Sequence Generation

Hung-yi Lee

李宏毅

Outline

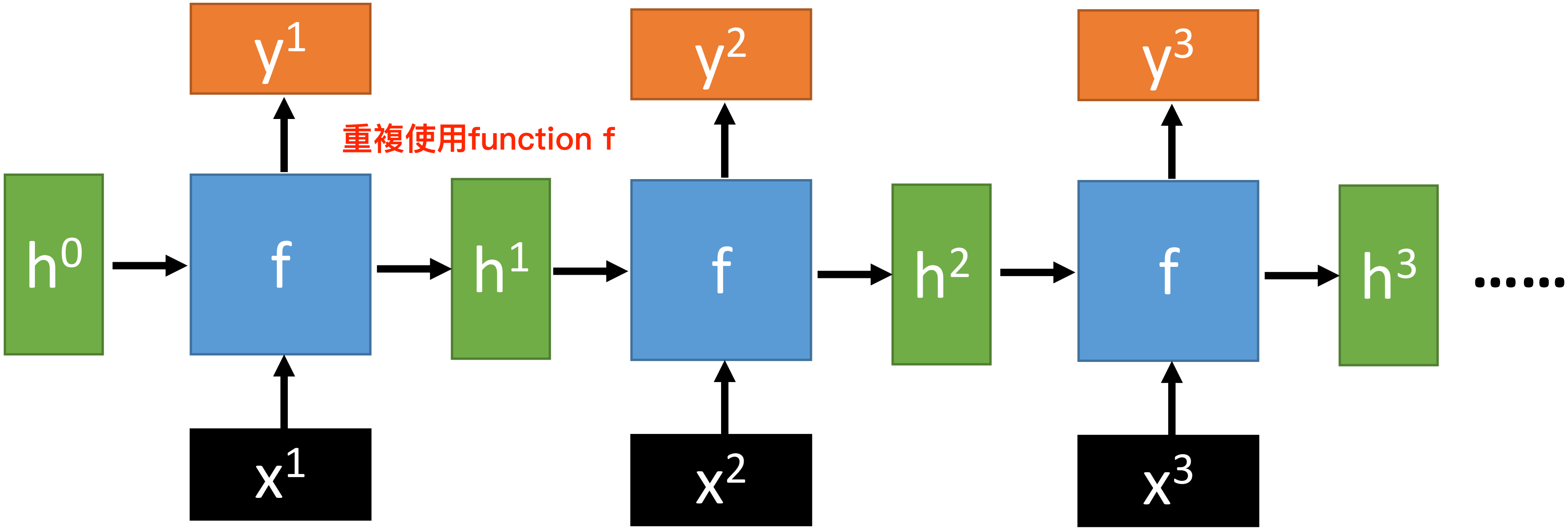
- RNN with Gated Mechanism
- Sequence Generation
- Conditional Sequence Generation
- Tips for Generation

RNN with Gated Mechanism

Recurrent Neural Network

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

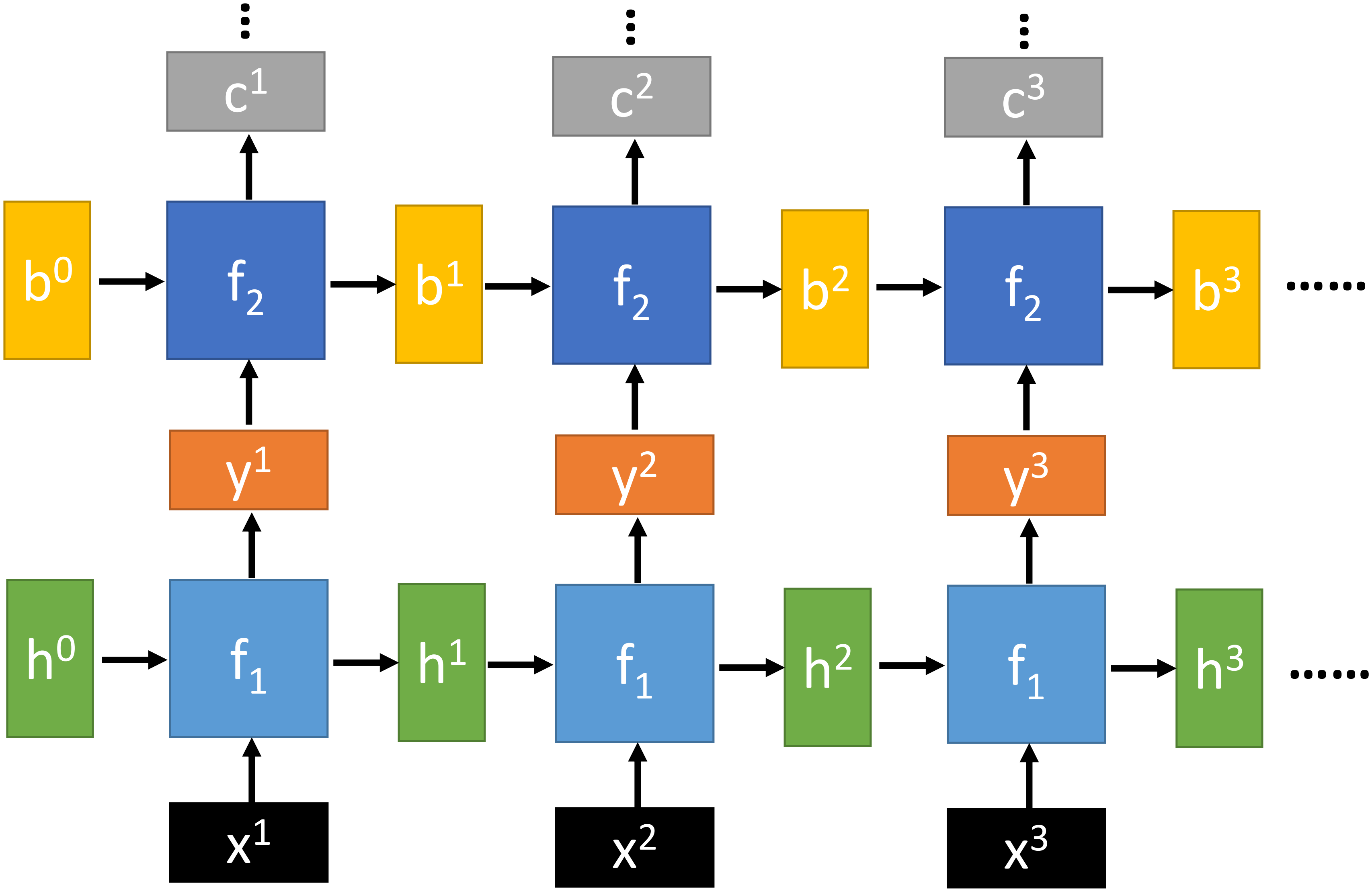
h and h' are vectors with the same dimension



No matter how long the input/output sequence is, we only need one function f

Deep RNN

$h', y = f_1(h, x) \quad b', c = f_2(b, y) \quad \cdots$

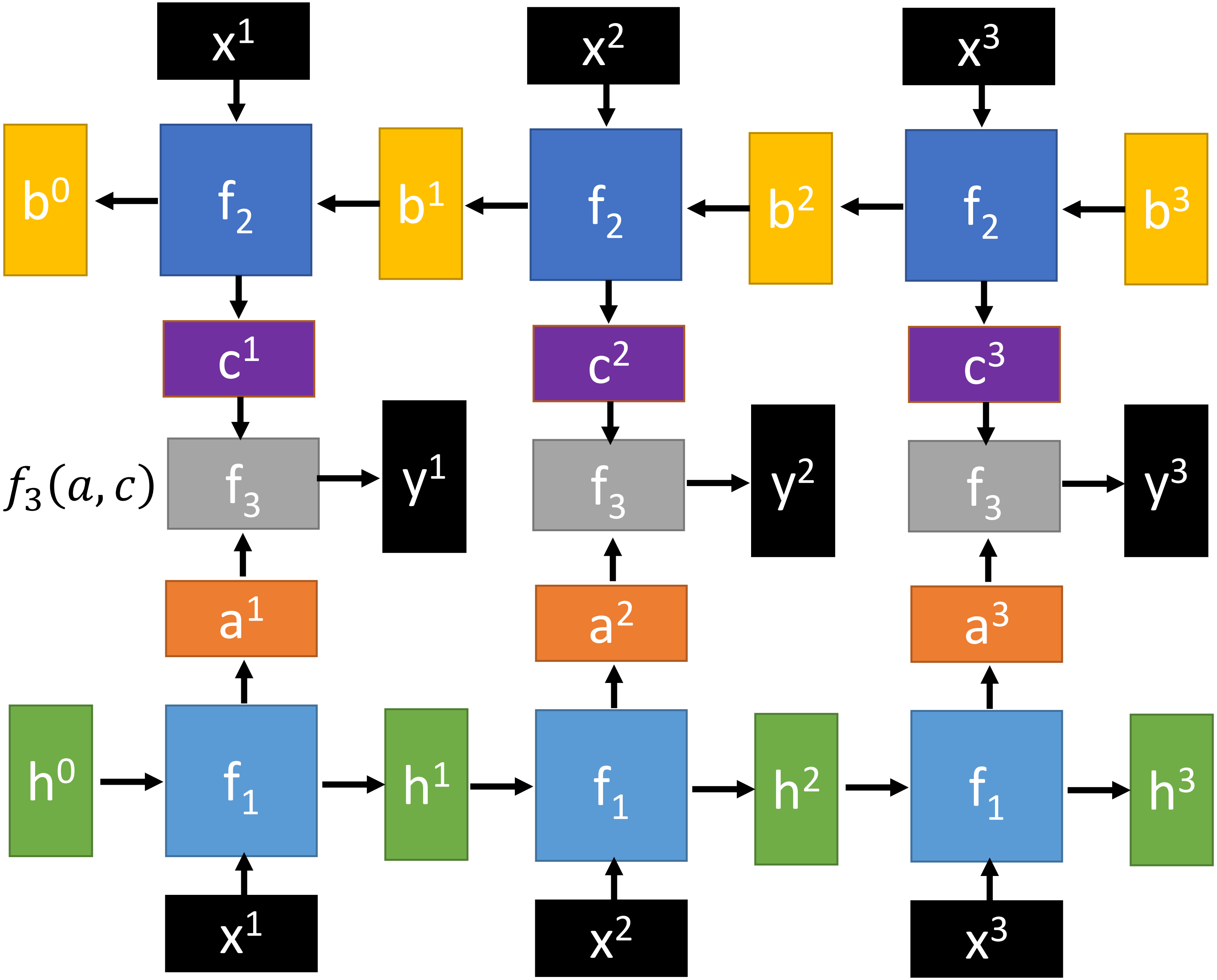


f1跟f2吃的state方向相反

Bidirectional RNN

$$h', a = f_1(h, x) \quad b', c = f_2(b, x)$$

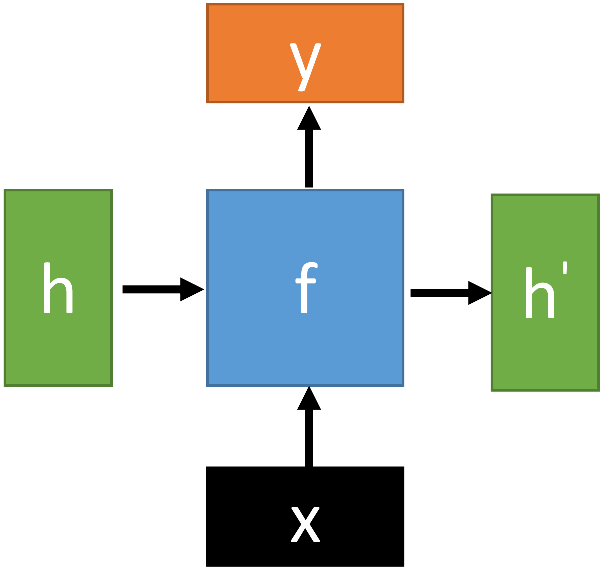
$$y = f_3(a, c)$$



Naïve RNN

一般RNN的activation function都是用tanh instead of ReLu, 如果用ReLu效果會變差

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



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

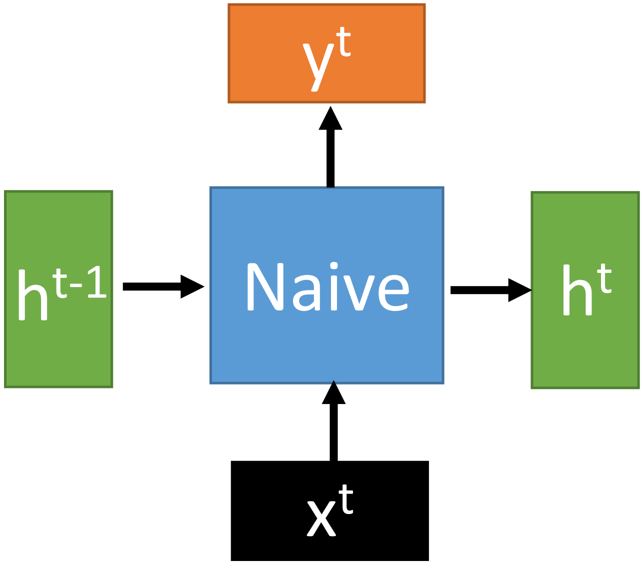
$$y = \sigma(W^o \; h')$$

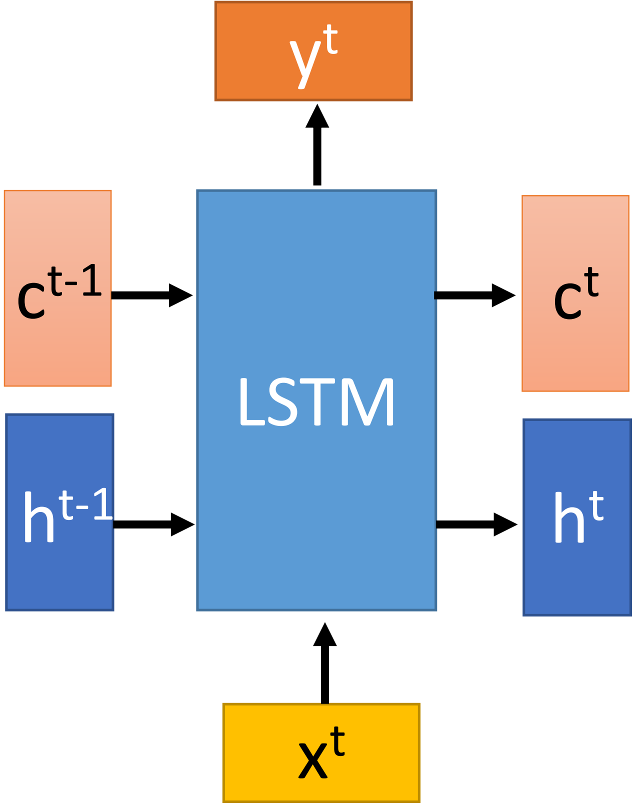
softmax

Ignore bias here

LSTM比較強的原因是因為可以記住較久以前的time stamp

LSTM





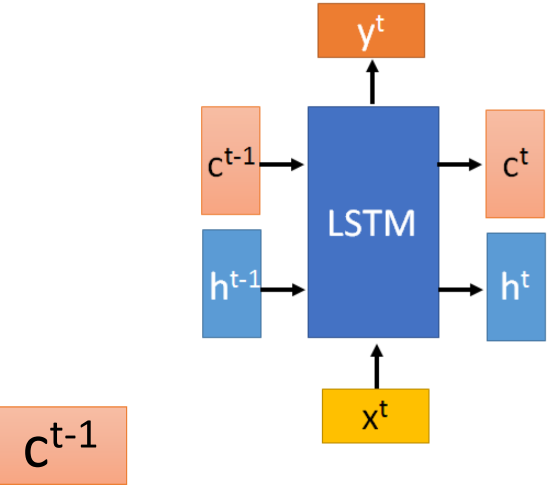
變化較慢的memory

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

變化較快的memory

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

四個維度相同但是value不同的transform matrix



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

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

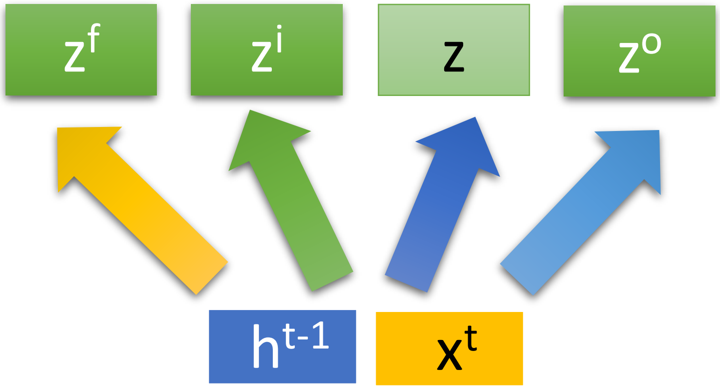
Input gate

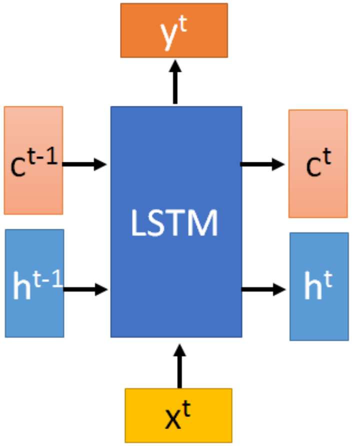
$$z^f = \sigma\left(W^f \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix} \right)$$

