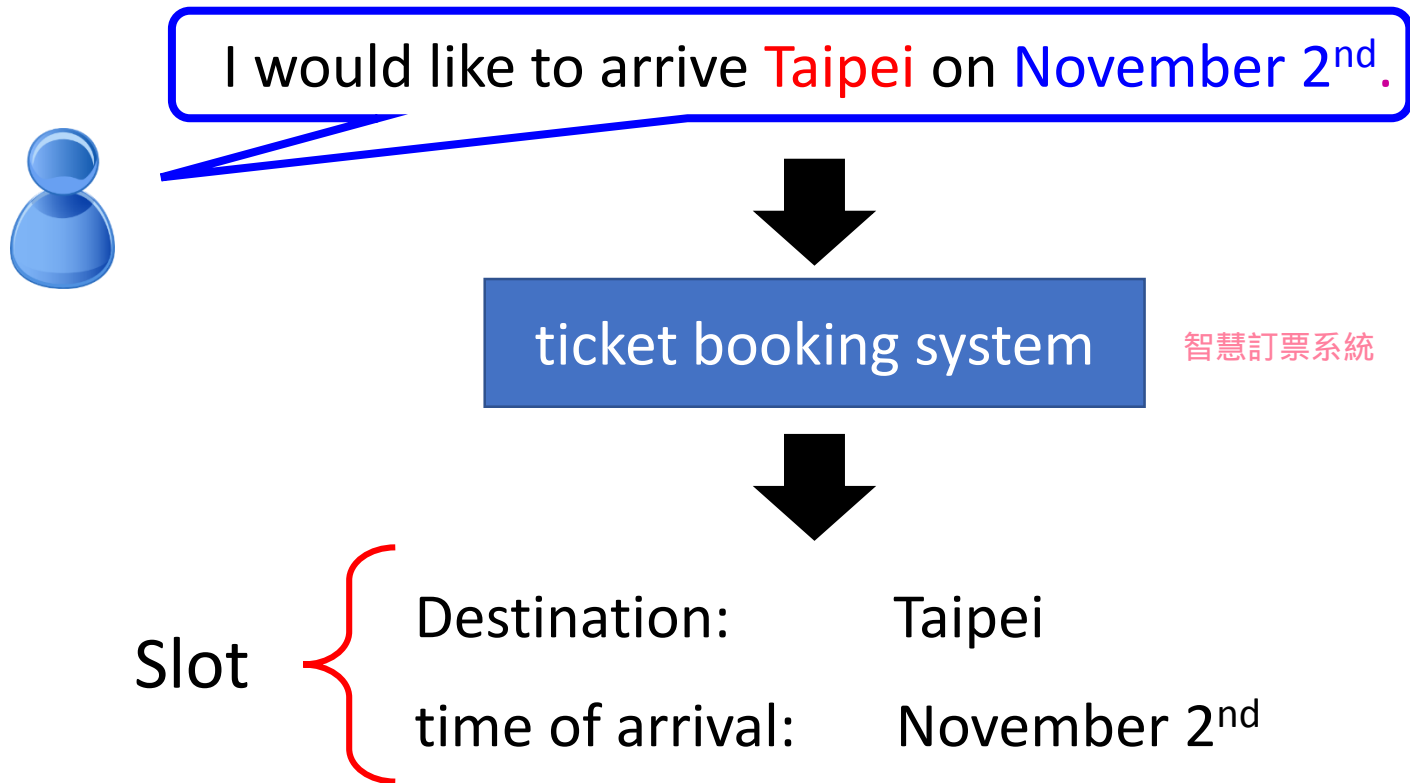


Recurrent Neural Network (RNN)

Example Application

- Slot Filling

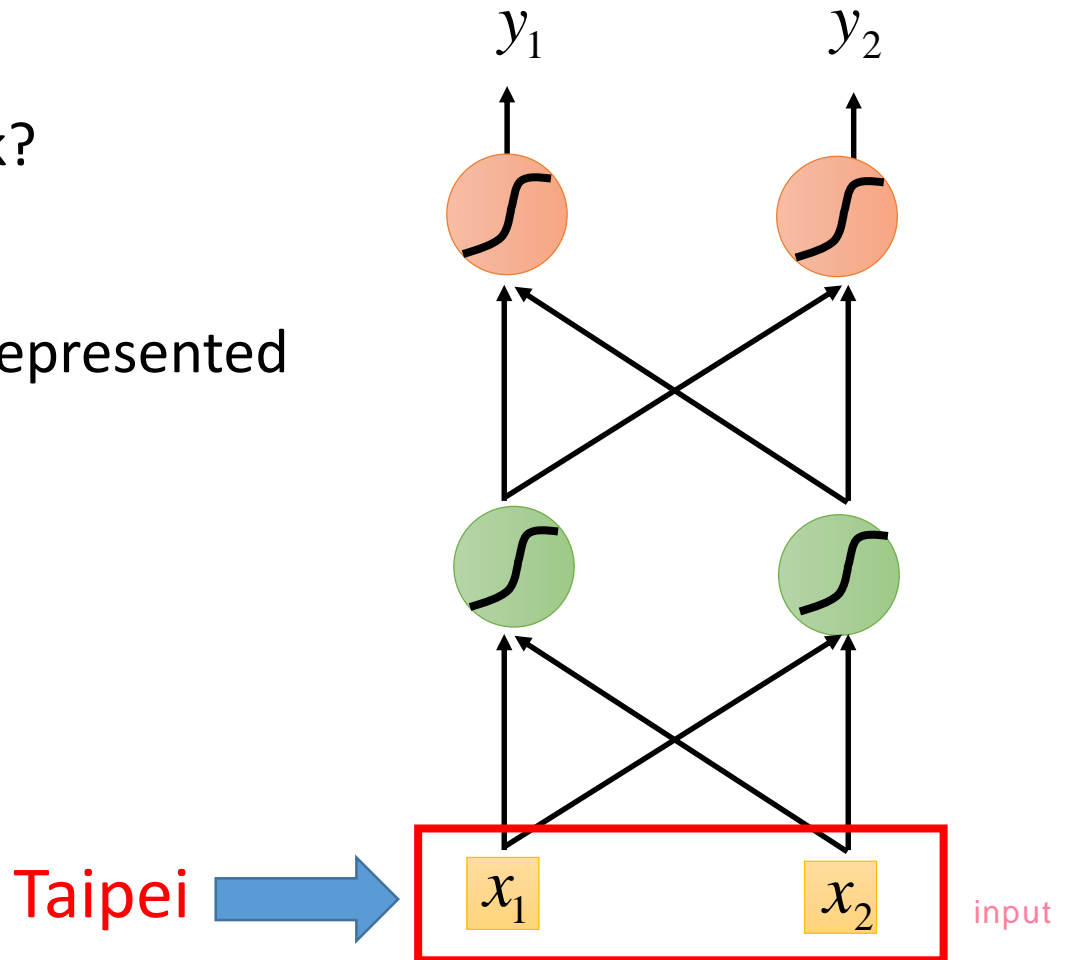


Example Application

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]

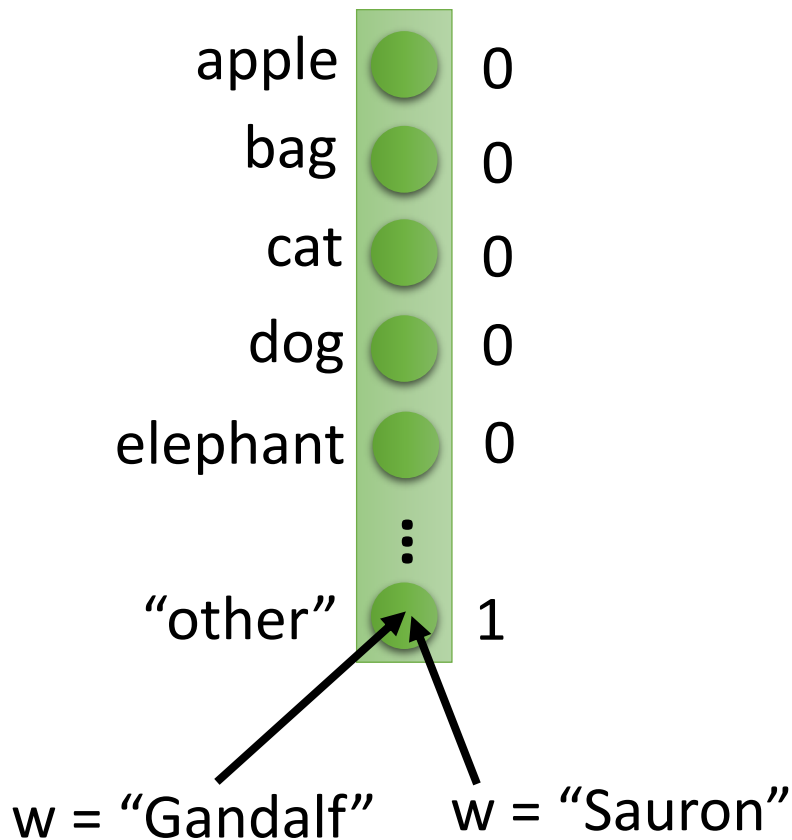
cat = [0 0 1 0 0]

dog = [0 0 0 1 0]

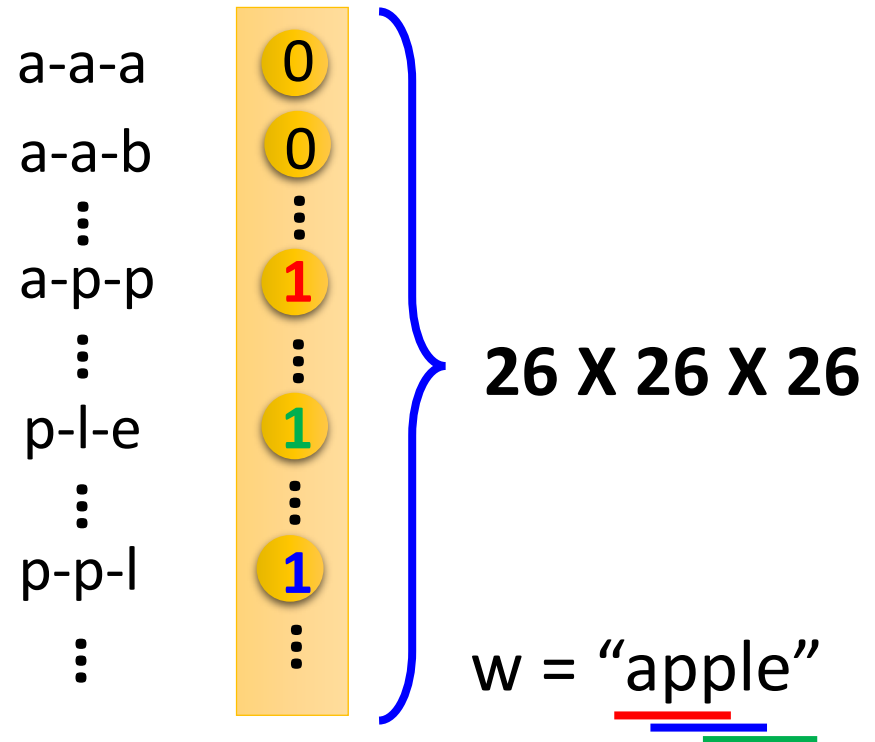
elephant = [0 0 0 0 1]

Beyond 1-of-N encoding

Dimension for “Other”



Word hashing



Example Application

Solving slot filling by
Feedforward network?

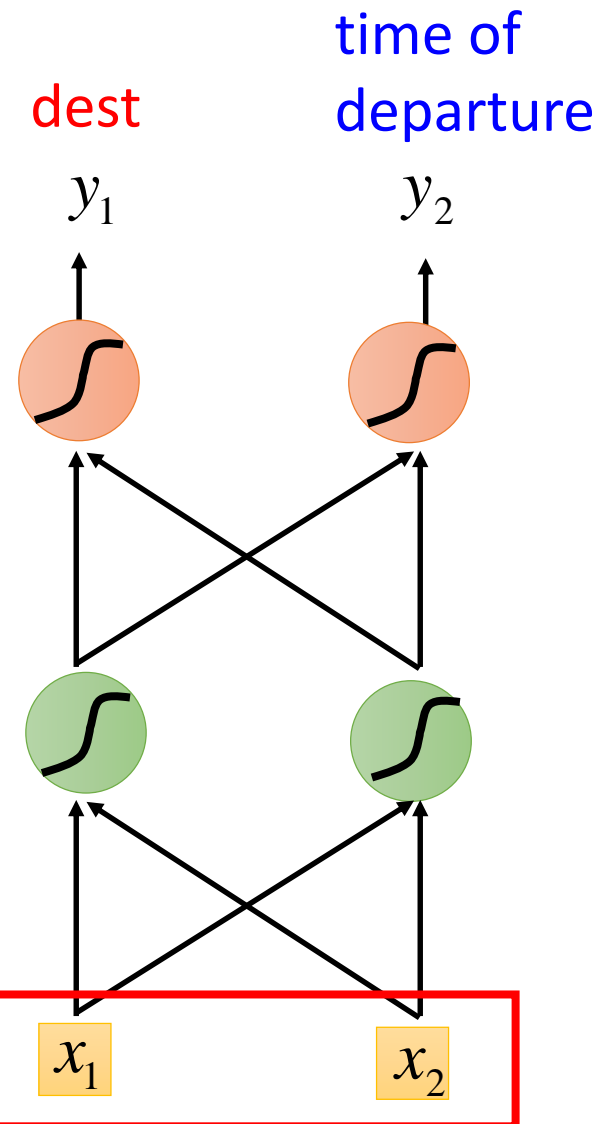
Input: a word

(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 2nd

other

dest

other

time

time

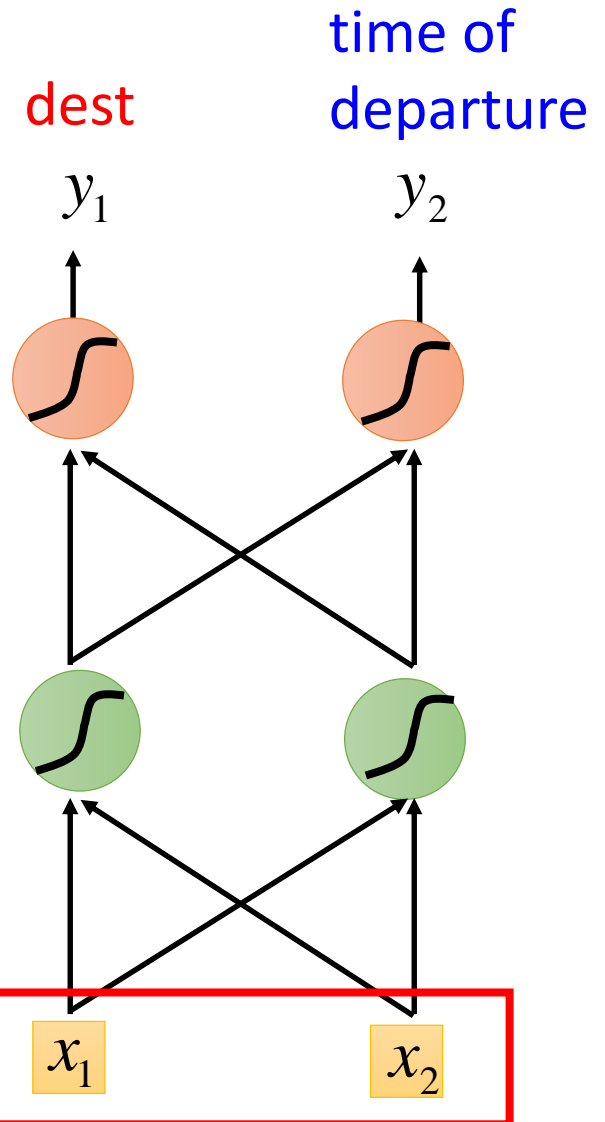
Problem?

leave Taipei on November 2nd

place of departure

Neural network
needs memory!

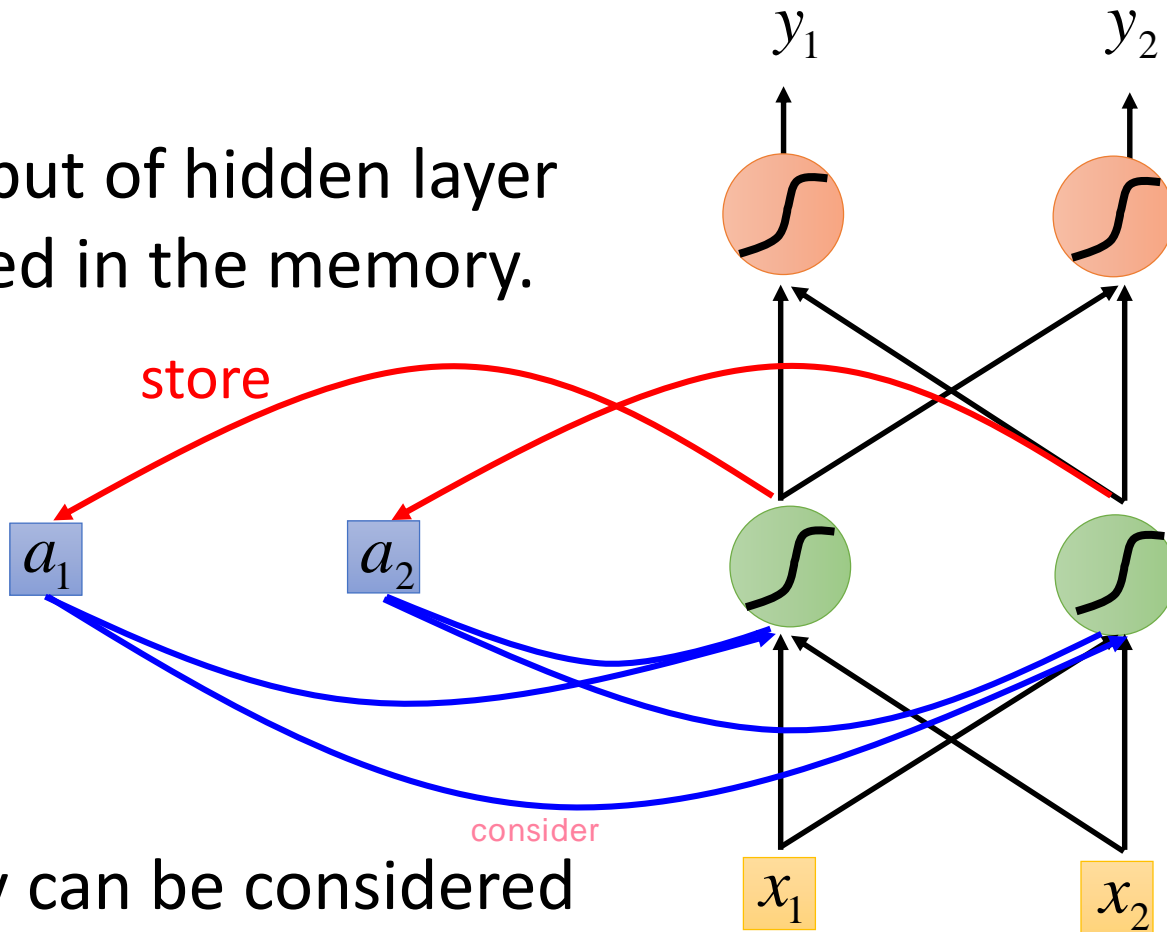
Taipei



記得Taipei之前的arrive&leave(上下文)

Recurrent Neural Network (RNN)

The output of hidden layer are stored in the memory.

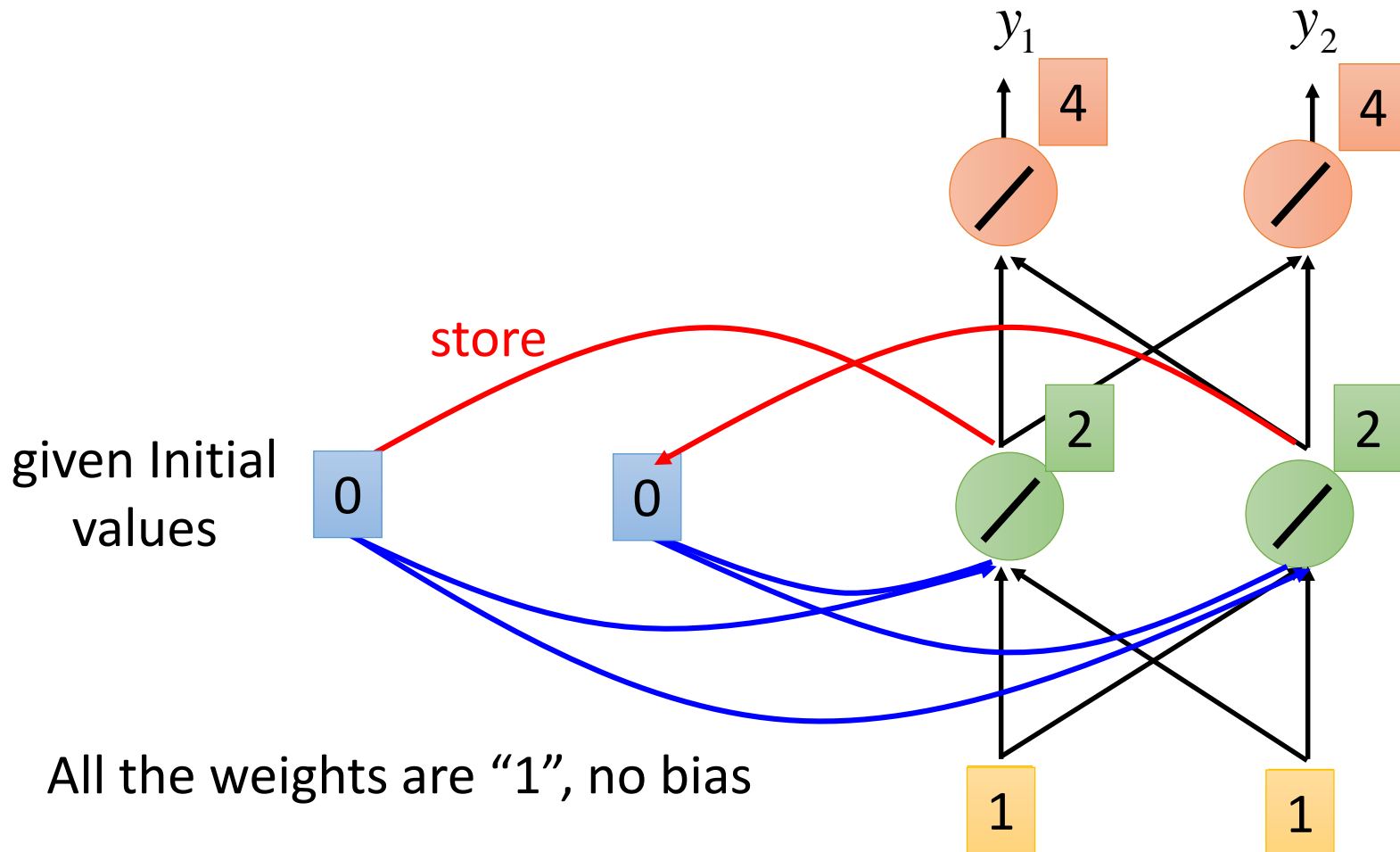


Memory can be considered as another input.

Example

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

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



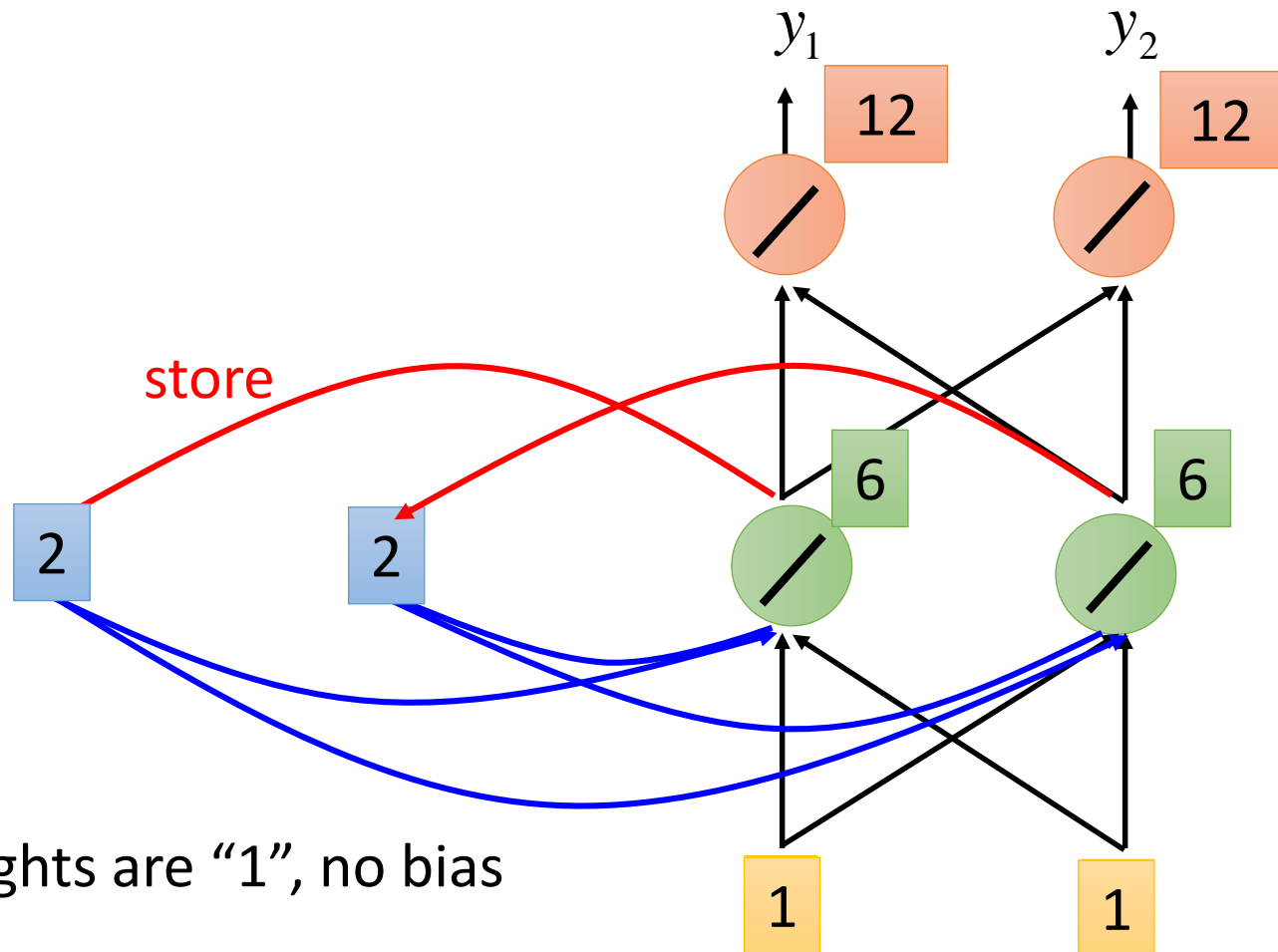
All the weights are "1", no bias

All activation functions are linear

Example

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

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

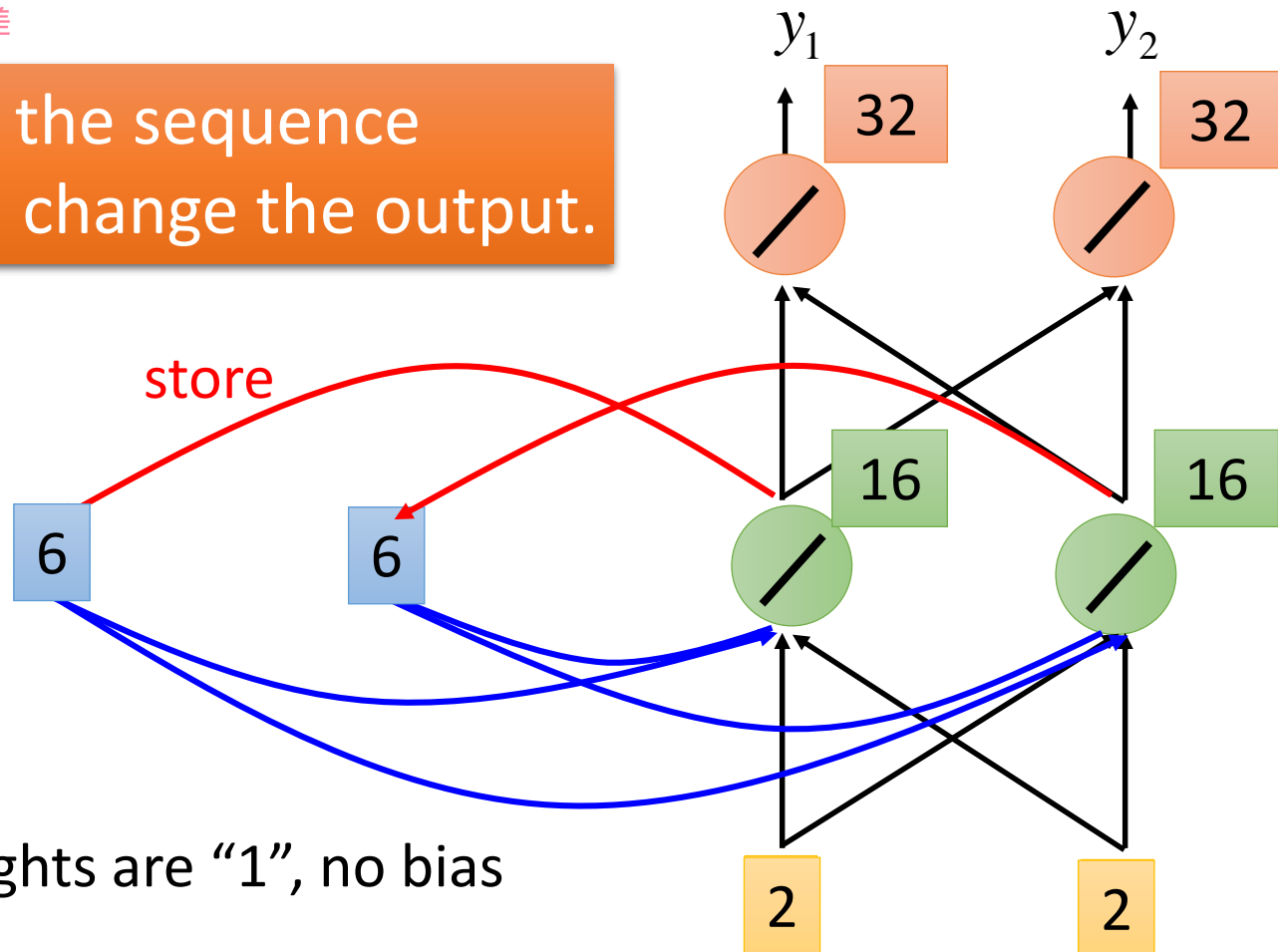
Example

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

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

input的順序有差

Changing the sequence order will change the output.



