

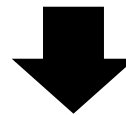
# Recurrent Neural Network (RNN)

# Example Application

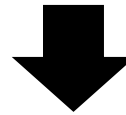
- Slot Filling



I would like to arrive **Taipei** on **November 2<sup>nd</sup>**.



ticket booking system



Slot

Destination:

Taipei

time of arrival:

November 2<sup>nd</sup>

# Example Application

Solving slot filling by  
Feedforward network?

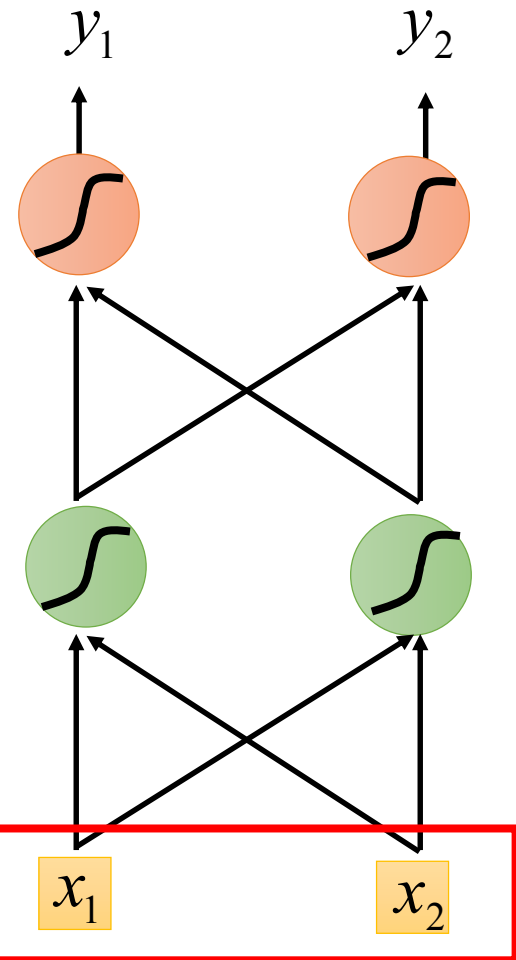
Input: a word

(Each word is represented  
as a vector)

若使用一般的 Feedforward Network 來解決 Slot Filling 問題：輸入一個詞彙，輸出即是詞彙屬於每一個 Slot 的機率

前提：必須將輸入的詞彙用「Vector」表示，才能丟進 Neural Network 中！

Taipei



用 Vector 表示詞彙最簡單的方法！

# 1-of-N encoding

How to represent each word as a vector?

**1-of-N Encoding**    lexicon = {apple, bag, cat, dog, elephant}

The vector is lexicon size.

Each dimension corresponds  
to a word in the lexicon

The dimension for the word  
is 1, and others are 0

apple = [ 1   0   0   0   0 ]

bag    = [ 0   1   0   0   0 ]

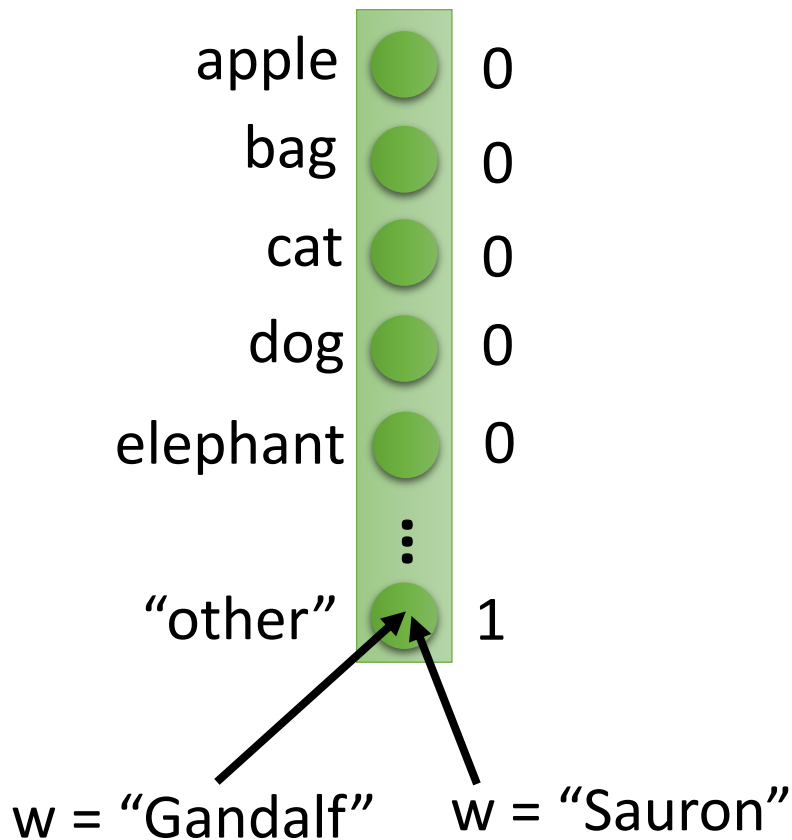
cat    = [ 0   0   1   0   0 ]

dog    = [ 0   0   0   1   0 ]

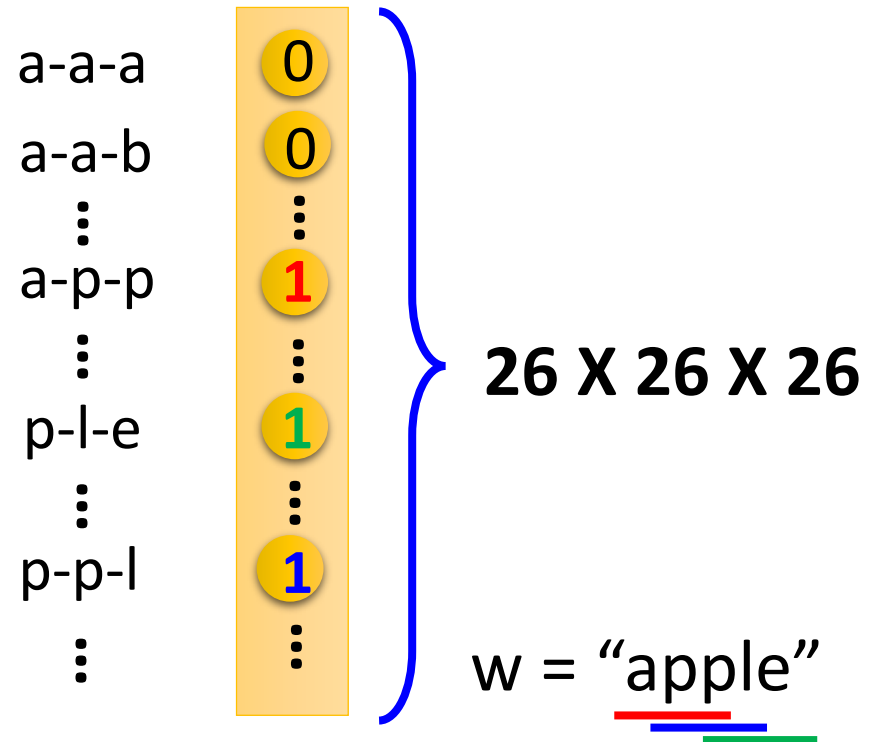
elephant = [ 0   0   0   0   1 ]

# Beyond 1-of-N encoding

## Dimension for “Other”



## Word hashing



# Example Application

Solving slot filling by  
Feedforward network?

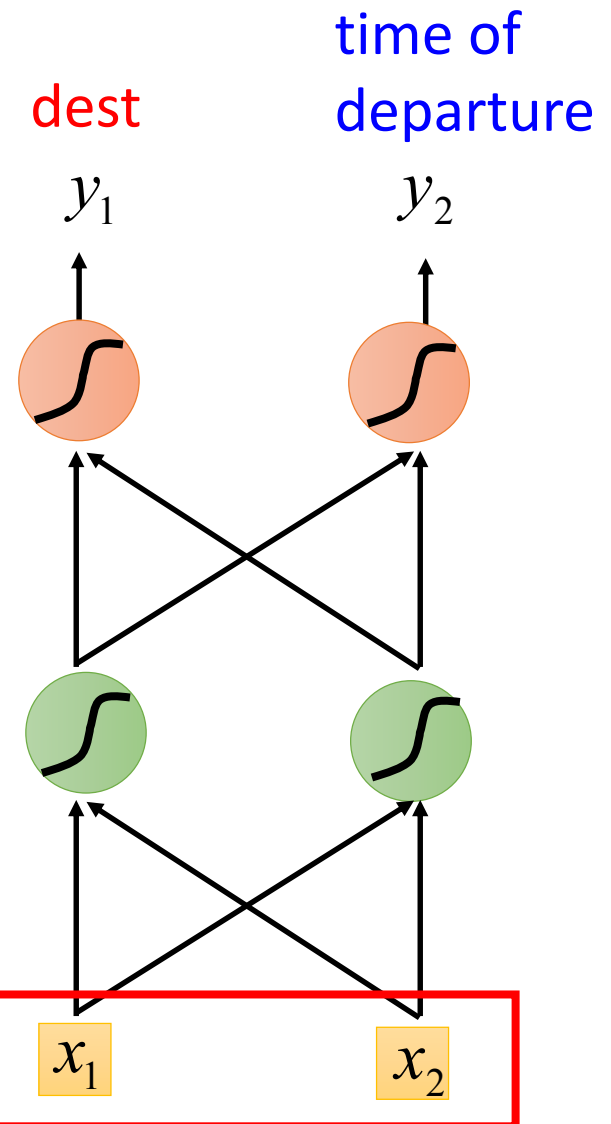
Input: a word

(Each word is represented  
as a vector)

Output:

Probability distribution that  
the input word belonging to  
the slots

Taipei →



# Example Application

arrive Taipei on November 2<sup>nd</sup>

other dest other time time

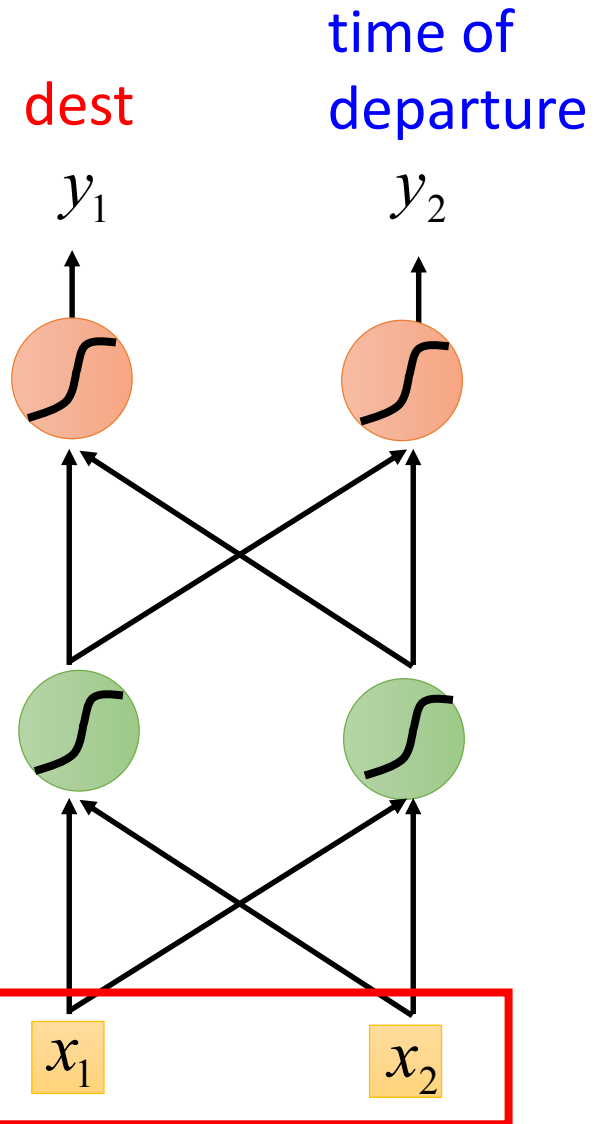
Problem?

