GRU

Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation

황주훈

MADE BY HENDO

INDEX

01. 배경지식

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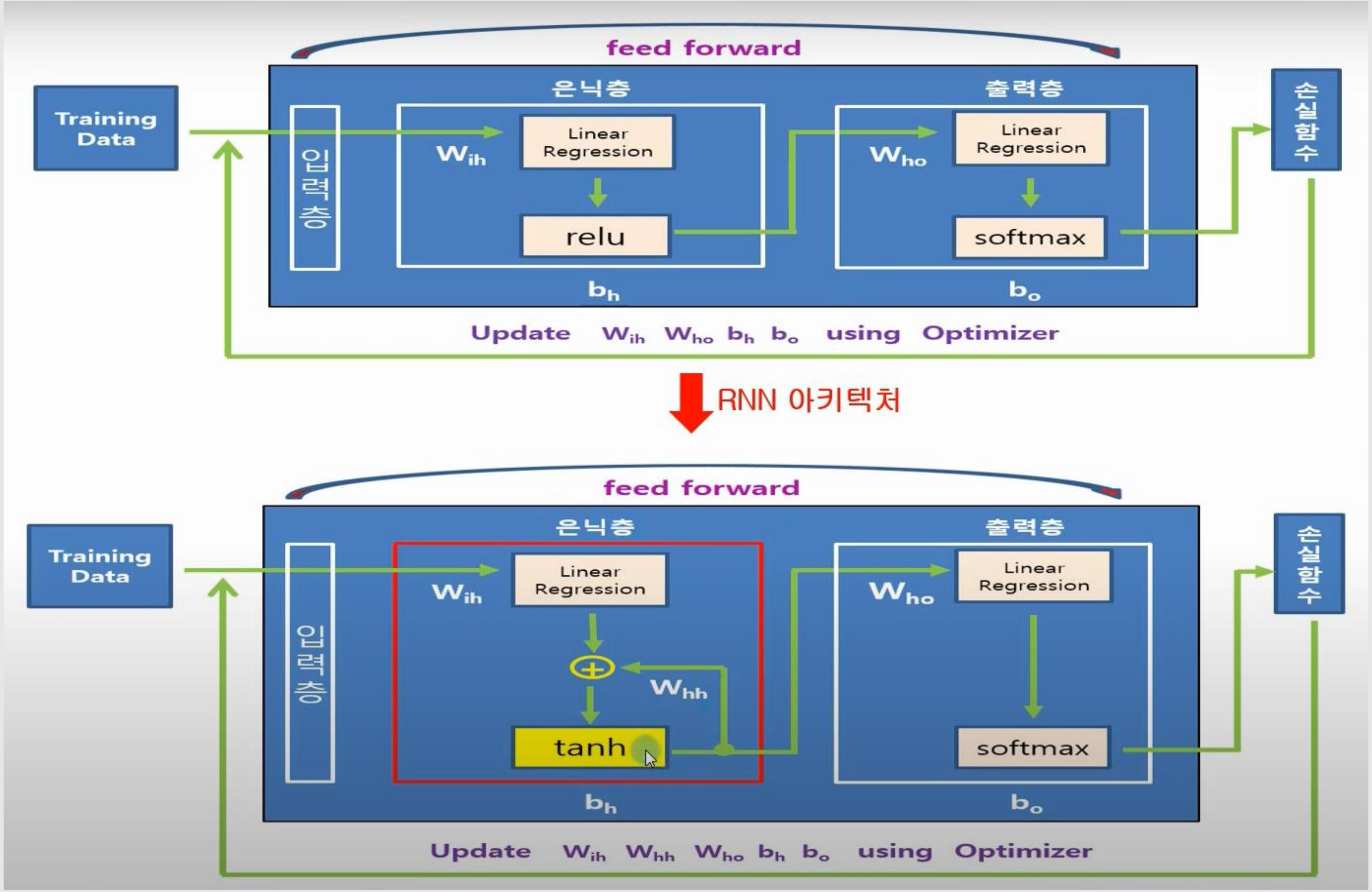
01. 배경지식 (RNN)



feed forward
Training Data
은닉층
출력층
입력층
Linear Regression
relu
Linear Regression
softmax
W_{ih}
W_{ho}
b_h
b_o
손실함수
Update W_{ih} W_{ho} b_h b_o using Optimizer
RNN 아키텍처
feed forward
Training Data
은닉층
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입력층
Linear Regression
tanh
W_{hh}
Linear Regression
softmax
W_{ih}
W_{ho}
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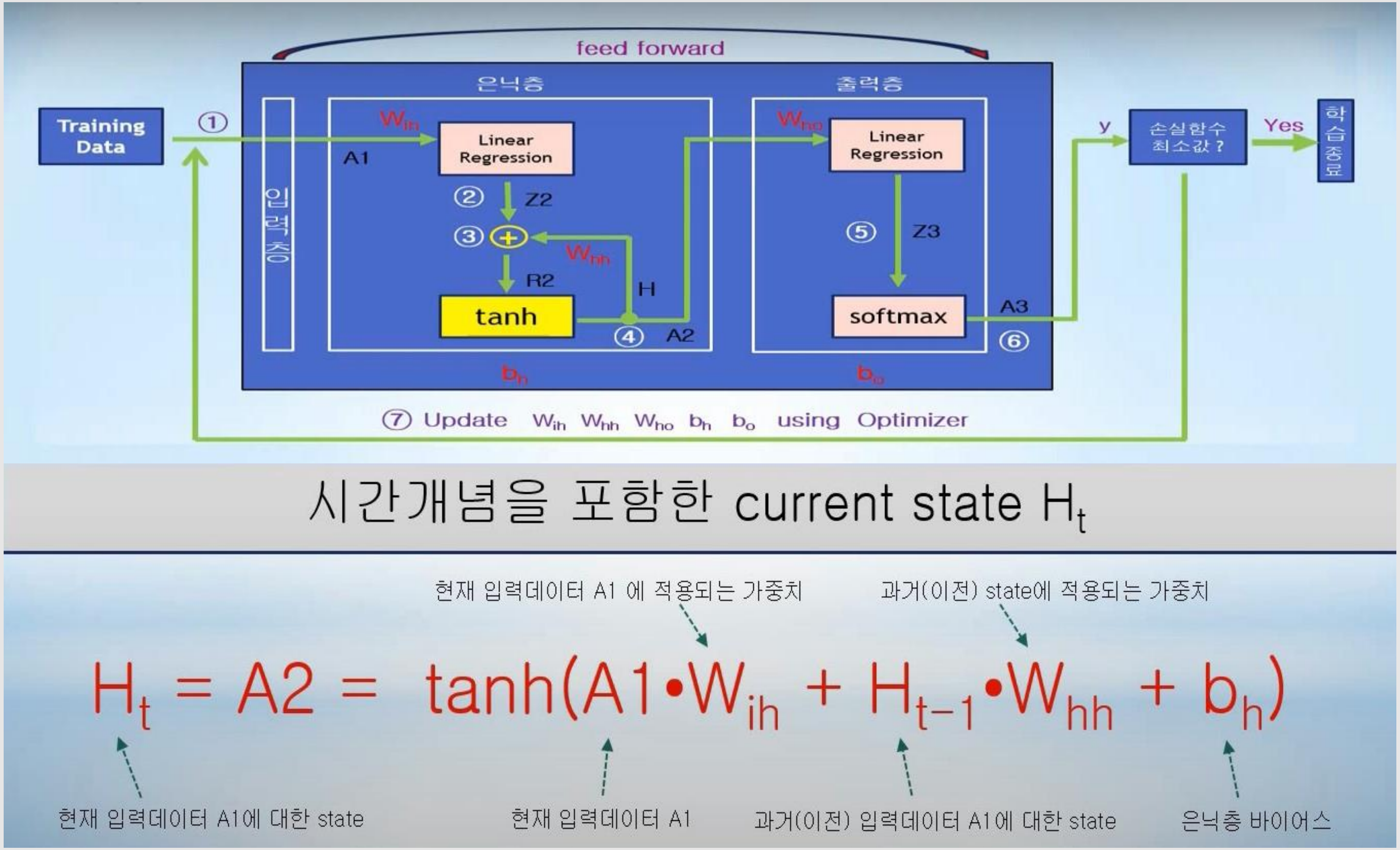
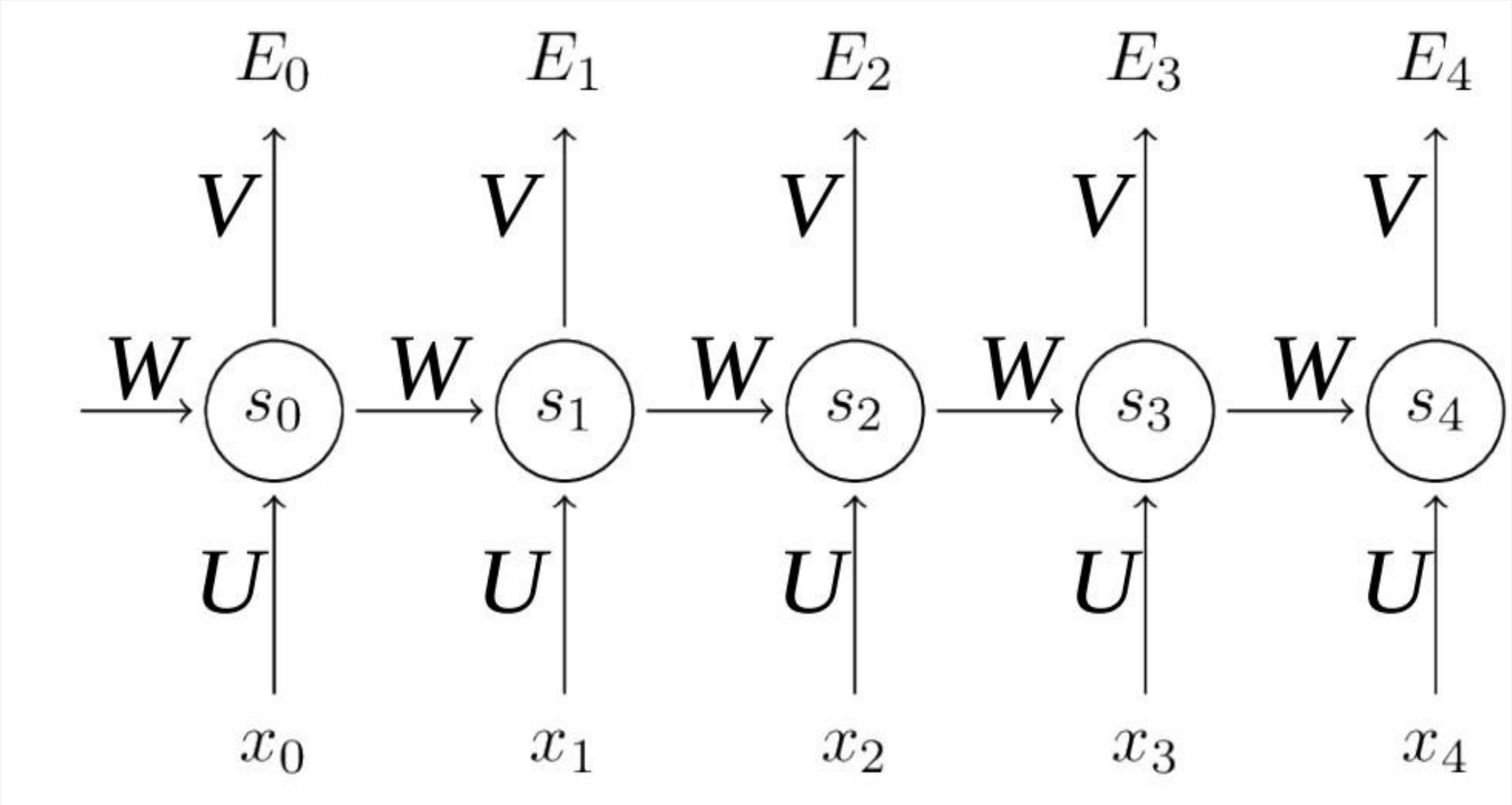
Update W_{ih} W_{hh} W_{ho} b_h b_o using Optimizer

01. 배경지식 (RNN)

