ADVANCED DEEP LEARNING MODELS FOR NATURAL LANGUAGE PROCESSING

自然語言處理的進階深度模型

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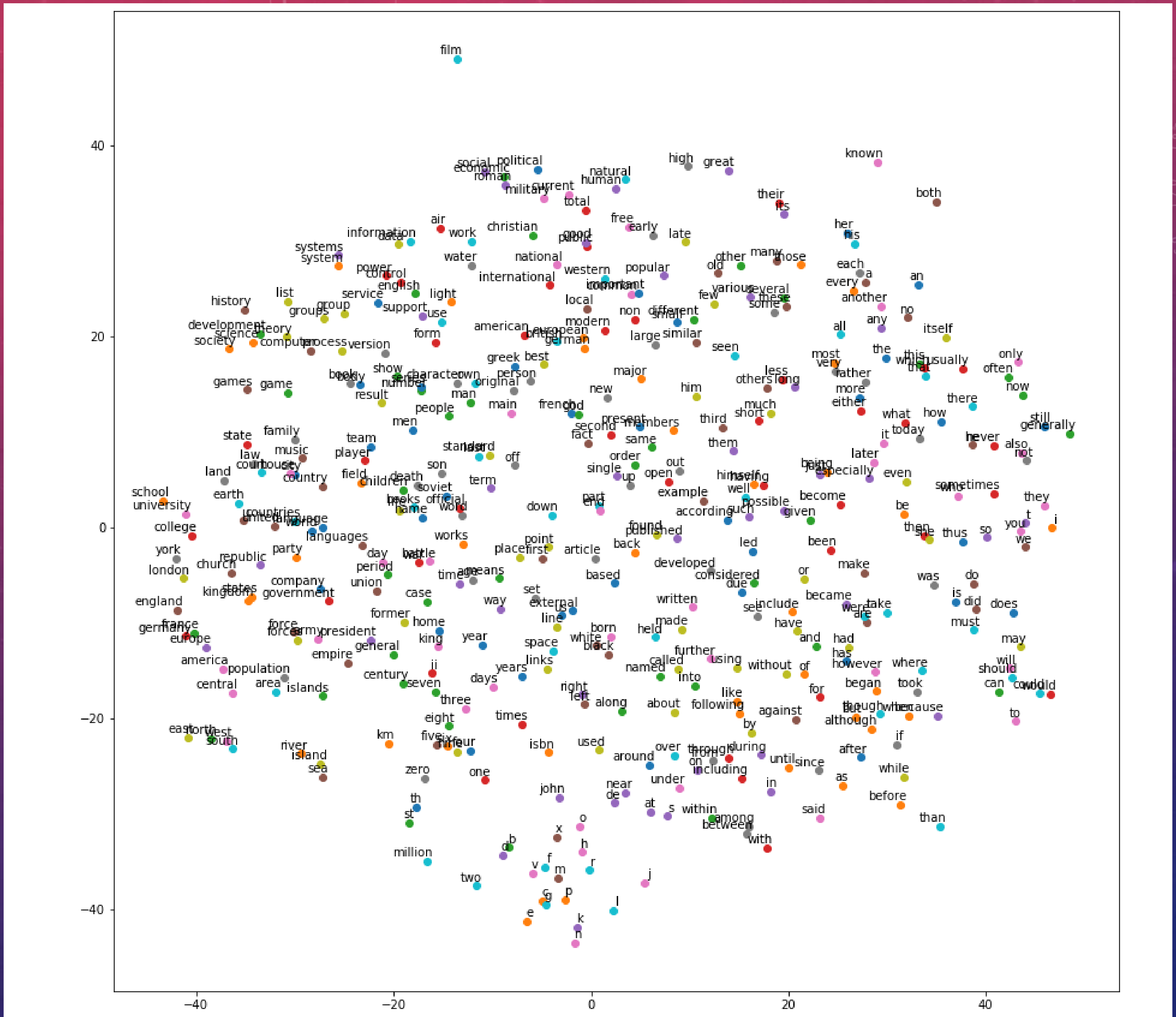
REVIEW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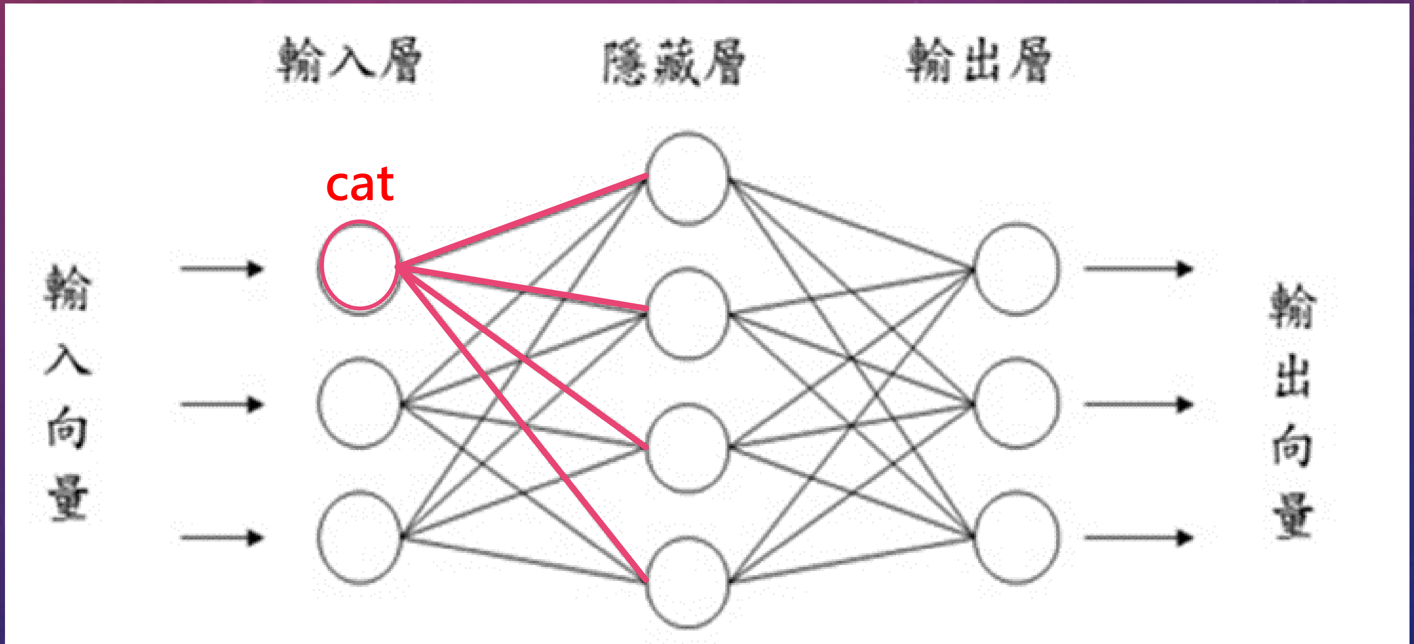
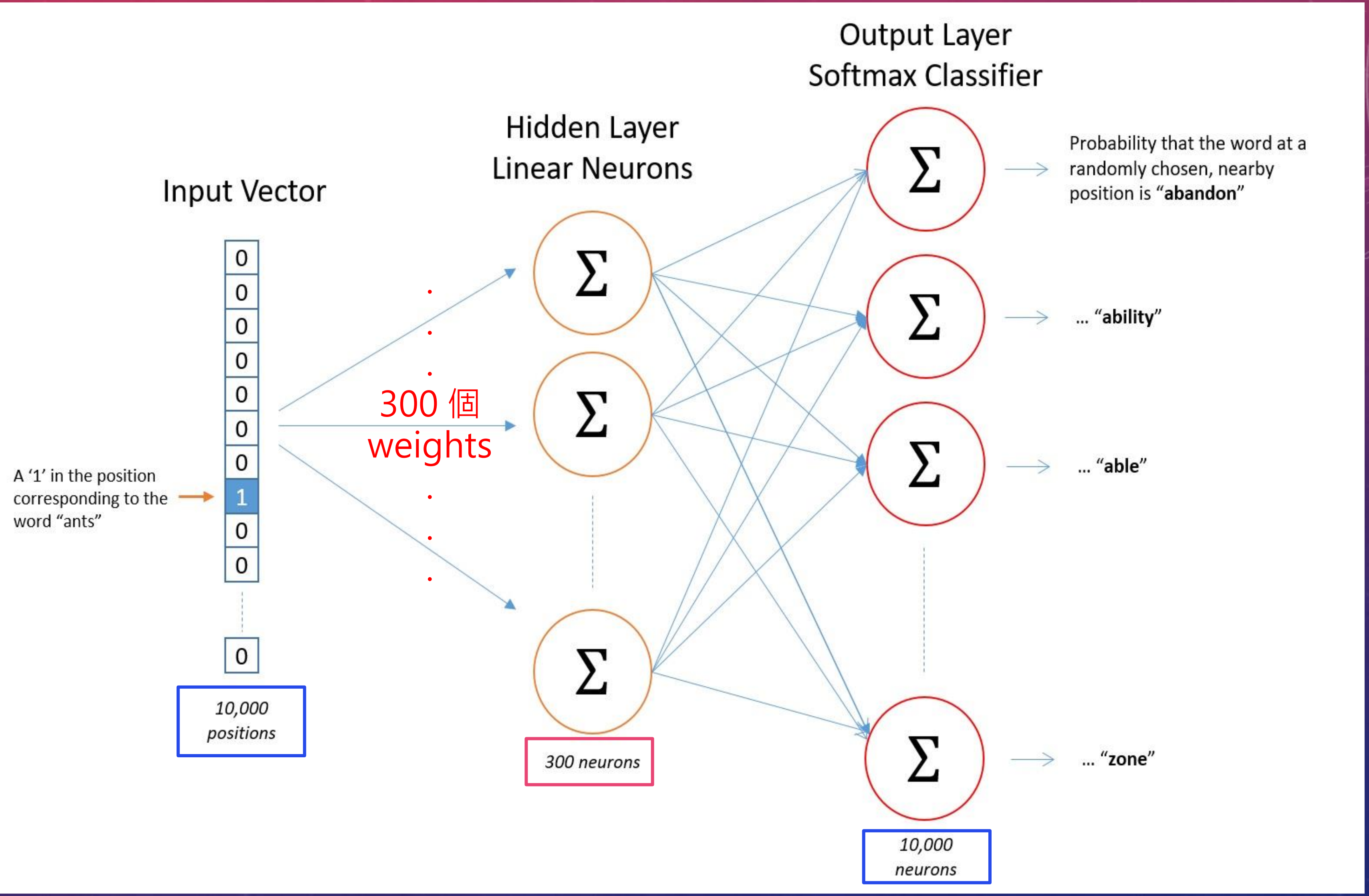
0
20
40

