19기 정규세션

ToBig's 18기 강의자 이다인

Neural Network Basic

Contents

01 | Perceptron

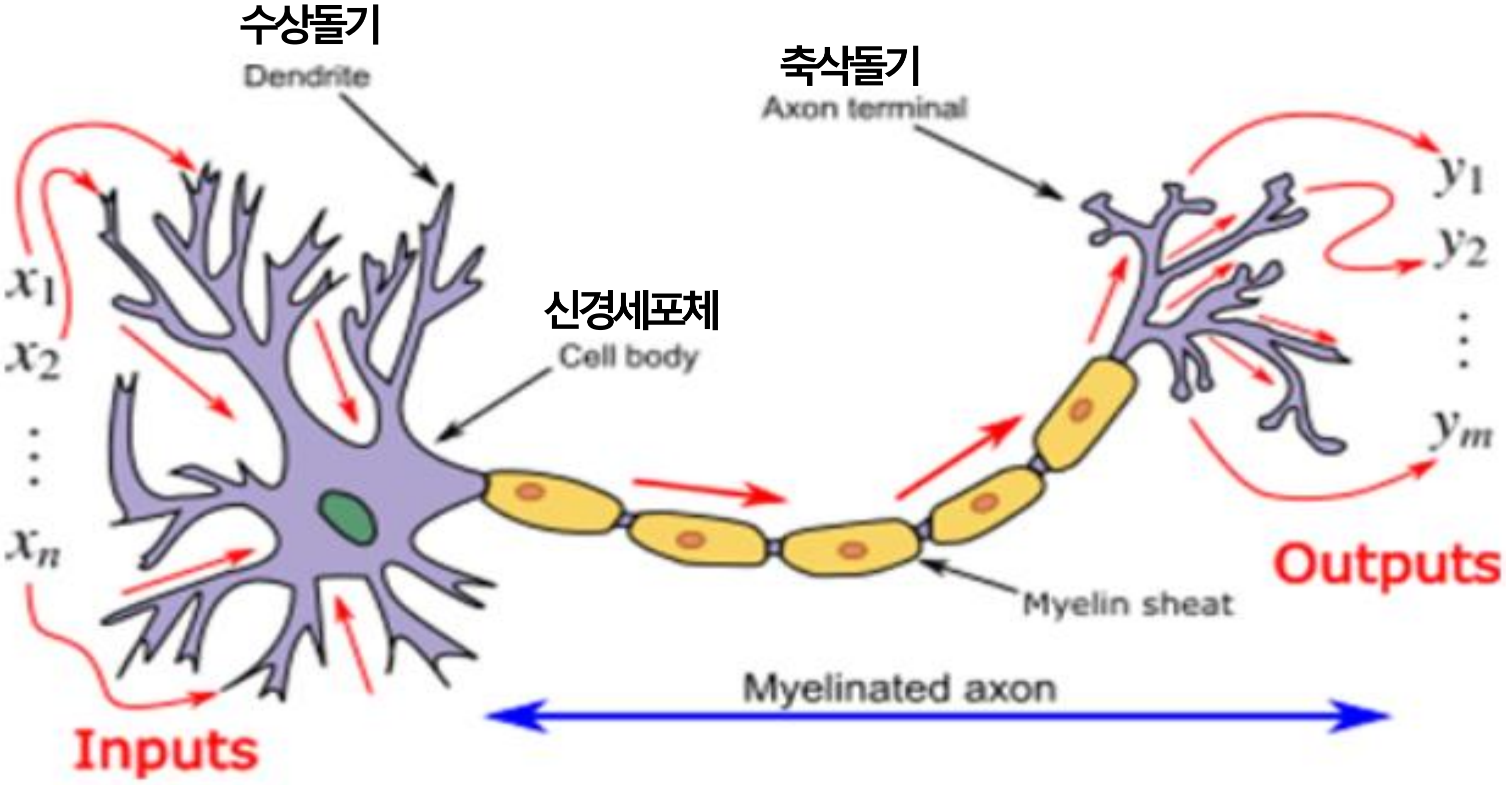
인공신경망이란?

What is Artificial neural network(ANN)?

“ 수학적 논리학이 아닌 인간의 두뇌를 모방하여
수많은 뉴런이 연결되어 있는 네트워크를 통해
문제를 해결하는 기계학습 모델 ”

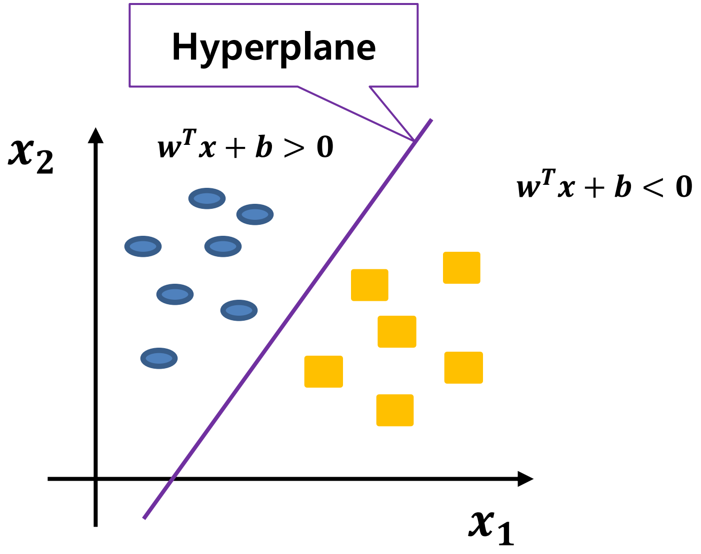
Unit 01 | Perceptron

Neuron (신경세포)



Perceptron

- Binary Classification (i.e., $y = \{-1, +1\}$)
- There exists a linear hyperplane that separates (i.e., data is linearly separable)
- 데이터가 linearly separable 하다는 것은 모든 데이터가 하나의 linear model을 통해서 완벽하게 분류될 수 있어야 한다는 것(error가 0이 되어야 함).

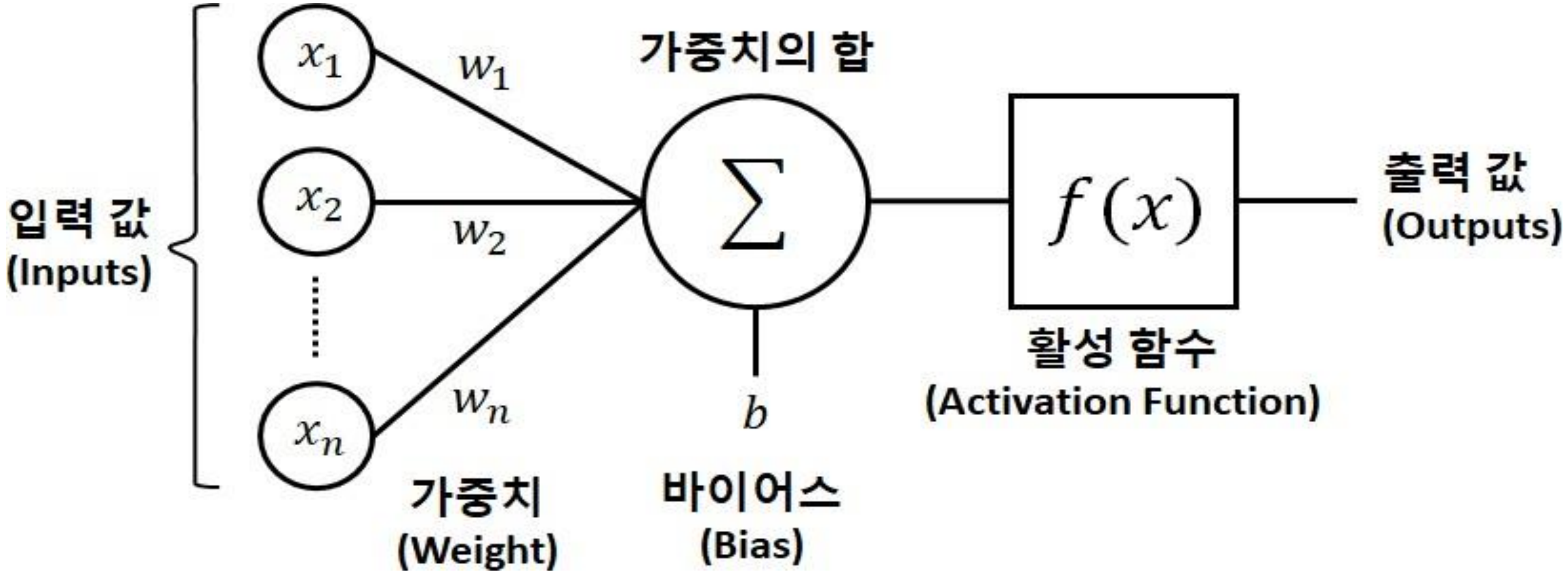


$$hypothesis\ class\ H = \{x: w^T x + b = 0\}$$

$$classifier\ h(x) = sign(w^T x + b)$$

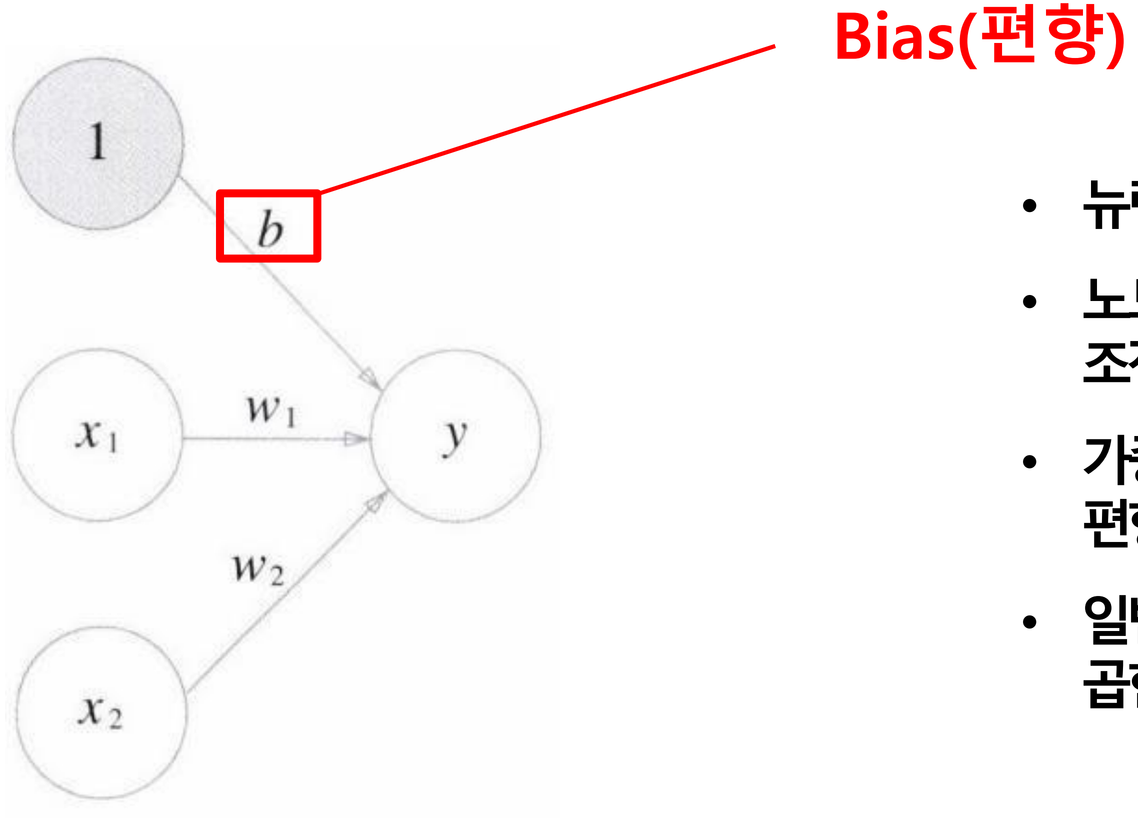
* x : 입력값
  b : bias (편향)
  w : weight (가중치)

Perceptron



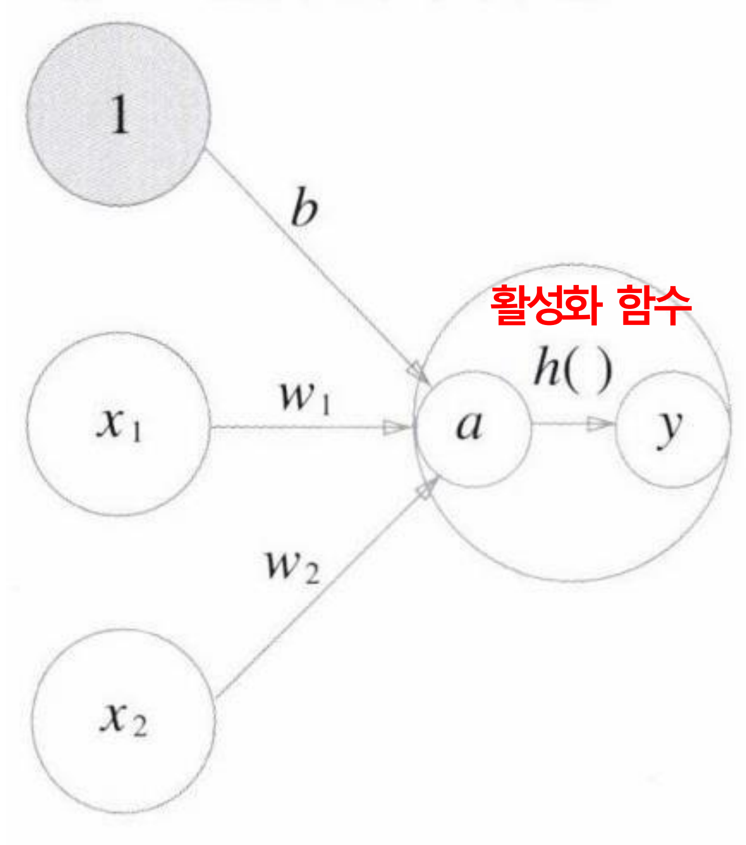
- **가중치(weight) : 각각의 입력에 대해 중요도를 부여 하는 수치**

Perceptron



- 뉴런이 얼마나 쉽게 활성화 되느냐를 제어
- 노드의 민감도를 조정하거나 활성화를 조정하는 역할
- 가중치 만으로 세밀한 조정이 되지 않을 시 편향을 주어 조정이 가능하다.
- 일반적으로 입력값을 1로 고정하고 편향 b를 곱한 변수로 표현한다.