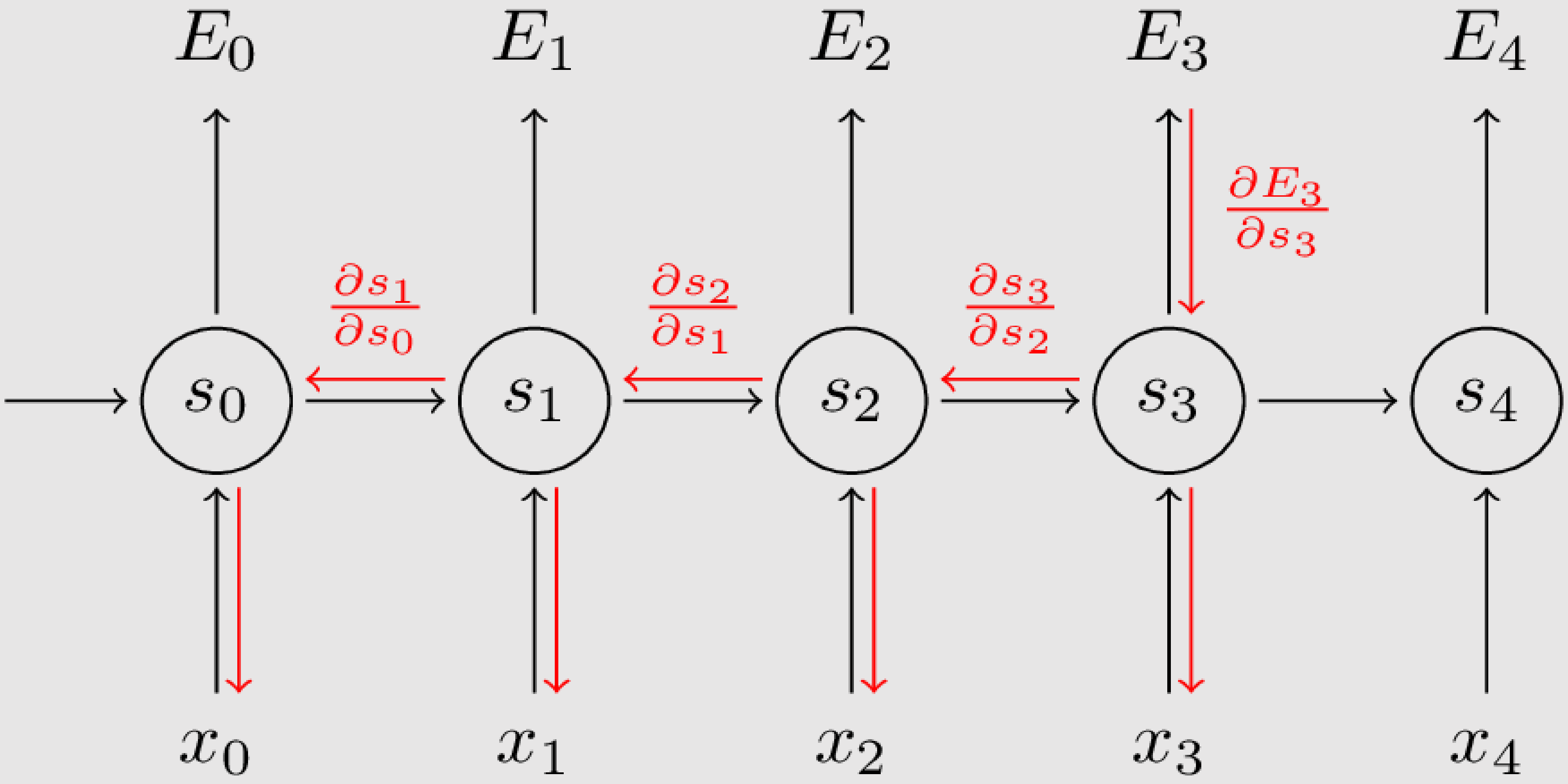

feed forward
은닉층
출력층
Training Data
①
입력층
A1
Linear Regression
② Z2
③ +
W_{hh}
R2
H
tanh
④ A2
W_{ho}
Linear Regression
⑤ Z3
softmax
A3
⑥
b_h
b_o
y
손실함수 최소값 ?
Yes
학습종료
⑦ Update W_{ih} W_{hh} W_{ho} b_h b_o using Optimizer
시간개념을 포함한 current state H_t
현재 입력데이터 A1 에 적용되는 가중치
과거(이전) state에 적용되는 가중치
$H_t = A2 = \tanh(A1 \cdot W_{ih} + H_{t-1} \cdot W_{hh} + b_h)$
현재 입력데이터 A1에 대한 state
현재 입력데이터 A1
과거(이전) 입력데이터 A1에 대한 state
은닉층 바이어스

01. 배경지식 (RNN)



E=Error
E=Y - ŷ

01. 배경지식 (RNN)



$$s_t = \tanh(Ux_t + Ws_{t-1})$$

$$\hat{y}_t = softmax(Vs_t)$$

$$\frac{\partial E_3}{\partial W_s} = \frac{\partial E_3}{\partial \bar{y}_3}\frac{\partial \bar{y}_3}{\partial \bar{s}_3}\frac{\partial \bar{s}_3}{\partial W_s}$$

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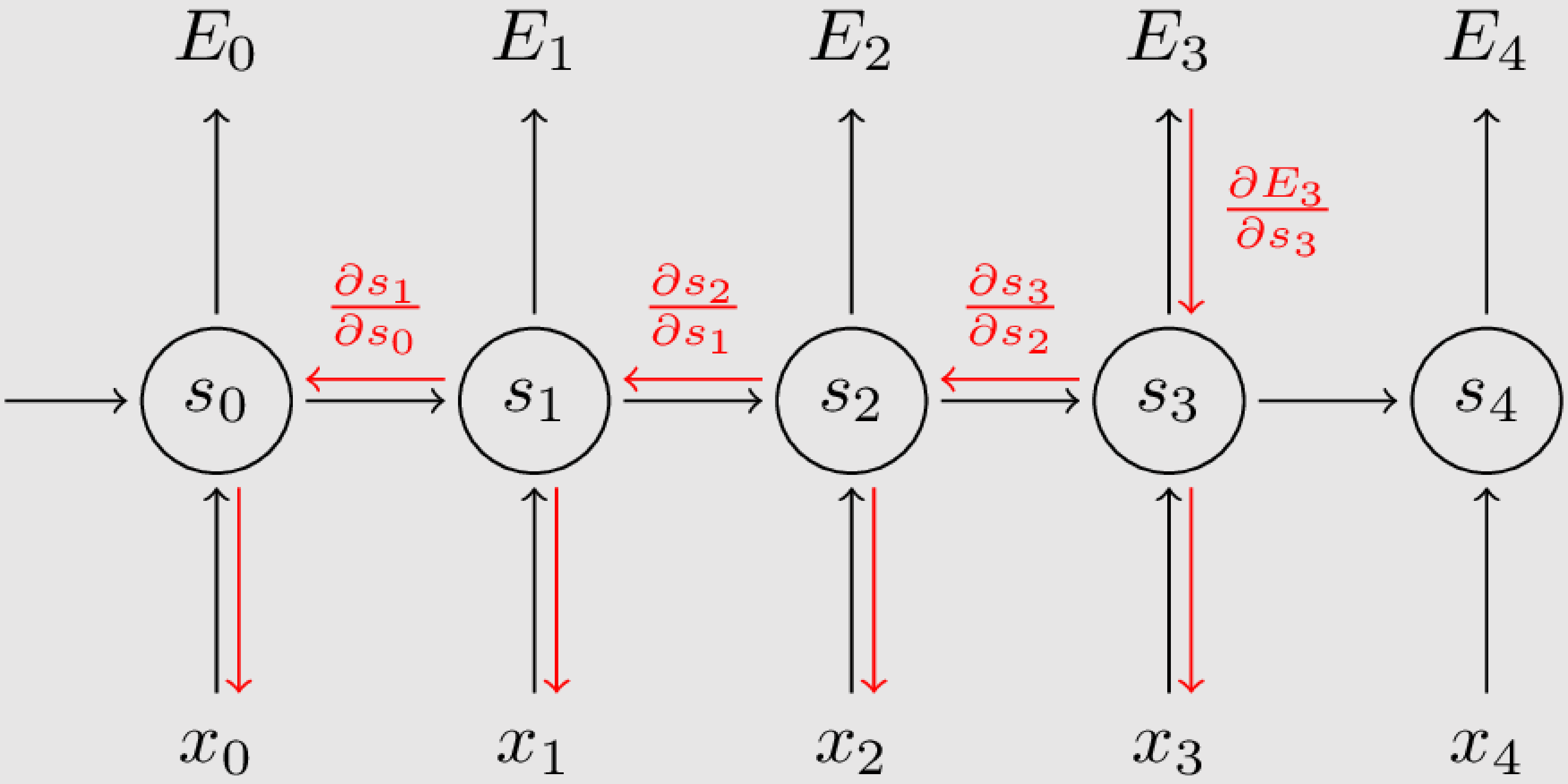

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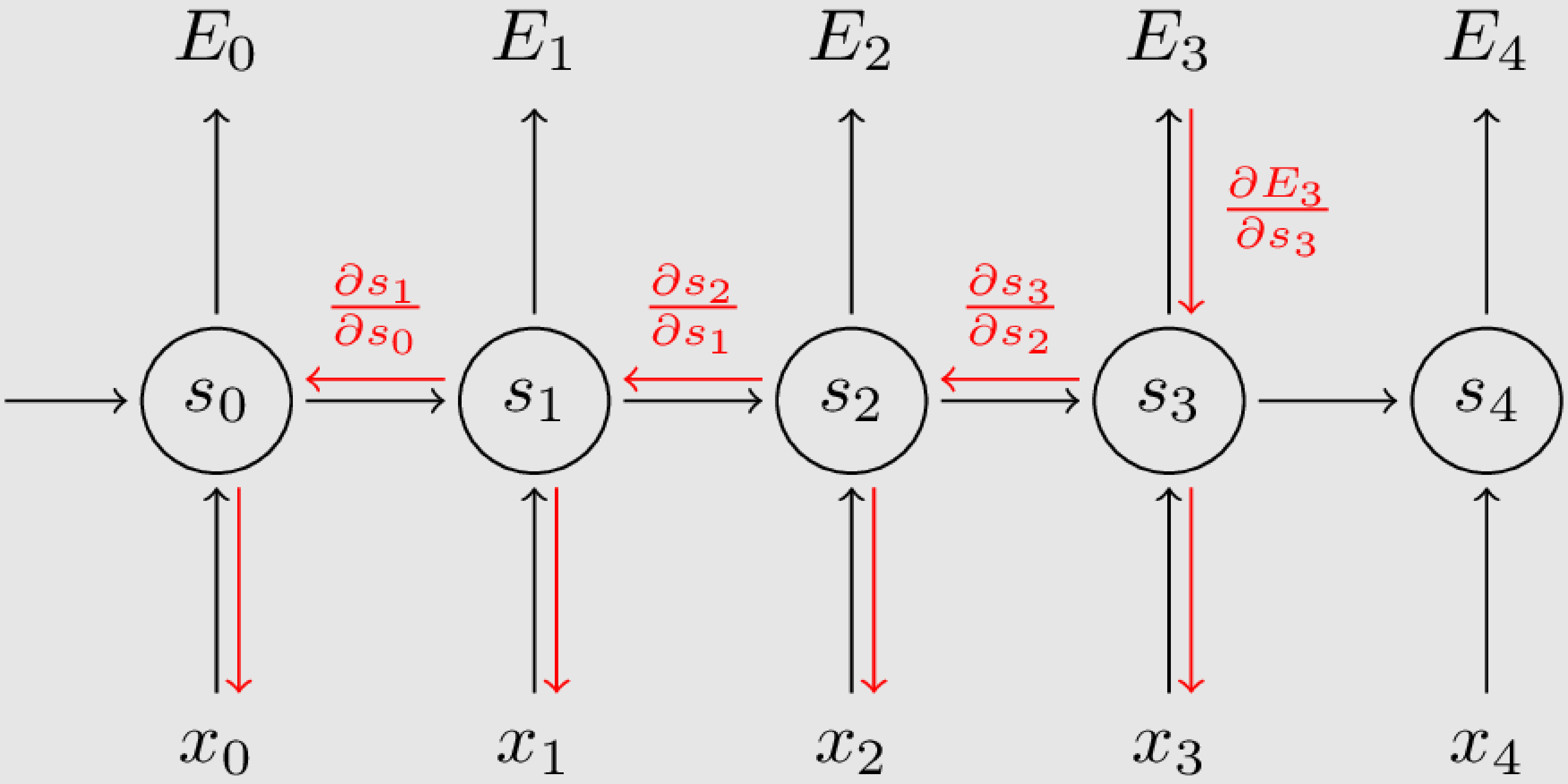

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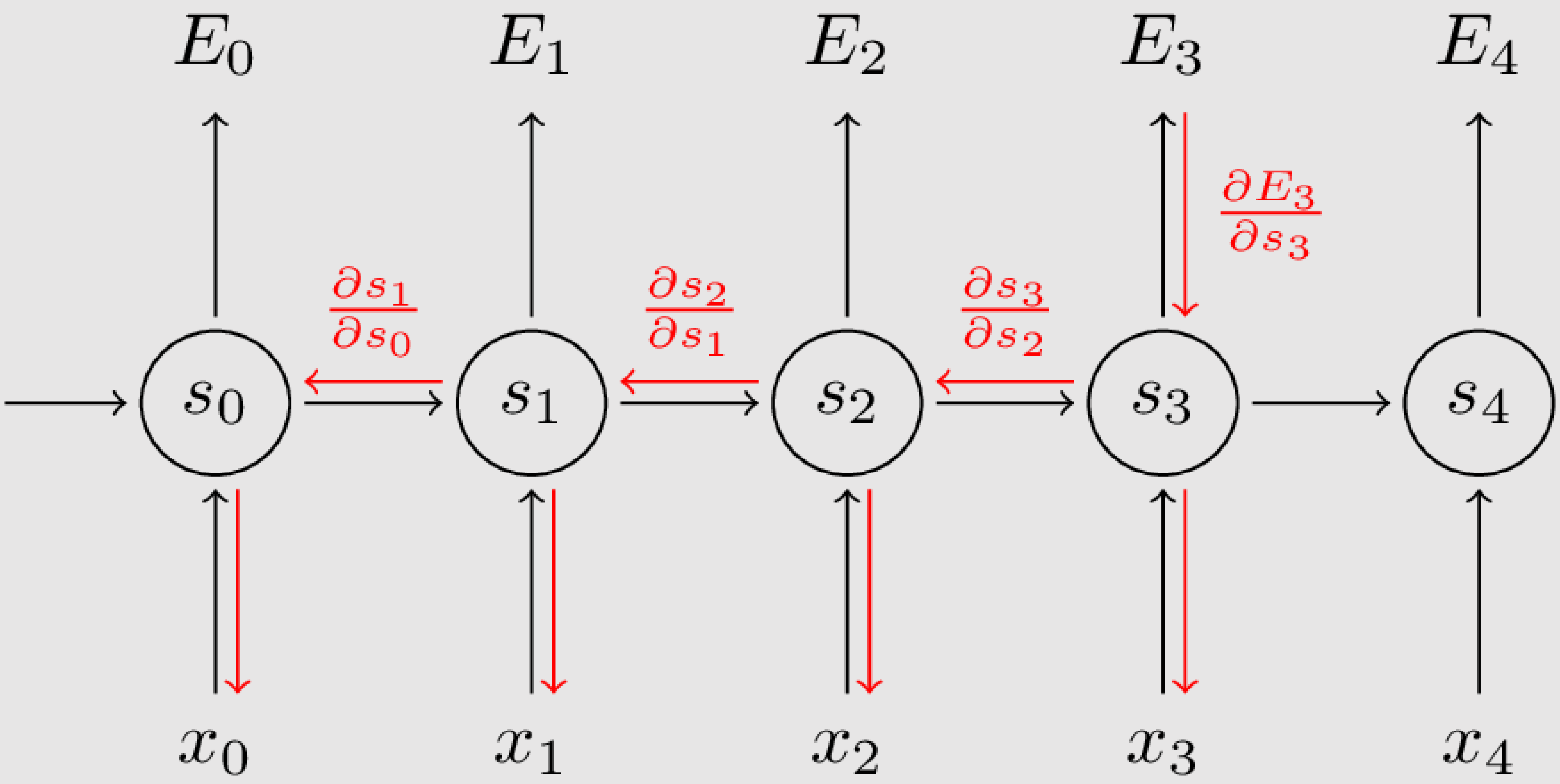