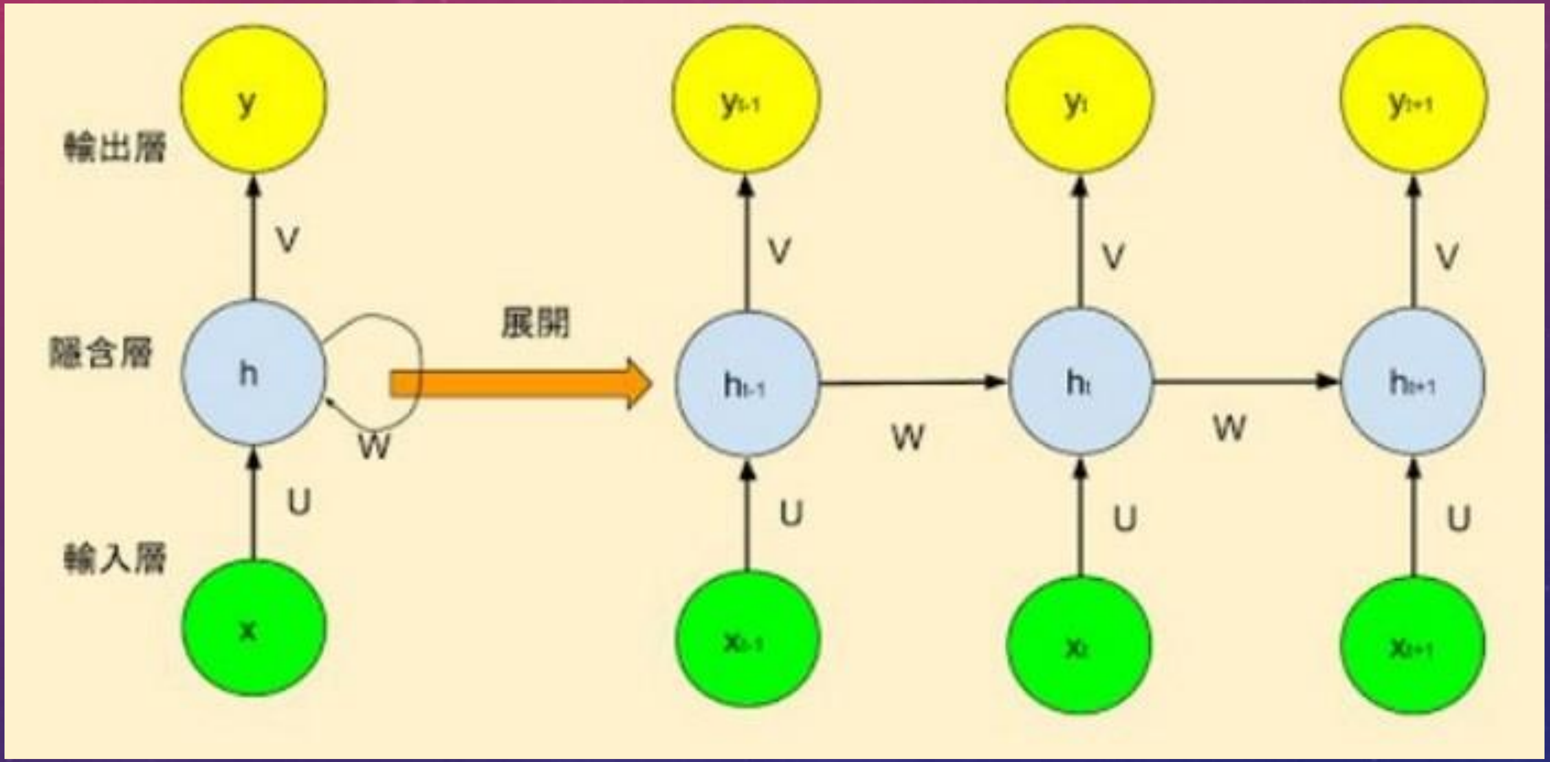
```
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
cat -> [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
jump -> [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
over -> [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
the -> [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
The -> [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
dog -> [0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
ate -> [0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
my -> [0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
homework -> [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
```




Input Vector
0
0
0
0
0
0
0
1
0
0
0
10,000 positions
A '1' in the position corresponding to the word "ants"
300 個 weights
Hidden Layer
Linear Neurons
300 neurons
Output Layer
Softmax Classifier
Probability that the word at a randomly chosen, nearby position is "**abandon**"
… "**ability**"
… "**able**"
… "**zone**"
10,000 neurons