All the weights are "1", no bias

All activation functions are linear

同一個network在三個不同時間點，被使用了三次(綠色框框)

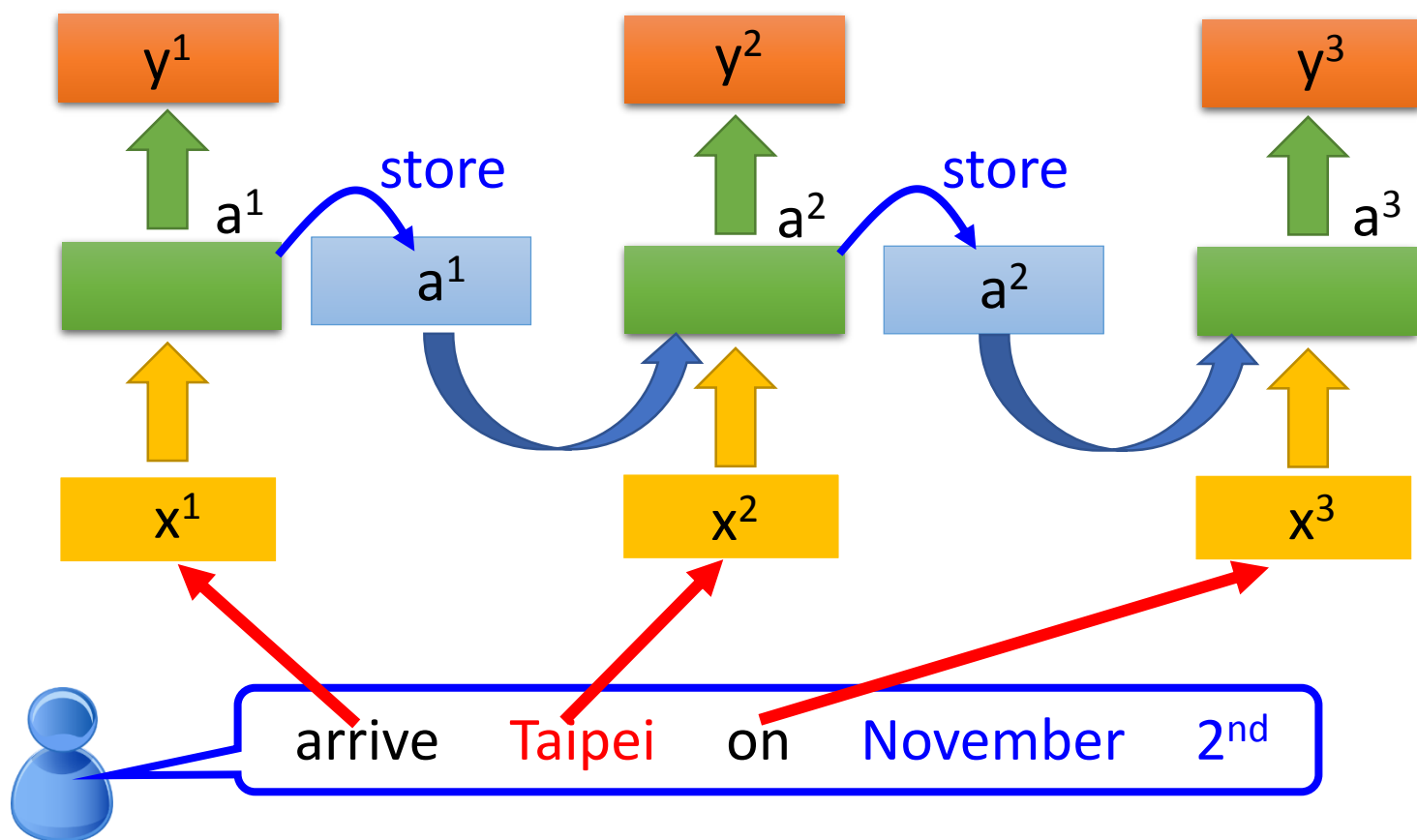
RNN

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

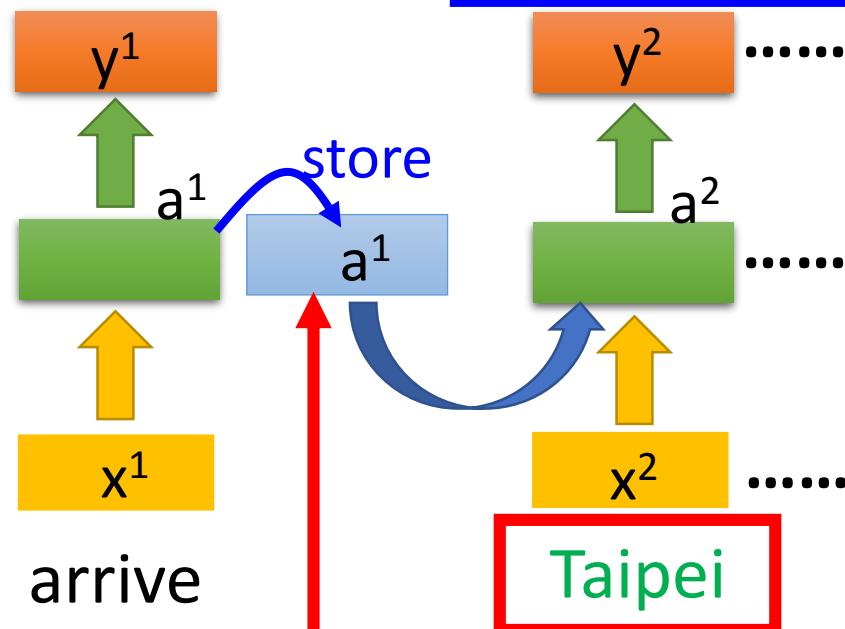
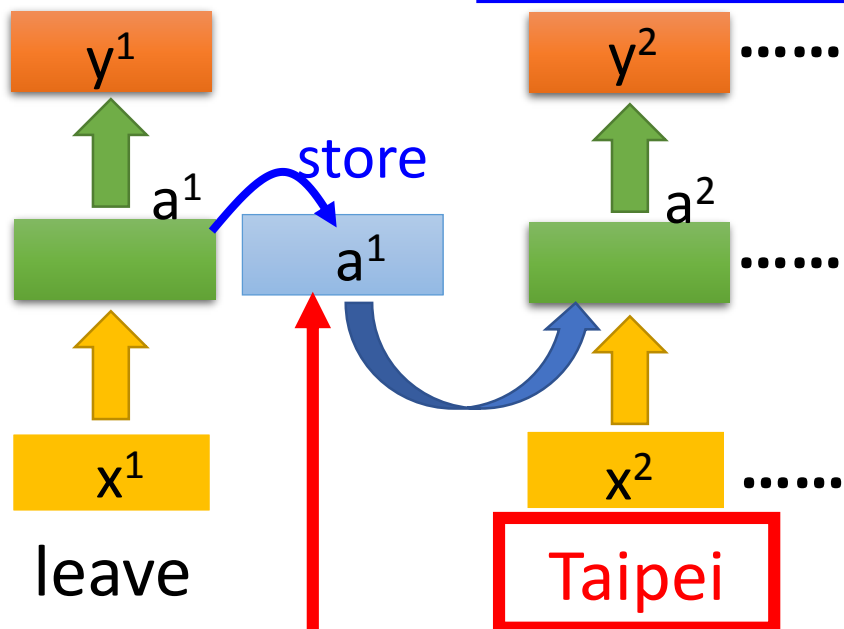
Different

Prob of “leave”
in each slot

Prob of “**Taipei**”
in each slot

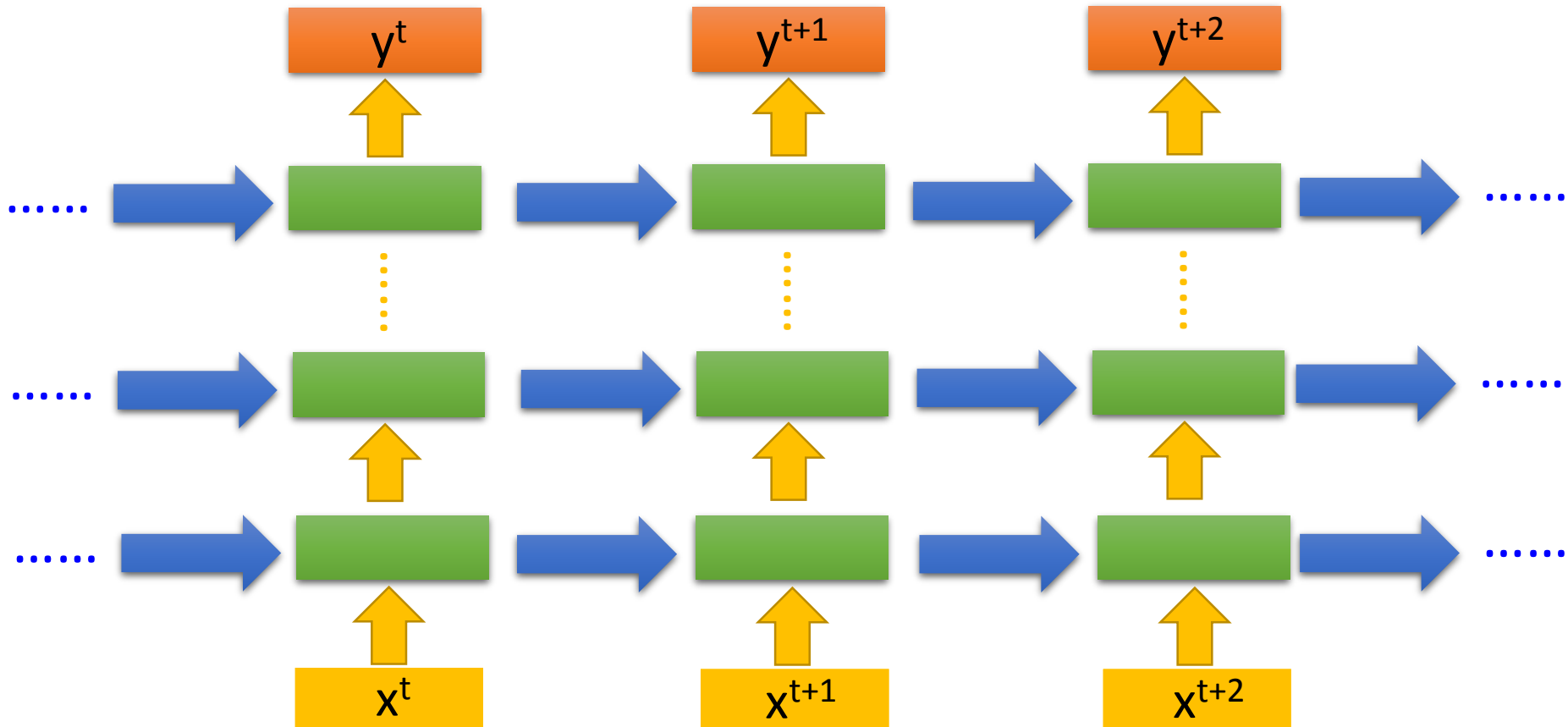
Prob of “arrive”
in each slot

Prob of “**Taipei**”
in each slot



The values stored in the memory is different.

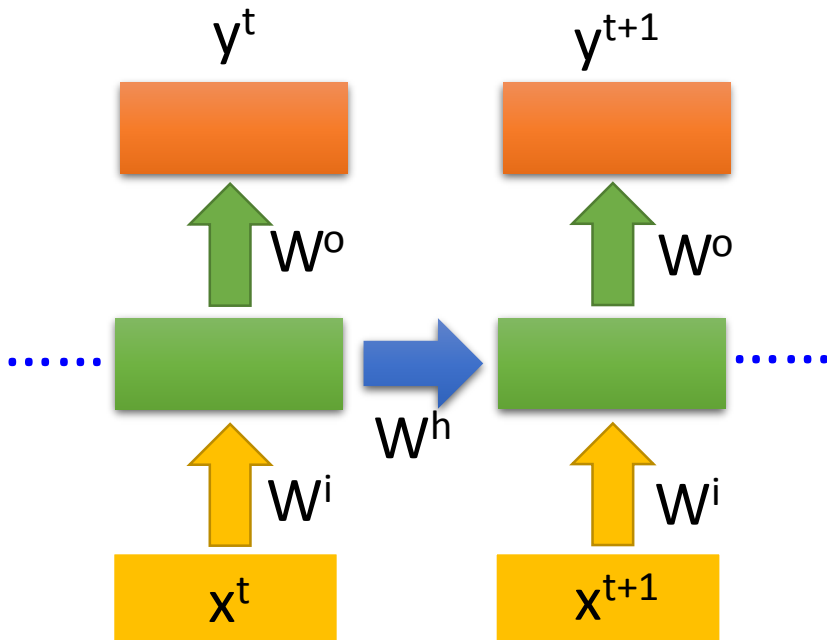
Of course it can be deep ...



Elman Network & Jordan Network

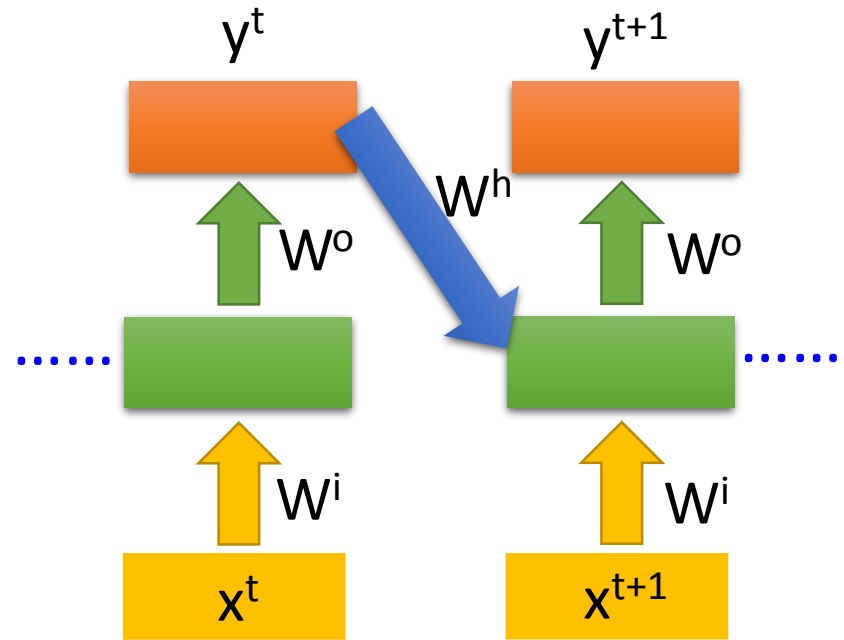
存hidden layer的值

Elman Network



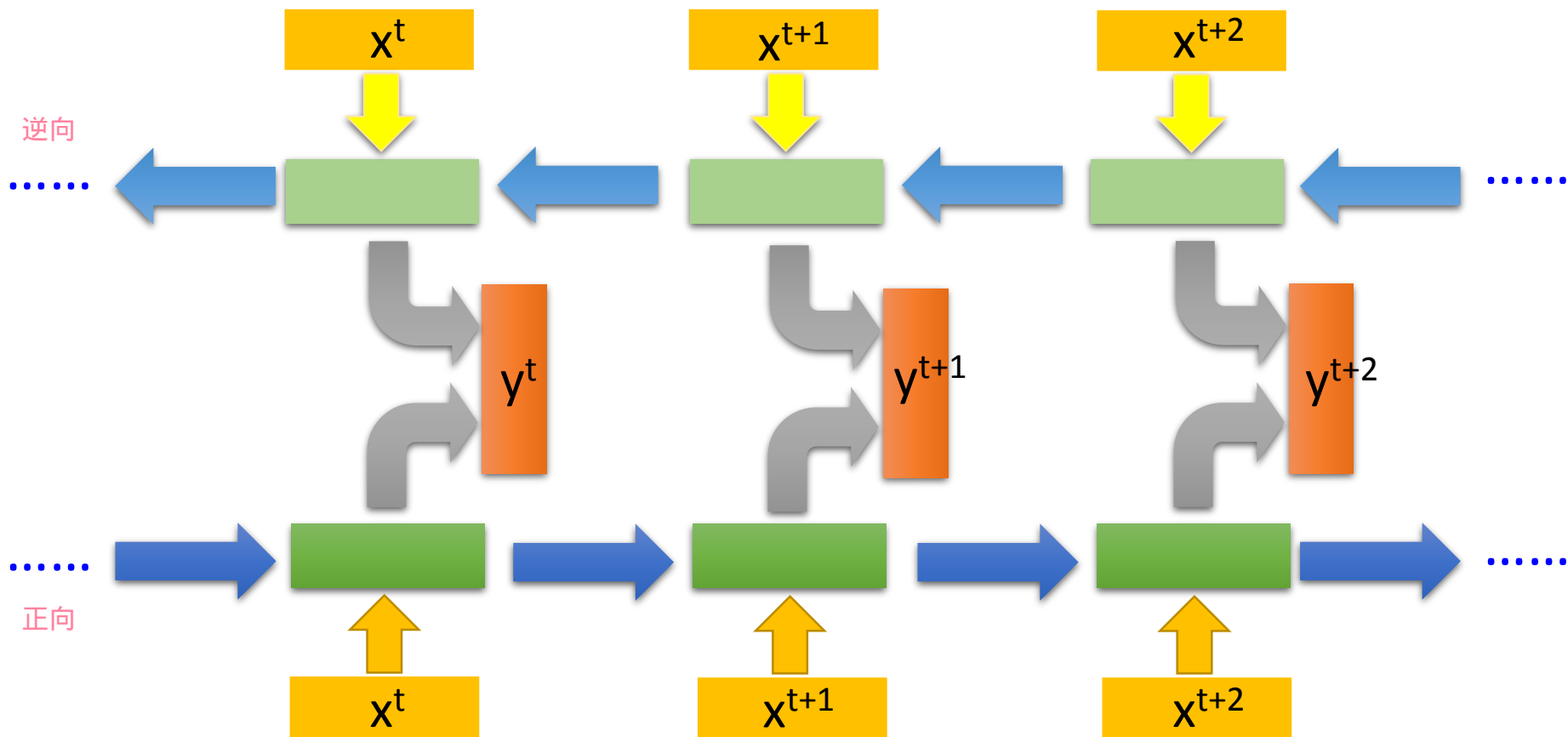
存output

Jordan Network

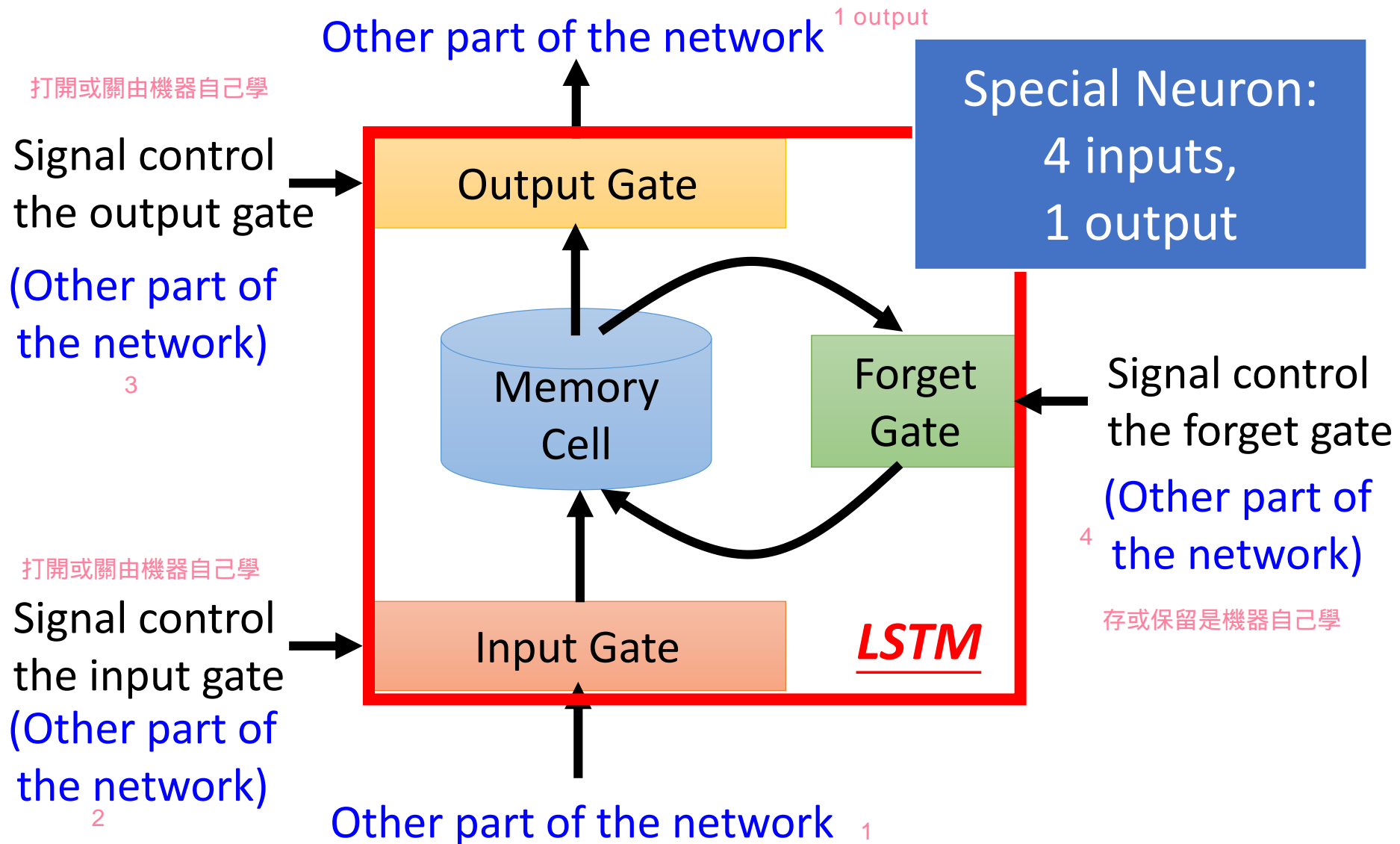


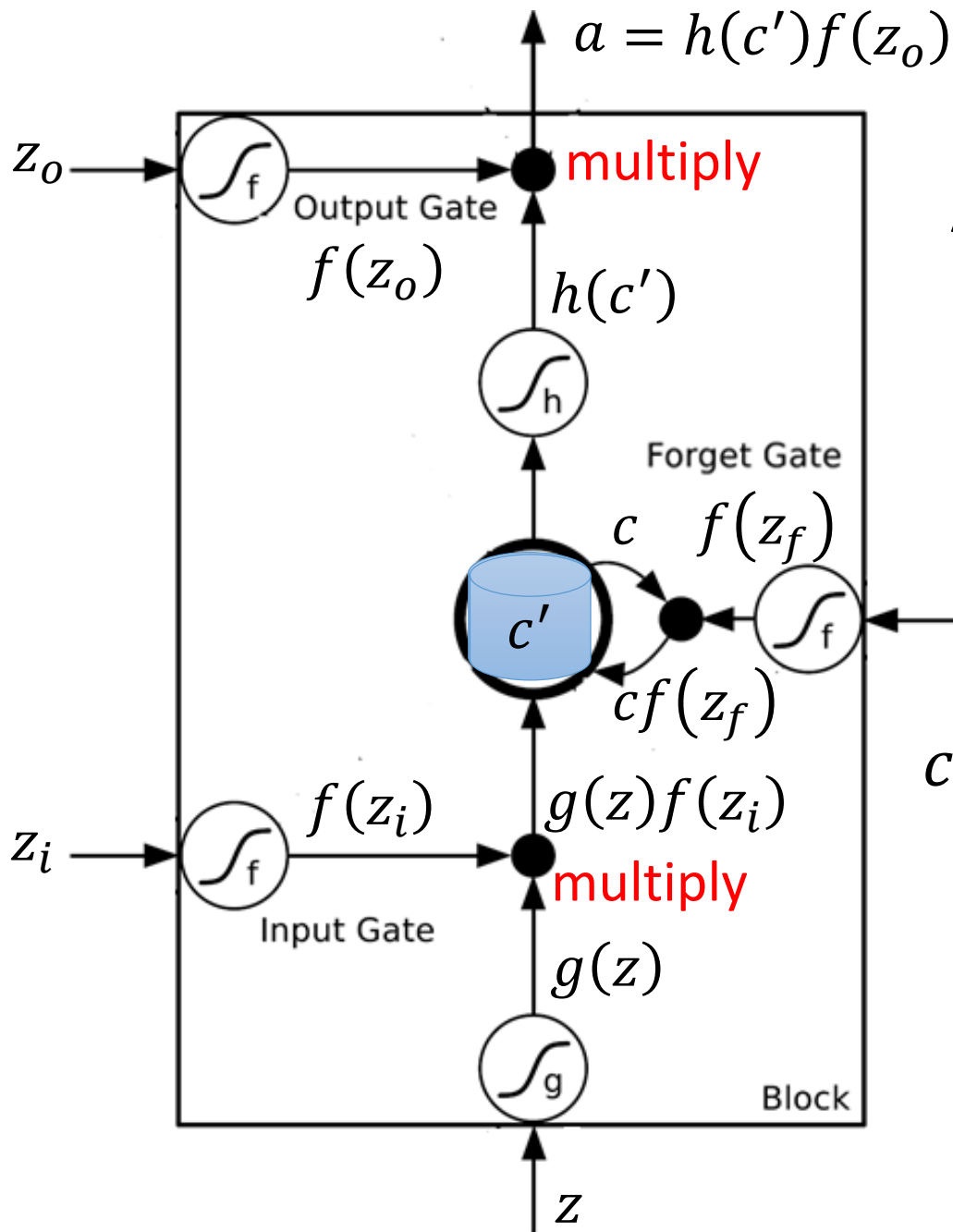
Bidirectional RNN

看的範圍較廣，故會有較好的表現



Long Short-term Memory (LSTM)





Activation function f is usually a sigmoid function

gate關 gate打開

Between 0 and 1

Mimic open and close gate

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

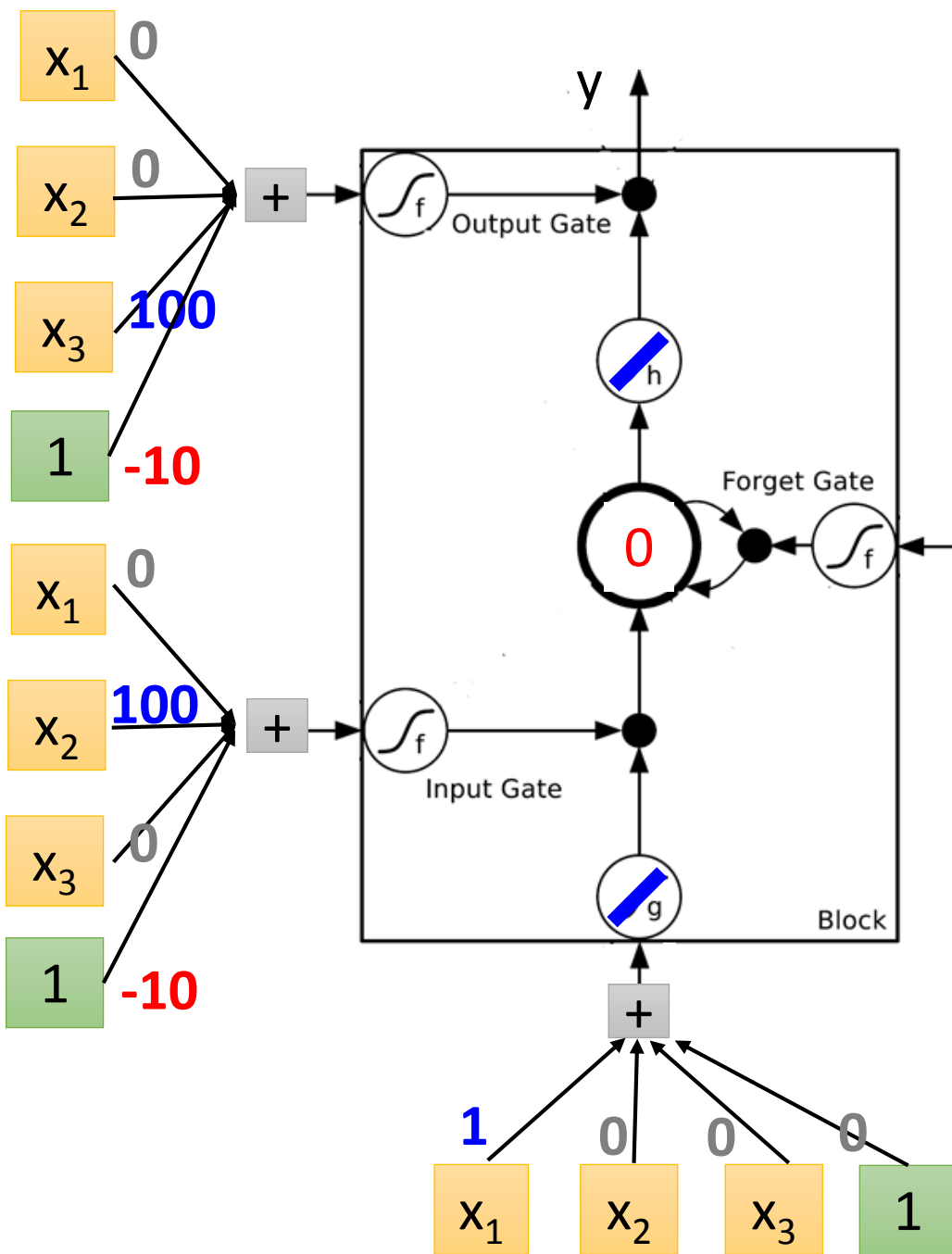
LSTM - Example

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

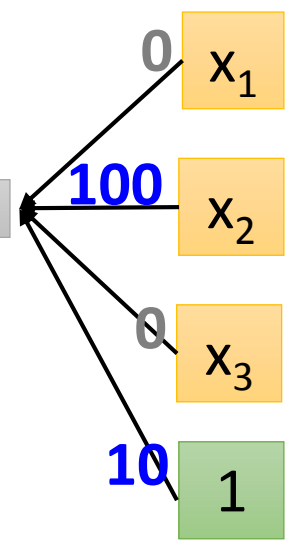
When $x_2 = 1$, add the numbers of x_1 into the memory

When $x_2 = -1$, reset the memory

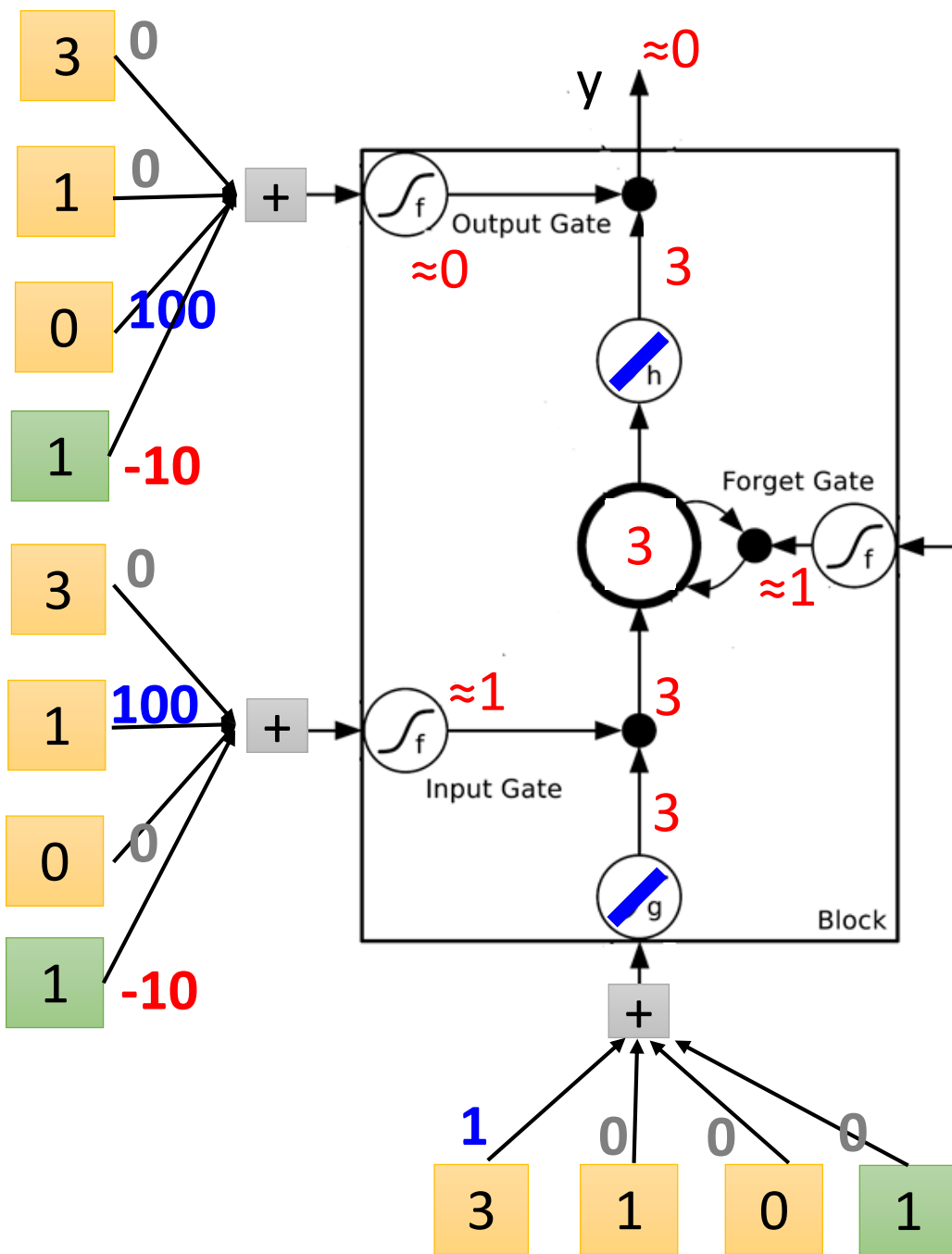
When $x_3 = 1$, output the number in the memory.