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$$\frac{\partial E_3}{\partial W_s} = \frac{\partial E_3}{\partial \bar{y}_3}\frac{\partial \bar{y}_3}{\partial \bar{s}_3}\frac{\partial \bar{s}_3}{\partial W_s} + \frac{\partial E_3}{\partial \bar{y}_3}\frac{\partial \bar{y}_3}{\partial \bar{s}_3}\frac{\partial \bar{s}_3}{\partial \bar{s}_2}\frac{\partial \bar{s}_2}{\partial W_s} + \frac{\partial E_3}{\partial \bar{y}_3}\frac{\partial \bar{y}_3}{\partial \bar{s}_3}\frac{\partial \bar{s}_3}{\partial \bar{s}_2}\frac{\partial \bar{s}_2}{\partial \bar{s}_1}\frac{\partial \bar{s}_1}{\partial W_s}$$

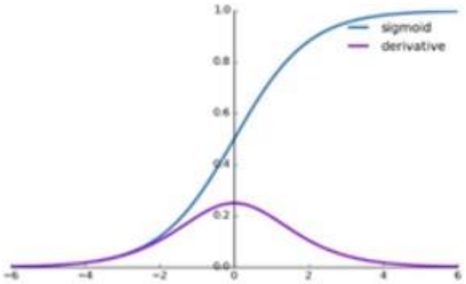
$$W = W - \text{learning\_rate} * \frac{\partial E}{\partial W}$$

01. 배경지식 (RNN)

왜 tanh를 쓰는가?

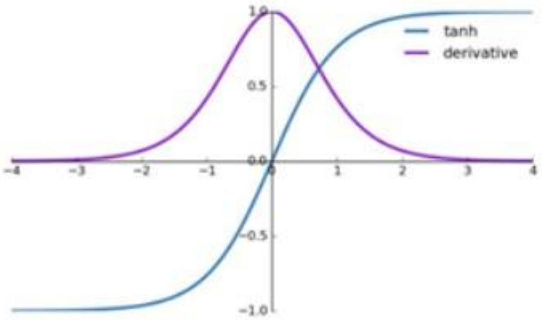
Activation Function

- Sigmoid



Sigmoid	
$f(x)$	$\frac{1}{1+e^{-x}}$ (y: 0 ~ 1)
$\frac{d}{dx}f(x)$	$\frac{1}{1+e^{-x}}\left(1-\frac{1}{1+e^{-x}}\right)$ (y′: 0~0.25)

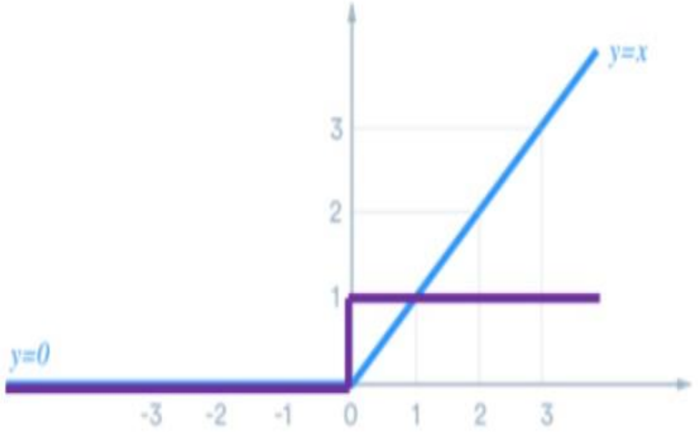
- Tanh



Tanh	
$f(x)$	$\frac{e^x - e^{-x}}{e^x + e^{-x}}$ (y: −1~1)
$\frac{d}{dx}f(x)$	$1-\tanh(x)^2$ (y′: 0~1)

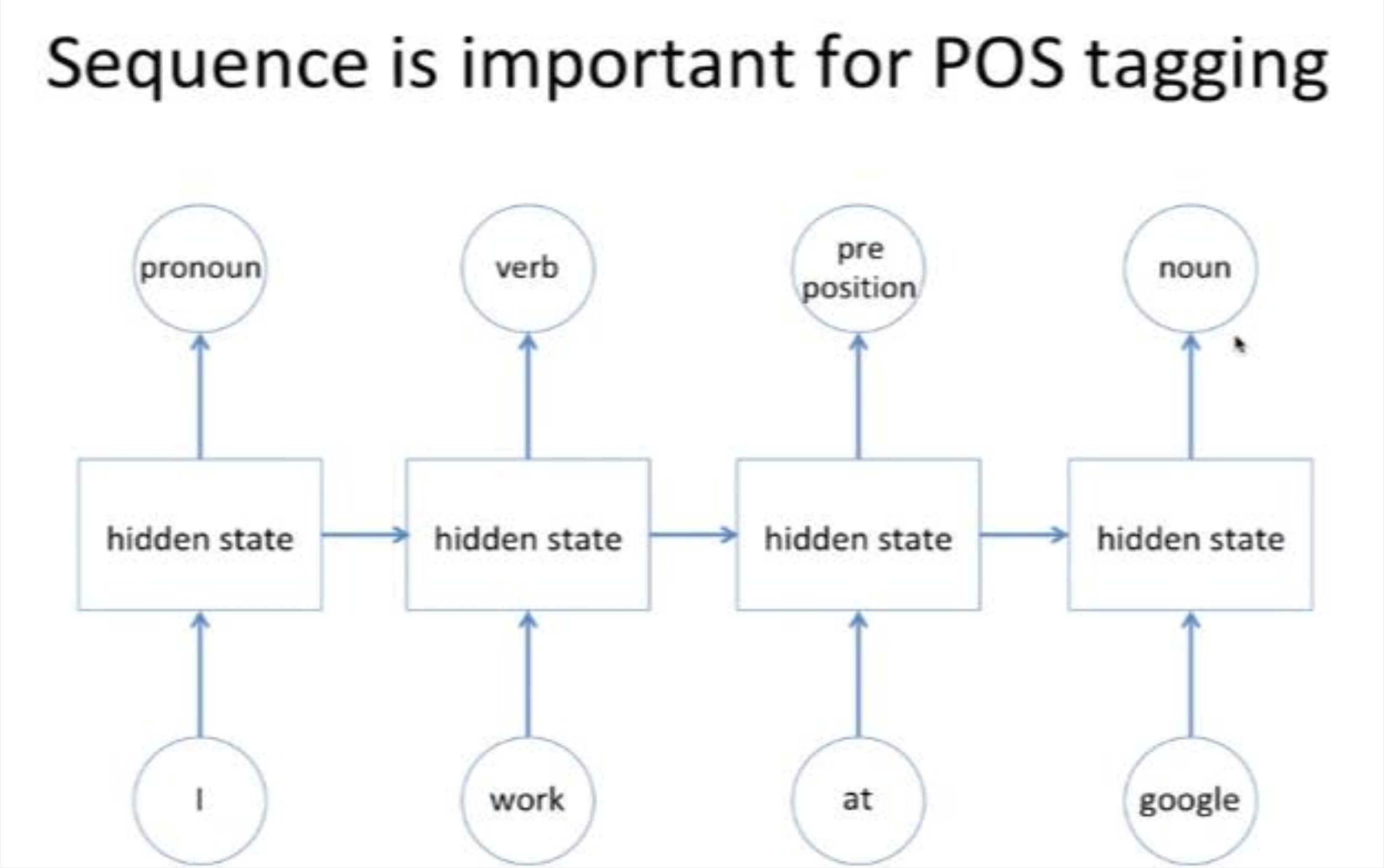
01. 배경지식 (RNN)

왜 tanh를 쓰는가?

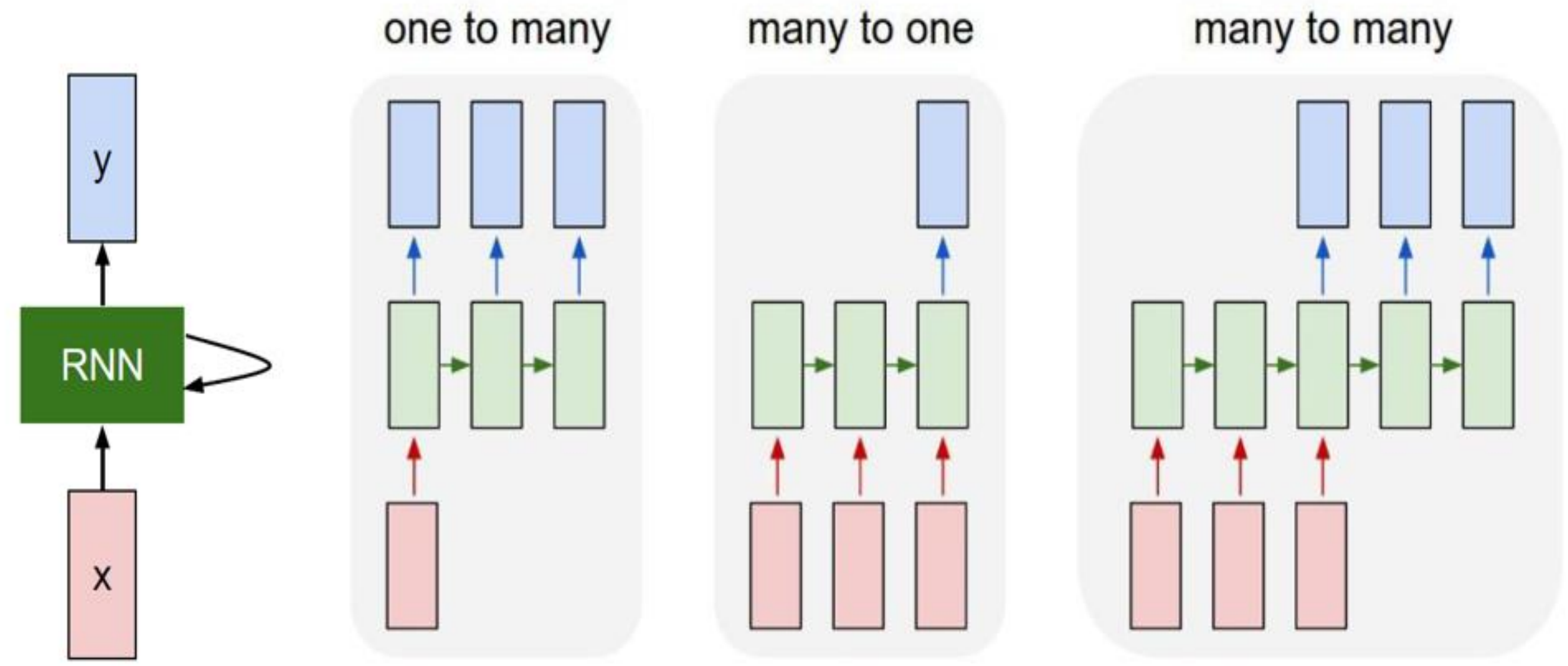


ReLU	
$f(x)$	$\max(0,x)$
$\frac{d}{dx}f(x)$	$\begin{cases} 1 & (x \geq 0) \\ 0 & (x < 0) \end{cases}$

01. 배경지식 (RNN)


Sequence is important for POS tagging
pronoun
verb
pre position
noun
hidden state
hidden state
hidden state
hidden state
I
work
at
google

01. 배경지식 (RNN)



