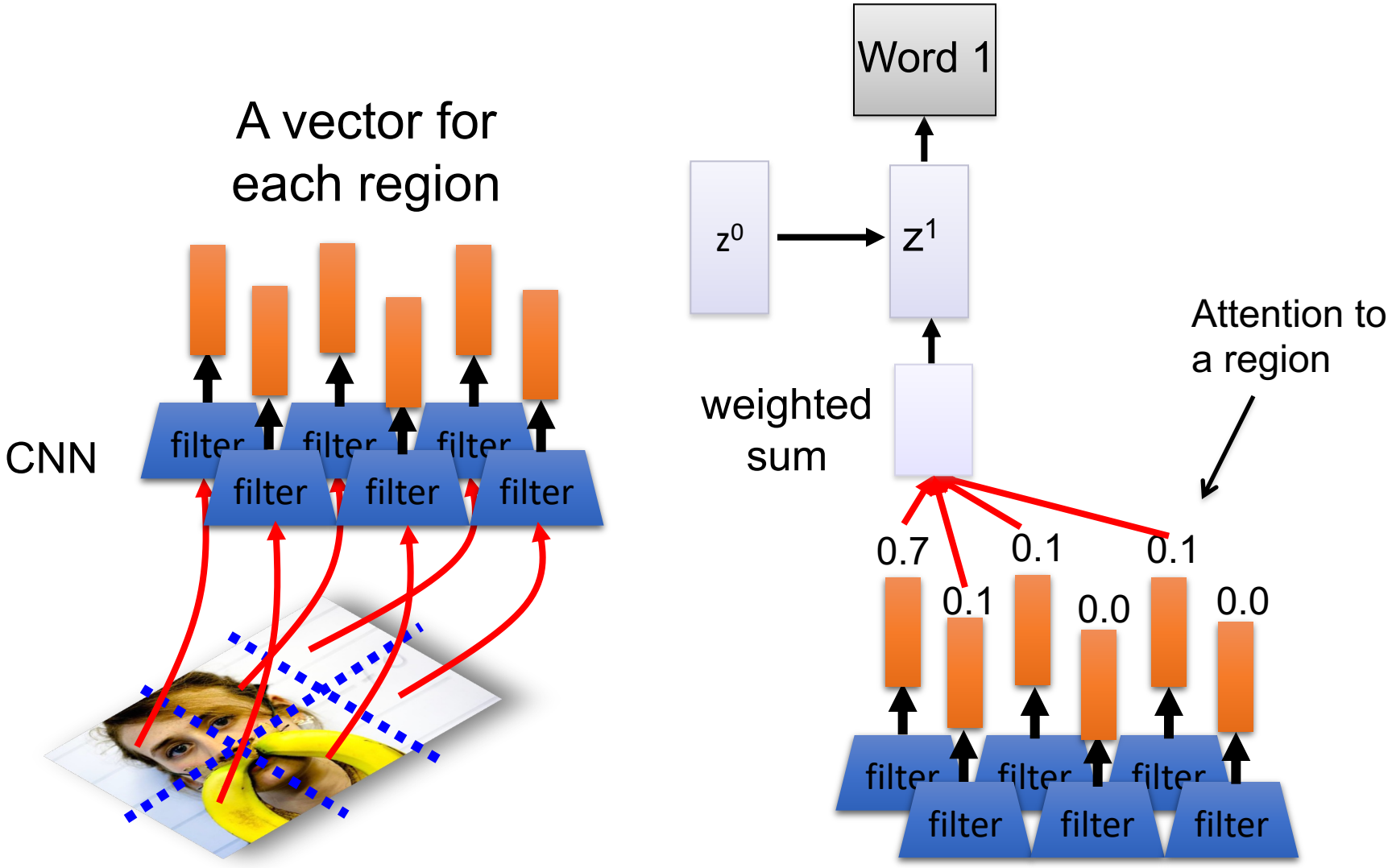

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Image caption generation using attention