leave Taipei on November 2<sup>nd</sup>

place of departure

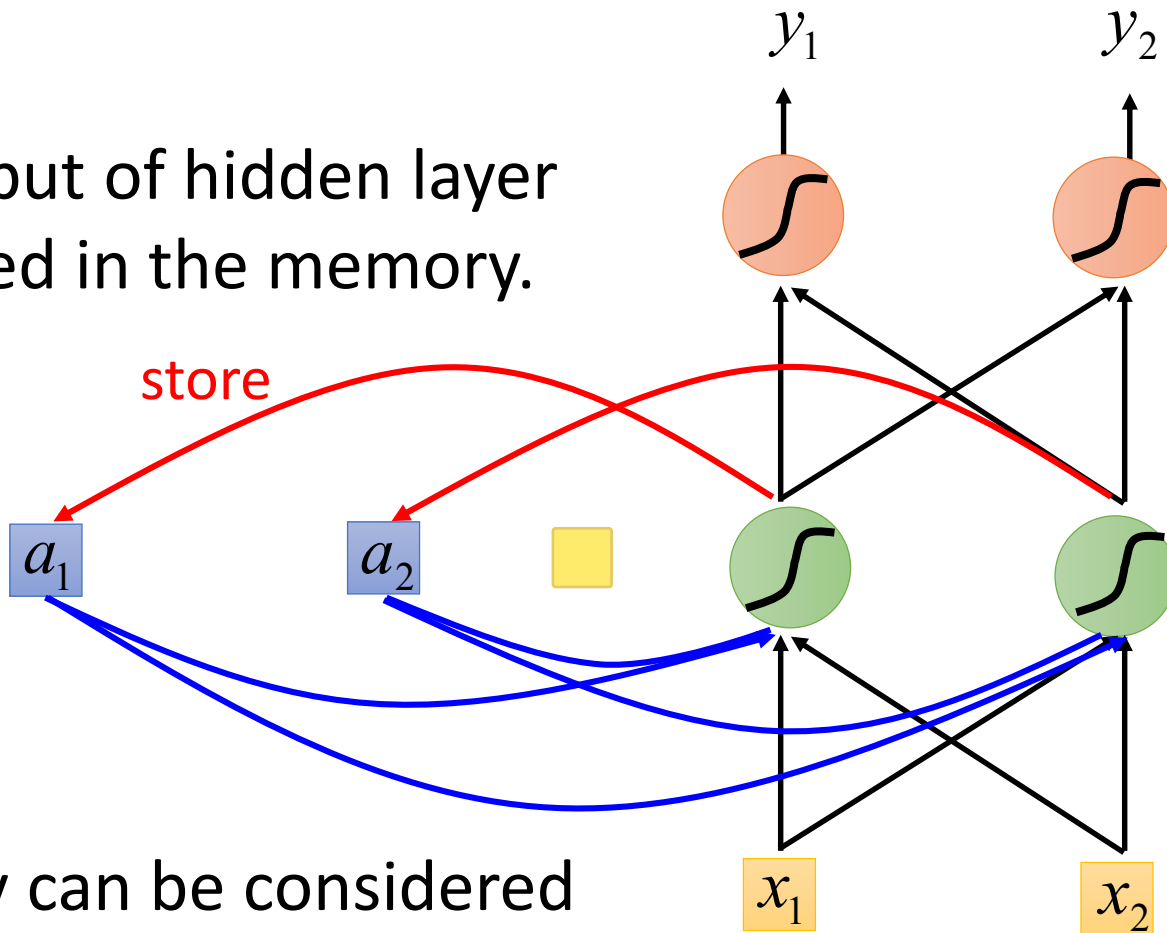
Neural network  
needs memory!

Taipei



# Recurrent Neural Network (RNN)

The output of hidden layer are stored in the memory.



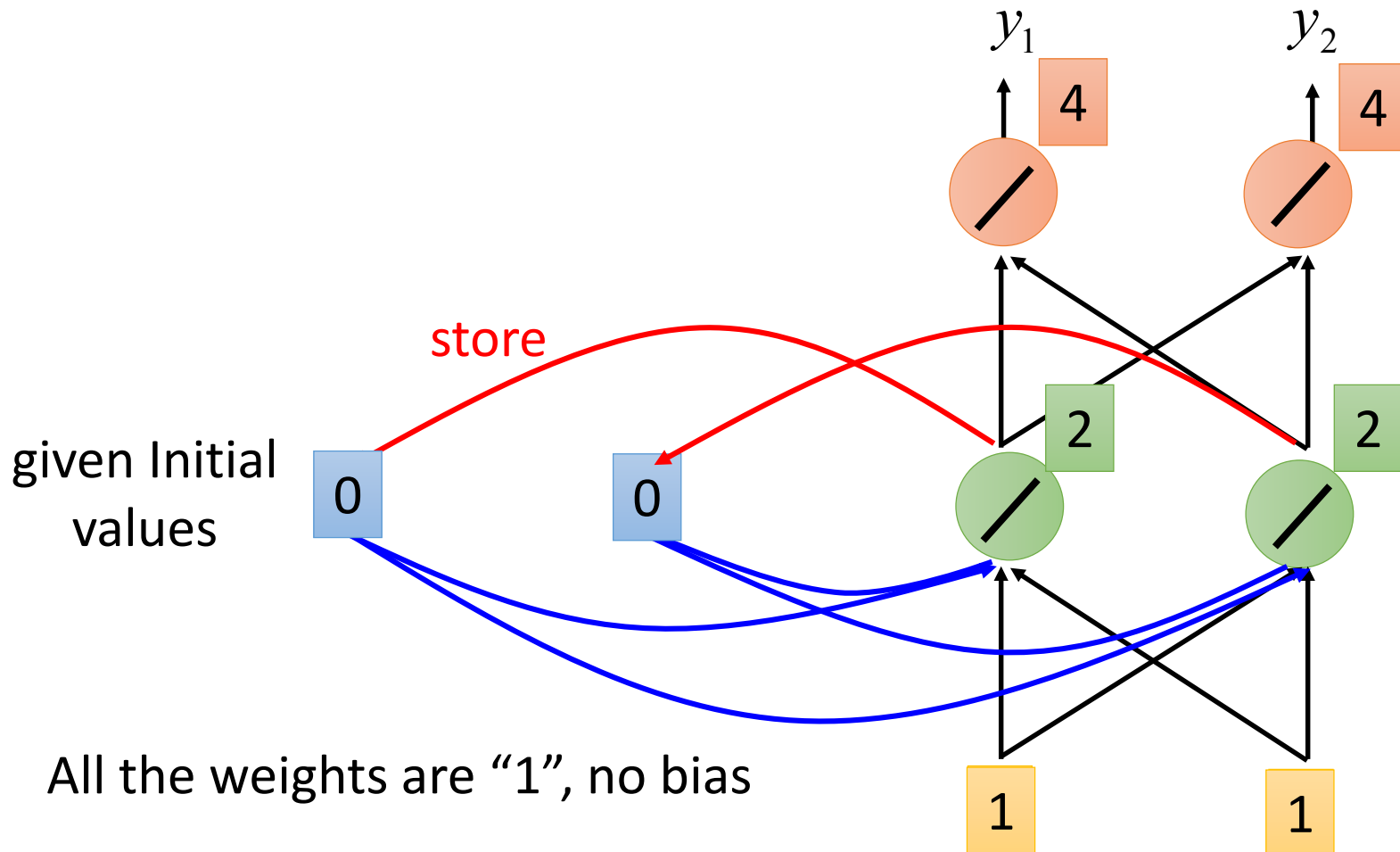
Memory can be considered as another input.



# Example

Input sequence:  $\begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} \dots$

output sequence:  $\begin{bmatrix} 4 \\ 4 \end{bmatrix}$



All the weights are "1", no bias

All activation functions are linear

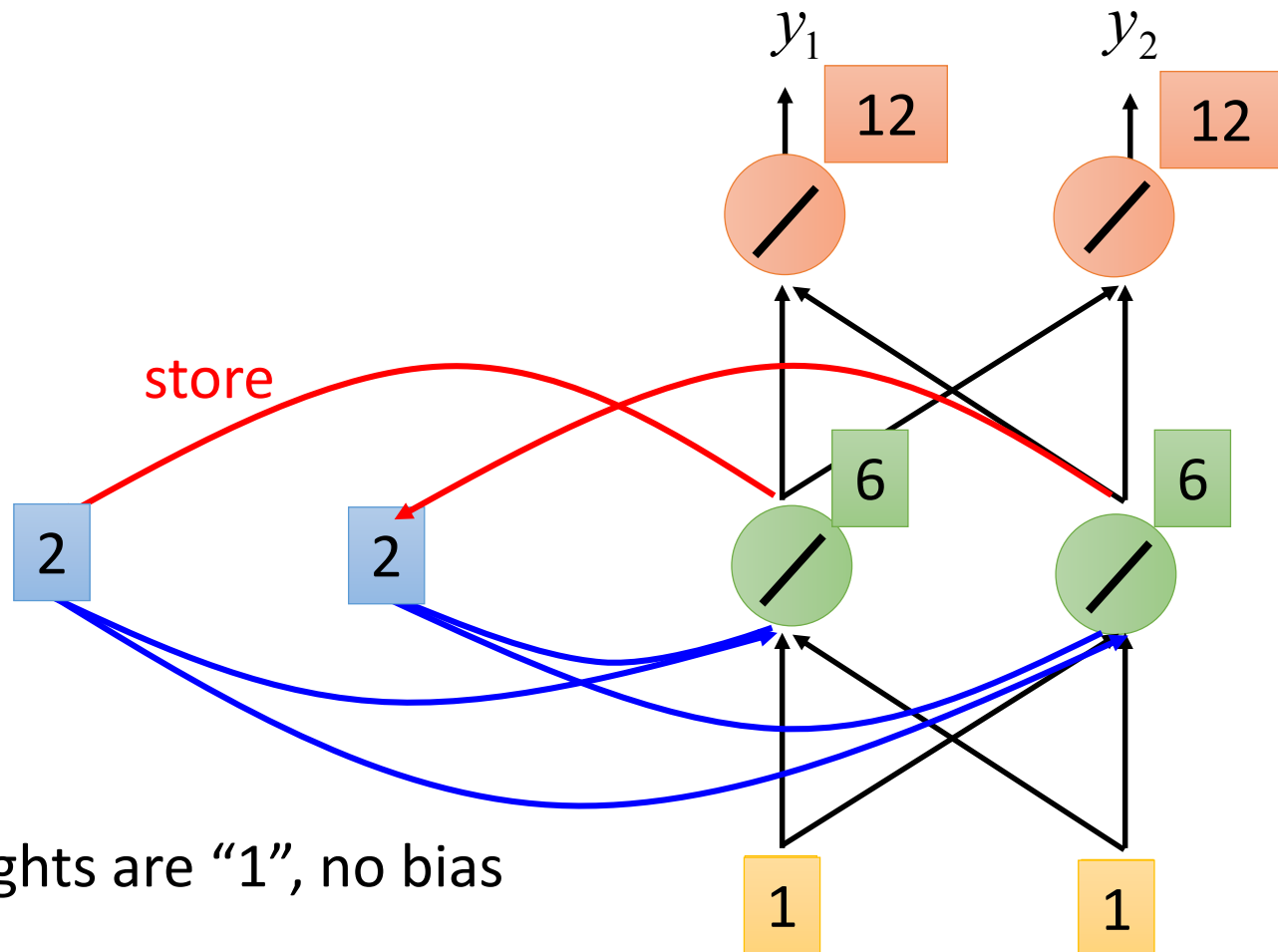
# Example

Input sequence:

$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$   $\begin{bmatrix} 1 \\ 1 \end{bmatrix}$   $\begin{bmatrix} 2 \\ 2 \end{bmatrix}$  ... ..

output sequence:

$\begin{bmatrix} 4 \\ 4 \end{bmatrix}$   $\begin{bmatrix} 12 \\ 12 \end{bmatrix}$



