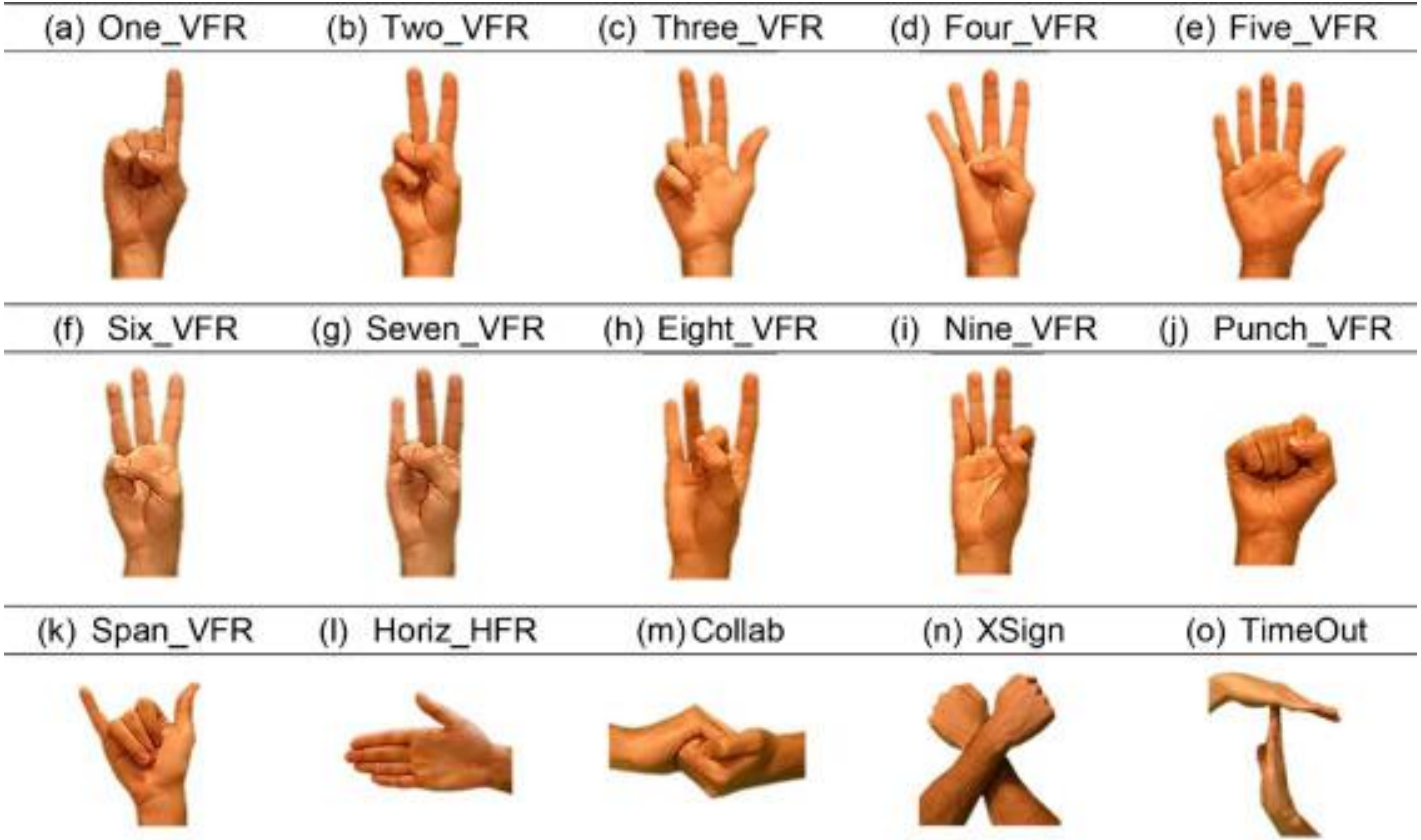
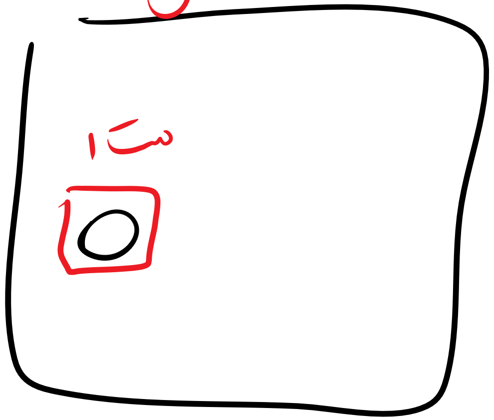
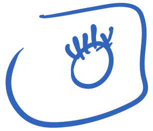
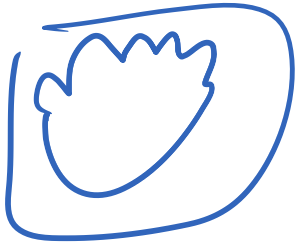

(a) One_VFR
(b) Two_VFR
(c) Three_VFR
(d) Four_VFR
(e) Five_VFR
(f) Six_VFR
(g) Seven_VFR
(h) Eight_VFR
(i) Nine_VFR
(j) Punch_VFR
(k) Span_VFR
(l) Horiz_HFR
(m) Collab
(n) XSign
(o) TimeOut