RECURRENT NEURAL NETWORK, RNN

RNN STRUCTURE



*tanh is usually used to be the activation function in RNN

PROBLEMS OF RNN

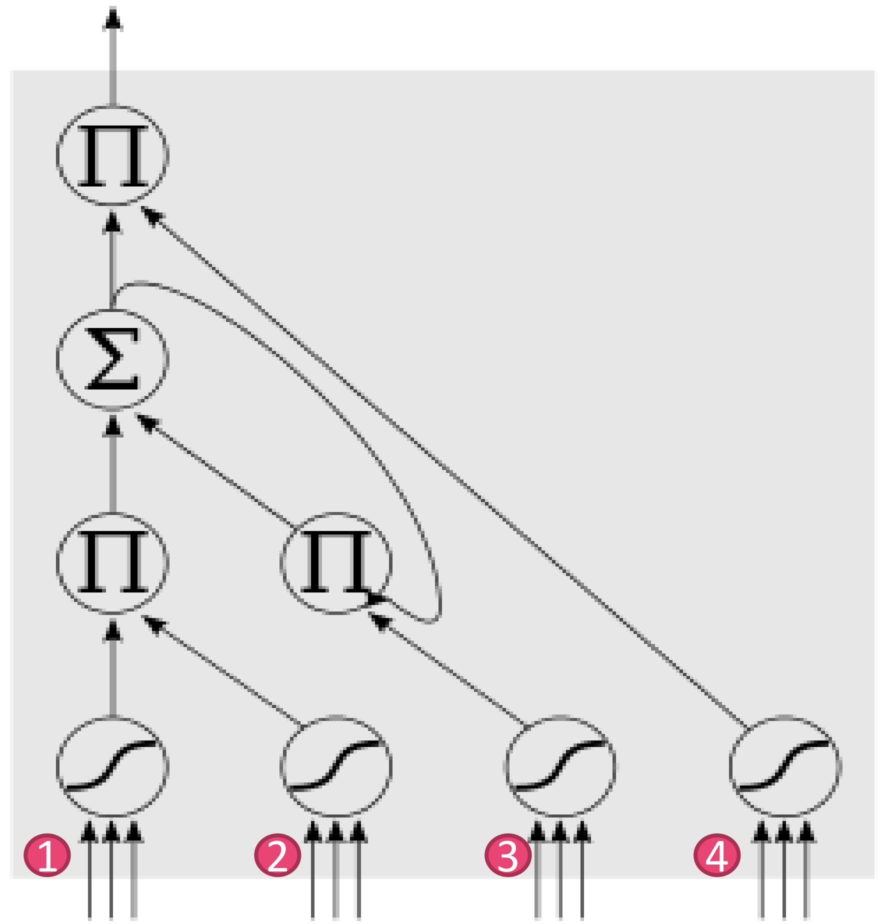
- RNN 對 short-term 敏感
- RNN 對 long-term 容易遺忘
- 越前面的字越會遺忘... 這就是RNN的梯度消失...

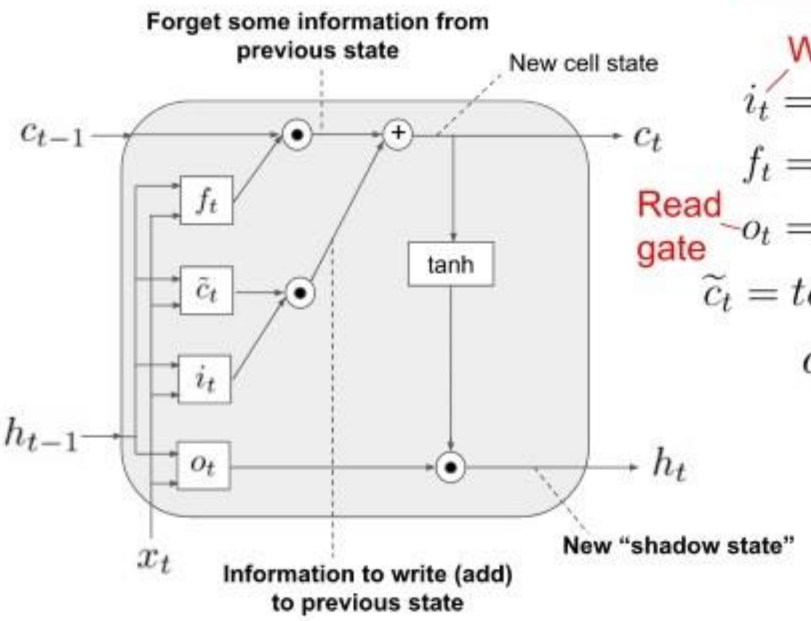
$$h_t = W * h_{t-1} + U * x_t + b$$
$$h_t = (W^2 * h_{t-2} + W * U * x_{t-1} + W * b) + U * x_t + b$$
$$\dots$$
$$h_t = (W^t * h_0 + \dots) + U * x_t + b$$

公式 h_0 對 h_t 的影響力為 w 的 t 次方，通常，w 會小於 1，離目標字越遠的字詞經過越多次傳遞(連乘)... 影響力幾乎不見了

LONG SHORT TERM MEMORY, LSTM

LSTM STRUCTURE





Conceptually, we lose information

We use shadow state to calculate gates

LSTM equations

Write gate

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_i)$$ Input gate

$$f_t = \sigma(W_f h_{t-1} + U_f x_t + b_f)$$ Forget gate

Read gate

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o)$$ Output gate

$$\tilde{c}_t = tanh(W h_{t-1} + U x_t + b)$$ Memory cell candidate

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$ Memory cell

$$h_t = o_t \circ tanh(c_t)$$ Shadow state

$$y_t = h_t$$ Cell Output

Read occurs after writing

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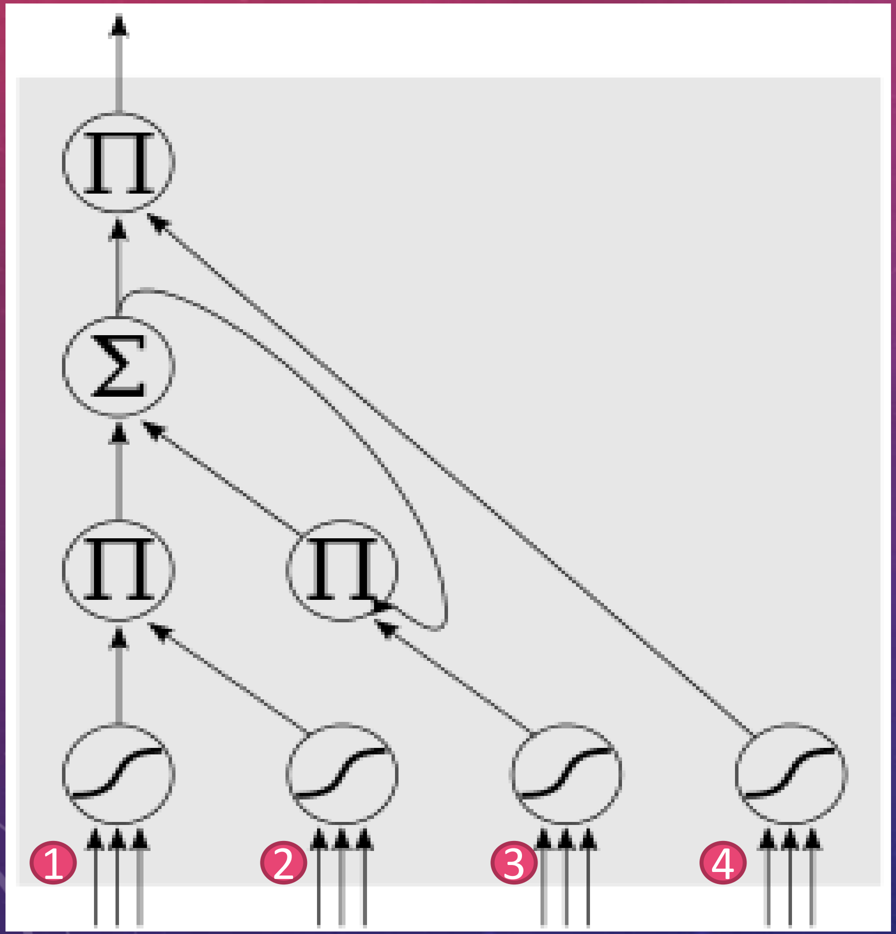
deepsystems.ai

