ICT이노베이션스퀘어 AI복합교육 고급 언어과정

자연어처리를 위한
RNN (Recurrent Neural Network)

현청천

2021.04.19

What is RNN

- 시계열(Sequential Data) 데이터를 처리하기 위한 모델
  - 음성, 언어, 주가, 센서 데이터 등

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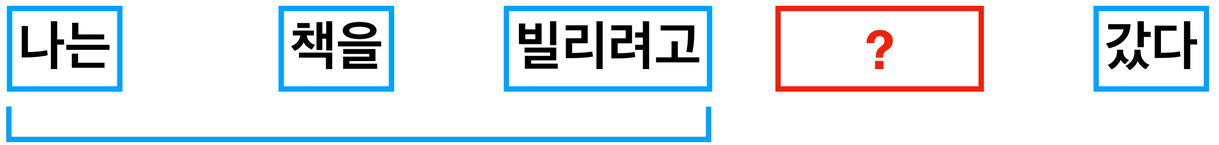
- 문장에서 이전에 나온 단어를 보가 다음단어를 예측



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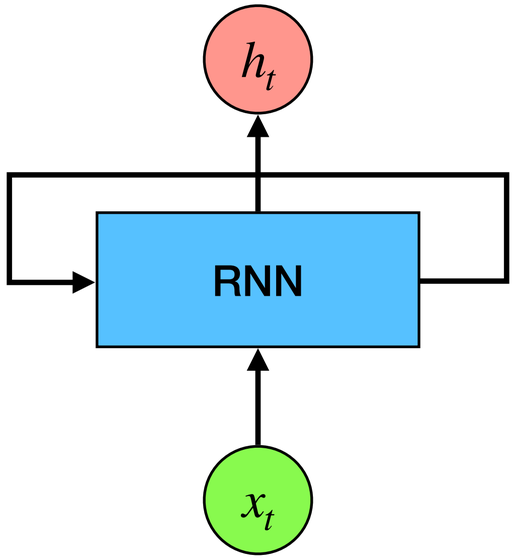
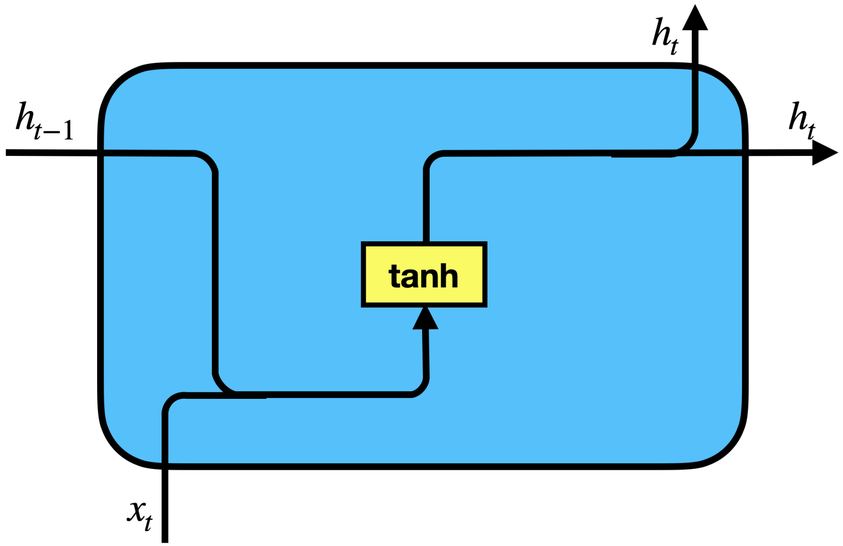
- 문장에서 이전에 나온 단어를 보가 다음단어를 예측
- 동일한 Weight와 Bias가 모든 입력 값에 대해서 동일하게 사용 됨



RNN

$$h_t = tanh(W_h h_{t-1} + W_x x_t + b)$$



Sequencial Data | I | went | to | home

RNN

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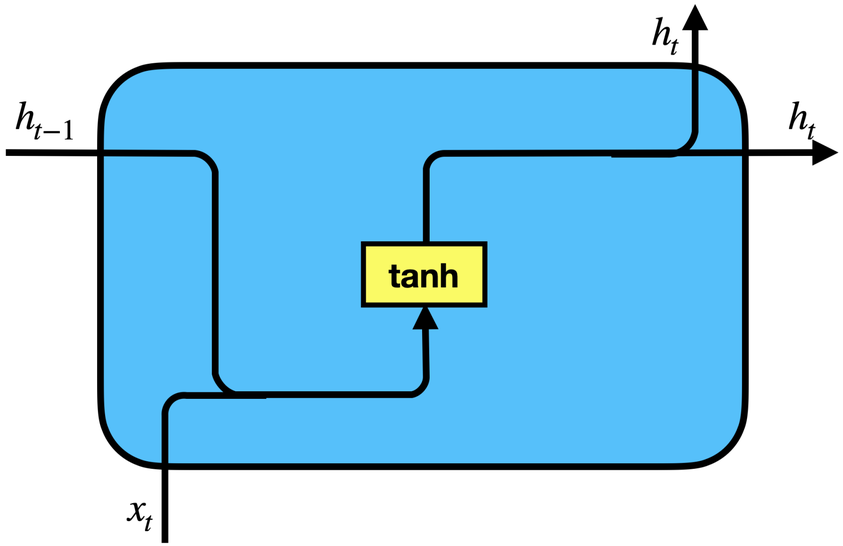

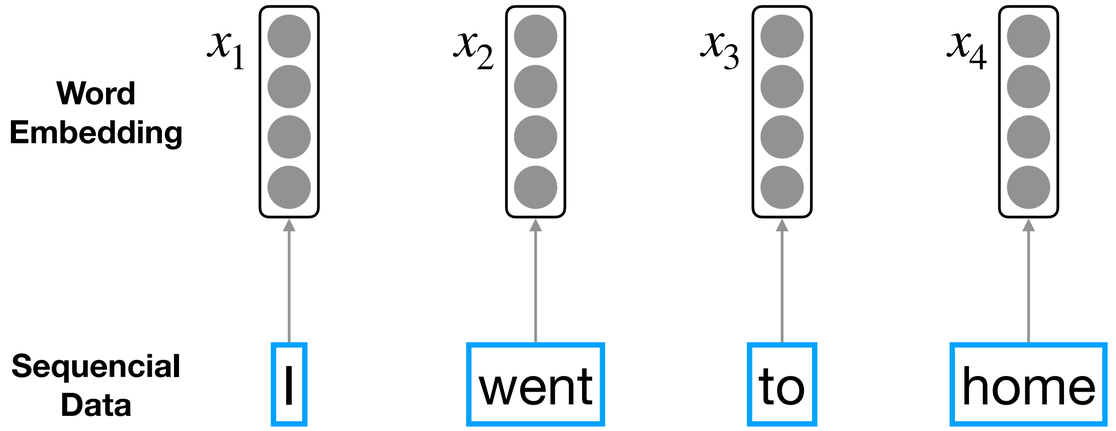

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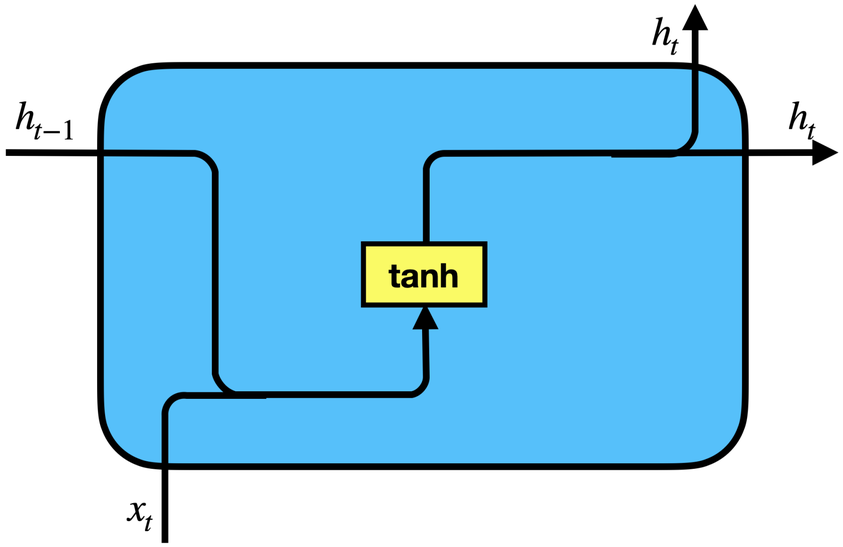