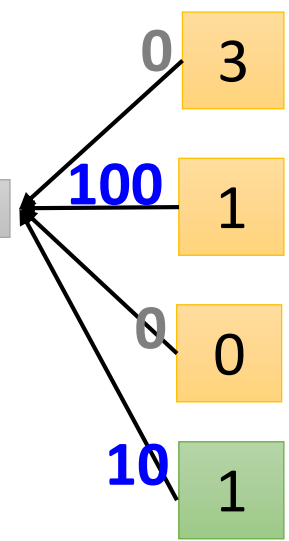
y 0 0 0 7 0



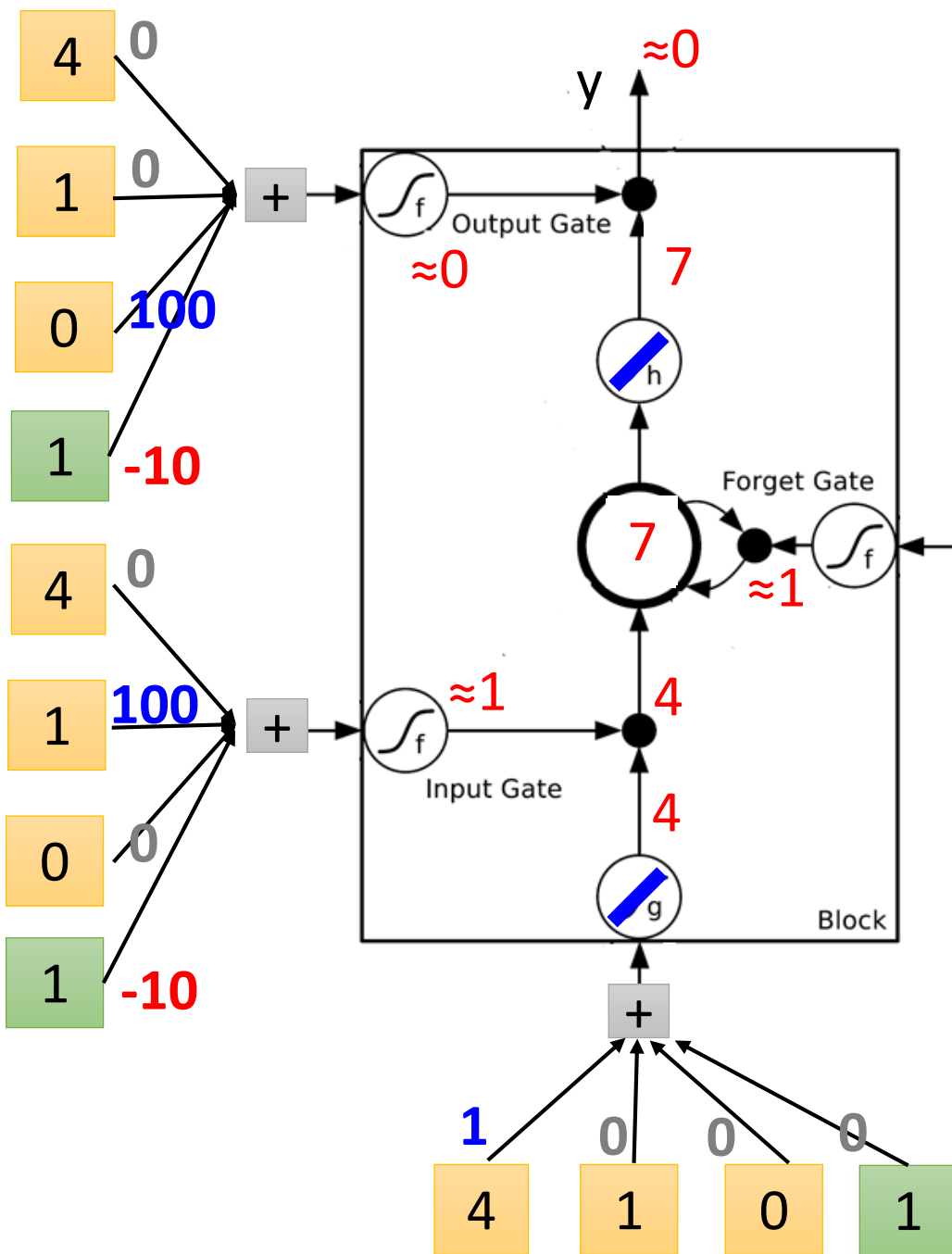
	1	2	3	4	5
x_1	3	4	2	1	3
x_2	1	1	0	0	-1
x_3	0	0	0	1	0



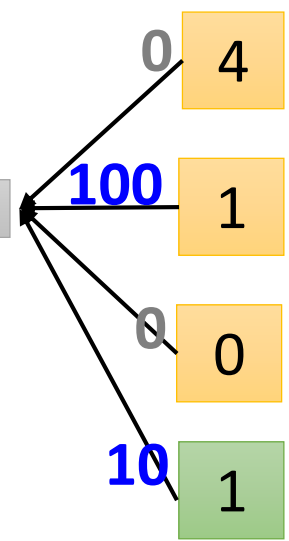
y 0 0 0 7 0



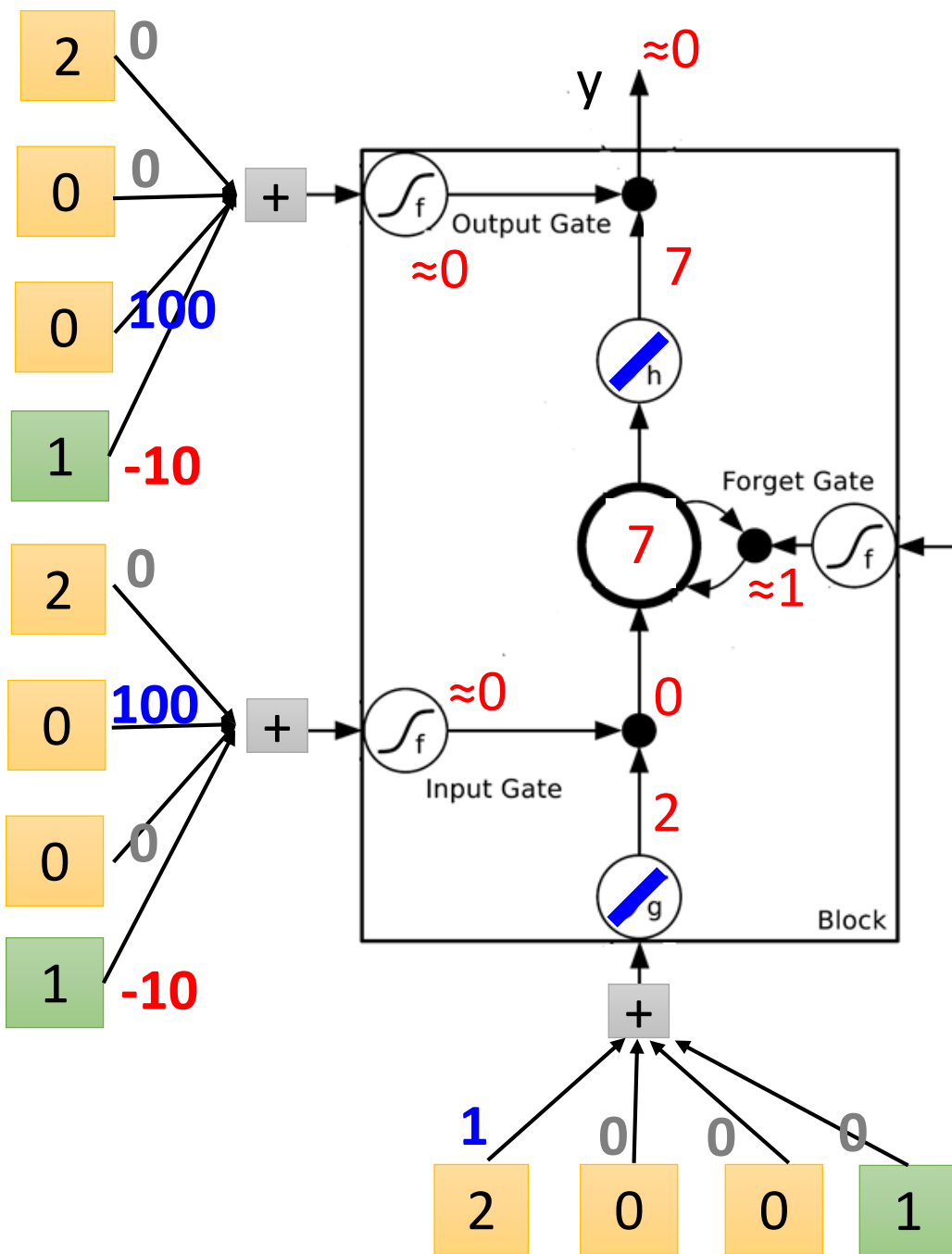
x_1 3 4 2 1 3
 x_2 1 1 0 0 -1
 x_3 0 0 0 1 0



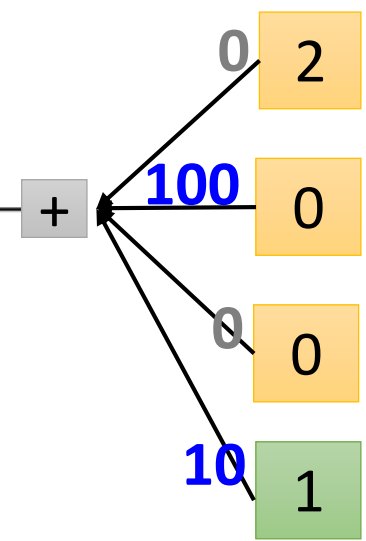
y 0 0 0 7 0



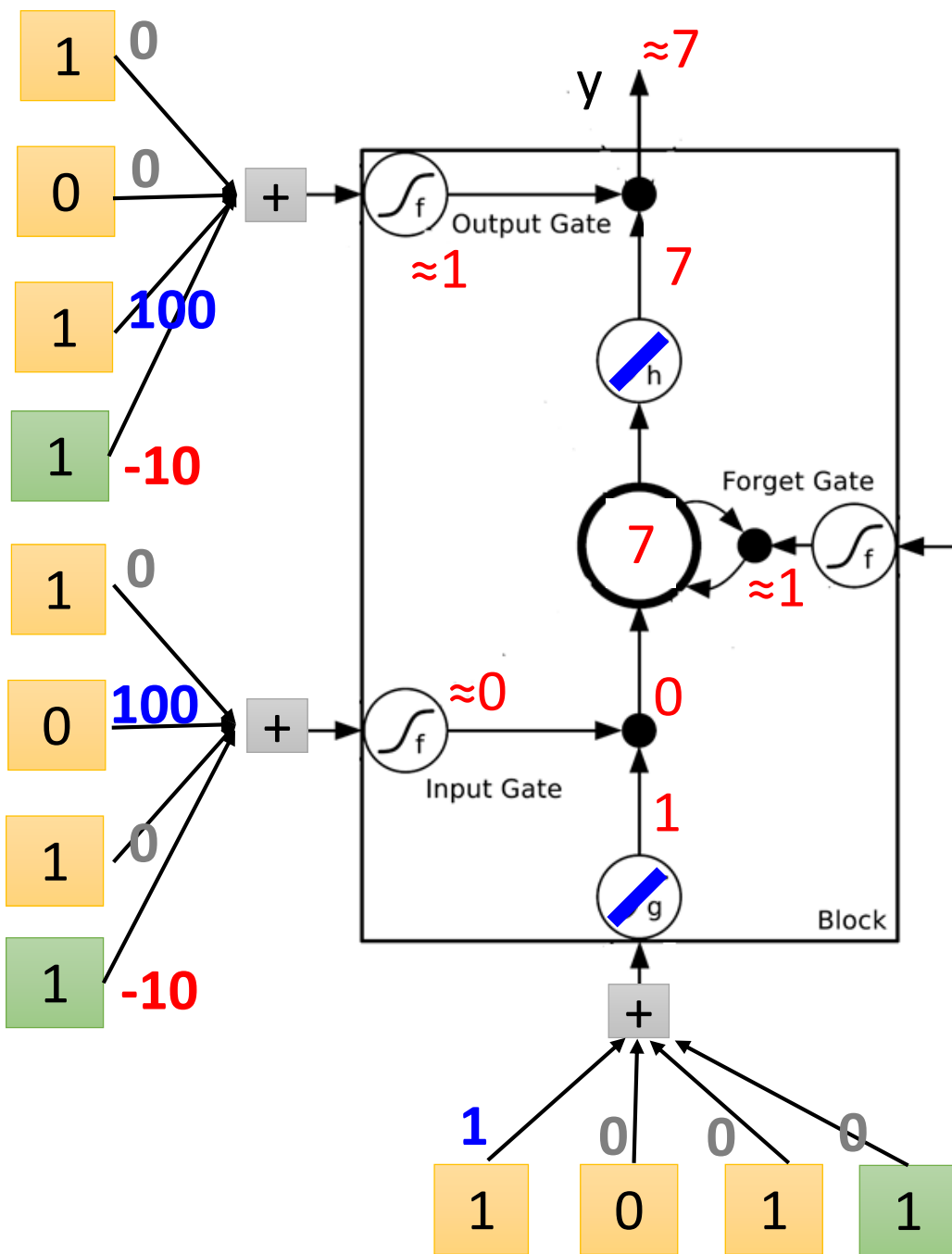
	x_1	x_2	x_3
x_1	3	4	2
x_2	1	1	0
x_3	0	0	1



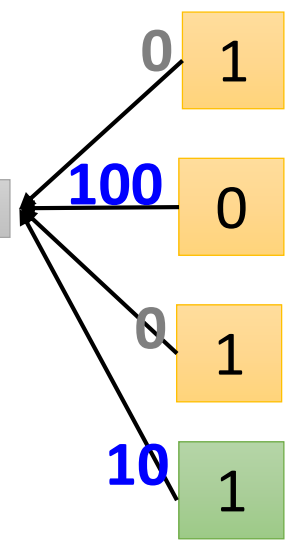
y 0 0 0 7 0



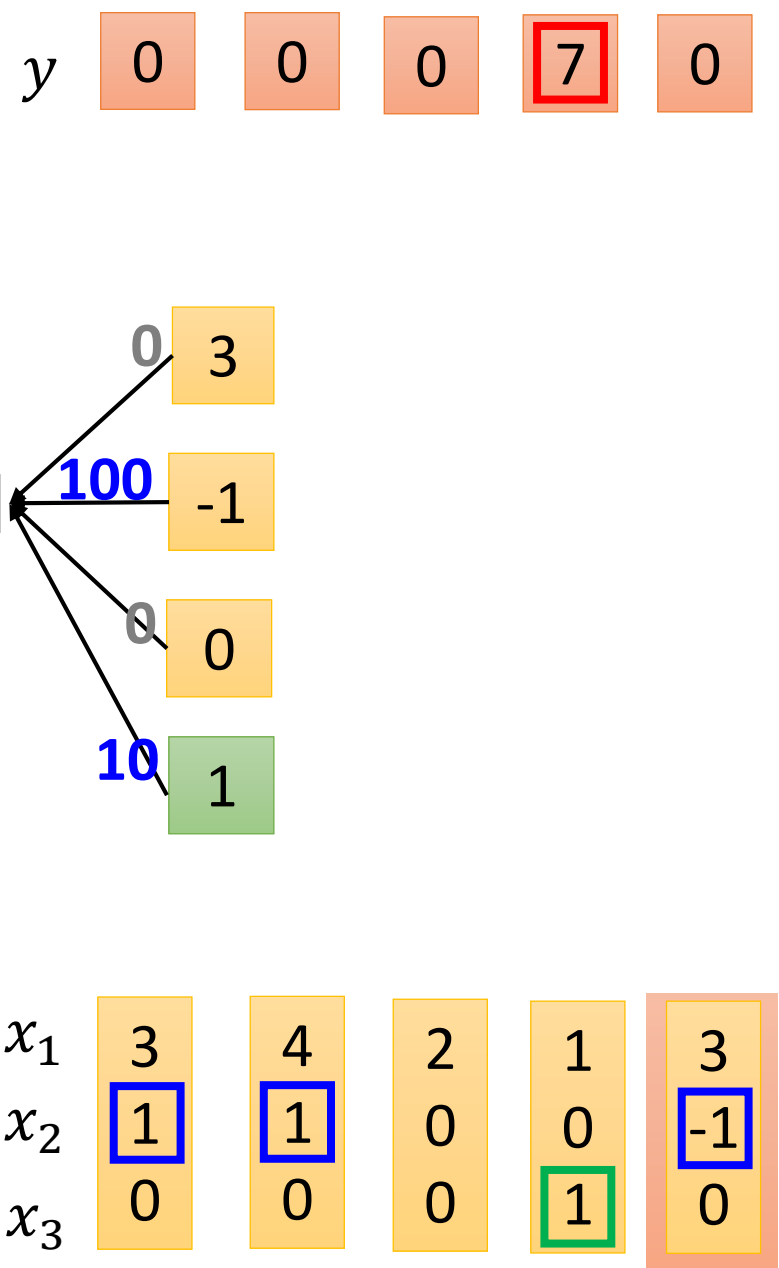
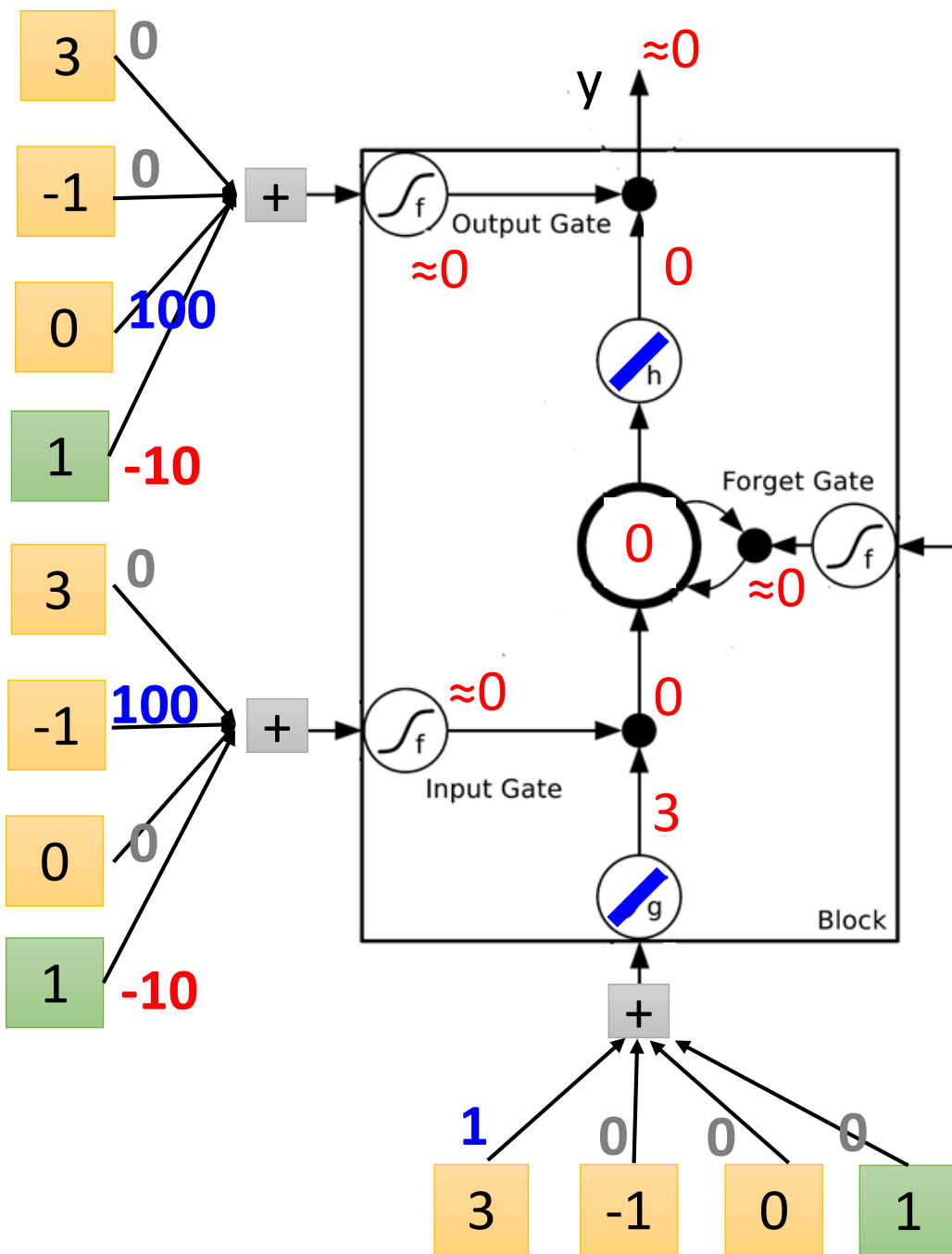
	x_1		x_2		x_3
	3		4		2
	1		1		0
	0		0		0
	0		0		0
	1		0		1
	0		0		0
	3		-1		0



y 0 0 0 7 0

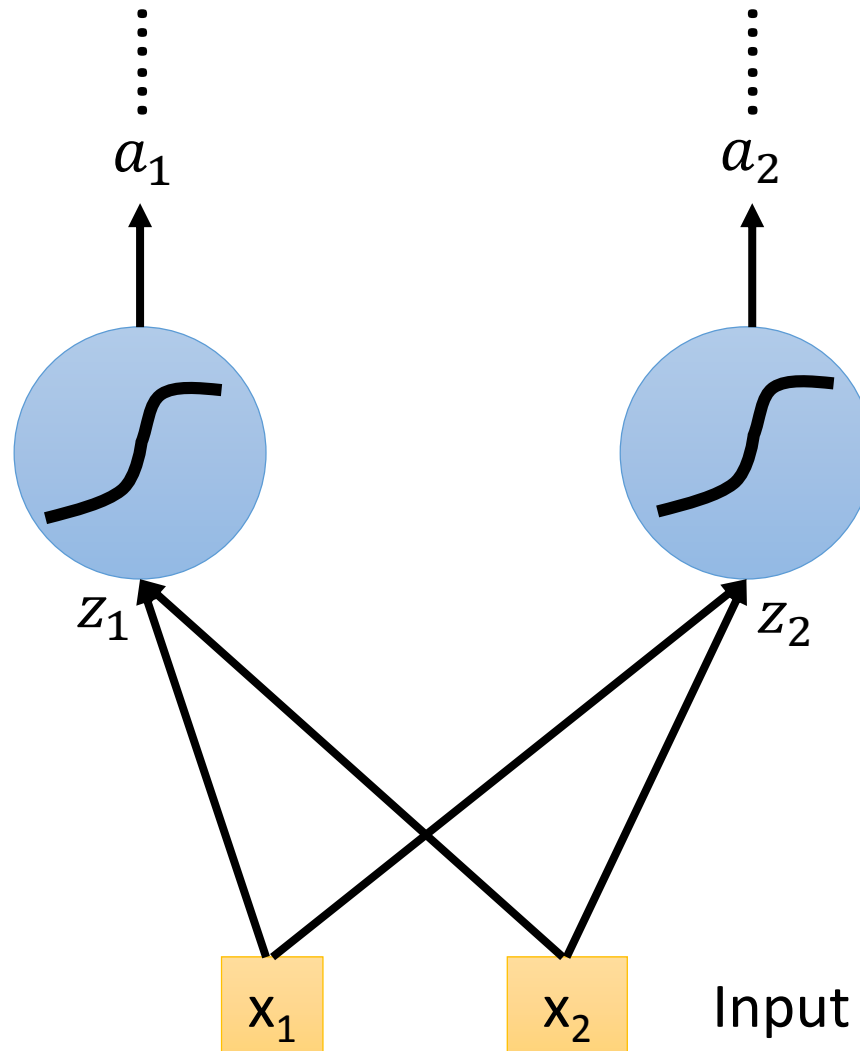


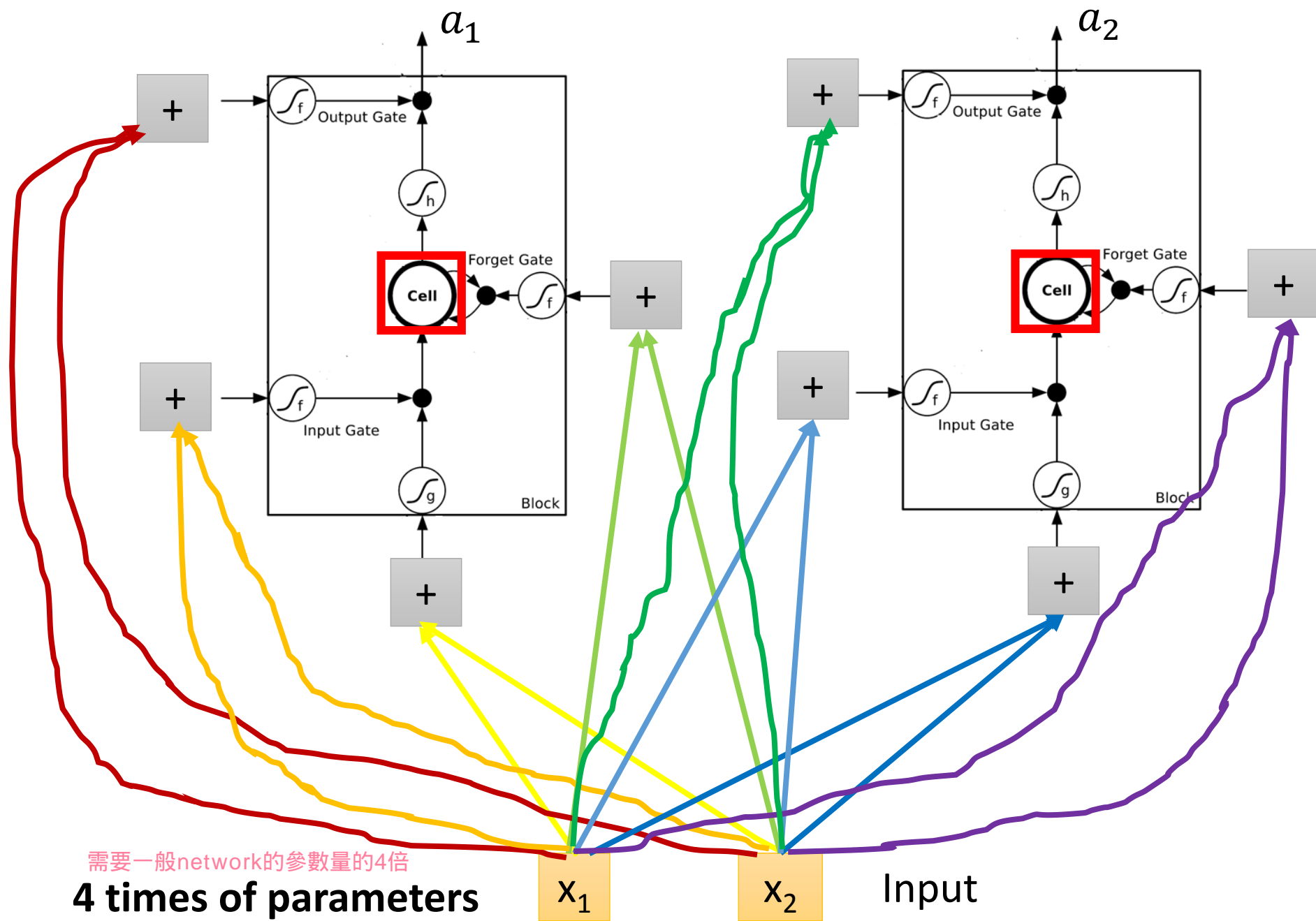
	x_1		x_2		x_3
	3		4		2
	1		1		0
	0		0		0
	1		0		1
	3		-1		0



Original Network:

- Simply replace the neurons with LSTM

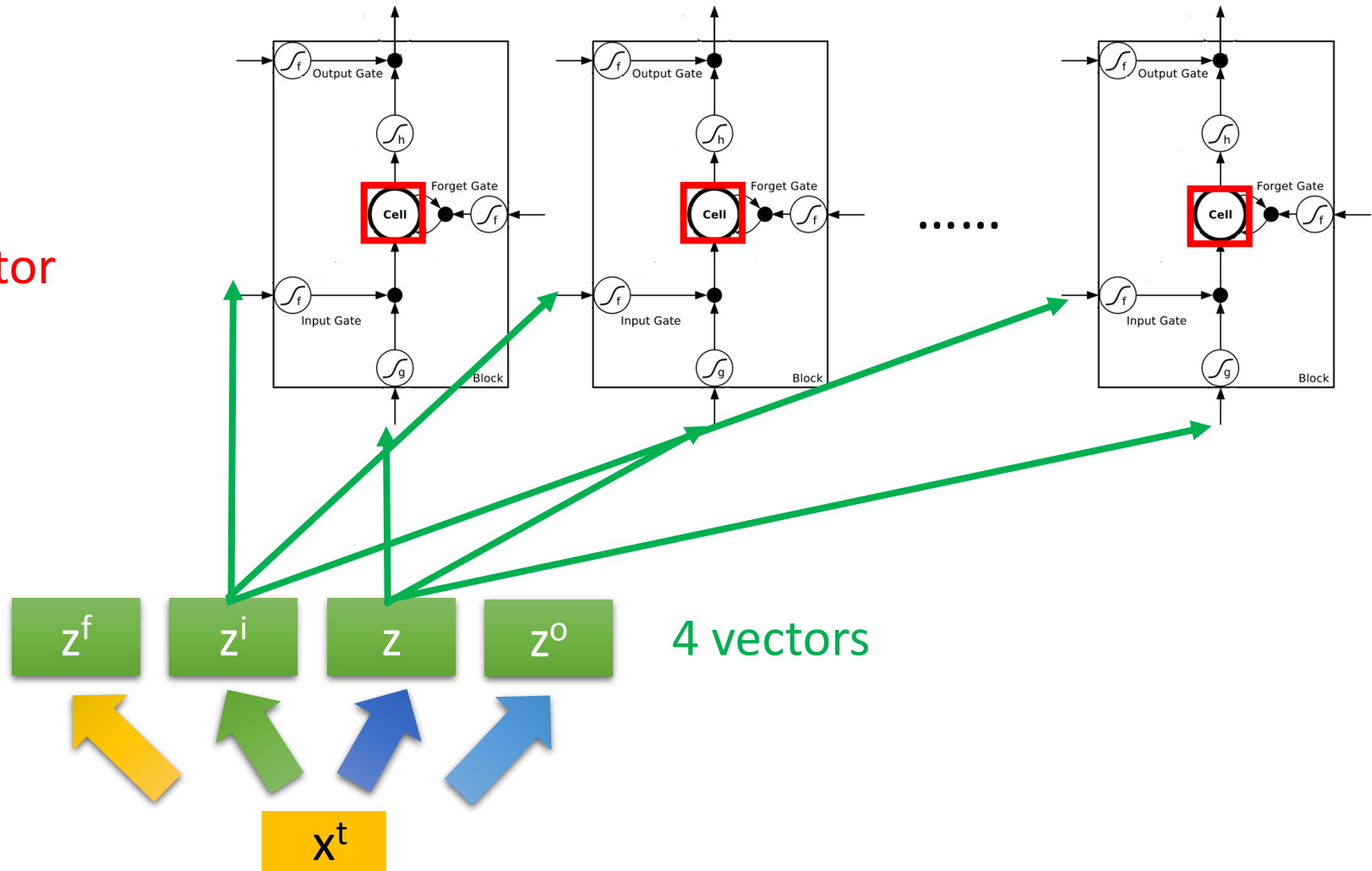




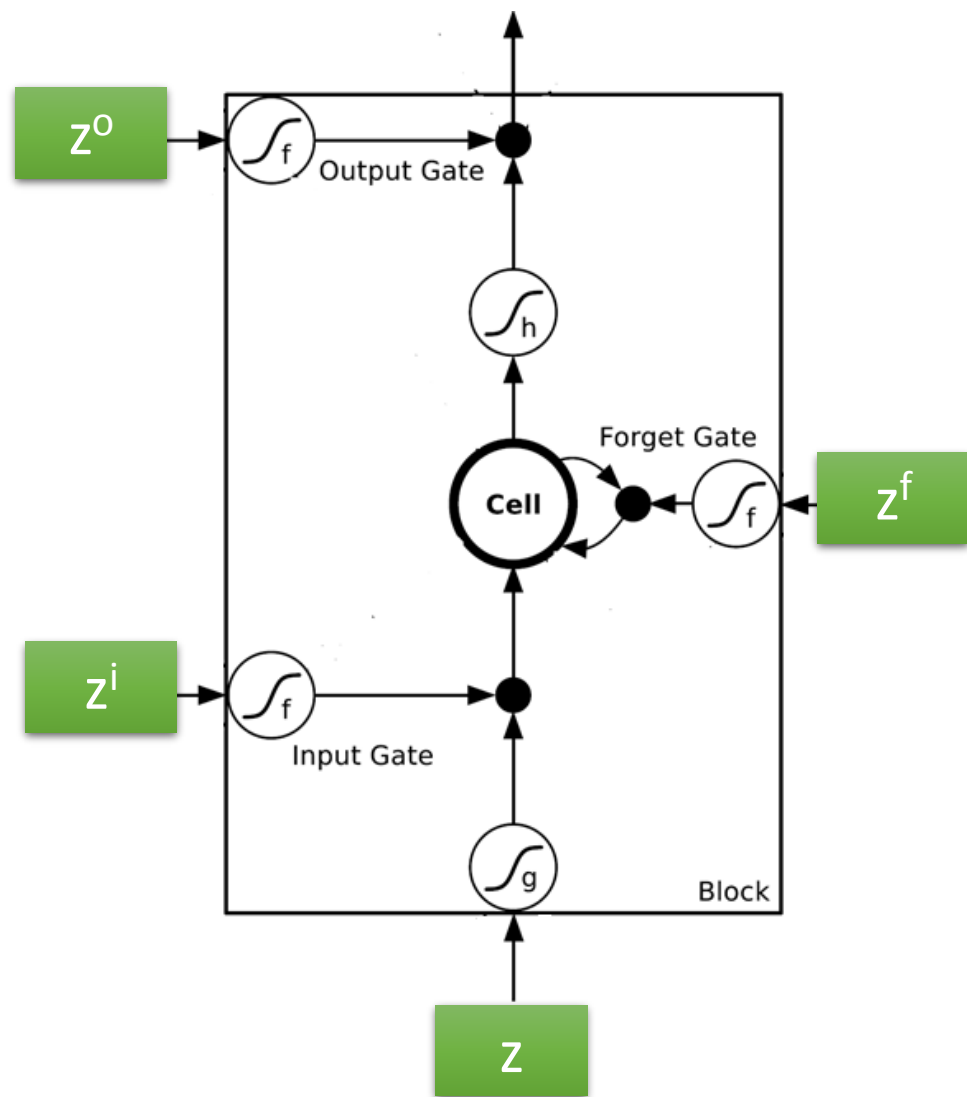
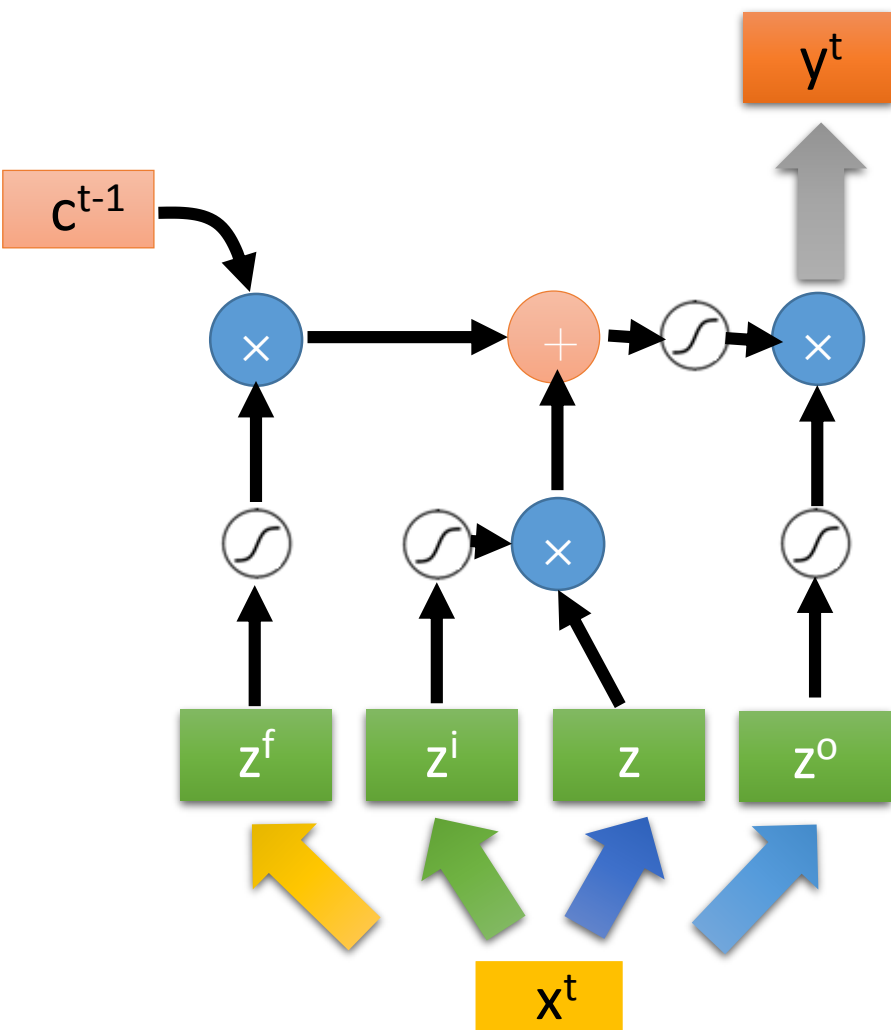
LSTM

 C^{t-1}

vector

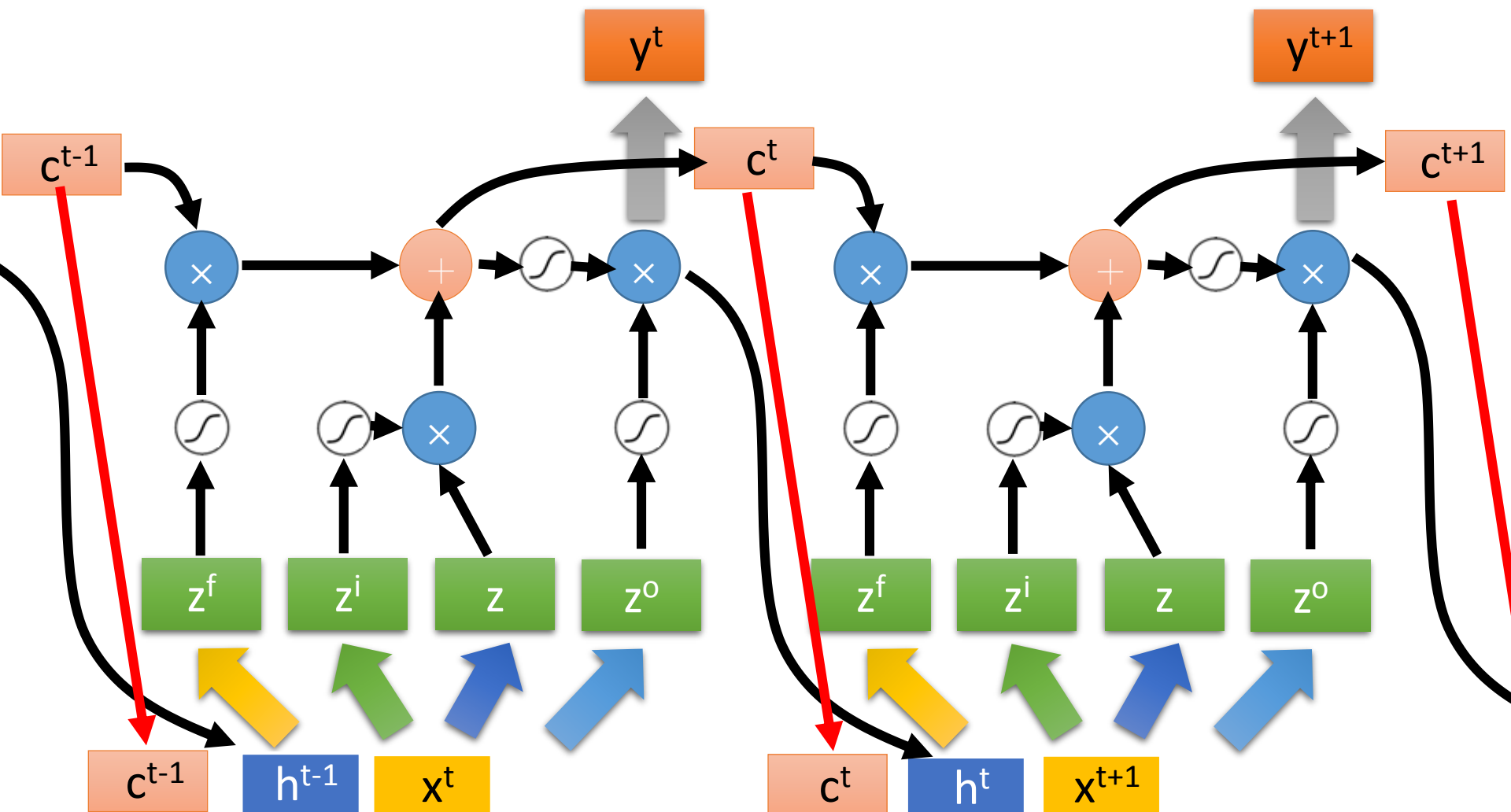


LSTM



LSTM

Extension: “peephole”



Multiple-layer LSTM

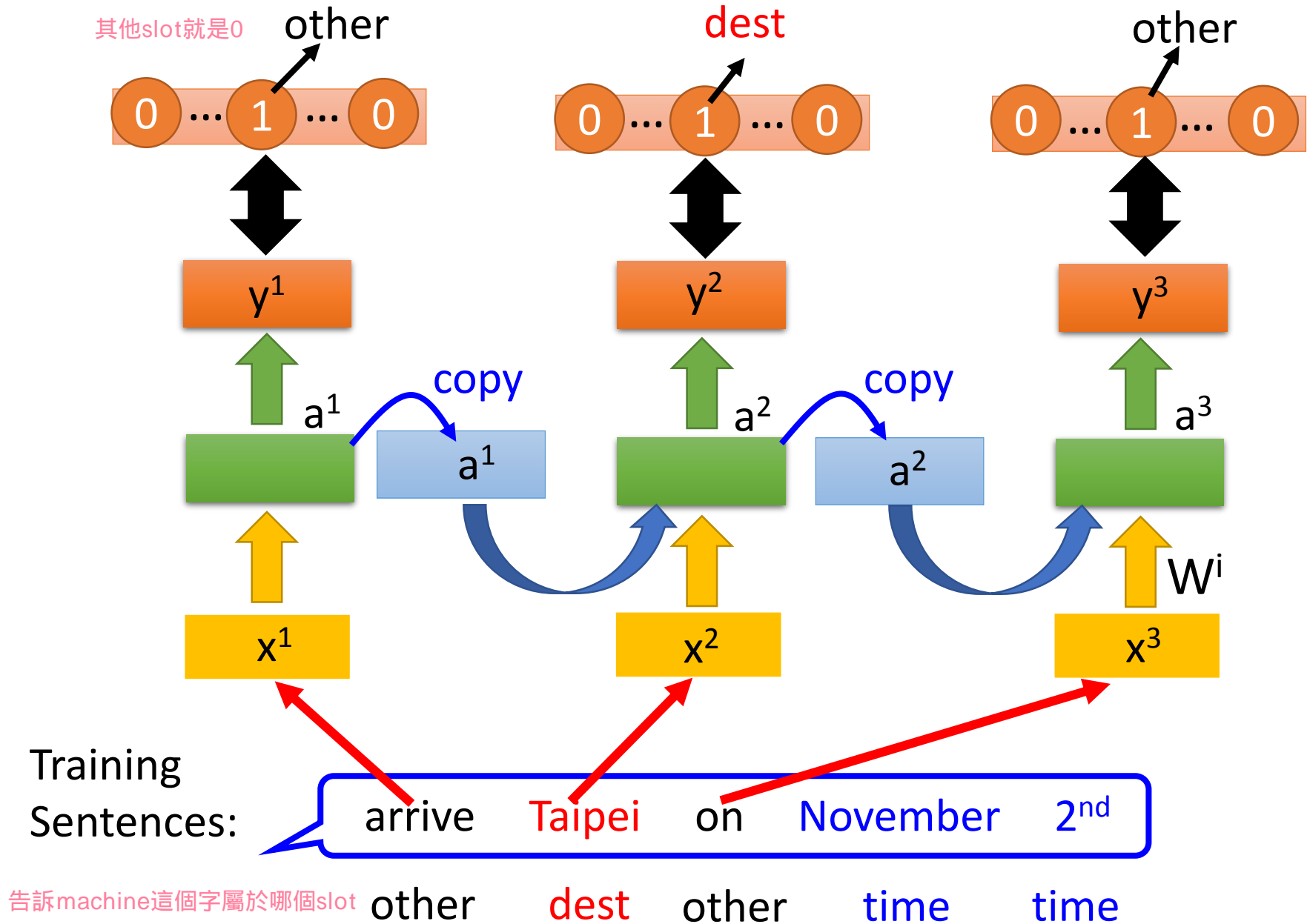
Don't worry if you cannot understand this.
Keras can handle it.

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

This is quite
standard now.

我到底看了什麼？

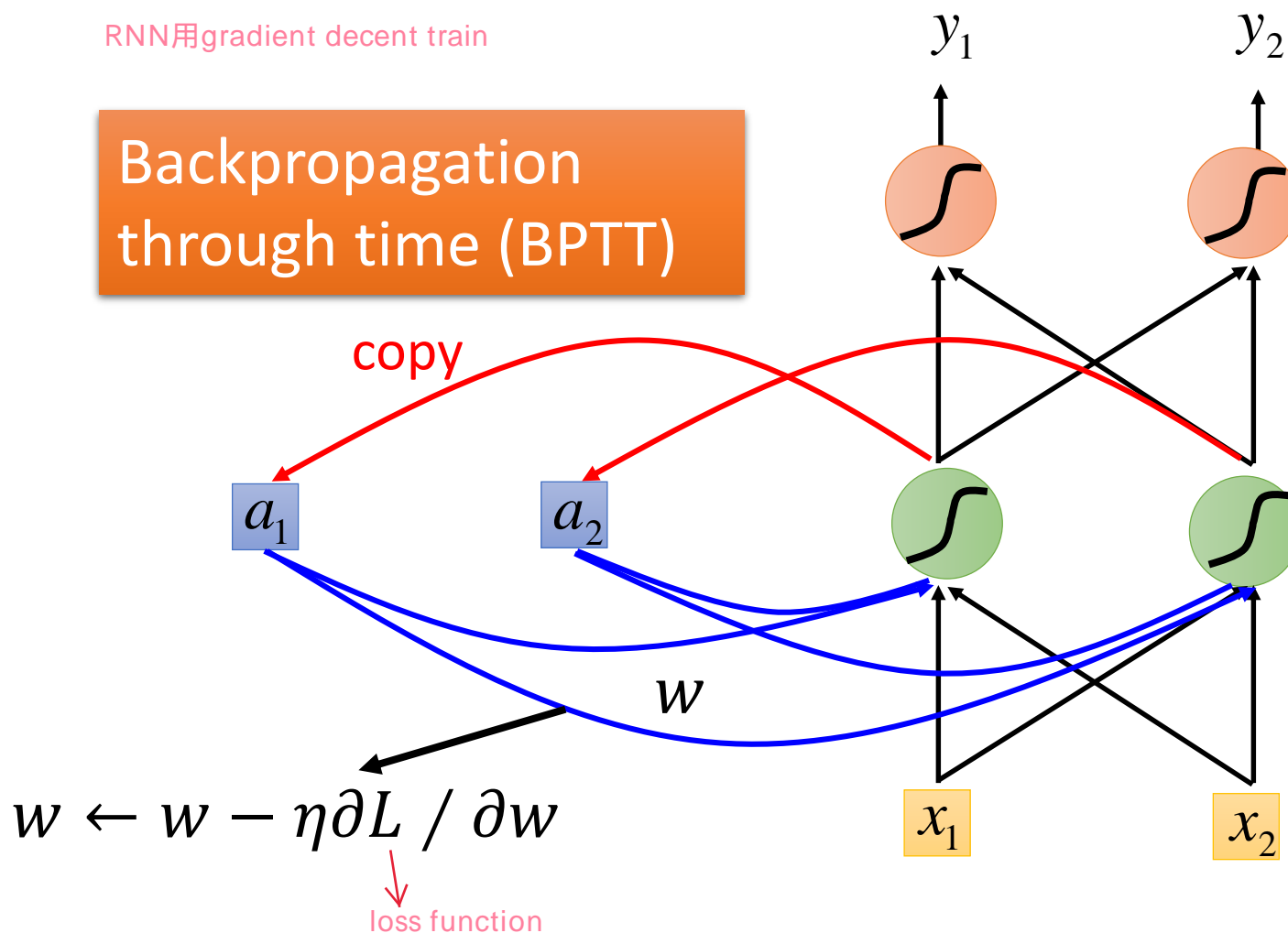
Learning Target



Learning

RNN用gradient decent train

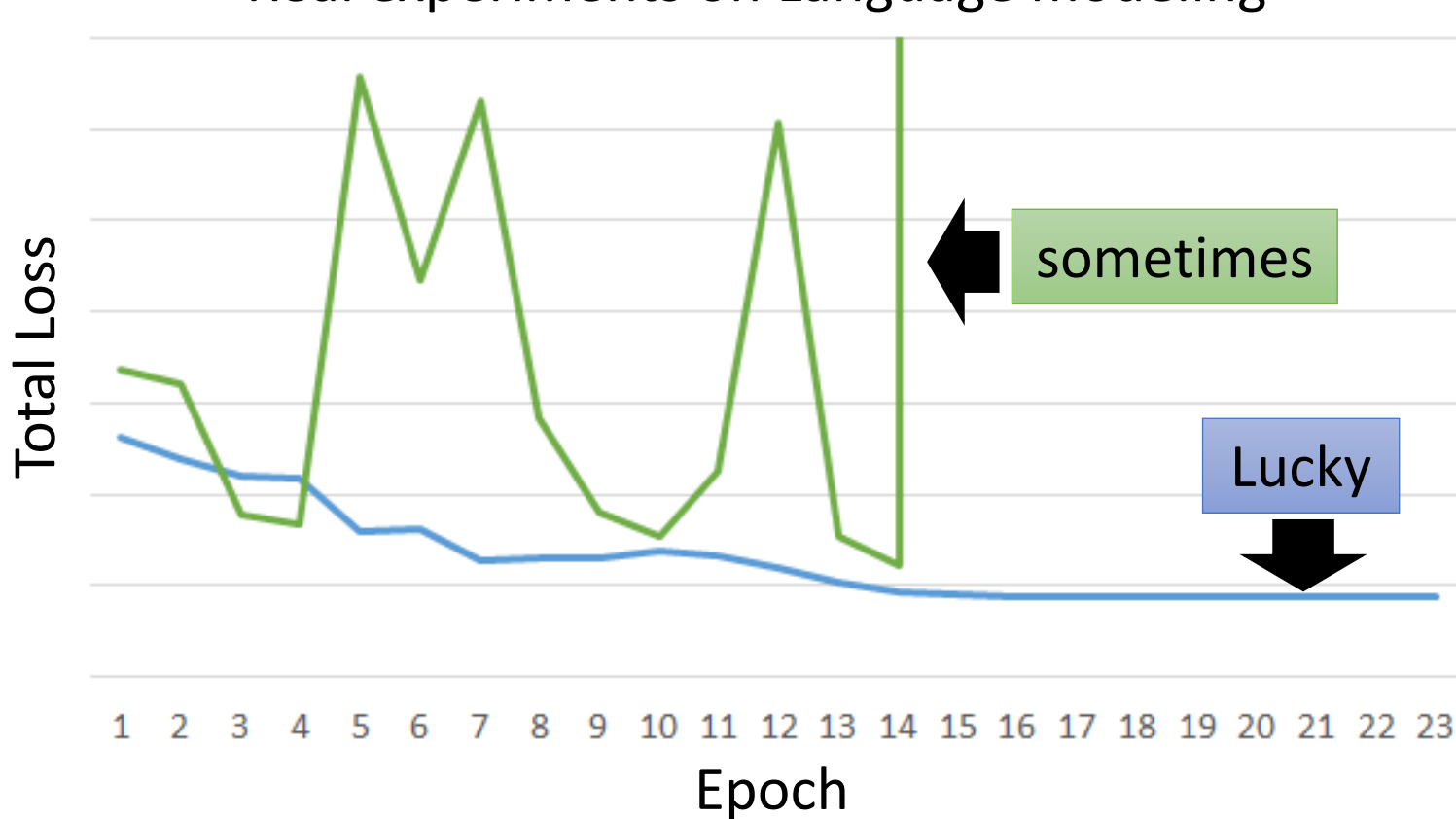
Backpropagation
through time (BPTT)



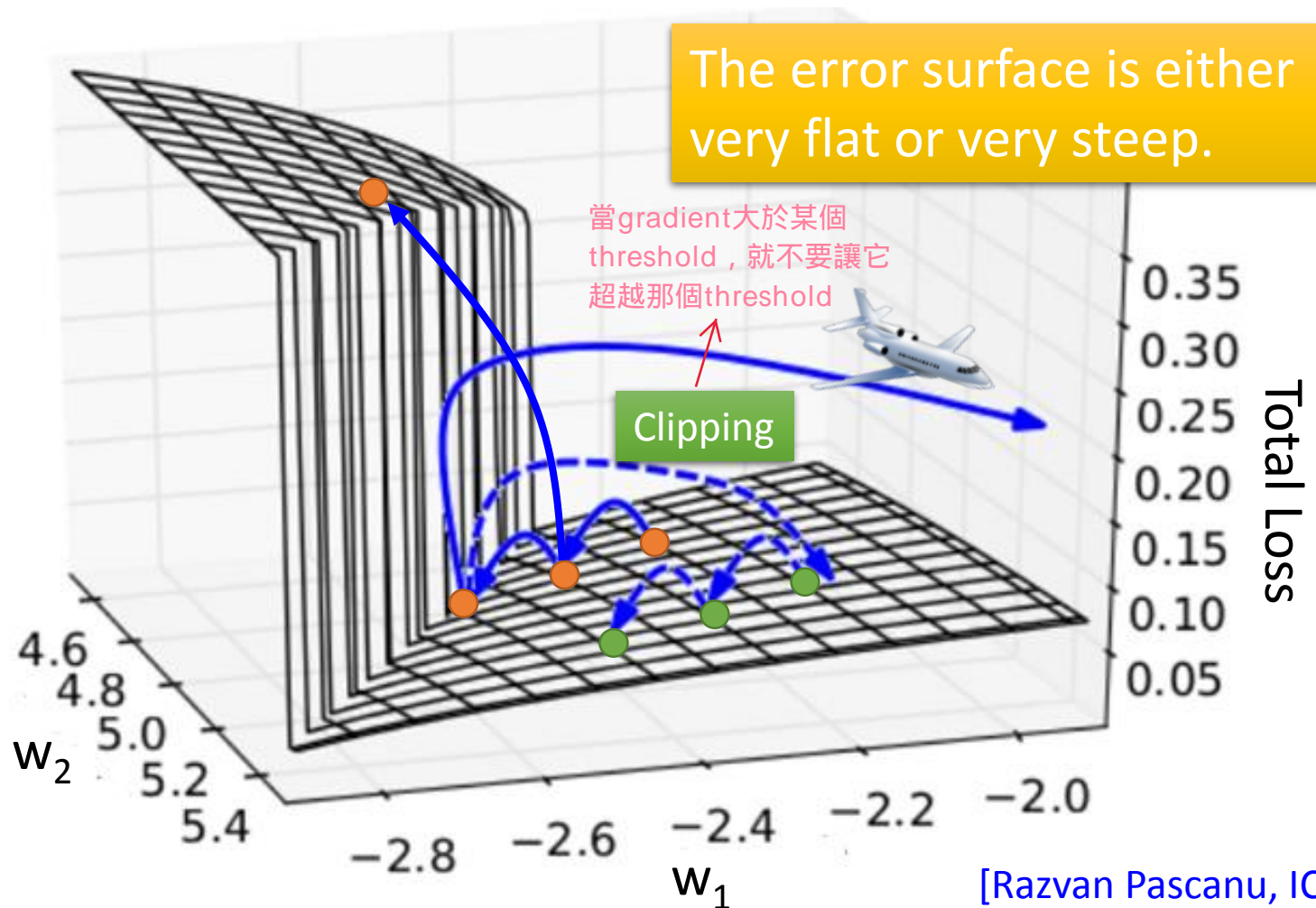
Unfortunately

- RNN-based network is not always easy to learn

Real experiments on Language modeling



The error surface is rough.



[Razvan Pascanu, ICML'13]

Why?

為什麼RNN會有那麼陡峭的特性?
因有time sequence, 同樣的weight
在不同時間點會被重複使用。

在非常短的區域內, gradient有很大的
變化, 因此很難設learning rate

$$w = 1 \quad \longrightarrow \quad y^{1000} = 1$$

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

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

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

很大的gradient

Large
 $\partial L / \partial w$

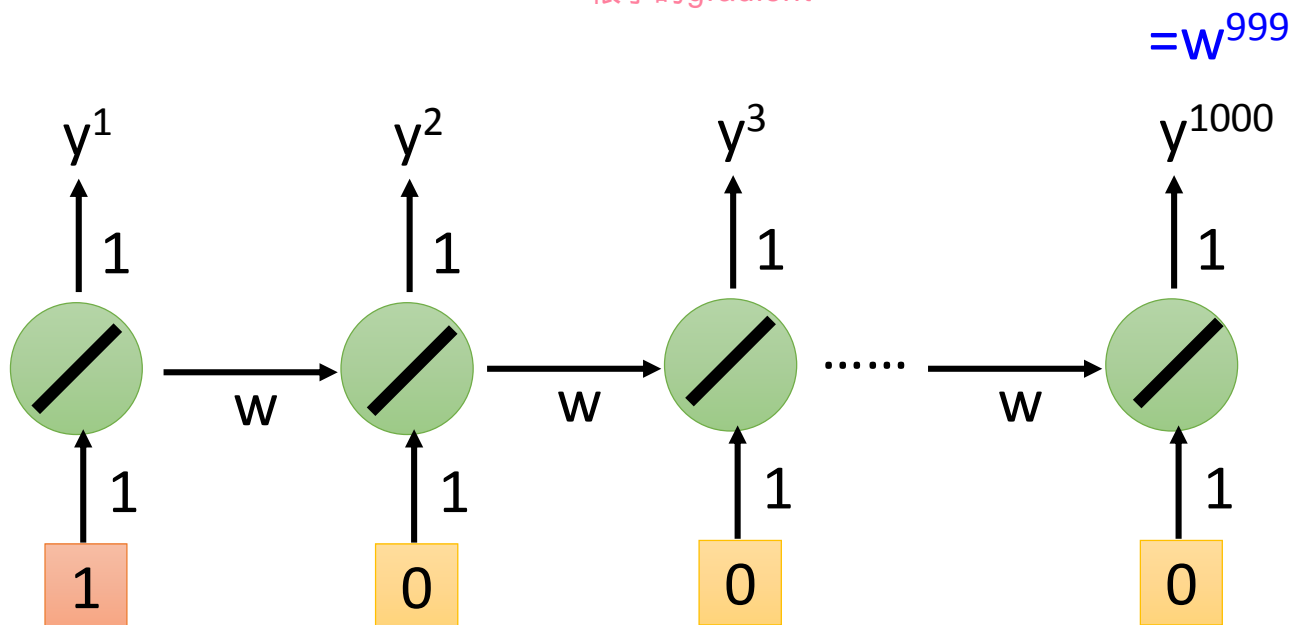
Small
Learning rate?

small
 $\partial L / \partial w$

很小的gradient

Large
Learning rate?

