Lab3

CNN & RNN

Seoul National University

Human Interface Laboratory

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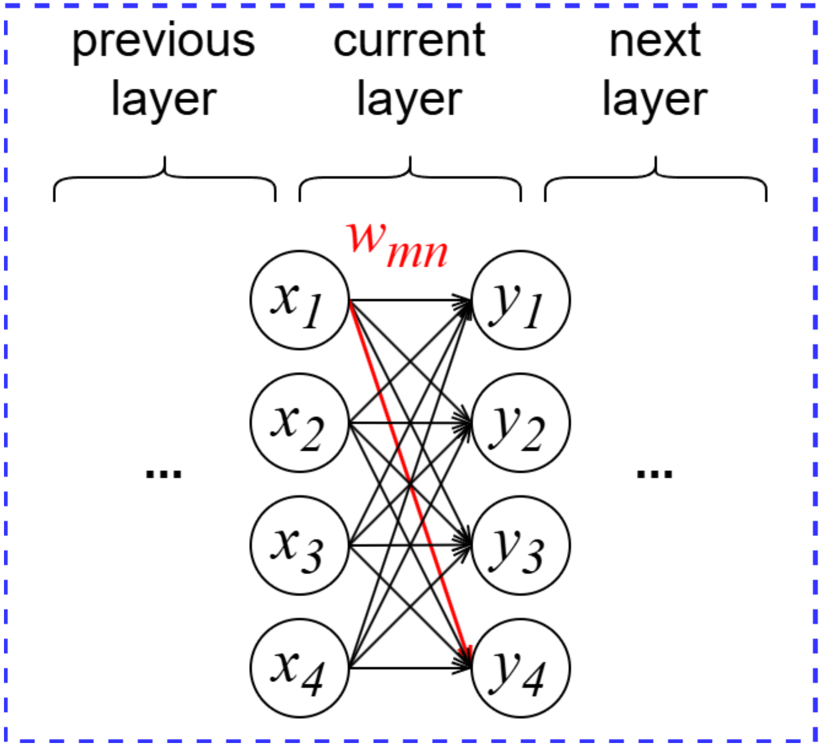
Fully Connected Layer 복습

Deep Neural Network



- Fully Connected Layer

$$y_m = \sum_n w_{mn} \cdot x_n + b_m$$

$$Y = W \cdot X + B$$

➢ 학습할 parameter $\theta = [W, B]$

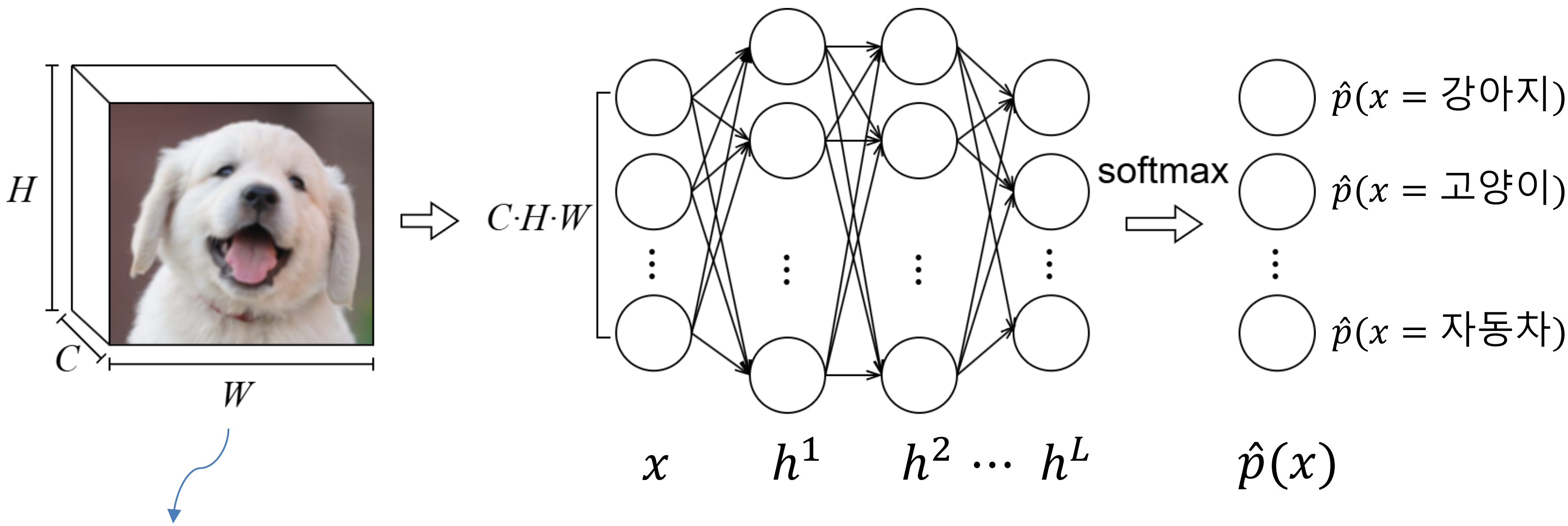
Image Classification

$N.N.$ 의 출력 $\hat{y} = f_\theta($  $) = \begin{bmatrix} \hat{p}(x = \text{강아지}) \\ \hat{p}(x = \text{고양이}) \\ \vdots \\ \hat{p}(x = \text{자동차}) \end{bmatrix}$

$$\text{원하는 출력 } y = \begin{bmatrix} p(x = \text{강아지}) \\ p(x = \text{고양이}) \\ \vdots \\ p(x = \text{자동차}) \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