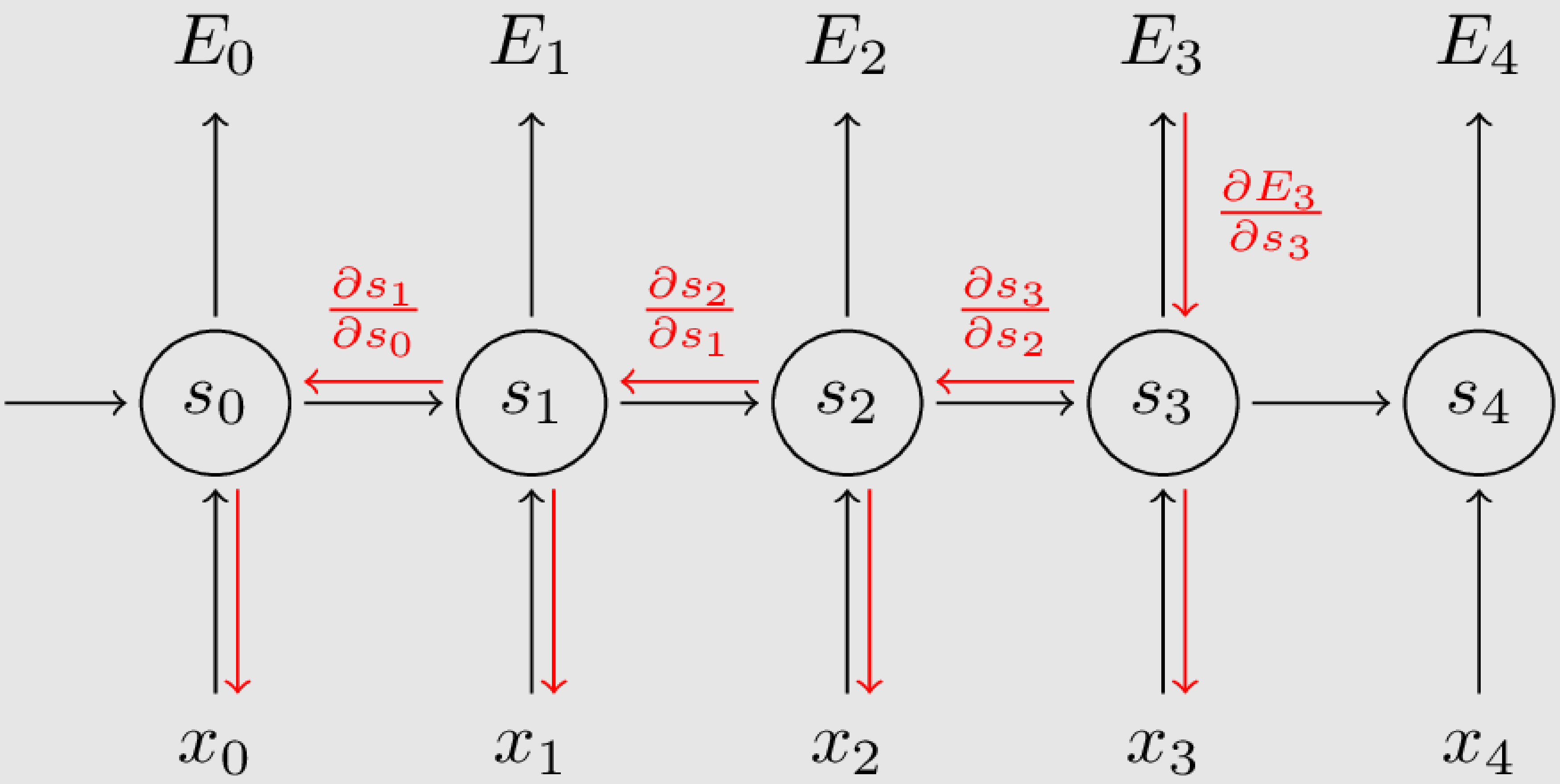
<기본구조>

<사진설명 붙이기>
사진 → 단어들

<감성분석>
단어들 → 감성점수

<번역>
단어들 → 단어들

01. 배경지식 (RNN)



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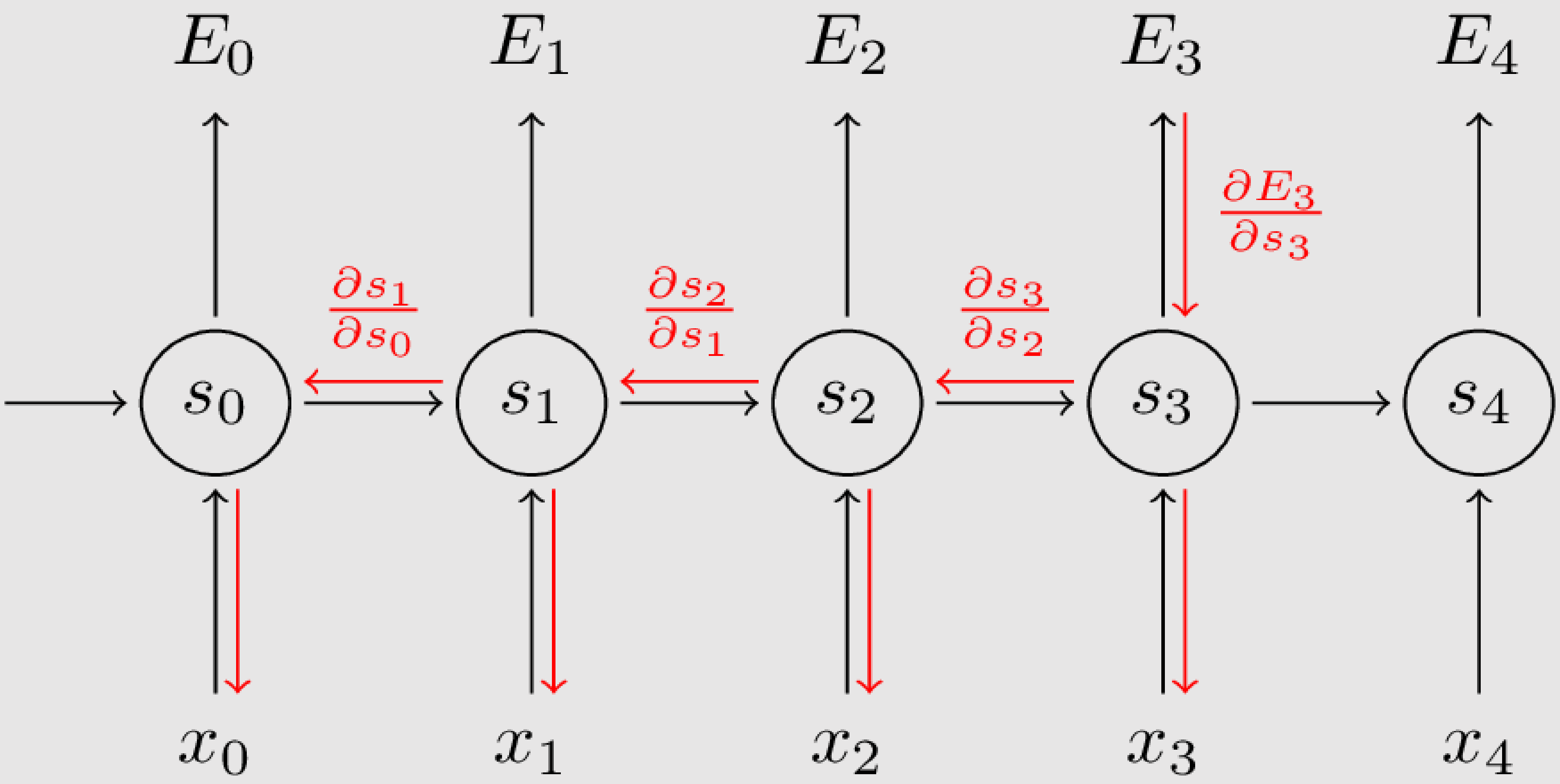
$$W = W - learning\_rate * \frac{\partial E}{\partial W}$$

1보다 미분값이 클경우
Gradient Exploding

01. 배경지식 (RNN)



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1보다 미분값이 클경우
Gradient Exploding → Gradient cliffing

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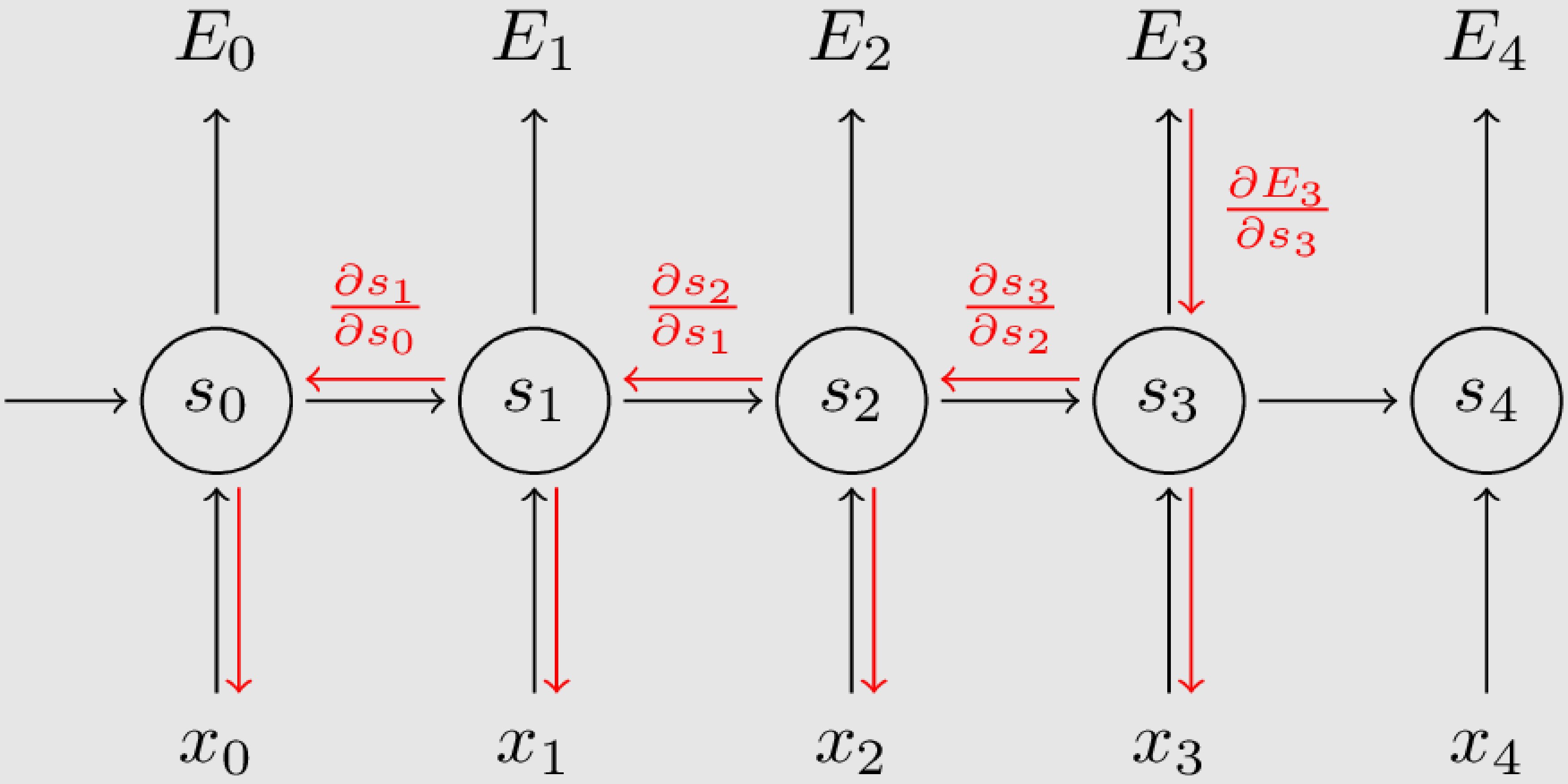

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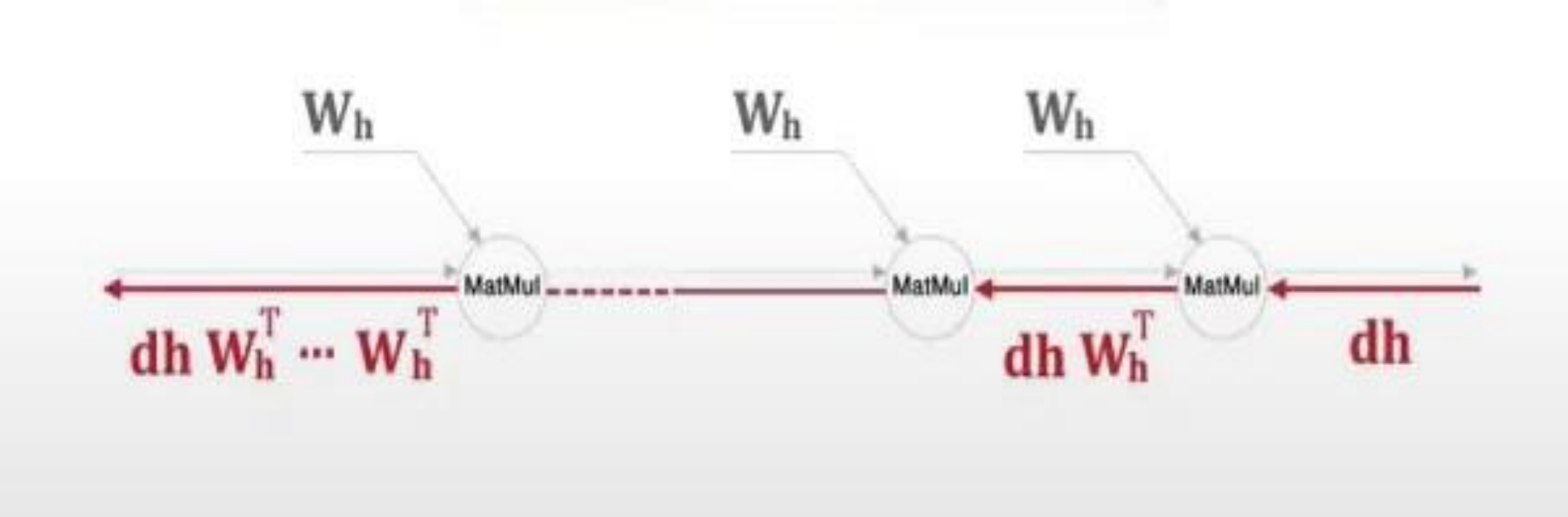
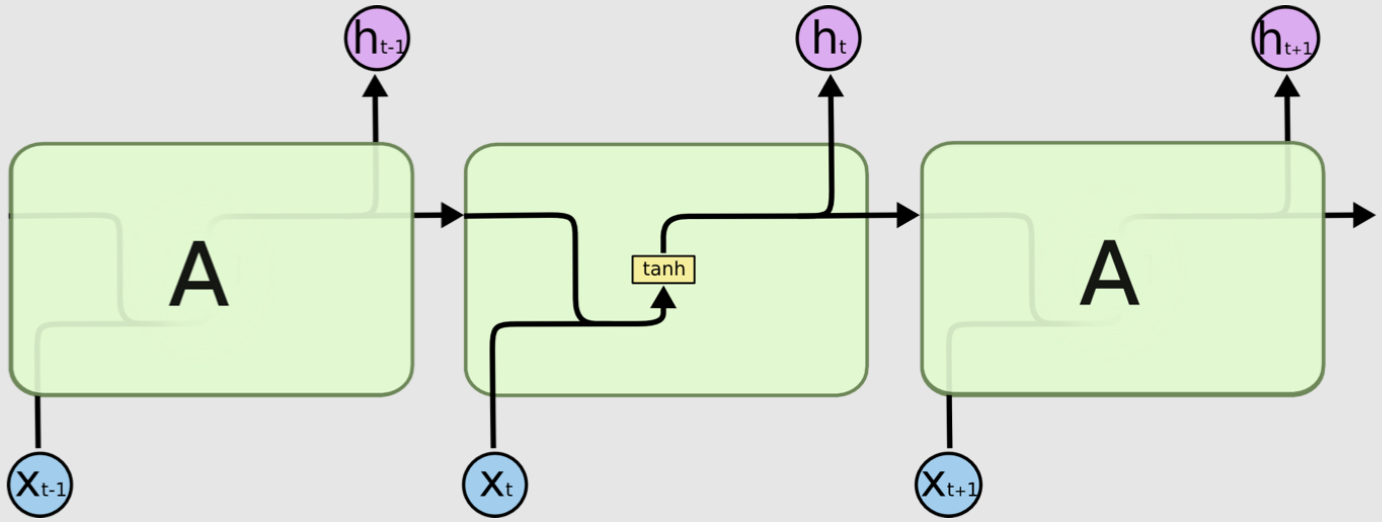
$$W = W - learning\_rate * \frac{\partial E}{\partial W}$$

