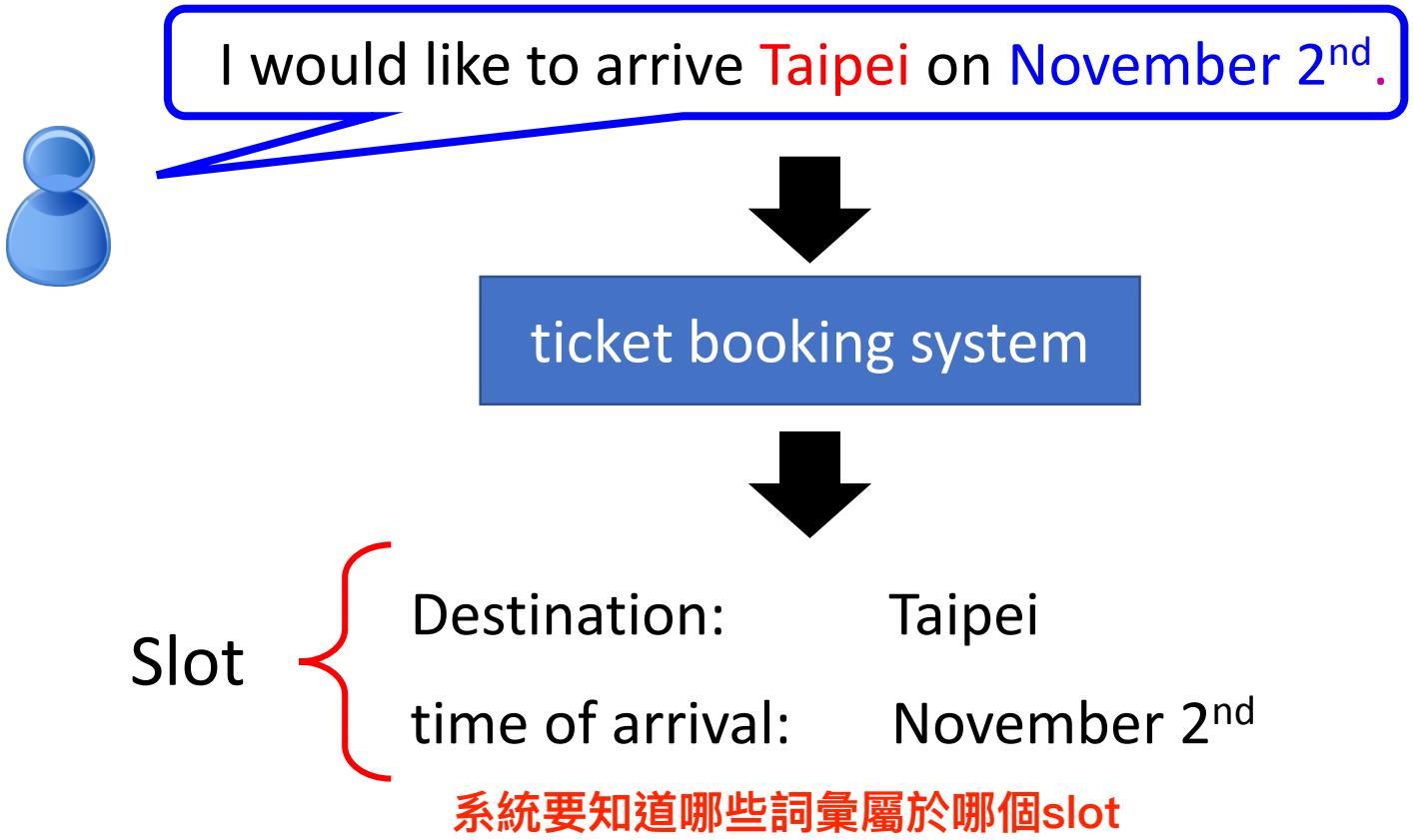
Recurrent Neural Network (RNN)

Example Application

- Slot Filling

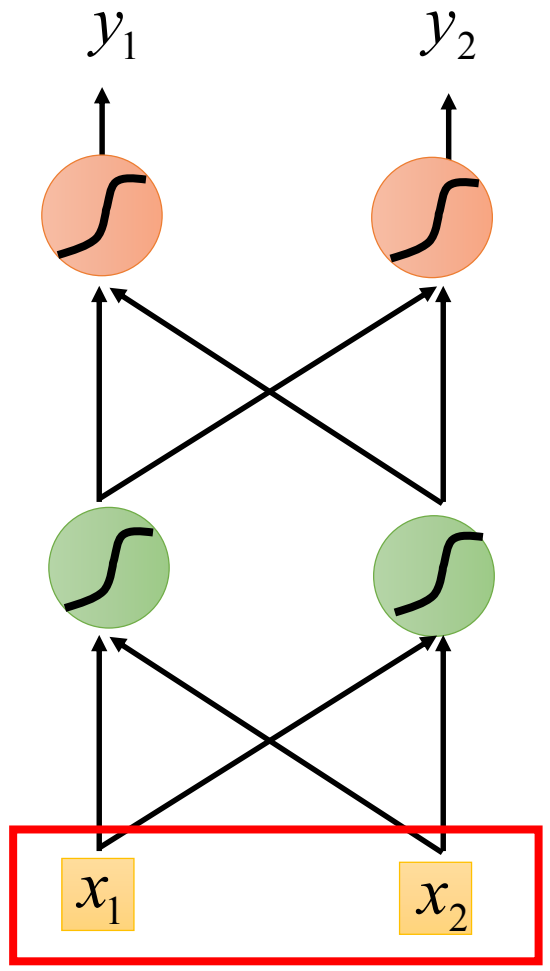


Example Application

Solving slot filling by Feedforward network?

Input: a word

(Each word is represented as a vector)



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]

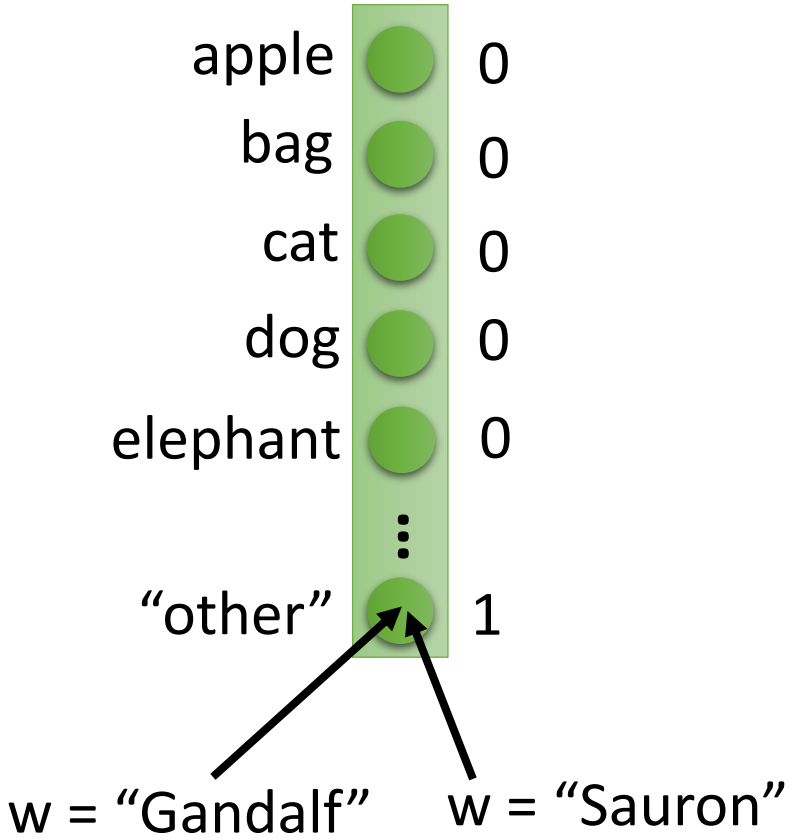
dog = [0 0 0 1 0]

elephant = [0 0 0 0 1]

Beyond 1-of-N encoding

用word是否出現來代表詞彙

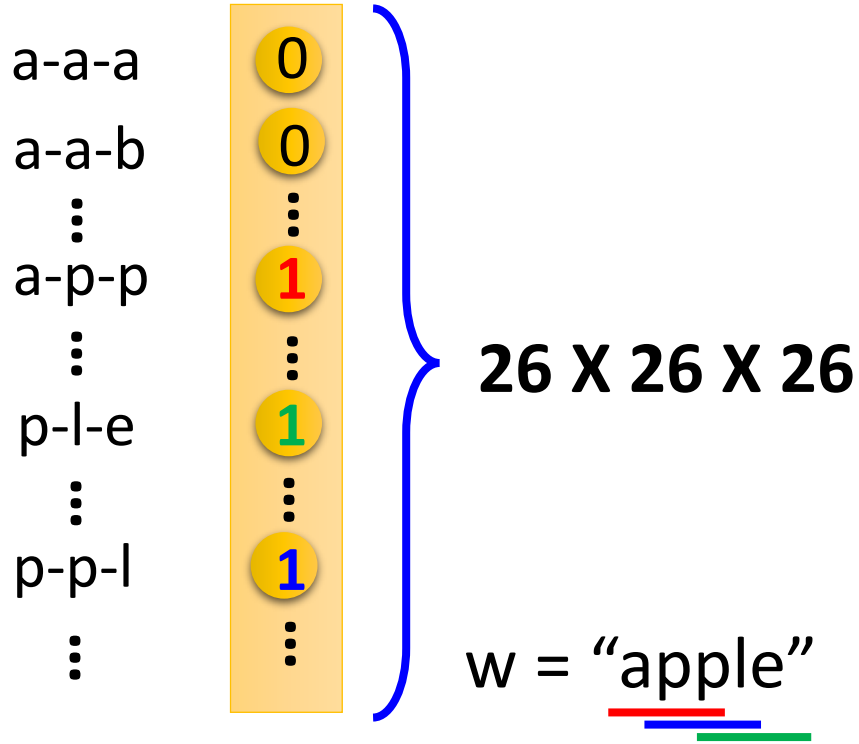
Dimension for "Other"



因為有很多其他的詞彙沒看過

用字母是否出現來代表詞彙，
避免沒見過的詞彙

Word hashing



Example Application

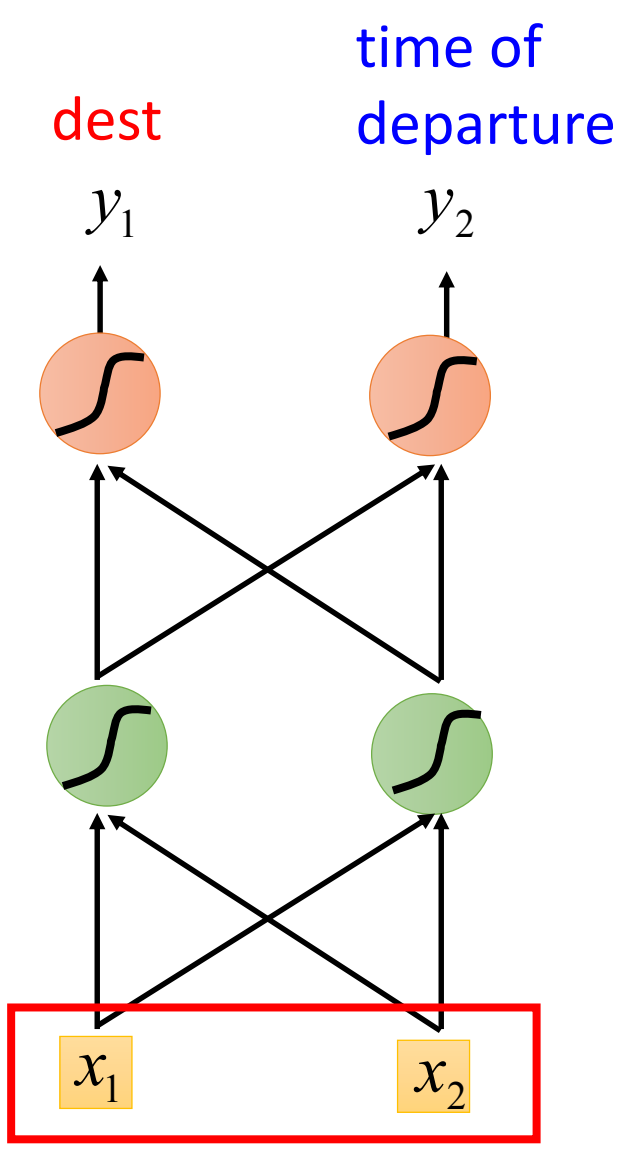
Solving slot filling by Feedforward network?

Input: a word

(Each word is represented as a vector)

Output:

Probability distribution that the input word belonging to the slots



如果機器記得在看過台北之前先看過arrive或是leave，就可以解決input同個詞彙output不同結果

Example Application

目的地

arrive Taipei on November 2nd

other dest other time time

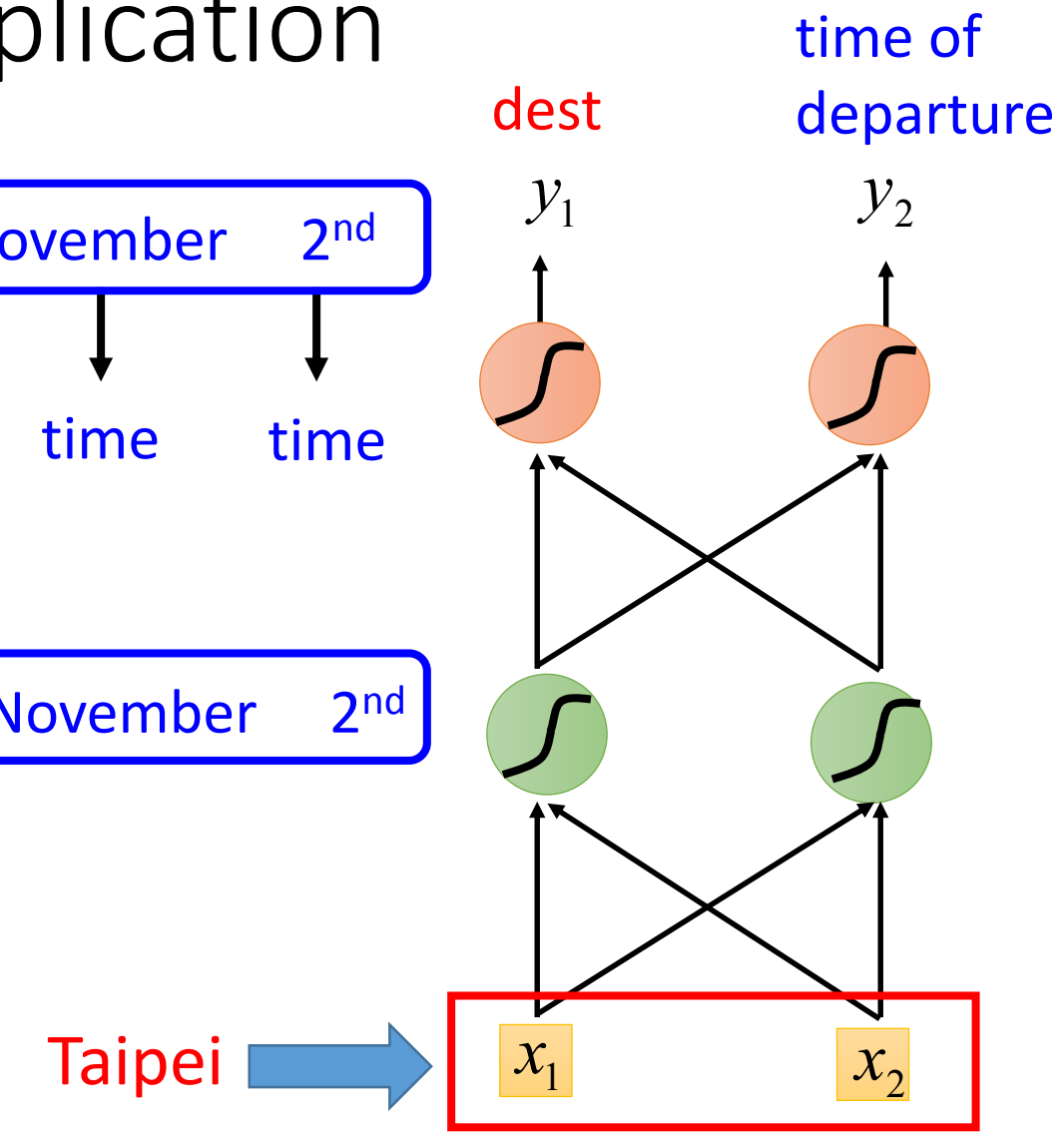
Problem?

出發地

leave Taipei on November 2nd

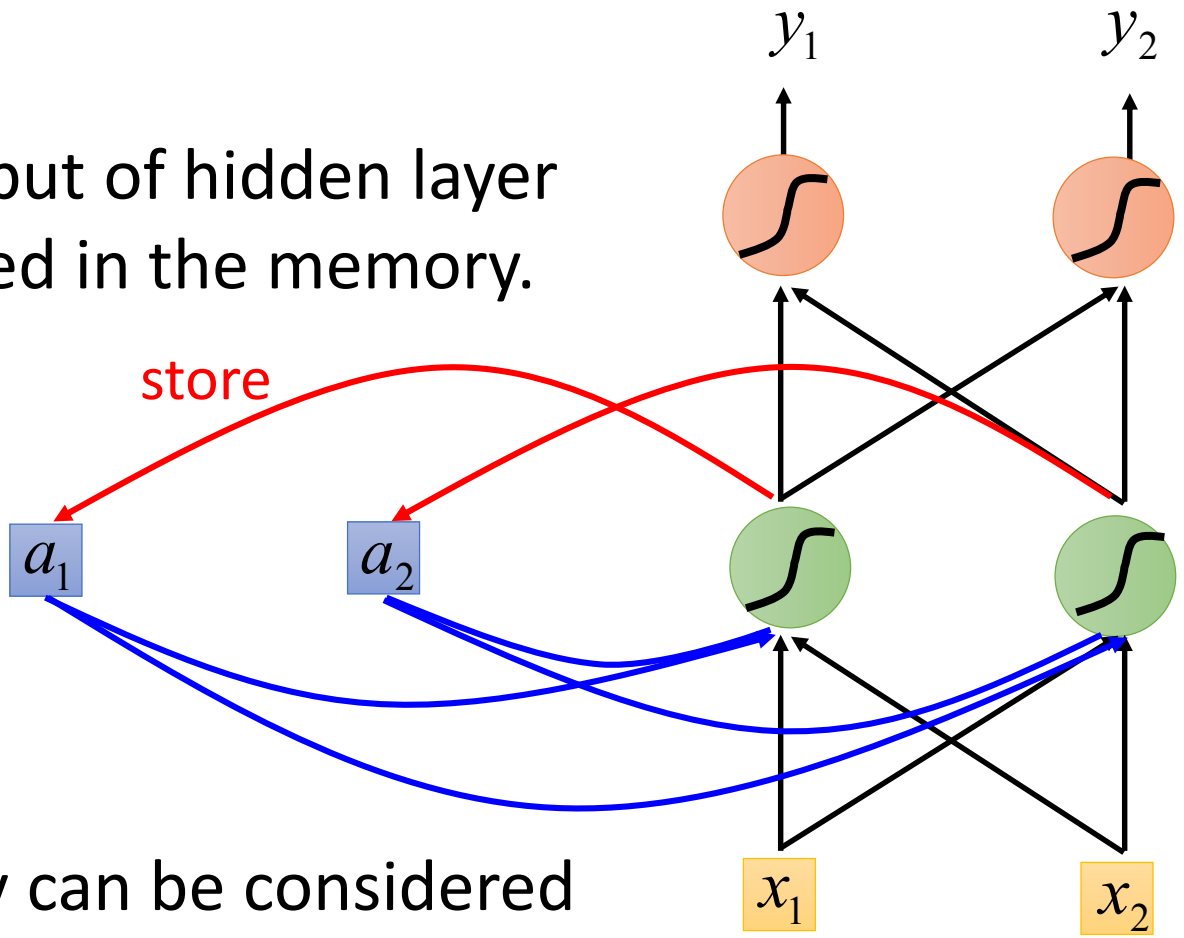
place of departure

Neural network needs memory!



Recurrent Neural Network (RNN)

The output of hidden layer are stored in the memory.

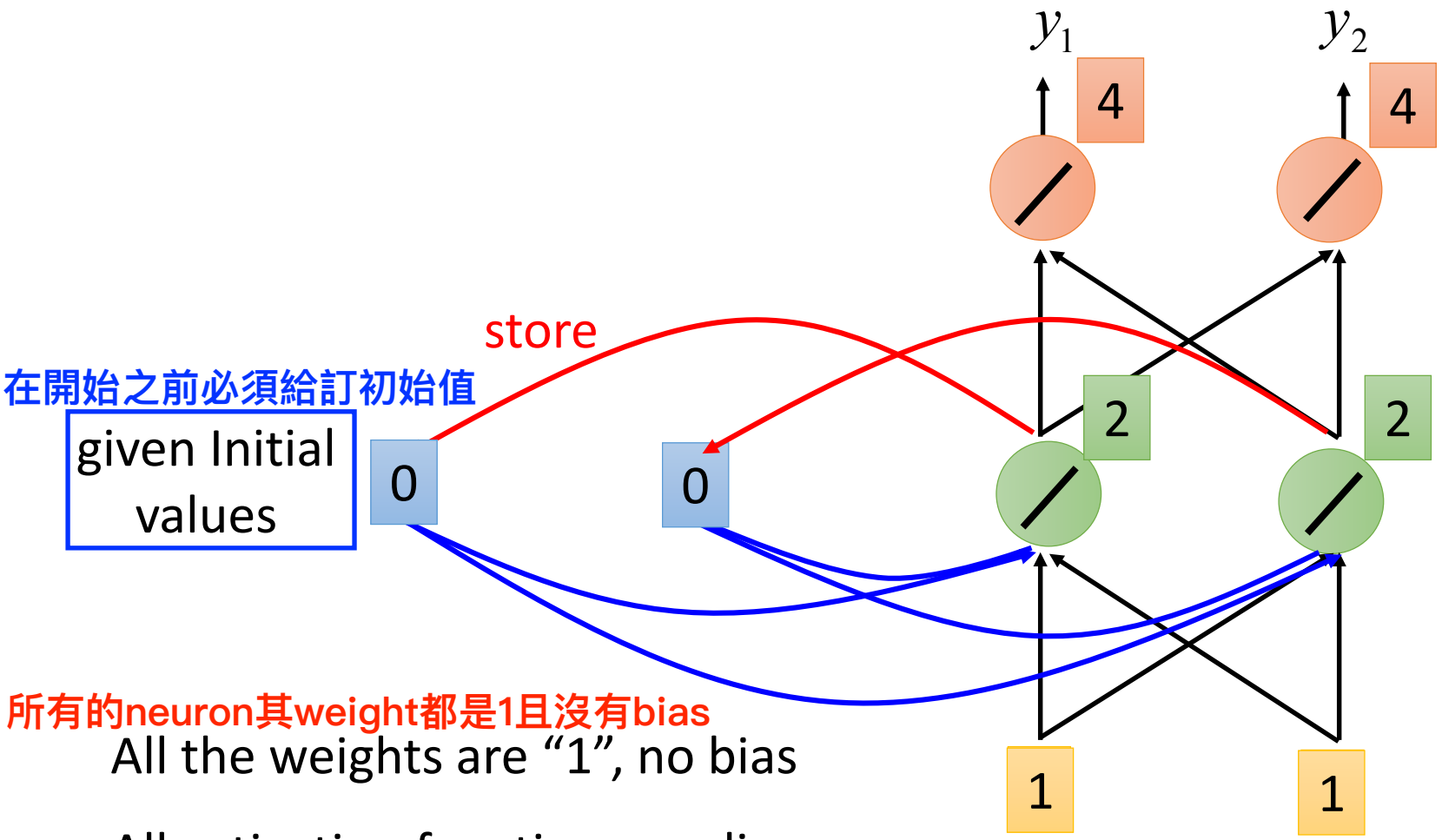


Memory can be considered as another input.

Example

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

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



在開始之前必須給訂初始值

所有的neuron其weight都是1且沒有bias

All the weights are “1”, no bias

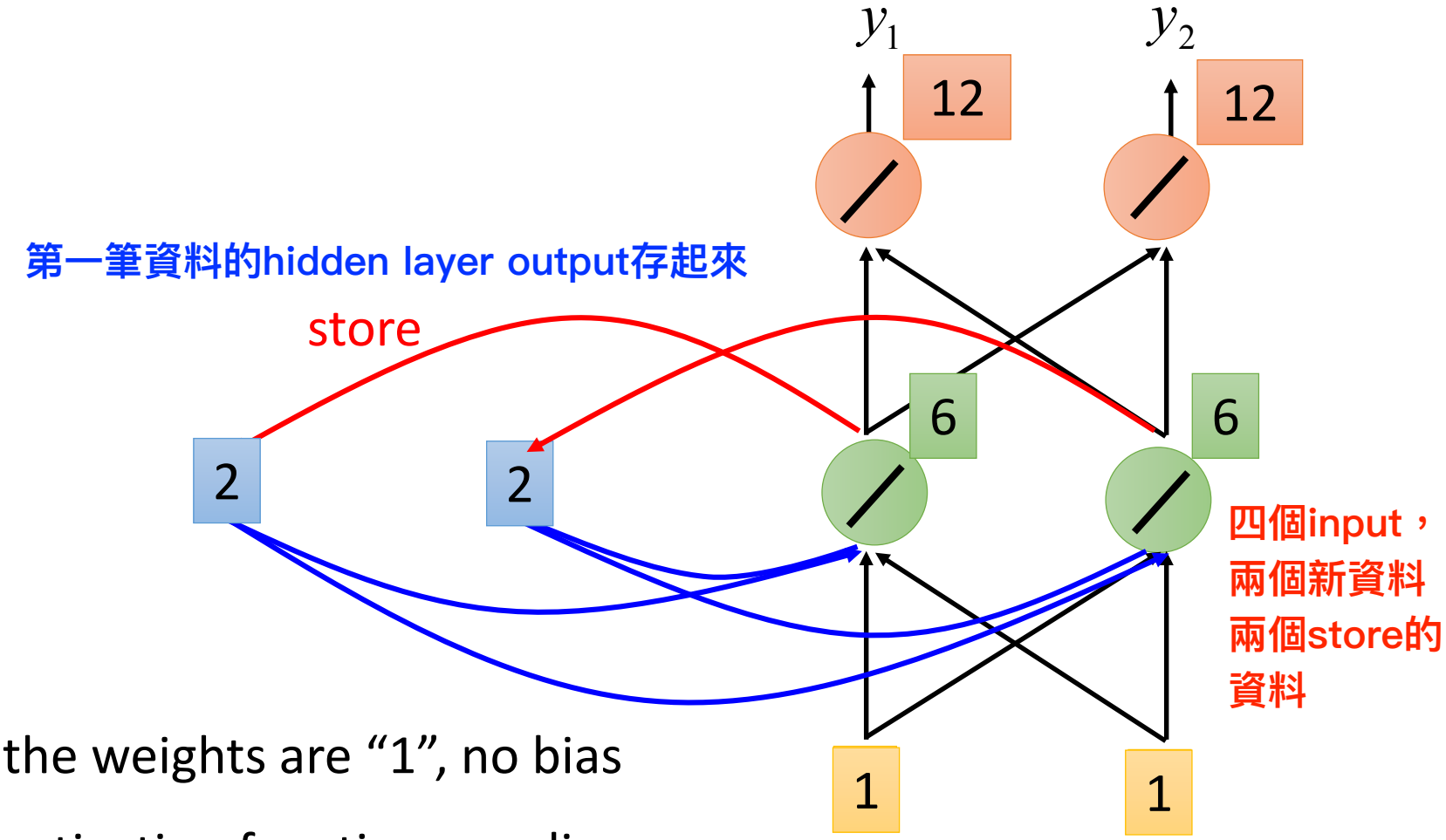
All activation functions are linear

activation function的output為全部input相加

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

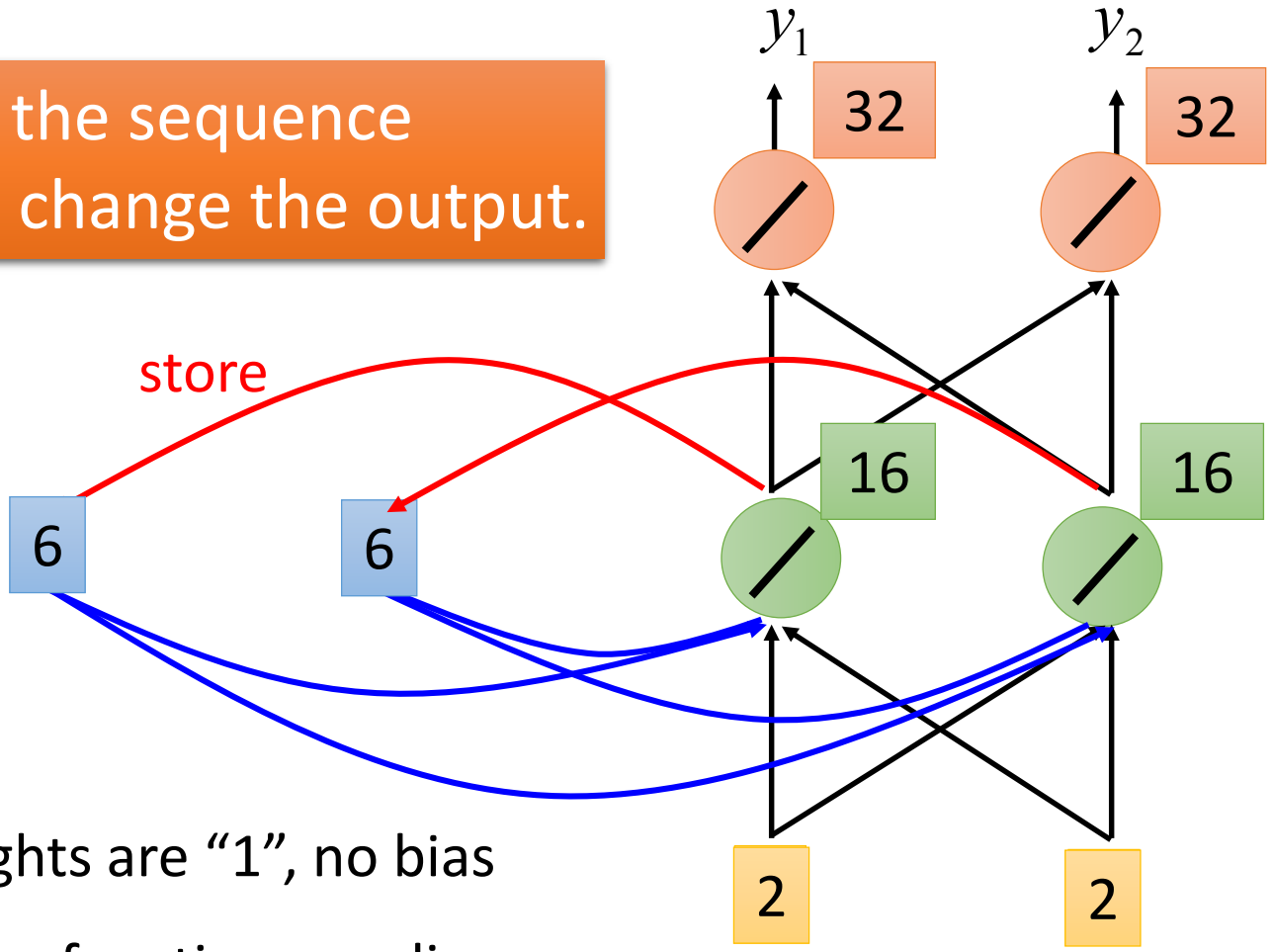
All activation functions are linear

Example

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

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

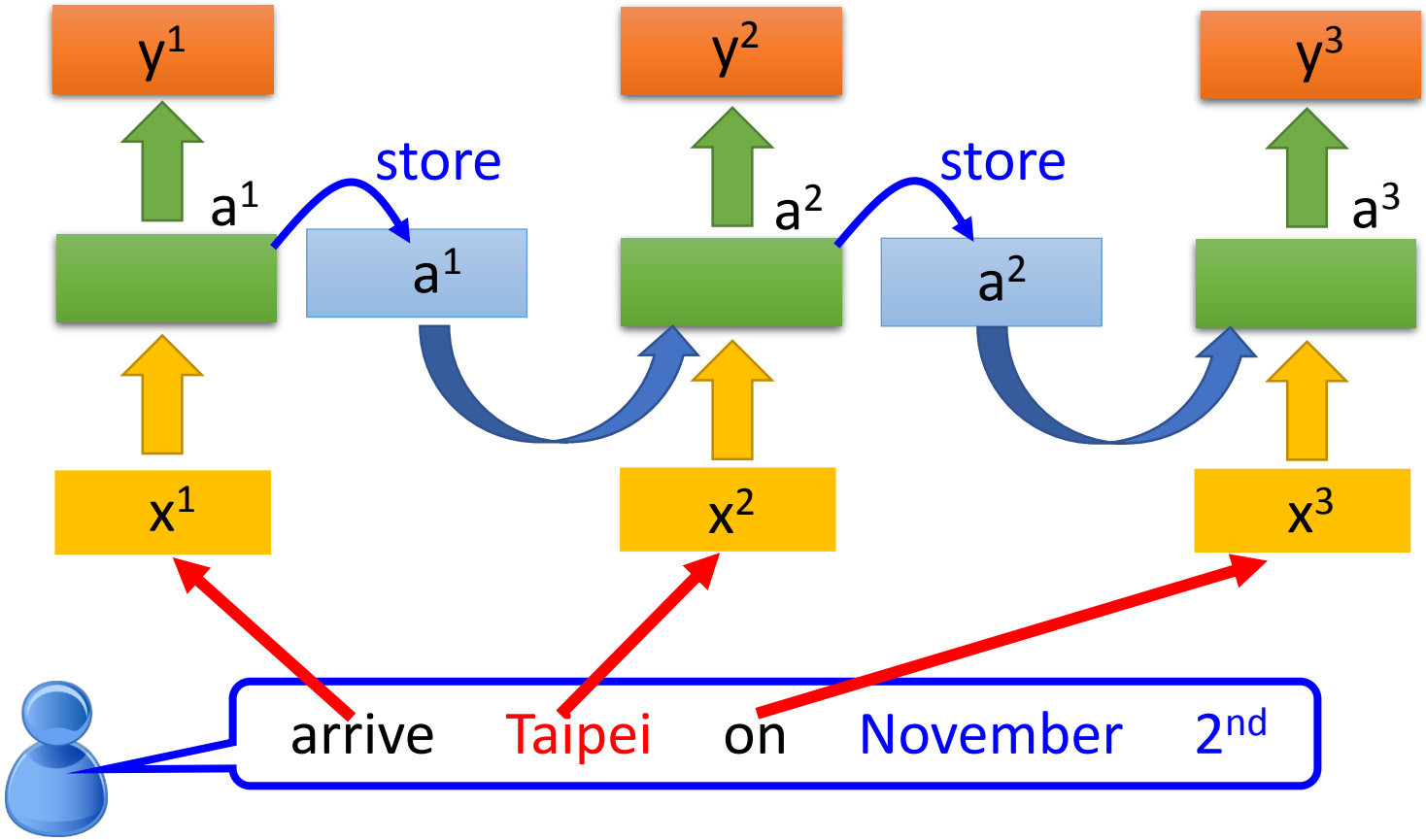
The same network is used again and again.

