

Linear Regression & Neural Network

2018.02.28

최건호

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- Loss
- Gradient Descent
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- 활용

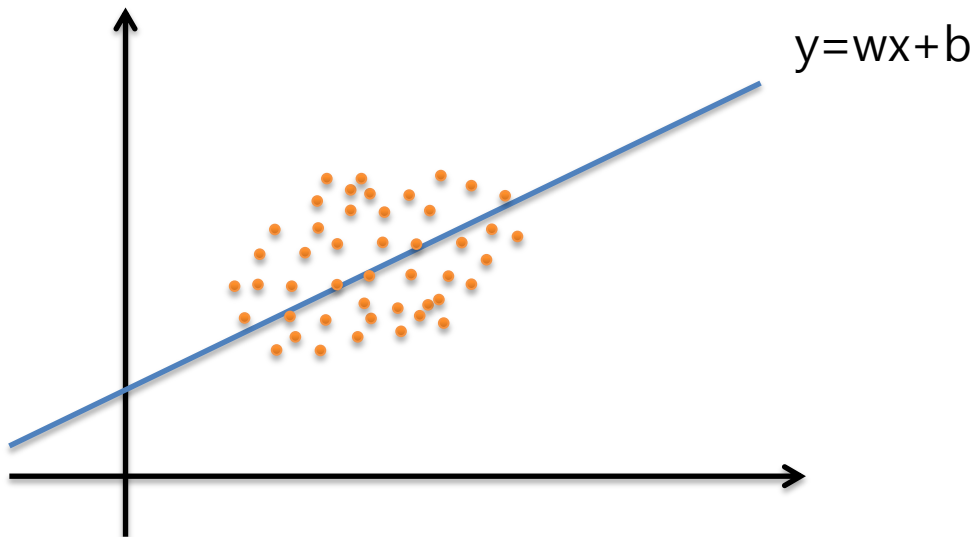
03

Propagation

