



# Natural Language Processing

## 第五周 循环神经网络

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# Overview



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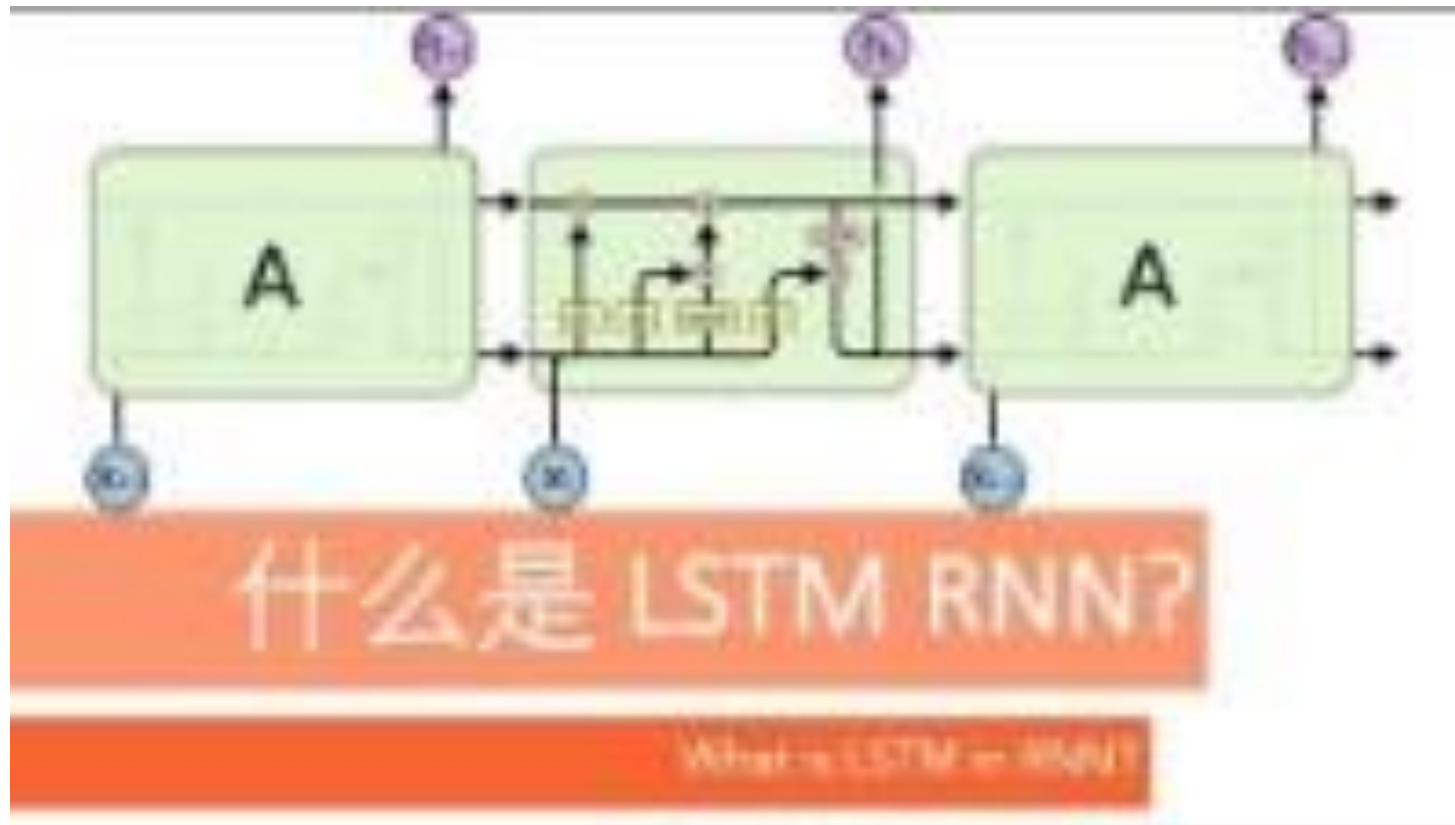
01

# Recurrent Neural Network

循环神经网络

Spring 2023

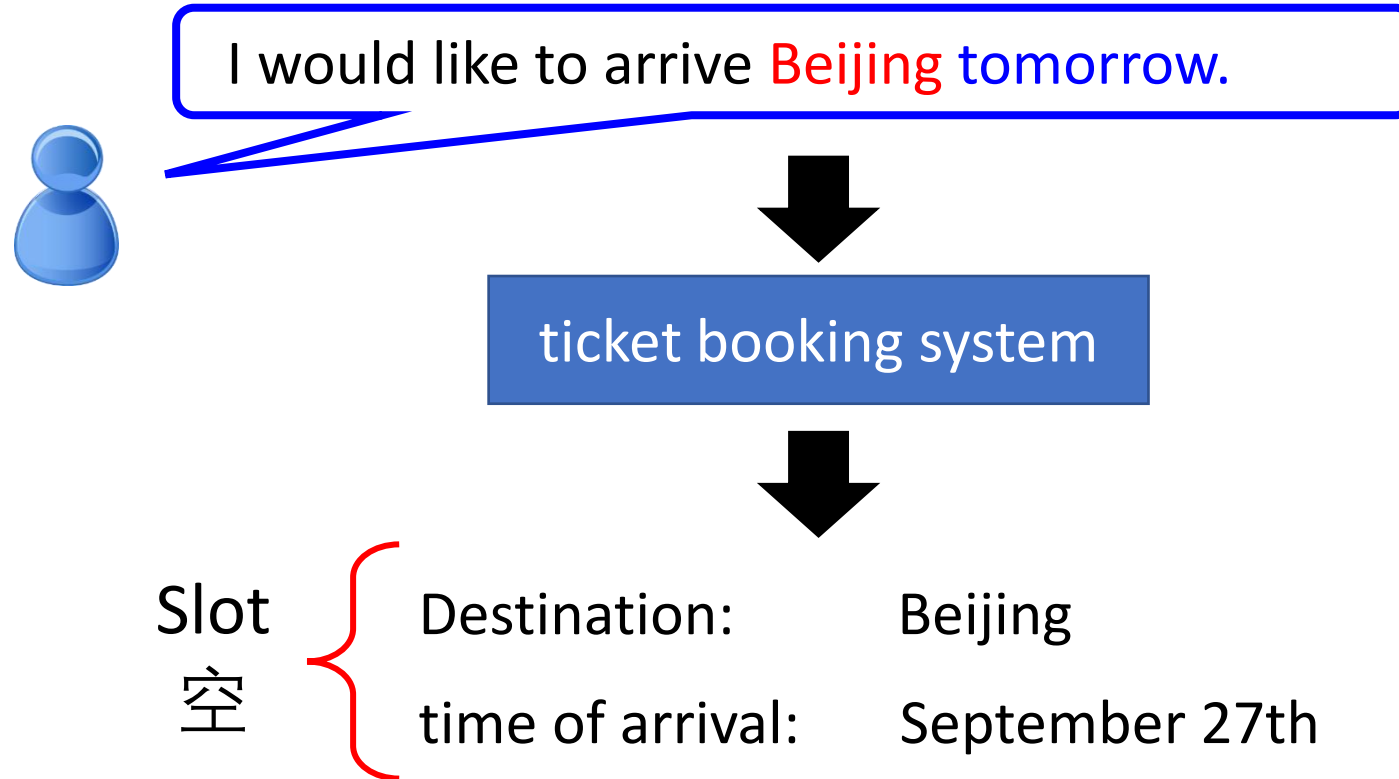
# Introduction Video



# Example Application



填空



# Example Application



Solving slot filling by Feedforward network? 正反馈网络

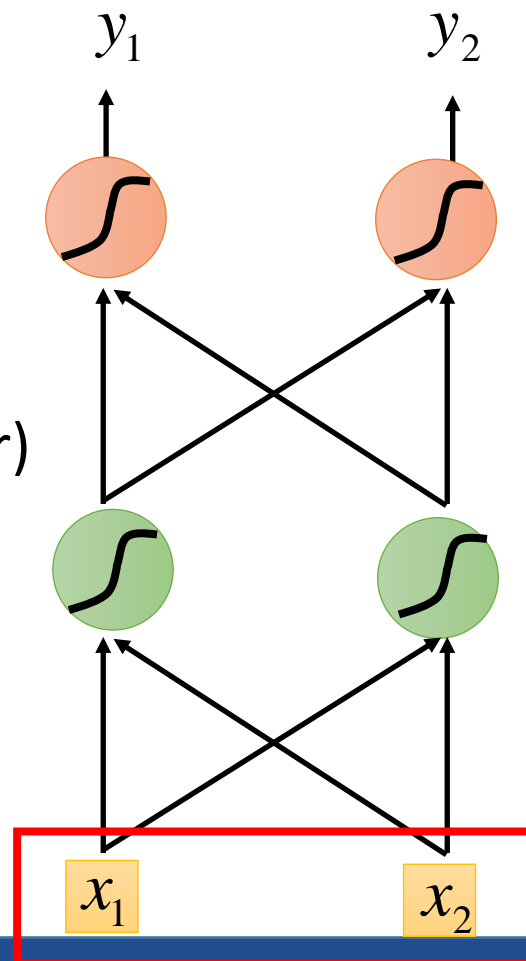
Input: a word

输入: 单词

(Each word is represented as a vector)

单词可以用矢量来表示

Beijing



# 1-of-N encoding



How to represent each word as a vector?  
如何将单词表达成为一个矢量?

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

单一矢量长度为词典长度

每个维度都有固定的含义

数值只能0或1

apple = [ 1 0 0 0 0 ]

bag = [ 0 1 0 0 0 ]

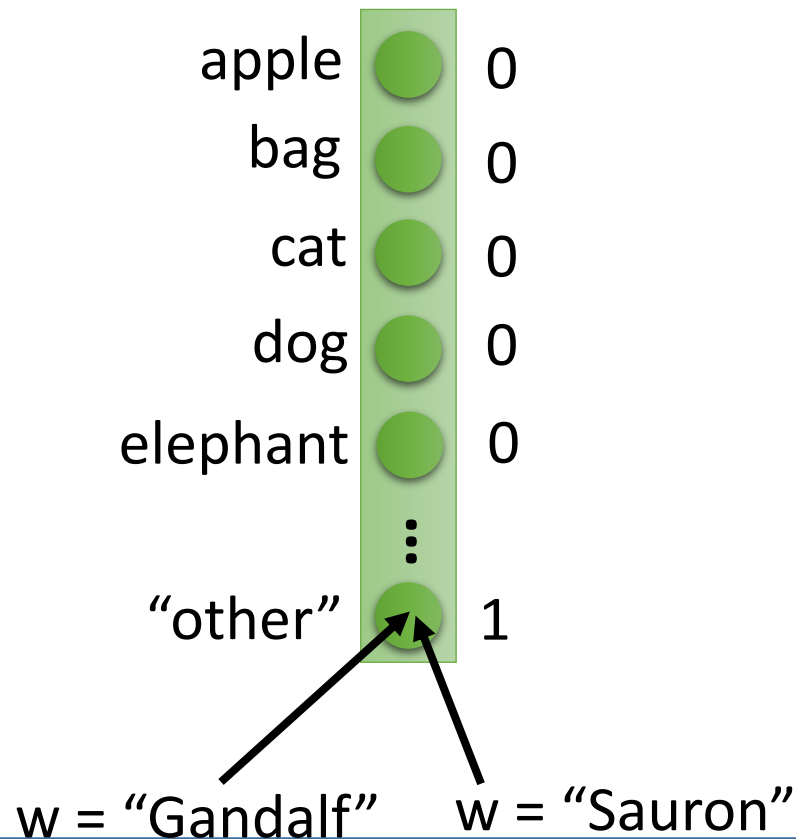
cat = [ 0 0 1 0 0 ]

dog = [ 0 0 0 1 0 ]

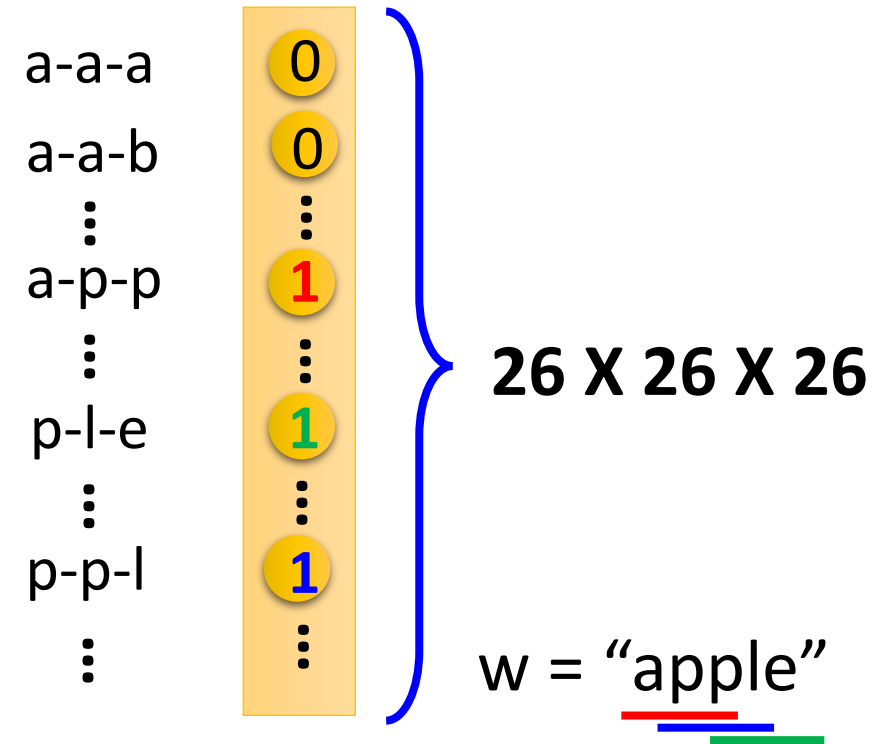
elephant = [ 0 0 0 0 1 ]

# Beyond 1-of-N encoding

## Dimension for "Other"



## Word hashing





# Example Application



Solving slot filling by Feedforward network? 正反馈网络

Input: a word

输入: 单词

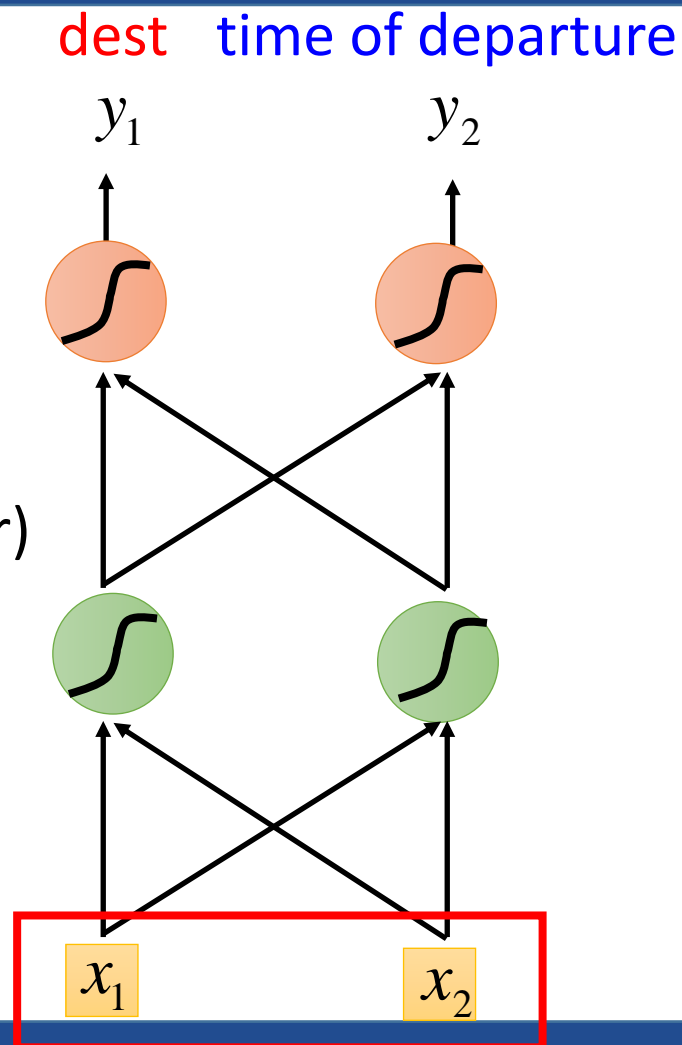
(Each word is represented as a vector)