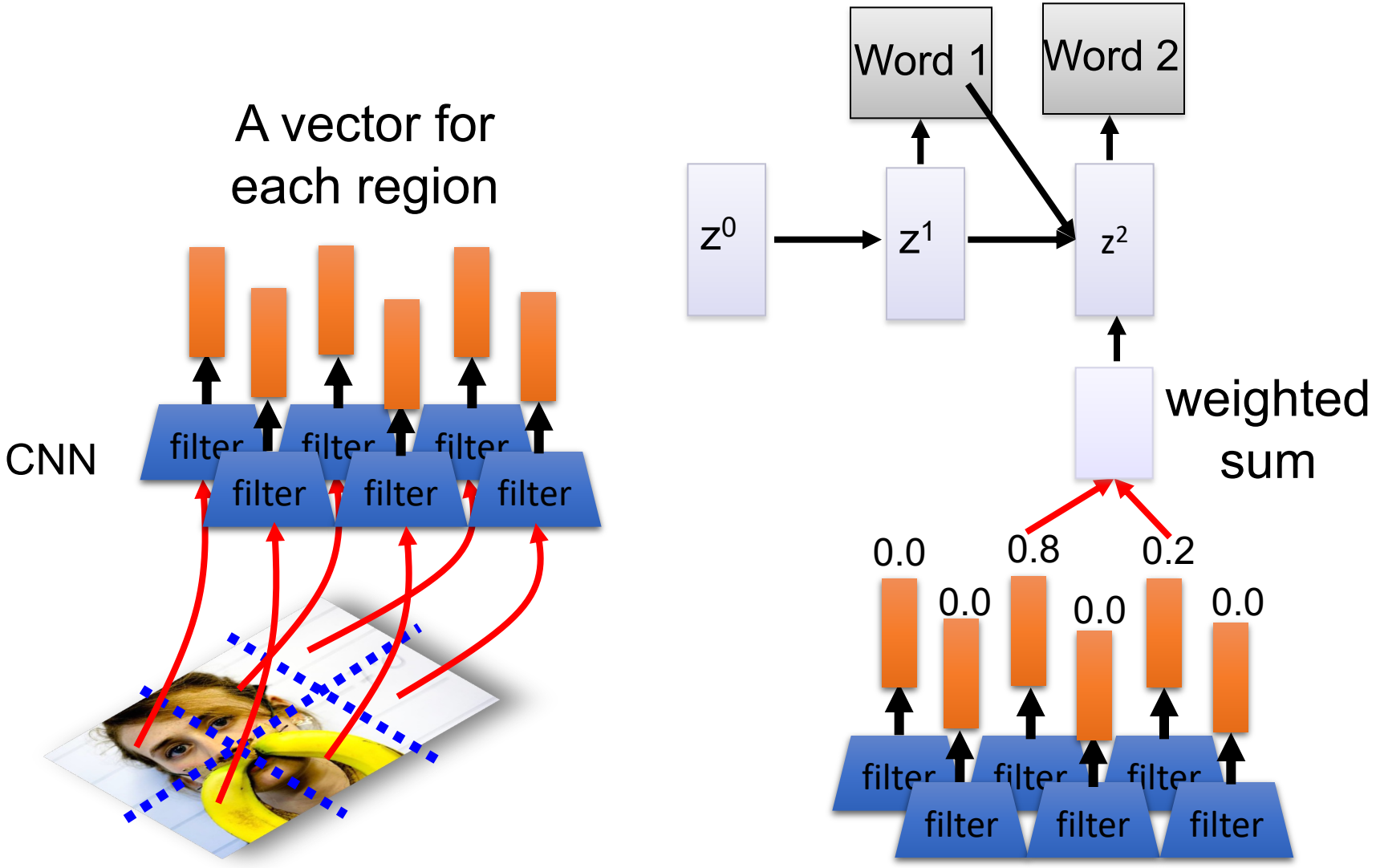

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Image caption generation using attention

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard Zemel, Yoshua Bengio, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML, 2015

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Image caption generation using attention

A large white bird standing in a forest.

A woman holding a clock in her hand.

A man wearing a hat and a hat on a skateboard.

A person is standing on a beach with a surfboard.

A woman is sitting at a table with a large pizza.

A man is talking on his cell phone while another man watches.

Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard Zemel, Yoshua Bengio, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML, 2015

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Ref: A man and a woman ride a motorcycle

A **man** and a **woman** are **talking** on the **road**

* Possible project?

Ref: A woman is frying food

Someone is **frying** a **fish** in a **pot**

Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher Pal, Hugo Larochelle, Aaron Courville, “Describing Videos by Exploiting Temporal Structure”, ICCV, 2015

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Bài tập 12 - RNN

- Tìm hiểu về tập dữ liệu phân loại cảm xúc của các review IMDB:

https://www.kaggle.com/datasets/lakshmi25npathi/imdb-dataset-of-50k-movie-reviews

- Load tập dữ liệu imdb: “keras.datasets.imdb.load_data”:
  - Chỉ sử dụng 10.000 từ vựng có tần số xuất hiện nhiều nhất
- Padding 0 để các câu có kích thước giống nhau là 500:
  - “keras.preprocessing.sequence.pad_sequences”
  - “torch.nn.utils.rnn.pad_sequence”
- Sử dụng “Embedding” để chuyển đầu vào về kích thước 100
- Huấn luyện với các mạng Naive RNN, LSTM, GRU, Bi-RNN, Bi-LSTM và Bi-GRU so sánh tốc độ huấn luyện, tốc độ suy luận và độ chính xác.