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-

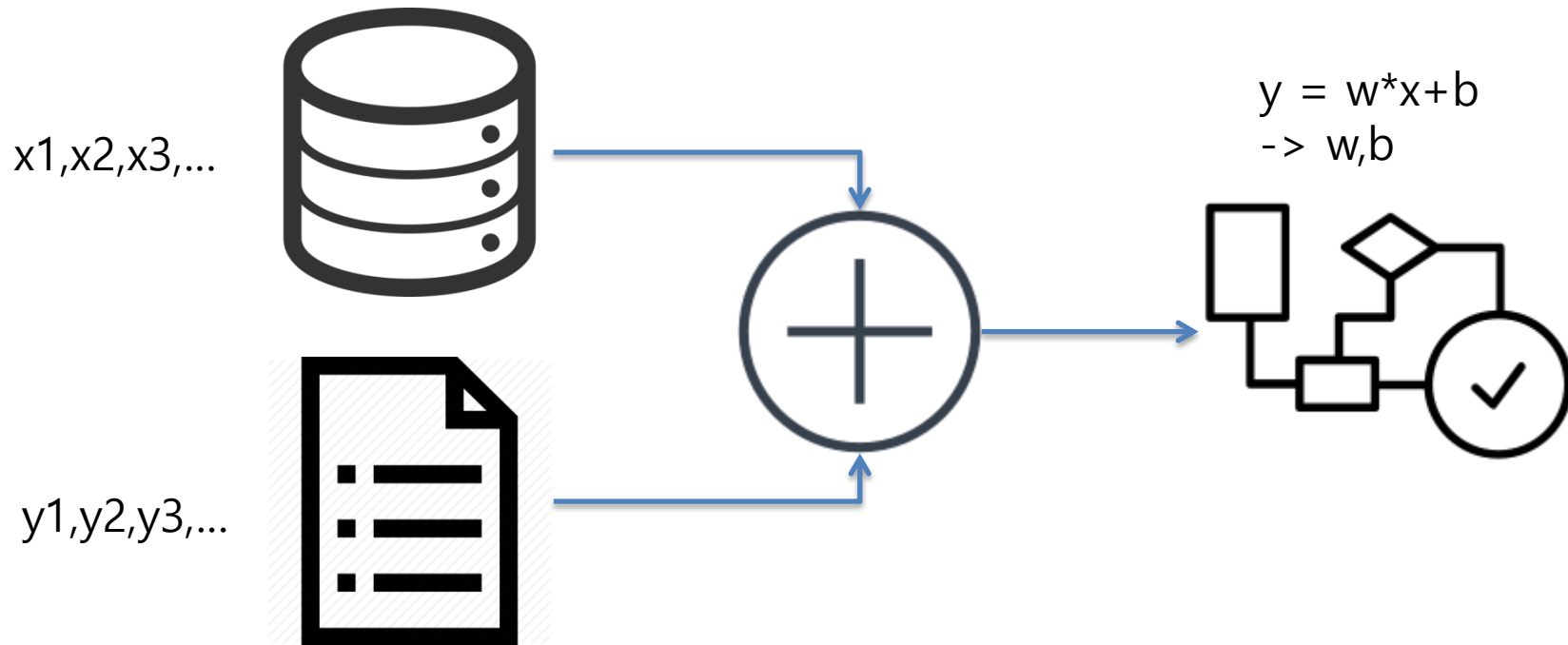
Linear Regression

x에 대한 y값을 가장 잘 설명하는
변수 w , b 를 찾는 것

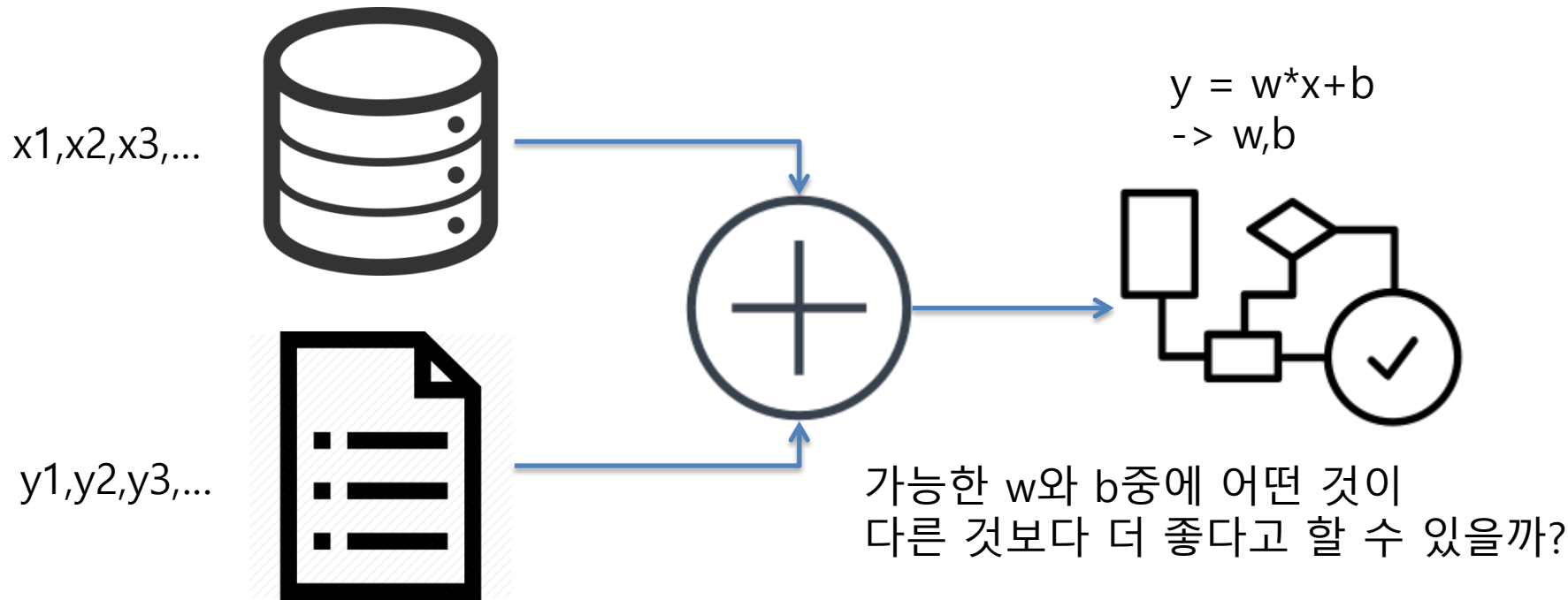


종속 변수 y 와 한 개 이상의 독립 변수 x 와의
선형 상관 관계를 모델링하는 회귀분석 기법
(출처: 위키피디아)

