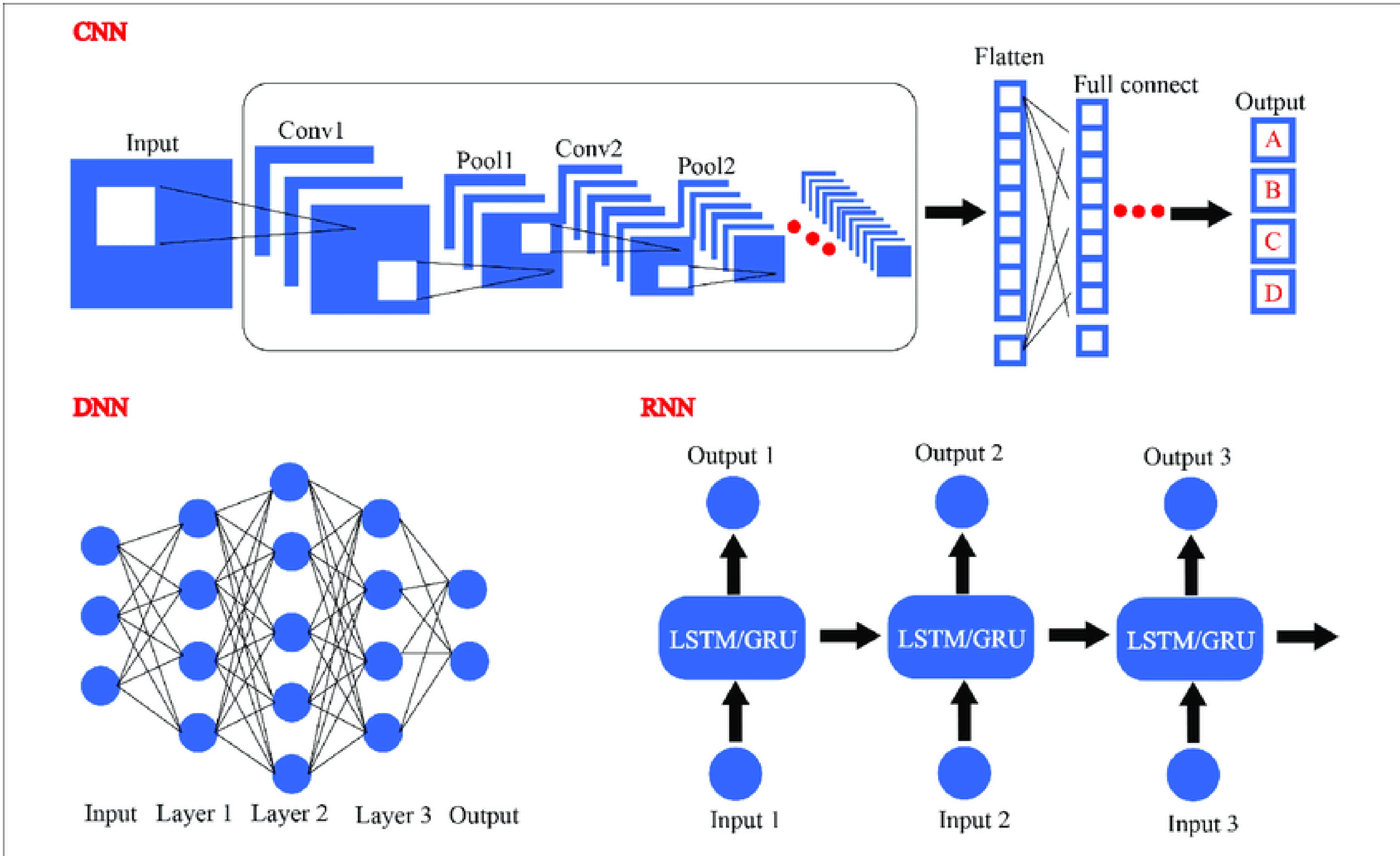
神經與行為模型建構
(Neural & Behavioral Modeling)