同一個network在三個不同的時間點被使用了三次

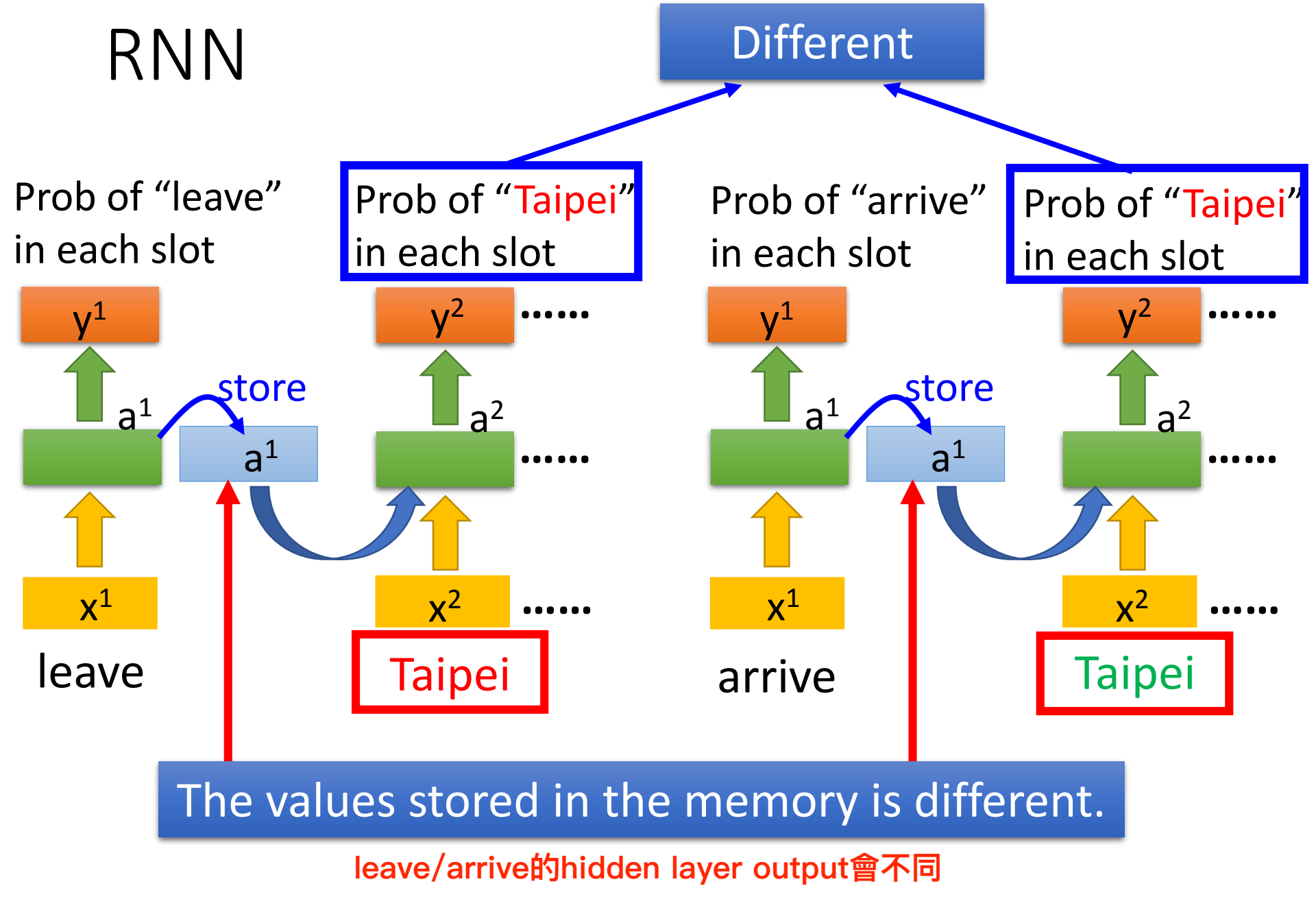
Probability of "arrive" in each slot

Probability of "Taipei" in each slot

Probability of "on" in each slot

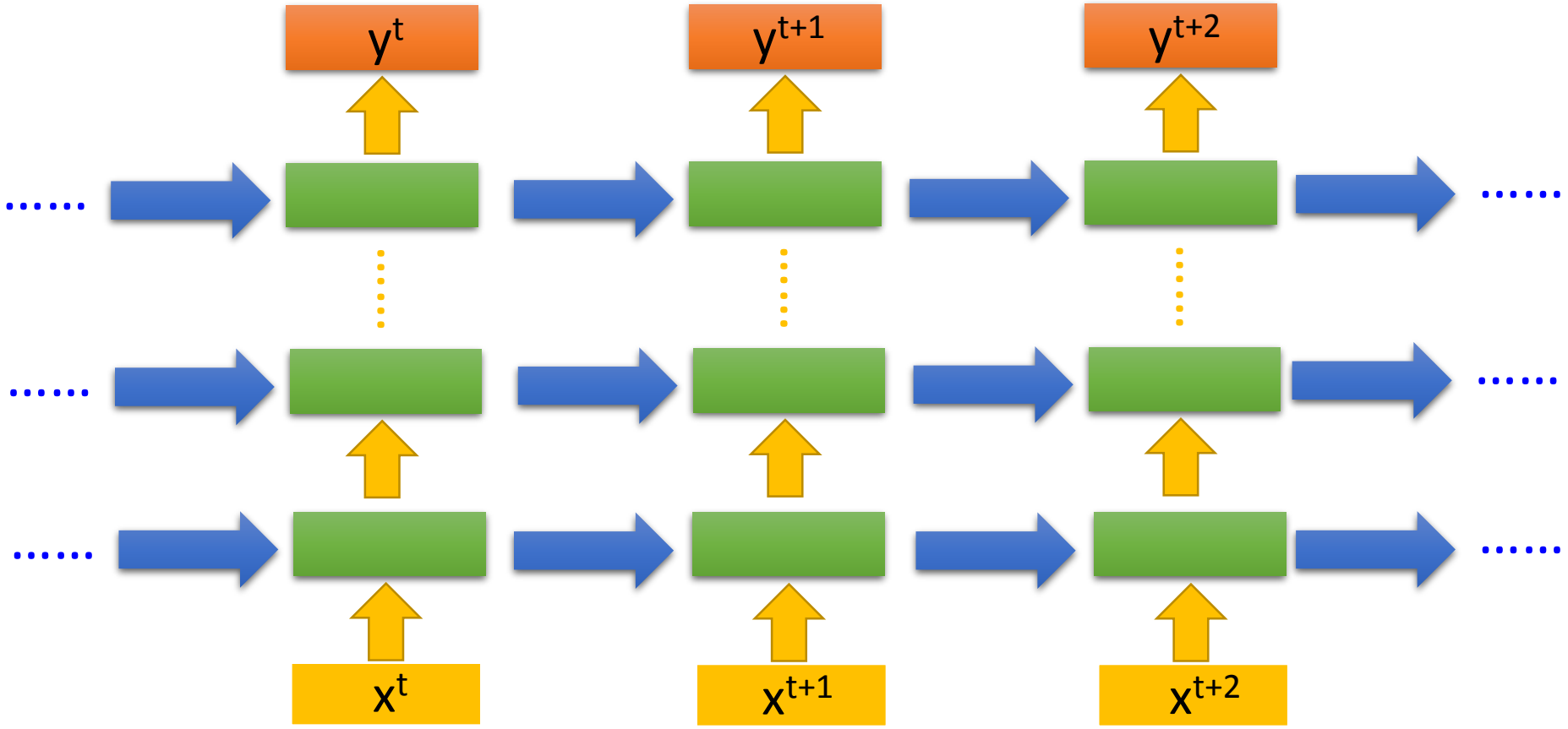


RNN

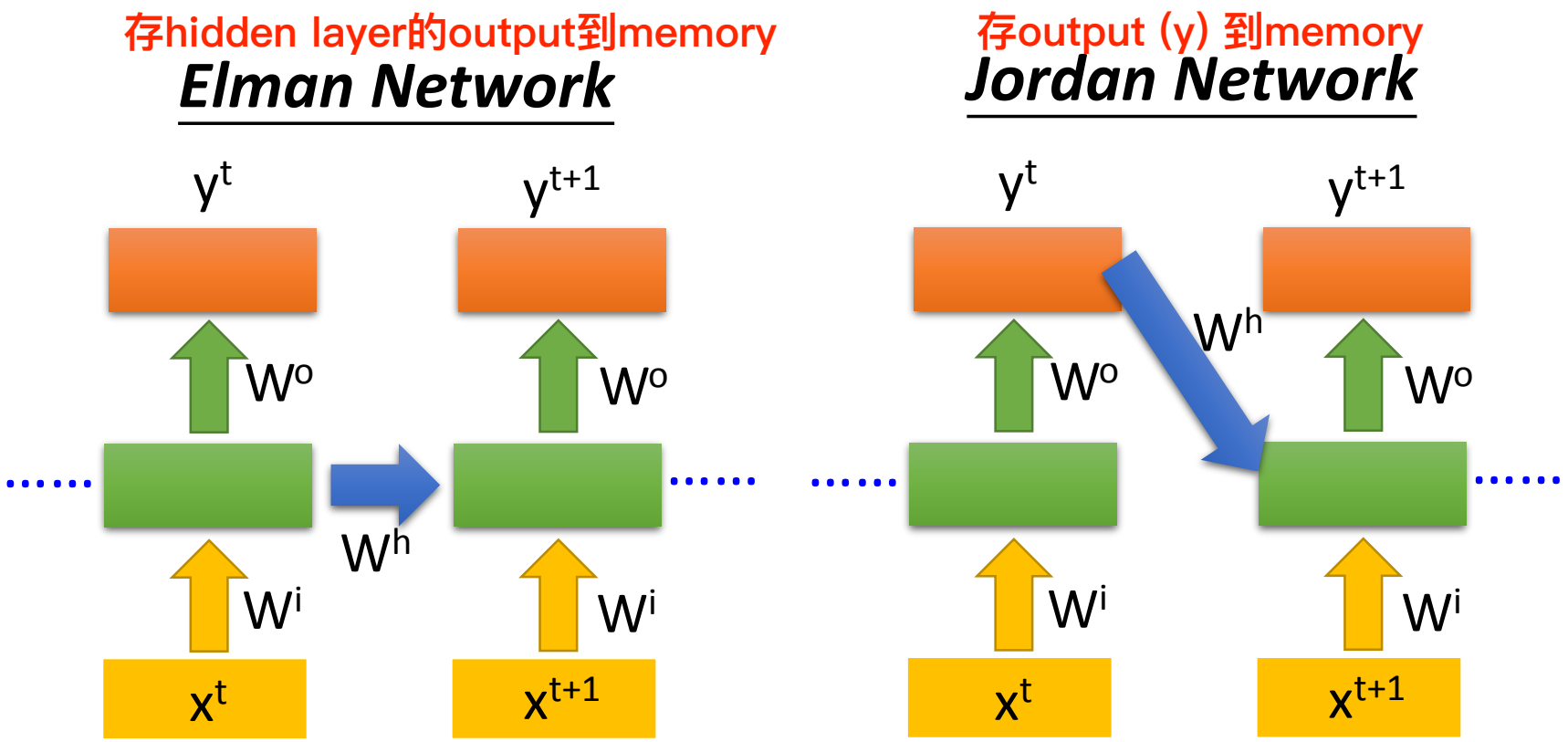


leave/arrive的hidden layer output會不同

Of course it can be deep …



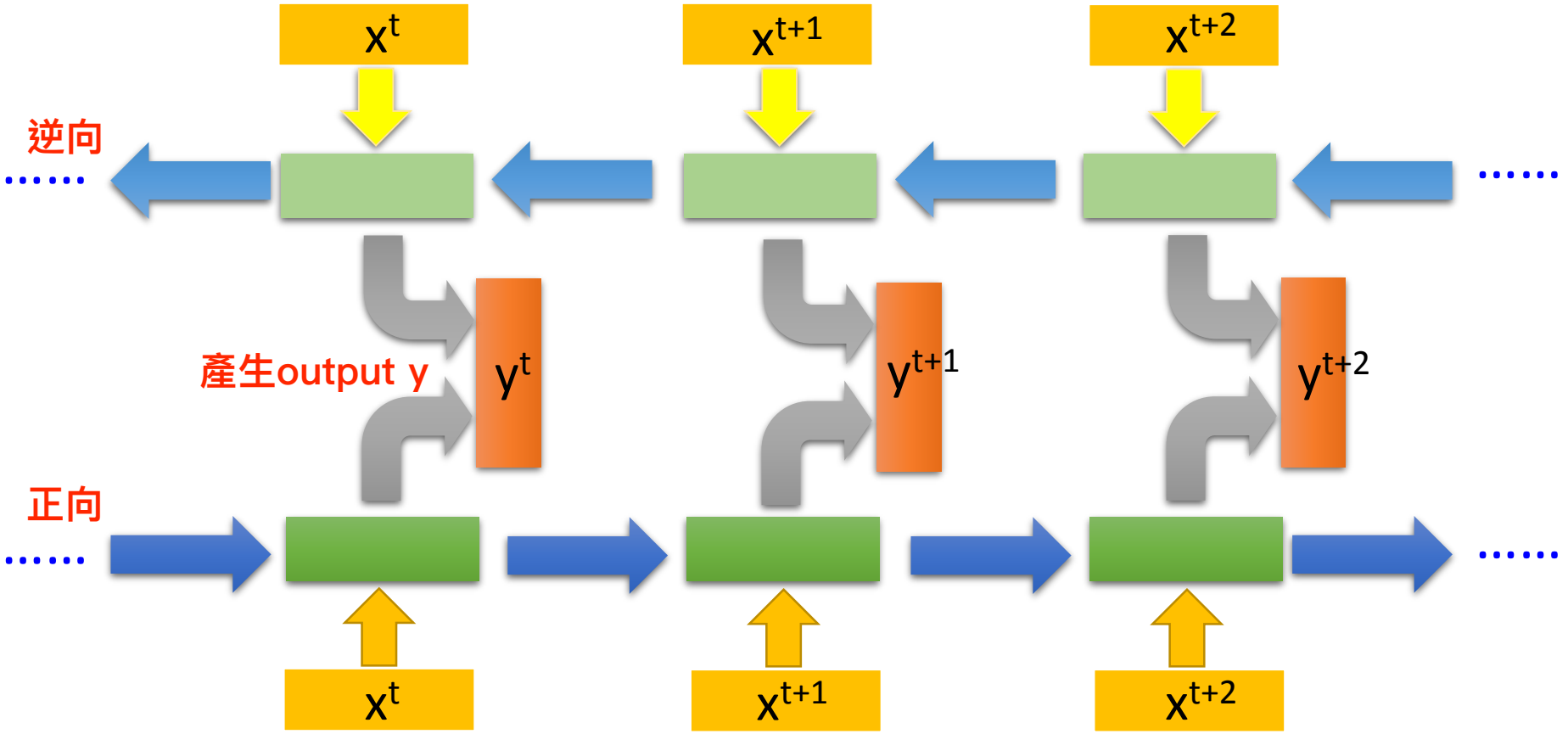
Elman Network & Jordan Network



RNN可雙向

好處：看的範圍比較廣，network相當於看了整個句子才決定該predict什麼

Bidirectional RNN

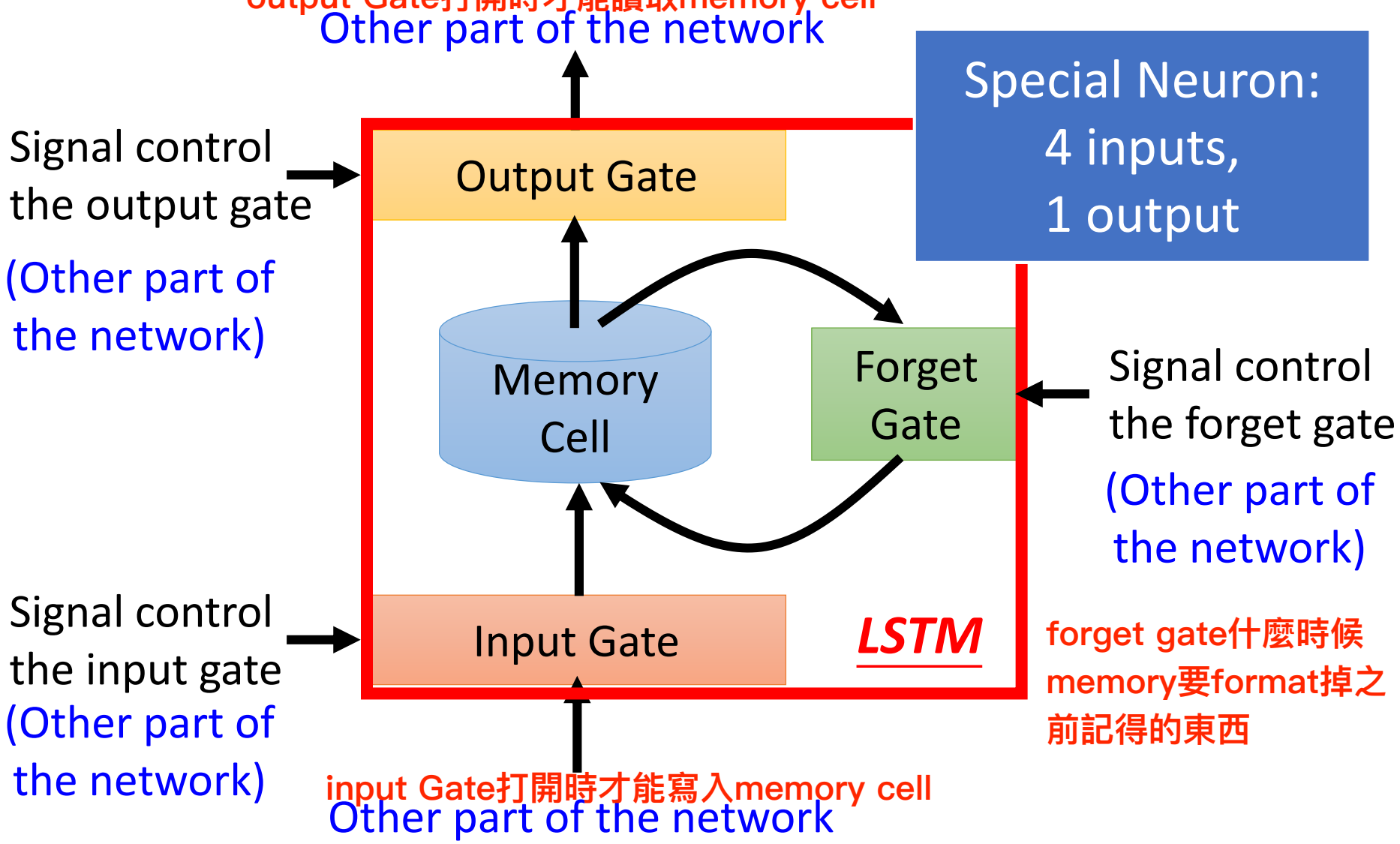


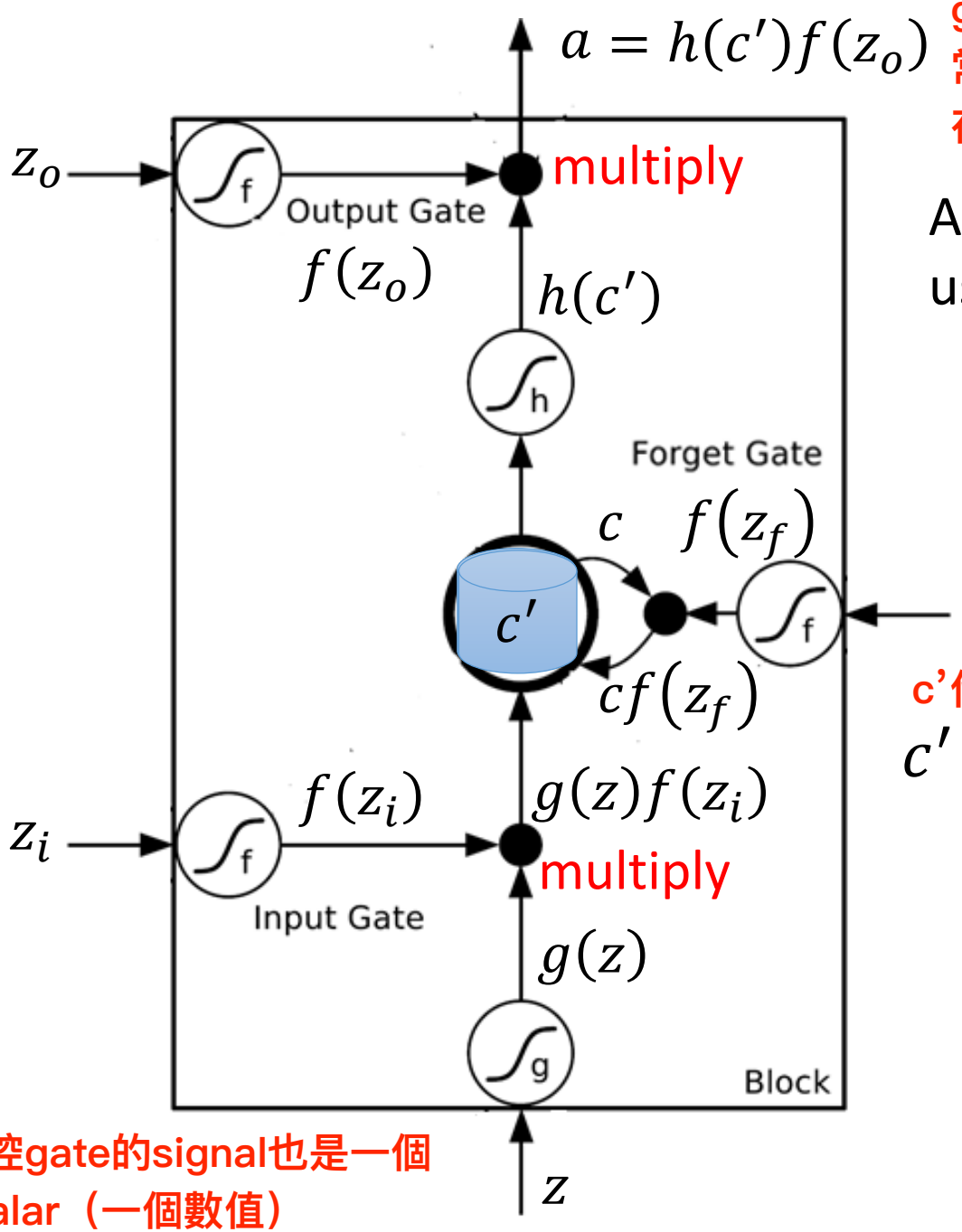
比較長的short term memory

4個input: 一個input data以及控制三個gate的信號

Long Short-term Memory (LSTM)

