神經與行為模型建構
(Neural & Behavioral Modeling)

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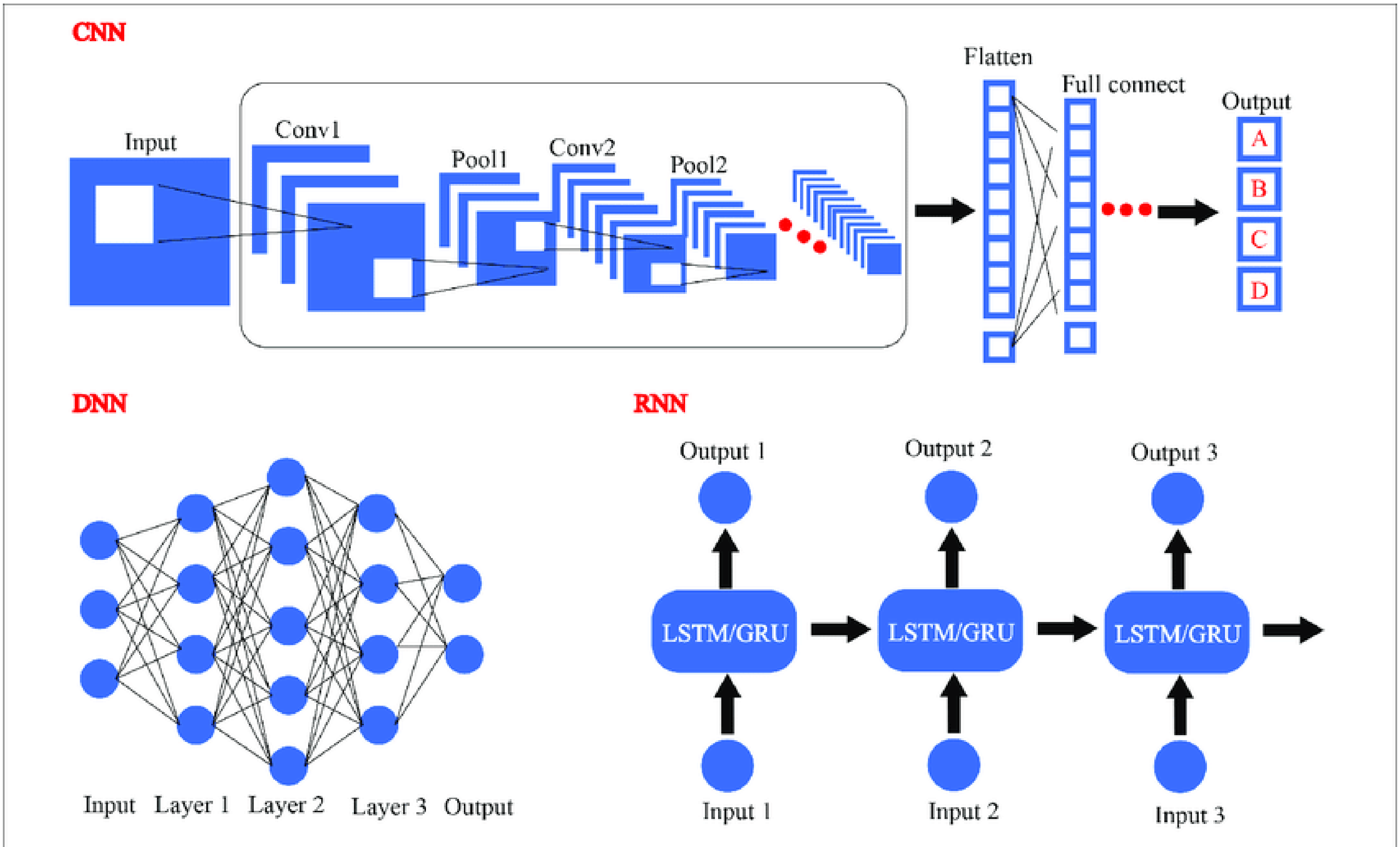
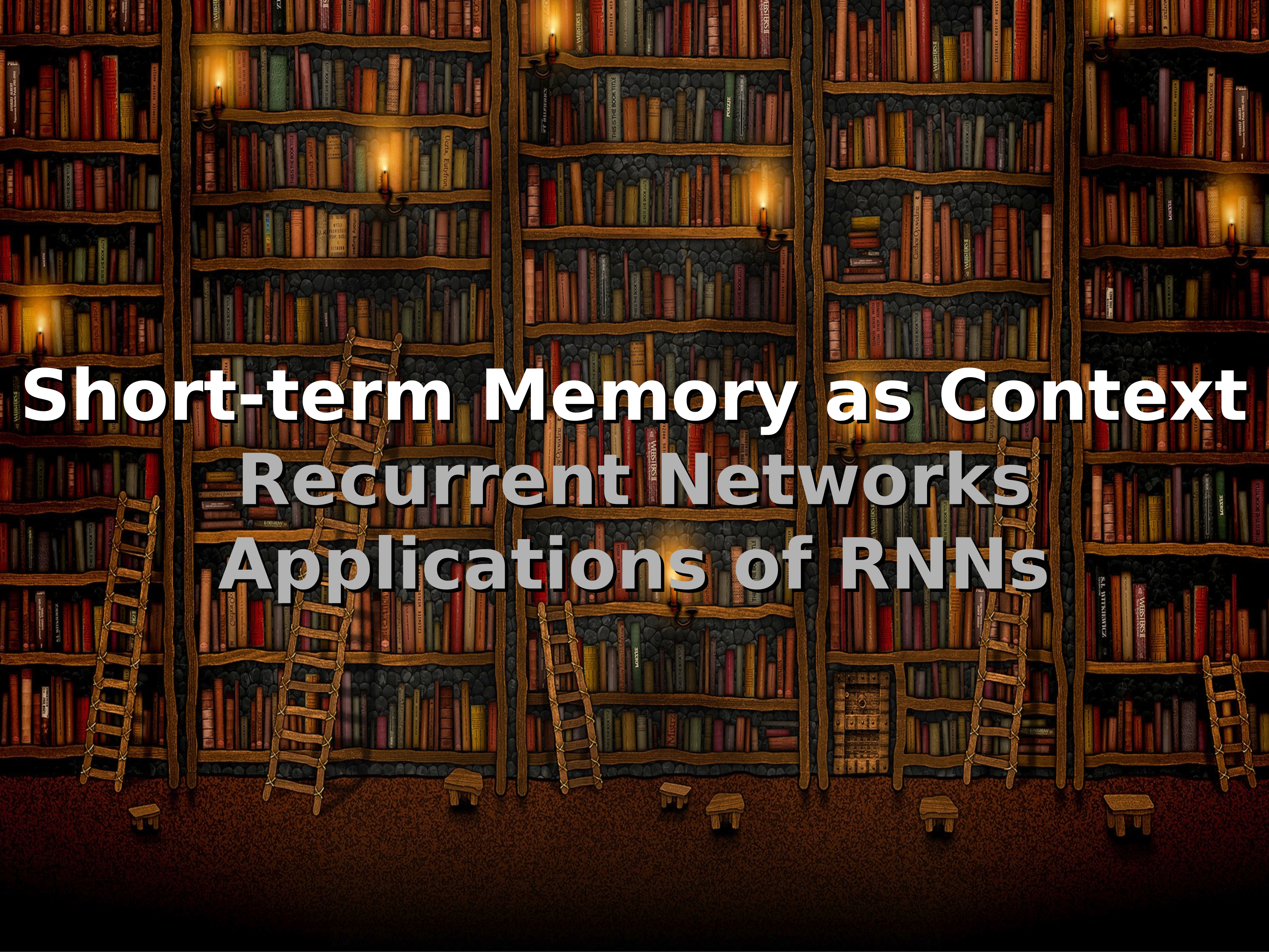
黃從仁

Deep Neural Networks 的分類

CNN 通常處理影像資料；RNN 通常處理語言資料




本周介紹 RNN
!