单词可以用矢量来表示

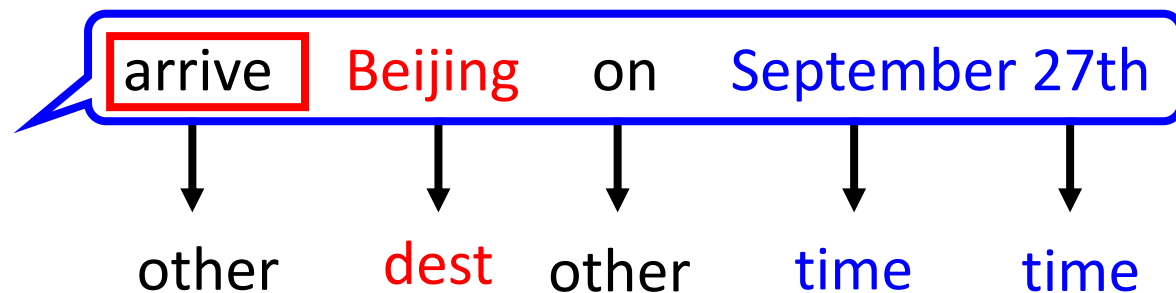
Output: 输出

输入单词是正确填空的概率

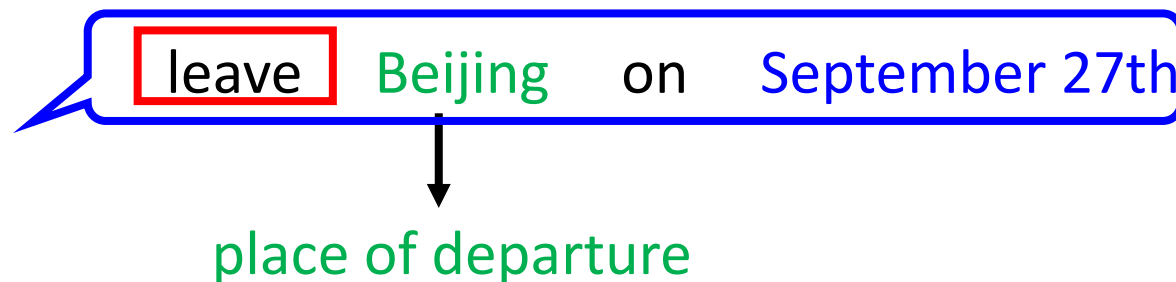
Beijing



# Example Application



Problem?

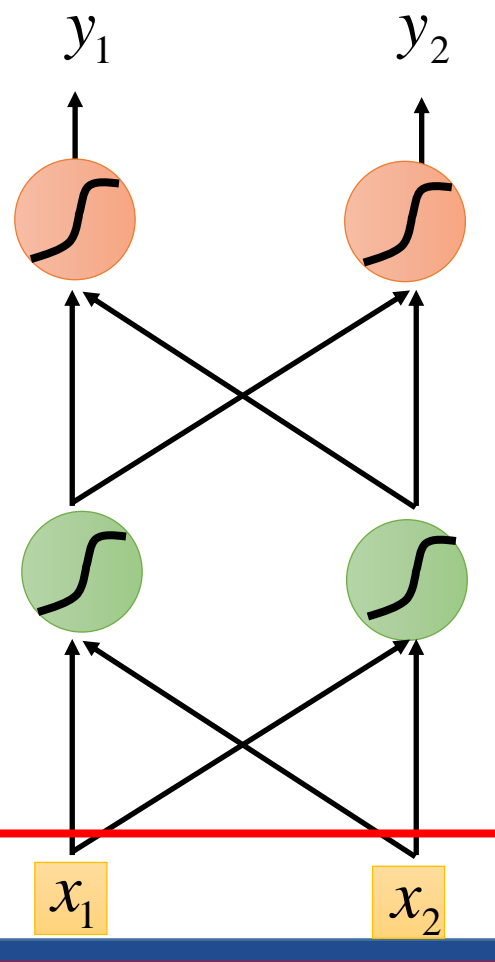


Neural network  
needs memory!

Beijing

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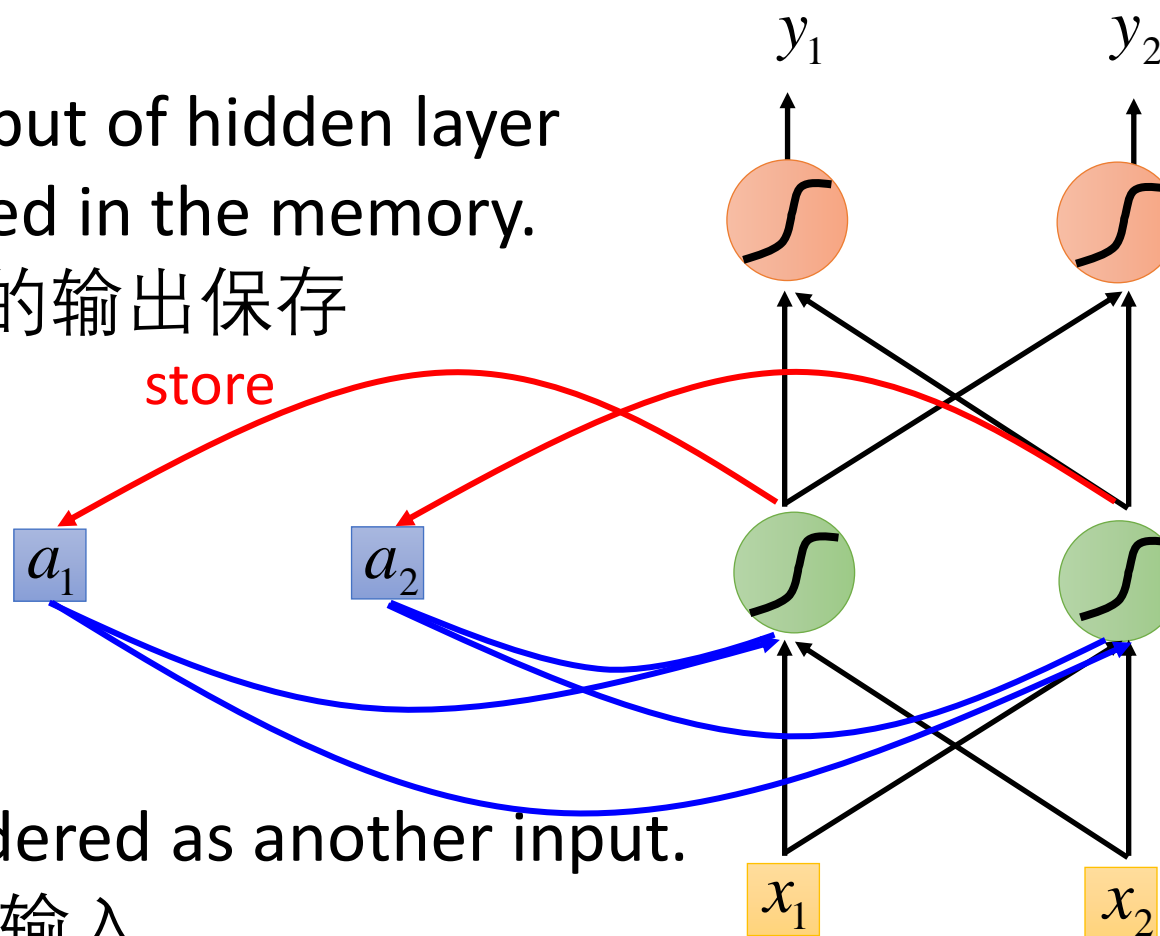
dest time of departure



# Recurrent Neural Network (RNN)



The output of hidden layer  
are stored in the memory.  
隐藏层的输出保存



Memory can be considered as another input.  
存储值可视为额外的输入

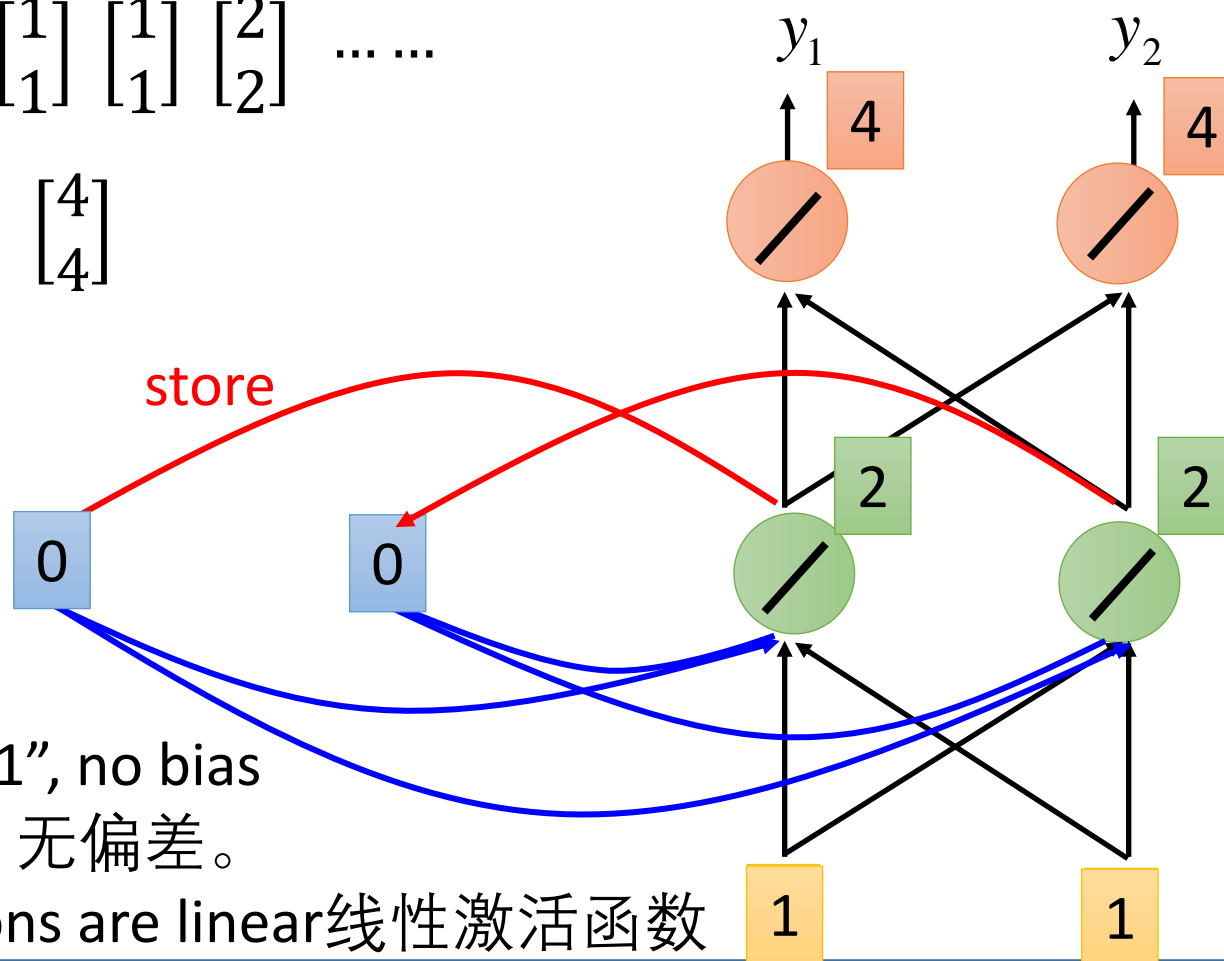
# Example



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

output sequence:  $\begin{bmatrix} 4 \\ 4 \end{bmatrix}$   
输出序列

given Initial values  
初始化值



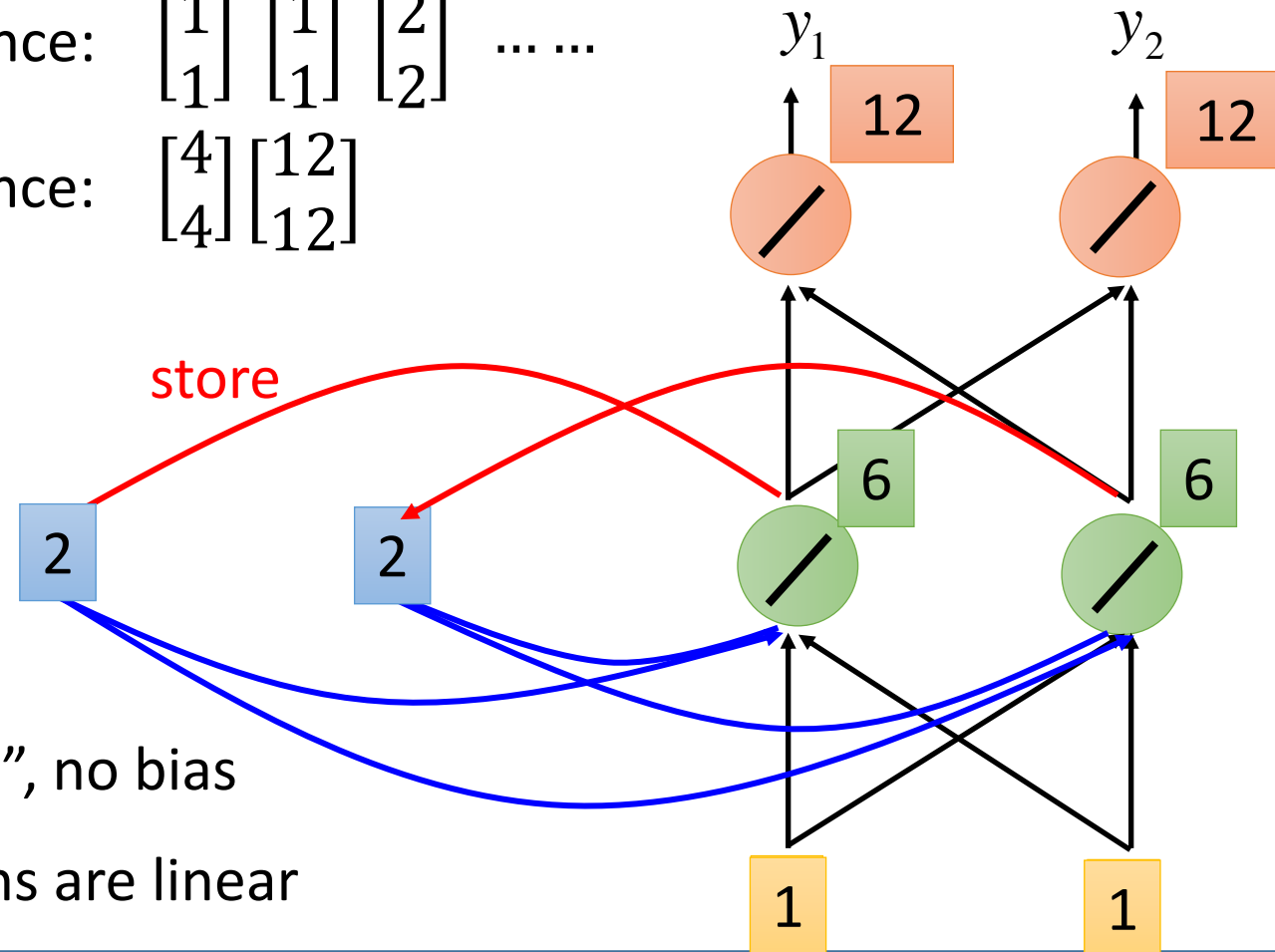
All the weights are "1", no bias  
所有的权重都为1，无偏差。