a.jpg



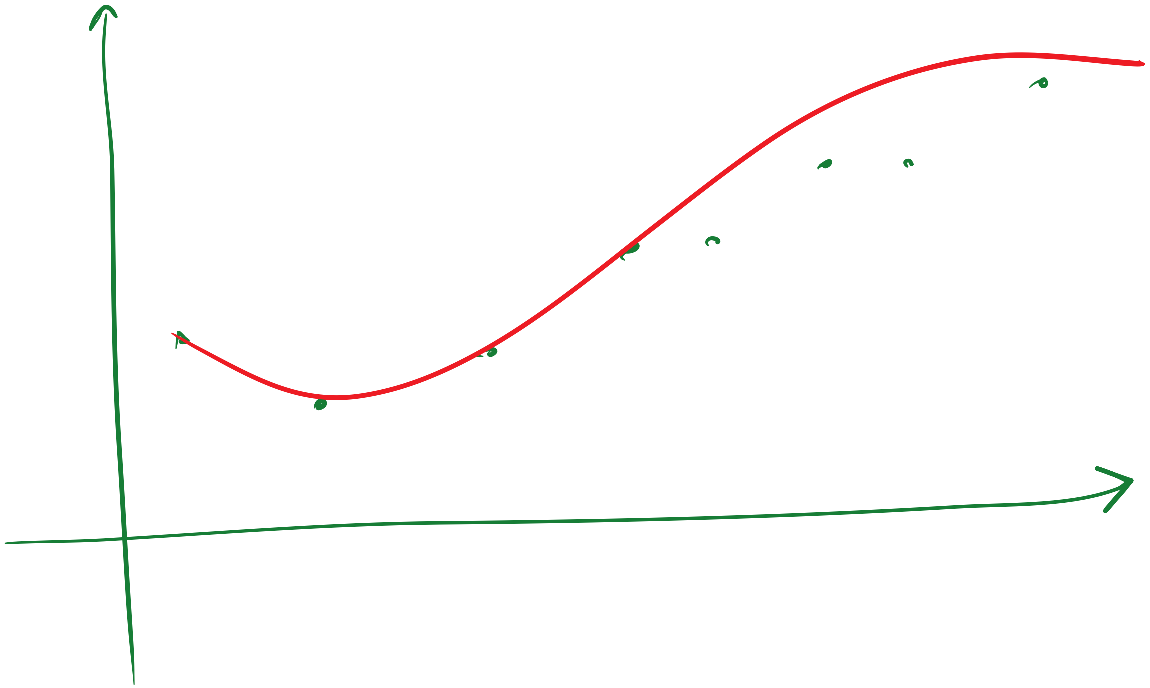




Yolo

a.jpg xy w h 1
b.jpg xywh 5

Time Series



Regression

Time Series

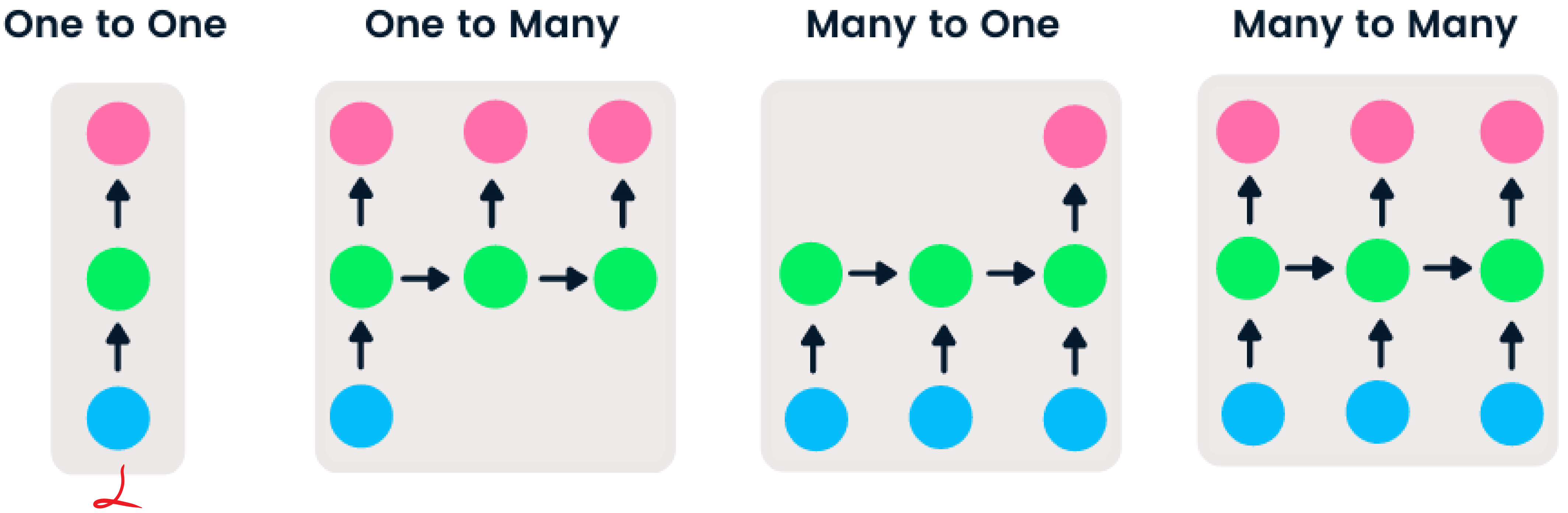
RNN

Recurrent NN 1993

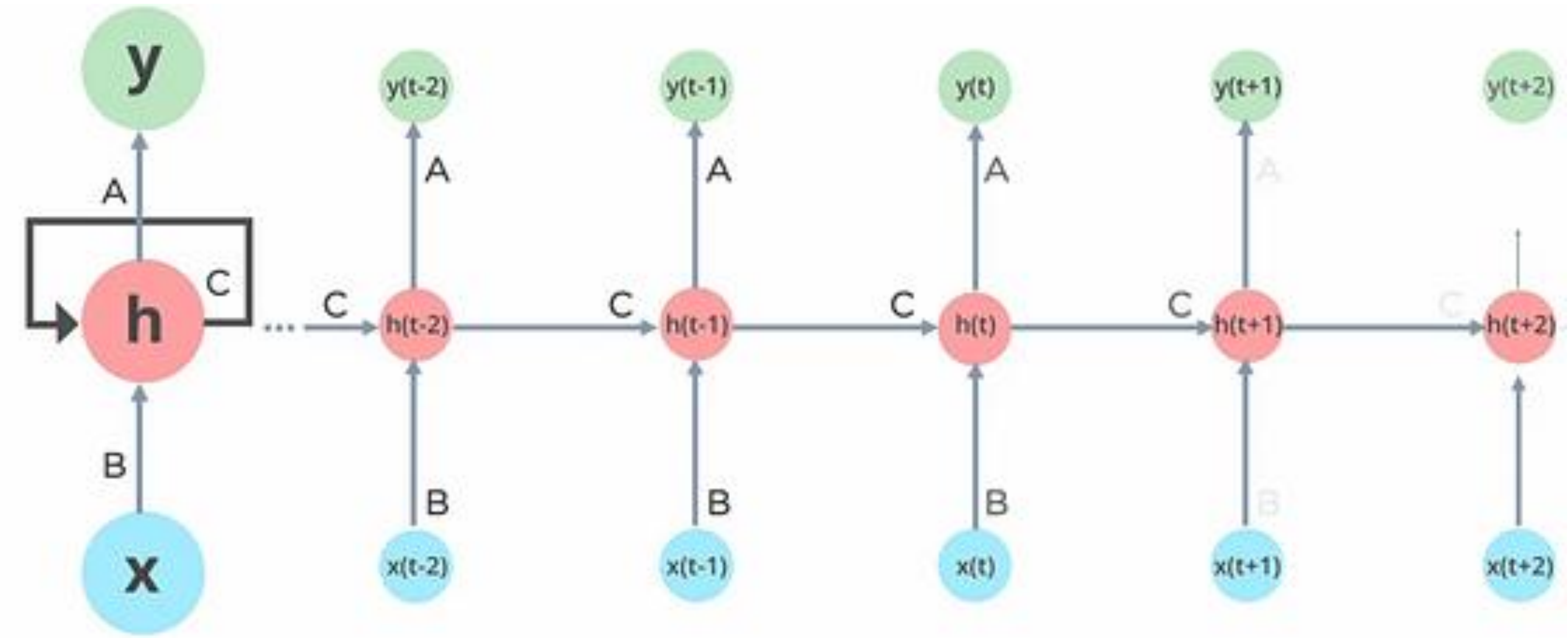
image Captioning

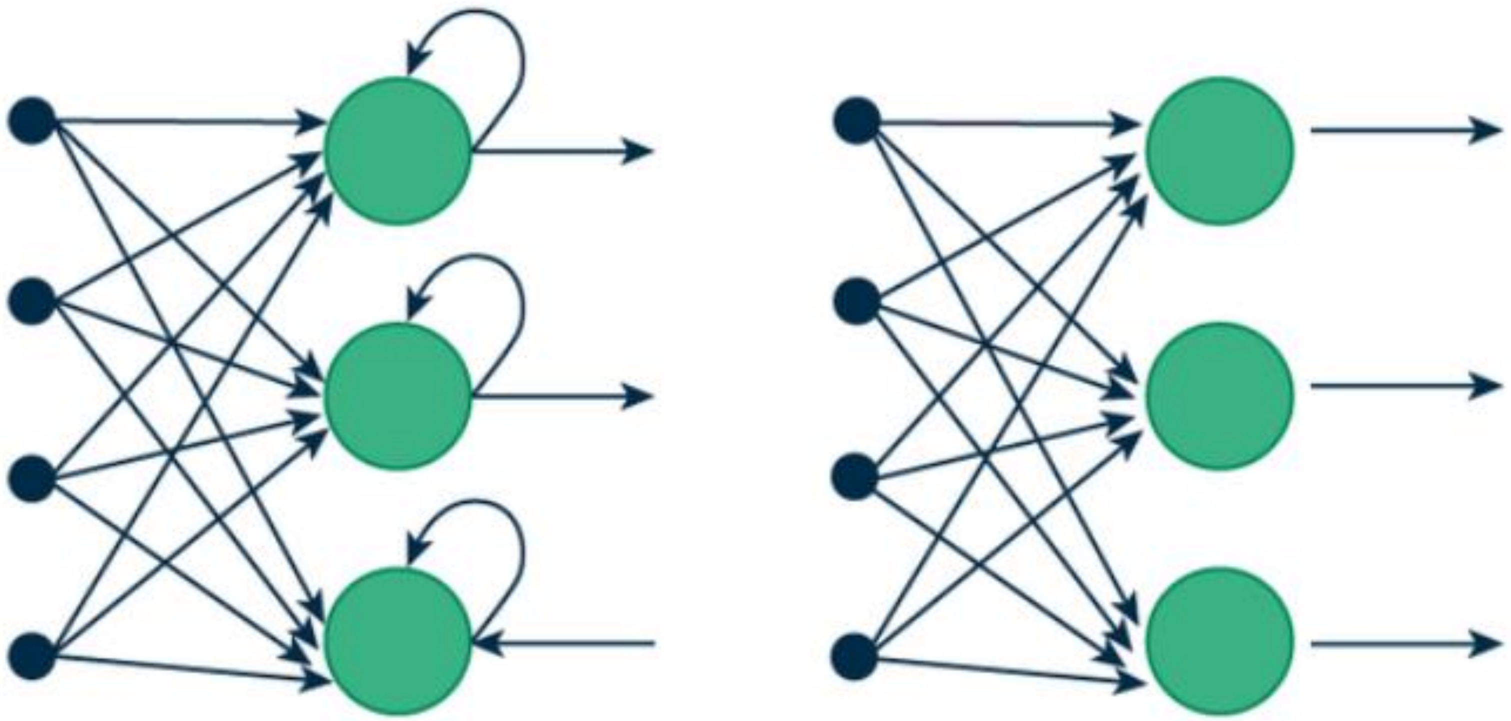
text Classification

Translate

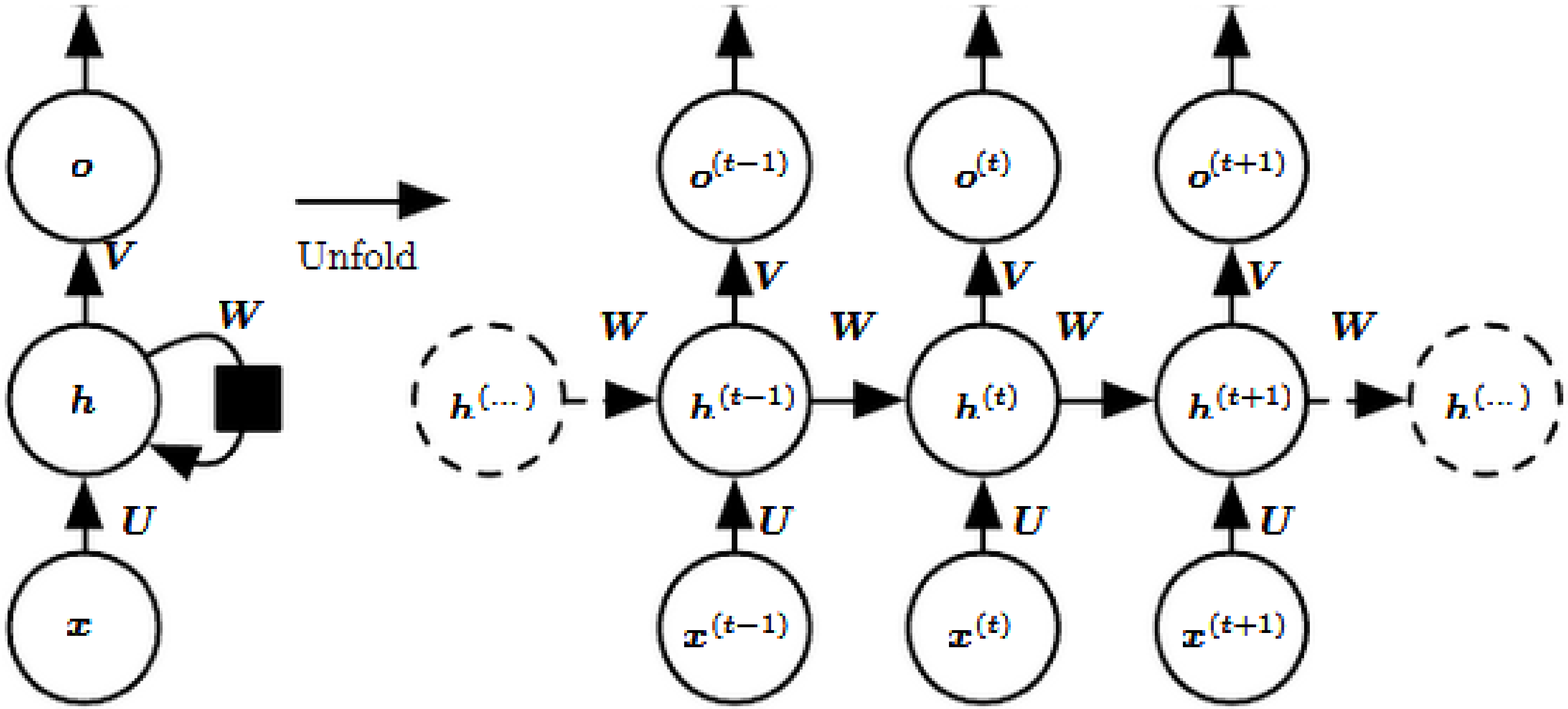


RNN



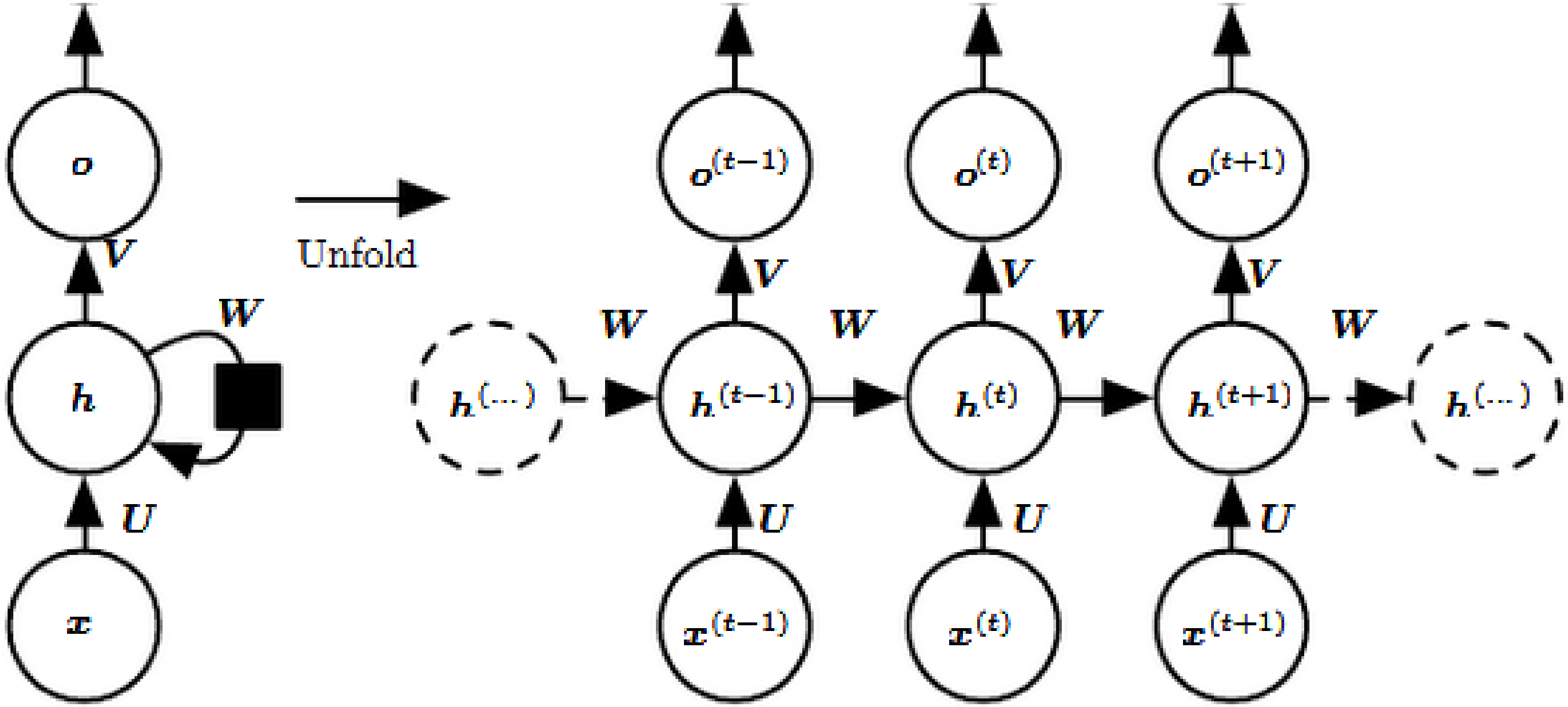


(a) Recurrent Neural Network (b) Feed-Forward Neural Network



o
V
W
h
U
x
Unfold
$o^{(t-1)}$
$o^{(t)}$
$o^{(t+1)}$
W
V
W
V
W
V
W
$h^{(...)}$
$h^{(t-1)}$
$h^{(t)}$
$h^{(t+1)}$
$h^{(...)}$
U
U
U
$x^{(t-1)}$
$x^{(t)}$
$x^{(t+1)}$

forward

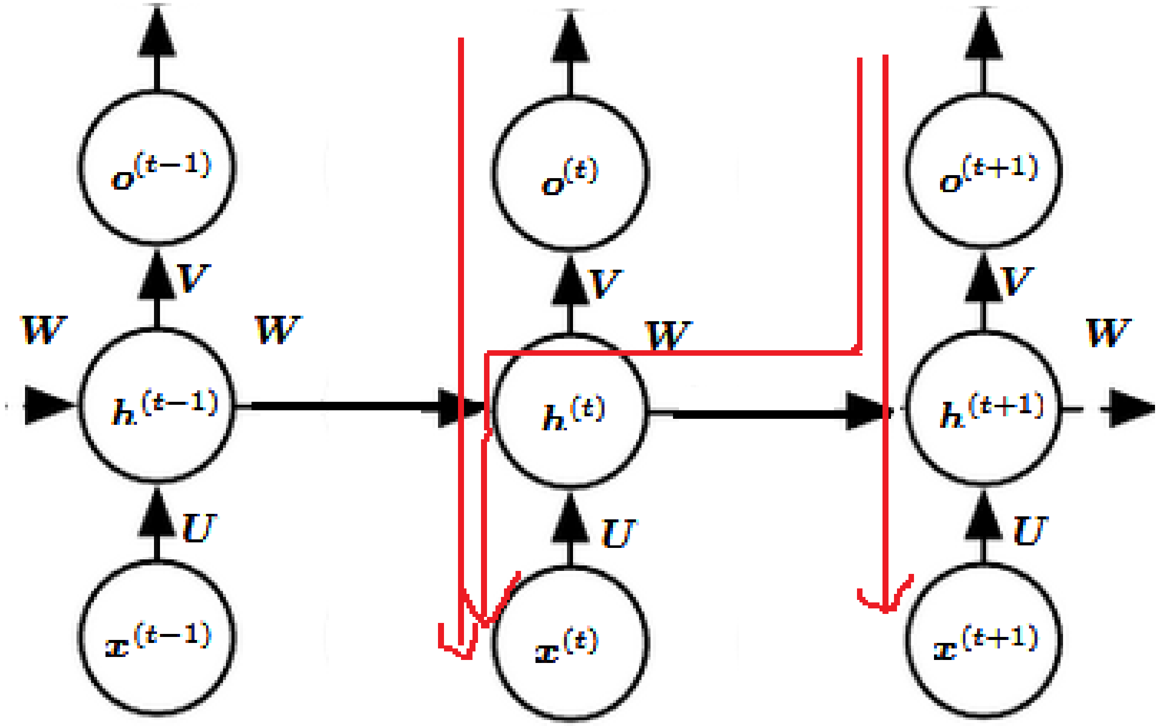


$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)} \\
\hat{\boldsymbol{y}}^{(t)} &= \text{softmax}(\boldsymbol{o}^{(t)})
\end{aligned}
$$

$$
{}_{\text{units}}n + ({}_{\text{units}}n \times {}_{\text{units}}n) + ({}_{\text{units}}n \times {}_{\text{input}}n)
$$

Train

(Back propagation)



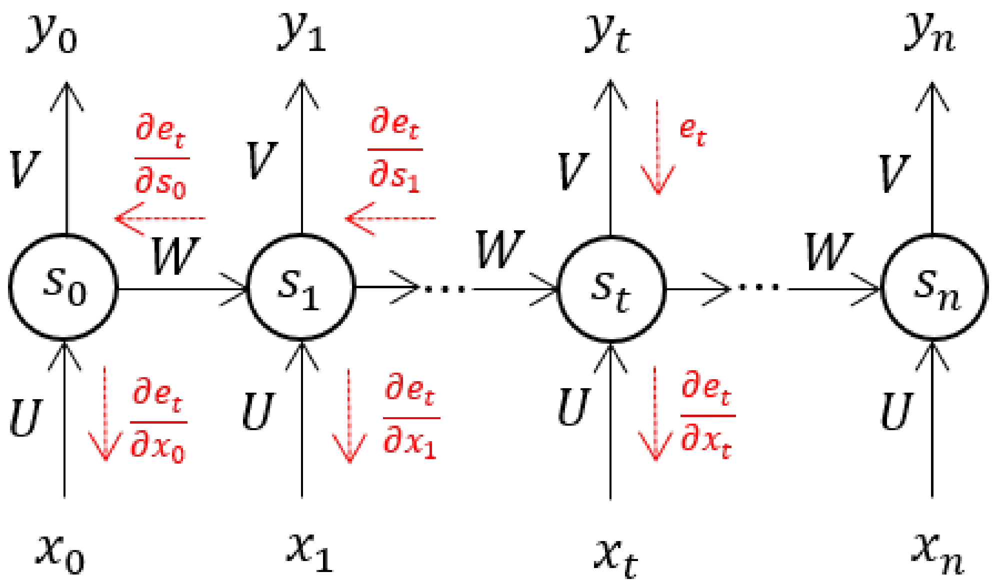
$$\nabla_c L = \sum_t \left(\frac{\partial o^{(t)}}{\partial c}\right)^\top \nabla_{o^{(t)}} L = \sum_t \nabla_{o^{(t)}} L$$