Short-term Memory as Context

Recurrent Networks

Applications of RNNs

從知覺到動作

相同 / 類似的知覺不一定產生一樣的動作

知覺 → 學習/記憶 → 動作

紅	黑	綠	藍
黃	橙	黑	棕
紫	黃	藍	黃
綠	棕	紅	紫

function 一對多

數學上無解：

x= 紅 → y= 紅（叫意）

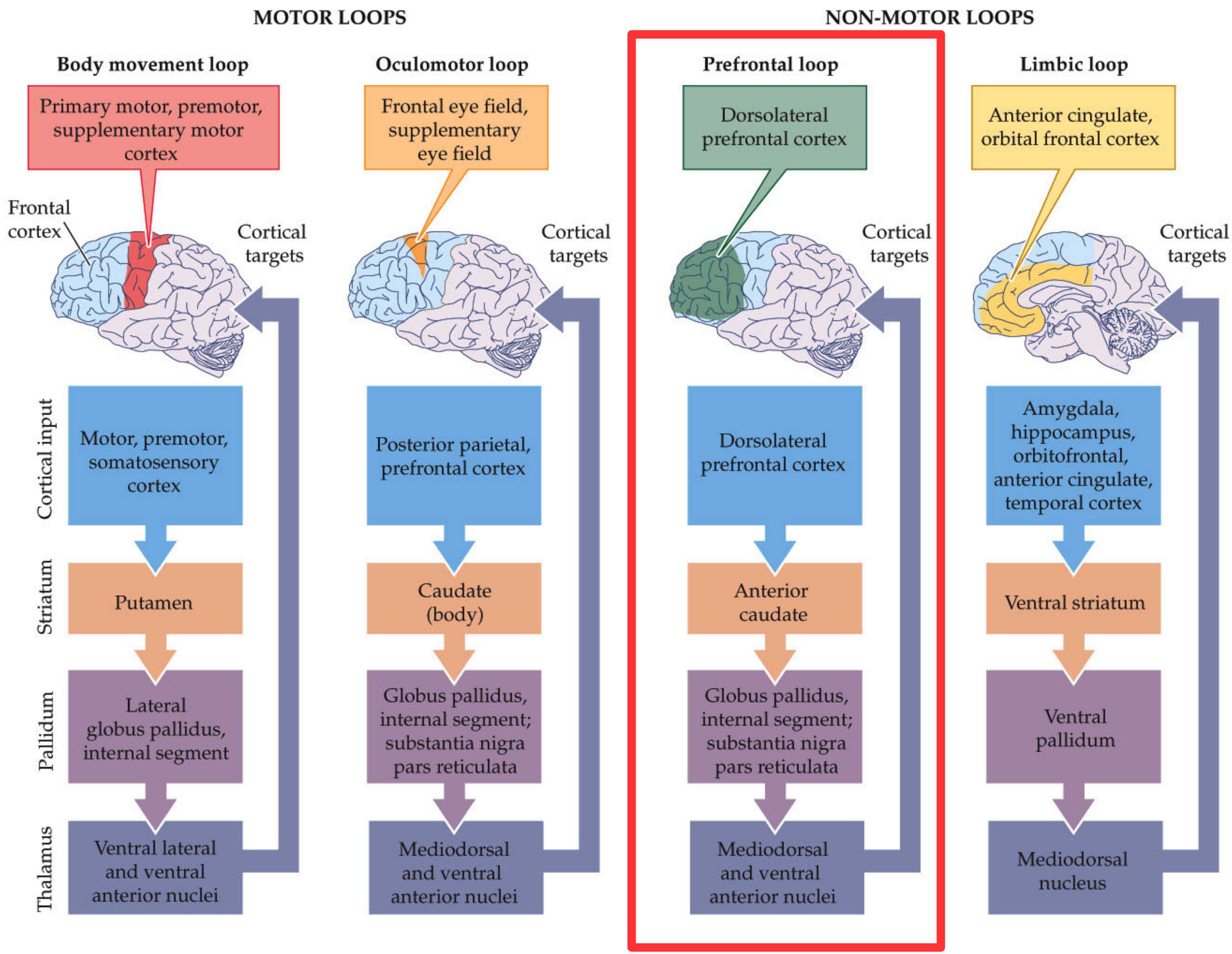
x= 紅 → y= 綠（叫色）

數學上有解：

x=(紅 , 叫意) → y= 紅

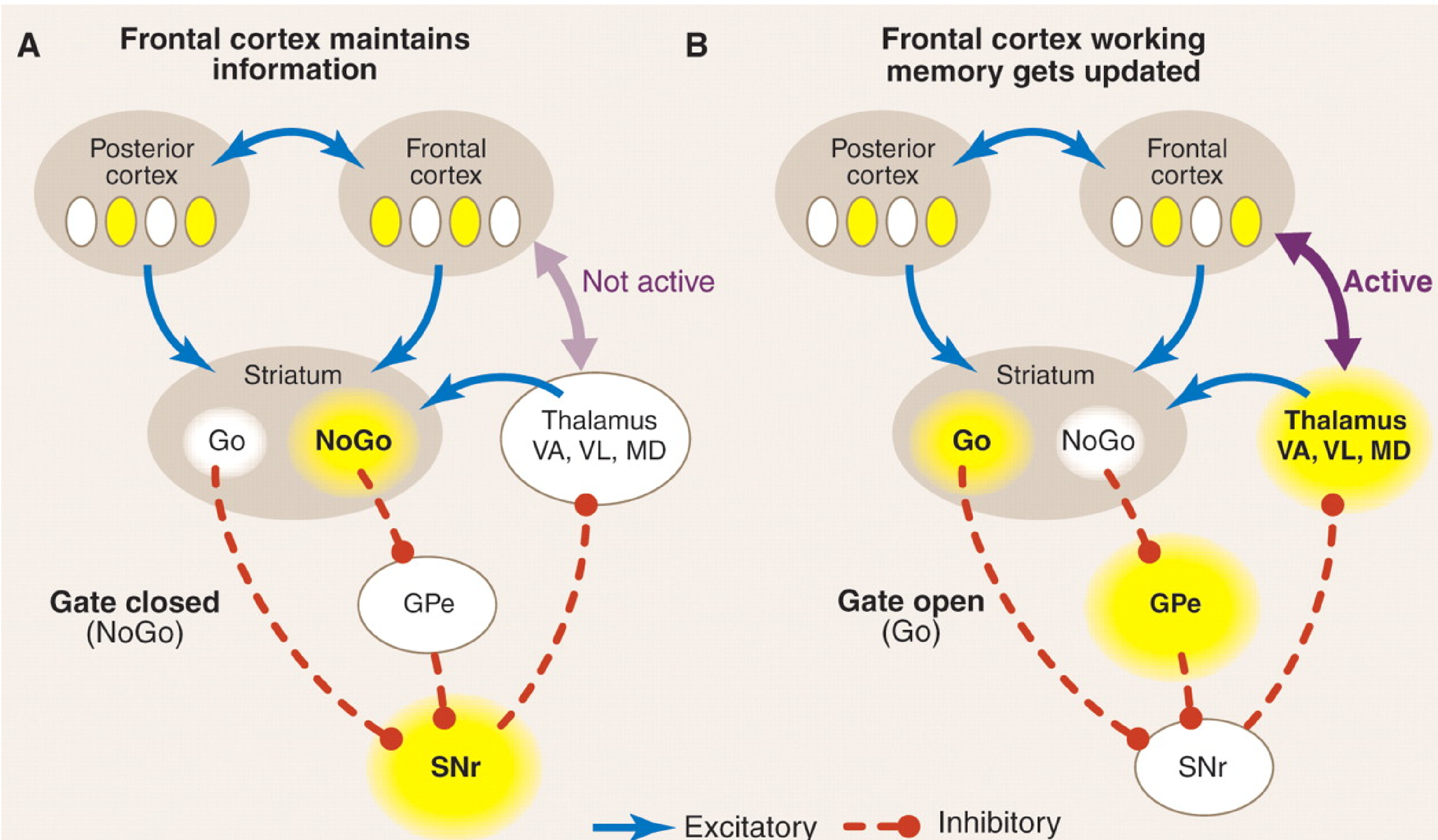
x=(紅 , 叫色) → y= 綠

Cortico-Basal Ganglia Loops



BG-modulated PFC

= Prefrontal cortex Basal ganglia Working Memory

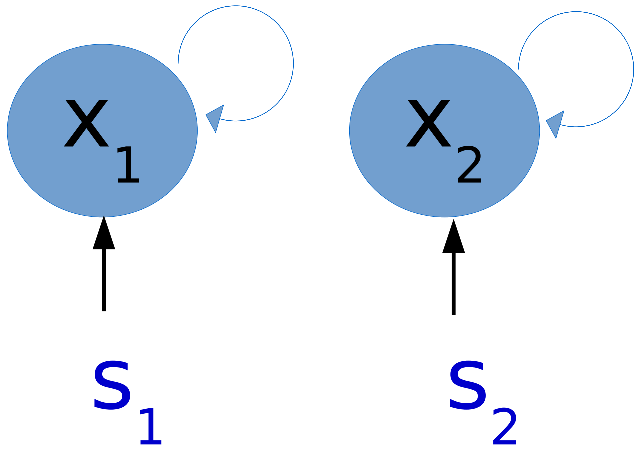


例子：https://www.google.com/search?q=delay+response+task+monkey&hl=zh-TW&sxsrf=ALeKk01nwPcgtZXu5QBDhIy87BE-shS_SA:1
07651057012&source=lnms&tbm=isch&sa=X&ved=2ahUKEwiA8rPx5sTtAhUJHaYKHf1-AnMQ_AUoAXoECAoQAw&biw=1368&bih=774&d

Short-term Memory as Context
Recurrent Networks
Applications of RNNs

Self-Recurrent Excitations

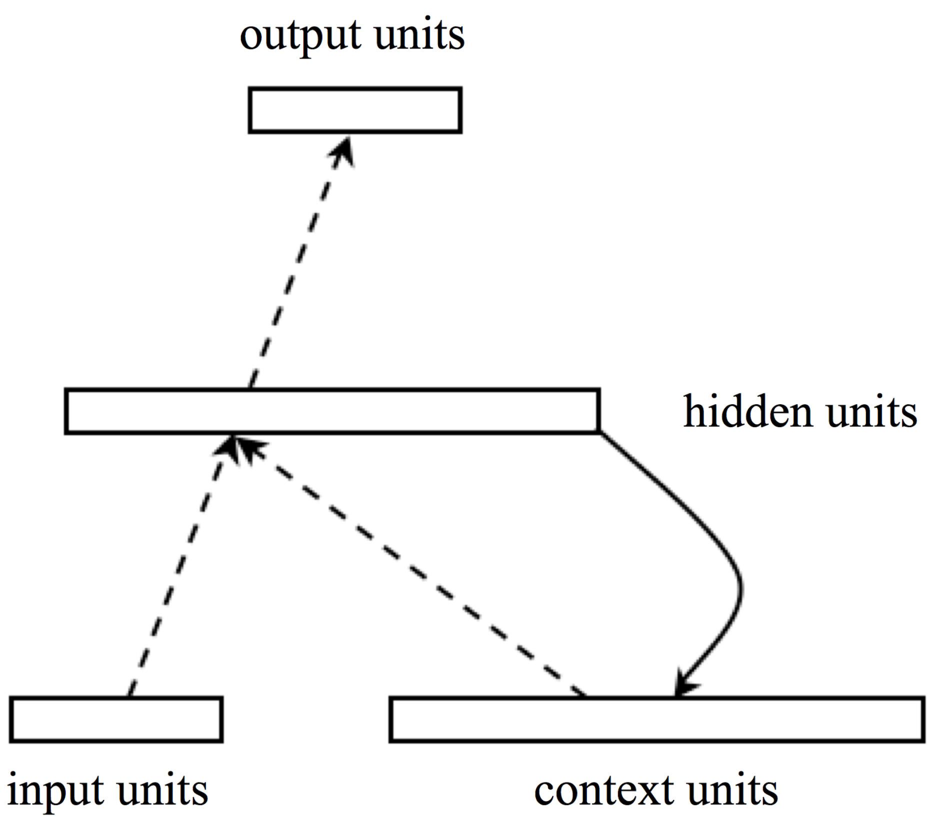
自我連結的刺激可維持反應卻無法維持刺激對比

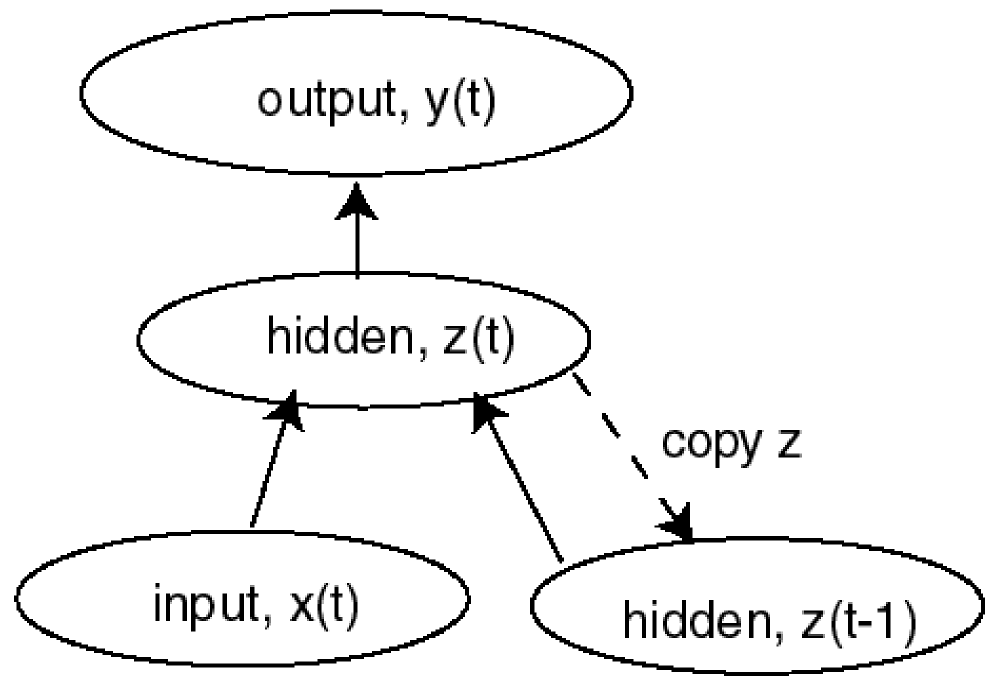



```
x=[0,0]; dt=0.1
for t in arange(0,10,dt):
    s=[1,10] if t<1 else [0,0]
    x[0]=x[0]+dt*(-0.1*x[0]+(1-x[0])*(s[0]+x[0]))
    x[1]=x[1]+dt*(-0.1*x[1]+(1-x[1])*(s[1]+x[1]))
    clf(); plot([1,2],x,'-o')
    ylim([0,1]); title('t='+str(t))
    display(gcf()); clear_output(wait=True)
```

Simple RNN (1/2)

by Elman (1990)





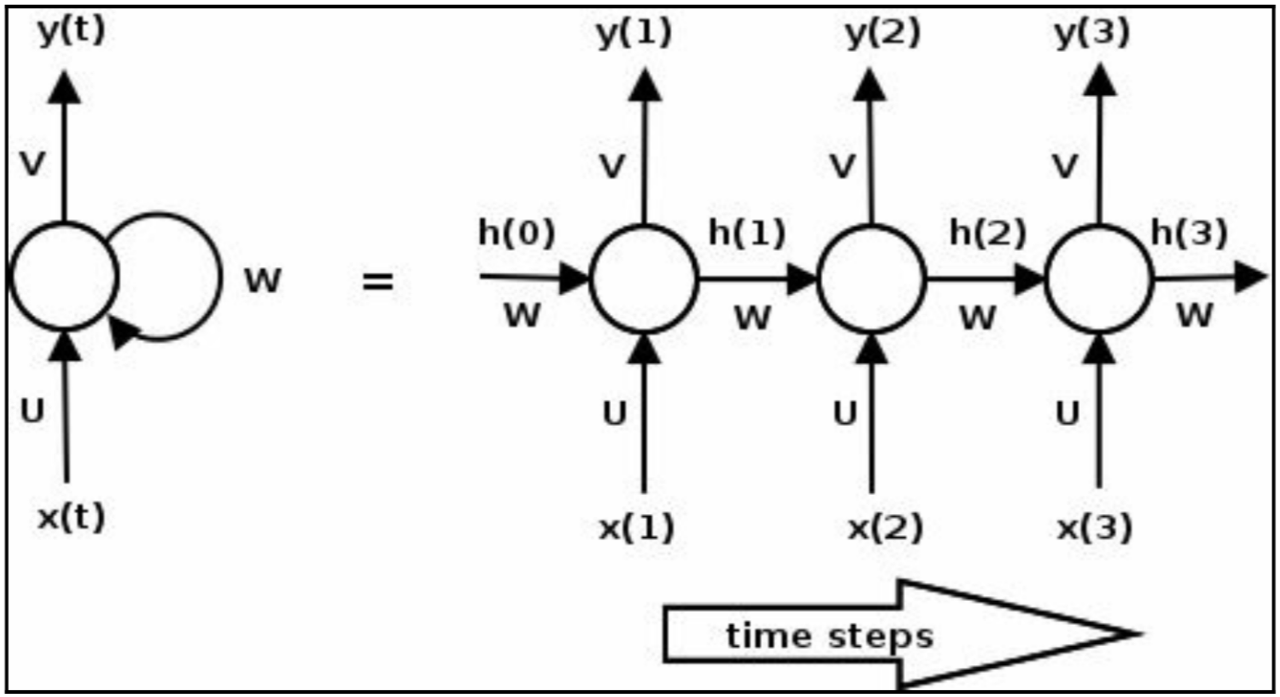
上一次的資訊留下來,
跟新的資訊一起去predict

例如一連串的語音訊號，我們可以把字詞轉成向量

to process sequential information

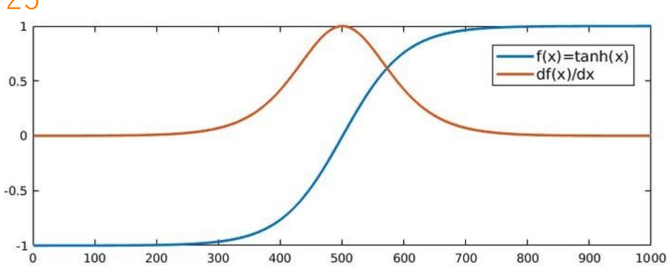
Simple RNN (2/2)