課號：Psy5352　　教室： 普 101
識別碼：227U2810　　時間： 一 234

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

數學上無解：

x= 紅 → y= 紅（叫意）

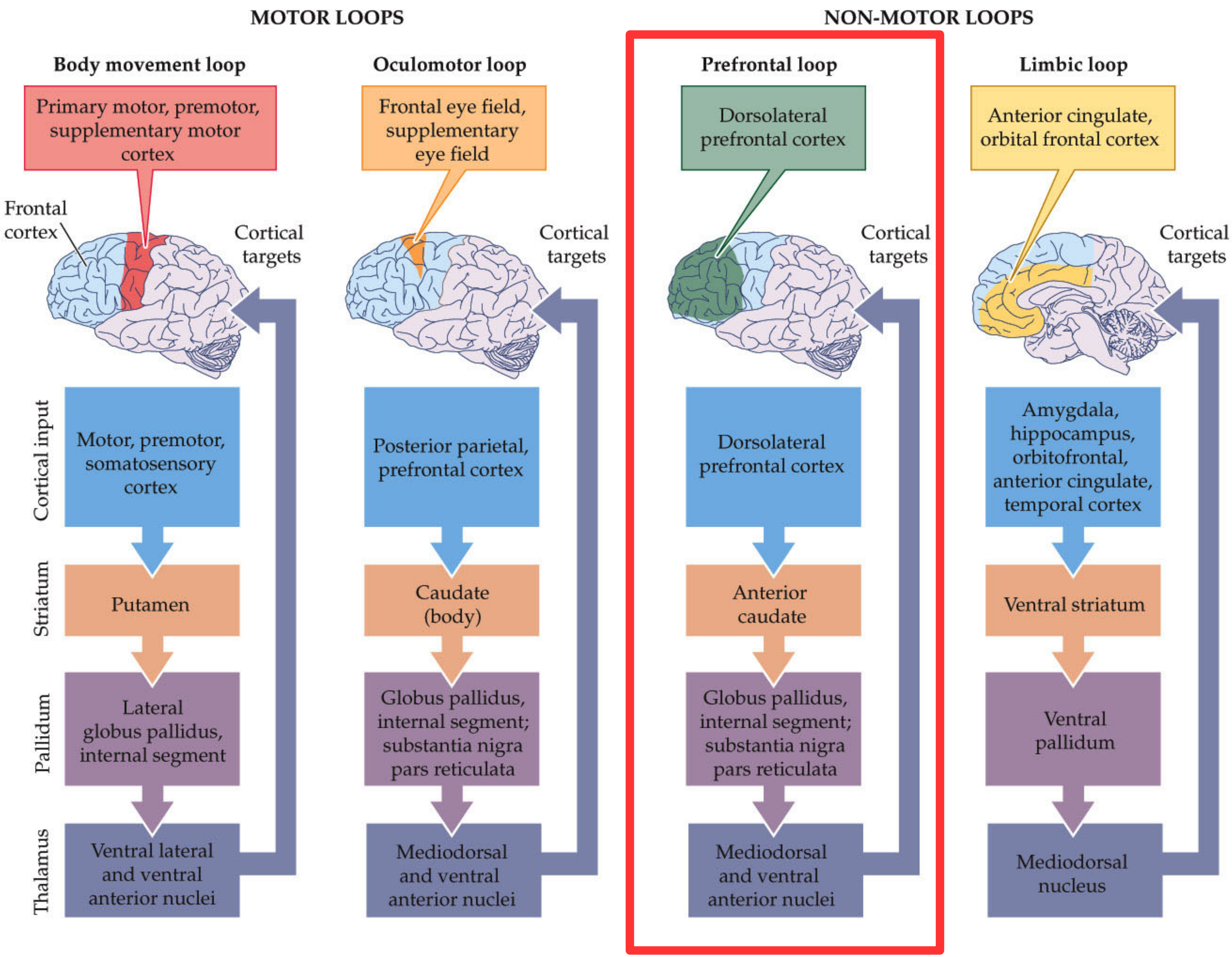
x= 紅 → y= 綠（叫色）

數學上有解：

x=(紅 , 叫意) → y= 紅

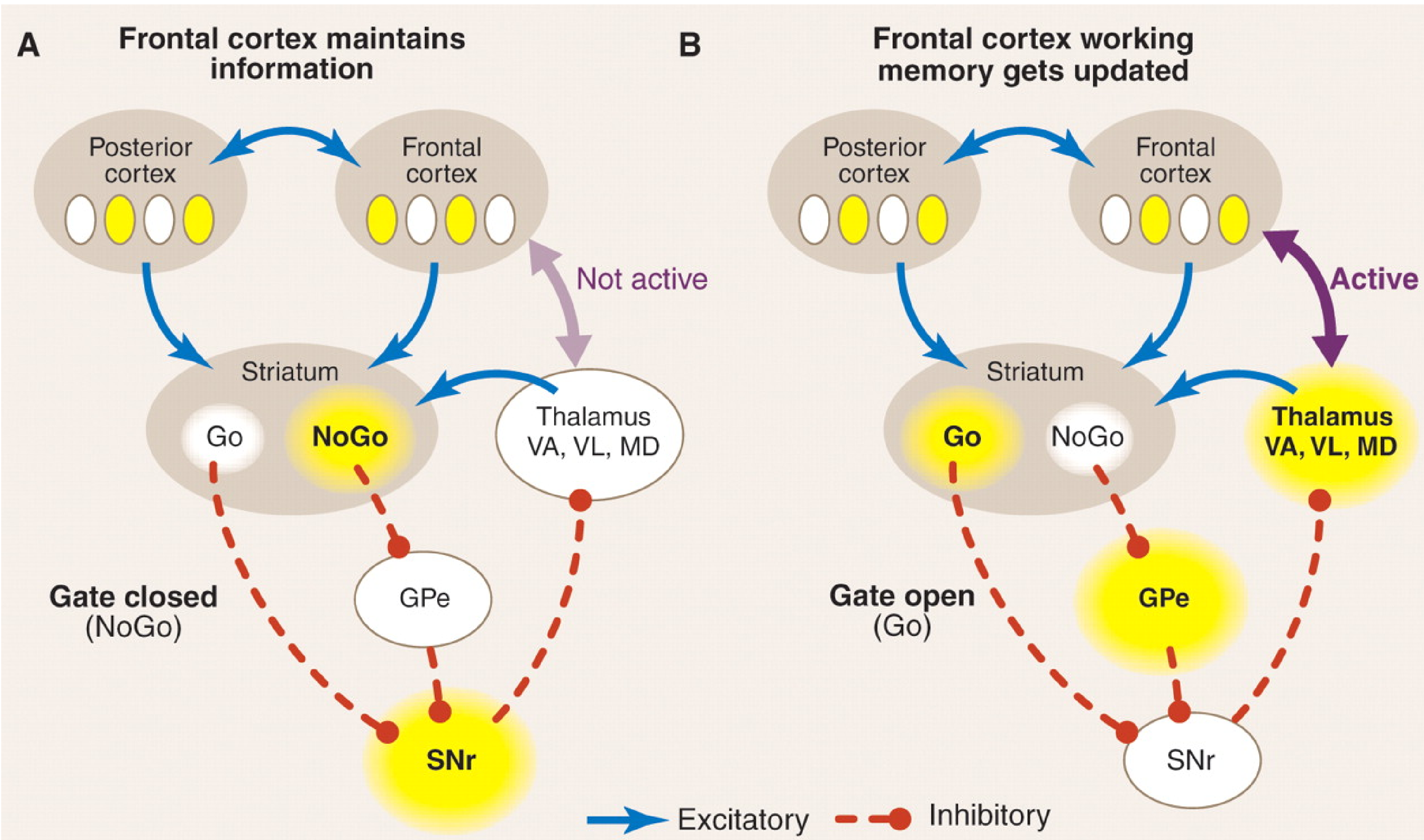
x=(紅 , 叫色) → y= 綠

Cortico-Basal Ganglia Loops



BG-modulated PFC

= Prefrontal cortex Basal ganglia Working Memory



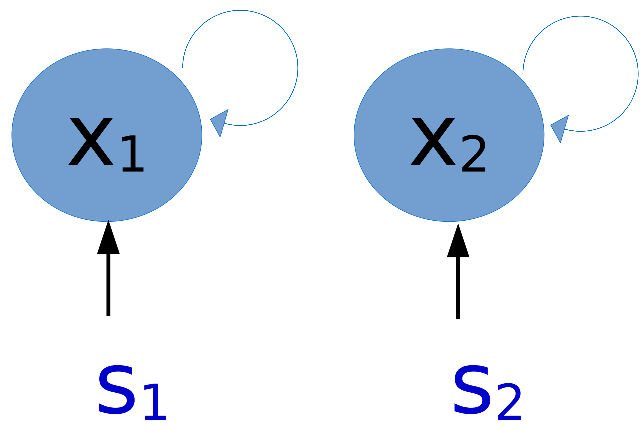
Short-term Memory as Context

Recurrent Networks

Applications of RNNs

Self-Recurrent Excitations

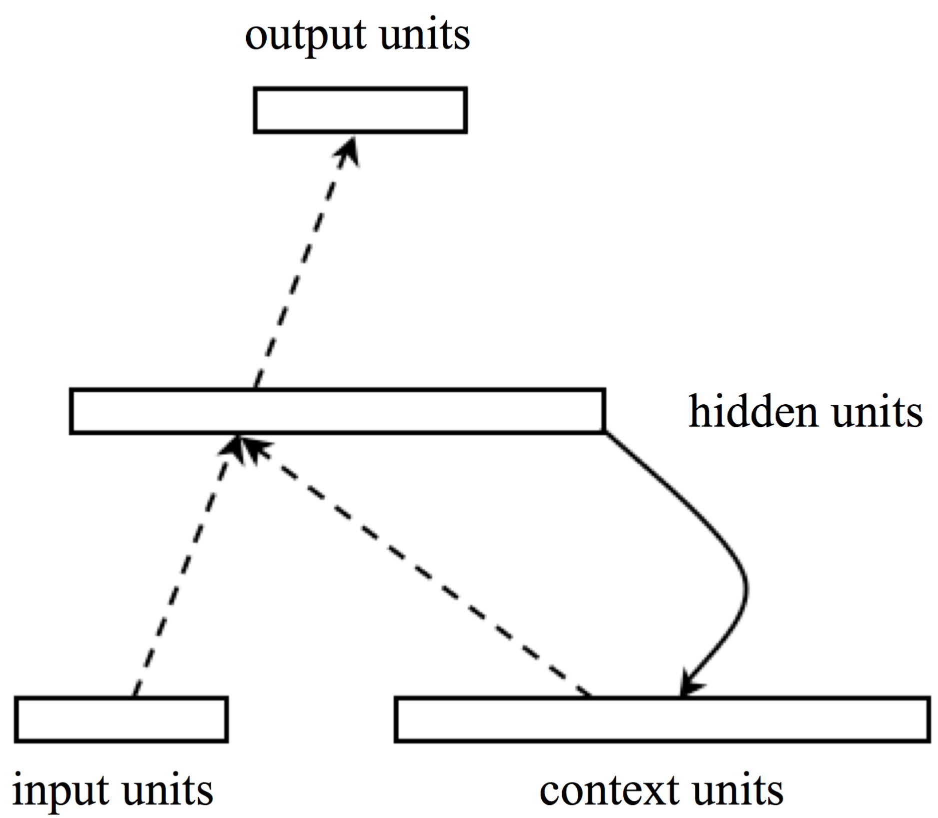
自我連結的刺激可維持反應卻無法維持刺激對比

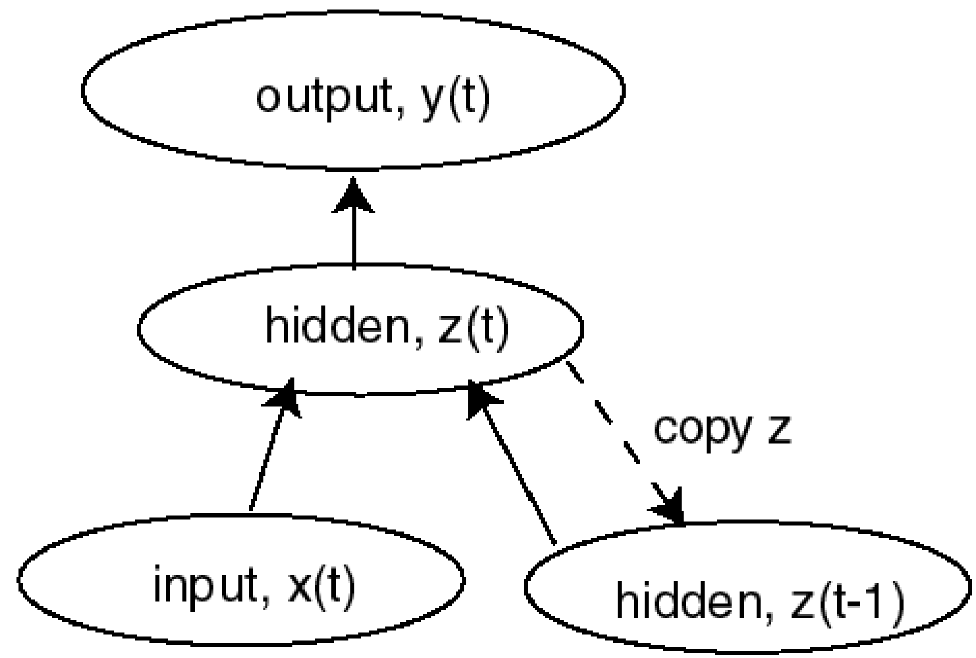



```
x=[0,0]; dt=0.1
for t in arange(0,10,dt):
    s=[1,10] if t<1 else [0,0]
    x[0]=x[0]+dt*(-0.1*x[0]+(1-x[0])*(s[0]+x[0]))
    x[1]=x[1]+dt*(-0.1*x[1]+(1-x[1])*(s[1]+x[1]))
    clf(); plot([1,2],x,'-o')
    ylim([0,1]); title('t='+str(t))
    display(gcf()); clear_output(wait=True)
```

Simple RNN (1/2)

by Elman (1990)

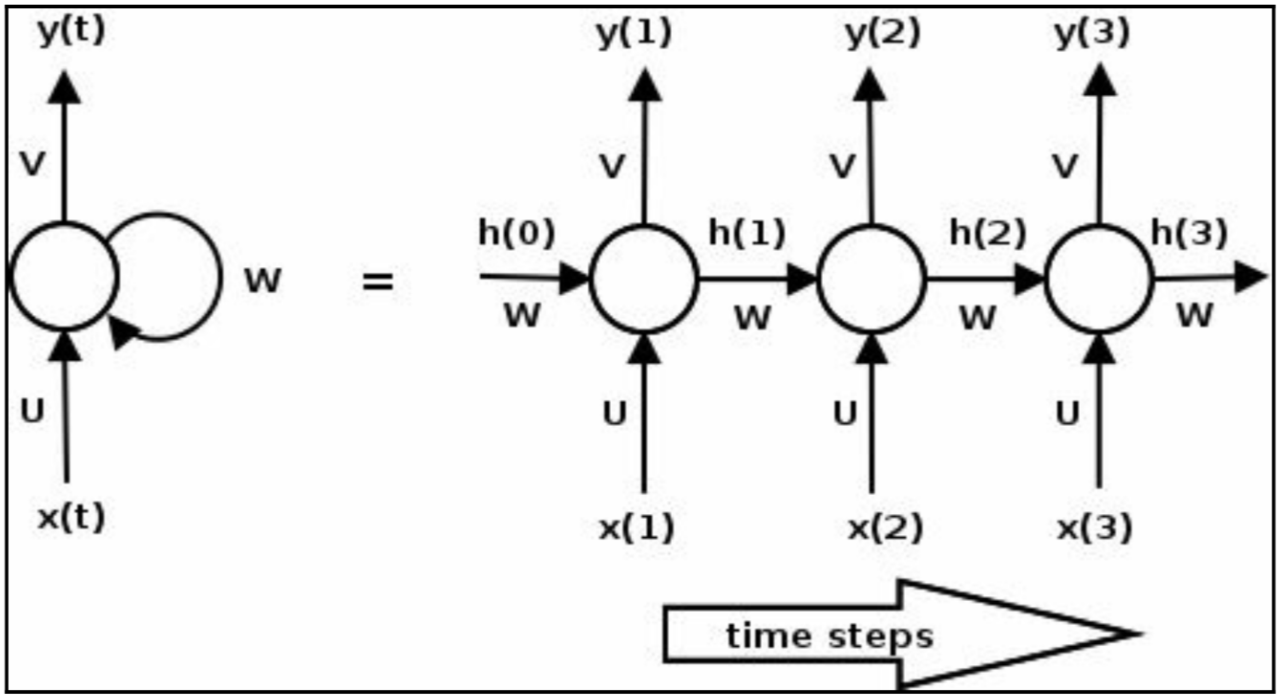




to process sequential information

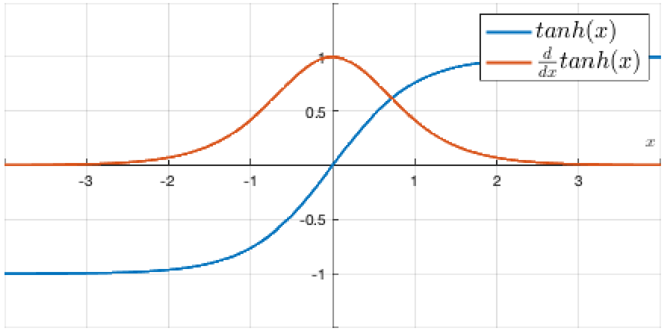
Simple RNN (2/2)