forget gate

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

output gate



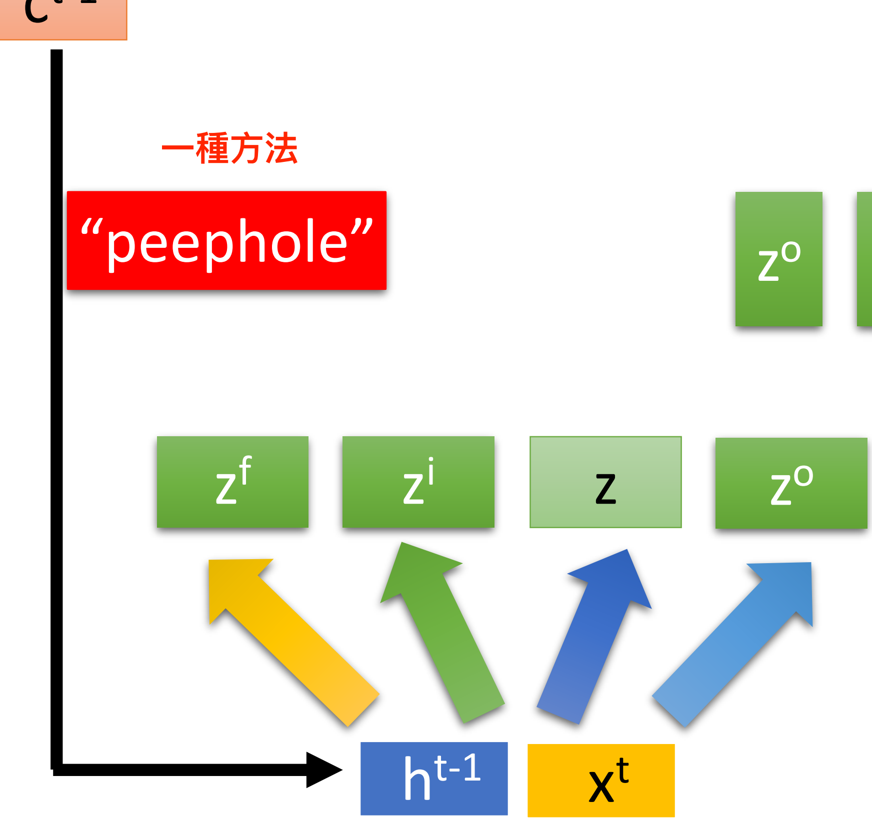


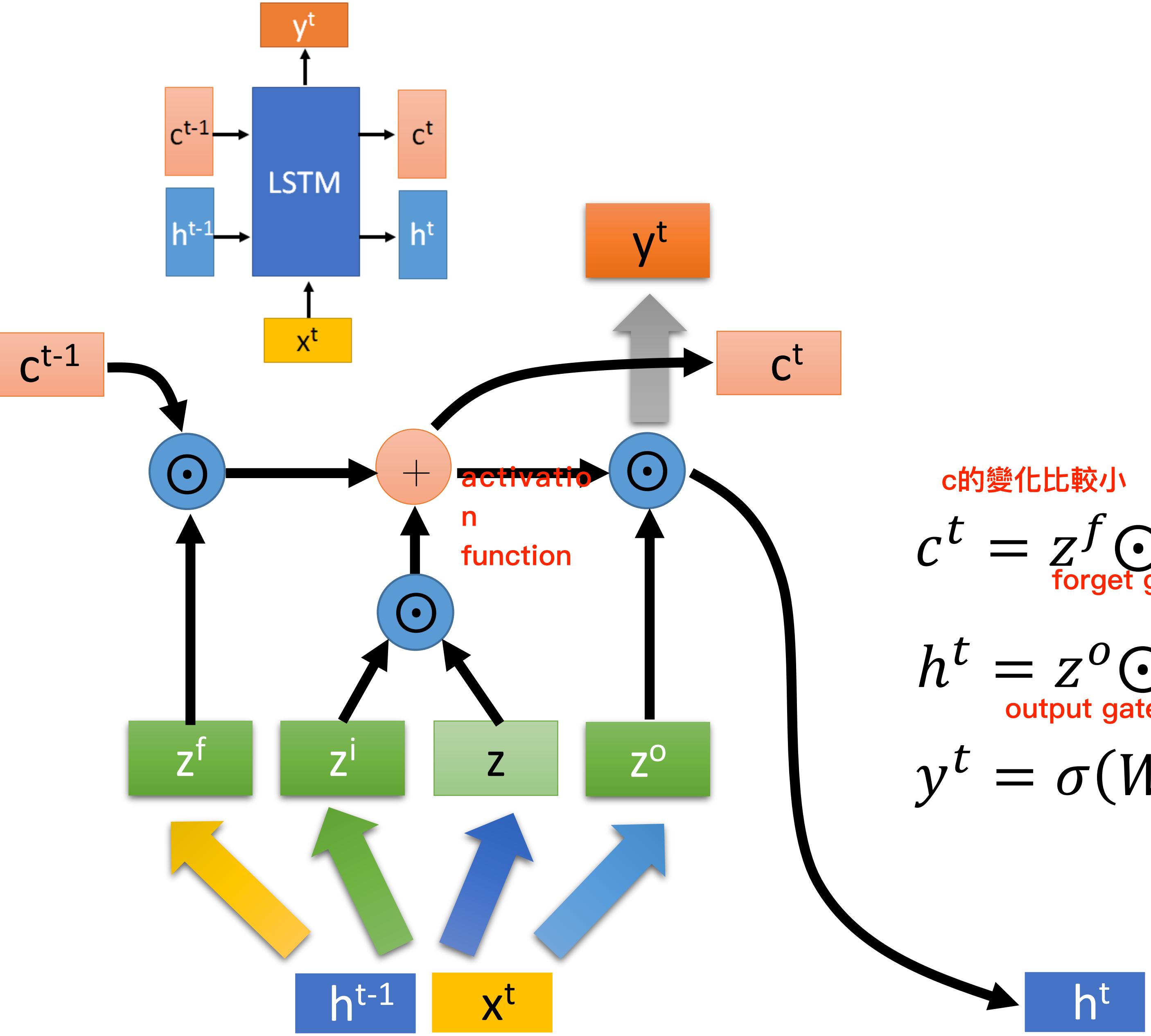
把三個串在一起呈上一個超大的transform matrix
然而為了怕參數過多造成overfitting，強迫與c相乘的部分為diagonal　matrix，也就是他只能做scalar變化

obtained by the same way

一種方法

“peephole”





c的變化比較小

input gate

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

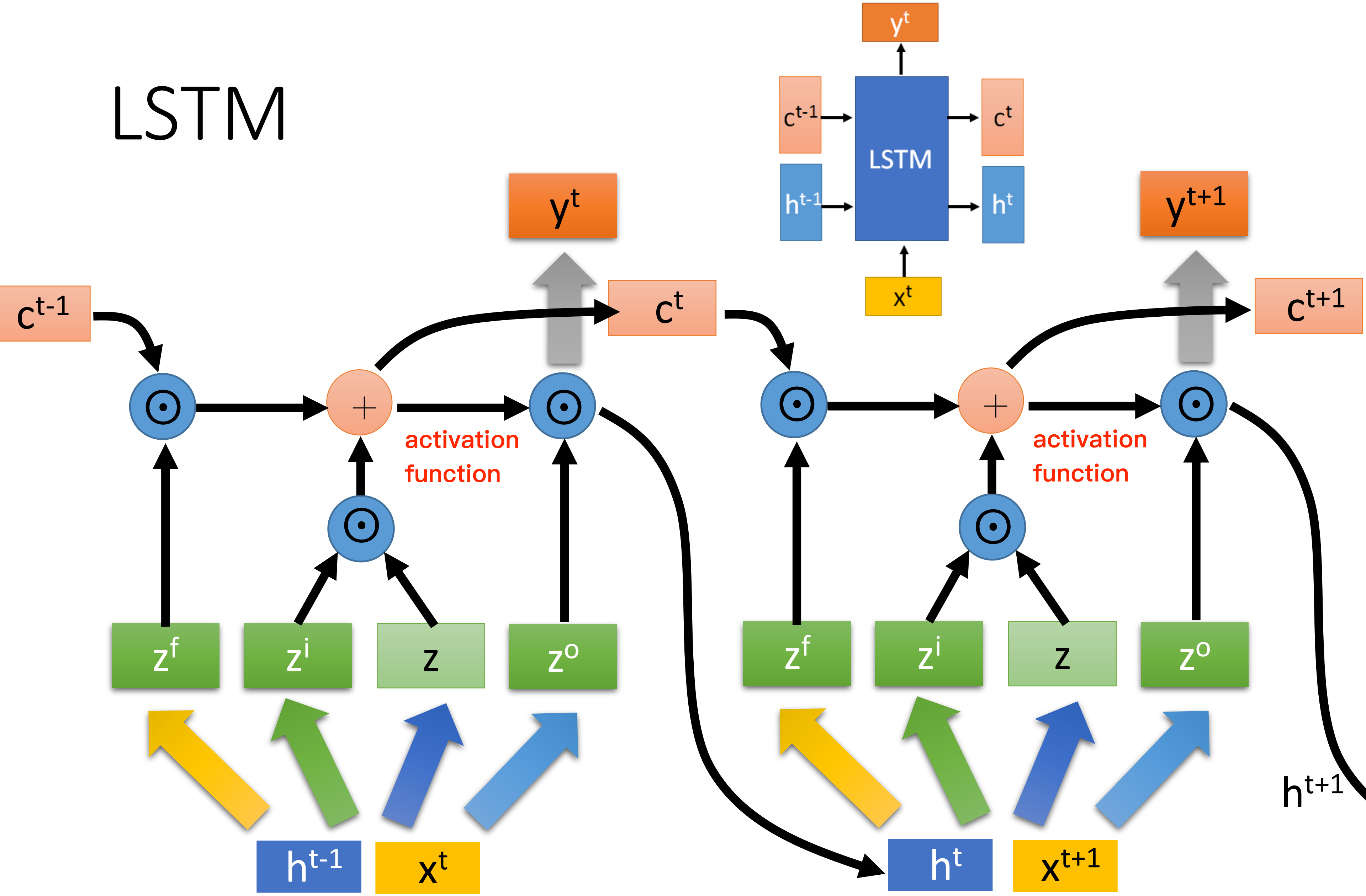
forget gate

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

output gate

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

LSTM



y^t
c^{t-1}
LSTM
c^t
h^{t-1}
h^t
x^t
y^t
y^{t+1}
c^{t-1}
c^t
c^{t+1}
⊙
+
activation function
z^f
z^i
z
z^o
h^{t-1}
x^t
h^t
x^{t+1}
h^{t+1}

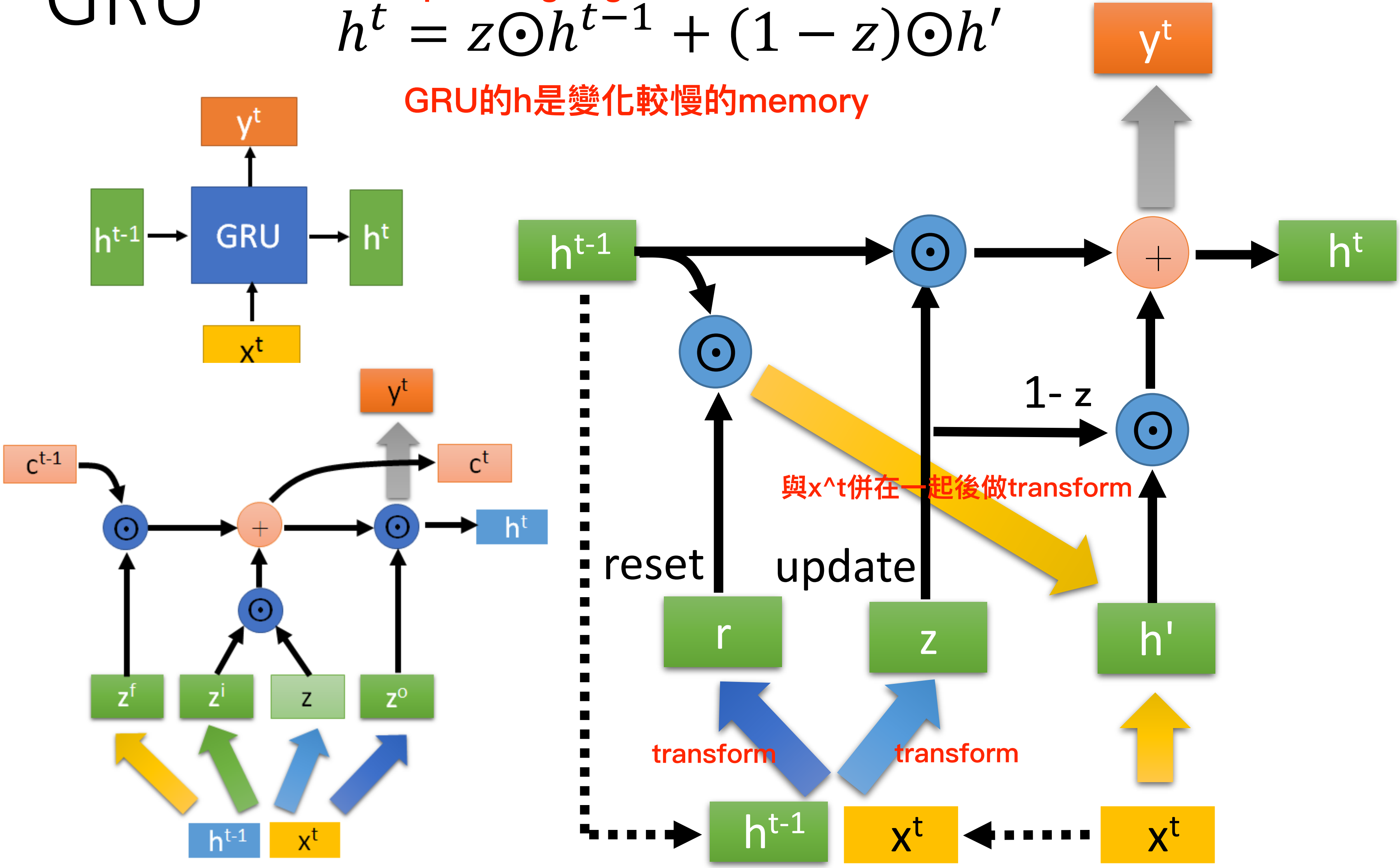
參數量減少避免overfitting

GRU

input/forget gate是連動的概念

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

GRU的h是變化較慢的memory

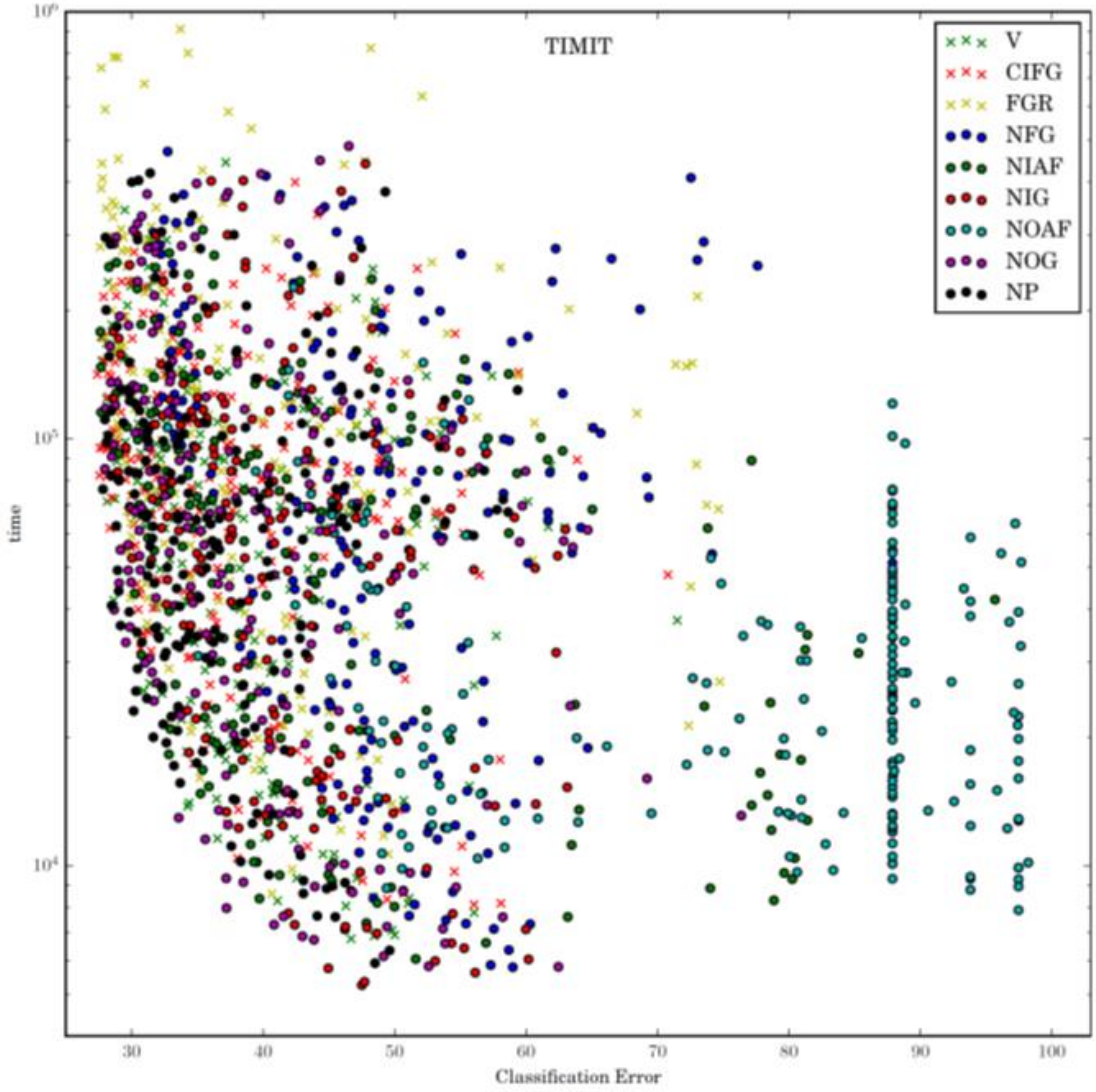


與x^t併在一起後做transform

transform

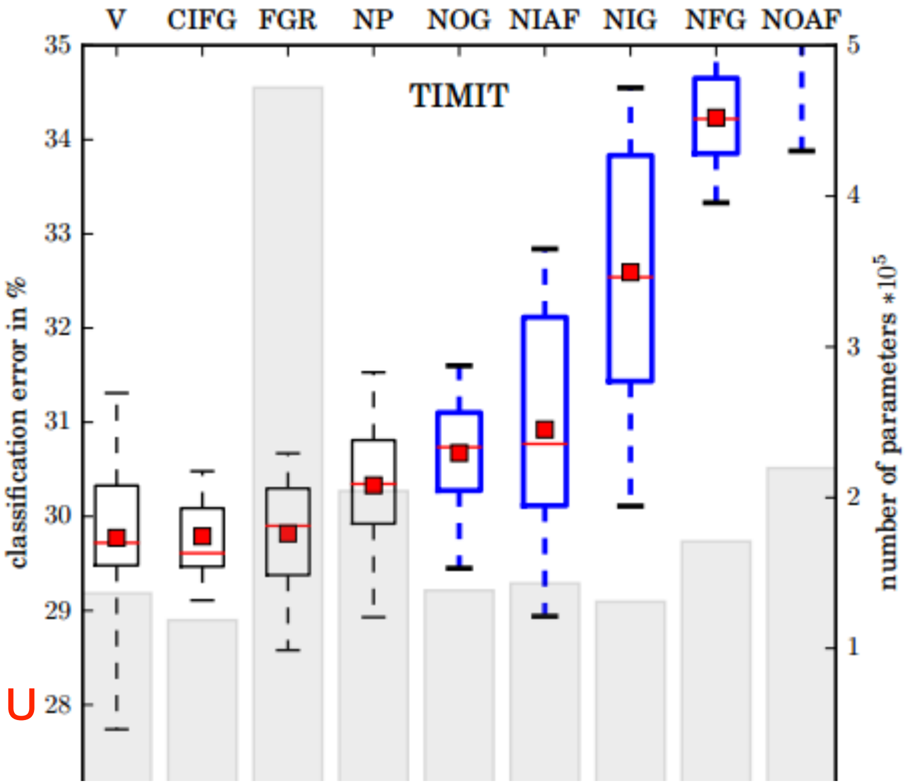
transform

LSTM: A Search Space Odyssey



LSTM: A Search Space Odyssey

1. No Input Gate (NIG)
2. No Forget Gate (NFG)
3. No Output Gate (NOG)
4. No Input Activation Function (NIAF)
5. No Output Activation Function (NOAF)
6. No Peepholes (NP)
7. Coupled Input and Forget Gate (CIFG) GRU
8. Full Gate Recurrence (FGR)



Standard LSTM works well

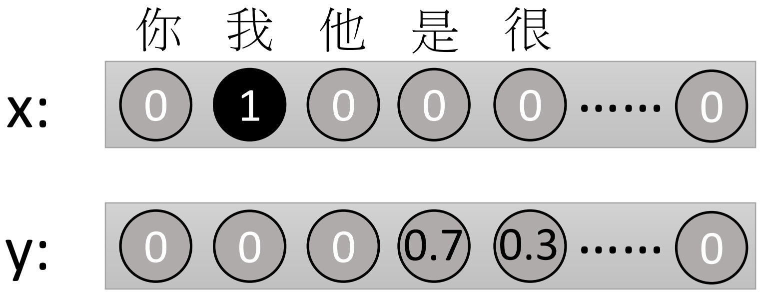
Simply LSTM: coupling input and forget gate, removing peephole

Forget gate is critical for performance

Output gate activation function is critical

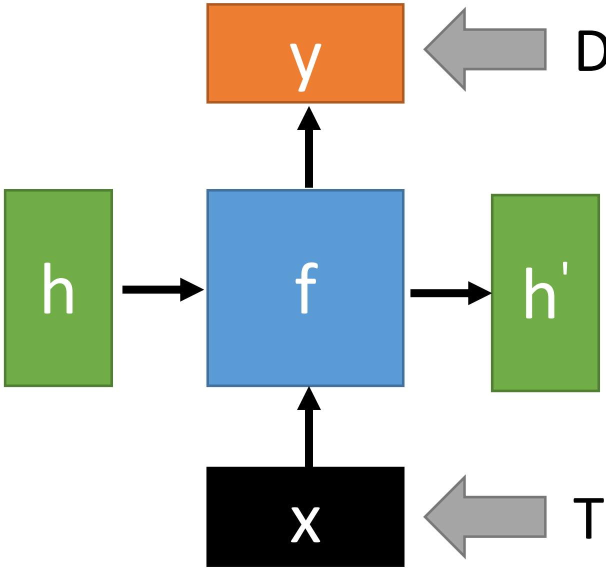
Sequence Generation

Generation



- Sentences are composed of characters/words
- Generating a character/word at each time by RNN

最後要做的事情是從y這個distribution做sampling



Distribution over the token

(sampling from the distribution to generate a token)

The token generated at the last time step.