effectively has VERY deep layers



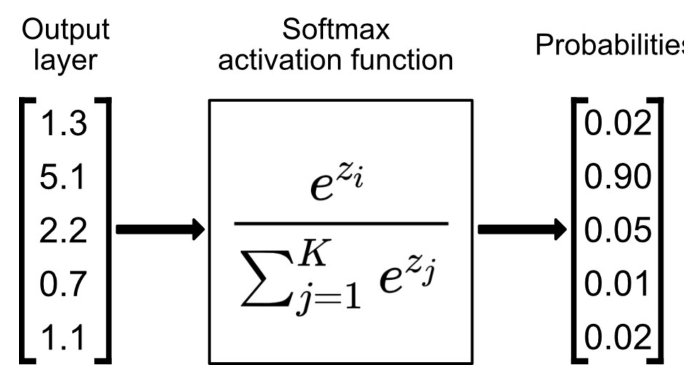
hyperbolictangent，有upper lower bond
dh/dt 最高可以到 1，所以較能減緩
vanishing gradiend problem

不像 logistic regression dy/dt 最高才 0.
25



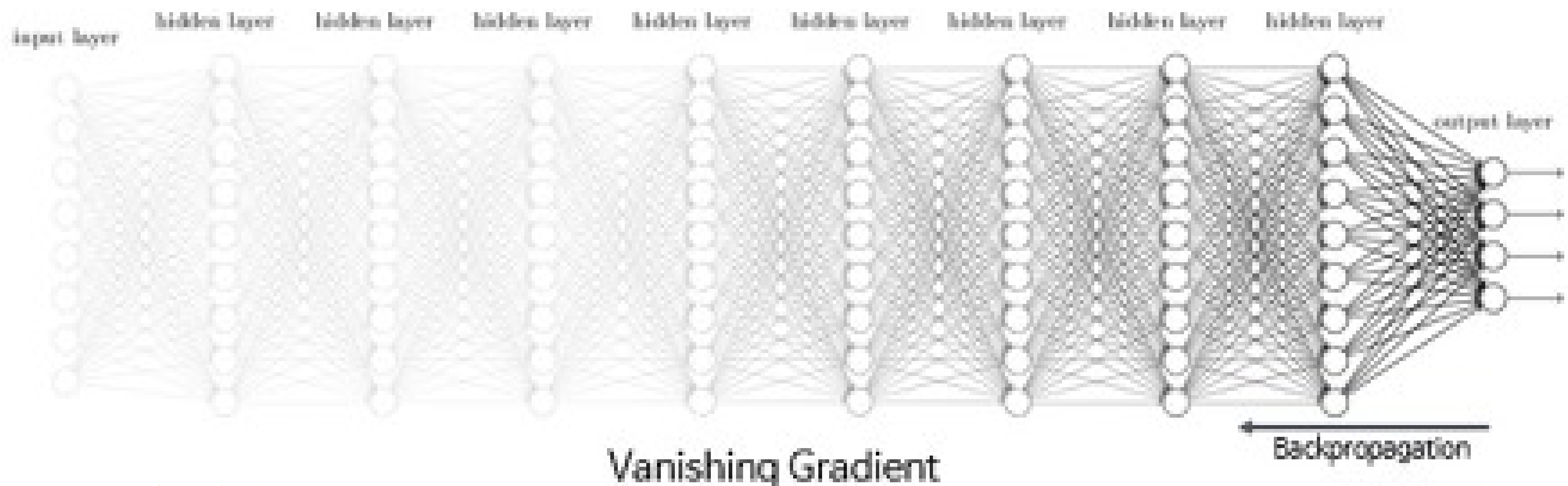
$$h_t = \tanh(W h_{t-1} + U X_t)$$ \in [-1, 1]

$$y_t = \mathrm{softmax}(V h_t)$$



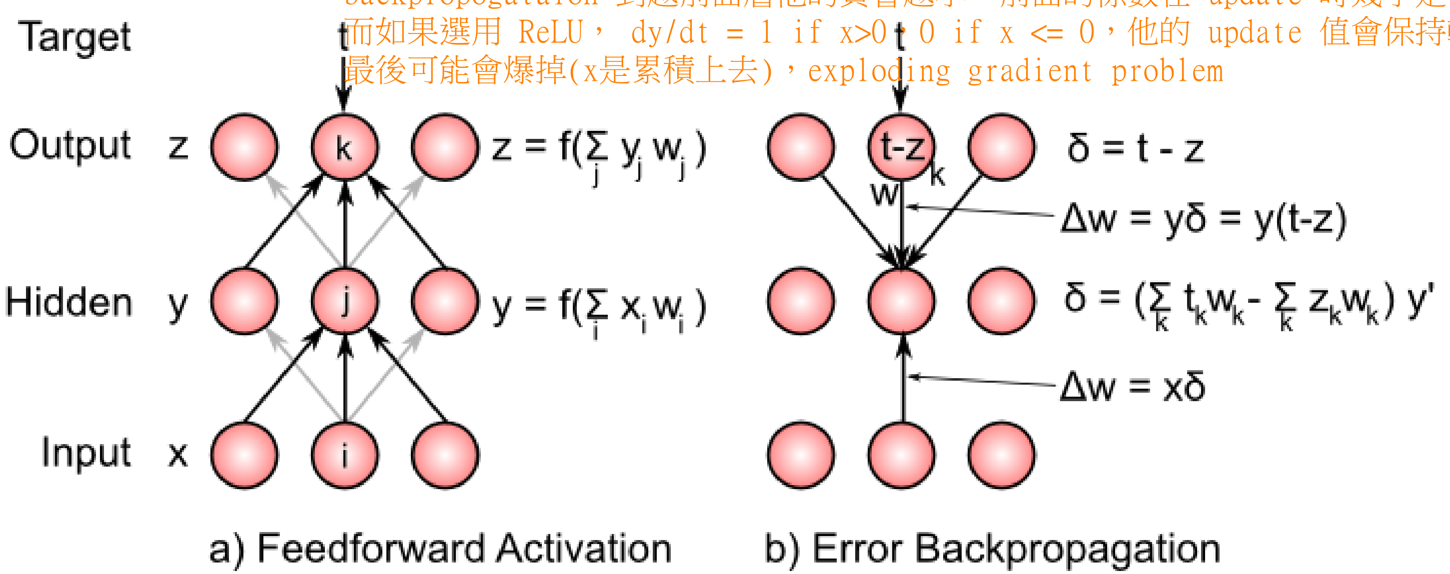
Temporal Backpropagation

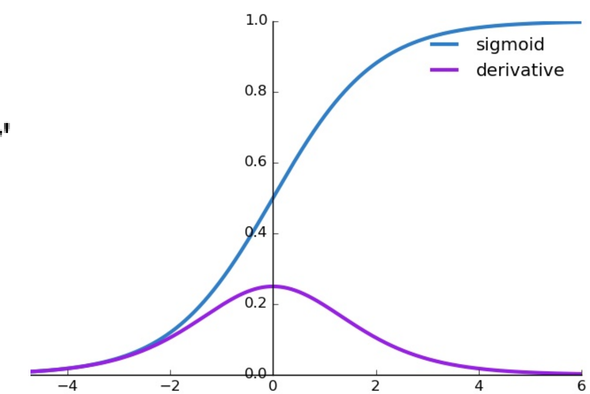
<u>suffers from vanishing & exploding gradient problem</u>



現在不喜歡 logistic function 原因在於 dy/dt = y(1-y)，y \in [0, 1]，因此 y' = dy/dt 最大值才0.25，這會導致 backpropogataion 到越前面層他的質會越小，前面的係數在 update 時幾乎是不動的，vanishing gradient problem

而如果選用 ReLU， dy/dt = 1 if x>0 , 0 if x <= 0，他的 update 值會保持較大，但是它用在 RNN (超級超級多層)，最後可能會爆掉(x是累積上去)，exploding gradient problem

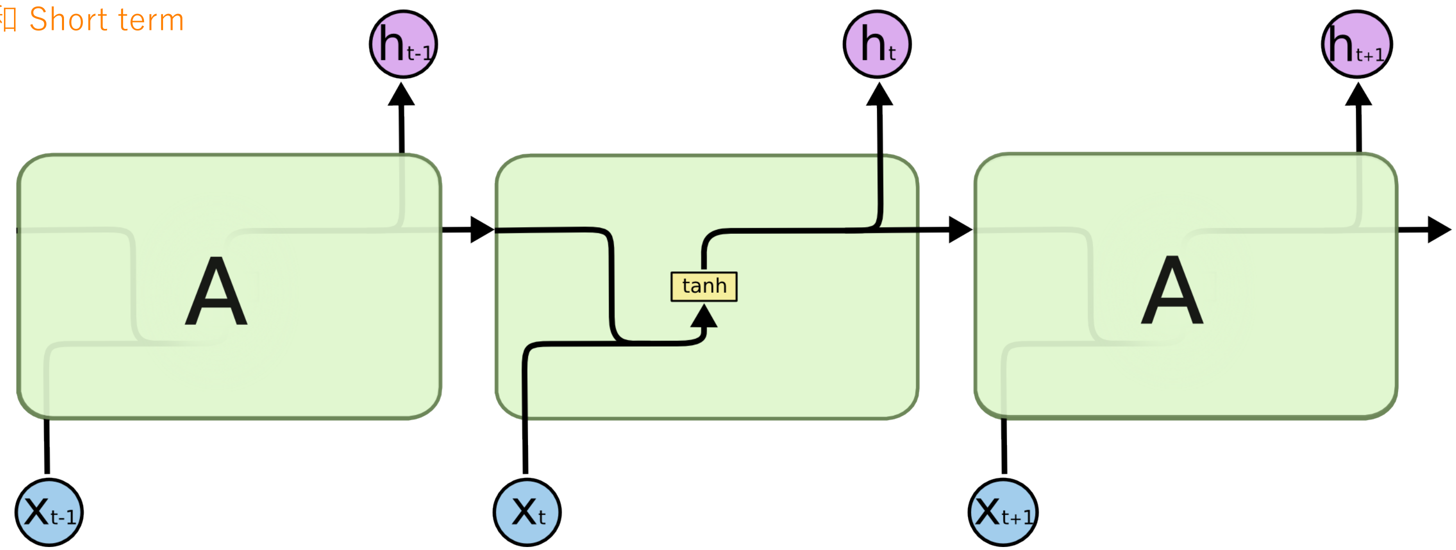




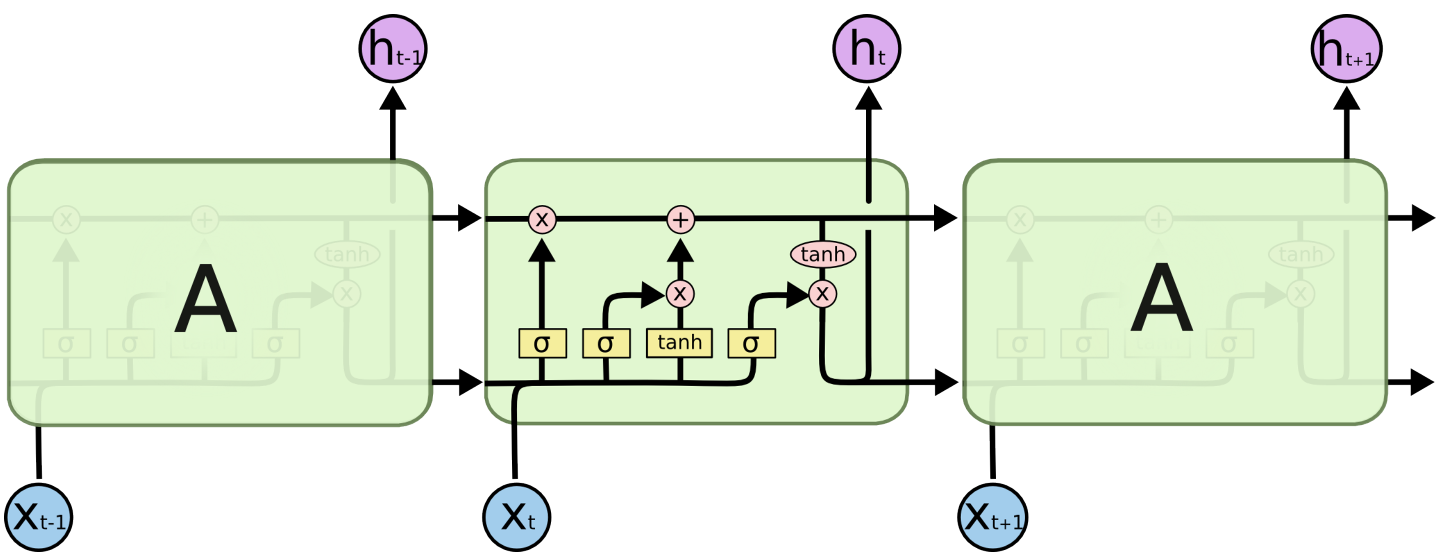
Long Short-term Memory (1/2)