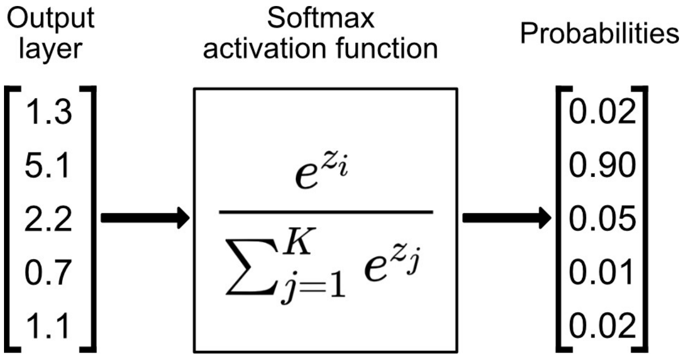
effectively has VERY deep layers



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

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





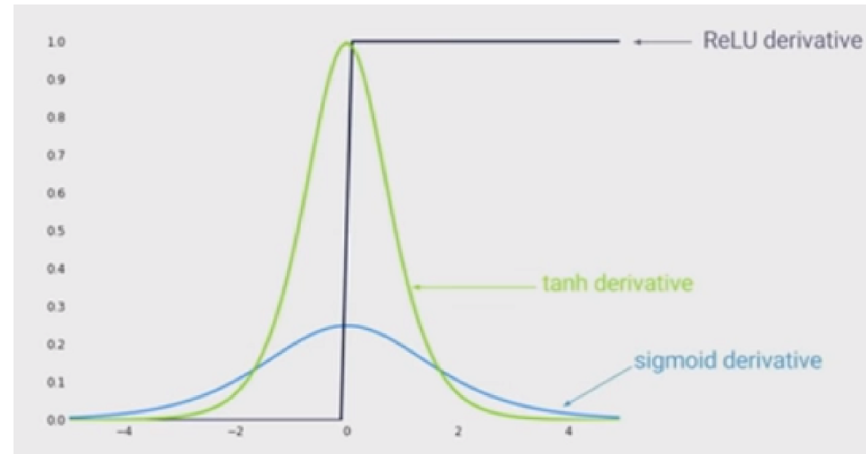
Temporal Backpropagation

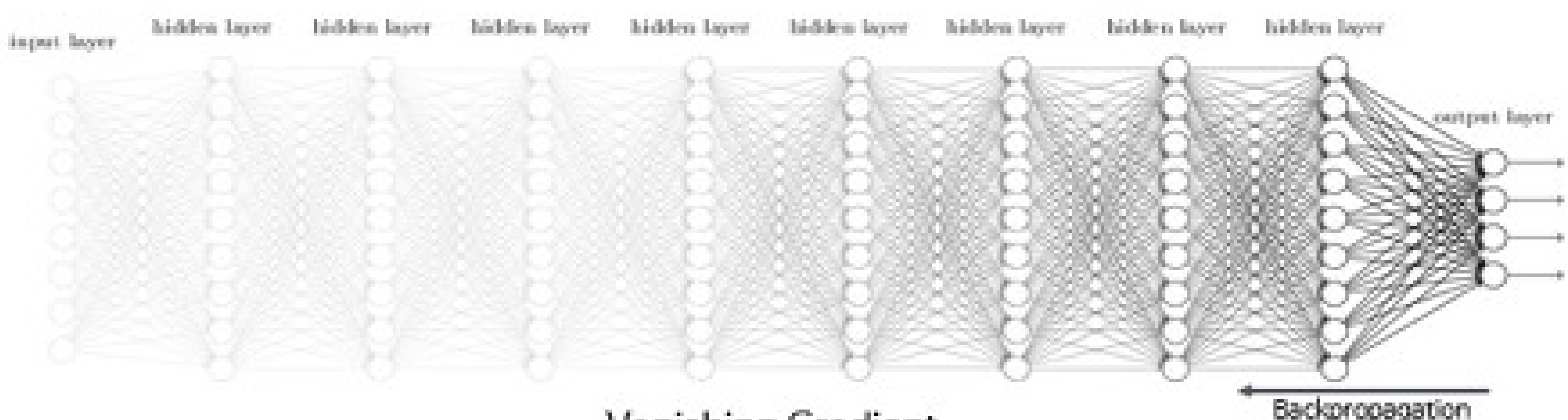
suffers from vanishing & exploding gradient problem

$$\delta_j = \frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial \text{net}_j} = \begin{cases} \frac{\partial L(o_j,t)}{\partial o_j}\frac{d\varphi(\text{net}_j)}{d\text{net}_j} & \text{if } j \text{ is an output neuron,} \\ \left(\sum_{\ell \in L} w_{j\ell}\delta_\ell\right)\frac{d\varphi(\text{net}_j)}{d\text{net}_j} & \text{if } j \text{ is an inner neuron.} \end{cases}$$

if φ is the logistic function, and the error is the square error:

$$\delta_j = \frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial \text{net}_j} = \begin{cases} (o_j - t_j)o_j(1-o_j) & \text{if } j \text{ is an output neuron,} \\ \left(\sum_{\ell \in L} w_{j\ell}\delta_\ell\right)o_j(1-o_j) & \text{if } j \text{ is an inner neuron.} \end{cases}$$

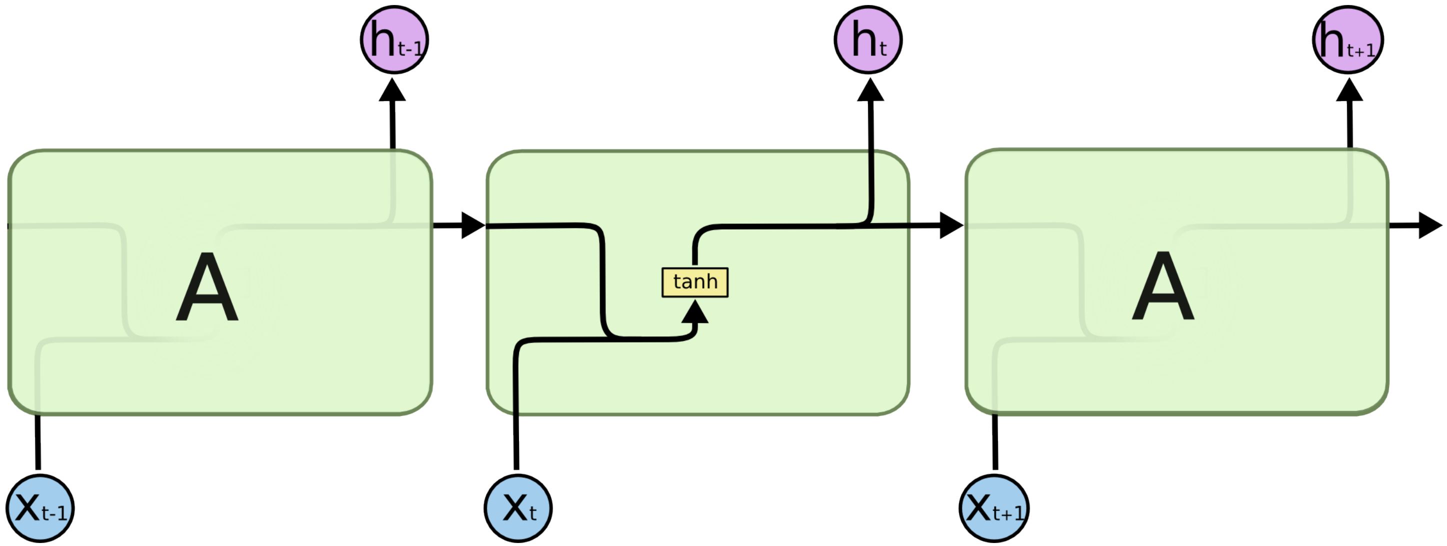


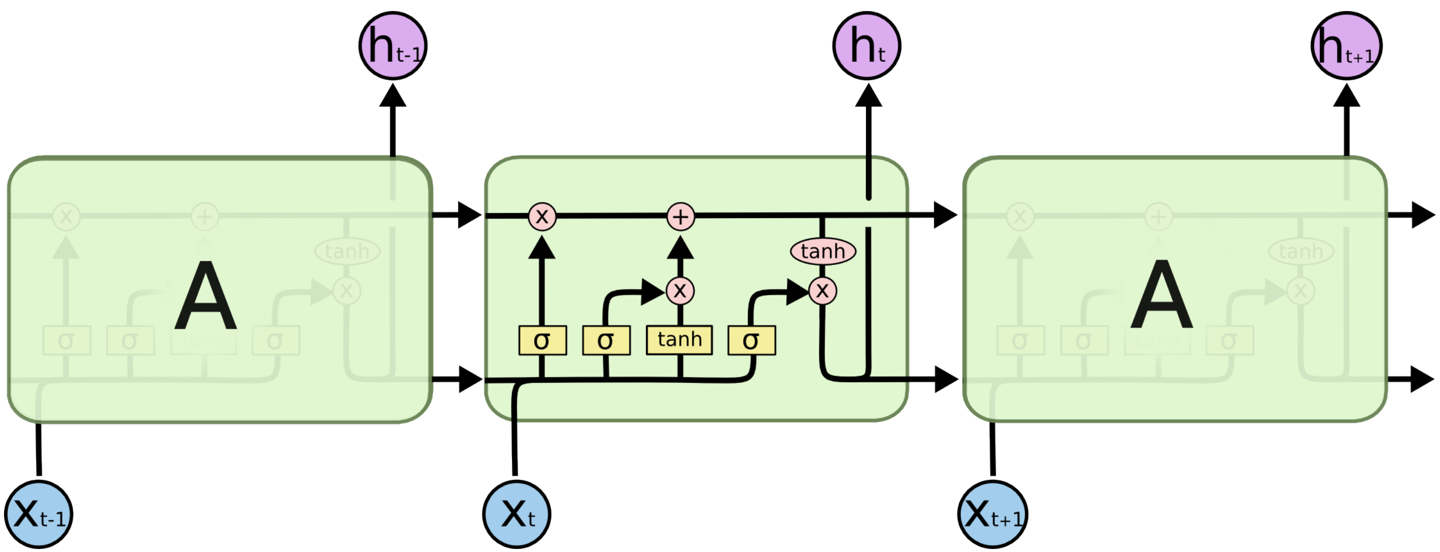


Vanishing Gradient

Long Short-term Memory (1/2)