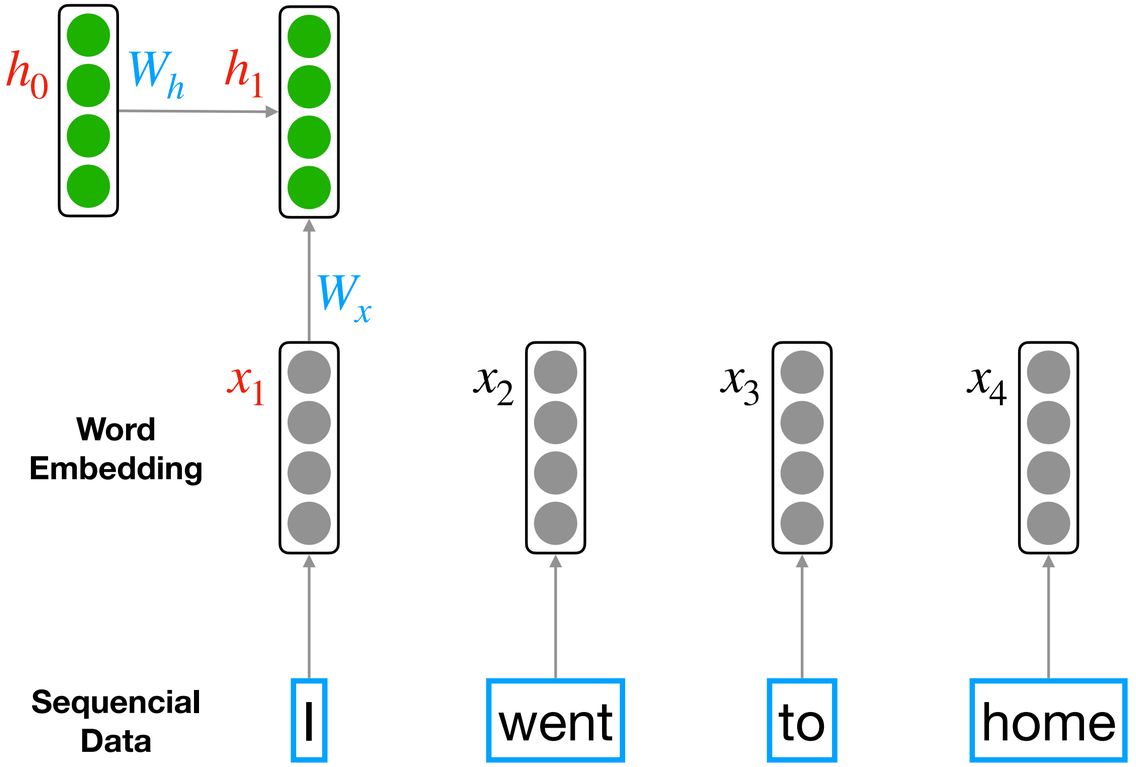

RNN

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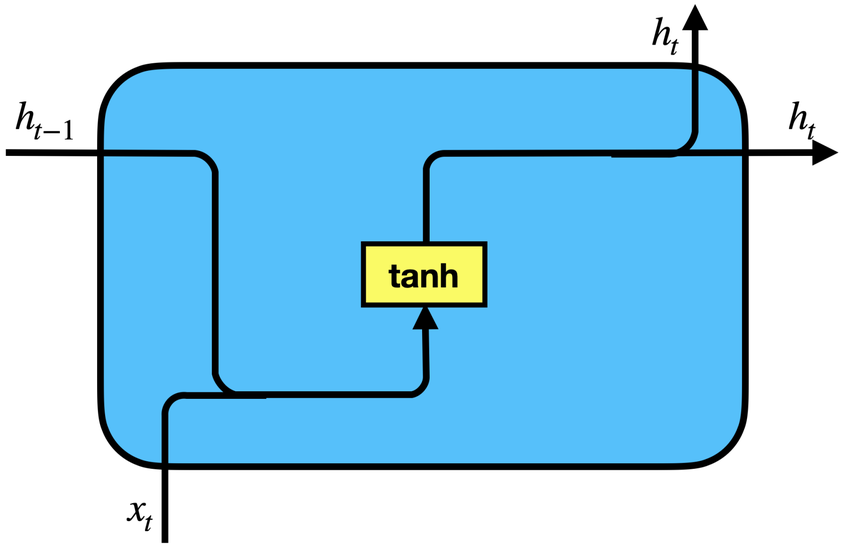

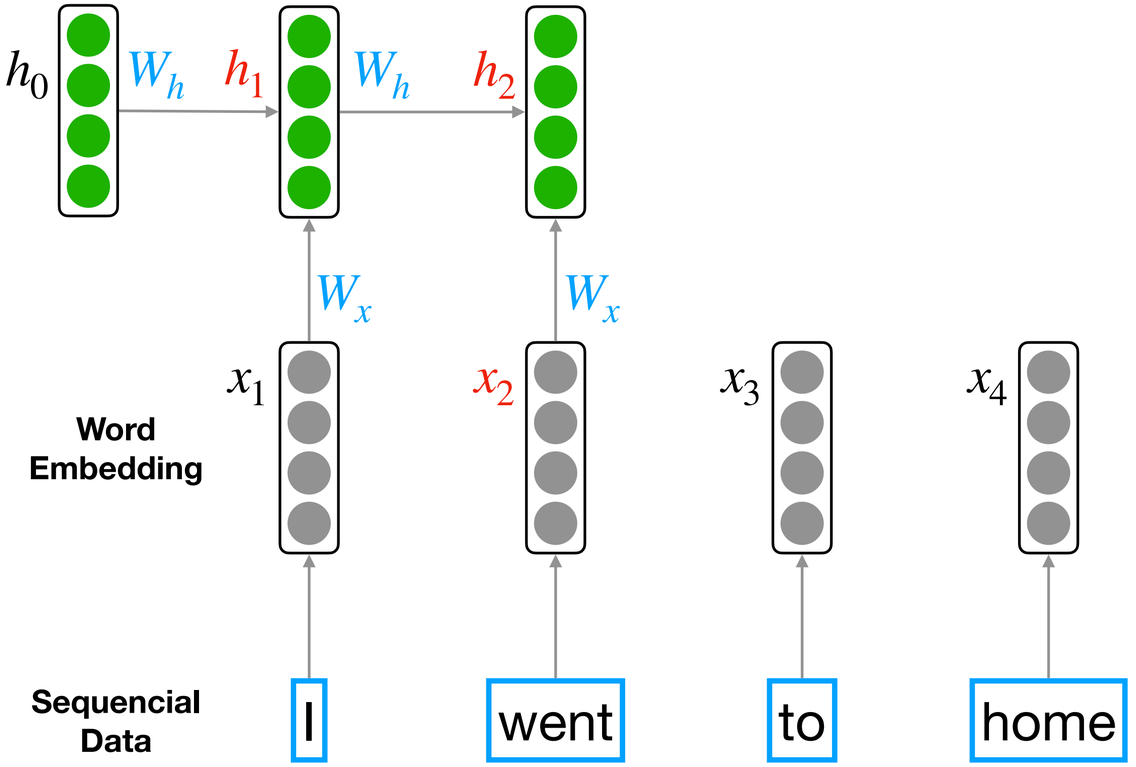

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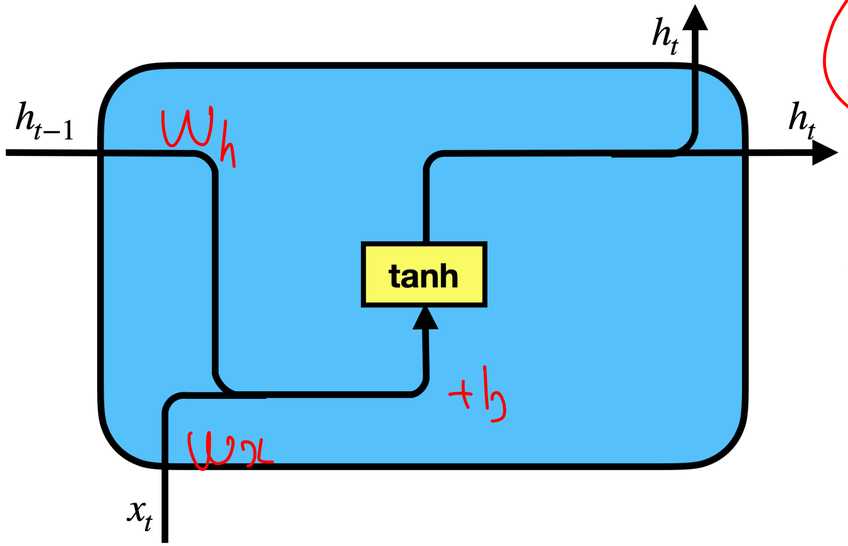
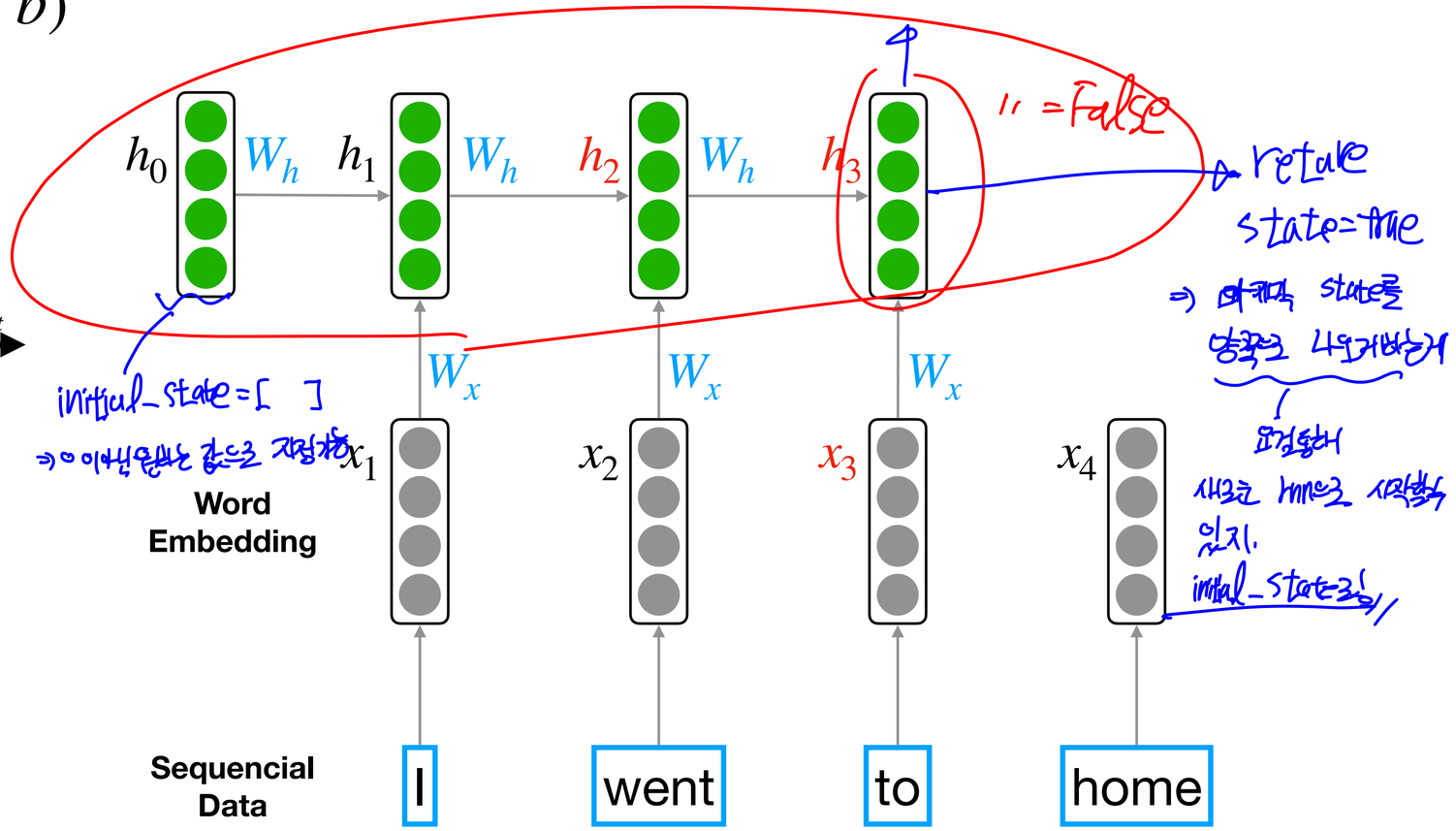