- $\hat{y} \approx y$ 되도록 (Loss 작아지도록) Neural Network의 parameter θ 학습

Image Classification Using FC Layers



C: Channels (RGB 3 channels)
H: Height
W: Width

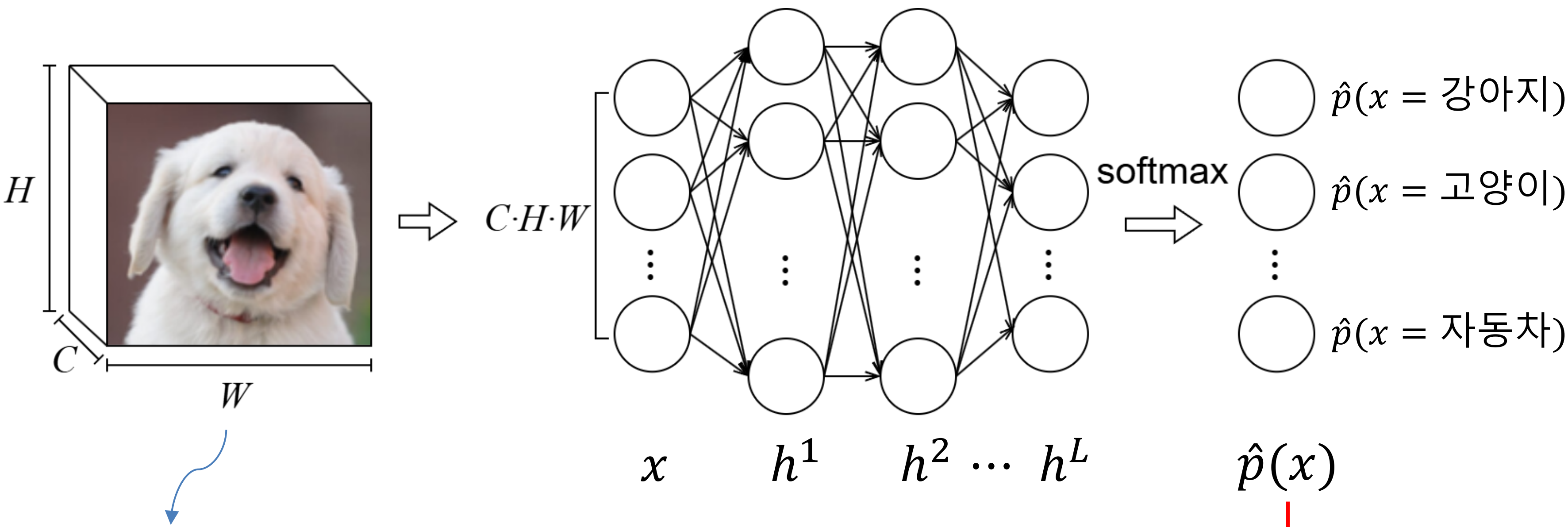
Softmax

- 모델의 출력이 $\hat{y}_n = \hat{p}(x = n)$ 확률을 모델링 하기 위한 조건
  1. $\sum_n \hat{y}_n = 1$
  2. $\hat{y}_n \geq 0$
- 두 조건 모두 만족하는 activation function이 Softmax

N.N. Output　　Softmax　　Probability

$$h = \begin{bmatrix} 1.3 \\ 2.1 \\ -1.2 \\ 0.7 \end{bmatrix} \Rightarrow \boxed{\hat{y}_n = \frac{e^{h_n}}{\sum_m e^{h_m}}} \Rightarrow \hat{y} = \begin{bmatrix} 0.26 \\ 0.58 \\ 0.02 \\ 0.14 \end{bmatrix}$$

Image Classification Using FC Layers



C: Channels (RGB 3 channels)
H: Height
W: Width

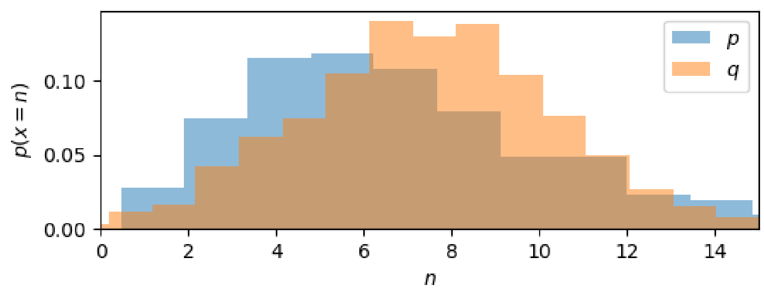
$$Loss = \mathcal{L}(p, \hat{p})$$

정답 $p(x)$

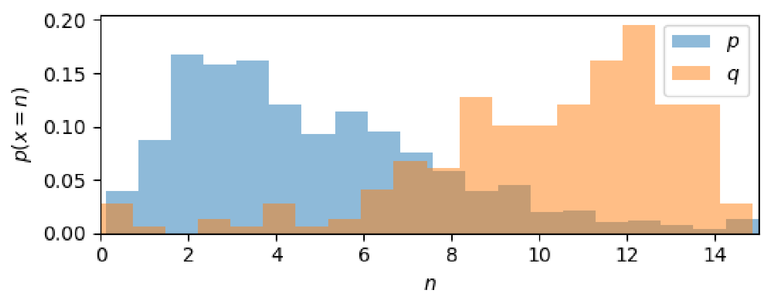
Cross Entropy Loss

$$\mathcal{L}(p,q) = -\frac{1}{N}\sum_{n=1}^{N} p(x=n)\cdot \log q(x=n)$$

- 두 확률분포 간의 차이를 측정 (정보이론)
- 작을수록 두 확률분포가 비슷함을 의미
- 클수록 두 확률분포가 많이 다름을 의미

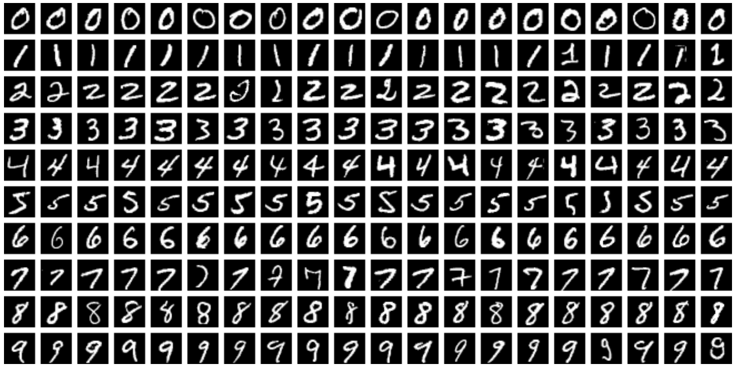


$\Rightarrow$ $\mathcal{L}(p,q) = 2.61$



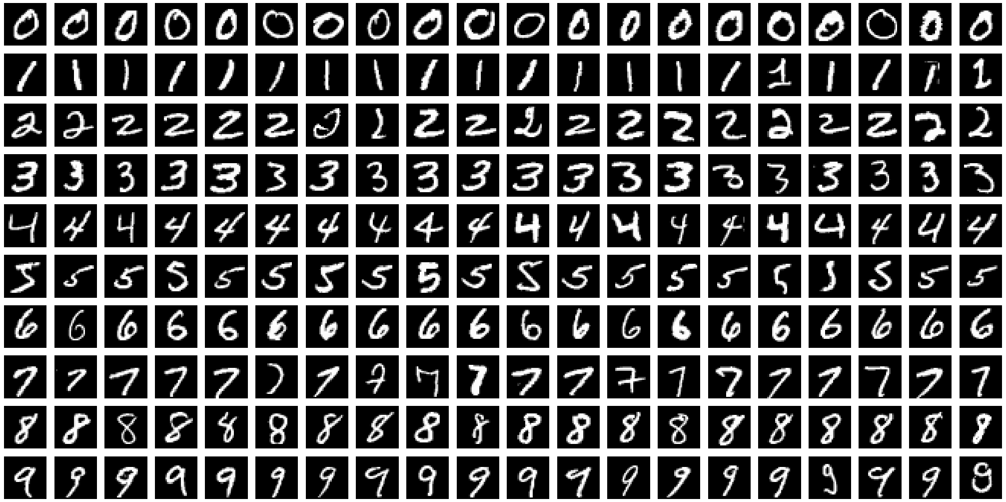
$\Rightarrow$ $\mathcal{L}(p,q) = 3.82$

Mini-batch Training



- 오른쪽과 같은 손글씨 인식 Task에서
- 전체 학습 데이터 개수: 20000개 라면
- 전체 데이터(20000개)를 한 번 학습하는 것을 one epoch.
- 이미지 하나하나마다 $\mathcal{L}$ 를 구해서 θ를 학습하는 것이 아니라 (20000 iteration / 1 epoch)
- 200개의 이미지에 대해 $\mathcal{L}$를 구해서 평균값으로 θ를 학습 (100 iteration / 1 epoch)