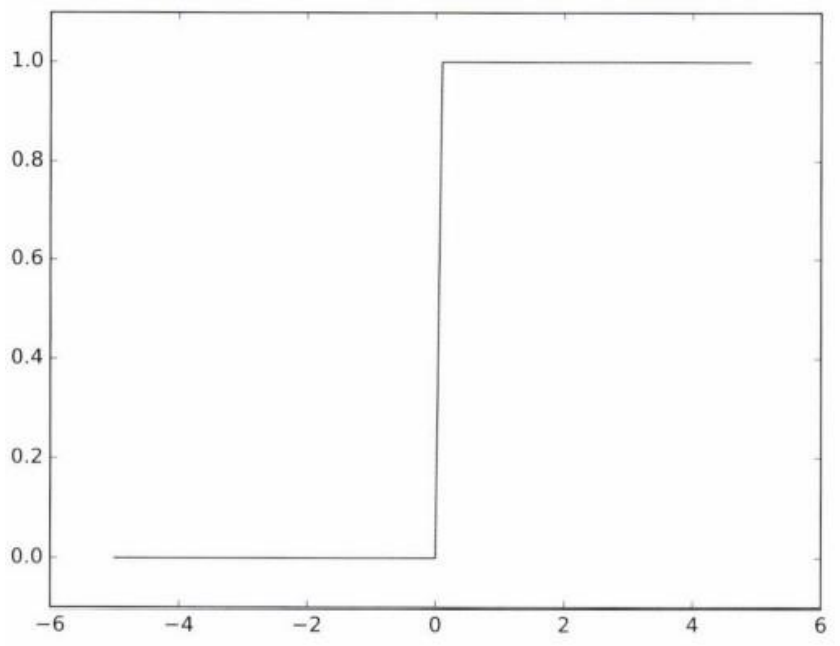
활성화 함수



Activation Function (활성화 함수)

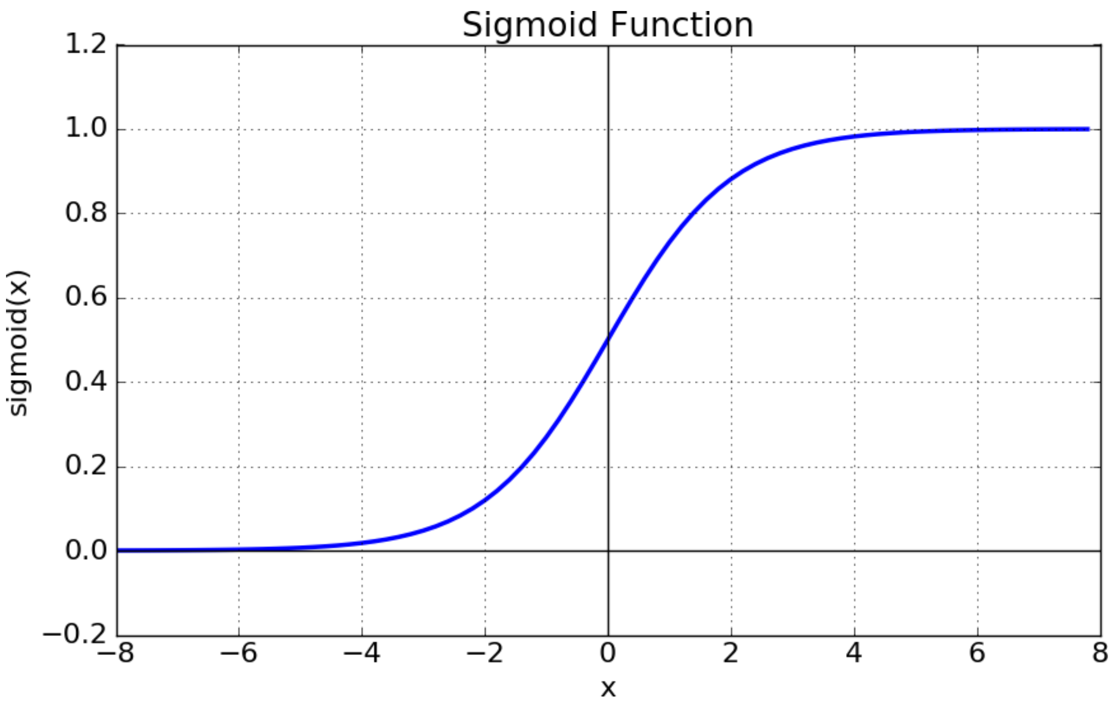
- 입력신호의 총합을 출력 신호로 변환하는 함수
- 활성화 함수로는 Step function, Relu, Sigmoid, tanh 등 여러 함수 존재

활성화 함수 – Step function



- 출력이 0 또는 1
- 활성화할지 말 지 여부만 반환

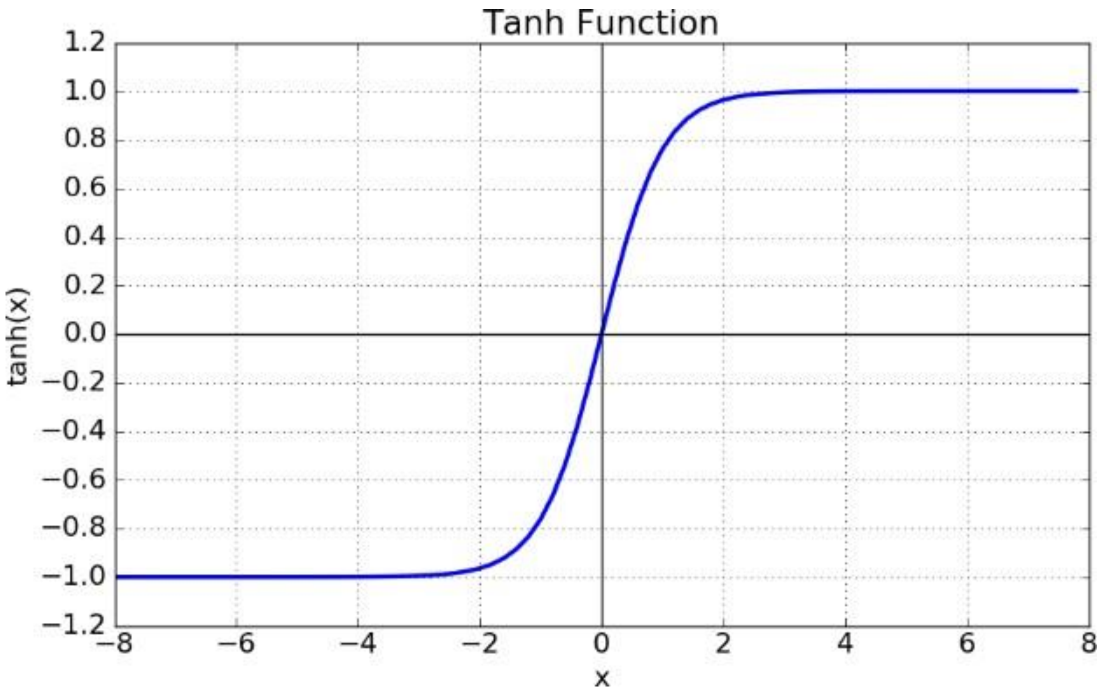
활성화 함수 – Sigmoid



$$h(x) = \frac{1}{1 + \exp(-x)}$$

- 0에서 1 사이의 값 출력
- 활성화 여부가 아닌, 활성화 정도를 반환
- 1에 가까울수록 많이 활성화됐다는 뜻

활성화 함수 – Tanh

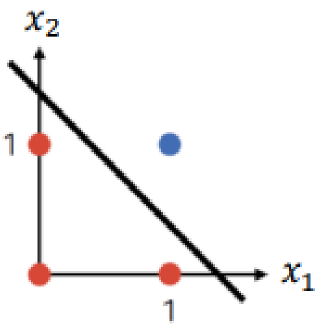


$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

- -1에서 1 사이의 값 출력
- 시그모이드 함수보다 범위가 넓어 출력값의 변화폭이 더 크고 이로 인해 기울기 소실 증상이 적음.

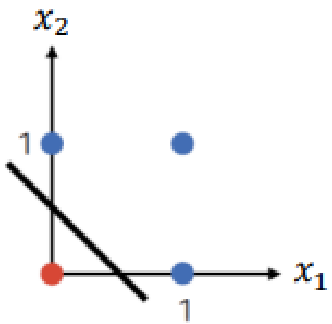
Perceptron 연산

AND



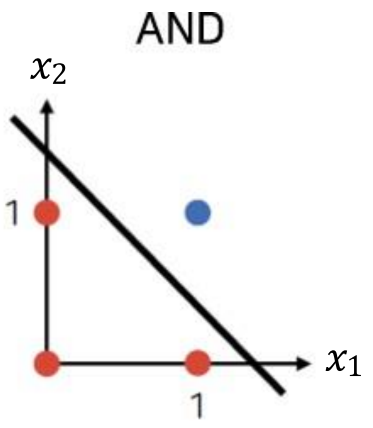
x_1	x_2	y
1	1	1
1	0	0
0	1	0
0	0	0

OR



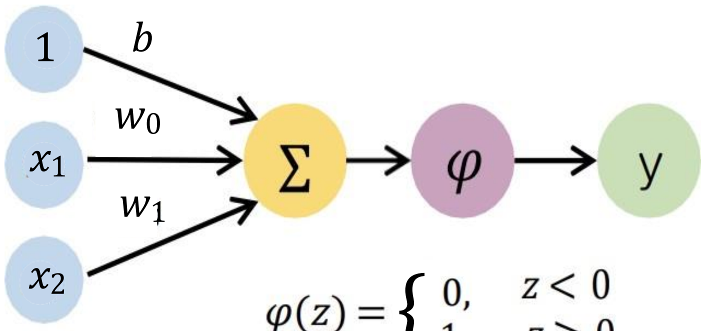
x_1	x_2	y
1	1	1
1	0	1
0	1	1
0	0	0

Perceptron 연산



$w_0 = 1.0, w_1 = 1.0, b = -1.5$

x_1	x_2	S	y
0	0	-1.5	0
0	1	-0.5	0
1	0	-0.5	0
1	1	0.5	1



$$\varphi(z) = \begin{cases} 0, & z < 0 \\ 1, & z \geq 0 \end{cases}$$

$$\varphi(w_1x_1 + w_2x_2 + w_3) = y$$

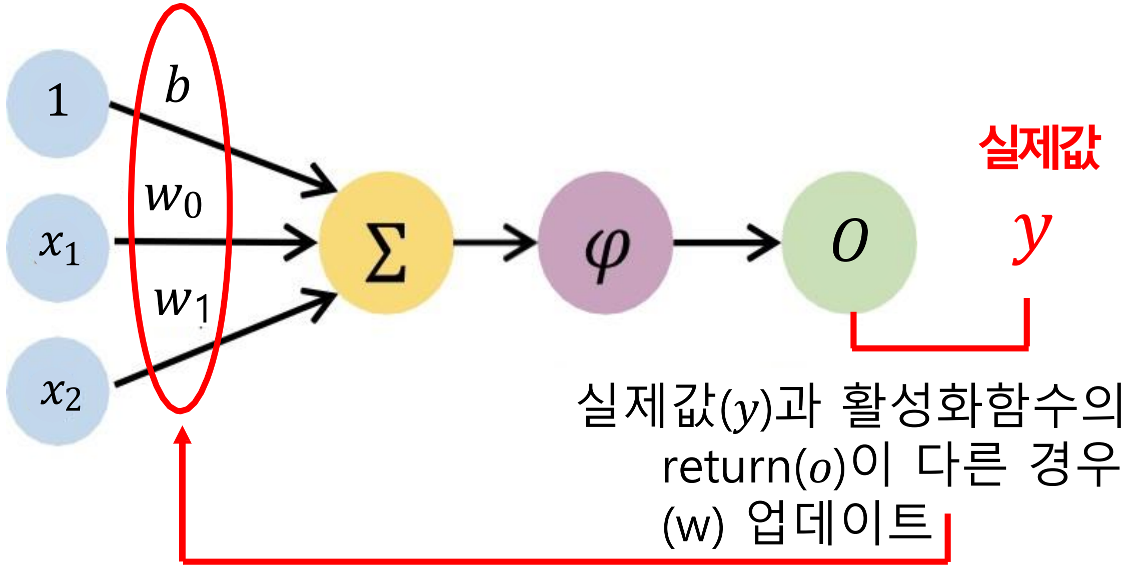
① $(1.0\times0) + (1.0\times0) + (-1.5) = -1.5$
$\varphi((1.0\times0) + (1.0\times0) + (-1.5)) = 0$