All the weights are "1", no bias

All activation functions are linear

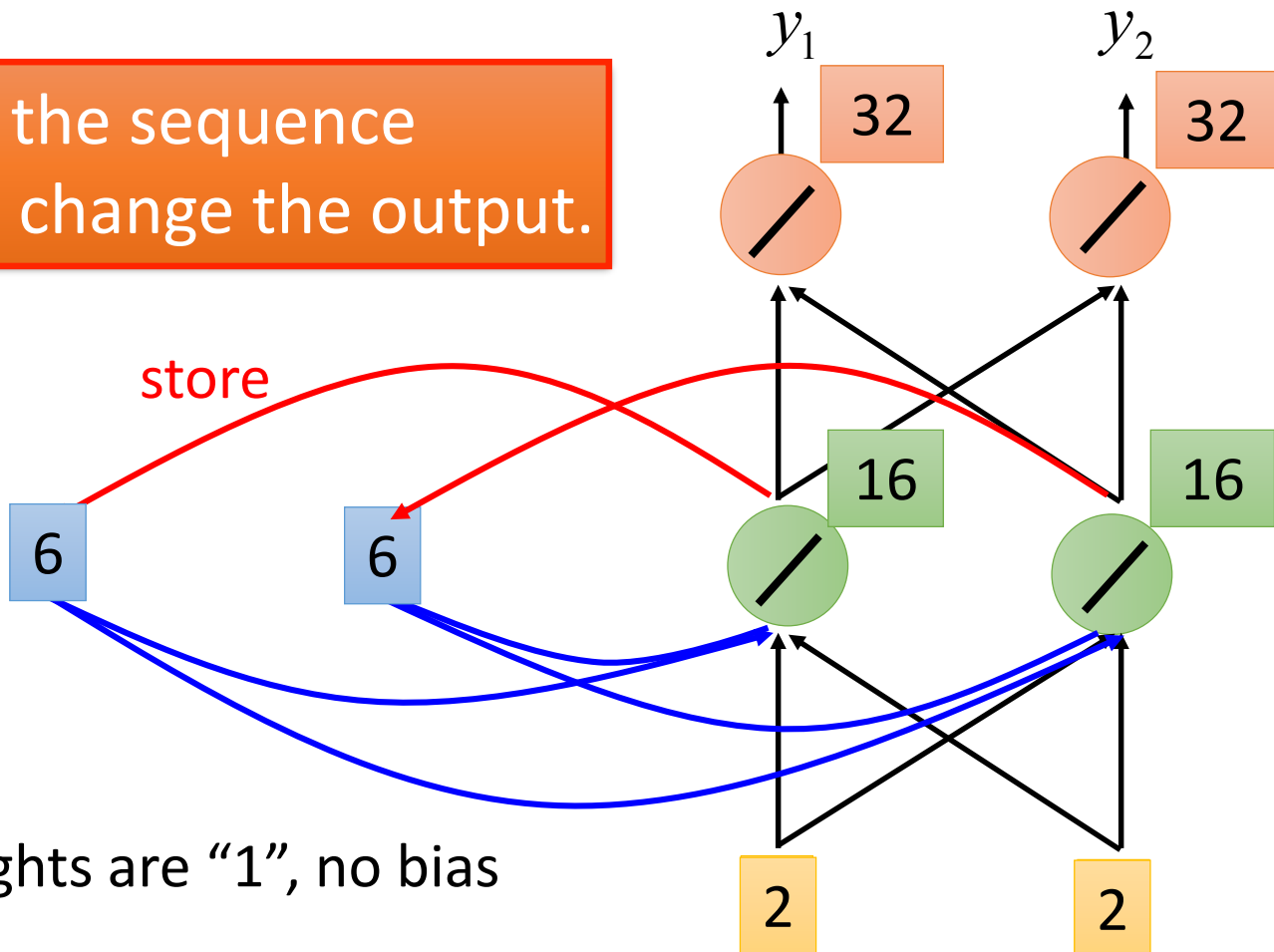
# Example

Input sequence:  $\begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \end{bmatrix} \dots \dots$

output sequence:  $\begin{bmatrix} 4 \\ 4 \end{bmatrix} \begin{bmatrix} 12 \\ 12 \end{bmatrix} \begin{bmatrix} 32 \\ 32 \end{bmatrix}$



Changing the sequence order will change the output.



All the weights are "1", no bias

All activation functions are linear

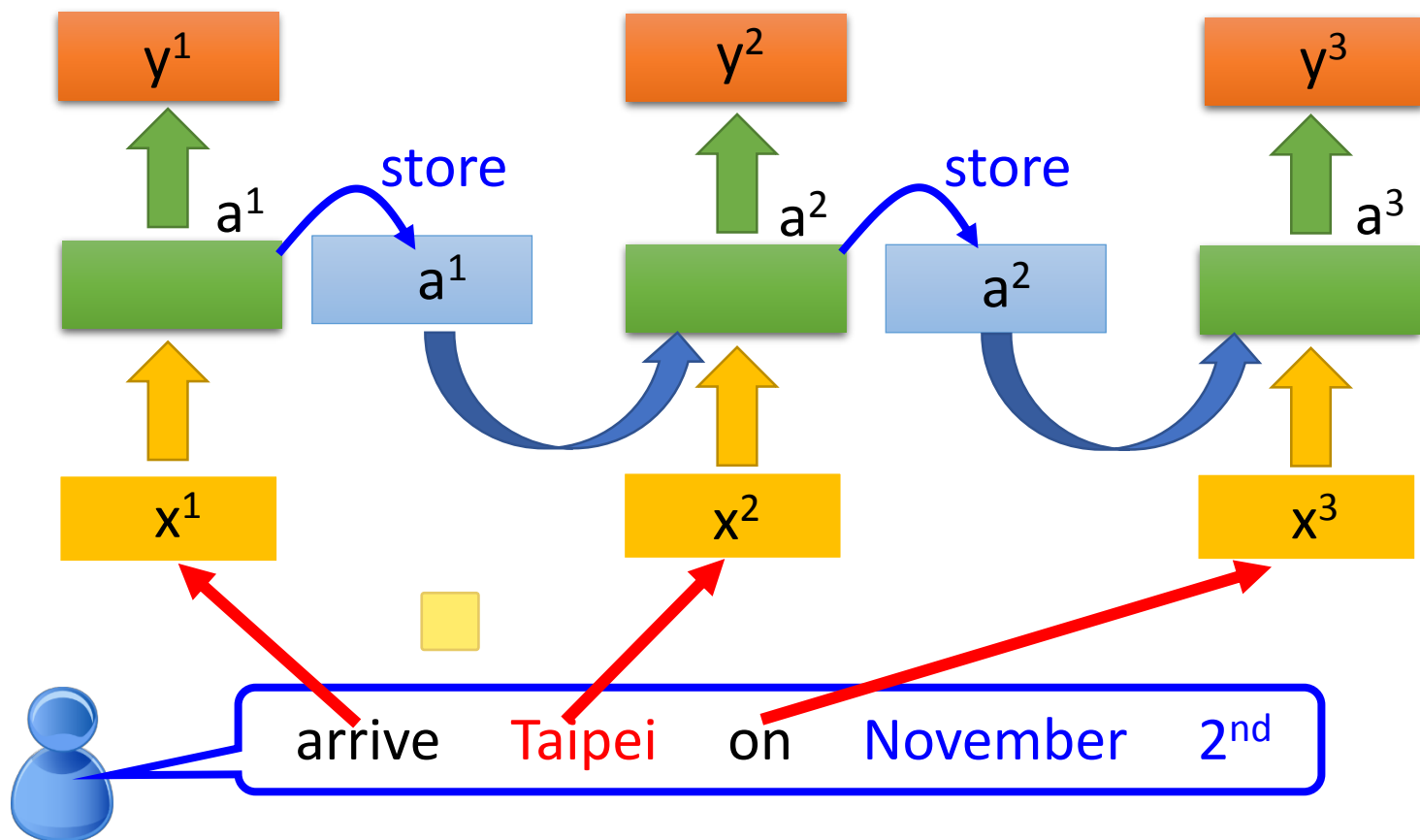
# RNN

The same network is used again and again.

Probability of  
“arrive” in each slot

Probability of  
“**Taipei**” in each slot

Probability of  
“on” in each slot



# RNN

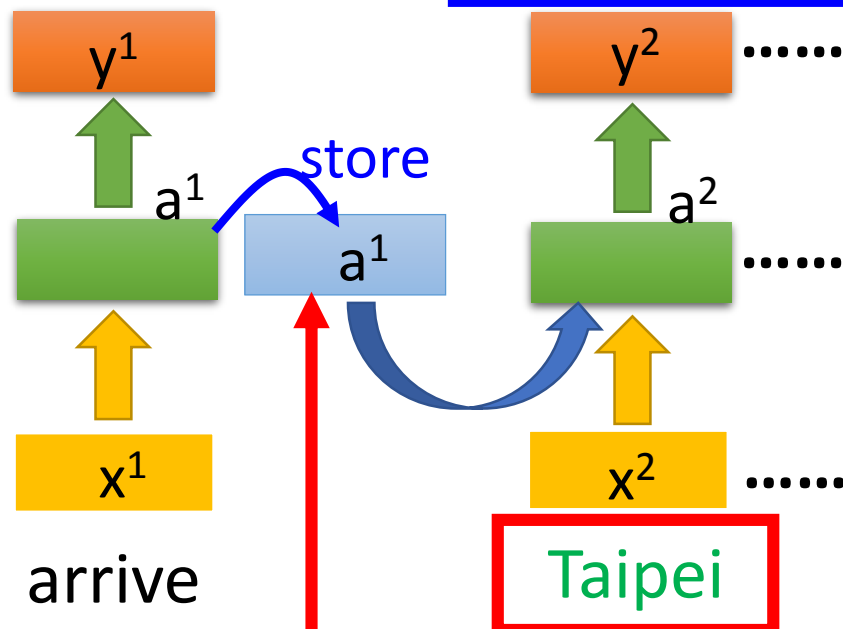
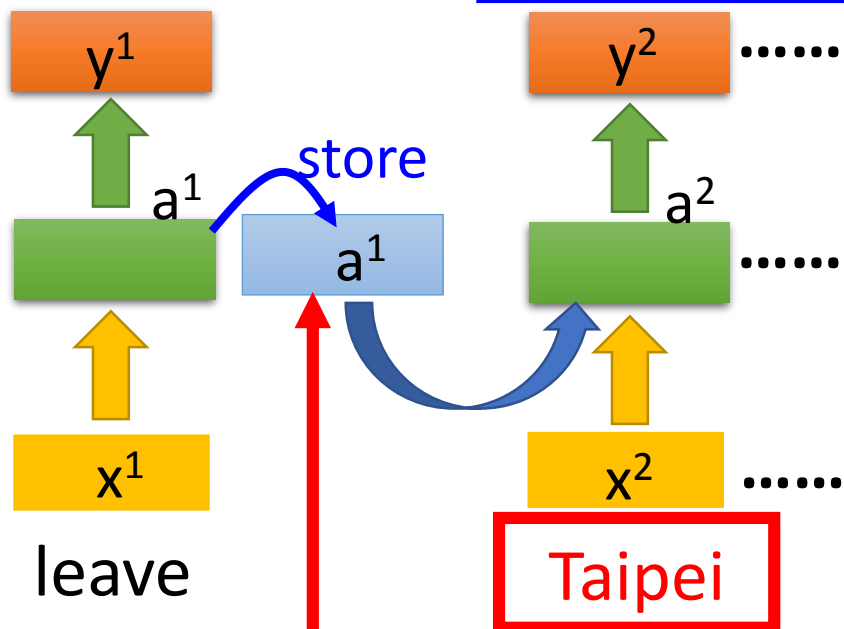
Different

Prob of "leave"  
in each slot

Prob of "Taipei"  
in each slot

Prob of "arrive"  
in each slot

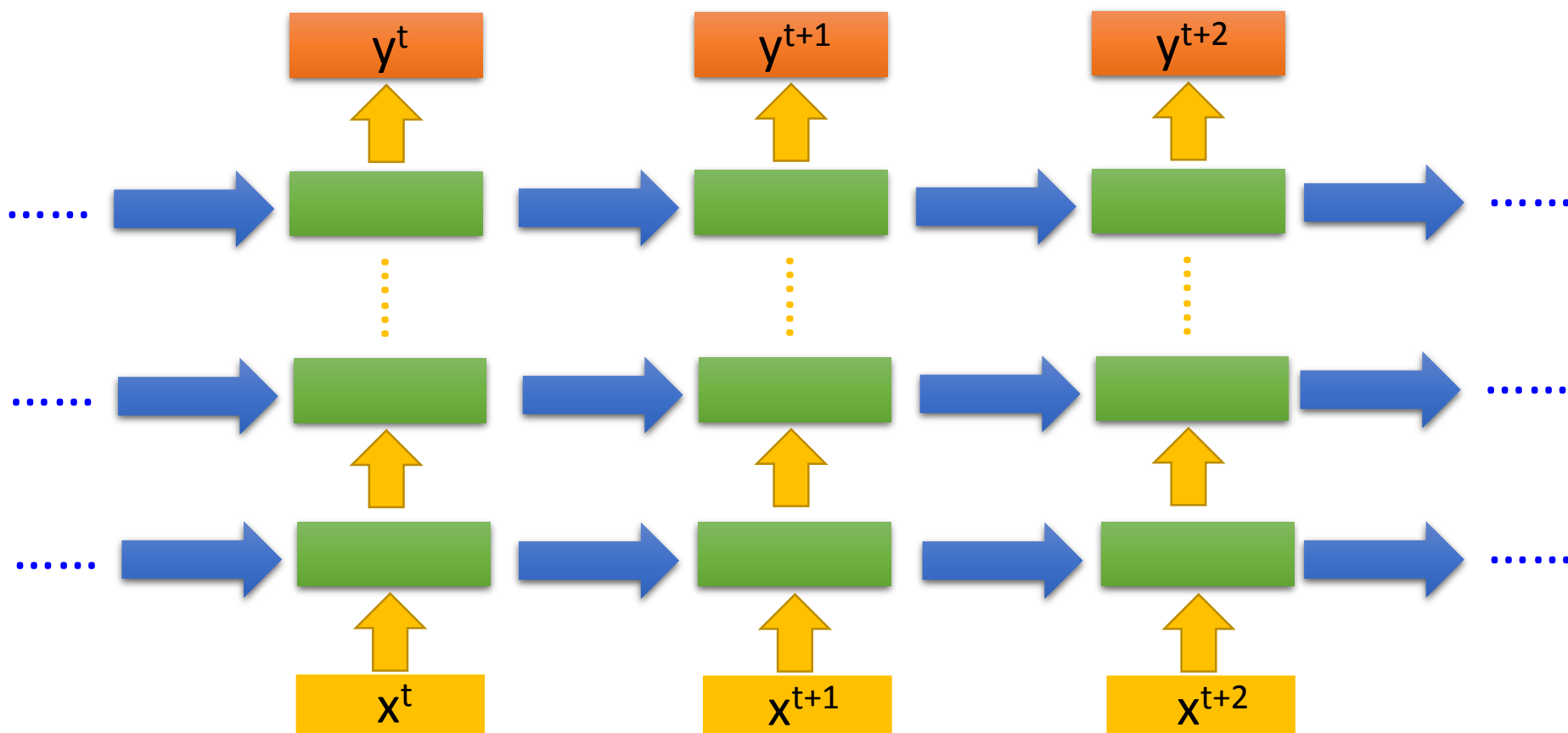
Prob of "Taipei"  
in each slot



The values stored in the memory is different.