Linear Regression



Linear Regression

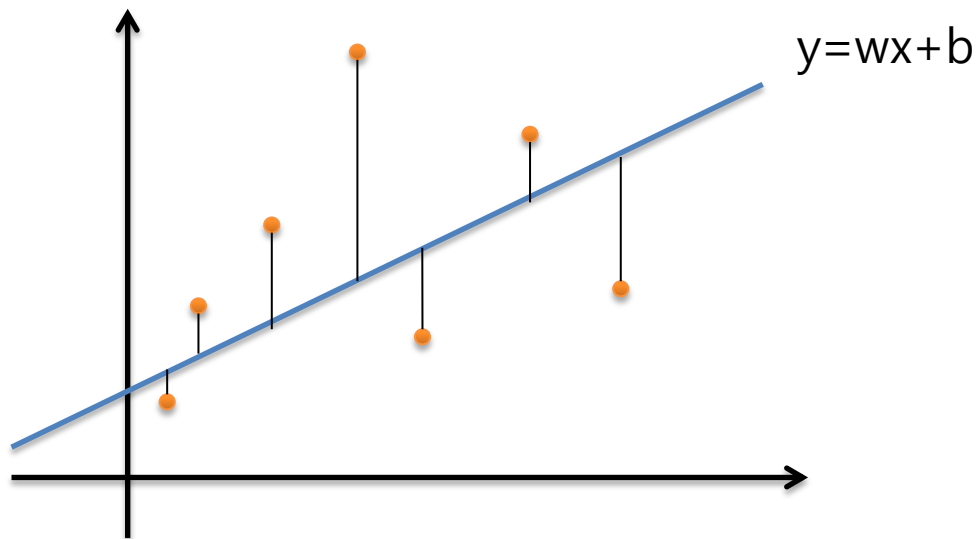


Linear Regression

잘 예측했는지 아닌지 측정할 척도(metric)가 필요함

Linear Regression

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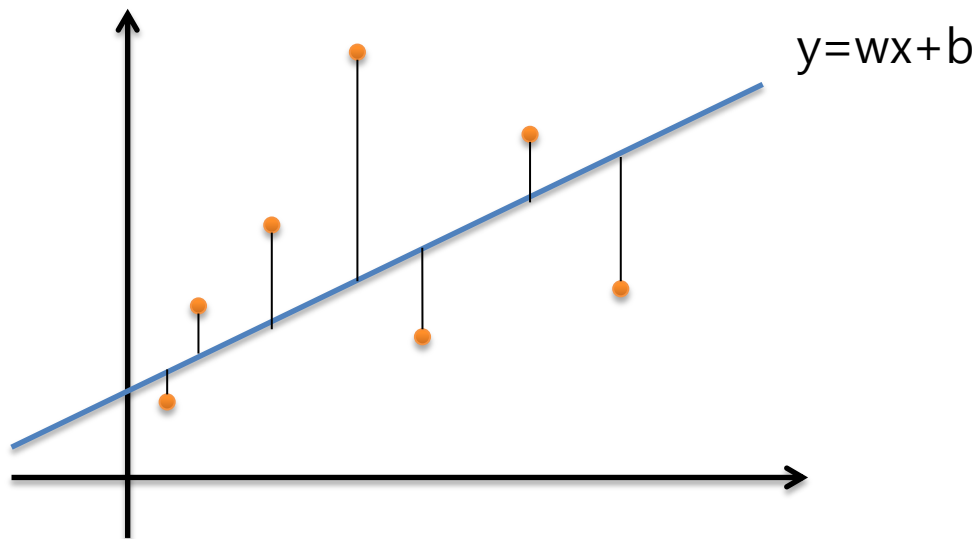
Linear Regression