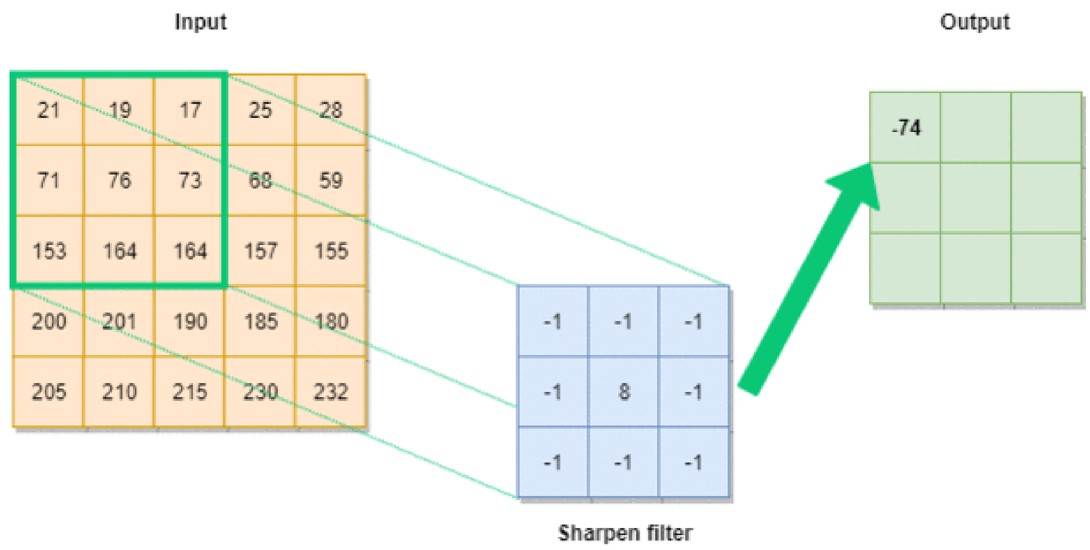
실습 (Image Classification Using FC Layers)



- Lab3-1.Image Classification Using FC Layers

➢ Image에서 Fully Connected Layer가 최선일까?