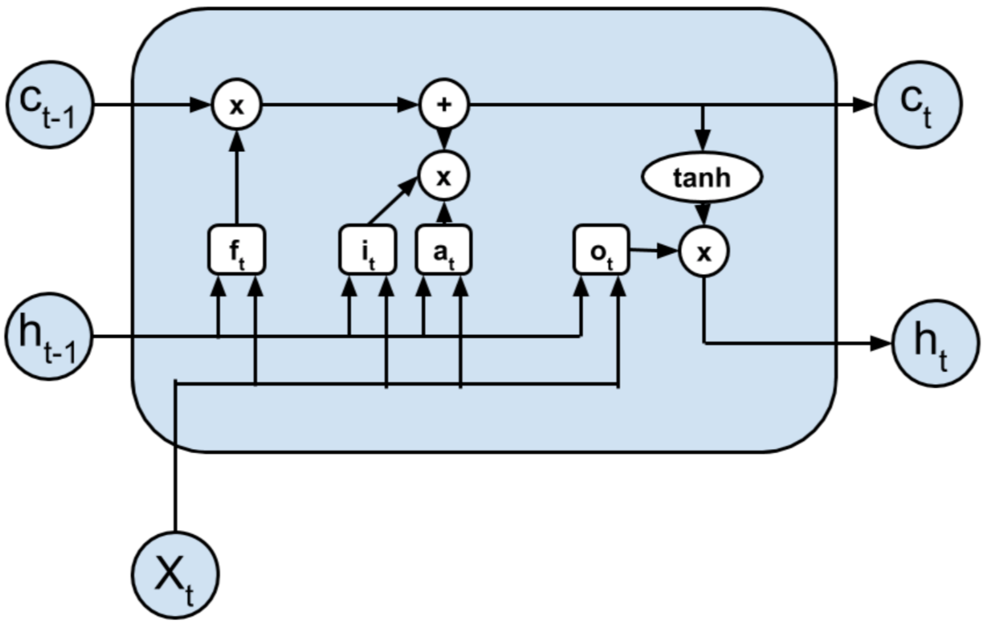
introduces forget, input, & output gates





Long Short-term Memory (2/2)

E.g., reset context for '.', ignore '\n', & cued response



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

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

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

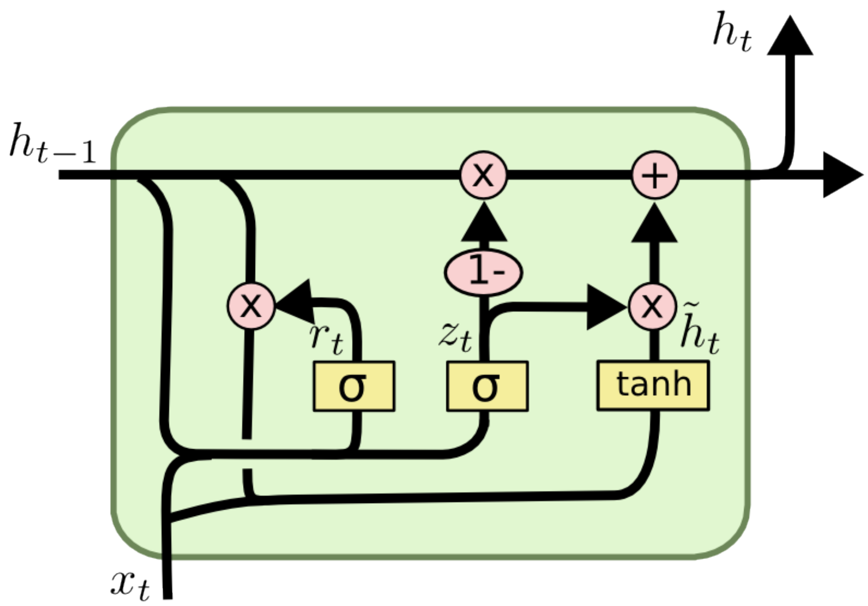
$$o_t = \sigma\left(W_o h_{t-1} + U_o x_t + b_o\right)$$

$$\boxed{\begin{aligned} c_t &= f_t * c_{t-1} + i_t * a_t \\ h_t &= o_t * \tanh\left(c_t\right) \end{aligned}}$$

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

Gated Recurrent Unit

GRU is a simplified LSTM without an output gate



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

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

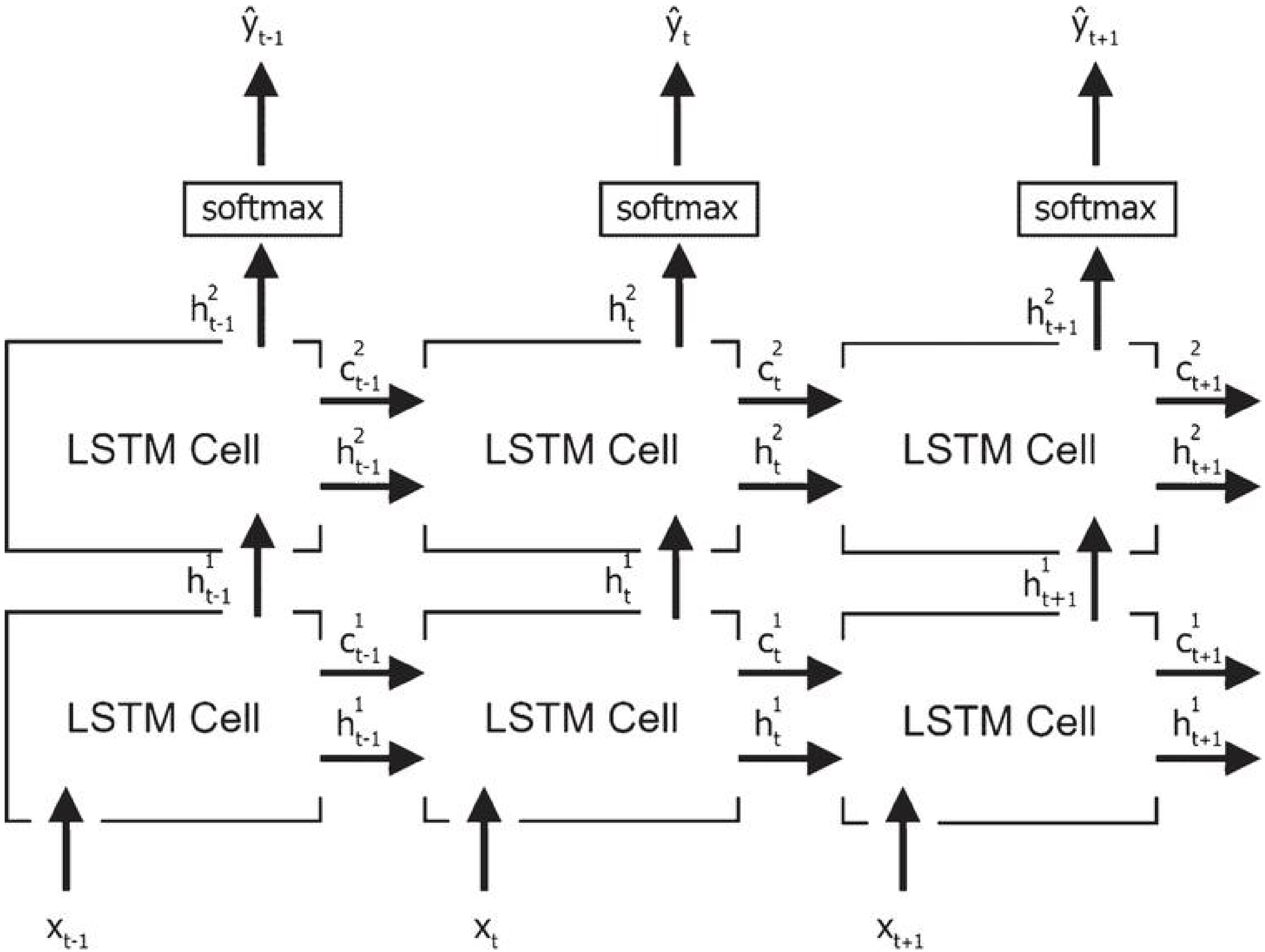
$$\boxed{\begin{aligned}\tilde{h}_t &= \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)\\ h_t &= (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t\end{aligned}}$$

