Intro to RNN

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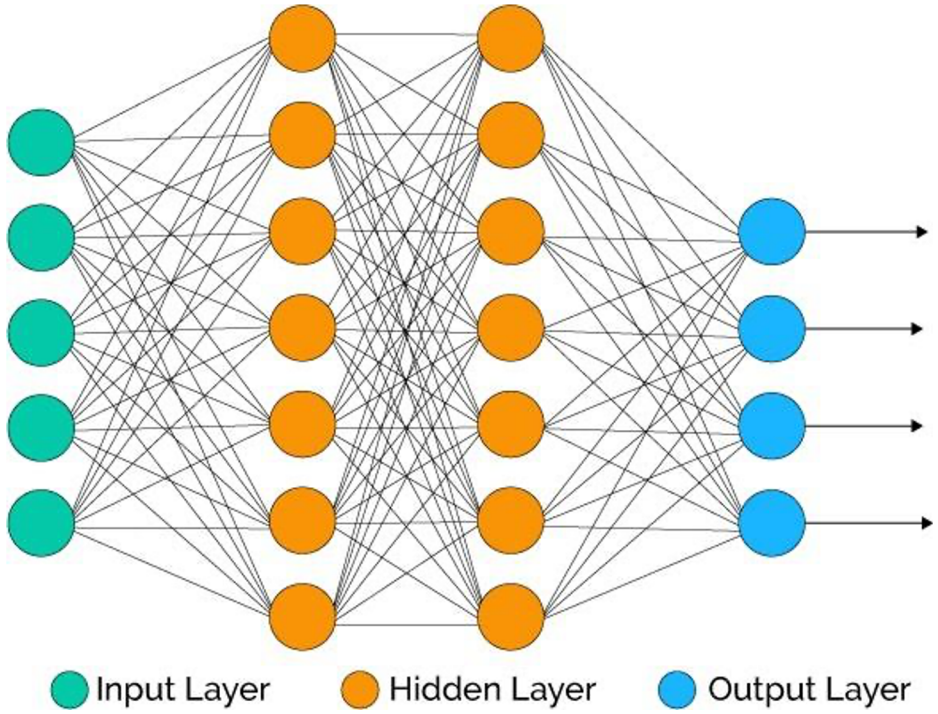
Sequential Data

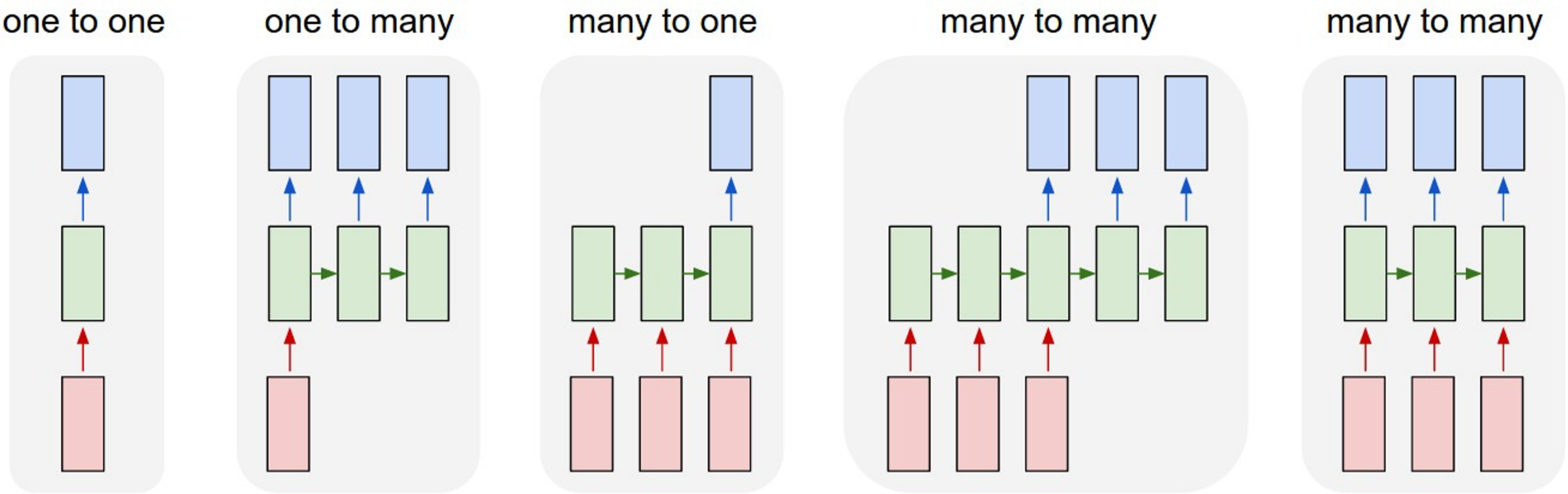
- sequential data – 순서가 의미가 있는 데이터
  - temporal sequence – 시간적 의미가 있는 데이터
  - time series – 일정한 주기가 존재하는 데이터
- resampling을 통해 temporal sequence를 time series로 변환할 수 있다.

신경망의 한계

- 신경망은 자기가 '이전에 뭘 했는지'에 관심이 없다
- 입력 데이터 길이가 매번 바뀌는 경우에 대응할 수 없다.
- 분류가 무수히 많은 경우 매핑이 어렵다.



RNN 구성사례



고정된 갯수의 layer를 재사용하므로 입출력단의 순열(Sequence) 길이를 미리 제한할 필요가 없다

RNN 구성사례

- one to one: 이미지 입력->이미지 분류 (개 사진/고양이 사진)
- one to many: 이미지 입력->이미지 Captioning (문장)
- many to one: 문장 입력->감정분석 결과 (긍정/부정)
- many to many: 문장 입력->문장 출력 (기계 번역)
- many to many: 비디오 입력->(동기화된)결과 출력 (비디오 프레임별 분류)

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What makes RNN so special?

- CNN은 제한적이다.
  - 고정된 크기의 인풋 (이미지 등)
  - 고정된 크기의 아웃풋
  - 고정된 크기의 계산 절차 (layer 갯수가 고정)
- '안'고정된 것을 다뤄보고 싶다
  - 쓰다 만 '문장' 이라든지
  - 그리다 만 '그림' 이라든지
  - 연주하다 만 '노래' 라든지

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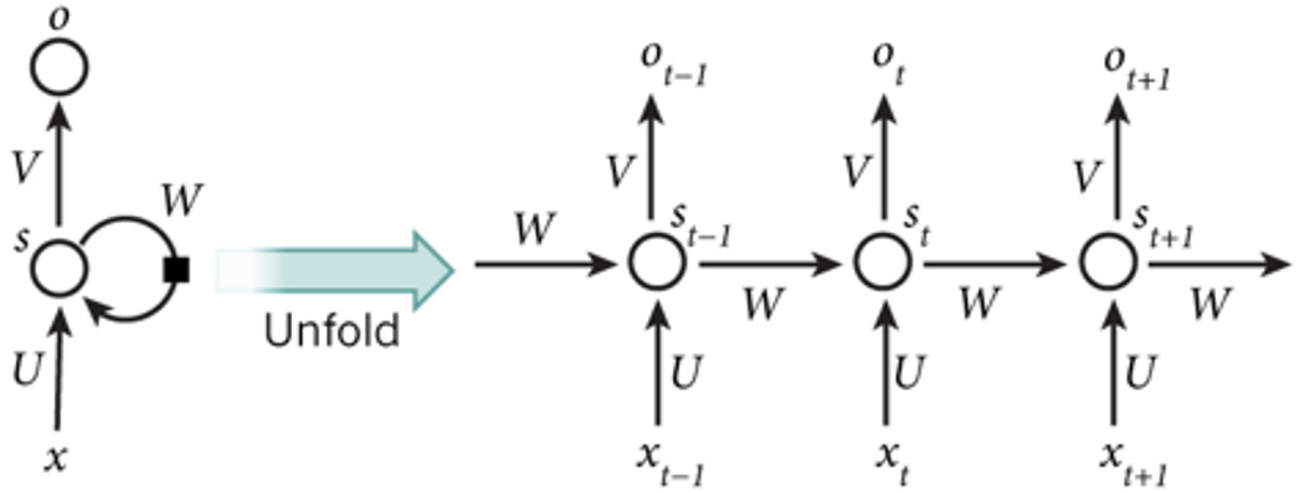
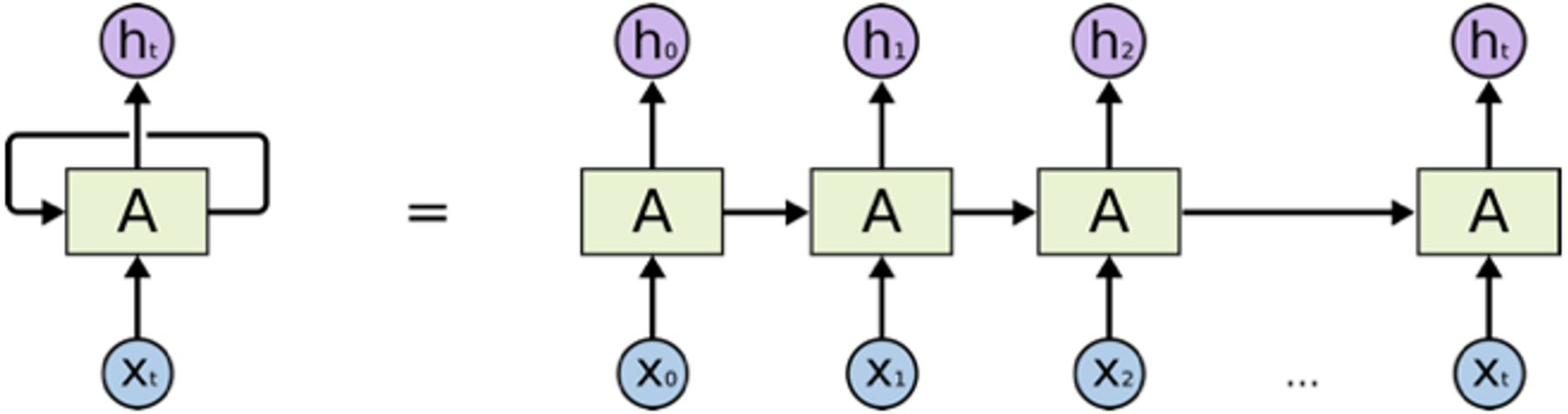
vanilla RNN