잘 예측했는지 아닌지 측정할 척도(metric)가 필요함

Mean Squared Error(MSE)

$$MSE = \frac{(x1 - x2)^2}{n}$$

두 값의 거리의 제곱의 평균



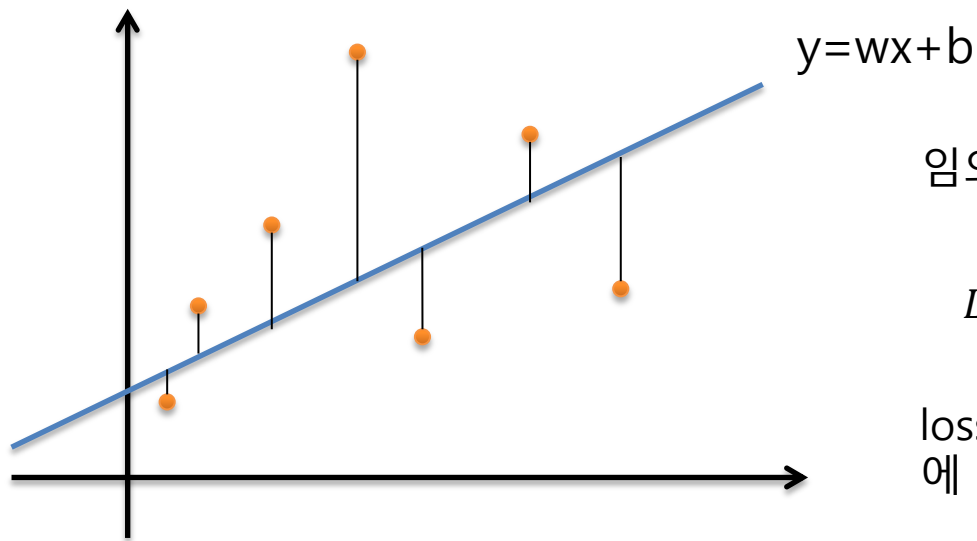
Linear Regression

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두 값의 거리의 제곱의 평균



임의의 w^*, b^* 를 초기값으로 한다면

$$Loss = \frac{(y^* - y)^2}{n} = \frac{(w^*x + b^* - y)^2}{n}$$

loss값은 고정된 x, y (데이터)에서 w^*, b^* 에 의해 구해짐

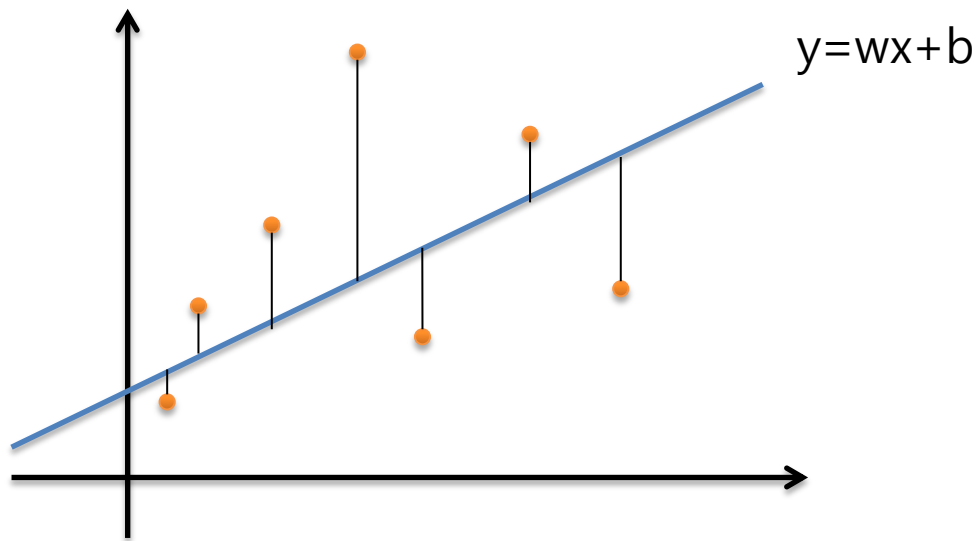
Linear Regression

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두 값의 거리의 제곱의 평균



예시)
 $y = 0.5x + 4$ 이고 $w^*=2$,