return_sequences = True



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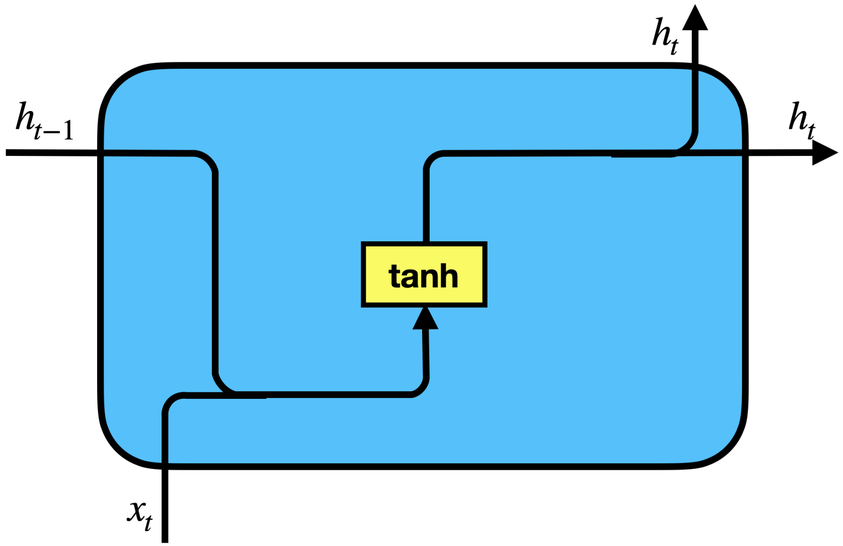
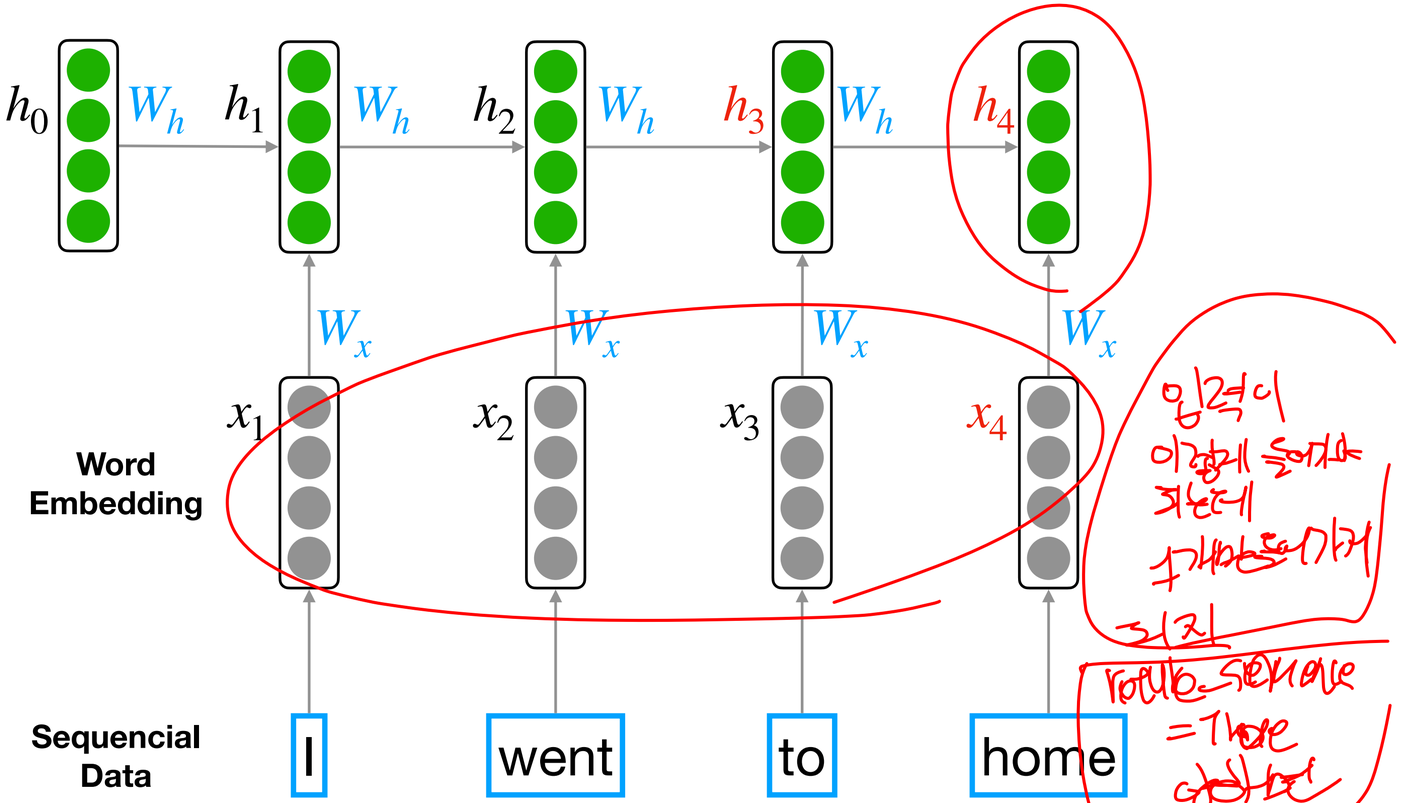
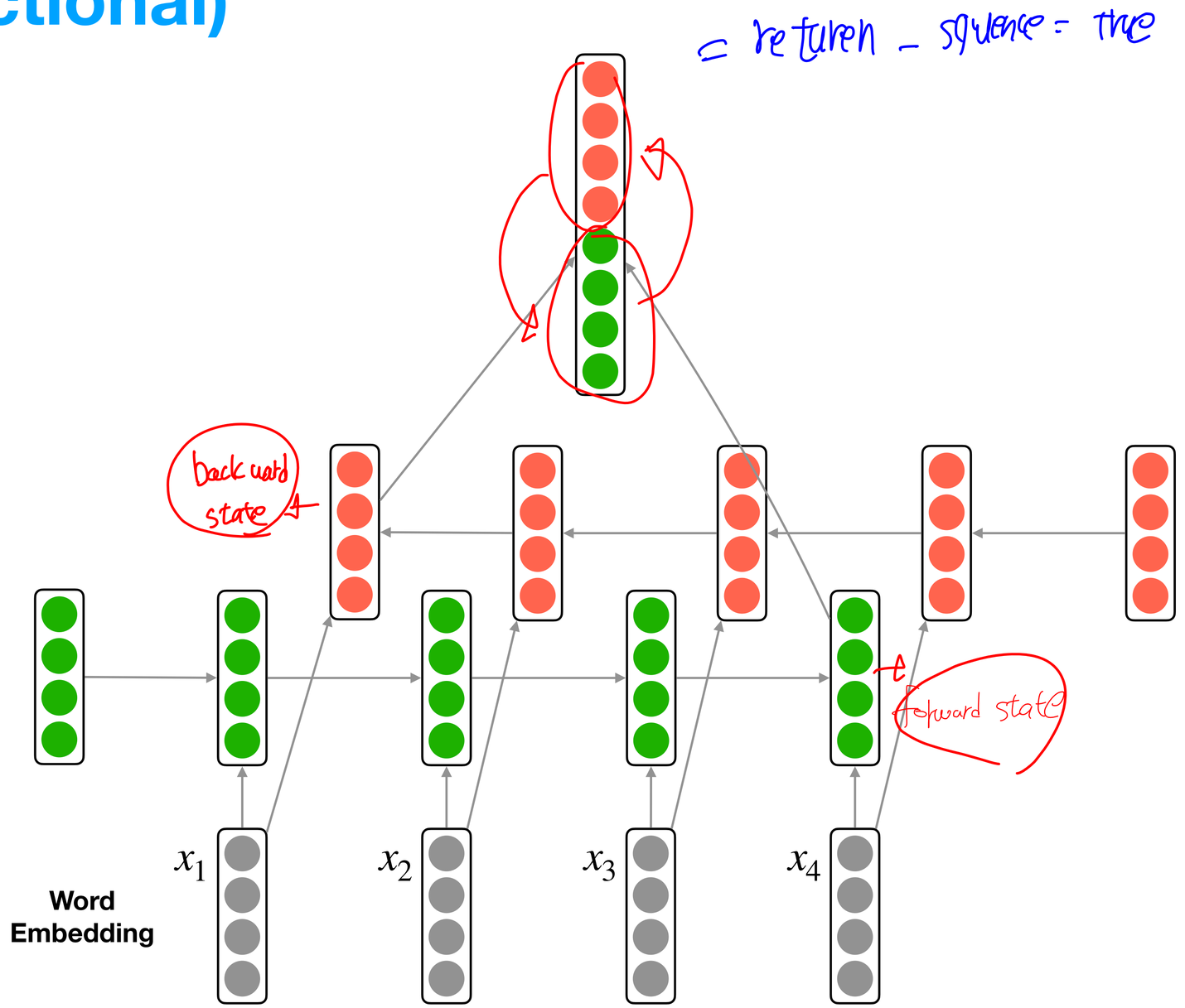




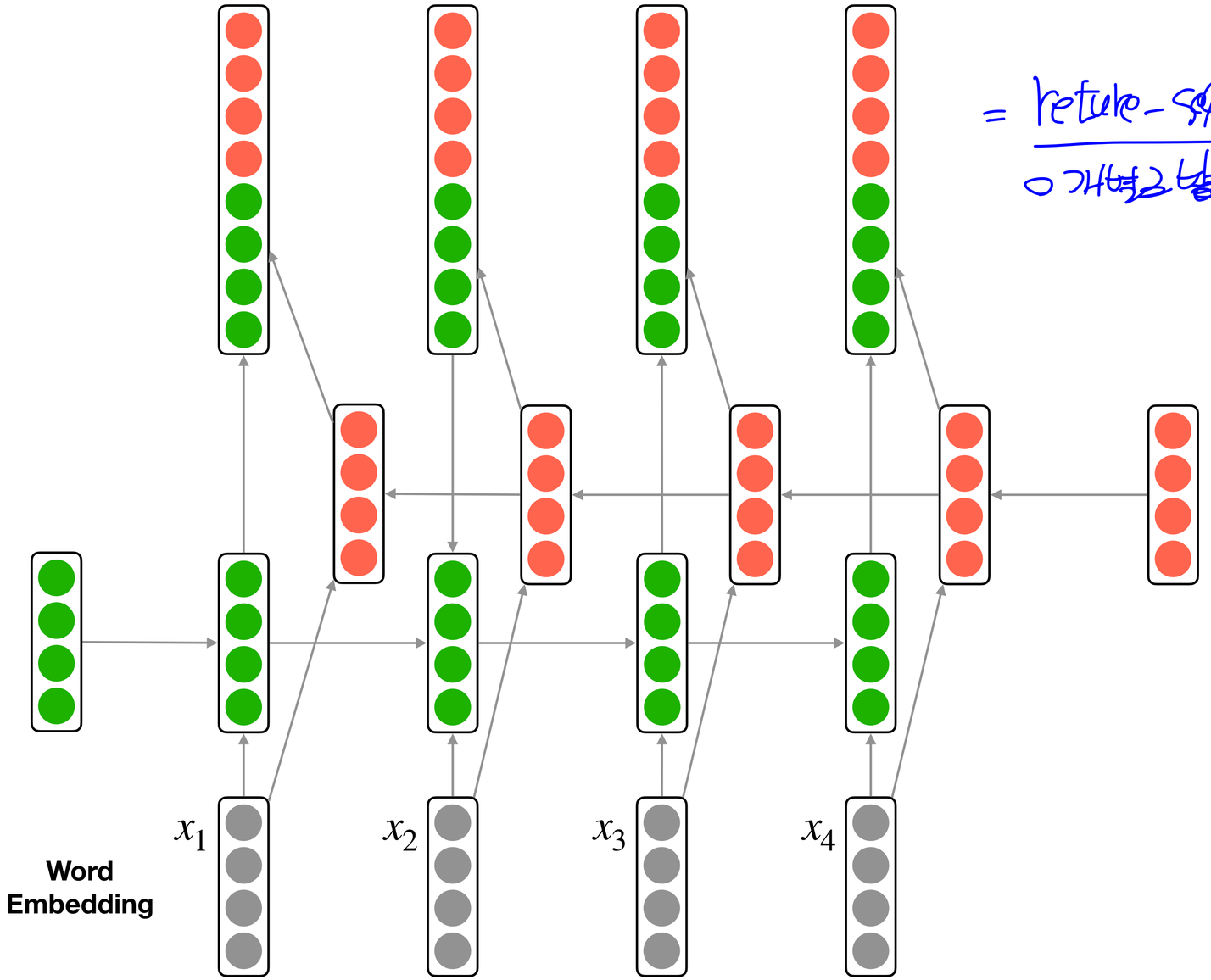
RNN (Bi-directional)

