RNN 이론 및 실습

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DAVIAN Lab.

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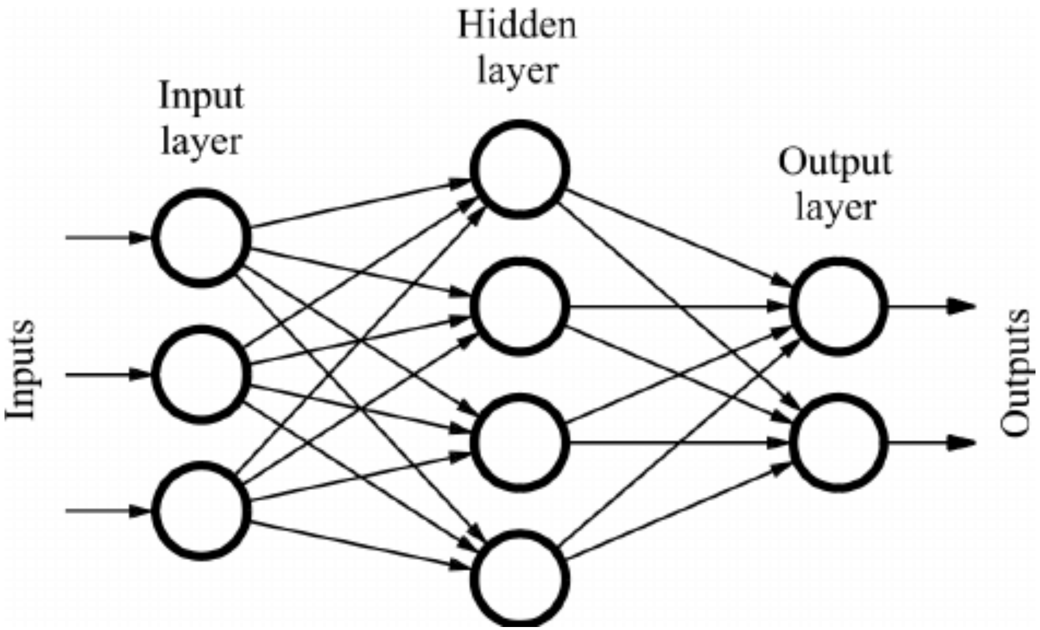
Feed Forward Neural Networks

FFN은 각 피쳐들의 조합을 통해 추론함.

하지만 FFN은 **시간적/순서적** 정보를
고려할 수 없음!



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Sequntial Information

"나는 공부하러 학교에 ____"

"나는 술마시러 술집에 ____"

가다

Sequntial Information

"나는 학교에 <u>간다</u>" → "나" -> "는" -> "학교" -> "에" -> <u>"간다"</u>

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Sequntial Information

"나는 학교에 간다" → "나" -> "는" -> "학교" -> "에" -> "간다"

State 1 - "나": 대상

Sequntial Information

"나는 학교에 <u>간다</u>" → "나" -> "는" -> "학교" -> "에" -> <u>"간다"</u>

State 1 - "나": 대상
State 2 - "나는": 대상의 상태

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Sequntial Information

"나는 학교에 <u>간다</u>" → "나" -> "는" -> "학교" -> "에" -> <u>"간다"</u>

State 1 - "나": 대상
State 2 - "나는": 대상의 상태
State 3 – "나는 학교": 대상의 상태와 객체

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Sequntial Information

"나는 학교에 <u>간다</u>" → "나" -> "는" -> "학교" -> "에" -> <u>"간다"</u>

State 1 - "나": 대상
State 2 - "나는": 대상의 상태
State 3 – "나는 학교": 대상의 상태와 객체
State 4 – "나는 학교에": 대상이 객체를 향해