Toy Example



Helpful Techniques

GRU: "舊的不去，新的不來"
會連動input & forget gate，當
input gate被打開時，forget gate會
自動關閉。
=要把存在memory裡的值清掉，才
可把新值存進來。

- Long Short-term Memory (LSTM)

- Can deal with gradient vanishing (not gradient explode) 處理平坦的部分，但仍有崎嶇的地方

- Memory and input are

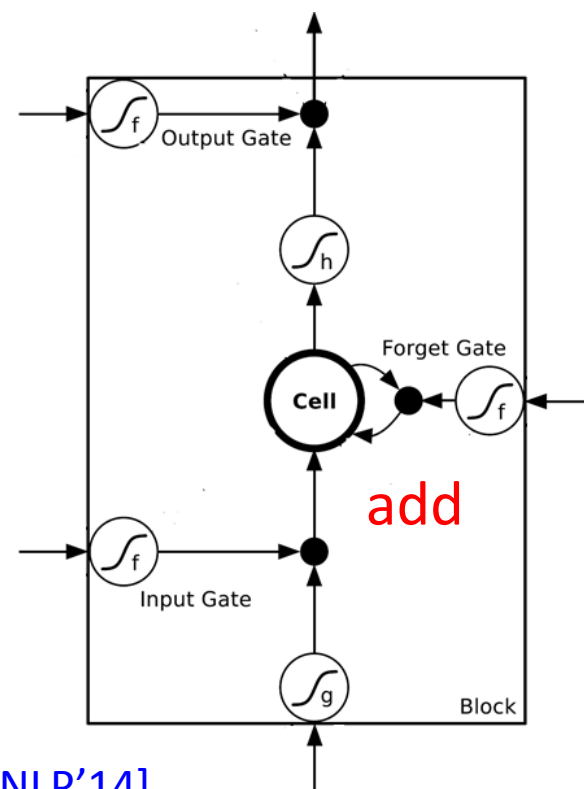
- added** memory和input是相加的

- The influence never disappears unless forget gate is closed

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

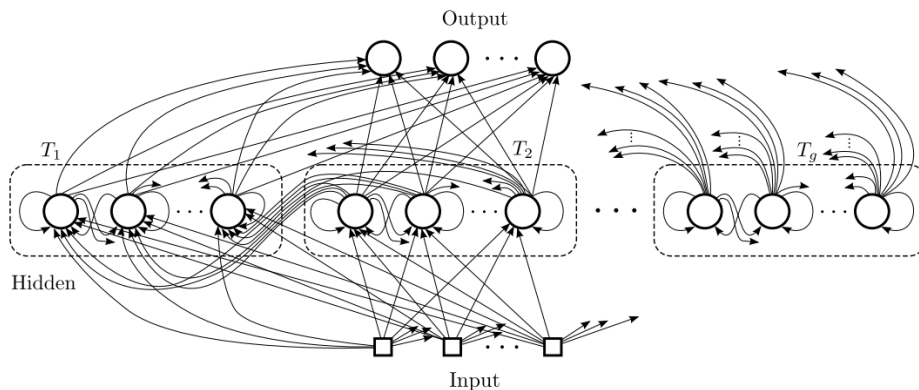
Gated Recurrent Unit (GRU):
simpler than LSTM 只有2個gate

[Cho, EMNLP'14]



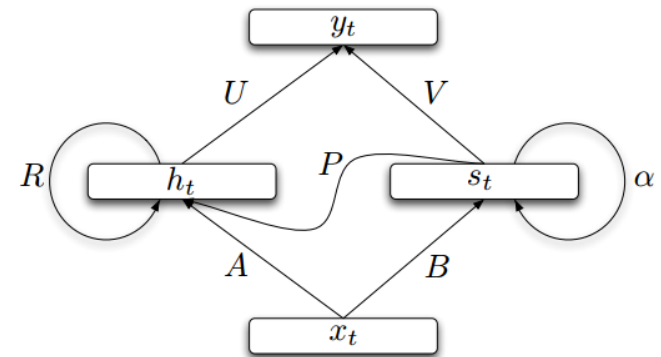
Helpful Techniques

Clockwise RNN



[Jan Koutnik, JMLR'14]

Structurally Constrained Recurrent Network (SCRN)



[Tomas Mikolov, ICLR'15]

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

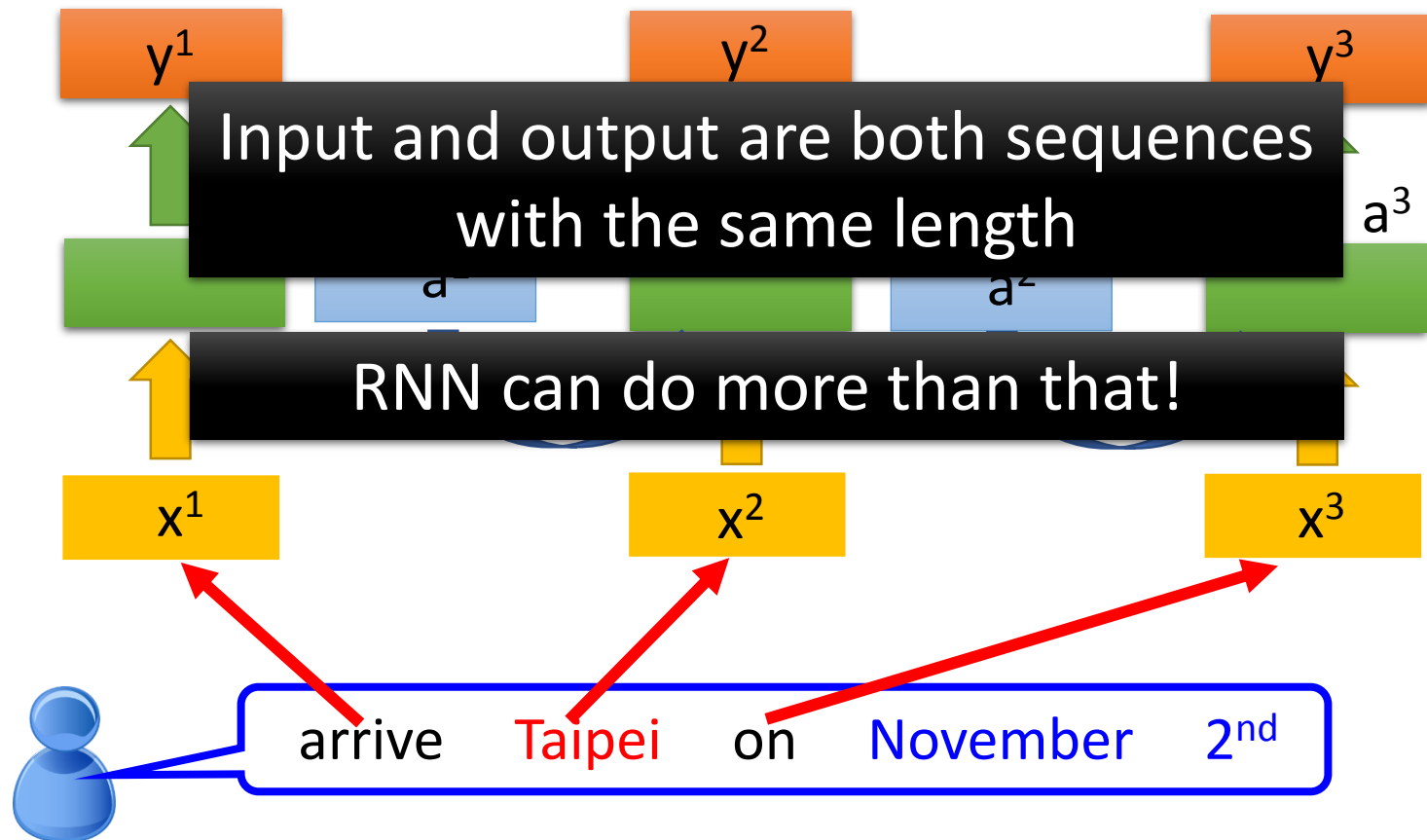
➤ Outperform or be comparable with LSTM in 4 different tasks

More Applications

Probability of
“arrive” in each slot

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

Probability of
“on” in each slot

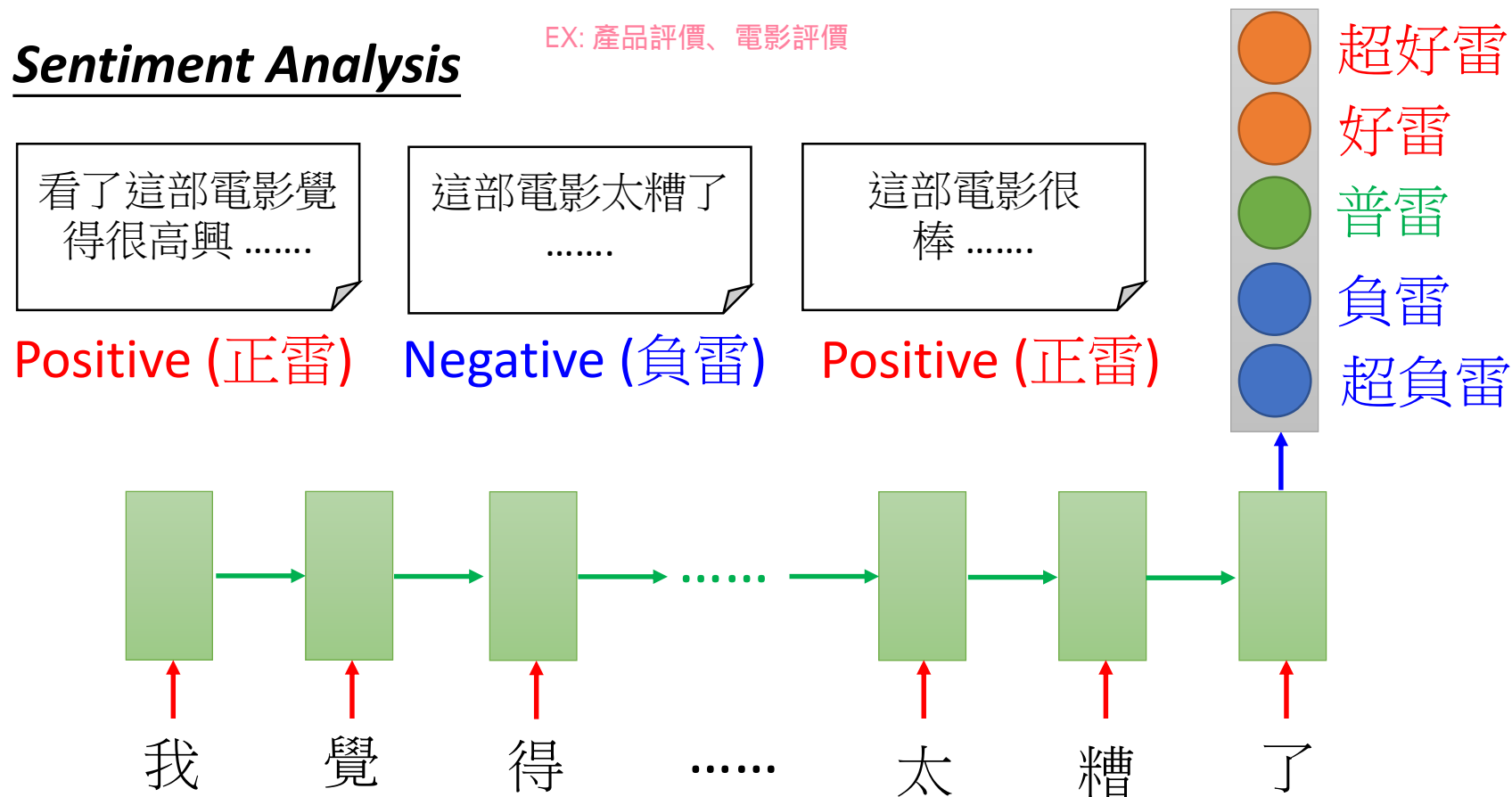


Many to one

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

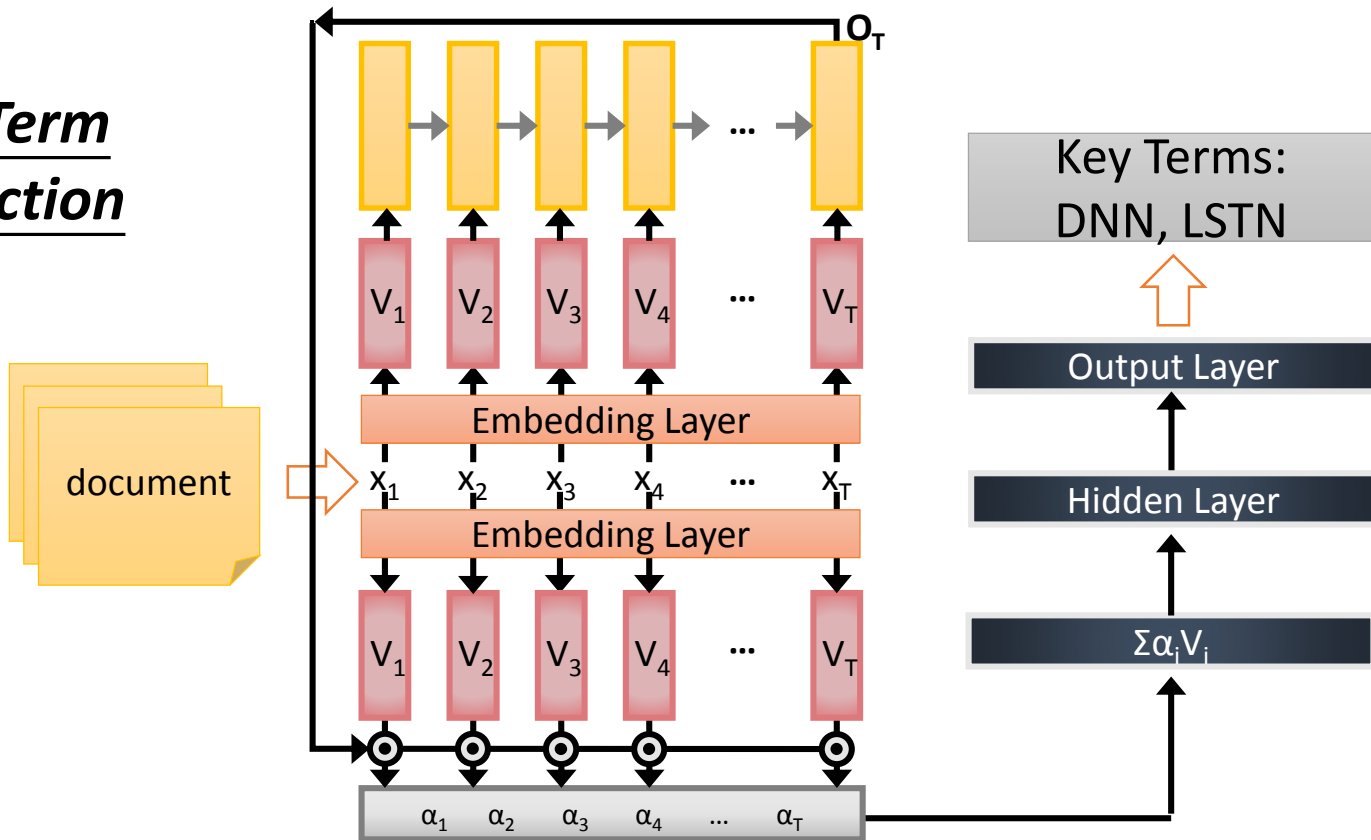
Sentiment Analysis

EX: 產品評價、電影評價



[Shen & Lee, Interspeech 16]

- ## Key Term Extraction



Many to Many (Output is shorter)

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

Problem?

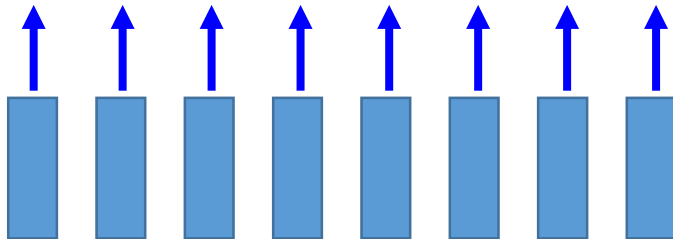
Why can't it be
“好棒棒”

Output: “好棒” (character sequence)



Trimming

好 好 好 棒 棒 棒 棒 棒



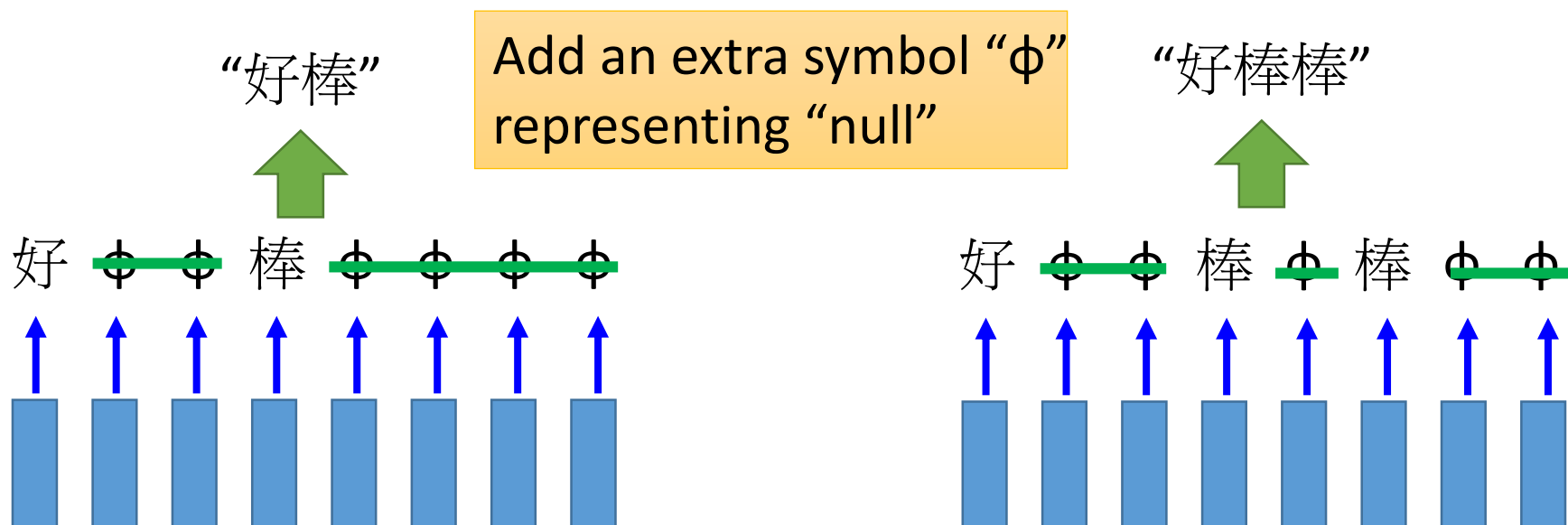
Input:

(vector
sequence)



Many to Many (Output is shorter)

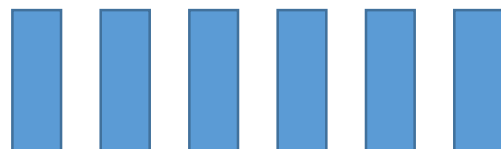
- Both input and output are both sequences, **but the output is shorter.**
- Connectionist Temporal Classification (CTC) [Alex Graves, ICML'06][Alex Graves, ICML'14][Haşim Sak, Interspeech'15][Jie Li, Interspeech'15][Andrew Senior, ASRU'15]



Many to Many (Output is shorter)







- CTC: Training







Acoustic
Features:









Label: 好 棒

All possible alignments are
considered as correct.

					
好	ϕ	棒	ϕ	ϕ	ϕ

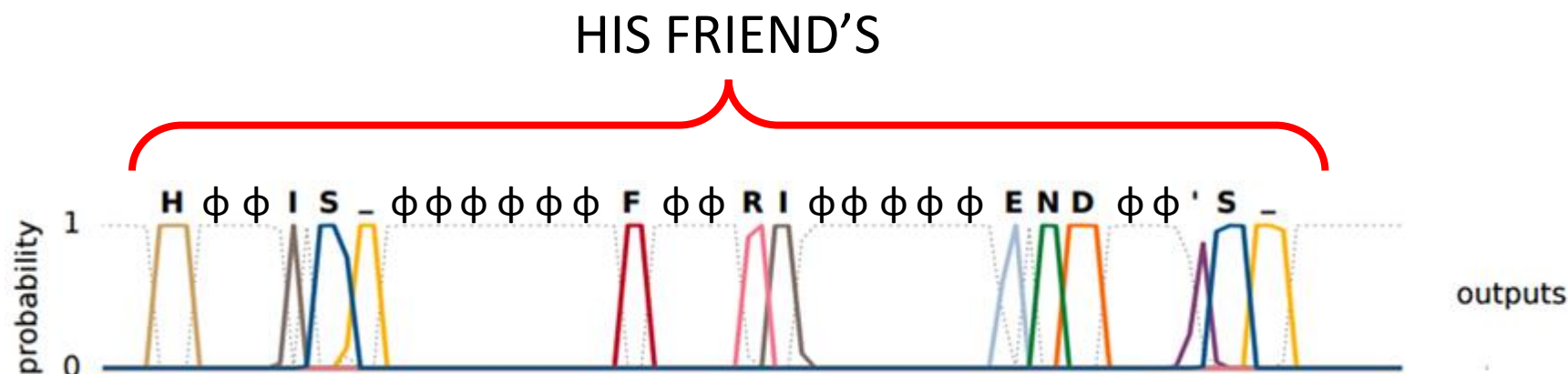
					
好	ϕ	ϕ	棒	ϕ	ϕ

					
好	ϕ	ϕ	ϕ	棒	ϕ

⋮

Many to Many (Output is shorter)

- CTC: example



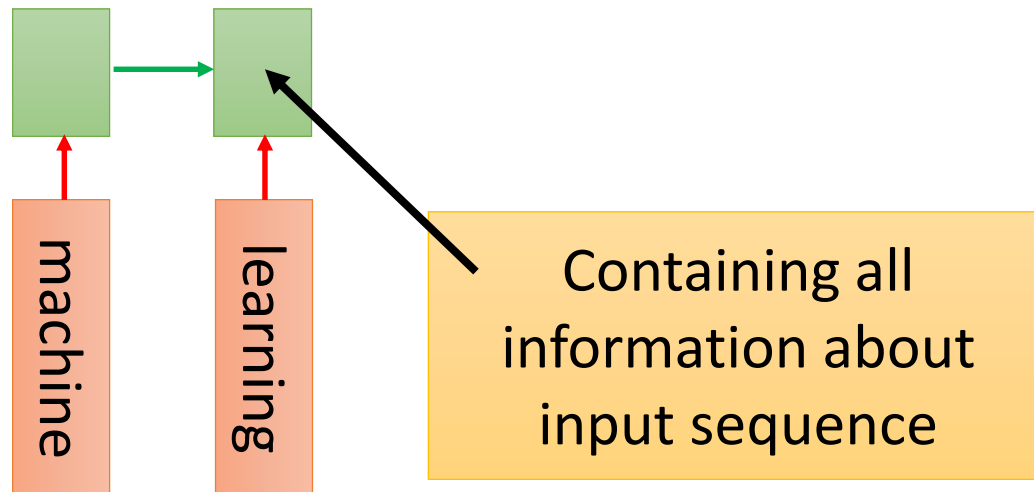
Graves, Alex, and Navdeep Jaitly. "Towards end-to-end speech recognition with recurrent neural networks." *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*. 2014.

Many to Many (No Limitation)

不知道input/output誰長誰短

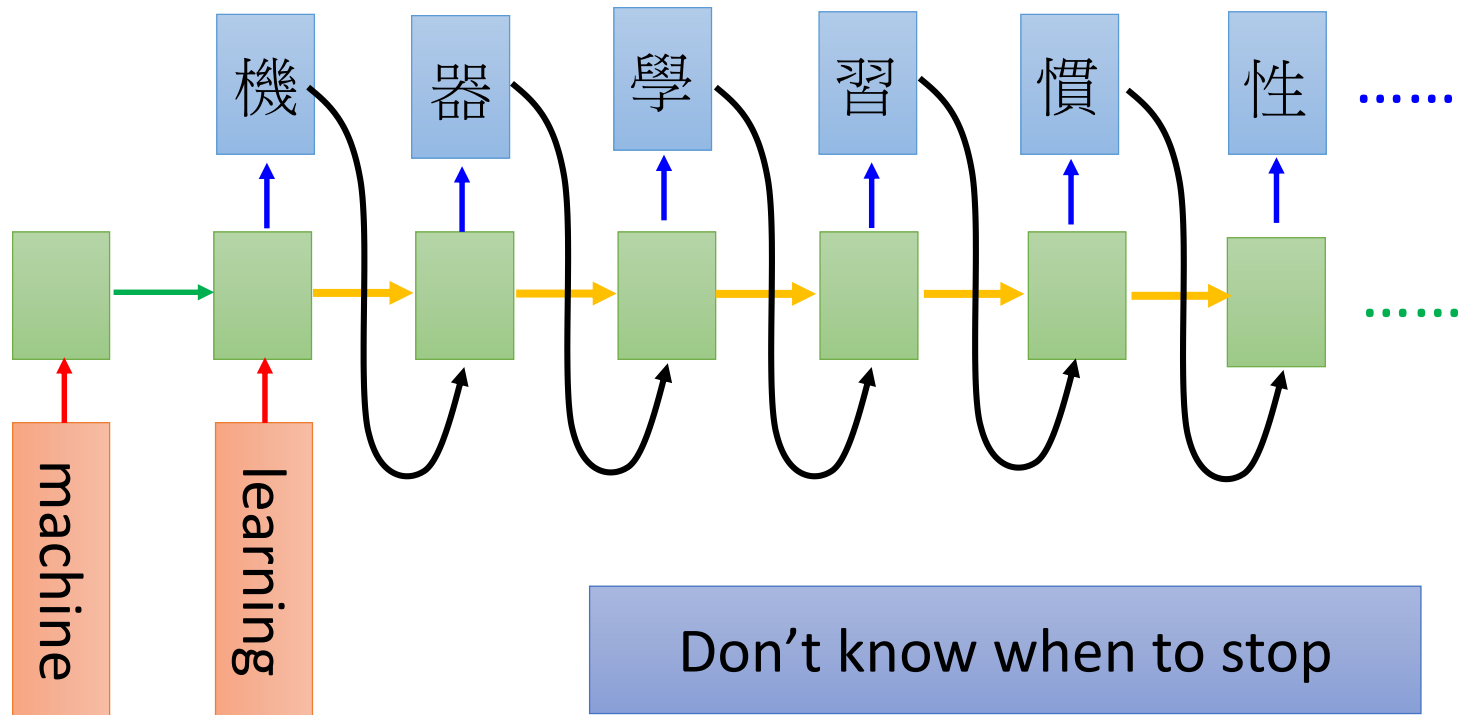
- Both input and output are both sequences **with different lengths**. → **Sequence to sequence learning**
 - E.g. **Machine Translation** (machine learning → 機器學習)

英翻中



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)



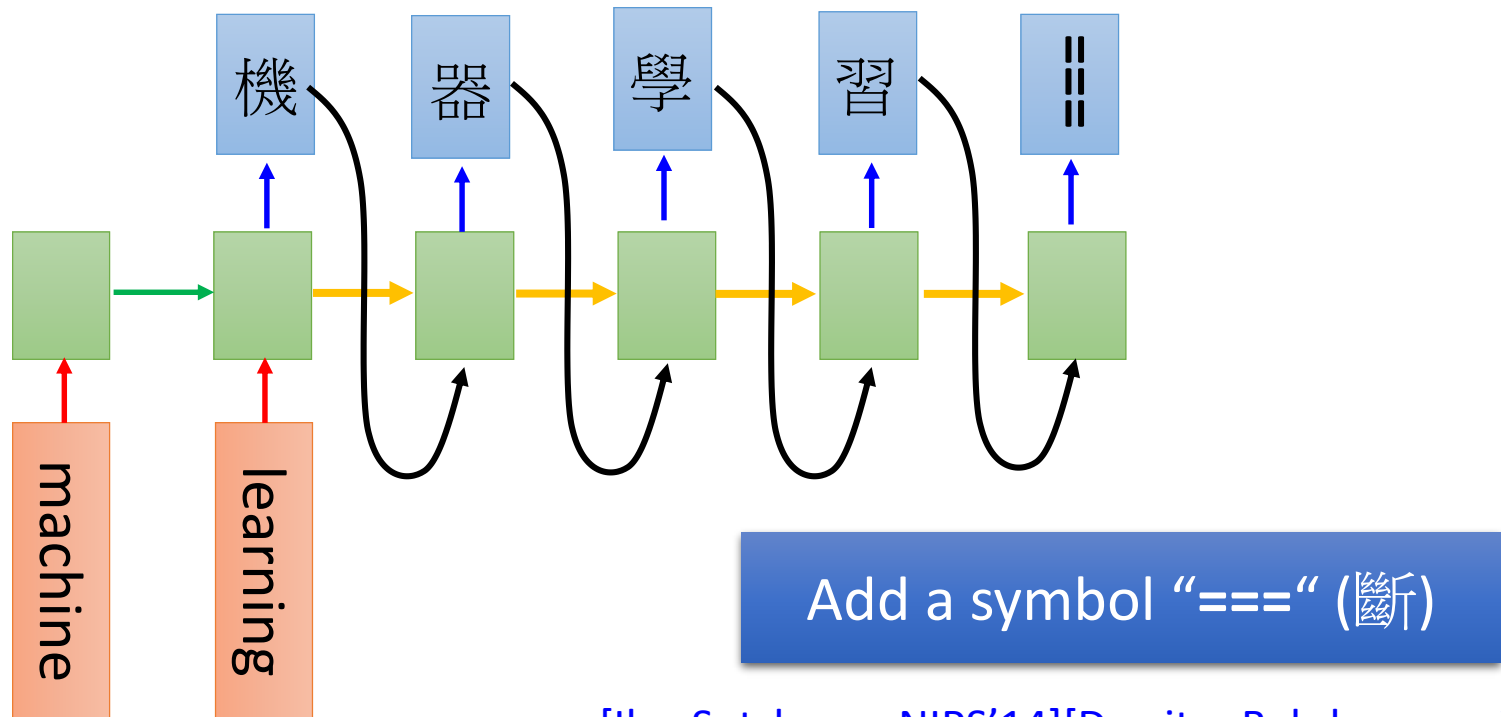
Many to Many (No Limitation)