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vanilla RNN 기본 개념

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

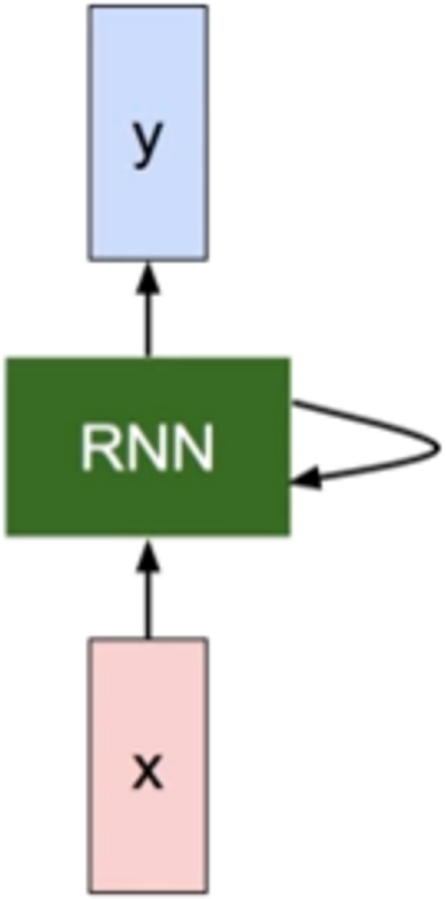
$$h_t = f_W(h_{t-1}, x_t)$$

new state

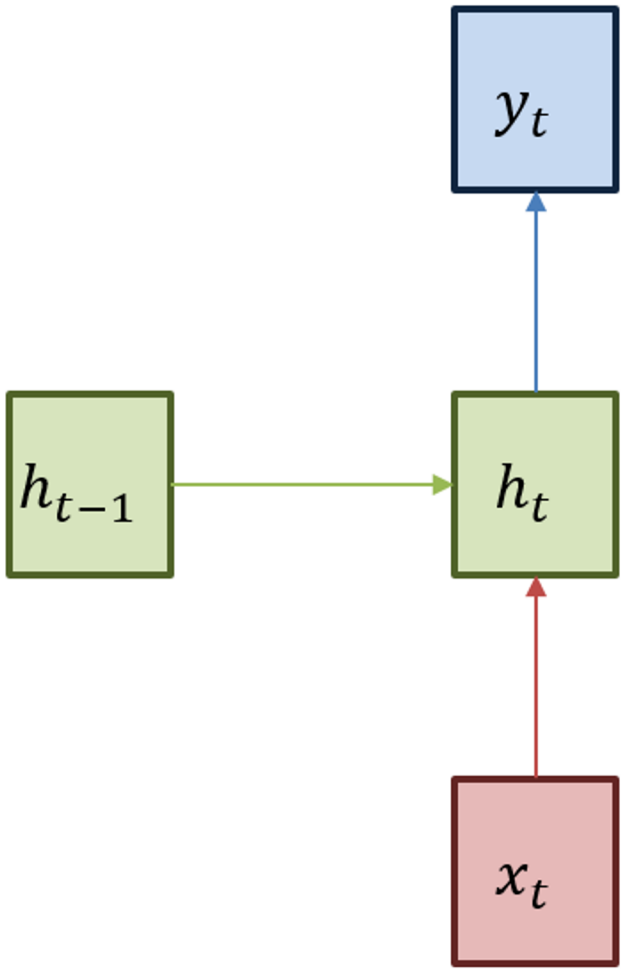
some function with parameters W

old state

input vector at some time step



RNN 기본 개념

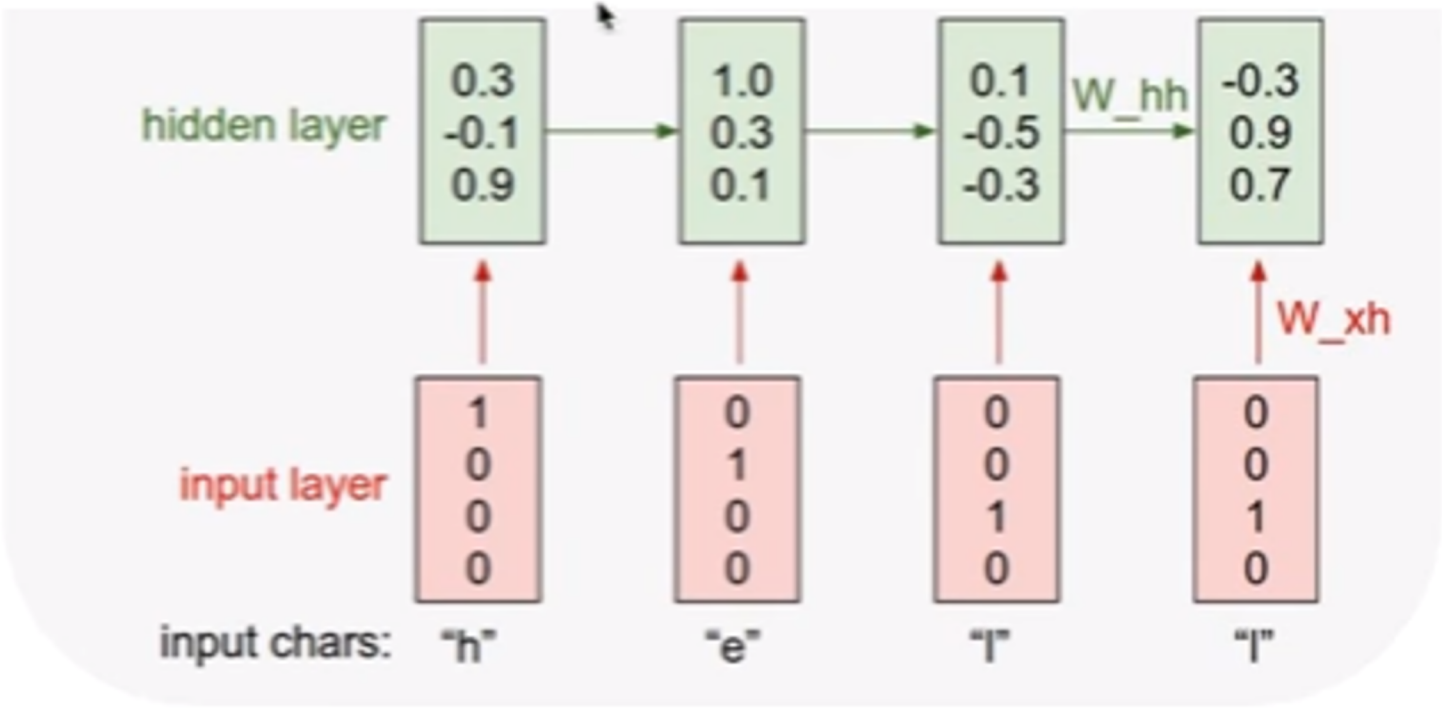


$$y_t = W_{hy} h_t + b_y$$

$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t + b_h)$$

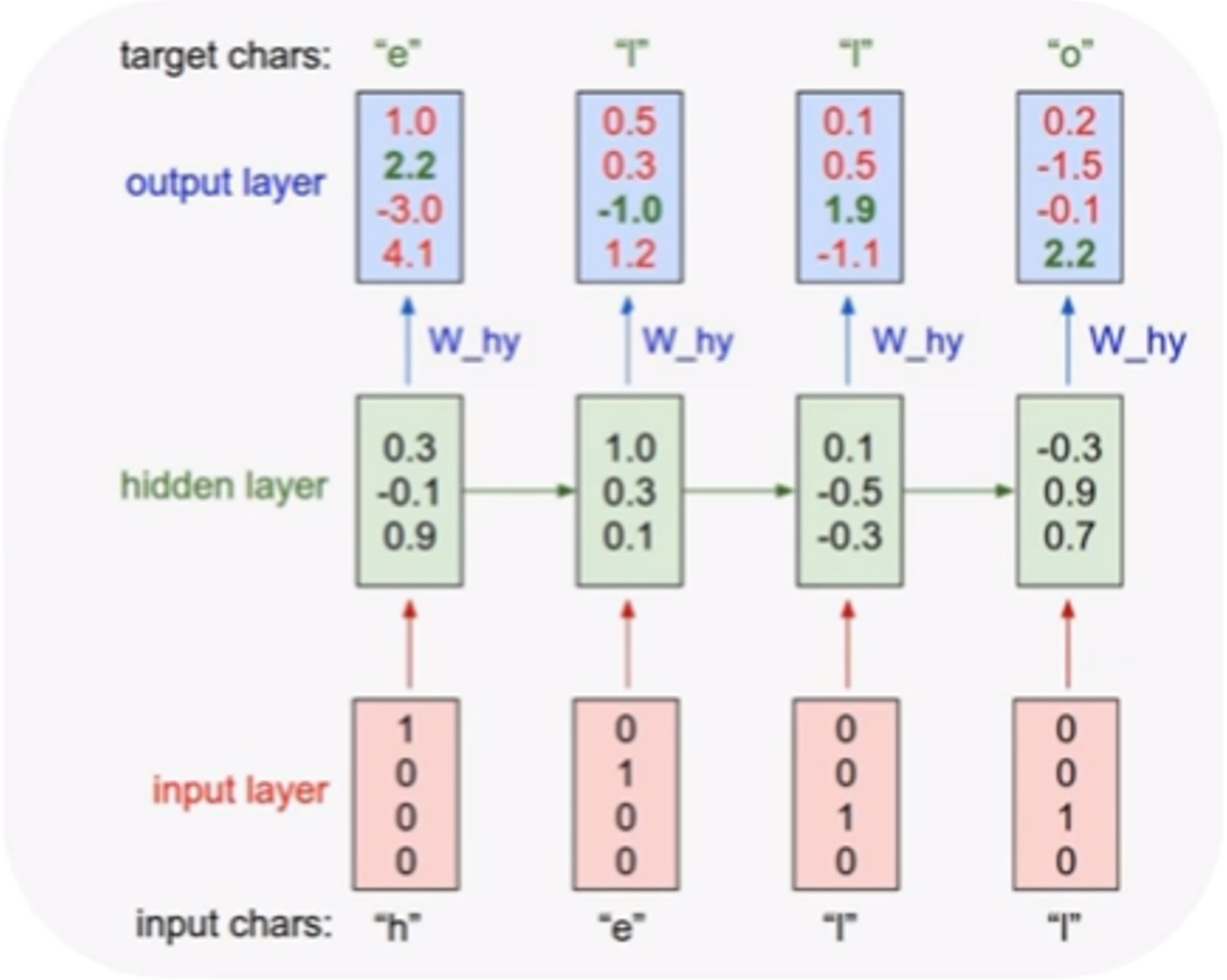
RNN 입력

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