② $(1.0\times0) + (1.0\times1) + (-1.5) = -0.5$
$\varphi((1.0\times0) + (1.0\times1) + (-1.5)) = 0$

③ $(1.0\times1) + (1.0\times0) + (-1.5) = -0.5$
$\varphi((1.0\times1) + (1.0\times0) + (-1.5)) = 0$

④ $(1.0\times1) + (1.0\times1) + (-1.5) = 0.5$
$\varphi((1.0\times1) + (1.0\times1) + (-1.5)) = 1$

Perceptron 학습



실제값(y)과 활성화함수의 return(o)이 다른 경우 가중치 (w) 업데이트

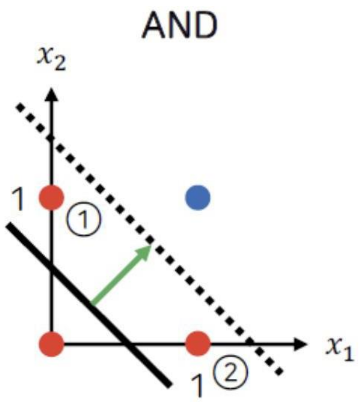
가중치 조정 식

$$w_i \leftarrow w_i + \eta(y - o)x_i$$

학습률(learning rate)

너무 작으면 학습 속도가 매우 느리고 너무 크면 가중치를 미세하게 조정하지 못하기 때문에 최적의 가중치를 찾기 어려움

Perceptron 학습



$w_1 = 0.55, w_2 = 0.55, b = -0.65$

x_1	x_2	o	y	
0	0	0	0	
0	1	1	0	①
1	0	1	0	②
1	1	1	1	

$$w_i \leftarrow w_i + \eta(y-o)x_i \qquad \eta = 0.05$$

①

$$b \leftarrow b + 0.05(0-1) \times 1$$
$$w_1 \leftarrow w_1 + 0.05(0-1) \times 0$$
$$w_2 \leftarrow w_2 + 0.05(0-1) \times 1$$

$$b \leftarrow -0.65 + 0.05(0-1) \times 1 = -0.7$$
$$w_1 \leftarrow 0.55 + 0.05(0-1) \times 0 = 0.55$$
$$w_2 \leftarrow 0.55 + 0.05(0-1) \times 1 = 0.5$$

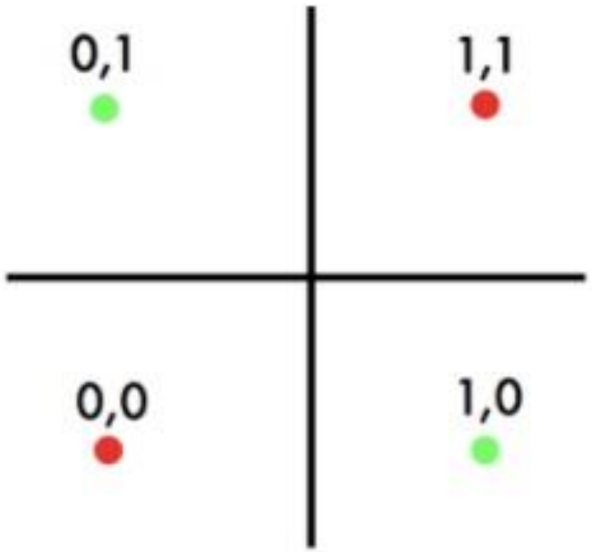
②

$$b \leftarrow b + 0.05(0-1) \times 1$$
$$w_1 \leftarrow w_1 + 0.05(0-1) \times 1$$
$$w_2 \leftarrow w_2 + 0.05(0-1) \times 0$$

$$b \leftarrow -0.65 + 0.05(0-1) \times 1 = -0.7$$
$$w_1 \leftarrow 0.55 + 0.05(0-1) \times 1 = 0.5$$
$$w_2 \leftarrow 0.55 + 0.05(0-1) \times 0 = 0.55$$

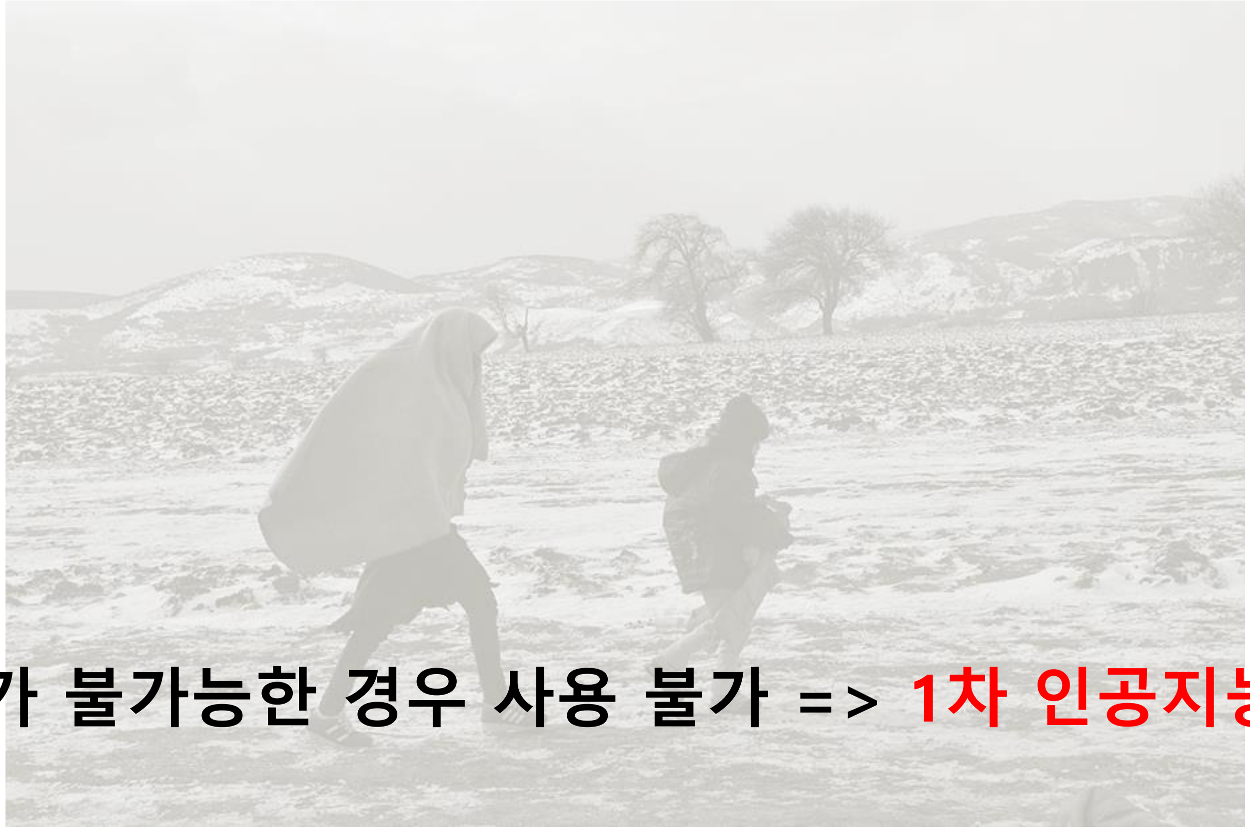
Perceptron의 한계

XOR

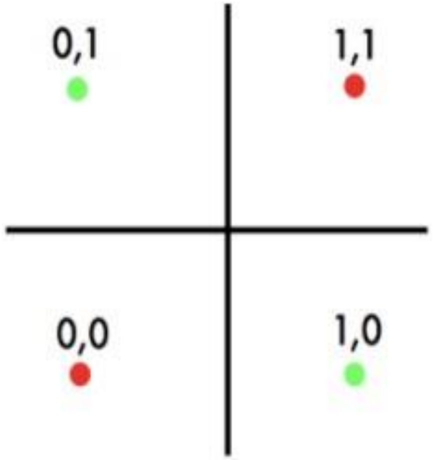


1969년 MIT AI랩 창립자 Minskey& Papert
'현재의 퍼셉트론으로는 XOR 문제를 해결할 수 없다!'

Perceptron의 한계



XOR

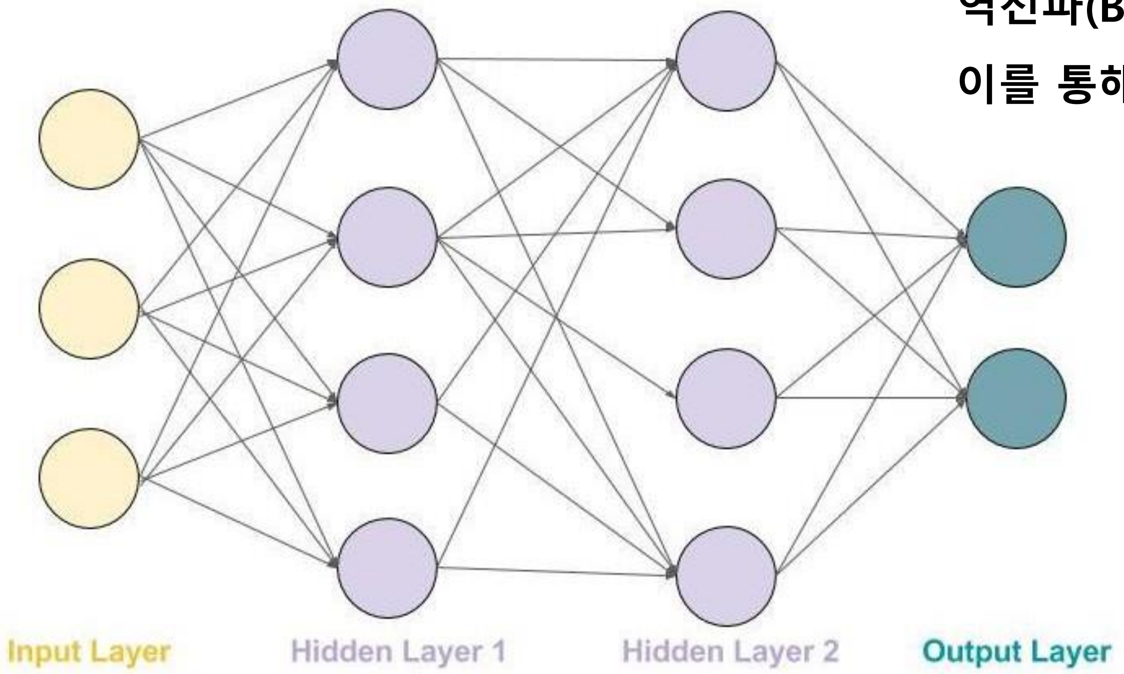


선형 분리가 불가능한 경우 사용 불가 => 1차 인공지능의 겨울

02 | Backpropagation

Unit 02 | Backpropagation

Multi Layer Perceptron

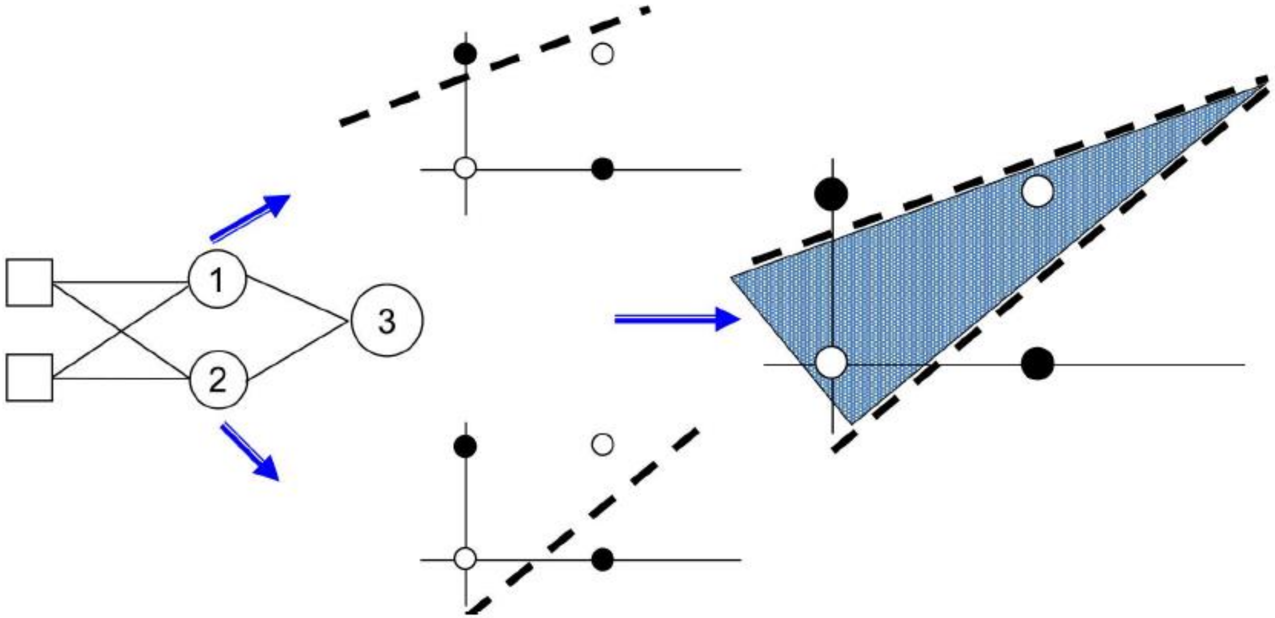


1986년 제프리 힌튼이 다층 퍼셉트론(Multi Layer Perceptron), 역전파(Back Propagation)을 실험적으로 증명.
이를 통해 오랜 AI의 겨울을 불러 온 XOR 문제 해결