(represented by 1-of-N encoding)

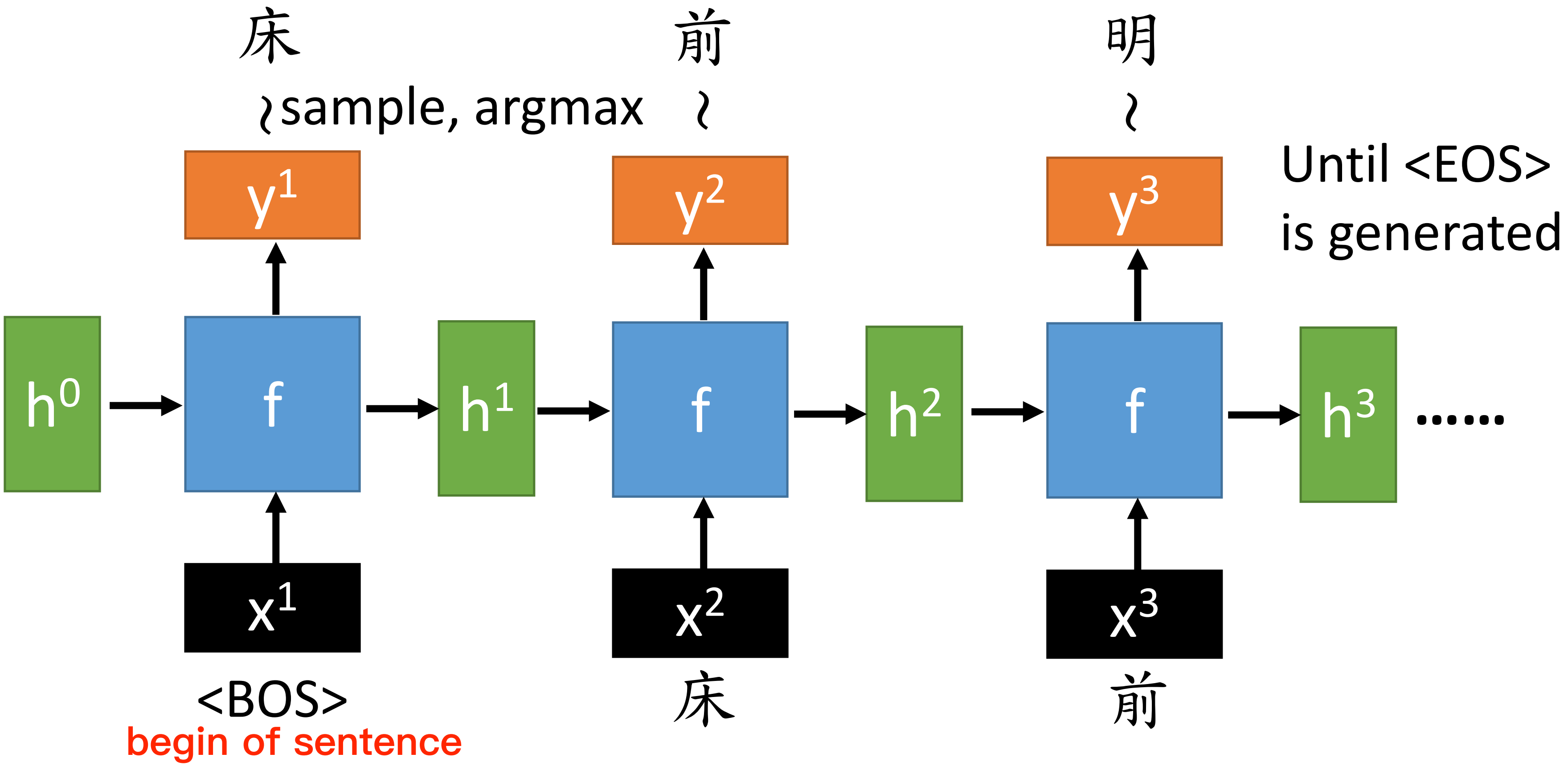
Generation

y^1: P(w|<BOS>)

y^2: P(w|<BOS>,床)

y^3: P(w|<BOS>,床,前)

- Sentences are composed of characters/words
- Generating a character/word at each time by RNN



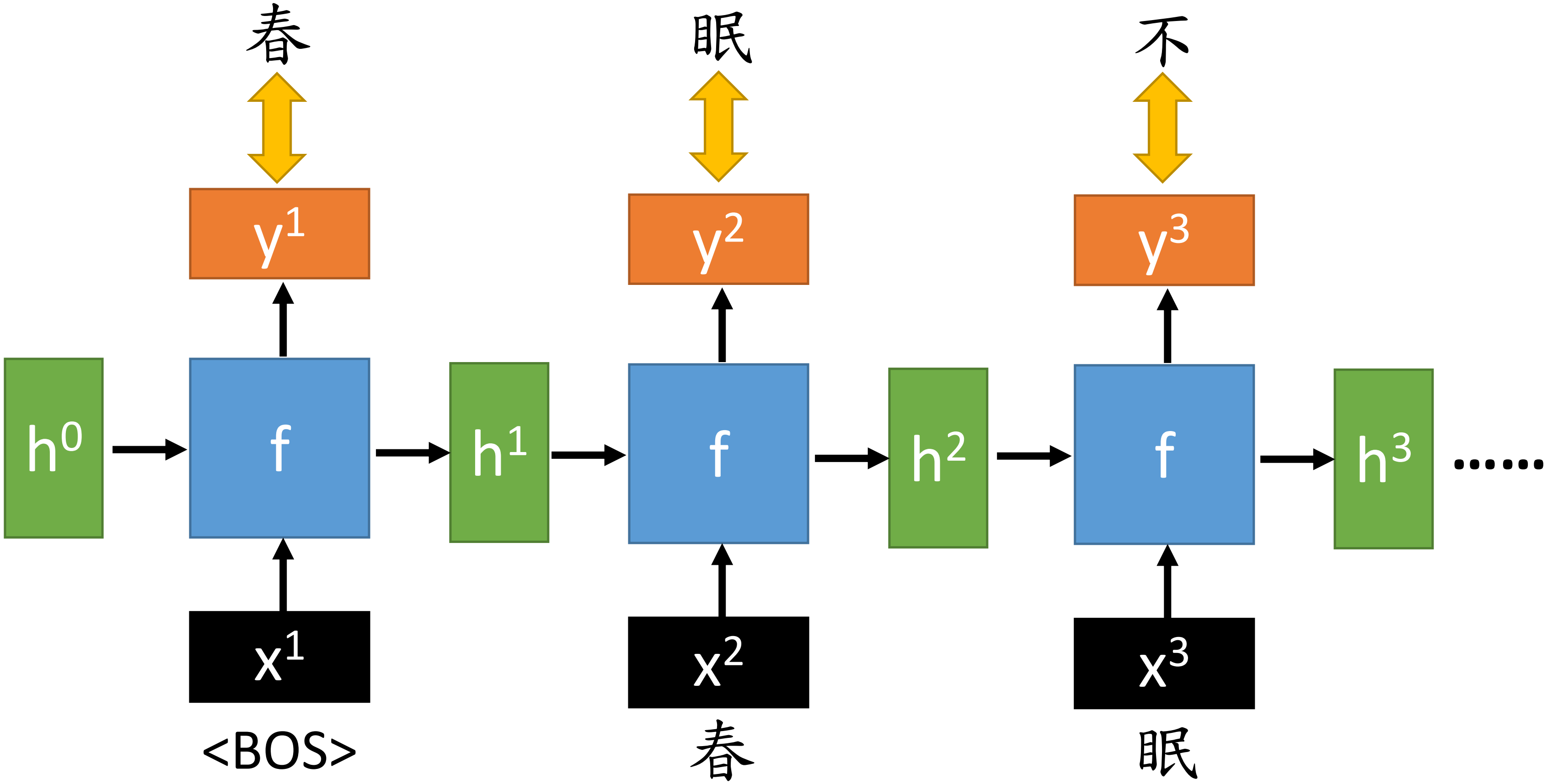
Until <EOS> is generated

Generation

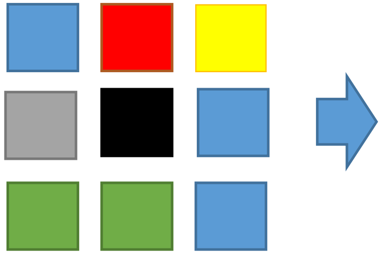
⇕ : minimizing cross-entropy

- ***Training***

Training data: 春 眠 不 覺 曉



Generation

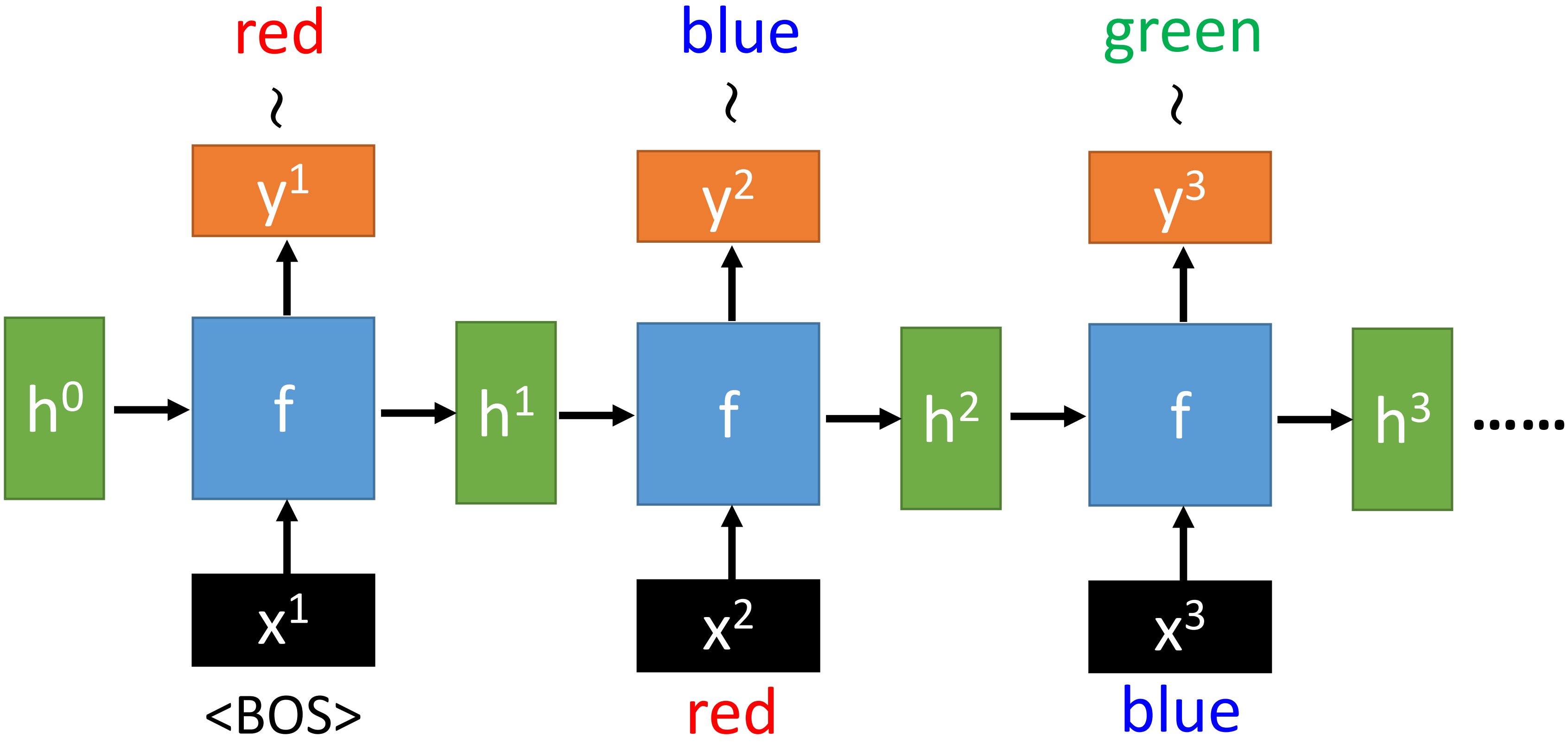


Consider as a sentence

blue red yellow gray ……

Train a RNN based on the "sentences"

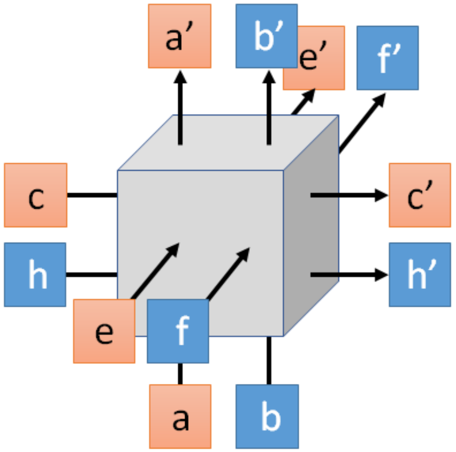
- Images are composed of pixels
- Generating a pixel at each time by RNN

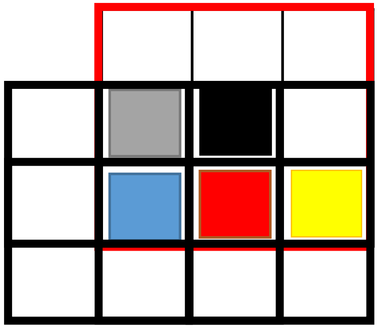


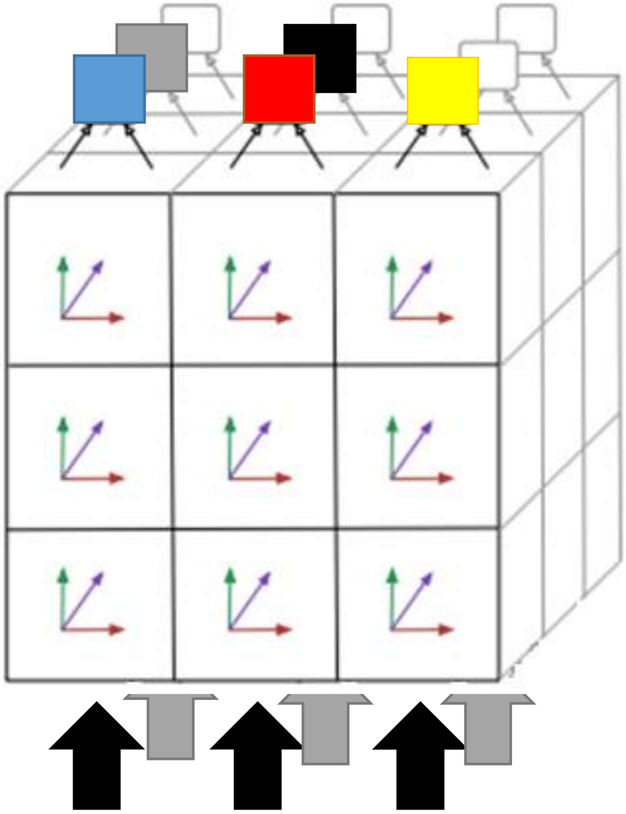
Generation - PixelRNN

只看上下左右附近的pixel

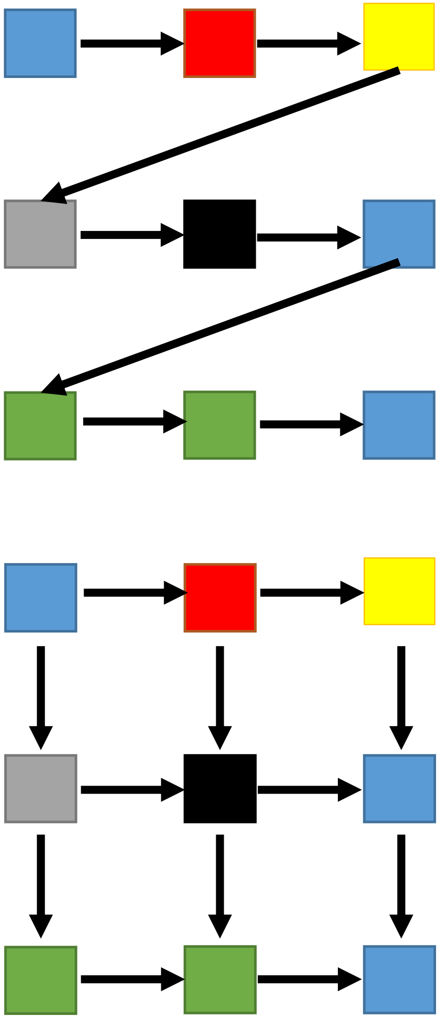
- Images are composed of pixels







3 x 3 images



Conditional Sequence Generation

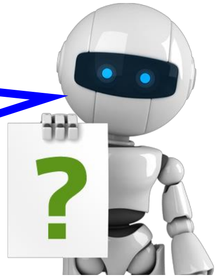
Conditional Generation

- We don’t want to simply generate some random sentences.
- Generate sentences based on conditions:

Caption Generation

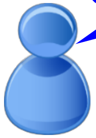
Given condition:

“A young girl is dancing.”



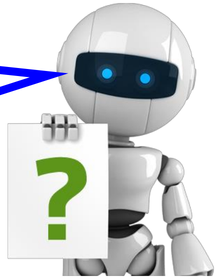
Chat-bot

Given condition:



“Hello”

“Hello. Nice to see you.”