문장의 특징 추출



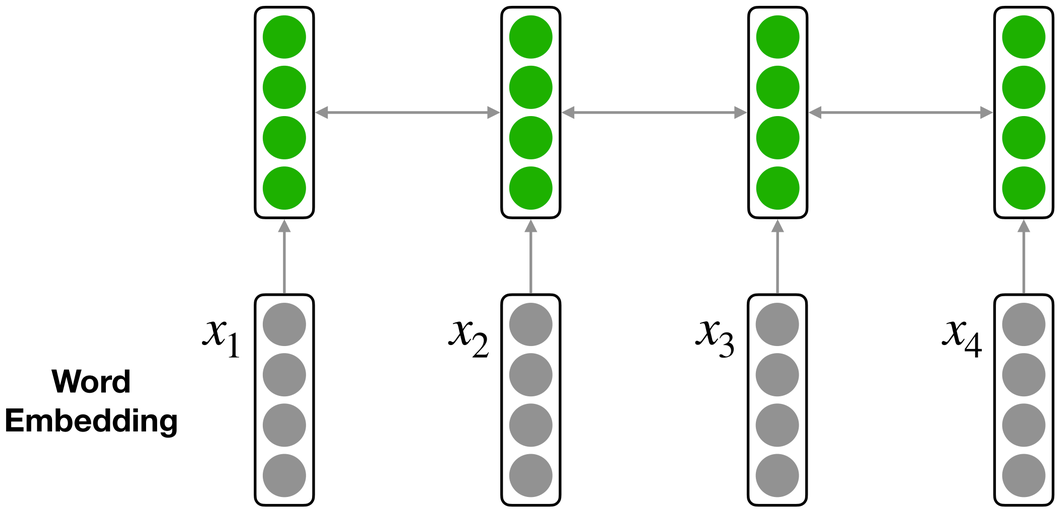
RNN (Bi-directional)

단어별 특징 추출



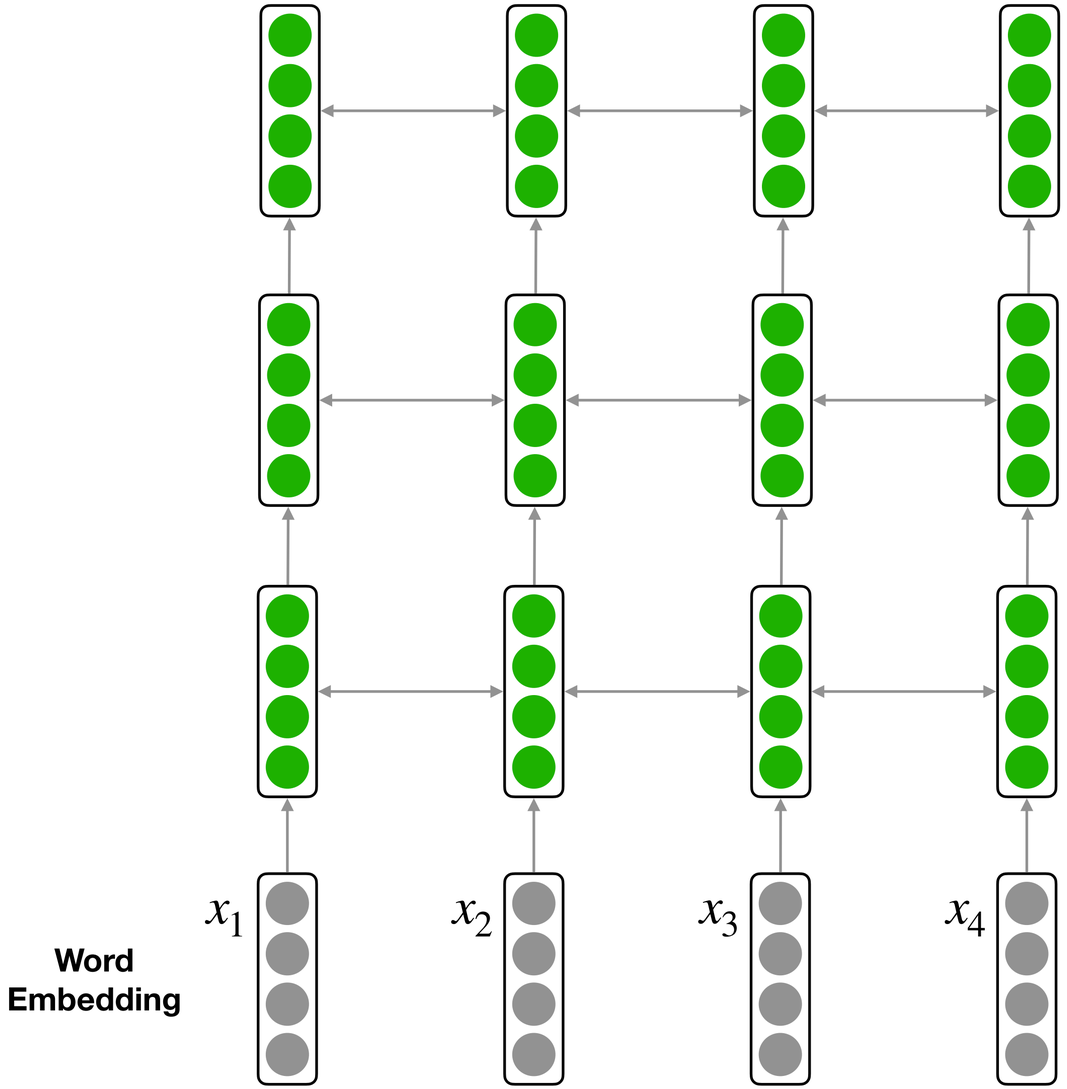
RNN (Bi-directional)

간단한 표현



RNN (Bi-directional)

Multi layer stack



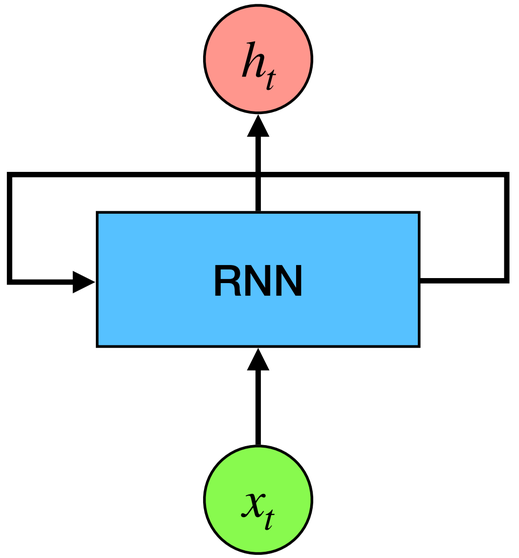
// = false or True

// = true

return_sequence= True

RNN

- **길이에 상관이 없음**
- 순서대로 처리해야 하므로 느림
- 오랜 과거의 정보를 접근하기 어려움
- Vanishing gradient problem
- Exploding gradient problem



RNN 네트워크를 재귀적으로 사용하므로 길이에 상관 없음

RNN

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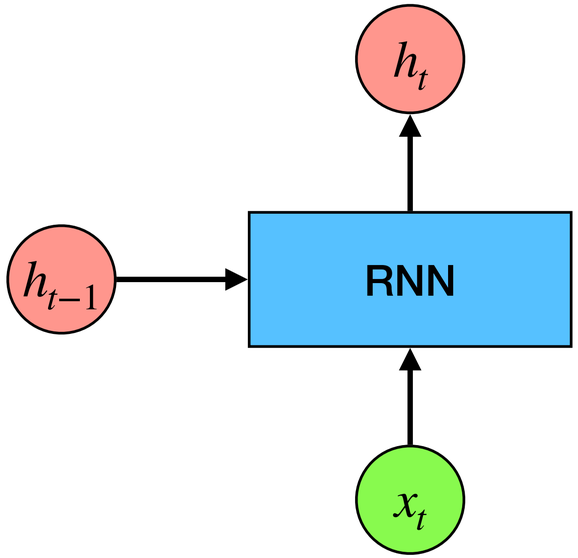

h_t를 계산하기 위해서는 h_{t-1}이 필요해서 병렬처리 불가

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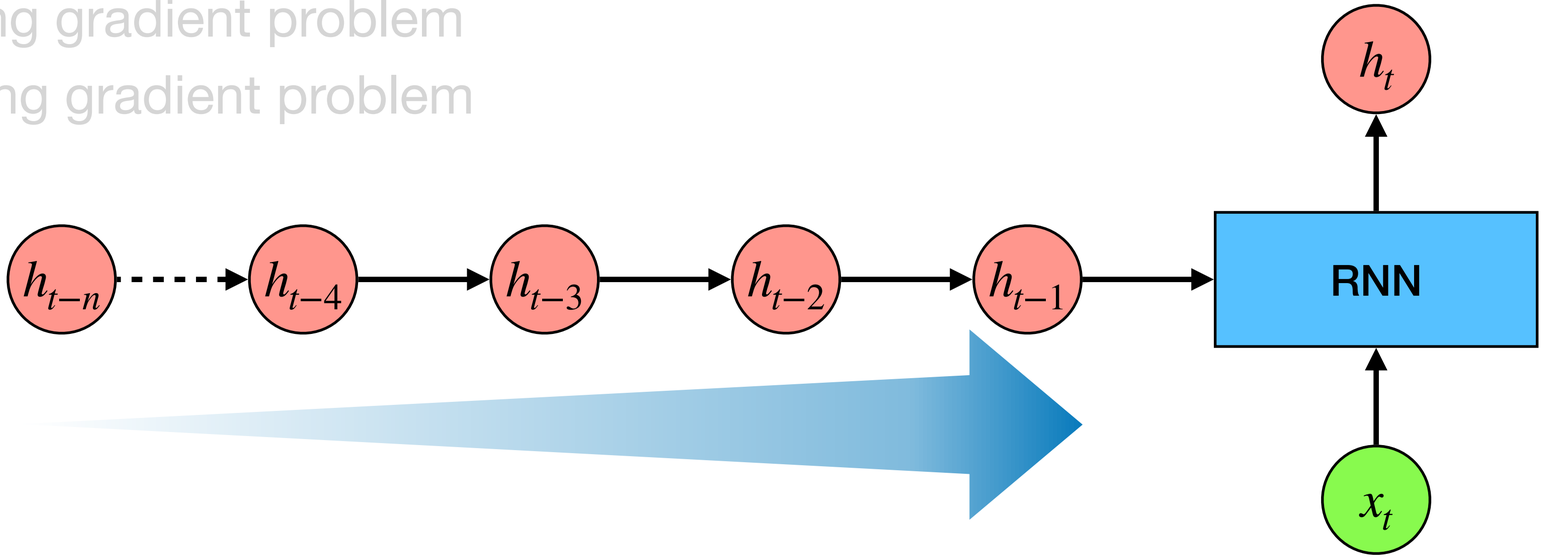