Convolutional Layer

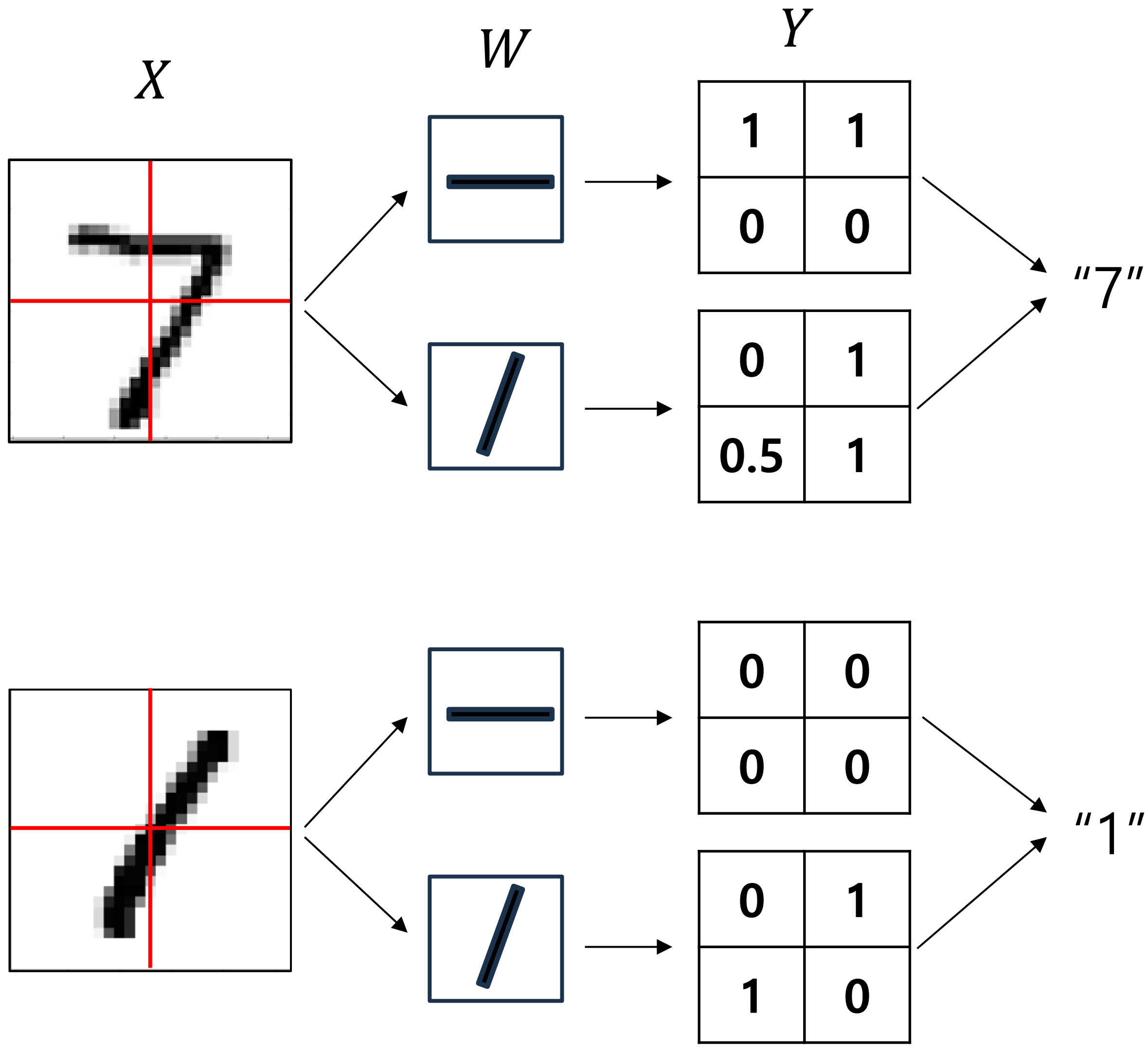


$$y[m,n] = \sum_{s,t} w[s,t] \cdot x[m+s, n+t] + b$$

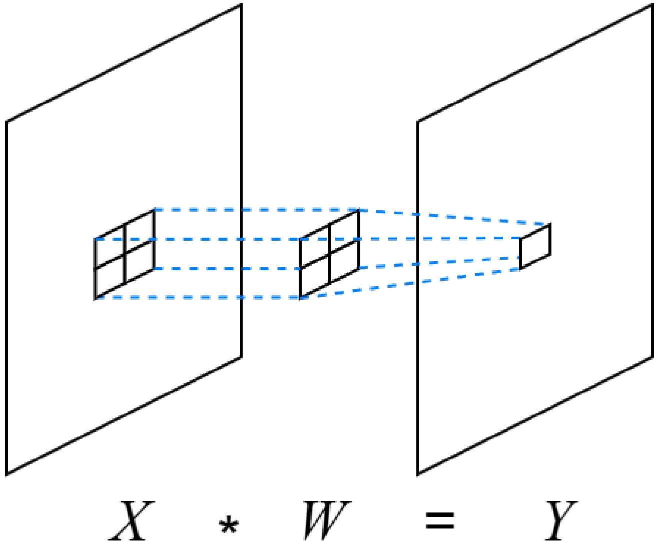
$$Y = W * X + b$$

- 학습할 parameter $\theta = [W, b]$

Motivation



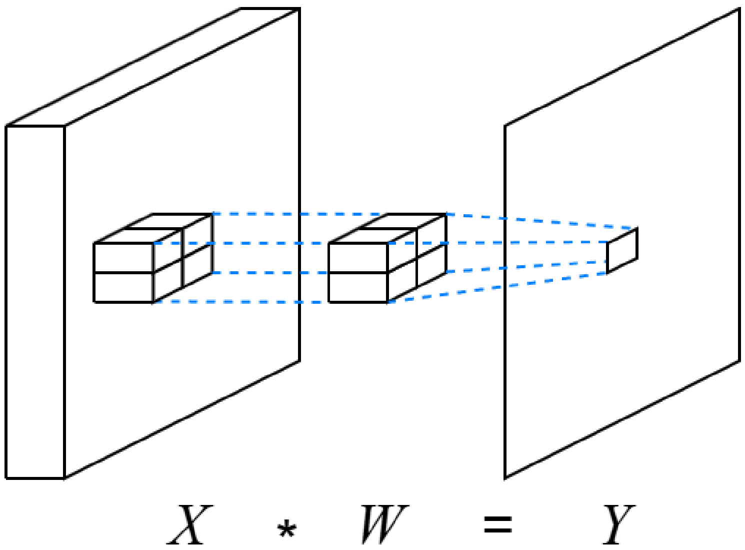
Convolutional Layer



X의 shape: $H_i \times W_i$
W의 shape: $K_h \times K_w$
B의 shape: 1
Y의 shape: $H_o \times W_o$

$$y[m,n] = \sum_{s,t} w[s,t] \cdot x[m+s, n+t] + b$$

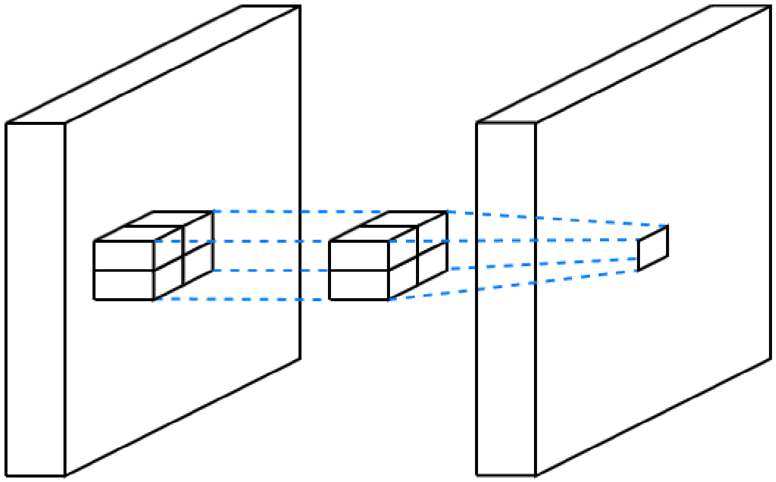
Convolutional Layer ($C_{in} > 1$)



X의 shape: $C_i \times H_i \times W_i$
W의 shape: $C_i \times K_h \times K_w$
B의 shape: 1
Y의 shape: $H_o \times W_o$

$$y[m,n] = \sum_{c_i,s,t} w[c_i,s,t] \cdot x[c_i,m+s,n+t] + b$$

Convolutional Layer ($C_{out} > 1$)

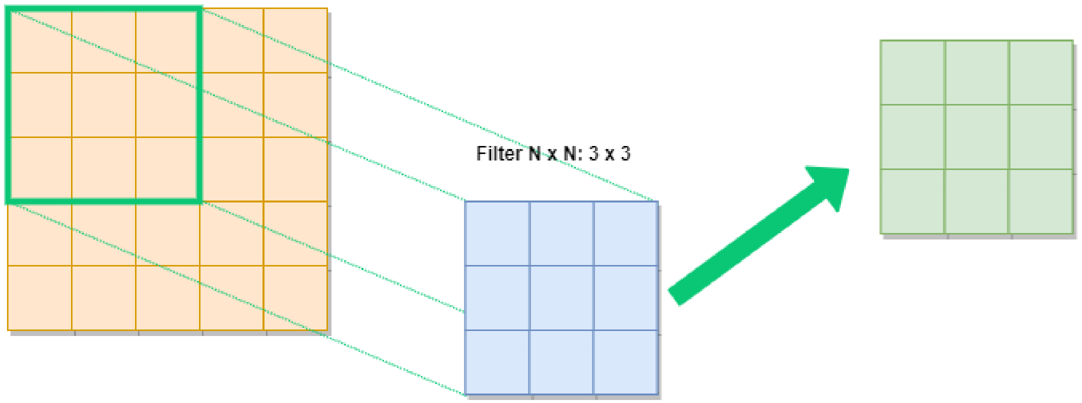


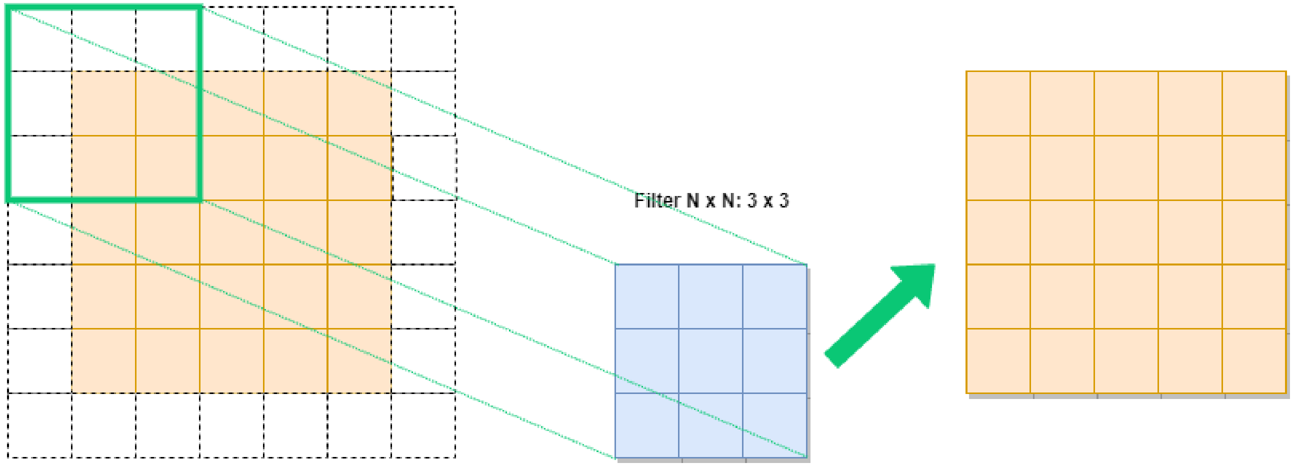
$X * W[c_o] = Y[c_o]$

X의 shape: $C_i \times H_i \times W_i$
W의 shape: $C_o \times C_i \times K_h \times K_w$
B의 shape: C_o
Y의 shape: $C_o \times H_o \times W_o$

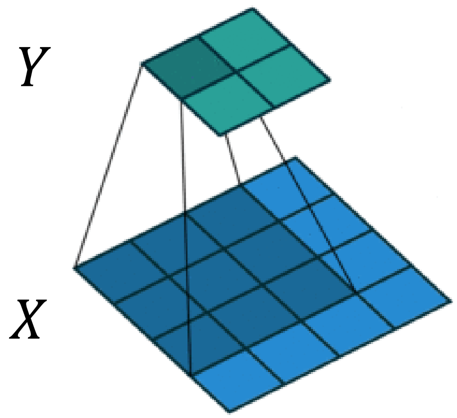
$$y[c_o, m, n] = \sum_{c_i, s, t} w[c_o, c_i, s, t] \cdot x[c_i, m+s, n+t] + b[c_o]$$