意思：在 RNN 中，也可以有很多層 Hidden Layer！

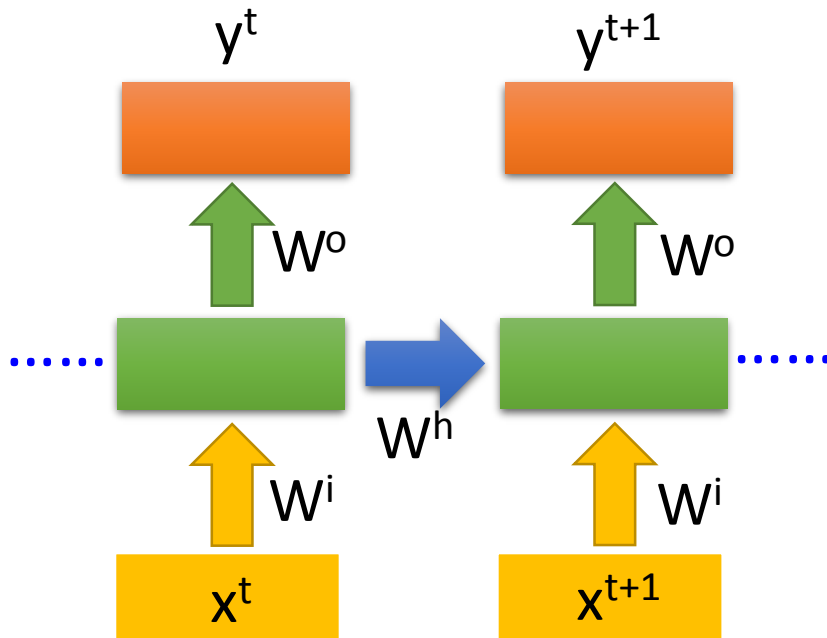
Of course it can be deep ...