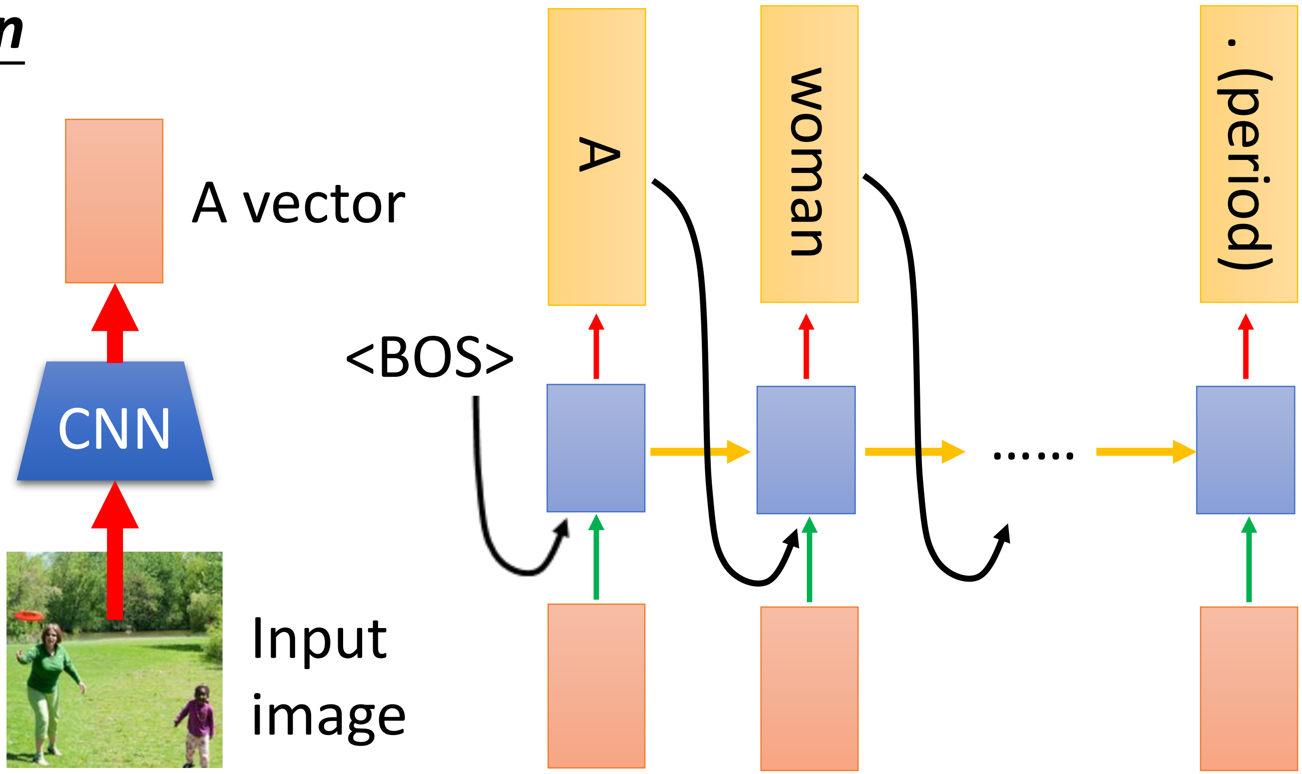


Conditional Generation

為了避免machine忘記input image的vector，在每一個time stamp都餵進去image轉換的vector

- Represent the input condition as a vector, and consider the vector as the input of RNN generator

Image Caption Generation



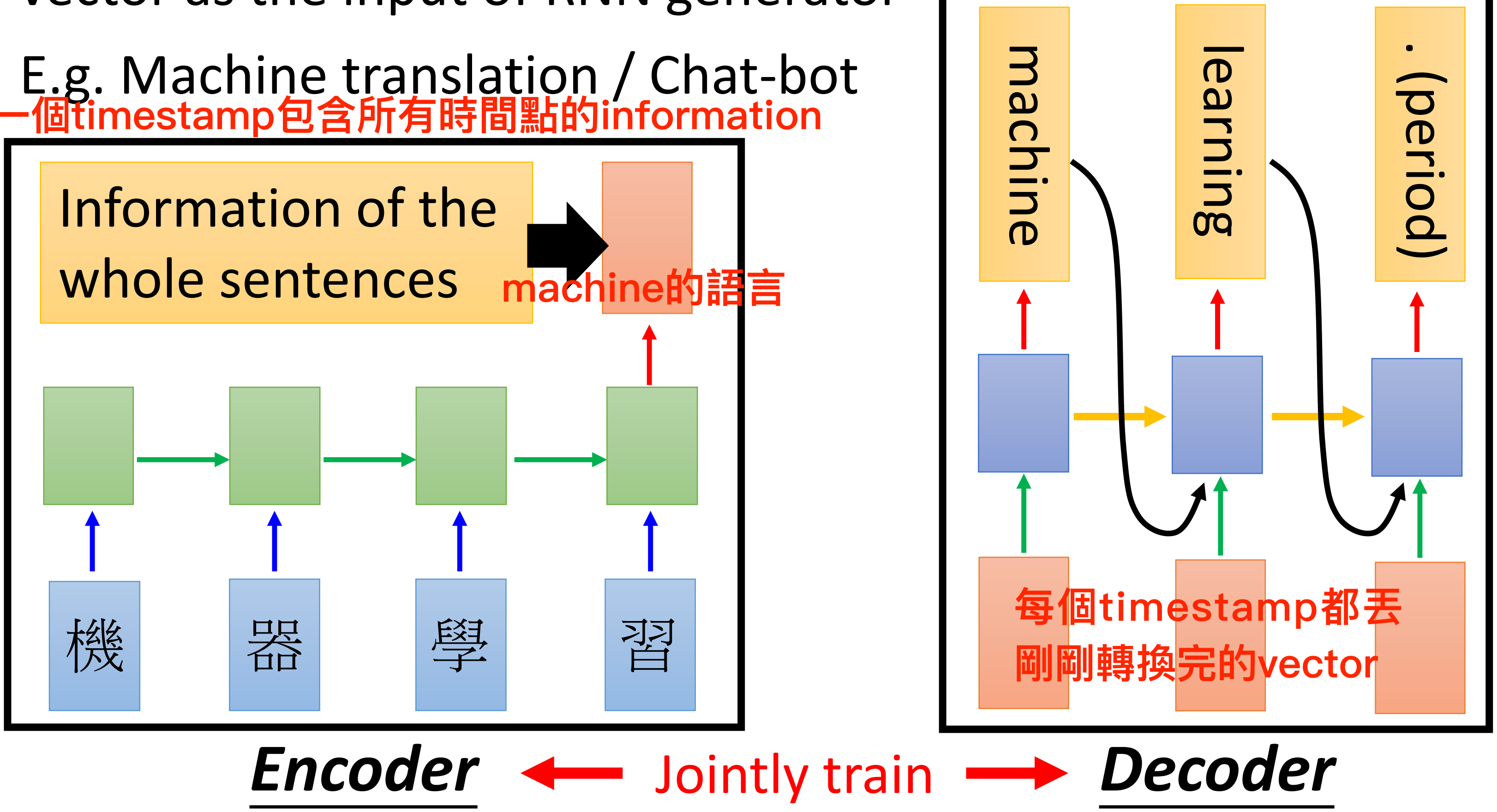
想辦法把input image轉換成一個vector

Conditional Generation

Sequence-to-sequence learning

- Represent the input condition as a vector, and consider the vector as the input of RNN generator
- E.g. Machine translation / Chat-bot

最後一個timestamp包含所有時間點的information



Conditional Generation

M: Hello

U: Hi

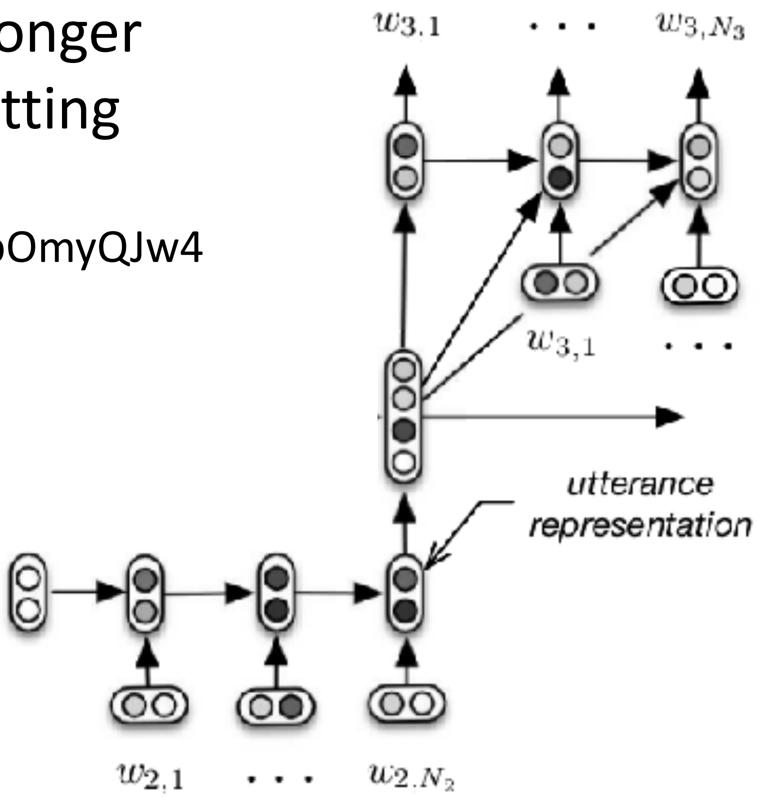
M: Hi

Need to consider longer context during chatting

https://www.youtube.com/watch?v=e2MpOmyQJw4

machine不只要看當下的input vector，
還要包含觀看history產生過的句子

M: Hi ✗



M: Hello

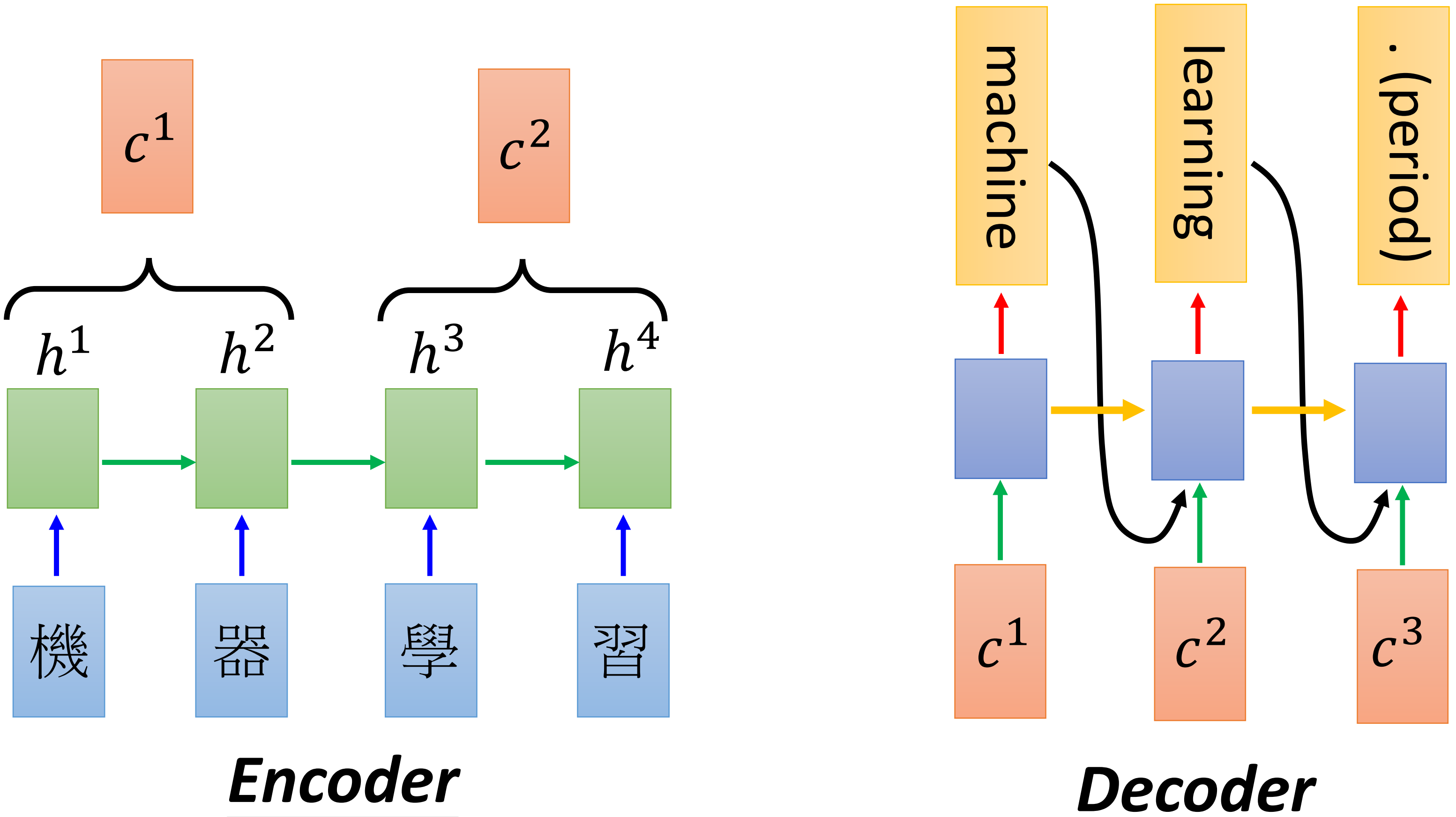
U: Hi

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

原本每個timestamp都吃encoder最後一個timestamp output的結果，但是我們沒有辦法保證所有的資訊都可以被encode盡最後一個vector，因此希望每個timestamp有decoder自己決定的input vector

Dynamic Conditional Generation

Attention based model
decoder在每個timestamp吃到的information都是不一樣的

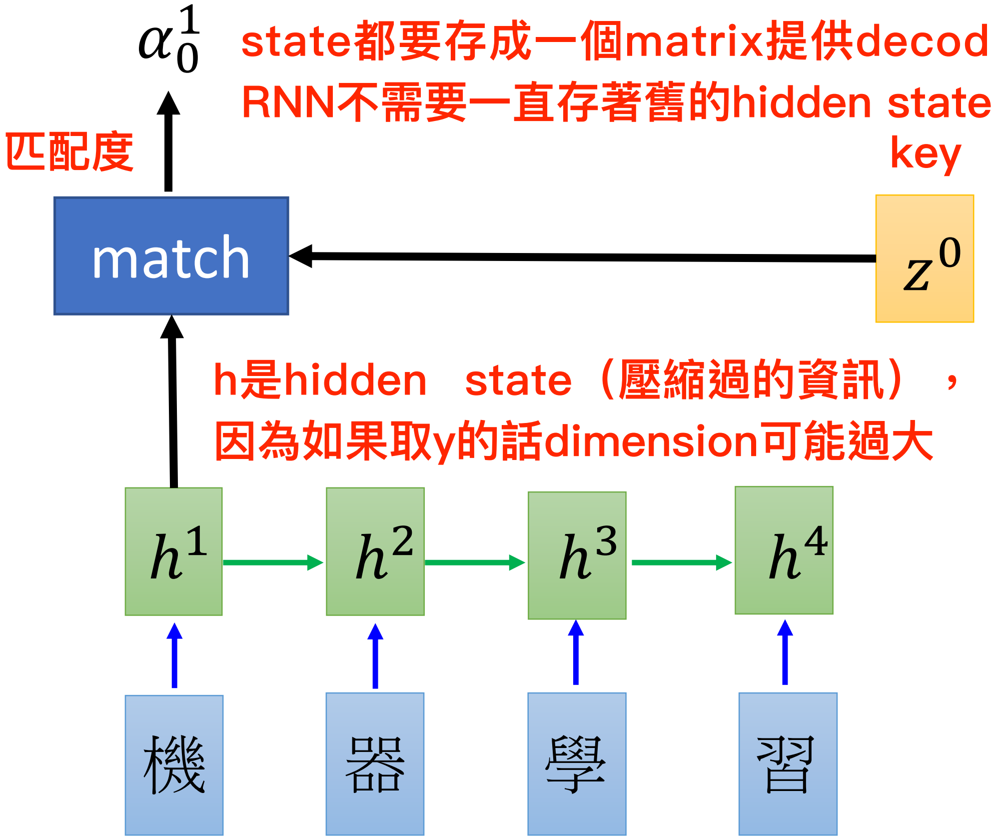


每次input vector都是decoder從encoder output的database搜尋找出相關的information轉換成vector

Machine Translation

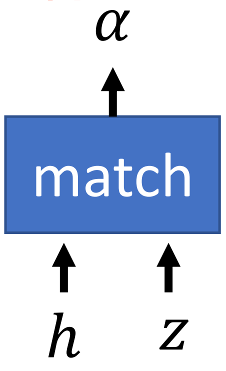
- Attention-based model

在attention base model中encoder所有的hidden state都要存成一個matrix提供decoder搜尋，傳統RNN不需要一直存著舊的hidden state



h是hidden state（壓縮過的資訊），因為如果取y的話dimension可能過大

與encoder/dcoder同時學出來的



Jointly learned with other part of the network

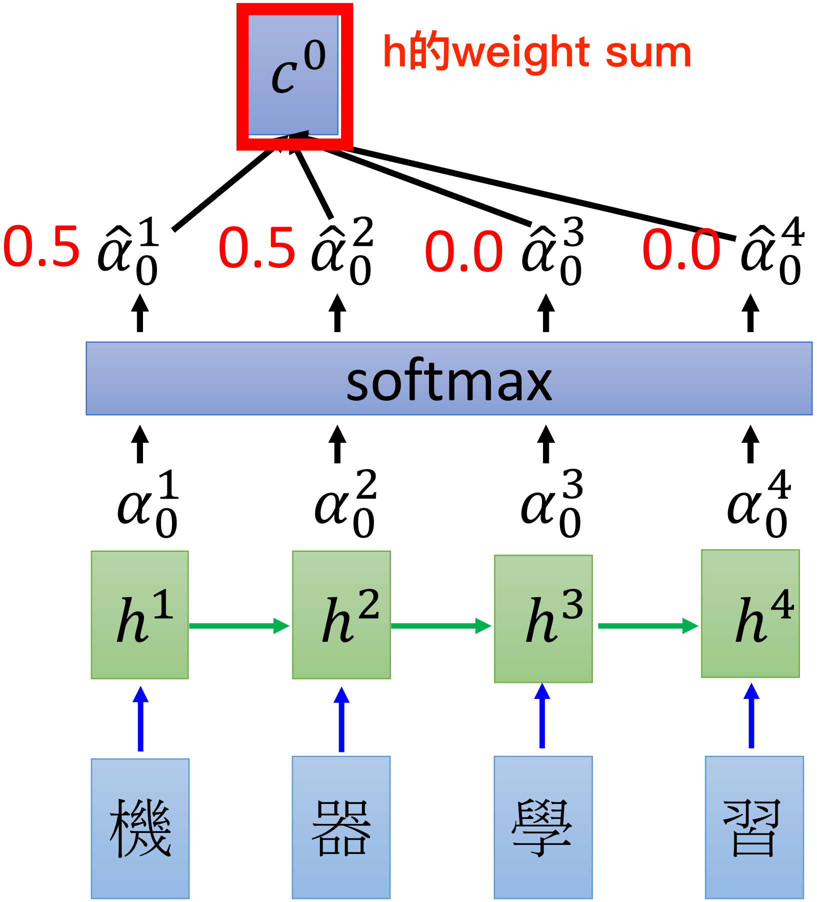
What is **match** ?

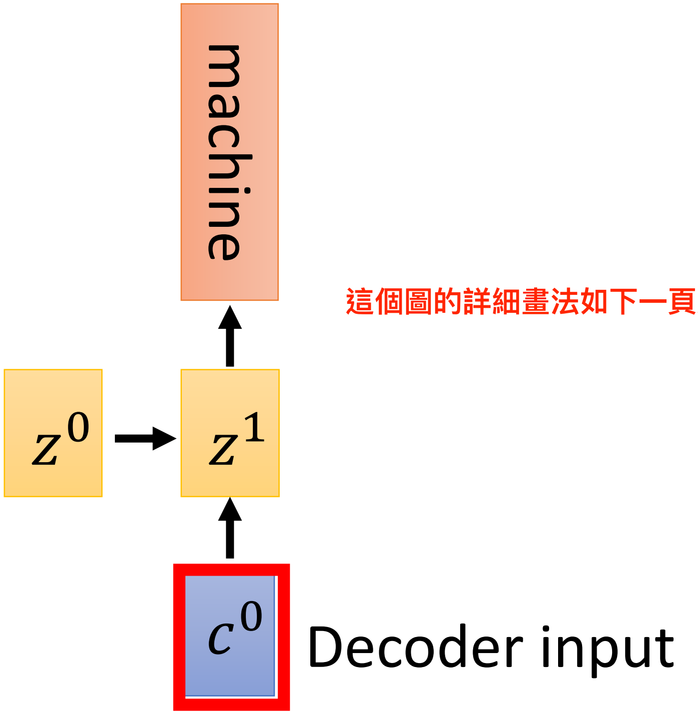
Design by yourself

- ➢ Cosine similarity of z and h inner product
- 小network
  ➢ Small NN whose input is z and h, output a scalar
- ➢ $\alpha = h^T W z$
  做一個transform