Padding

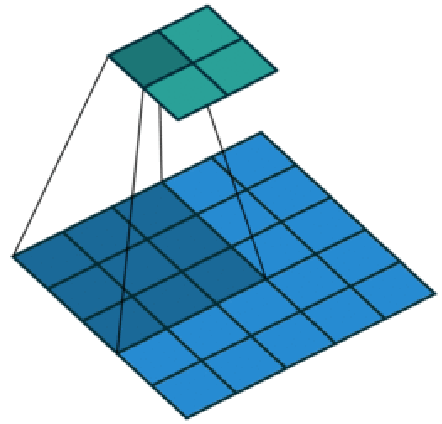




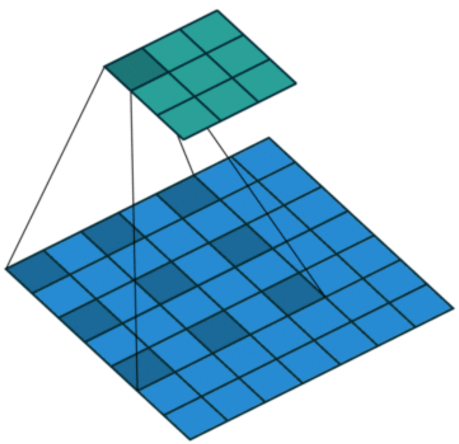
Stride, Dilation, Transposed



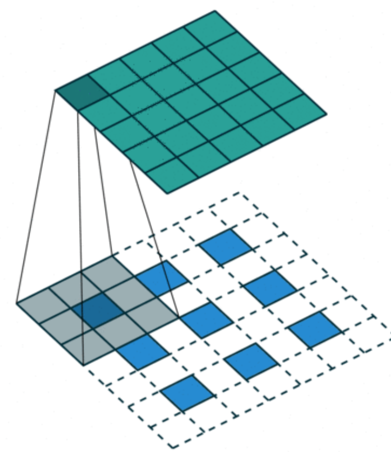
Default Convolution



Convolution (Stride=2)



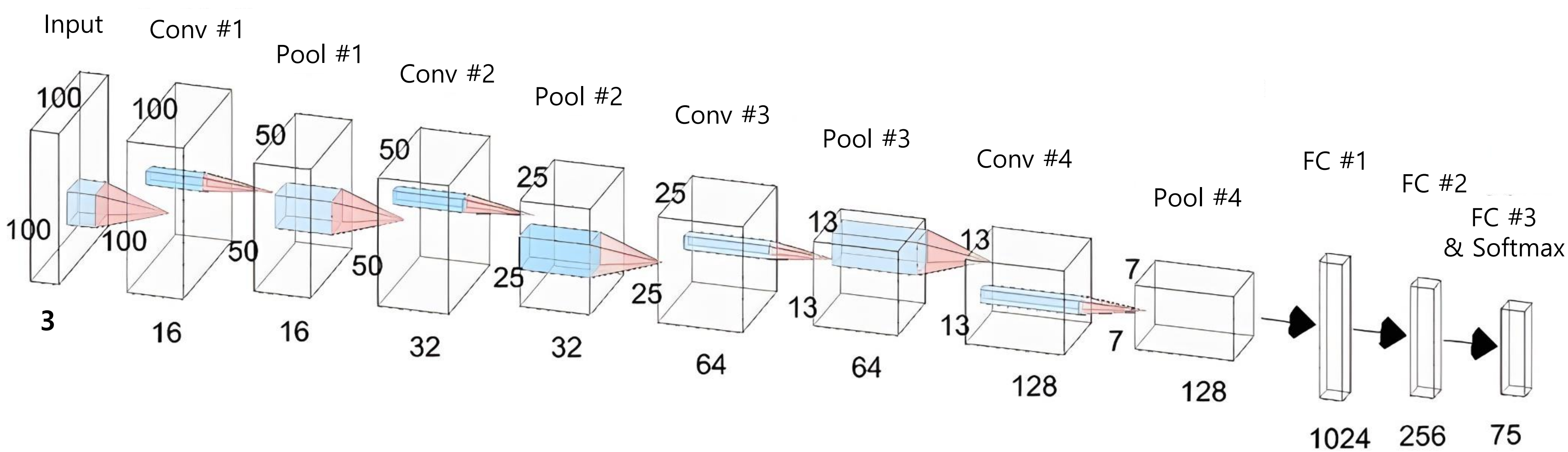
Convolution (Dilation=2)



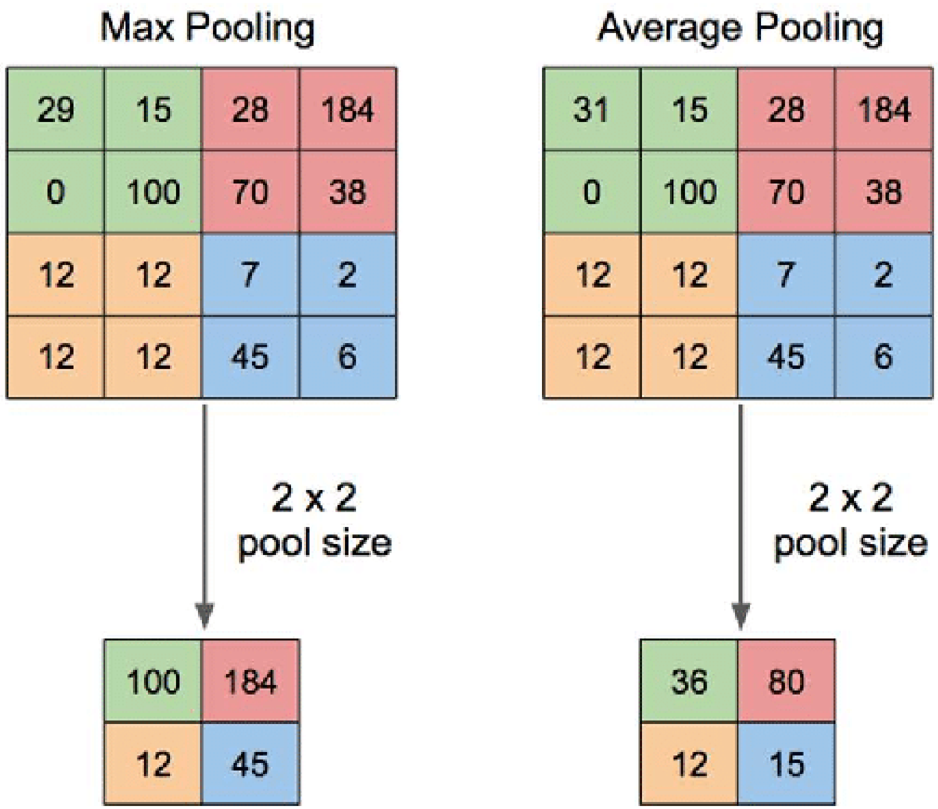
Transposed Convolution (Stride=2)