h_t는최근 정보가 강하고 과거의 정보는 점차 약해짐

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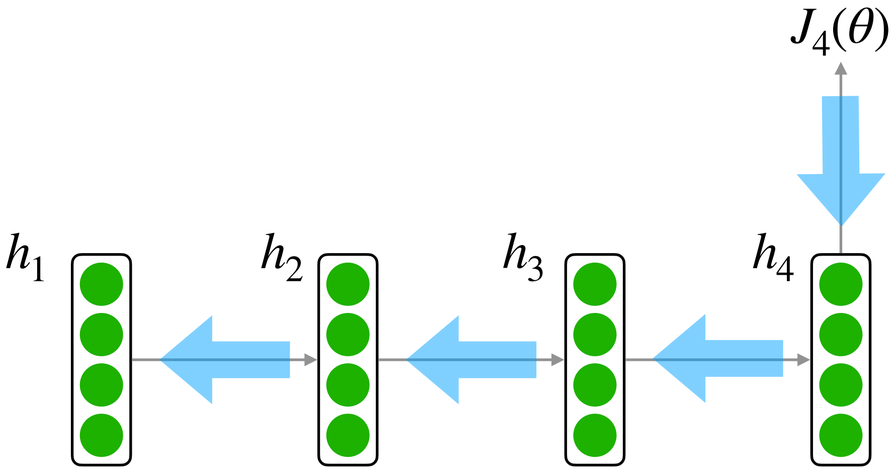

Chain rule!

$$\frac{\partial J_4(\theta)}{\partial h_1} = \frac{\partial h_2}{\partial h_1} \times \frac{\partial h_3}{\partial h_2} \times \frac{\partial h_4}{\partial h_3} \times \frac{\partial J_4(\theta)}{\partial h_4}$$

이 값들이 작으면 거리가 멀 수록 gradient가 감소함

참조: http://web.stanford.edu/class/cs224n/slides/cs224n-2020-lecture06-rnnlm.pdf

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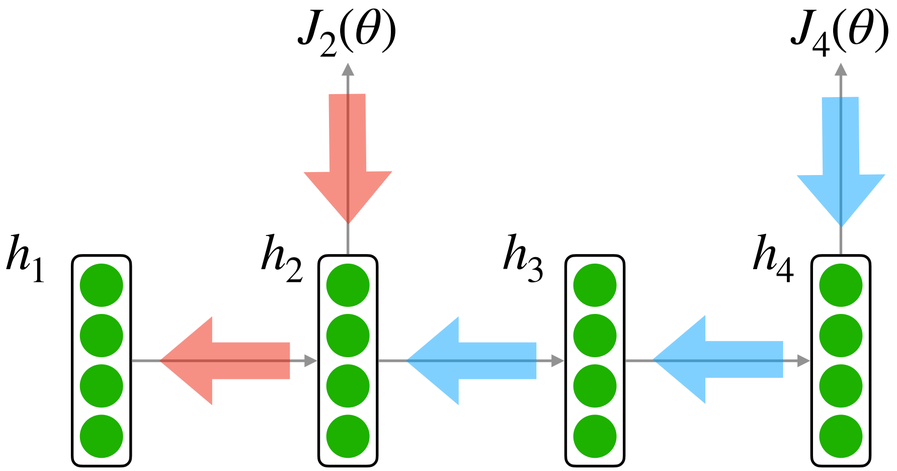

먼 거리의 gradient는 사라지고
가까운 거리의 gradient만 영향을 받음

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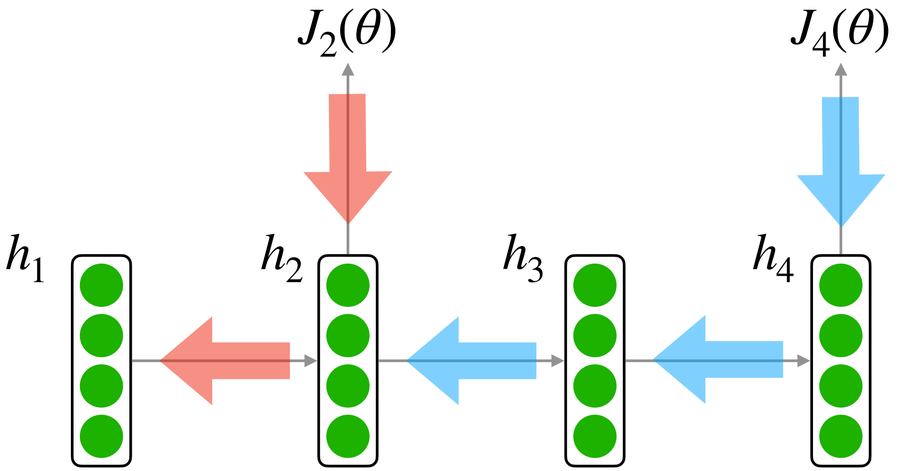

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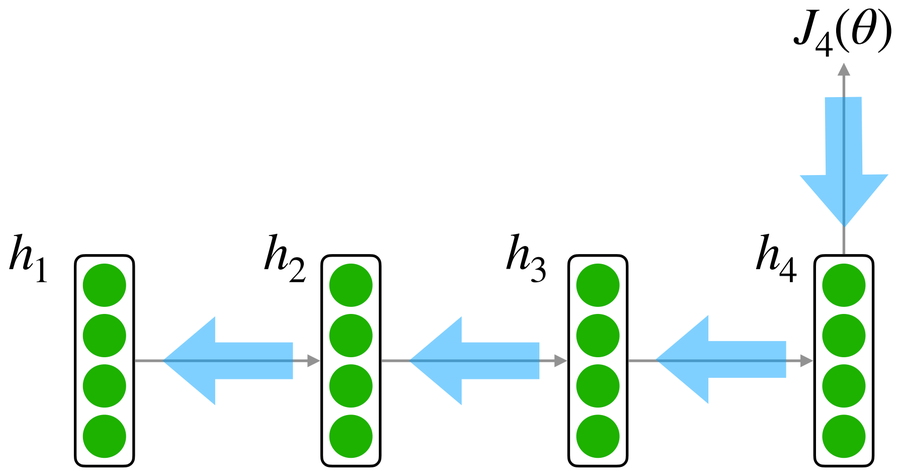

$$\frac{\partial J_4(\theta)}{\partial h_1} = \frac{\partial h_2}{\partial h_1} \times \frac{\partial h_3}{\partial h_2} \times \frac{\partial h_4}{\partial h_3} \times \frac{\partial J_4(\theta)}{\partial h_4}$$

이 값들이 크면 거리가 멀 수록 gradient가 증가함

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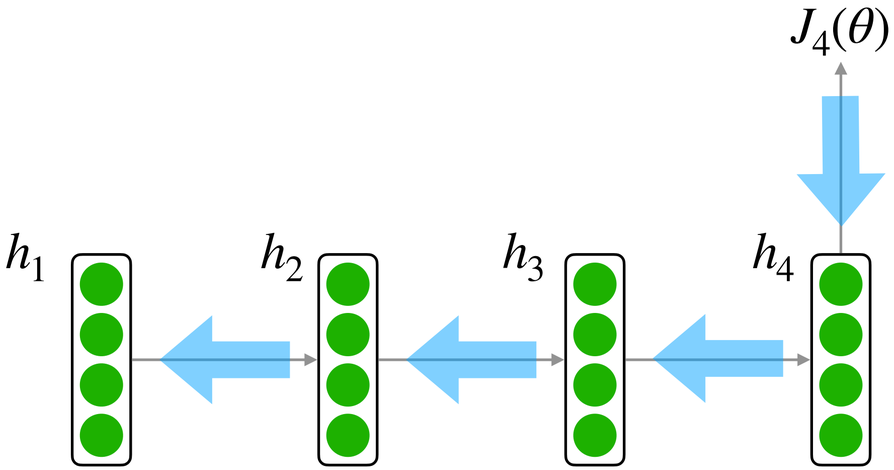

학습이 잘 안되거나

Inf, NaN 등의 loss가 발생할 수 있음

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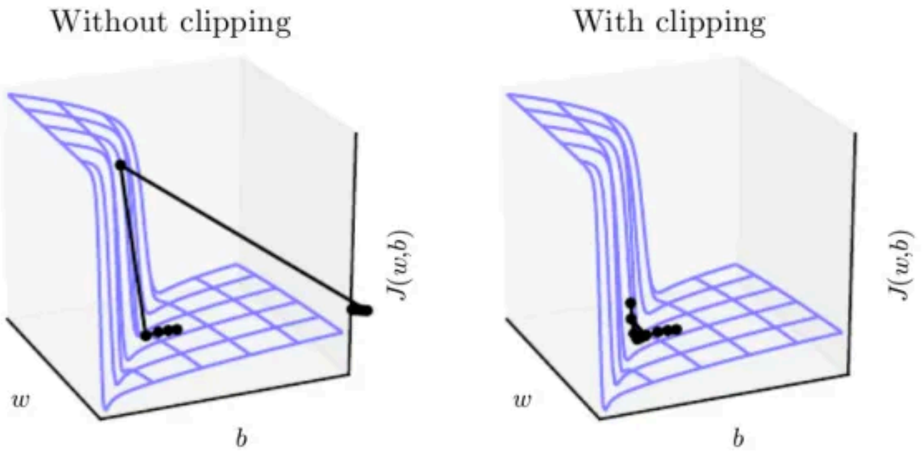


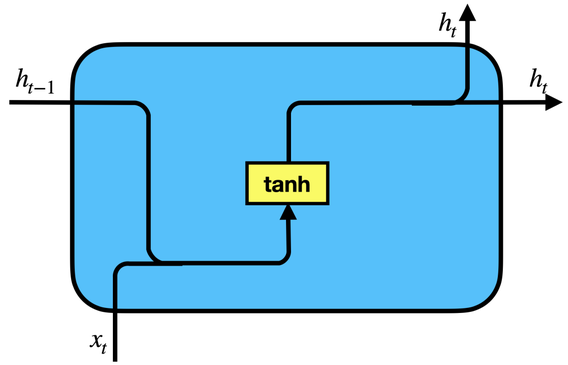
Algorithm 1 Pseudo-code for norm clipping the gradients whenever they explode