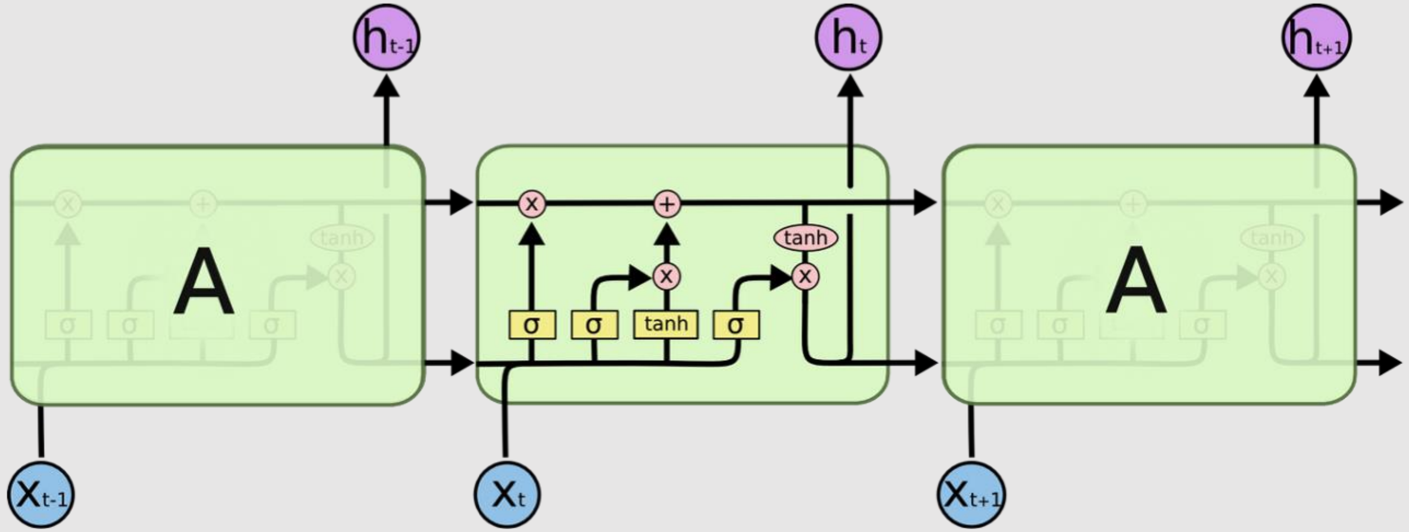
1보다 미분값이 작을경우
Gradient Vanishing

01. 배경지식 (RNN)



01. 배경지식 (LSTM)





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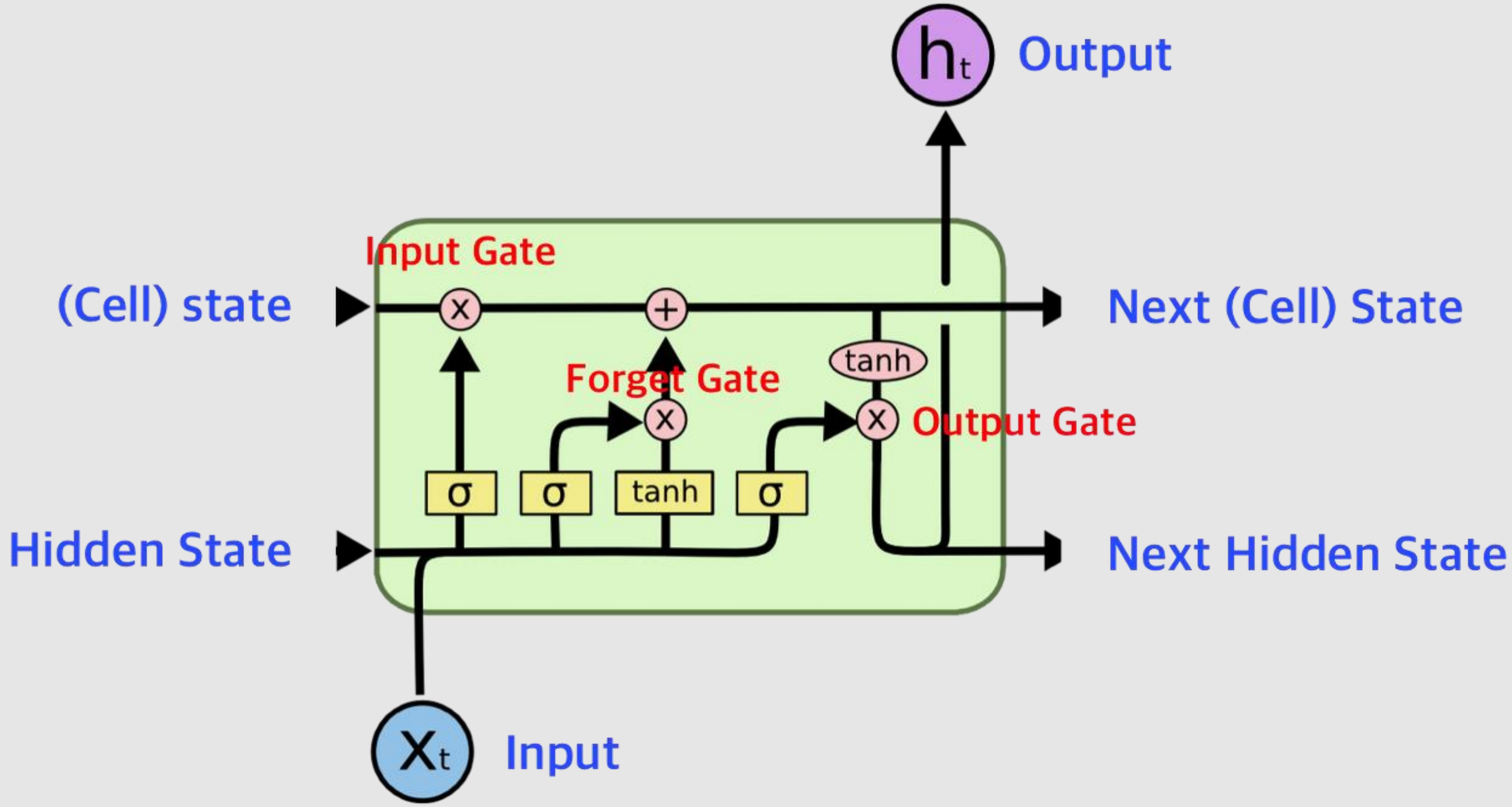
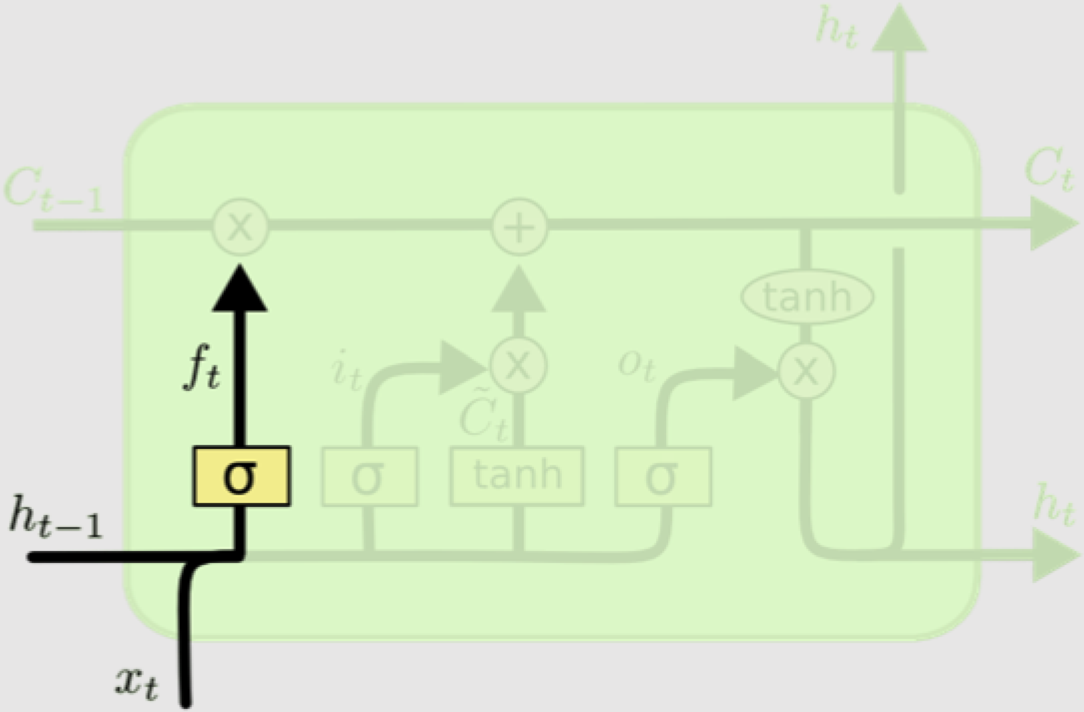
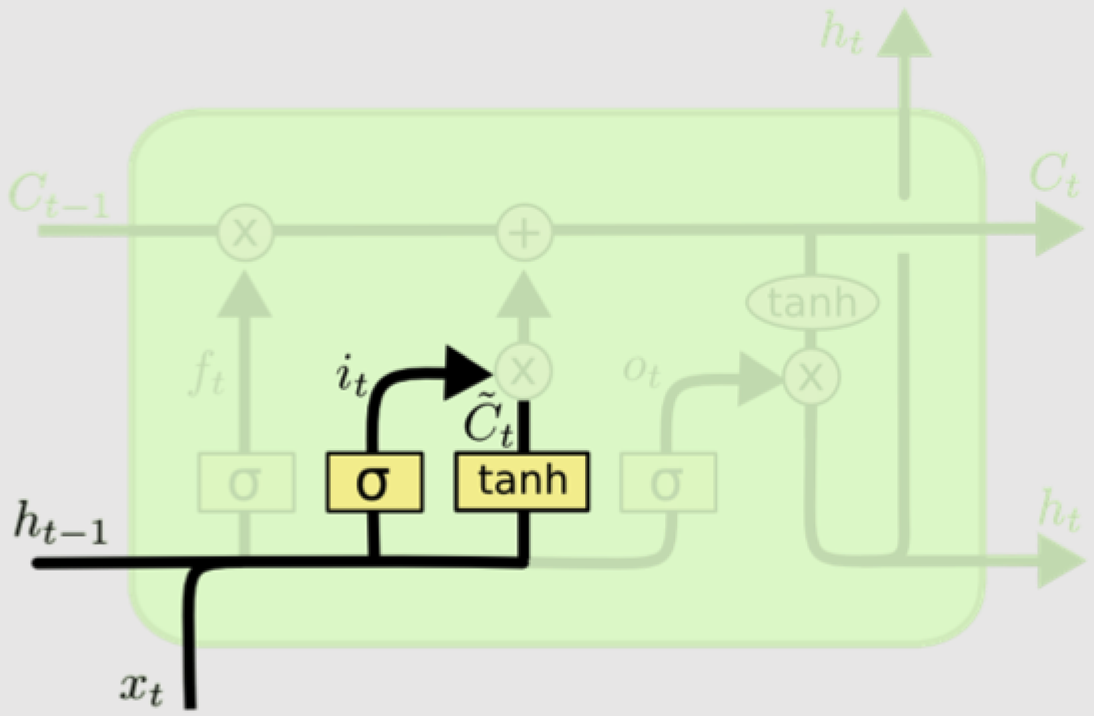

ht
Output
Input Gate
(Cell) state
Next (Cell) State
Forget Gate
tanh
Output Gate
σ
σ
tanh
σ
Hidden State
Next Hidden State
Xt
Input