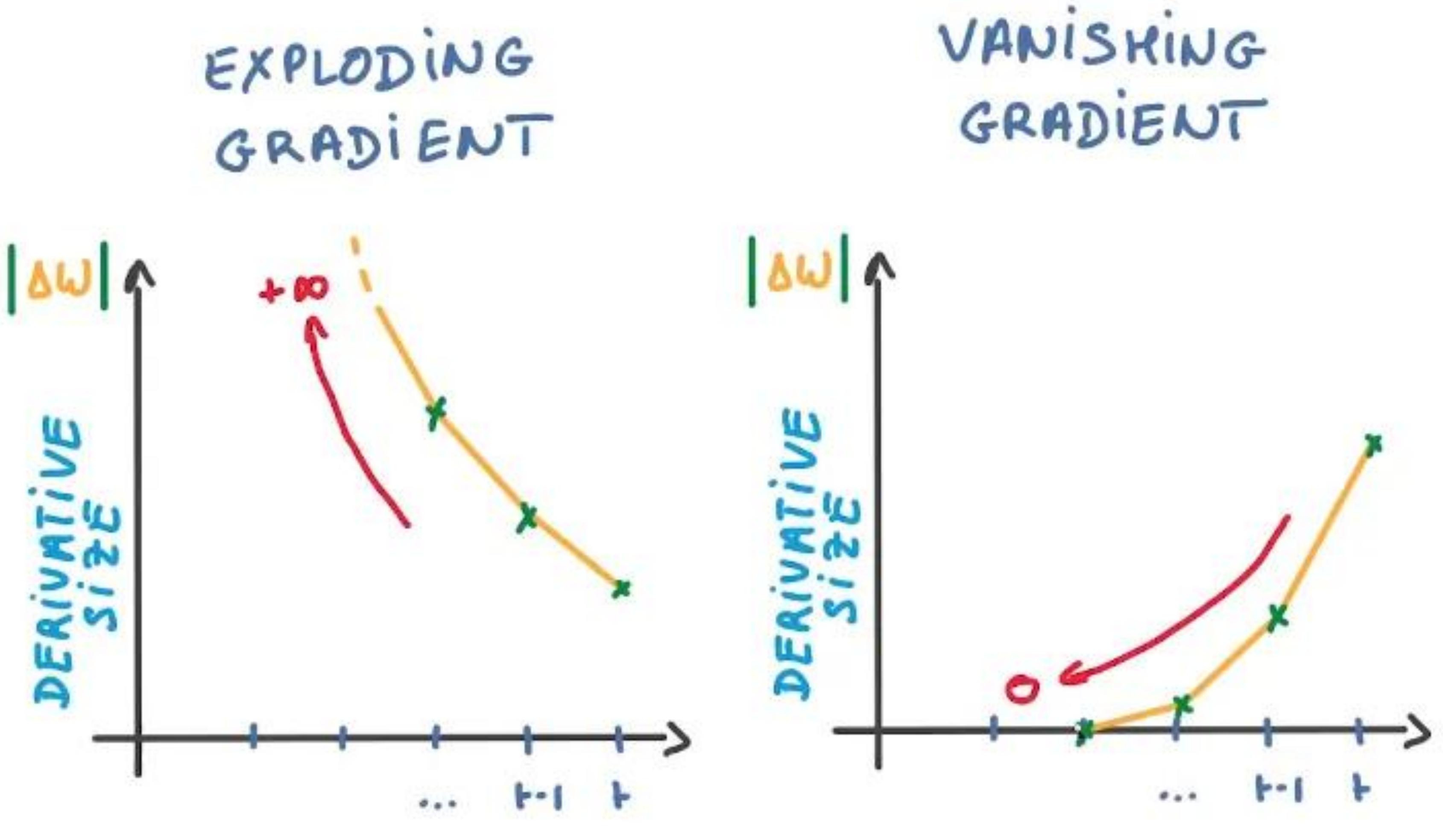
$$\nabla_b L = \sum_t \left(\frac{\partial h^{(t)}}{\partial b^{(t)}}\right)^\top \nabla_{h^{(t)}} L = \sum_t \text{diag}\left(1 - \left(h^{(t)}\right)^2\right) \nabla_{h^{(t)}} L$$

$$\nabla_V L = \sum_t \sum_i \left(\frac{\partial L}{\partial o_i^{(t)}}\right) \nabla_{V^{(t)}} o_i^{(t)} = \sum_t (\nabla_{o^{(t)}} L)\, h^{(t)^\top}$$

$$\nabla_W L = \sum_t \sum_i \left(\frac{\partial L}{\partial h_i^{(t)}}\right) \nabla_{W^{(t)}} h_i^{(t)} = \sum_t \text{diag}\left(1 - \left(h^{(t)}\right)^2\right) (\nabla_{h^{(t)}} L)\, h^{(t-1)^\top}$$

$$\nabla_U L = \sum_t \sum_i \left(\frac{\partial L}{\partial h_i^{(t)}}\right) \nabla_{U^{(t)}} h_i^{(t)} = \sum_t \text{diag}\left(1 - \left(h^{(t)}\right)^2\right) (\nabla_{h^{(t)}} L)\, x^{(t)^\top}$$


y_0
y_1
y_t
y_n
V
V
V
V
$\frac{\partial e_t}{\partial s_0}$
$\frac{\partial e_t}{\partial s_1}$
e_t
W
W
W
s_0
s_1
s_t
s_n
U
U
U
U
$\frac{\partial e_t}{\partial x_0}$
$\frac{\partial e_t}{\partial x_1}$
$\frac{\partial e_t}{\partial x_t}$
x_0
x_1
x_t
x_n


EXPLODING GRADIENT
|ΔW|
+∞
DERIVATIVE SIZE
... t-1 t
VANISHING GRADIENT
|ΔW|
0
DERIVATIVE SIZE
... t-1 t

This is a classroom

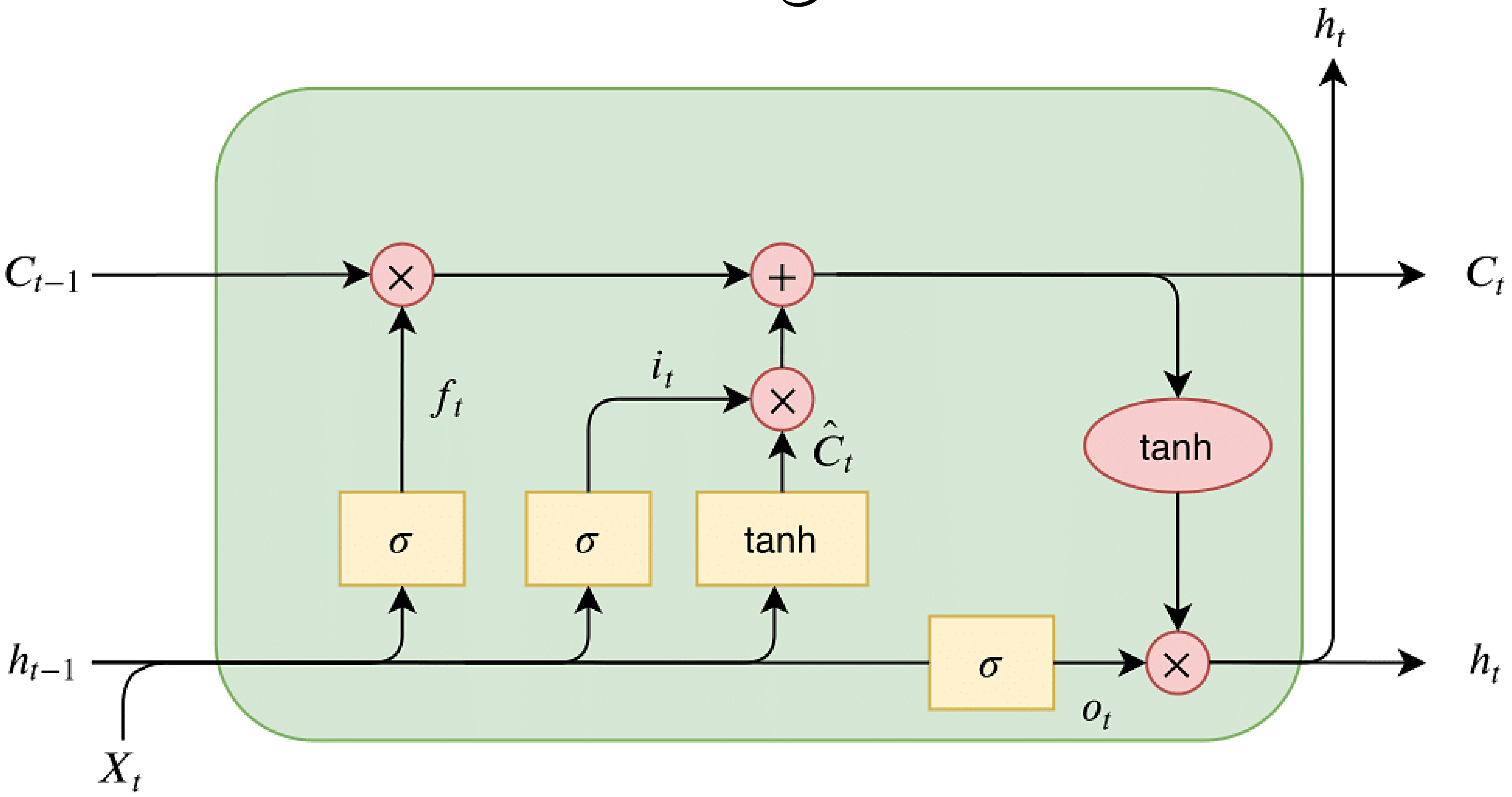
T h i → s

h i s → ' '