All activation functions are linear 线性激活函数

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



All the weights are "1", no bias

All activation functions are linear

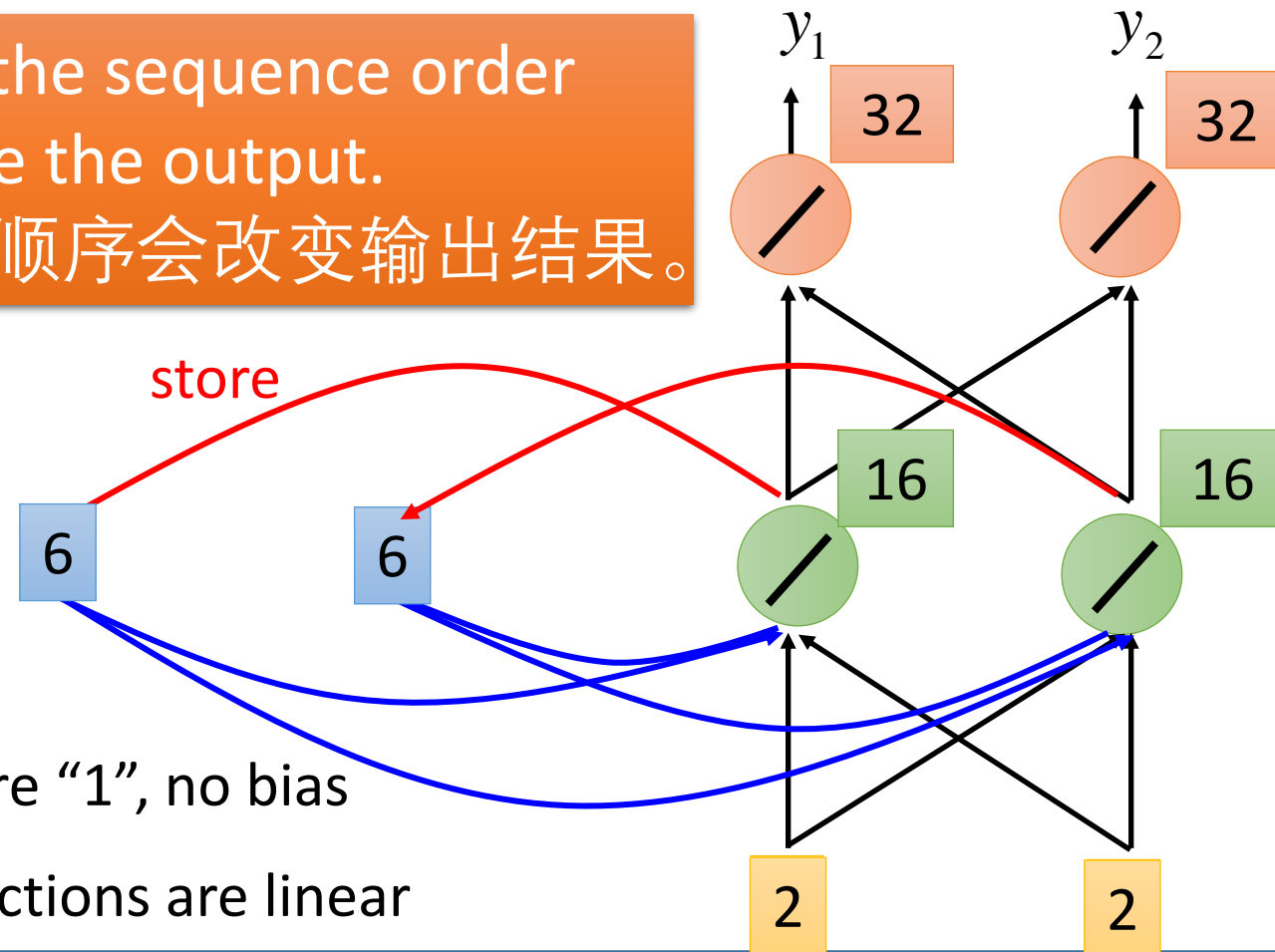
# Example

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

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.  
改变序列顺序会改变输出结果。



All the weights are “1”, no bias

All activation functions are linear

# RNN

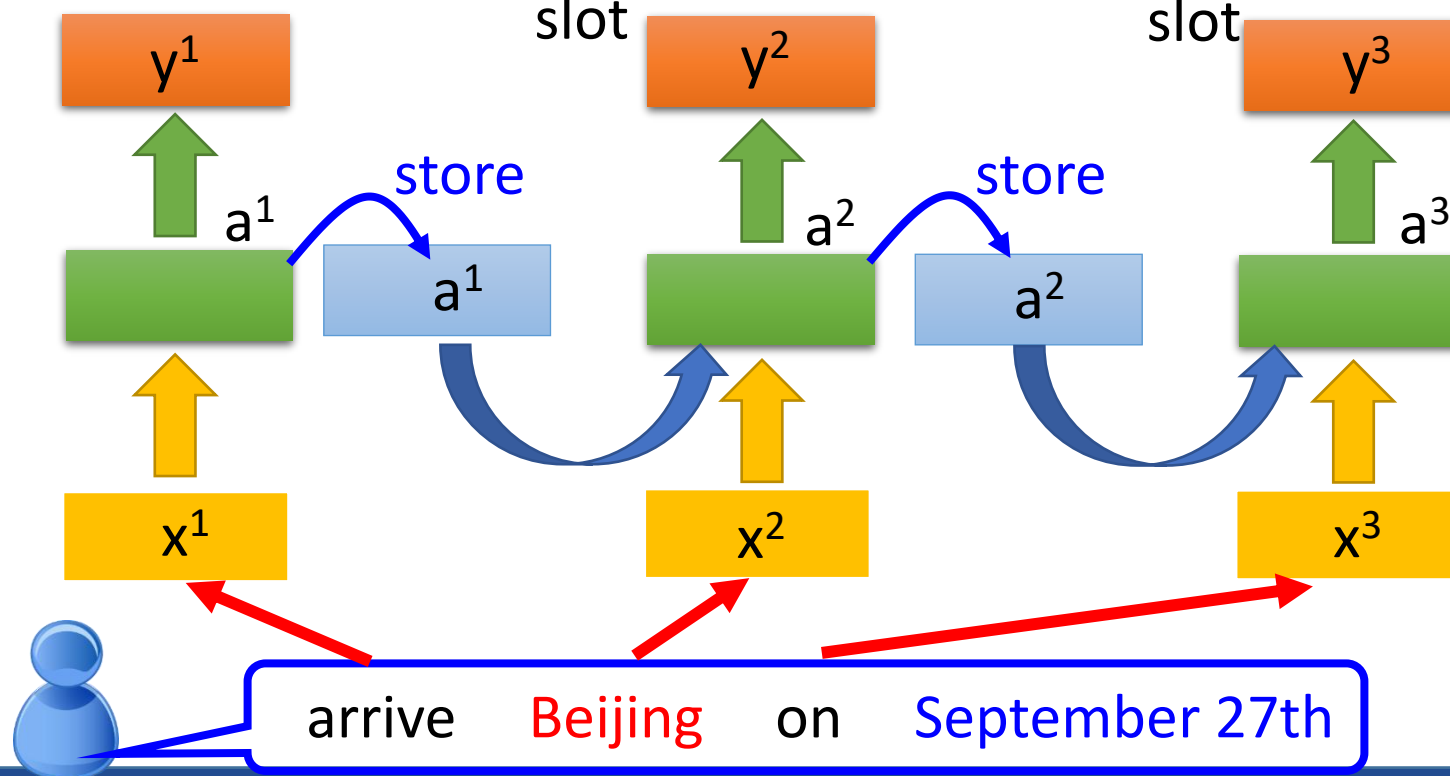


同样的网络重复计算

概率Probability of  
“arrive” in each slot

概率Probability of  
“Beijing” in each  
slot

概率Probability of  
“on” in each  
slot

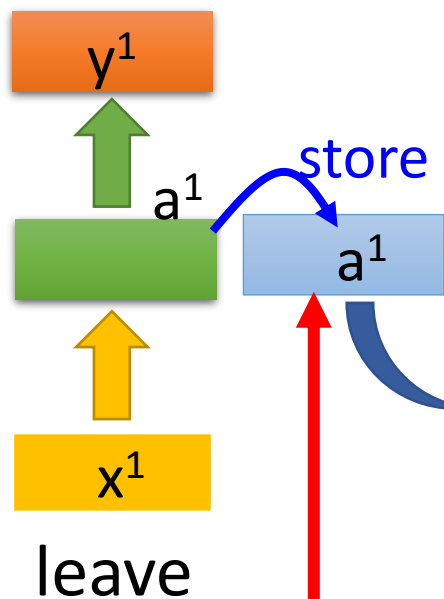


# RNN

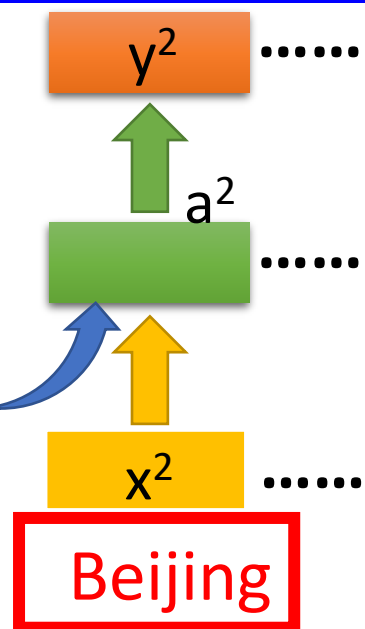


Different 差异

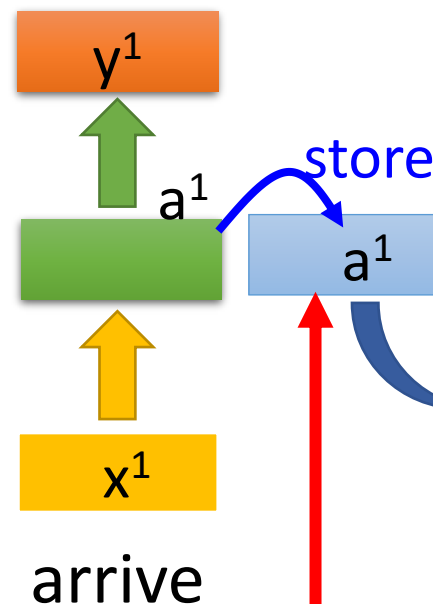
Prob of "leave"  
in each slot



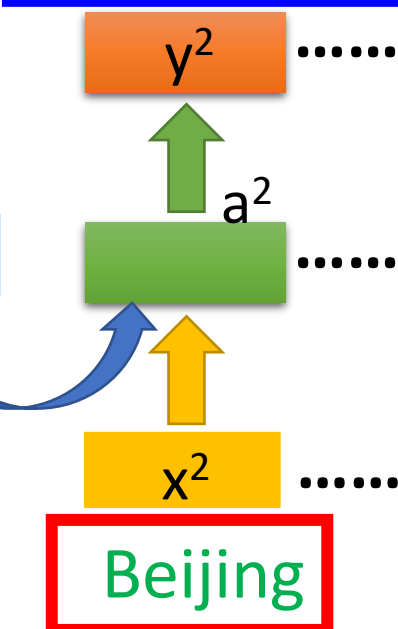
Prob of "Beijing"  
in each slot



Prob of "arrive"  
in each slot



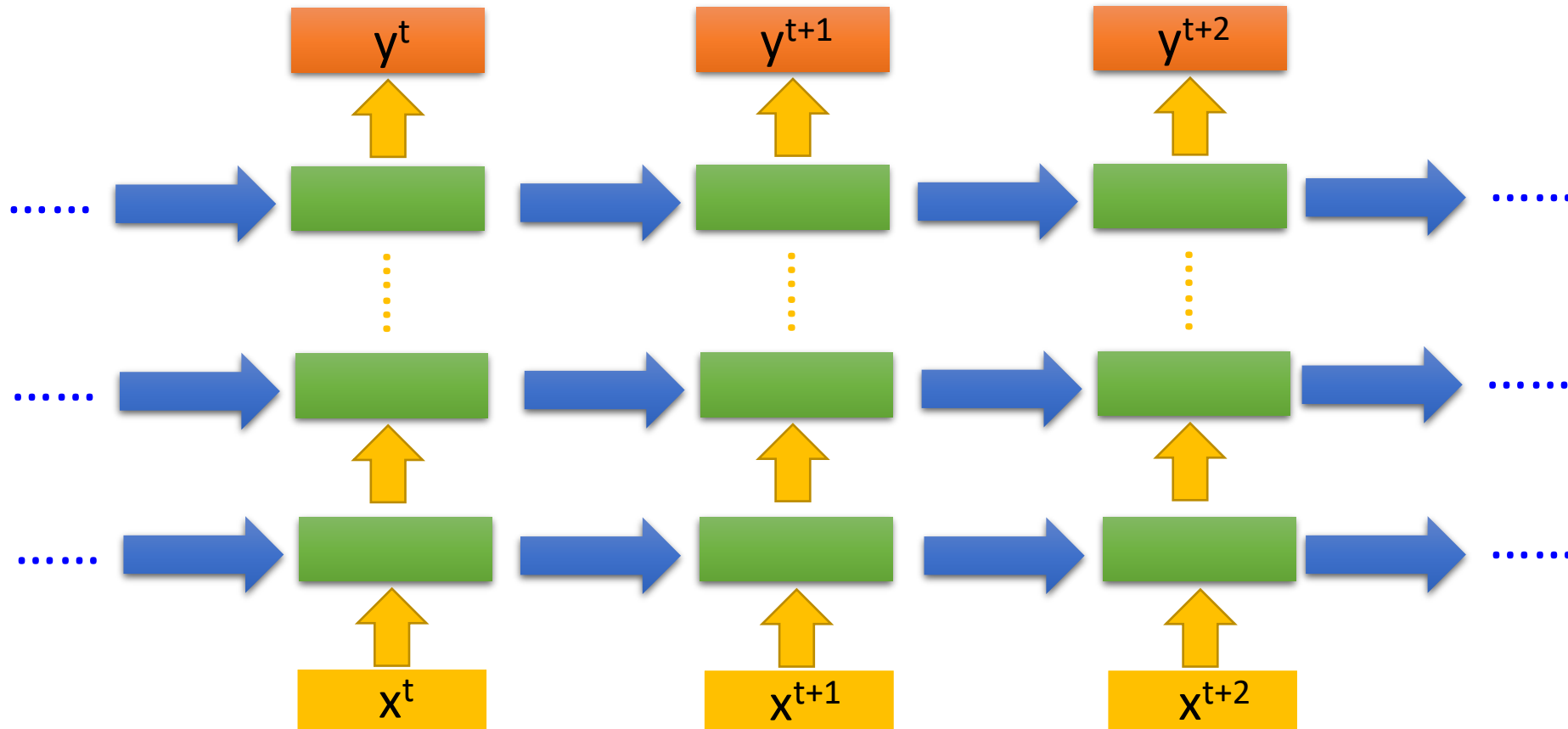
Prob of "Beijing"  
in each slot



The values stored in the memory is different.  
存储值不同



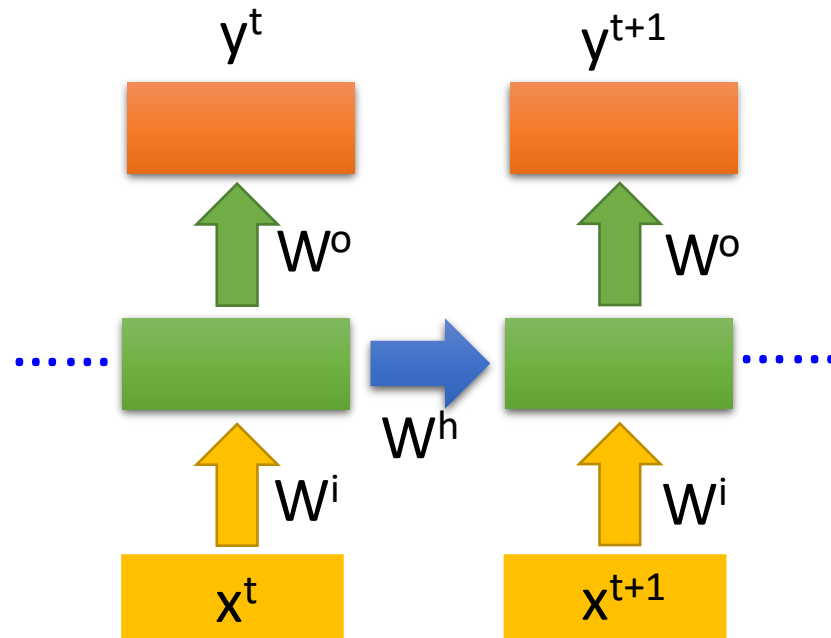
# Of course it can be deep ...