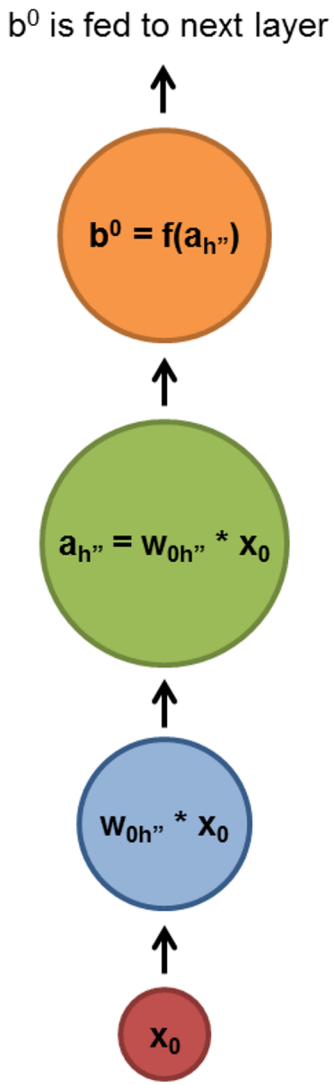


RNN 출력

$$y_t = W_{hy} h_t$$



How RNN Works



RNN code

```
1 import tensorflow as tf
2
3 # vanilla RNN
4 model = tf.keras.models.Sequential()
5 model.add(tf.keras.layers.Input(shape = (7, 5)))
6
7 cell = tf.keras.layers.SimpleRNNCell(15)
8 model.add(tf.keras.layers.RNN(cell))
9
10 model.add(tf.keras.layers.Dense(1))
11
12 model.compile(
13     loss=tf.keras.losses.mse,
14     optimizer=tf.keras.optimizers.Adam(lr=0.01)
15 )
```

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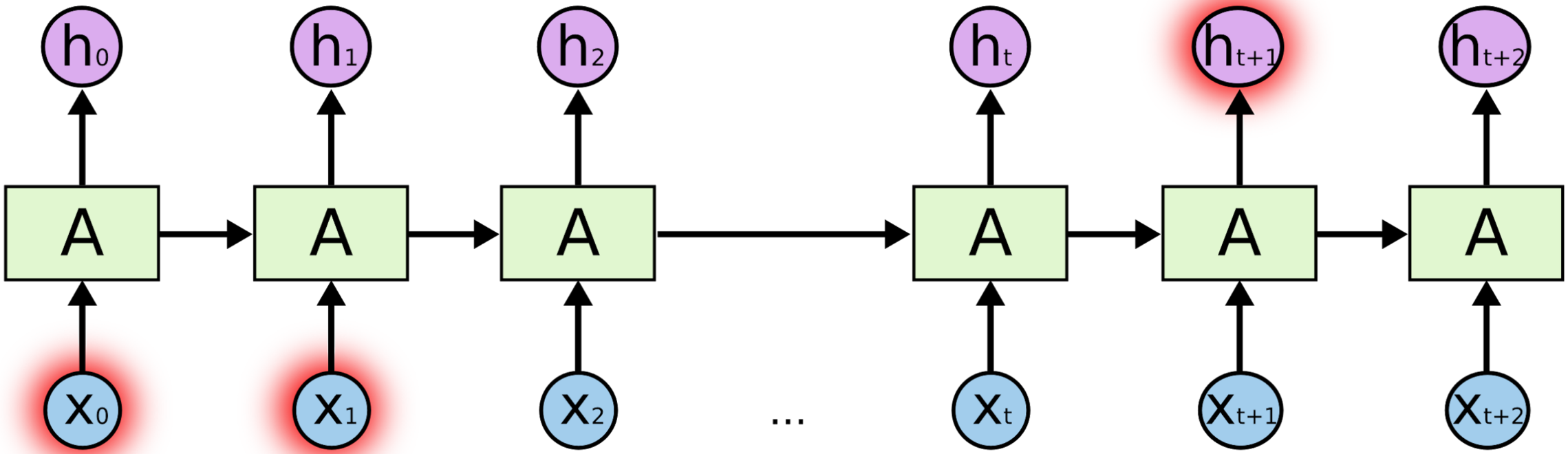
RNN의 기울기 소실 문제