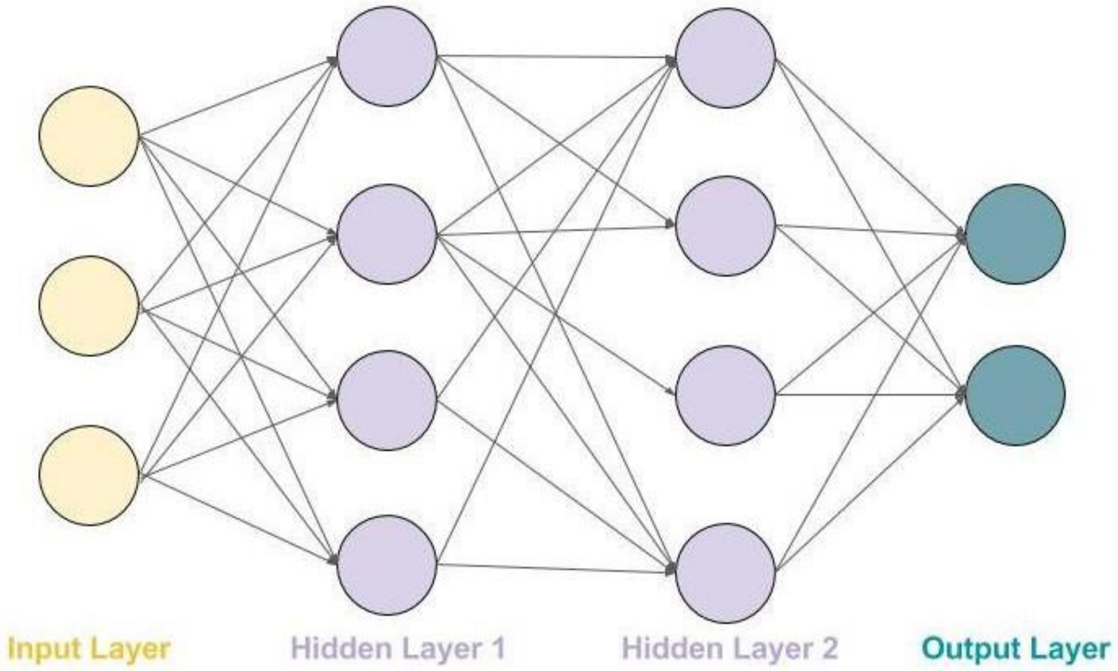
Multi Layer Perceptron

하나의 퍼셉트론으로는 해결하지 못했던 xor문제도 여러 퍼셉트론을 쌓는다면 해결 가능

XOR



Multi Layer Perceptron



MLP를 학습시키는 방법

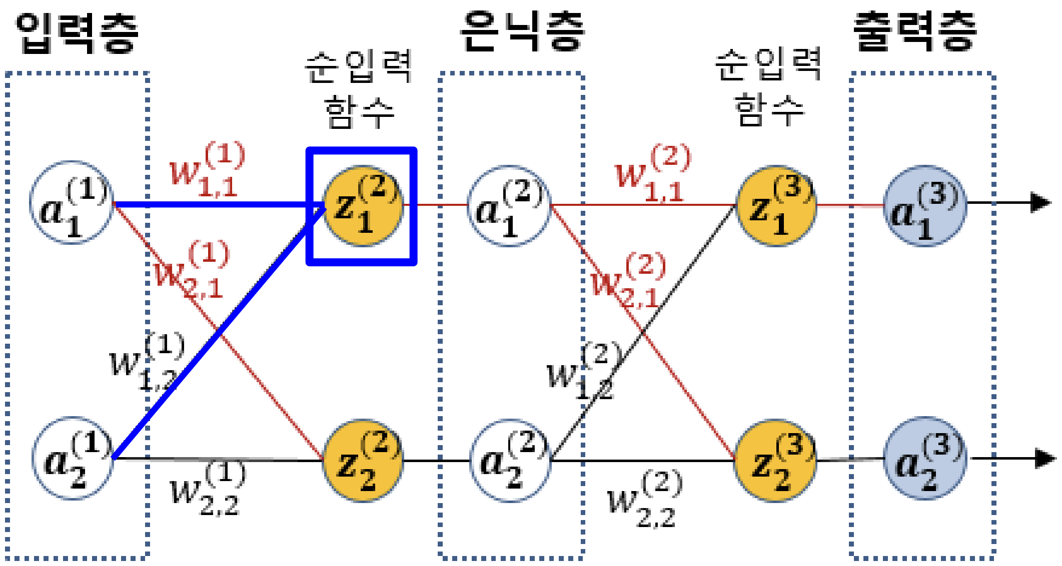
: 오류 역전파

역전파(Backpropagation)

순전파(Feedforward) 알고리즘에서 발생한 오차를 줄이기 위해
새로운 가중치를 업데이트하고, 새로운 가중치로 다시 학습하는 과정

순전파(Feedforward)

$$\phi(z) = \frac{1}{1+e^{-z}}$$



$$\boxed{z_1^{(2)} = w_{1,1}^{(1)} a_1^{(1)} + w_{1,2}^{(1)} a_2^{(1)}}$$

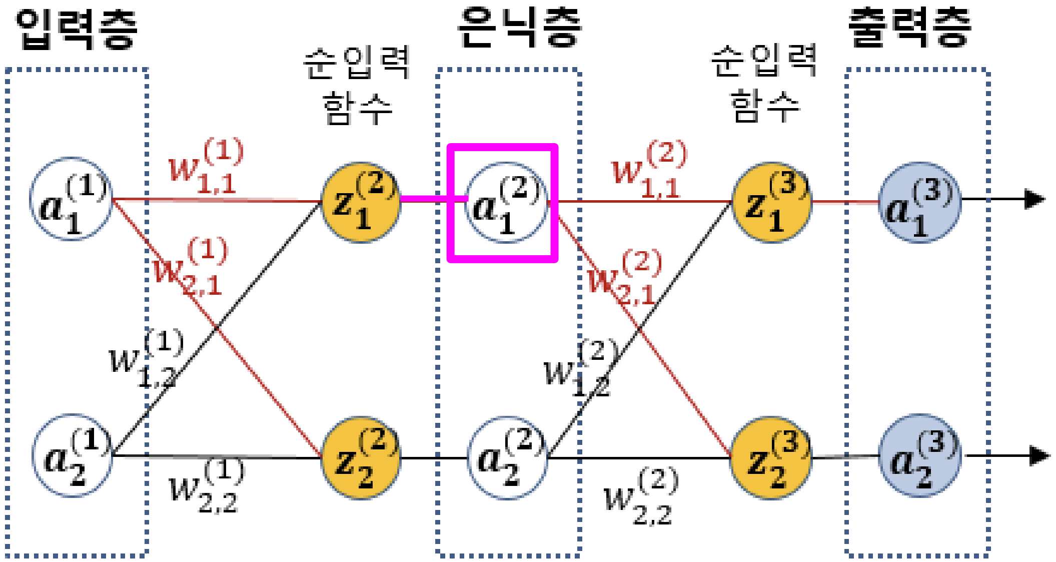
$$a_1^{(2)} = \phi(z_1^{(2)})$$

$$z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}$$

$$a_1^{(3)} = \phi(z_1^{(3)})$$

순전파(Feedforward)

$$\phi(z) = \frac{1}{1+e^{-z}}$$



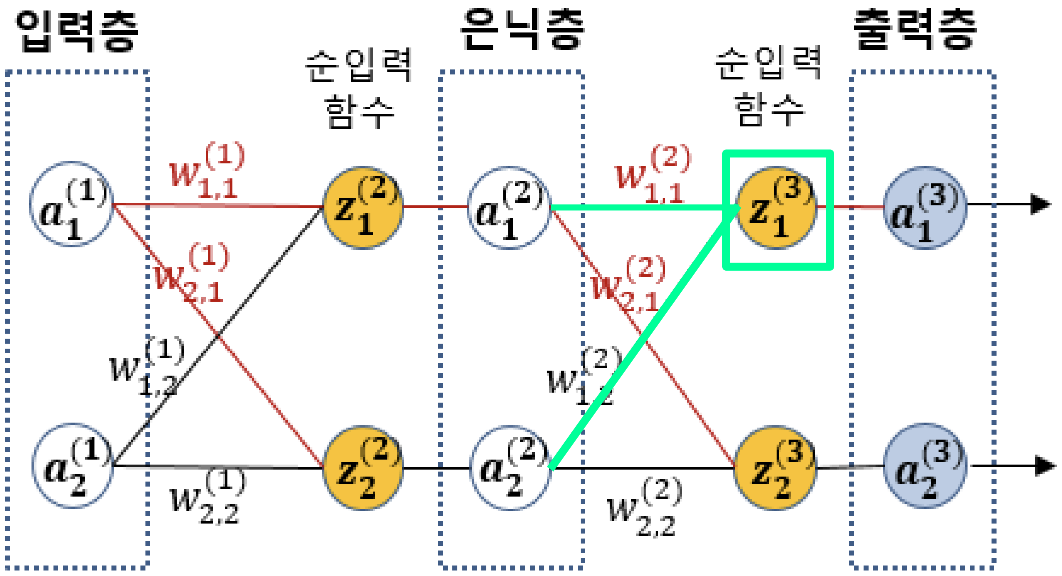
$$z_1^{(2)} = w_{1,1}^{(1)} a_1^{(1)} + w_{1,2}^{(1)} a_2^{(1)}$$

$$\boxed{a_1^{(2)} = \phi(z_1^{(2)})}$$

$$z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}$$

$$a_1^{(3)} = \phi(z_1^{(3)})$$

순전파(Feedforward)



$$\phi(z) = \frac{1}{1+e^{-z}}$$

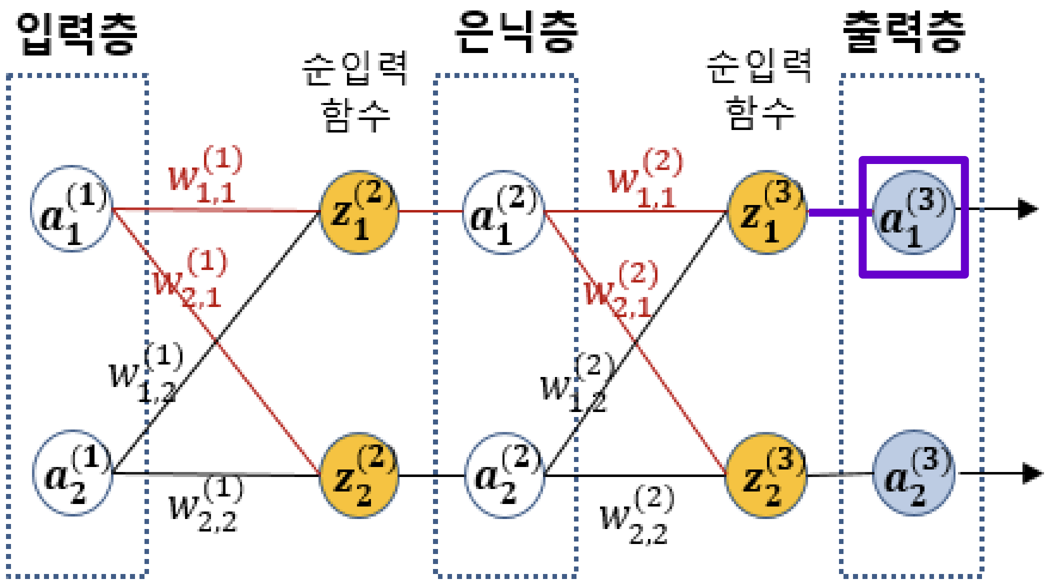
$$z_1^{(2)} = w_{1,1}^{(1)} a_1^{(1)} + w_{1,2}^{(1)} a_2^{(1)}$$

$$a_1^{(2)} = \phi(z_1^{(2)})$$

$$\boxed{z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}}$$

$$a_1^{(3)} = \phi(z_1^{(3)})$$

순전파(Feedforward)



$$\phi(z) = \frac{1}{1 + e^{-z}}$$

$$z_1^{(2)} = w_{1,1}^{(1)} a_1^{(1)} + w_{1,2}^{(1)} a_2^{(1)}$$

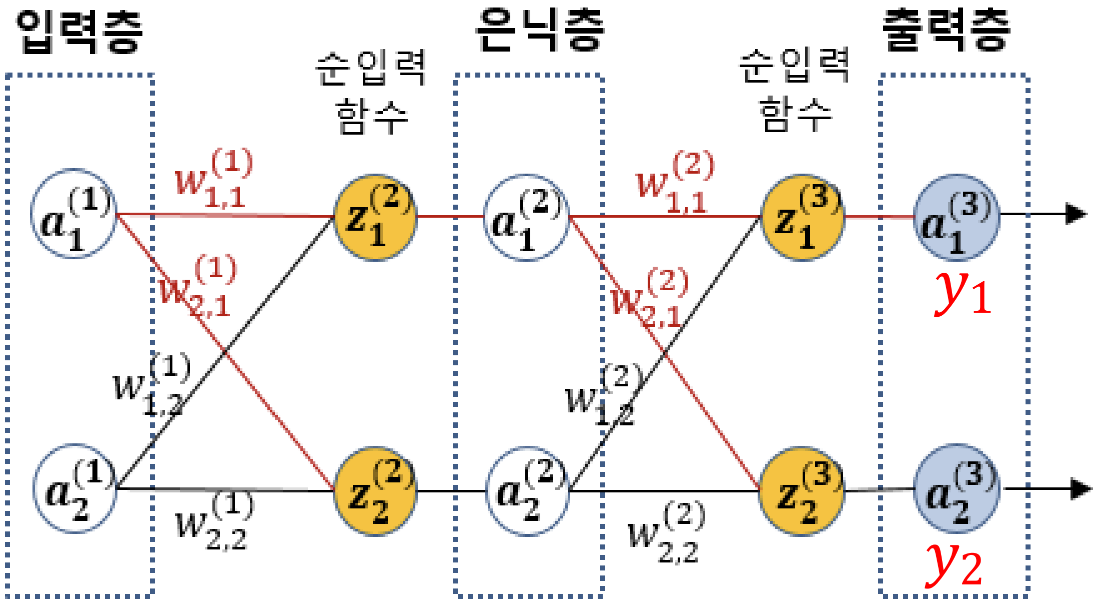
$$a_1^{(2)} = \phi(z_1^{(2)})$$

$$z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}$$

$$\boxed{a_1^{(3)} = \phi(z_1^{(3)})}$$

손실함수(Cost Function)