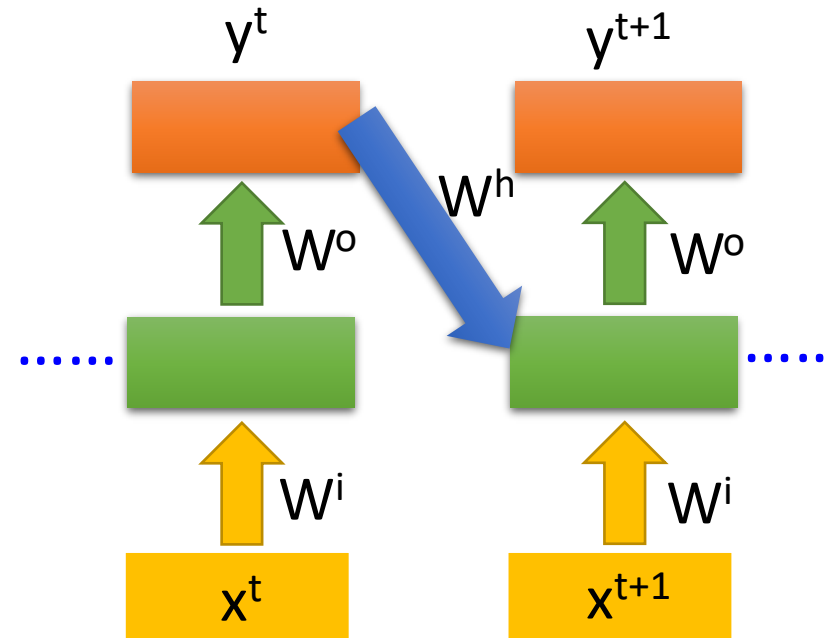
# Elman Network & Jordan Network



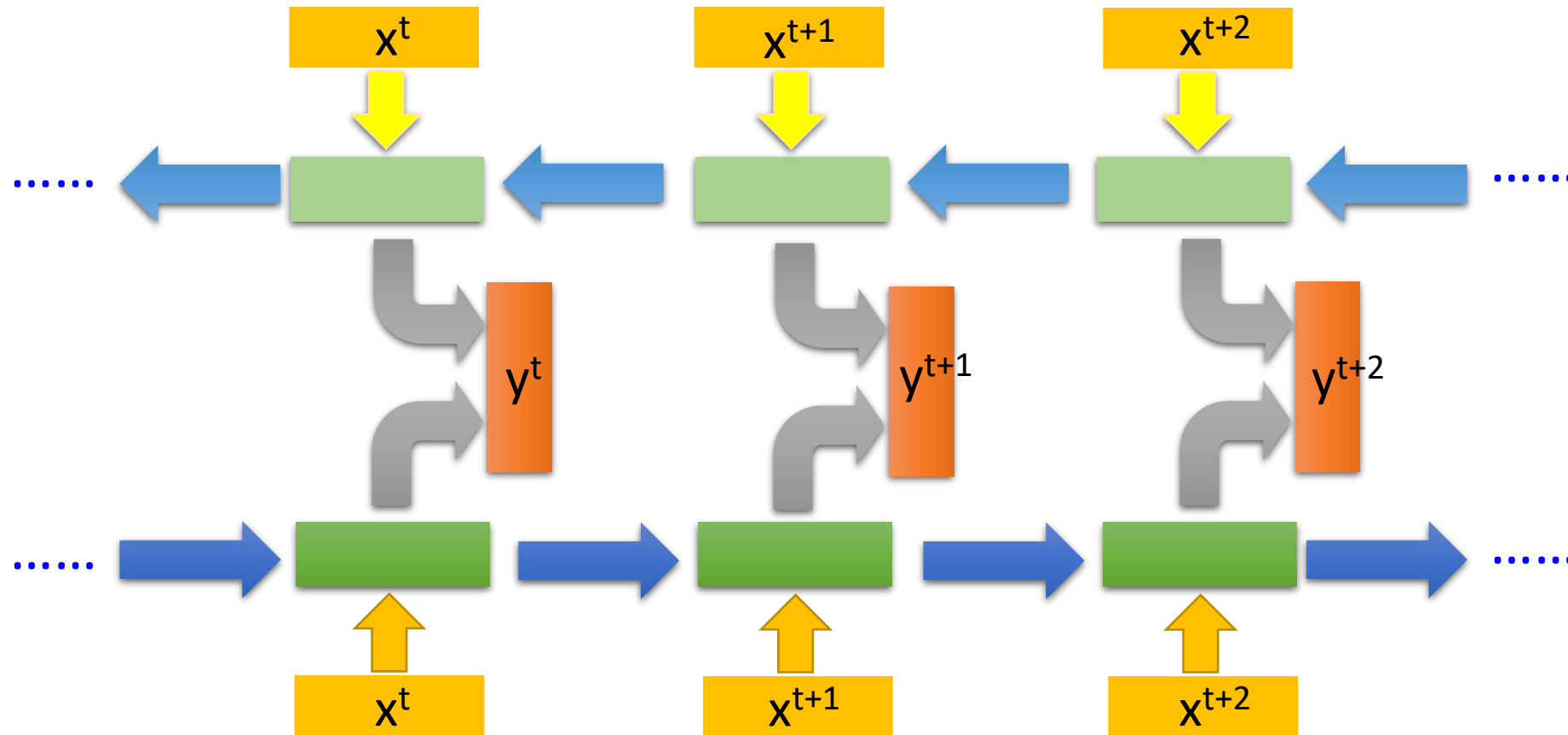
*Elman Network*



*Jordan Network*



# Bidirectional RNN





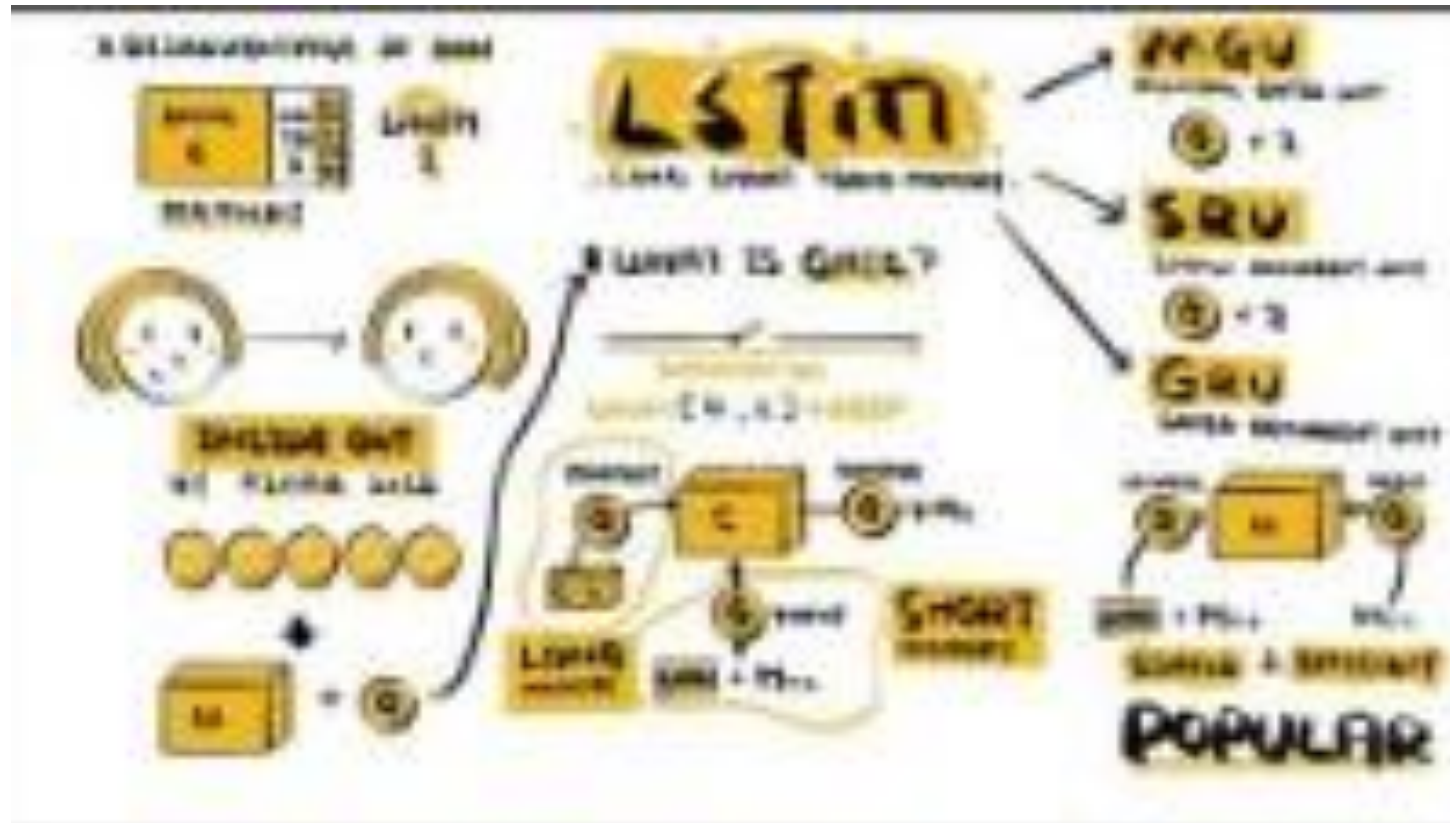
02

Long Short-term Memory

长短期记忆网络

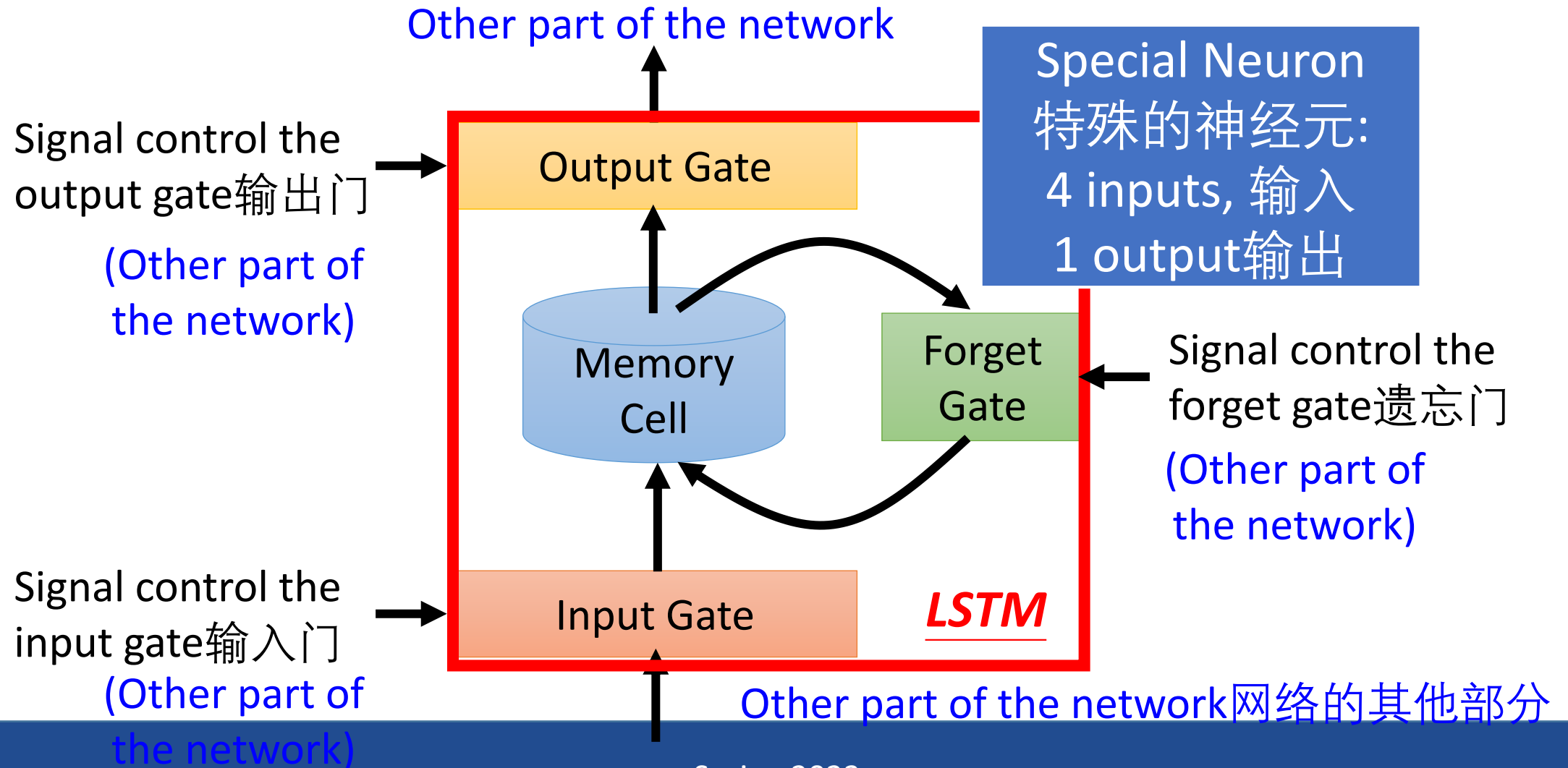
Spring 2023

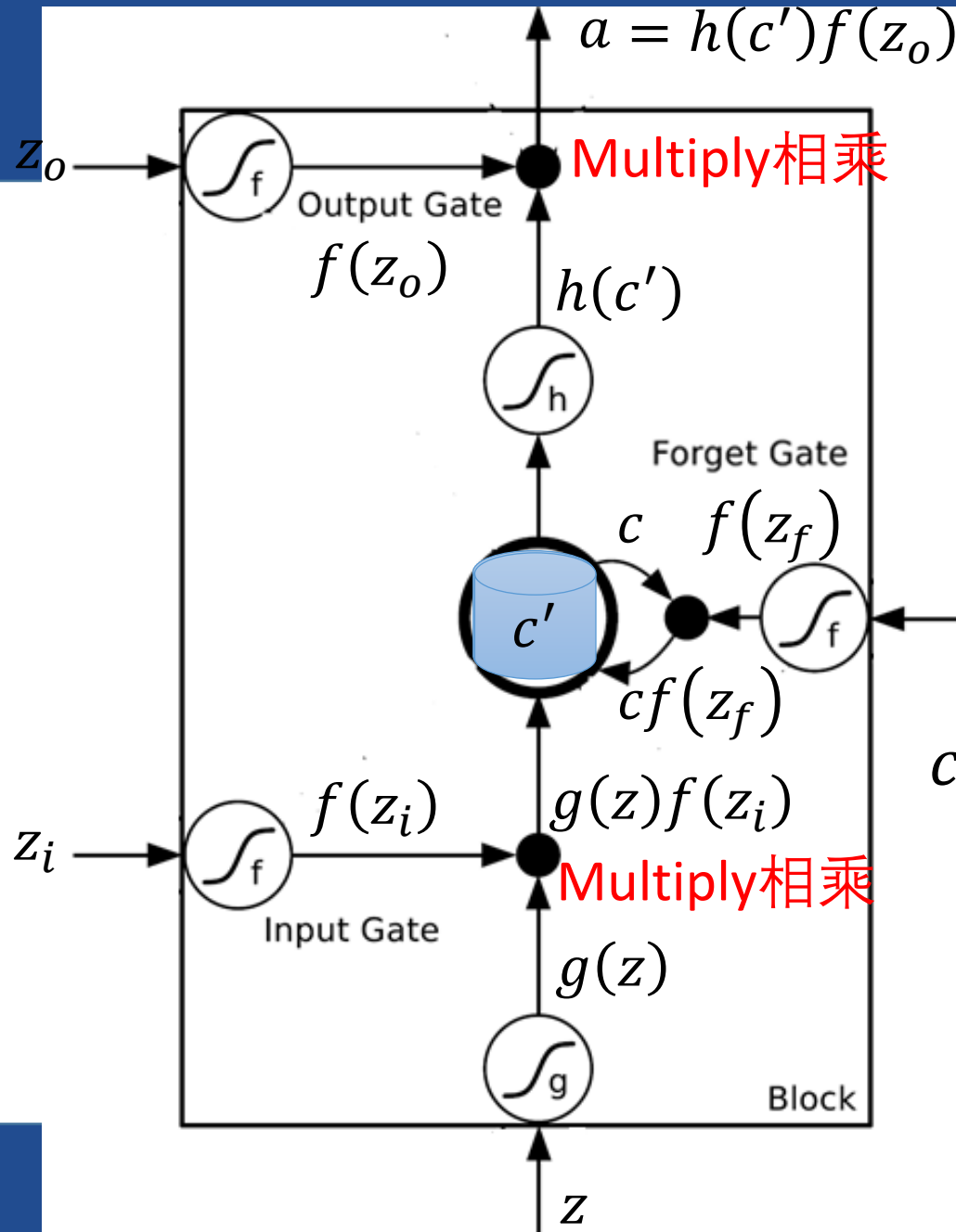
# Introduction Video





# Long Short-term Memory (LSTM)





Activation function  $f$  is usually a sigmoid function 激活函数

Between 0 and 1

Mimic open and close gate  
模仿门的开关

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