introduces input, forget, output gates

RNN 發現太長遠的東西會記不太住
因此看 Long term 和 Short term
memory



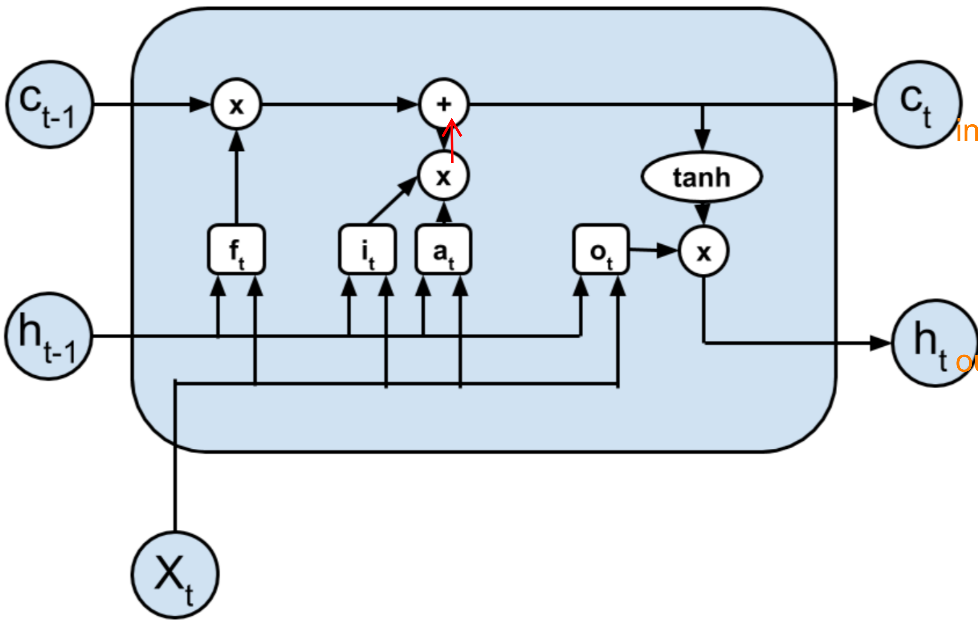
long term
(跟RNN展開一樣)



Long Short-term Memory (2/2)

Example: ignore '\n' & reset context for '.'

gate 是 sigmoid funciton，
要馬很接近0要馬很接近1



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

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

$$a_t = \tanh\left(W_c h_{t-1} + U_c x_t + b_c\right)$$

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

$$c_t = f_t * c_{t-1} + i_t * a_t$$

forget gate * 過去資訊 + input gate * 現在資訊

$$h_t = o_t * \tanh\left(c_t\right)$$

真真要做出的資訊取決於 = output gatie * tanh(綜合資訊)

gate 那些參數也是透過 try and error 學來的

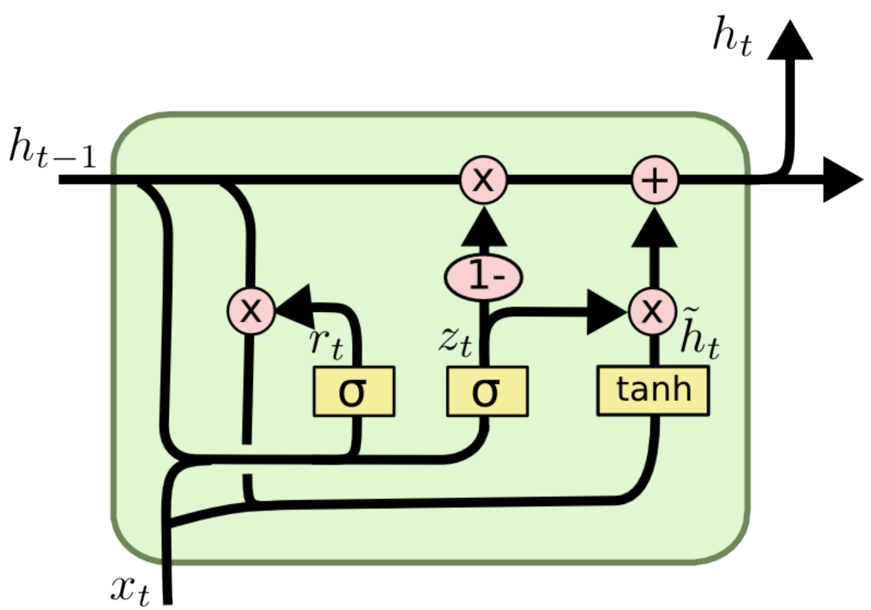
$(f_t, i_t) = (1, 0)$ to maintain perfect memory

long 的 short-term memory

Gated Recurrent Unit

GRU is a simplified LSTM without an output gate

gate 數目變少，參數也變少



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\boxed{\begin{aligned} \tilde{h}_t &= \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right) \\ h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \end{aligned}}$$

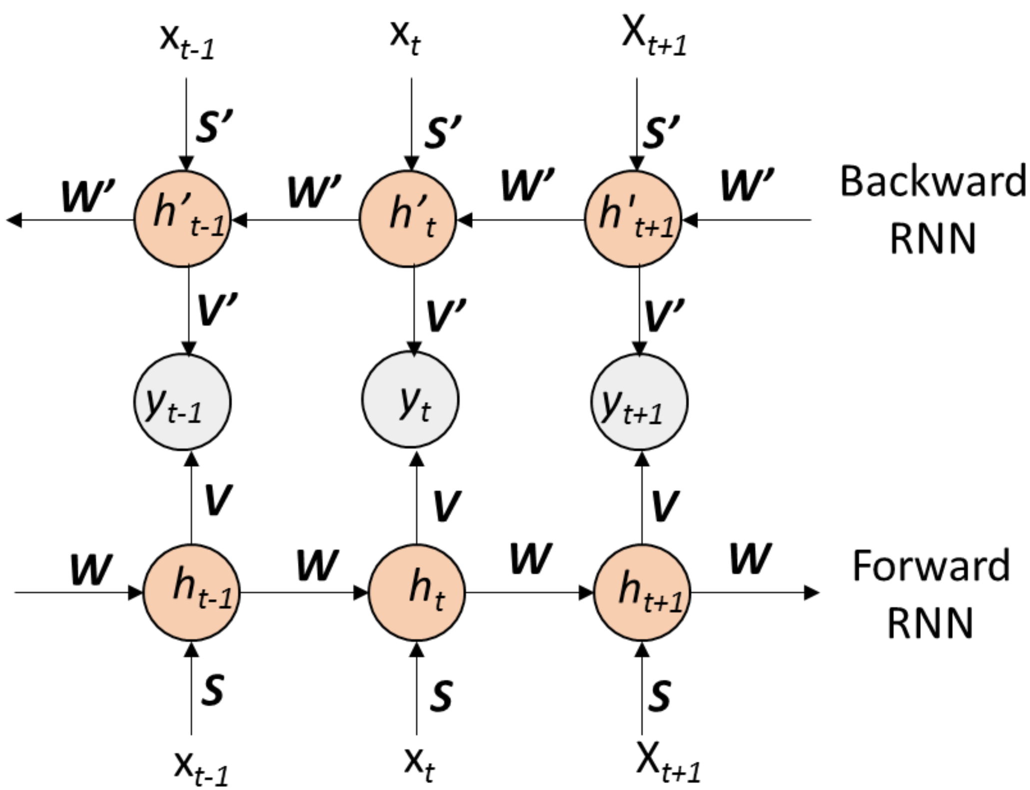
memory input

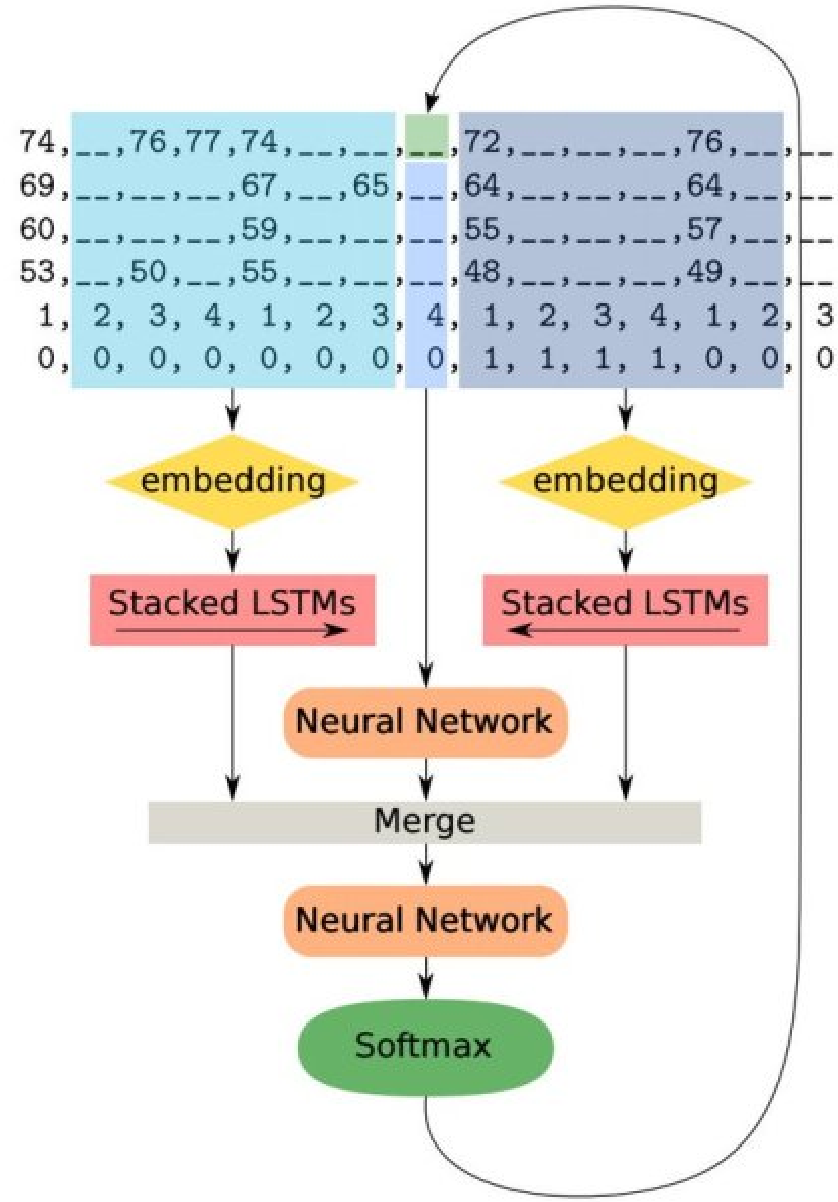
r_t = reset/forget gate ; z_t = update/input gate

Bidirectional RNN

DeepBach uses a similar idea

本來是過去預測現在
先再也加入未來的資訊共同來預測現在





Attention replacing RNN (1/3)