Machine Translation

- Attention-based model

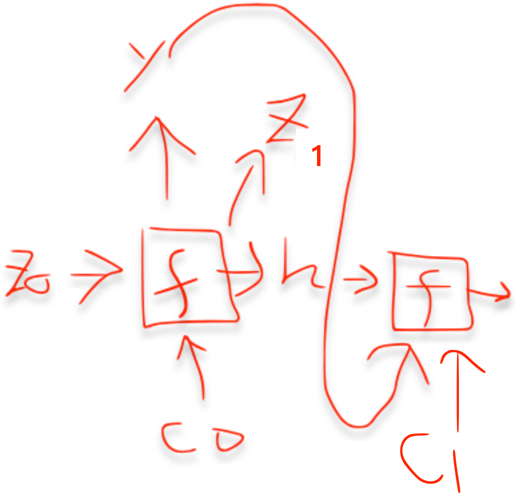




這個圖的詳細畫法如下一頁所示

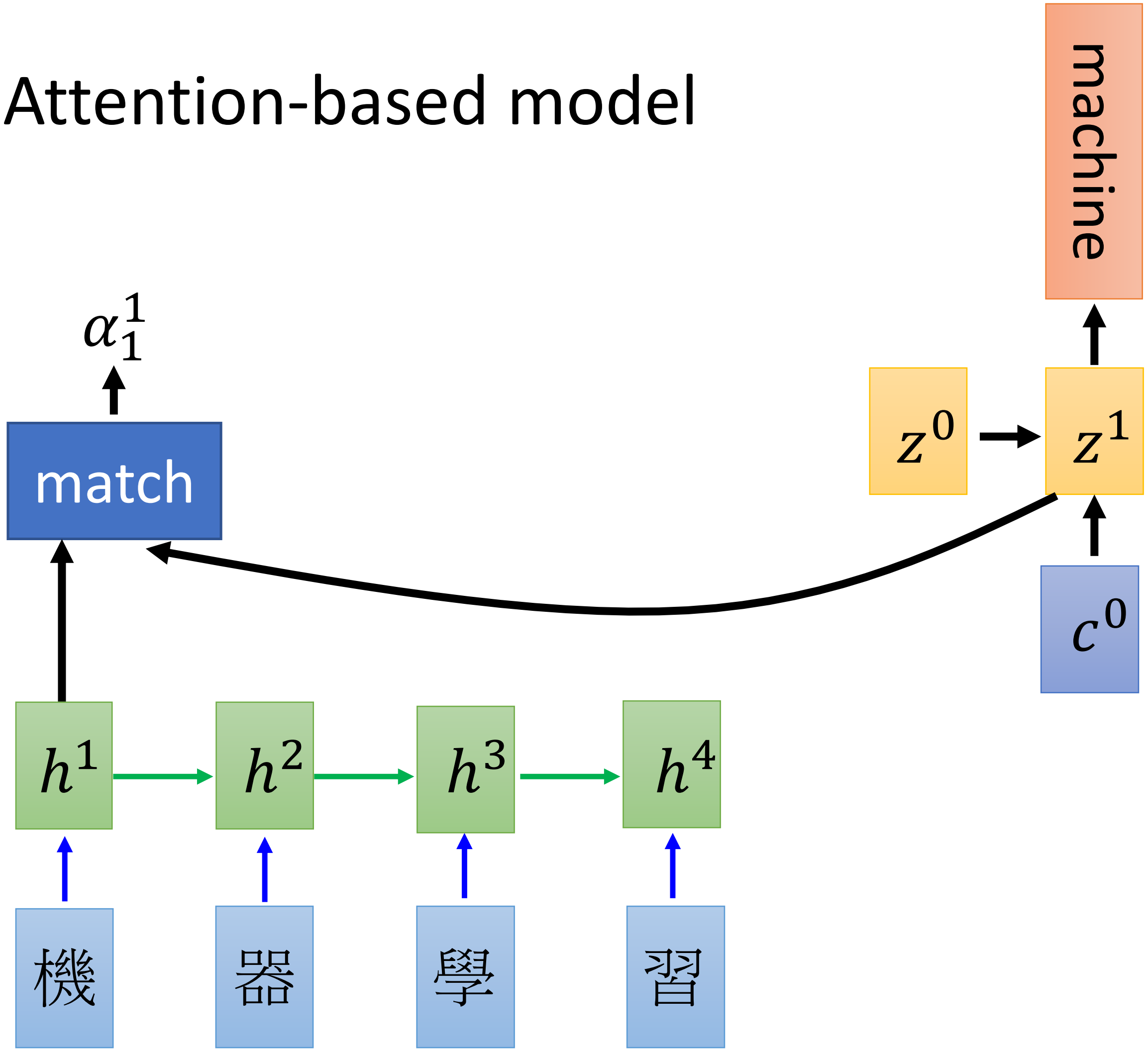
$$c^0 = \sum \hat{\alpha}_0^i h^i$$

$$= 0.5h^1 + 0.5h^2$$


y
z
1
z0
f
h
f
c0
c1

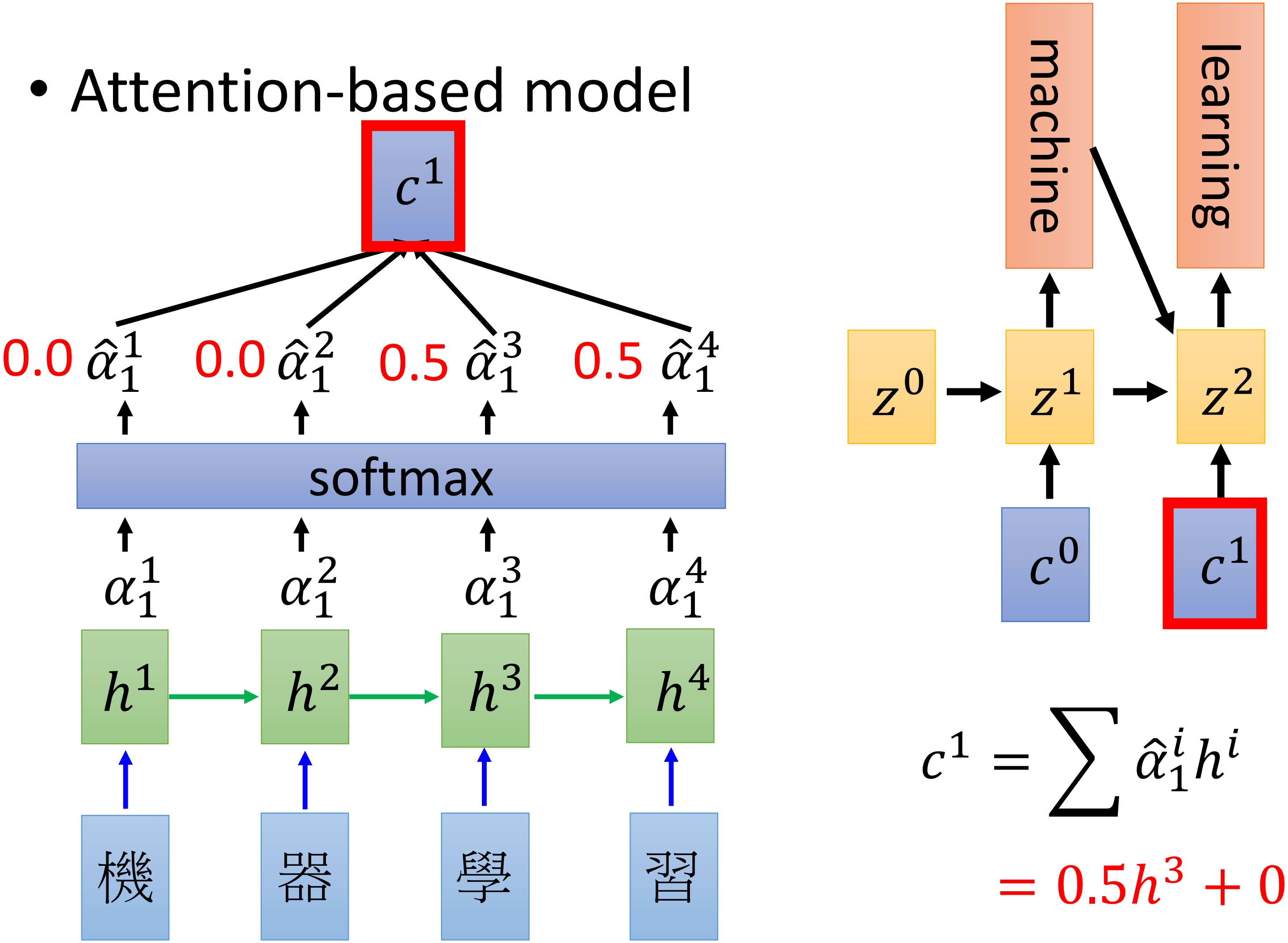
Machine Translation

- Attention-based model



Machine Translation

- Attention-based model

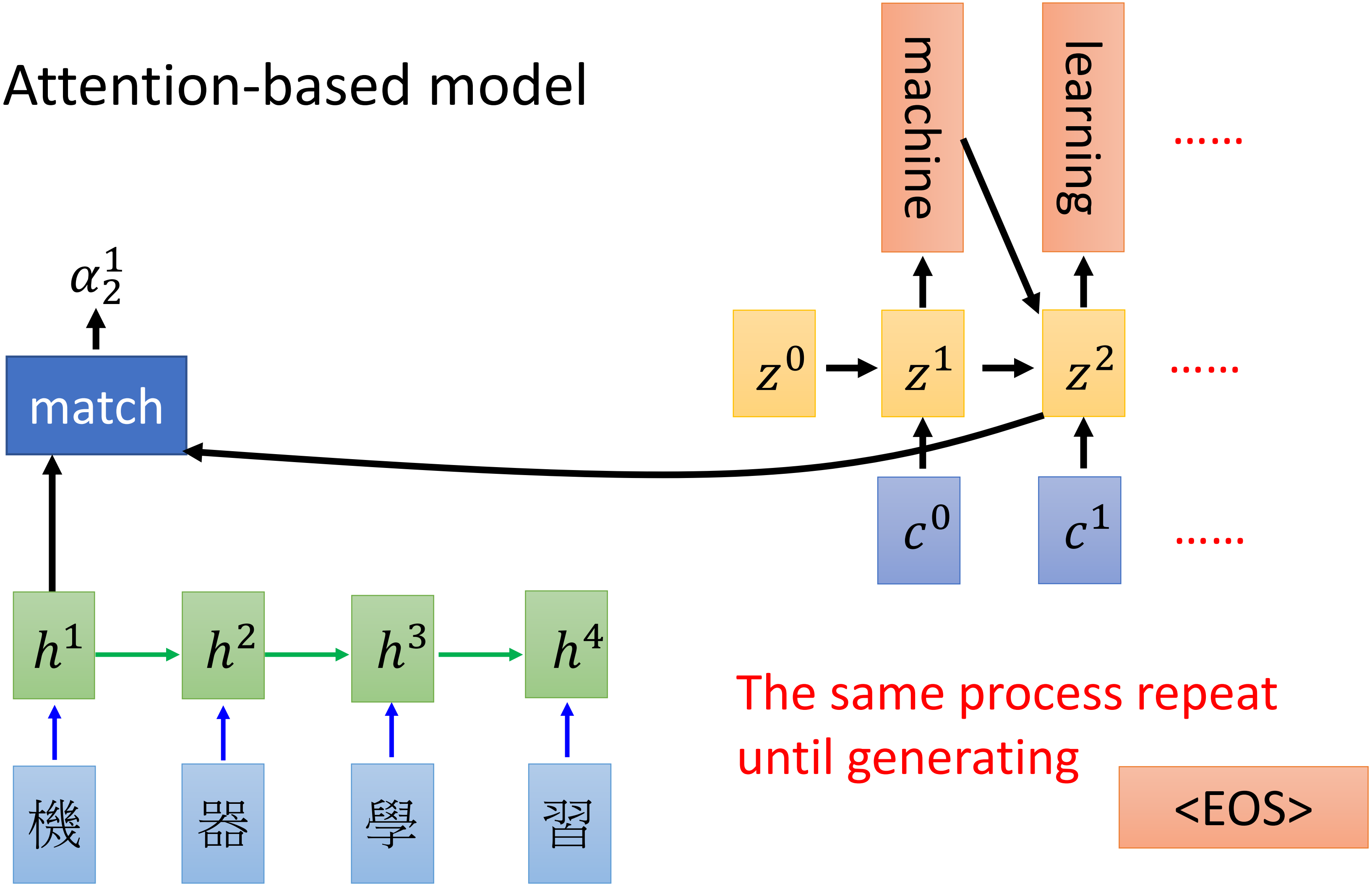


$$c^1 = \sum \hat{\alpha}_1^i h^i$$

$$= 0.5h^3 + 0.5h^4$$

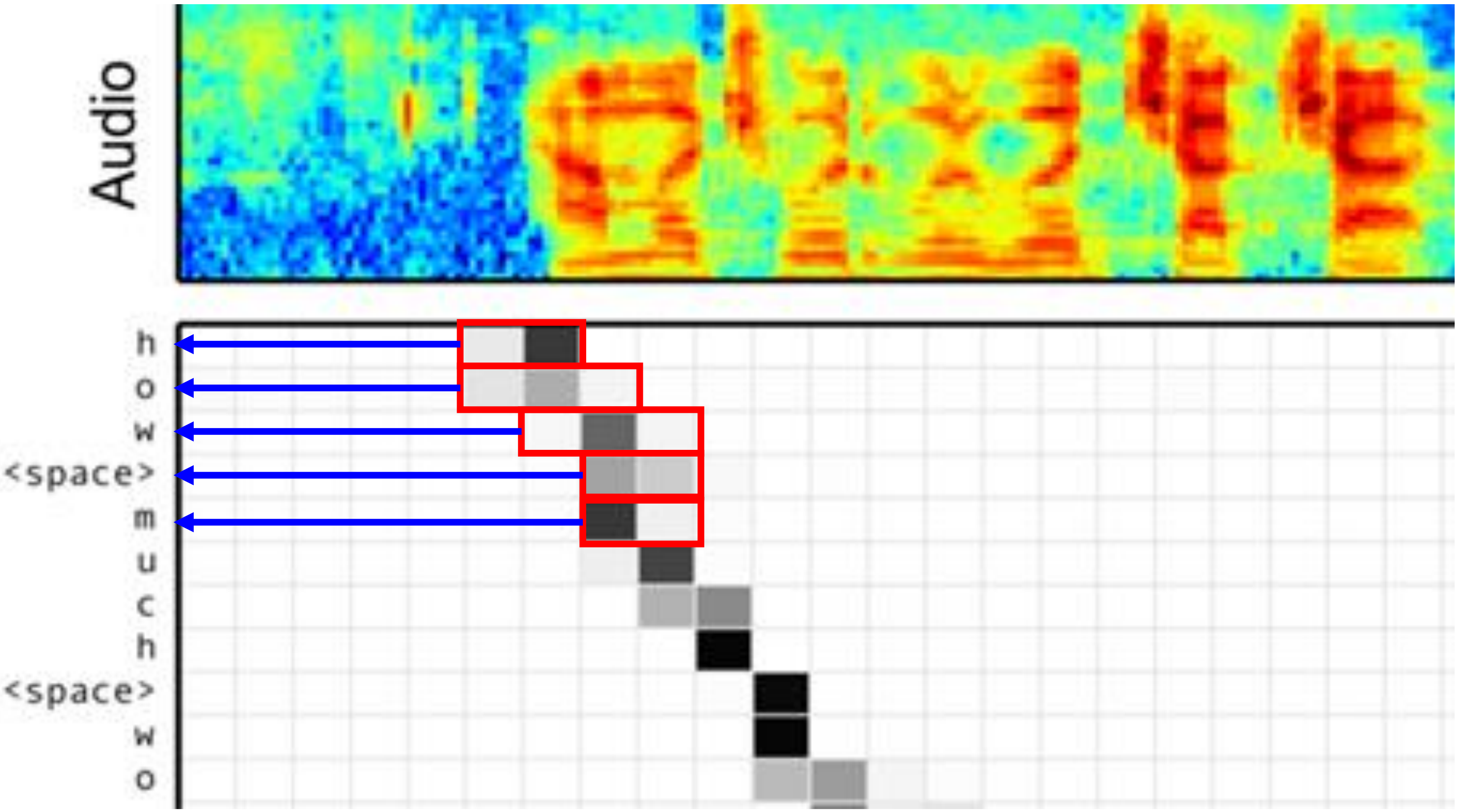
Machine Translation

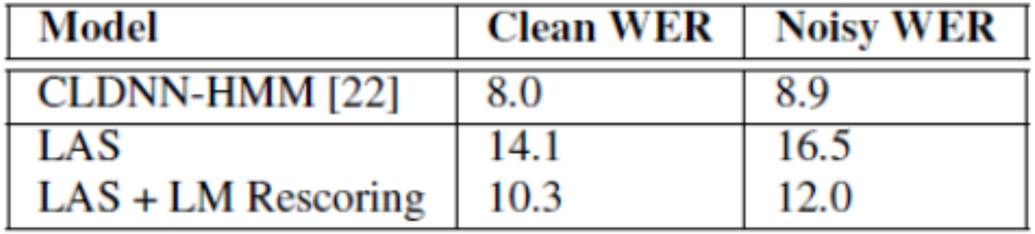
- Attention-based model



The same process repeat until generating <EOS>

Speech Recognition



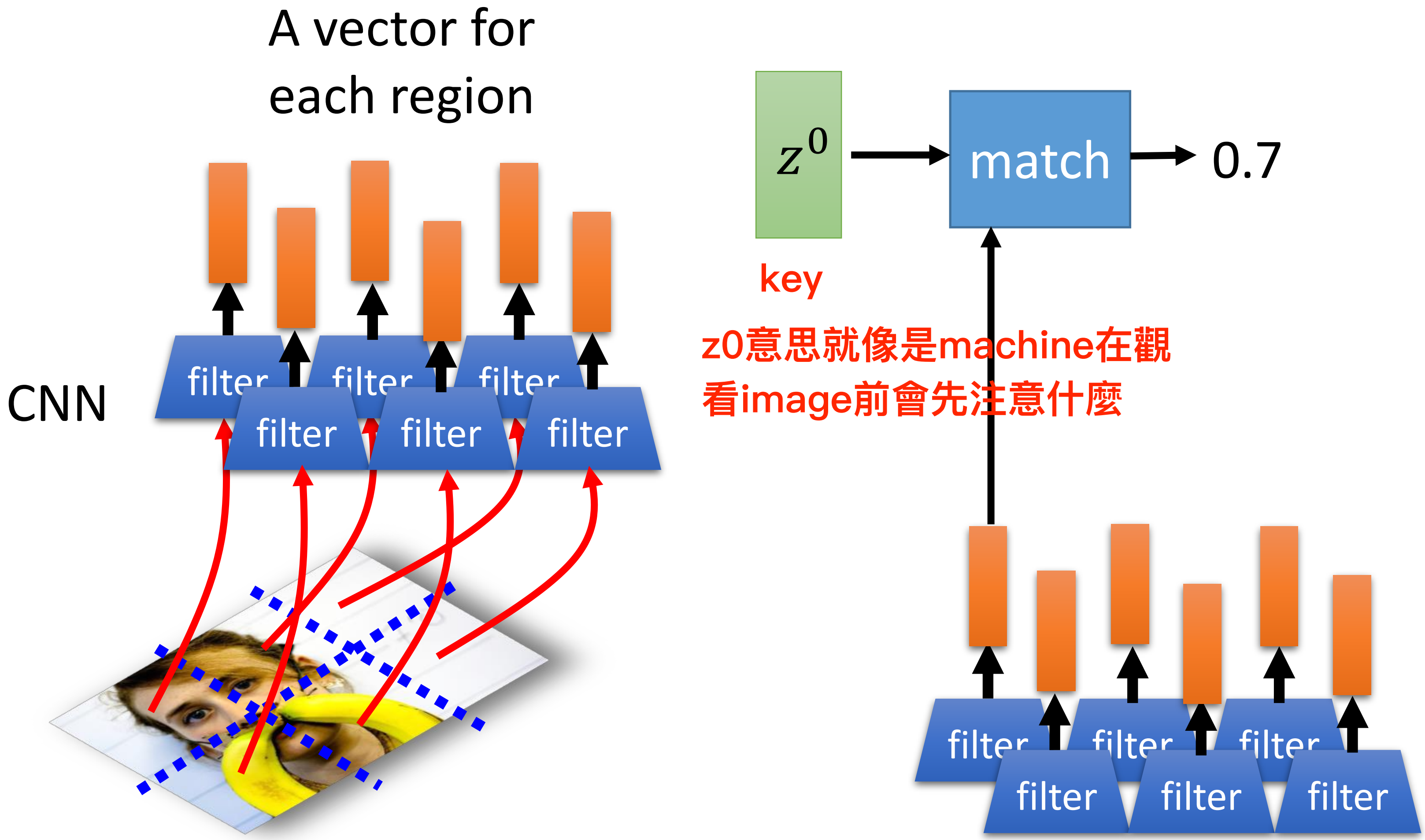


Model	Clean WER	Noisy WER
CLDNN-HMM [22]	8.0	8.9
LAS	14.1	16.5
LAS + LM Rescoring	10.3	12.0

William Chan, Navdeep Jaitly, Quoc V. Le, Oriol Vinyals, “Listen, Attend and Spell”, ICASSP, 2016