推	:	超	06/12 10:39
推	n:	人	06/12 10:40
推	tion:	正	06/12 10:41
→	host:	大	06/12 10:47
推	:	中	06/12 10:59
推	403:	天	06/12 11:11
推	:	外	06/12 11:13
推	527:	飛	06/12 11:17
→	990b:	仙	06/12 11:32
→	512:	草	06/12 12:15
推	tlkagk:	=====斷=====	

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)

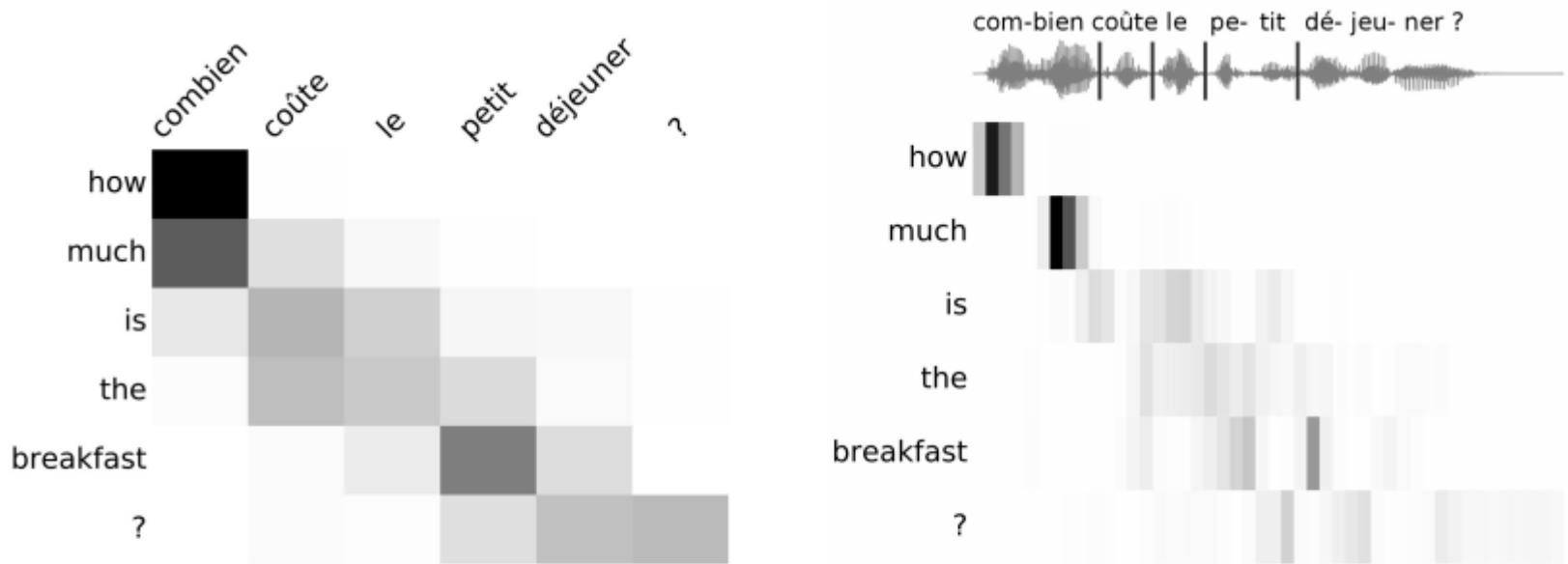
- Both input and output are both sequences **with different lengths**. → **Sequence to sequence learning**
 - E.g. **Machine Translation** (machine learning → 機器學習)



Many to Many (No Limitation)

直接input聲音訊號，然後output其他語言的翻譯文字

- 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

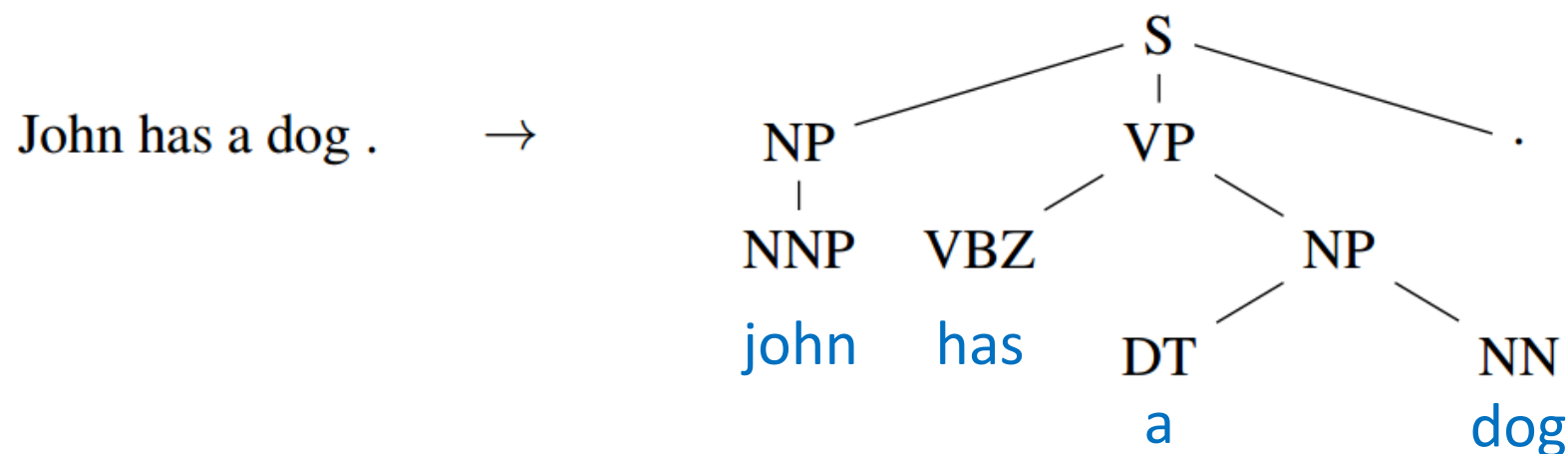
(b) Speech translation alignment

Figure 1: Alignments performed by the attention model during training

Beyond Sequence

- Syntactic parsing

文法結構樹

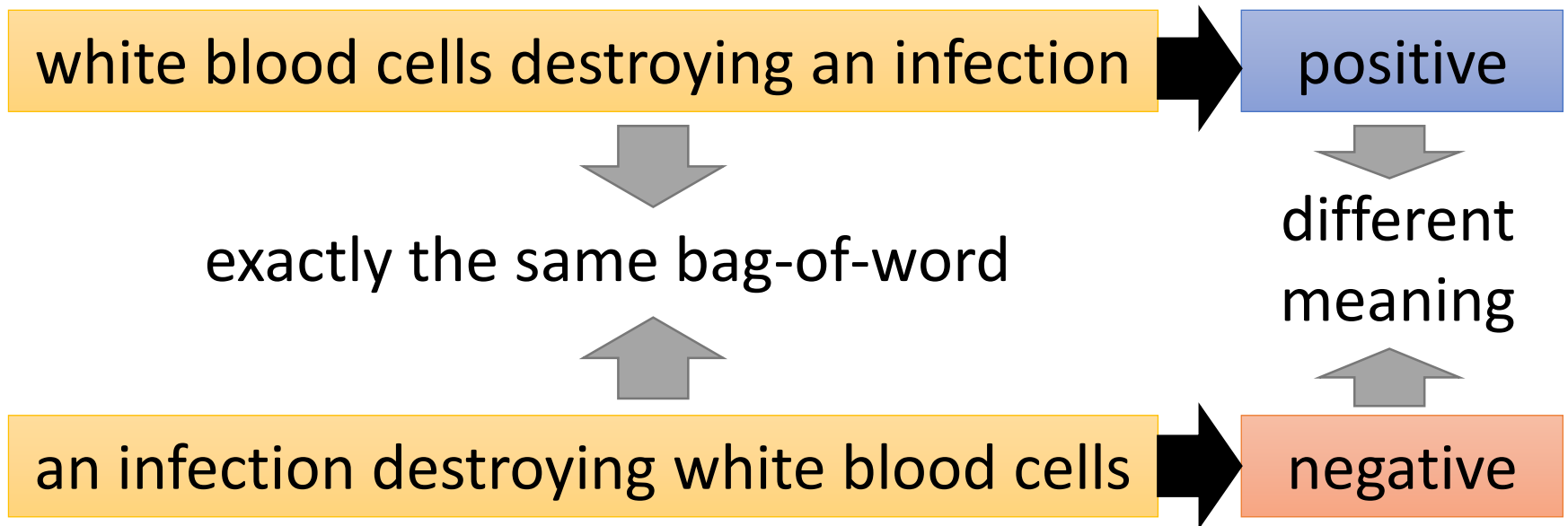


John has a dog . → (S (NP NNP)_{NP} (VP VBZ (NP DT NN)_{NP})_{VP} .)_S

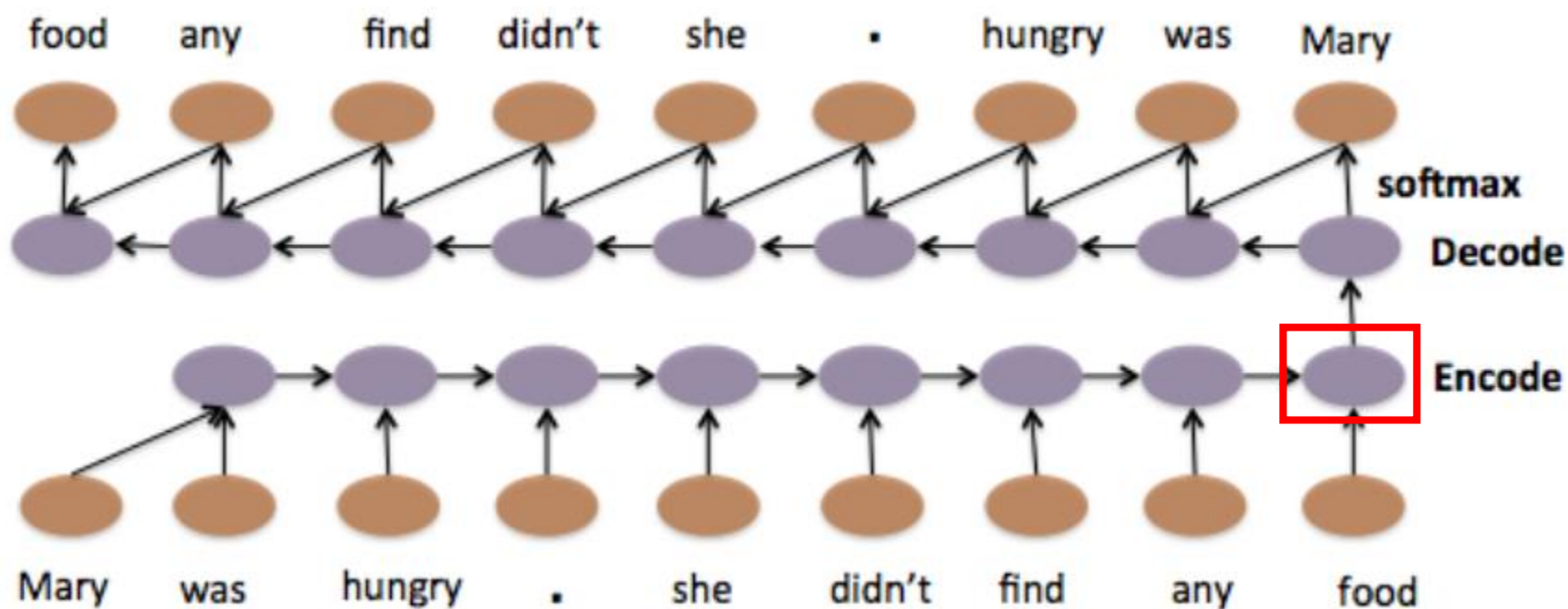
Oriol Vinyals, Lukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, Geoffrey Hinton,
Grammar as a Foreign Language, NIPS 2015

Sequence-to-sequence Auto-encoder - Text

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

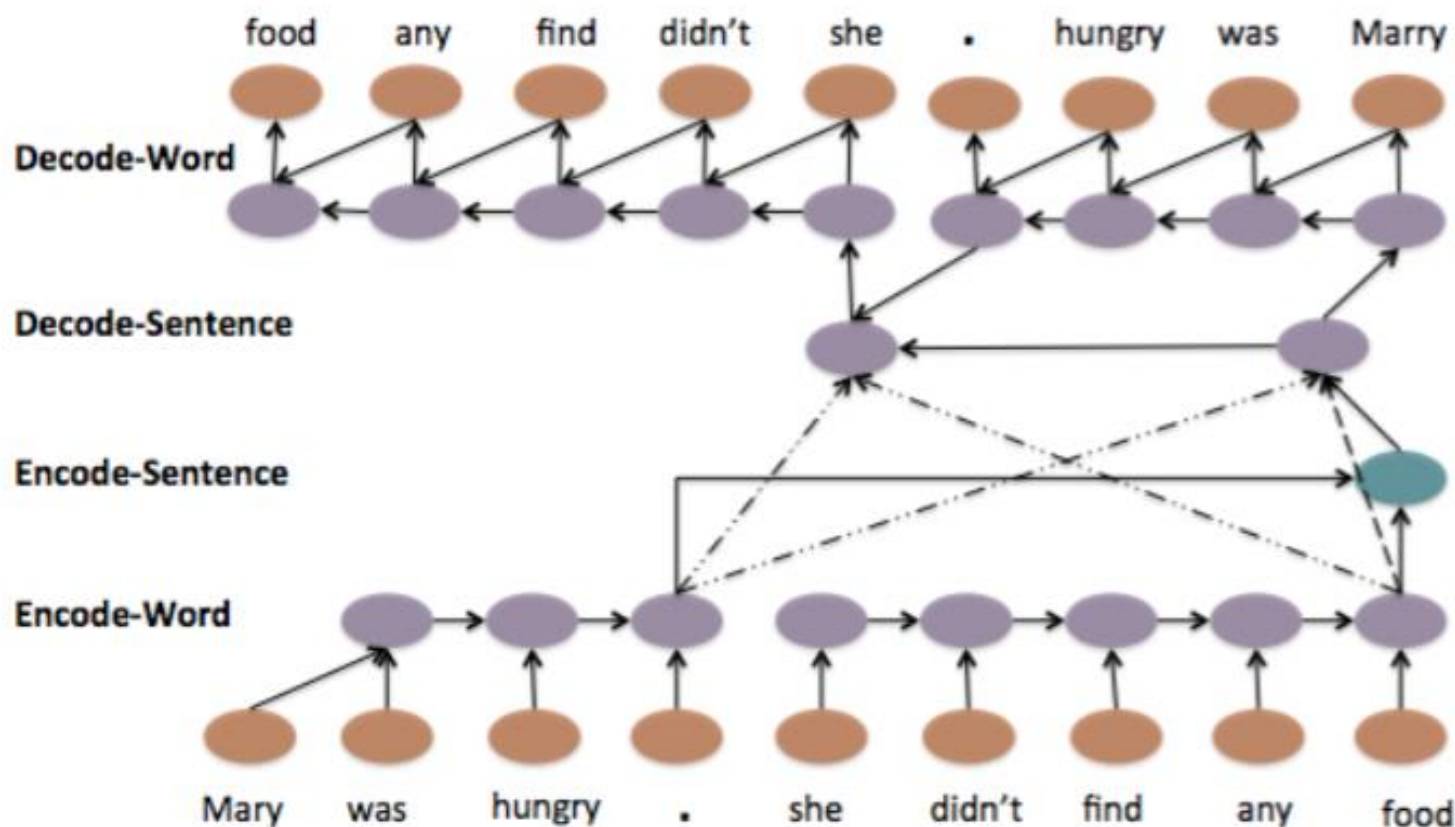


Sequence-to-sequence Auto-encoder - Text



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

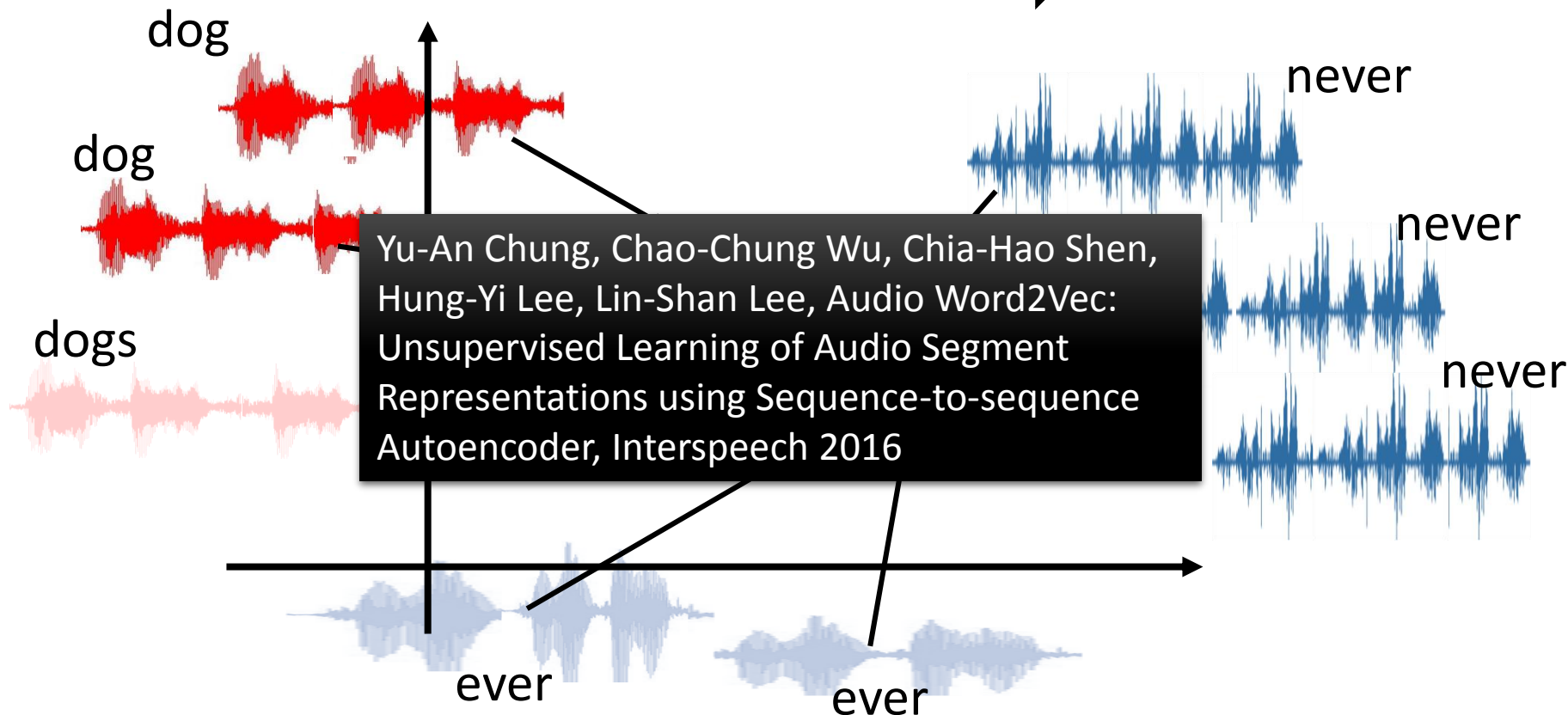


Li, Jiwei, Minh-Thang Luong, and Dan Jurafsky. "A hierarchical neural autoencoder for paragraphs and documents." *arXiv preprint arXiv:1506.01057*(2015).

Sequence-to-sequence Auto-encoder - Speech

- Dimension reduction for a sequence with variable length

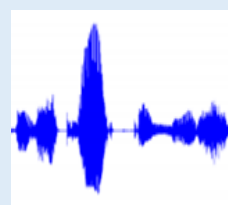
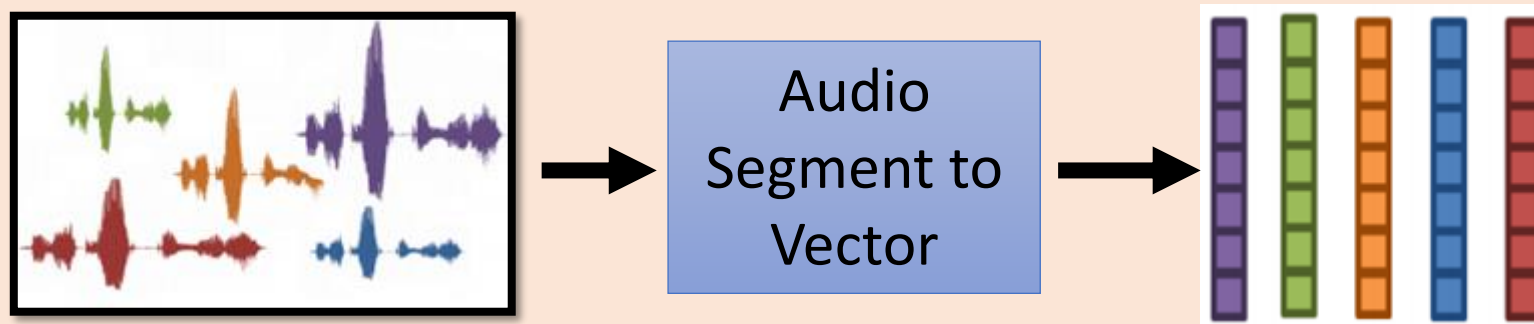
audio segments (word-level)  Fixed-length vector



Sequence-to-sequence Auto-encoder - Speech

Audio archive divided into variable-length audio segments

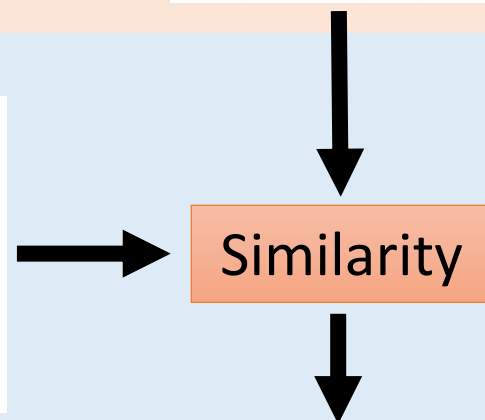
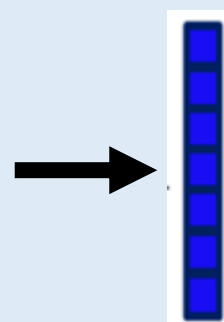
Off-line



Spoken
Query



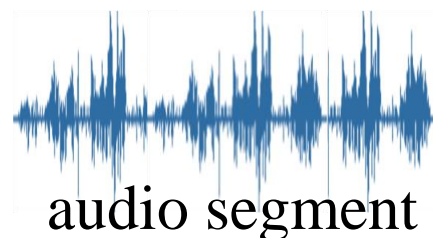
On-line



Search Result

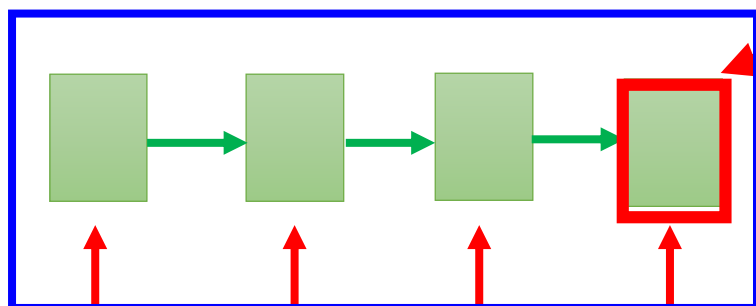


Sequence-to-sequence Auto-encoder - Speech



vector

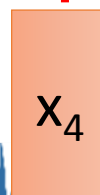
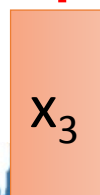
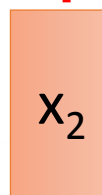
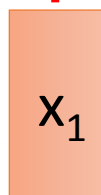
RNN Encoder



The values in the memory
represent the whole audio
segment

The vector we want

How to train RNN Encoder?



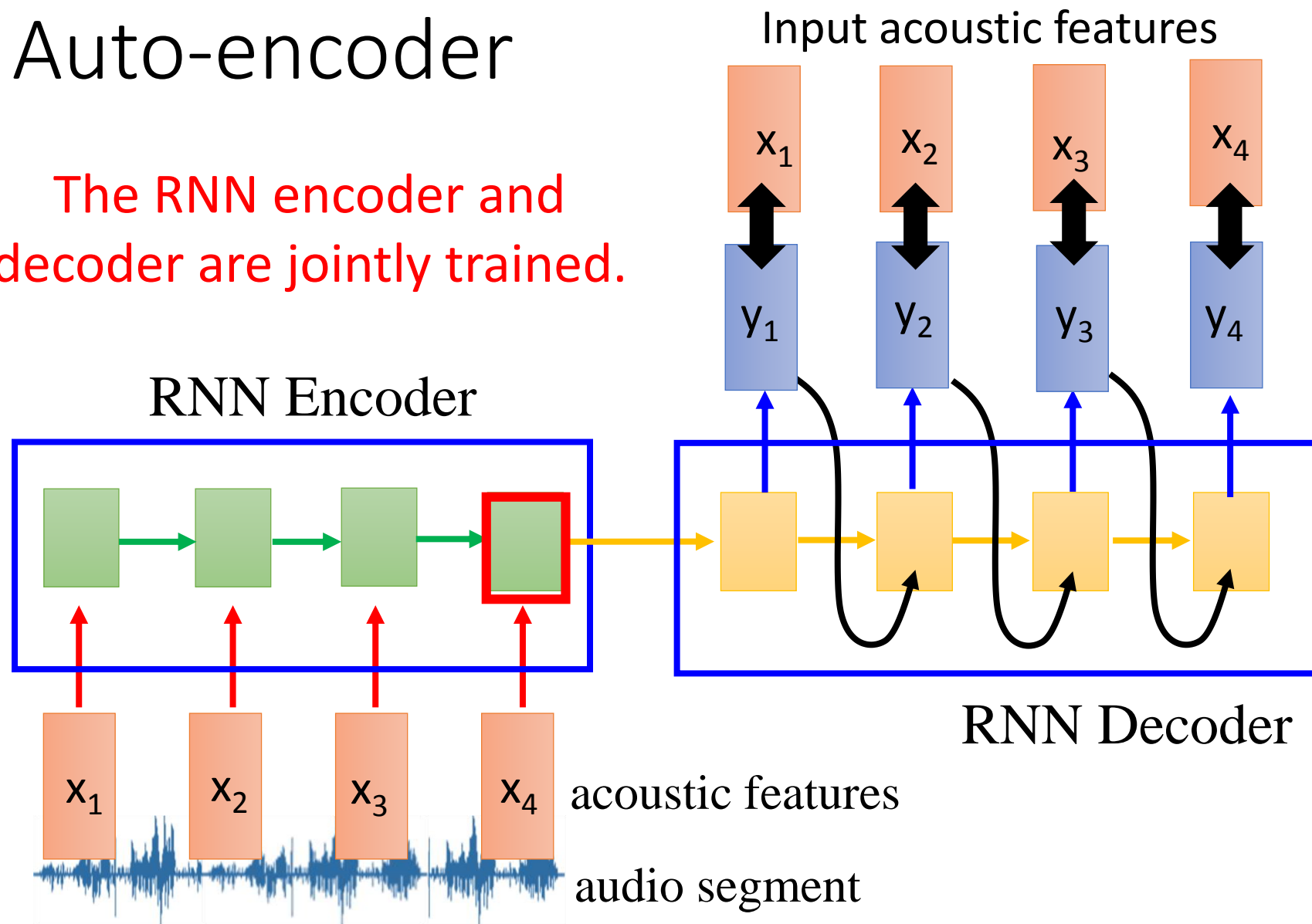
acoustic features



audio segment

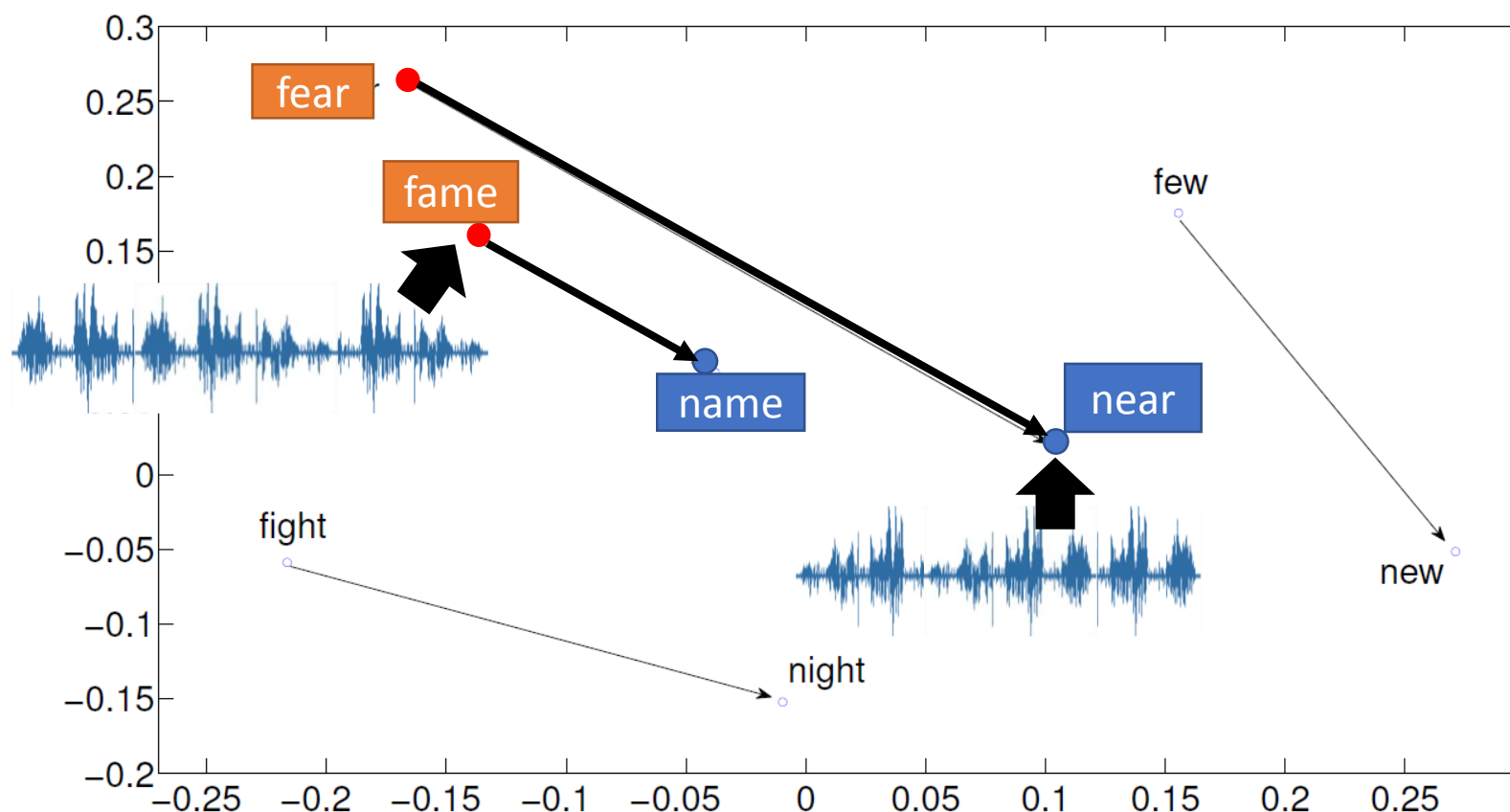
Sequence-to-sequence Auto-encoder

The RNN encoder and decoder are jointly trained.