Convolutional Neural Network (CNN)

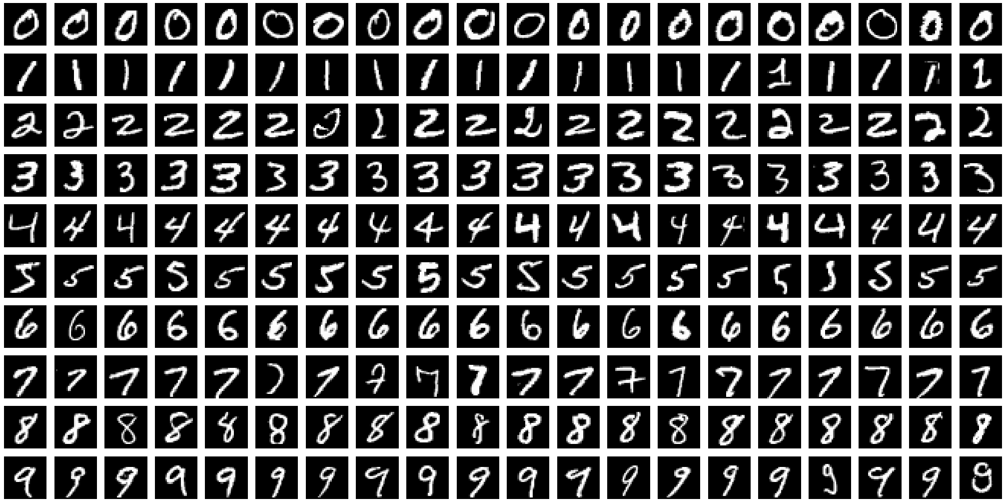
- Convolutional Layers로 구성된 Neural Network



Pooling


Max Pooling
29 15 28 184
0 100 70 38
12 12 7 2
12 12 45 6
2 x 2
pool size
100 184
12 45
Average Pooling
31 15 28 184
0 100 70 38
12 12 7 2
12 12 45 6
2 x 2
pool size
36 80
12 15

실습 (Image Classification Using CNN)



- Lab3-2.Image Classification Using CNN

Sequence Data

Text Classification

$p(x = \text{긍정}) = 0.9$

$p(x = \text{부정}) = 0.1$

$\uparrow$

$\boxed{f_\theta}$

$\uparrow$

"꿀잼. 넘 재밌다."

Text-to-Speech

$\uparrow$

$\boxed{f_\theta}$

$\uparrow$

" 안녕하세요?"

ChatGPT

"Answer"

$\uparrow$

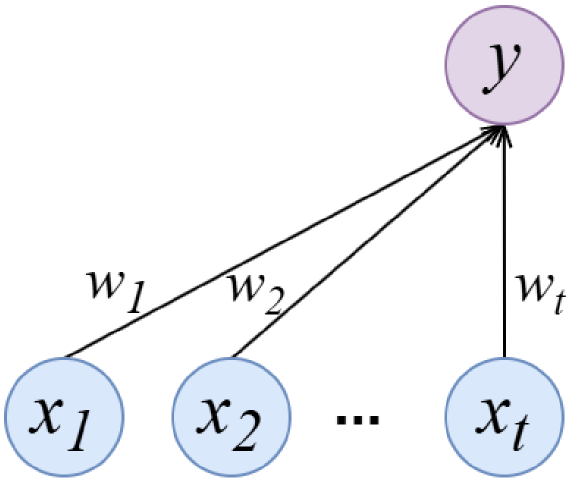
$\boxed{f_\theta}$

$\uparrow$

"Question"

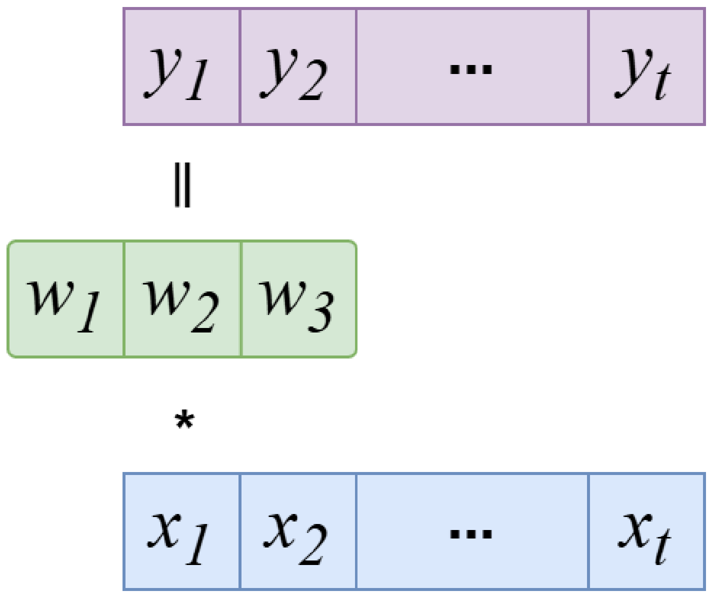
- $y = f_\theta(x_1, x_2, \cdots)$
- $y_1, y_2, \ldots = f_\theta(x)$
- $y_1, y_2, \ldots = f_\theta(x_1, x_2, \cdots)$

FC for Sequence Data?



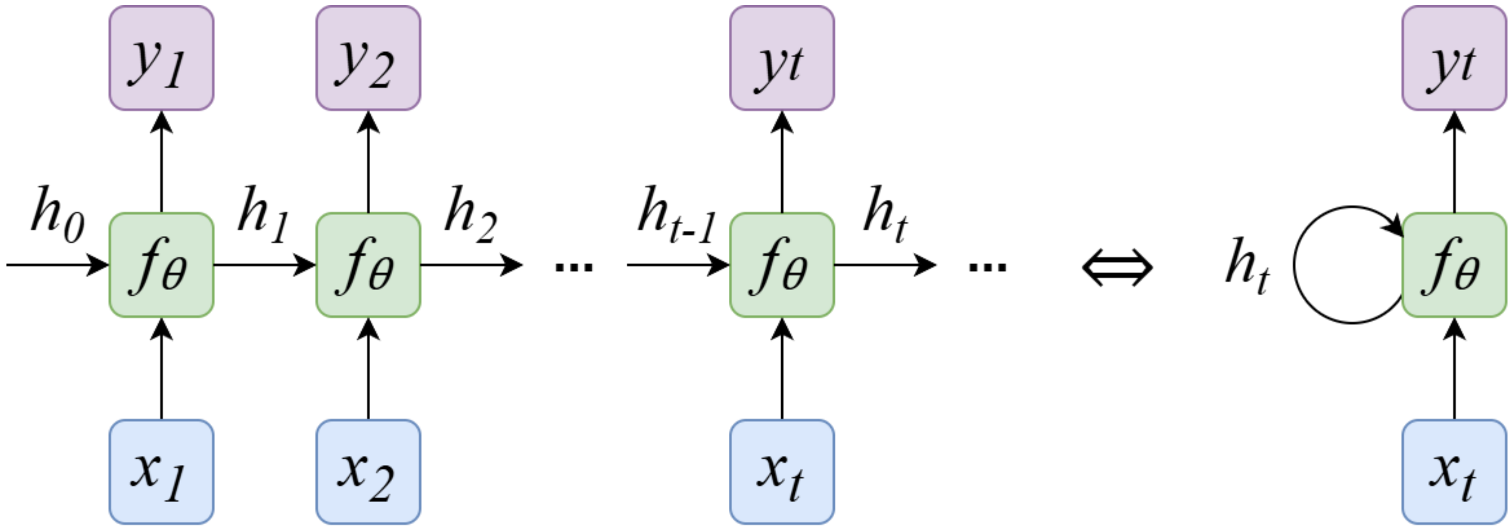
- 입력 길이가 달라지면?