LSTM STRUCTURE



1. 純的 input，下面三個gate會影響這個input能否被記住或作為輸出

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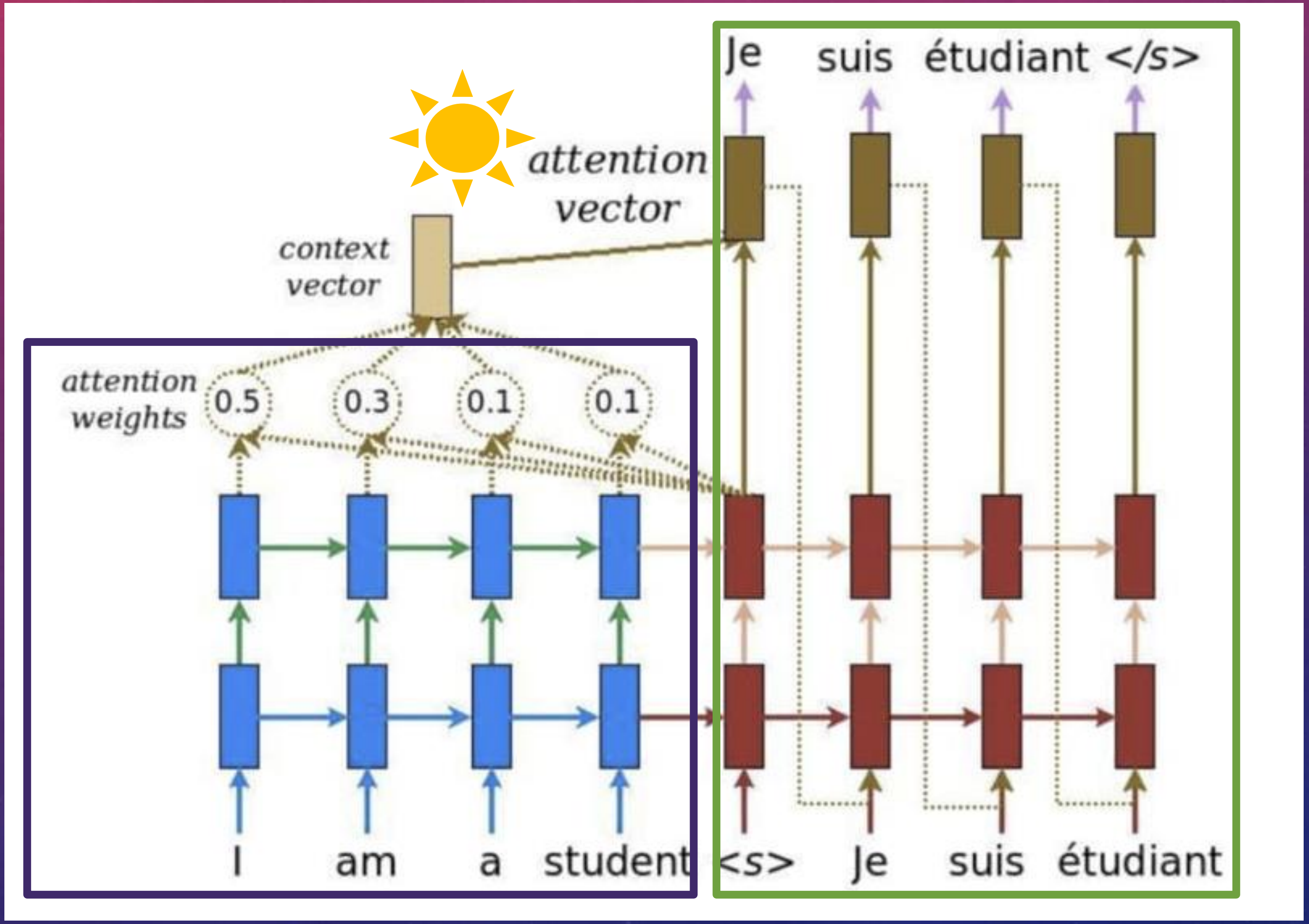
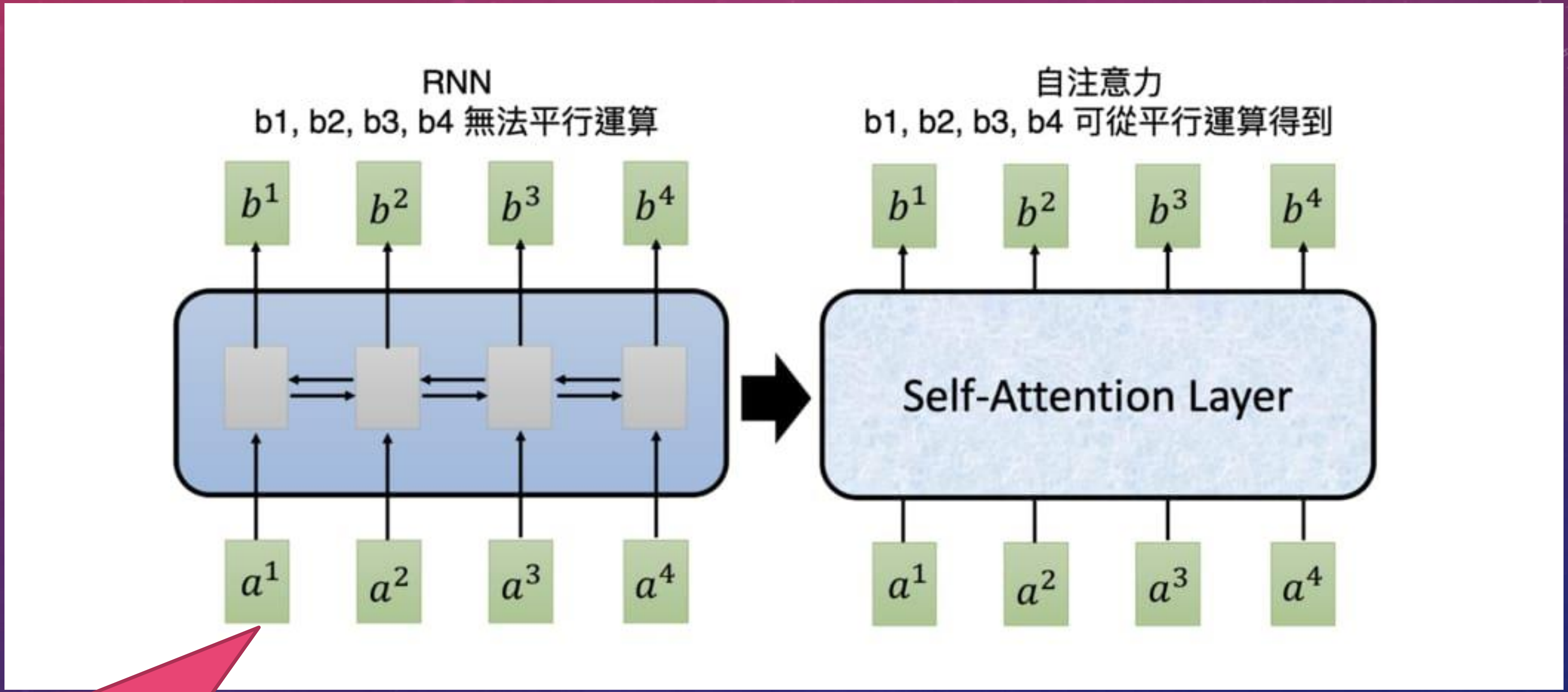
2. Input gate，如果值為0就擋住，不給進下一層 (sigmoid)
3. Forget gate，如果值近似0，就把區塊裡記住的值忘掉 (sigmoid)
4. Output gate，決定在區塊記憶中的input是否能輸出 (sigmoid)

TRANSFORMER

WHAT IS ATTENTION?