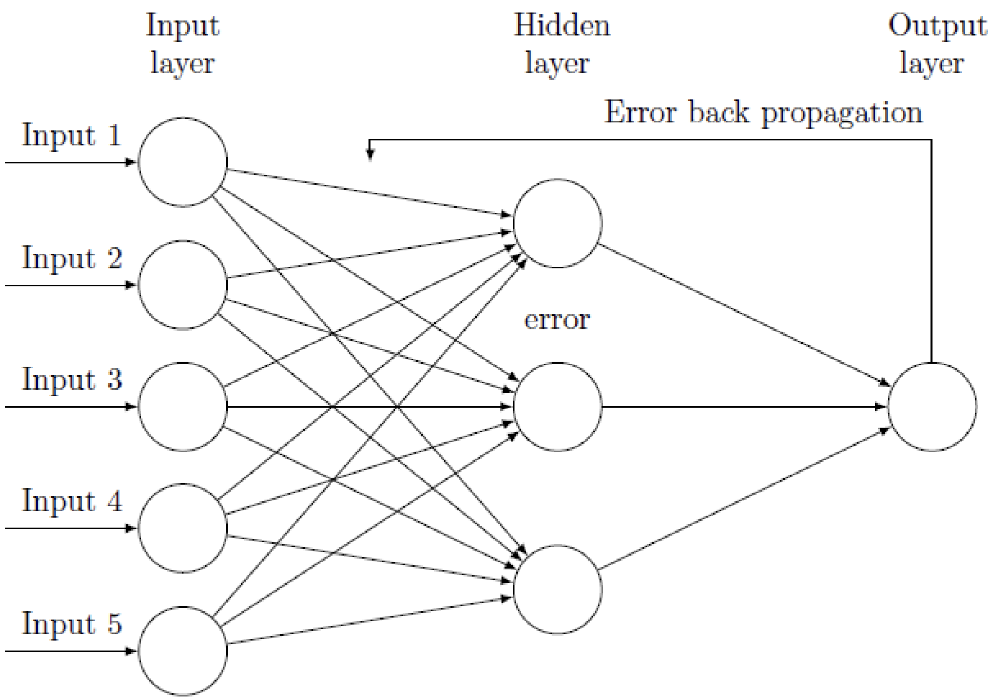
$$\mathrm{MSE} = \frac{1}{2N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$



$$J_1 = \frac{1}{2}(a_1^{(3)} - y_1)^2$$

$$J_2 = \frac{1}{2}(a_2^{(3)} - y_2)^2$$

역전파(Backpropagation)



- Input과 output 값을 알고 있는 상태에서 신경망을 학습시키는 방법
- 출력부터 반대 방향으로 순차적으로 편미분을 수행해 가면서 weight와 bias 값을 갱신시킴

$$w_j = w_j - \eta \frac{\partial J_{total}}{\partial w_j}$$

가중치 업데이트 식

편미분

다변수함수의 특정 변수를 제외한 나머지 변수를 상수로 생각하여 미분

$$z = f(x, y) = x^2 + xy + y^2$$

$$\frac{\partial z}{\partial x} = 2x + y, \qquad \frac{\partial z}{\partial y} = 2y + x$$

$$\Delta f(x, y) = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right) = (2x + y, 2y + x)$$

Chain Rule

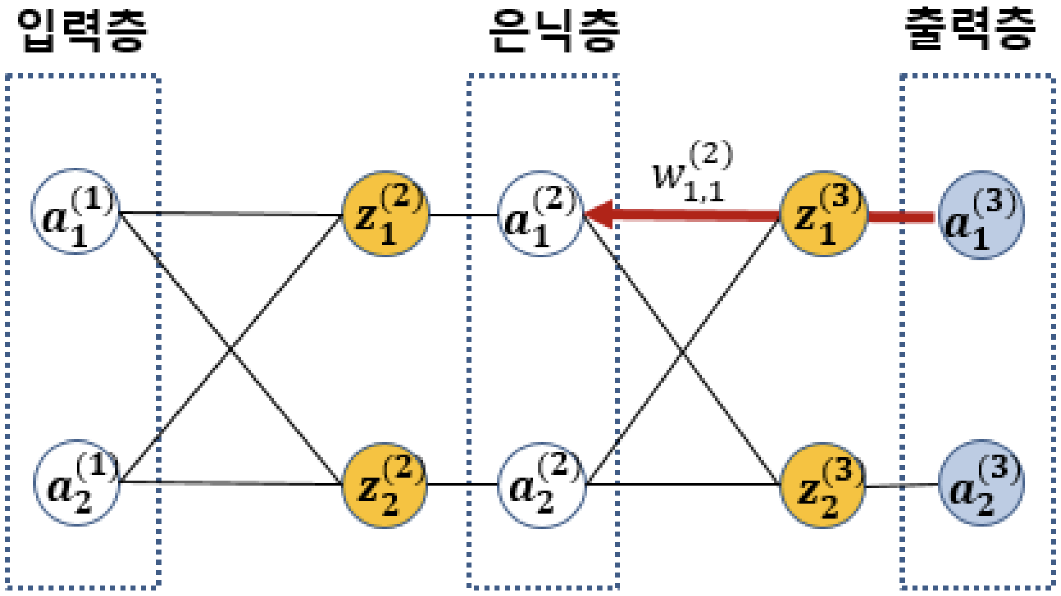
연쇄 법칙, 합성 함수를 미분할 때의 계산 공식

$$f(g(x))' = f'\left(g(x)\right)g'(x)$$

$y = f(\mathrm{u}), u = g(x)$일 때, $\dfrac{\partial y}{\partial x} = \dfrac{\partial y}{\partial u} \cdot \dfrac{\partial u}{\partial x}$ 성립

역전파(Backpropagation)

$$w_j = w_j - \eta \frac{\partial J_{total}}{\partial w_j}$$



손실함수

J_1

J_2

$$w_{1,1}^{(2)} = w_{1,1}^{(2)} - \frac{\partial J_{total}}{\partial w_{1,1}^{(2)}}$$

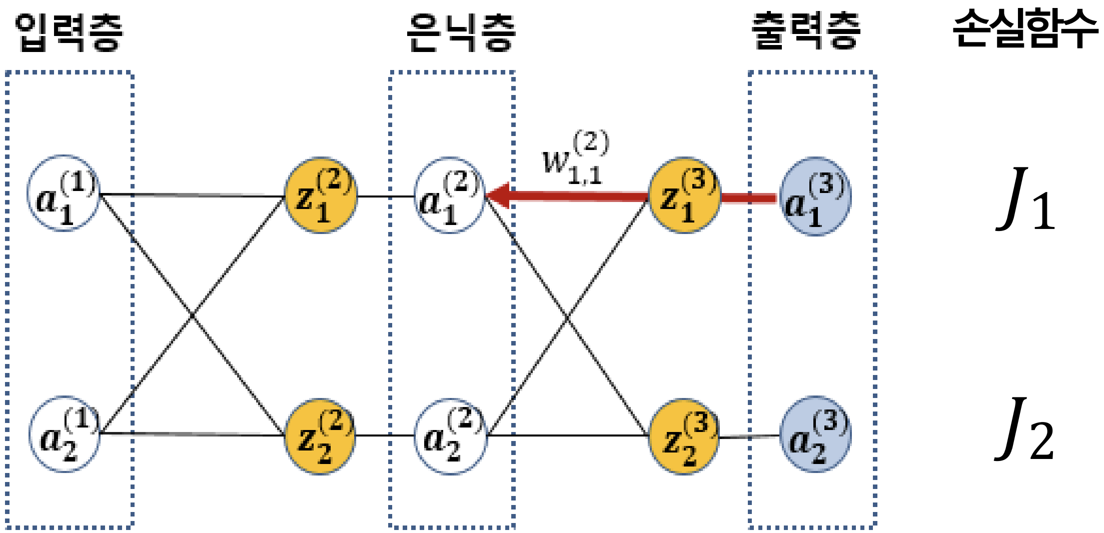
역전파의 출발노드인 $a_1^{(3)}$의 J_{total}은 J_1

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \frac{\partial J_1}{\partial a_1^{(3)}} \times \frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} \times \frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}}$$

역전파(Backpropagation)

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \frac{\partial J_1}{\partial a_1^{(3)}} \times \frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} \times \frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}}$$

① ② ③



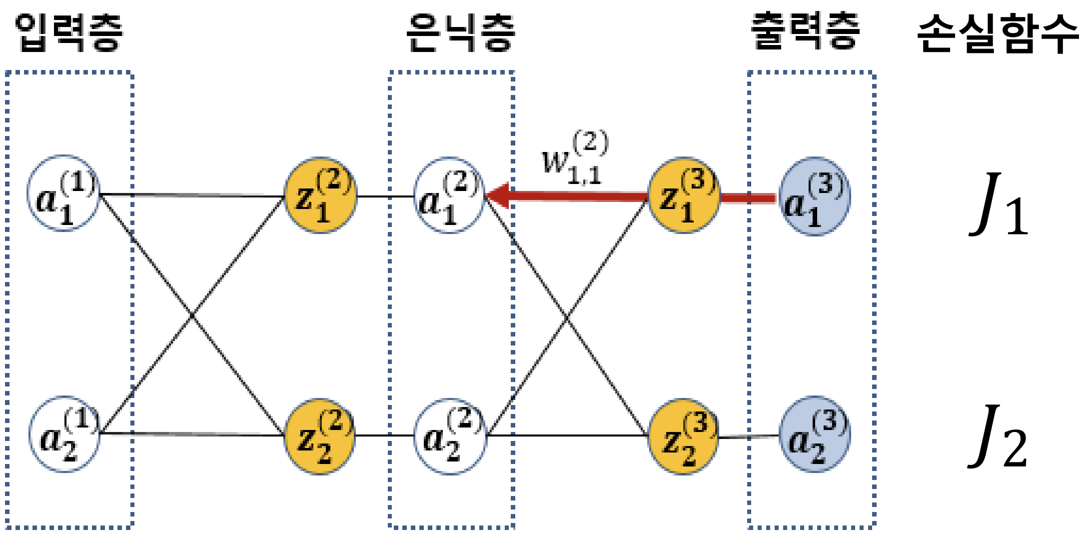
참고: $J_1 = \frac{1}{2}\left(a_1^{(3)} - y_1\right)^2$

① $\frac{\partial J_1}{\partial a_1^{(3)}} = \frac{1}{2}\frac{\partial}{\partial a_1^{(3)}}\left(a_1^{(3)} - y_1\right)^2 = \left(a_1^{(3)} - y_1\right)$

역전파(Backpropagation)

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \frac{\partial J_1}{\partial a_1^{(3)}} \times \frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} \times \frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}}$$

① ② ③



참고: $a_1^{(3)} = \phi(z_1^{(3)})$

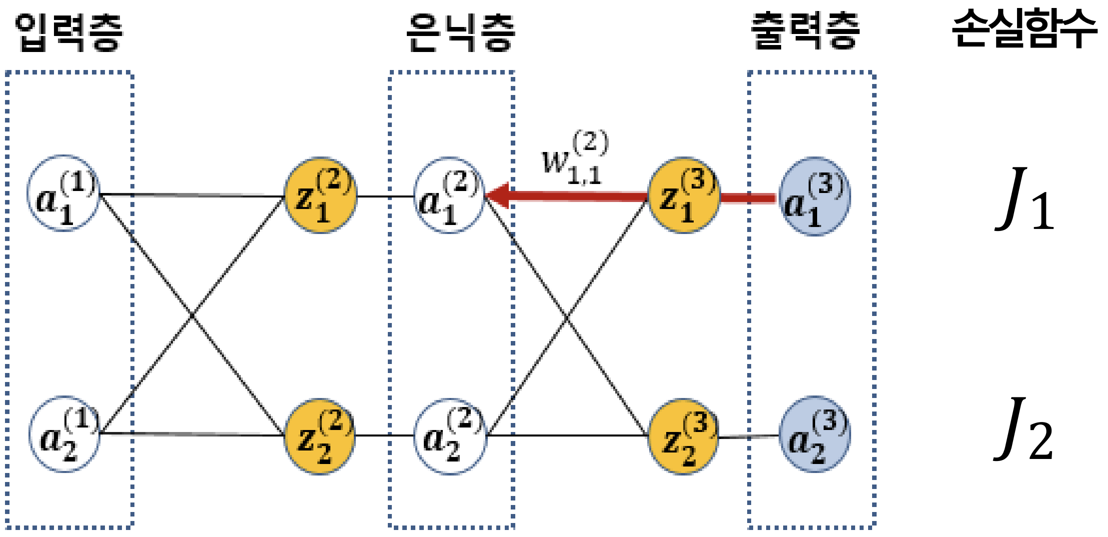
$$\begin{aligned}\sigma'(x) &= \frac{\partial}{\partial x}\frac{1}{1+e^{-x}} \\ &= \frac{e^{-x}}{(1+e^{-x})^2} \\ &= \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}} \\ &= \sigma(x)(1-\sigma(x))\end{aligned}$$