memory input

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

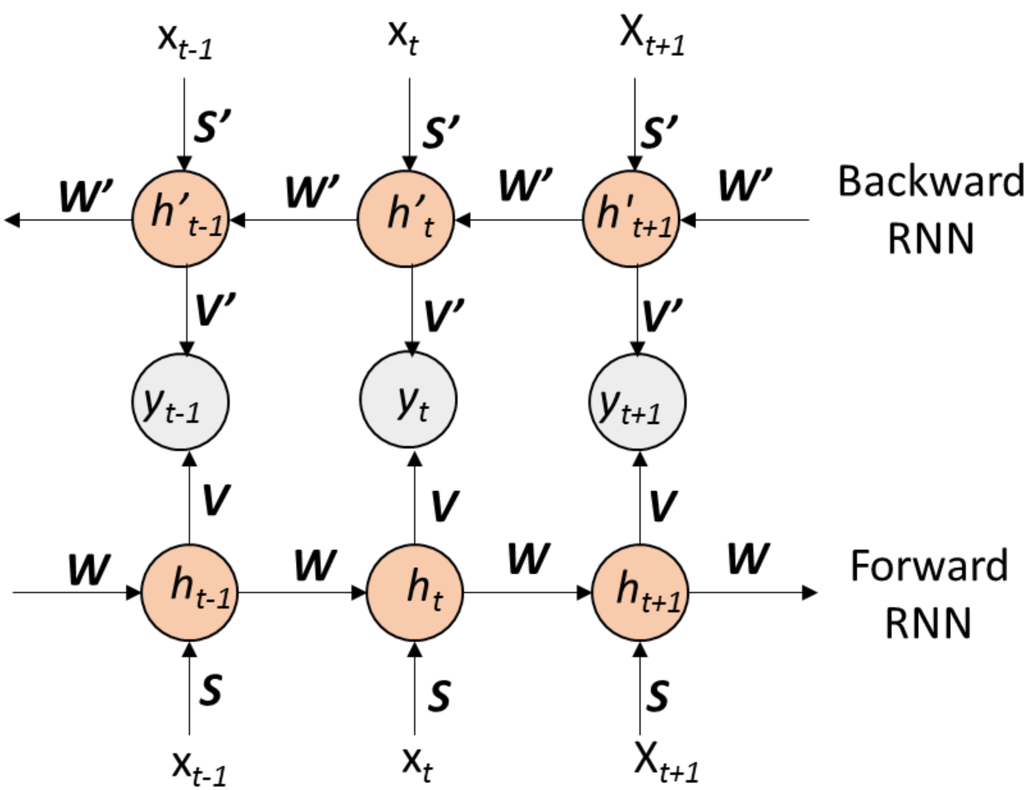
Stacked LSTMs

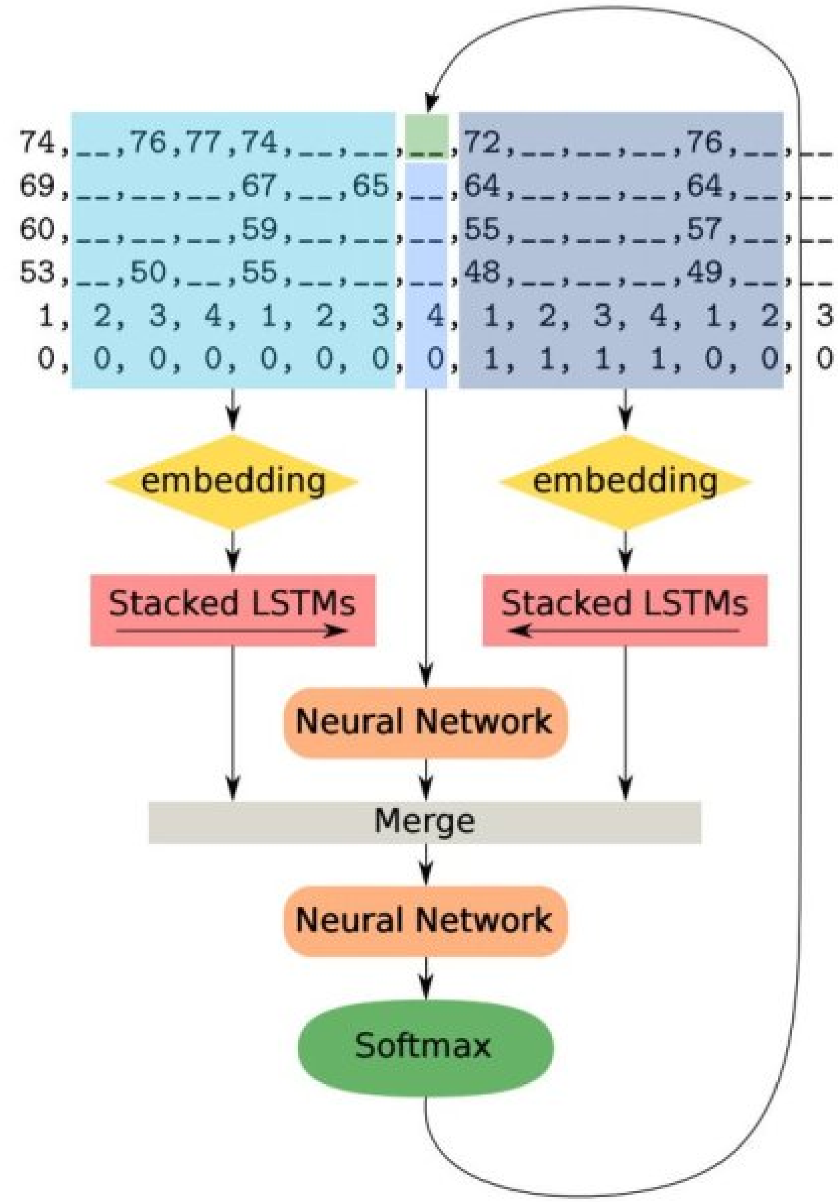
Namely LSTM with more hidden layers



Bidirectional RNN

c.f. BERT=Bidirectional Encoder Representations from Transformers





Attention replacing RNN (1/2)

Attention Is All You Need

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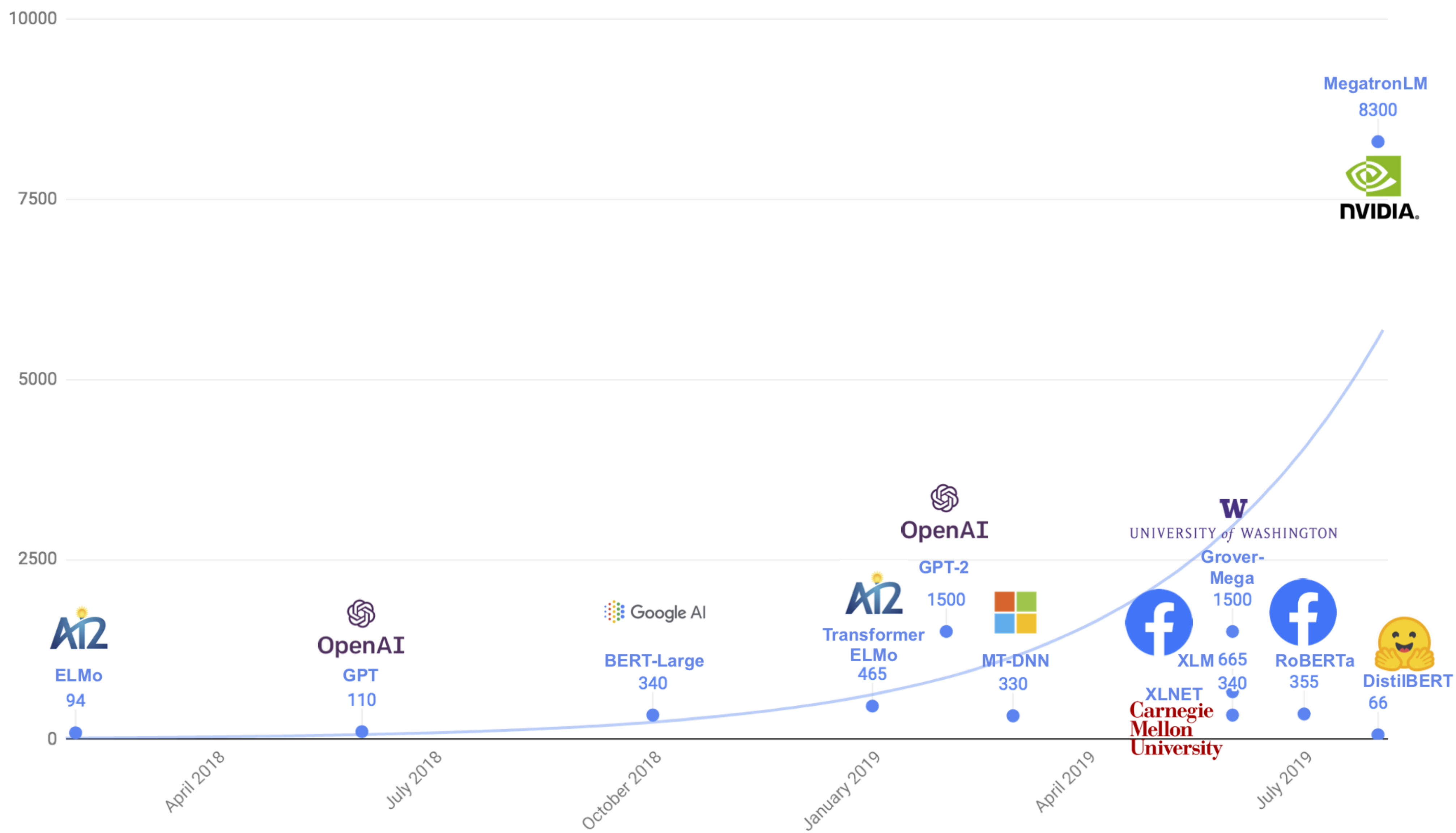
Abstract

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 (2/2)

Variants of Transformer:



Attention-modulated Input

Same input ---attention---> Different outputs

Query 1: How many people are there?
Query 2: What are they doing?
Query 3: How wealthy is the house owner?

Transformer

Encoder: Parallel Inputs;Decoder: Sequential Outputs

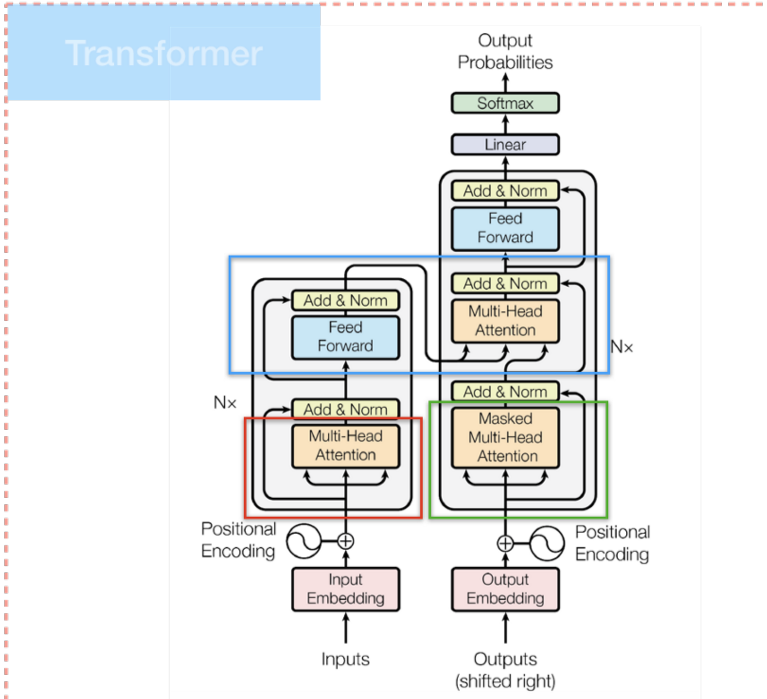


Figure 1: The Transformer - model architecture.

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**

Attention Ai= Softmax((Q* Ki) / Scale)