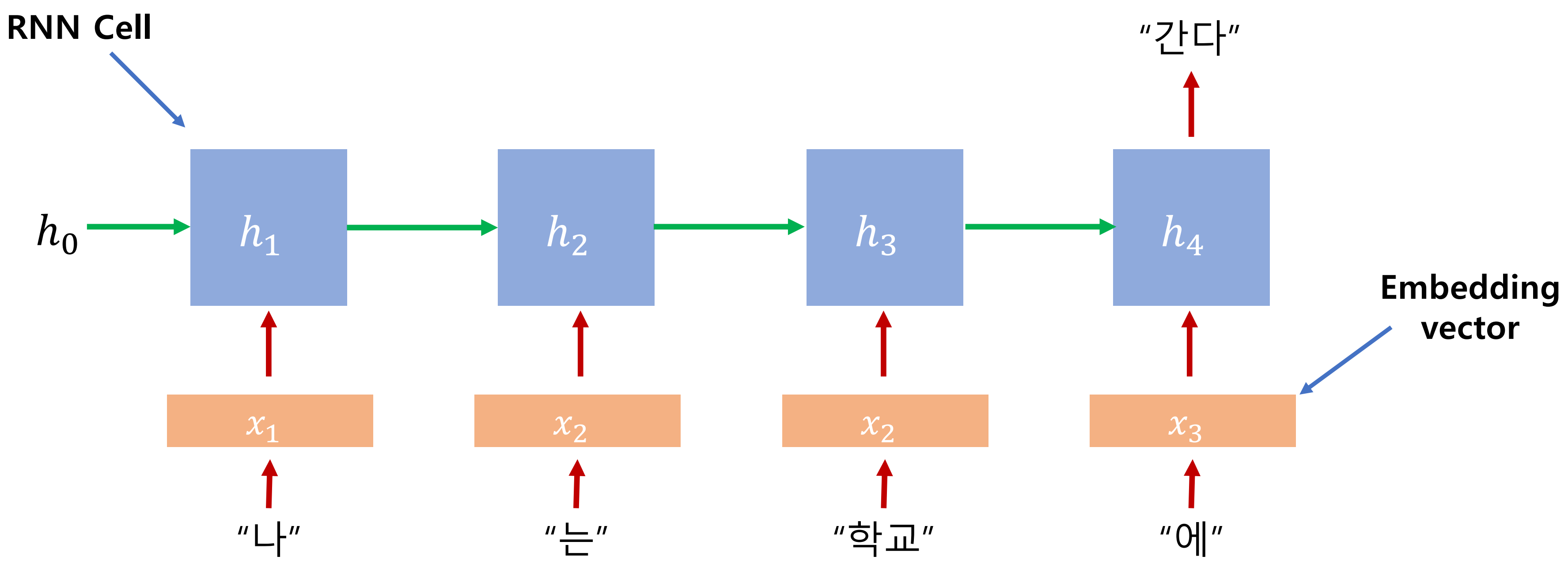
Sequntial Information

"나는 학교에 간다" → "나" -> "는" -> "학교" -> "에" -> "간다"

State 1 - "나": 대상
State 2 - "나는": 대상의 상태
State 3 – "나는 학교": 대상의 상태와 객체
State 4 – "나는 학교에": 대상이 객체를 향해

~을 장소를 향해 가는 것이므로 그 다음 상태는 간다는 동사가 어울림!

Recurrent Neural Networks (RNN)



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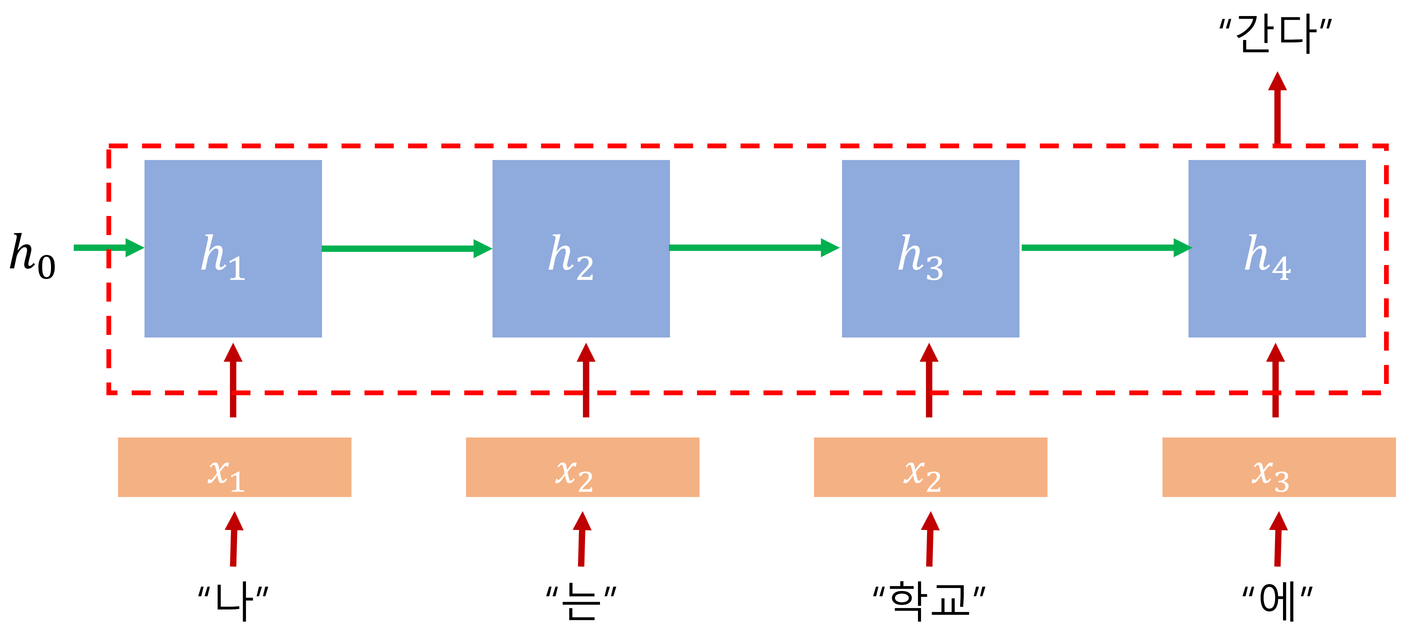
Recurrent Neural Networks (RNN)