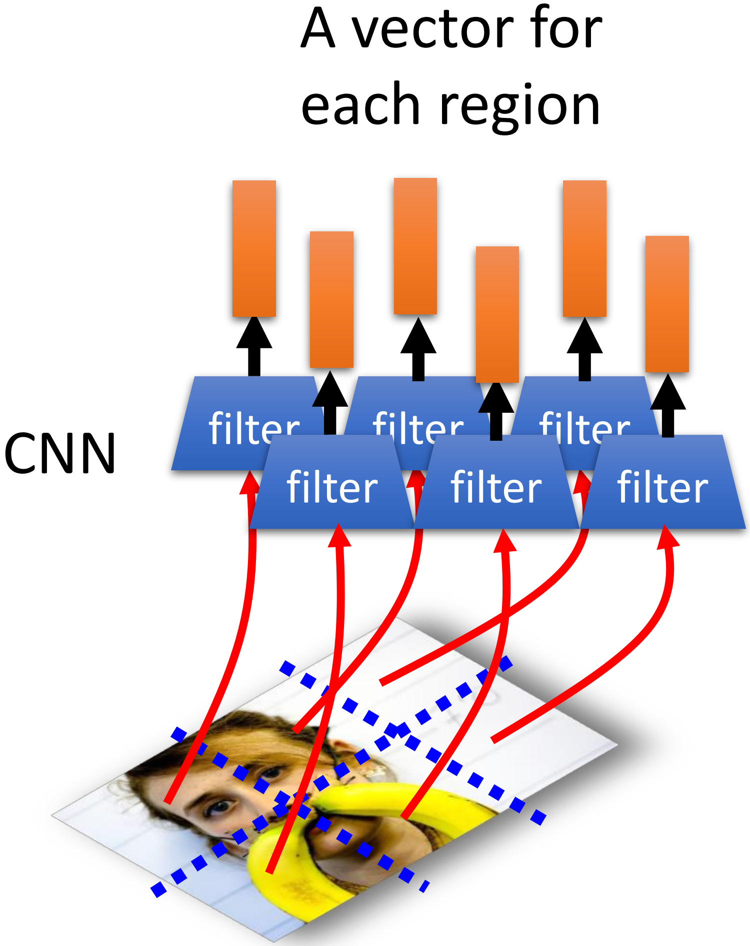
Image Caption Generation

把image先做segmentation後轉換成一把vector（sequence），就可以套用attention based model(RNN)



z0意思就像是machine在觀看image前會先注意什麼

Image Caption Generation



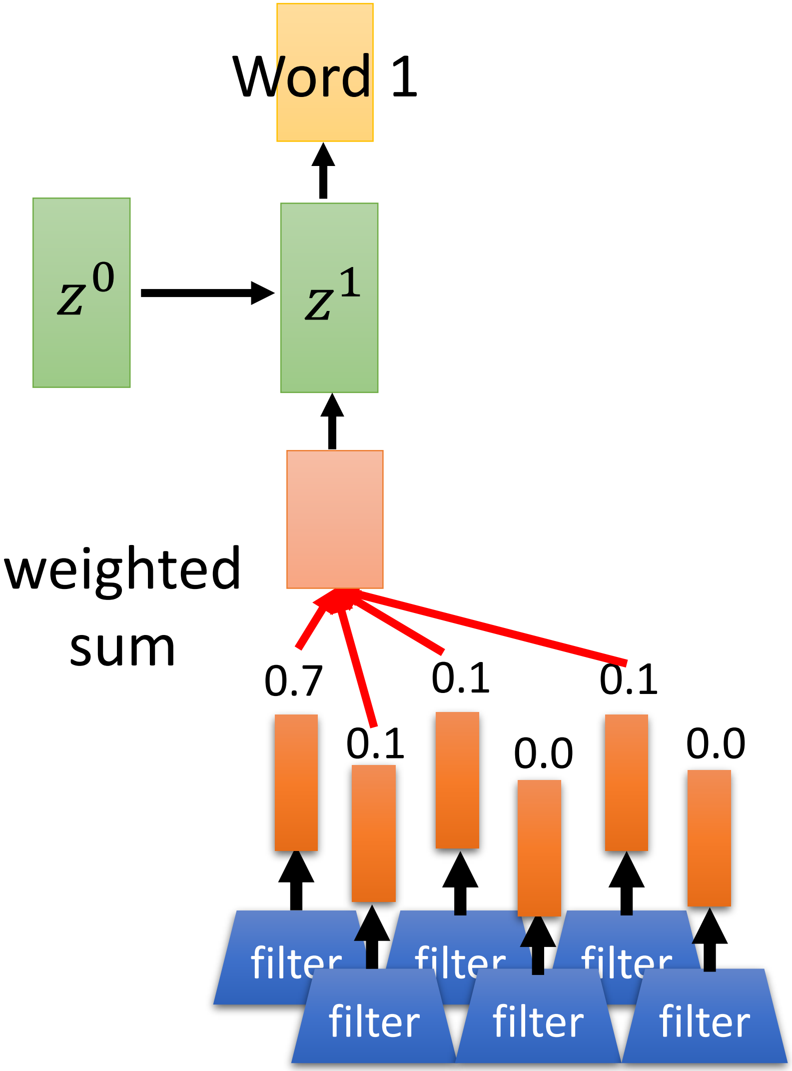


Image Caption Generation

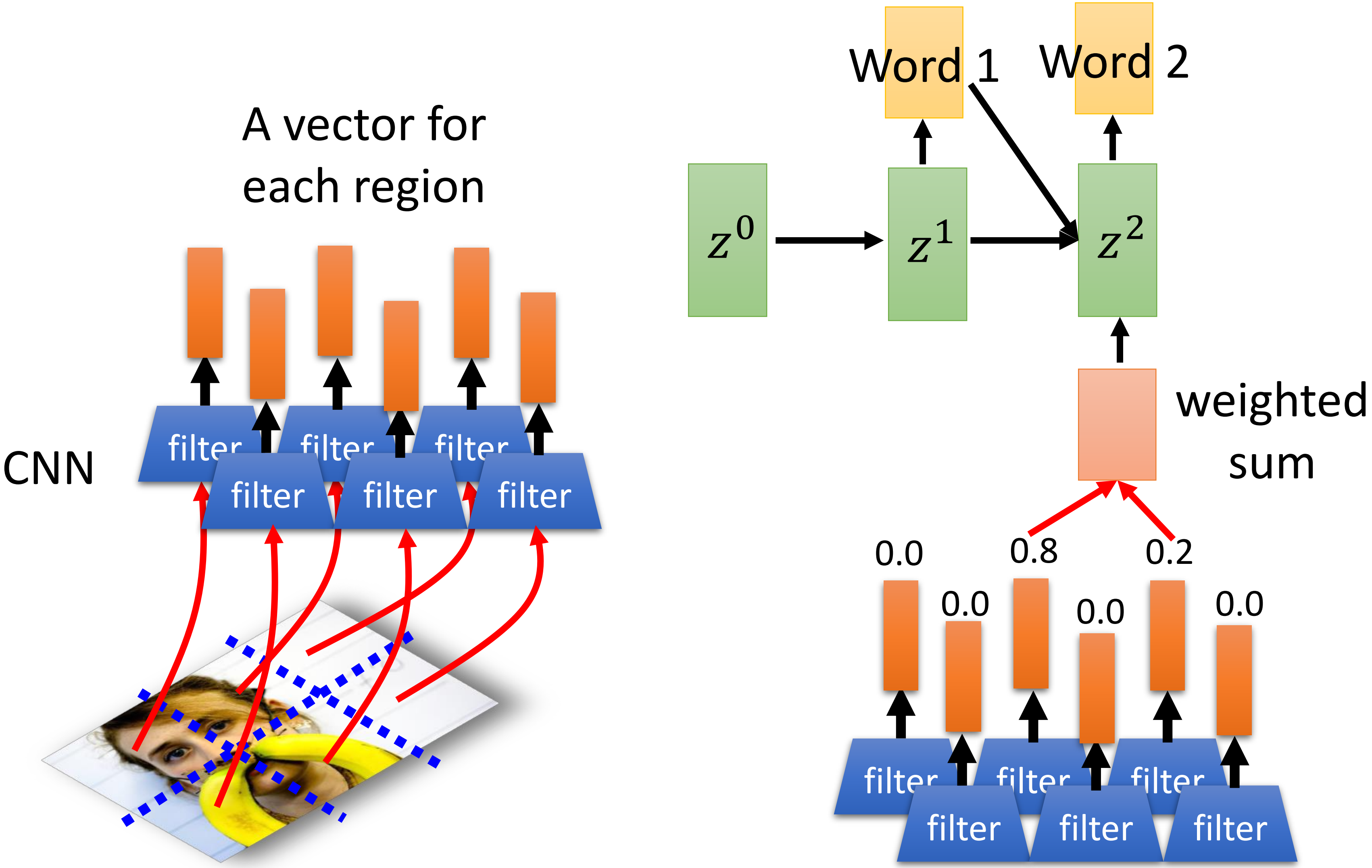


Image Caption Generation

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

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

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

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

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

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

Image Caption Generation

A large white bird standing in a forest.

A woman holding a clock in her hand.

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

A person is standing on a beach
with a surfboard.

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

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

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

可以使用VGG19的convolutional layer最後一層找出的feature map當作segmentation

這些feature map就像是一把vector

Ref: A man and a woman ride a motorcycle

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

Ref: A woman is frying food

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

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

Tips for Generation

希望machine在觀看video的時候不是只特定專注在某個frame，希望每個frame的attention要能夠平均分佈，避免machine指透過一個frame產生整個句子

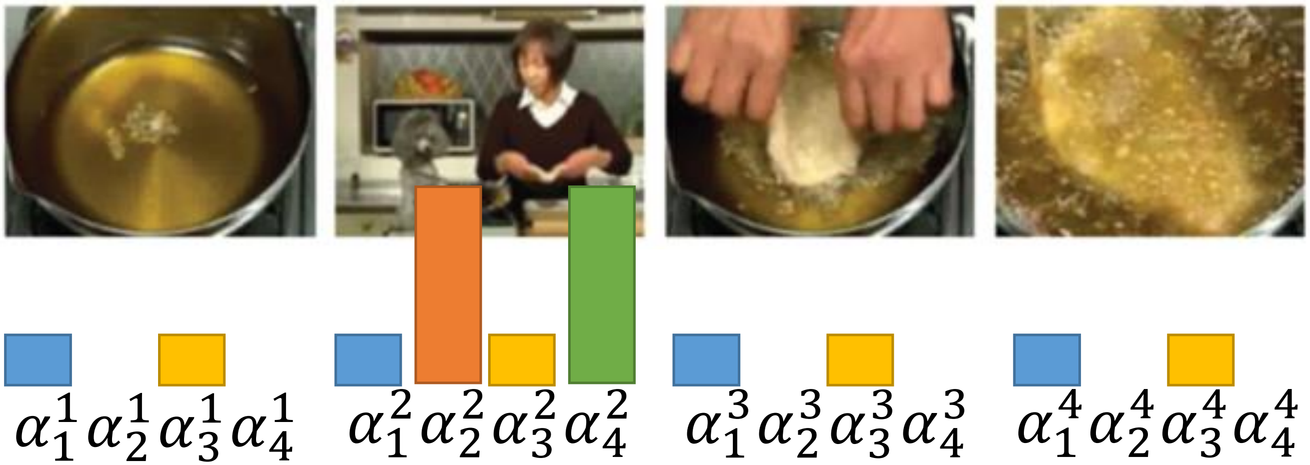
Attention

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

α_t^i → component

α_t^i → time

Bad Attention



w_1 w_2 (woman) w_3 w_4 (woman) …… no cooking

Good Attention: each input component has approximately the same attention weight

E.g. Regularization term: $$\sum_i \left(\tau - \sum_t \alpha_t^i\right)^2$$

因此可以加個regularization，強迫一個frame在所有time stamp總合能夠接近某個數值tau

For each component

Over the generation

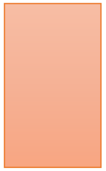
在training的時候每個timestamp的input我們都是將正確答案餵進去，然而在testing的時候我們沒有正確答案

Mismatch between Train and Test

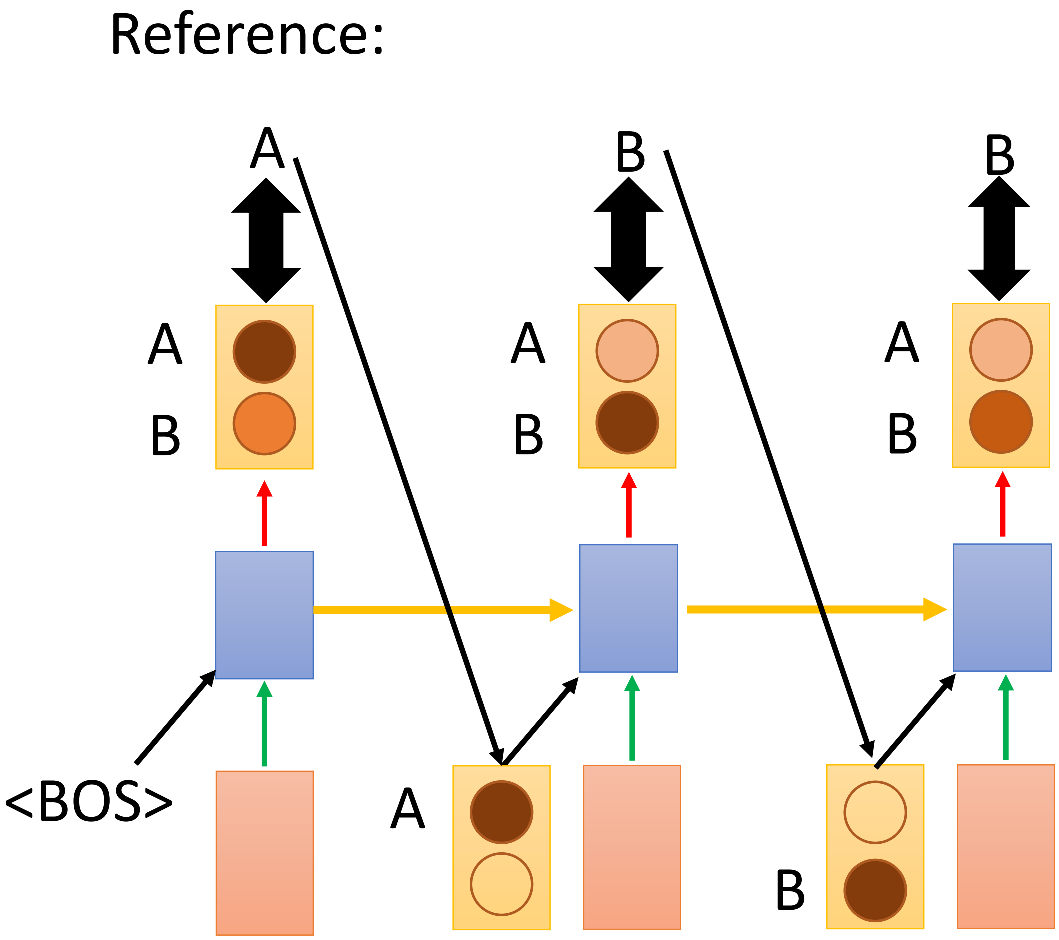
- ***Training***

$$C = \sum_{t} C_t$$

Minimizing cross-entropy of each component



: condition



Mismatch between Train and Test

只好假設每個timestamp產生的結果都是正確的，然而這可能導致一步錯步步錯

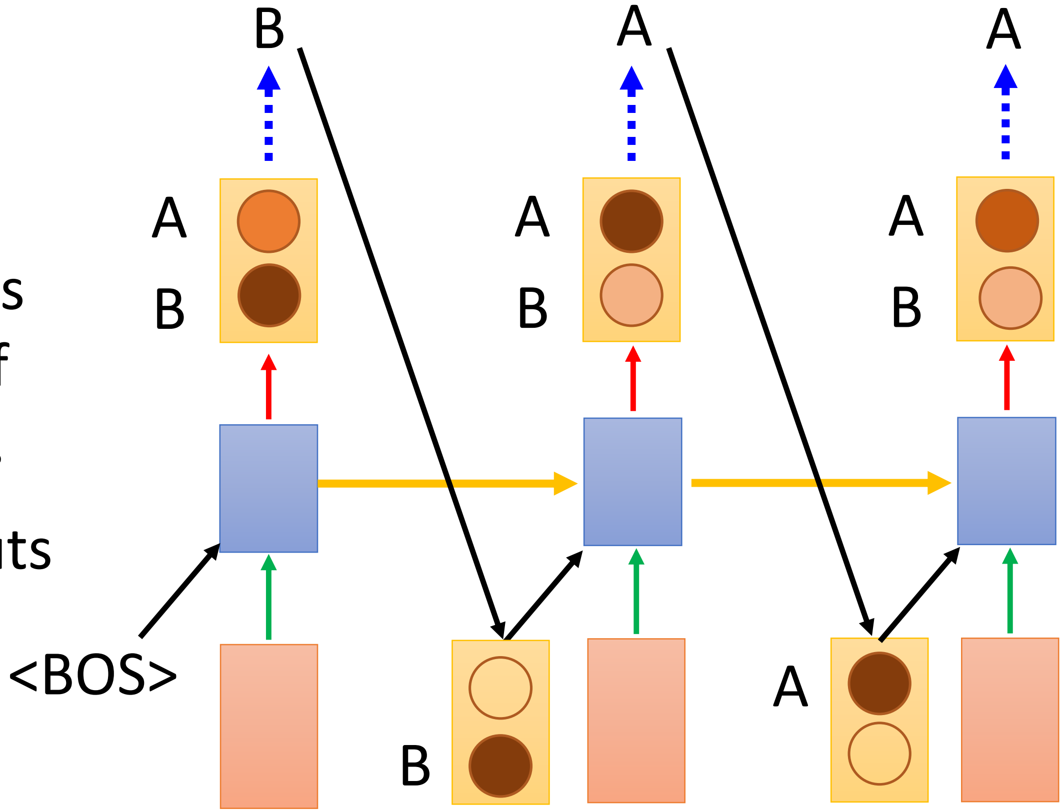
- ***Generation***

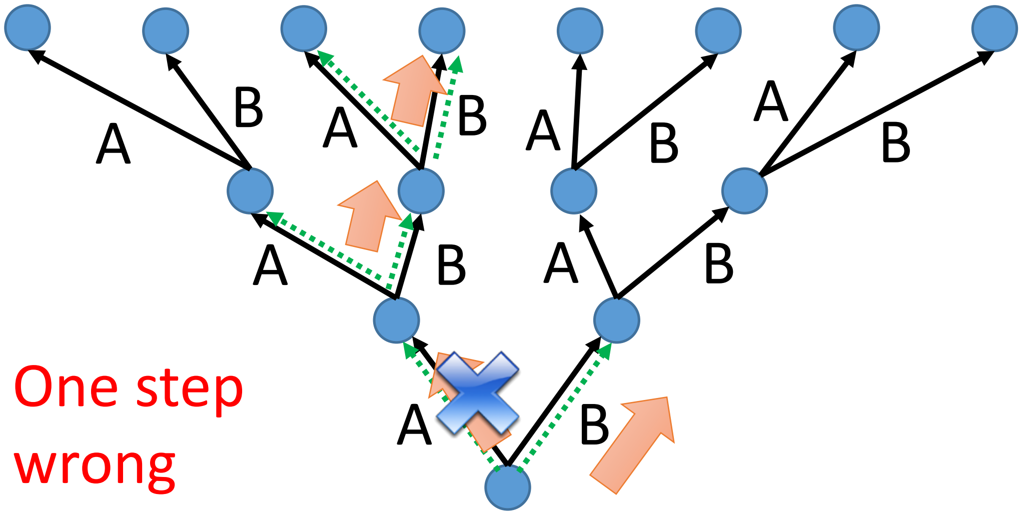
We do not know the reference

Testing: The inputs are the outputs of the last time step.

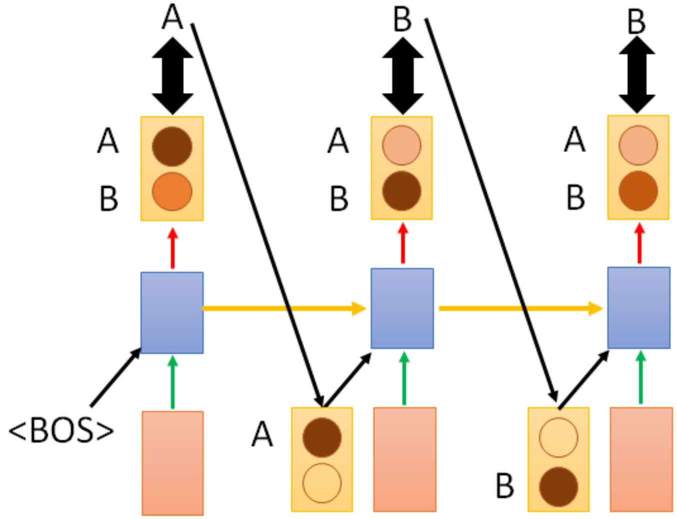
Training: The inputs are reference.