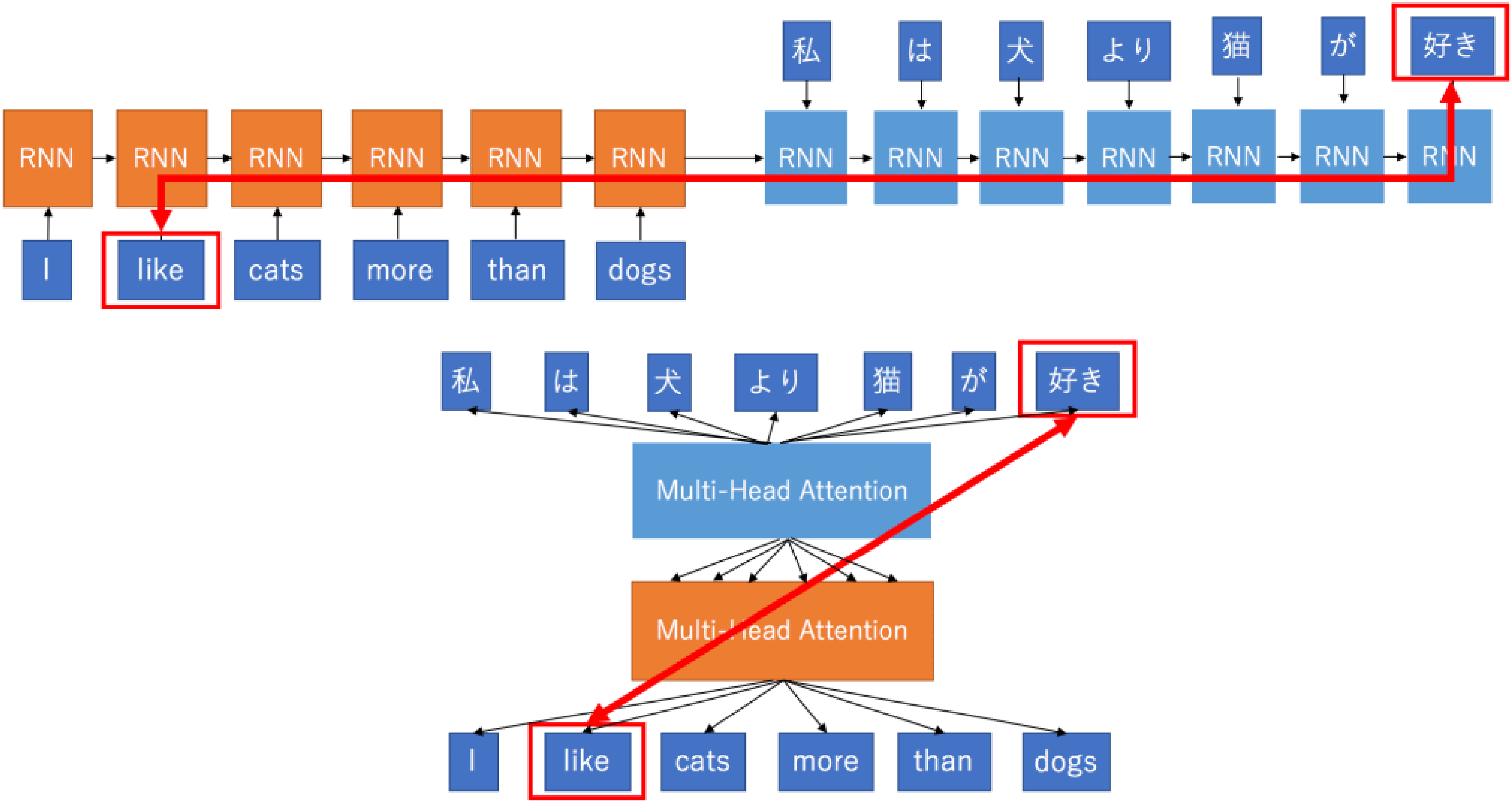
Attention-modulated embedding= ΣAi*Vi

Attention: (Nov 21 2022, Q=null)→2022; (Nov 21 2022, Q=2022)→11; (Nov 21 2022, Q=11)→21

Self-Attention: (We gave bananas to monkeys because *they* were ripe/hungry, Q= 因為)→ *它 / 牠*

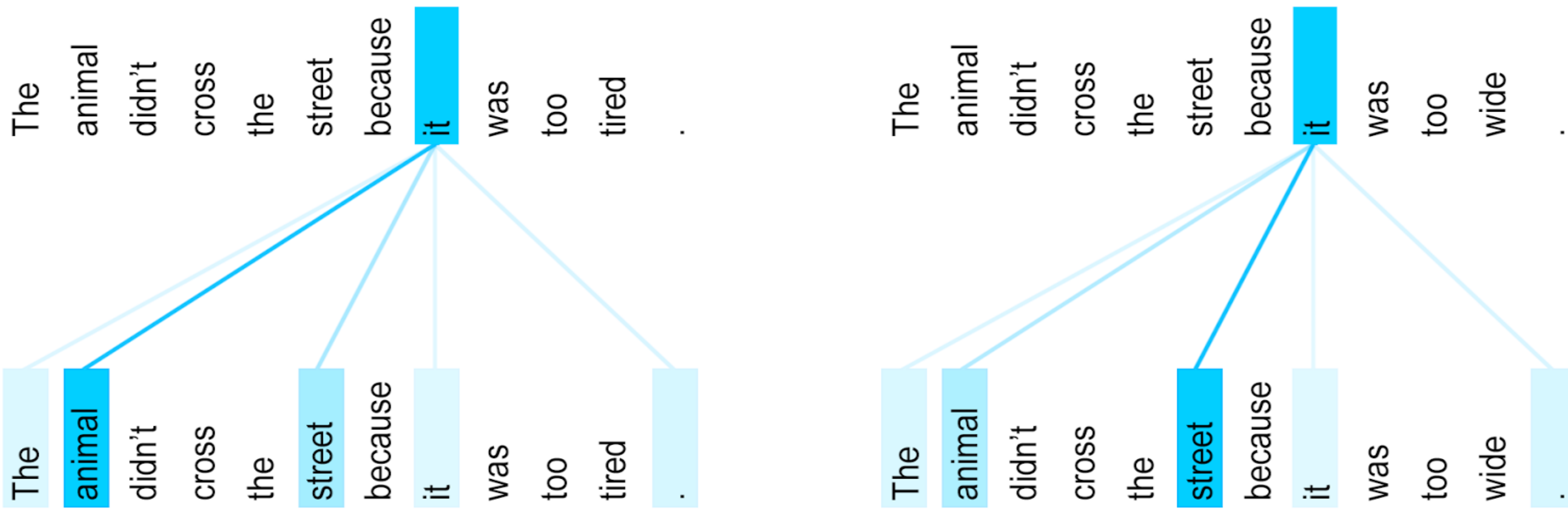
Encoder-Decoder Attention

Attention helps to focus on predictive input/features



Encode/Decoder Self-Attention

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

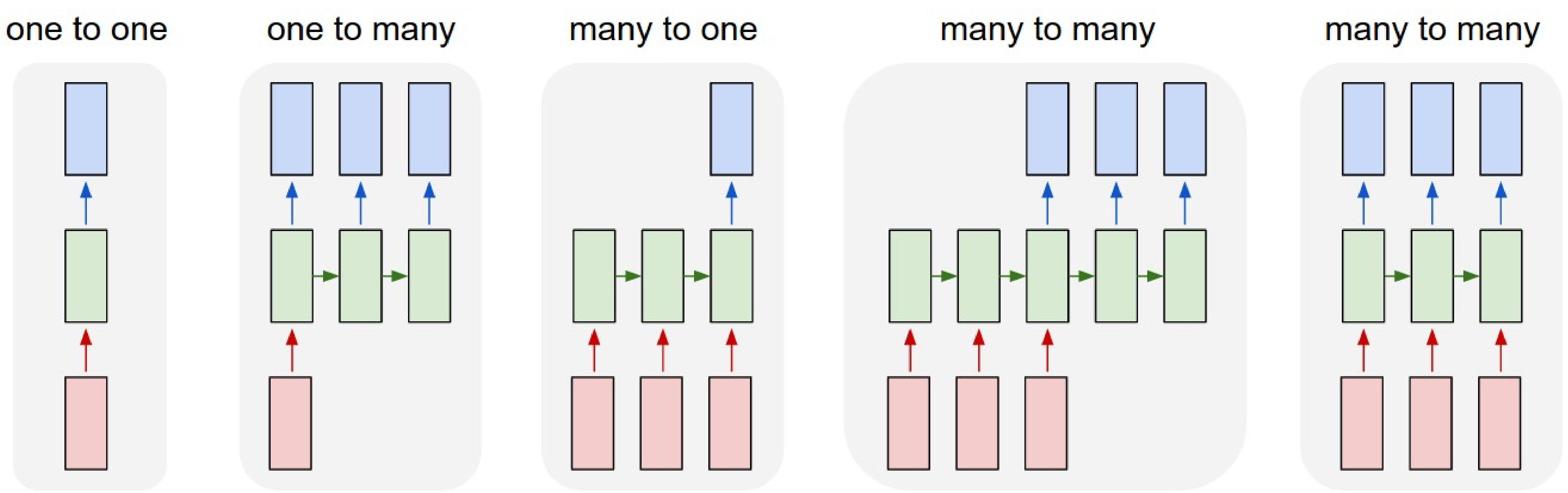


Self-attention helps to convert the *context-independent* embedding vector of a word Vi to a *context-dependent* embedding= ΣAi*Vi where Ai=Q*Ki and Q=embedding of “it”.