바로 잠깐 전에 했던 말만 기억한다

‘시간’이 오래 지나면 예전 정보가 ‘희석’되어 사라지는 문제



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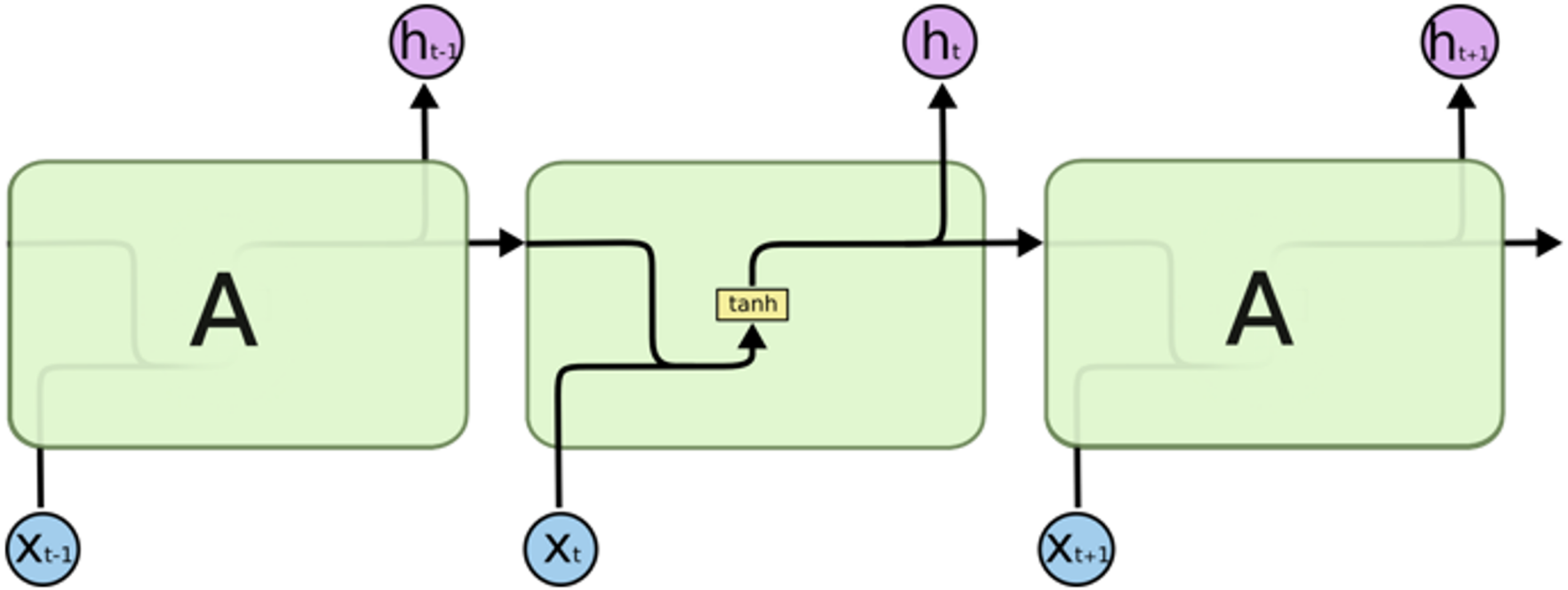
RNN의 기울기 소실 문제

원인은 tanh, 중첩되면 0에 수렴한다



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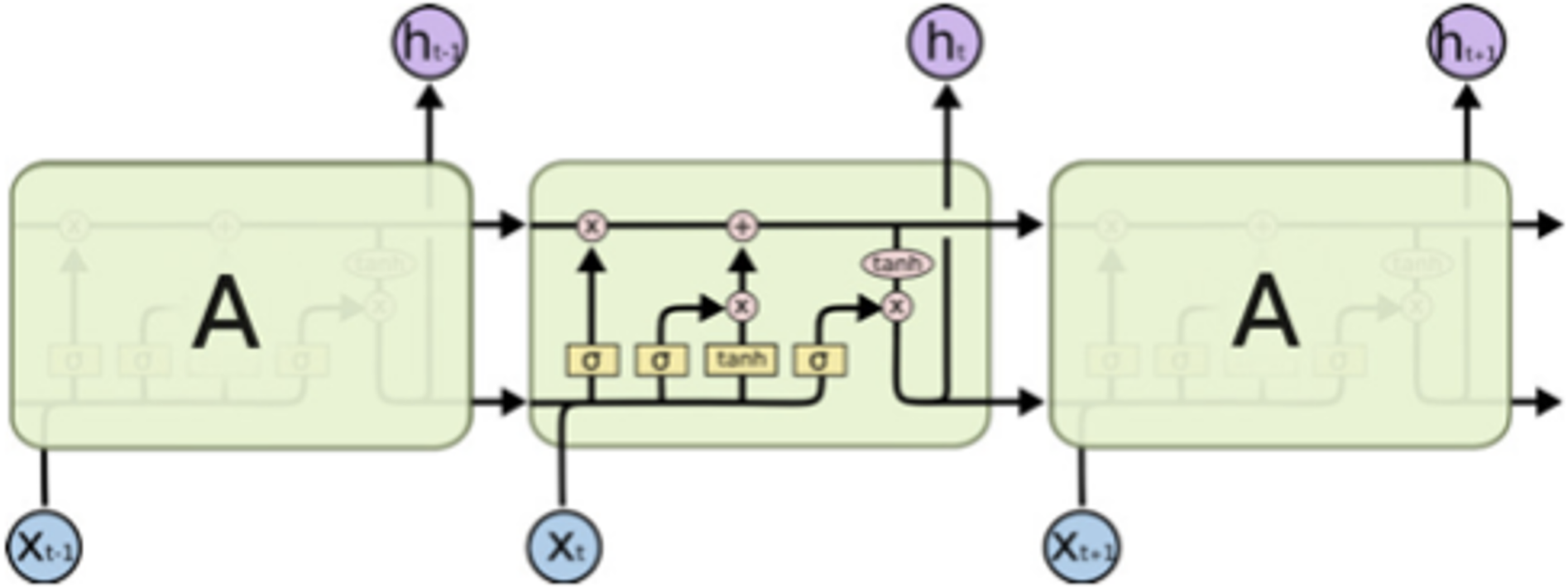
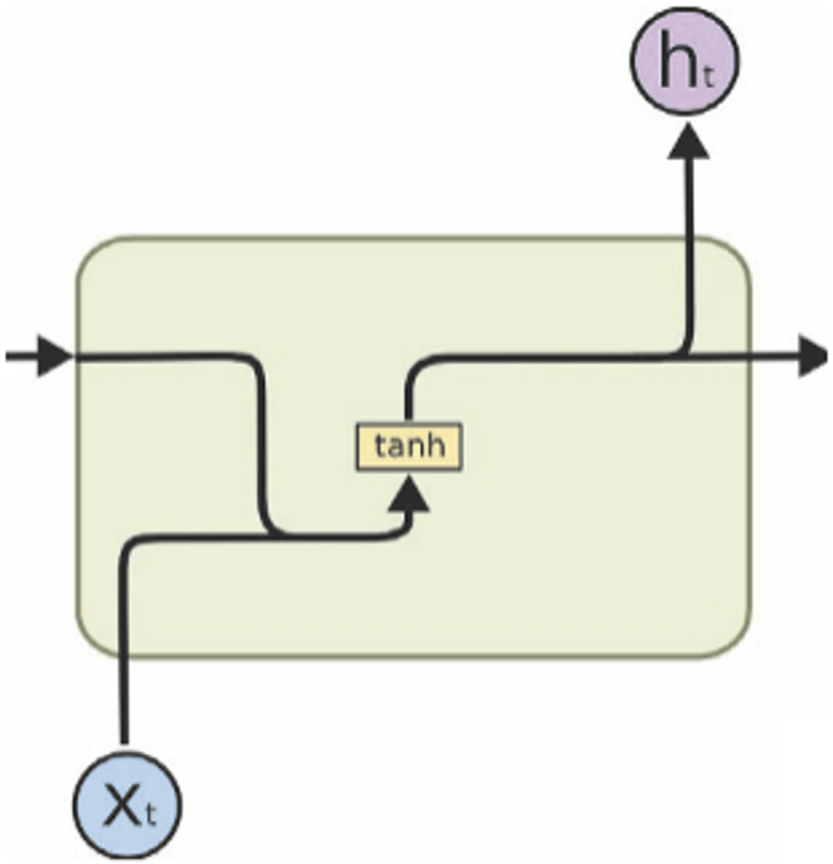
LSTM (long short term memory)

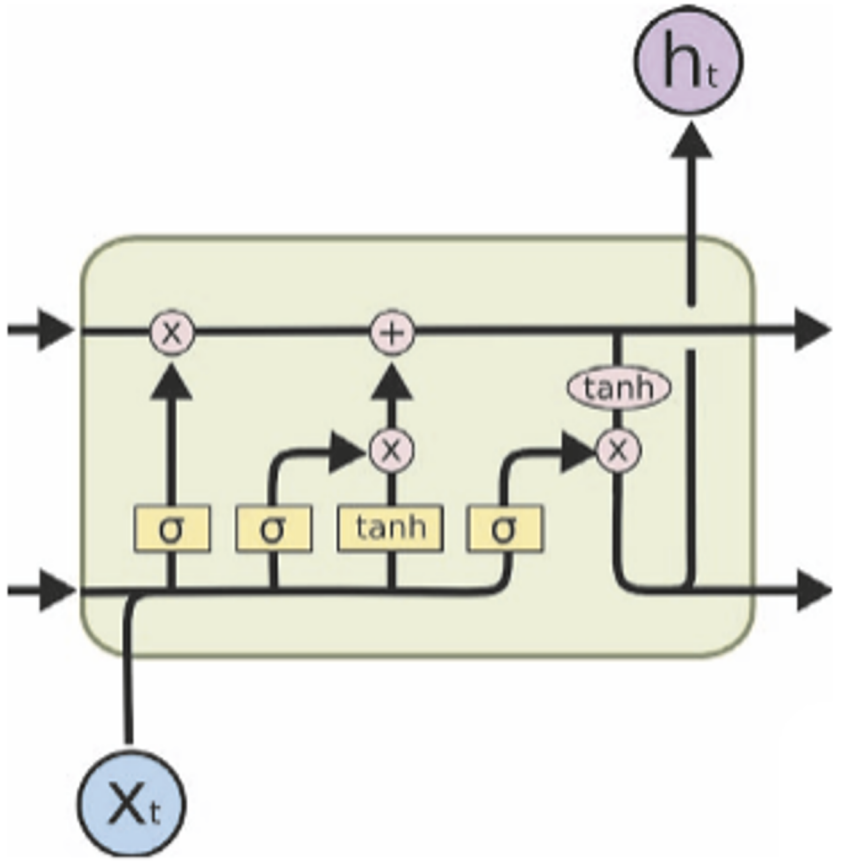
잊을 것은 잊고, 기억할 것만 기억한다.