1. 각 인풋이 들어올 때마다
   그 때의 상태(벡터)를 계산

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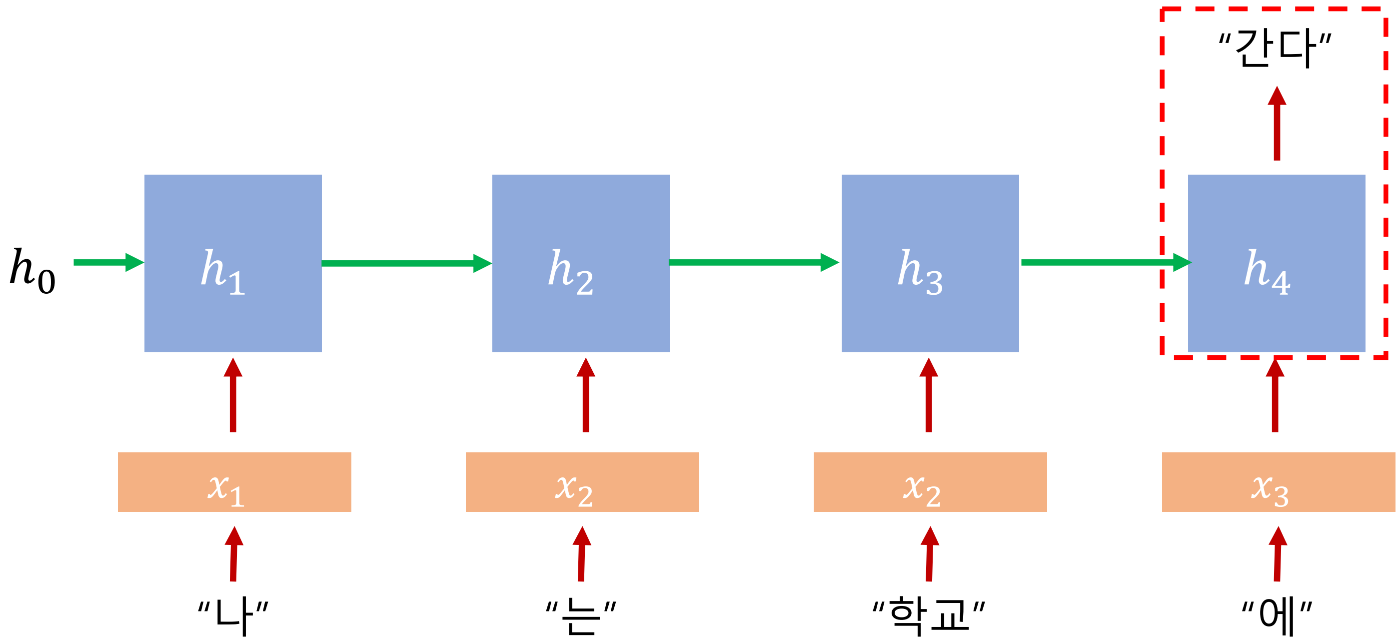
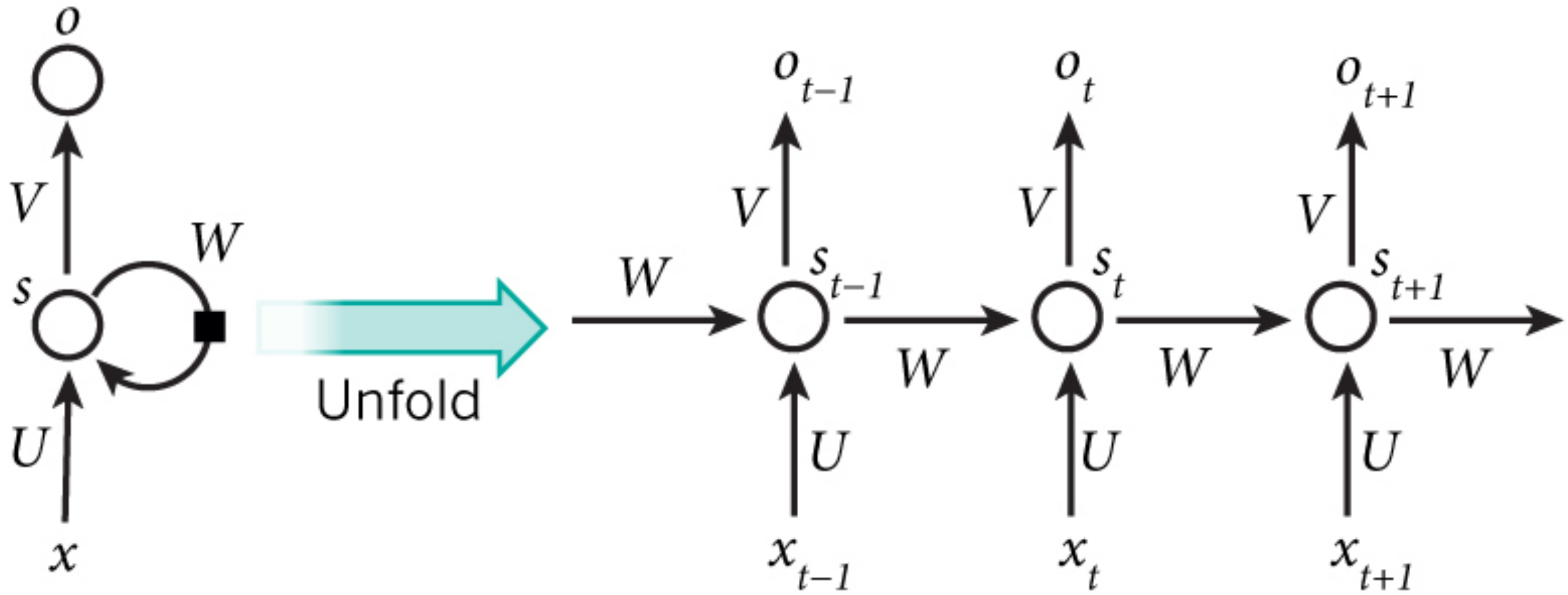
Recurrent Neural Networks (RNN)