Forget Gate



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

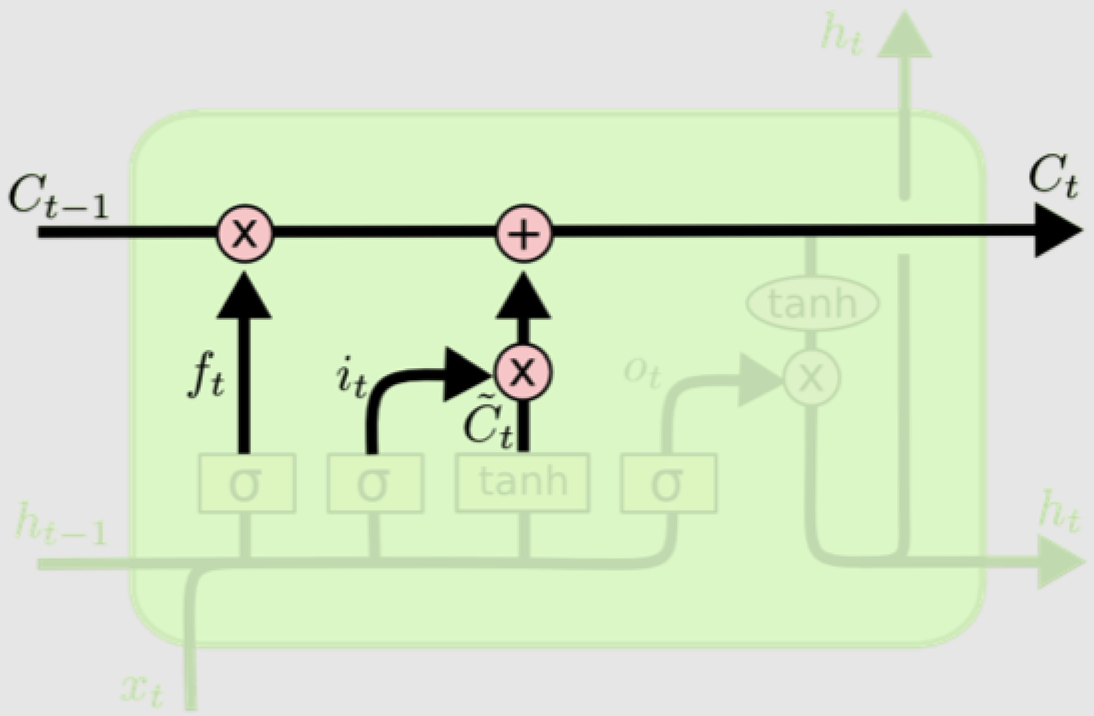
Input Gate



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

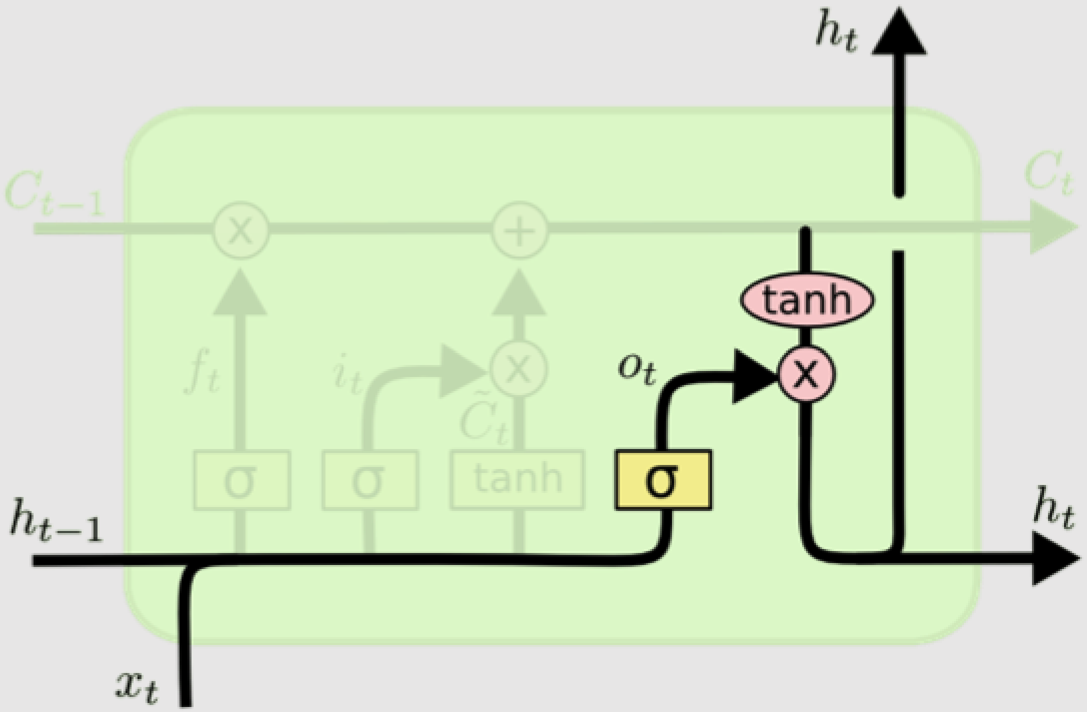
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Cell update



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output Gate



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

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

02.GRU Model

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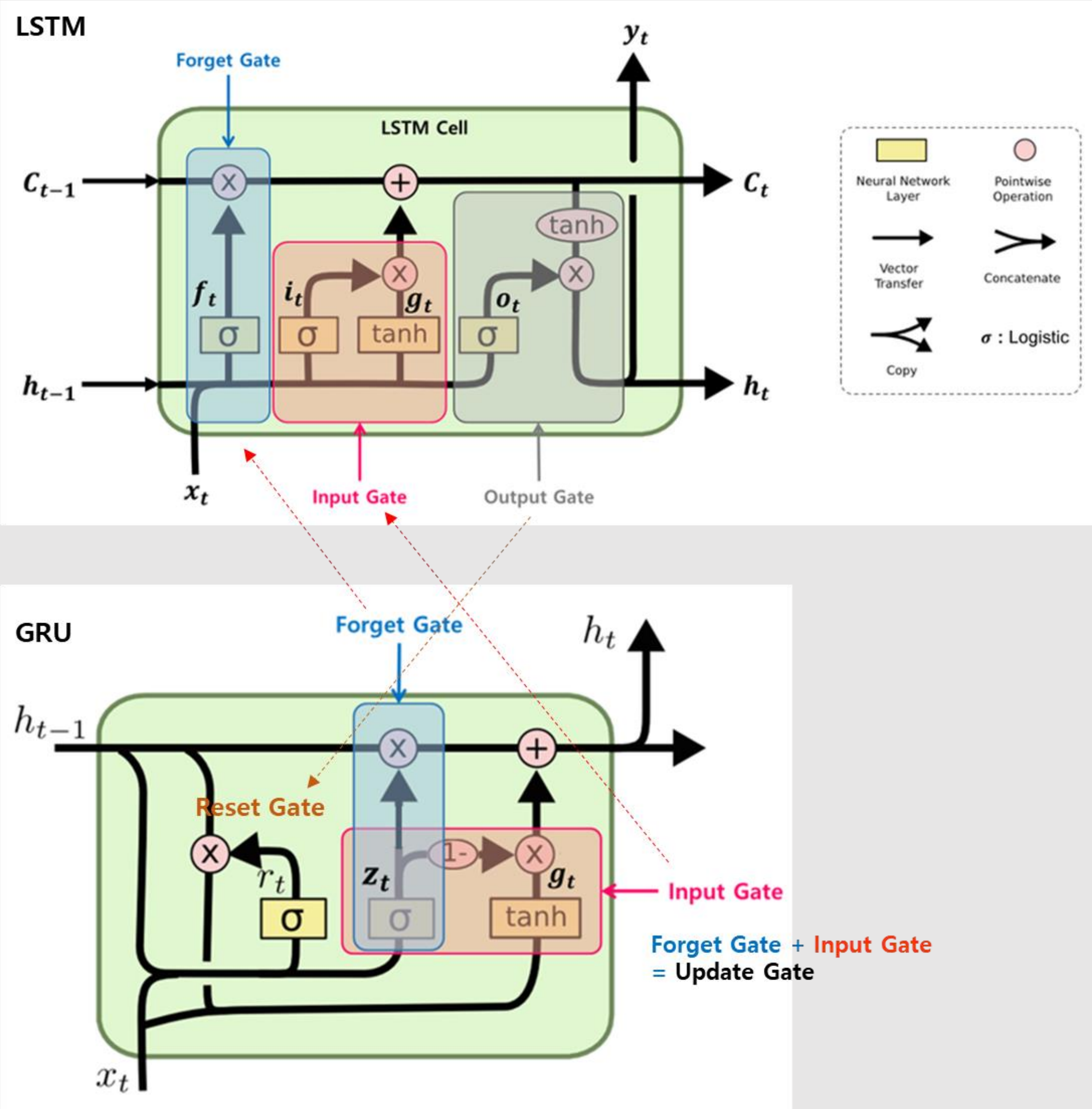
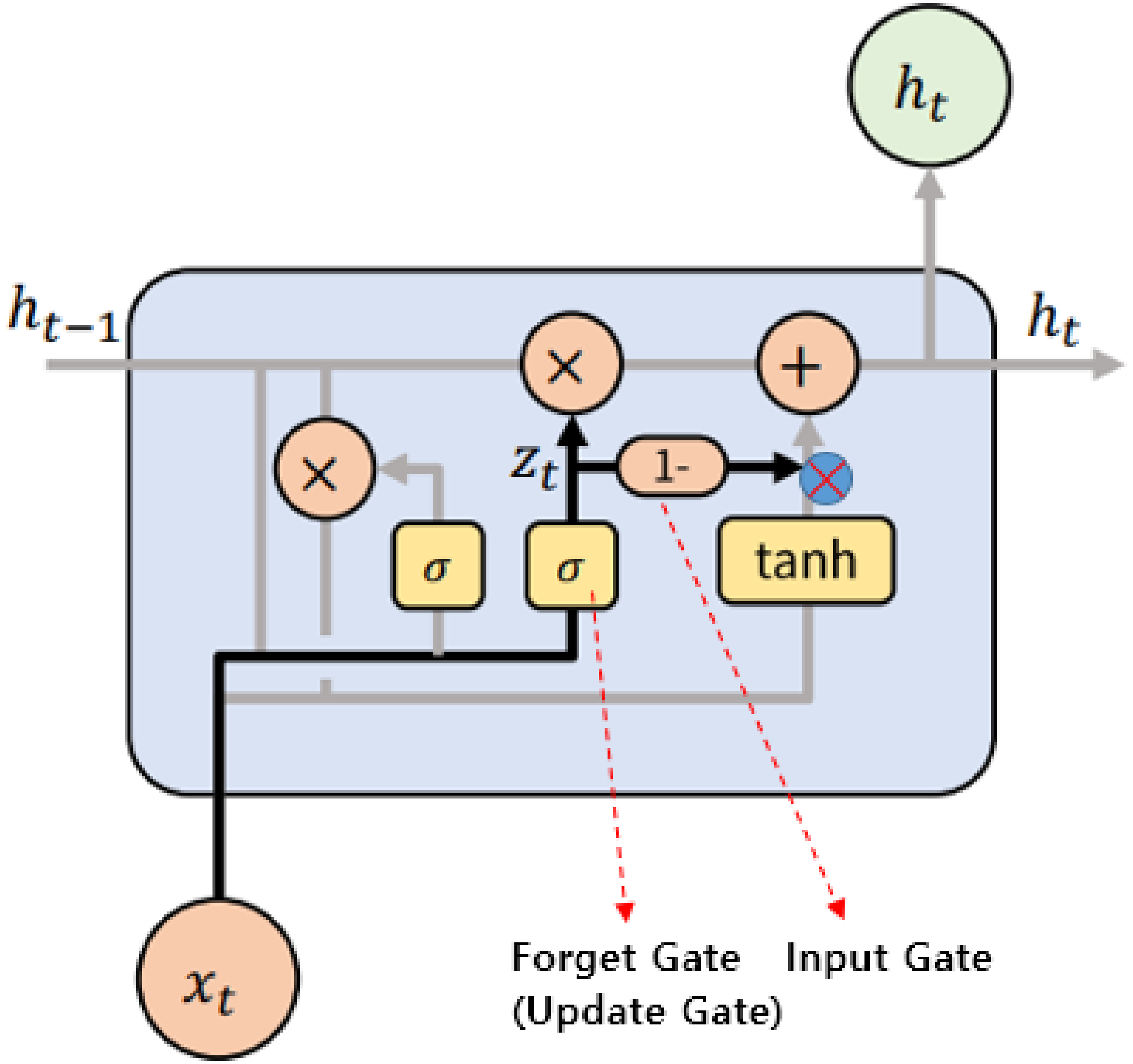
03. Model