CNN for Sequence Data?



- y_t 생성할 때 x_1은 못보는데?

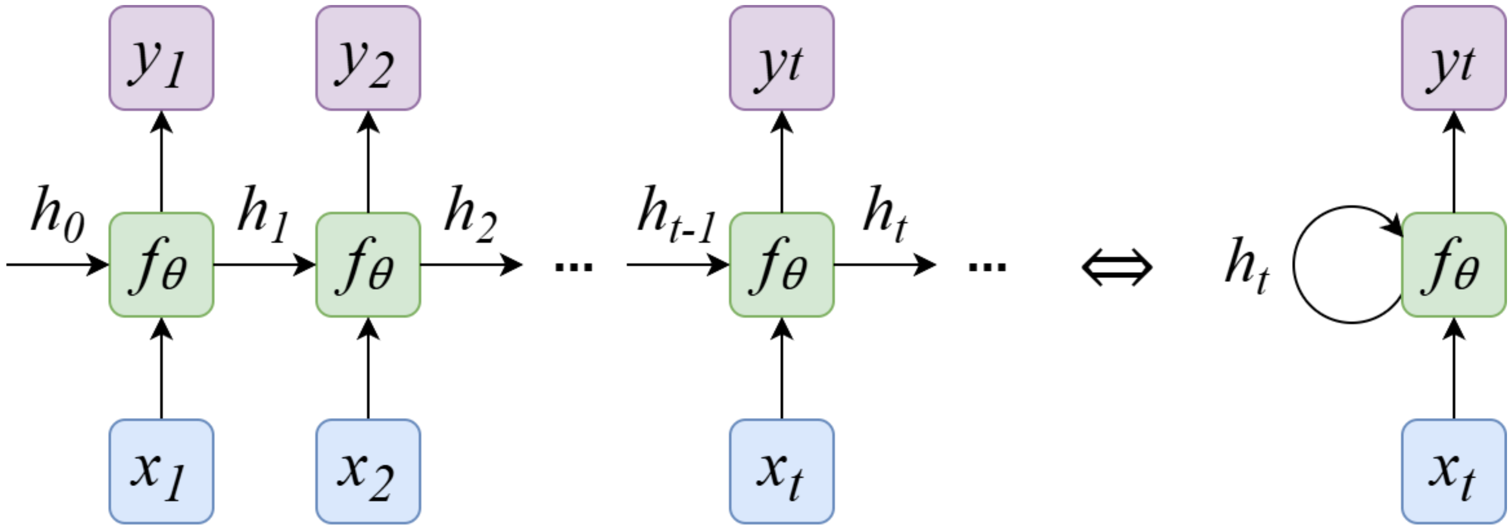
Recurrent Neural Network (RNN)



$$h_t = f_\theta(x_t, h_{t-1})$$

- 입력 길이가 일정하지 않아도 OK
- y_t 생성할 때 $x_1 \sim x_t$ 정보 모두 담고 있음

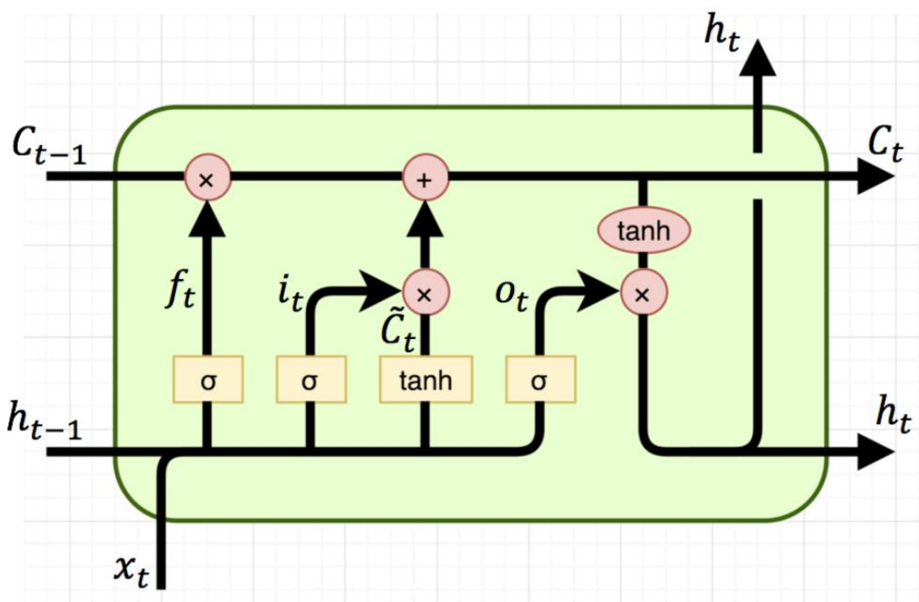
Plain RNN



$$h_t = \sigma(w_x x_t + w_h h_{t-1} + b)$$

- 학습할 parameter $\theta = [w_x, w_h, b]$
- 성능이 별로 좋지 못함

LSTM



학습할 parameter θ

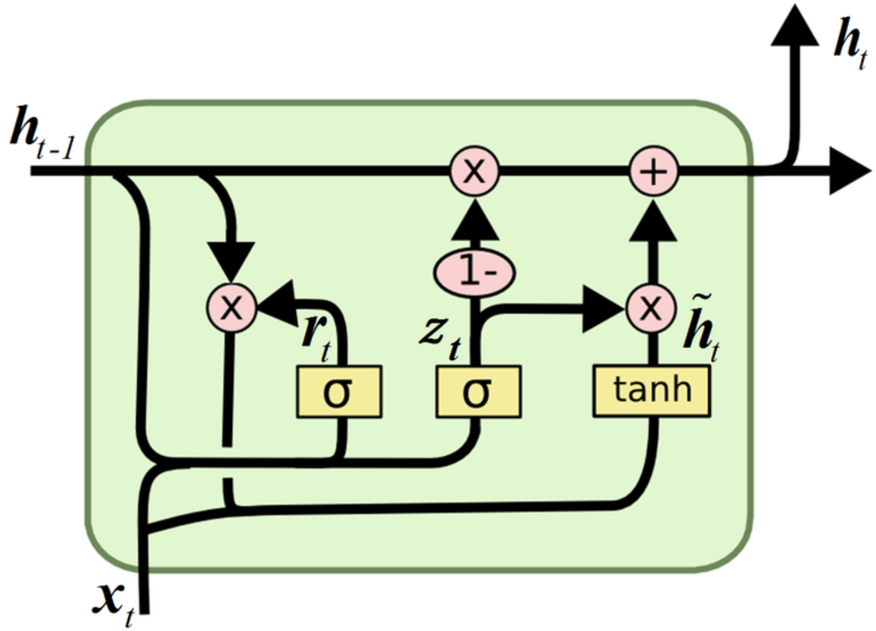
$$f_t = \sigma(w_{xf}x_t + w_{hf}h_{t-1} + b_f)$$
$$i_t = \sigma(w_{xi}x_t + w_{hi}h_{t-1} + b_i)$$
$$\tilde{c}_t = \tanh(w_{xc}x_t + w_{hc}h_{t-1} + b_c)$$
$$o_t = \sigma(w_{xo}x_t + w_{ho}h_{t-1} + b_o)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$h_t = o_t \odot \tanh(c_t)$$