 $b^*=2$ 일 때, $x=3$ 에서 loss는?

$$Loss = \frac{(8 - 5.5)^2}{n} = \frac{(2.5)^2}{n}$$

Linear Regression

Loss를 minimize하는 w, b 를 구하고 싶다.



Linear Regression

Loss를 minimize하는 w, b 를 구하고 싶다.

-> Random Search?

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Loss를 minimize하는 w, b 를 구하고 싶다.

- > Random Search? 어느 세월에..
- > Loss 값을 통해서 구할 수 있을까?

Linear Regression

Loss를 minimize하는 w, b 를 구하고 싶다.

-> Random Search? 어느 세월에..

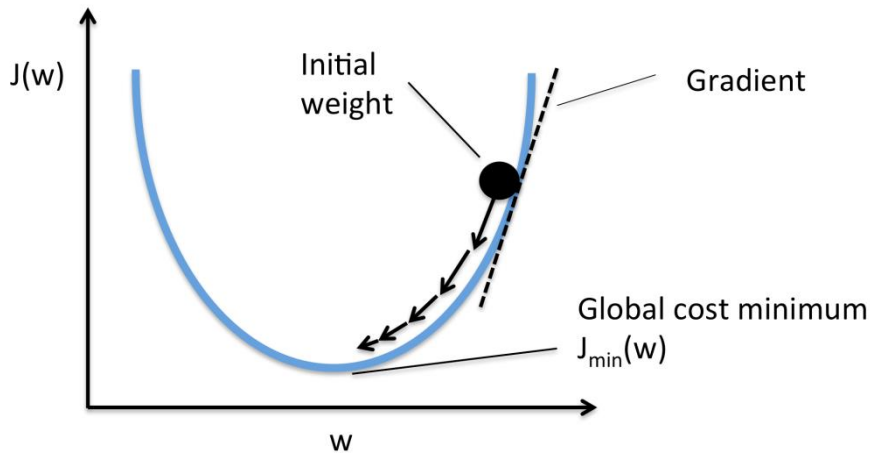
-> Loss 값을 통해서 구할 수 없을까? Gradient Descent!