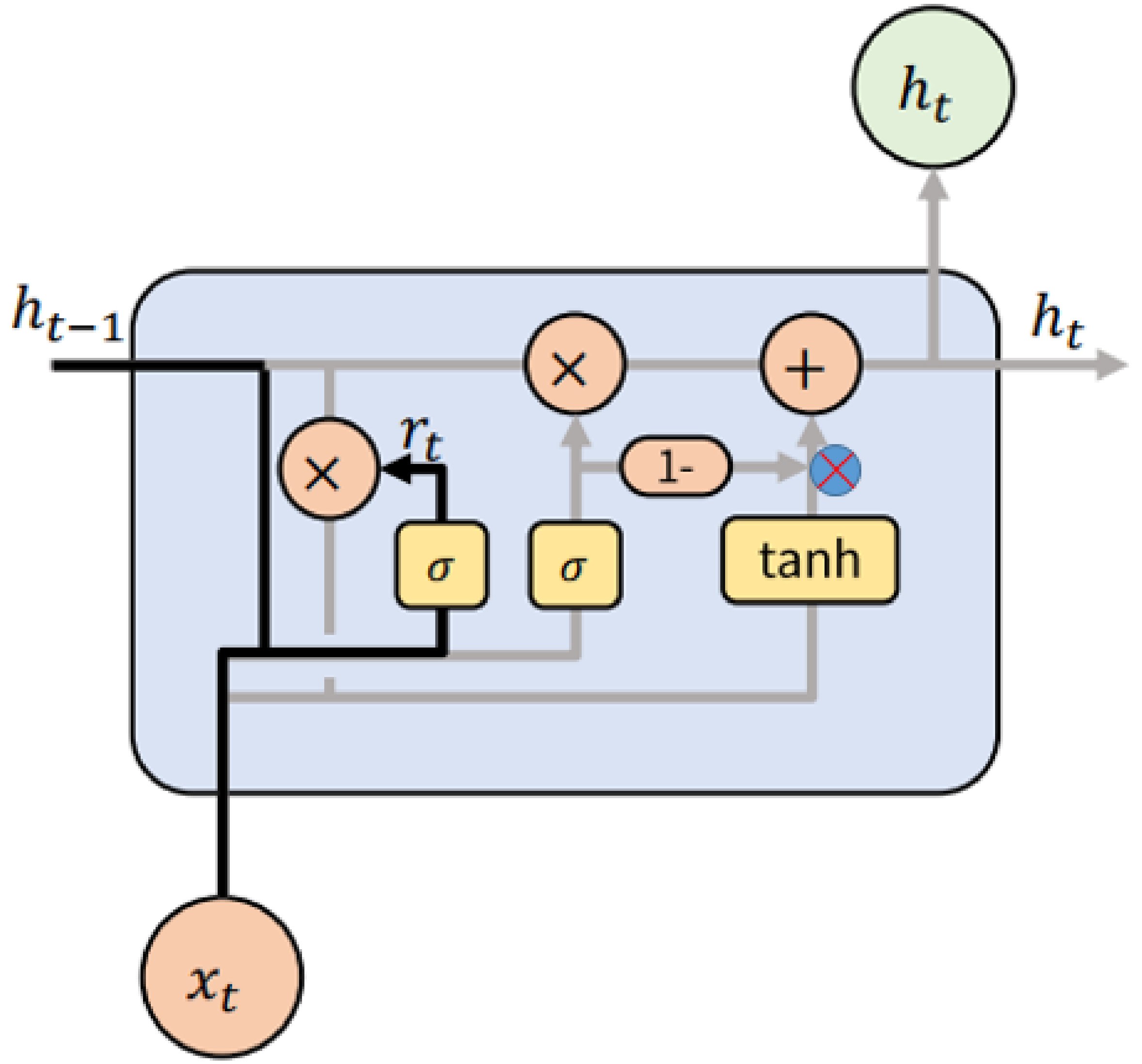
LSTM
Forget Gate
LSTM Cell
y_t
C_{t-1}
C_t
f_t
i_t
g_t
o_t
σ
tanh
h_{t-1}
h_t
x_t
Input Gate
Output Gate
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy
σ : Logistic
GRU
Forget Gate
h_t
h_{t-1}
Reset Gate
r_t
z_t
1-
g_t
Input Gate
x_t
Forget Gate + Input Gate
= Update Gate

03. Model



Gate	Equation
Reset Gate	$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$
Forget Gate	$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$
Input Gate	$1 - z_t$
Hidden State	$g_t = tanh(W_{xg}x_t + W_{hg}(r_t \odot h_{t-1}) + b_g)$ $h_t = z_t \odot h_{t-1} + (1 - z_t) \odot g_t$

03. Model



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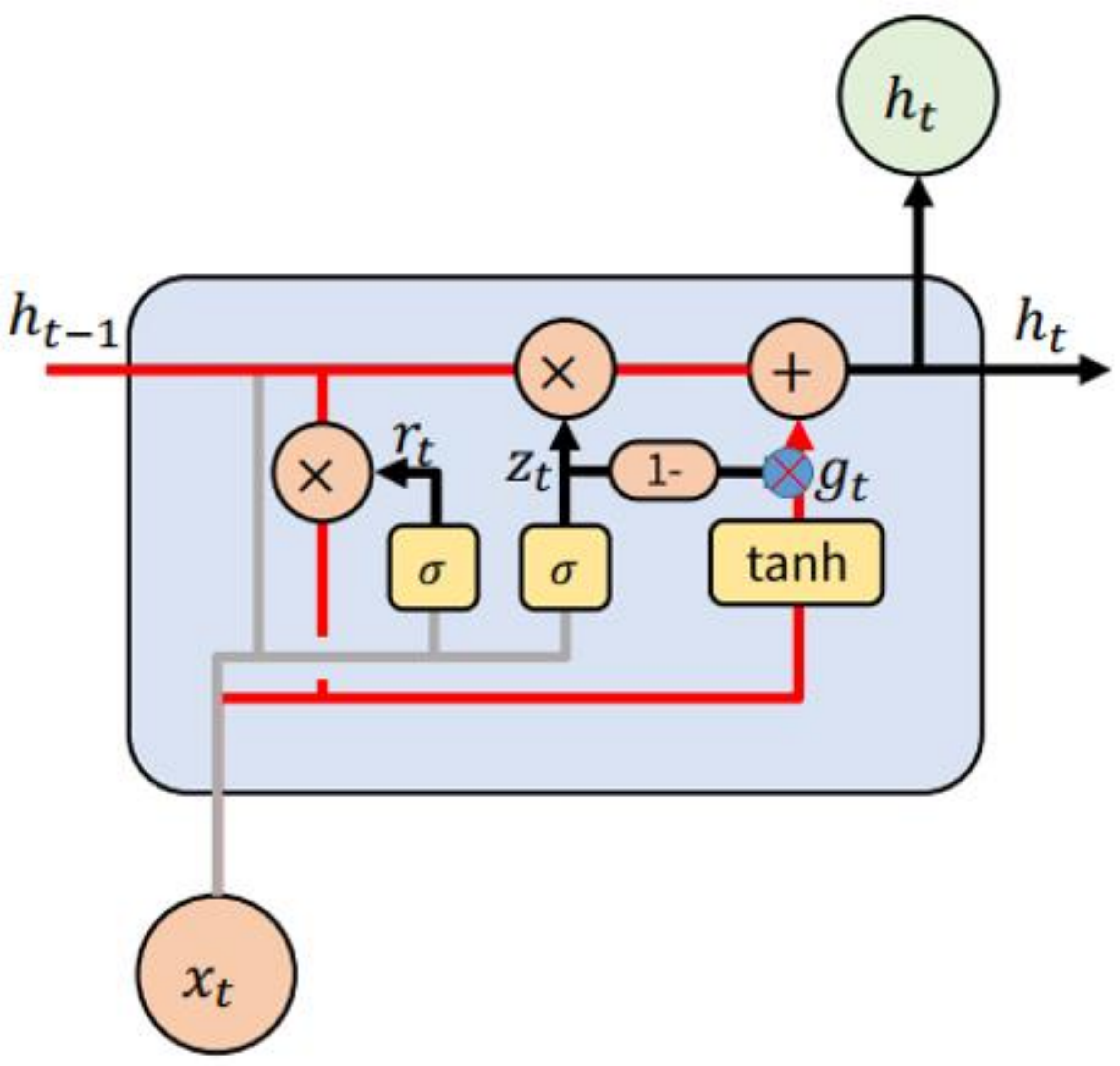
03. Model



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03. Model

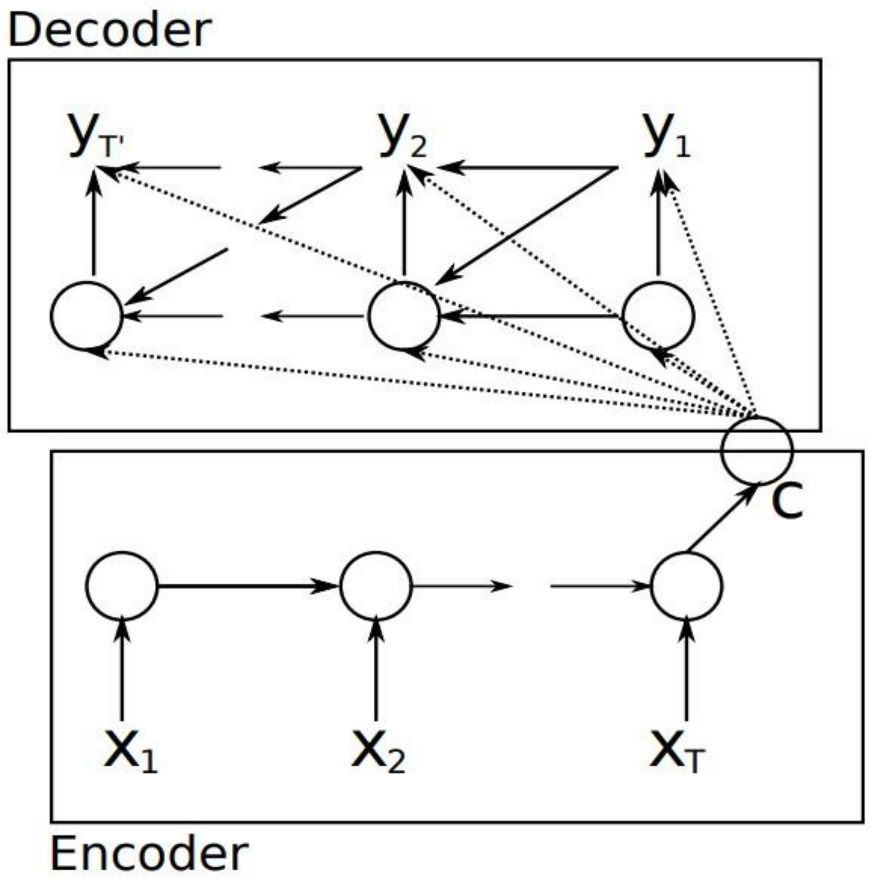


Figure 1: An illustration of the proposed RNN Encoder–Decoder.

$$p(y_1, \ldots, y_{T'} \mid x_1, \ldots, x_T),$$

Encoder

$$\mathbf{h}_{\langle t \rangle} = f\left(\mathbf{h}_{\langle t-1 \rangle}, x_t\right),$$

03. Model

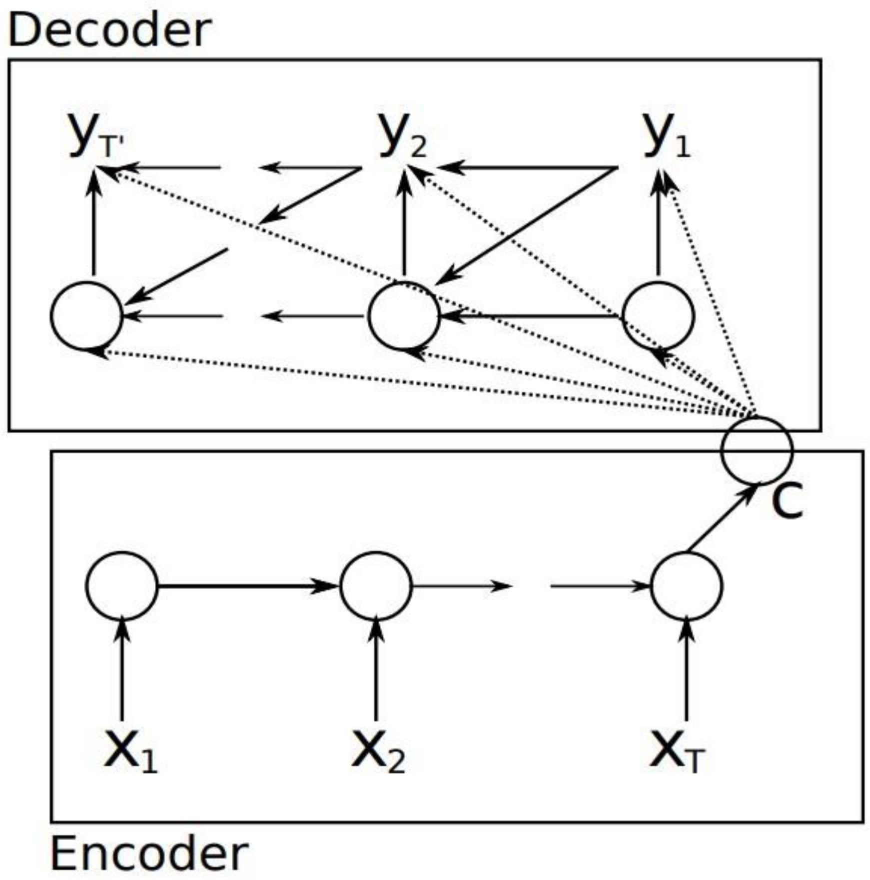


Figure 1: An illustration of the proposed RNN Encoder–Decoder.

$$p(y_1, \ldots, y_{T'} \mid x_1, \ldots, x_T),$$

Encoder → $\mathbf{h}_{\langle t \rangle} = f\left(\mathbf{h}_{\langle t-1 \rangle}, x_t\right),$

Decoder → $\mathbf{h}_{\langle t \rangle} = f\left(\mathbf{h}_{\langle t-1 \rangle}, y_{t-1}, \mathbf{c}\right),$