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
end if

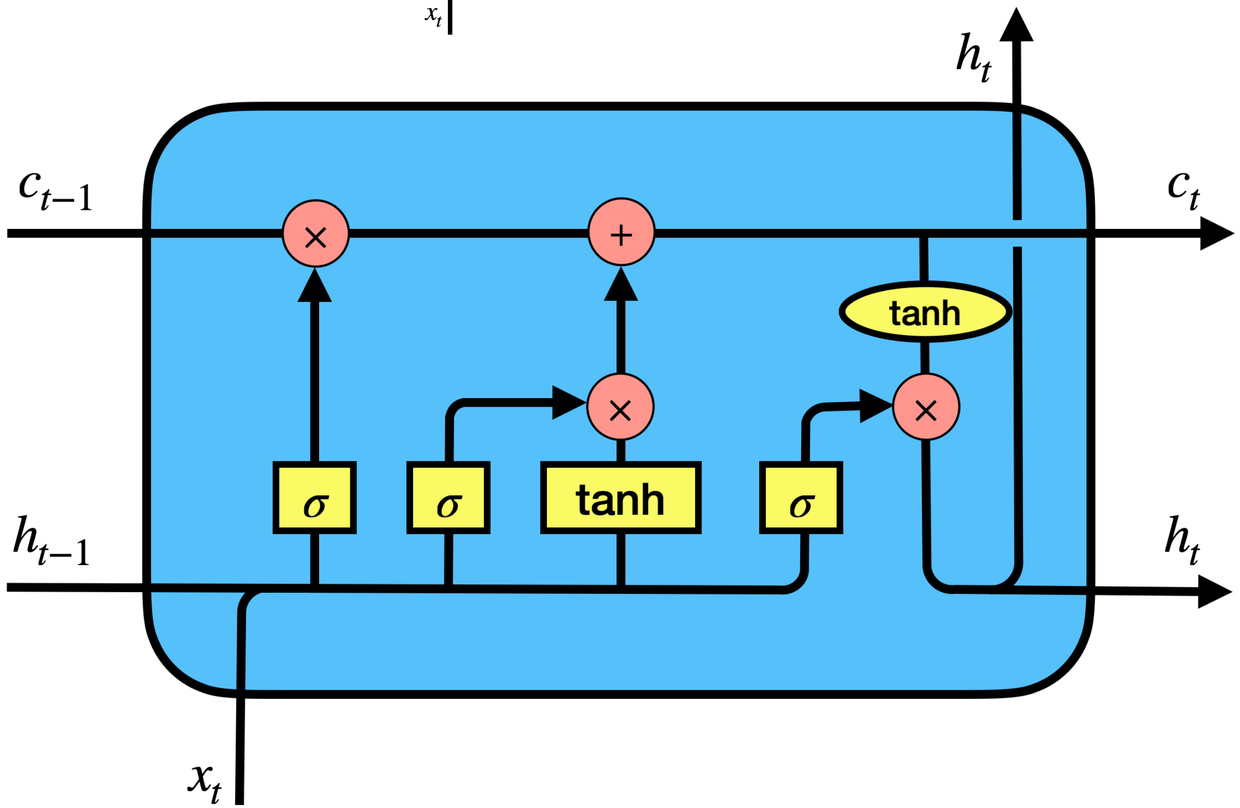
이미지 참조: https://neptune.ai/blog/understanding-gradient-clipping-and-how-it-can-fix-exploding-gradients-problem
수식참조: https://arxiv.org/abs/1211.5063

LSTM (Long-Short Term Memory)

RNN

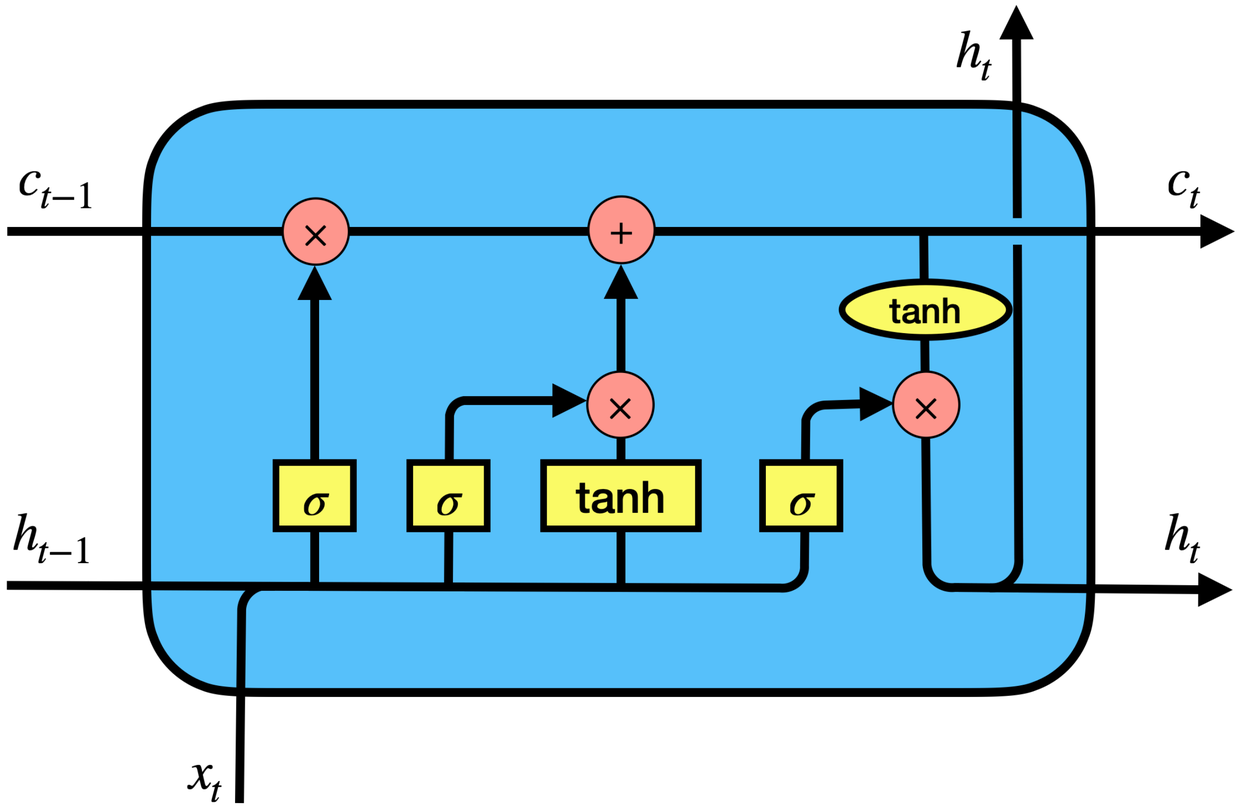


LSTM



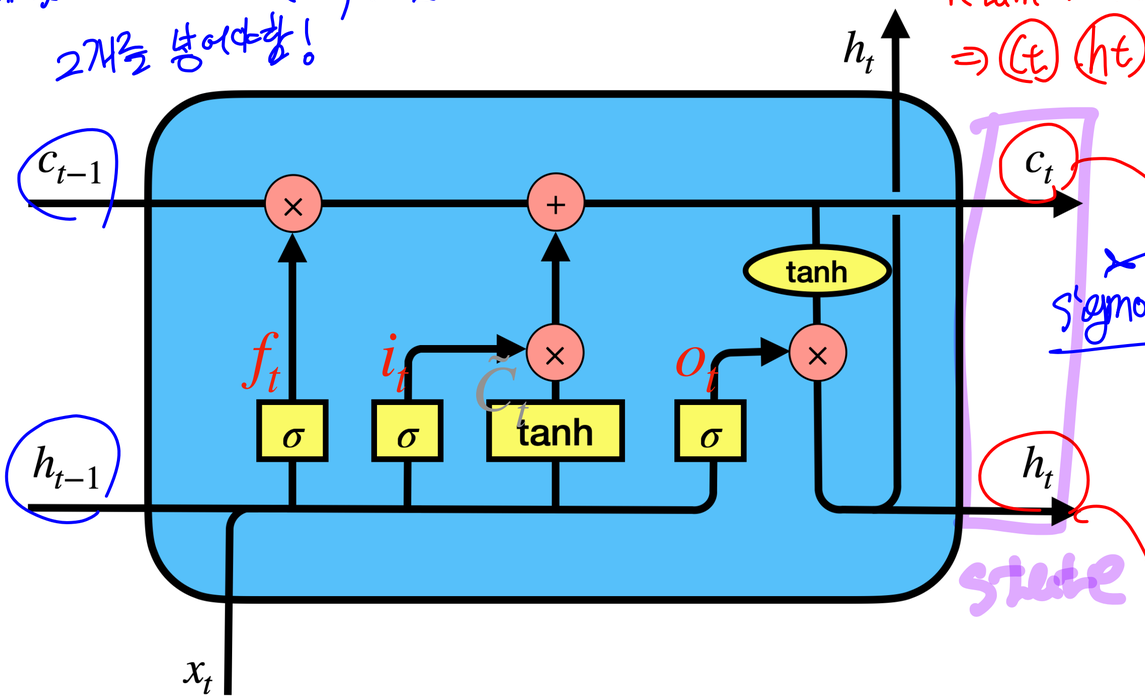
What is LSTM

- RNN의 Vanishing gradient 문제를 해결하기 위한 모델
  - Memory cell을 추가 함 (long term state)
  - $c_t = c_{t-1} + function(h_{t-1}, x_t)$



LSTM (gates)

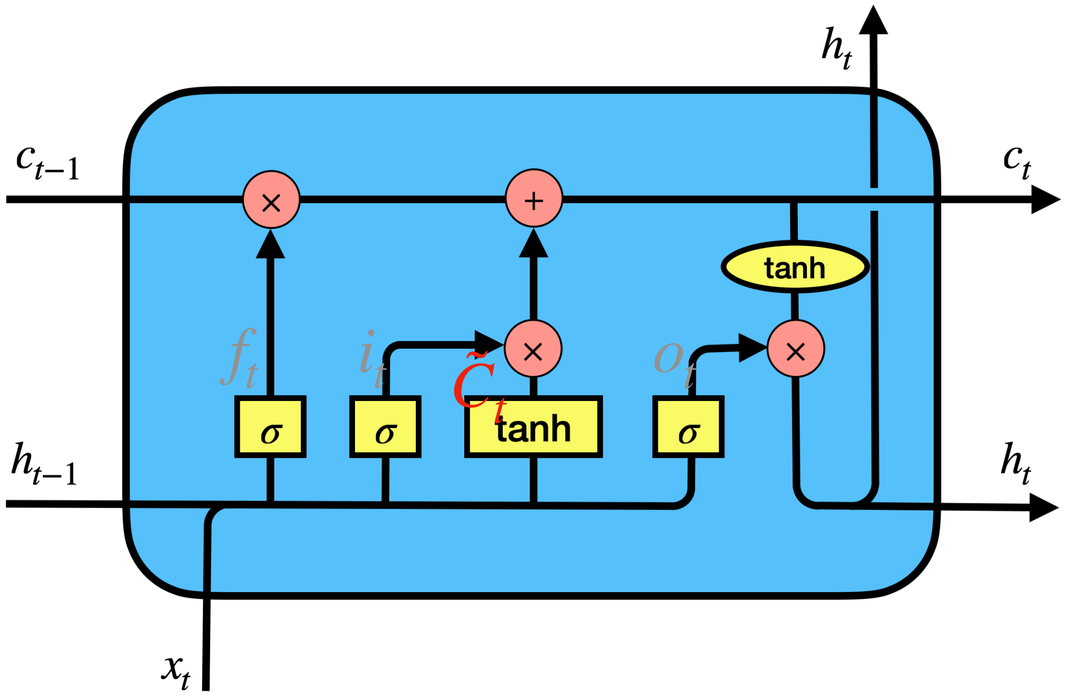
- Forget Gate: 이전 step Memory cell의 정보를 얼마나 사용할지 결정
- Input Gate: 새로 계산된 Memory cell을 얼마나 사용할지 결정
- Output Gate: Memory cell값을 얼마만큼 사용할 것인지 결정