# LSTM - Example



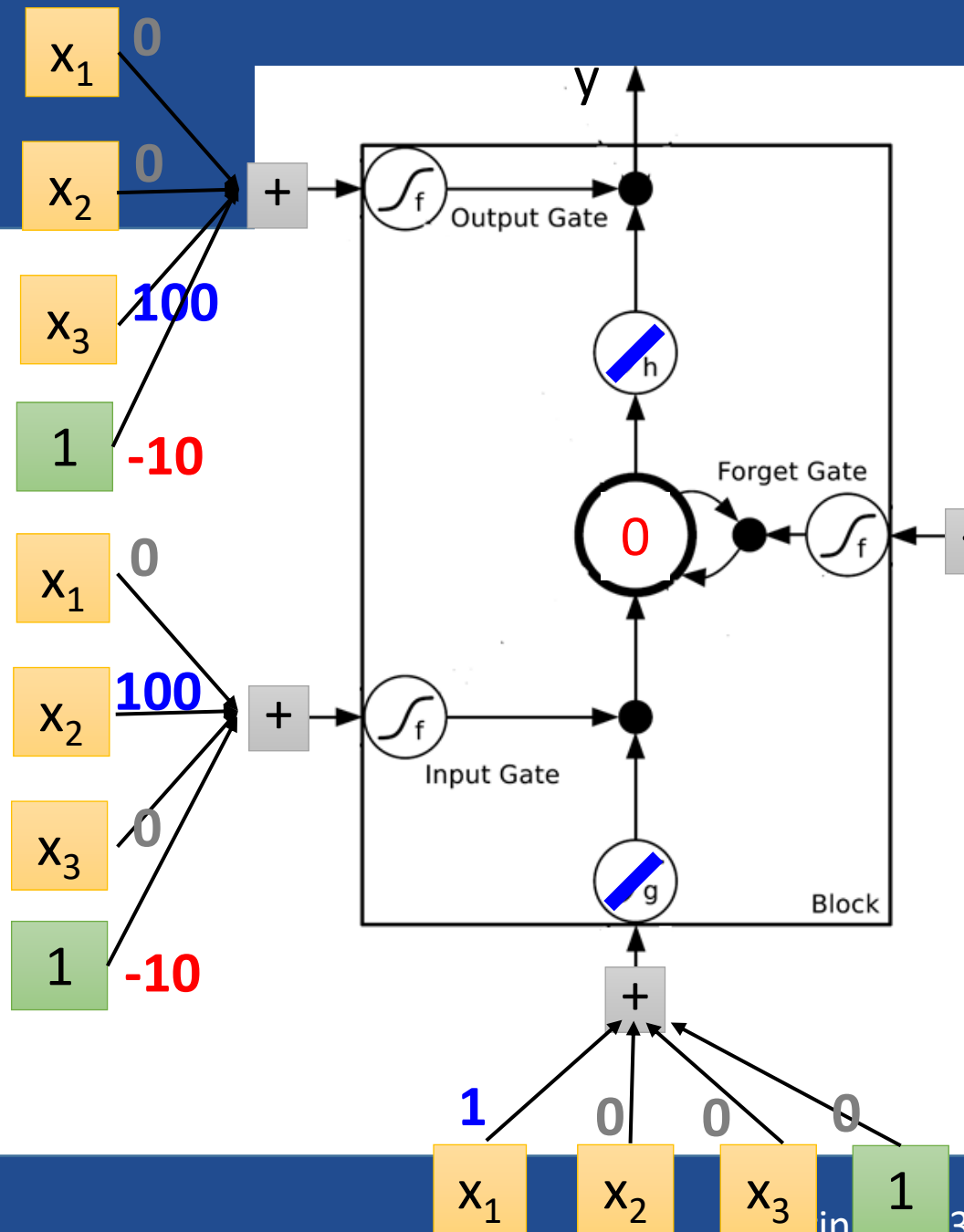
	0	0	3	3	7	7	7	0	6
$x_1$	1	3	2	4	2	1	3	6	1
$x_2$	0	1	0	1	0	0	-1	1	0
$x_3$	0	0	0	0	0	1	0	0	1
$y$	0	0	0	0	0	7	0	0	6

When  $x_2 = 1$ , add the numbers of  $x_1$  into the memory 输入存储

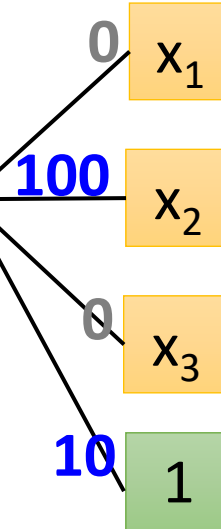
When  $x_2 = -1$ , reset the memory 重置存储

When  $x_3 = 1$ , output the number from the memory. 从存储输出

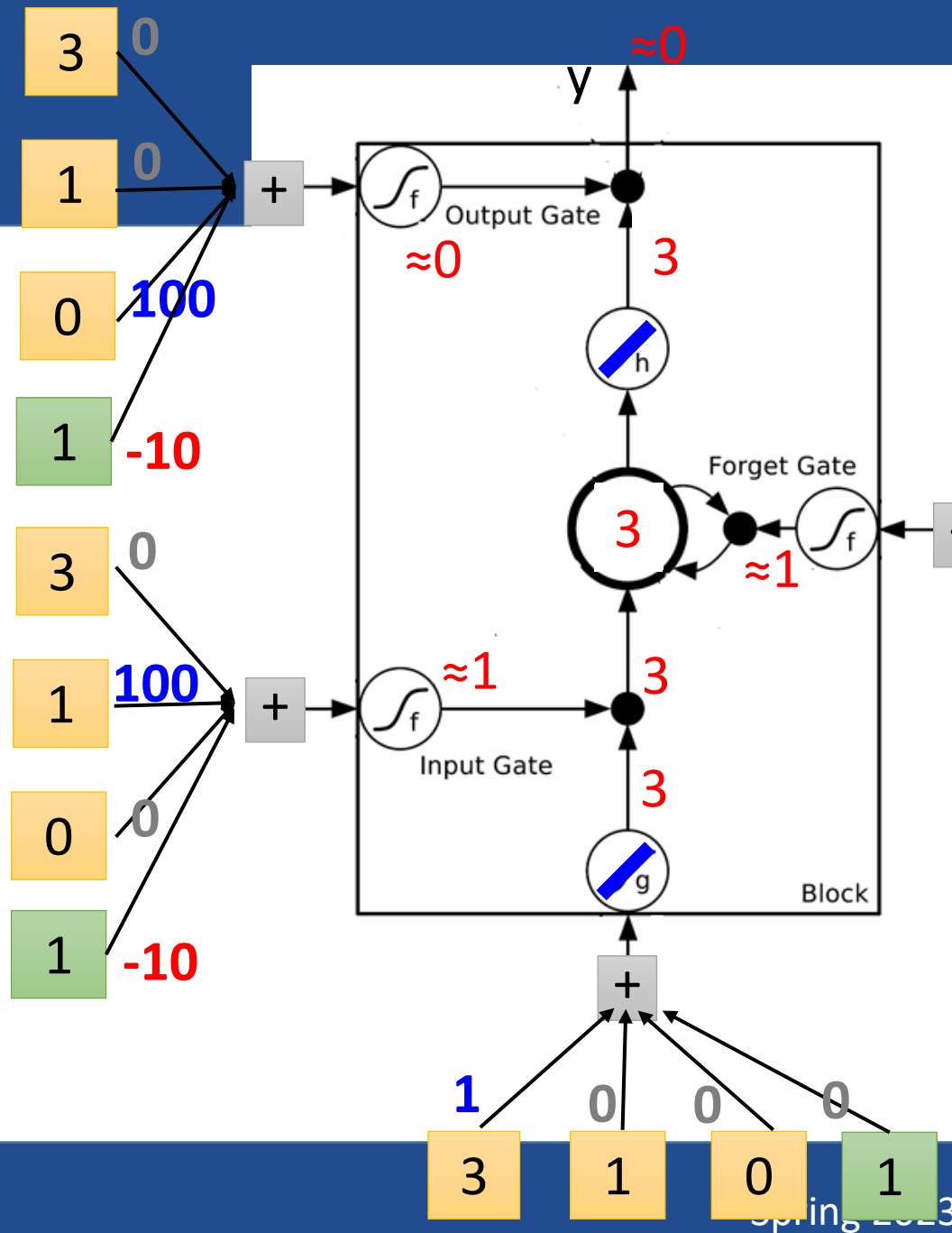




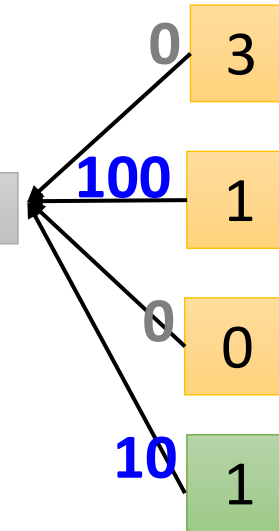
$y$  0 0 0 7 0



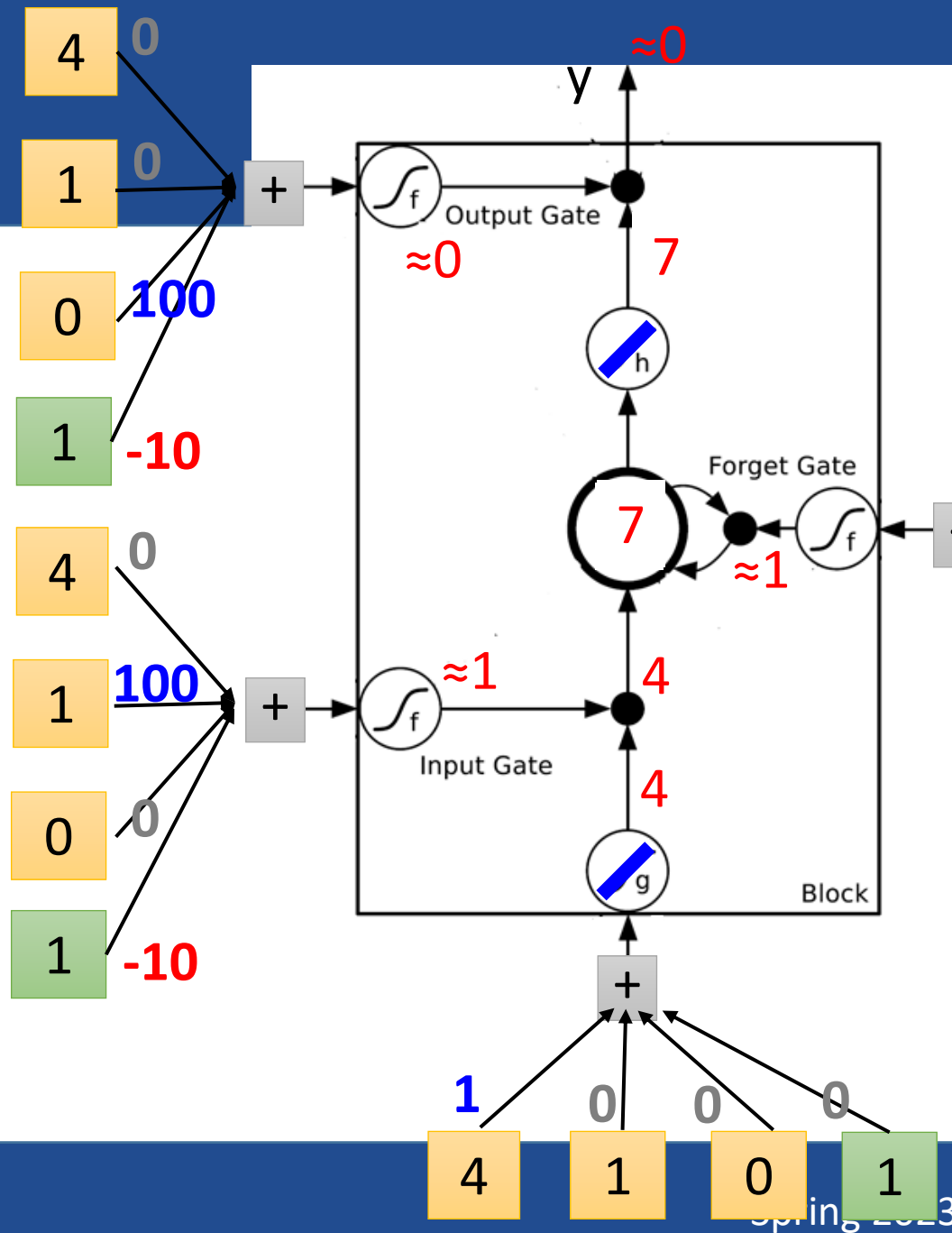
$x_1$	3	4	2	1	3
$x_2$	1	1	0	0	-1
$x_3$	0	0	0	1	0