03. Model

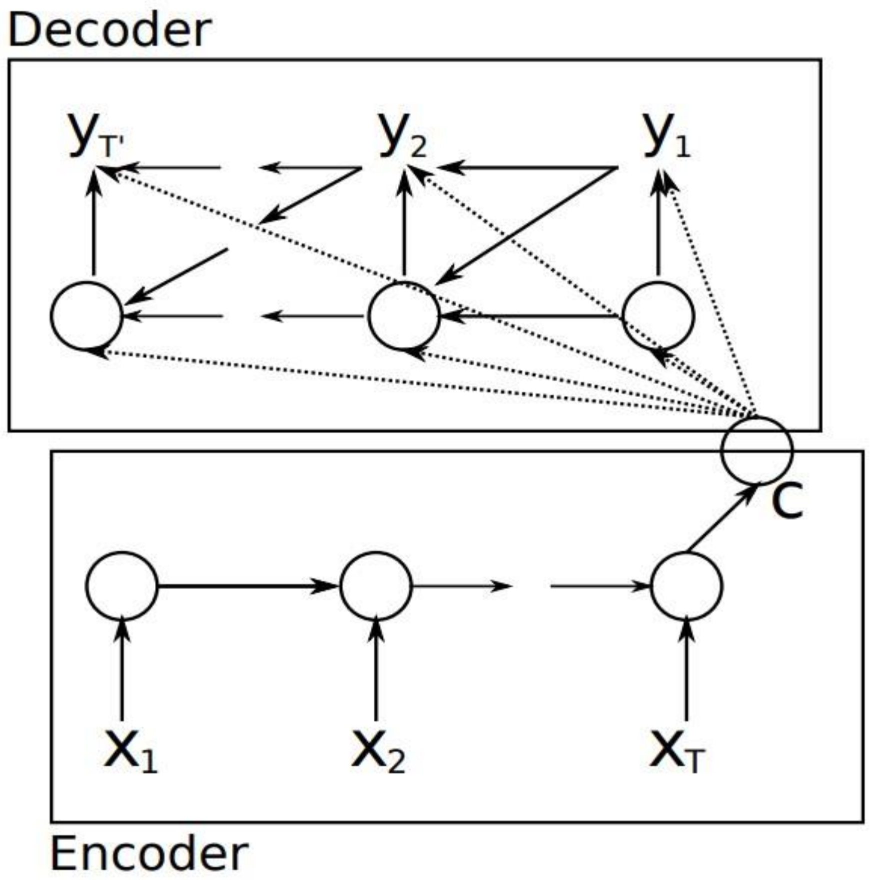
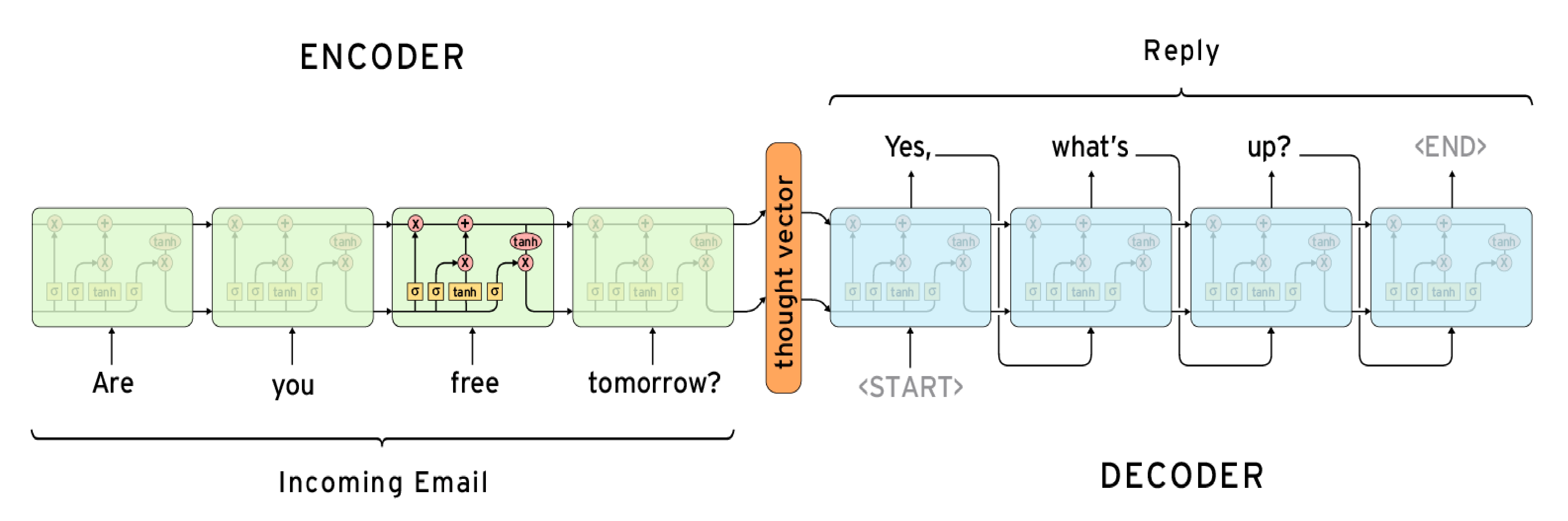


Figure 1: An illustration of the proposed RNN Encoder–Decoder.

$$P(y_t | y_{t-1}, y_{t-2}, \ldots, y_1, \mathbf{c}) = g\left(\mathbf{h}_{\langle t \rangle}, y_{t-1}, \mathbf{c}\right).$$

$$\max_{\boldsymbol{\theta}} \frac{1}{N} \sum_{n=1}^{N} \log p_{\boldsymbol{\theta}}(\mathbf{y}_n \mid \mathbf{x}_n),$$

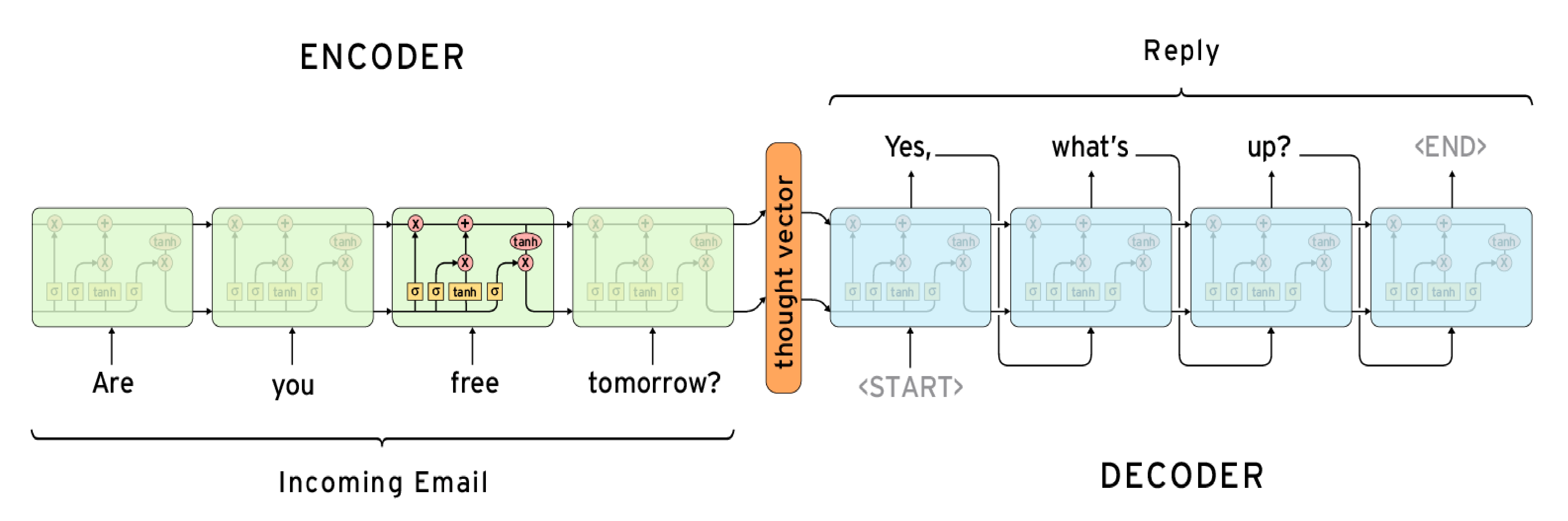
03. Model



학습목표

$$\max_{\boldsymbol{\theta}} \frac{1}{N} \sum_{n=1}^{N} \log p_{\boldsymbol{\theta}}(\mathbf{y}_n \mid \mathbf{x}_n),$$

03. Model



학습목표 →

$$\max_{\theta} \frac{1}{4}\left(\log P_{(Are)} + \log P_{(you)} + \log P_{(free)} + \log P_{(tomorrow)}\right)$$

03. Model-smt

$$p(e|f)$$

F가 주어졌을때 e가 나올 확률

$$p(e|f) \propto p(f|e)p(e)$$

비례관계

$$\tilde{e} = arg\max_{e \in e^*} p(e|f) = arg\max_{e \in e^*} p(f|e)p(e)$$

가장 높은 확률로 나오는 표현을 골라 번역 e를 찾는다

03. Model-활용

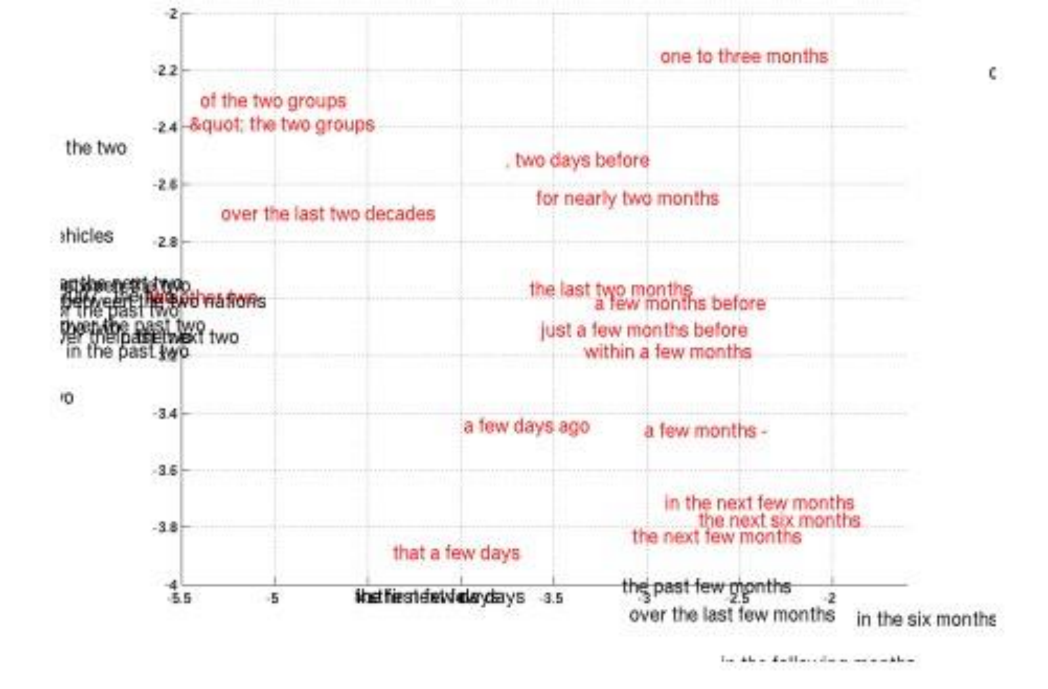
$$\log p(\mathbf{f} \mid \mathbf{e}) = \sum_{n=1}^{N} w_n f_n(\mathbf{f}, \mathbf{e}) + \log Z(\mathbf{e}), \quad (9)$$

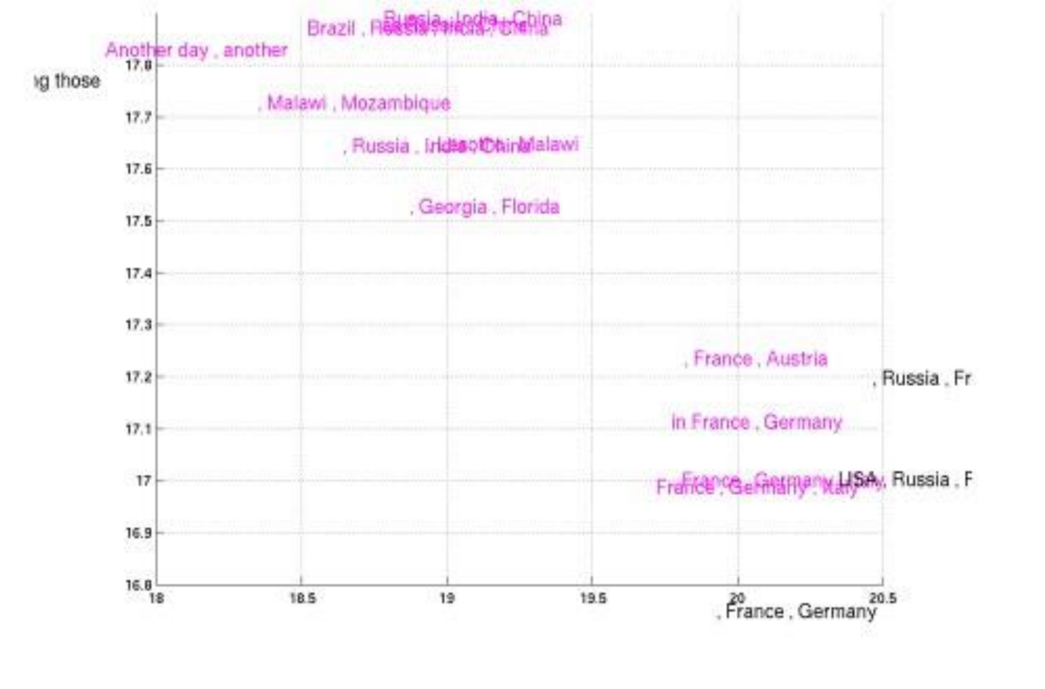
03. Result & Conclusion

03. Model-활용

Models	BLEU	
	dev	test
Baseline	30.64	33.30
RNN	31.20	33.87
CSLM + RNN	31.48	34.64
CSLM + RNN + WP	31.50	34.54

03. Model-활용


one to three months
of the two groups
" the two groups
the two
, two days before
for nearly two months
over the last two decades
the last two months
a few months before
just a few months before
within a few months
in the past two
a few days ago
a few months -
in the next few months
the next six months
the next few months
that a few days
the past few months
over the last few months
in the six months


Another day , another
Brazil ,
, Malawi , Mozambique
, Georgia , Florida
, France , Austria
, Russia , Fr
In France , Germany
, France , Germany

THANK YOU!

MADE BY HENDO