- $f_t = \sigma(W_{hf} h_{t-1} + W_{xf} x_t + b_f)$
- $i_t = \sigma(W_{hi} h_{t-1} + W_{xi} x_t + b_i)$
- $o_t = \sigma(W_{ho} h_{t-1} + W_{xo} x_t + b_o)$
- $\tilde{C}_t = tanh(W_{hc} h_{t-1} + W_{xc} x_t + b_c)$
- $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$
- $h_t = o_t \odot tanh(C_t)$

LSTM (cell & hidden)

- New Cell Content: 현재 시점의 Memory cell 값
- Cell State: 과거 Cell State와 현재 시점의 Cell Content의 합
- Hidden State: 현재 시점의 출력 값



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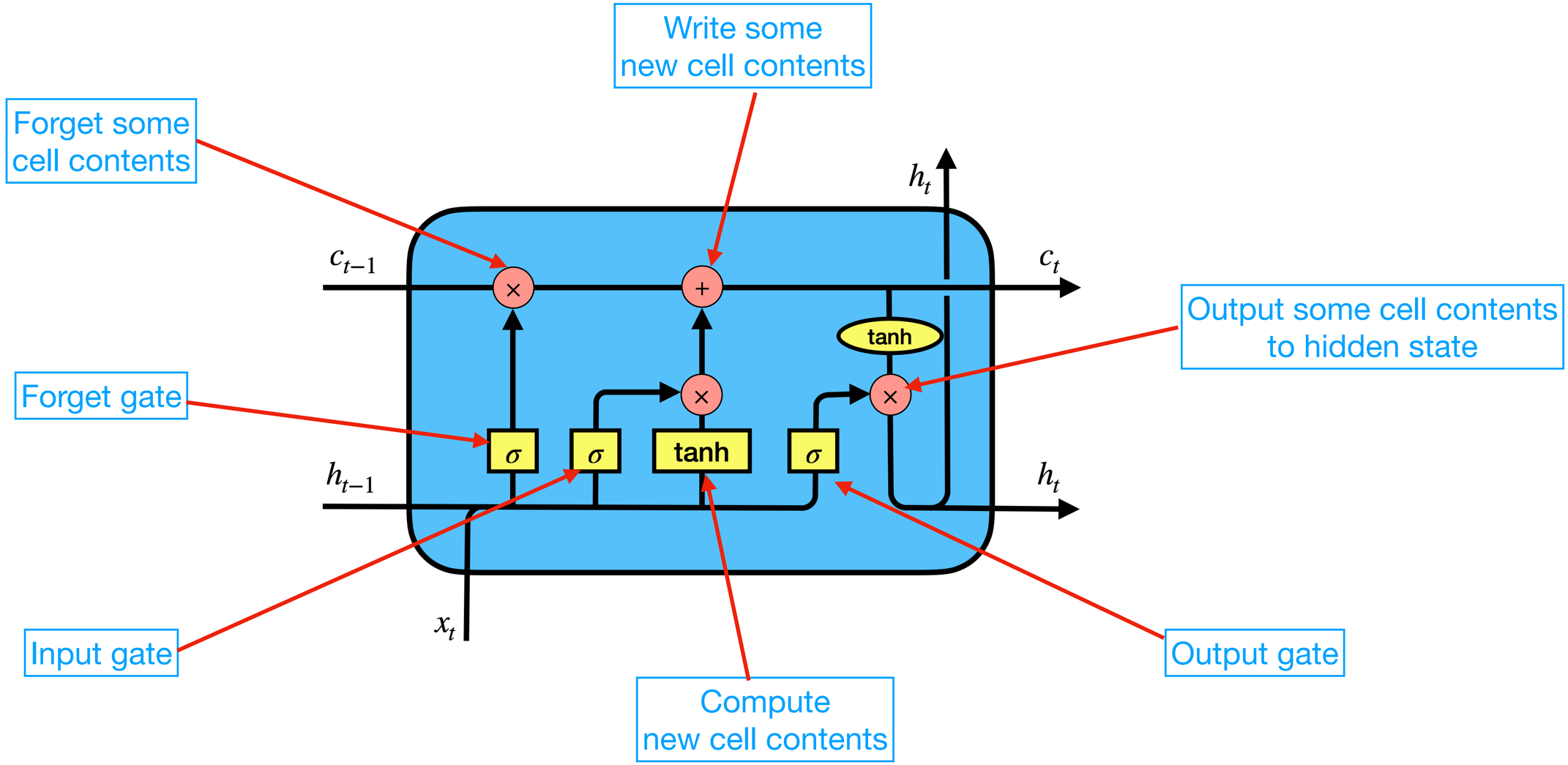
- $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$
- $h_t = o_t \odot tanh(C_t)$

LSTM



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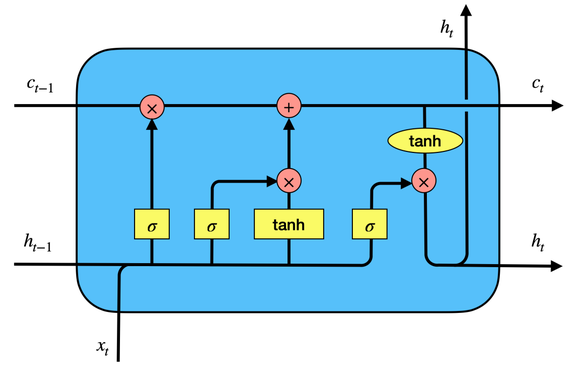
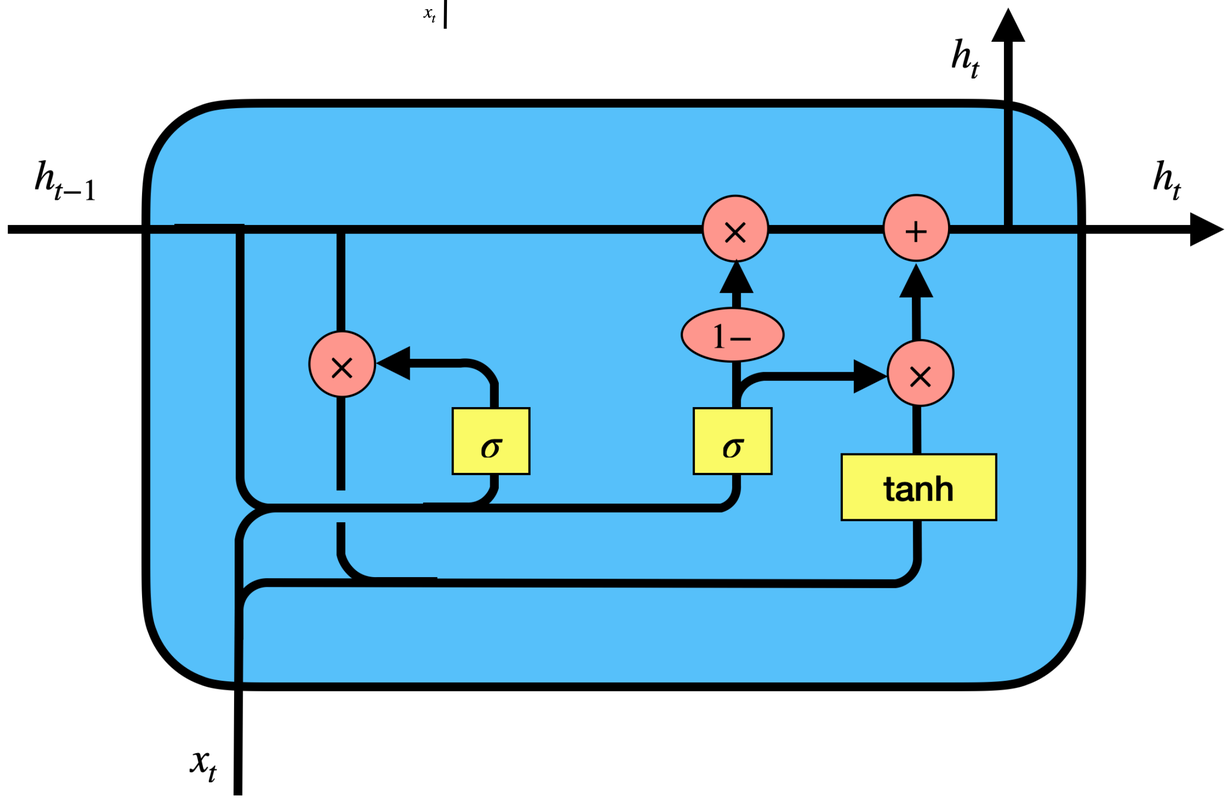
GRU (Gated Recurrent Unit)