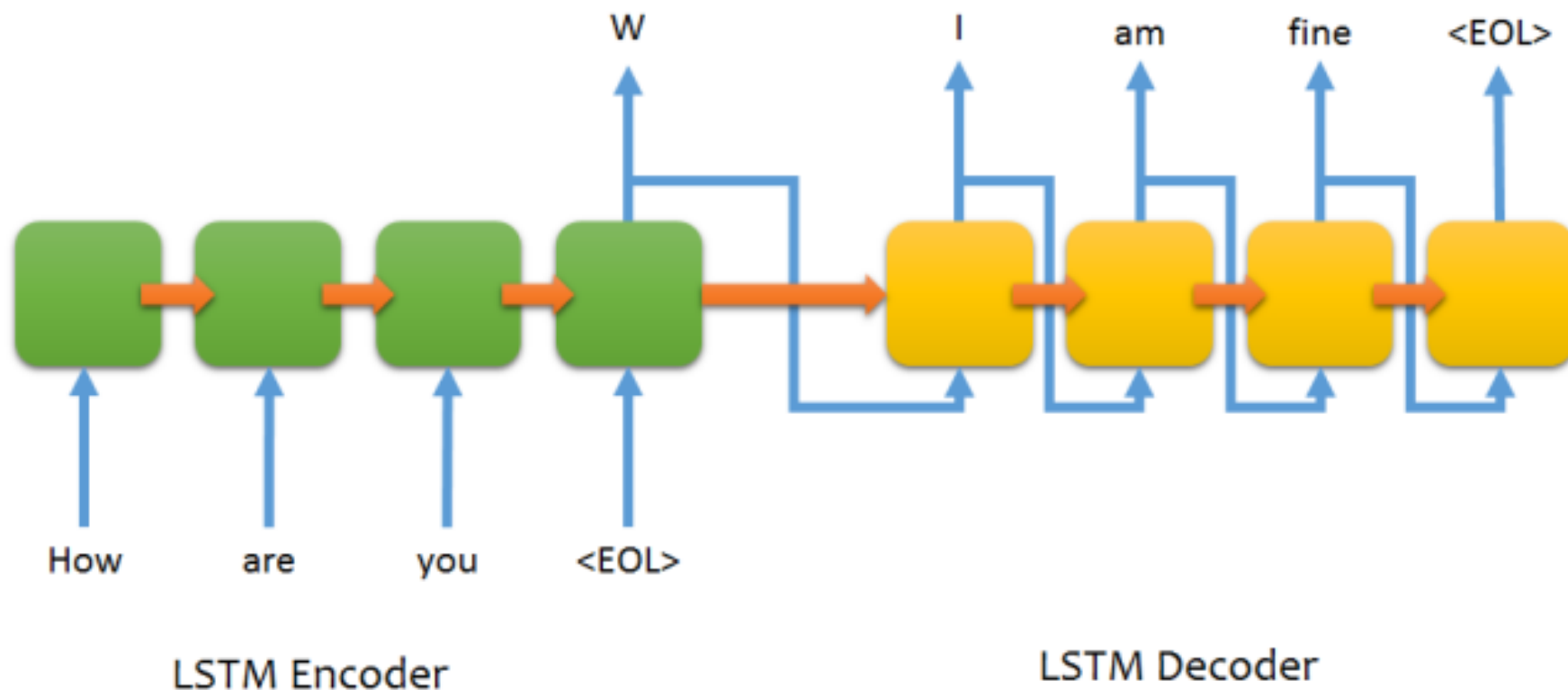


Sequence-to-sequence Auto-encoder - Speech

- Visualizing embedding vectors of the words



Demo: Chat-bot



電視影集 (~40,000 sentences)、美國總統大選辯論

Demo: Chat-bot

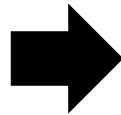
- Develop Team

- 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

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.

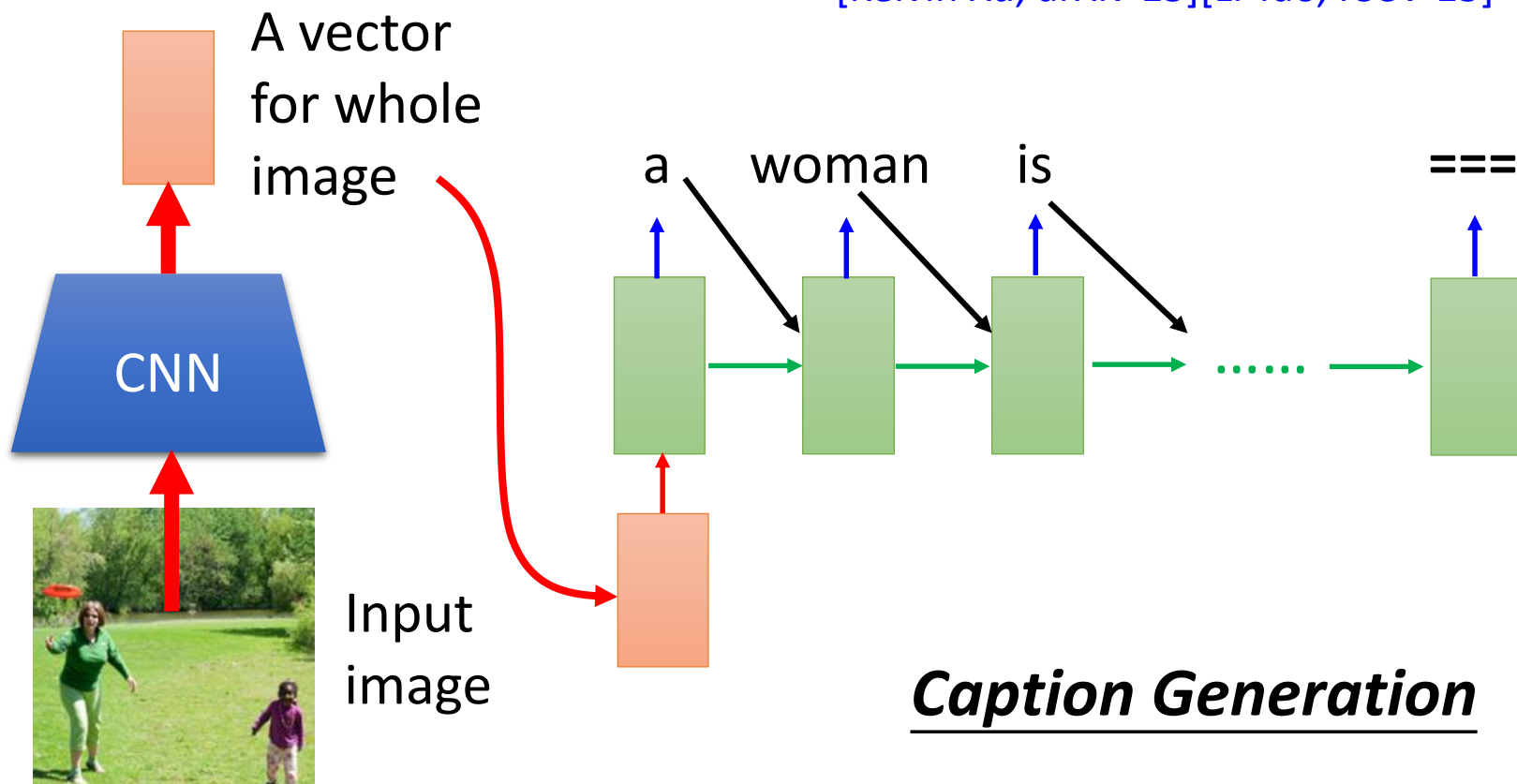
Demo: Video Caption Generation

- 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]



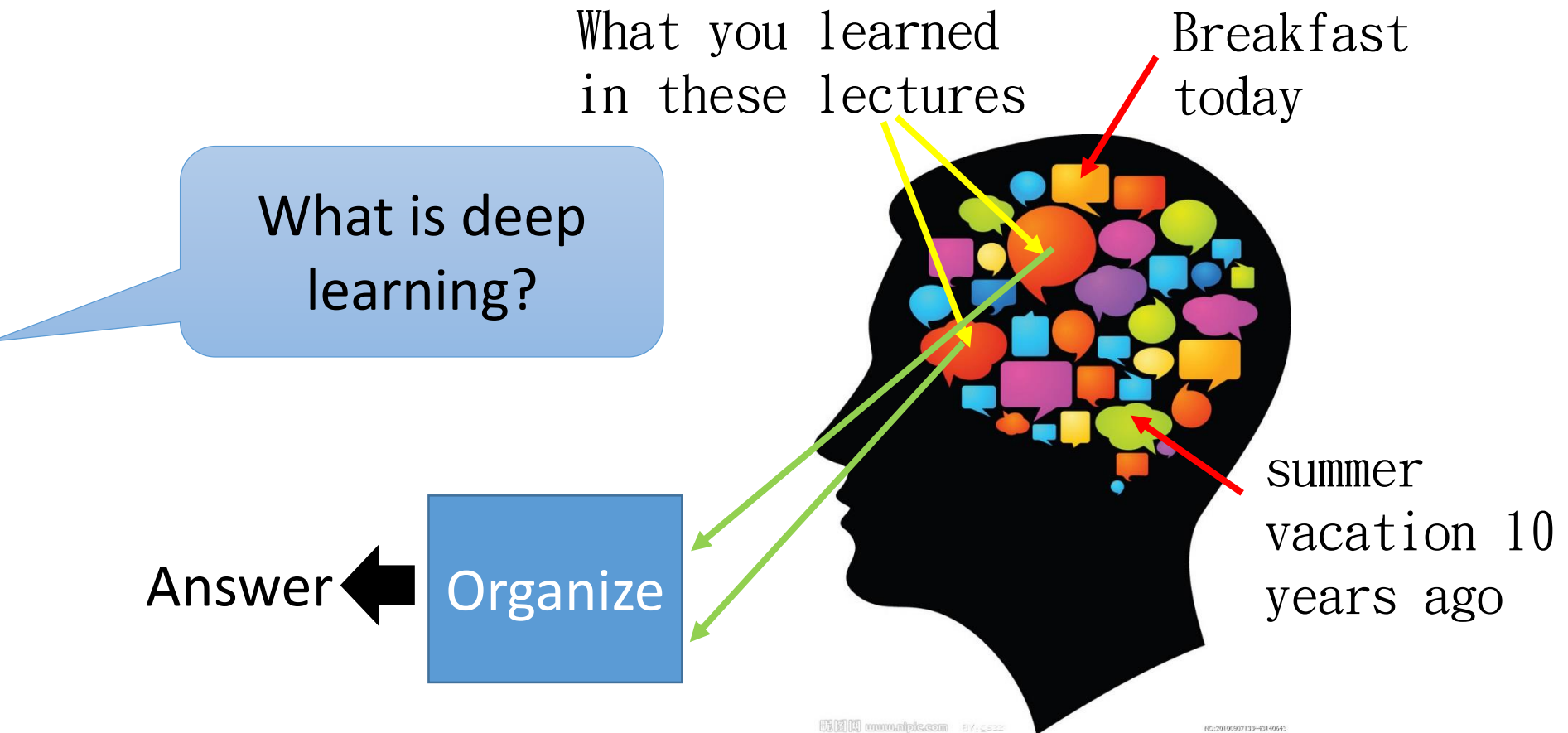
Demo: Image Caption Generation

- 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

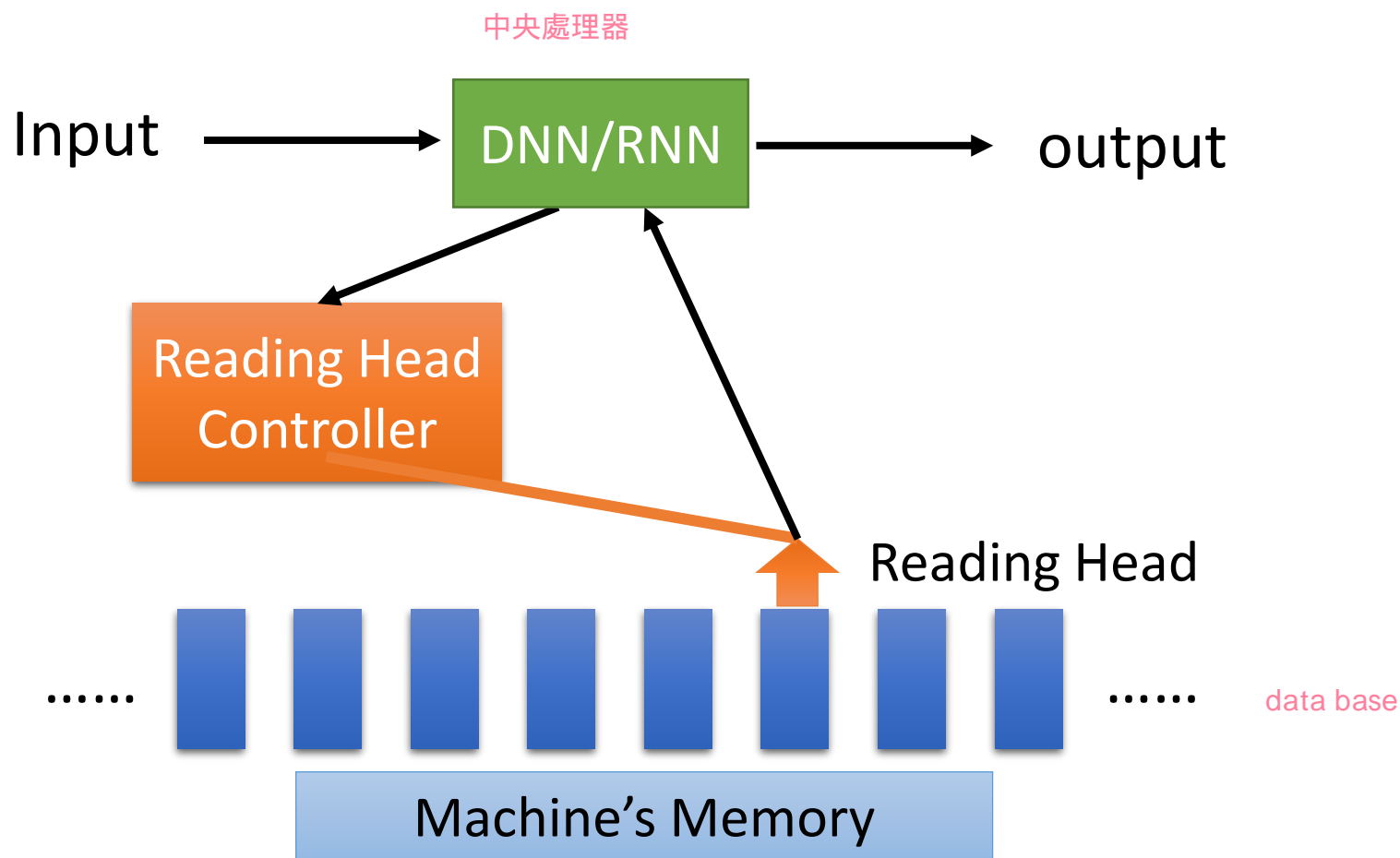
http://news.ltn.com.tw/photo/politics/breakingnews/975542_1



Attention-based Model



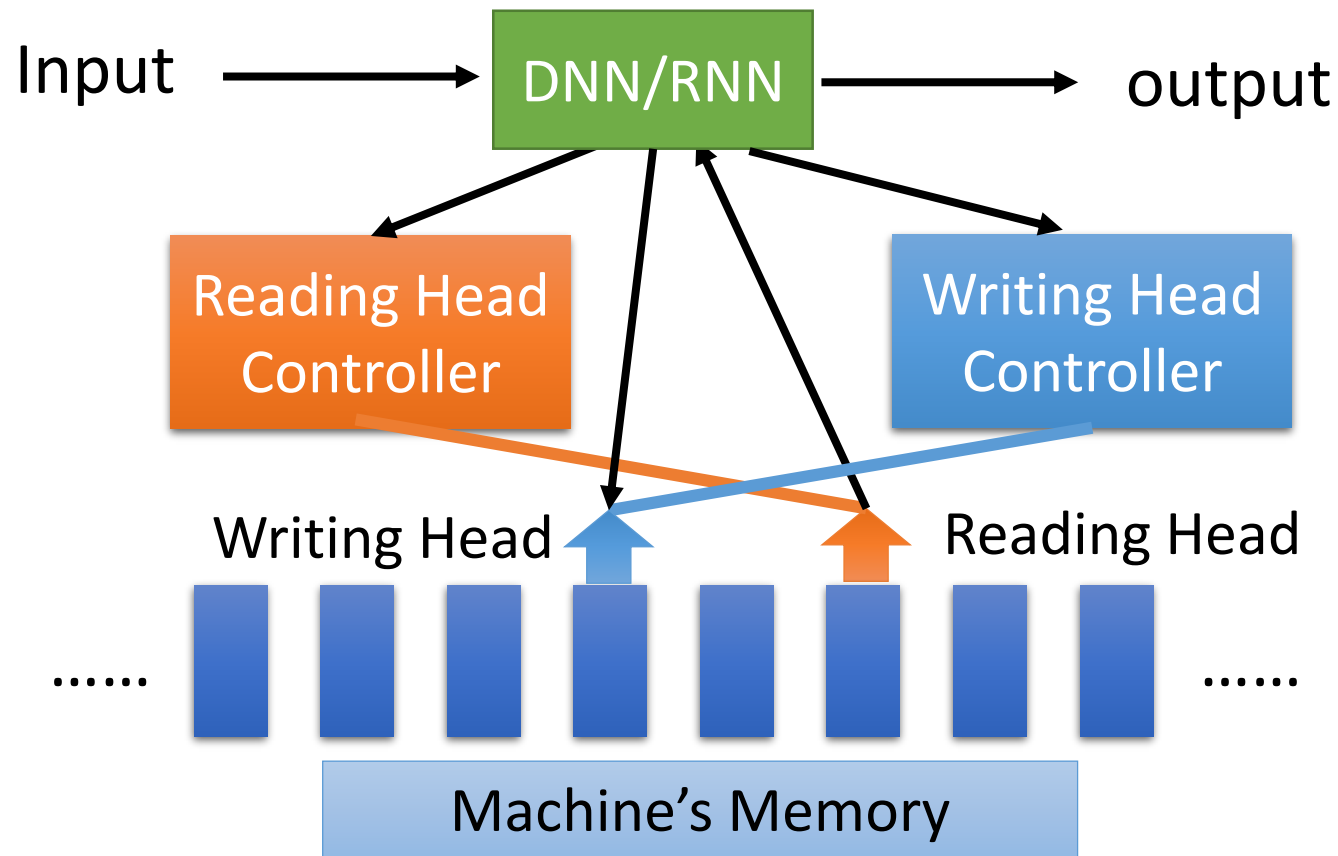
Attention-based Model



Ref:

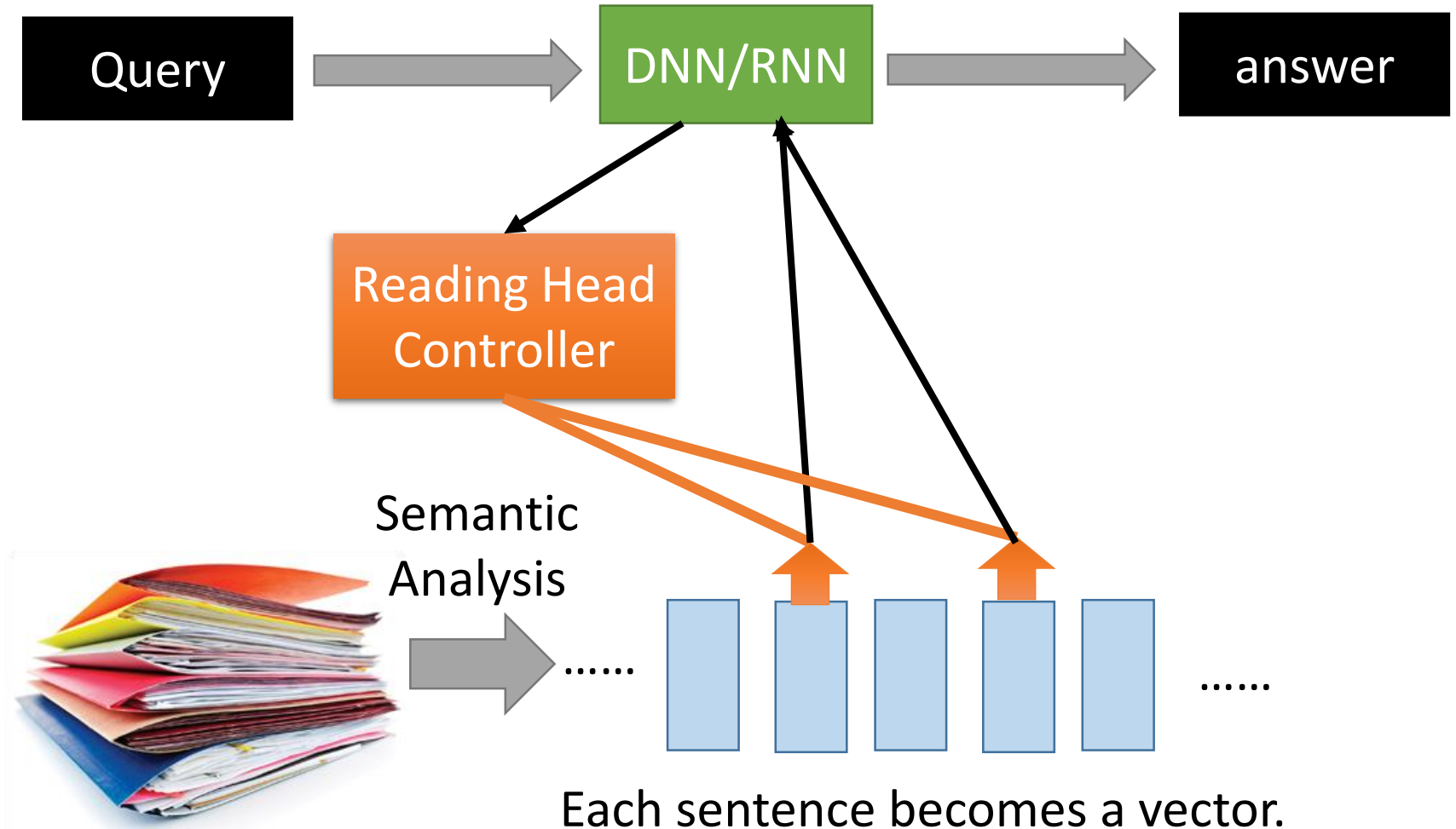
[http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Attain%20\(v3\).e cm.mp4/index.html](http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Attain%20(v3).e cm.mp4/index.html)

Attention-based Model v2



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:

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



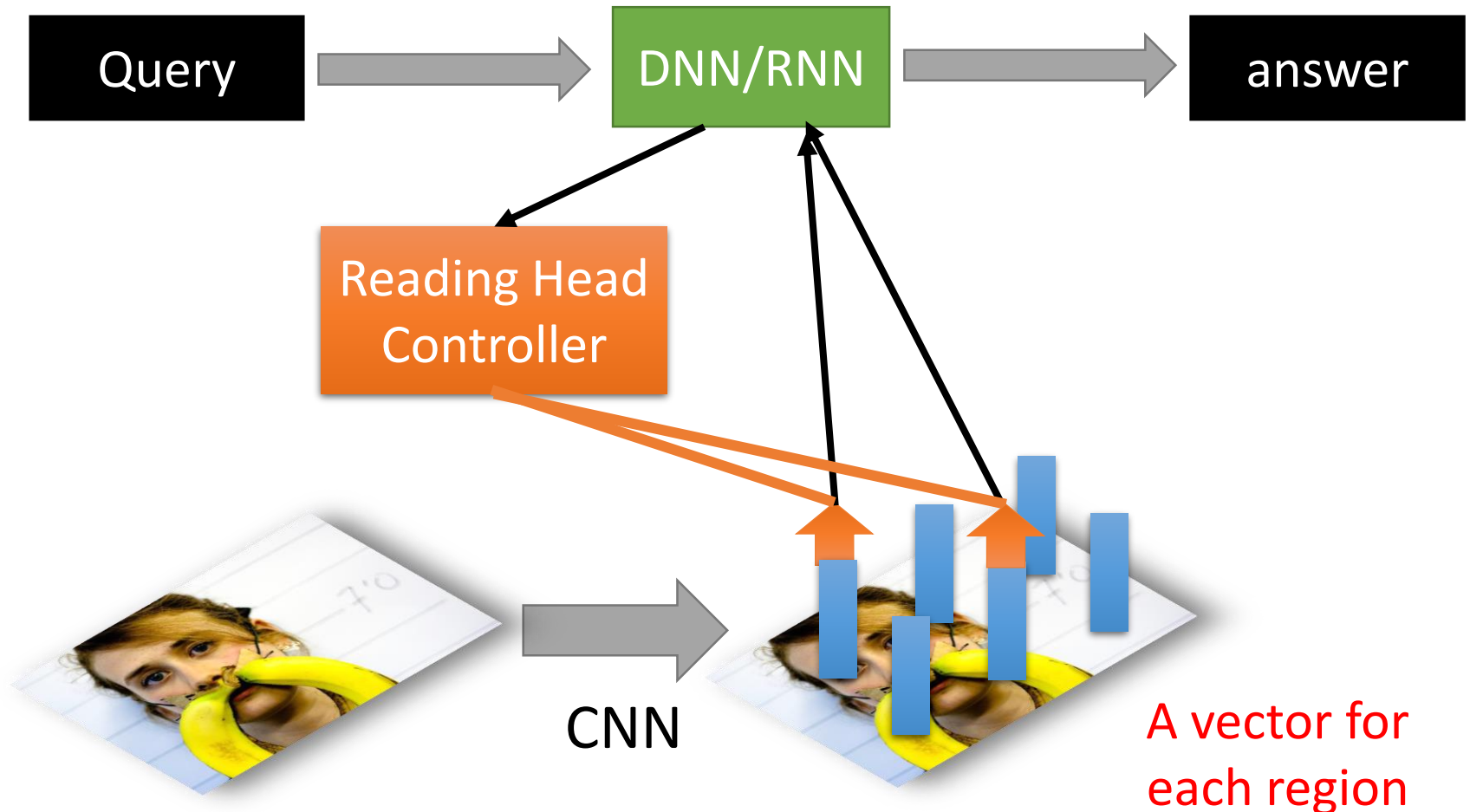
What is the mustache
made of?

AI System

bananas

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.)