Attention Is All You Need

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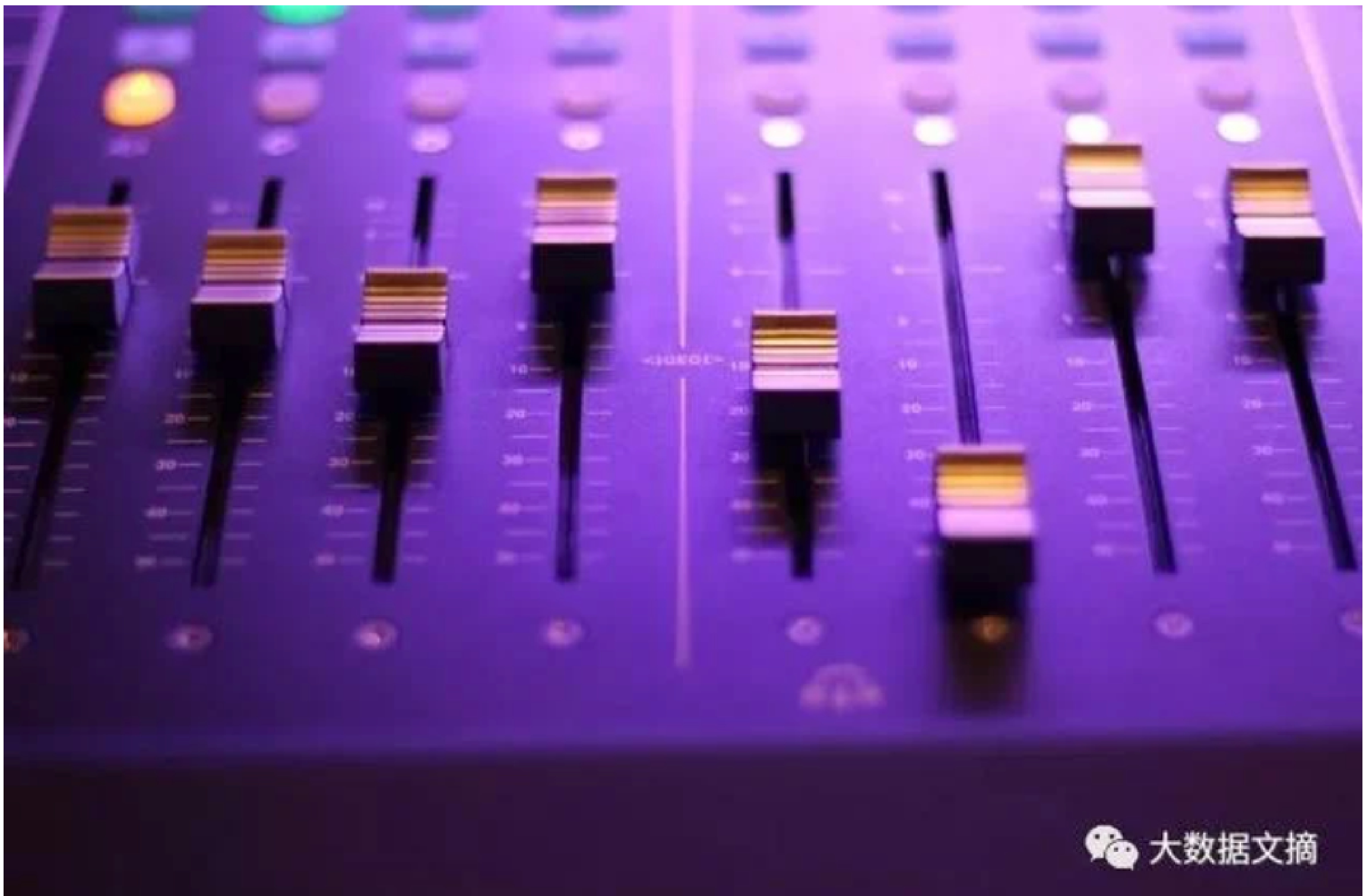
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.0 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature.

Attention replacing RNN (2/3)

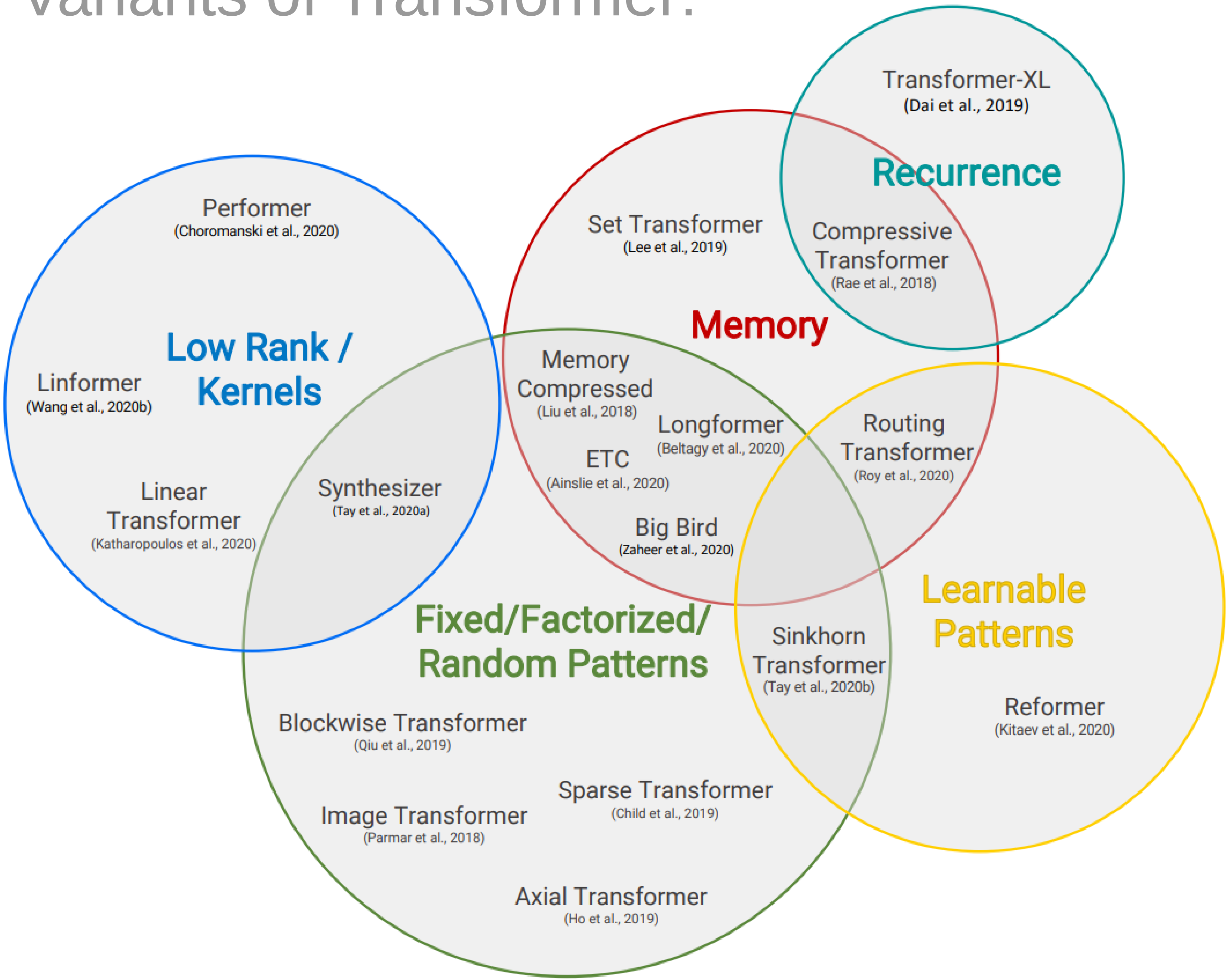
别再用RNN和LSTM了！注意力模型才是王道

2018-05-02 *由 大數據文摘 發表于科技*

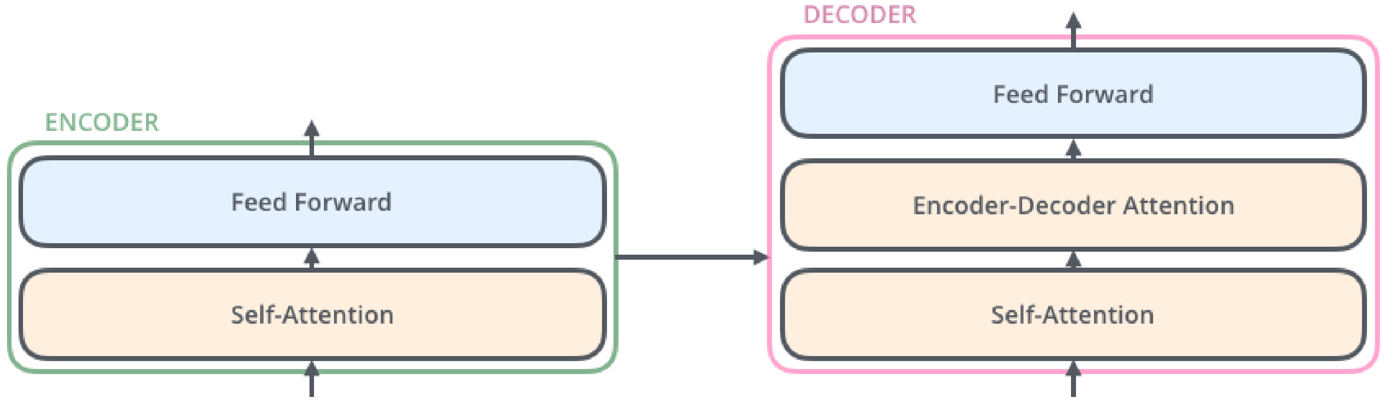


Attention replacing RNN (3/3)

Variants of Transformer:



Attention in Transformer



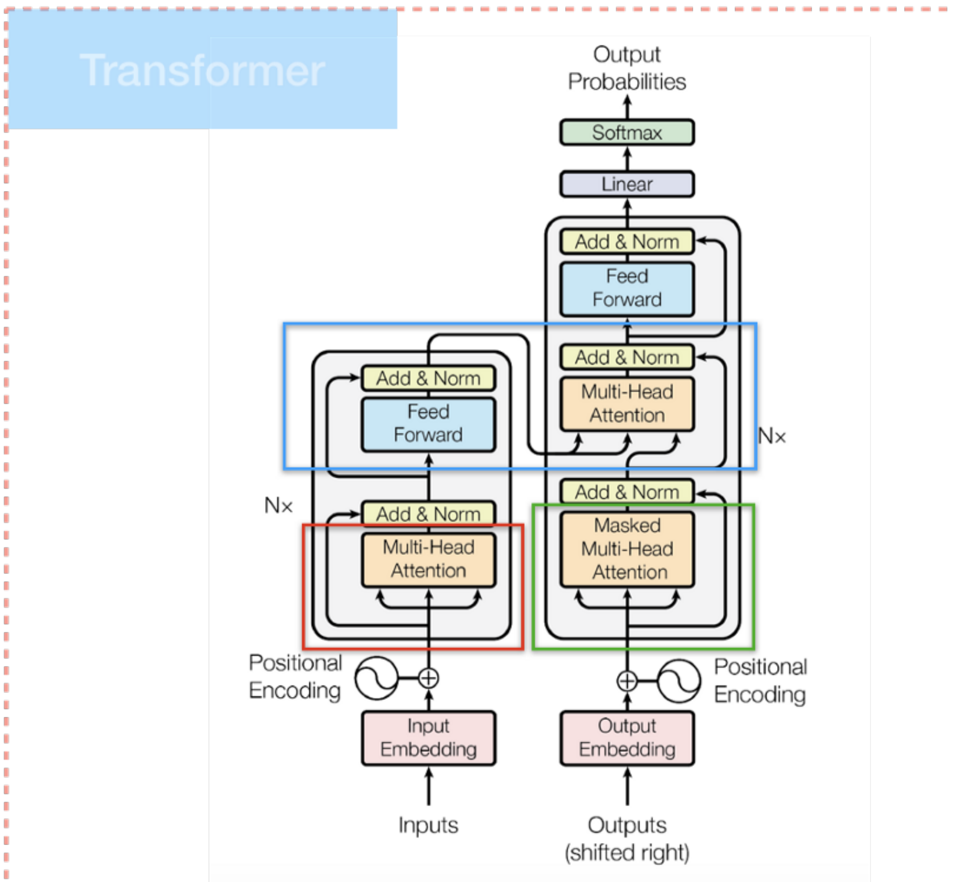


Figure 1: The Transformer - model architecture.

encoder self attention

1. Multi-head Attention
2. Query=Key=Value

decoder self attention

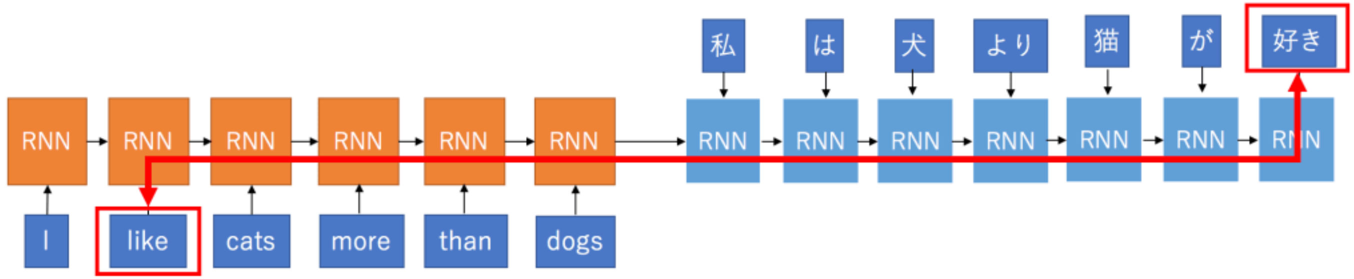
1. Masked Multi-head Attention
2. Query=Key=Value