output Gate打開時才能讀取memory cell





gate signal的activation function通常選擇sigmoid function，因為職介在0~1，代表gate被打開的程度

Activation function f is usually a sigmoid function

Between 0 and 1

Mimic open and close gate

c'代表新的存在memory裡面的值

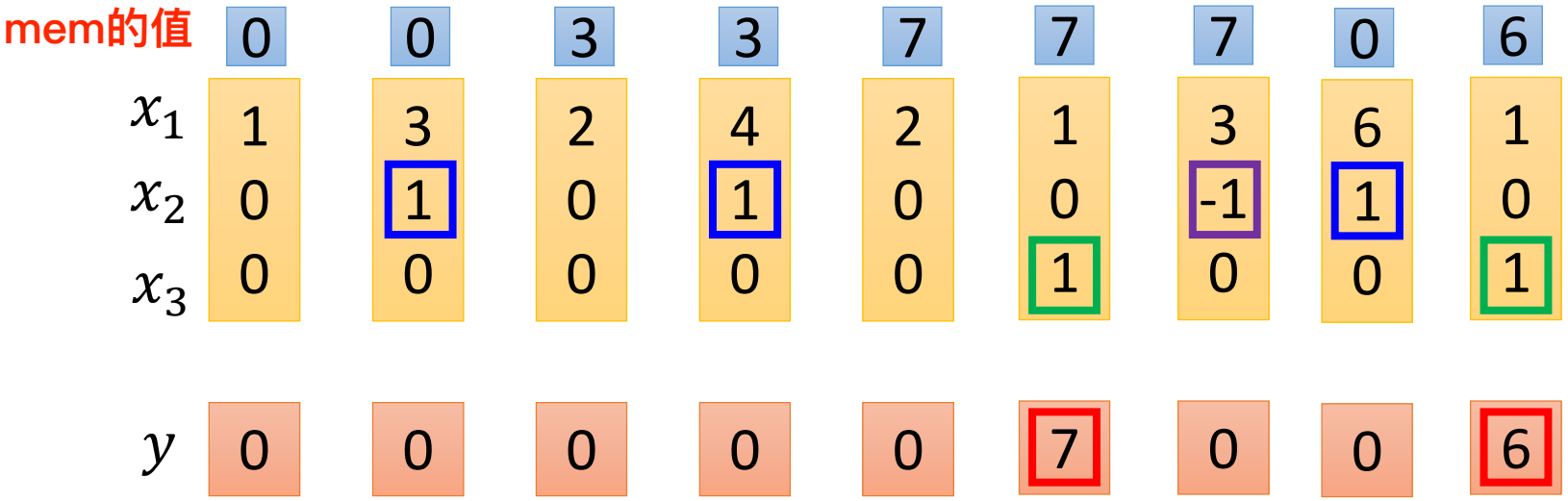
$$c' = g(z)f(z_i) + cf(z_f)$$

input data 要寫入的值

過去存在mem的值

操控gate的signal也是一個scalar（一個數值）

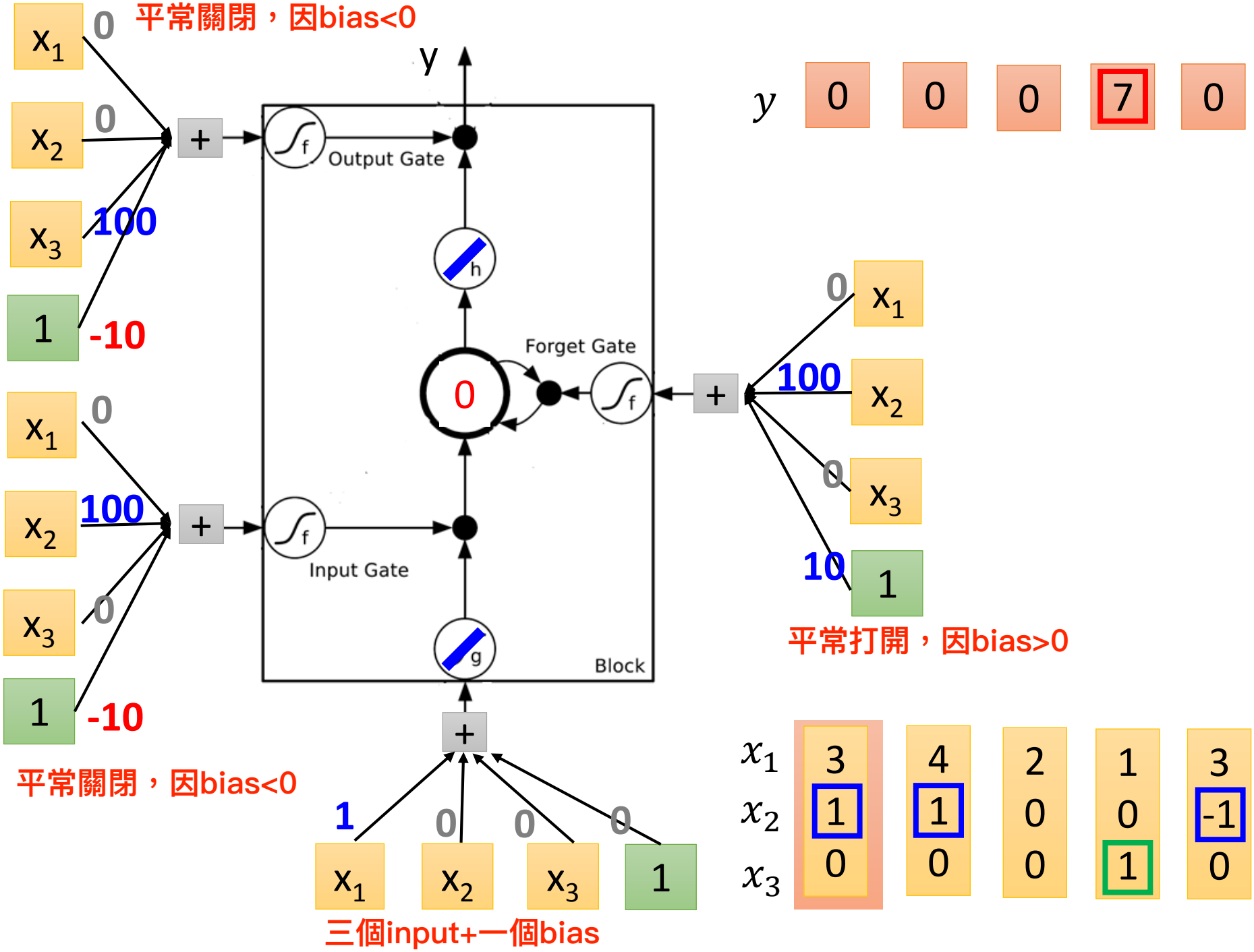
LSTM - Example

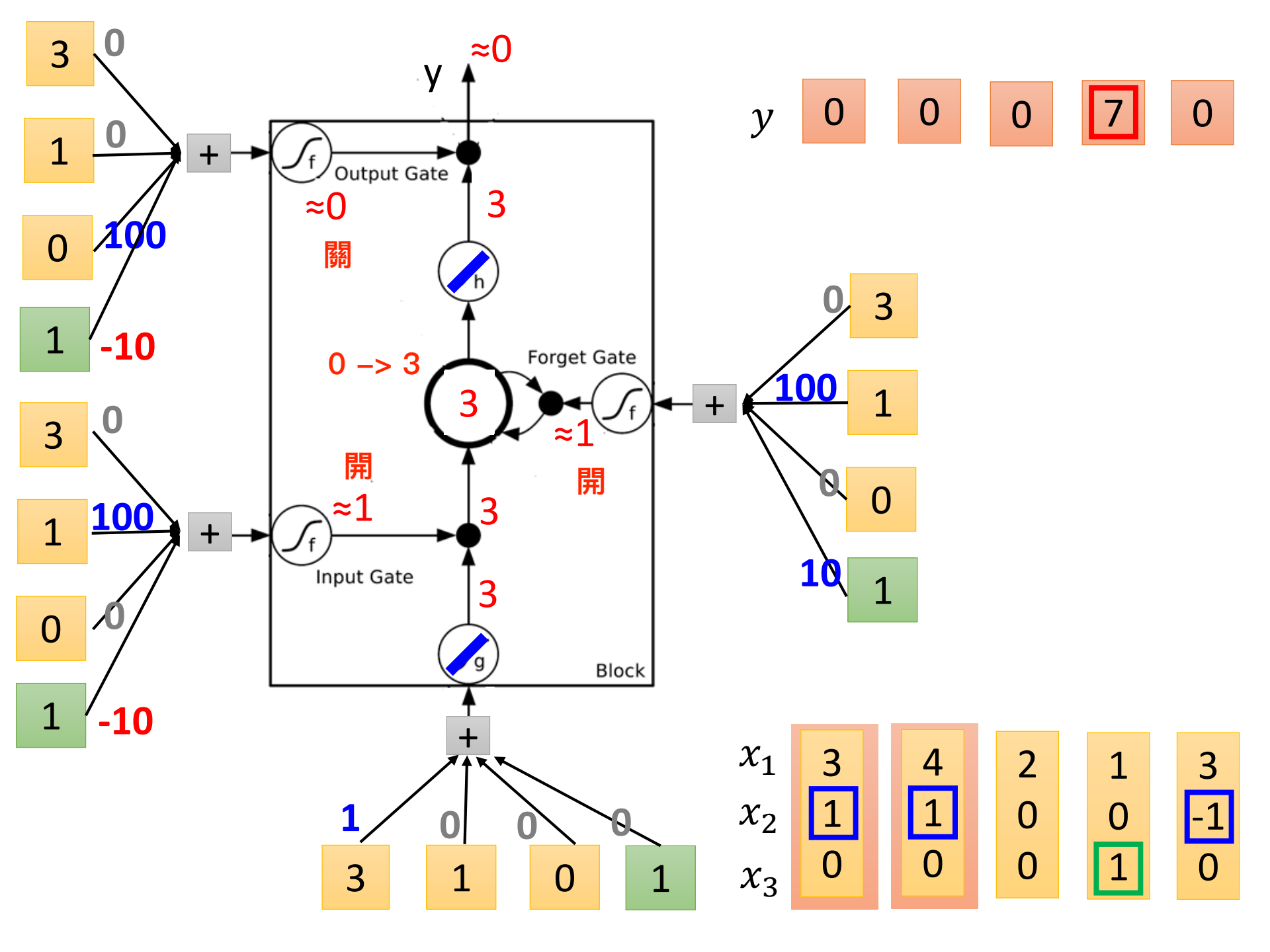


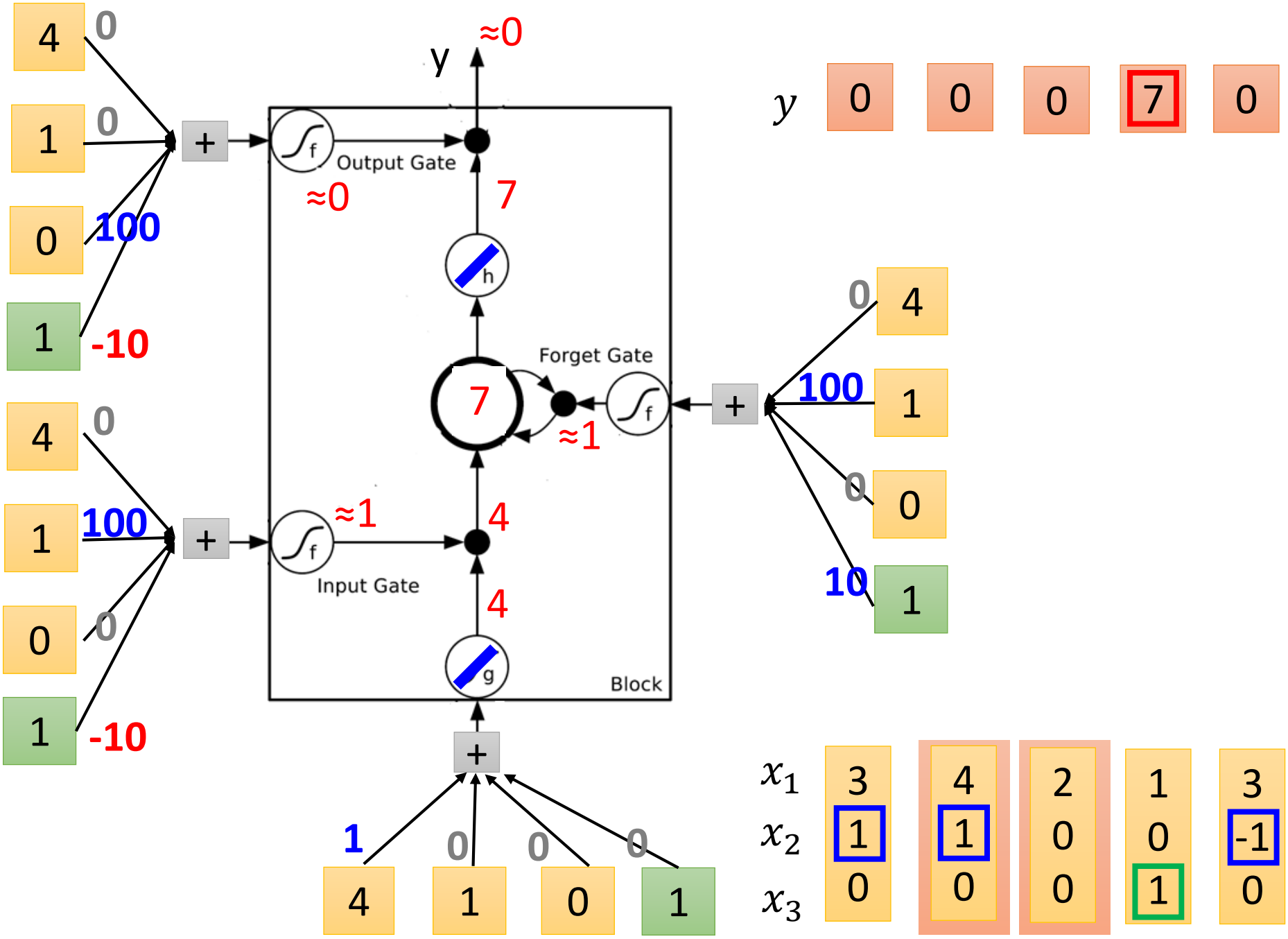
When x_2 = 1, add the numbers of x_1 into the memory

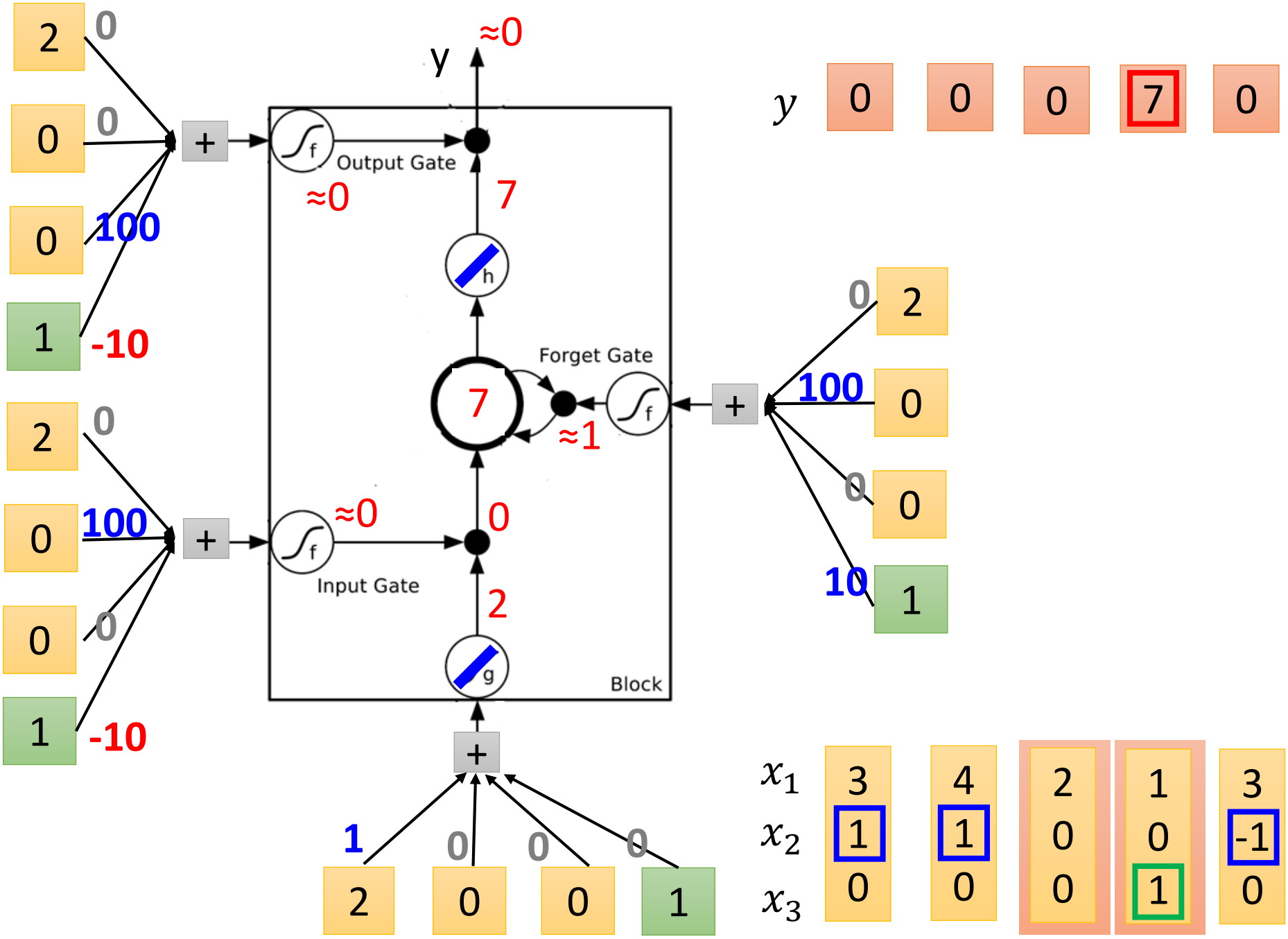
When x_2 = -1, reset the memory

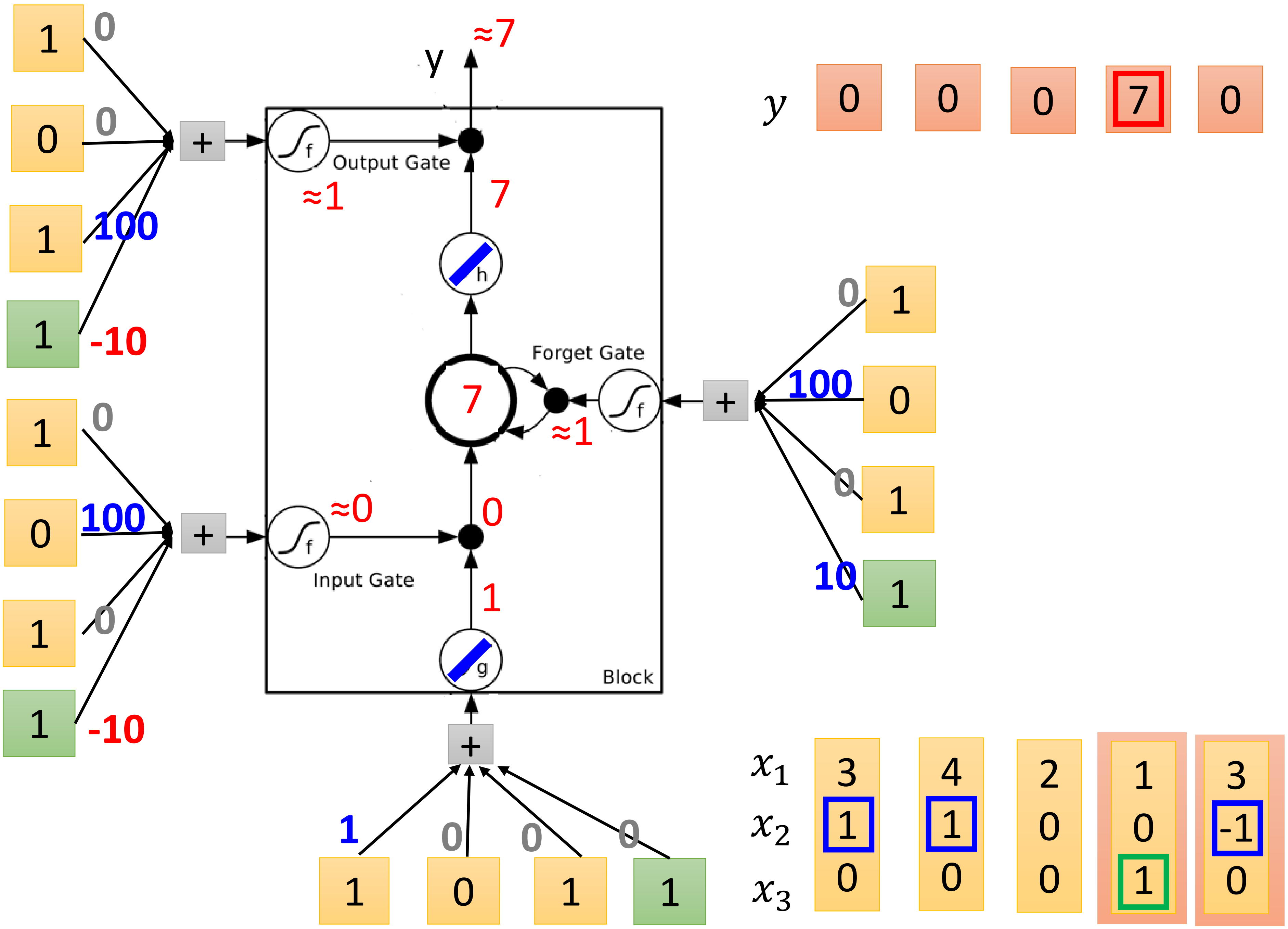
When x_3 = 1, output the number in the memory.


平常關閉，因bias<0
y
Output Gate
Forget Gate
Input Gate
Block
f
h
g
0
+
x_1
x_2
x_3
1
100
-10
平常打開，因bias>0
平常關閉，因bias<0
三個input+一個bias
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

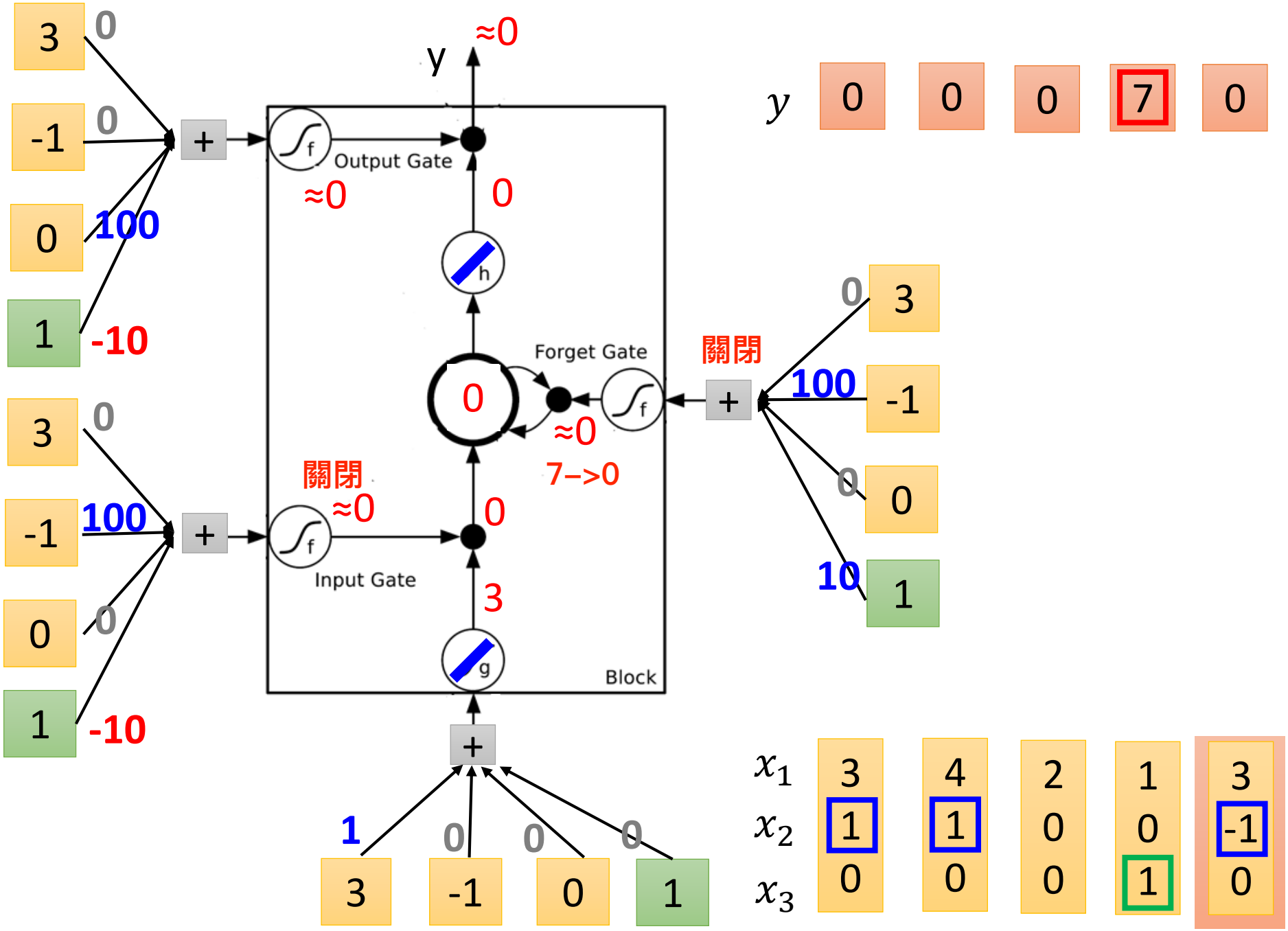

y
≈0
Output Gate
≈0
關
3
0 –> 3
Forget Gate
3
≈1
開
開
≈1
3
Input Gate
3
Block
3
0
1
100
-10
0
3
100
1
0
10
1
3
0
1
100
0
1
-10
1
0
0
0
3
1
0
1
y 0 0 0 7 0
x_1 3 4 2 1 3
x_2 1 1 0 0 -1
x_3 0 0 0 1 0


y
≈0
Output Gate
≈0
7
Forget Gate
7
≈1
Input Gate
≈1
4
4
Block
Block
4
0
1
100
0
0
1
-10
4
0
1
100
0
0
1
-10
0
4
1
100
0
0
10
1
1
0
0
0
4
1
0
1
y
0
0
0
7
0
x_1
x_2
x_3
3
1
0
4
1
0
2
0
0
1
0
1
3
-1
0


y
≈0
Output Gate
≈0
7
Forget Gate
7
≈1
Input Gate
≈0
0
2
Block
+
f
h
g
2
0
0
1
0
0
0
100
-10
0
2
0
100
0
0
1
-10
0
2
0
0
100
0
0
10
1
1
0
0
0
2
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

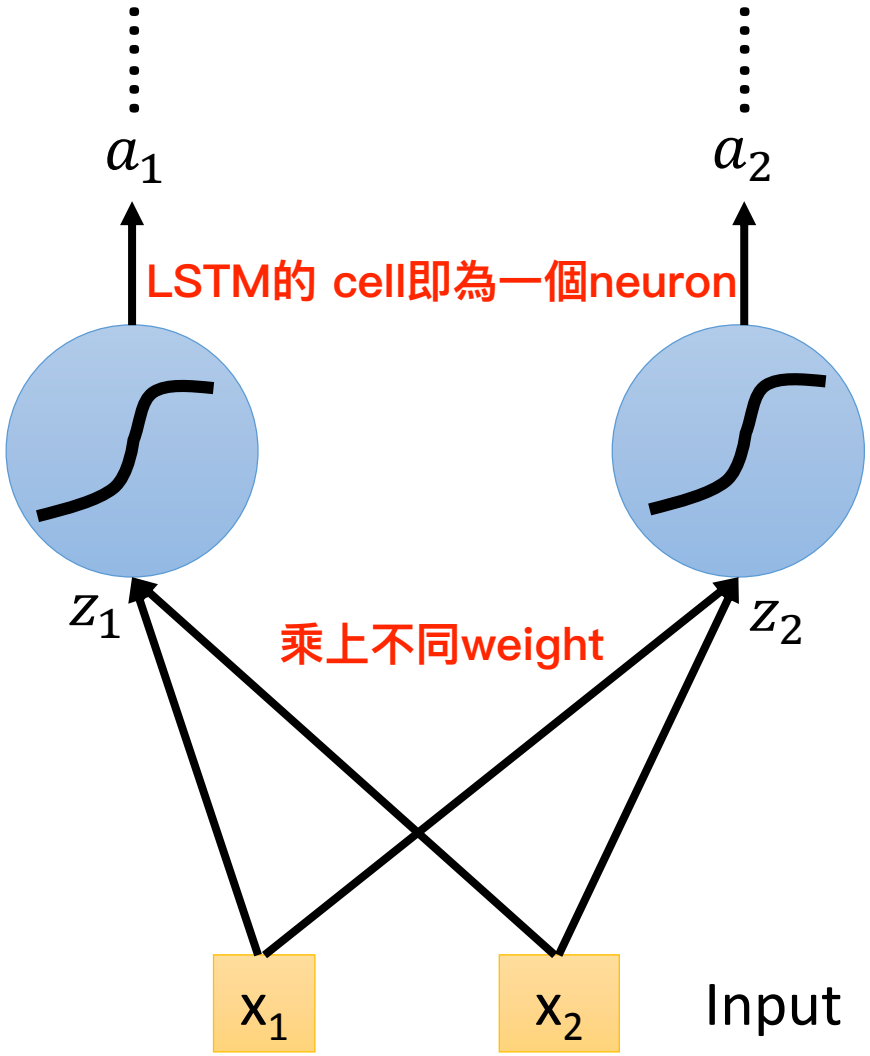


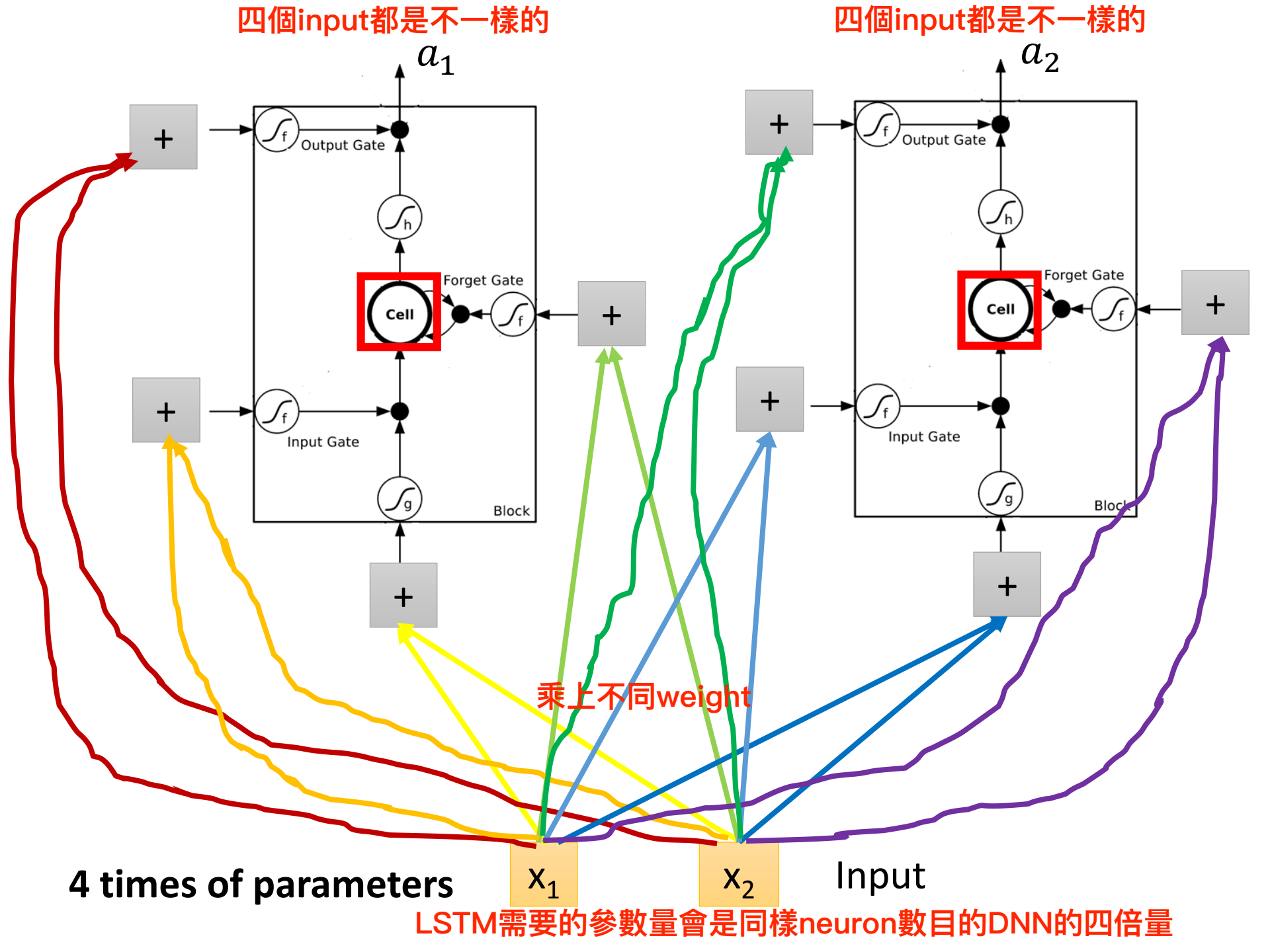
y
≈7
Output Gate
≈1
7
Forget Gate
7
≈1
≈0
0
Input Gate
1
Block
1 0
0 0
1 100
1 -10
1 0
0 100
1 0
1 -10
0 1
100 0
0 1
10 1
1 0 0 0
1 0 1 1
y 0 0 0 7 0
x_1 3 4 2 1 3
x_2 1 1 0 0 -1
x_3 0 0 0 1 0


3
-1
0
1
0
0
100
-10
+
f
Output Gate
≈0
≈0
y
≈0
0
h
Forget Gate
0
f
+
≈0
7–>0
關閉
0
3
100
-1
0
0
10
1
3
-1
0
1
0
0
100
-10
+
f
Input Gate
關閉
≈0
0
3
g
Block
+
1
0
0
0
3
-1
0
1
Block
y
0
0
0
7
0
x_1
x_2
x_3
3
1
0
4
1
0
2
0
0
1
0
1
3
-1
0

Original Network:

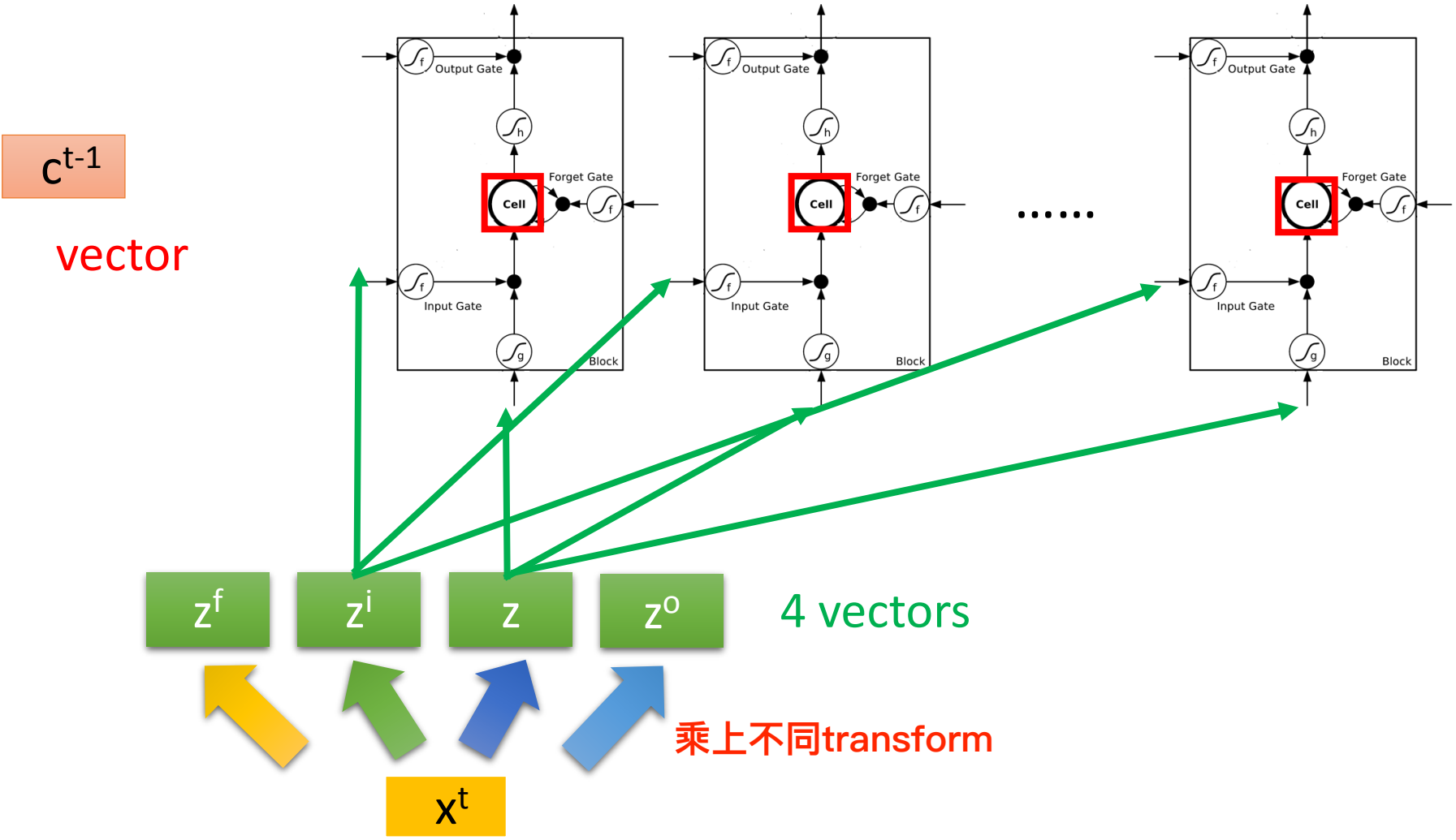
- Simply replace the neurons with LSTM



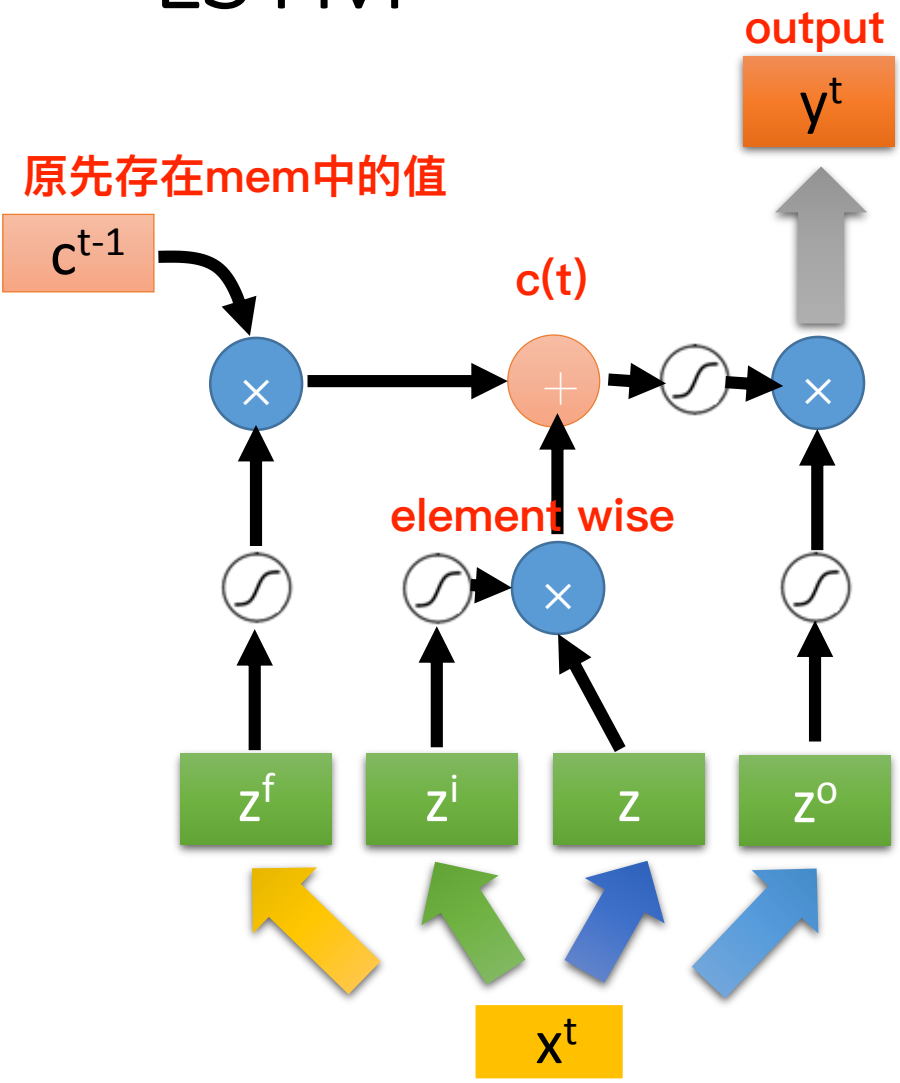

四個input都是不一樣的
四個input都是不一樣的
a_1
a_2
Output Gate
Forget Gate
Input Gate
Cell
Block
乘上不同weight
4 times of parameters
x_1
x_2
Input
LSTM需要的參數量會是同樣neuron數目的DNN的四倍量