# Elman Network & Jordan Network

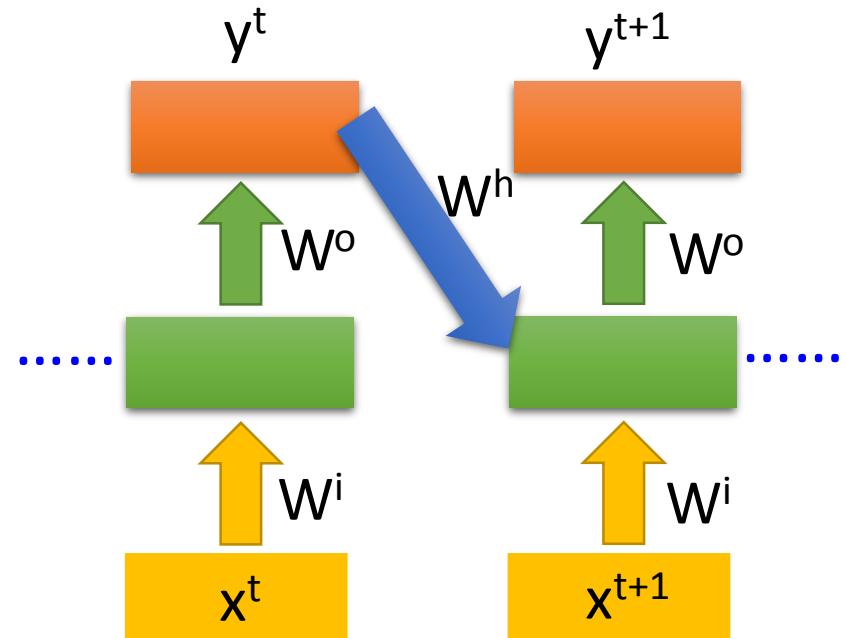
RNN 的種類 1：存下 Hidden Layer 的 Output

## Elman Network

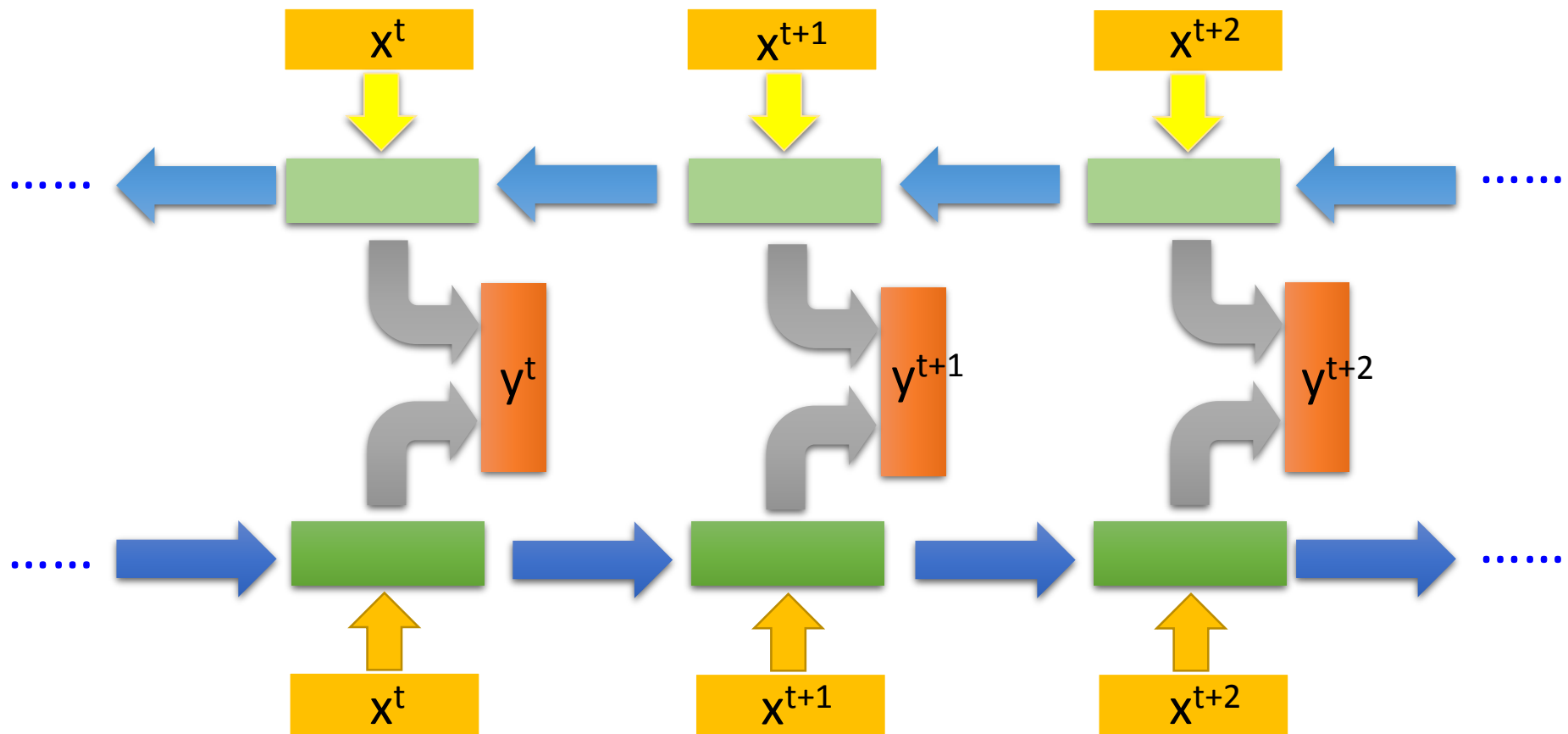


RNN 的種類 2：存下整個 Network 的 Output

## Jordan Network

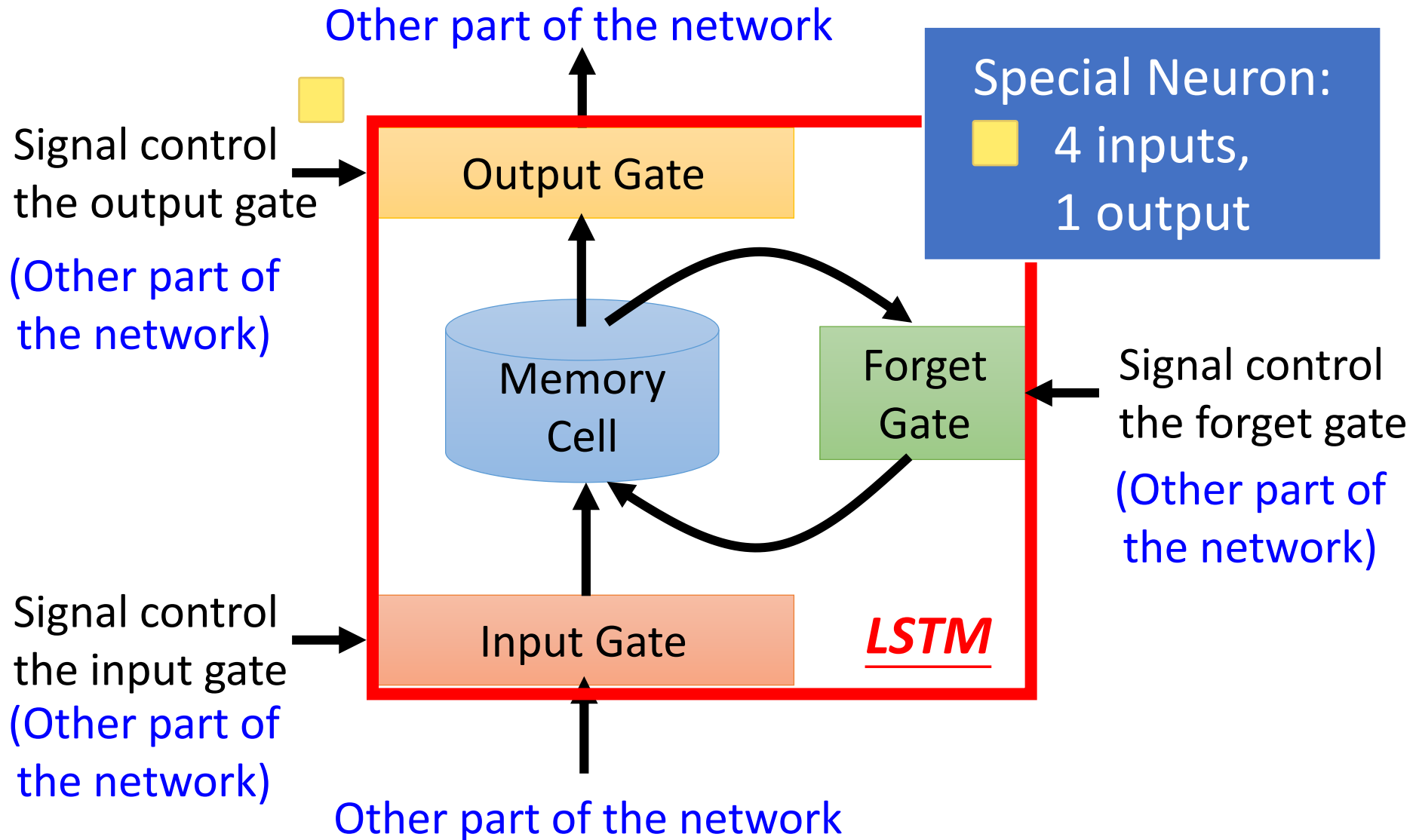


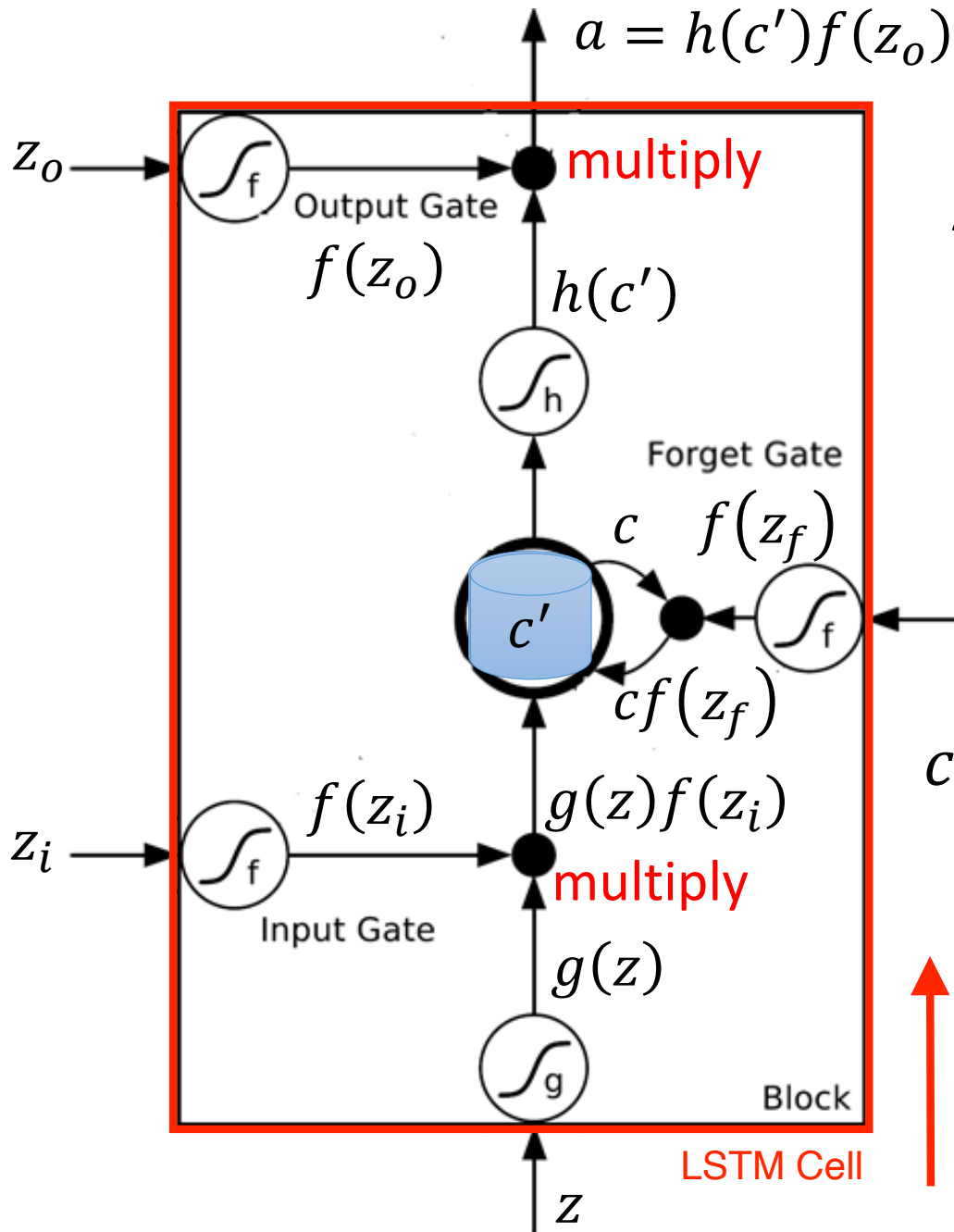
# Bidirectional RNN





# Long Short-term Memory (LSTM)



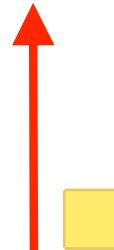


Activation function  $f$  is usually a sigmoid function

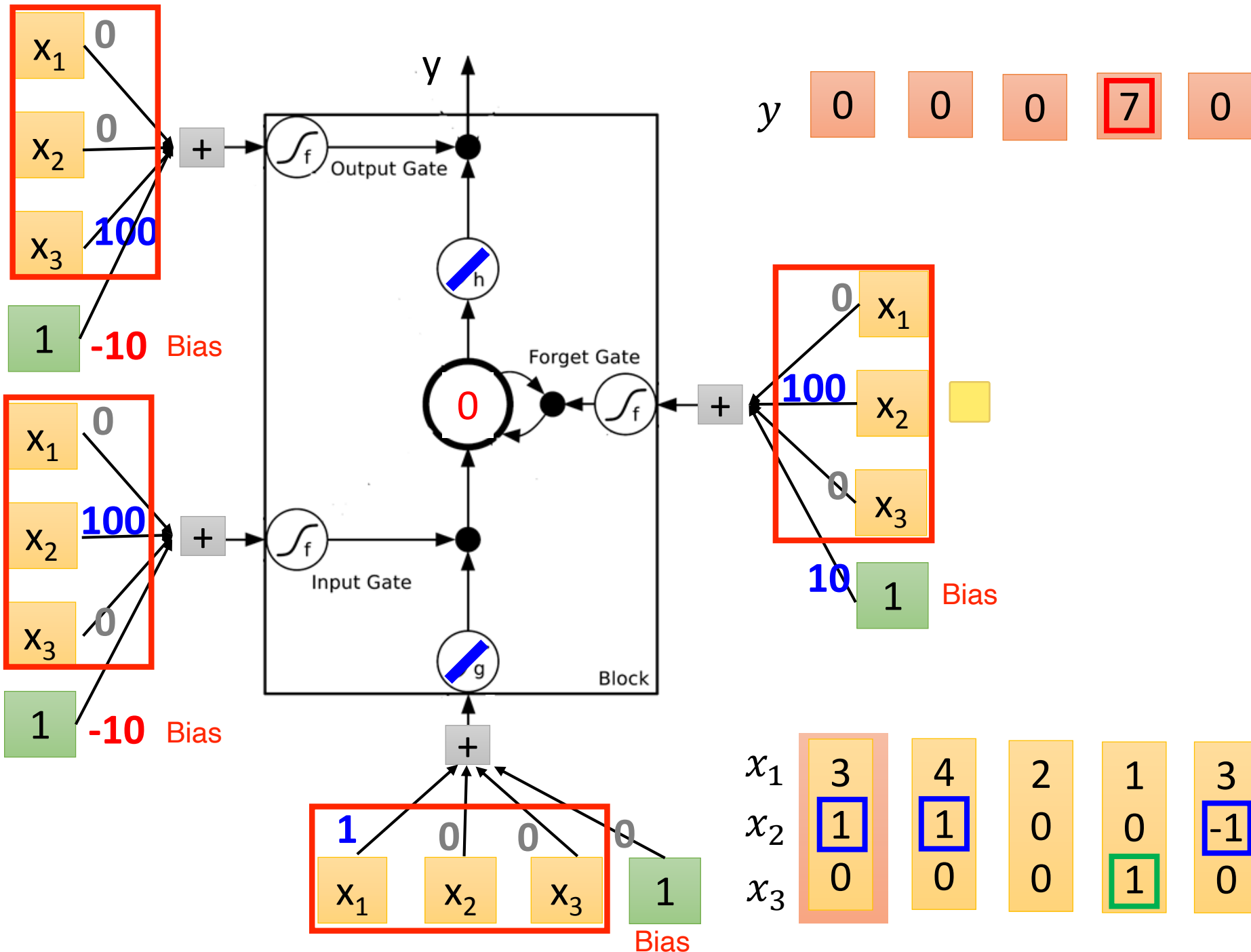
Between 0 and 1