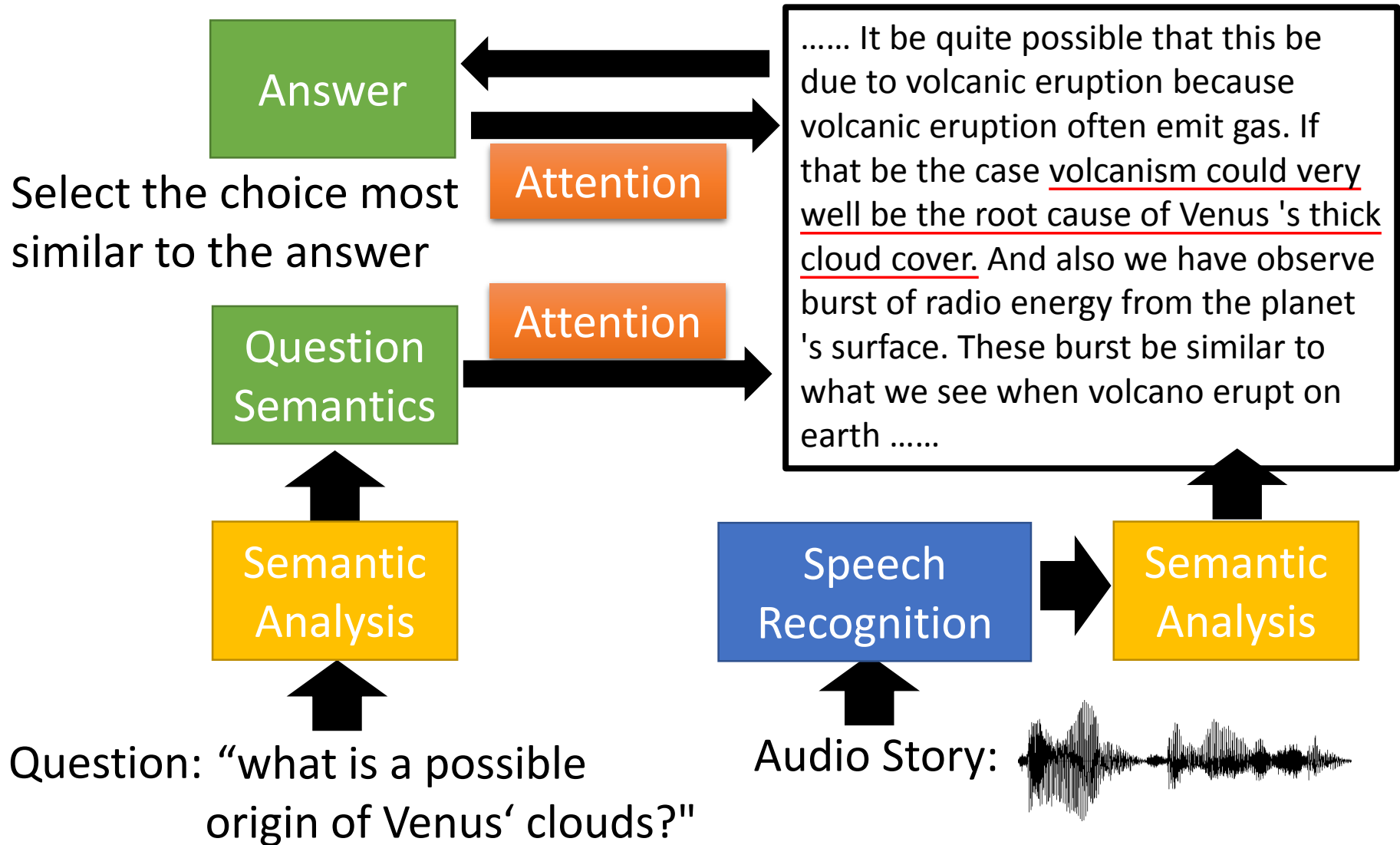
Question: “ What is a possible origin of Venus’ clouds? ”

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

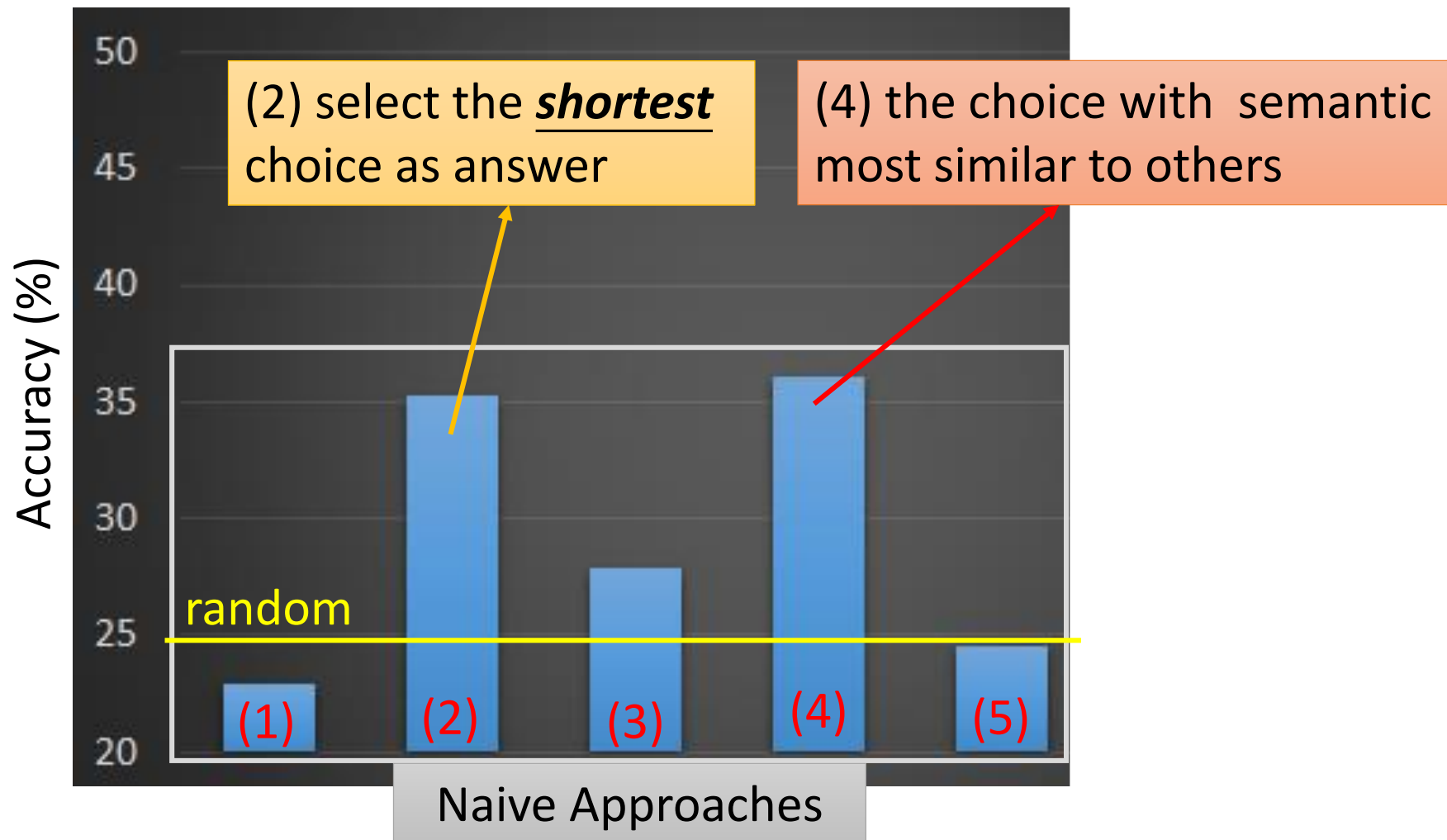
Model Architecture

Everything is learned from training examples

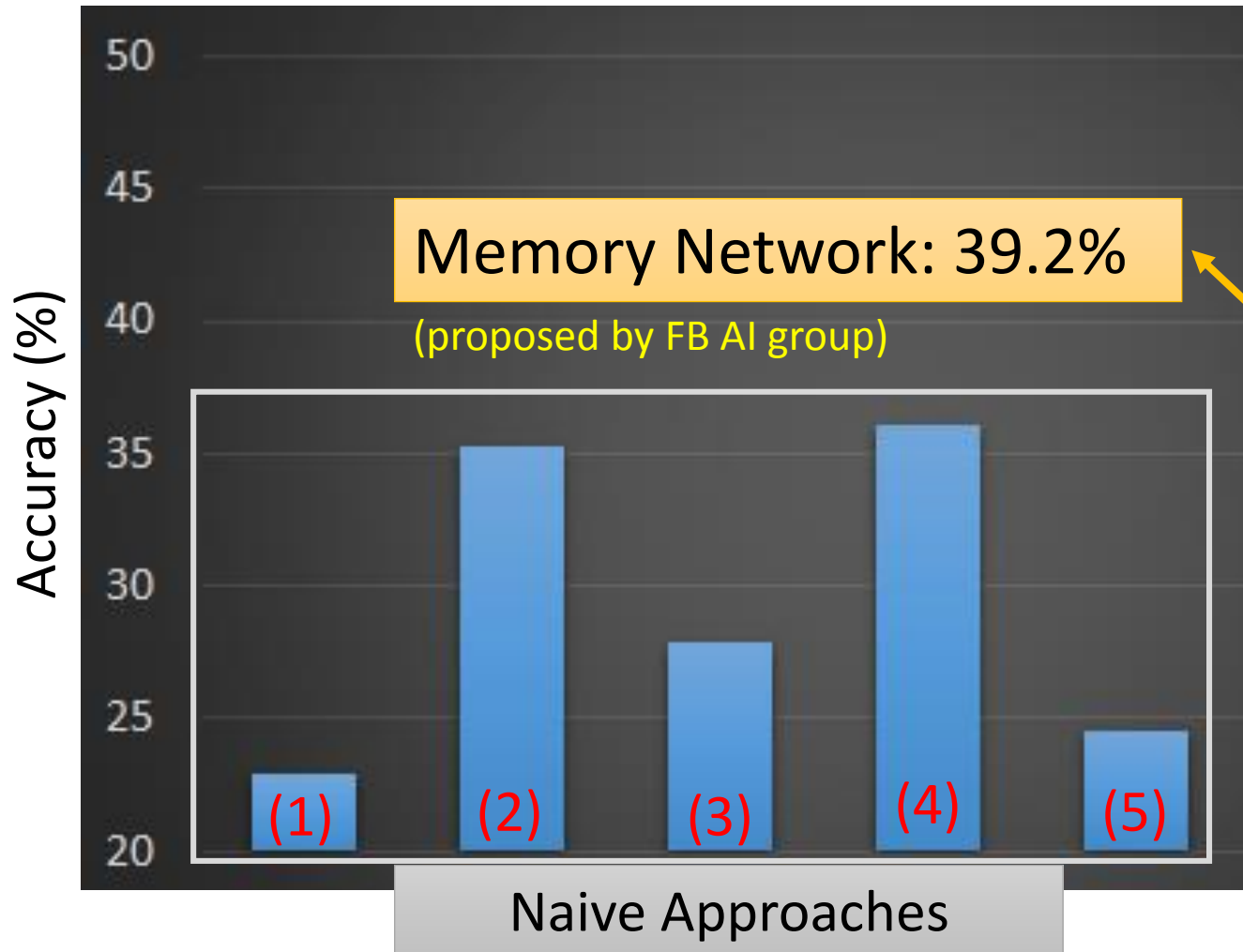


Simple Baselines

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



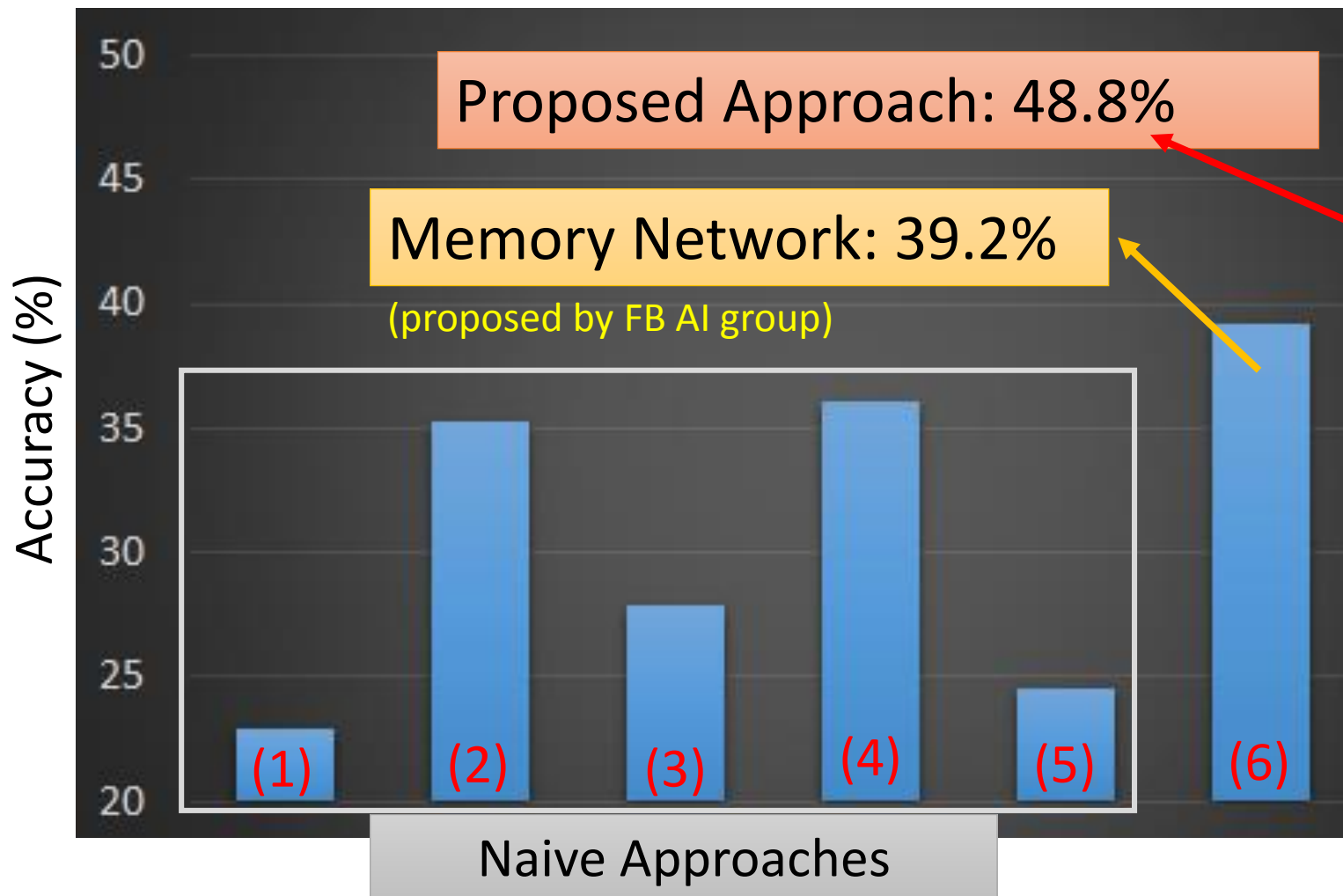
Memory Network



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

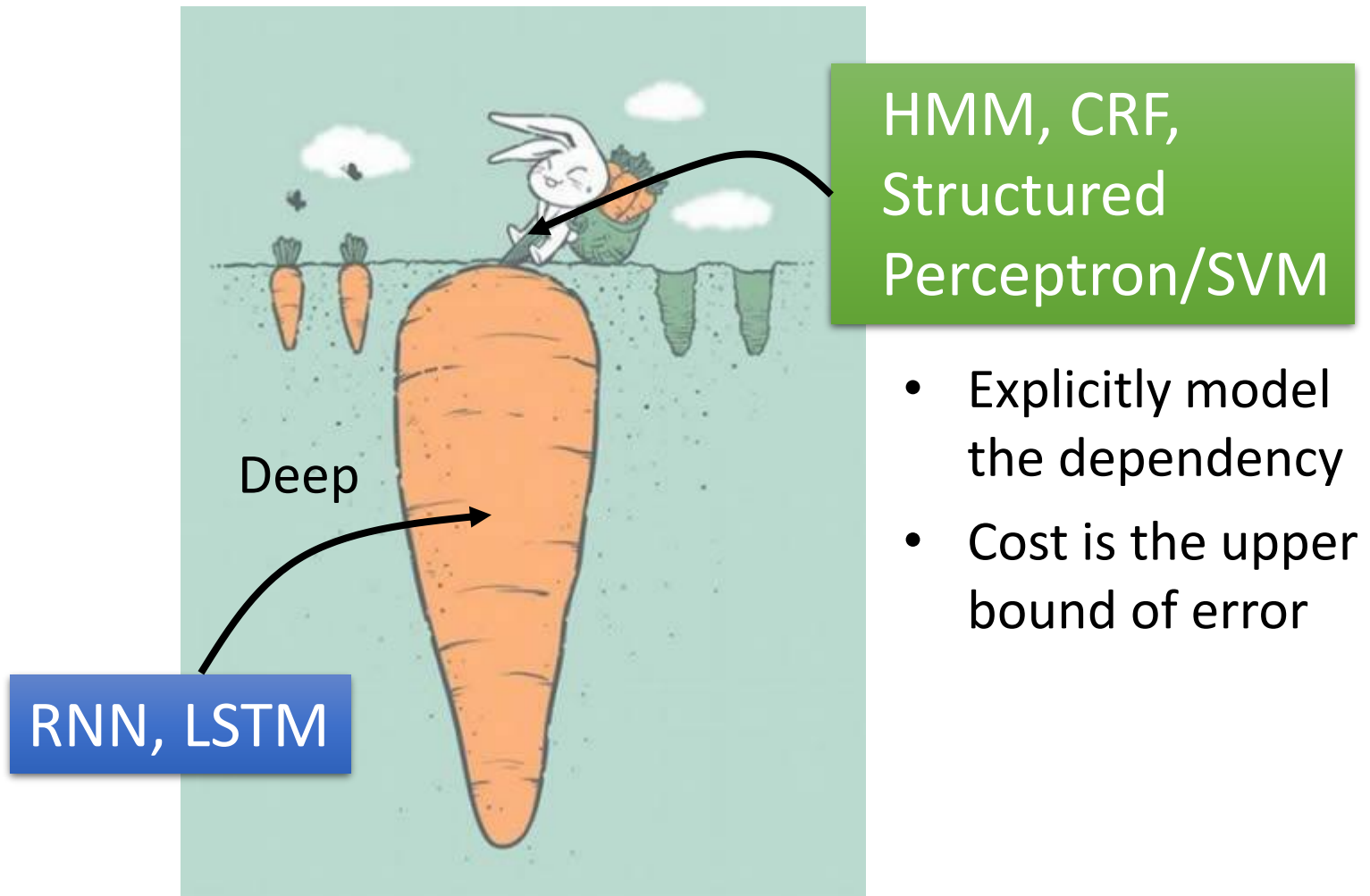
- Unidirectional RNN does NOT consider the whole sequence
- Cost and error not always related
- Deep 



- HMM, CRF, Structured Perceptron/SVM

- Using Viterbi, so consider the whole sequence  ?
- How about Bidirectional RNN?
- Can explicitly consider the label dependency 
- Cost is the upper bound of error 

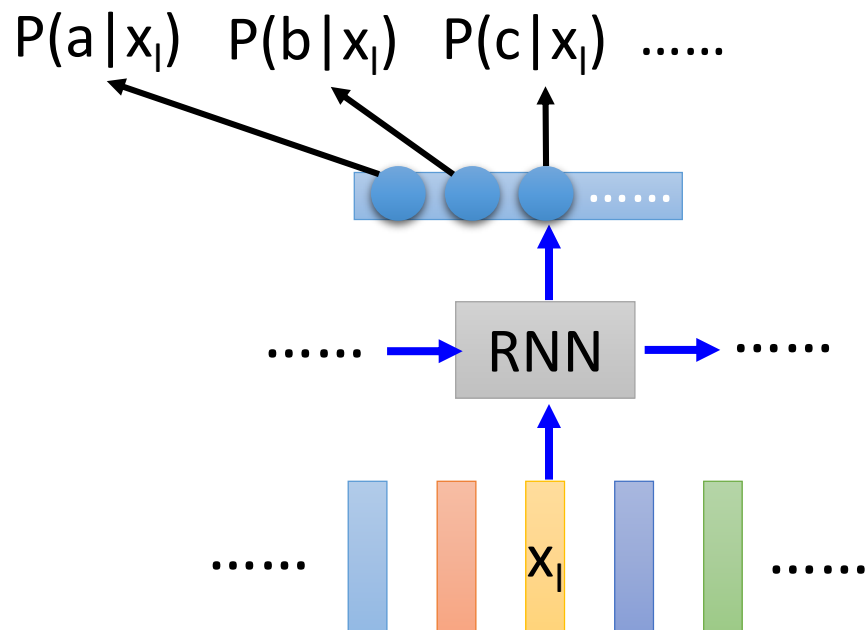
Integrated Together



Integrated together

- Speech Recognition: CNN/LSTM/DNN + HMM

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

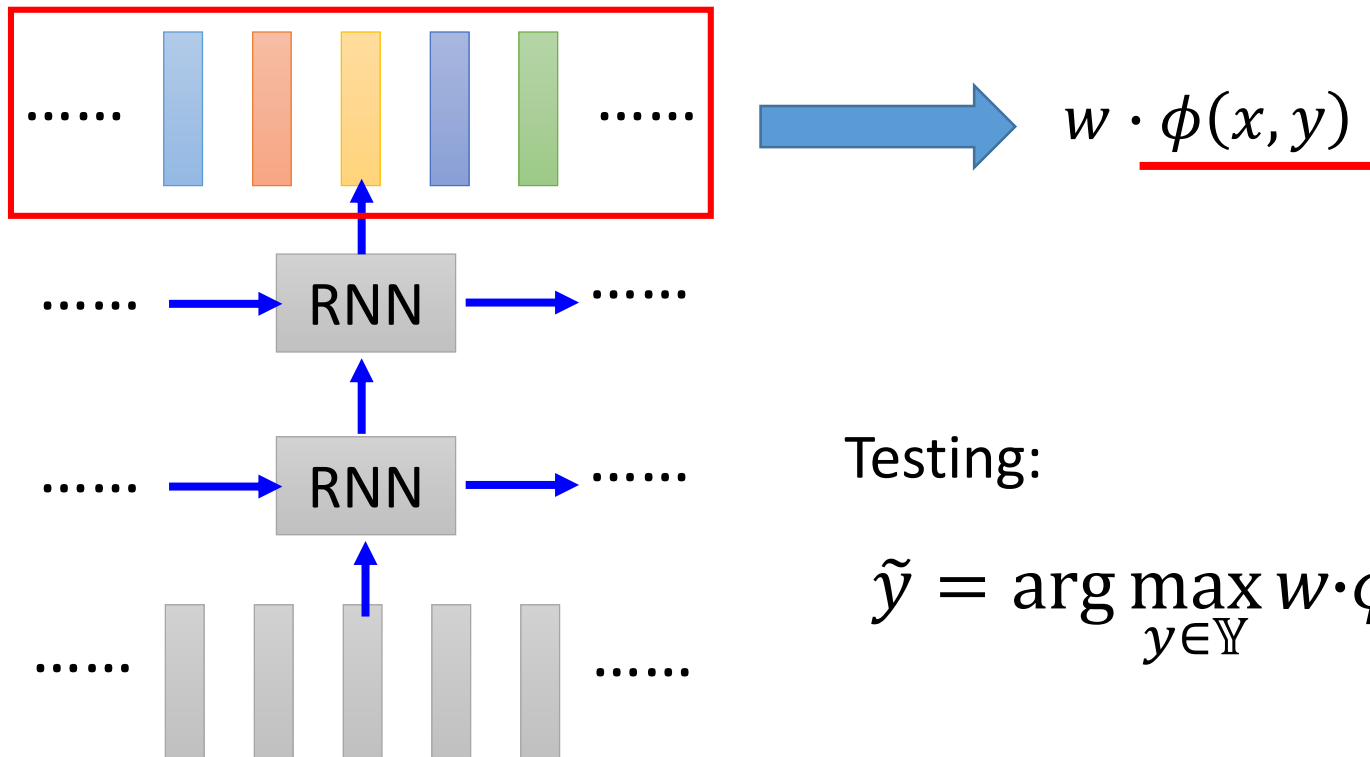


$$P(x_l | y_l) = \frac{P(x_l, y_l)}{P(y_l)}$$

$$= \frac{\overset{\text{RNN}}{P(y_l | x_l)} \cancel{P(x_l)}}{\underset{\text{Count}}{P(y_l)}}$$

Integrated together

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

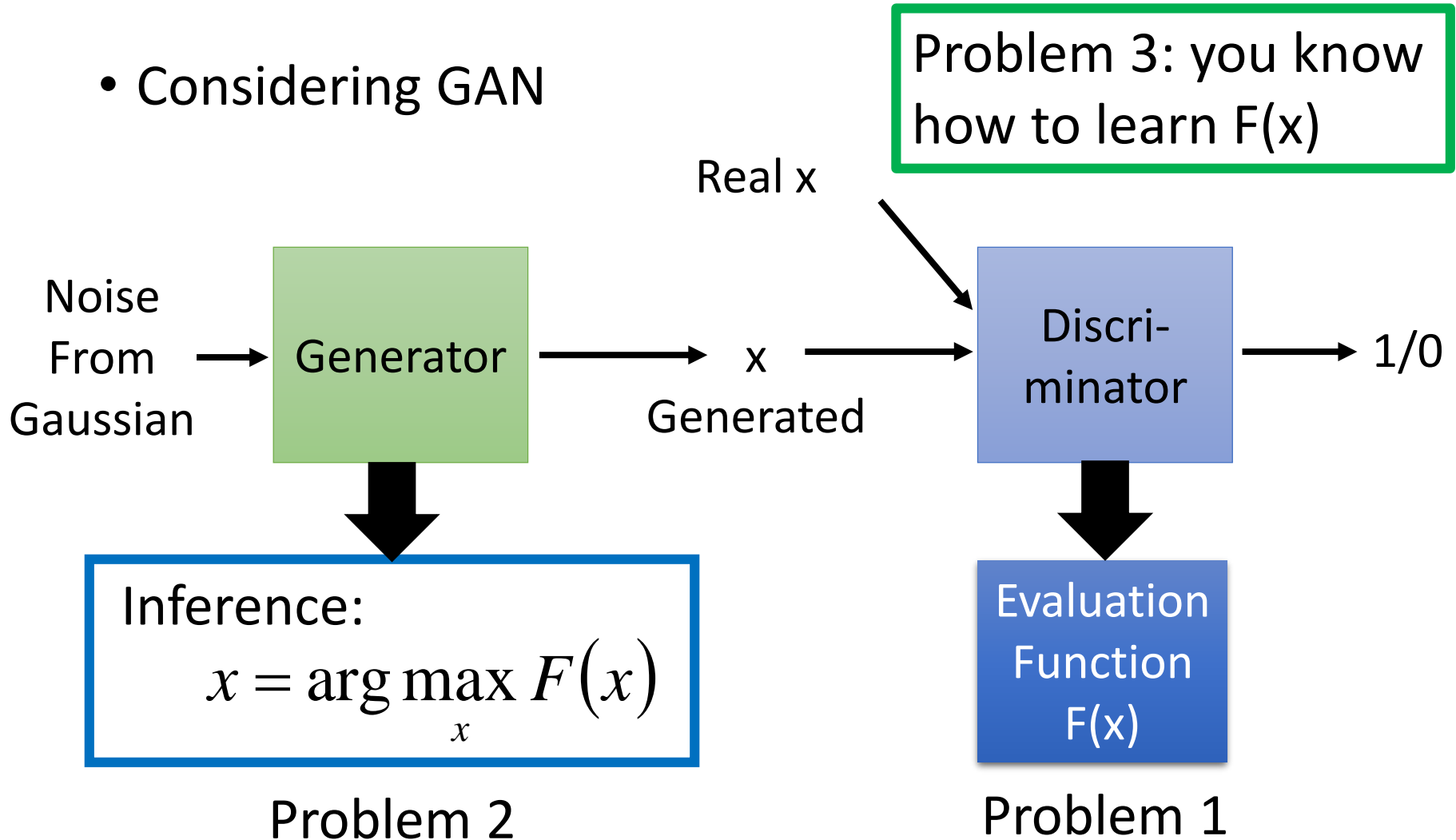


Testing:

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

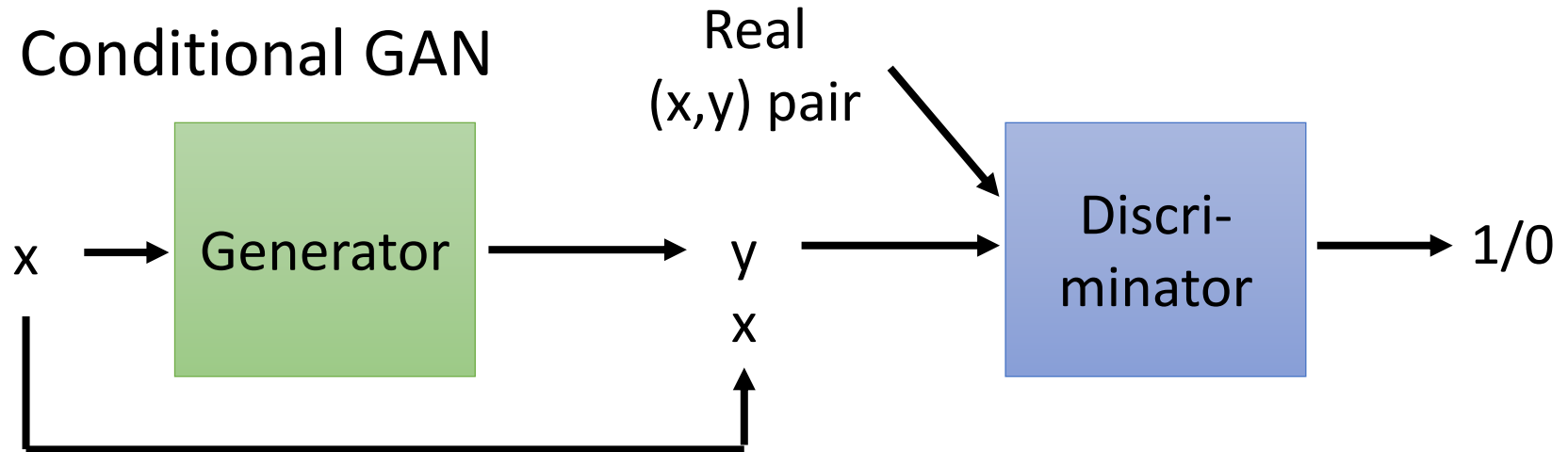
Is structured learning practical?

- Considering GAN

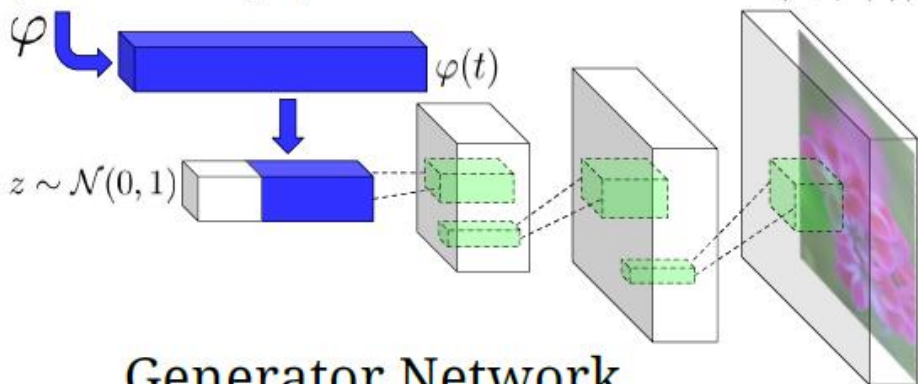


Is structured learning practical?

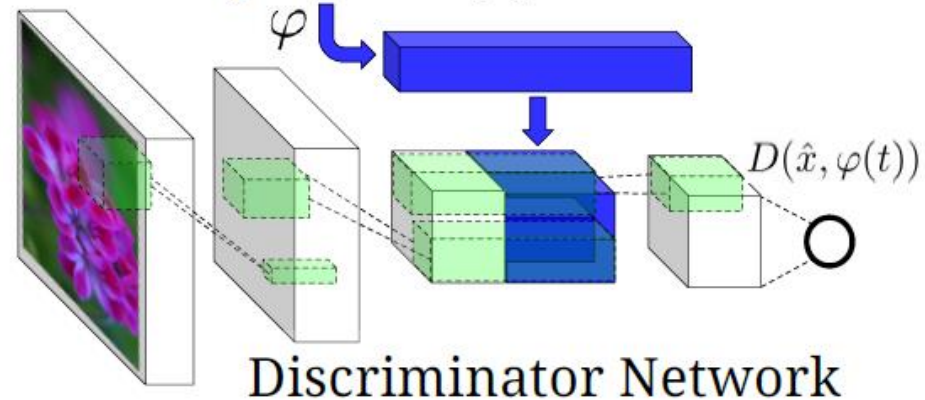
- Conditional GAN



This flower has small, round violet petals with a dark purple center



This flower has small, round violet petals with a dark purple center



Deep and Structured
will be the future.

Sounds crazy?

People do think in this way ...

- 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

- Part II: Modern Practical Deep Networks
 - 6 Deep Feedforward Networks
 - 7 Regularization for Deep Learning
 - 8 Optimization for Training Deep Models
 - 9 Convolutional Networks
 - 10 Sequence Modeling: Recurrent and Recu
 - 11 Practical Methodology
 - 12 Applications

- Part III: Deep Learning Research
 - 13 Linear Factor Models
 - 14 Autoencoders
 - 15 Representation Learning
 - 16 Structured Probabilistic Models for Deep Learning
 - 17 Monte Carlo Methods
 - 18 Confronting the Partition Function
 - 19 Approximate Inference
 - 20 Deep Generative Models

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）