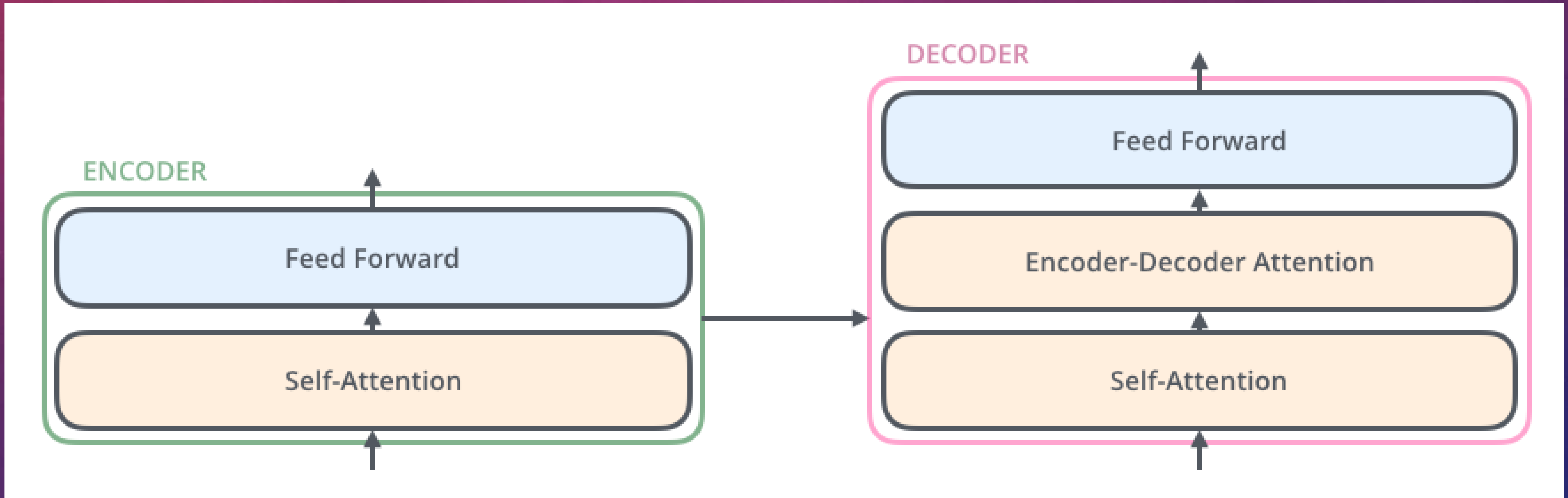


WHY

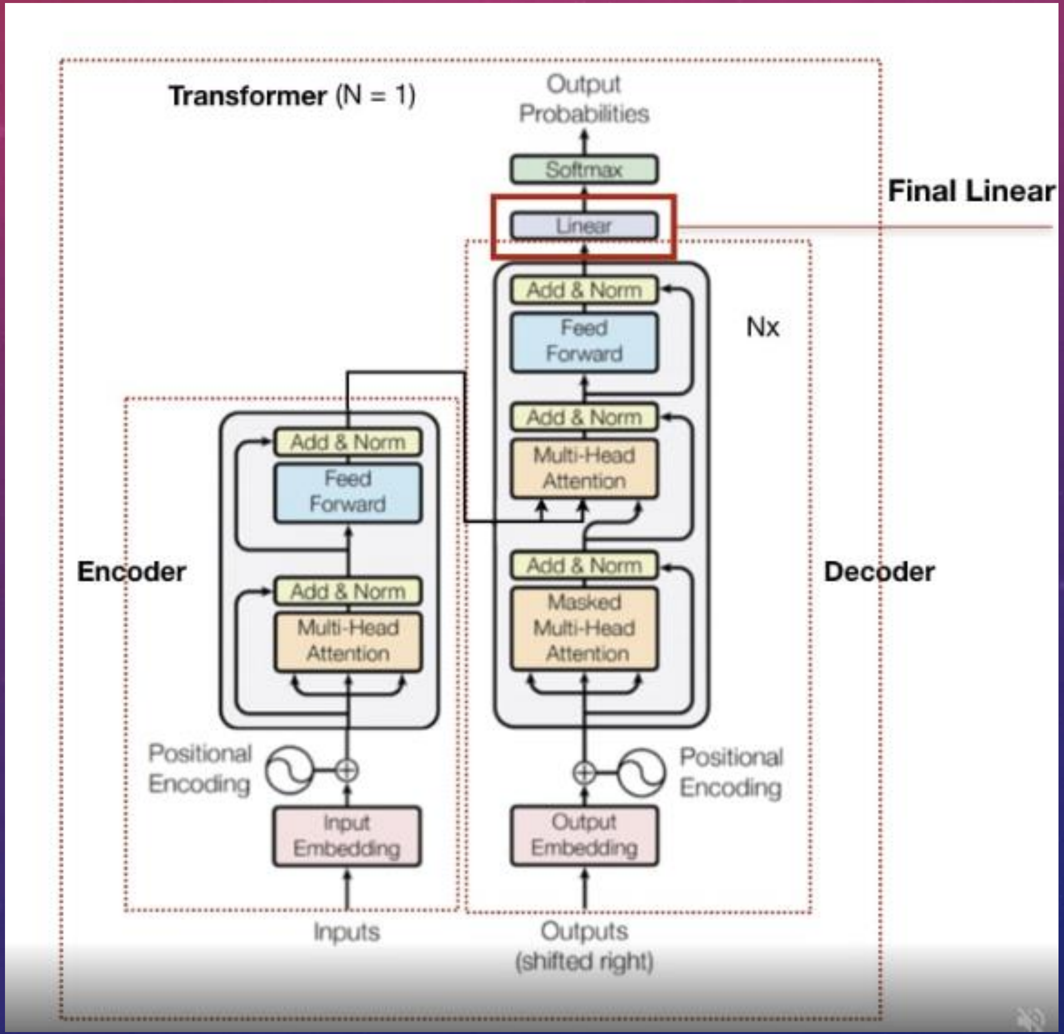


無法有效地平行運算

TRANSFORMER STRUCTURE



TRANSFORMER STRUCTURE