Linear Regression

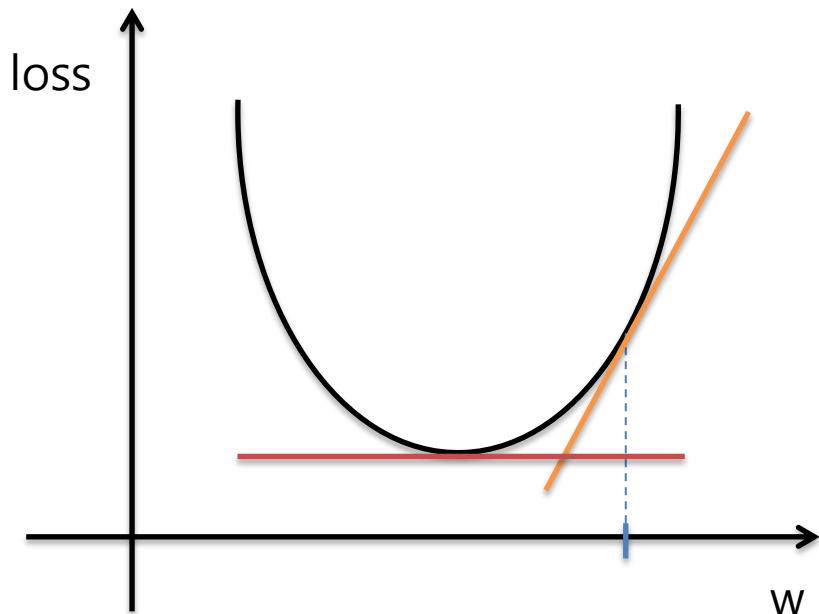
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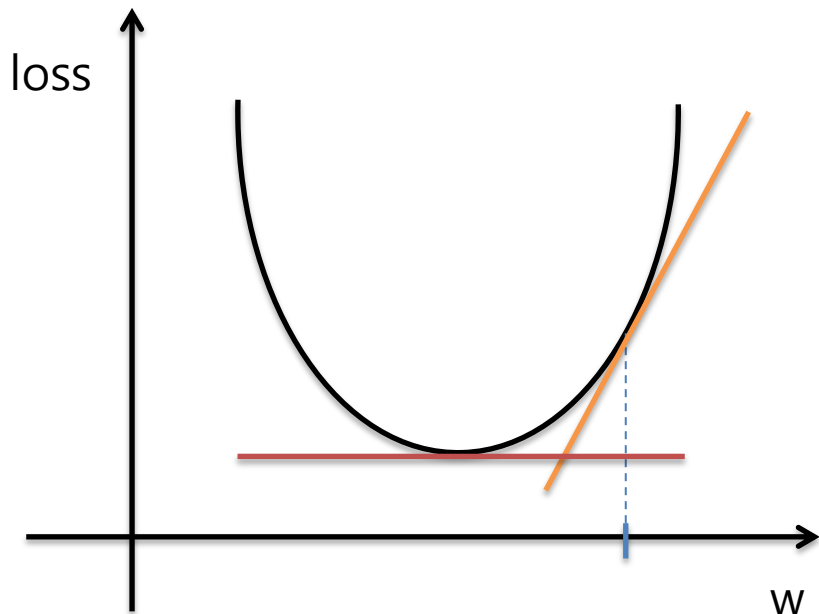


Linear Regression



그냥 바로 loss를 w 에 대해 미분
했을 때 그 값이 0이 되는 w 를
찾으면 안될까?

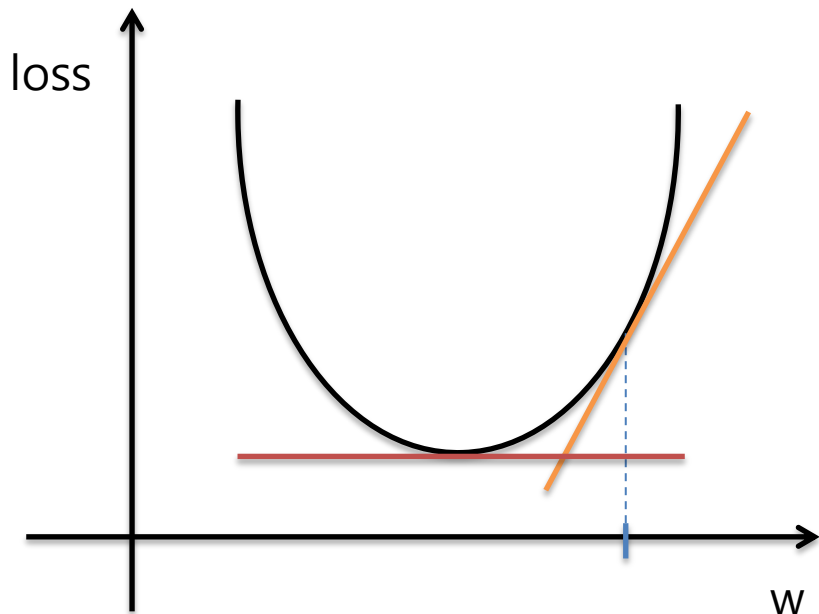
Linear Regression



그냥 바로 loss를 w 에 대해 미분했을 때 그 값이 0이 되는 w 를 찾으면 안될까?