σ : sigmoid

tanh: hyperbolic tangent

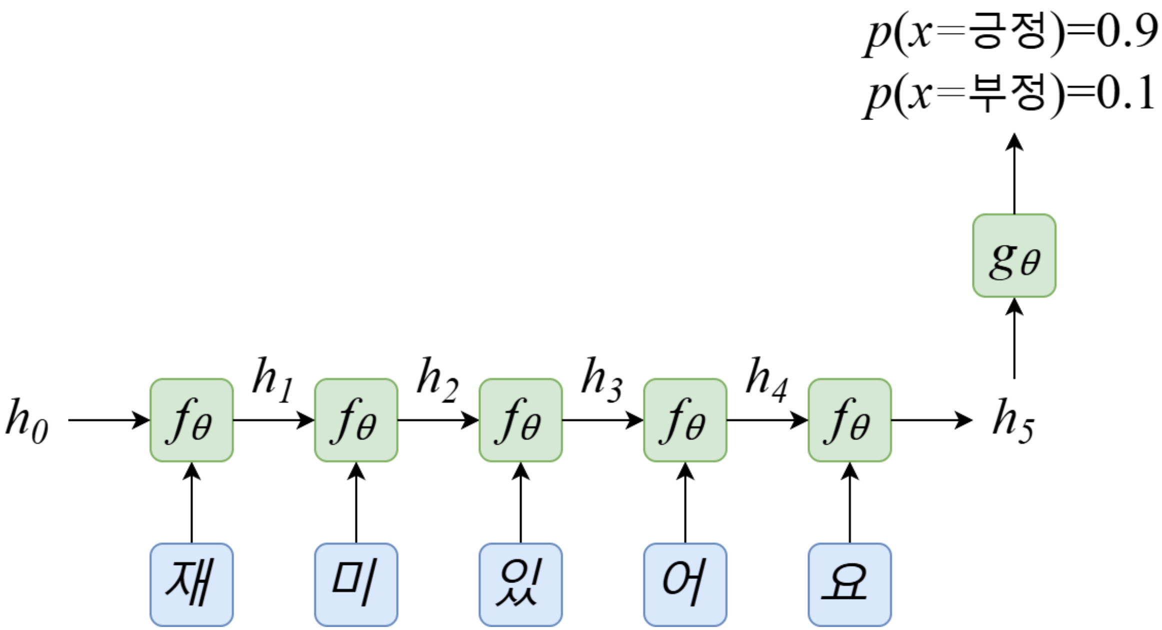
$\odot$: element-wise multiplication

GRU

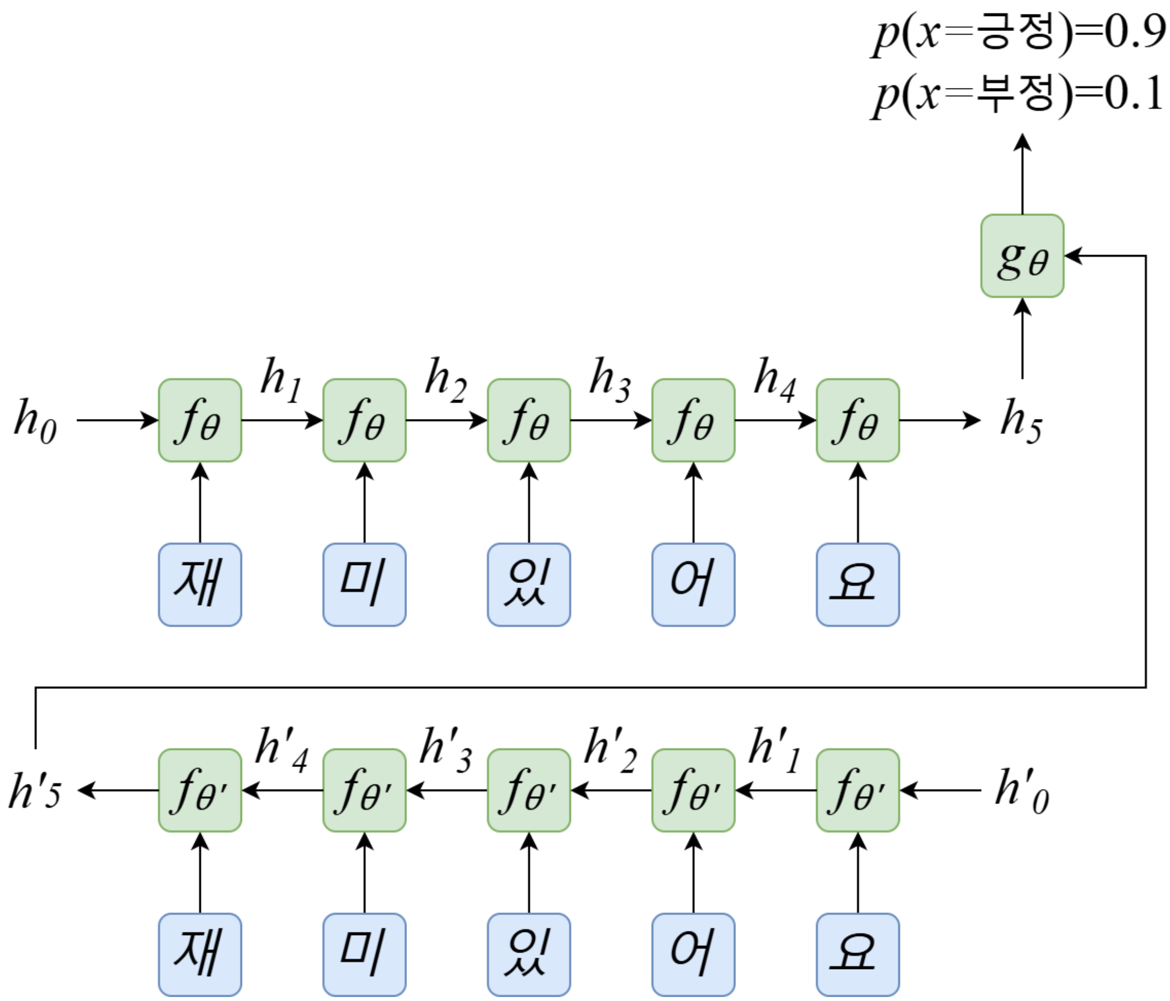


$$r_t = \sigma(w_{xr}x_t + w_{hr}h_{t-1} + b_r)$$
$$z_t = \sigma(w_{xz}x_t + w_{hz}h_{t-1} + b_z)$$
$$\tilde{h}_t = \tanh\left(w_{xh}x_t + b_{h_1} + r_t \odot \left(w_{hh}h_{t-1} + b_{h_2}\right)\right)$$
$$h_t = (1 - z_t) \odot \tilde{h}_t + z_t \odot h_{t-1}$$

Text Classification Using RNN



Bi-directional RNN



실습 (Text Classification Using RNN)

- Lab3-3.Text Classification Using RNN