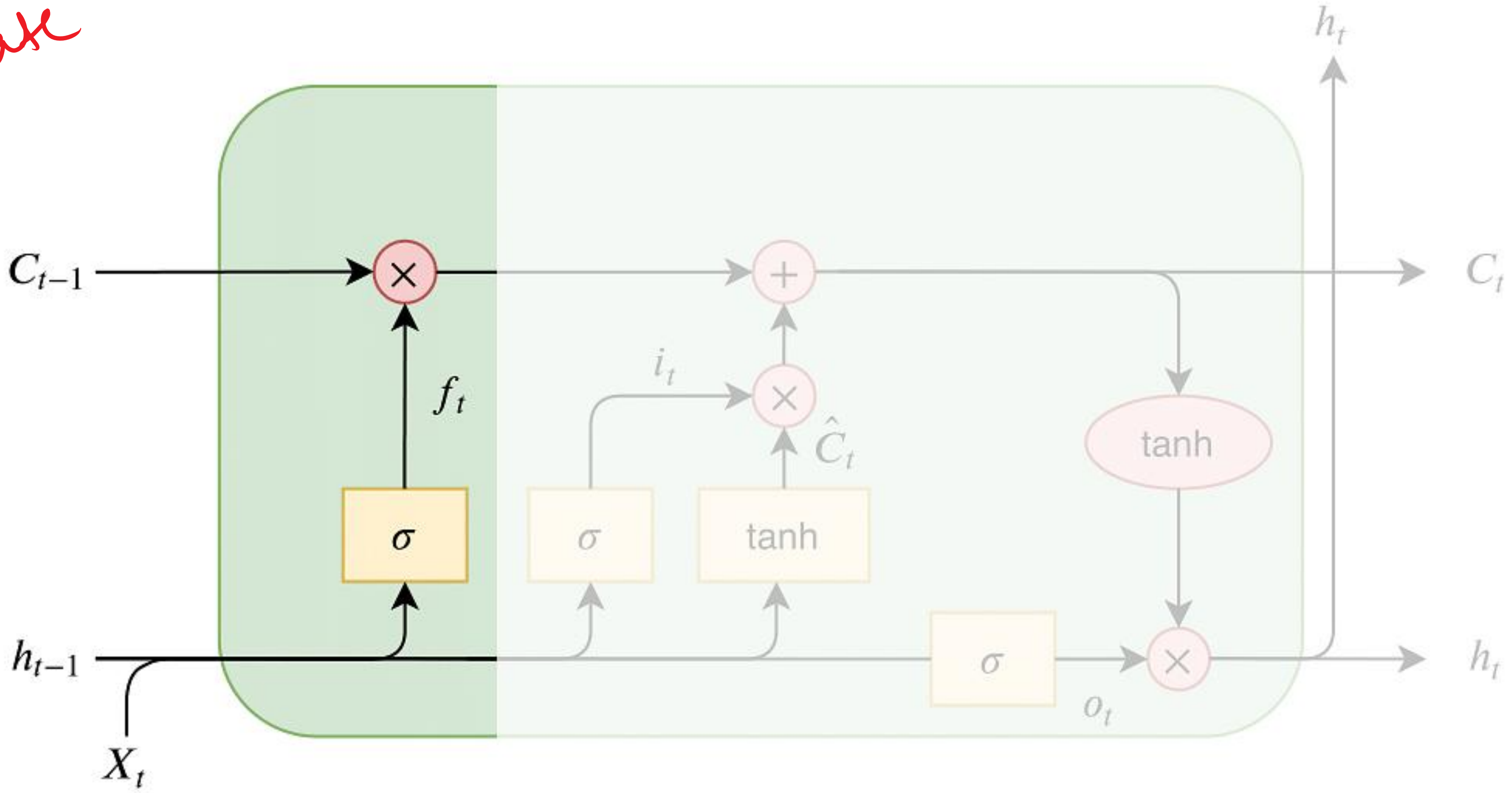
' i s ' → i

1997

LSTM long short term memory

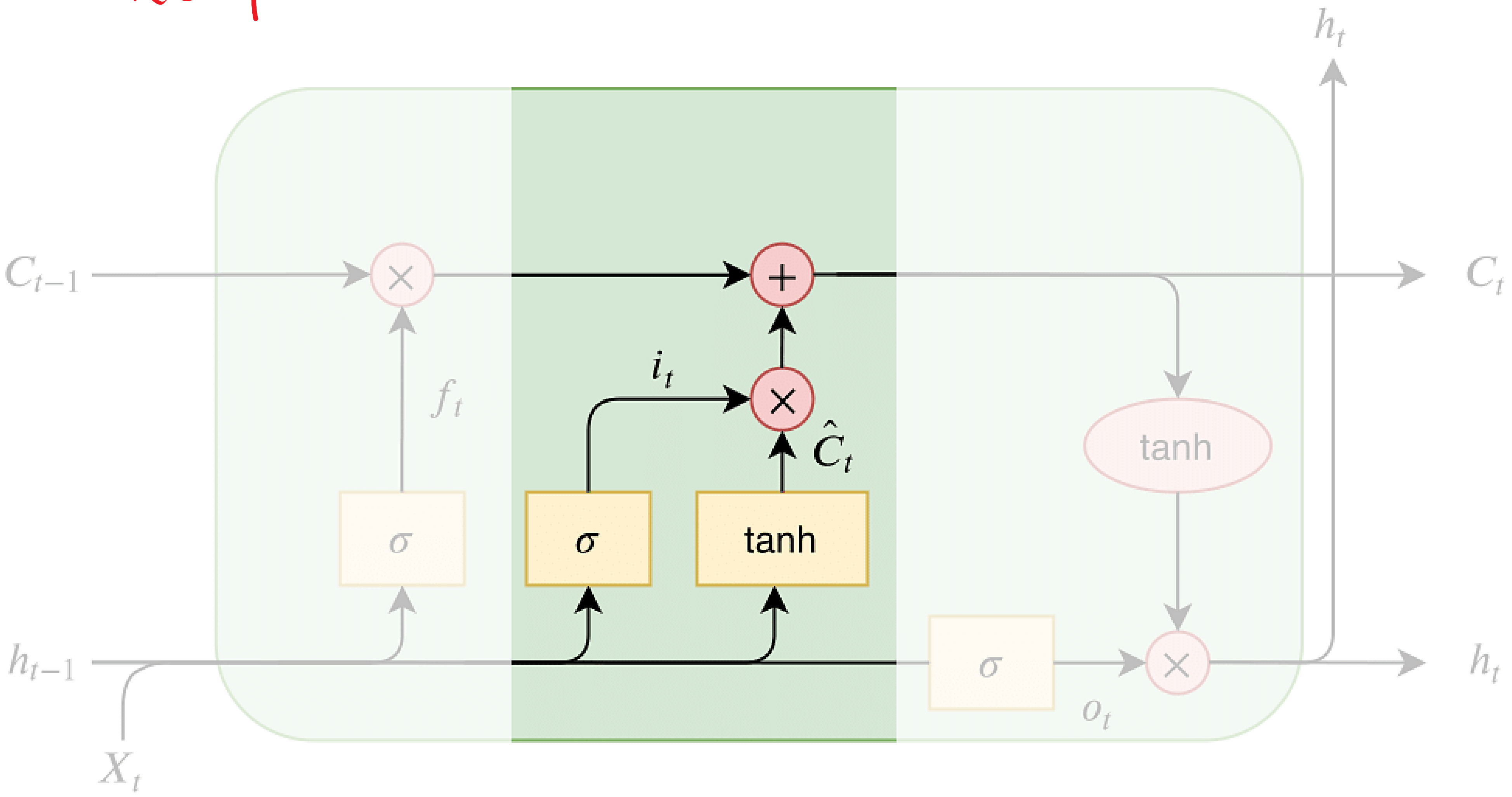


forget gate

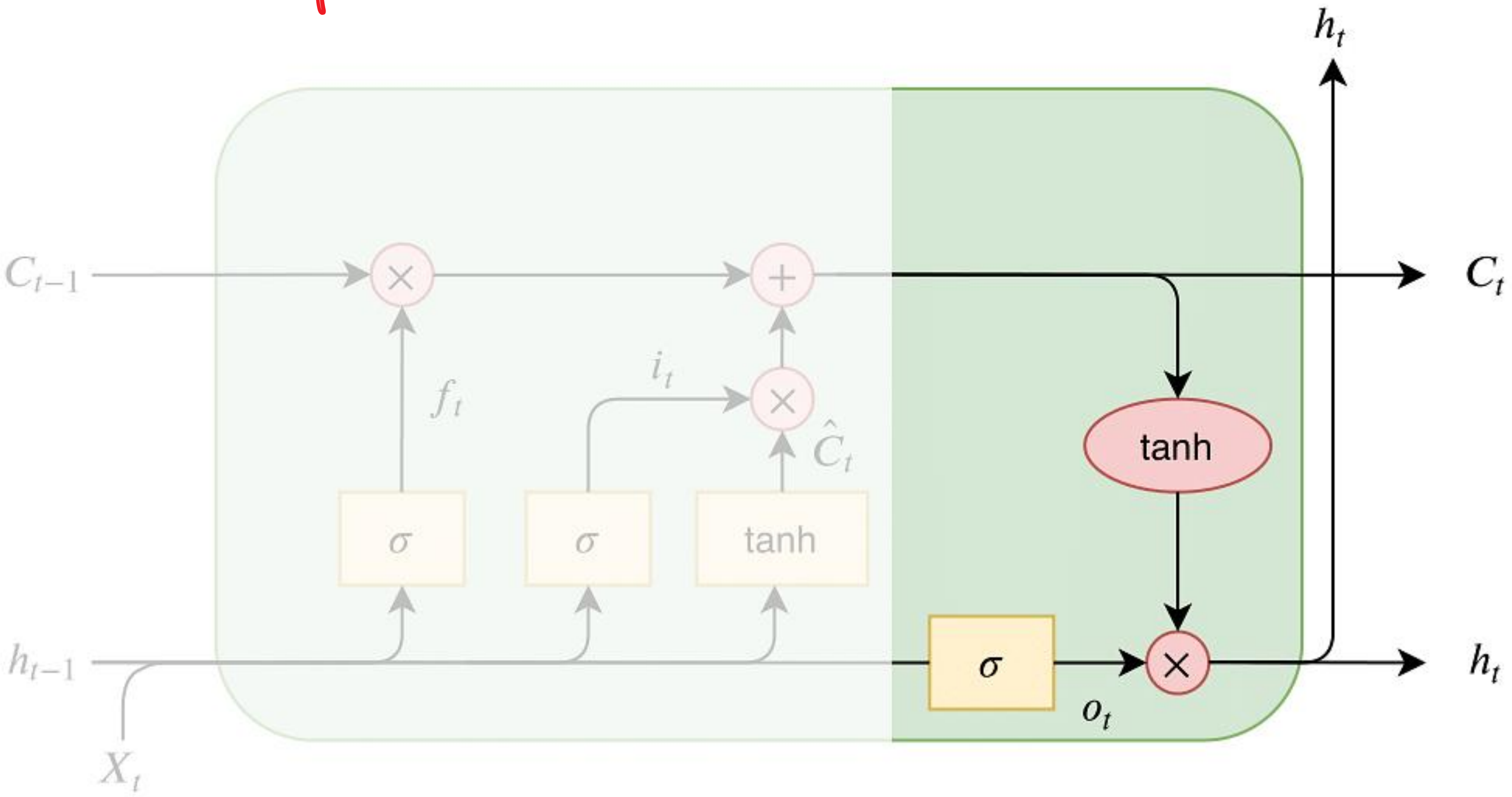


update

keep

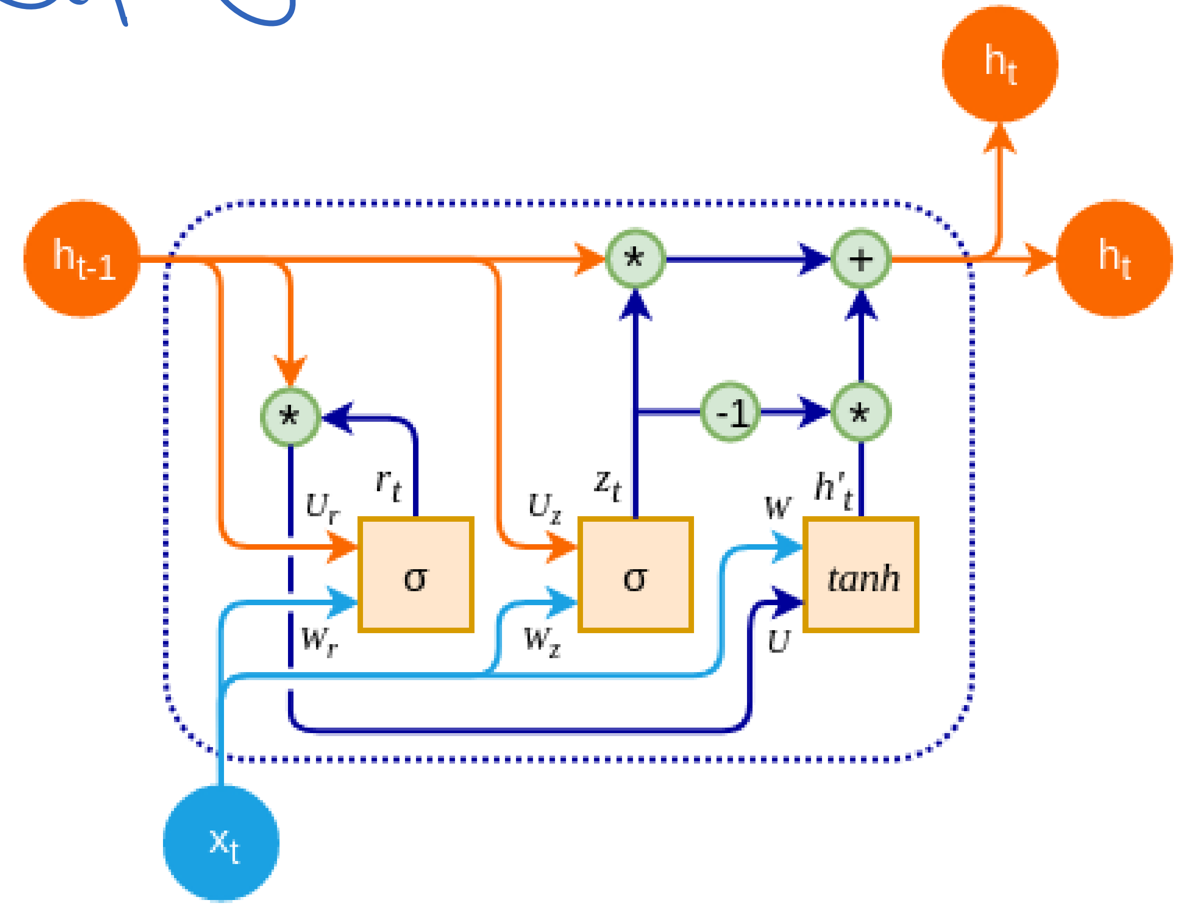


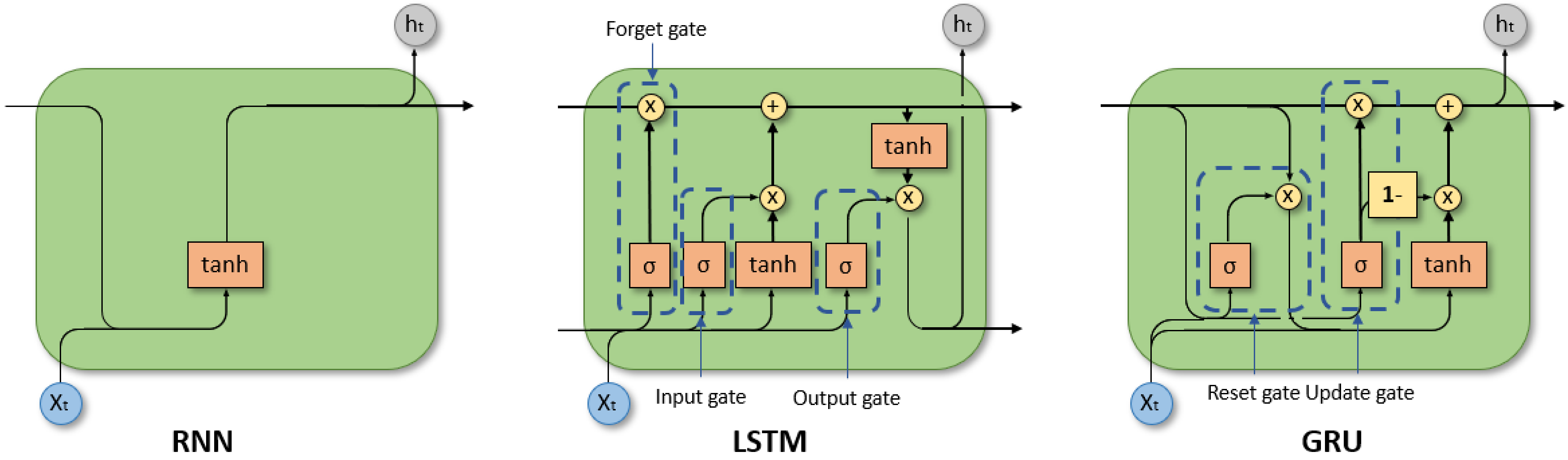
Output

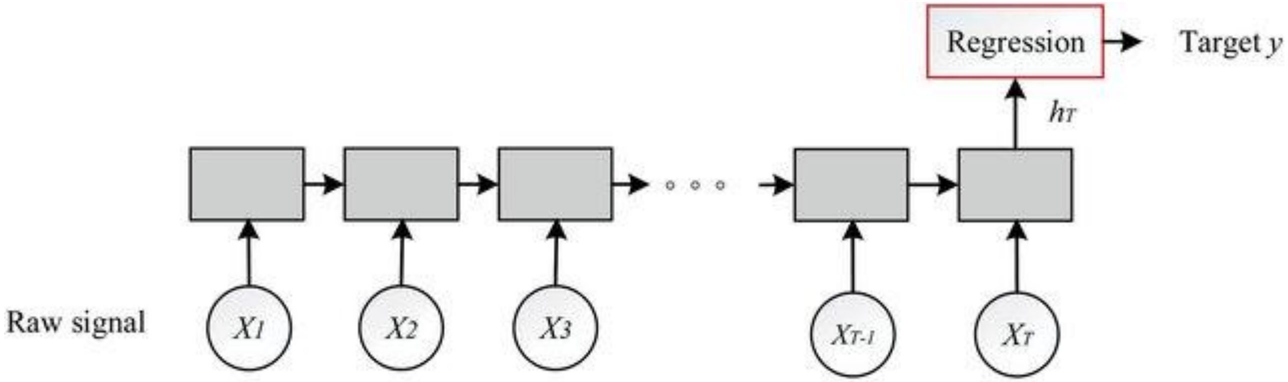


2014

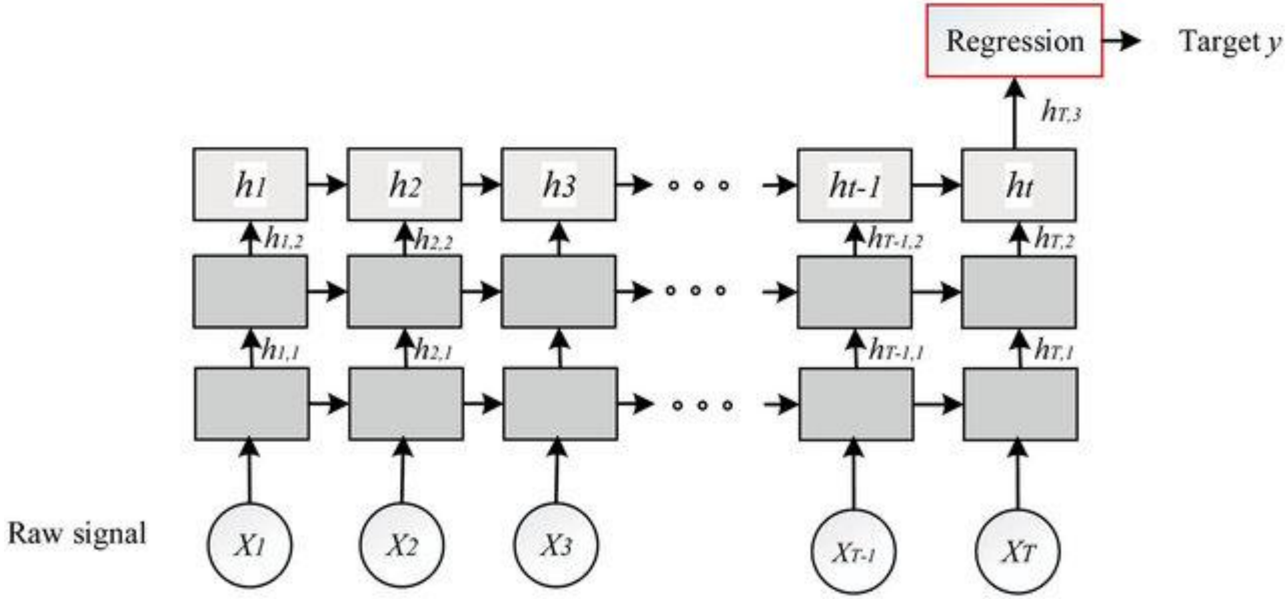
GRU



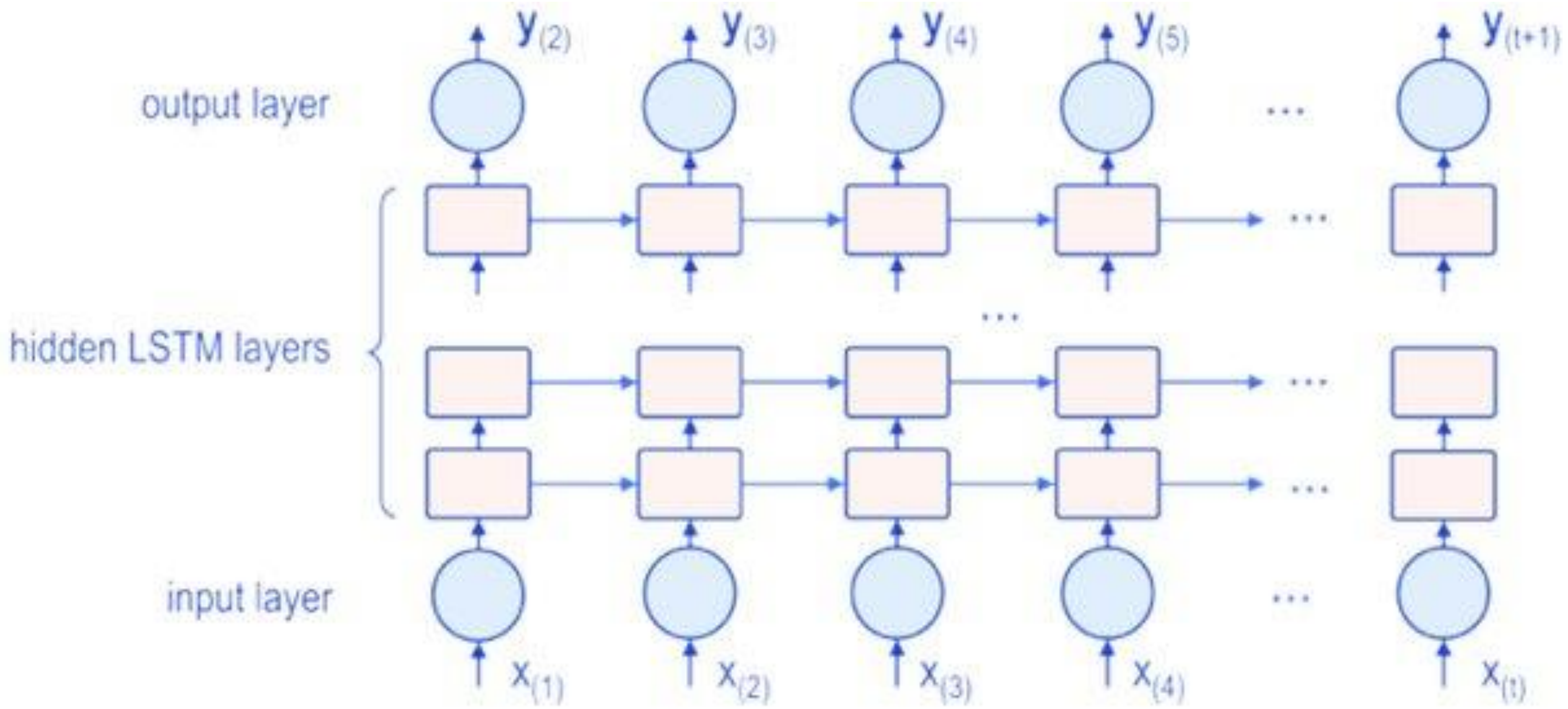

ht
tanh
Xt
RNN
Forget gate
ht
x
+
tanh
x
x
σ
σ
tanh
σ
Xt
Input gate