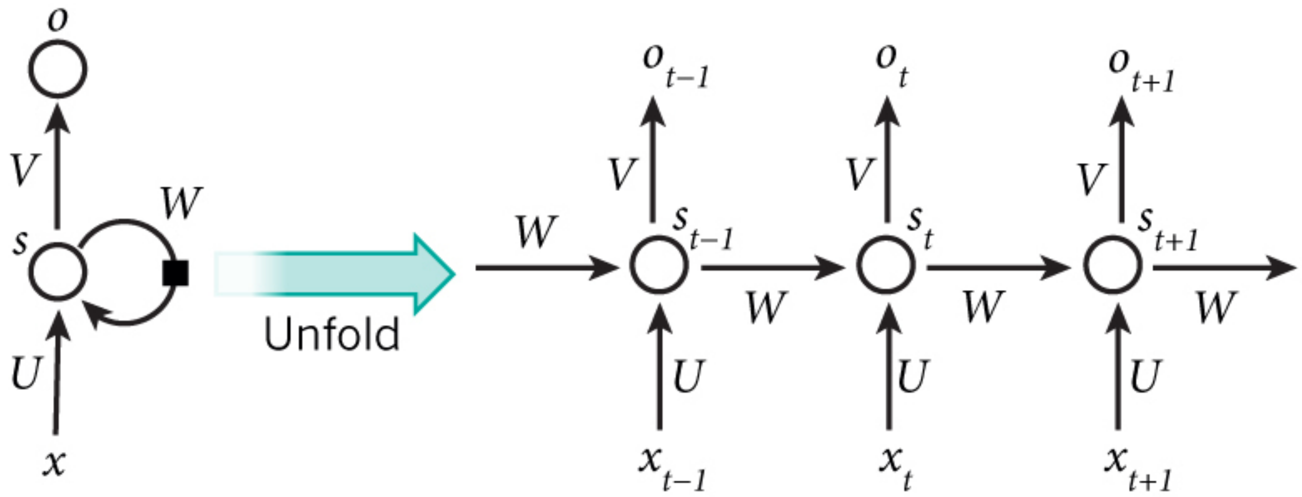


1. 각 인풋이 들어올 때마다 그 때의 상태(벡터)를 계산
2. 예측할 순간의 상태를 이용하여 예측

Recurrent Neural Networks (RNN)



Recurrent Neural Networks (RNN)