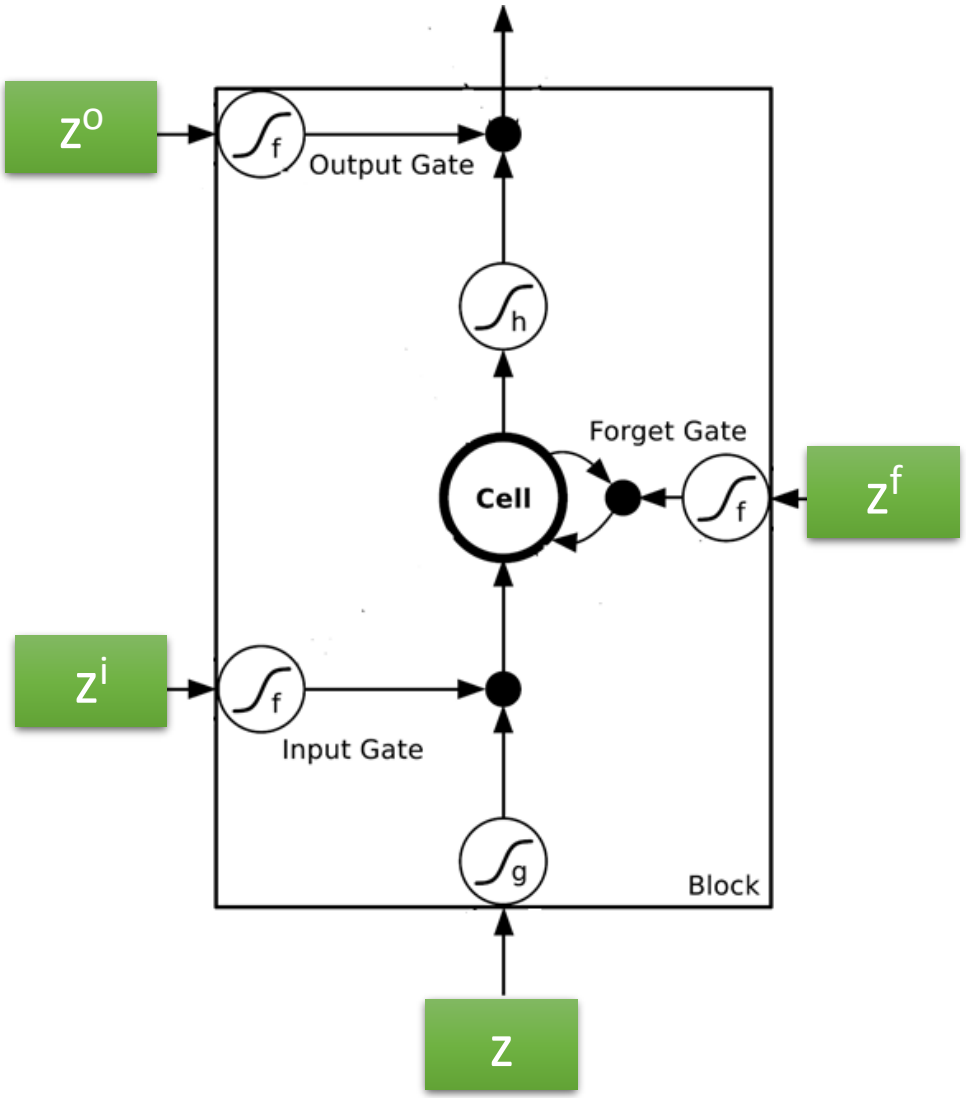
所有memory裡存的scalar代表vector （c）的一個dimension

LSTM



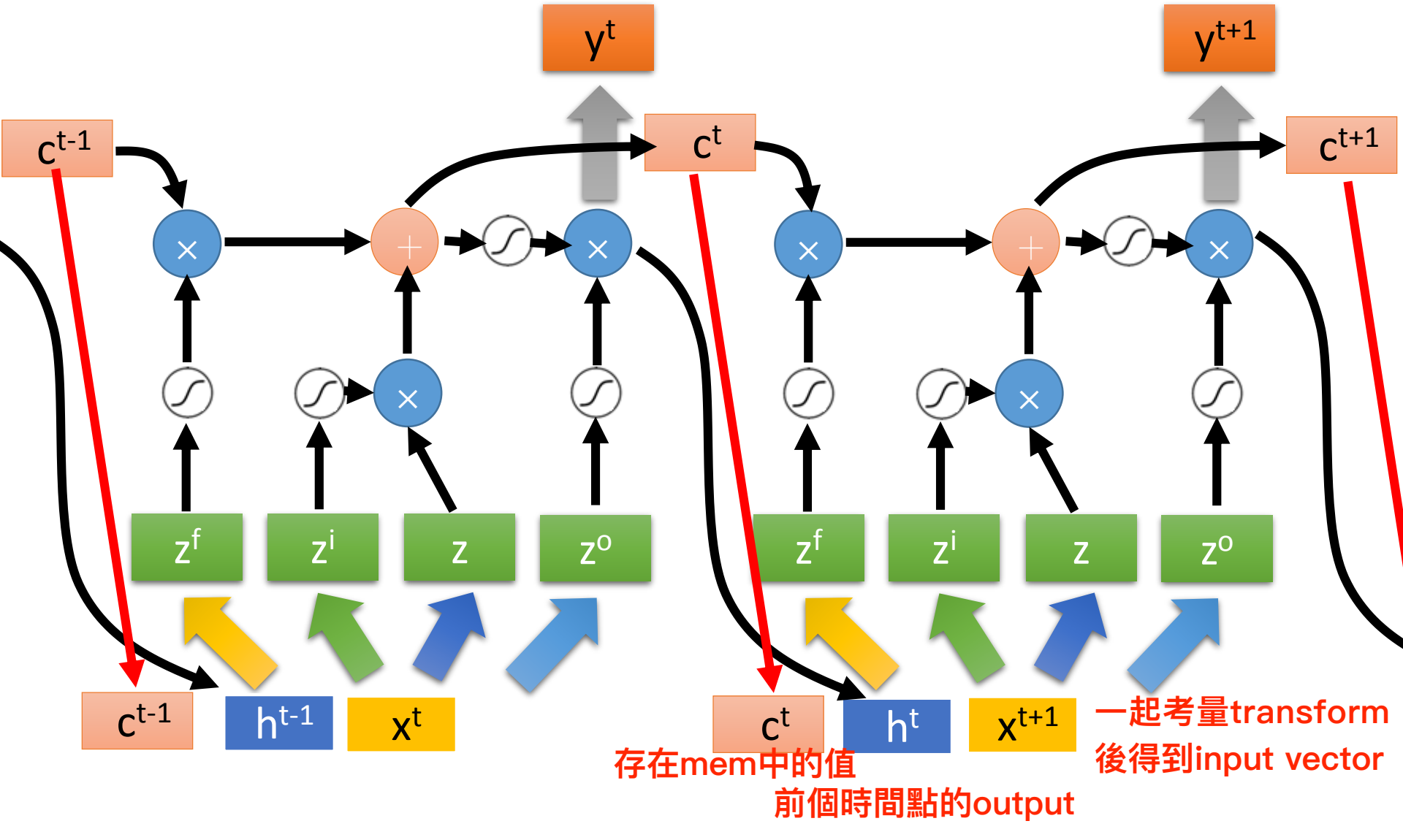
LSTM


output
y^t
原先存在mem中的值
c^{t-1}
c(t)
element wise
z^f
z^i
z
z^o
x^t


z^o
Output Gate
h
Forget Gate
Cell
z^f
z^i
Input Gate
g
Block
z

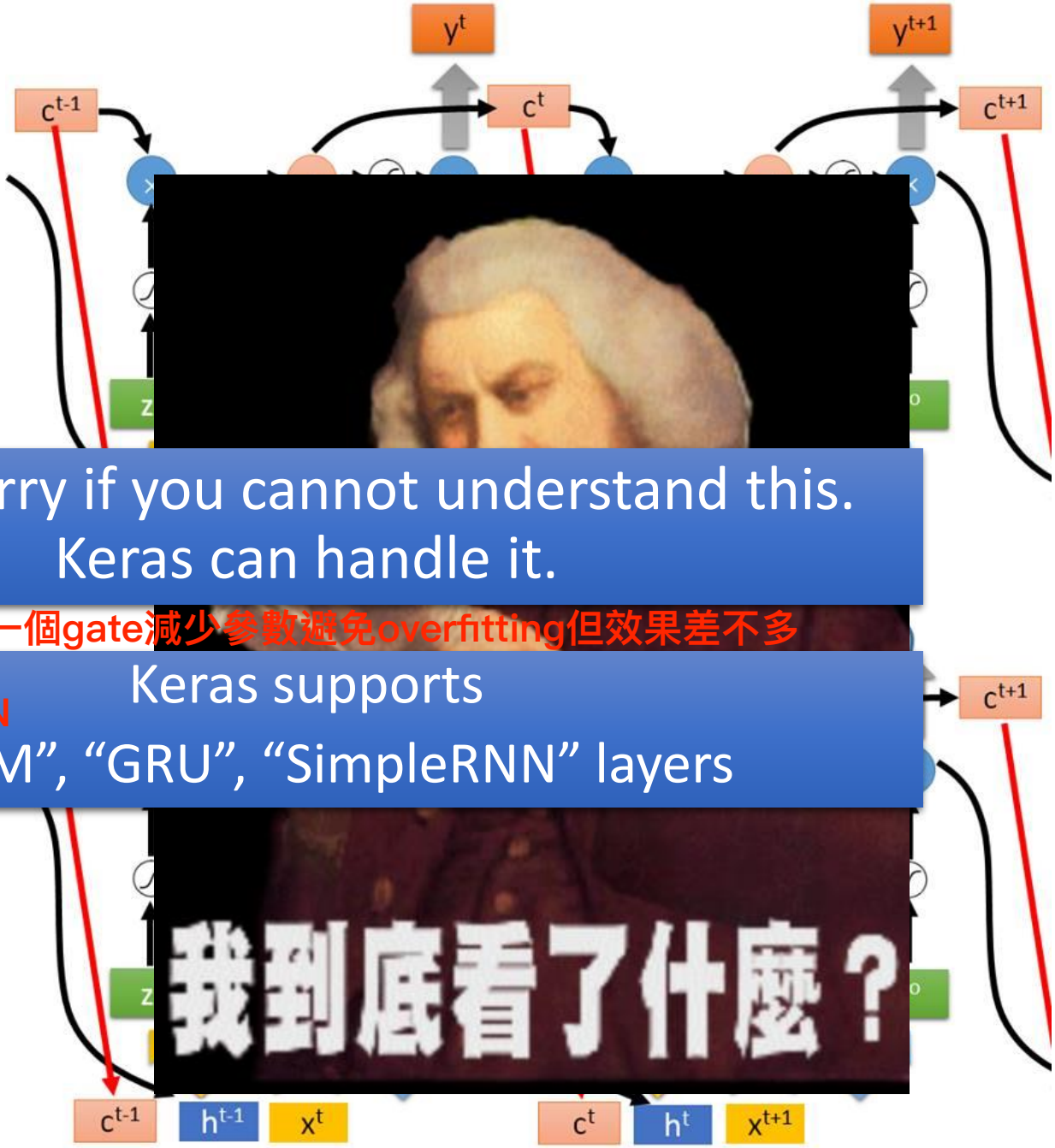
LSTM

Extension: “peephole”



Multiple-layer LSTM

ＲＮＮ現在已經被認為standard為LSTM



Don’t worry if you cannot understand this.
Keras can handle it.

GRU為LSTM簡化版，少了一個gate減少參數避免overfitting但效果差不多

Keras supports
“LSTM”, “GRU”, “SimpleRNN” layers

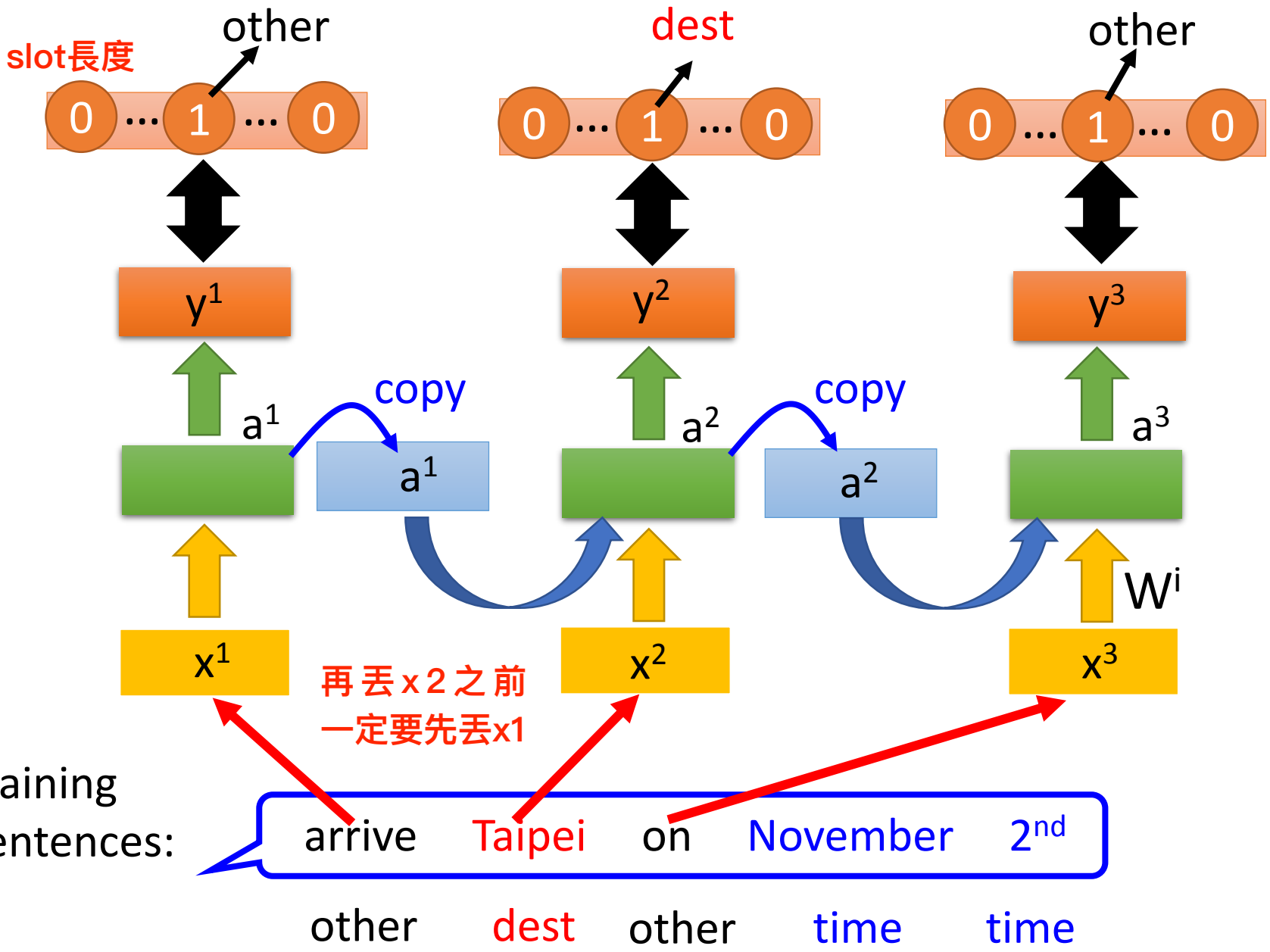
RNN

This is quite standard now.

https://img.komicolle.org/2015-09-20/src/14426967627131.gif

Learning Target

在做training時不可以把word打散來看

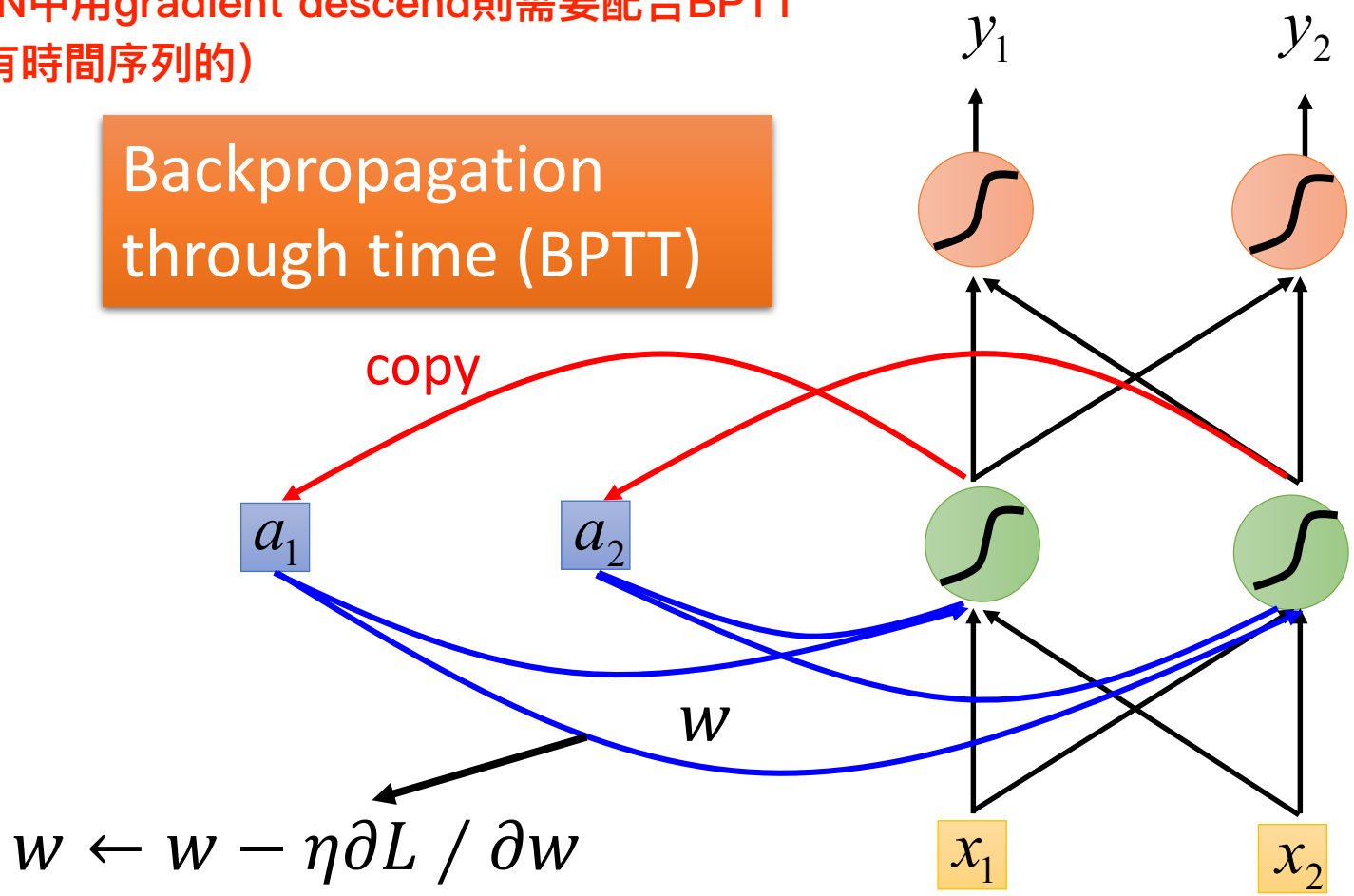


在feedforward的neural network中使用gradient descend要配合back propagation

Learning

RNN中用gradient descend則需要配合BPTT
（有時間序列的）

Backpropagation through time (BPTT)

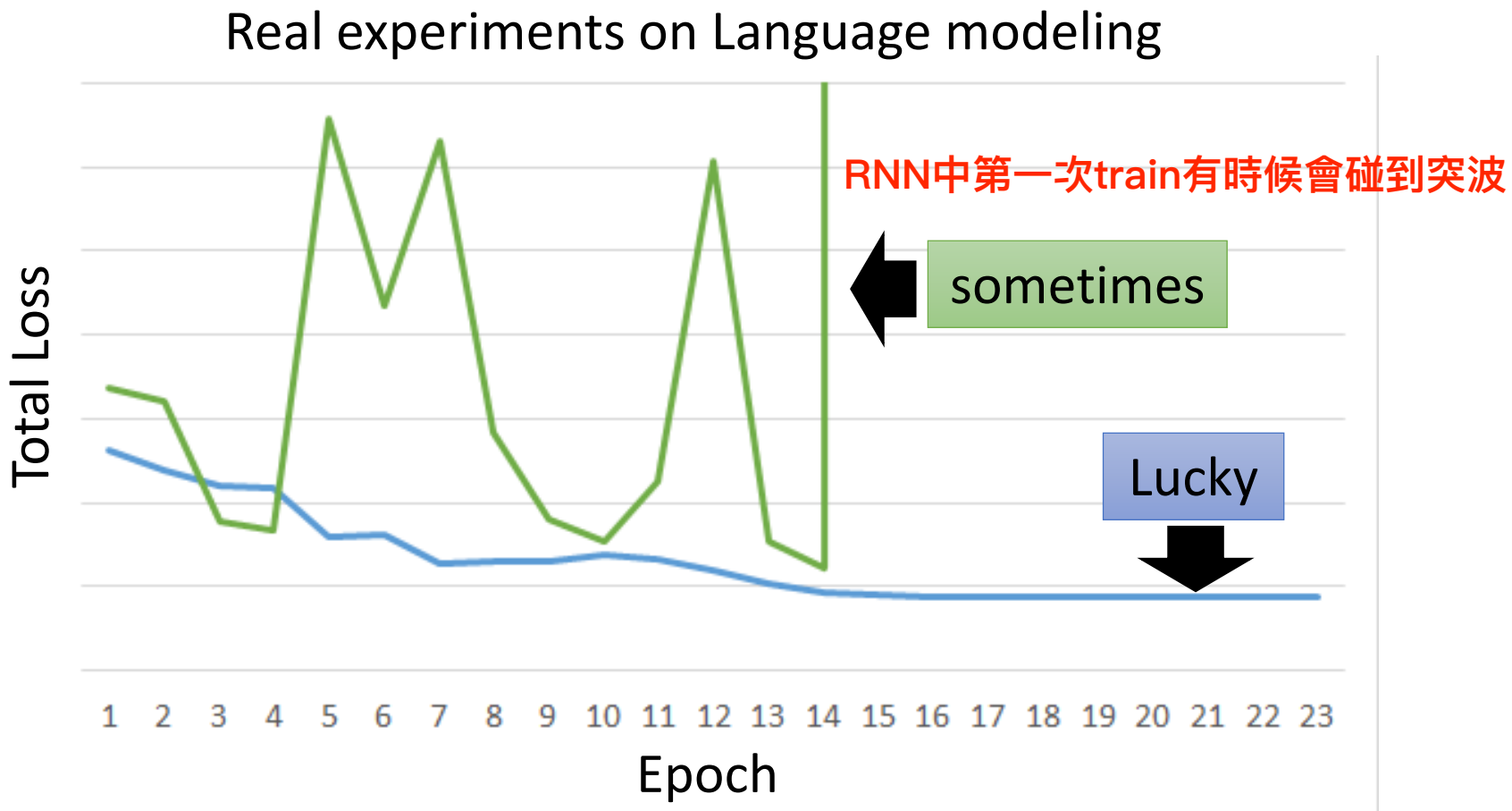


$$w \leftarrow w - \eta \partial L / \partial w$$

感謝 曾柏翔 同學
提供實驗結果

Unfortunately ……

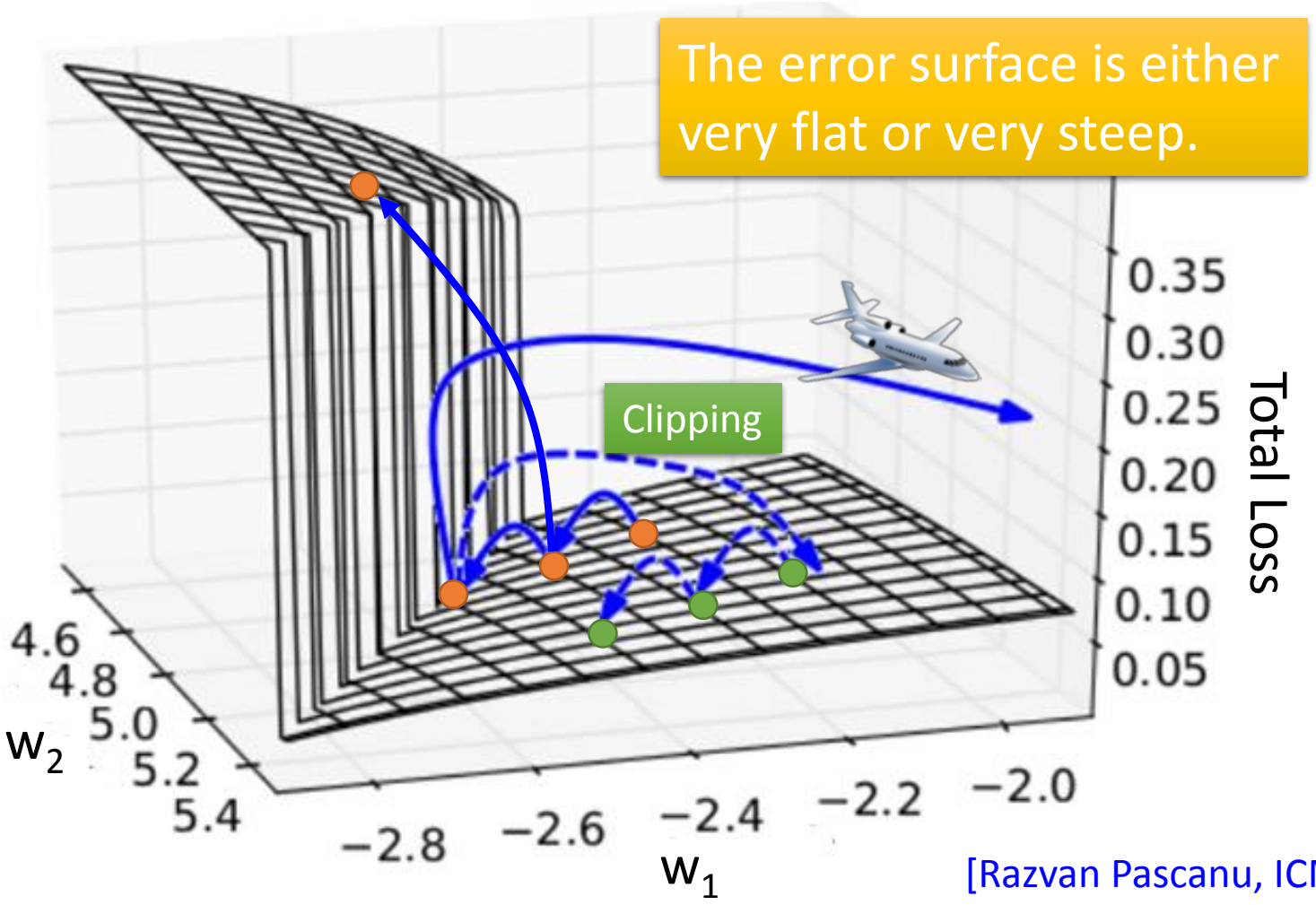
- RNN-based network is not always easy to learn



有時候會一腳踩在懸堐上，因此gradiant太大，再加上learning rate大，一乘的結果就會overflow(NaN)，因此需要做clipping（設天花板threshold）

The error surface is rough.

RNN對參數調整的error surface是很陡峭的



[Razvan Pascanu, ICML'13]

RNN的gradient忽大忽小！！

Why?

w只提升一點點但最後上升很大

$w = 1 \Rightarrow y^{1000} = 1$

$w = 1.01 \Rightarrow y^{1000} \approx 20000$

Large $\partial L/\partial w$ → Small Learning rate?