Short-term Memory as Context
Recurrent Networks
Applications of RNNs

Recurrent Neural Networks

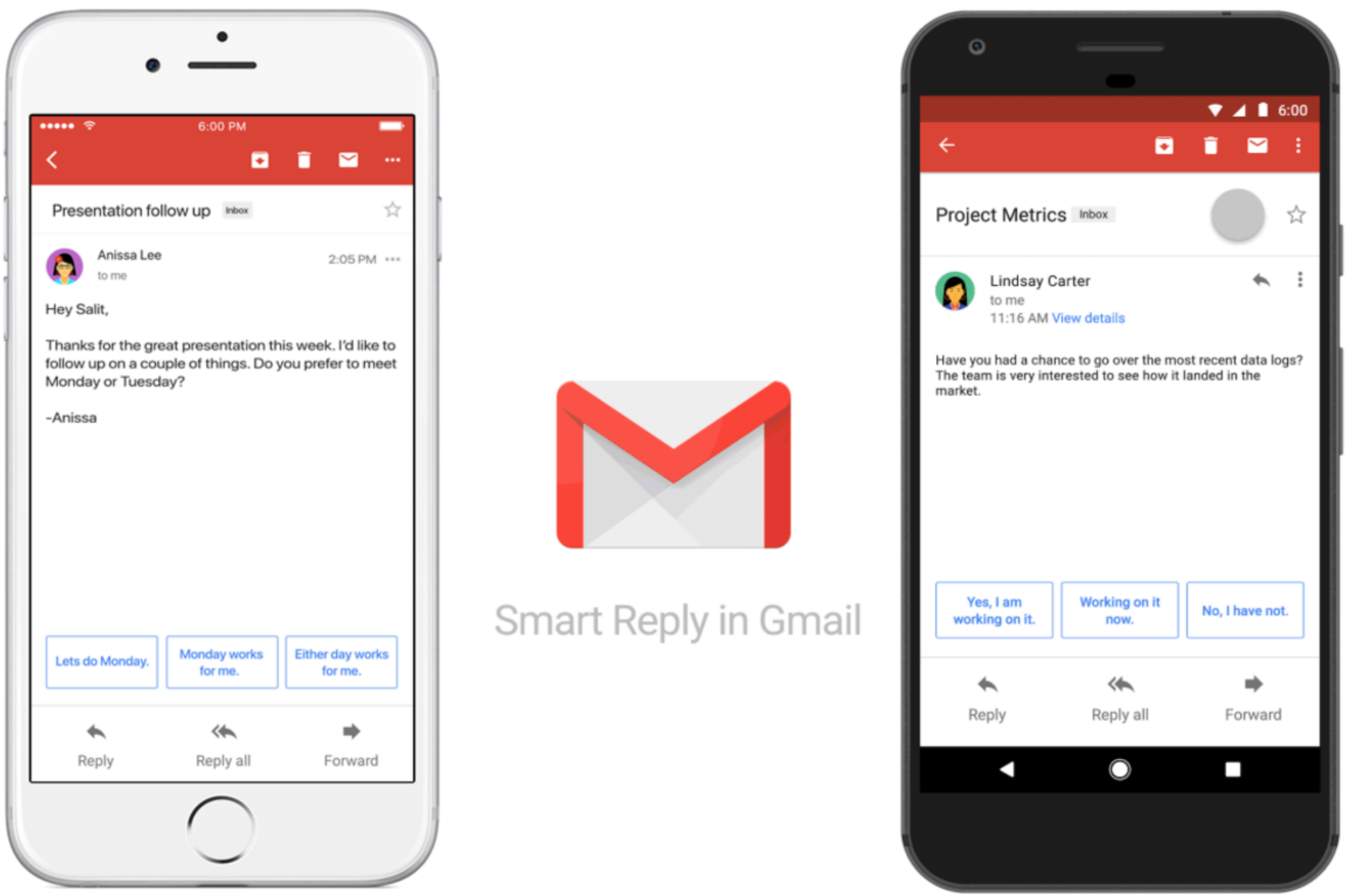
take many forms



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

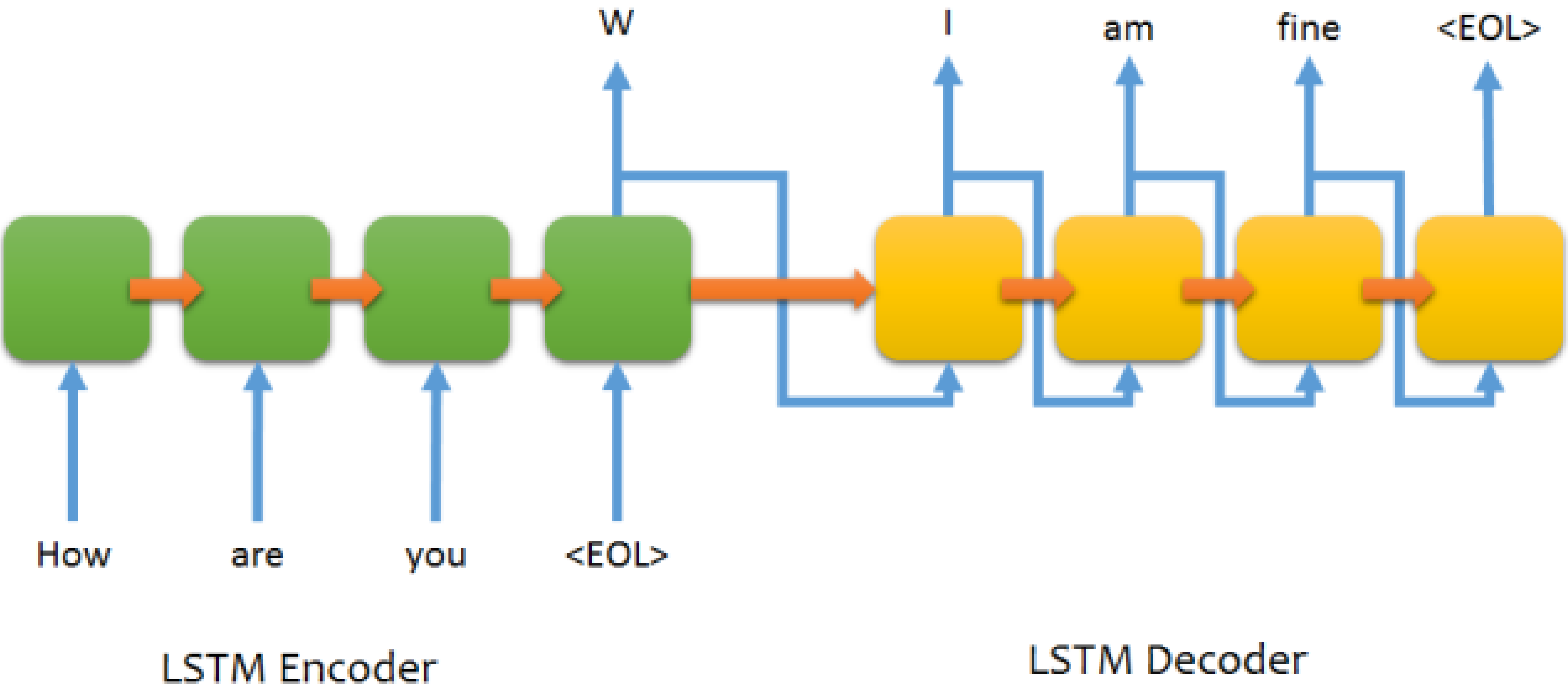
Google SmartReply

Guessing what you want to reply



Chatbots (using Seq2Seq)

Guessing what you want to know



Generating Scripts for Movies

Here is the Chinese version of Sunspring

Speech Synthesis

The reverse problem of Speech Recognition

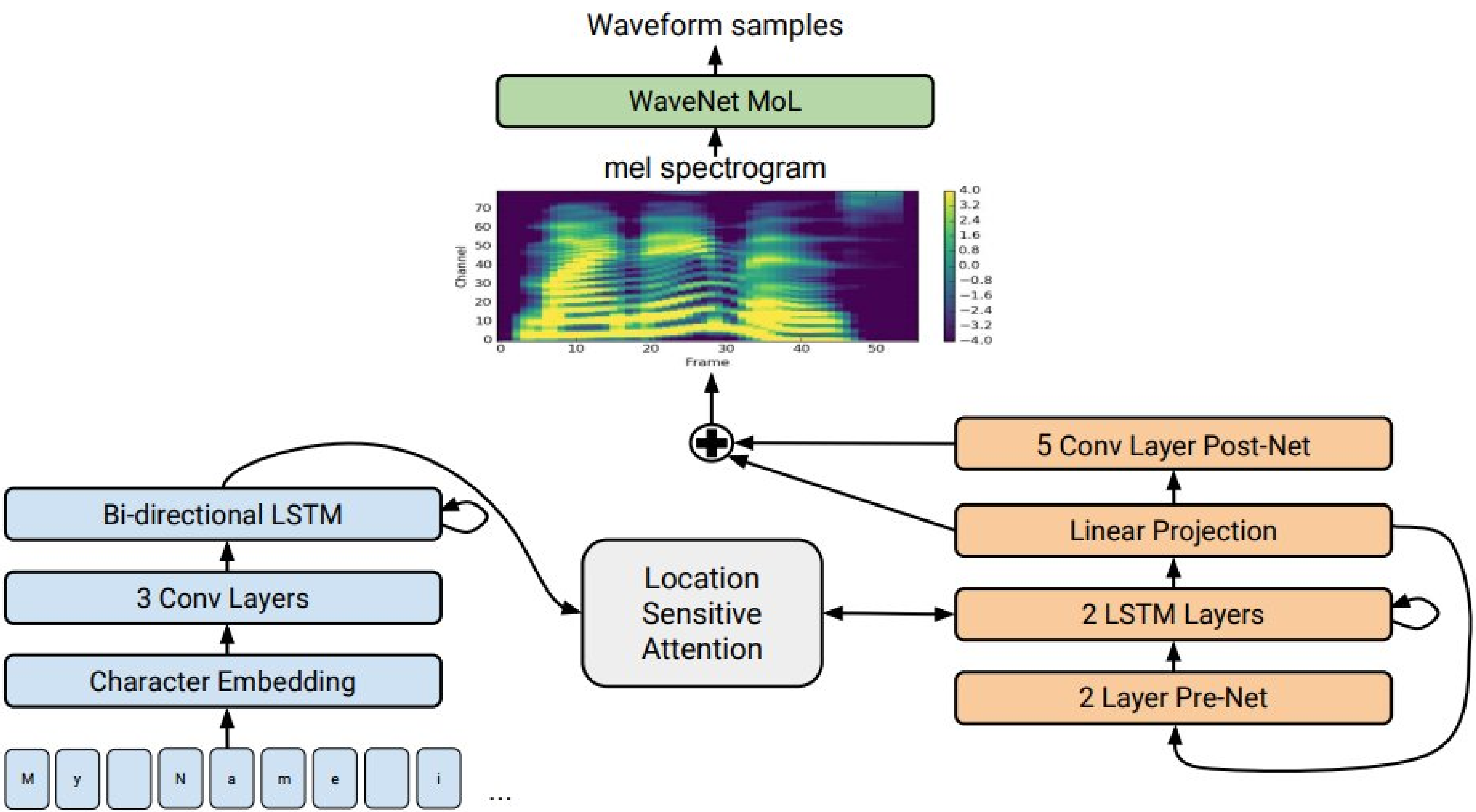
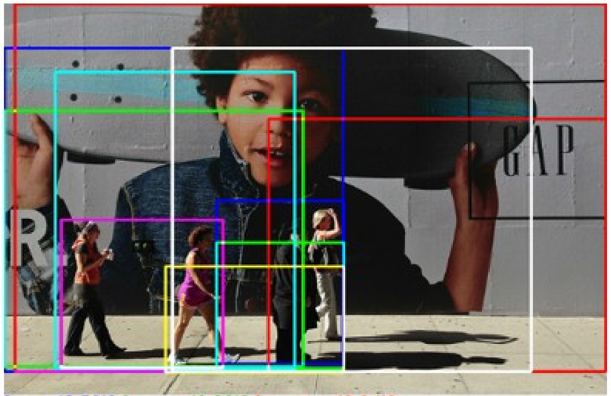


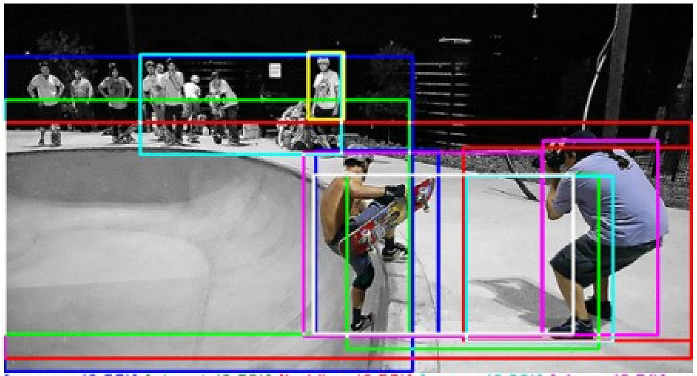
Image Captioning

Image to text



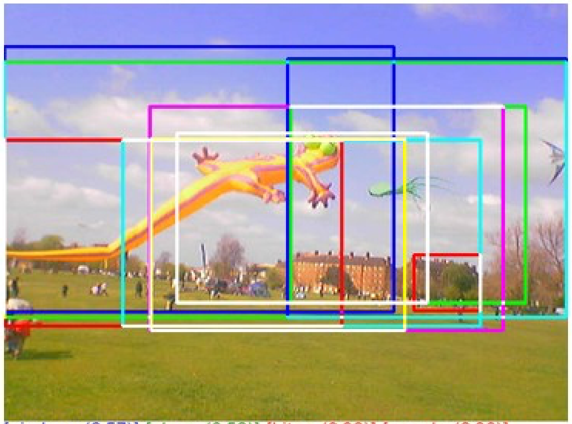
[men (0.59)] [group (0.66)] [woman (0.64)]
[people (0.89)] [holding (0.60)] [playing (0.61)] [tennis (0.69)]
[court (0.51)] [standing (0.59)] [skis (0.58)] [street (0.52)]
[man (0.77)] [skateboard (0.67)]