Exposure Bias

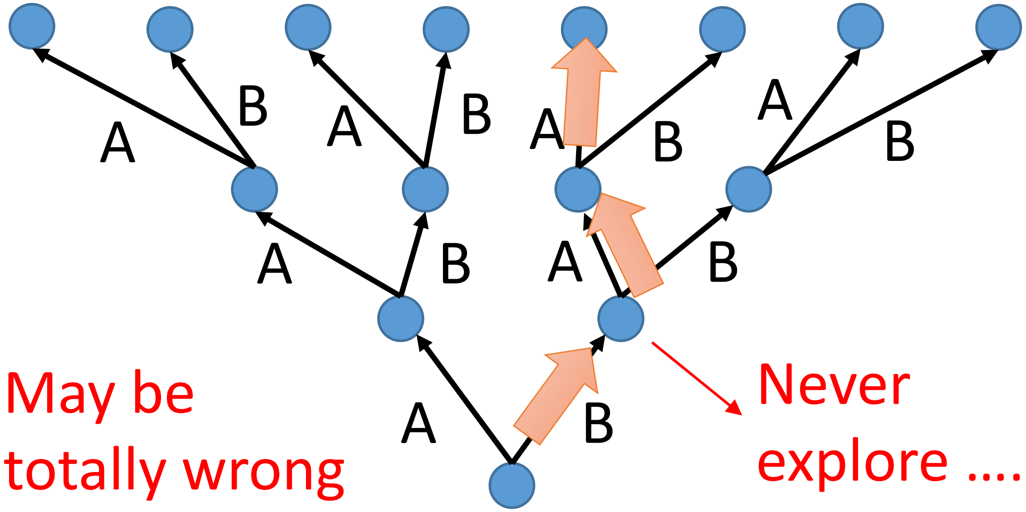




One step
wrong

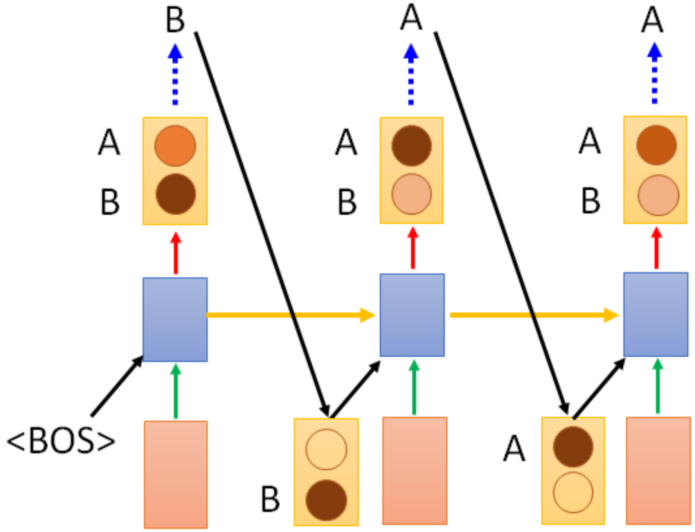


testing的時候可能走到training時完全沒有走過的地方



May be
totally wrong

Never
explore ……

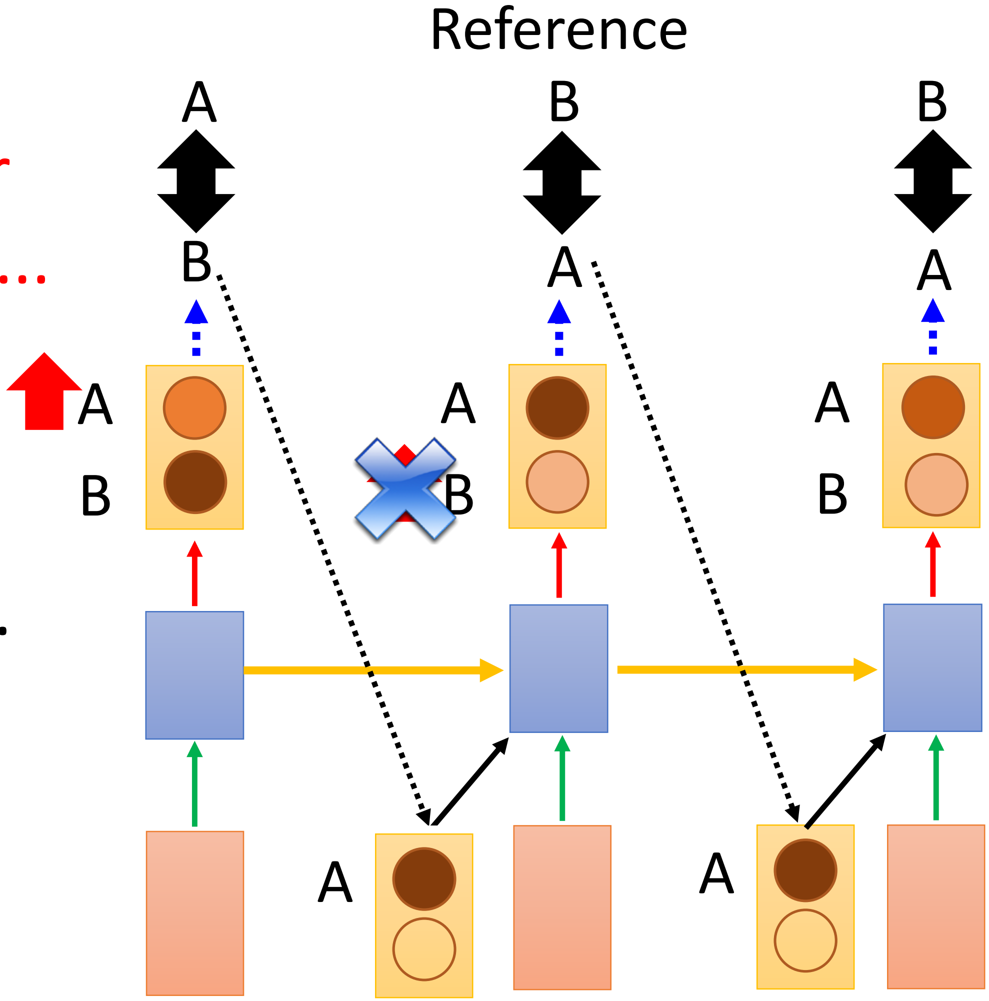


一步錯，步步錯

如果說把training process改成如testing process，順著上一部產生的結果繼續產生的話，training會變成不穩定
因為如果train到中後期，某個timestamp結果被翻轉了，則後面train出來的東西都白學了

Modifying Training Process?

When we try to decrease the loss for both steps 1 and 2 …..



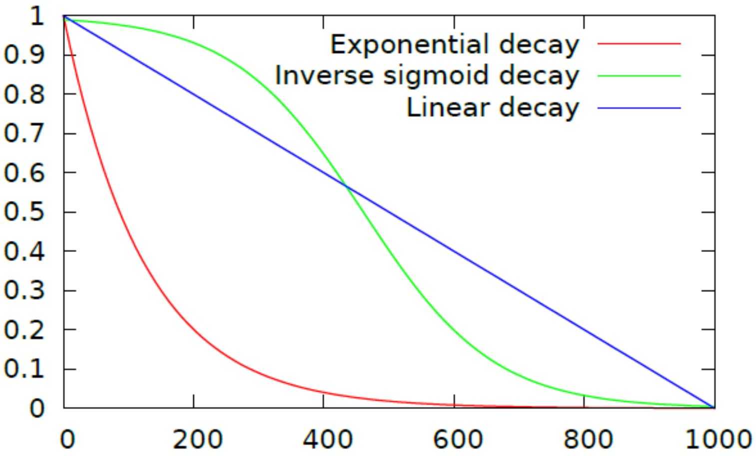
Training is matched to testing.

In practice, it is hard to train in this way.

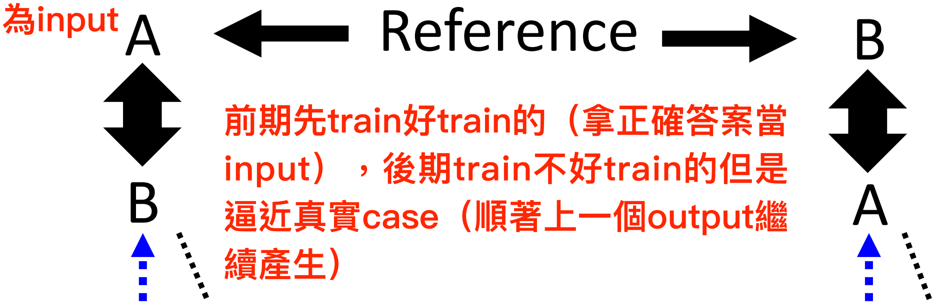
Scheduled Sampling

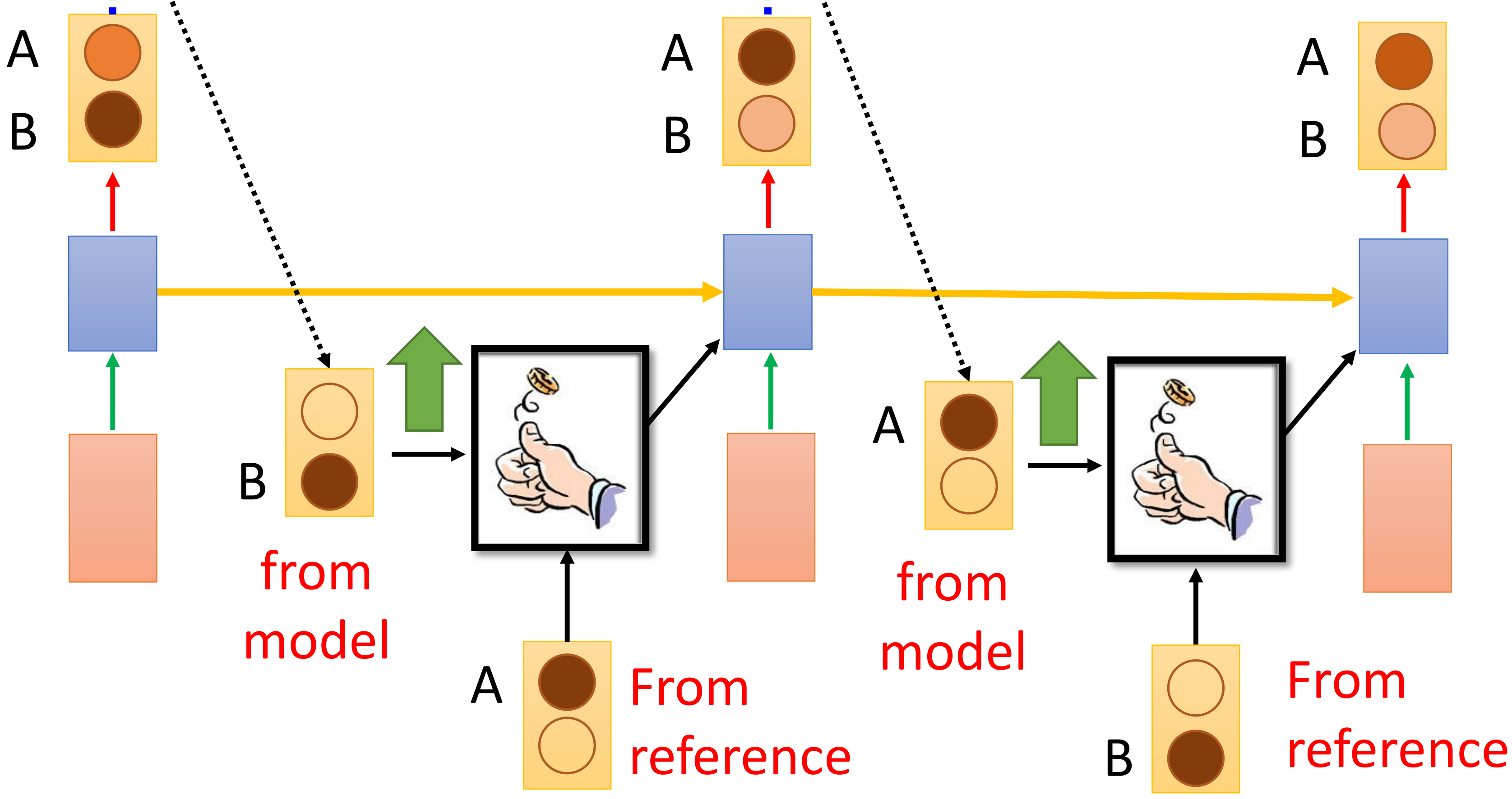
採取折衷措施

利用骰子決定到底要採取正確答案或是上個timestamp產生的結果作為input

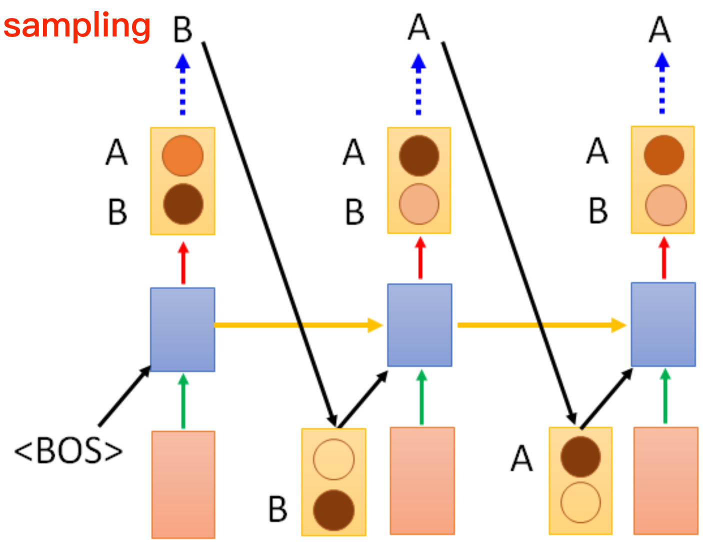


前期先train好train的（拿正確答案當input），後期train不好train的但是逼近真實case（順著上一個output繼續產生）





Beam Search

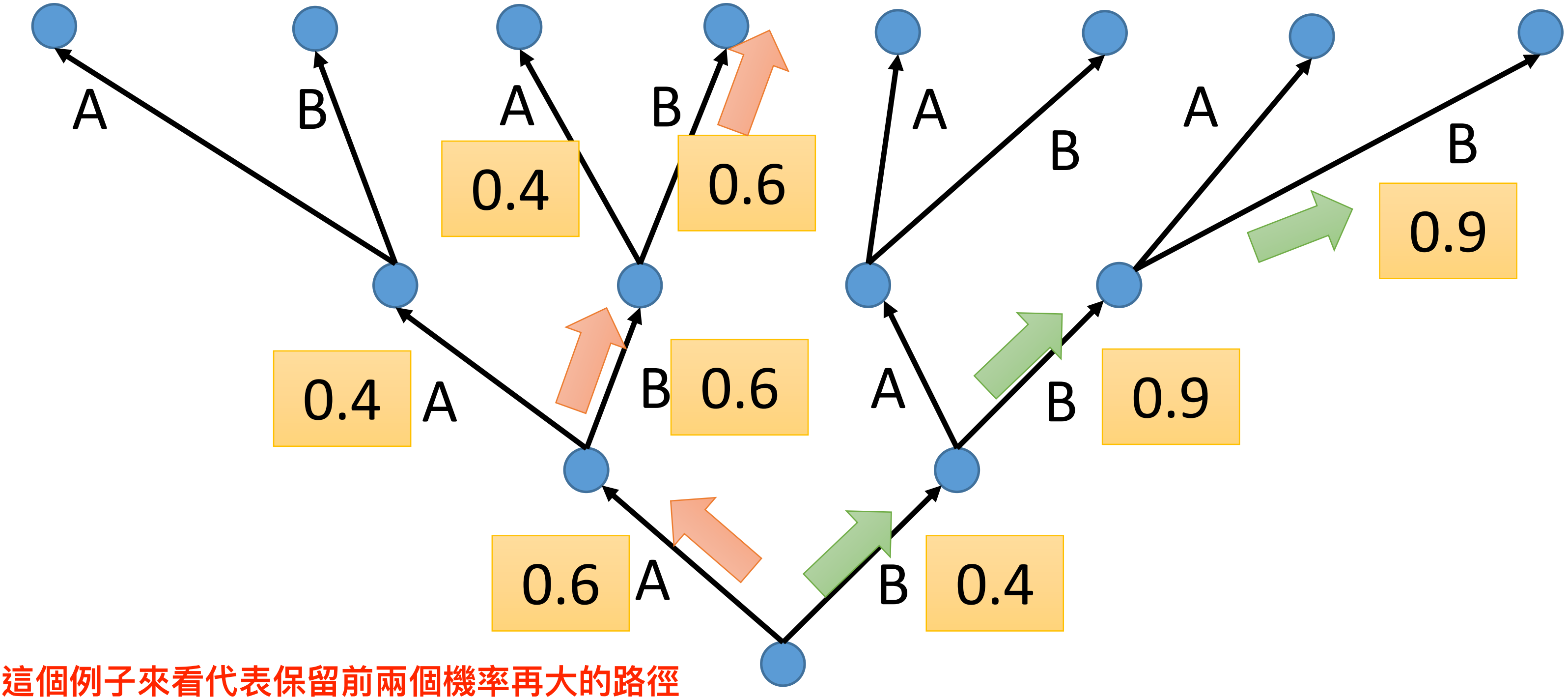


The green path has higher score.