$w = 0.99 \Rightarrow y^{1000} \approx 0$

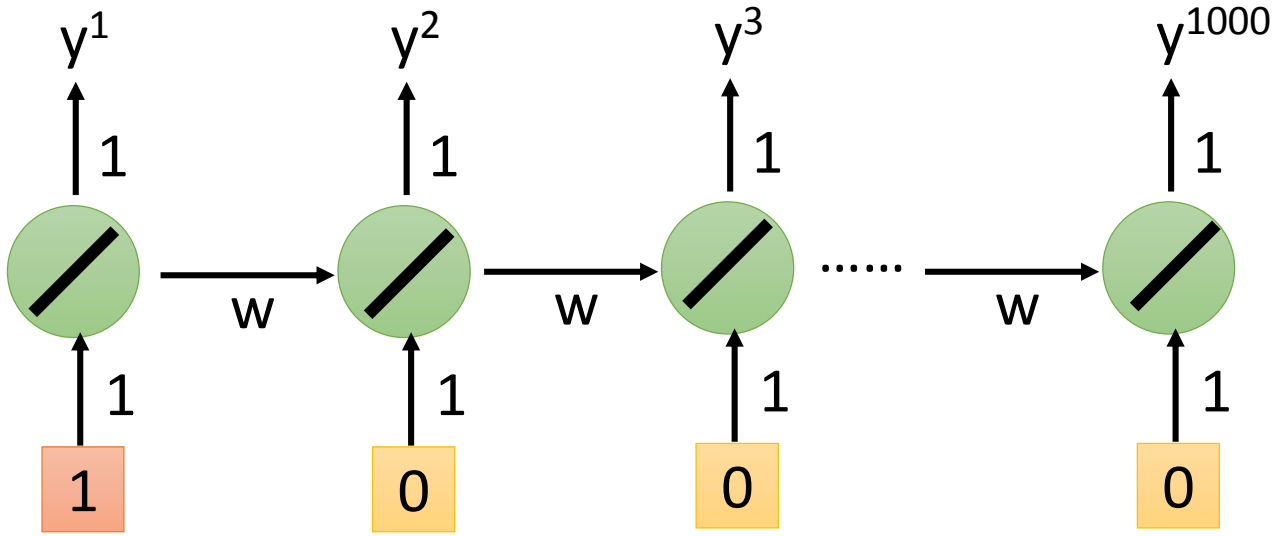
$w = 0.01 \Rightarrow y^{1000} \approx 0$

small $\partial L/\partial w$ → Large Learning rate?

w<0則最後會趨近於零

=w^{999}

Toy Example



可以讓error surface不會有特別平緩的地方，因此其gradient都很大，可以將learning rate放心的調小

在LSTM中，會影響到mem的值會一直被留在裡面除非forget Gate被使用，因此可避免gradiant vanish問題

Helpful Techniques

在RNN裡面每個時間點mem都會被洗掉重新覆蓋新的值

- Long Short-term Memory (LSTM)

但過度陡峭仍無法避免

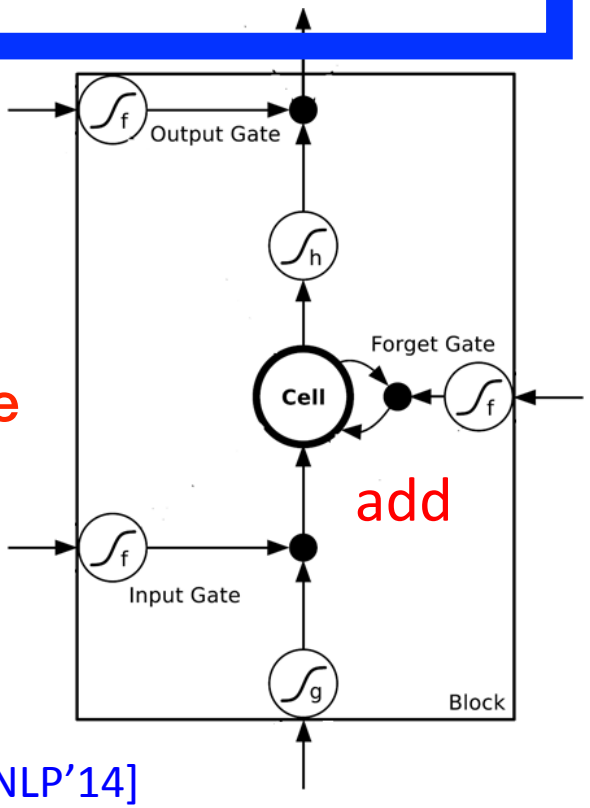
Can deal with gradient vanishing (not gradient explode)

- Memory and input are ***added***
- The influence never disappears unless forget gate is closed

GRU只有兩個gate: reset gate以及update date

→ No Gradient vanishing (If forget gate is opened.)

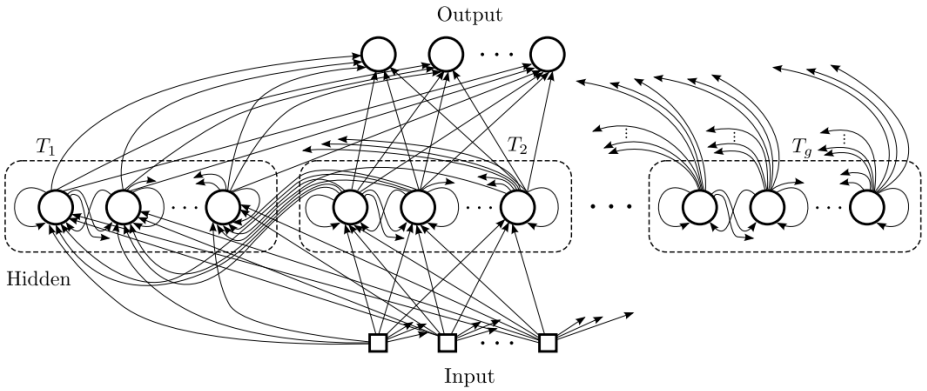
Gated Recurrent Unit (GRU): simpler than LSTM



[Cho, EMNLP'14]

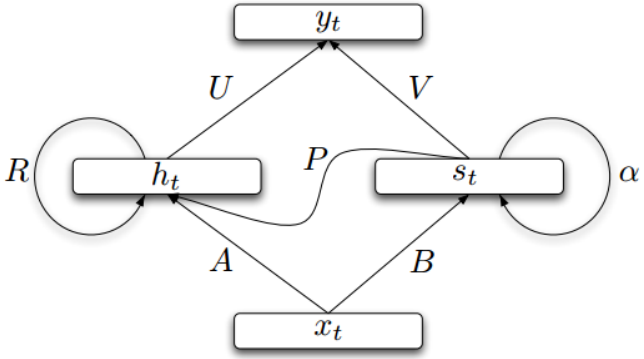
Helpful Techniques

Clockwise RNN



[Jan Koutnik, JMLR'14]

Structurally Constrained Recurrent Network (SCRN)



[Tomas Mikolov, ICLR'15]

initial weight (random) 用sigmoid比較好

Vanilla RNN Initialized with Identity matrix + ReLU activation function [Quoc V. Le, arXiv'15]

initial weight (identity) 用ReLU比較好

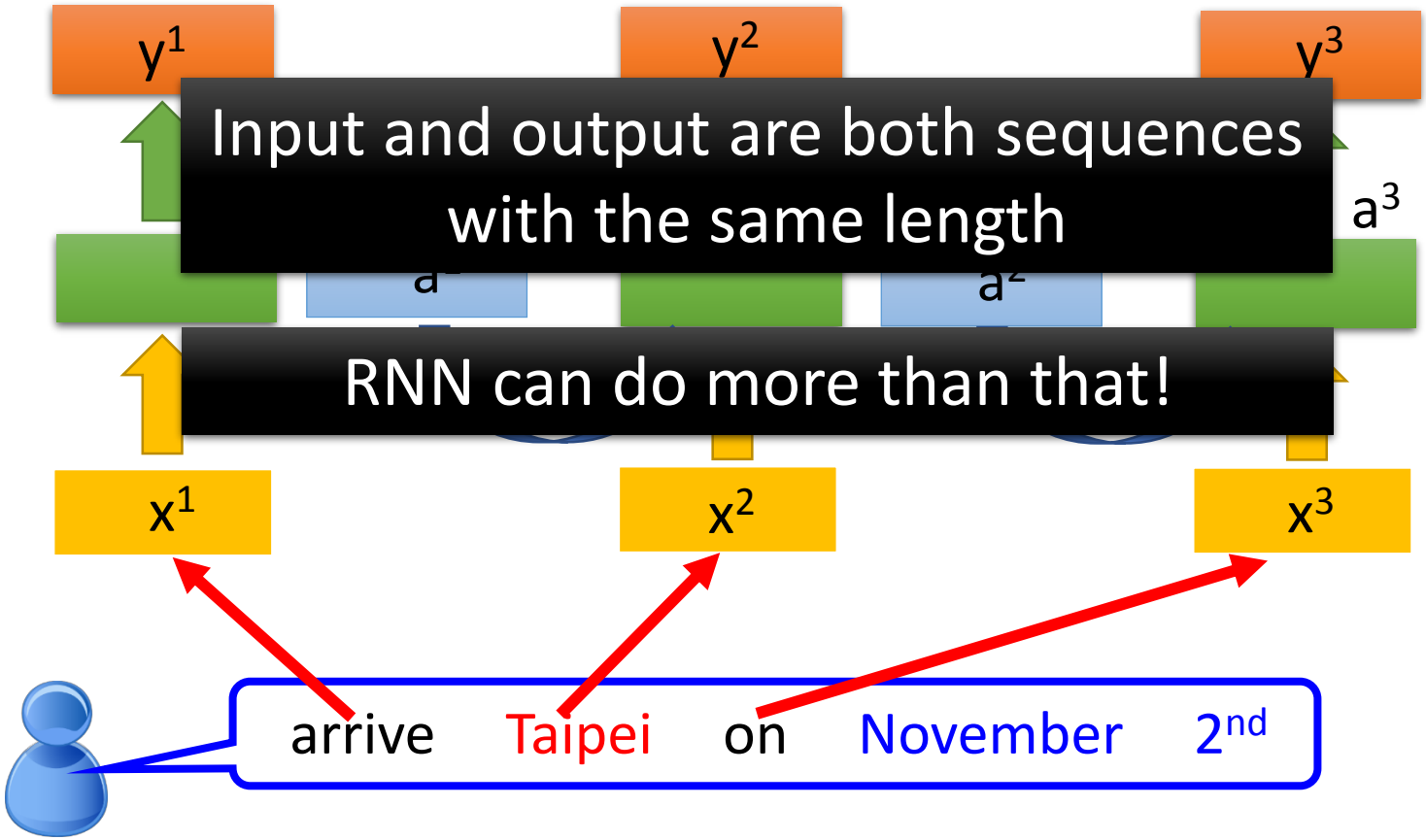
- Outperform or be comparable with LSTM in 4 different tasks

More Applications ……

Probability of "arrive" in each slot

Probability of "Taipei" in each slot

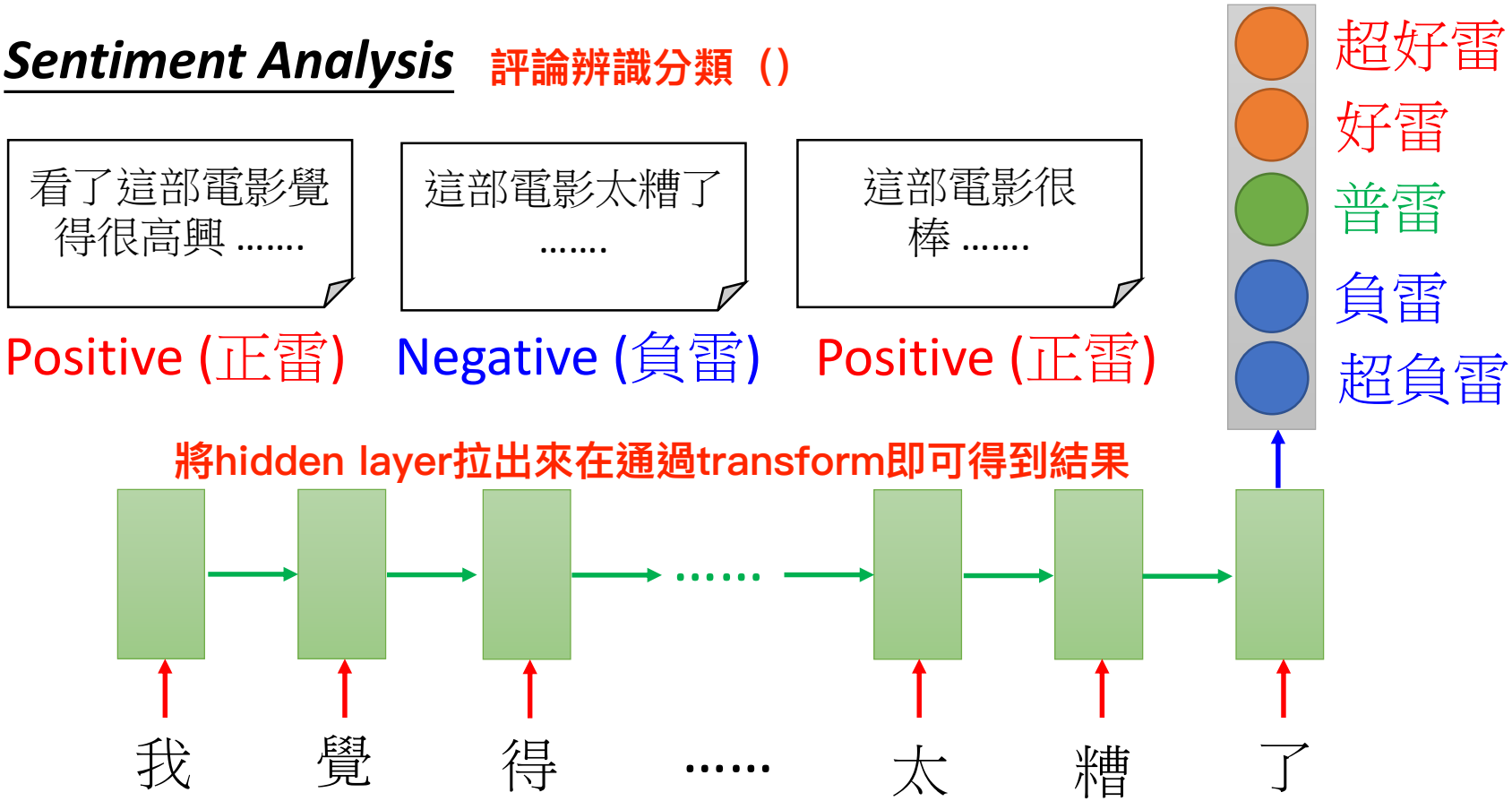
Probability of "on" in each slot



Many to one

input: character sequence, output: vector

- Input is a vector sequence, but output is only one vector



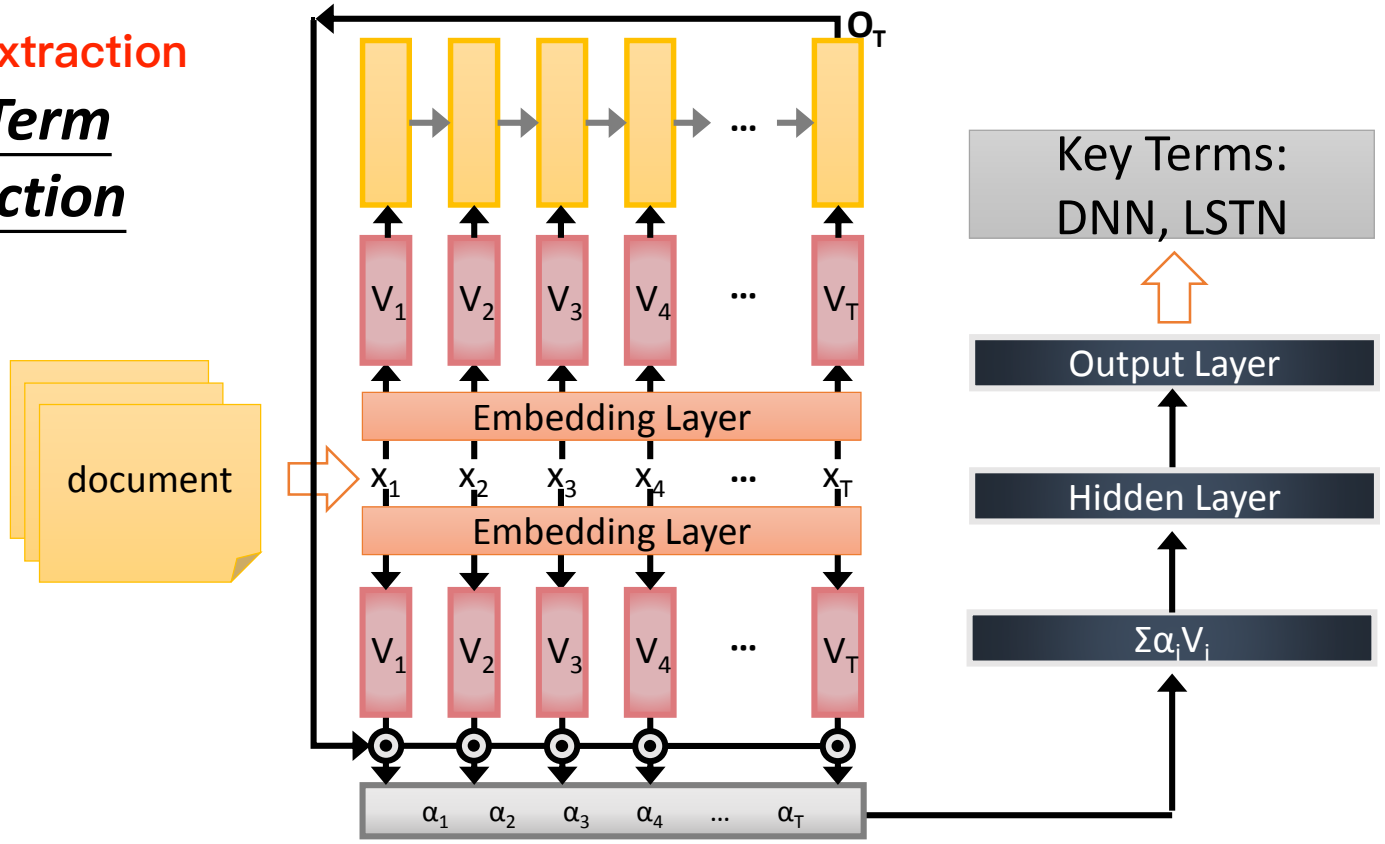
Many to one

[Shen & Lee, Interspeech 16]

- Input is a vector sequence, but output is only one vector

feature extraction

Key Term Extraction



Many to Many (Output is shorter)

input sequence長，output sequence短

- Both input and output are both sequences, ***but the output is shorter.***
  - E.g. ***Speech Recognition***

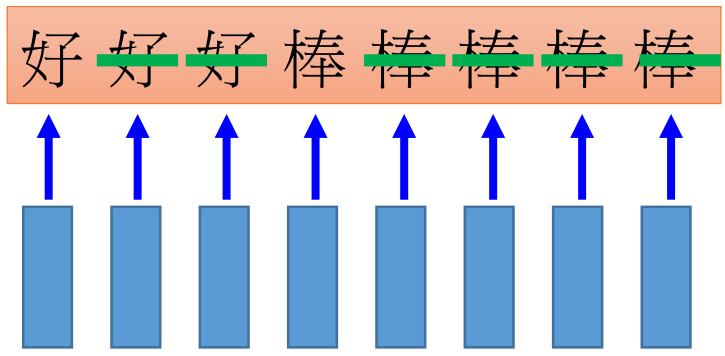
Output: “好棒” (character sequence)

Trimming

去掉重複的結果

Problem?

Why can’t it be “好棒棒”



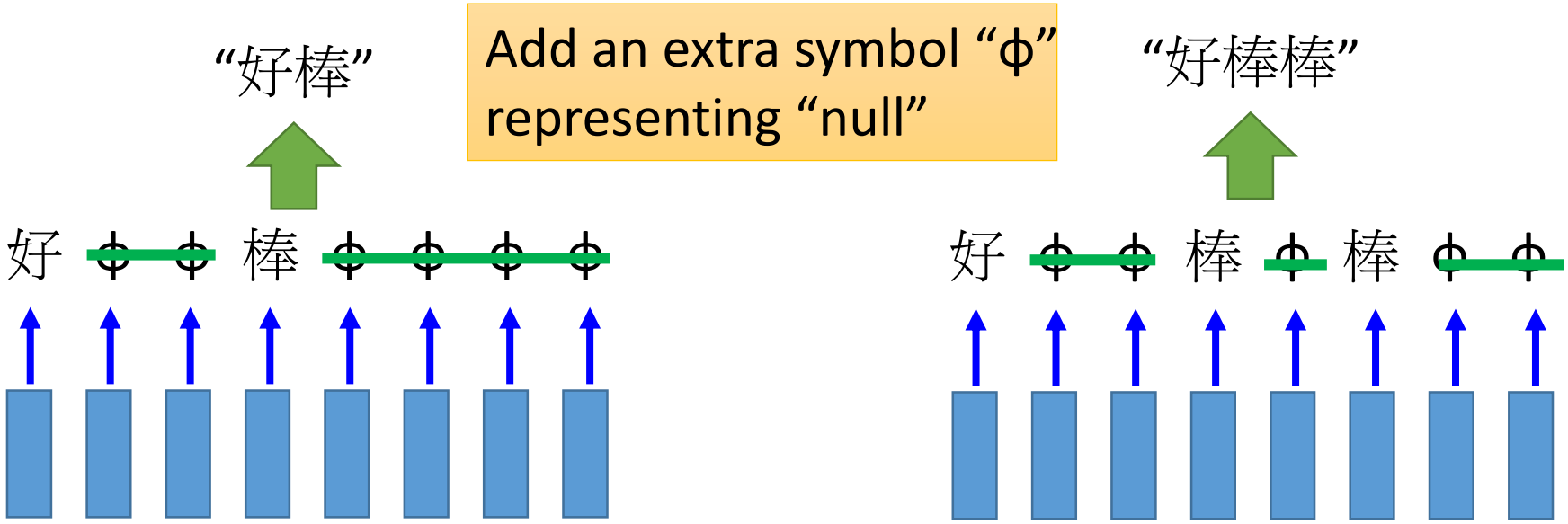
Input: (vector sequence)

但有些字詞做了trimming會改變意思
因此需要做區分

Many to Many (Output is shorter)

- Both input and output are both sequences, ***but the output is shorter.***
- Connectionist Temporal Classification (CTC) [Alex Graves, ICML'06][Alex Graves, ICML'14][Haşim Sak, Interspeech'15][Jie Li, Interspeech'15][Andrew Senior, ASRU'15]

output不只characters，也包含null符號，可解決疊字問題



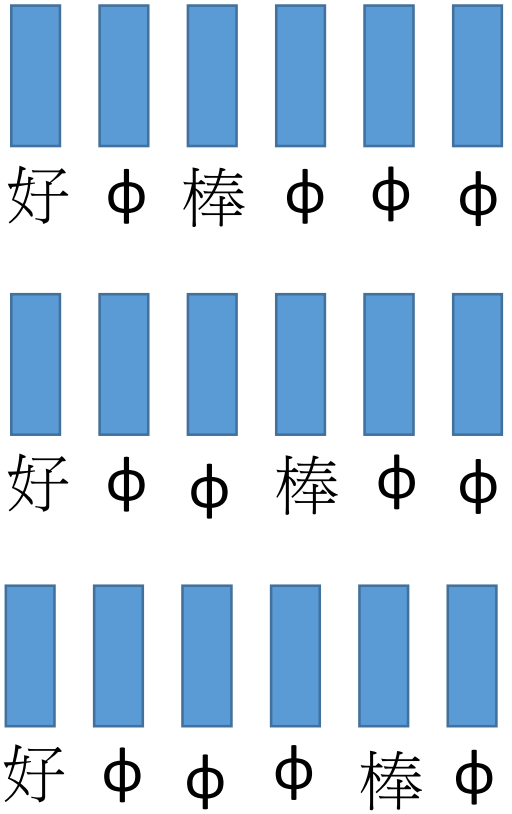
Many to Many (Output is shorter)

- CTC: Training

Acoustic Features:

Label: 好 棒

All possible alignments are considered as correct.



不知道哪幾個frame對應到哪個字詞，因此窮舉所有可能性
有巧妙的演算法可解決複雜性太高的問題

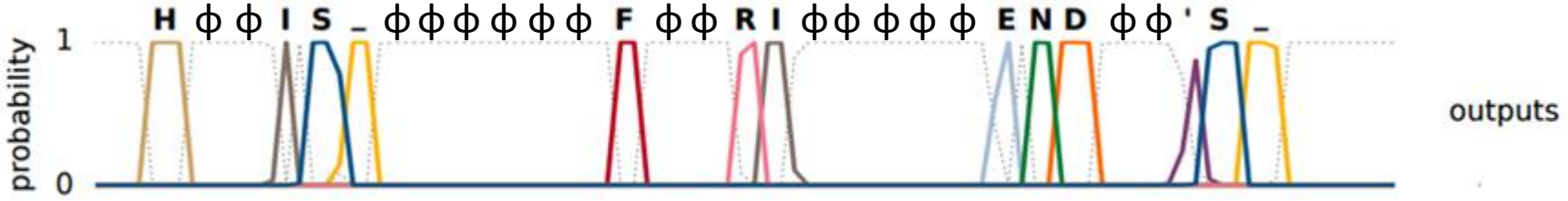
Many to Many (Output is shorter)

google 現在都用這個做語音辨識

- CTC: example

利用null以及空白，使機器有機會
output出從來沒看過的詞彙

HIS FRIEND'S



Graves, Alex, and Navdeep Jaitly. "Towards end-to-end speech recognition with recurrent neural networks." *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*. 2014.

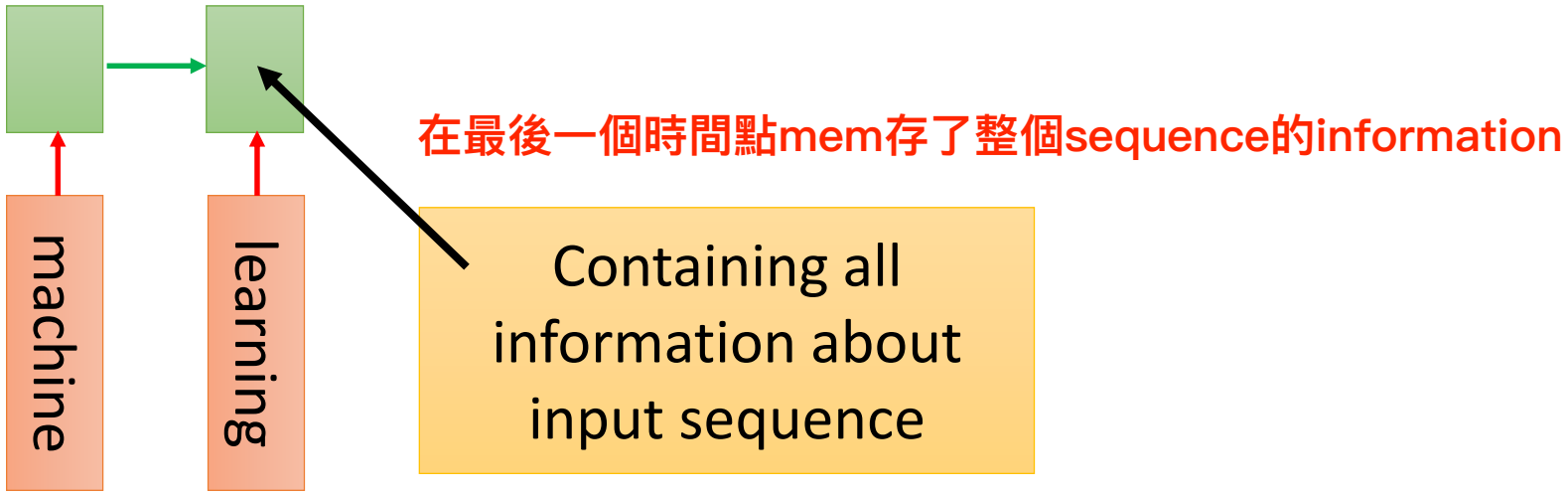
Many to Many (No Limitation)

input/output sequence長度不同

- Both input and output are both sequences ***with different lengths***. → ***Sequence to sequence learning***
  - E.g. ***Machine Translation*** (machine learning→機器學習)

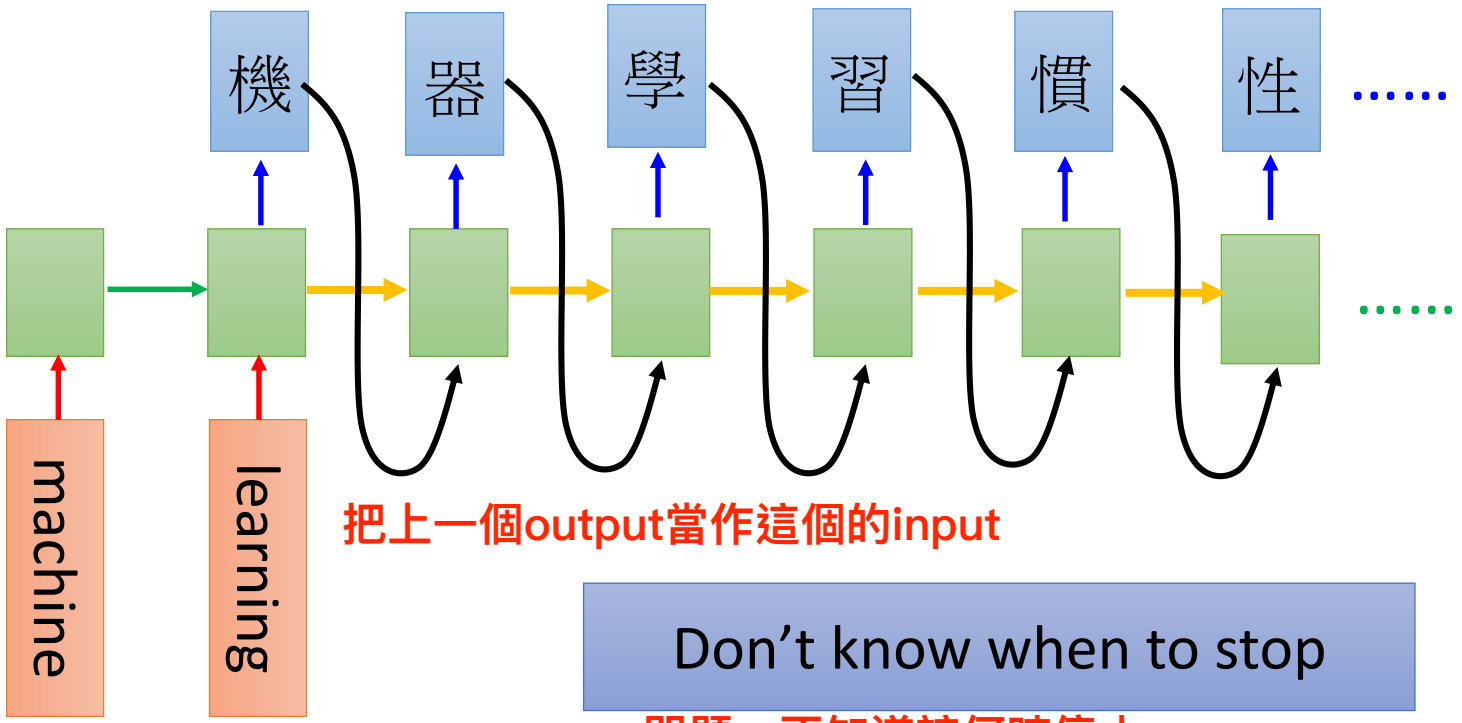
我們不知道input/output誰比較長

RNN

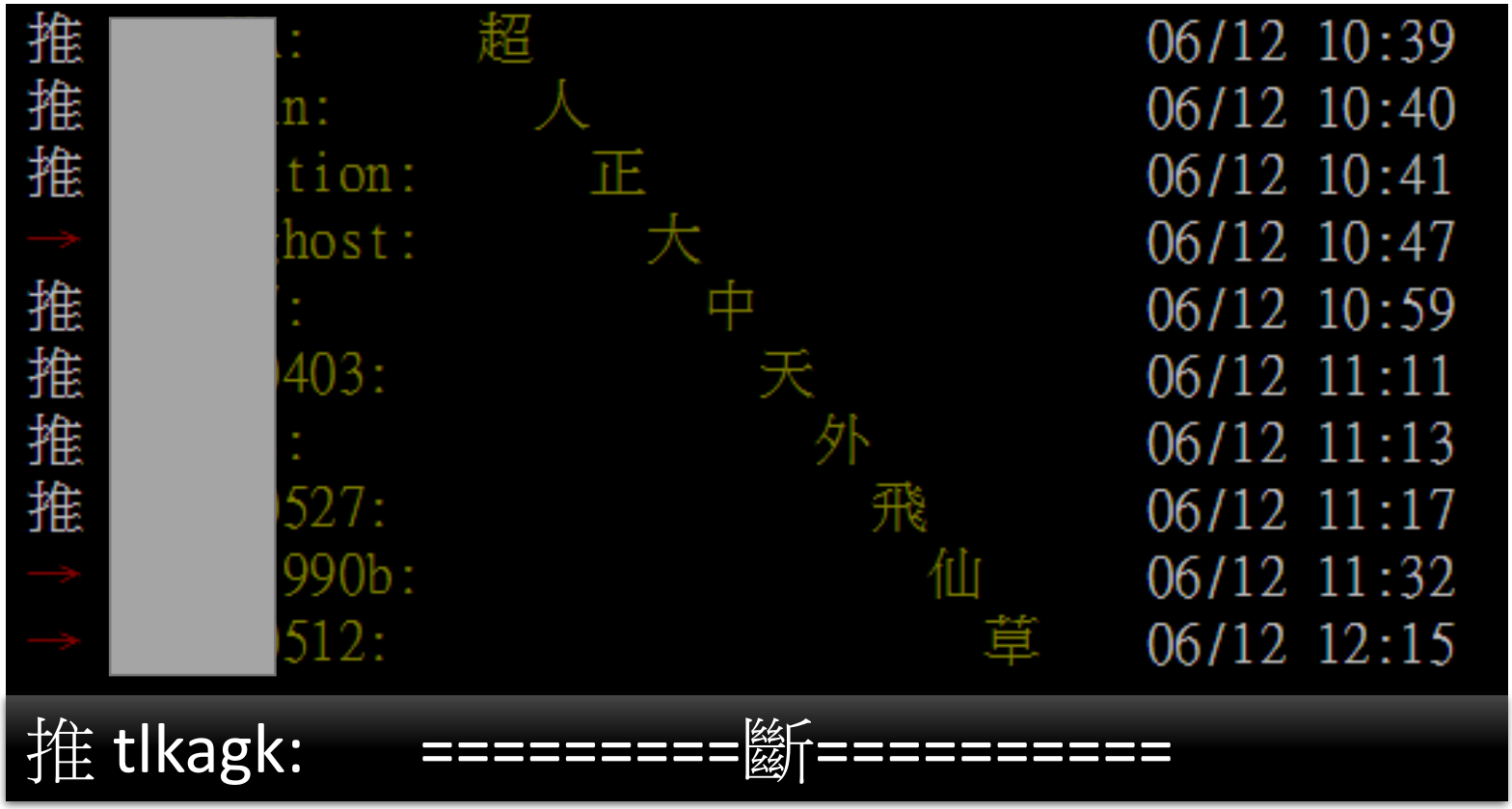


Many to Many (No Limitation)