Output gate
LSTM
ht
x
+
1-
x
x
σ
σ
tanh
Xt
Reset gate
Update gate
GRU


Regression
Target y
h_T
Raw signal
X_1
X_2
X_3
X_{T-1}
X_T

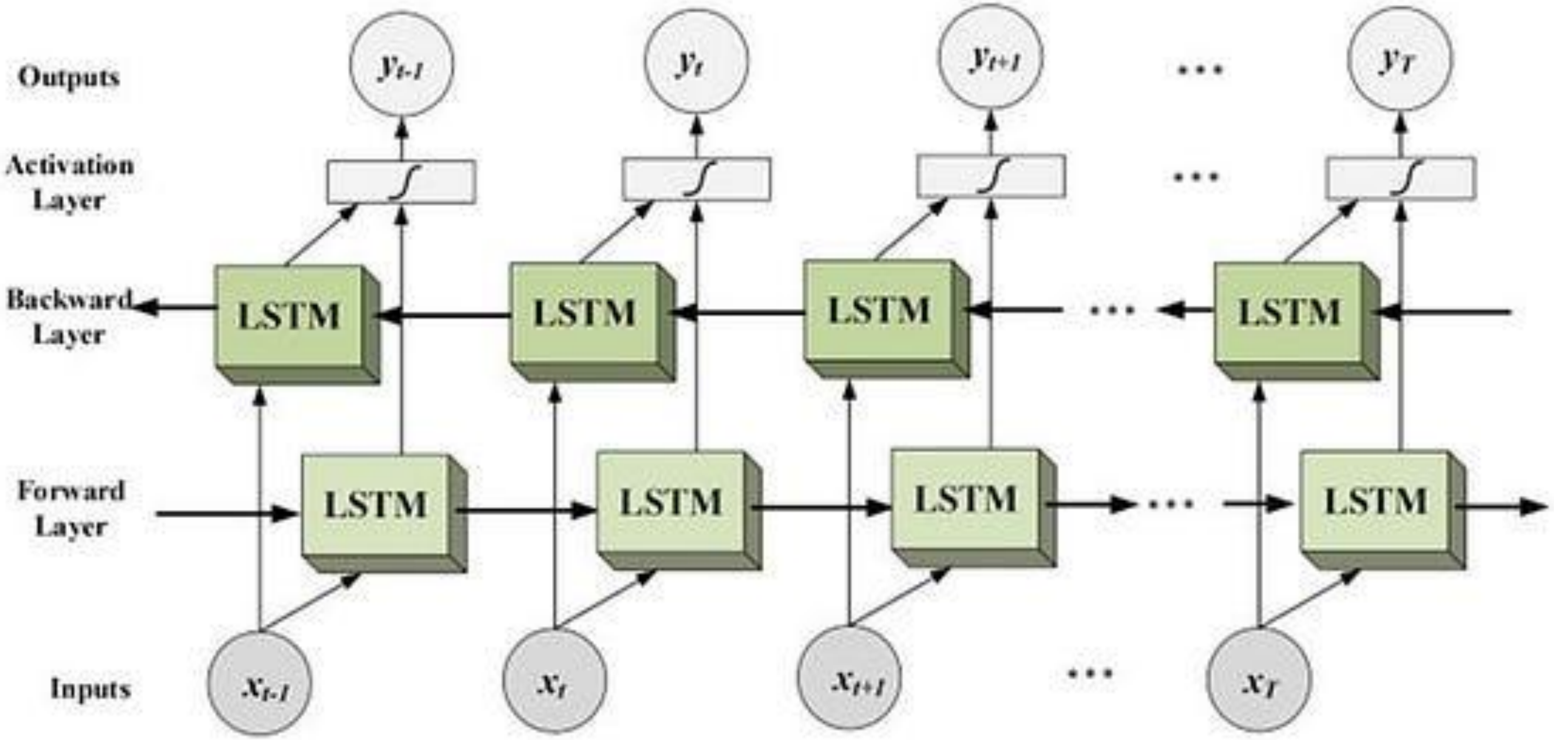
(a)


Regression
Target y
$h_{T,3}$
h_1
h_2
h_3
h_{t-1}
h_t
$h_{1,2}$
$h_{2,2}$
$h_{T-1,2}$
$h_{T,2}$
$h_{1,1}$
$h_{2,1}$
$h_{T-1,1}$
$h_{T,1}$
Raw signal
X_1
X_2
X_3
X_{T-1}
X_T

(b)


output layer
hidden LSTM layers
input layer
$y_{(2)}$
$y_{(3)}$
$y_{(4)}$
$y_{(5)}$
$y_{(t+1)}$
$x_{(1)}$
$x_{(2)}$
$x_{(3)}$
$x_{(4)}$
$x_{(t)}$