LSTM (long short term memory)



(a) RNN



(b) LSTM

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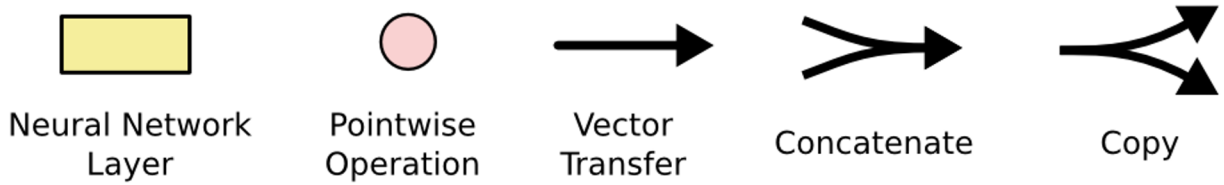
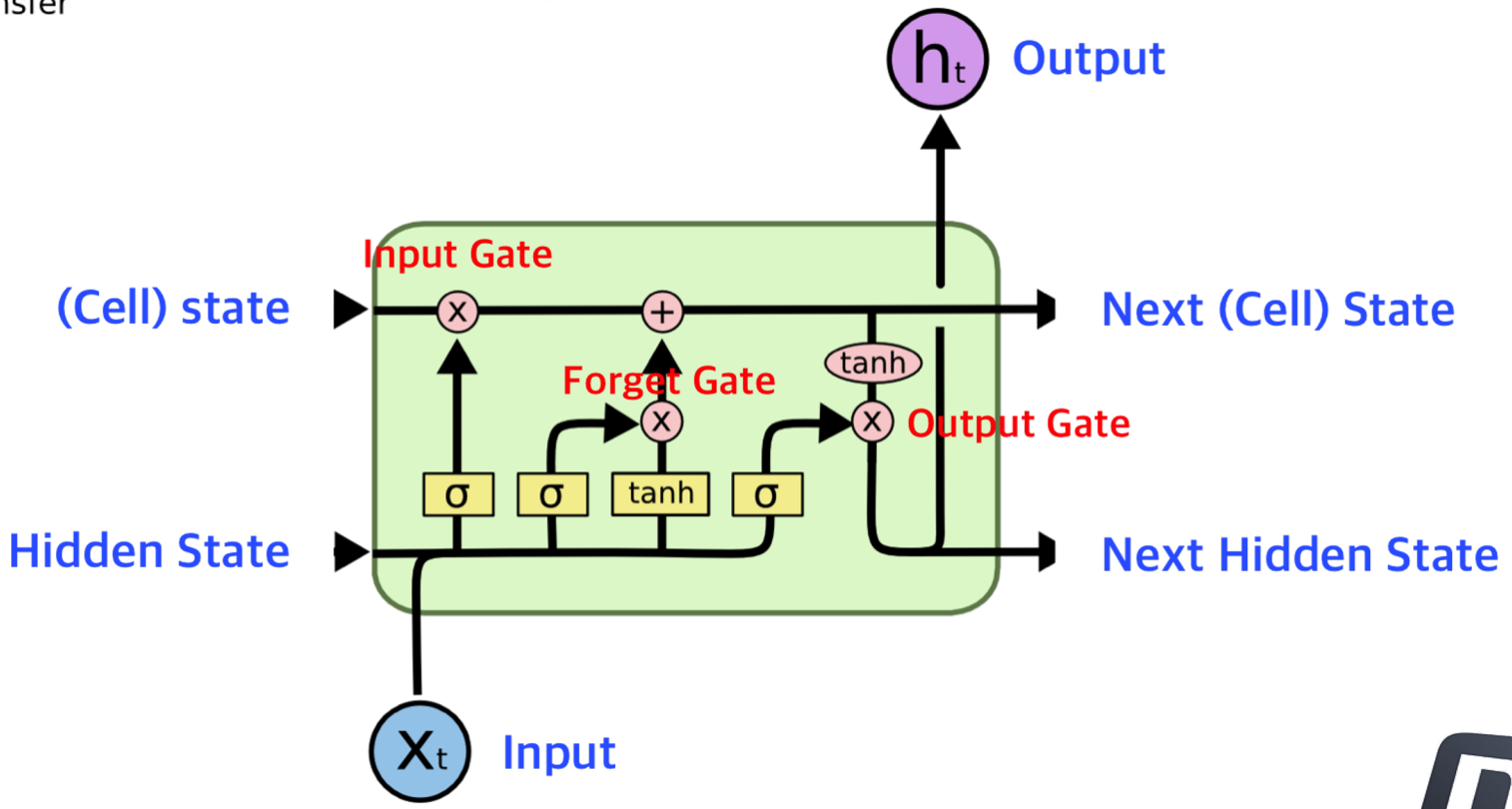
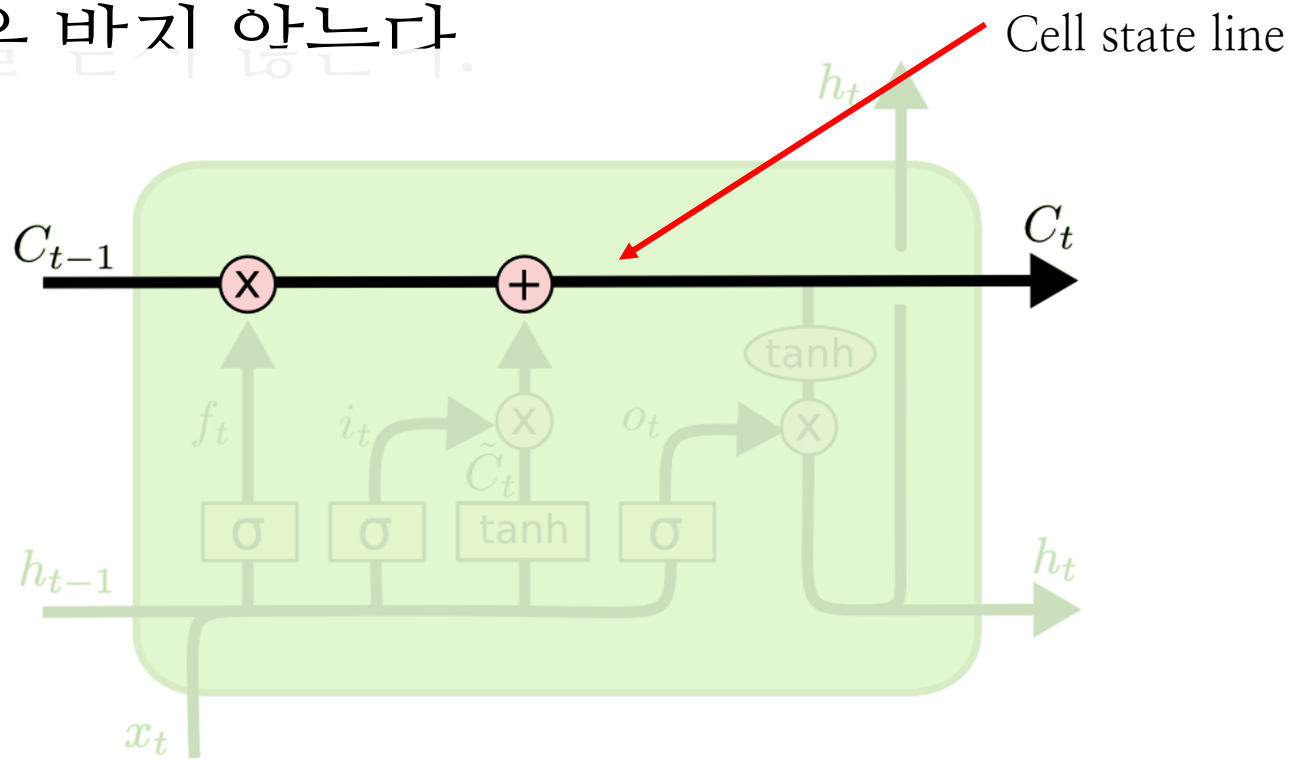
기억력을 만드는 도구들


Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

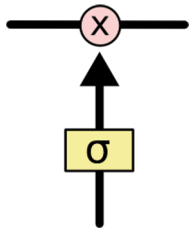

h_t
Output
Input Gate
(Cell) state
Next (Cell) State
Forget Gate
tanh
Output Gate
σ
σ
tanh
σ
Hidden State
Next Hidden State
X_t
Input

Cell State (기억장치)

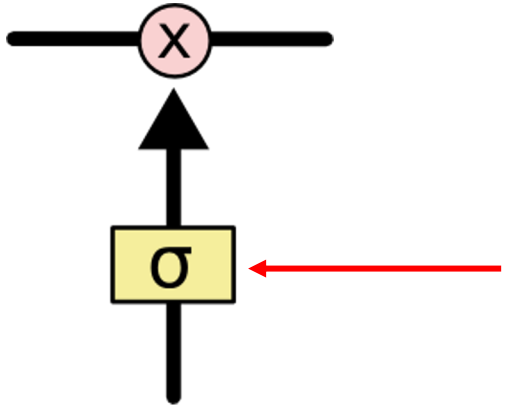
- 기억에 관한 부분을 담당
- tanh의 영향을 받지 않는다.



Gate



- 정보를 '선택적으로' 통과시키는 관문
- Sigmoid 활성함수와 곱셈으로 이루어짐
- cell state를 관리하기 위함
- 3종류의 gate가 있음



X가 통과시키는 정보의 비율을 정해서 0에서 1 사이의 숫자를 보낸다.

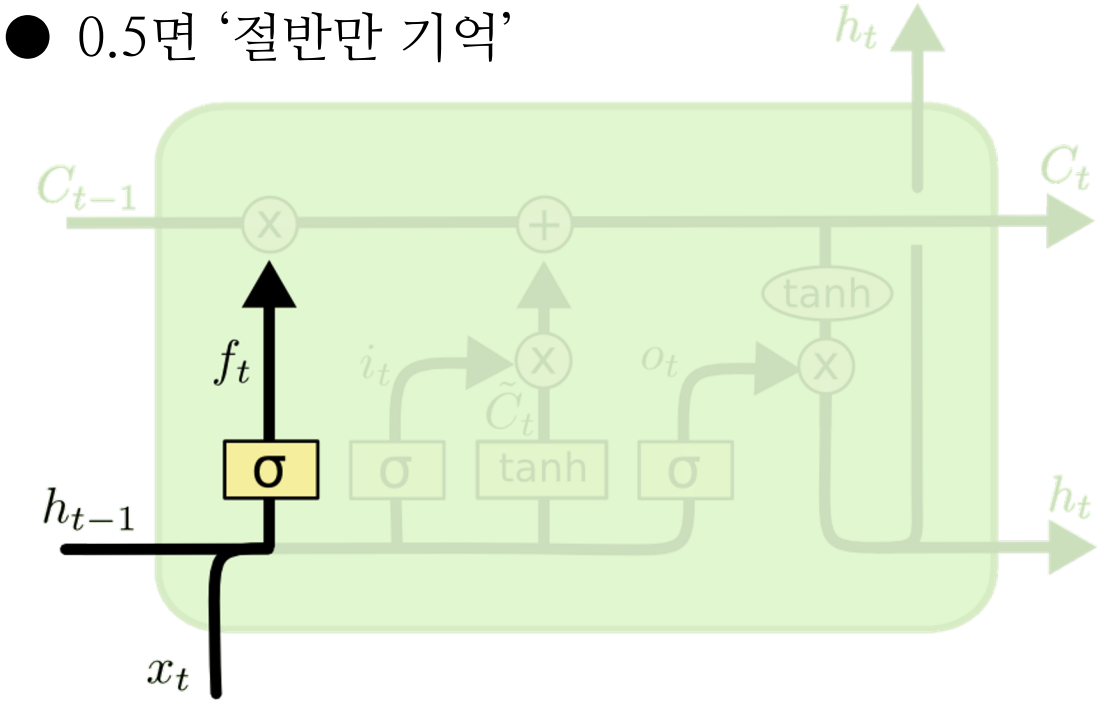
- 0이면 '차단'
- 1이면 '통과'
- 0.5면 '절반만 통과'

D:plus

Forget Gate

Cell state의 예전 값을 얼만큼 '잊을지' 결정해 줌

- 1이면 '전부 기억'
- 0이면 '전부 망각'
- 0.5면 '절반만 기억'



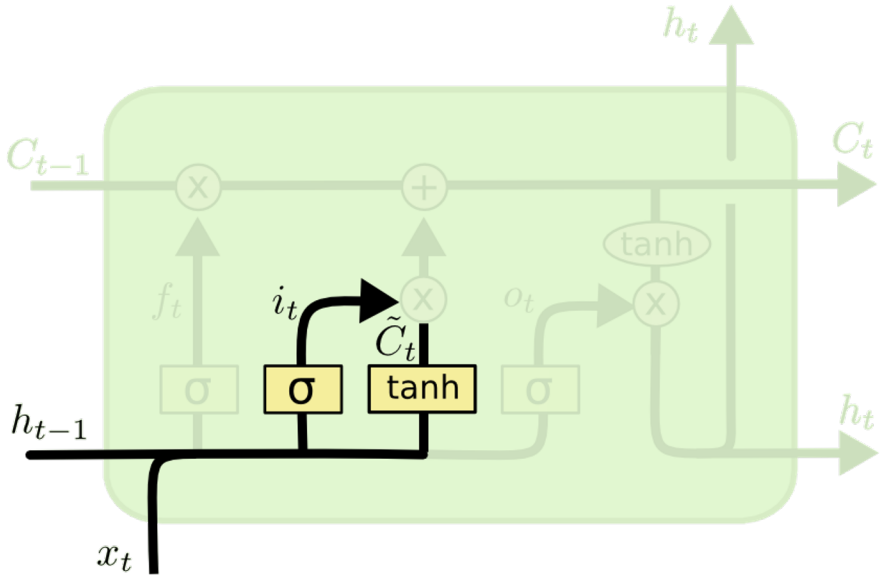
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

D:plus

Input Gate

Cell state에 추가로 무엇을 '기억시킬지' 결정해줌

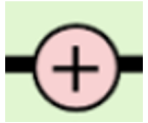
- 1이면 '전부 기억'
- 0이면 '전부 망각'
- 0.5면 '절반만 기억'

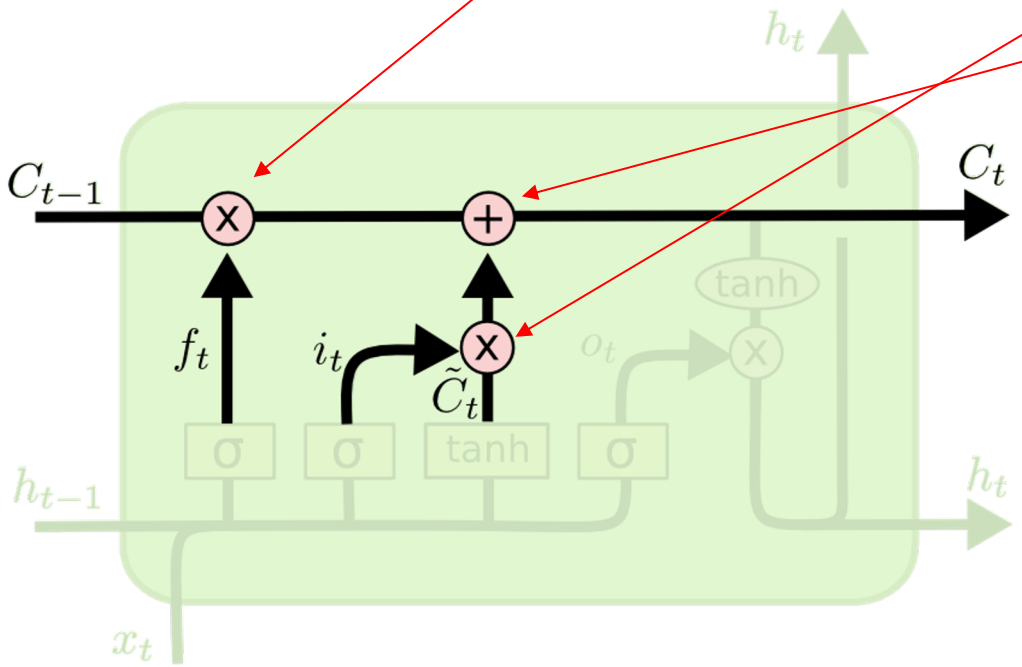


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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