- Both input and output are both sequences ***with different lengths***. → ***Sequence to sequence learning***
  - E.g. ***Machine Translation*** (machine learning→機器學習)



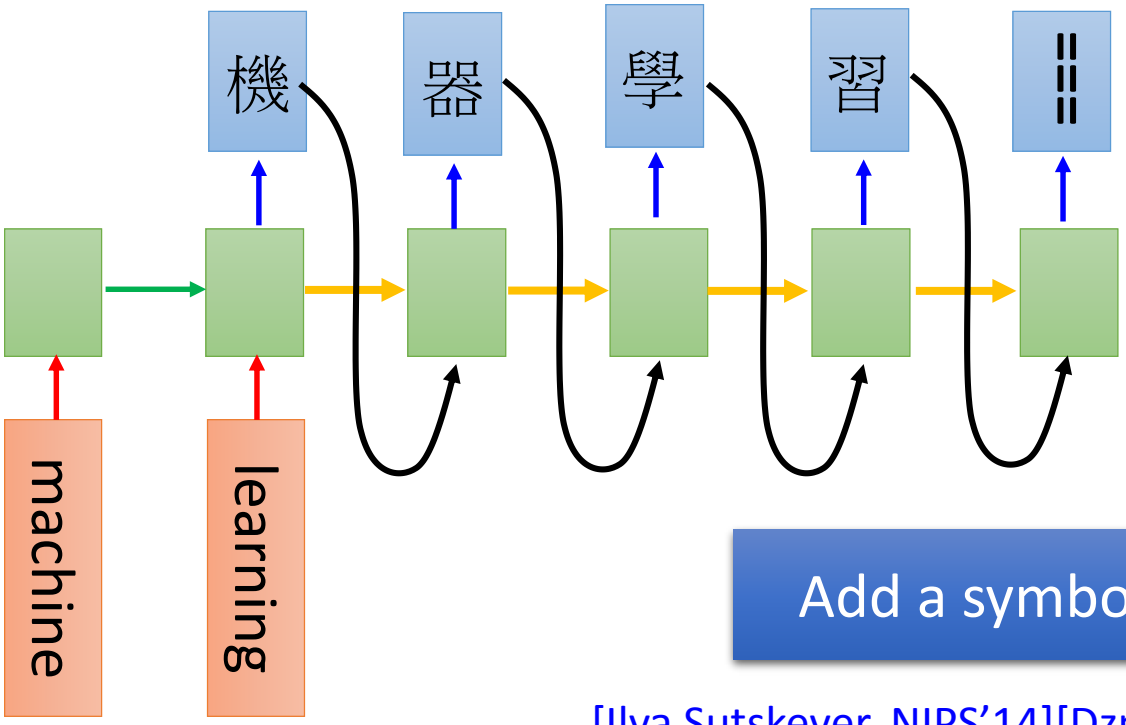
Many to Many (No Limitation)



接龍推文是ptt在推文中的一種趣味玩法，與推齊有些類似但又有所不同，是指在推文中接續上一樓的字句，而推出連續的意思。該類玩法確切起源已不可知(鄉民百科)

Many to Many (No Limitation)

- Both input and output are both sequences ***with different lengths***. → ***Sequence to sequence learning***
  - E.g. ***Machine Translation*** (machine learning→機器學習)



Add a symbol "===" (斷)

[Ilya Sutskever, NIPS'14][Dzmitry Bahdanau, arXiv'15]

https://arxiv.org/pdf/1612.01744v1.pdf

Many to Many (No Limitation)

- Both input and output are both sequences ***with different lengths***. → ***Sequence to sequence learning***
  - E.g. ***Machine Translation*** (machine learning→機器學習)

(a) Machine translation alignment

(b) Speech translation alignment

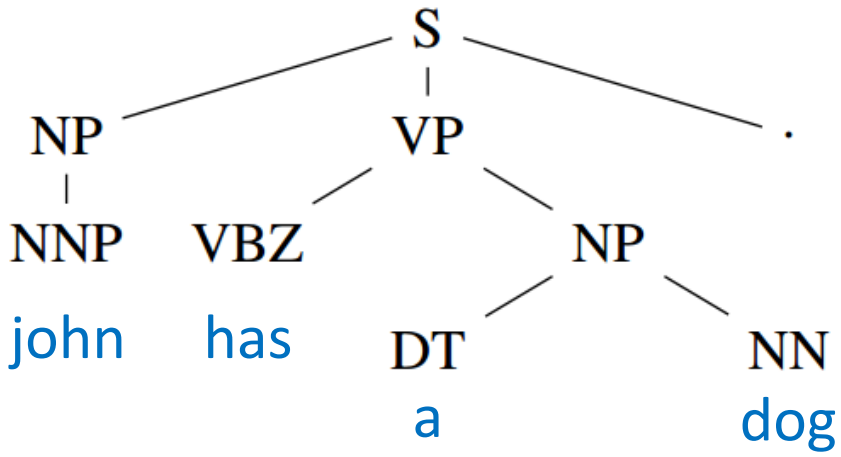
Figure 1: Alignments performed by the attention model during training

Beyond Sequence

- Syntactic parsing

讓machine看完句子後得到一個文法的結構樹狀圖

John has a dog . →

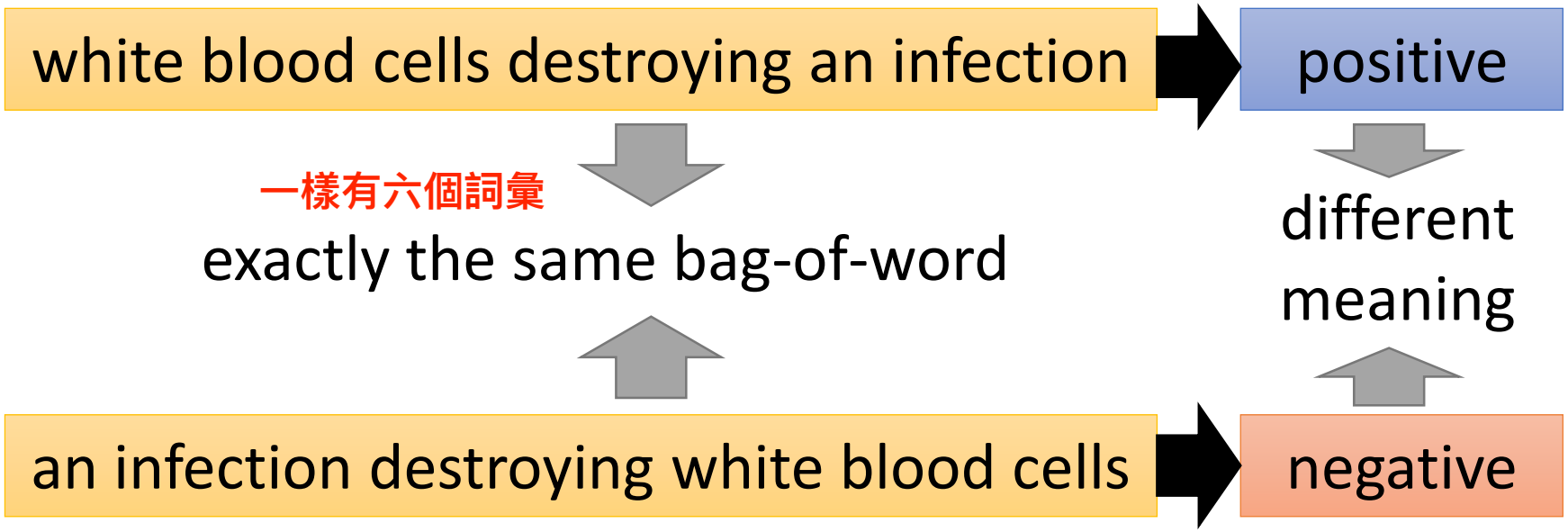


John has a dog . → (S (NP NNP)$_{NP}$ (VP VBZ (NP DT NN)$_{NP}$)$_{VP}$.)$_{S}$

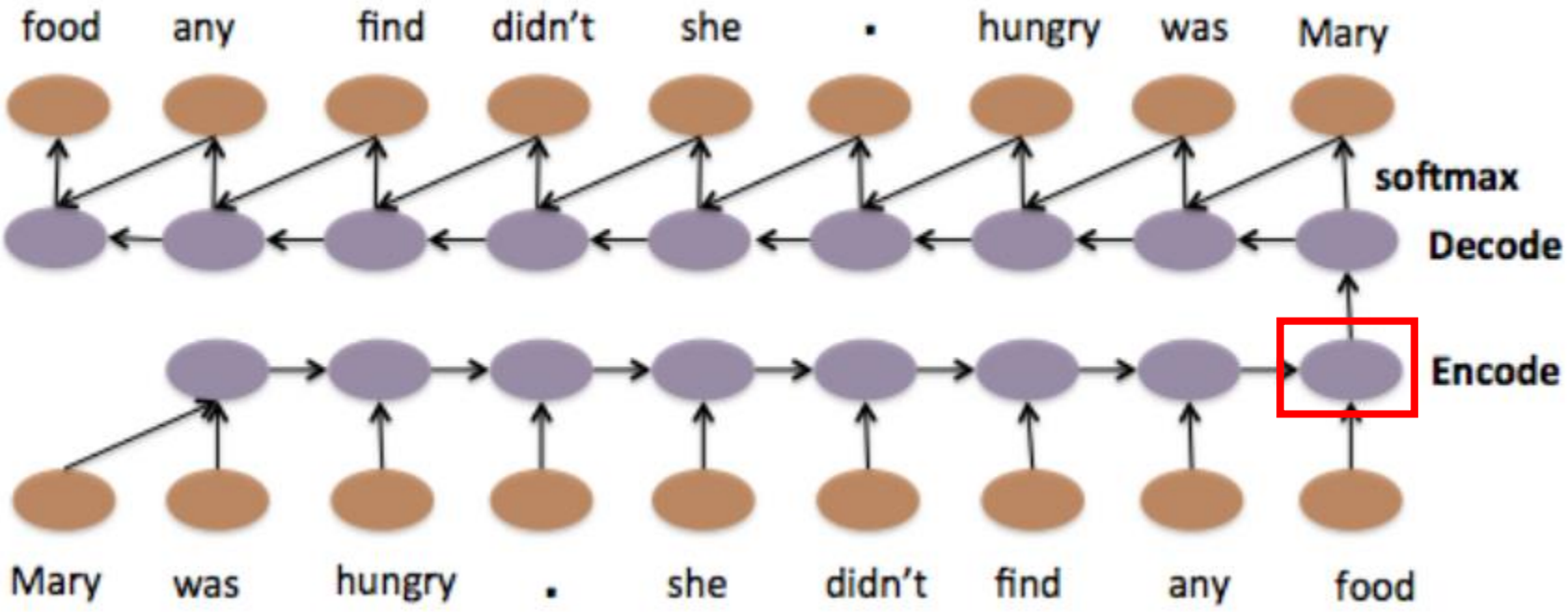
Oriol Vinyals, Lukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, Geoffrey Hinton, Grammar as a Foreign Language, NIPS 2015

Sequence-to-sequence Auto-encoder - Text

- To understand the meaning of a word sequence, the order of the words can not be ignored.

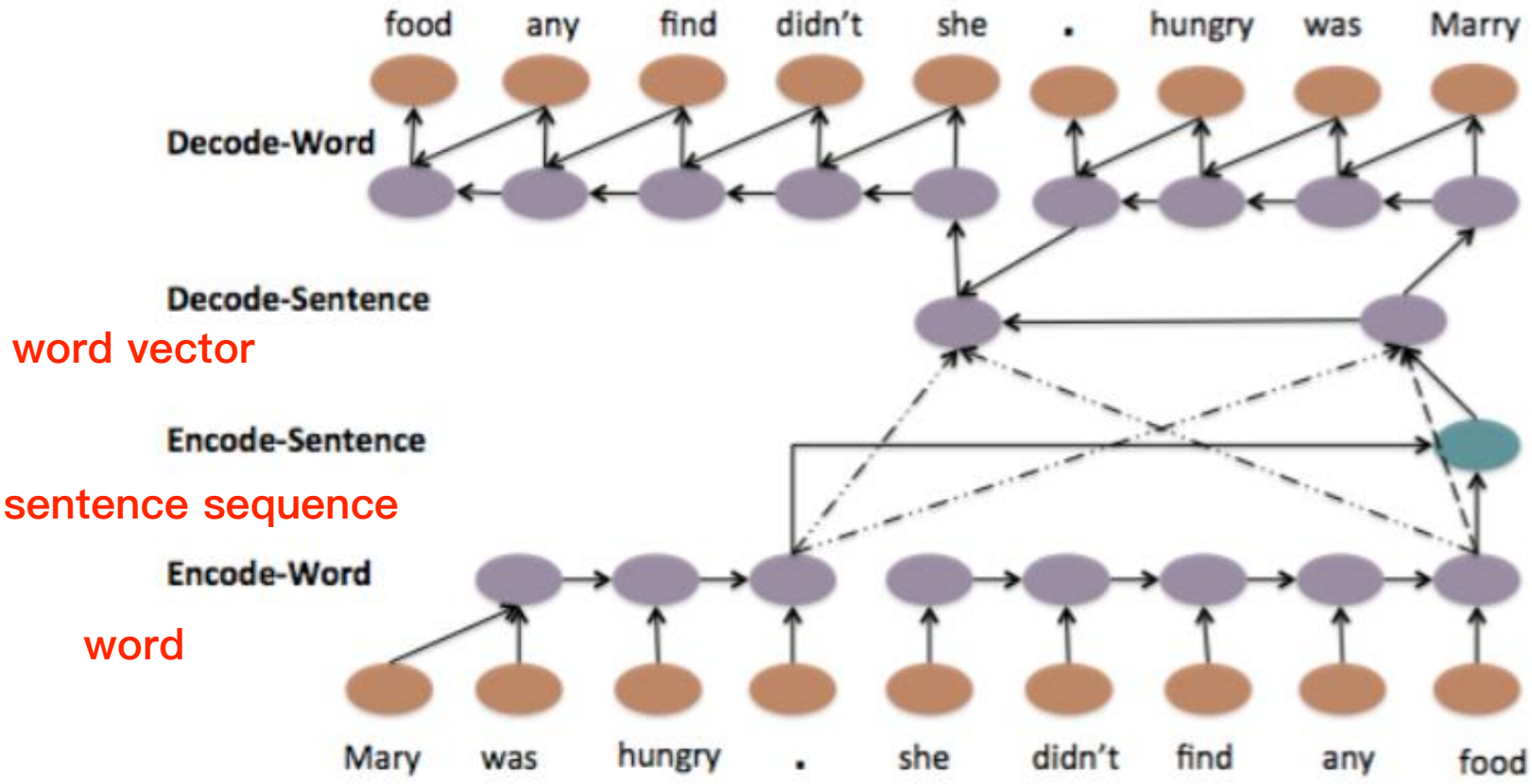


Sequence-to-sequence Auto-encoder - Text



Li, Jiwei, Minh-Thang Luong, and Dan Jurafsky. "A hierarchical neural autoencoder for paragraphs and documents." *arXiv preprint arXiv:1506.01057*(2015).

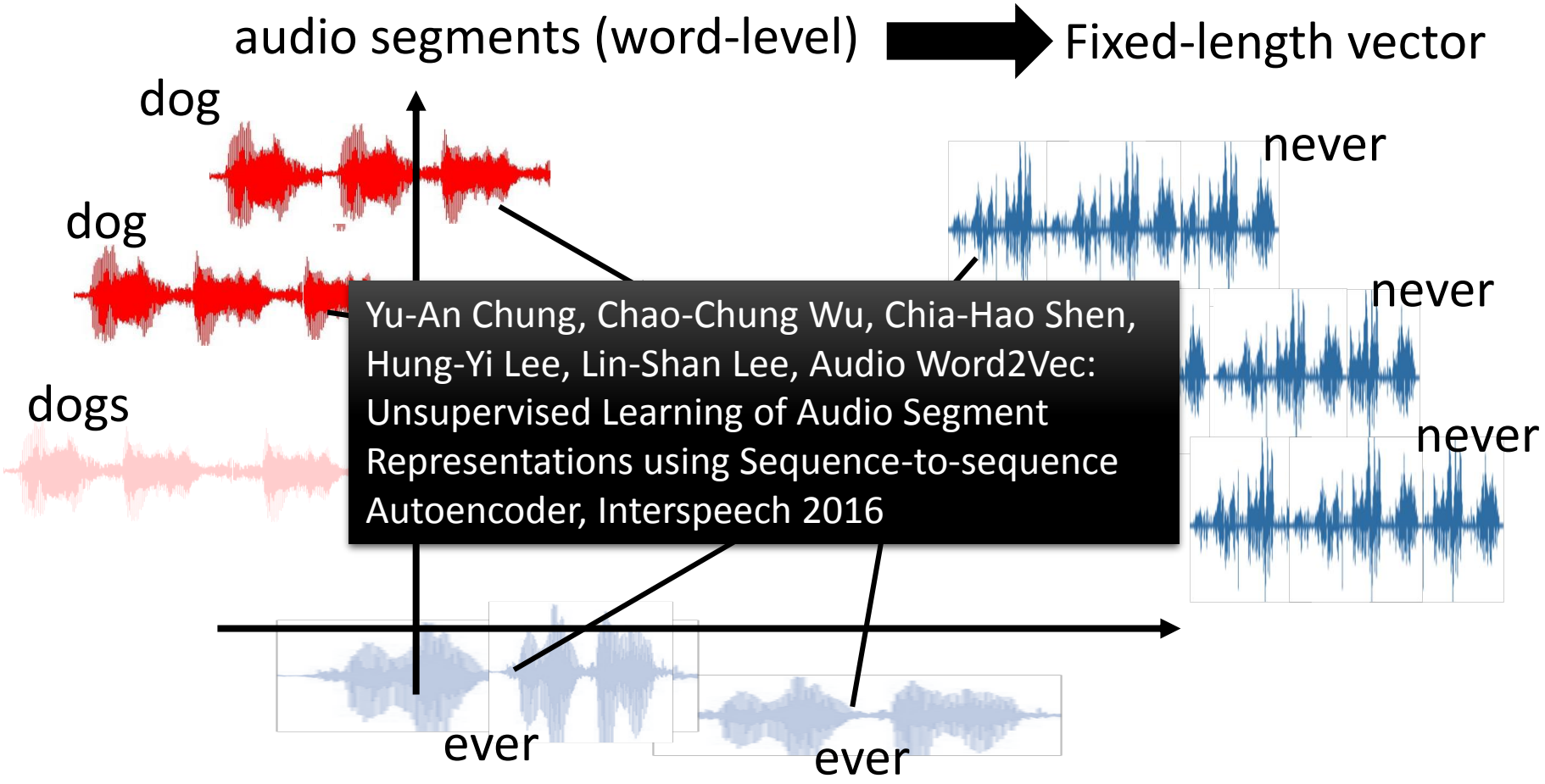
Sequence-to-sequence Auto-encoder - Text



Li, Jiwei, Minh-Thang Luong, and Dan Jurafsky. "A hierarchical neural autoencoder for paragraphs and documents." *arXiv preprint arXiv:1506.01057*(2015).

Sequence-to-sequence Auto-encoder - Speech

- Dimension reduction for a sequence with variable length

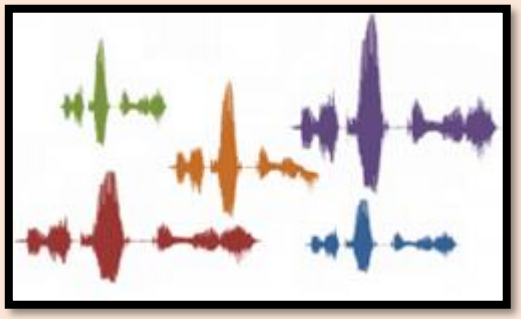


語音搜尋 – 比對訊號相似度

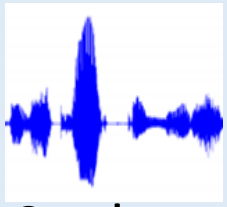
Sequence-to-sequence Auto-encoder - Speech

Audio archive divided into variable-length audio segments

Off-line



Audio Segment to Vector



Spoken Query

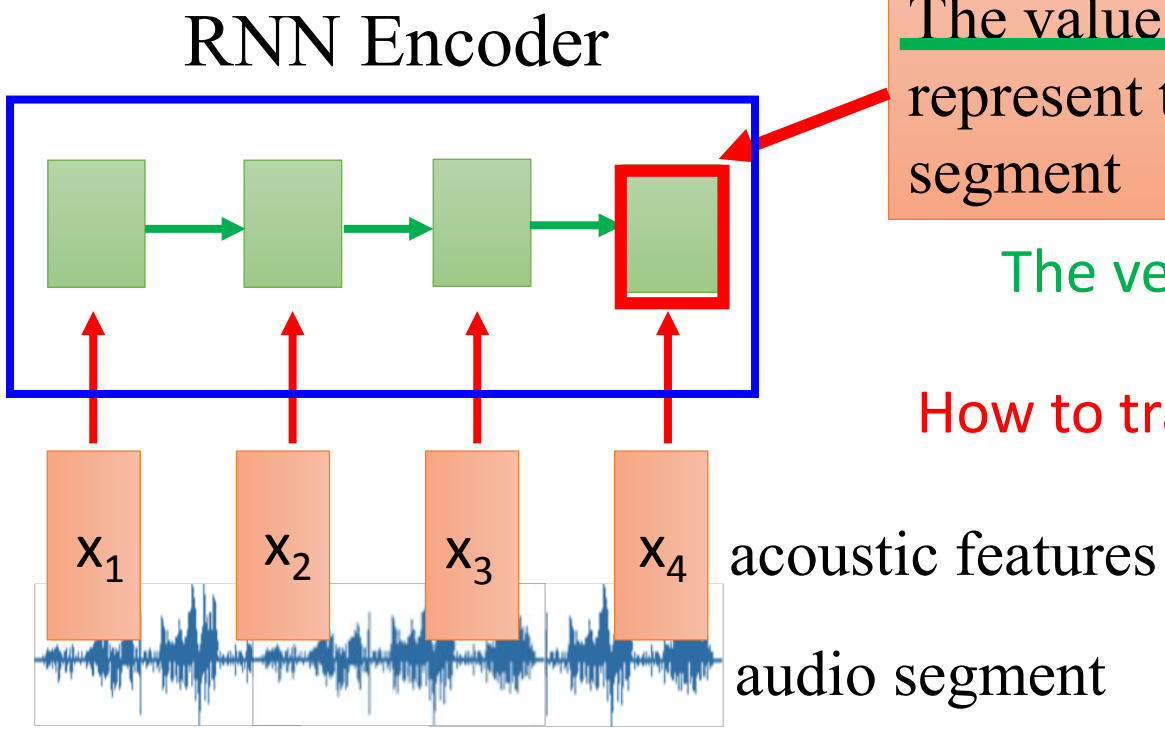
Audio Segment to Vector

Similarity

Search Result

On-line

Sequence-to-sequence Auto-encoder - Speech



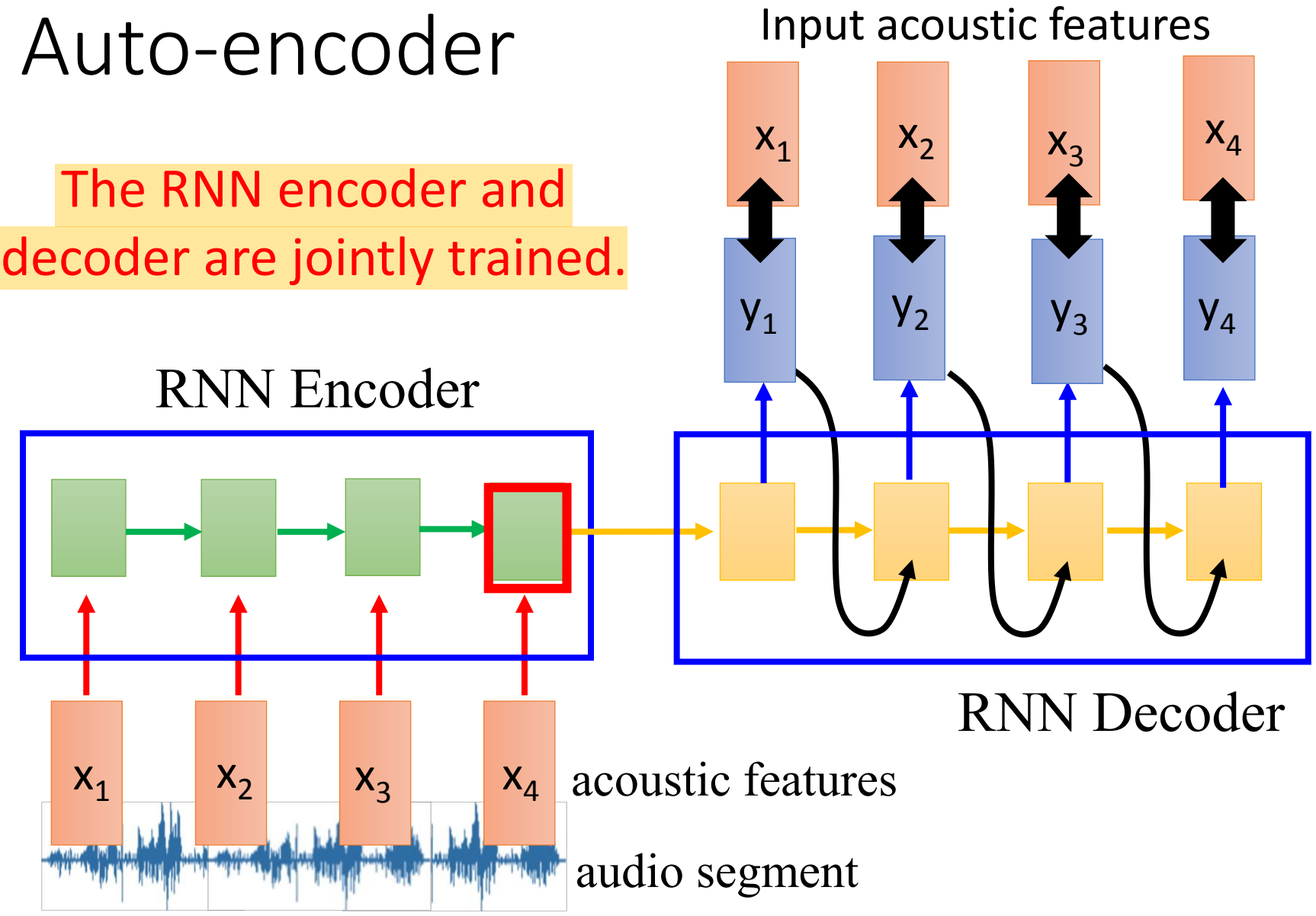
The values in the memory represent the whole audio segment

The vector we want

How to train RNN Encoder?

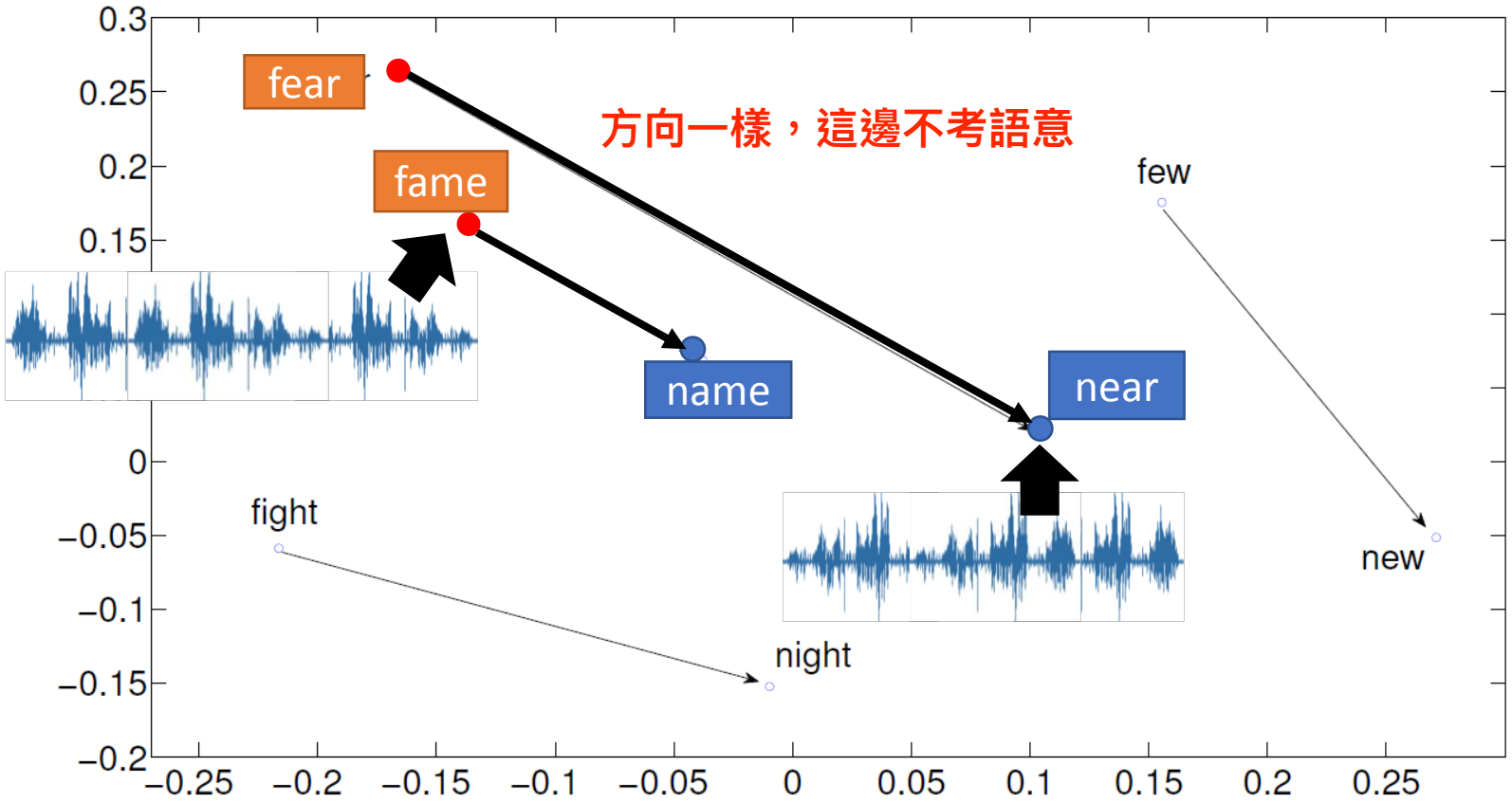
Sequence-to-sequence Auto-encoder

The RNN encoder and decoder are jointly trained.