Biderectional

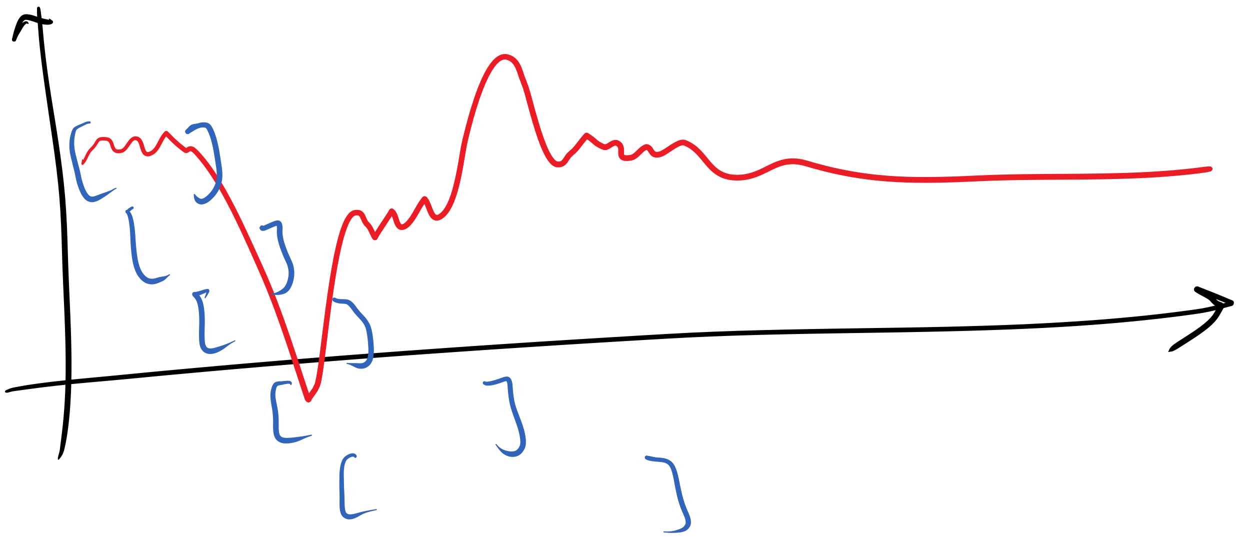


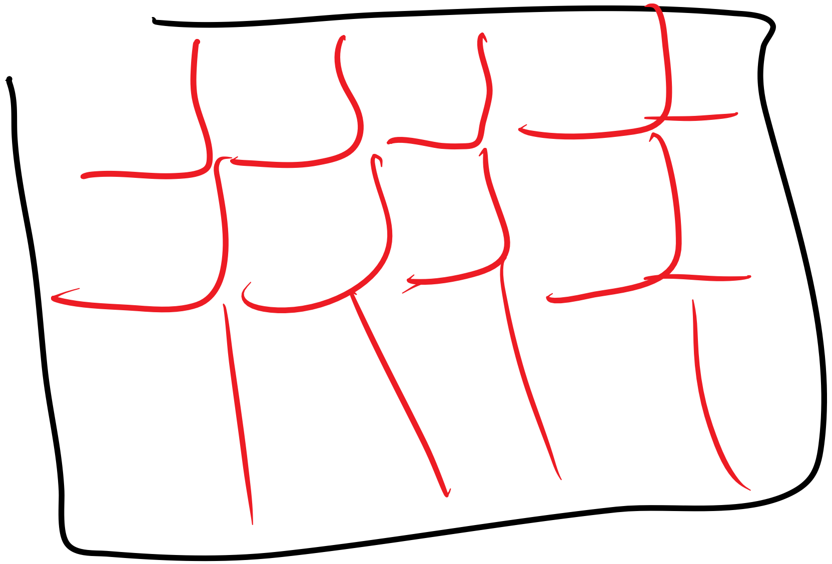
CNN + RNN

LSTM

تکمیل رفتار

Tracking



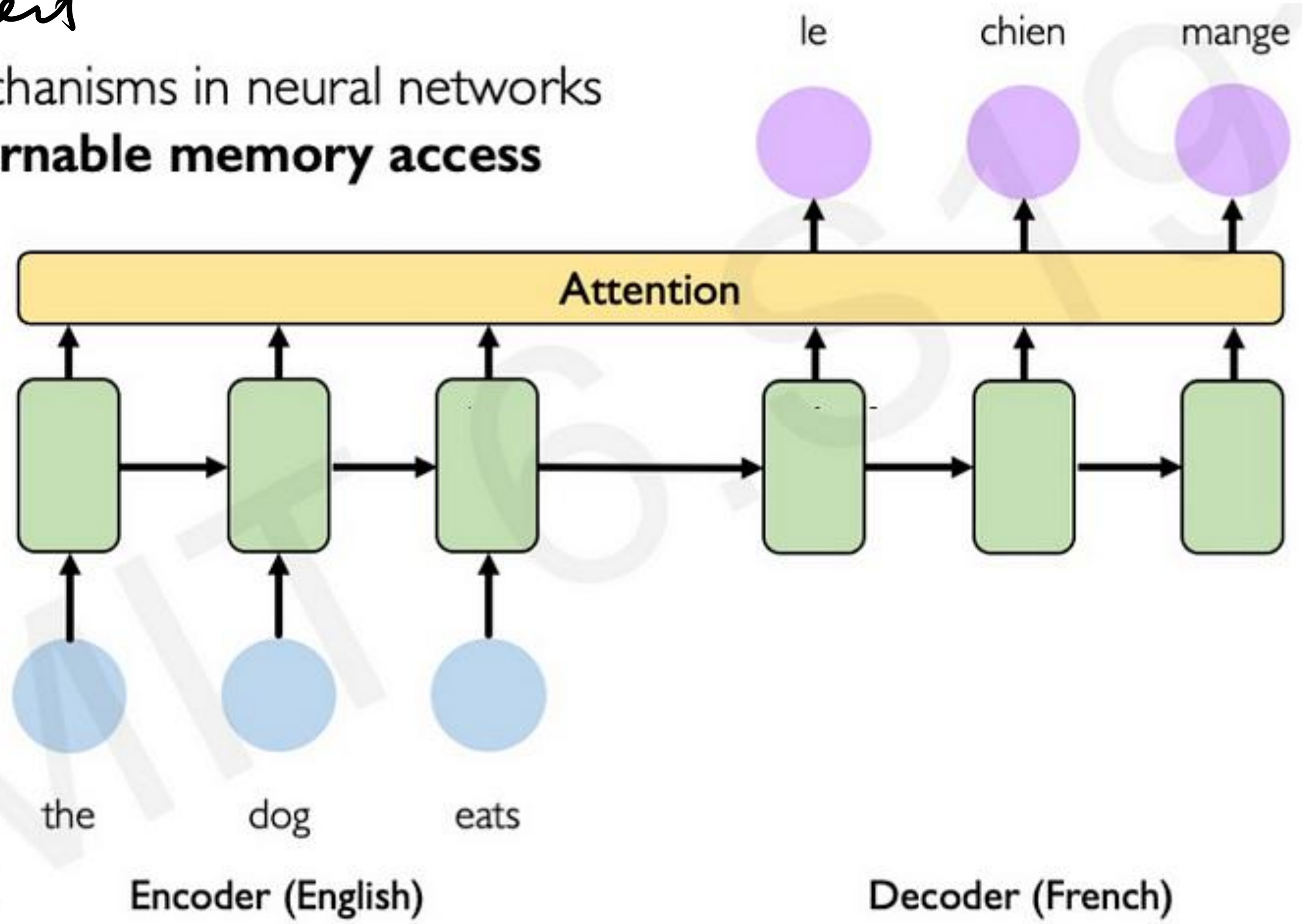


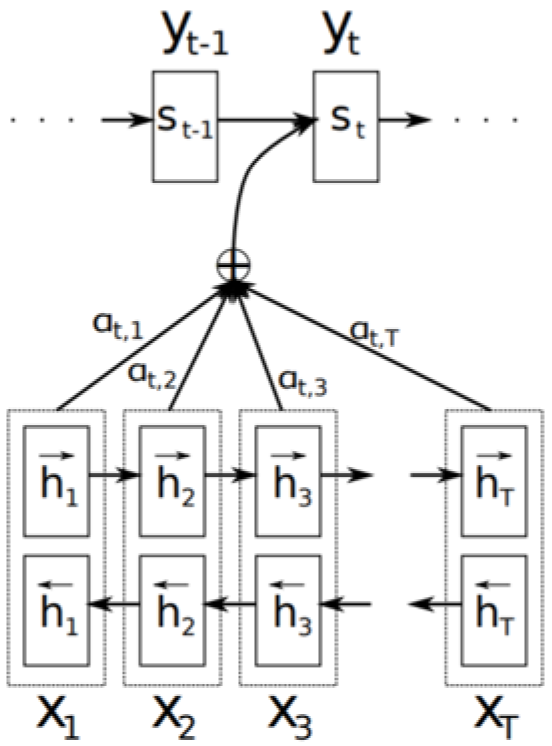
CNN + LSTM

من یک دانشجو هستم

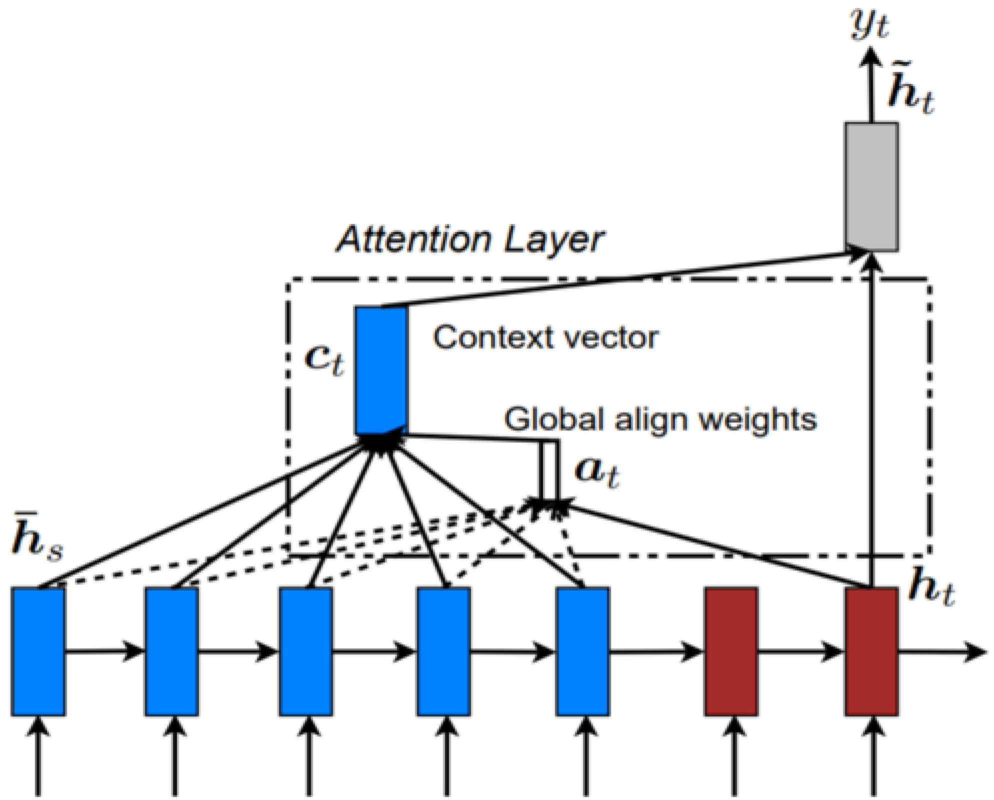
I am a student

Attention mechanisms in neural networks provide **learnable memory access**

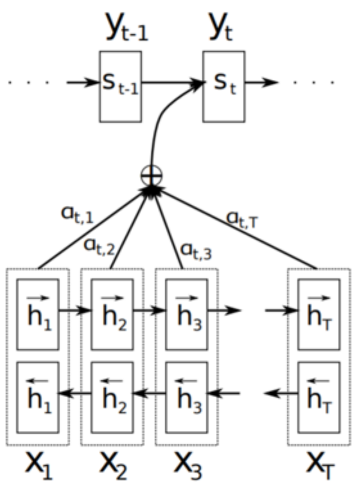




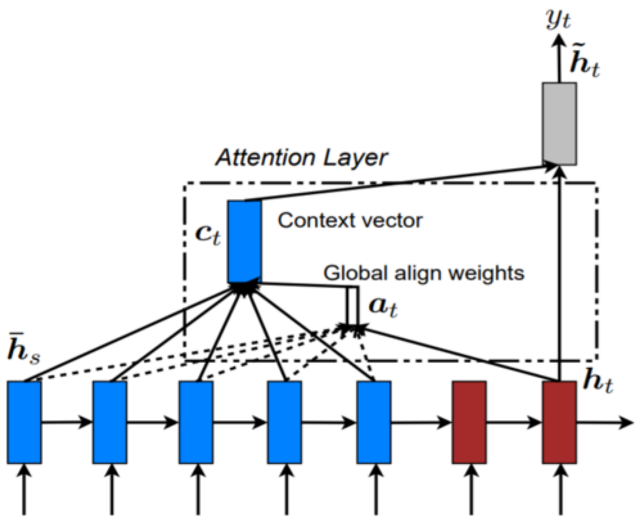
Bahdanau attention mechanism



Luong attention mechanism



Bahdanau attention mechanism



Luong attention mechanism

$$\alpha_{ts} = \frac{\exp\left(\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s)\right)}{\sum_{s'=1}^{S} \exp\left(\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_{s'})\right)} \qquad \text{[Attention weights]}$$

$$\boldsymbol{c}_t = \sum_s \alpha_{ts} \bar{\boldsymbol{h}}_s \qquad \text{[Context vector]}$$

$$\boldsymbol{a}_t = f(\boldsymbol{c}_t, \boldsymbol{h}_t) = \tanh(\boldsymbol{W_c}[\boldsymbol{c}_t; \boldsymbol{h}_t]) \qquad \text{[Attention vector]}$$

$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \boldsymbol{W} \bar{\boldsymbol{h}}_s & \text{[Luong's multiplicative style]} \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W_1} \boldsymbol{h}_t + \boldsymbol{W_2} \bar{\boldsymbol{h}}_s\right) & \text{[Bahdanau's additive style]} \end{cases}$$

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

Encoder
Decoder

ViT

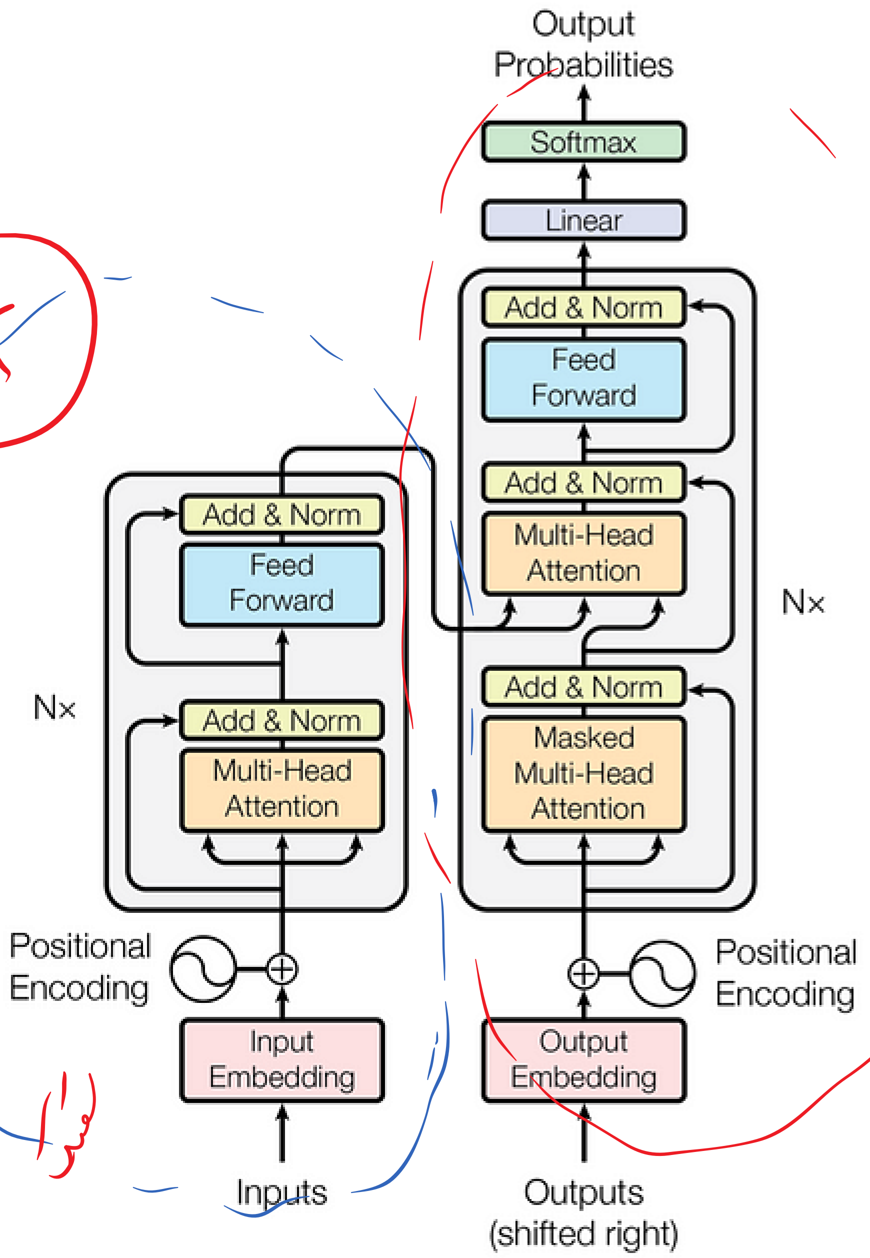
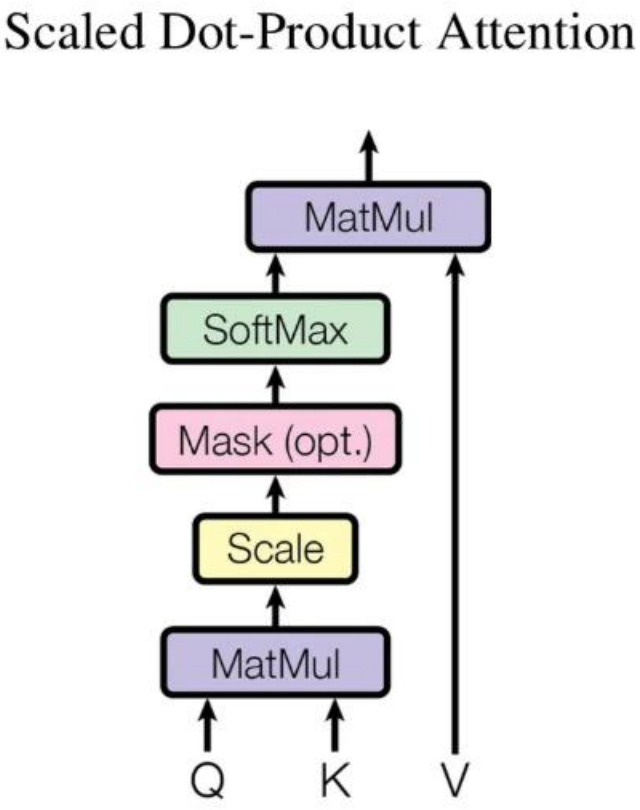
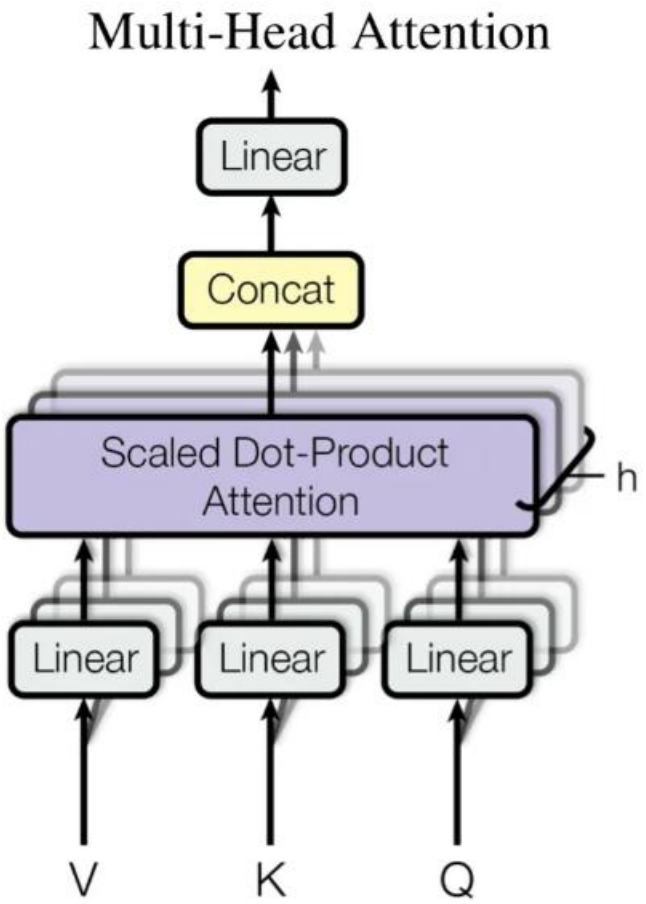
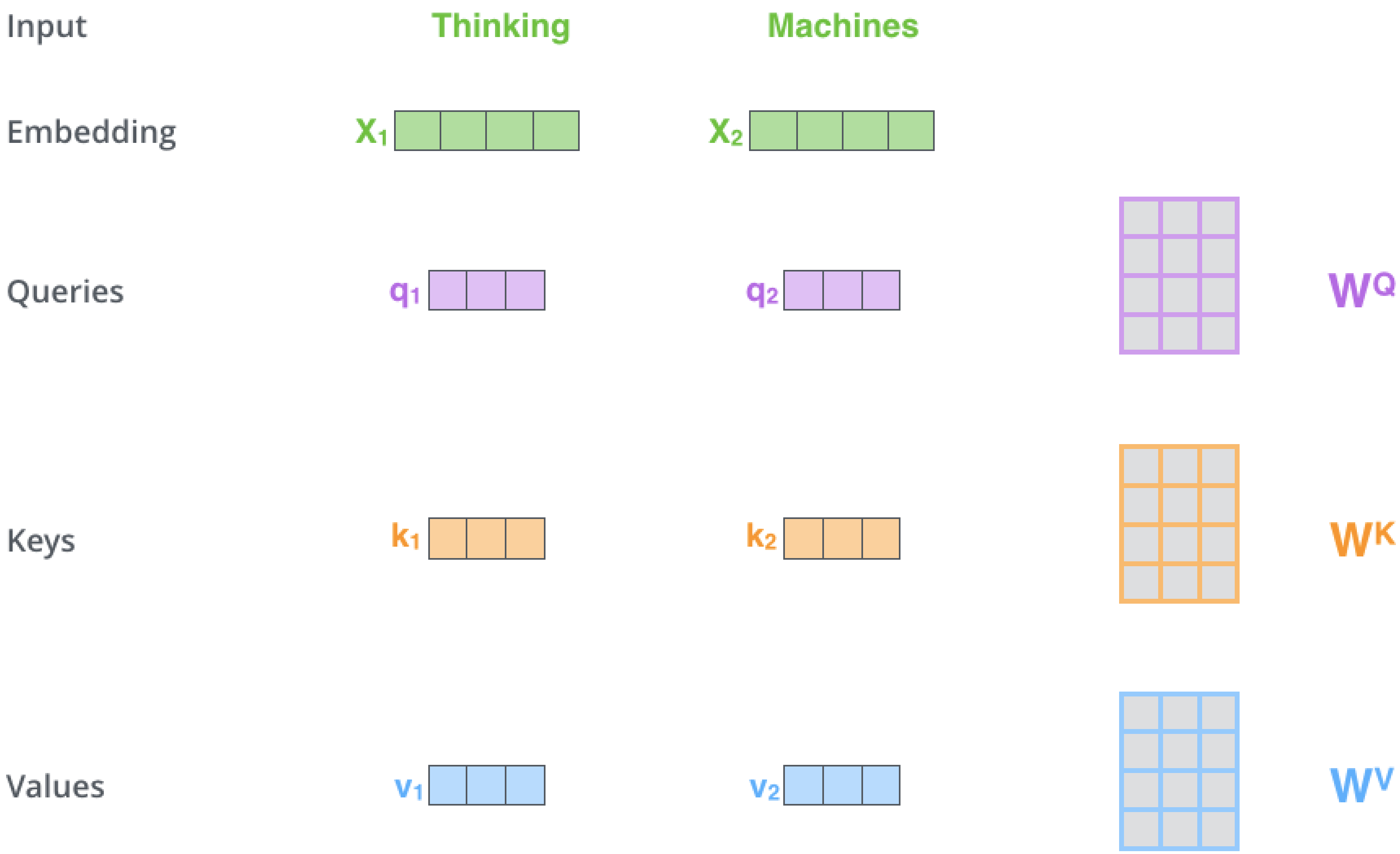