② $$\frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} = \phi\left(z_1^{(3)}\right)\left(1-\phi\left(z_1^{(3)}\right)\right) = a_1^{(3)}\left(1-a_1^{(3)}\right)$$

역전파(Backpropagation)

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \frac{\partial J_1}{\partial a_1^{(3)}} \times \frac{\partial a_1^{(3)}}{\partial z_1^{(3)}} \times \frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}}$$

① ② ③



참고: $z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}$

③ $\frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}} = a_1^{(2)}$

역전파(Backpropagation)

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \boxed{\frac{\partial J_1}{\partial a_1^{(3)}}} \times \boxed{\frac{\partial a_1^{(3)}}{\partial z_1^{(3)}}} \times \boxed{\frac{\partial z_1^{(3)}}{\partial w_{1,1}^{(2)}}} = \underbrace{\overset{①}{\boxed{(a_1^{(3)} - y_1)}} \times \overset{②}{\boxed{a_1^{(3)}(1 - a_1^{(3)})}}} \times \overset{③}{\boxed{a_1^{(2)}}}$$

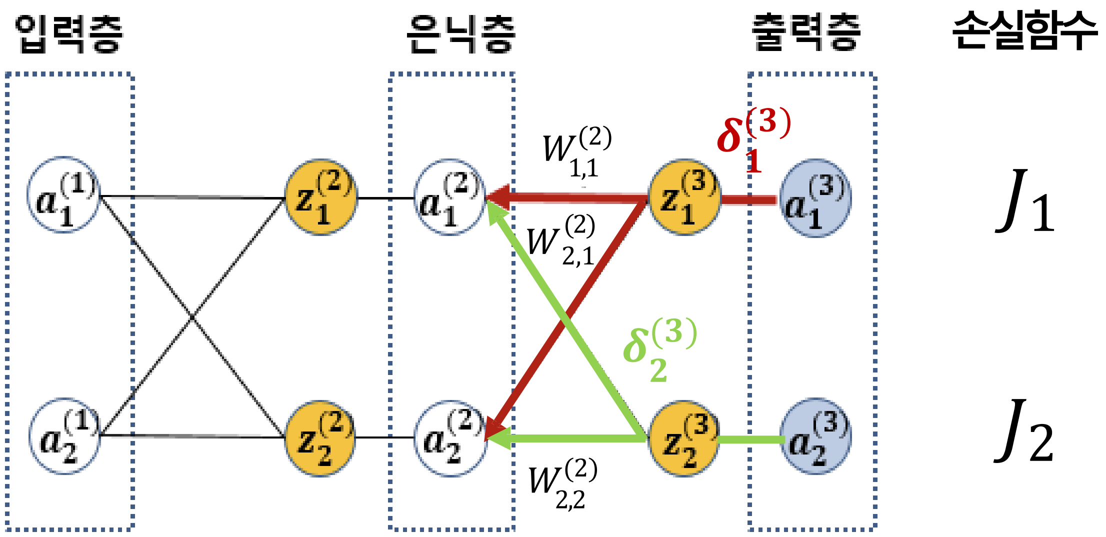
$$\delta_1^{(3)} = \frac{\partial J_1}{\partial z_1^{(3)}} = (a_1^{(3)} - y_1) \times a_1^{(3)}(1 - a_1^{(3)})$$

$$w_{1,1}^{(2)} = w_{1,1}^{(2)} - \frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = \boxed{w_{1,1}^{(2)} - \delta_1^{(3)} a_1^{(2)}}$$

역전파(Backpropagation)

$$\delta_1^{(3)} = \frac{\partial J_1}{\partial z_1^{(3)}} = (a_1^{(3)} - y_1) \times a_1^{(3)}(1 - a_1^{(3)})$$

$$w_{1,1}^{(2)} = w_{1,1}^{(2)} - \frac{\partial J_{total}}{\partial w_{1,1}^{(2)}} = w_{1,1}^{(2)} - \delta_1^{(3)} a_1^{(2)}$$



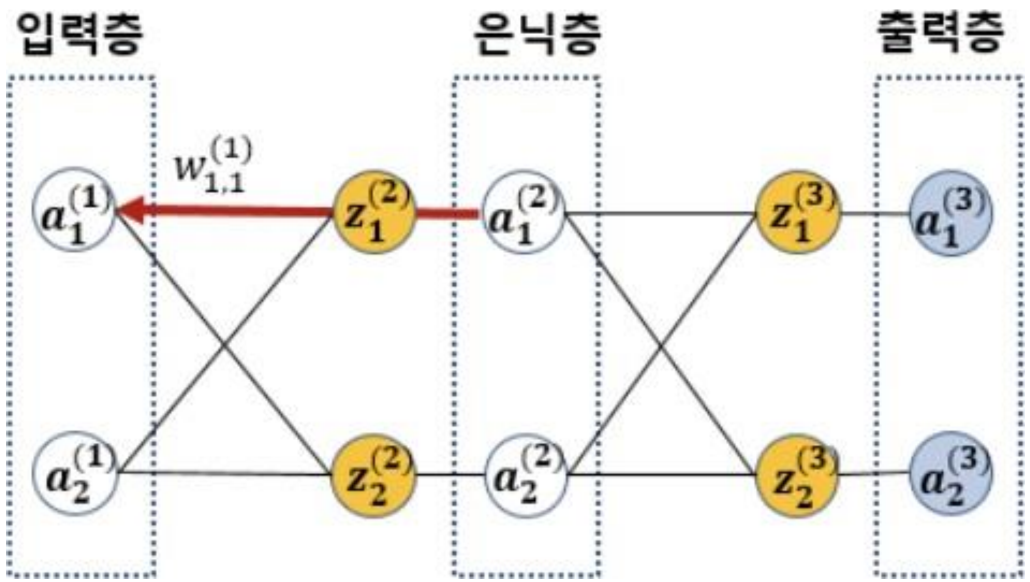
같은 방식으로

$$\delta_2^{(3)} = \frac{\partial J_2}{\partial z_2^{(3)}} = \left(a_2^{(3)} - y_2\right) \times a_2^{(3)} \left(1 - a_2^{(3)}\right)$$

$$w_{2,1}^{(2)} = w_{2,1}^{(2)} - \delta_2^{(3)} a_1^{(2)}$$

$$w_{2,2}^{(2)} = w_{2,2}^{(2)} - \delta_2^{(3)} a_2^{(2)}$$

역전파(Backpropagation)

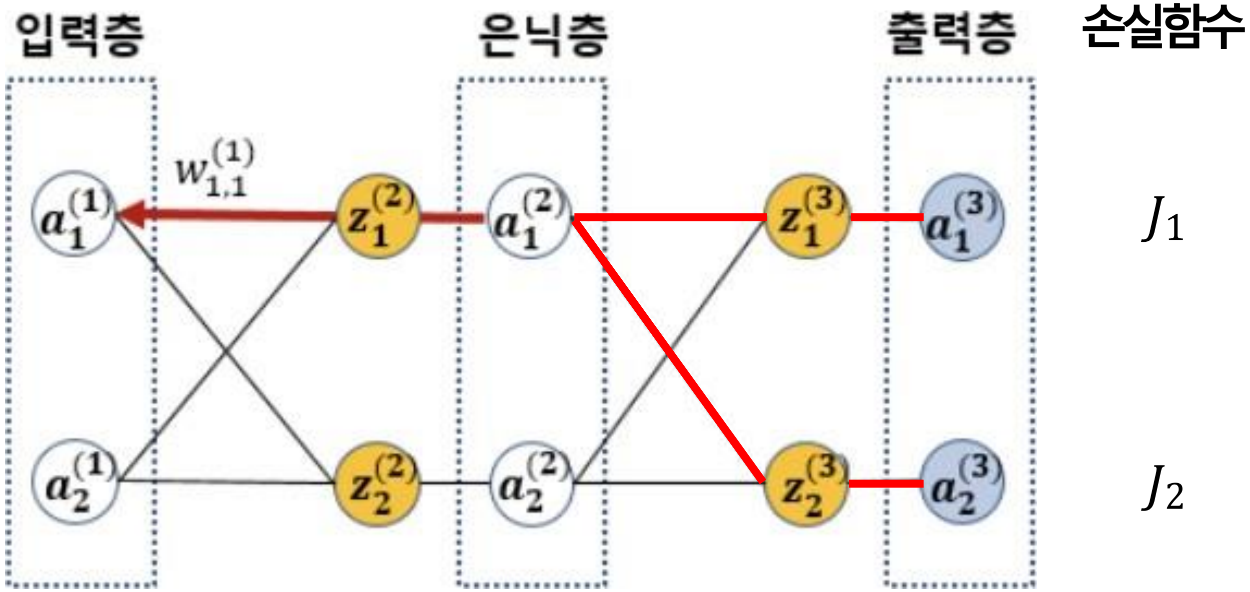


$$\boxed{w_j = w_j - \eta \frac{\partial J_{total}}{\partial w_j}}$$

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \frac{\partial J_{total}}{\partial a_1^{(2)}} \times \frac{\partial a_1^{(2)}}{\partial z_1^{(2)}} \times \frac{\partial z_1^{(2)}}{\partial w_{1,1}^{(1)}}$$

역전파(Backpropagation)

$$\boxed{w_j = w_j - \eta \frac{\partial J_{total}}{\partial w_j}}$$



$$\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \frac{\partial J_{total}}{\partial a_1^{(2)}} \times \frac{\partial a_1^{(2)}}{\partial z_1^{(2)}} \times \frac{\partial z_1^{(2)}}{\partial w_{1,1}^{(1)}}$$

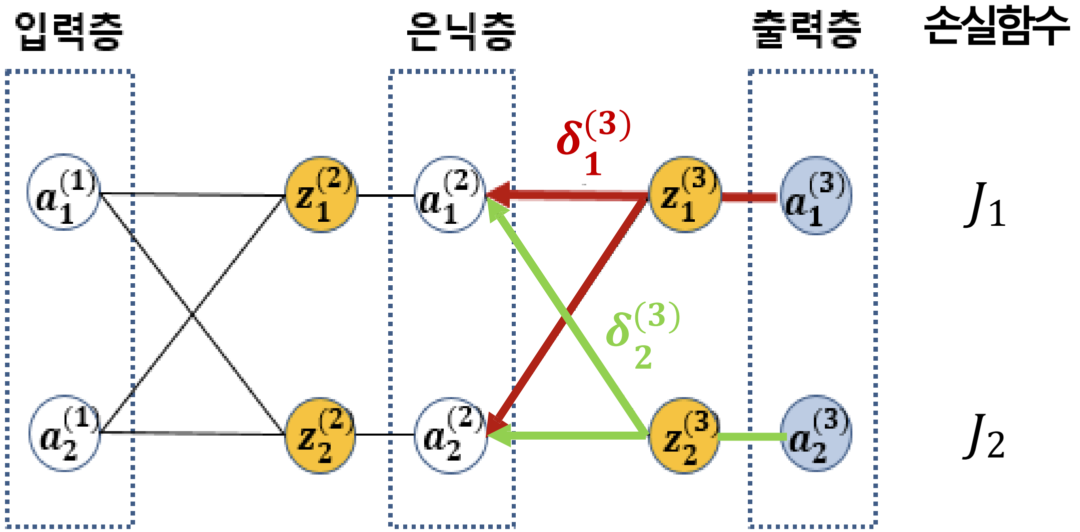
$a_1^{(2)}$의 J_{total}은 $J_1 + J_2$

$$\frac{\partial J_{total}}{\partial a_1^{(2)}} = \frac{\partial J_1}{\partial a_1^{(2)}} + \frac{\partial J_2}{\partial a_1^{(2)}} = \frac{\partial J_1}{\partial z_1^{(3)}} \times \frac{\partial z_1^{(3)}}{\partial a_1^{(2)}} + \frac{\partial J_2}{\partial z_2^{(3)}} \times \frac{\partial z_2^{(3)}}{\partial a_1^{(2)}}$$

Unit 02 | Backpropagation

역전파(Backpropagation)

$$\boxed{\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \frac{\partial J_{total}}{\partial a_1^{(2)}} \times \frac{\partial a_1^{(2)}}{\partial z_1^{(2)}} \times \frac{\partial z_1^{(2)}}{\partial w_{1,1}^{(1)}}}$$



$$\delta_1^{(3)} = \frac{\partial J_1}{\partial z_1^{(3)}} = \left(a_1^{(3)} - y_1\right) \times a_1^{(3)}\left(1 - a_1^{(3)}\right)$$