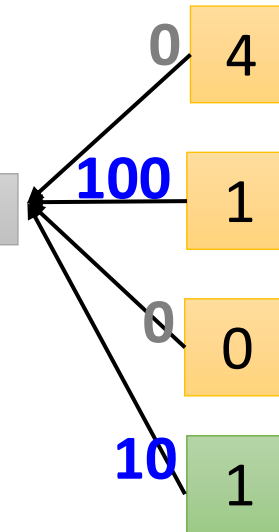
$y$  0 0 0 7 0



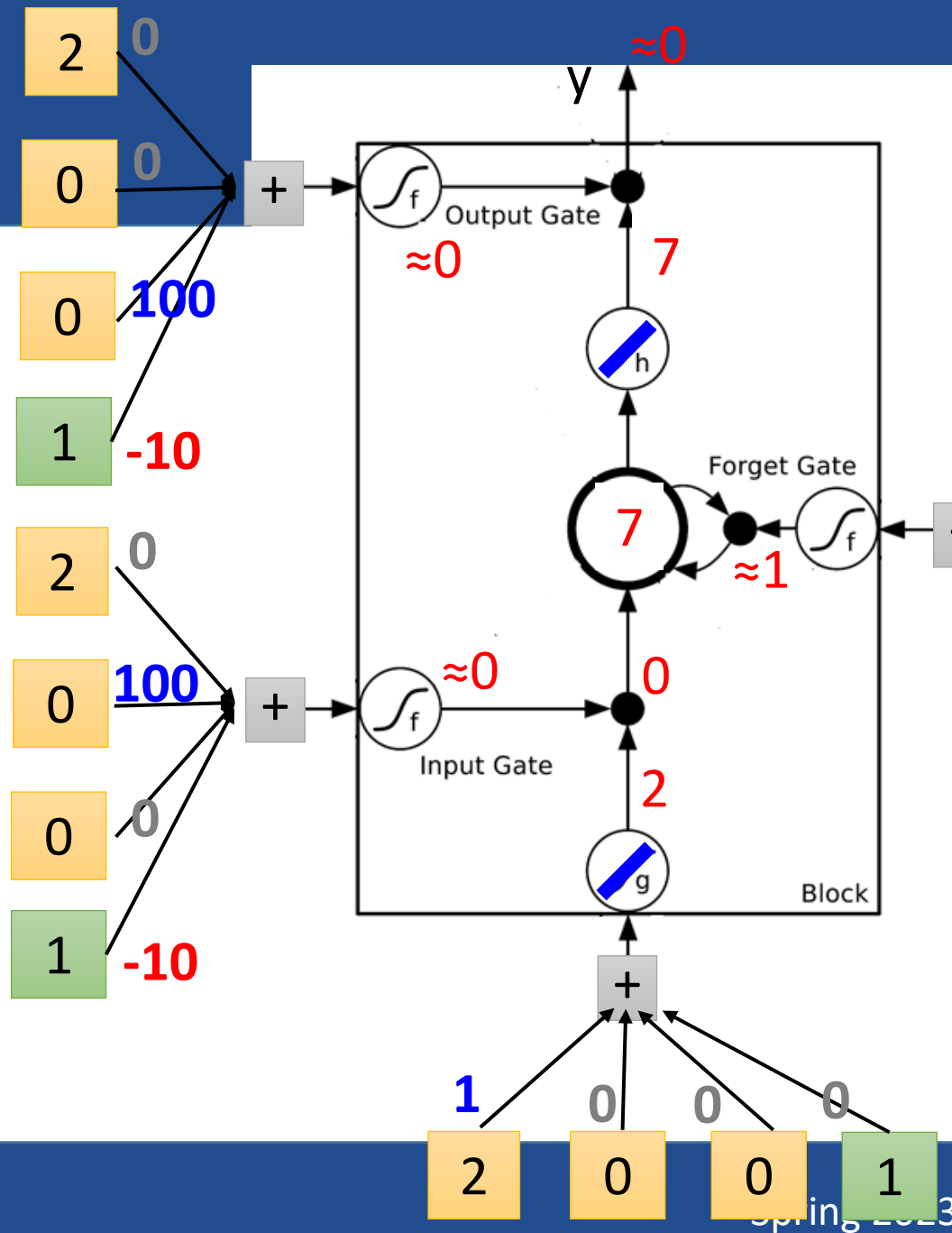
$x_1$	3	4	2	1	3
$x_2$	1	1	0	0	-1
$x_3$	0	0	0	1	0



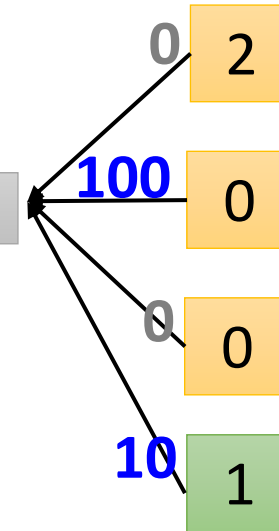
$y$  0 0 0 7 0



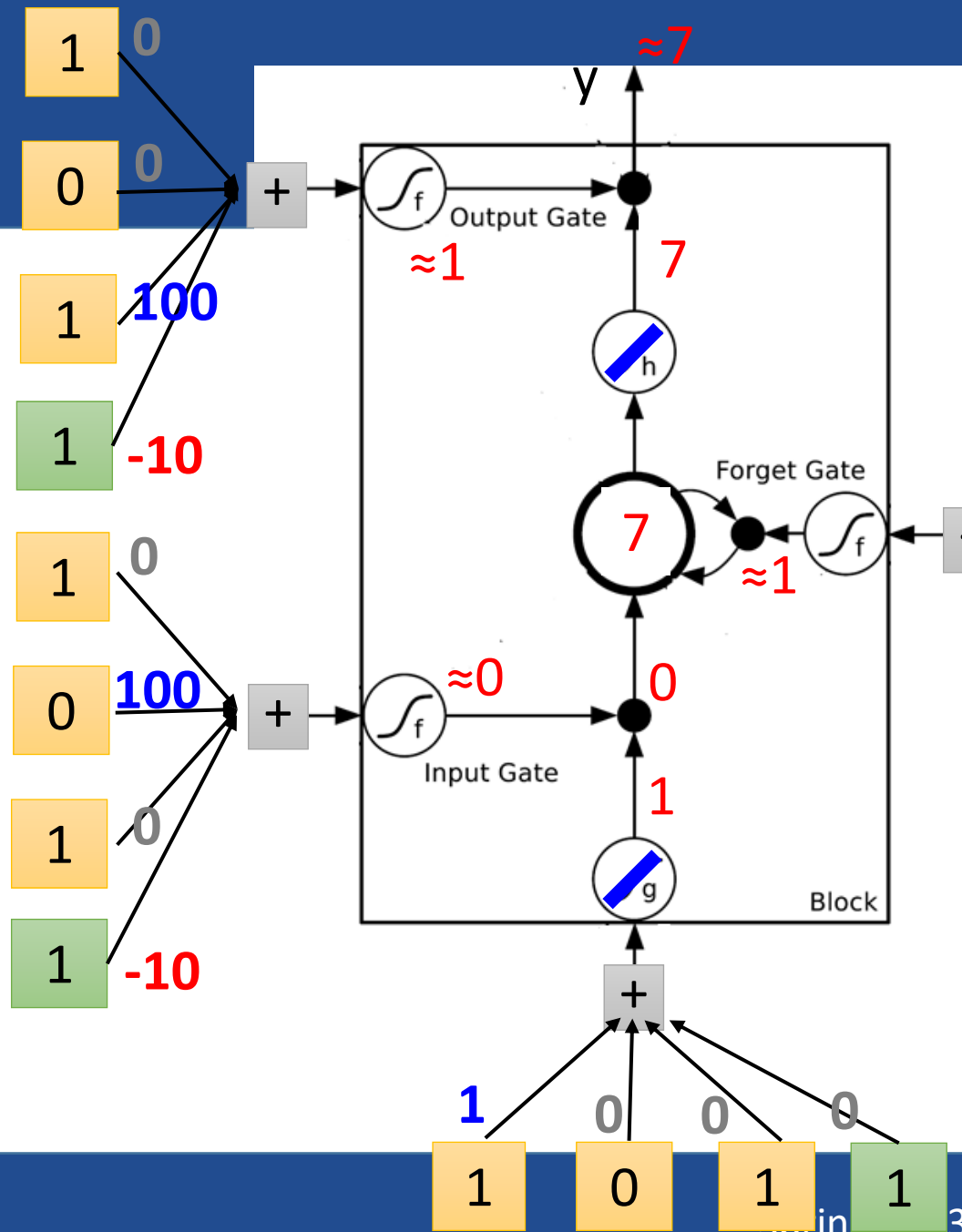
$x_1$  3 4 2 1 3  
 $x_2$  1 1 0 0 -1  
 $x_3$  0 0 0 1 0



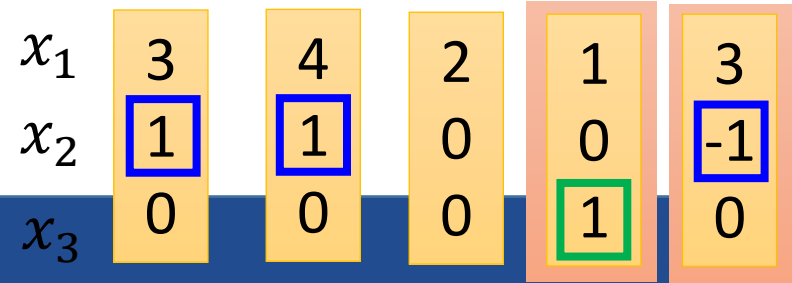
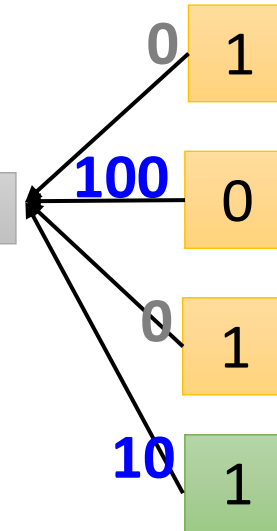
$y$  0 0 0 7 0