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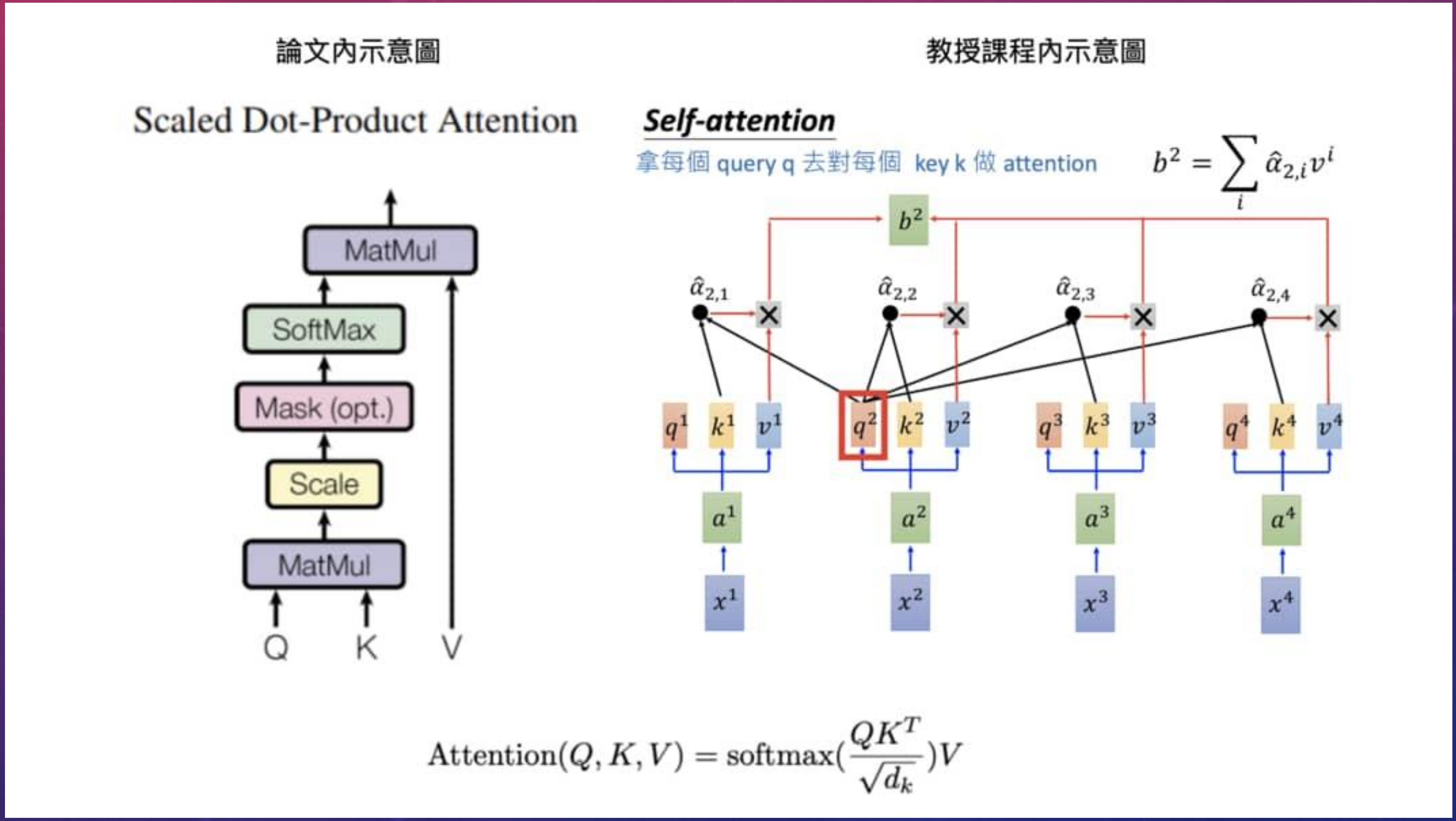
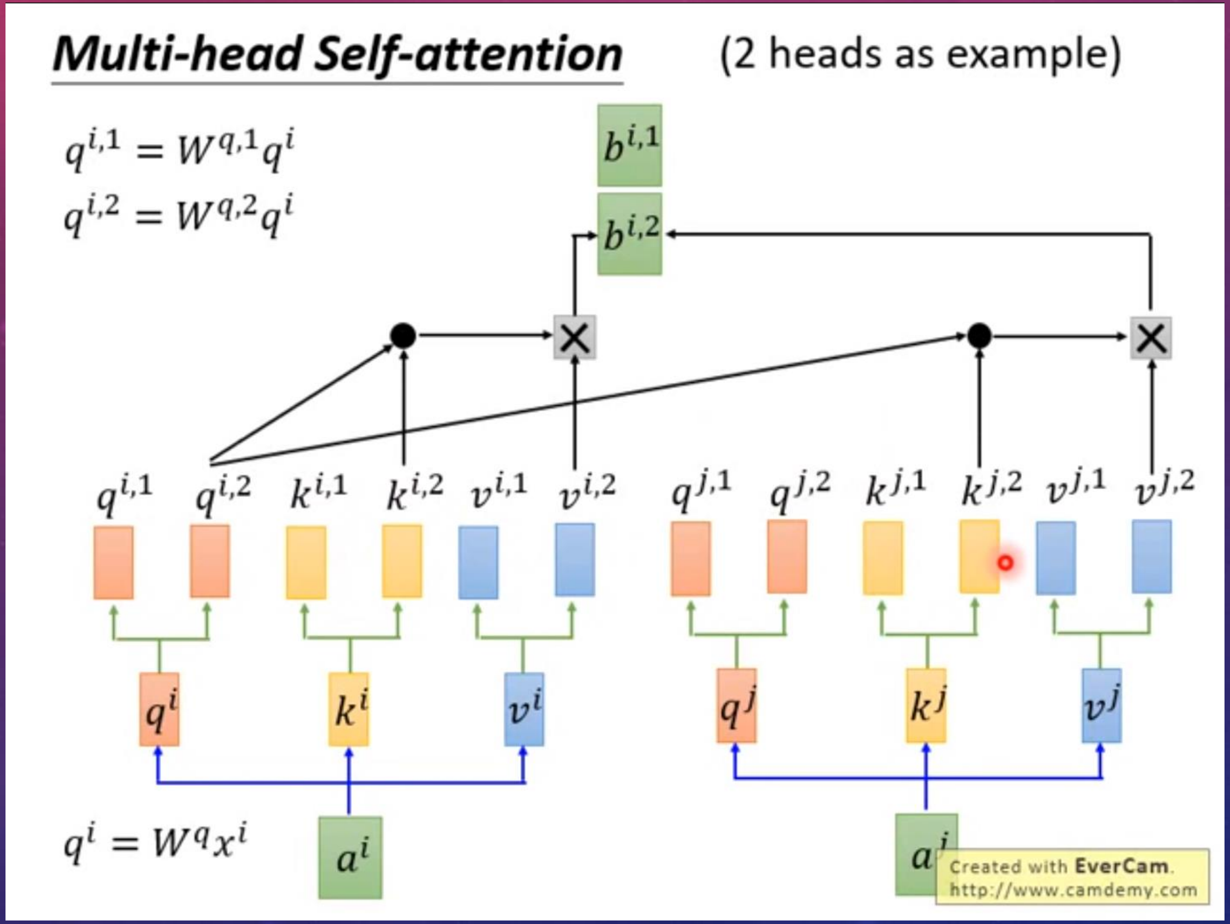
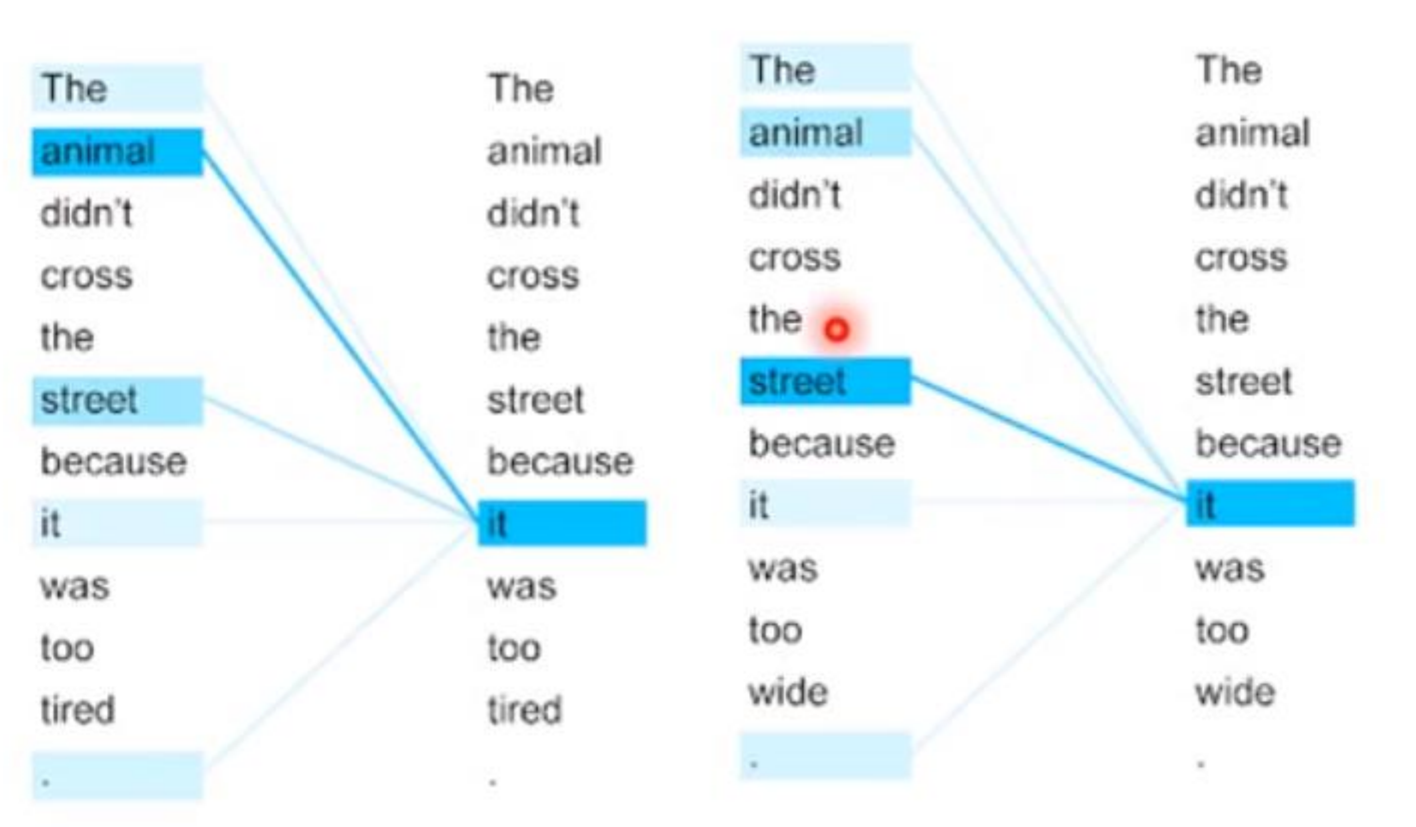