$$h_t = \tanh(Ux_{t-1} + Ws_{t-1})$$
$$o_t = Vs_t$$

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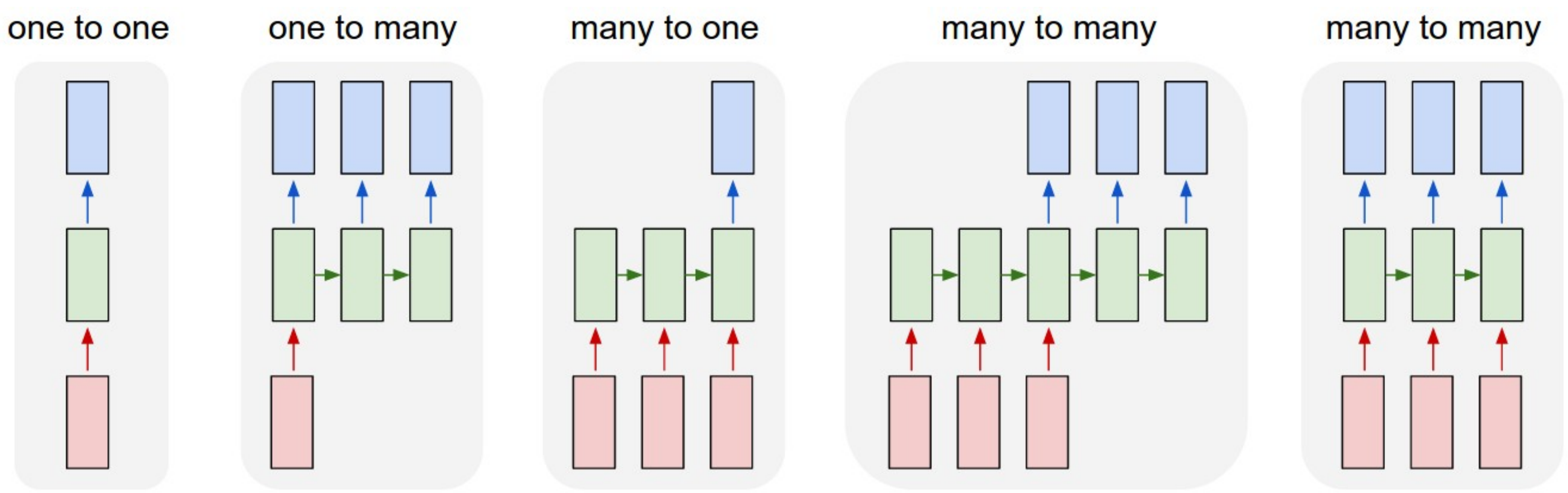
Recurrent Neural Networks (RNN)



one-to-one: FFN과 같음!
one-to-many: Image Captioning, Generation 등

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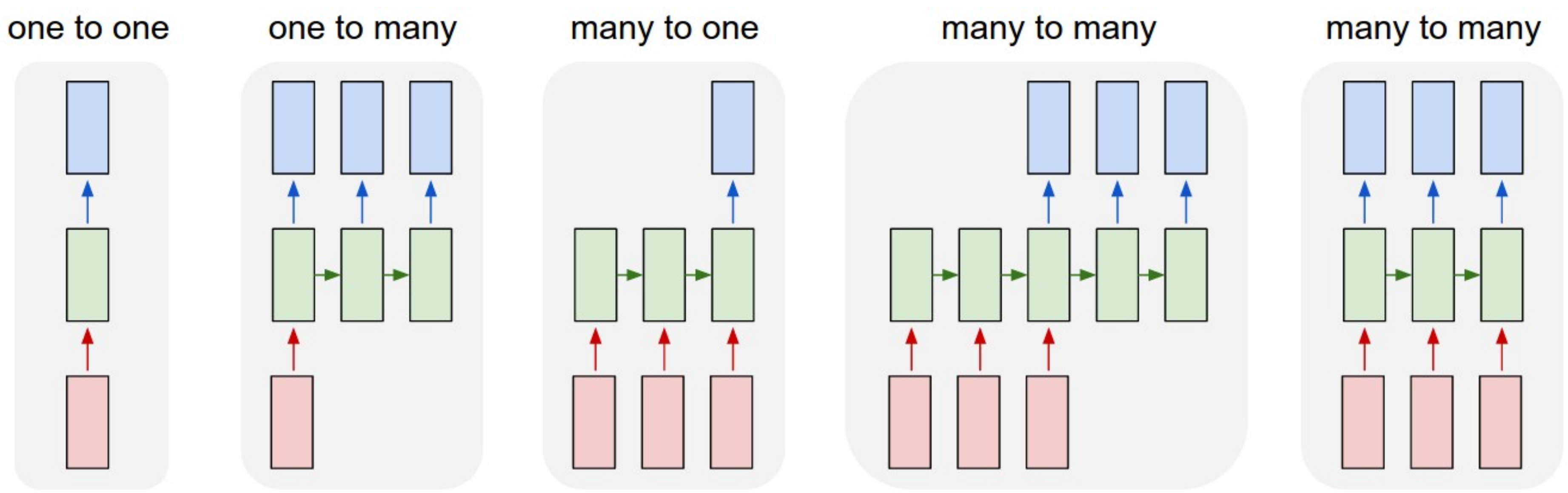
Recurrent Neural Networks (RNN)