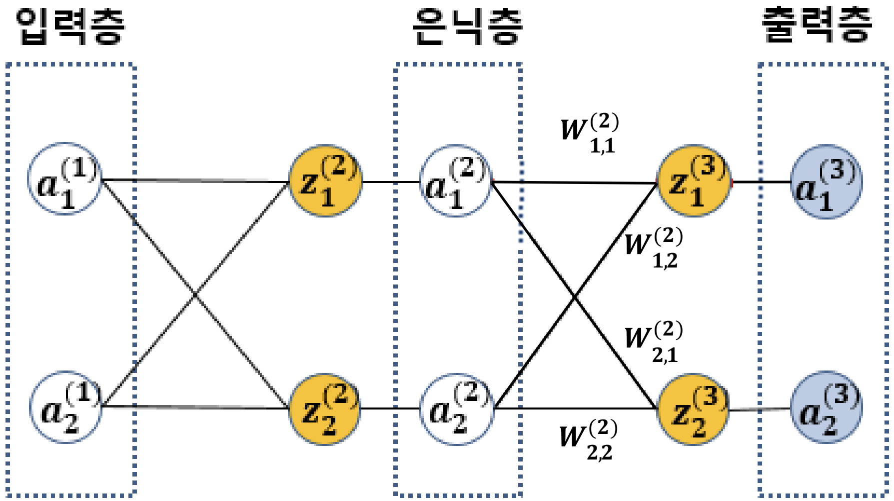
$$\delta_2^{(3)} = \frac{\partial J_2}{\partial z_2^{(3)}} = \left(a_2^{(3)} - y_2\right) \times a_2^{(3)}\left(1 - a_2^{(3)}\right)$$

$$\frac{\partial J_{total}}{\partial a_1^{(2)}} = \frac{\partial J_1}{\partial a_1^{(2)}} + \frac{\partial J_2}{\partial a_1^{(2)}} = \boxed{\frac{\partial J_1}{\partial z_1^{(3)}}} \times \frac{\partial z_1^{(3)}}{\partial a_1^{(2)}} + \boxed{\frac{\partial J_2}{\partial z_2^{(3)}}} \times \frac{\partial z_2^{(3)}}{\partial a_1^{(2)}}$$

$$= \boxed{\delta_1^{(3)}} w_{1,1}^{(2)} + \boxed{\delta_2^{(3)}} w_{2,1}^{(2)}$$

역전파(Backpropagation)

$$\boxed{\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \frac{\partial J_{total}}{\partial a_1^{(2)}} \times \frac{\partial a_1^{(2)}}{\partial z_1^{(2)}} \times \frac{\partial z_1^{(2)}}{\partial w_{1,1}^{(1)}}}$$



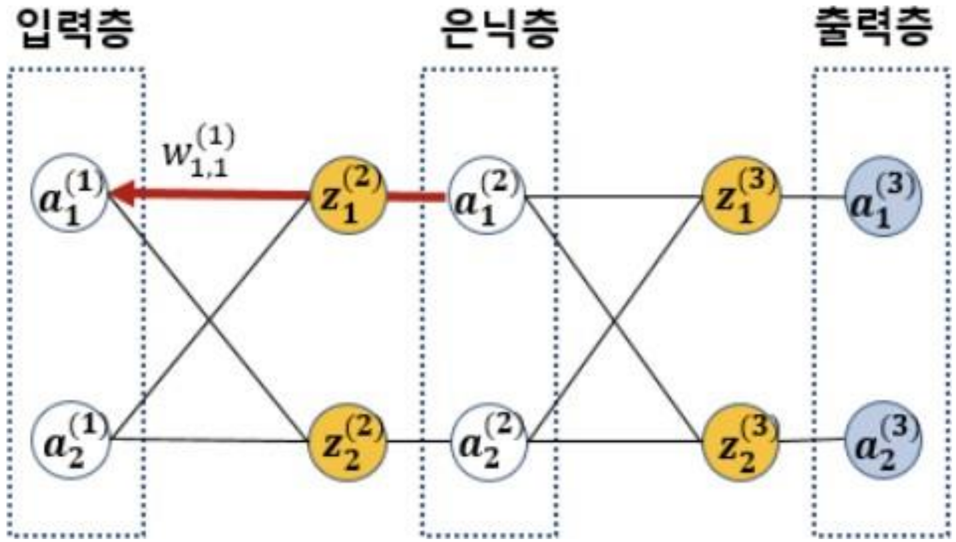
$$\frac{\partial J_{total}}{\partial a_1^{(2)}} = \frac{\partial J_1}{\partial a_1^{(2)}} + \frac{\partial J_2}{\partial a_1^{(2)}} = \frac{\partial J_1}{\partial z_1^{(3)}} \times \boxed{\frac{\partial z_1^{(3)}}{\partial a_1^{(2)}}} + \frac{\partial J_2}{\partial z_2^{(3)}} \times \boxed{\frac{\partial z_2^{(3)}}{\partial a_1^{(2)}}}$$

$$= \delta_1^{(3)} \boxed{w_{1,1}^{(2)}} + \delta_2^{(3)} \boxed{w_{2,1}^{(2)}}$$

$$z_1^{(3)} = w_{1,1}^{(2)} a_1^{(2)} + w_{1,2}^{(2)} a_2^{(2)}$$

$$z_2^{(3)} = w_{2,1}^{(2)} a_1^{(2)} + w_{2,2}^{(2)} a_2^{(2)}$$

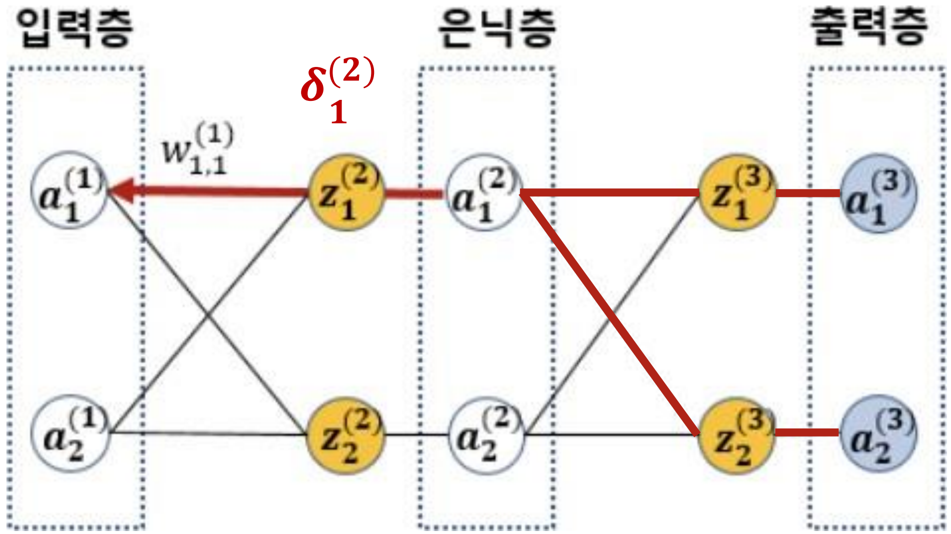
역전파(Backpropagation)



$$\boxed{\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \frac{\partial J_{total}}{\partial a_1^{(2)}} \times \frac{\partial a_1^{(2)}}{\partial z_1^{(2)}} \times \frac{\partial z_1^{(2)}}{\partial w_{1,1}^{(1)}}}$$

$$\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \underline{\left(\delta_1^{(3)} w_{1,1}^{(2)} + \delta_2^{(3)} w_{2,1}^{(2)}\right)} \times \underline{a_1^{(2)}\left(1 - a_1^{(2)}\right)} \times \underline{a_1^{(1)}}$$

역전파(Backpropagation)

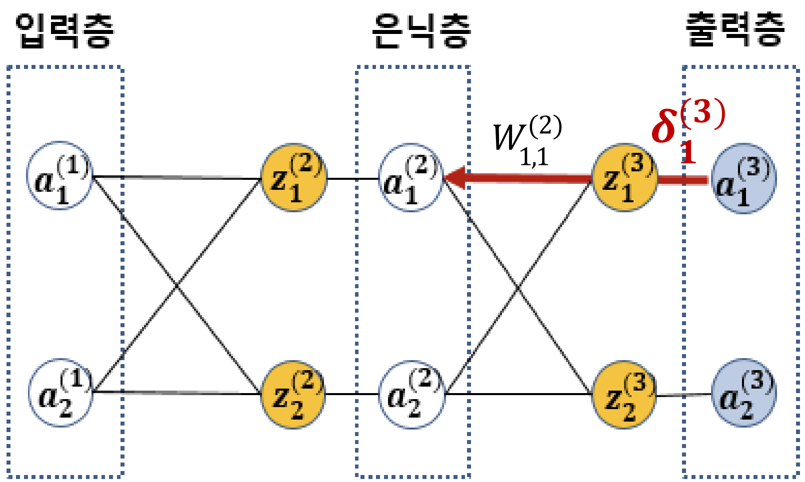


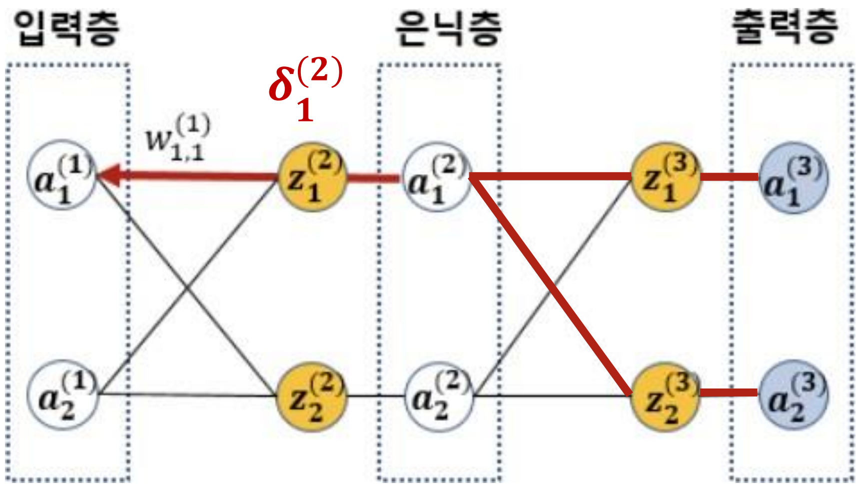
$$\frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \underline{\left(\delta_1^{(3)} w_{1,1}^{(2)} + \delta_2^{(3)} w_{2,1}^{(2)}\right) \times a_1^{(2)} \left(1 - a_1^{(2)}\right)} \times a_1^{(1)}$$

$$\delta_1^{(2)} = (\delta_1^{(3)} w_{1,1}^{(2)} - \delta_2^{(3)} w_{2,1}^{(2)}) \times a_1^{(2)}(1 - a_1^{(2)})$$

$$w_{1,1}^{(1)} = w_{1,1}^{(1)} - \frac{\partial J_{total}}{\partial w_{1,1}^{(1)}} = \boxed{w_{1,1}^{(1)} - \delta_1^{(2)} a_1^{(1)}}$$

역전파(Backpropagation)