Update Cell State

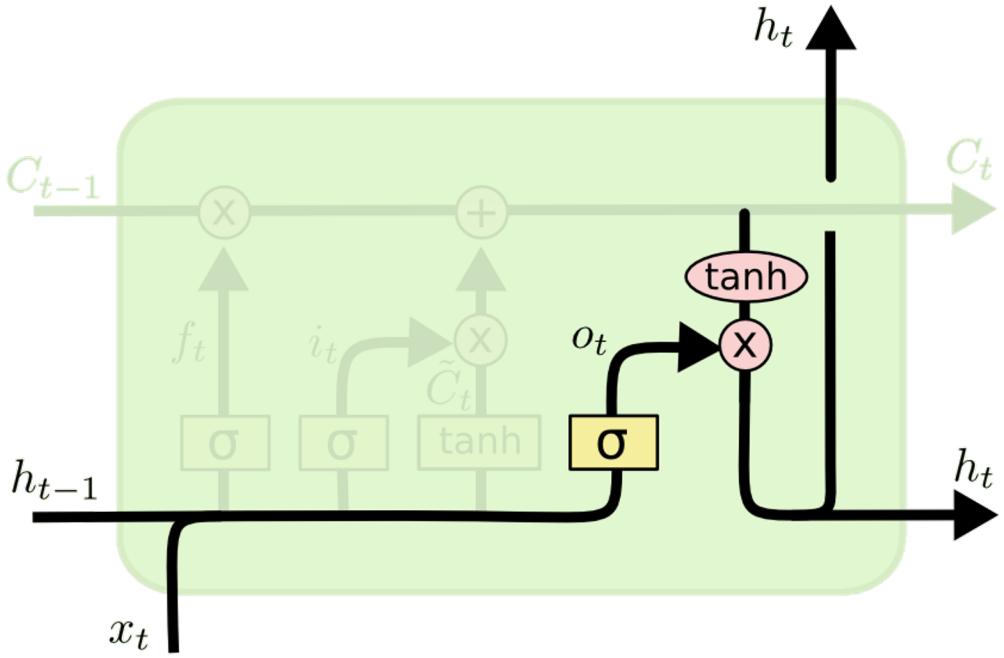
예전 값을 부분적으로 '잊고', 새 값을 부분적으로 '기억하고', 둘을 합쳐줌 



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

D:plus

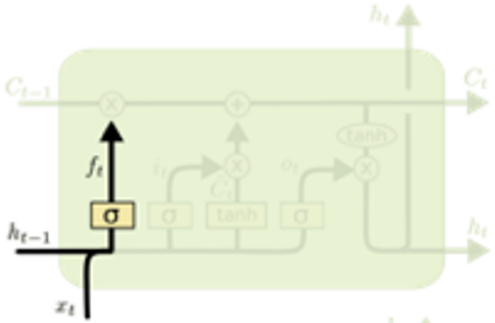
Output Gate - 결과내기



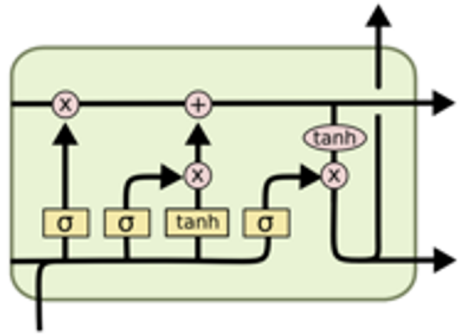
$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

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

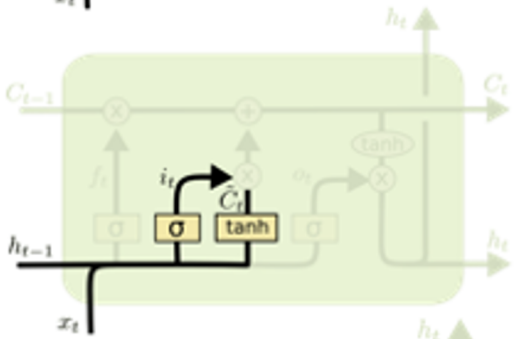
forget gate



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



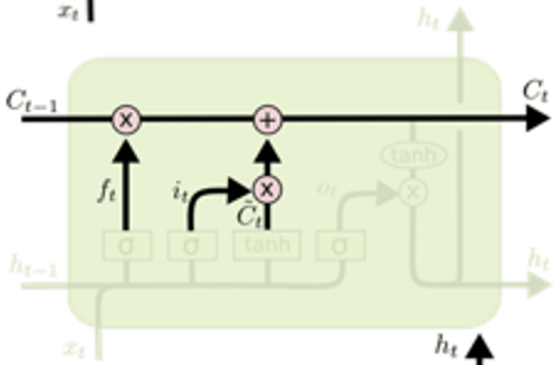
input gate



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

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

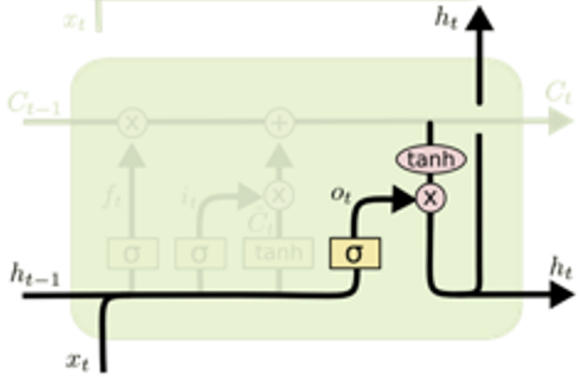
i_t decides what component is to be updated.
C'_t provides change contents



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

Updating the cell state

output gate



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

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

Decide what part of the cell state to output

D:plus

LSTM code

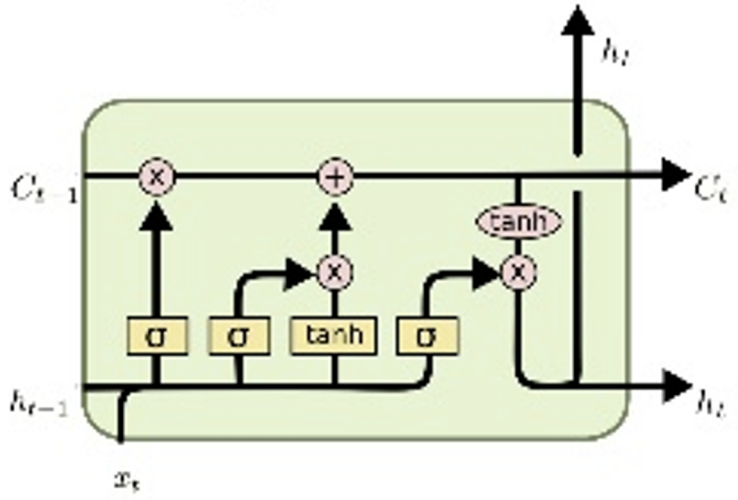
```
1 import tensorflow as tf
2
3 # LSTM
4 model = tf.keras.models.Sequential()
5 model.add(tf.keras.layers.Input(shape = (7, 5)))
6
7 cell = tf.keras.layers.LSTMCell(15)
8 model.add(tf.keras.layers.RNN(cell))
9
10 model.add(tf.keras.layers.Dense(1))
11
12 model.compile(
13     loss=tf.keras.losses.mse,
14     optimizer=tf.keras.optimizers.Adam(lr=0.01)
15 )
```

D:plus

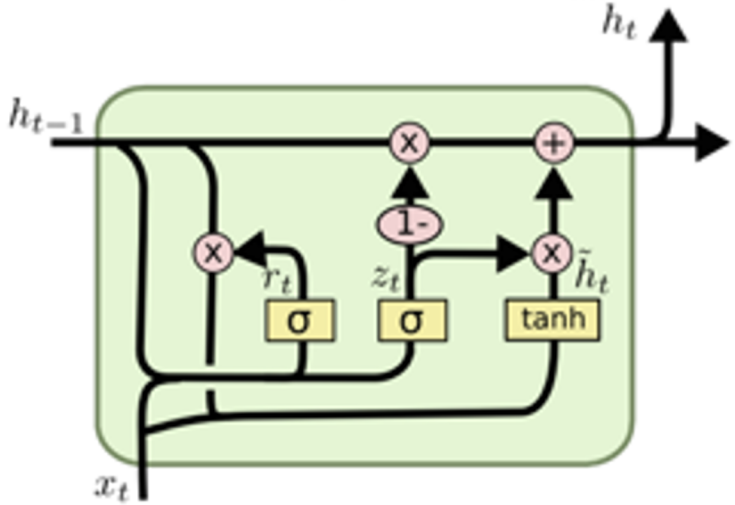
GRU (Gated Recurrent Unit)