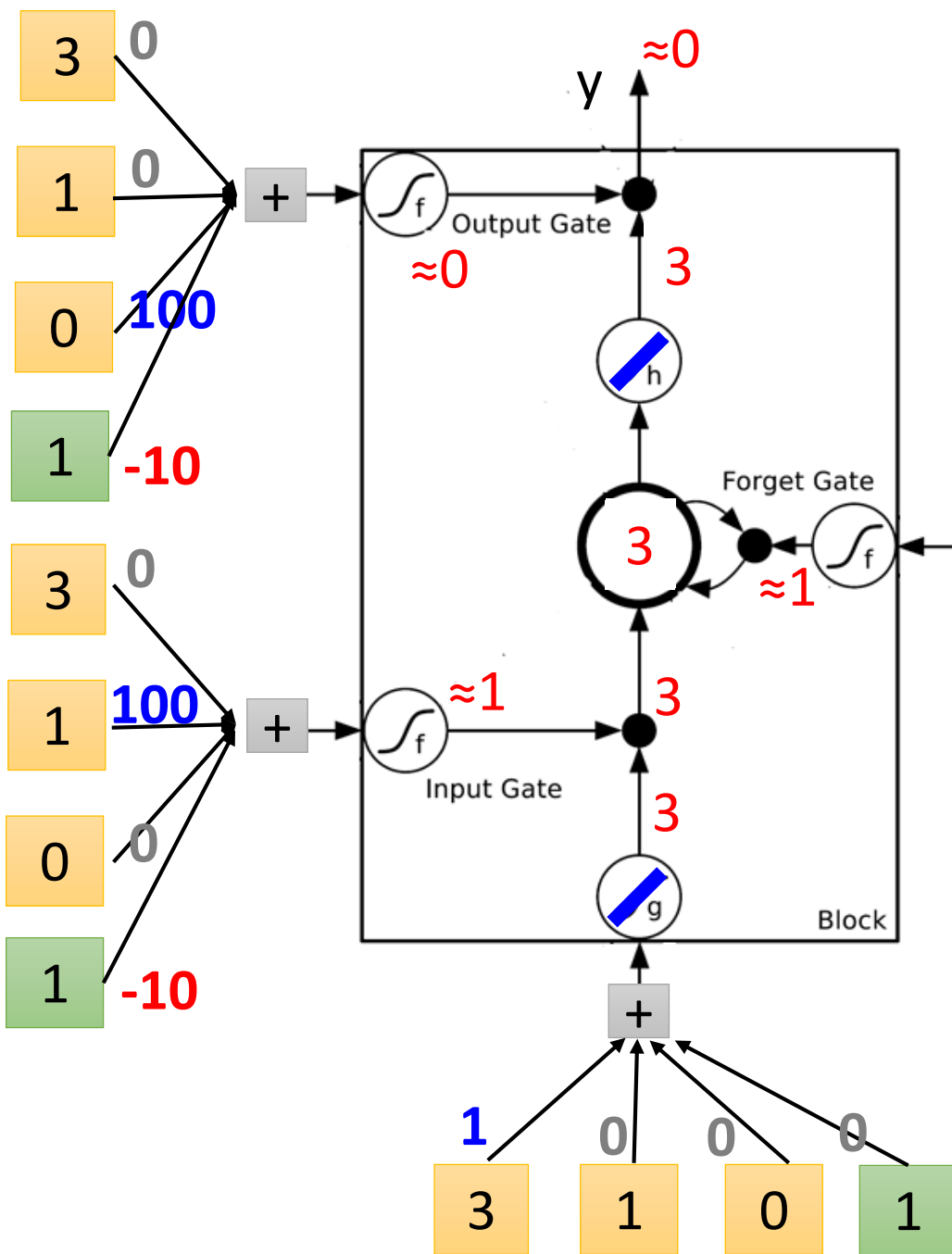
Mimic open and close gate

$$c' = g(z)f(z_i) + cf(z_f)$$

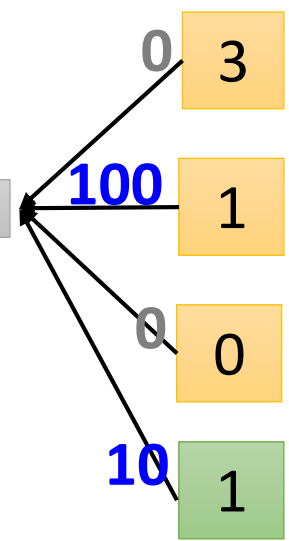


LSTM Cell

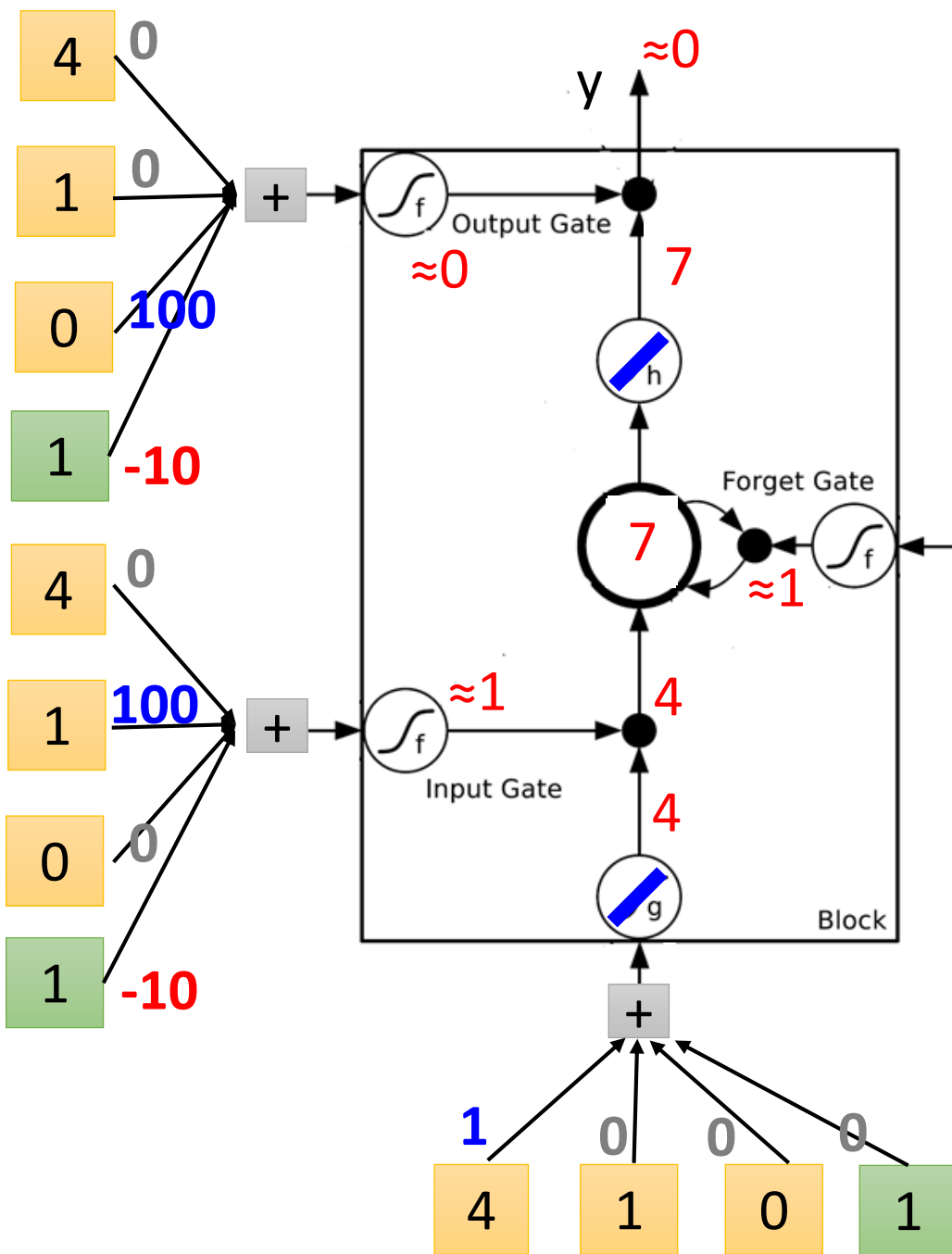




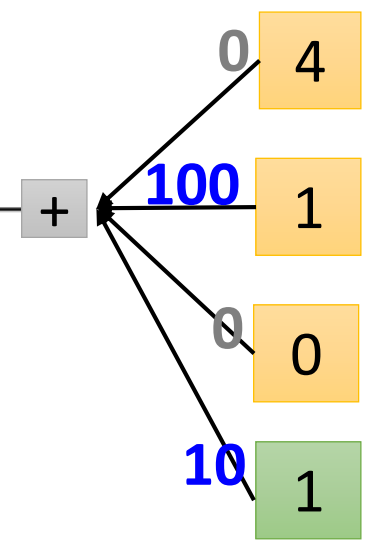
$y$  0 0 0 7 0



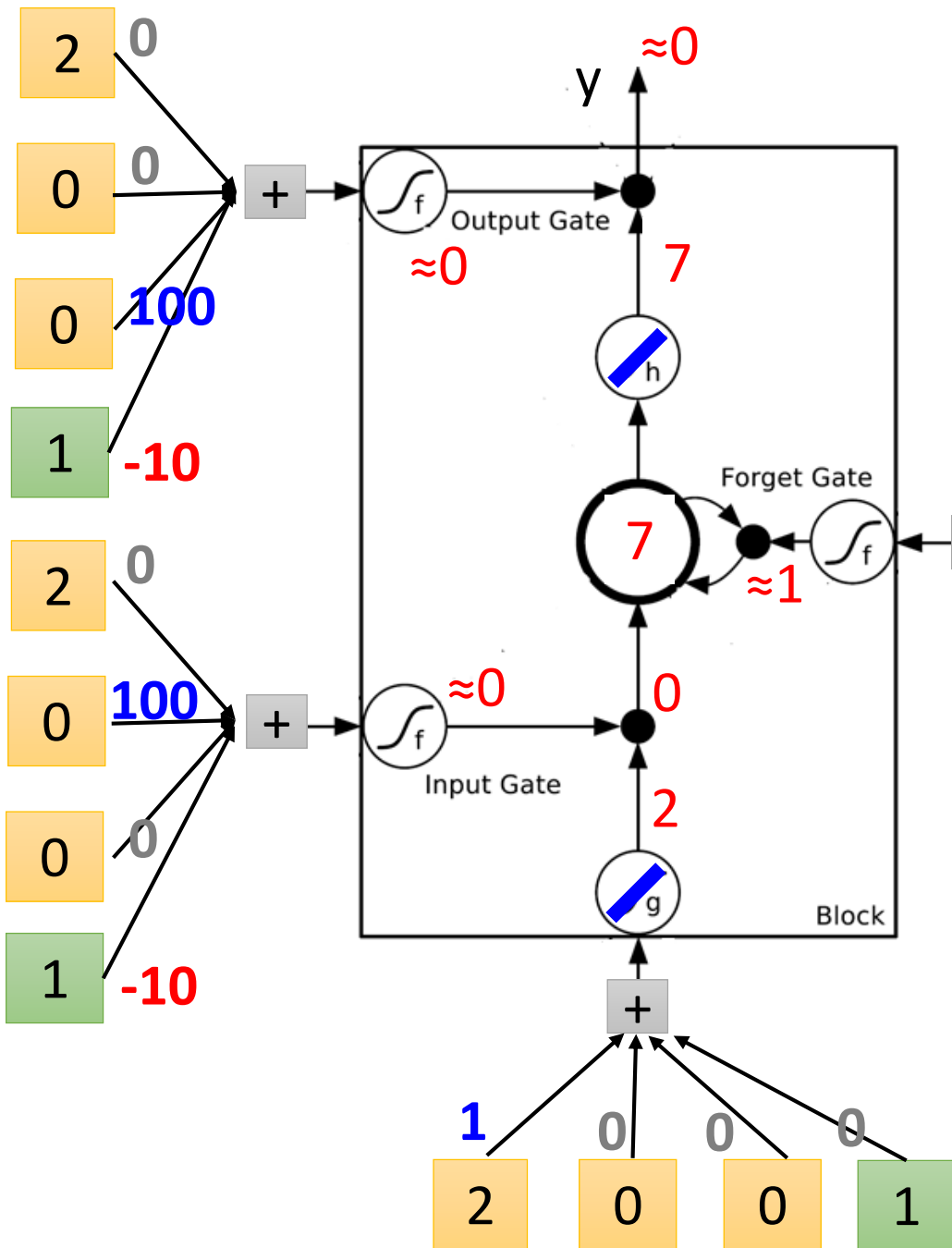
	$x_1$	$x_2$	$x_3$
$x_1$	3	4	2
$x_2$	1	1	0
$x_3$	0	0	1



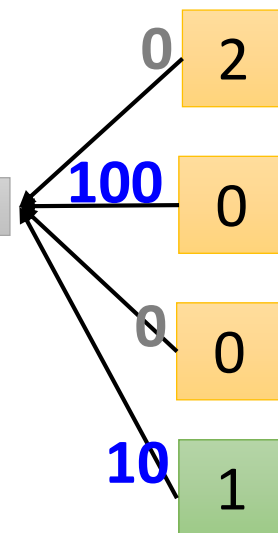
$y$  0 0 0 7 0



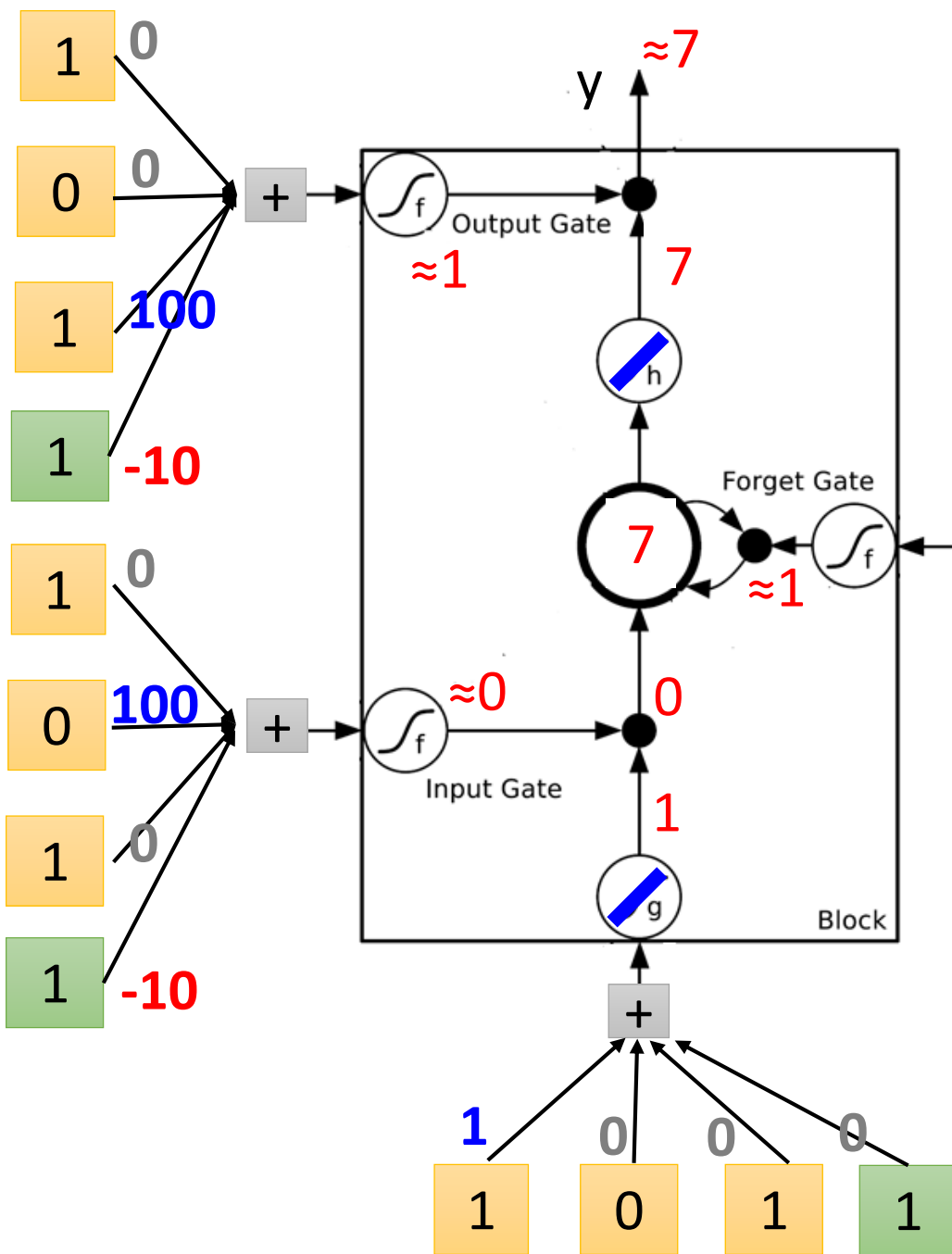
$x_1$  3 4 2 1 3  
 $x_2$  1 1 0 0 1  
 $x_3$  0 0 0 1 0