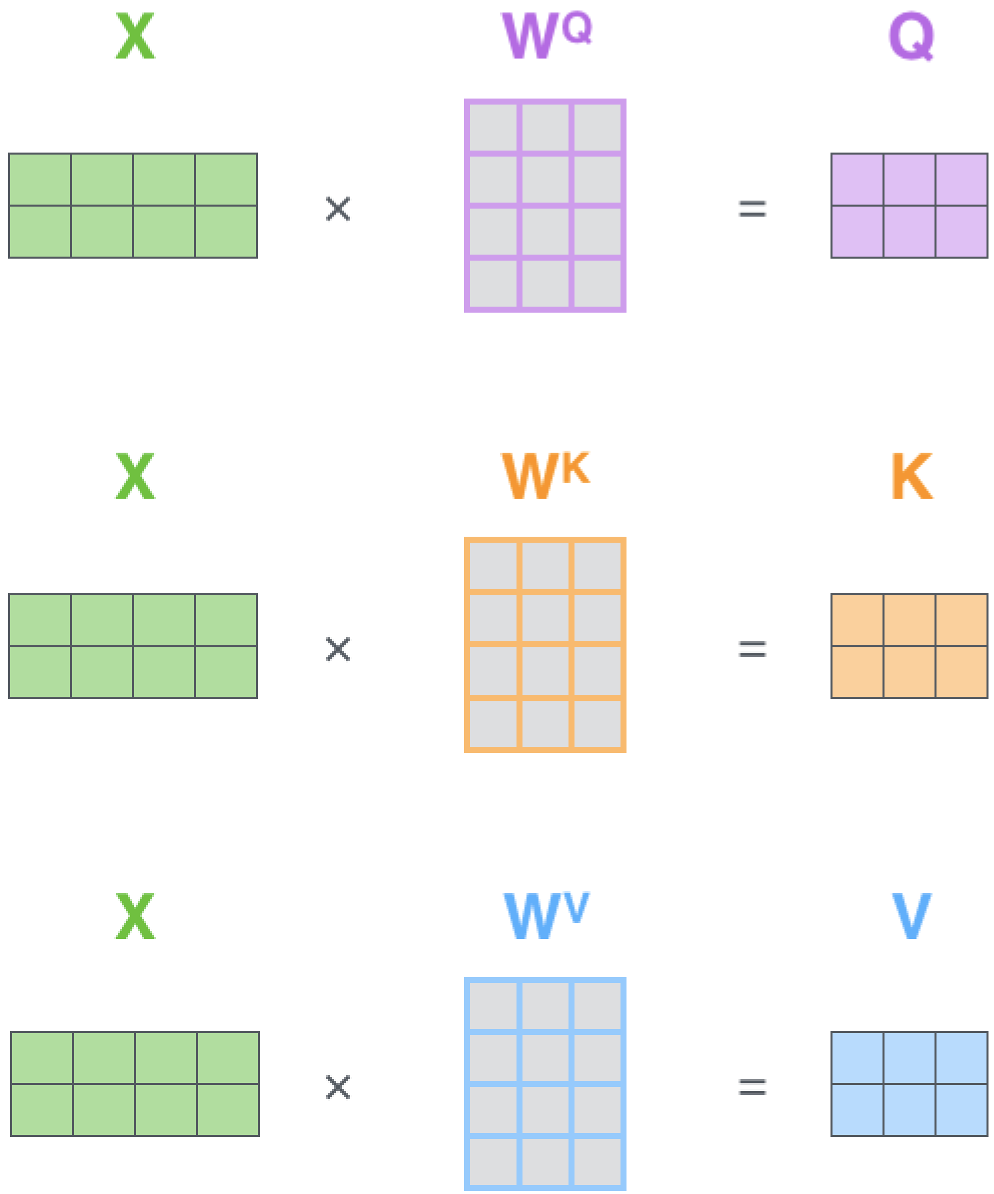
Figure 1: The Transformer - model architecture.





$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

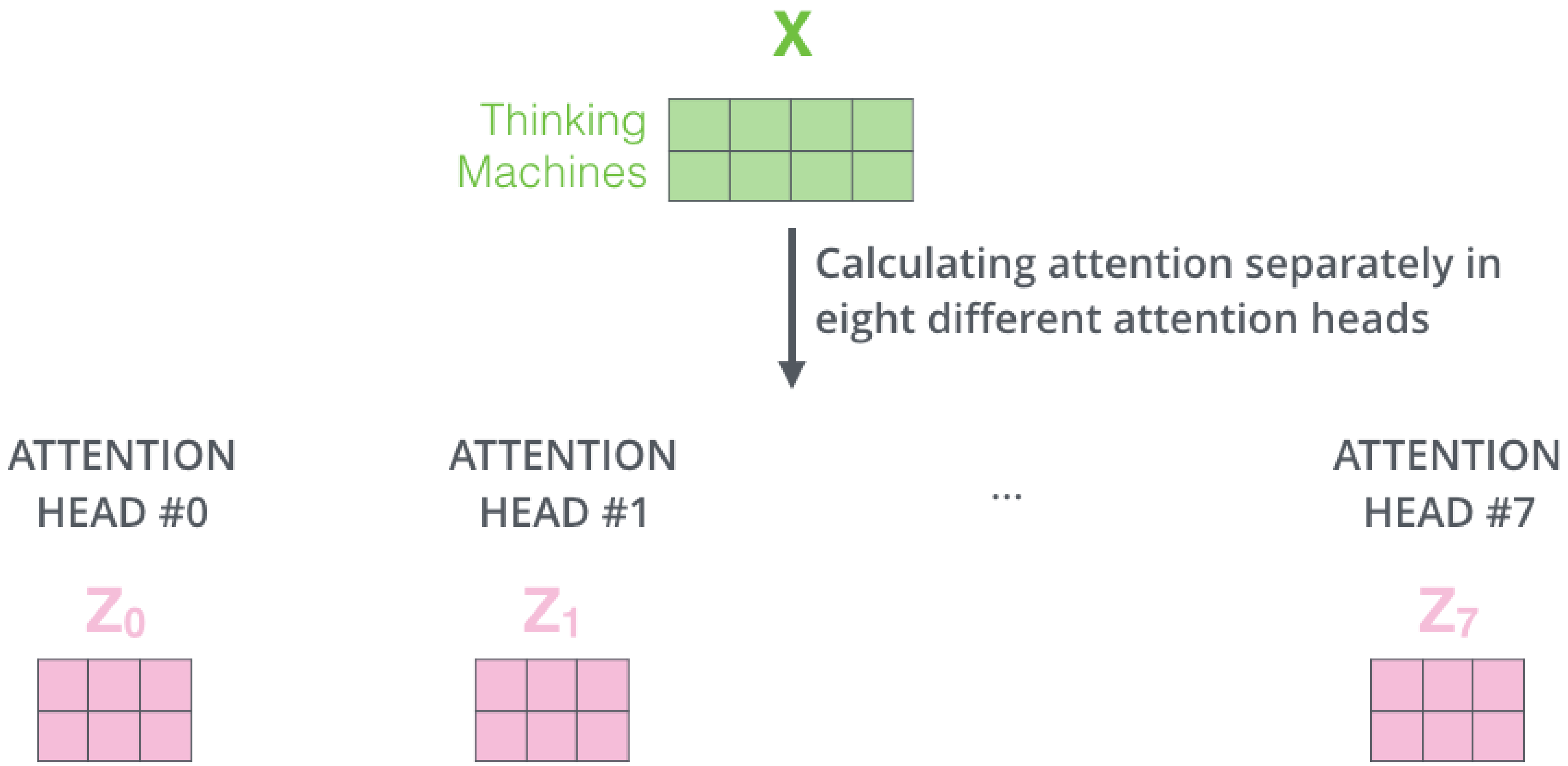

Input
Thinking
Machines
Embedding
X1
X2
Queries
q1
q2
WQ
Keys
k1
k2
WK
Values
v1
v2
WV