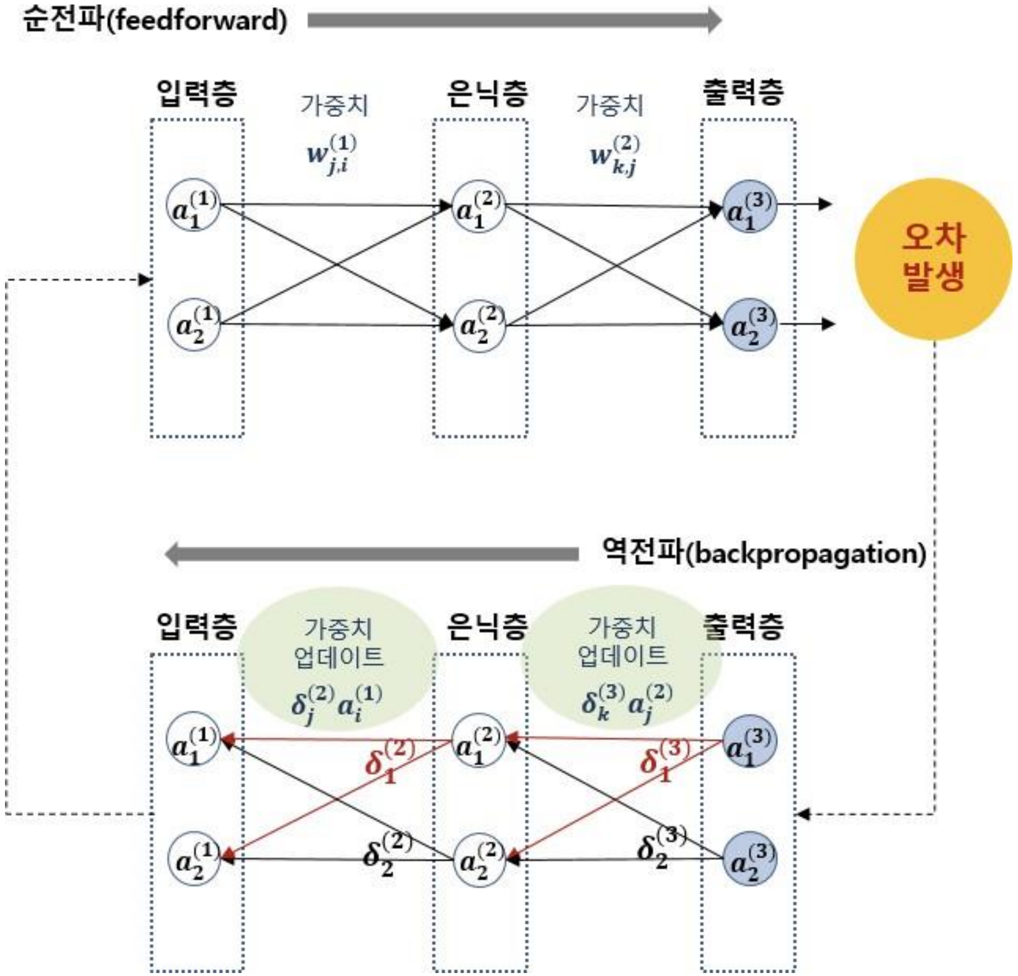


$$w_{1,1}^{(2)} = w_{1,1}^{(2)} - \delta_1^{(3)} a_1^{(2)}$$

$$w_{1,1}^{(1)} = w_{1,1}^{(1)} - \delta_1^{(2)} a_1^{(1)}$$

Unit 02 | Backpropagation

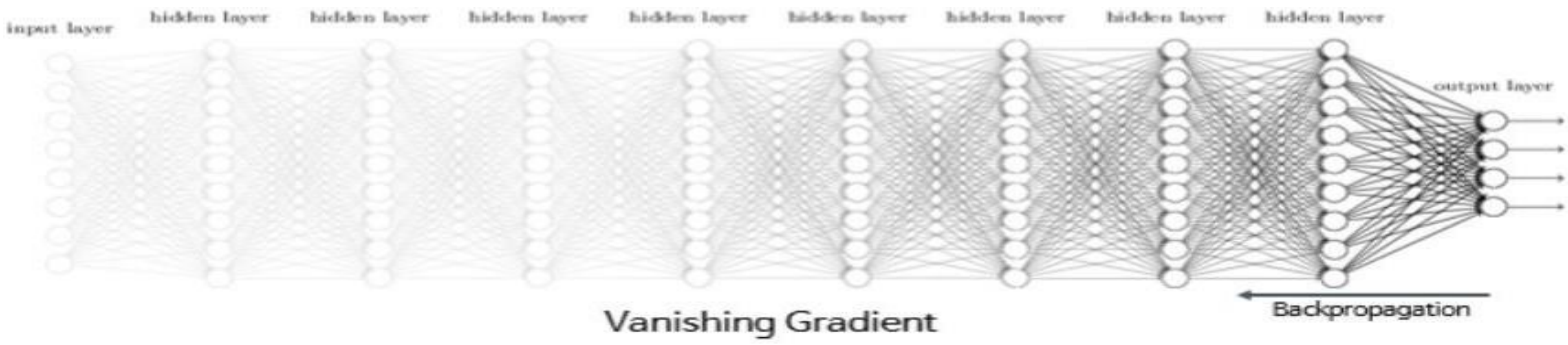
역전파 (Backpropagation)



Vanishing Gradient Problem

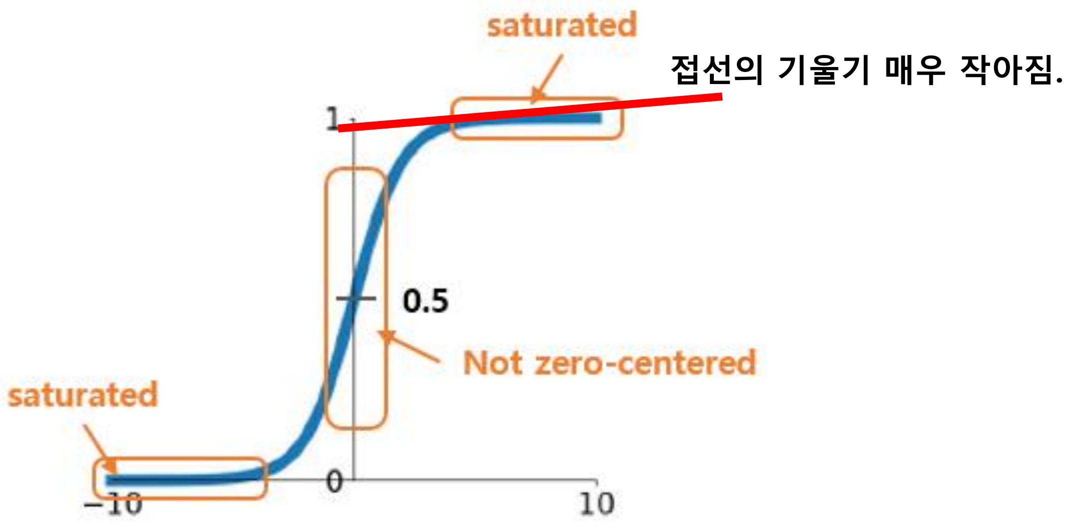
깊이가 깊은 심층신경망에서는 역전파 알고리즘이 입력층으로 전달됨에 따라

그래디언트가 점점 작아져 결국 가중치 매개변수가 업데이트 되지 않는 경우가 발생



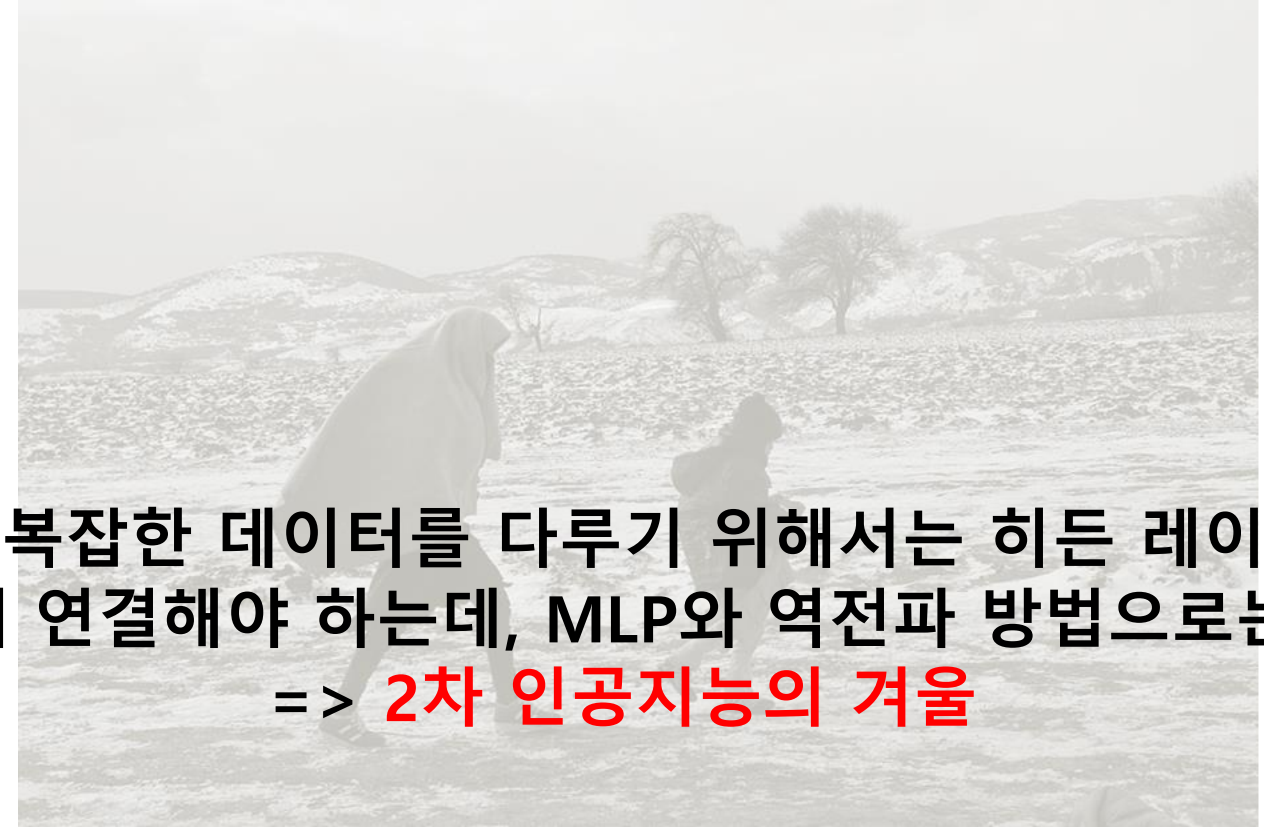
Vanishing Gradient Problem - sigmoid

Sigmoid



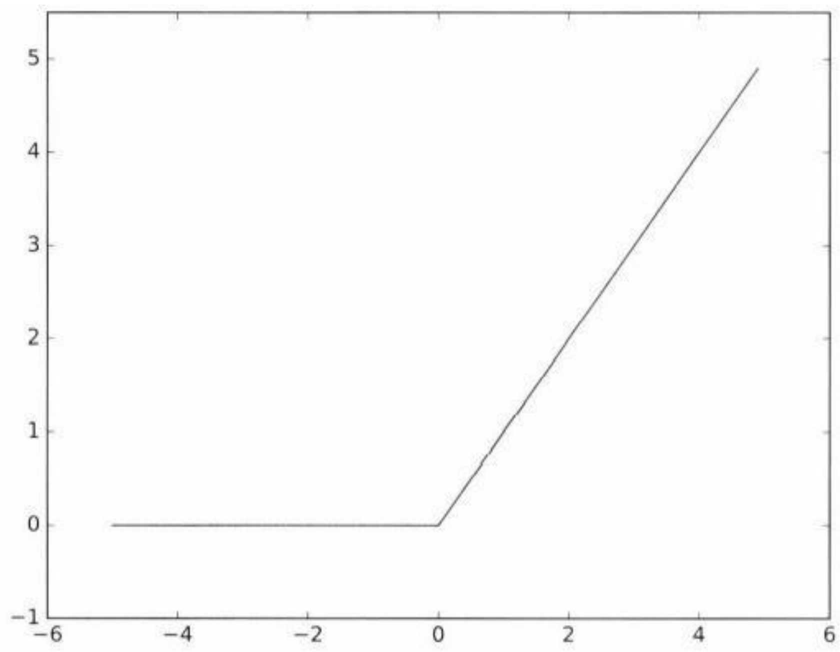
- 기울기가 작아지는 좌우 부분은 미분하면 0이 됨
- 역전파를 이용하여 편미분할 때 $\frac{dj_{total}}{dw}$ 가 0이되어 가중치 업데이트가 없어지는 현상이 saturated 현상

Vanishing Gradient Problem



크고 복잡한 데이터를 다루기 위해서는 히든 레이어를
여러 개 연결해야 하는데, MLP와 역전파 방법으로는 한계
=> 2차 인공지능의 겨울

활성화함수 - ReLU 함수



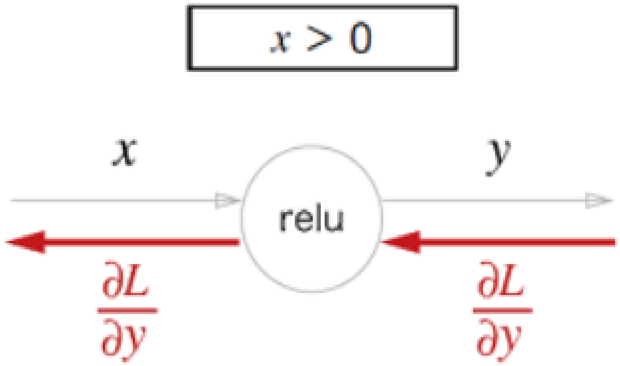
$$h(x) = \begin{cases} x & (x > 0) \\ 0 & (x \leq 0) \end{cases}$$

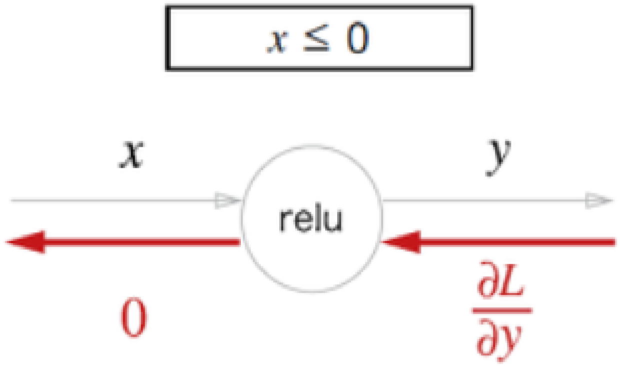
- Vanishing gradient problem 해결!
- 입력이 0 넘으면 값이 클수록 많이 활성화
- 입력이 0 보다 작으면 무조건 비활성화
- 다른 활성화 함수보다 계산 복잡도가 낮아서 학습 속도가 빠름
- 비선형함수

활성화함수 - ReLU 함수

$$y = \begin{cases} x & (x > 0) \\ 0 & (x \leq 0) \end{cases}$$

$$\frac{\partial y}{\partial x} = \begin{cases} 1 & (x > 0) \\ 0 & (x \leq 0) \end{cases}$$





Unit | 과제

"week3_NeuralNetworkBasic_assignment.pdf" 파일의 문제들을 상세한 풀이과정과 함께 풀어주세요.

"week3_NeuralNetworkBasic_실습.ipynb" 노트북 파일에서 코드 실습을 진행해 주세요.

Reference

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- https://heeya-stupidbutstudying.tistory.com/38
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- 딥러닝 Neural Network AND 함수, XOR 문제 해결 방법 (tistory.com)
- 퍼셉트론(Perceptron) (tistory.com)
- 실체가 손에 잡히는 딥러닝(3) "이것만은 꼭 알아두자! 딥러닝의 꽃 - 가중치, 편향, 활성화 함수, 역전파" | Popit
- [기계학습] Neural Networks 1 (velog.io)
- 활성화 함수 종료 : [ML] 활성화 함수(Activation Function) 종류 정리 (tistory.com)
- Vanishing Gradient Problem(기울기 소멸 문제) – 창의 컴퓨팅(Creative Computing)

Q & A

들어주셔서 감사합니다.