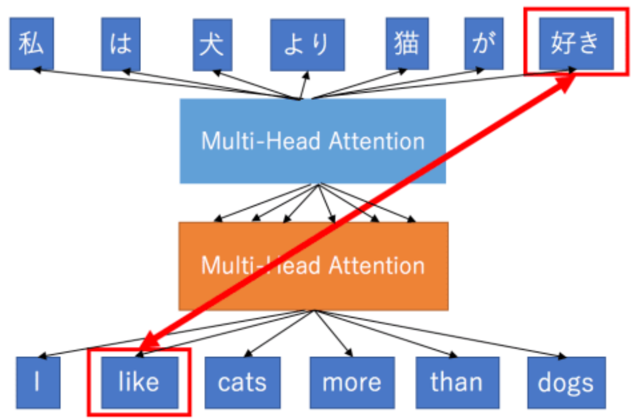
encoder-decoder attention

1. Multi-head Attention
2. Encoder Self attention=Key=Value
3. Decoder Self attention=Query

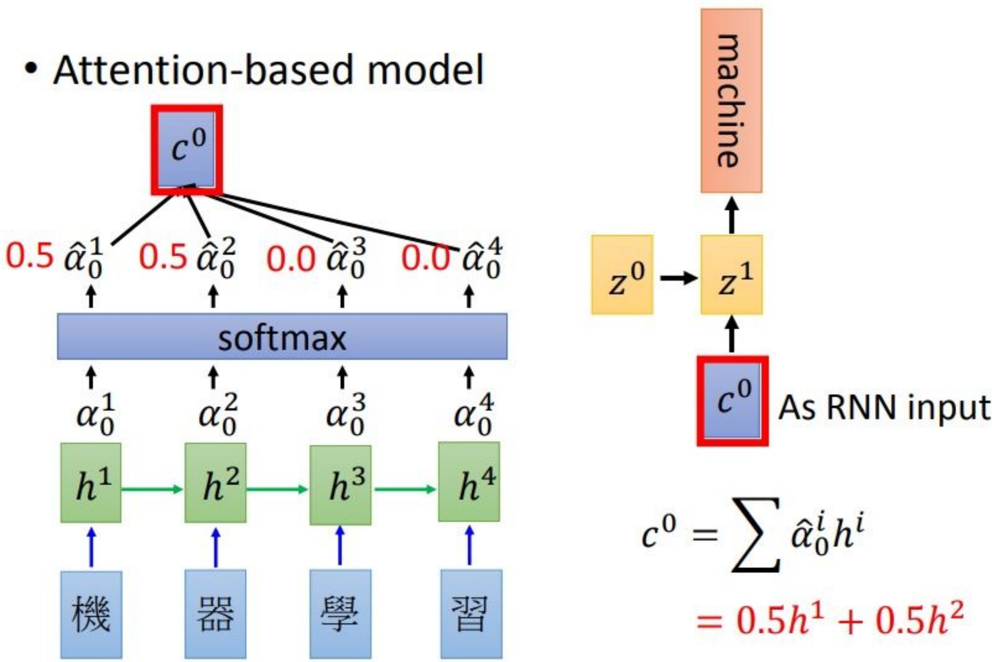
Encoder-Decoder Attention

google 翻譯



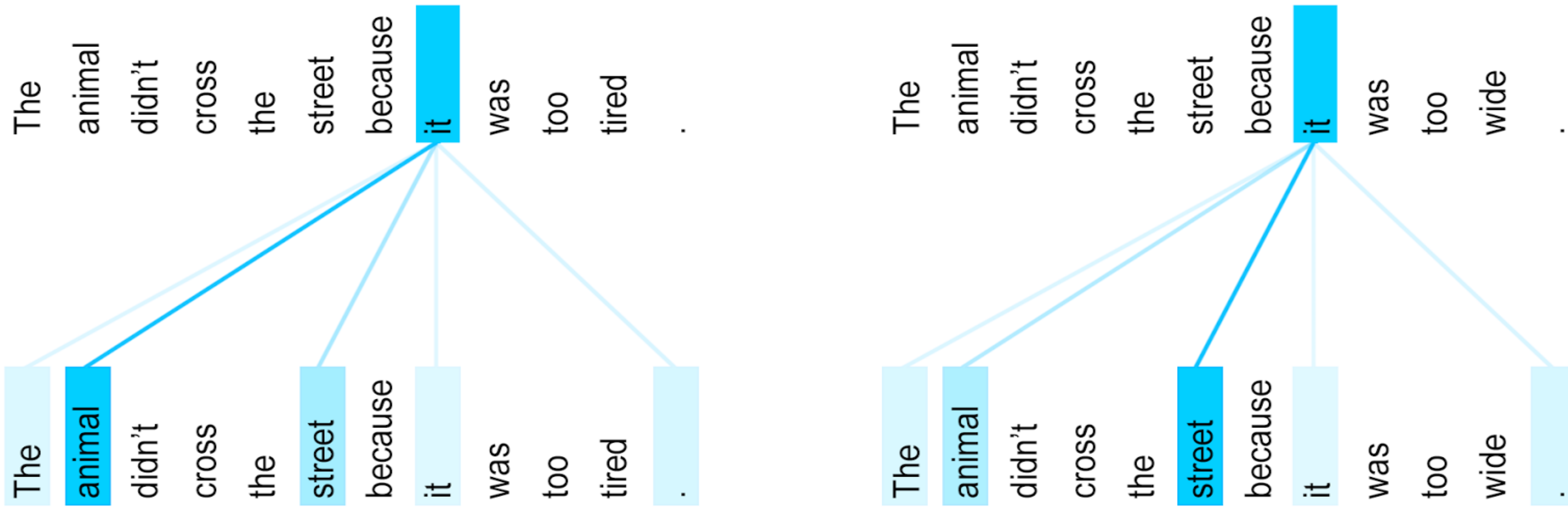


- Attention-based model



Encode/Decoder Self-Attention

Example: What’s the correct understanding of “it”?

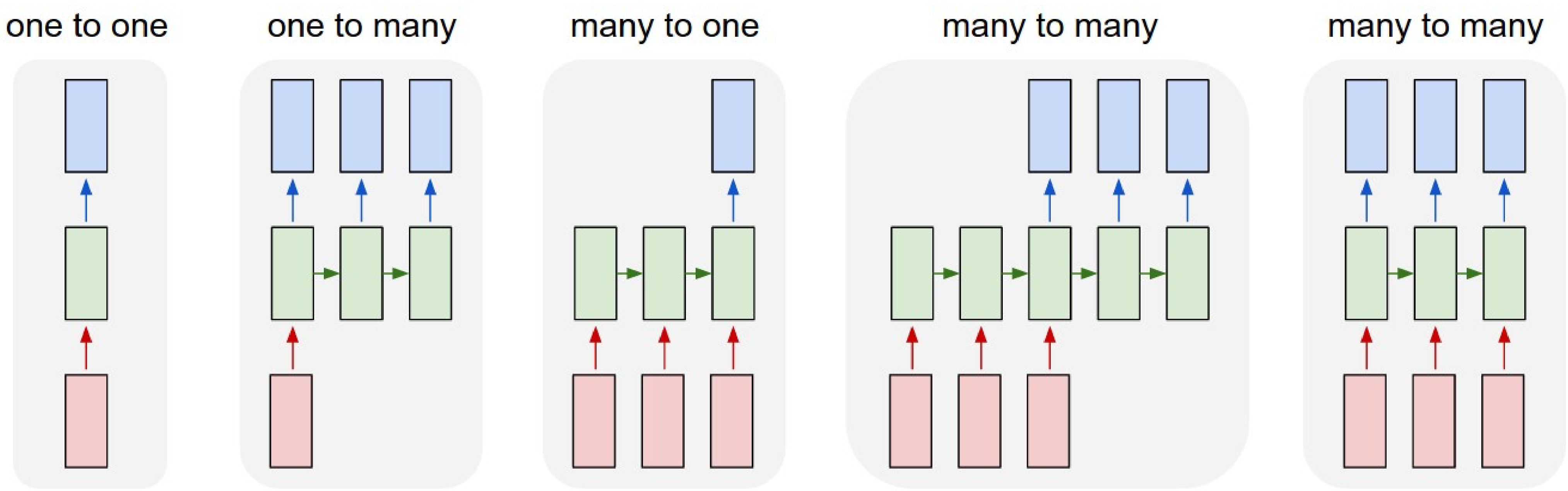


Different understanding of “it” = Different vector of “it”

Short-term Memory as Context
Recurrent Networks
Applications of RNNs

Recurrent Neural Networks

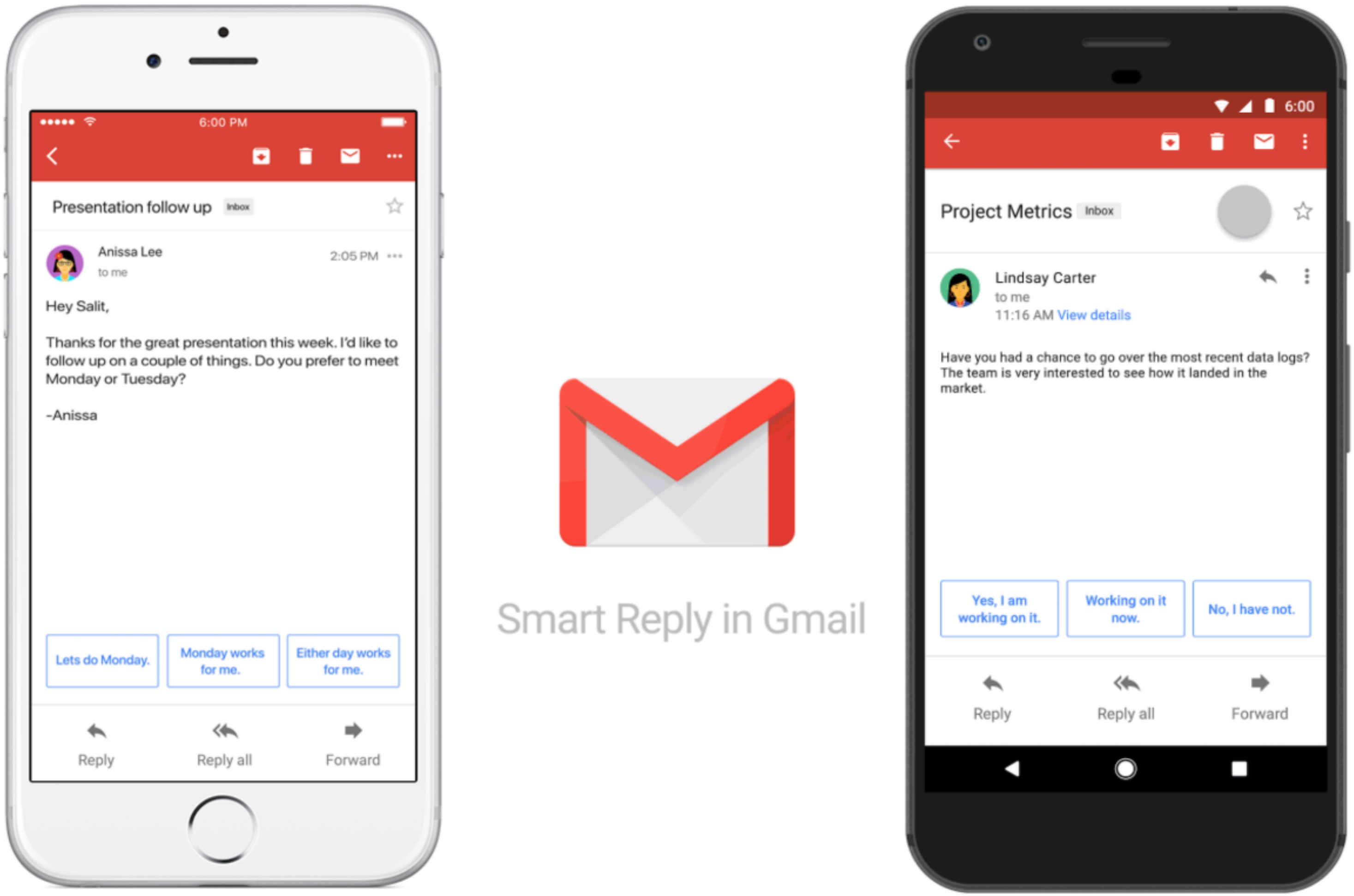
take many forms



for image classification, image captioning, sentiment classification, language translation, speech recognition, etc.