many-to-many: Machine translation, QA 등
many-to-many: Video recognition 등

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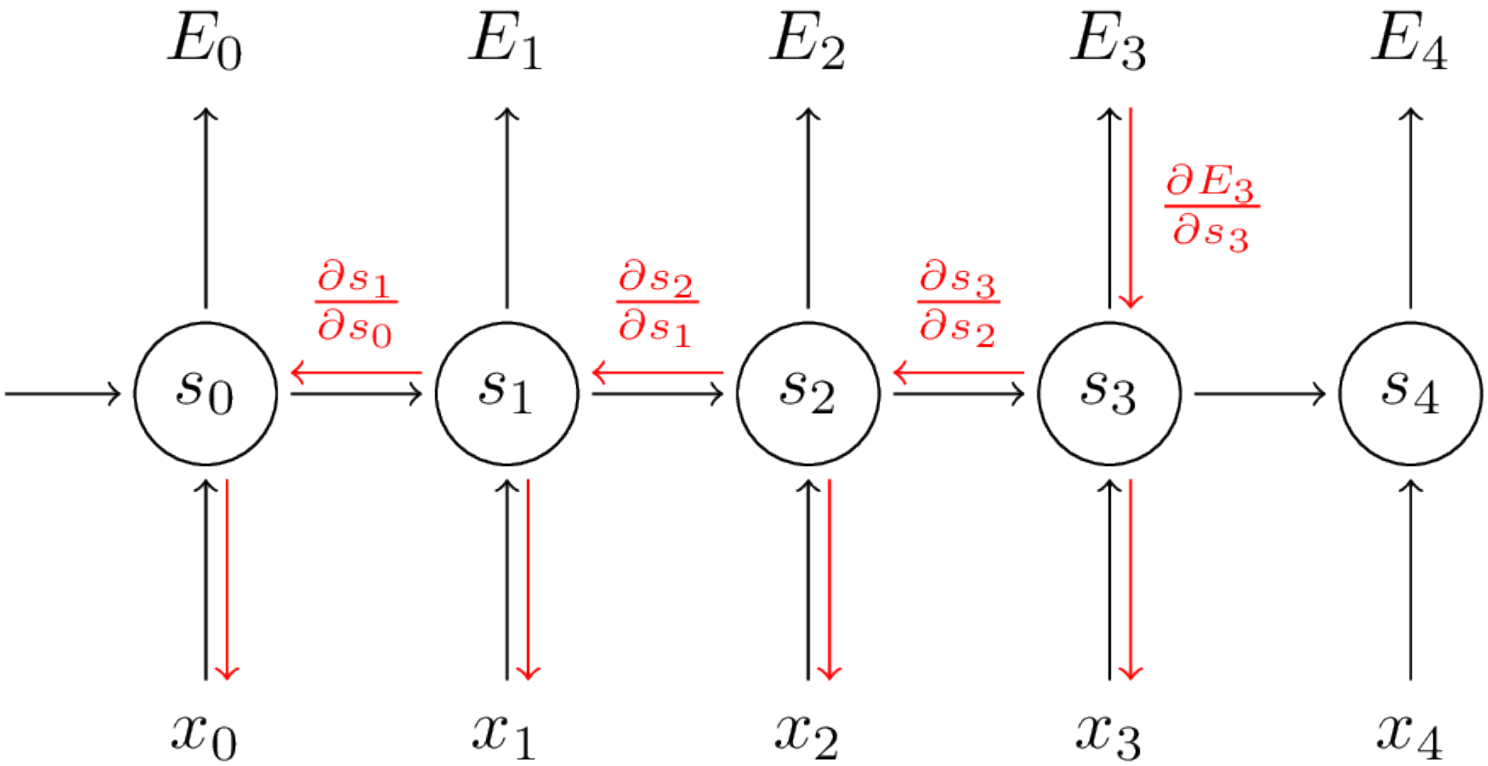
RNNs – Backpropagation through Time (BPTT)



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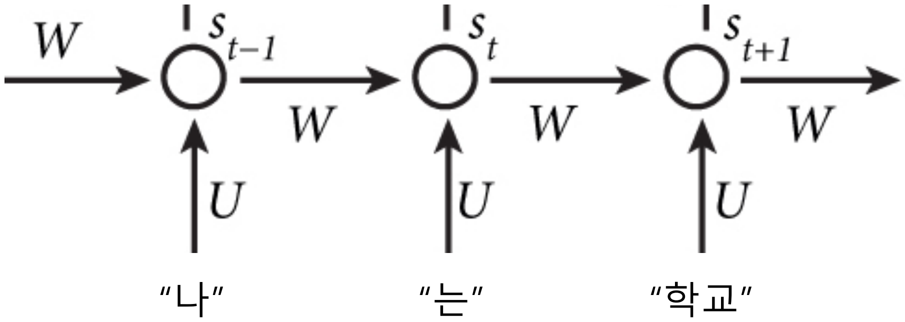
Weakness of RNNs – Information loss