Not possible to check all the paths

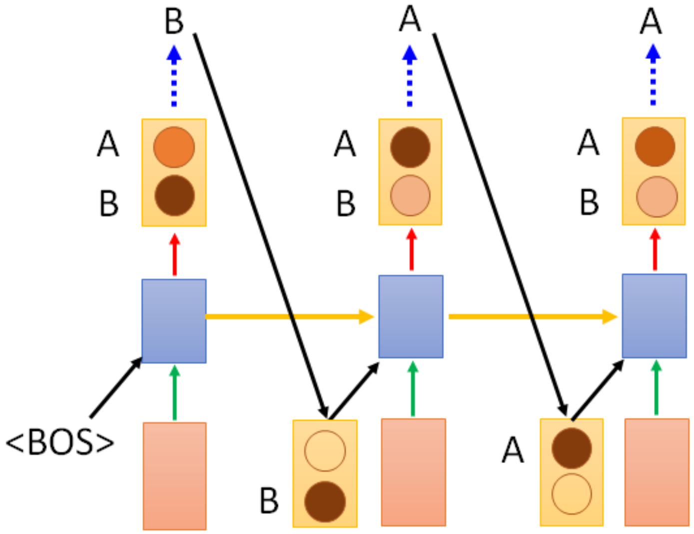
雖然一開始的機率小，但最後整條path機率大

然而無法窮舉所有可能，因此每次做beam search時都保留前N個機率最高的道路



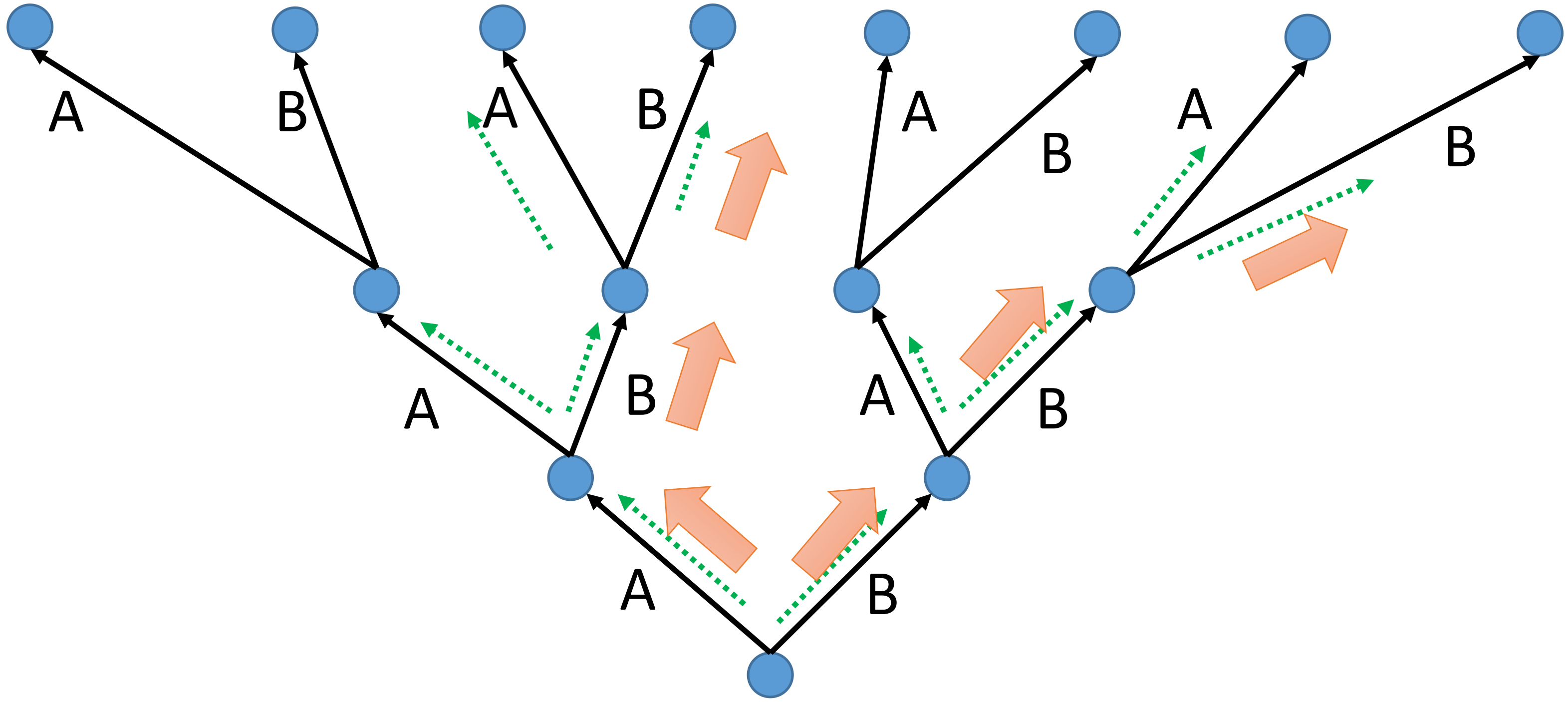
以這個例子來看代表保留前兩個機率再大的路徑

Beam Search



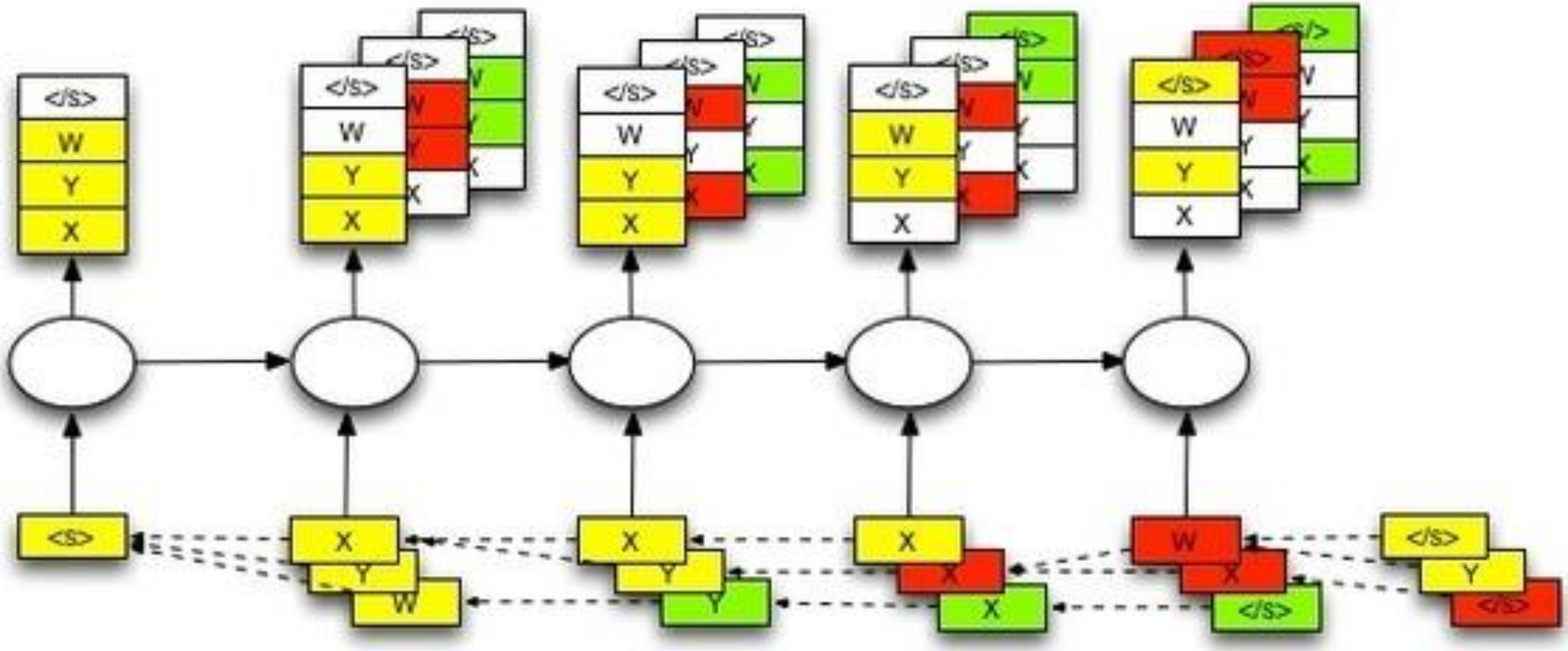
Keep several best path at each step

Beam size = 2



只有在testing才會用 training時無關

Beam Search



分開丟進去

The size of beam is 3 in this example.

https://github.com/tensorflow/tensorflow/issues/654#issuecomment-169009989

如果說不要分開丟進去，直接平均所有input呢

Better Idea?

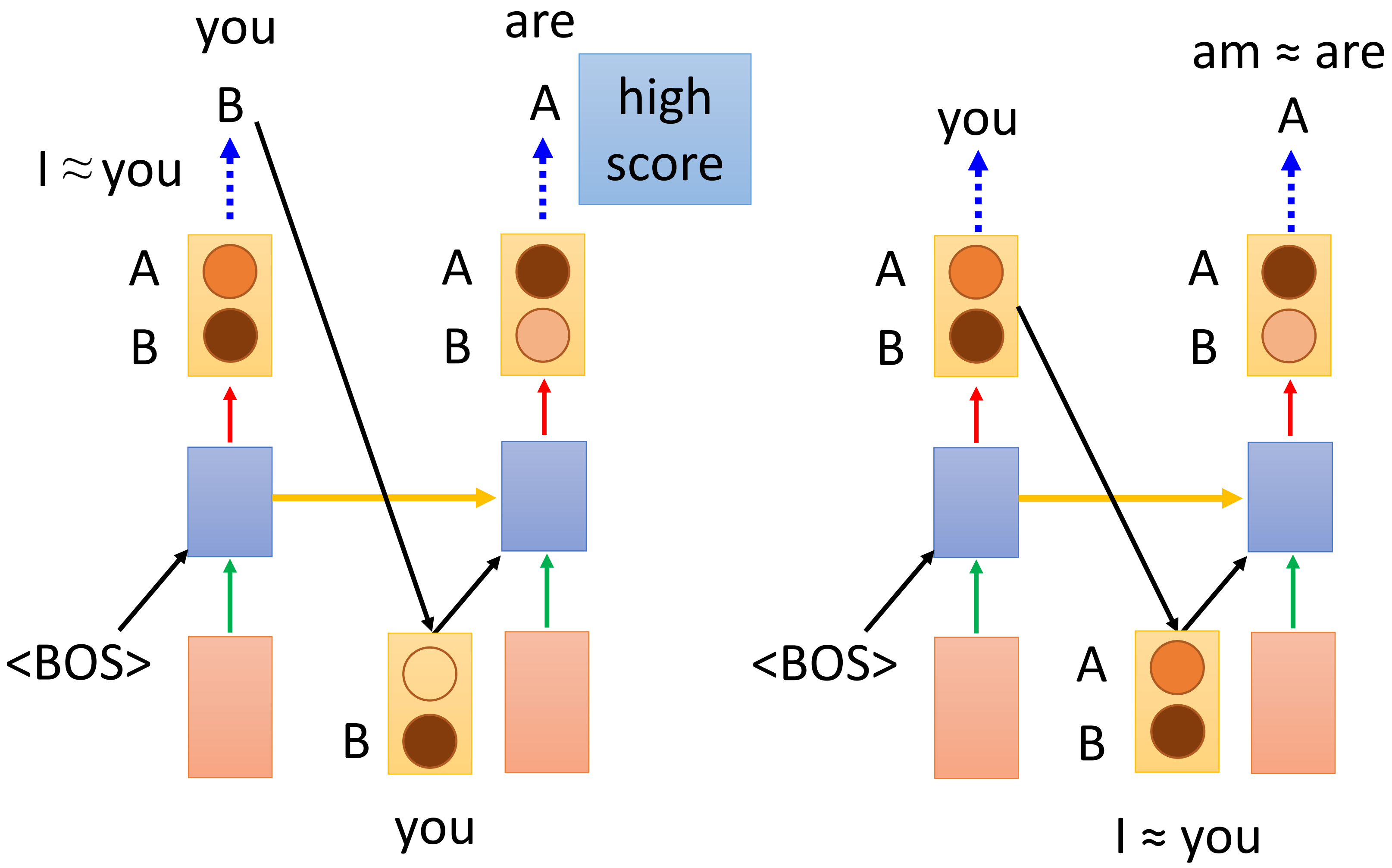
I am …… ✓

You are …… ✓

I are …… ✗

You am …… ✗

如果I/You機率都差不多有可能sample錯，造成mismatch



Object level v.s. Component level

Evaluation?

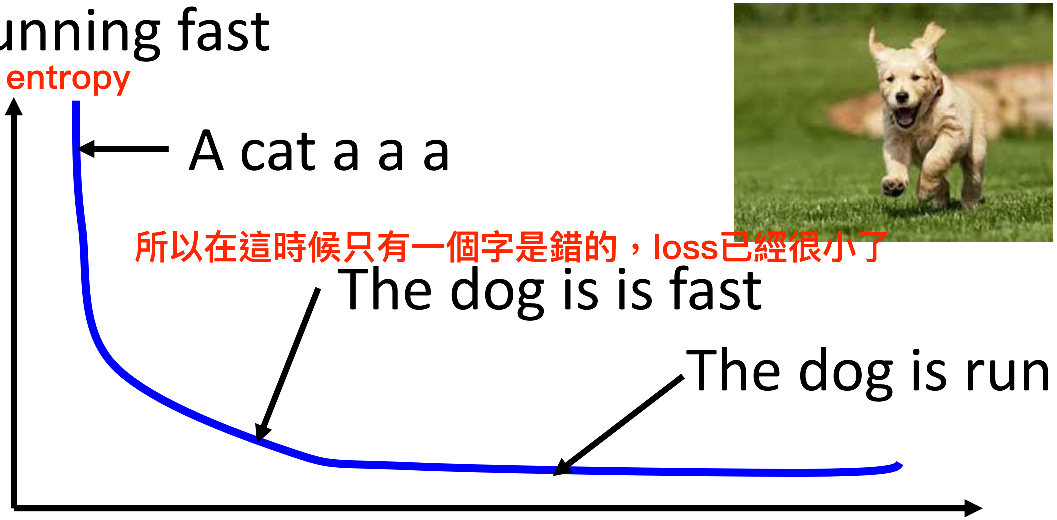
- Minimizing the error defined on component level is not equivalent to improving the generated objects

Ref: The dog is running fast

因為loss是每個詞彙分開做cross entropy

$$C = \sum_t C_t$$

Cross-entropy of each step



所以在這時候只有一個字是錯的，loss已經很小了

Optimize object-level criterion instead of component-level cross-entropy. object-level criterion: $R(y, \hat{y})$

Gradient Descent?

如果要設計好的loss function，通常都無法微分啊！

y: generated utterance, $\hat{y}$: ground truth

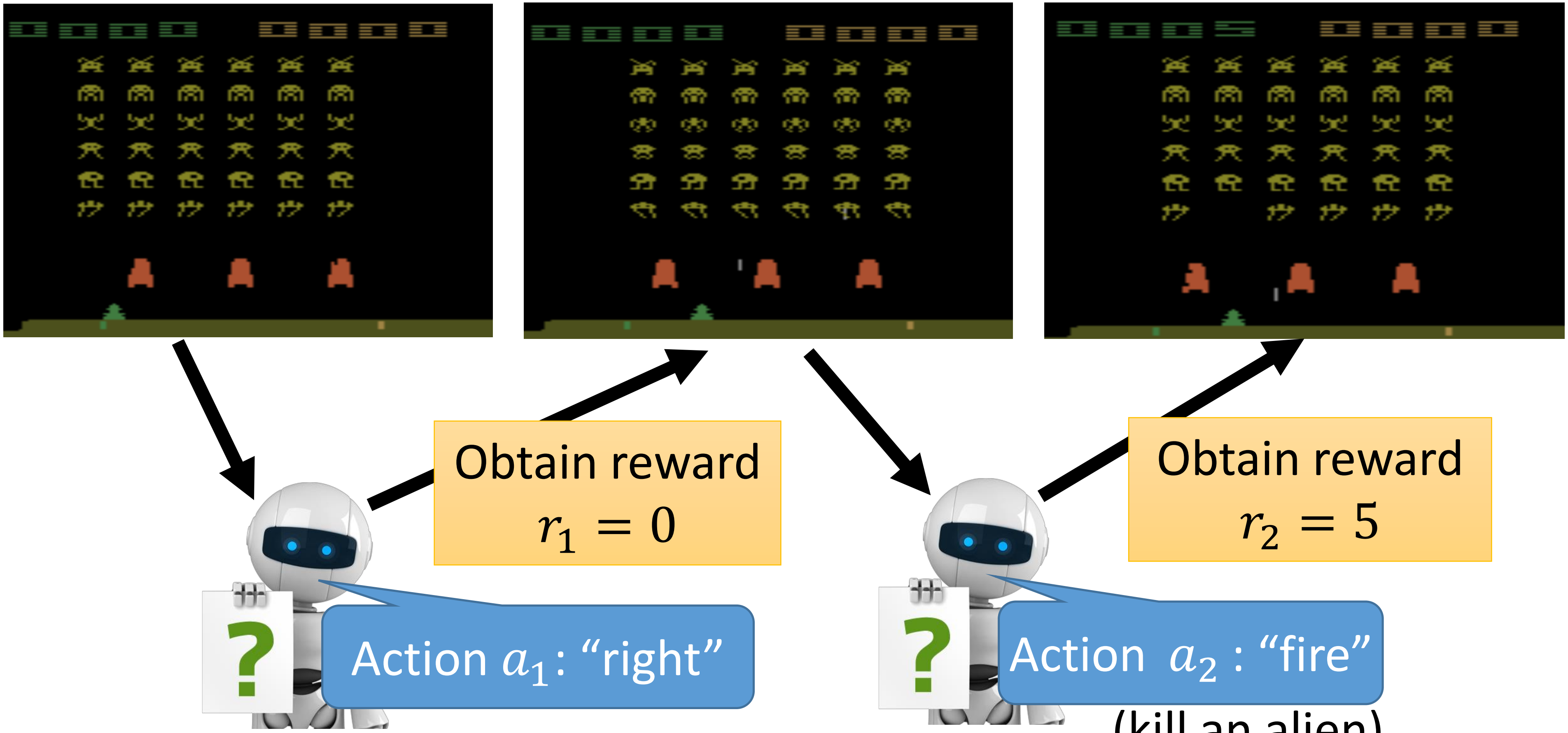
這年頭碰到不能微分的objective function，通通把它當成reinforcement learning的reward來train

Reinforcement learning?

Start with observation s_1

Observation s_2

Observation s_3



Obtain reward $r_1 = 0$

Action a_1: “right”

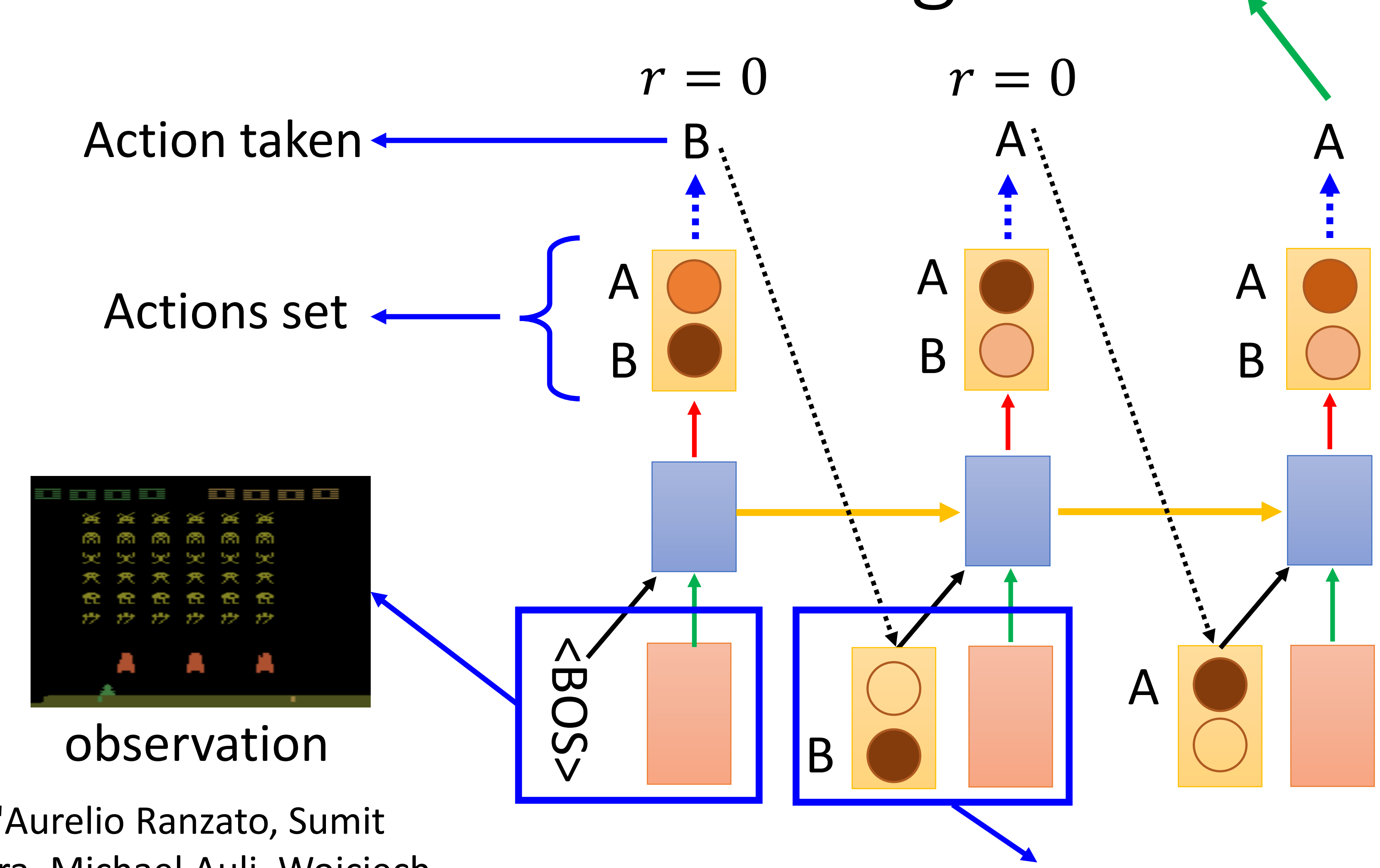
Obtain reward $r_2 = 5$

Action a_2 : “fire”

(kill an alien)

Reinforcement learning?

$reward$:
R("BAA", reference)



Action taken

Actions set

observation

The action we take influence the observation in the next step

Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, Wojciech Zaremba, "Sequence Level Training with Recurrent Neural Networks", ICLR, 2016