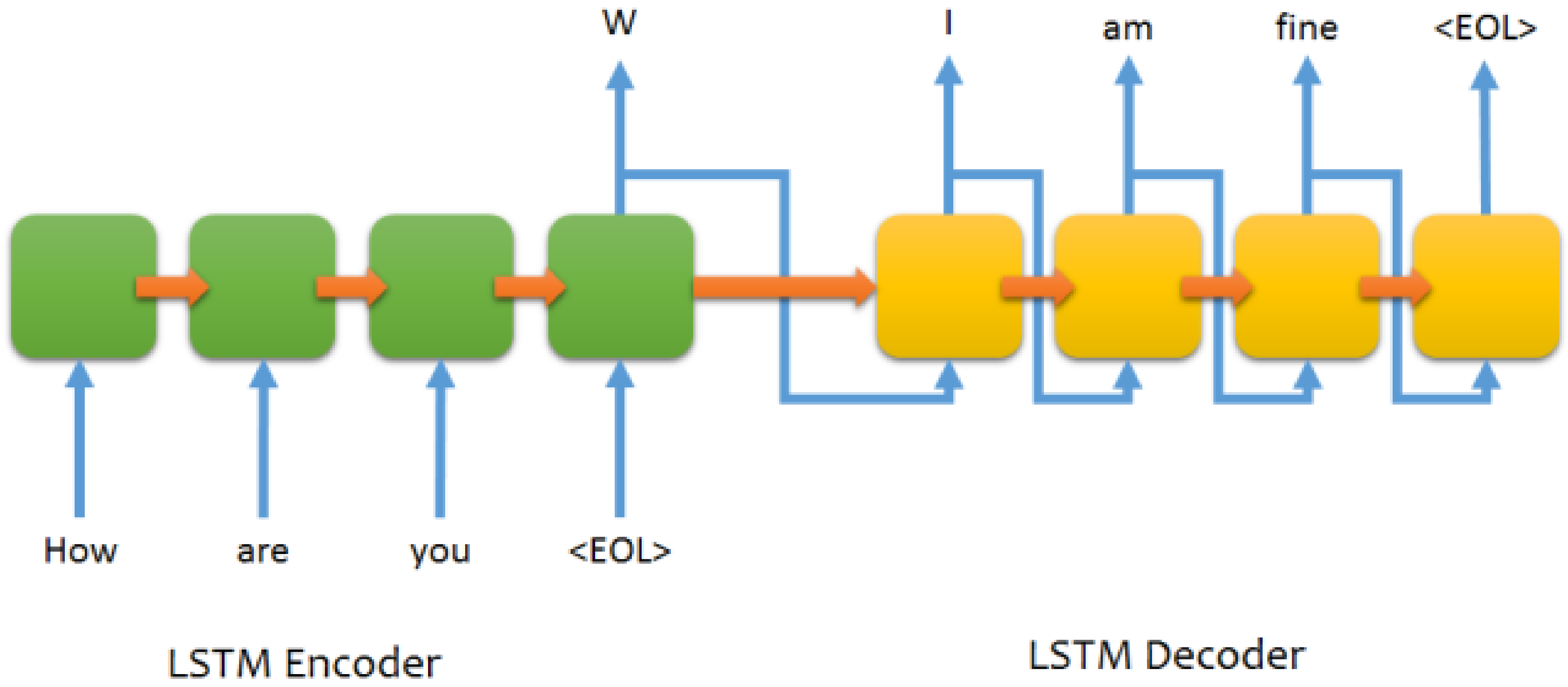
Google SmartReply

Guessing what you want to reply



Chatbots (using Seq2Seq)

Guessing what you want to know

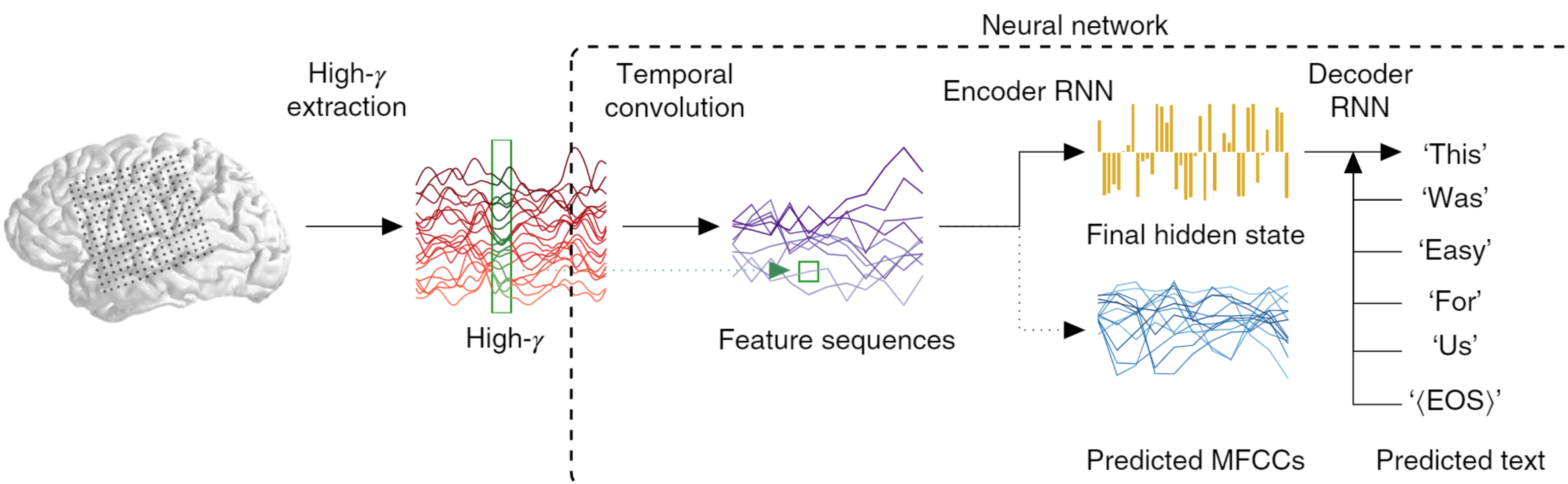


Data Modeling 範例

利用循環神經網路 (RNN) 來做 Brain Decoding

Machine translation of cortical activity to text with an encoder–decoder framework

Joseph G. Makin[1,2], David A. Moses[1,2] and Edward F. Chang[1,2]

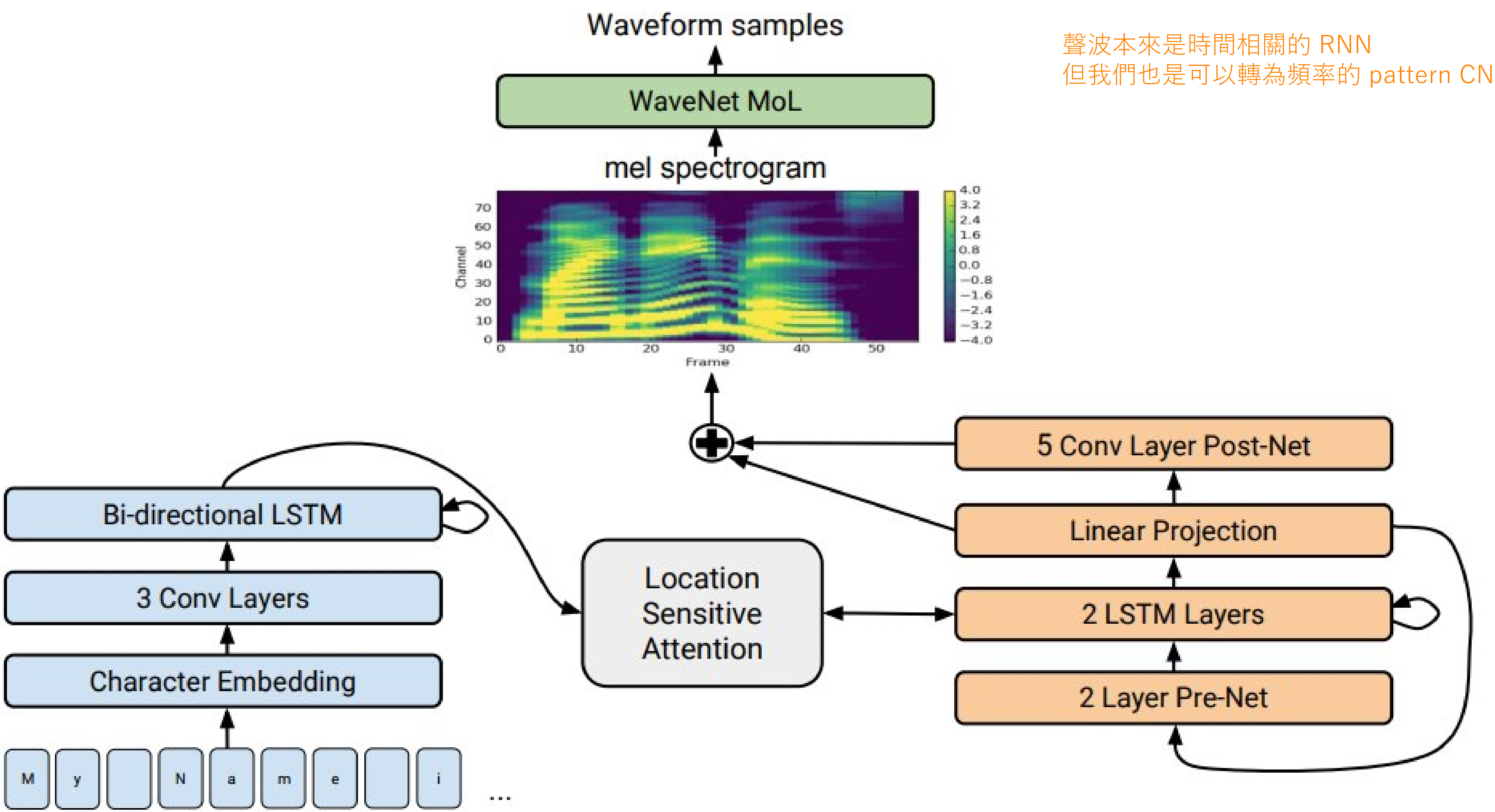


Generating Scripts for Movies

Here is the Chinese version of Sunspring

Speech Synthesis

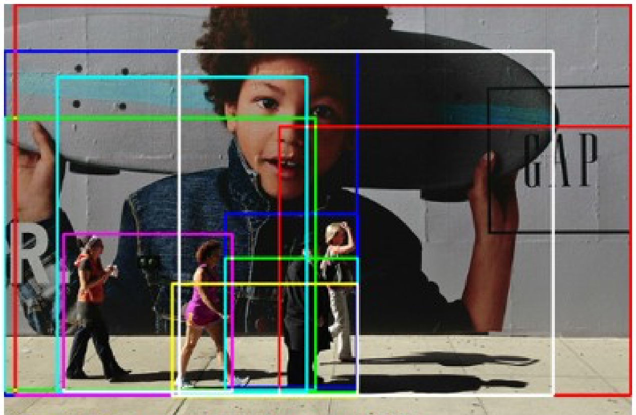
The reverse problem of Speech Recognition



聲波本來是時間相關的 RNN
但我們也是可以轉為頻率的 pattern CNN

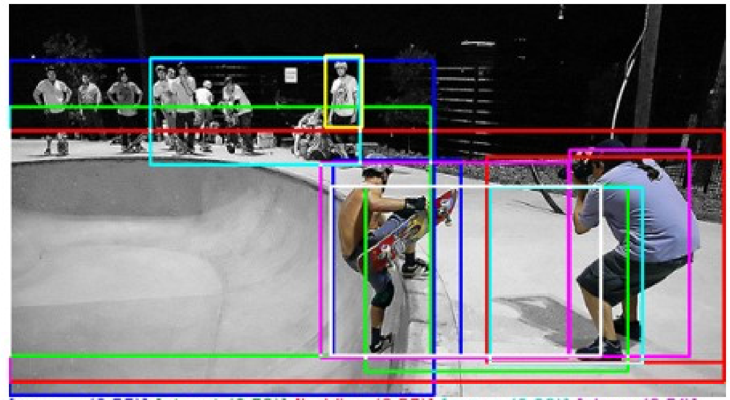
Image Captioning

Image to text



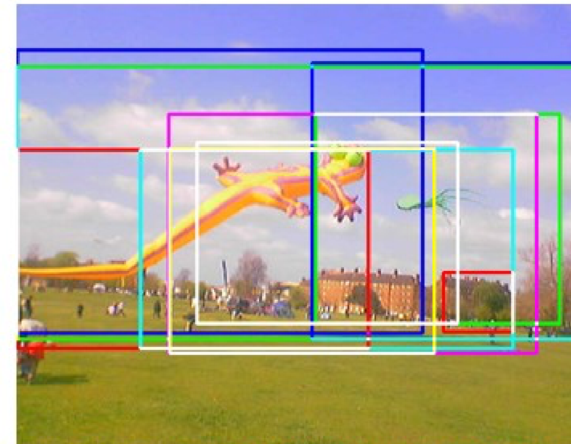
[men (0.59)] [group (0.66)] [woman (0.64)]
[people (0.89)] [holding (0.60)] [playing (0.61)] [tennis (0.69)]
[court (0.51)] [standing (0.59)] [skis (0.58)] [street (0.52)]
[man (0.77)] [skateboard (0.67)]

a group of people standing next to each other
people stand outside a large ad for gap featuring a young boy