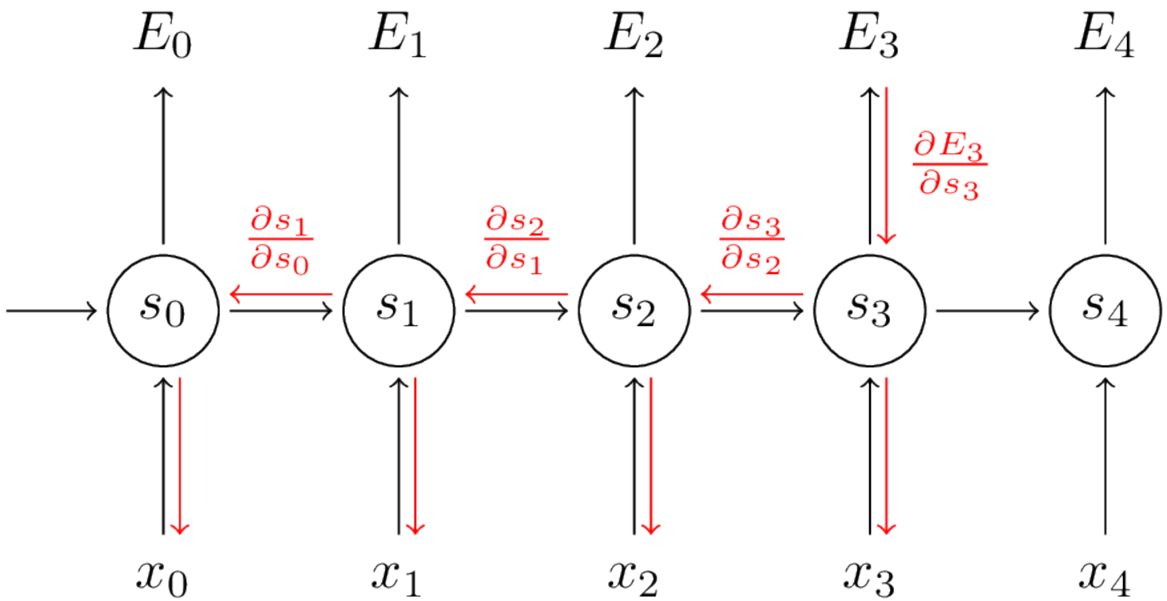
$$s_3 = \tanh(Ux_1 + Ws_0)$$

$$\begin{aligned} s_2 &= \tanh(Ux_2 + Ws_1) \\ &= \tanh(Ux_2 + W tanh(Ux_1 + Ws_0)) \end{aligned}$$

$$\begin{aligned} s_3 &= \tanh(Ux_3 + Ws_2) \\ &= \tanh(\mathrm{U}x_3 + W\ \tanh(Ux_2 + Ws_1)) \\ &= \tanh(\mathrm{U}x_3 + W\ \tanh(Ux_2 + W tanh(Ux_1 + Ws_0))) \end{aligned}$$

초기 상태 벡터는 거듭된 메트릭스 곱으로 0에 수렴함!

Weakness of RNNs – Gradient Vanishing/Exploding



거듭된 메트릭스 곱으로
gradient가 0으로 수렴하거나 ∞로 발산

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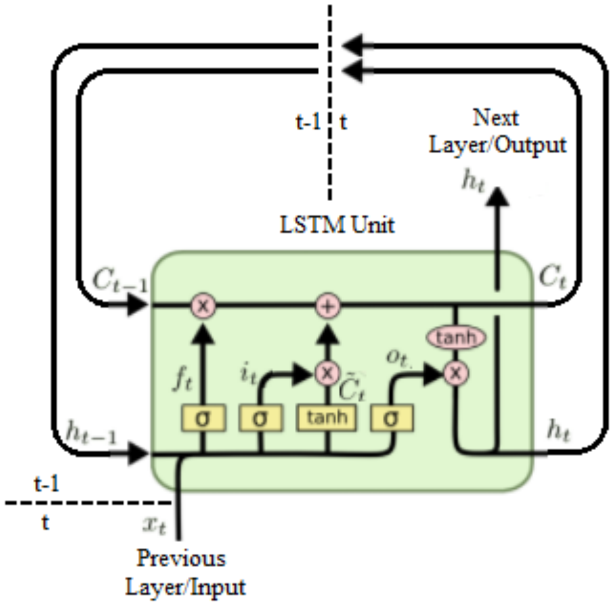
Long-Short Term Memory (LSTM)

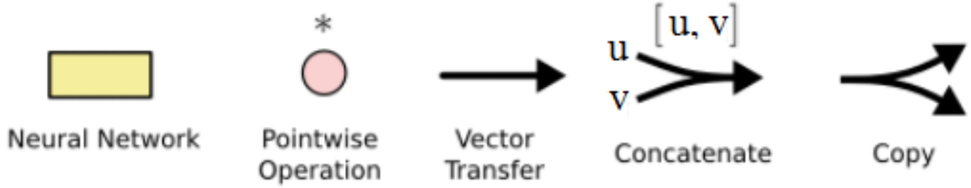


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$
$$o_t = \sigma\left(W_o \ [h_{t-1}, x_t] \ + \ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