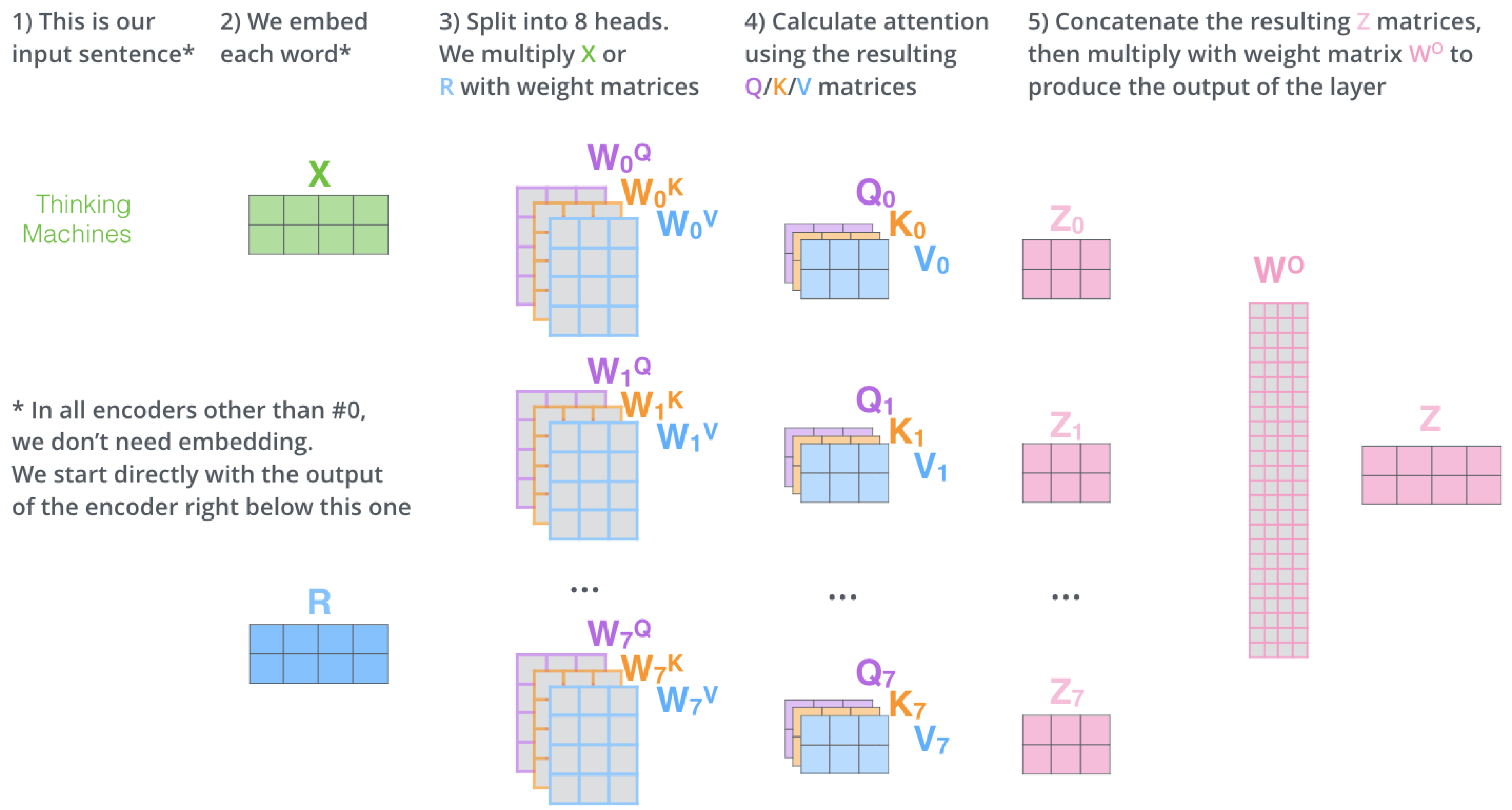

X
W^Q
Q
×
=
X
W^K
K
×
=
X
W^V
V
×
=

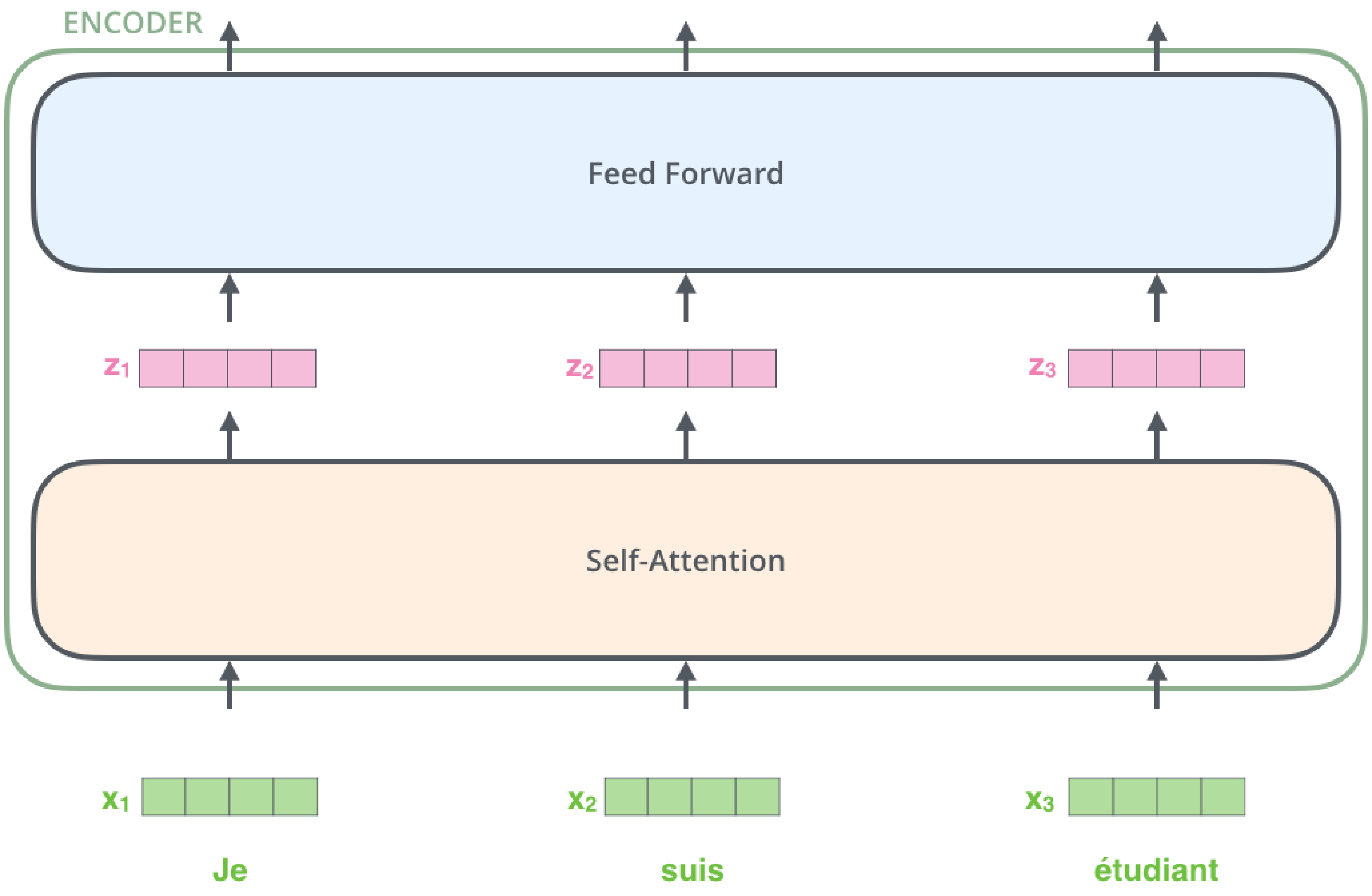
$\cos\theta : \dfrac{A.B}{\|A\|\|B\|}$

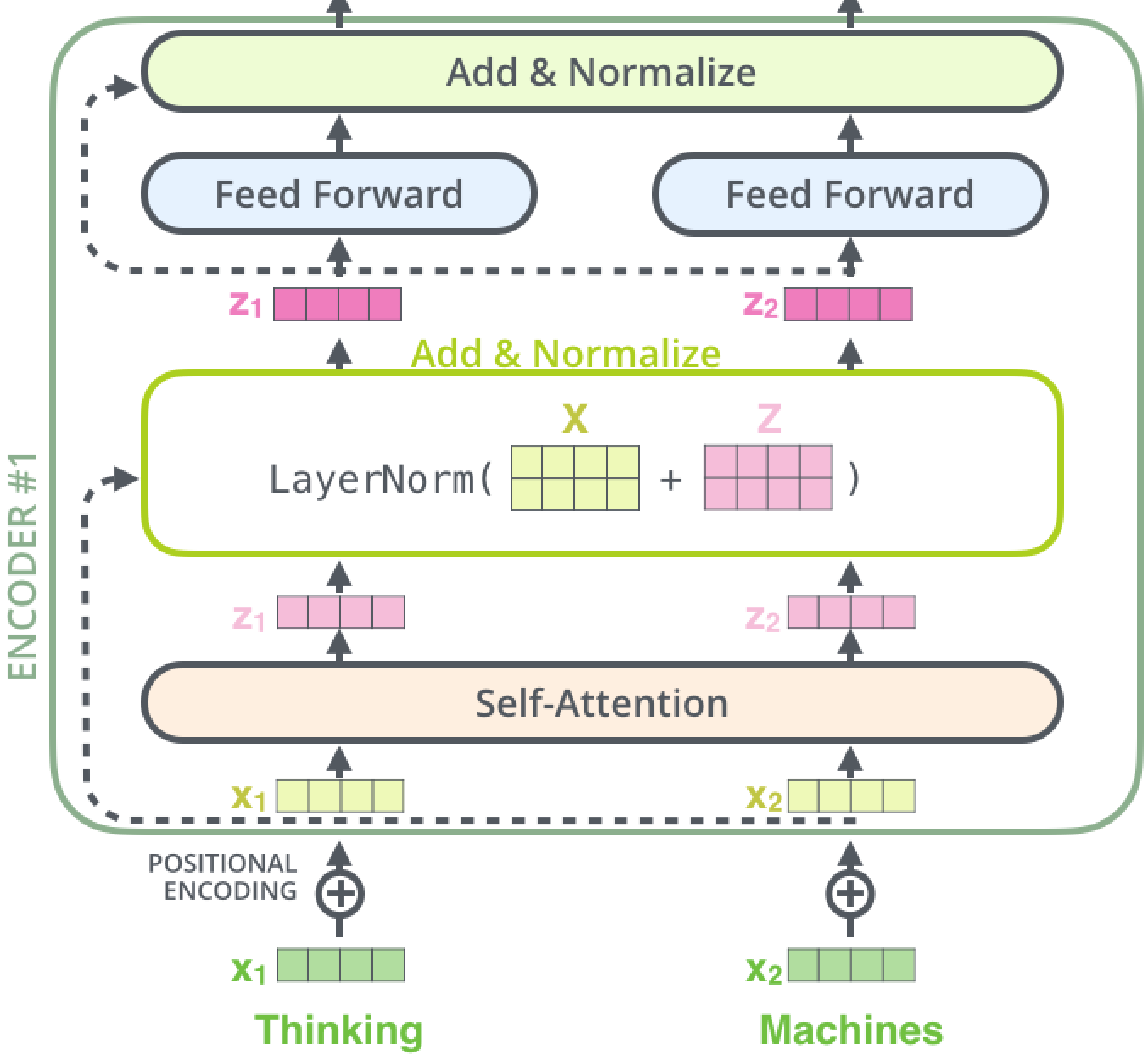
$$\text{softmax}\left(\frac{Q \times K^{T}}{\sqrt{d_k}}\right) V$$

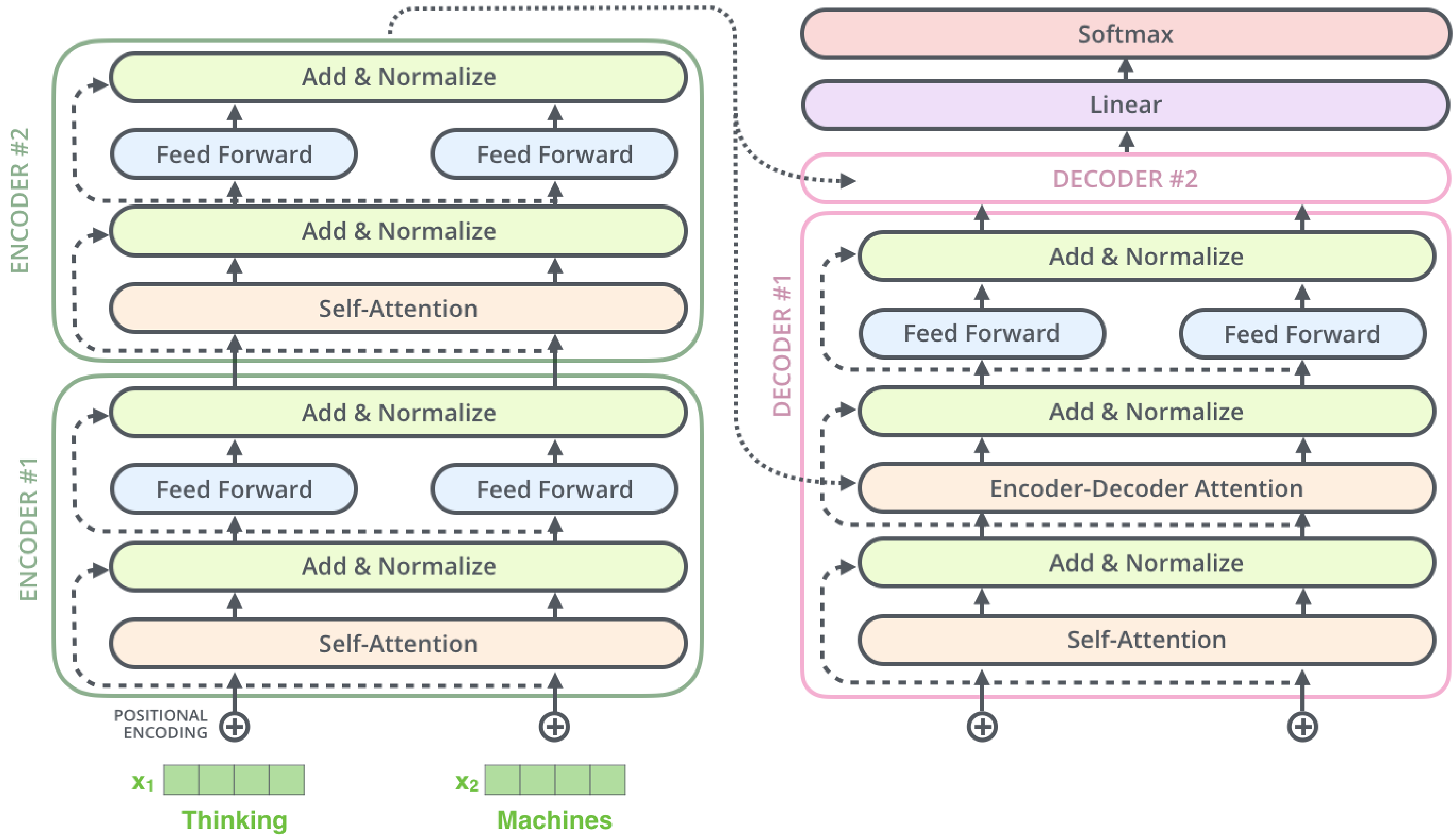
$$= Z$$


X
Thinking
Machines
Calculating attention separately in
eight different attention heads
ATTENTION
HEAD #0
Z0
ATTENTION
HEAD #1
Z1
...
ATTENTION
HEAD #7
Z7


1) This is our input sentence*
2) We embed each word*
3) Split into 8 heads. We multiply X or R with weight matrices
4) Calculate attention using the resulting Q/K/V matrices
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer
Thinking Machines
X
R
* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one
W_0^Q
W_0^K
W_0^V
W_1^Q
W_1^K
W_1^V
W_7^Q
W_7^K
W_7^V
...
Q_0
K_0
V_0
Q_1
K_1
V_1
Q_7
K_7
V_7
...
Z_0
Z_1
Z_7
...
W^O
Z


ENCODER
Feed Forward
z_1
z_2
z_3
Self-Attention
x_1
x_2
x_3
Je
suis
étudiant

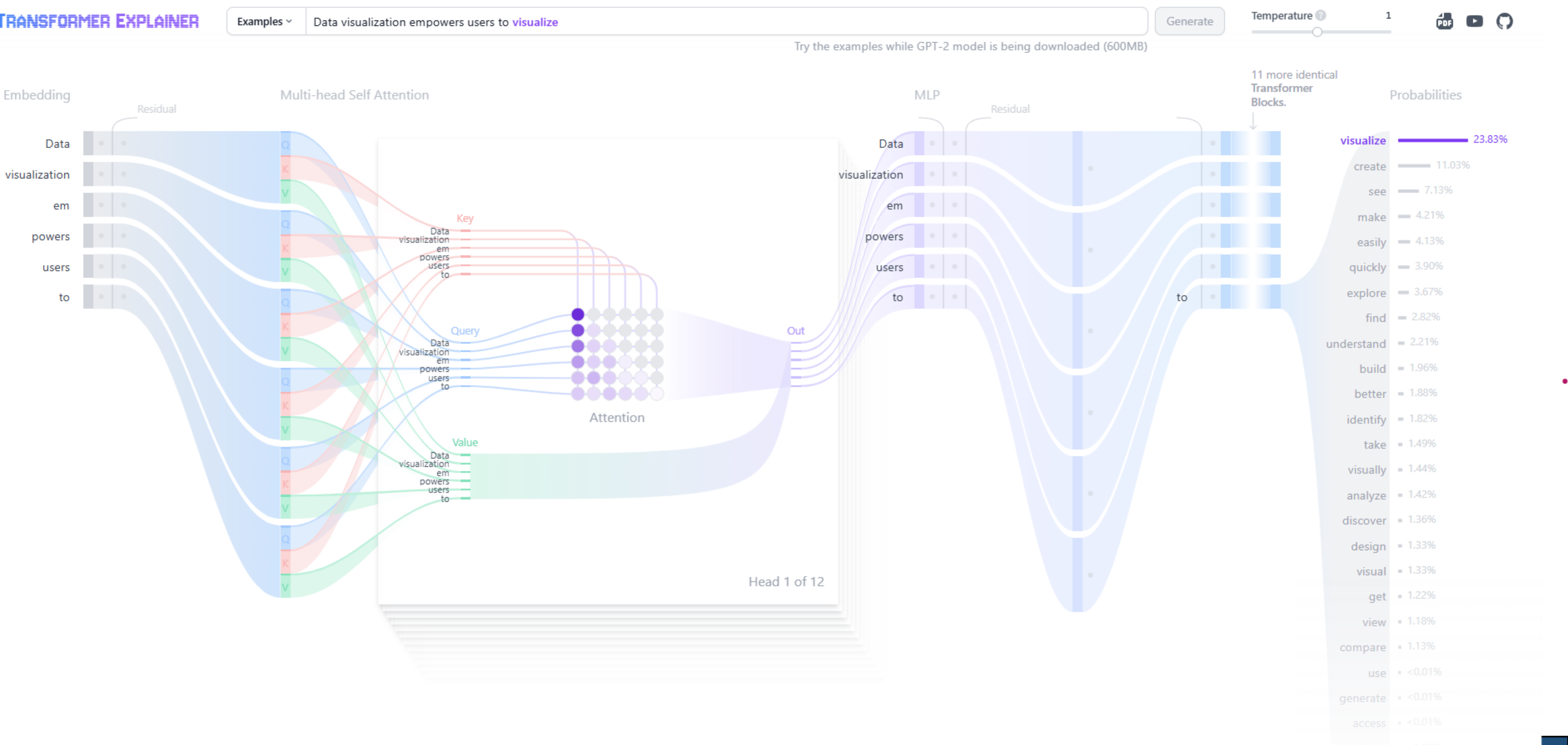

Add & Normalize
Feed Forward
Feed Forward
z1
z2
Add & Normalize
X
Z
LayerNorm(+)
z1
z2
Self-Attention
x1
x2
ENCODER #1
POSITIONAL
ENCODING
x1
x2
Thinking
Machines


Softmax
Linear
DECODER #2
DECODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Encoder-Decoder Attention
Add & Normalize
Self-Attention
ENCODER #2
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
POSITIONAL ENCODING
x_1
Thinking
x_2
Machines

$$PE(pos, 2i) = \sin(pos/10000^{2i/d})$$

$$PE(pos, 2i+1) = \cos(pos/10000^{2i/d})$$

https://poloclub.github.io/transformer-explainer/



https://poloclub.github.io/transformer-explainer/

Vision Transformer ViT