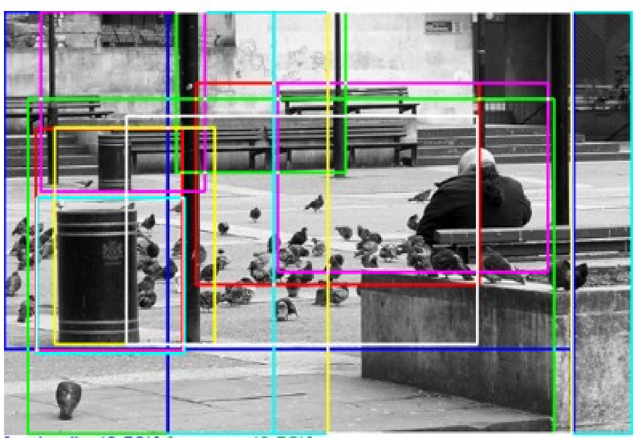
[person (0.55)] [street (0.53)] [holding (0.55)] [group (0.63)] [slope (0.51)]
[standing (0.62)] [snow (0.91)] [skis (0.74)] [player (0.54)]
[people (0.85)] [men (0.57)] [skiing (0.51)]
[skateboard (0.89)] [riding (0.75)] [tennis (0.74)] [trick (0.53)] [skate (0.52)]
[woman (0.52)] [man (0.86)] [down (0.61)]

a group of people riding skis down a snow covered slope
a guy on a skate board on the side of a ramp



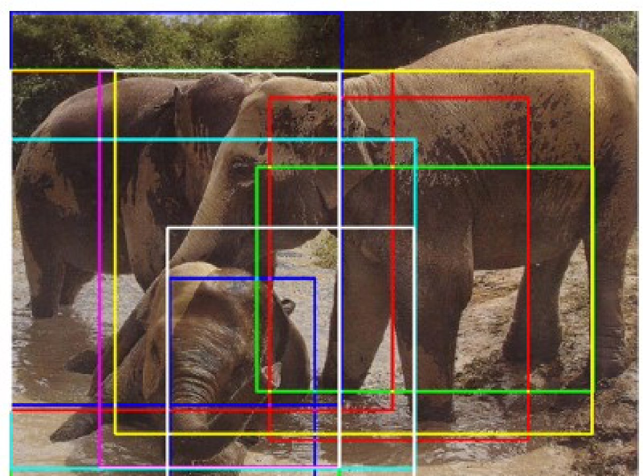
[airplane (0.57)] [plane (0.58)] [kites (0.93)] [people (0.80)]
[flying (0.93)] [man (0.57)] [beach (0.84)] [wave (0.61)]
[sky (0.61)] [kite (0.74)] [field (0.75)]

a couple of people flying kites in a field
people in a field flying different styles of kite



[umbrella (0.59)] [woman (0.52)]
[fire (0.96)] [hydrant (0.96)] [street (0.79)] [old (0.50)]
[bench (0.81)] [building (0.75)] [standing (0.57)] [baseball (0.55)]
[white (0.82)] [sitting (0.65)] [people (0.79)] [photo (0.53)]
[black (0.84)] [kitchen (0.54)] [man (0.72)] [water (0.56)]

a black and white photo of a fire hydrant
a courtyard full of poles pigeons and garbage cans also has benches on



[horse (0.53)] [bear (0.71)] [elephant (0.99)] [elephants (0.95)]
[brown (0.68)] [baby (0.62)] [walking (0.57)] [laying (0.61)]
[man (0.57)] [standing (0.79)] [field (0.65)]
[water (0.83)] [large (0.71)] [dirt (0.65)] [river (0.58)]

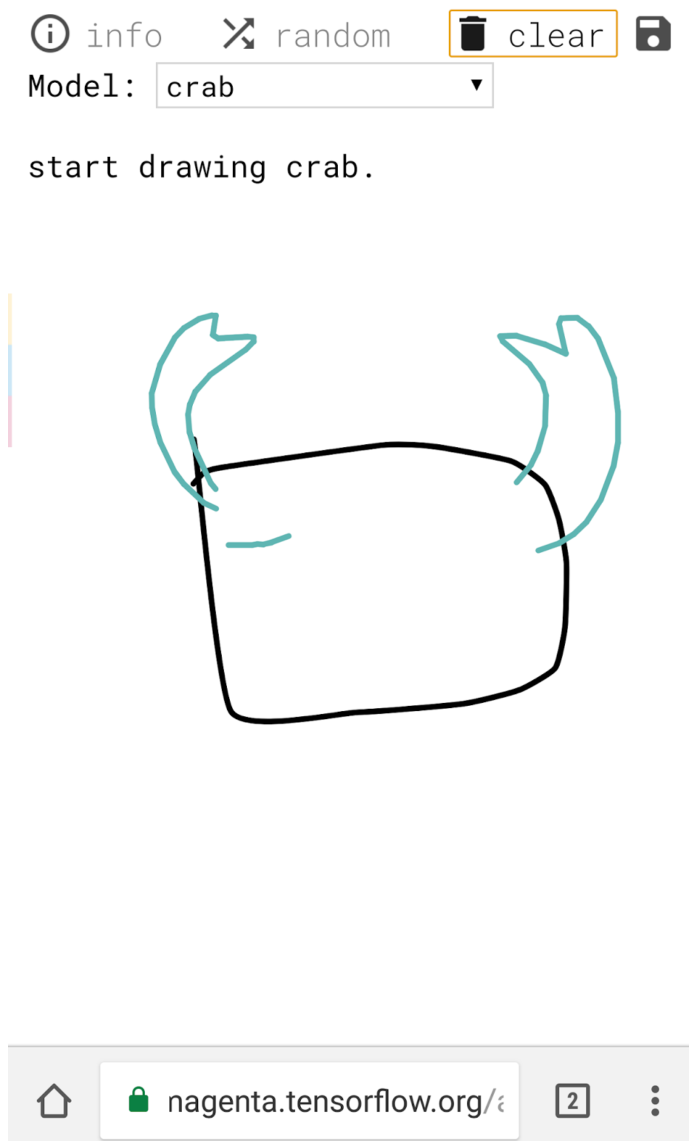
a baby elephant standing next to each other on a field

[man (0.59)] [beach (0.54)] [sky (0.53)] [bird (0.50)] [field (0.
[snow (0.86)] [mountain (0.59)] [standing (0.81)] [white (0.64)
[people (0.51)] [dog (0.60)] [cows (0.55)]
[sheep (0.97)] [black (0.84)] [grass (0.64)] [horse (0.60)]
[elephants (0.57)] [bear (0.81)]

a black bear standing on top of a grass covered

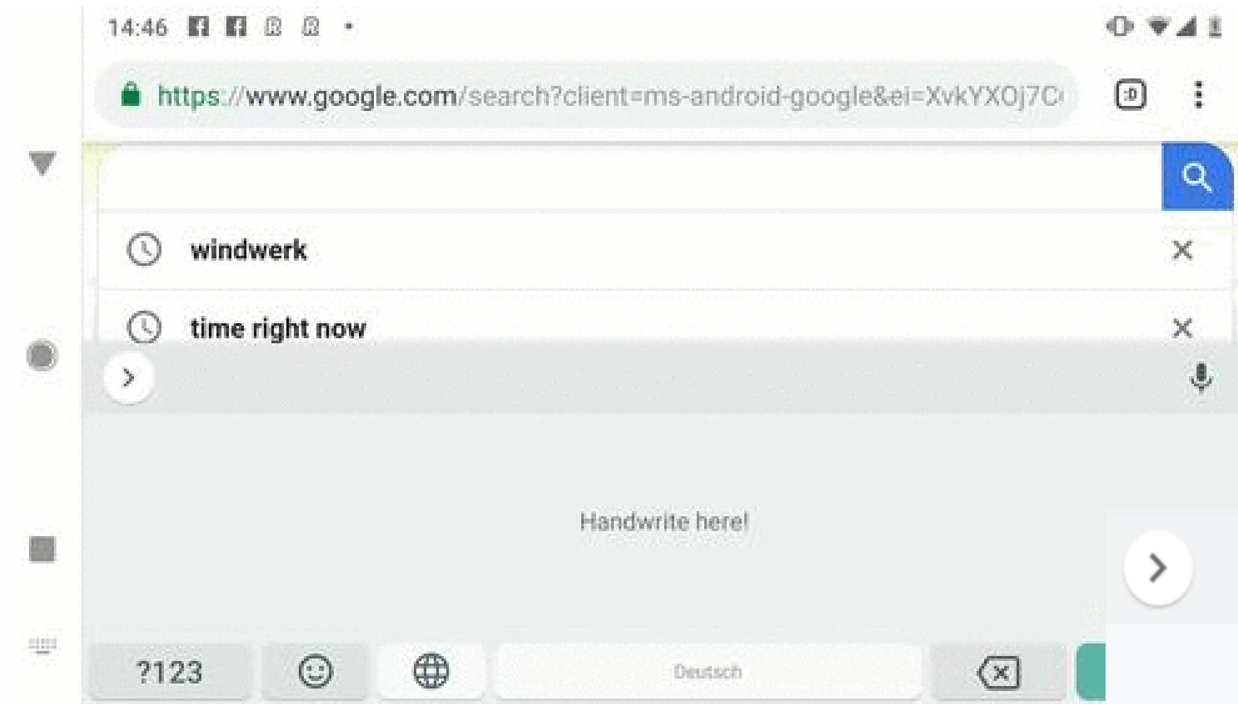
Sketch-RNN

Guessing what you want to draw

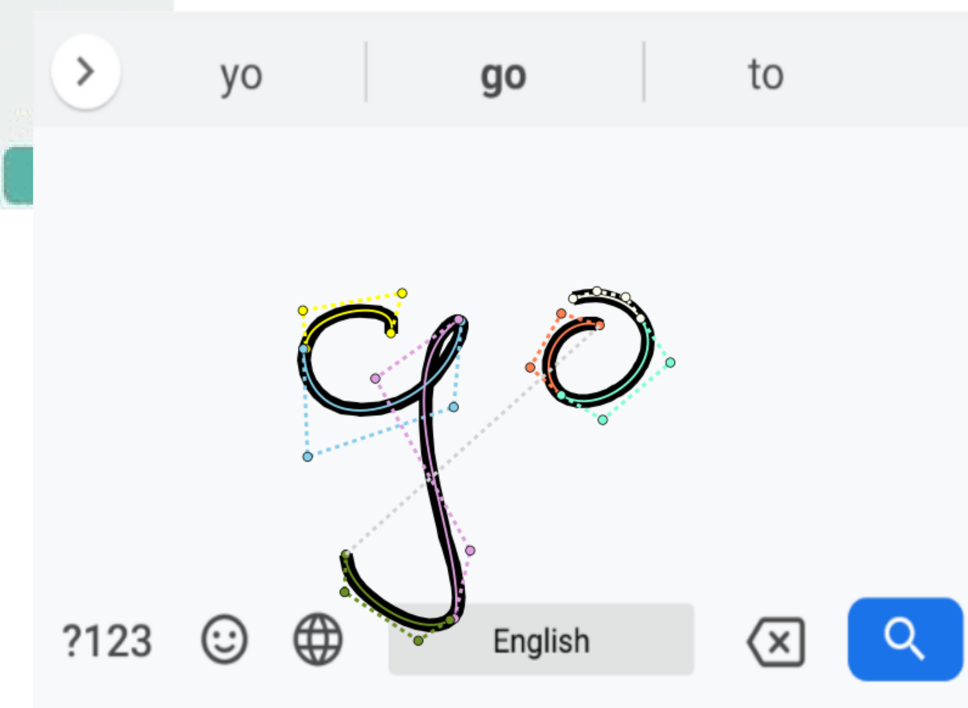


GBoard

Guessing what you are writing



用筆畫來預測
temporal regularity
RNN



Game Over