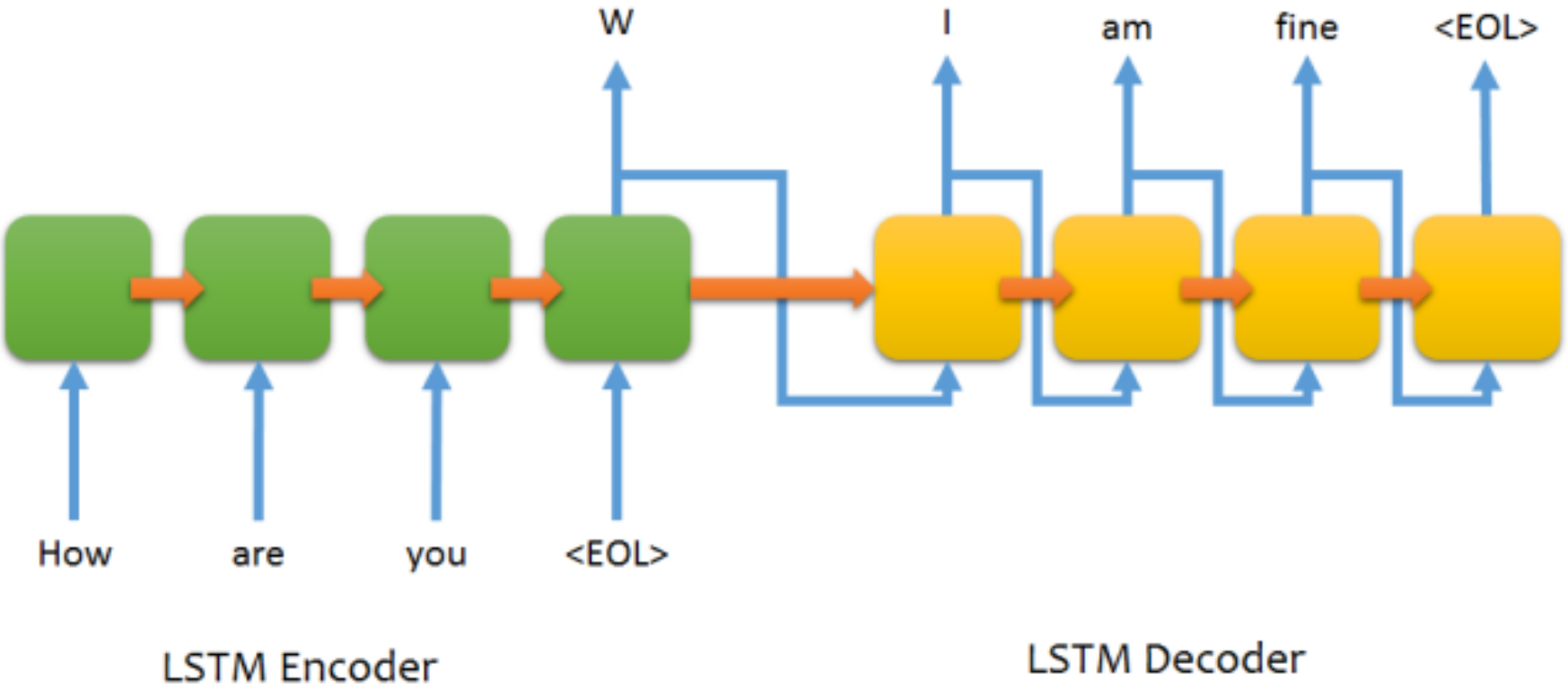
Sequence-to-sequence Auto-encoder - Speech

- Visualizing embedding vectors of the words



Demo: Chat-bot

sequence to sequence learning



電視影集 (~40,000 sentences)、美國總統大選辯論

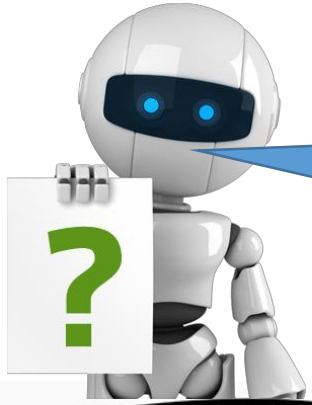
Demo: Chat-bot

- Develop Team
  - Interface design: Prof. Lin-Lin Chen & Arron Lu
  - Web programming: Shi-Yun Huang
  - Data collection: Chao-Chuang Shih
  - System implementation: Kevin Wu, Derek Chuang, & Zhi-Wei Lee (李致緯), Roy Lu (盧柏儒)
  - System design: Richard Tsai & Hung-Yi Lee

NTU IOX center

Demo: Video Caption Generation

Video



A girl is running.

A group of people is knocked by a tree.

A group of people is walking in the forest.

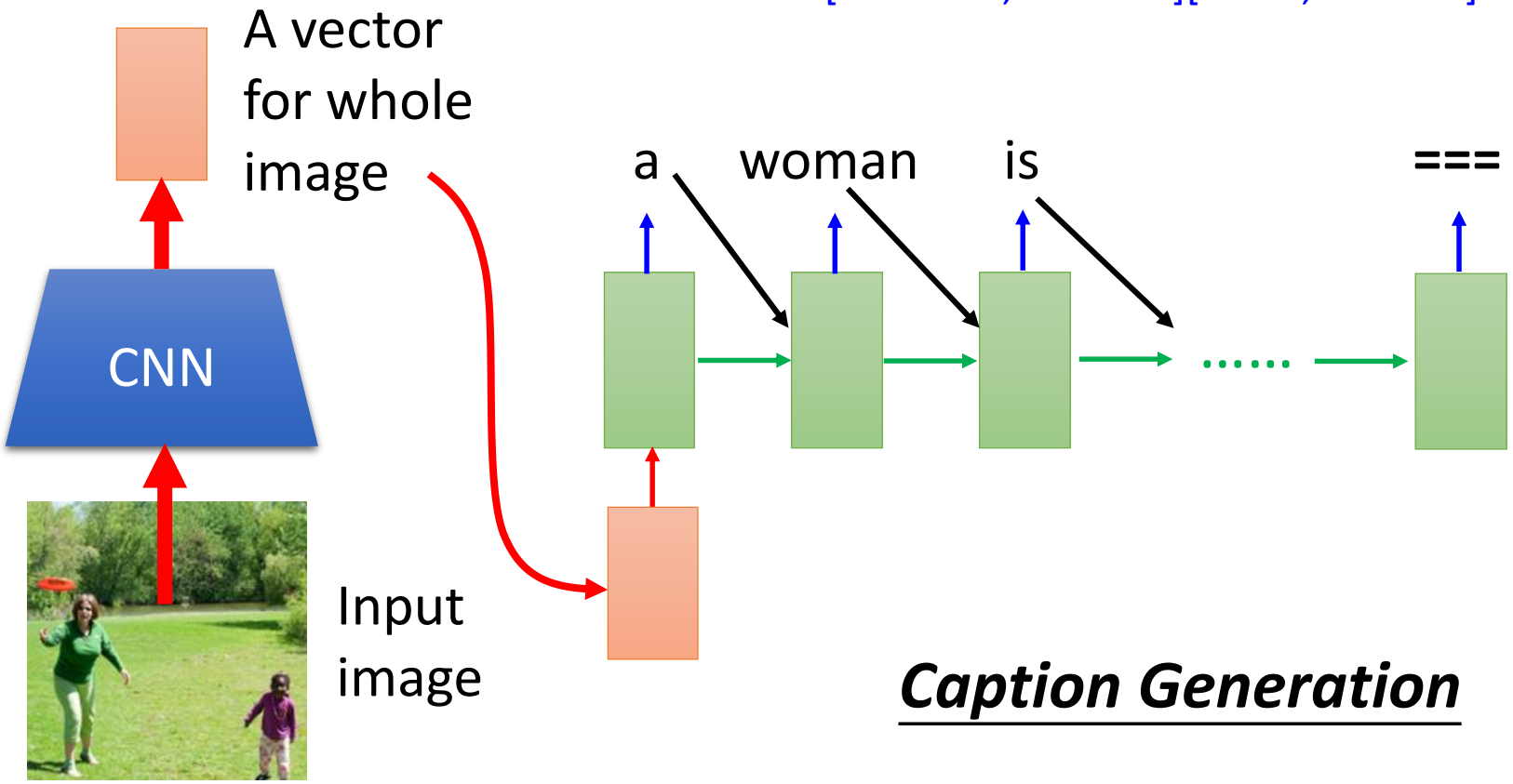
Demo: Video Caption Generation

- Can machine describe what it see from video?
- Demo: 台大語音處理實驗室 曾柏翔、吳柏瑜、盧宏宗
- Video: 莊舜博、楊棋宇、黃邦齊、萬家宏

Demo: Image Caption Generation

- Input an image, but output a sequence of words

[Kelvin Xu, arXiv'15][Li Yao, ICCV'15]

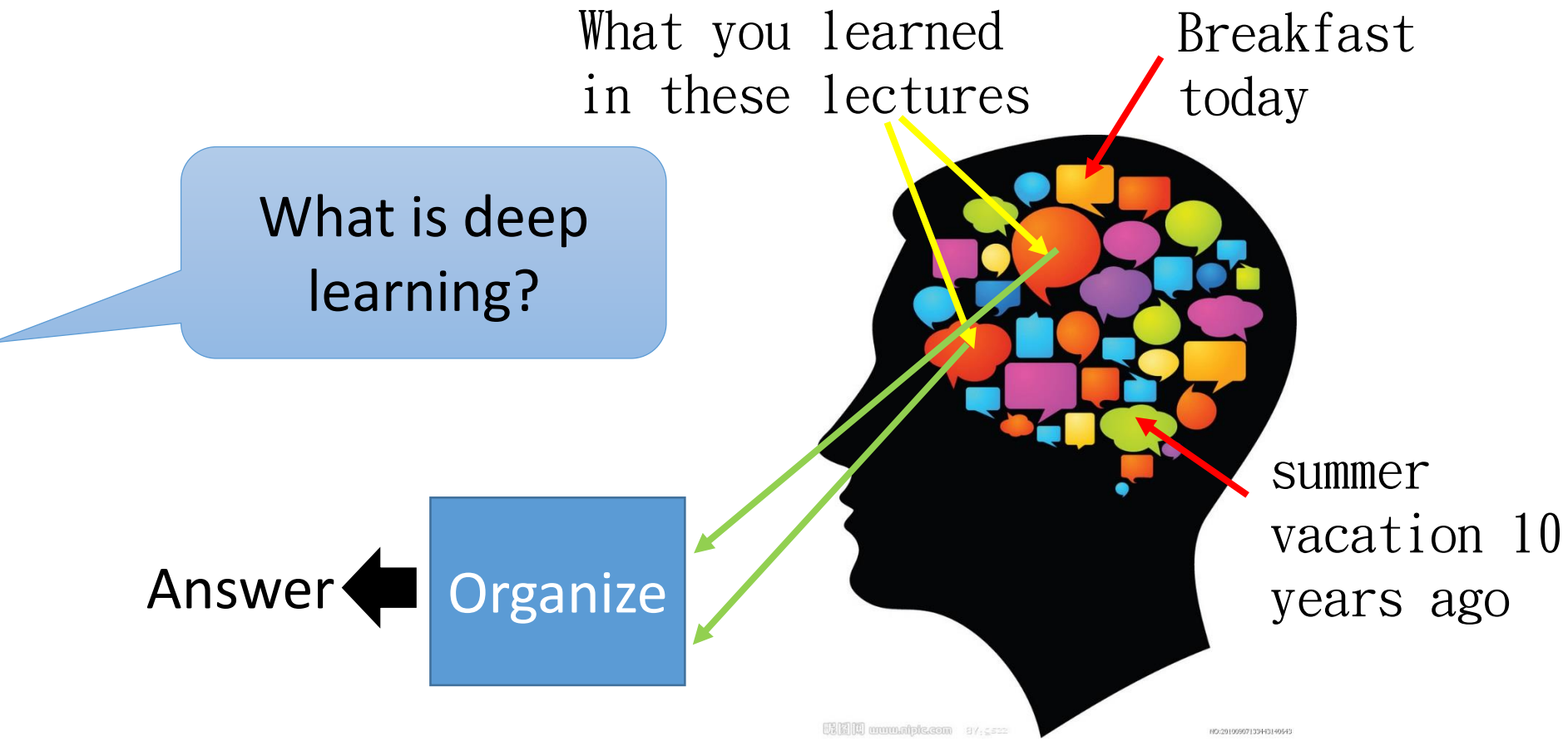


Demo: Image Caption Generation

- Can machine describe what it see from image?
- Demo:台大電機系 大四 蘇子睿、林奕辰、徐翊祥、陳奕安

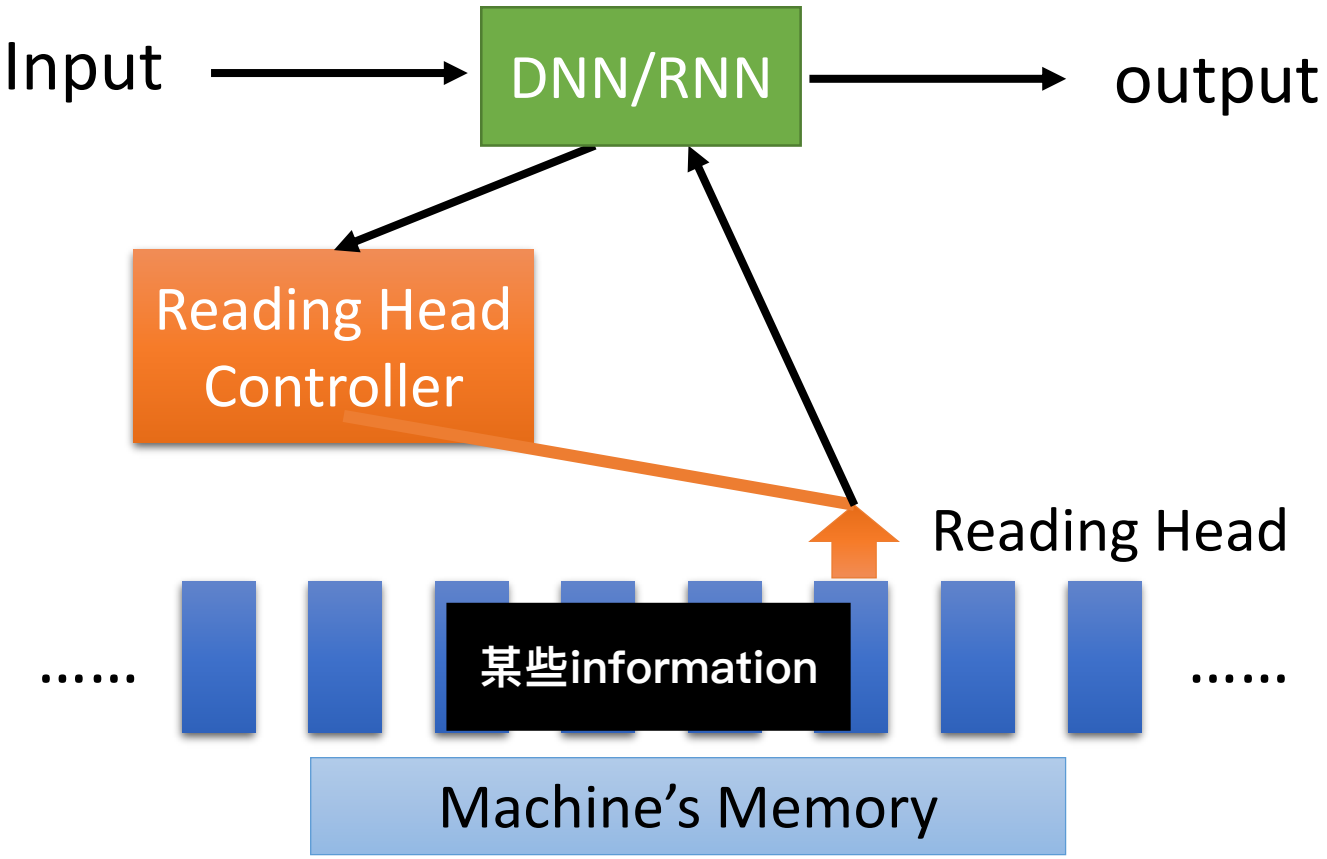
http://news.ltn.com.tw/photo/politics/breakingnews/975542_1

Attention-based Model



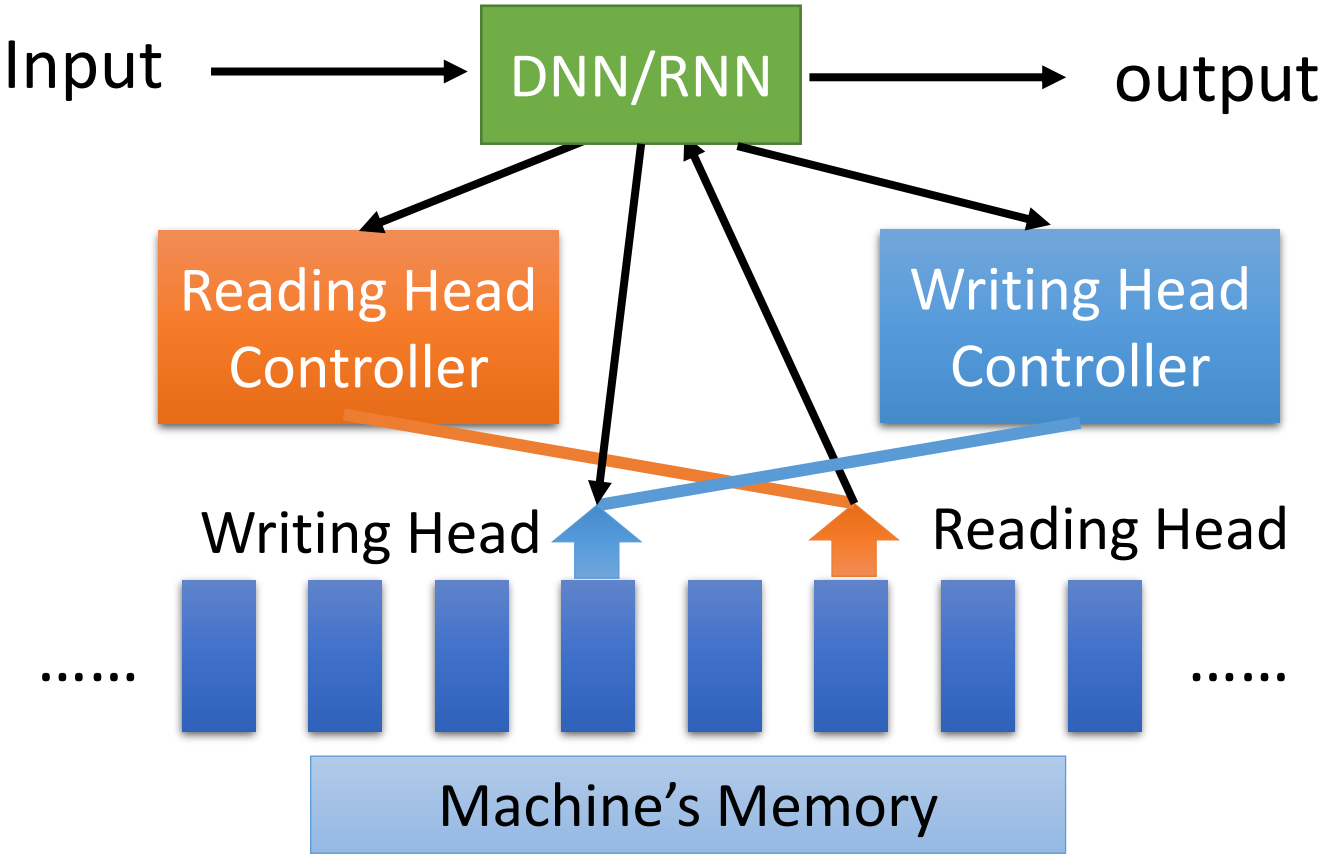
http://henrylo1605.blogspot.tw/2015/05/blog-post_56.html

Attention-based Model



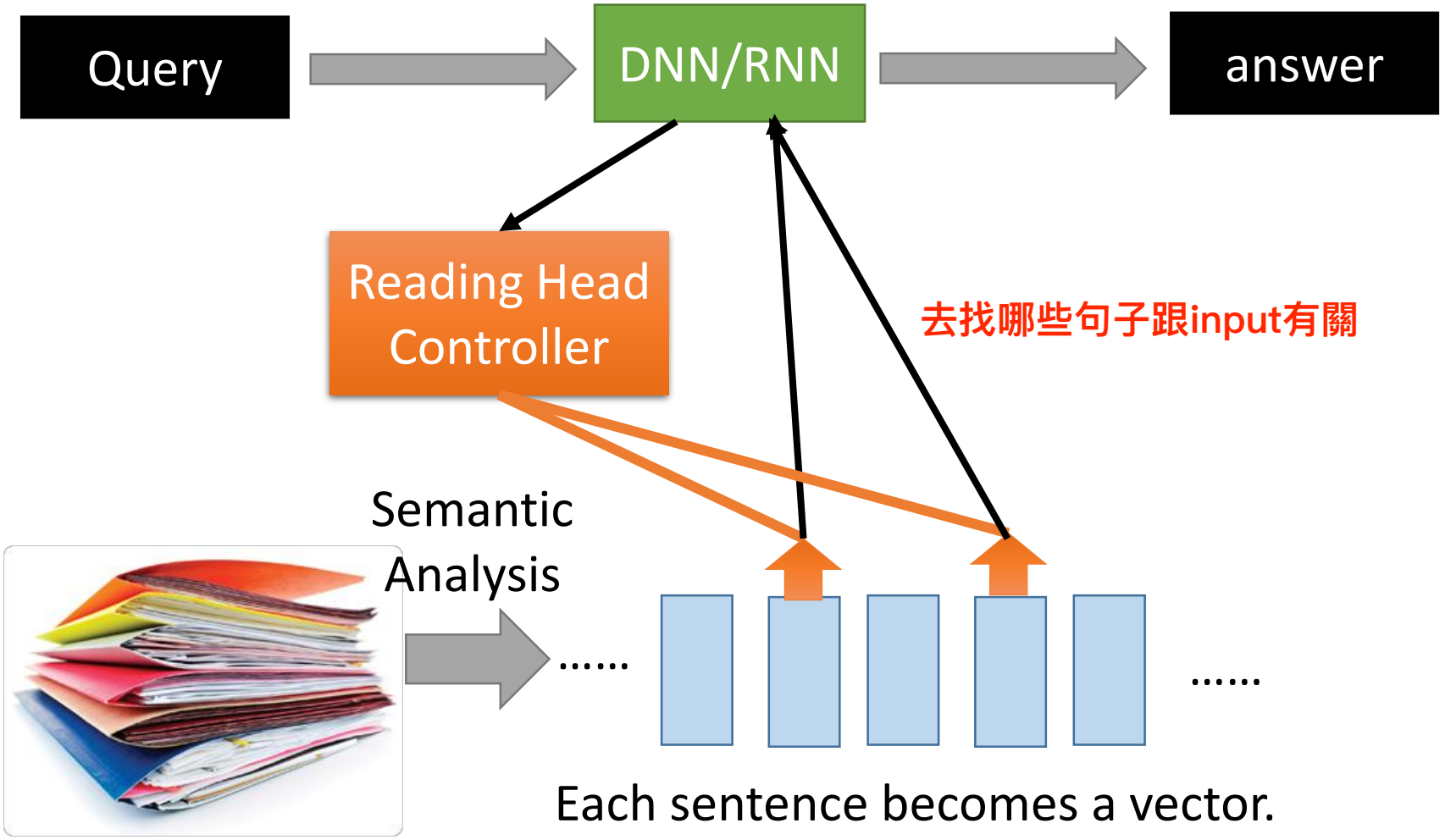
Ref:
http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Attain%20(v3).ecm.mp4/index.html

Attention-based Model v2



14'年底 Neural Turing Machine

Reading Comprehension



Reading Comprehension

- End-To-End Memory Networks. S. Sukhbaatar, A. Szlam, J. Weston, R. Fergus. NIPS, 2015.

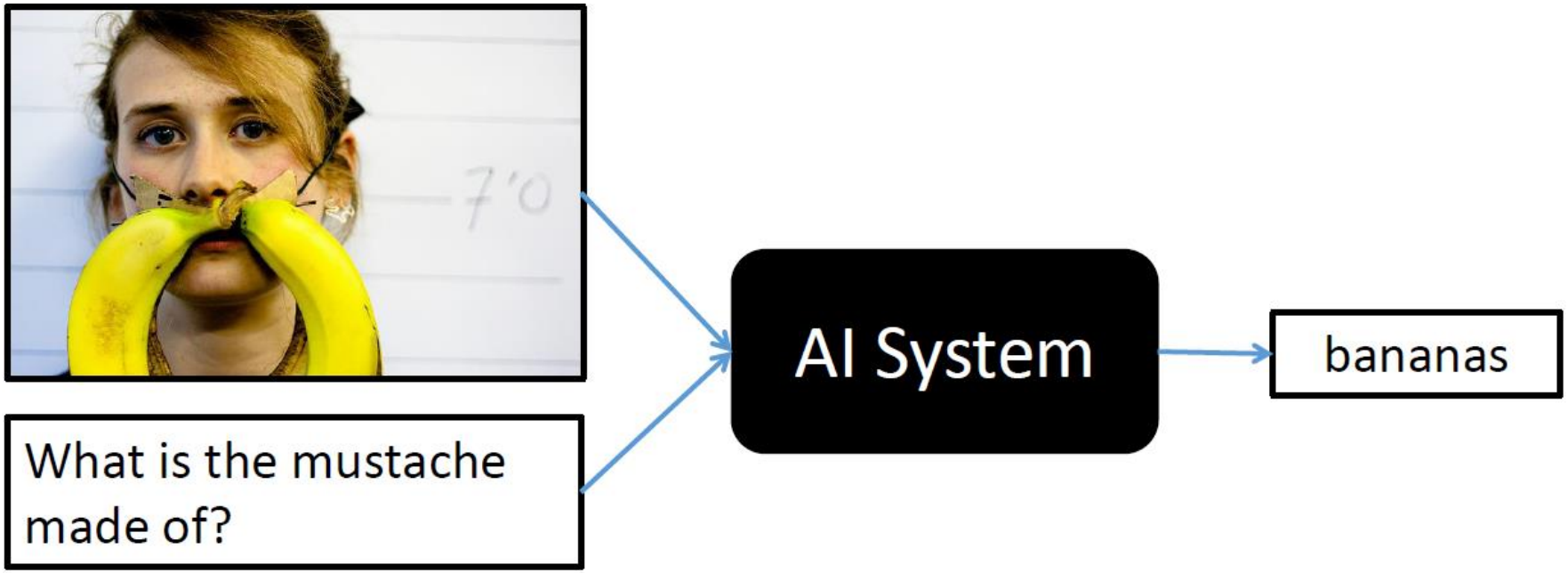
The position of reading head:

Hop代表時間點

Story (16: basic induction)	Support	Hop 1	Hop 2	Hop 3
Brian is a frog.	yes	0.00	0.98	0.00
Lily is gray.		0.07	0.00	0.00
Brian is yellow.	yes	0.07	0.00	1.00
Julius is green.		0.06	0.00	0.00
Greg is a frog.	yes	0.76	0.02	0.00
What color is Greg? Answer: yellow	**Prediction: yellow**			

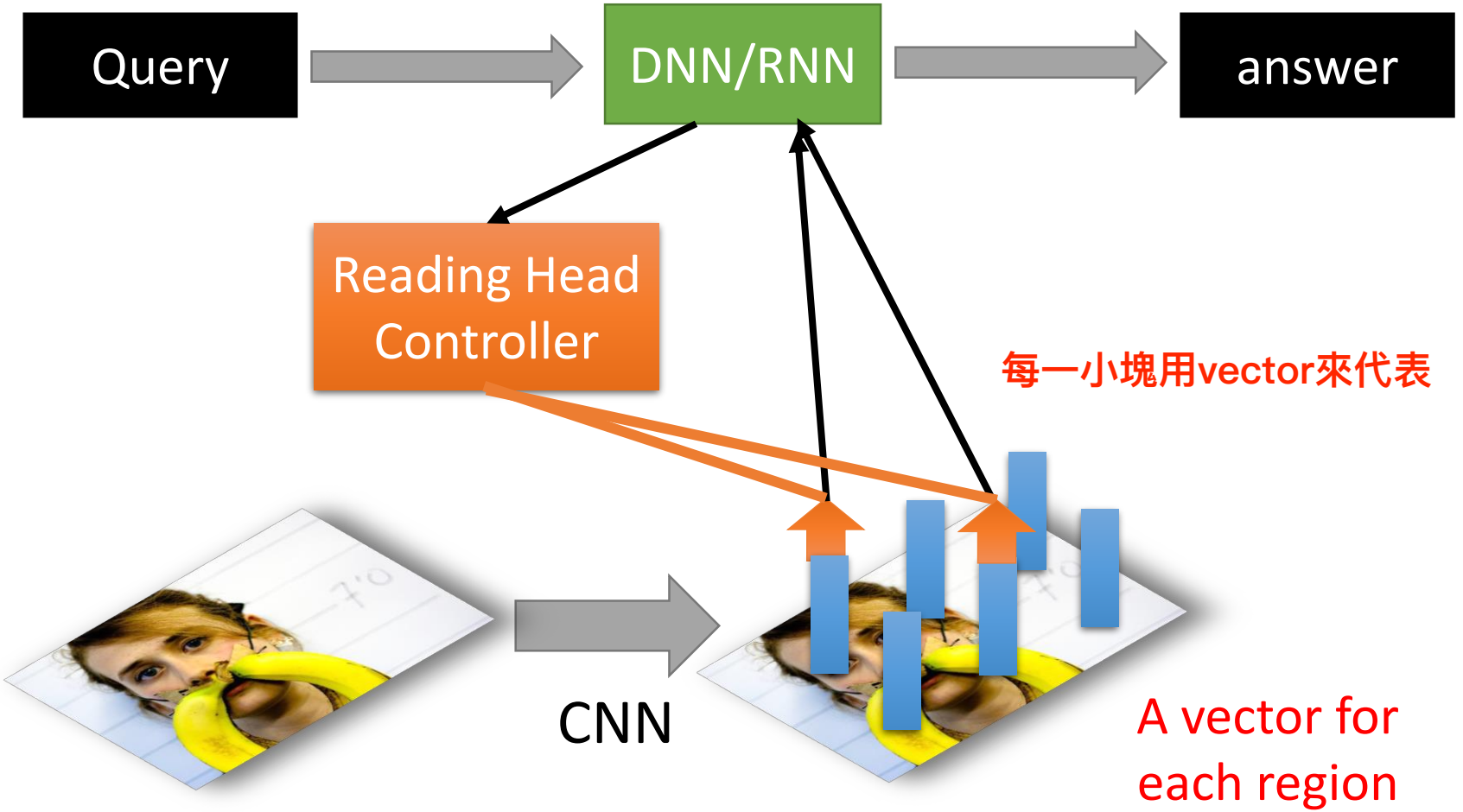
Keras has example:
https://github.com/fchollet/keras/blob/master/examples/babi_memnn.py

Visual Question Answering



source: http://visualqa.org/

Visual Question Answering



Speech Question Answering

- **TOEFL Listening Comprehension Test by Machine**
- Example:

  Audio Story:  (The original story is 5 min long.)