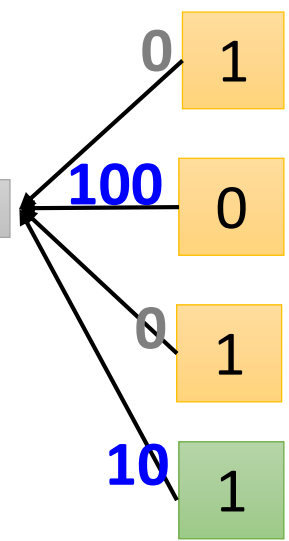
$y$  0 0 0 7 0



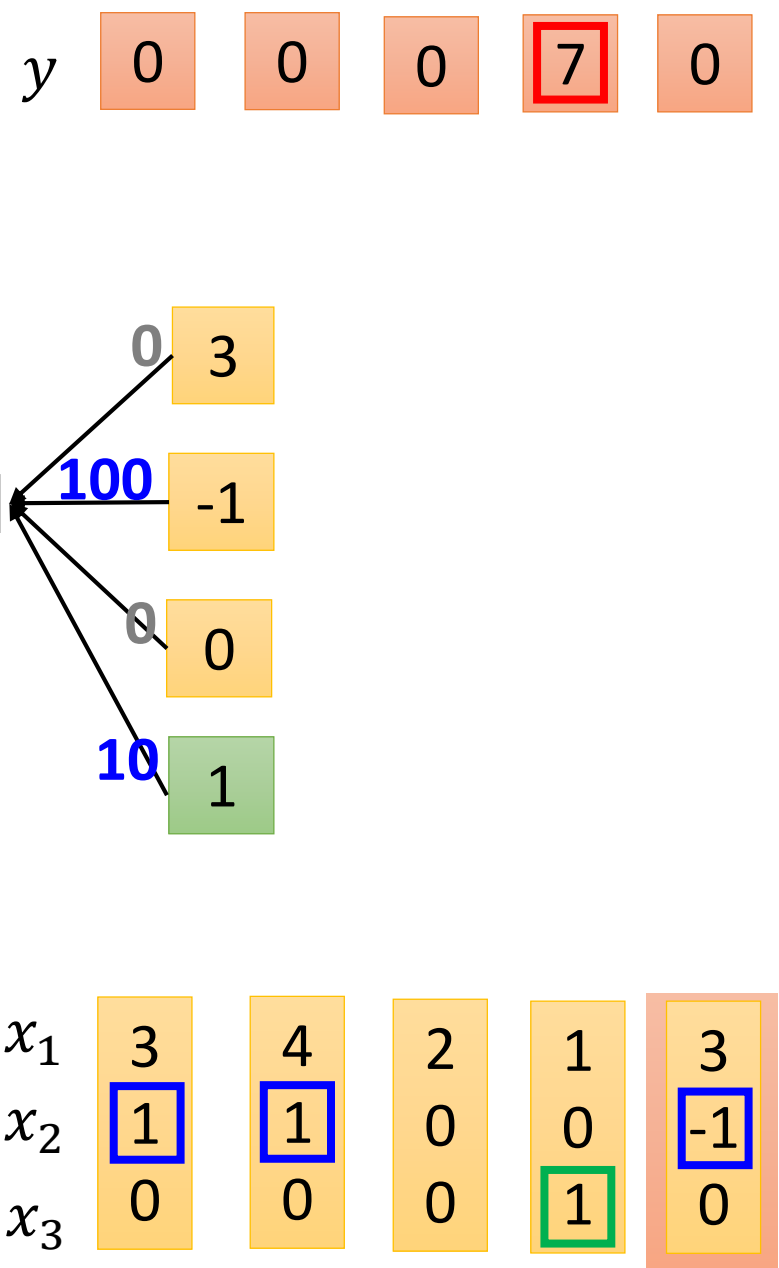
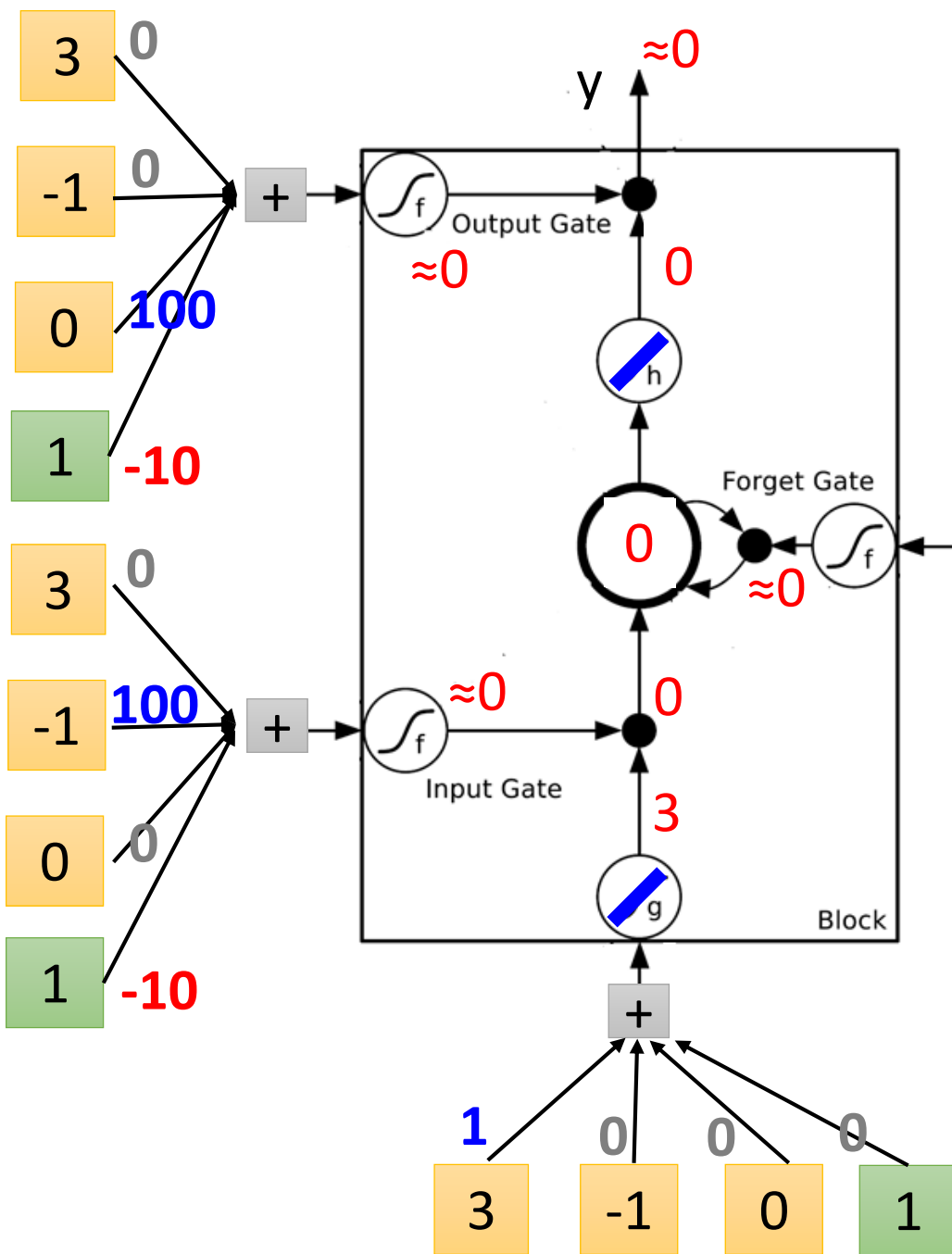
$x_1$  3 4 2 1 3  
 $x_2$  1 1 0 0 -1  
 $x_3$  0 0 0 1 0