- LSTM의 간소화 버전
- hidden state only

• LSTM [Hochreiter&Schmidhuber97]



• GRU [Cho+14]



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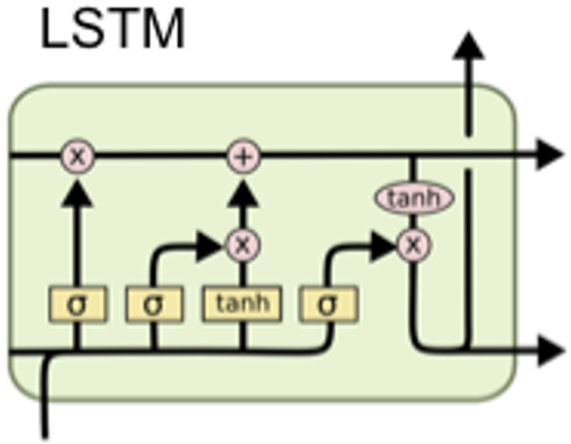
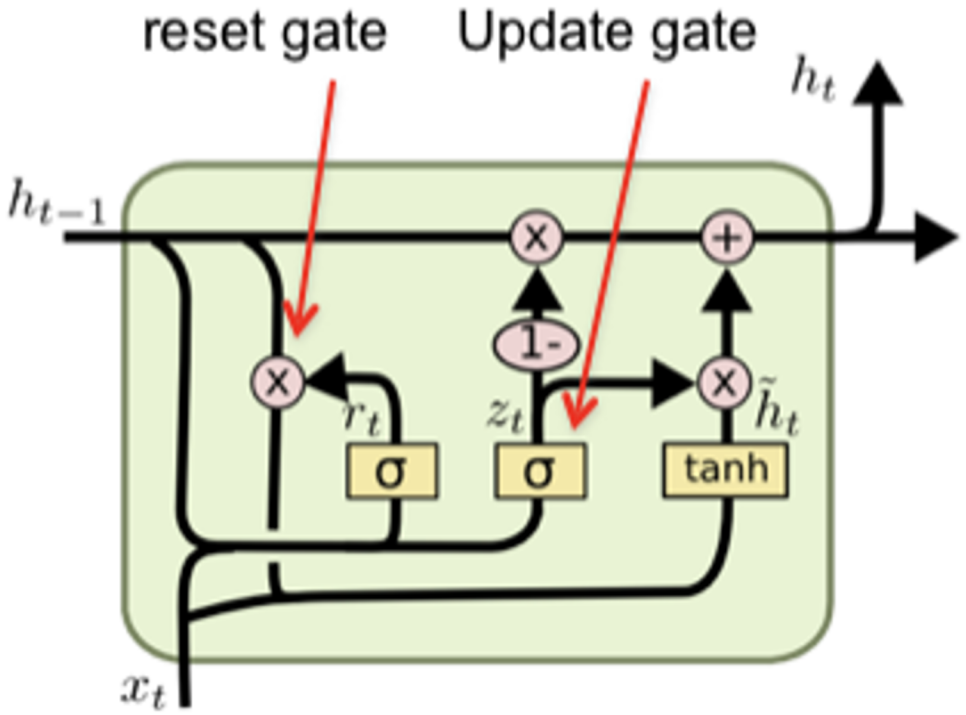
GRU – gated recurrent unit

(more compression)





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

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

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

D:plus

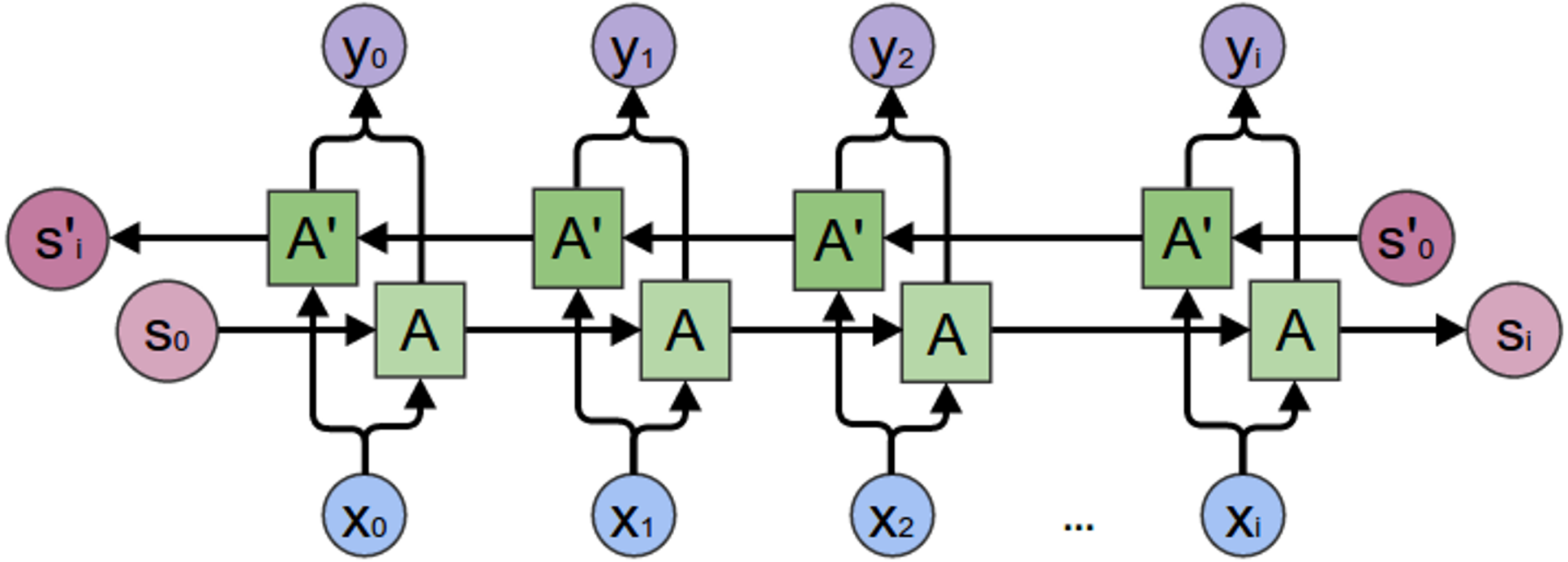
GRU code

```
1 import tensorflow as tf
2
3 # GRU
4 model = tf.keras.models.Sequential()
5 model.add(tf.keras.layers.Input(shape = (7, 5)))
6
7 cell = tf.keras.layers.GRUCell(15)
8 model.add(tf.keras.layers.RNN(cell))
9
10 model.add(tf.keras.layers.Dense(1))
11
12 model.compile(
13     loss=tf.keras.losses.mse,
14     optimizer=tf.keras.optimizers.Adam(lr=0.01)
15 )
```

D:plus

bidirectional

- 이전의 정보뿐 아니라 이후의 정보도 활용해보자.
- 전방향 후방향 각 1개의 cell을 가진다.



bidirectional code

```
1 import tensorflow as tf
2
3 # lstm + bidirectional
4 model = tf.keras.models.Sequential()
5 model.add(tf.keras.layers.Input(shape = (7, 5)))
6
7 cell = tf.keras.layers.LSTMCell(15)
8 lstm = tf.keras.layers.RNN(cell)
9 model.add(tf.keras.layers.Bidirectional(lstm))
10
11 model.add(tf.keras.layers.Dense(1))
12
13 model.compile(
14     loss=tf.keras.losses.mse,
15     optimizer=tf.keras.optimizers.Adam(lr=0.01)
16 )
```

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Embedding

- ‘차원의 저주’ 해법
  - ○ 원핫 인코딩으로 만든 벡터는 고차원의 희소벡터
- 밀집 벡터의 형태로 변환
- Embedding 두가지 방법
  - ○ 랜덤한 벡터로 시작해서 신경망의 가중치를 학습하는 것과 같은 방식으로 벡터를 학습합니다.
  - ○ 미리 계산(훈련)된 임베딩을 통해 벡터화합니다.

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Embedding code

```
import tensorflow as tf

model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Embedding(input_dim=256, output_dim=128))
model.add(tf.keras.layers.GlobalAveragePooling1D())
model.add(tf.keras.layers.Dense(128))
model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.Dense(10))
model.add(tf.keras.layers.Activation('softmax'))

# 모델 컴파일
model.compile(
    loss=keras.losses.categorical_crossentropy,
    optimizer=keras.optimizers.Adam(lr=0.01),
    metrics=[keras.metrics.categorical_accuracy]
)
```

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