Forget Gate
이전 상태를 얼마나 잊을지

Input Gate
현재 입력 정보를 얼마나 받을지

Output Gate
새로 계산된 정보를 얼마나 상태정보로 출력할지



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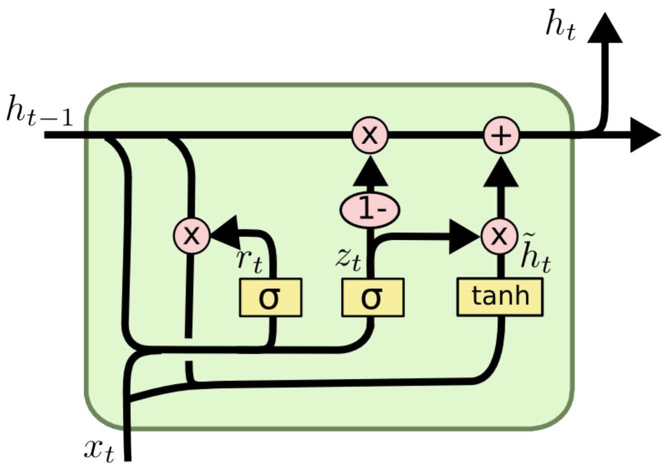
Gated Recurrent Unit (GRU)



Update Gate
새로 계산된 정보와 이전 정보를 어느 정도로 조합할지

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

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

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

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

Forget Gate
이전 상태를 얼마나 잊을지

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In PyTorch ...

CLASS `torch.nn.GRU(*args, **kwargs)`

Applies a multi-layer gated recurrent unit (GRU) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$
\begin{aligned}
r_t &= \sigma(W_{ir} x_t + b_{ir} + W_{hr} h_{(t-1)} + b_{hr}) \\
z_t &= \sigma(W_{iz} x_t + b_{iz} + W_{hz} h_{(t-1)} + b_{hz}) \\
n_t &= \tanh(W_{in} x_t + b_{in} + r_t * (W_{hn} h_{(t-1)} + b_{hn})) \\
h_t &= (1 - z_t) * n_t + z_t * h_{(t-1)}
\end{aligned}
$$

- **input_size** – The number of expected features in the input *x*
- **hidden_size** – The number of features in the hidden state *h*
- **num_layers** – Number of recurrent layers. E.g., setting `num_layers=2` would mean stacking two GRUs together to form a *stacked GRU*, with the second GRU taking in outputs of the first GRU and computing the final results. Default: 1
- **bias** – If `False`, then the layer does not use bias weights *b_ih* and *b_hh*. Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (batch, seq, feature). Default: `False`
- **dropout** – If non-zero, introduces a *Dropout* layer on the outputs of each GRU layer except the last layer, with dropout probability equal to `dropout`. Default: 0
- **bidirectional** – If `True`, becomes a bidirectional GRU. Default: `False`

Inputs: input, h_0

- **input** of shape (*seq_len, batch, input_size*): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` for details.
- **h_0** of shape (*num_layers * num_directions, batch, hidden_size*): tensor containing the initial hidden state for each element in the batch. Defaults to zero if not provided. If the RNN is bidirectional, num_directions should be 2, else it should be 1.

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In PyTorch …

CLASS `torch.nn.LSTM(*args, **kwargs)`

Applies a multi-layer long short-term memory (LSTM) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$
\begin{aligned}
i_t &= \sigma(W_{ii} x_t + b_{ii} + W_{hi} h_{(t-1)} + b_{hi}) \\
f_t &= \sigma(W_{if} x_t + b_{if} + W_{hf} h_{(t-1)} + b_{hf}) \\
g_t &= \tanh(W_{ig} x_t + b_{ig} + W_{hg} h_{(t-1)} + b_{hg}) \\
o_t &= \sigma(W_{io} x_t + b_{io} + W_{ho} h_{(t-1)} + b_{ho}) \\
c_t &= f_t * c_{(t-1)} + i_t * g_t \\
h_t &= o_t * \tanh(c_t)
\end{aligned}
$$

Inputs: input, (h_0, c_0)

- **input** of shape (*seq_len, batch, input_size*): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` or `torch.nn.utils.rnn.pack_sequence()` for details.
- **h_0** of shape (*num_layers * num_directions, batch, hidden_size*): tensor containing the initial hidden state for each element in the batch. If the LSTM is bidirectional, num_directions should be 2, else it should be 1.
- **c_0** of shape (*num_layers * num_directions, batch, hidden_size*): tensor containing the initial cell state for each element in the batch.

  If (*h_0, c_0*) is not provided, both **h_0** and **c_0** default to zero.

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In PyTorch …

CLASS `torch.nn.GRU(*args, **kwargs)`

Applies a multi-layer gated recurrent unit (GRU) RNN to an input sequence.

For each element in the input sequence, each layer computes the following function:

$$
\begin{aligned}
r_t &= \sigma(W_{ir} x_t + b_{ir} + W_{hr} h_{(t-1)} + b_{hr}) \\
z_t &= \sigma(W_{iz} x_t + b_{iz} + W_{hz} h_{(t-1)} + b_{hz}) \\
n_t &= \tanh(W_{in} x_t + b_{in} + r_t * (W_{hn} h_{(t-1)} + b_{hn})) \\
h_t &= (1 - z_t) * n_t + z_t * h_{(t-1)}
\end{aligned}
$$

Inputs: input, h_0

- **input** of shape (*seq_len, batch, input_size*): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` for details.
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감사합니다

Any Questions?

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