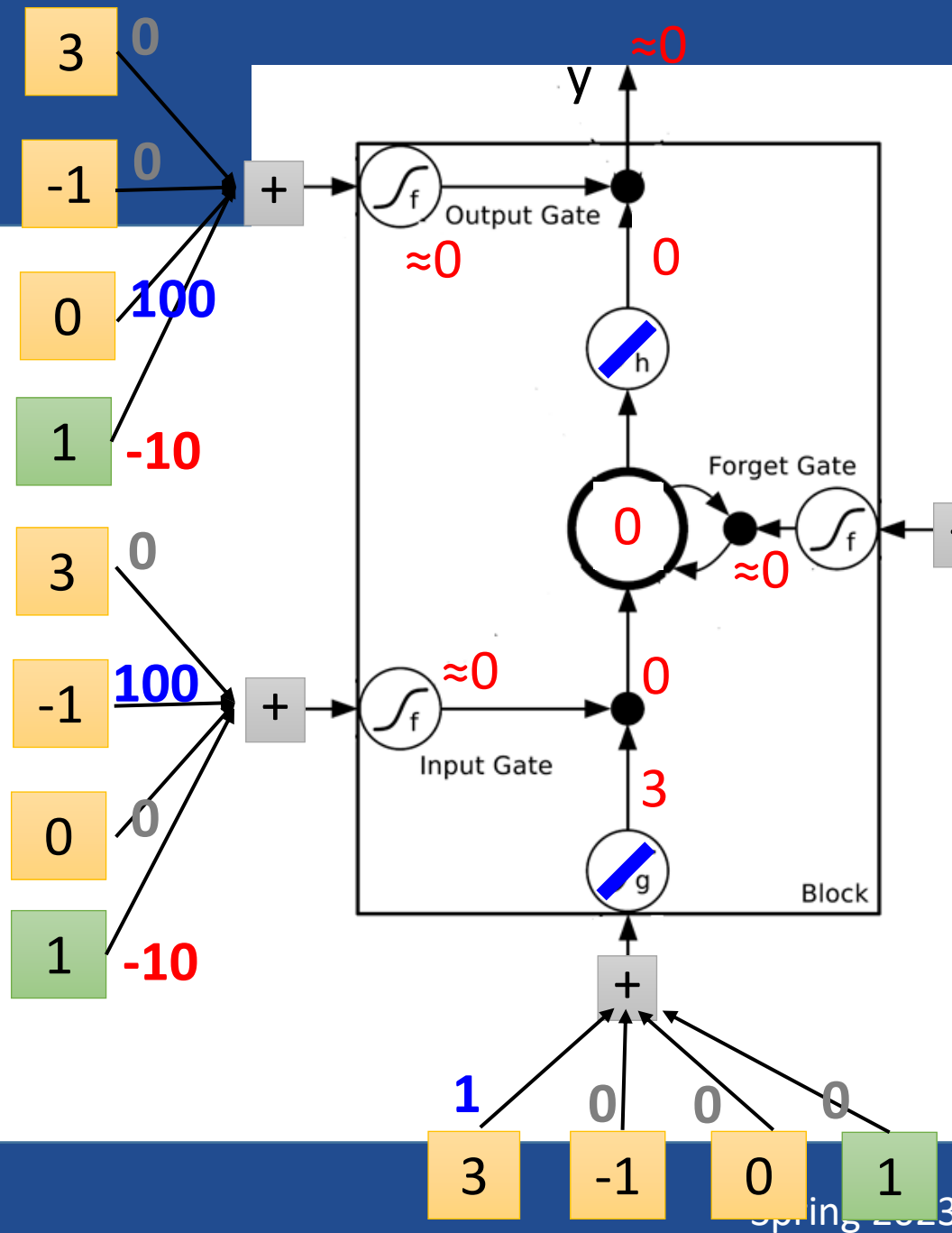


$x_1$  3 4 2 1 3  
 $x_2$  1 1 0 0 -1  
 $x_3$  0 0 0 1 0

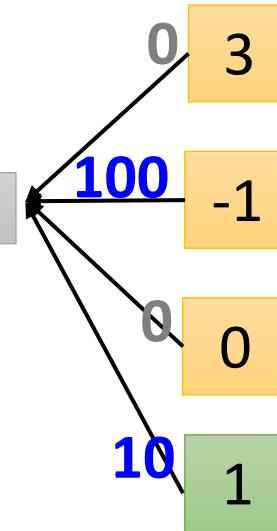


$y$  0 0 0 7 0





$y$  0 0 0 7 0

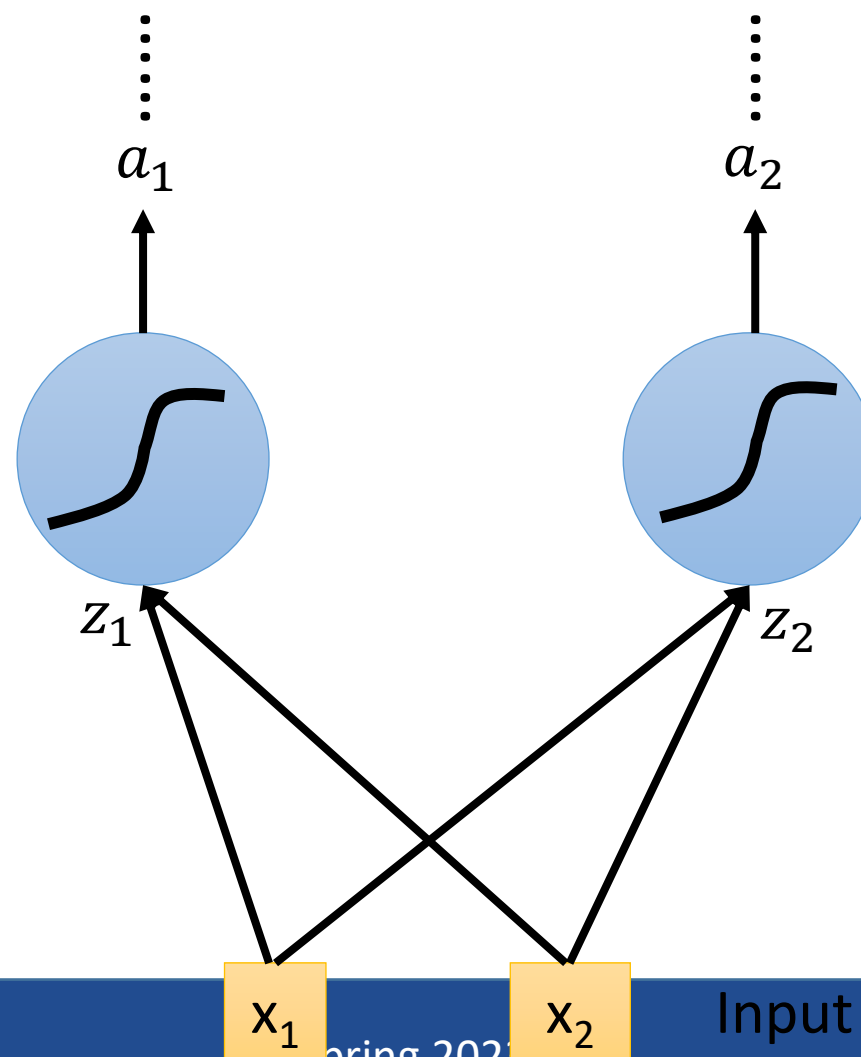


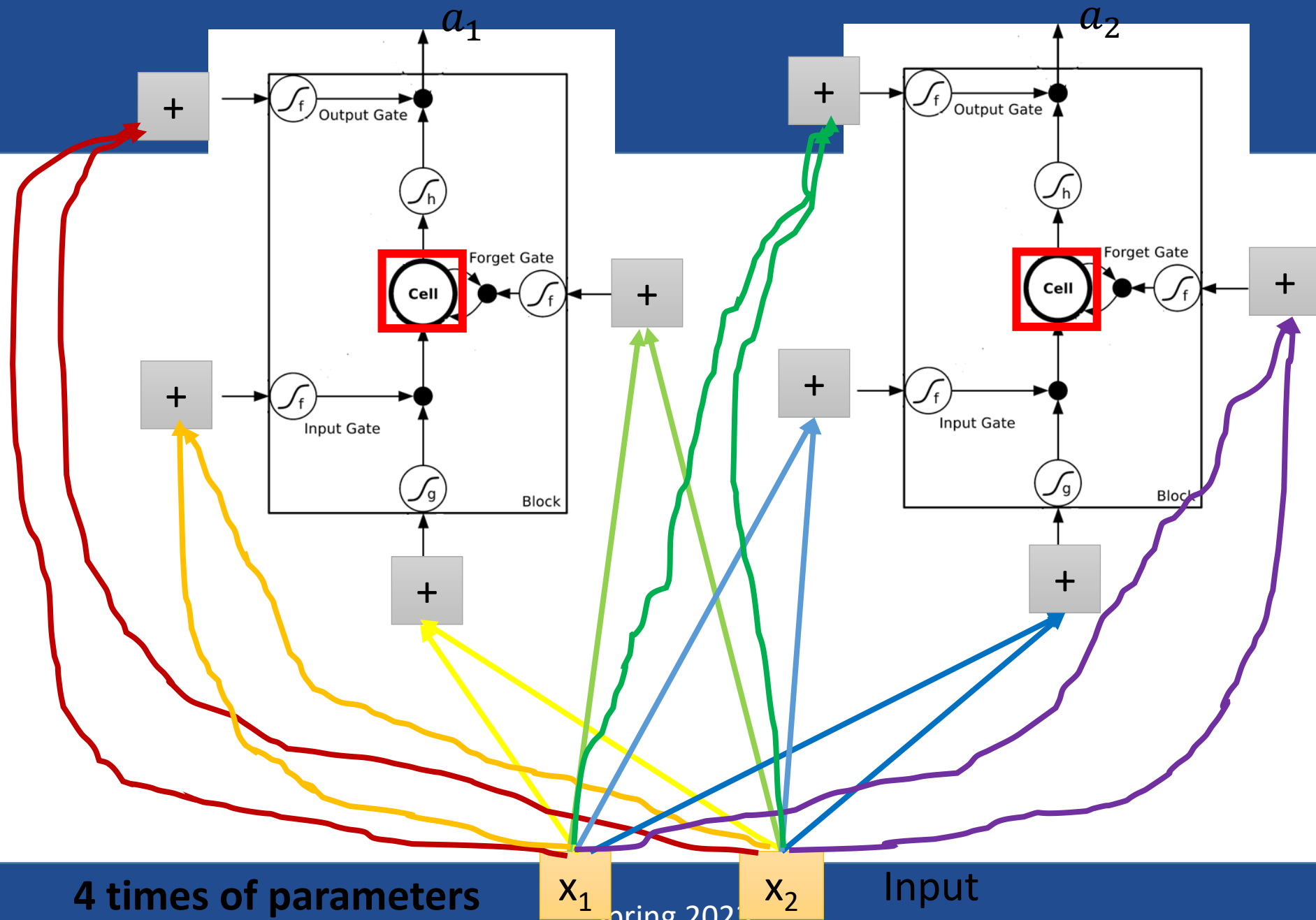
$x_1$	3	4	2	1	3
$x_2$	1	1	0	0	-1
$x_3$	0	0	0	1	0

# Original Network:原始的网络



➤ Simply replace the neurons with LSTM





4 times of parameters

$x_1$

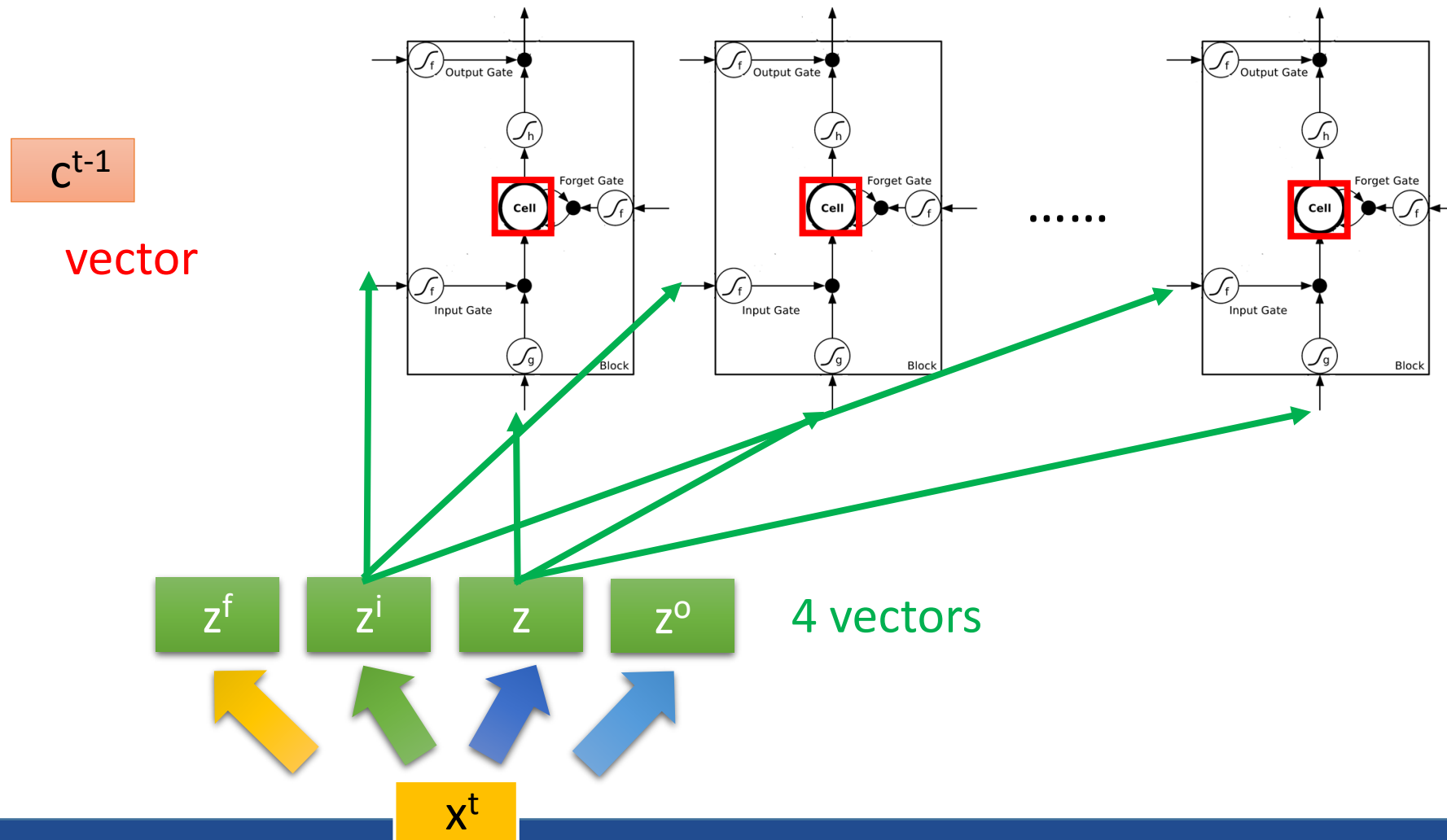
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$x_2$

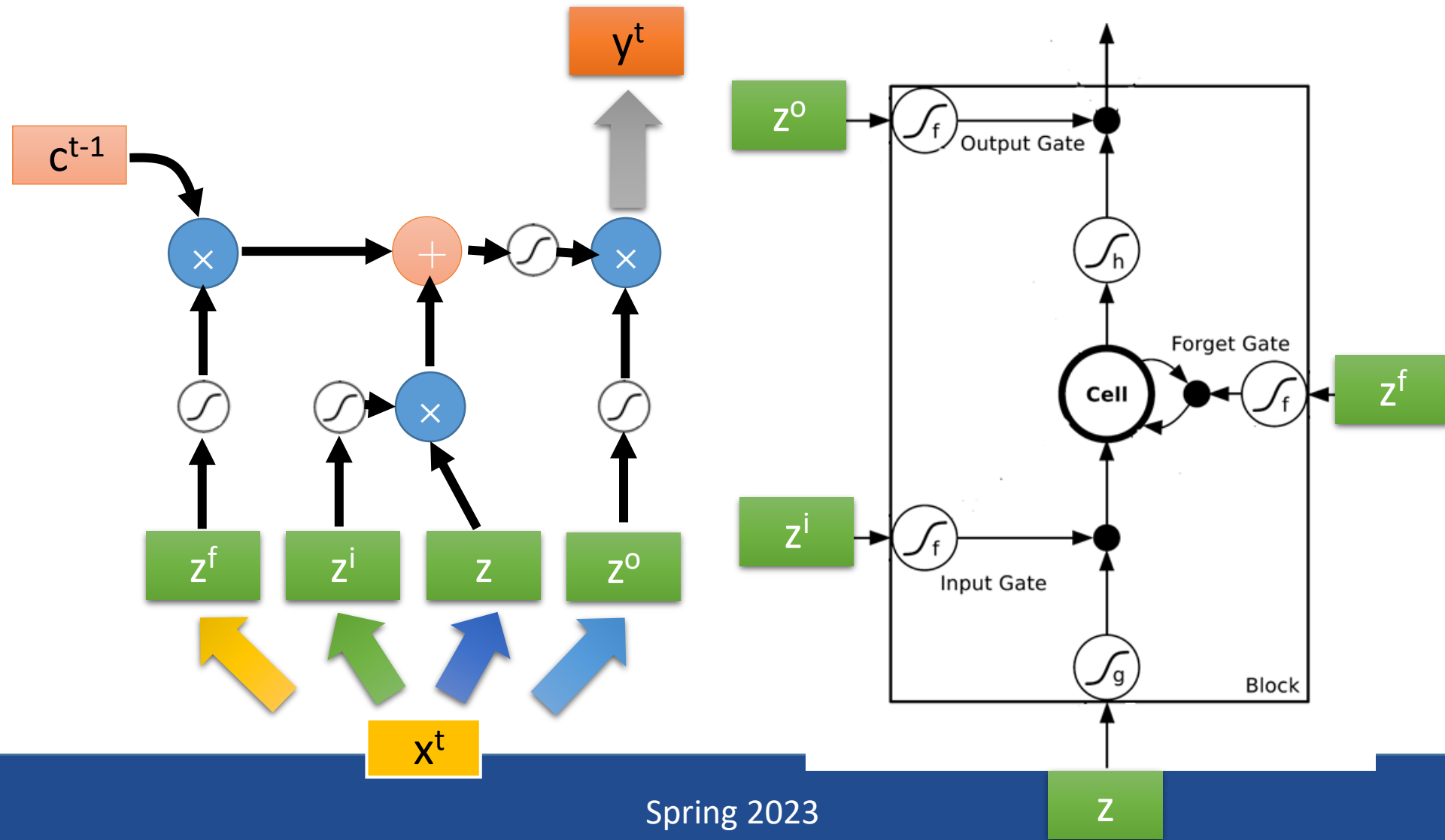
Input



# Long Short-term Memory (LSTM)



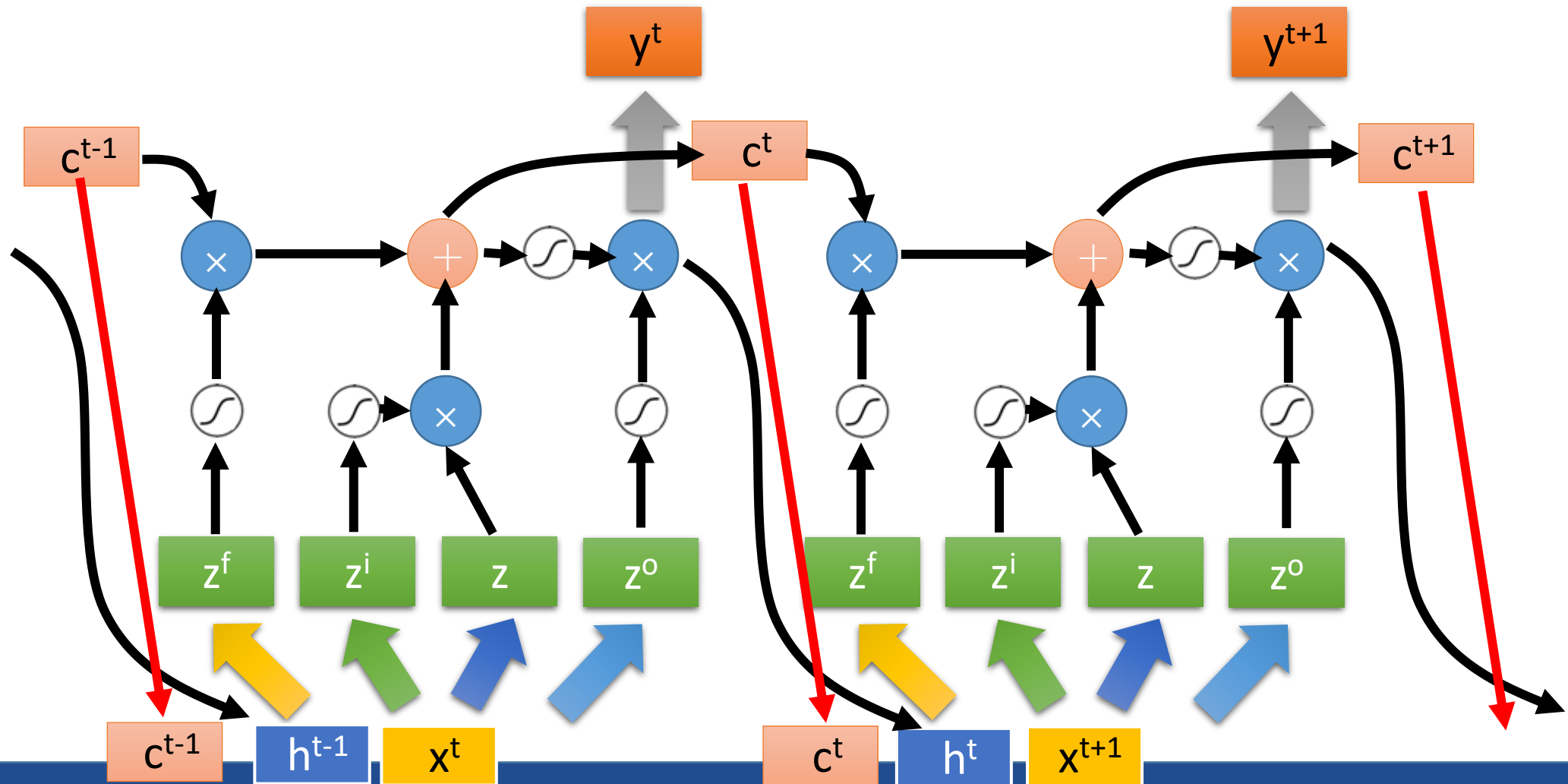
# Long Short-term Memory (LSTM)