TRANSFORMER STRUCTURE



RESULTS



The
animal
didn't
cross
the
street
because
it
was
too
tired
.
The
animal
didn't
cross
the
street
because
it
was
too
tired
.
The
animal
didn't
cross
the
street
because
it
was
too
wide
.
The
animal
didn't
cross
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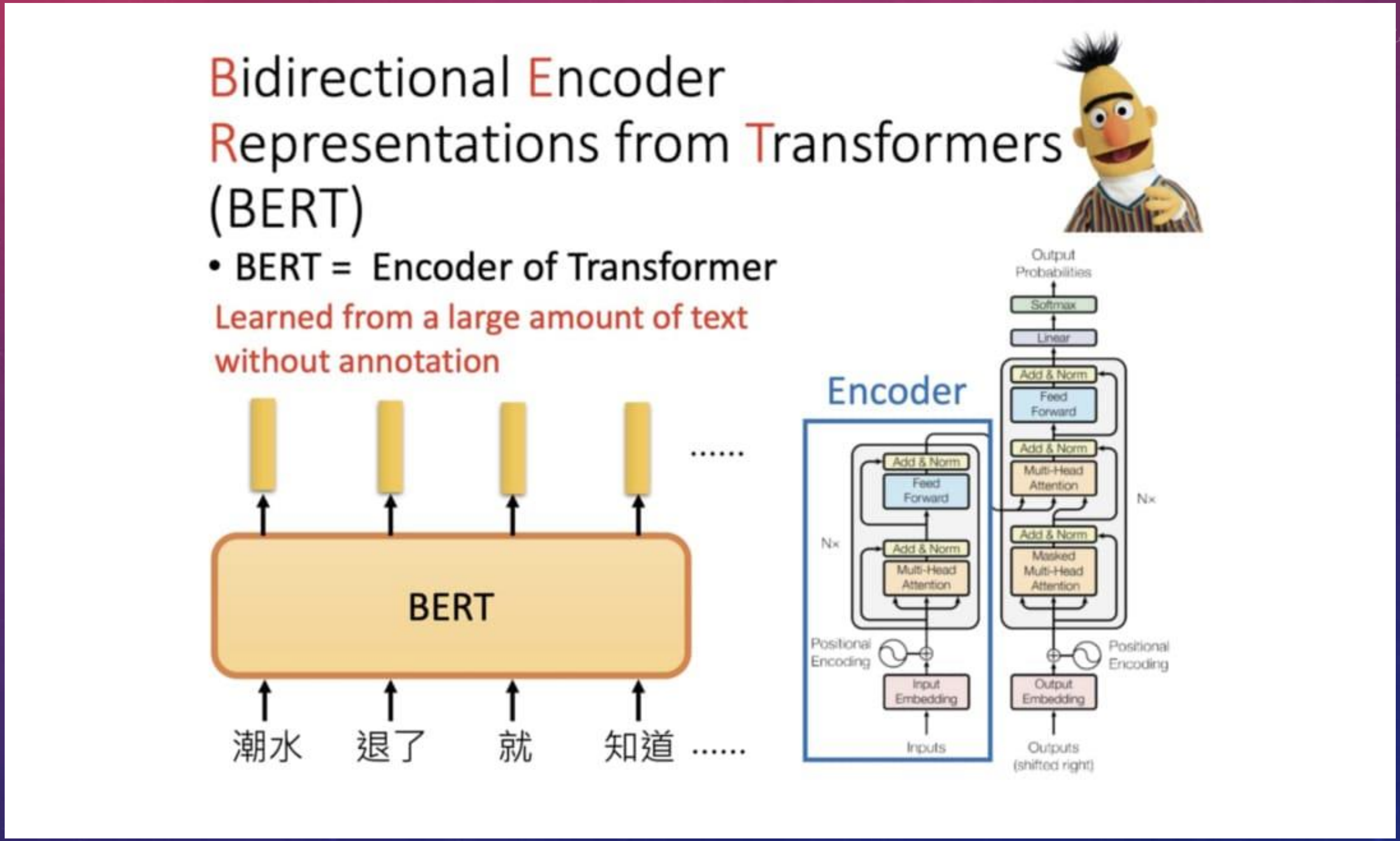
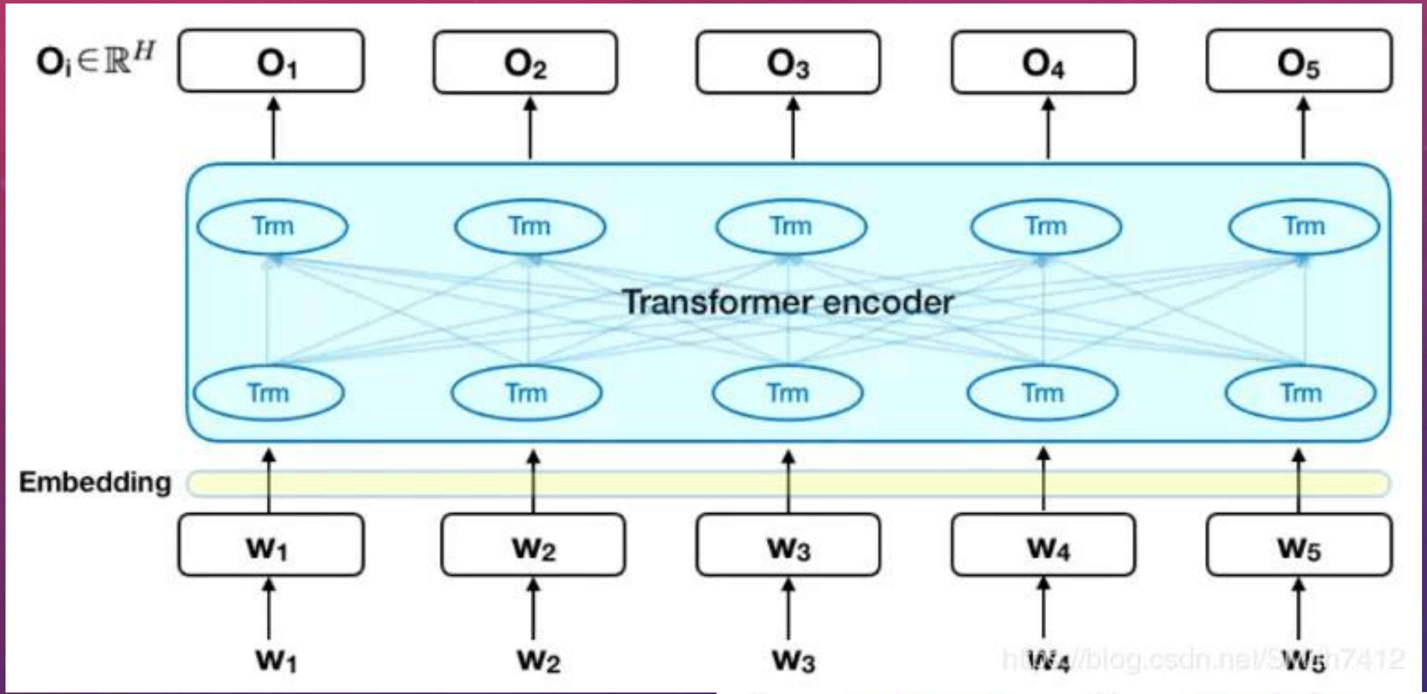
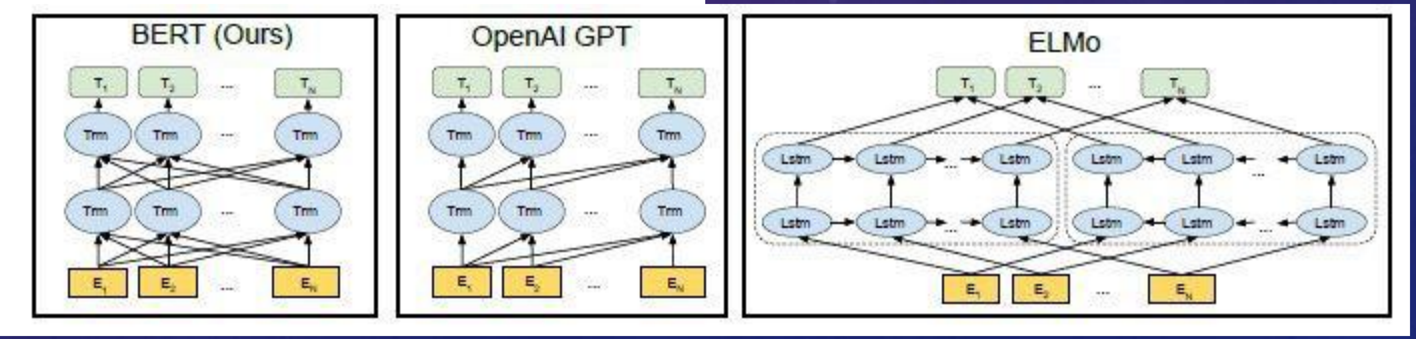
BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS, BERT