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



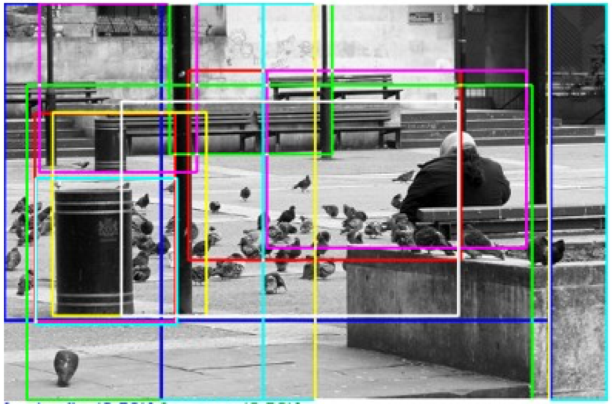
[person (0.55)] [street (0.53)] [holding (0.55)] [group (0.63)] [slope (0.51)]
[standing (0.62)] [snow (0.91)] [skis (0.74)] [player (0.54)]
[people (0.85)] [men (0.57)] [skiing (0.51)]
[skateboard (0.89)] [riding (0.75)] [tennis (0.74)] [trick (0.53)] [skate (0.52)]
[woman (0.52)] [man (0.86)] [down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



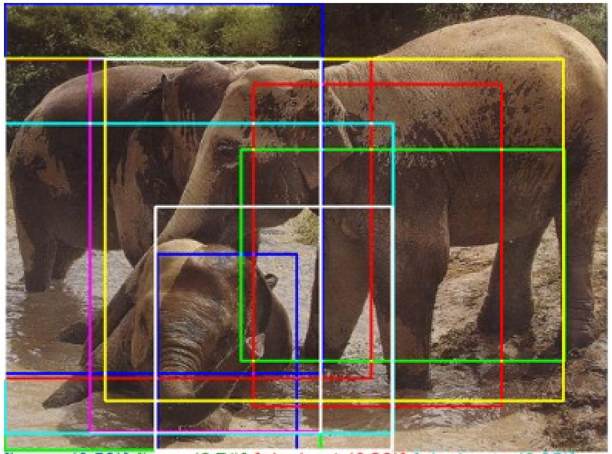
[airplane (0.57)] [plane (0.58)] [kites (0.93)] [people (0.80)]
[flying (0.93)] [man (0.57)] [beach (0.84)] [wave (0.61)]
[sky (0.61)] [kite (0.74)] [field (0.75)]

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



[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 either side of it one of which shows the back of a large person facin g in the direction of the pigeons



[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)]

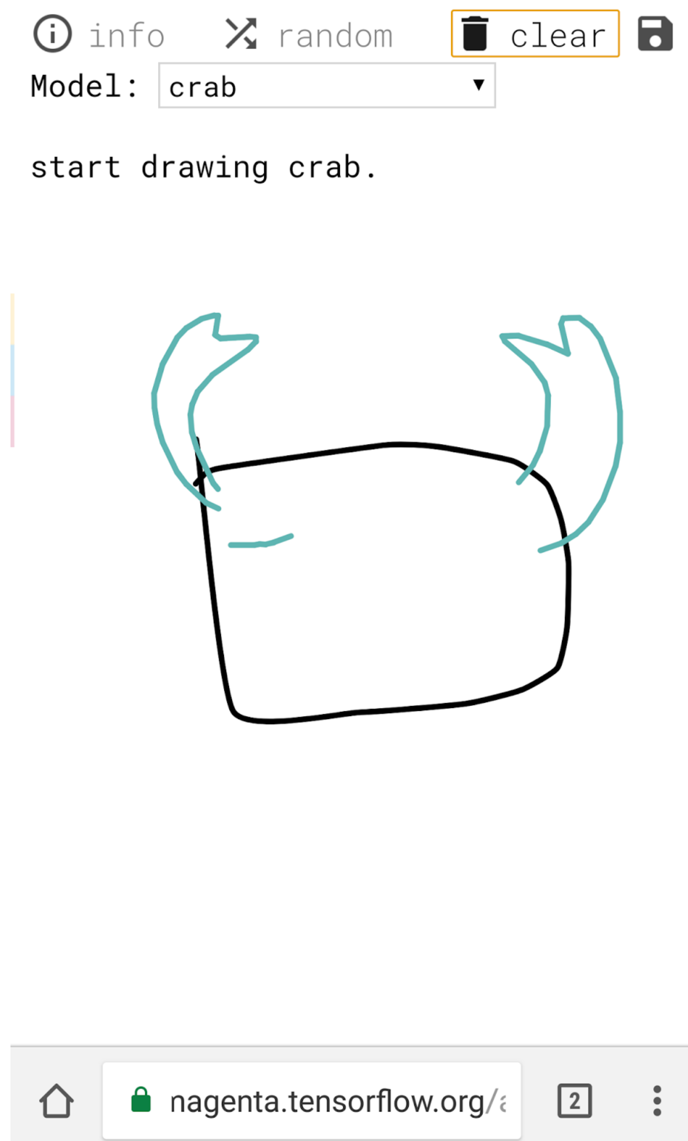
a baby elephant standing next to each other on a field
elephants are playing together in a shallow watering hole

[man (0.59)] [beach (0.54)] [sky (0.53)] [bird (0.50)] [field (0.88)]
[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 field
a couple of sheep standing up on a small hill

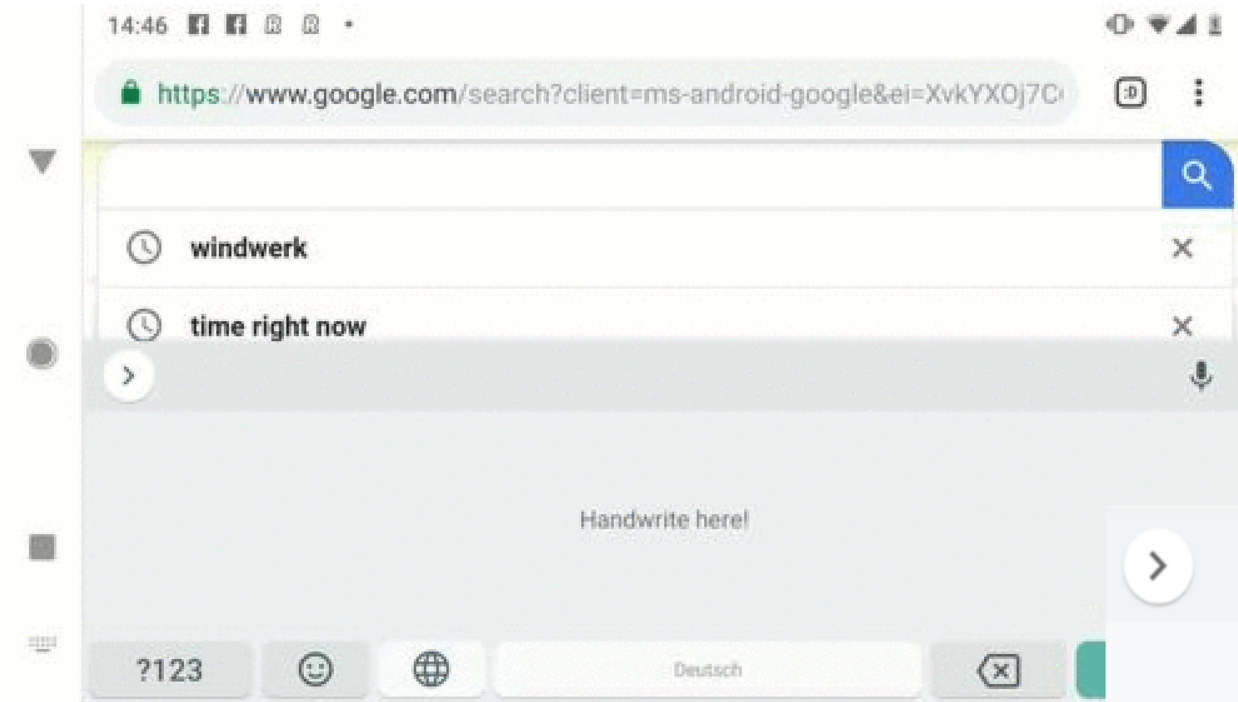
Sketch-RNN

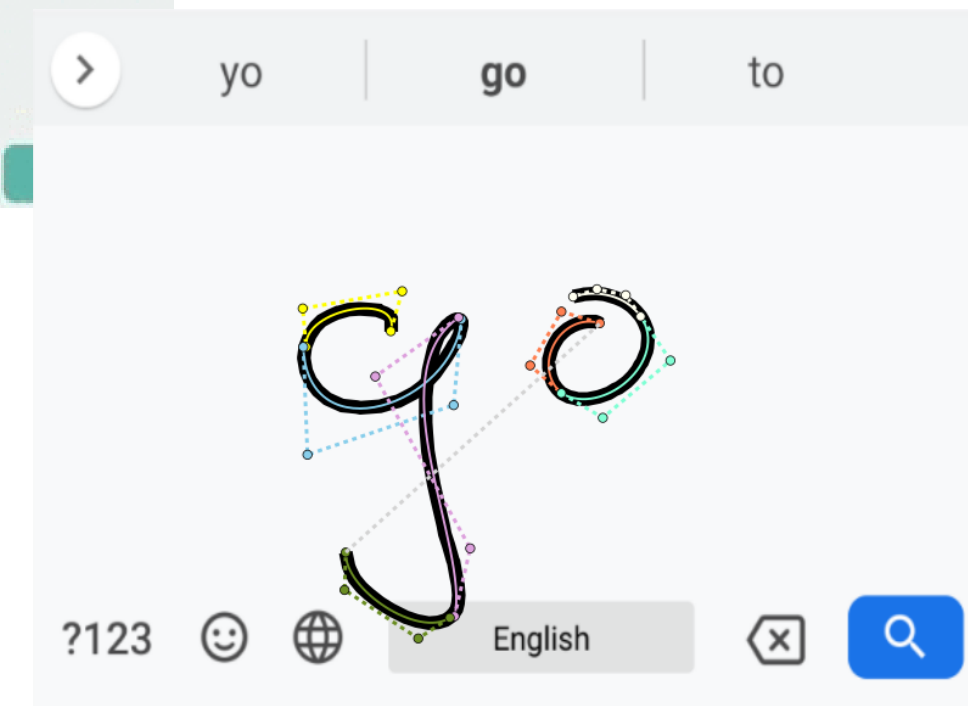
Guessing what you want to draw



GBoard

Guessing what you are writing





Game Over