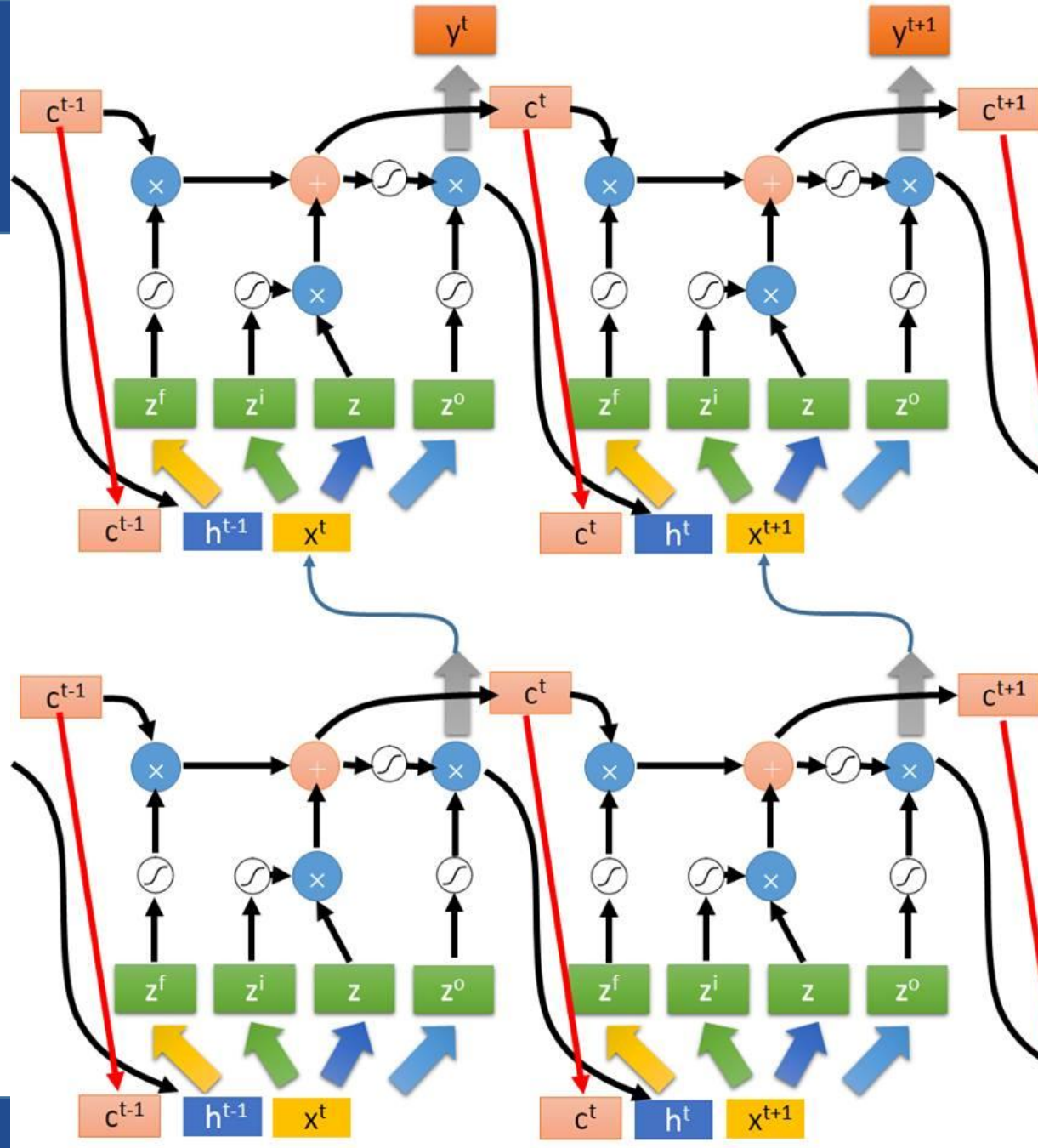
# LSTM



Extension: “peephole”



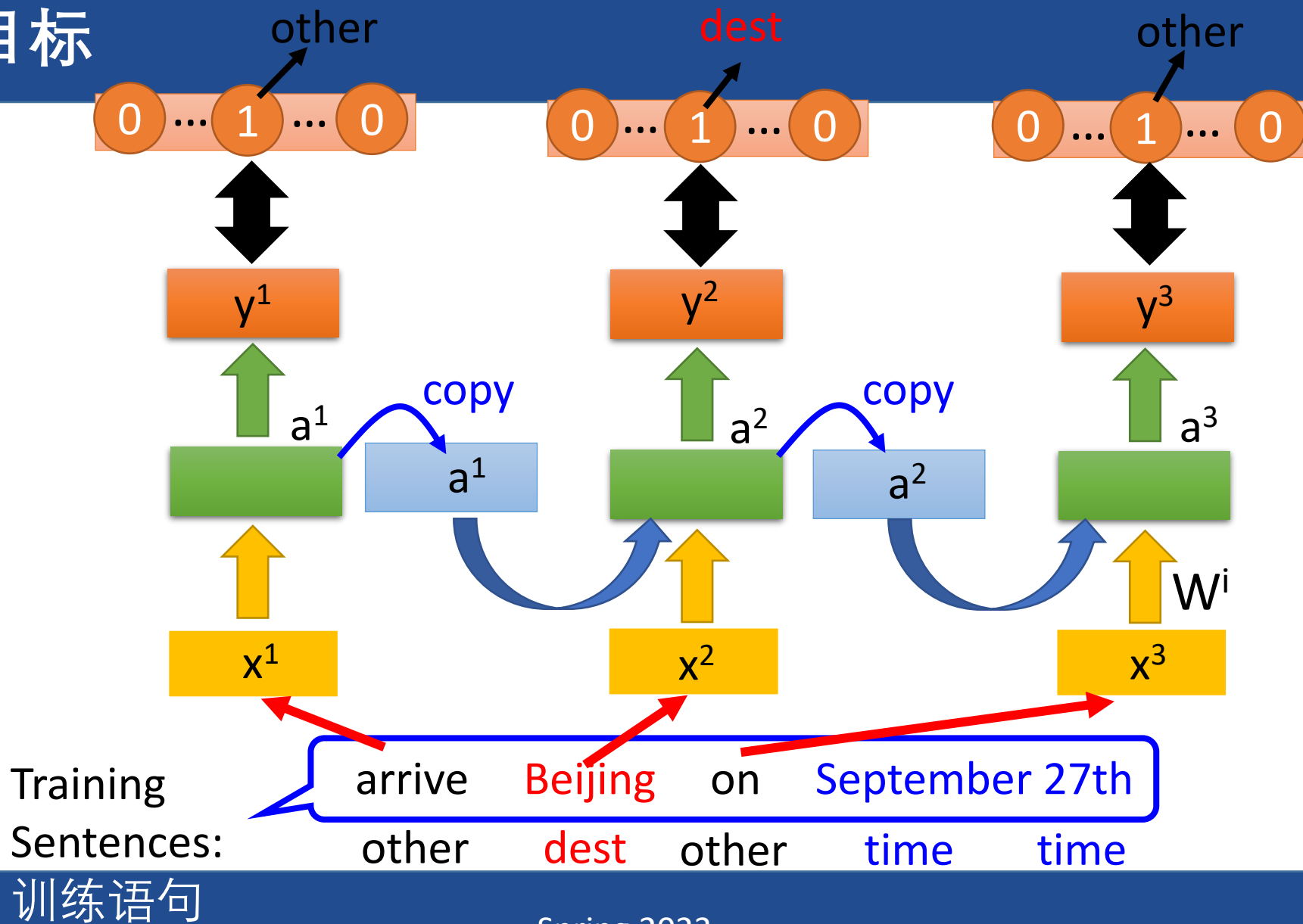
# Multiple-layer LSTM



This is quite  
standard now.

# Learning Target

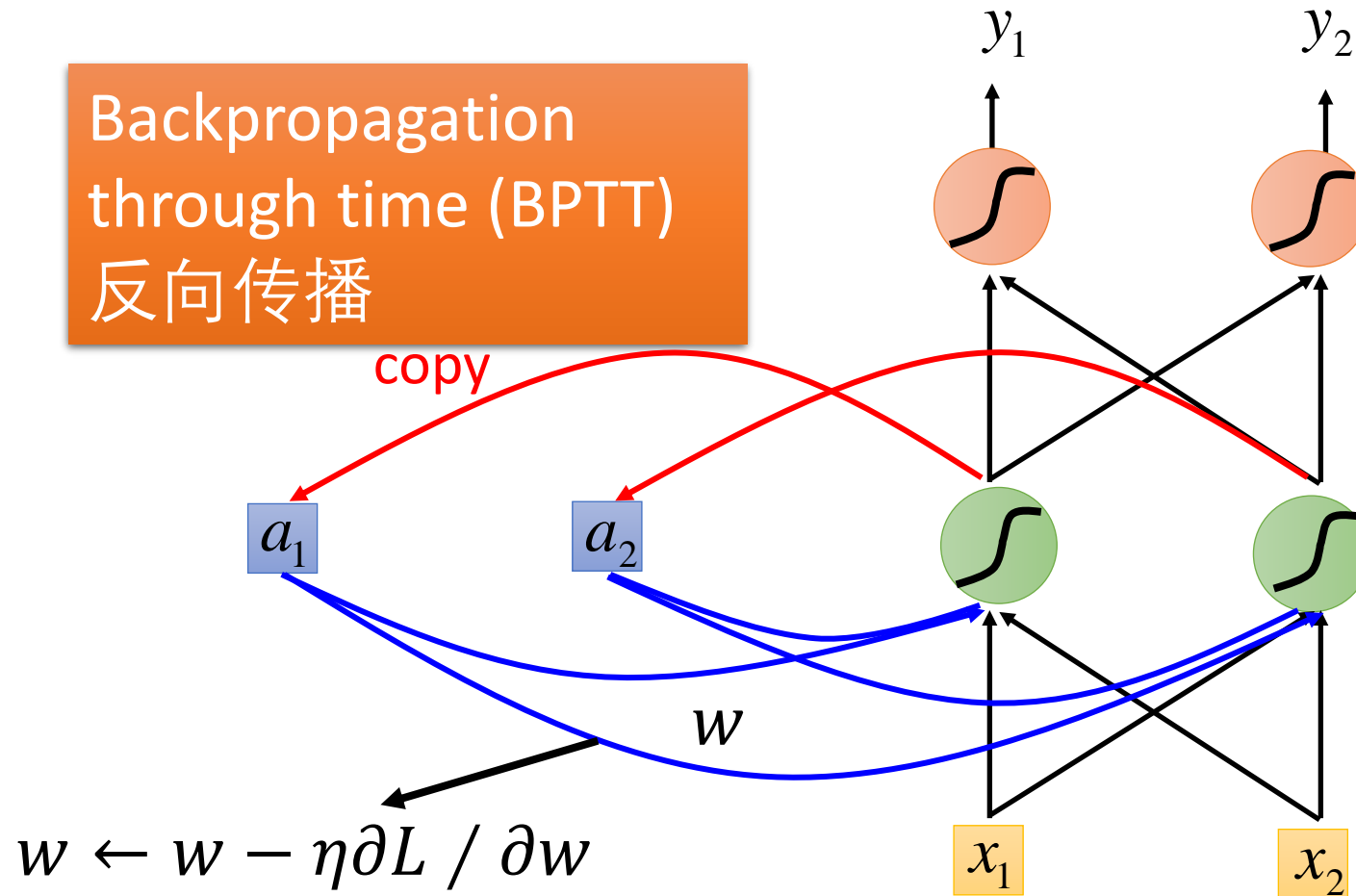
## 学习目标



# Learning



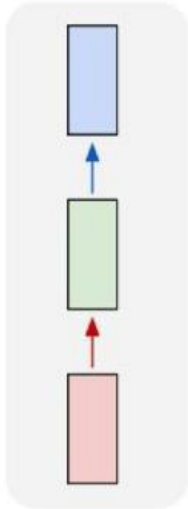
Backpropagation  
through time (BPTT)  
反向传播



# More Architecture



one to one



Vanilla  
Neural  
Network

one to many

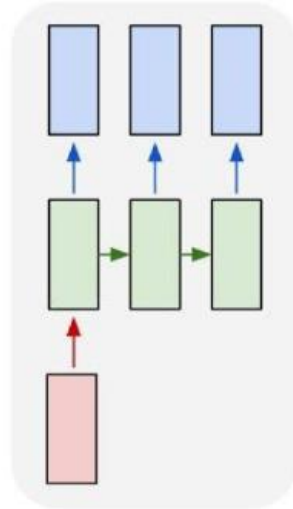
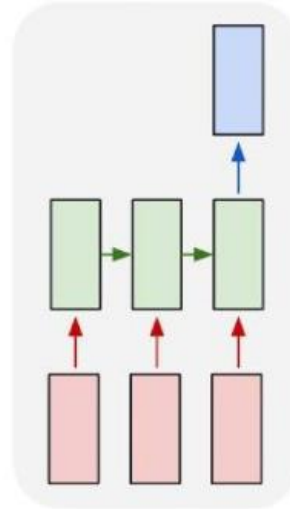


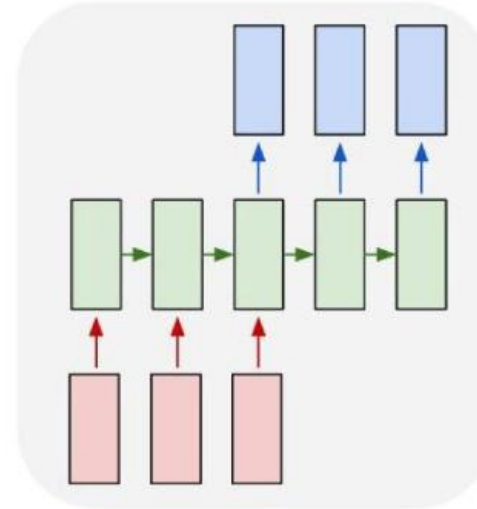
Image  
Captioning

many to one



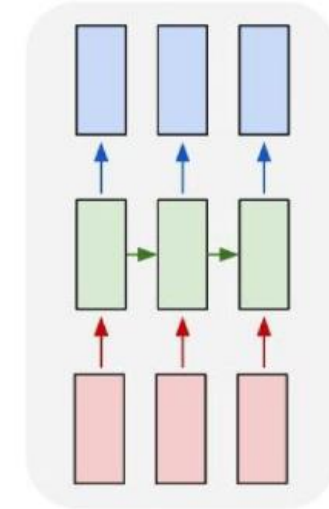
Sentiment  
Classification

many to many



Machine  
translation

many to many



video  
classification  
on frame level

# You Like More?



<https://www.youtube.com/watch?v=fLvJ8VdHLA0&t=77s>



# Q&A



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