y 0 0 0 7 0



$x_1$  3 4 2 1 3  
 $x_2$  1 1 0 0 -1  
 $x_3$  0 0 0 1 0

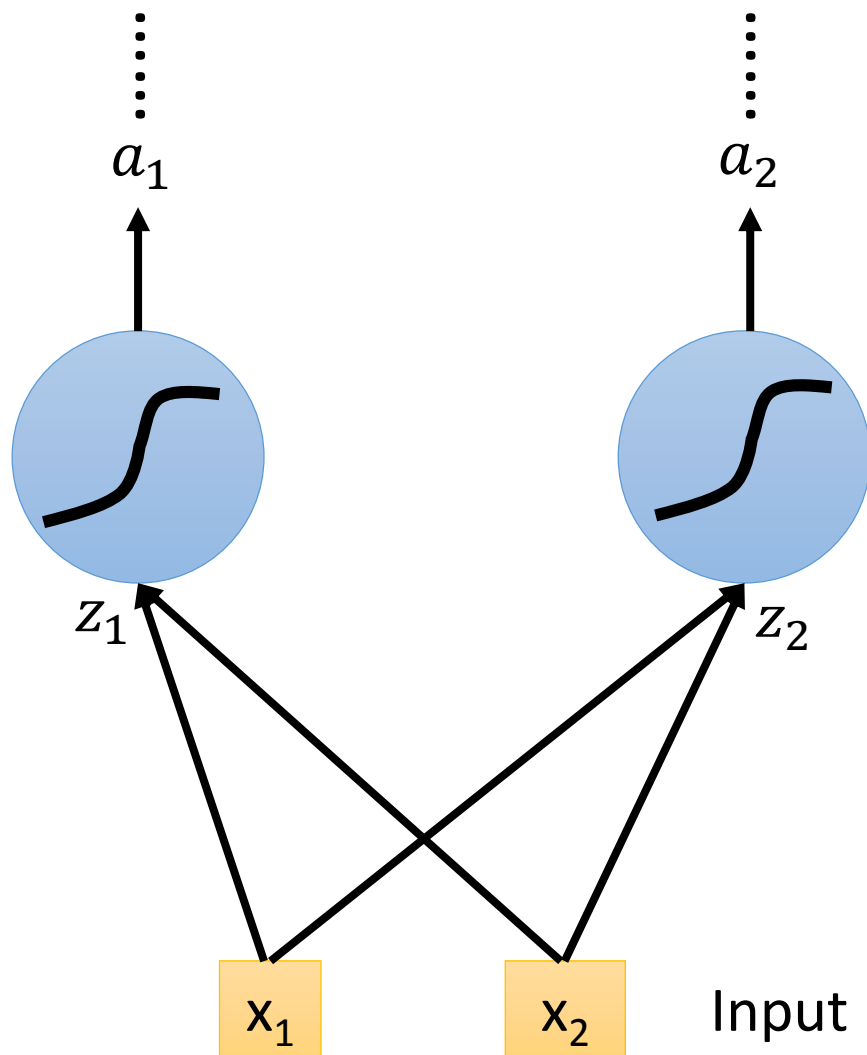


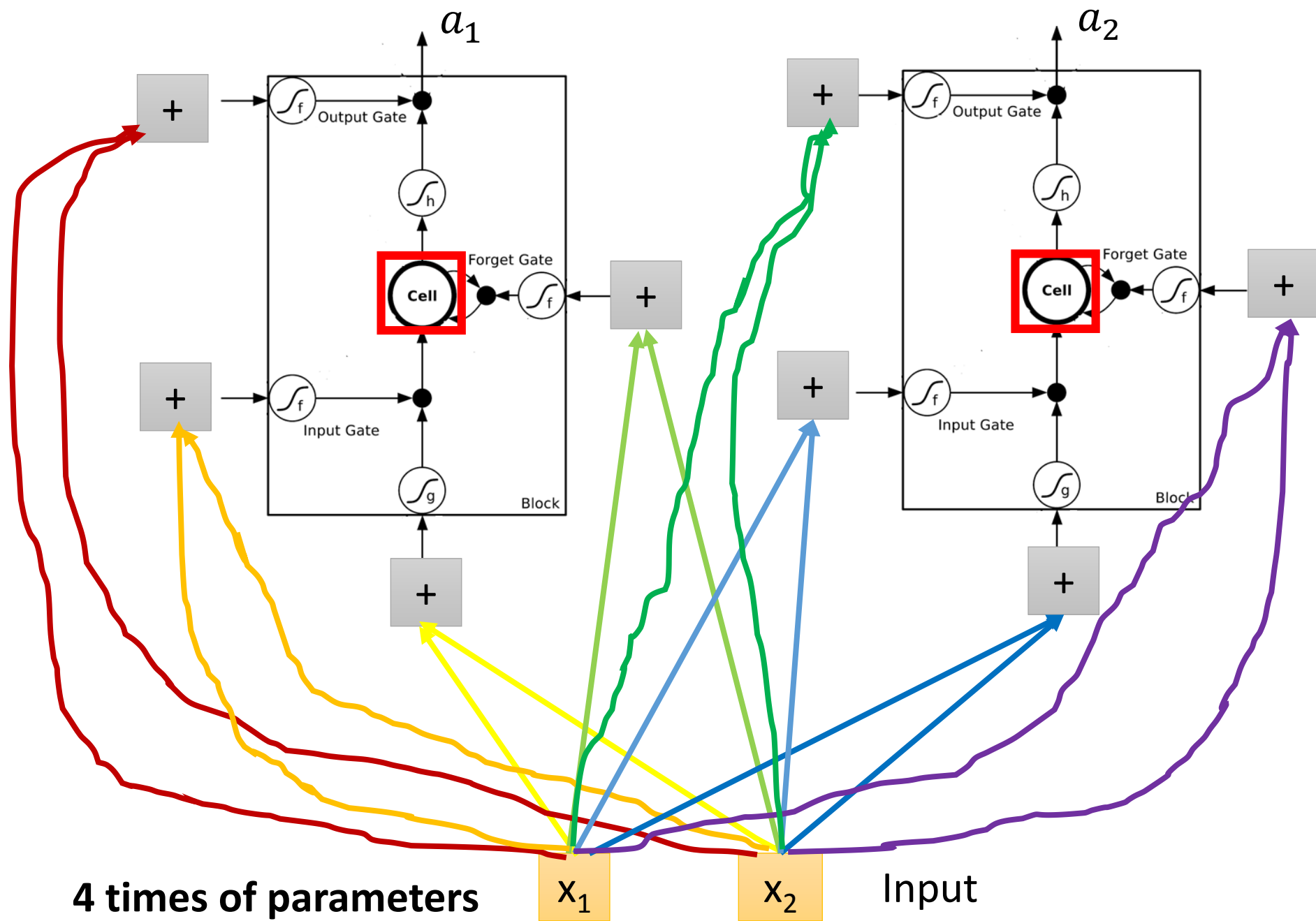


## Original Network:

➤ Simply replace the neurons with LSTM

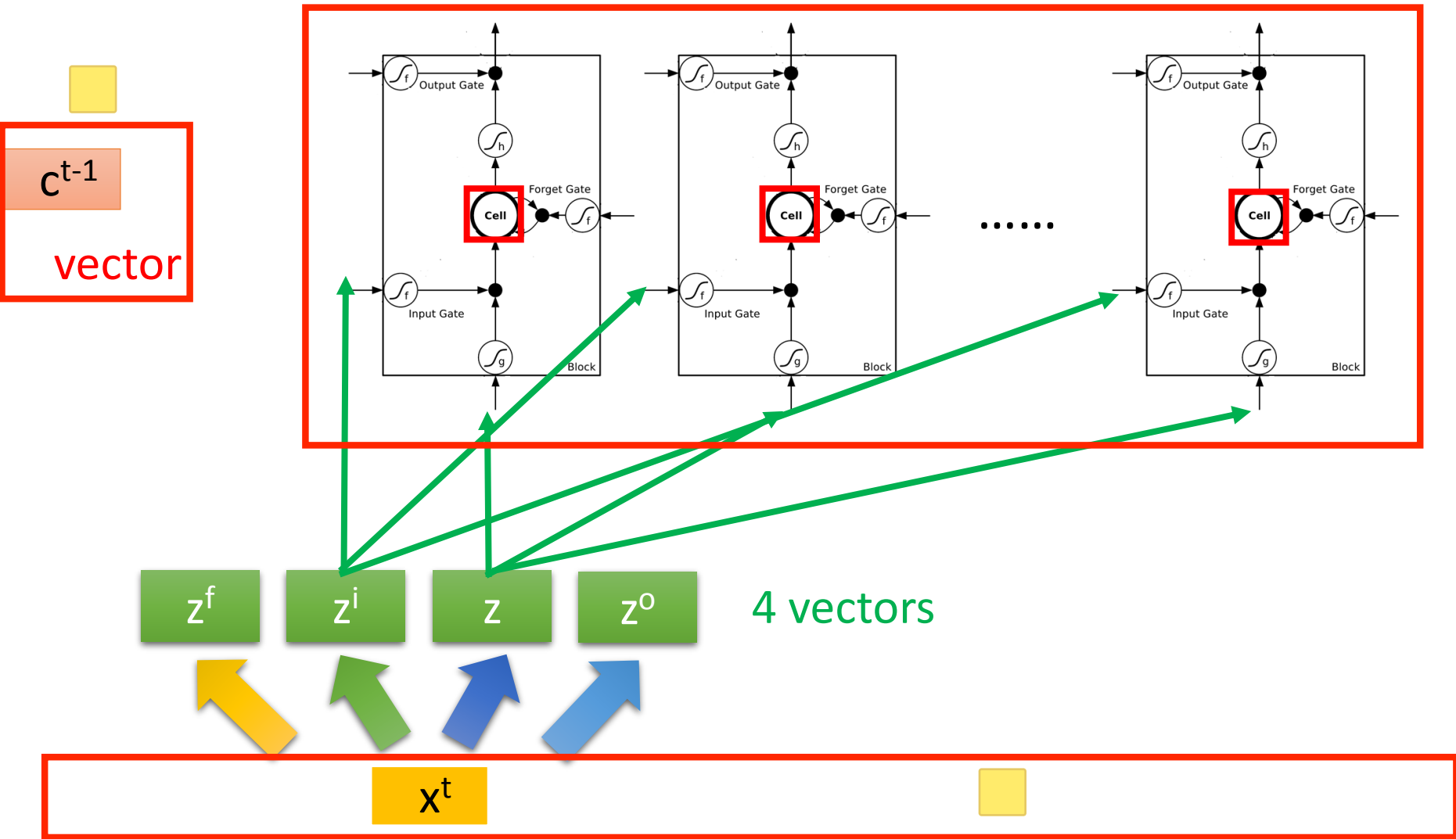
實際上，一個 LSTM Cell  
就是原本的 Neural  
Network 中的一個 Neuron





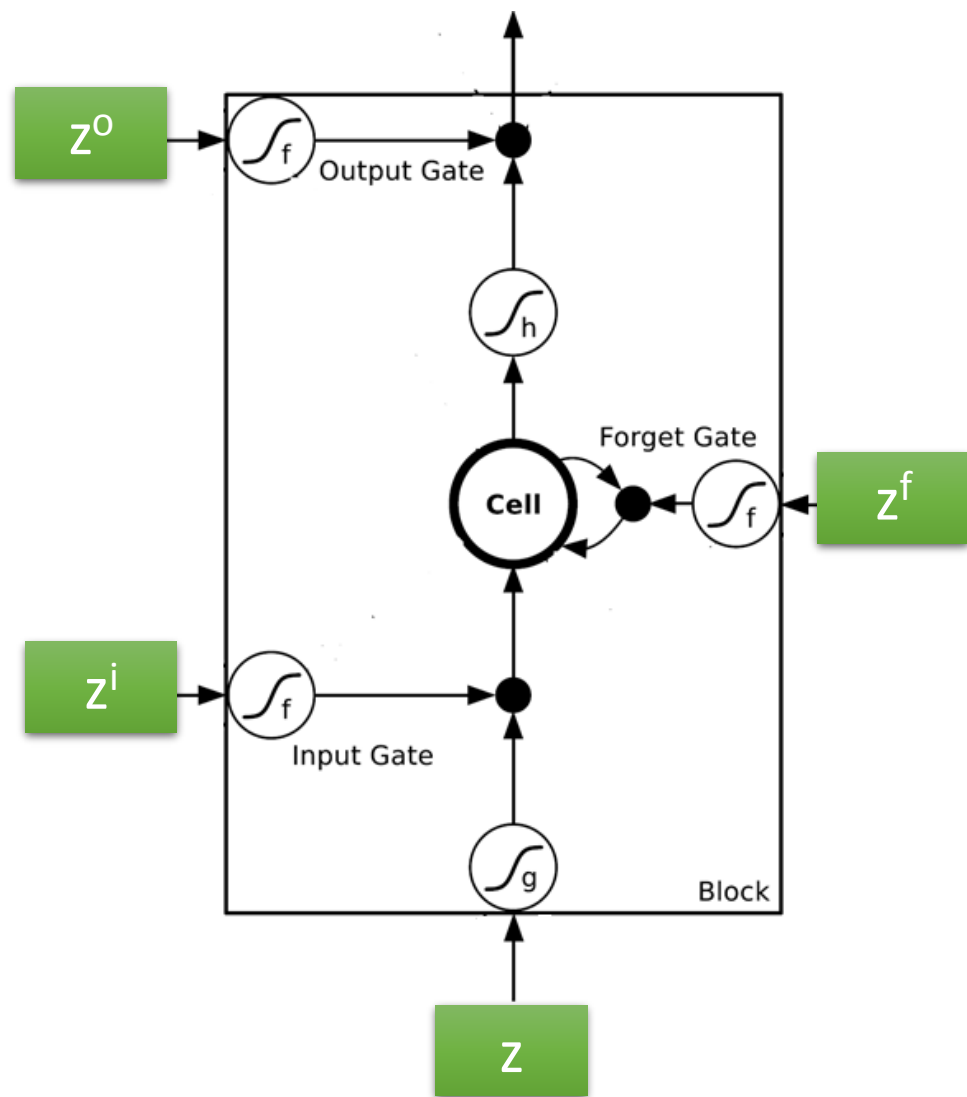
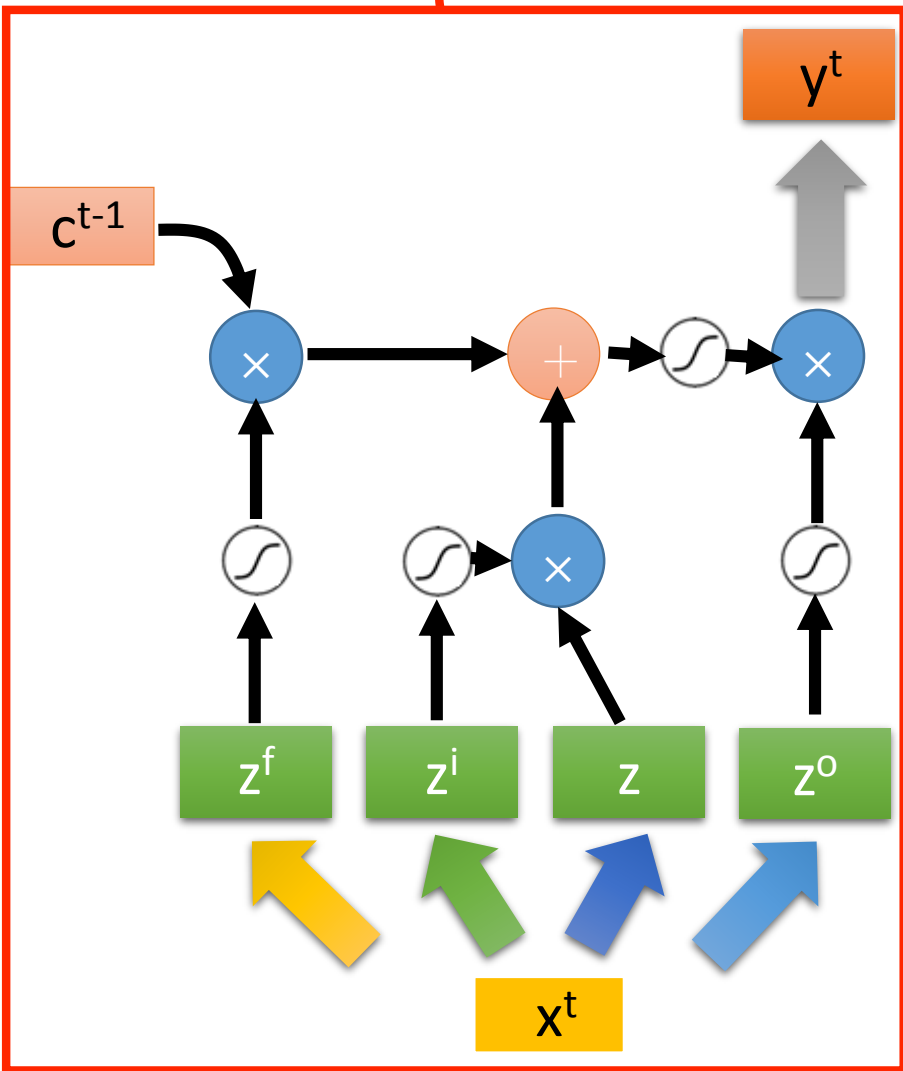
# LSTM

這是一個 Hidden Layer，裡面有很多  
Neuron，每一個 Neuron 都是一個 LSTM Cell



# LSTM

實際上，在同一層的所有 LSTM Cell 是可以一起運算的



# LSTM

Extension: "peephole"