BERT= ENCODER OF TRANSFORMER

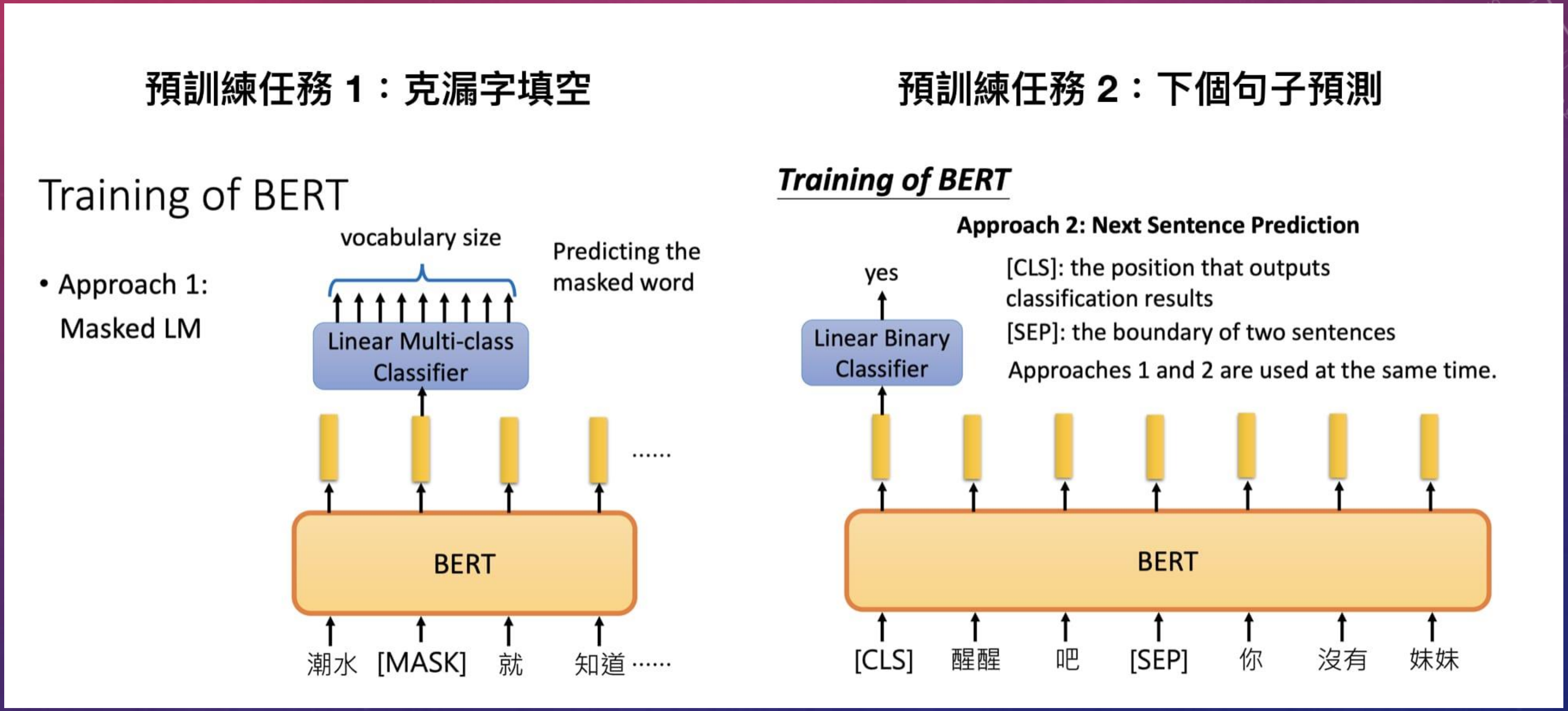


BERT STRUCTURE

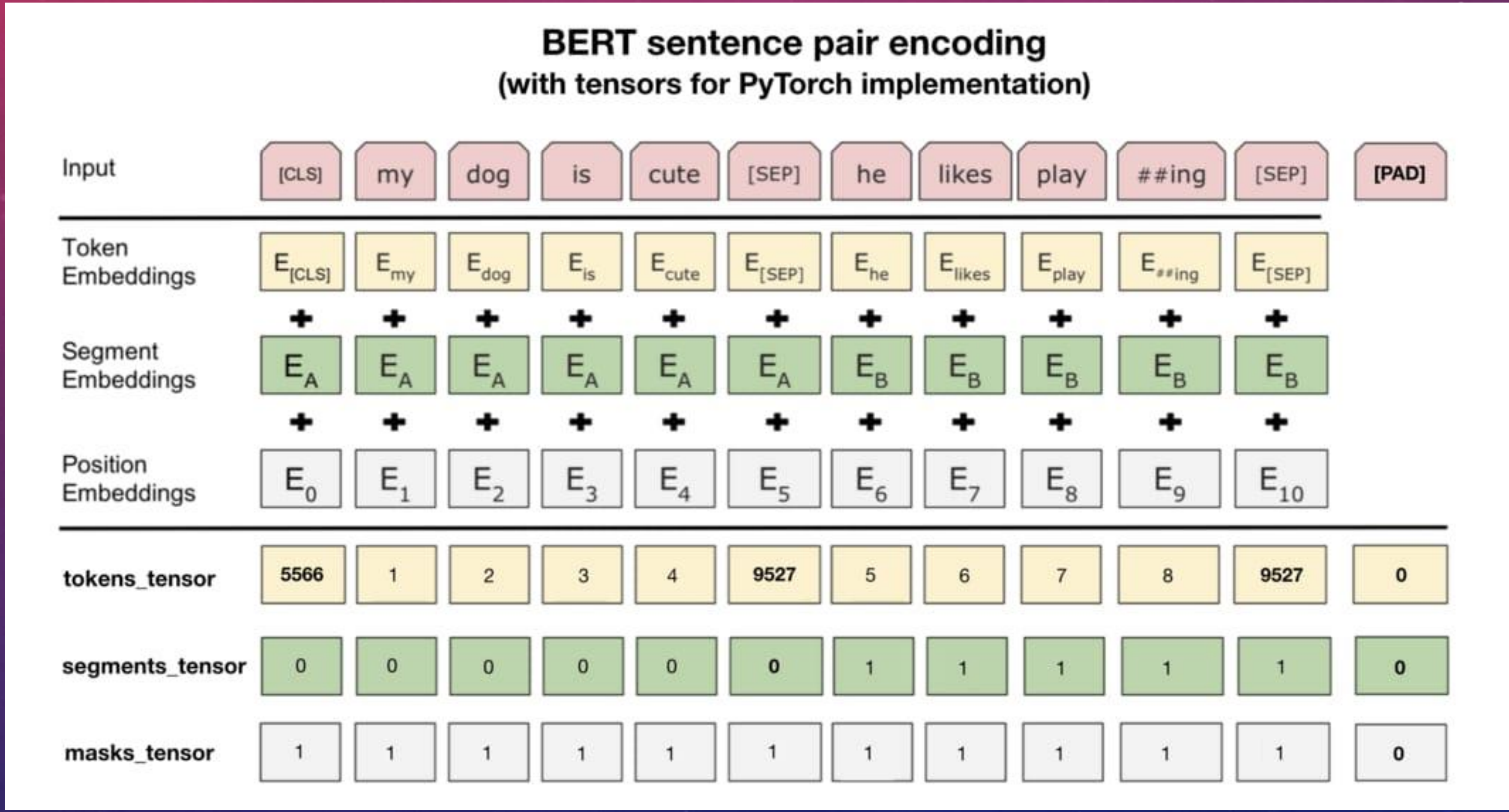




TRAINING OF BERT



KEY POINTS OF BERT



THANK YOU