  Question: “ What is a possible origin of Venus’ clouds? ”

  Choices:

  (A) gases released as a result of volcanic activity

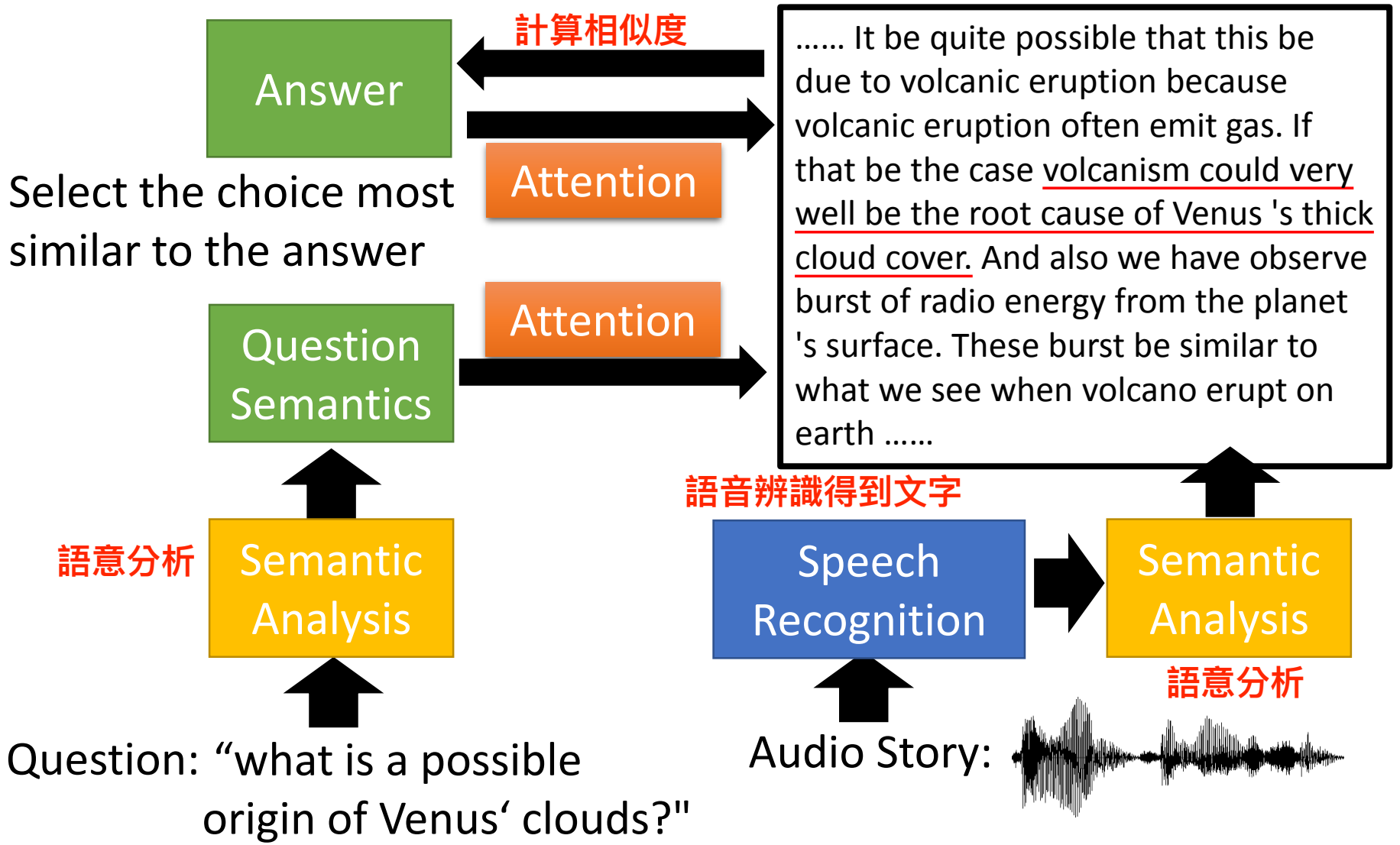
  (B) chemical reactions caused by high surface temperatures

  (C) bursts of radio energy from the plane's surface

  (D) strong winds that blow dust into the atmosphere

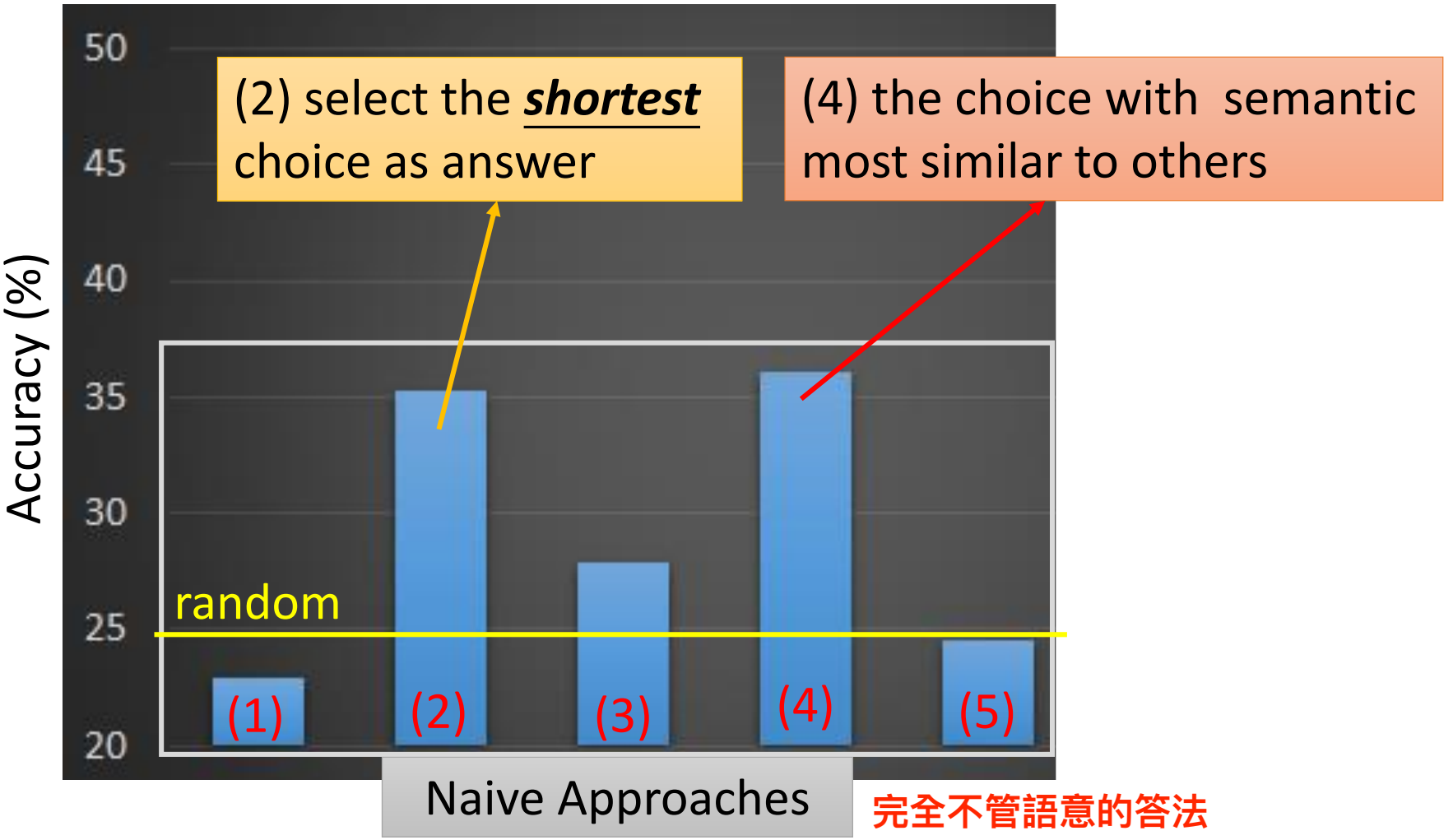
Model Architecture

Everything is learned from training examples

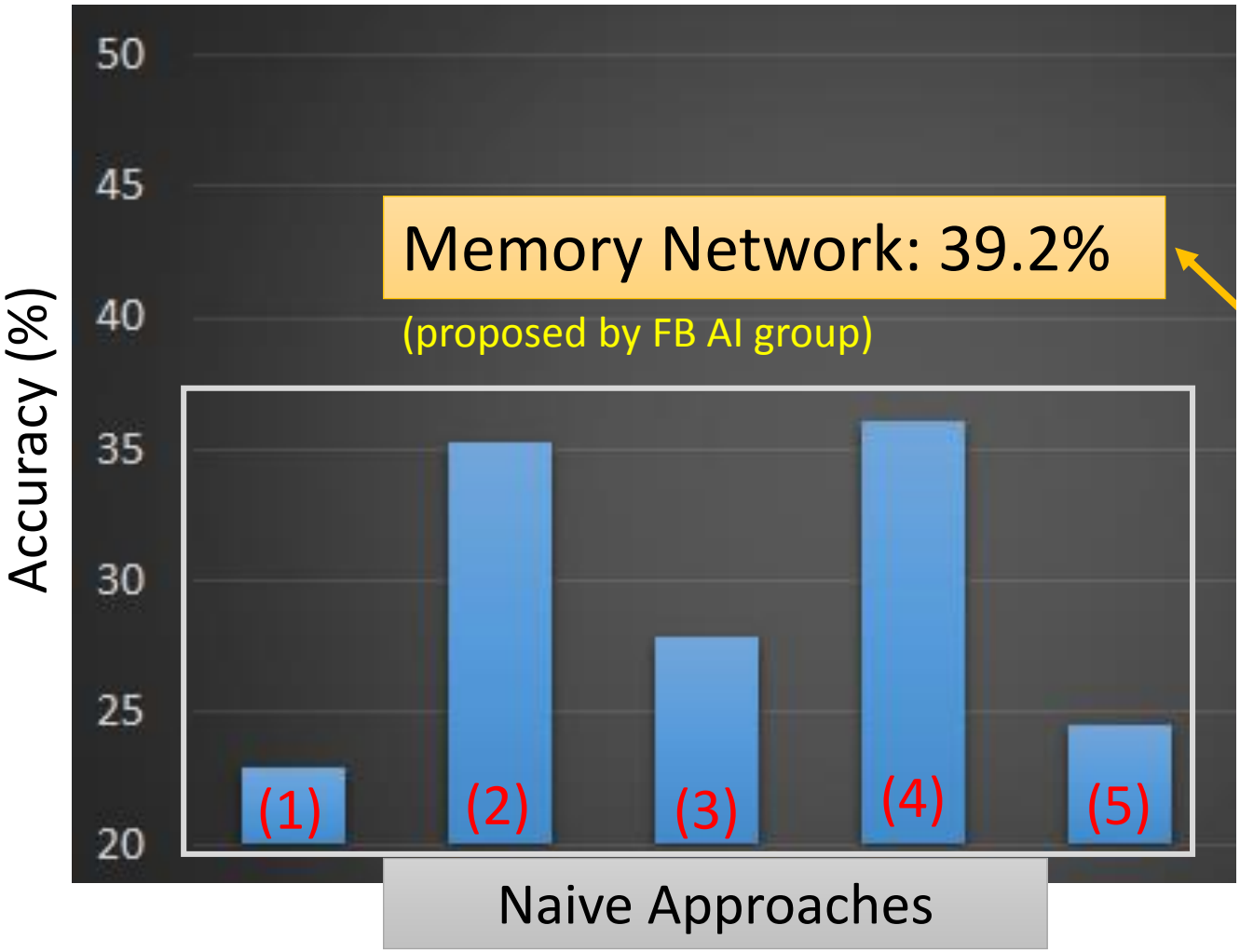


Simple Baselines

Experimental setup:
717 for training,
124 for validation, 122 for testing



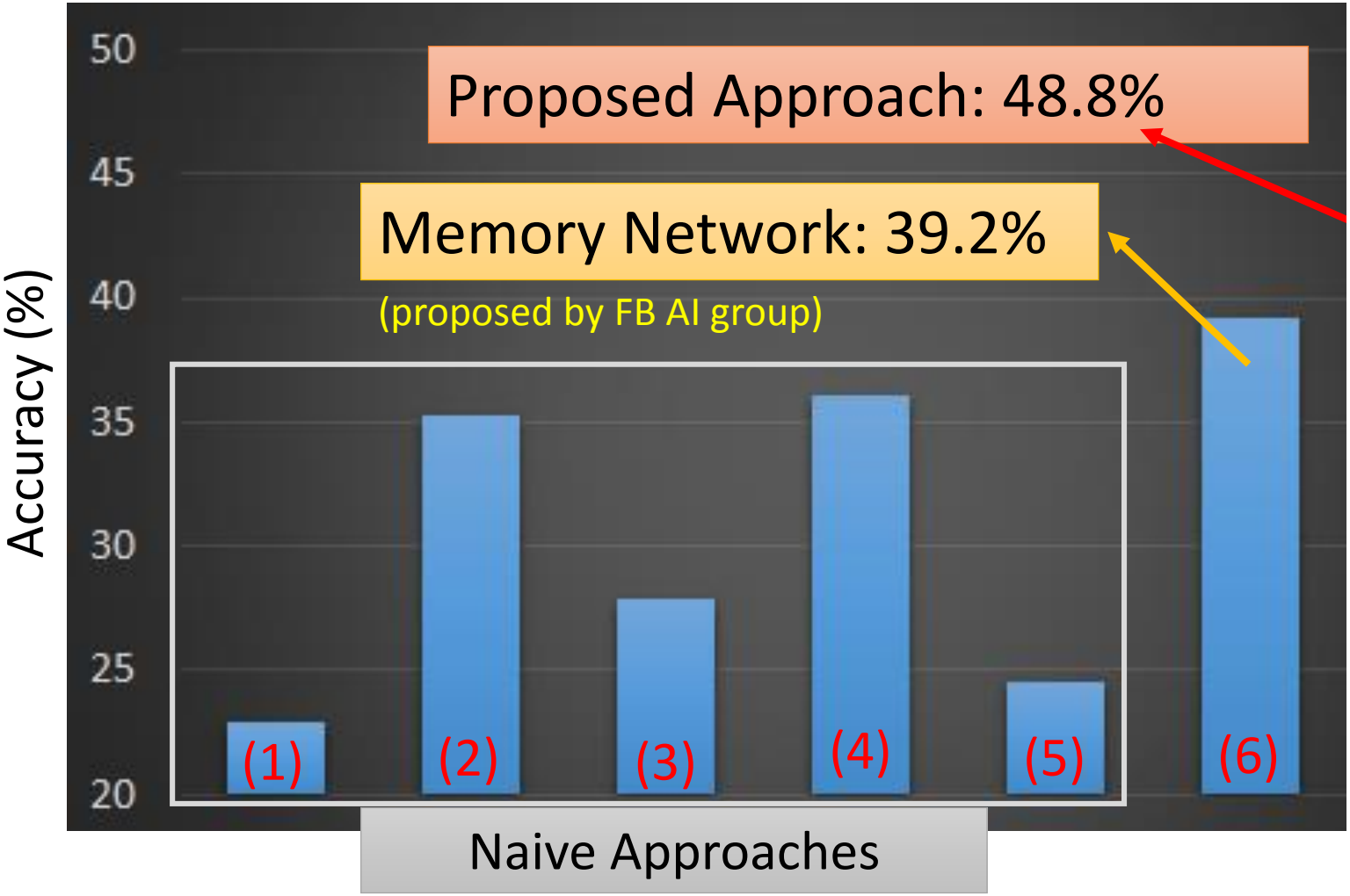
Memory Network



Proposed Approach

[Tseng & Lee, Interspeech 16]

[Fang & Hsu & Lee, SLT 16]



To Learn More ……

- The Unreasonable Effectiveness of Recurrent Neural Networks
  - http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Understanding LSTM Networks
  - http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Deep & Structured

RNN v.s. Structured Learning

- RNN, LSTM
  - Unidirectional RNN does not consider the whole sequence
  - Cost and error not always related
  - Deep 勝

只看了sentence的一半

cost: 每個時間點的cross entropy，與error不見得正相關

- HMM, CRF, Structured Perceptron/SVM
  - Using Viterbi, so consider the whole sequence 勝 ?
    - How about Bidirectional RNN?

可考慮整個句子的inform.

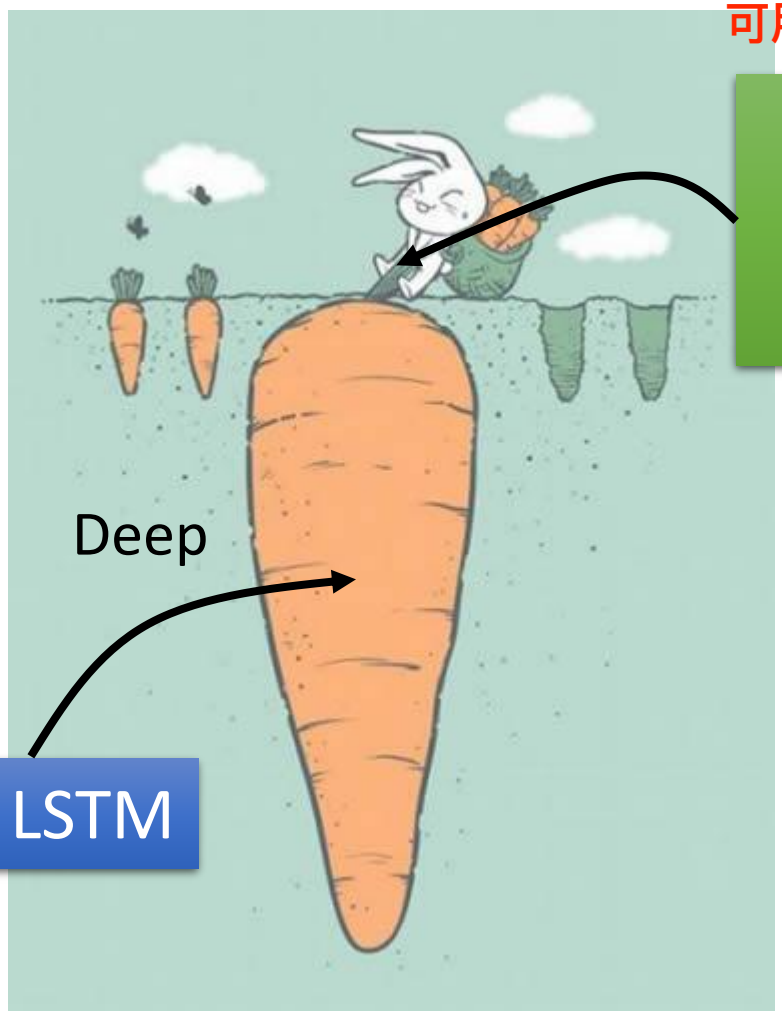
  - Can explicitly consider the label dependency 勝

viterbi可直接加入constrain

  - Cost is the upper bound of error 勝

Integrated Together 結合的先例

可用gradient descend做training



- Explicitly model the dependency
- Cost is the upper bound of error

http://photo30.bababian.com/upload1/20100415/42E9331A6580A46A5F89E98638B8FD76.jpg

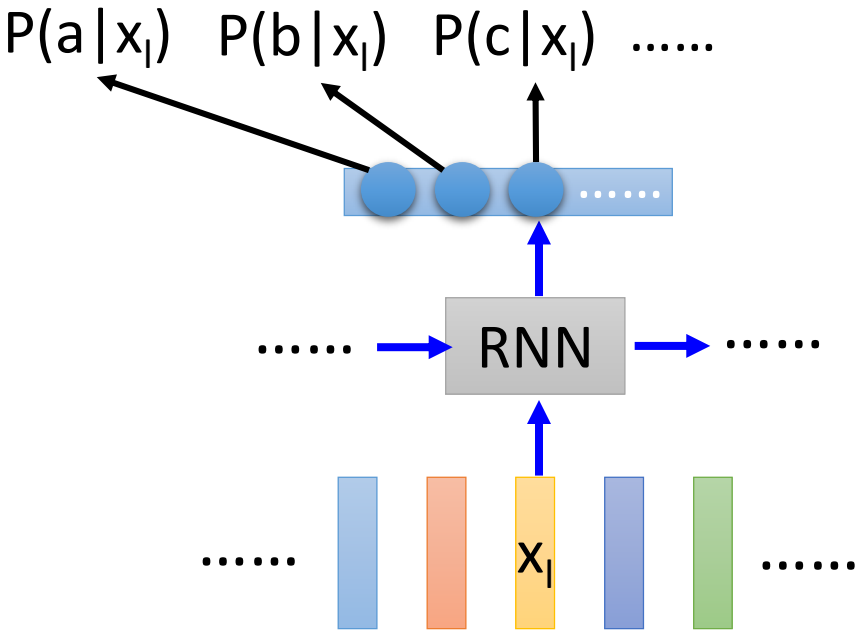
Integrated together

x:聲音signal

y:predict result

- Speech Recognition: CNN/LSTM/DNN + HMM

$$P(x,y) = P(y_1|start)\prod_{l=1}^{L-1} P(y_{l+1}|y_l)\, P(end|y_L)\prod_{l=1}^{L} P(x_l|y_l)$$



$$P(x_l|y_l) = \frac{P(x_l,y_l)}{P(y_l)}$$

RNN

$$= \frac{P(y_l|x_l)\cancel{P(x_l)}}{P(y_l)}$$

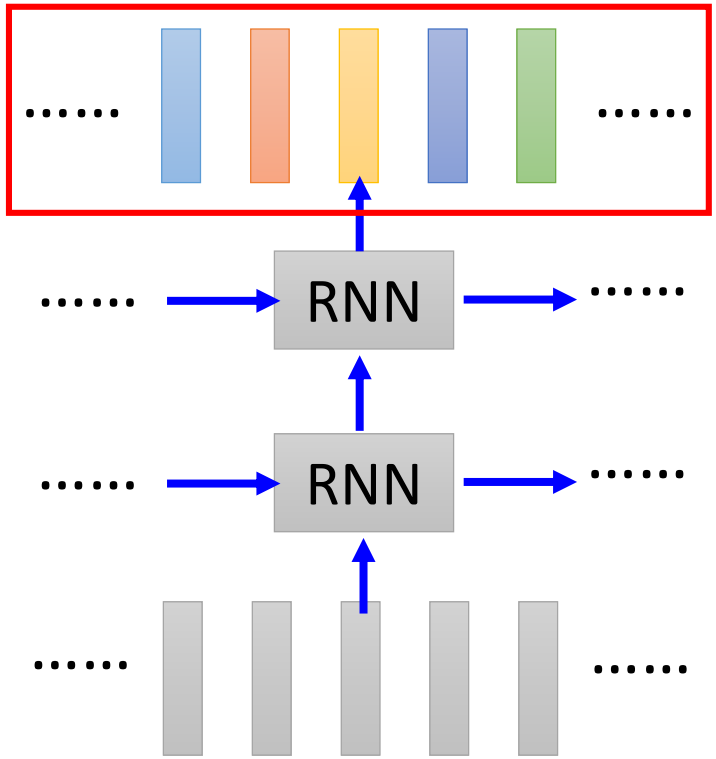
Count

從corpus裡直接統計

Integrated together

- Semantic Tagging: Bi-directional LSTM + CRF/Structured SVM

先抽出feature



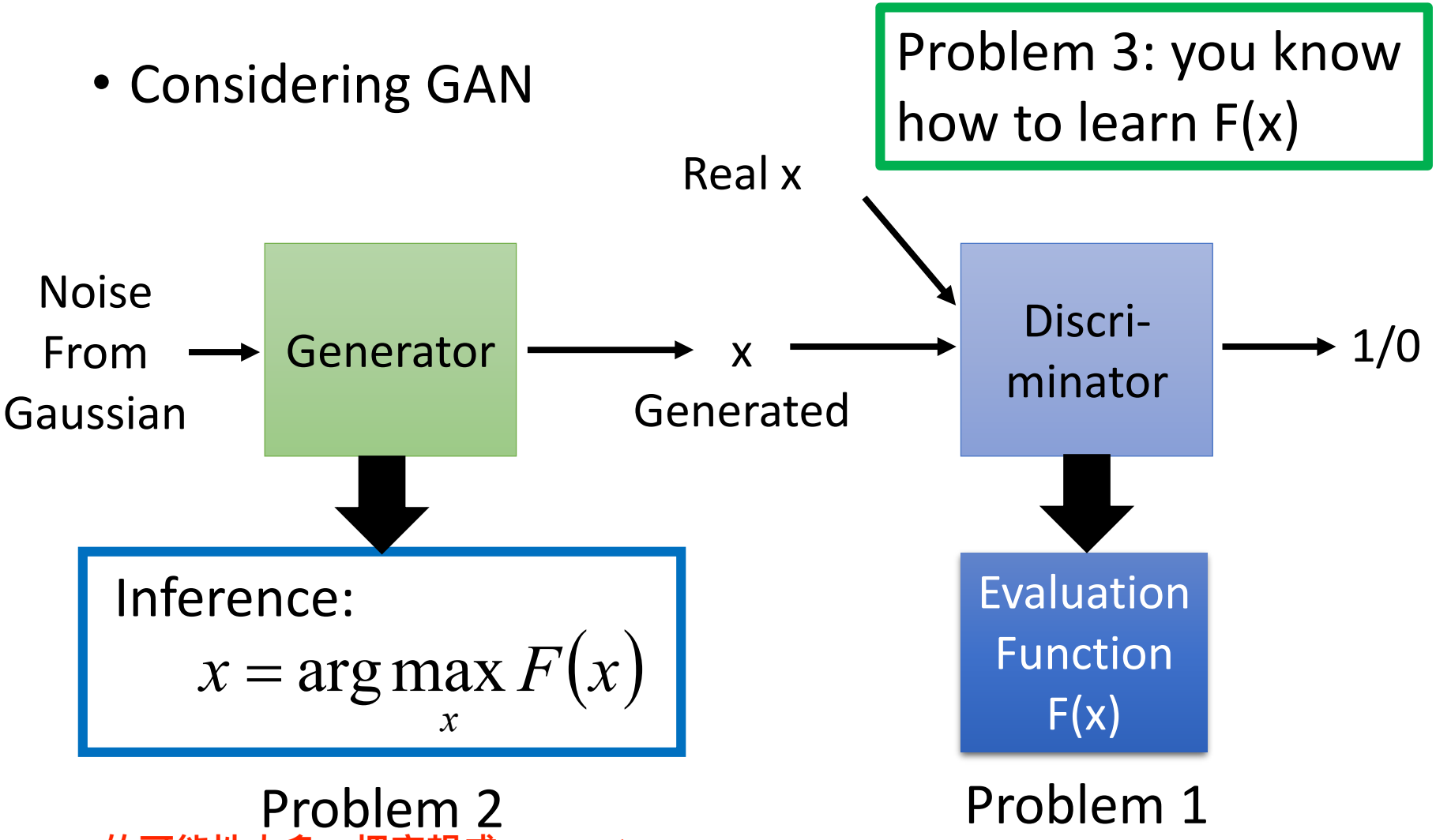
$w \cdot \phi(x, y)$

Testing:

$$\tilde{y} = \arg\max_{y \in \mathbb{Y}} w \cdot \phi(x, y)$$

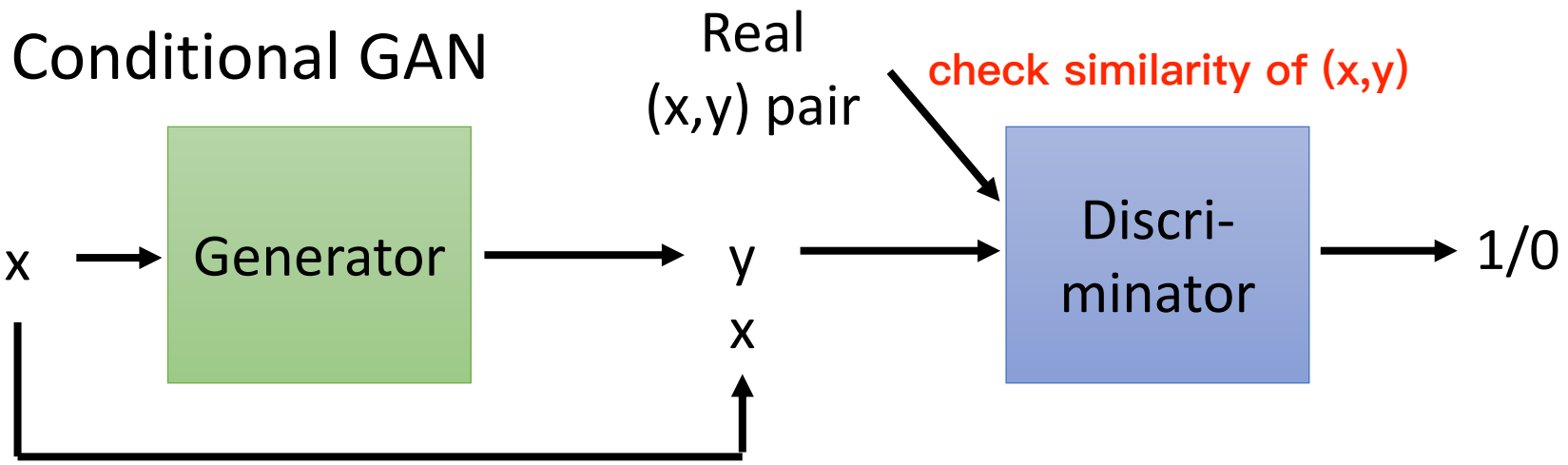
Is structured learning practical?

- Considering GAN

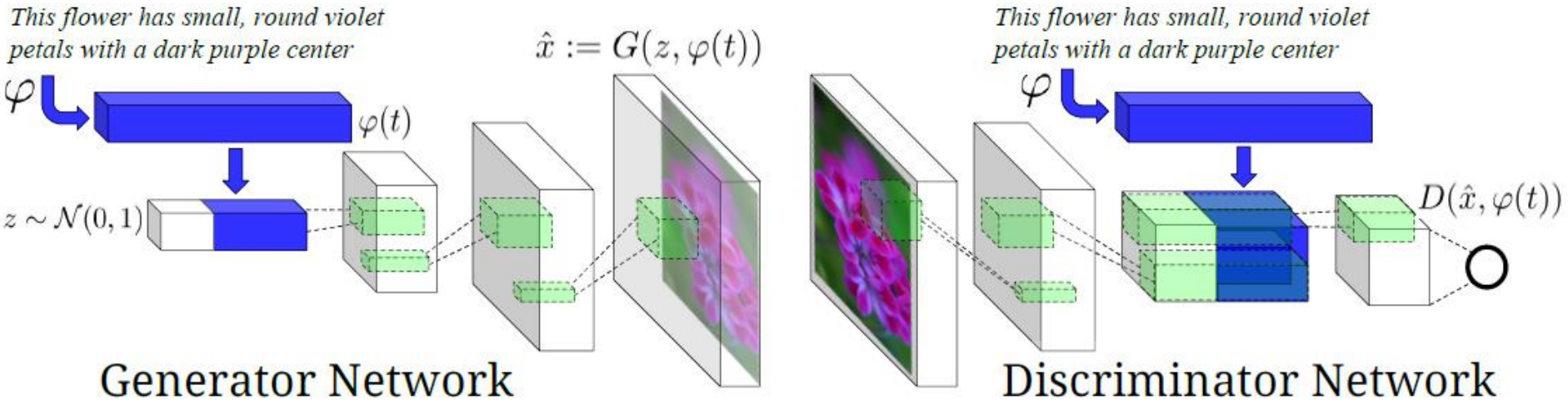


Is structured learning practical?

- Conditional GAN



discriminator即為evaluation function



Sounds crazy?
People do think in this way …

Deep and Structured will be the future.

structured learning

- Connect Energy-based model with GAN:
  - A Connection Between Generative Adversarial Networks, Inverse Reinforcement Learning, and Energy-Based Models
  - Deep Directed Generative Models with Energy-Based Probability Estimation
  - ENERGY-BASED GENERATIVE ADVERSARIAL NETWORKS
- Deep learning model for inference
  - Deep Unfolding: Model-Based Inspiration of Novel Deep Architectures
  - Conditional Random Fields as Recurrent Neural Networks

Machine learning and having it deep and structured (MLDS)

- 和 ML 的不同
  - 在這學期 ML 中有提過的內容 (DNN, CNN …)，在 MLDS 中不再重複，只做必要的復習
- 教科書：“Deep Learning” (http://www.deeplearningbook.org/)
  - Part II 是講 deep learning 、Part III 就是講 structured learning

Machine learning and having it deep and structured (MLDS)

- 所有作業都 2 ~ 4 人一組，可以先組好隊後一起來修
- MLDS 的作業和之前不同
  - RNN (把之前 MLDS 的三個作業合為一個)、Attention-based model 、Deep Reinforcement Learning 、Deep Generative Model 、Sequence-to-sequence learning
- MLDS 初選不開放加簽，以組為單位加簽，作業0的內容是做一個 DNN（可用現成套件）