LSTM

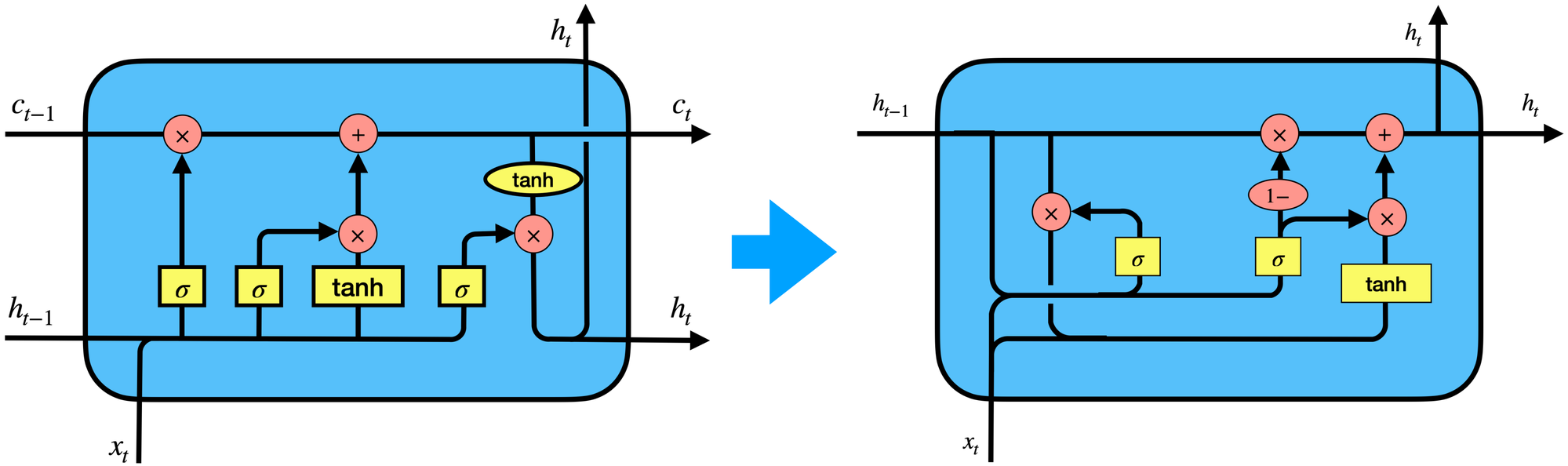


GRU



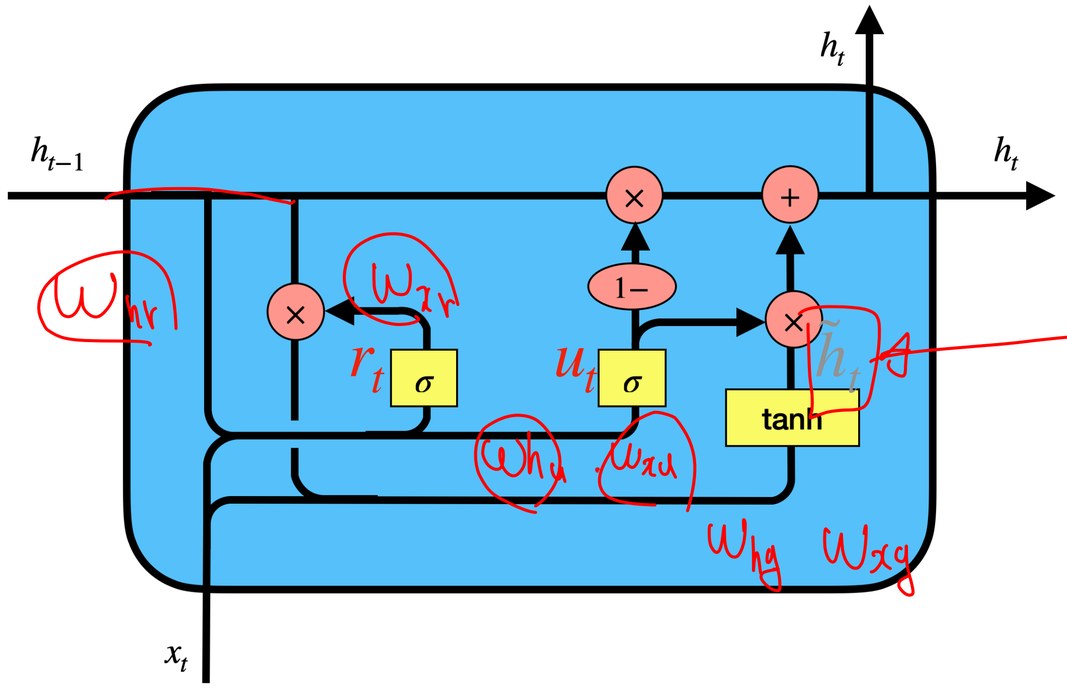
What is GRU

- LSTM보다 단순한 구조 이면서도 긴 데이터를 잘 처리함
  - Memory cell을 사용 안함
  - Gate 숫자를 2개로 줄임



GRU (gates)

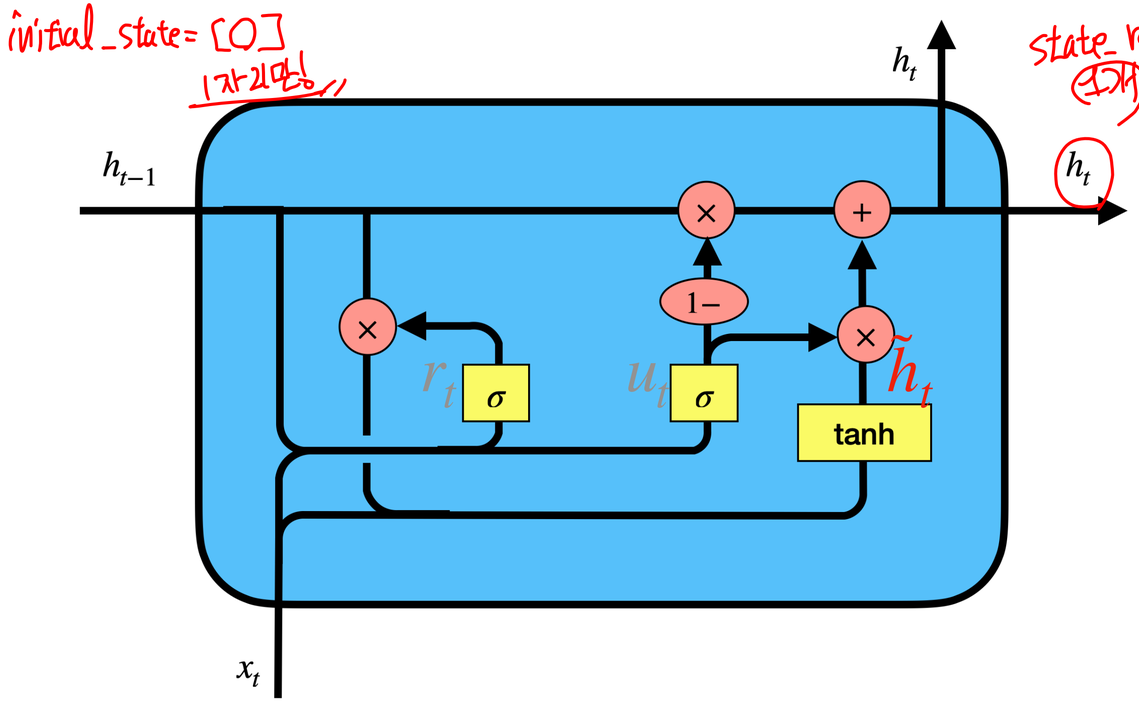
- Reset Gate: 이전 시점 h_{t-1}의 정보를 얼마나 사용할지 결정
- Update Gate: 현재 시점의 $\tilde{h}_t$의 정보를 얼마나 사용할지 결정



- $r_t = \sigma(W_{hr} h_{t-1} + b_{hr} + W_{xr} x_t + b_{xr})$
- $u_t = \sigma(W_{hz} h_{t-1} + b_{hz} + W_{xz} x_t + b_{xz})$
- $\tilde{h}_t = tanh(r \odot (W_{hg} h_{t-1} + b_{hg}) + W_{xg} x_t + b_{xg})$
- $h_t = u_t \odot h_{t-1} + (1 - u_t) \odot \tilde{h}_t$

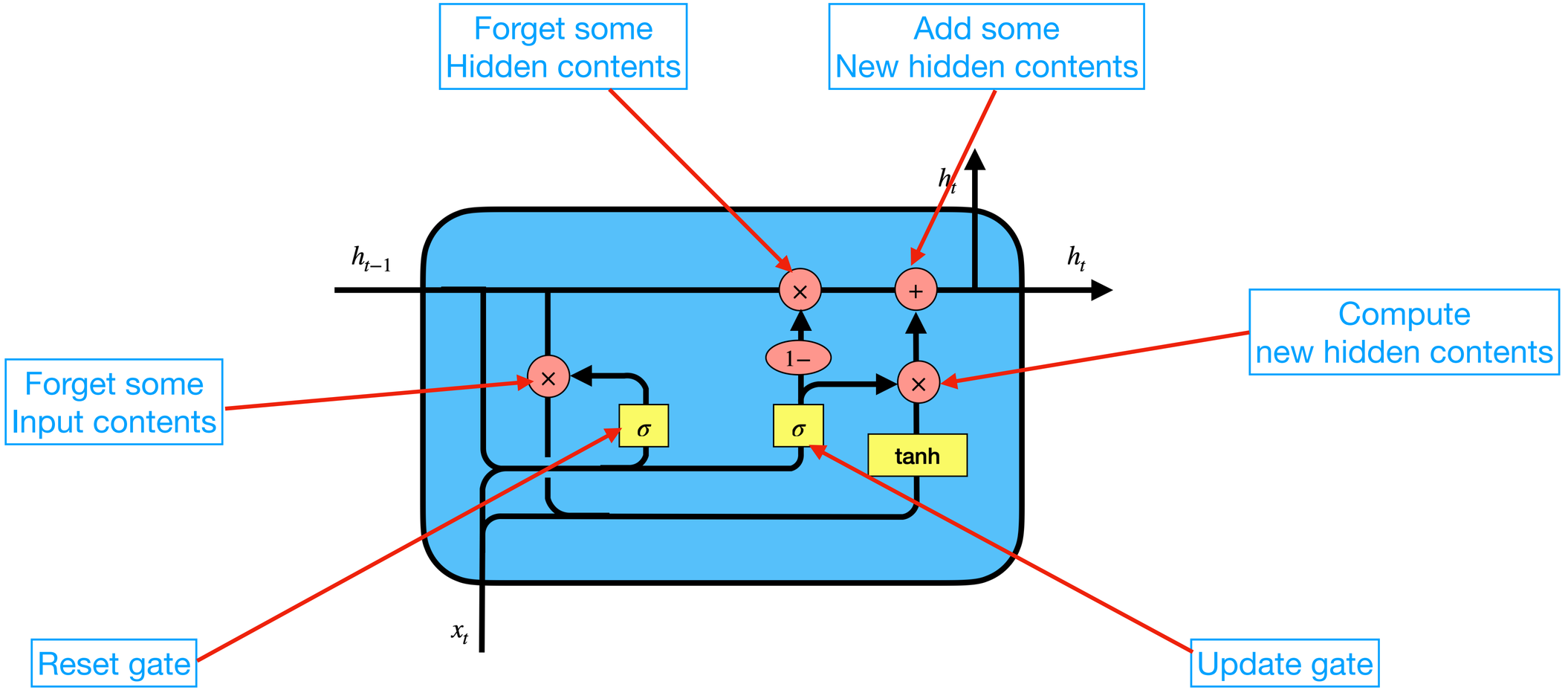
GRU (hidden)

- New Hidden content: 현재 시점의 Hidden state 값
- Hidden state: 현재 시점의 출력 값



- $r_t = \sigma(W_{hr}h_{t-1} + b_{hr} + W_{xr}x_t + b_{xr})$
- $u_t = \sigma(W_{hz}h_{t-1} + b_{hz} + W_{xz}x_t + b_{xz})$
- $\tilde{h}_t = tanh(r \odot (W_{hg}h_{t-1} + b_{hg}) + W_{xg}x_t + b_{xg})$
- $h_t = u_t \odot h_{t-1} + (1 - u_t) \odot \tilde{h}_t$

GRU



참조: http://web.stanford.edu/class/cs224n/slides/cs224n-2020-lecture06-rnnlm.pdf

감사합니다.