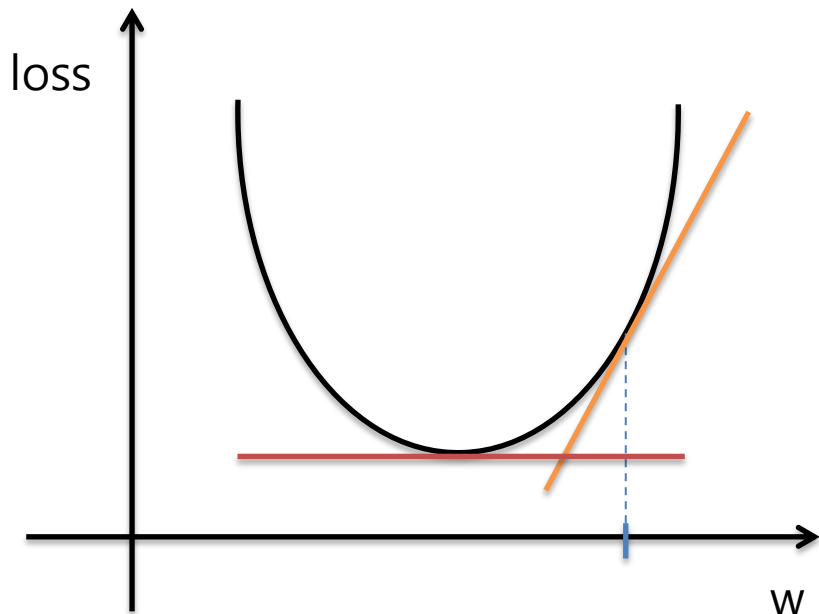
loss를 minimize하는 w 를 구하려면 $w = (x^T x)^{-1} x^T y$ 식을 풀어야 하는데, 변수가 많아지고 matrix가 커지면 복잡도가 $O(n^3)$ 이기 때문에 exponential 하게 증가한다. 변수가 많아질수록 계산이 거의 불가능.

Linear Regression



바로 minimum이 되는 지점을 구하기보다, 현재 loss에 대한 w 의 **gradient(경사도)**를 구하여 $\text{gradient} \times \text{learning rate}$ 만큼 w 를 업데이트

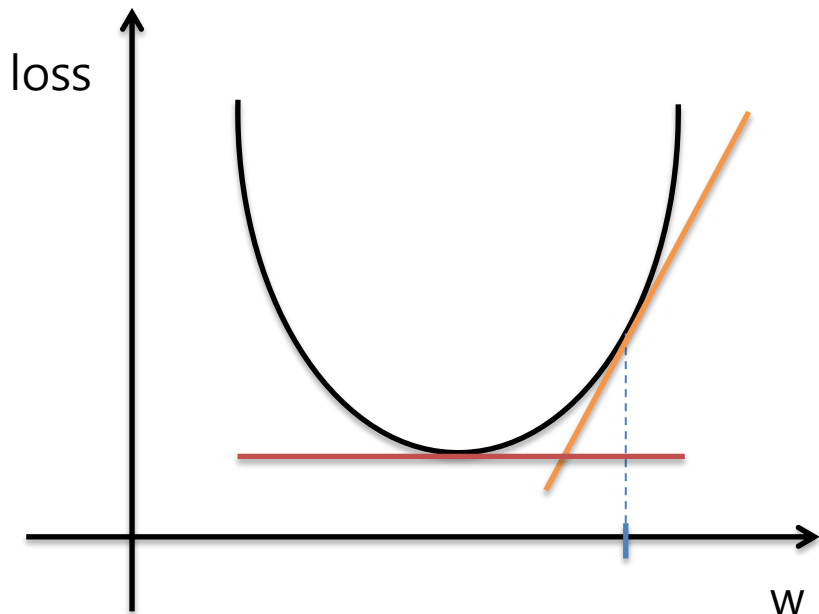
Linear Regression



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$$w_{t+1} = w_t - \text{gradient} * \text{learning_rate}$$

Linear Regression

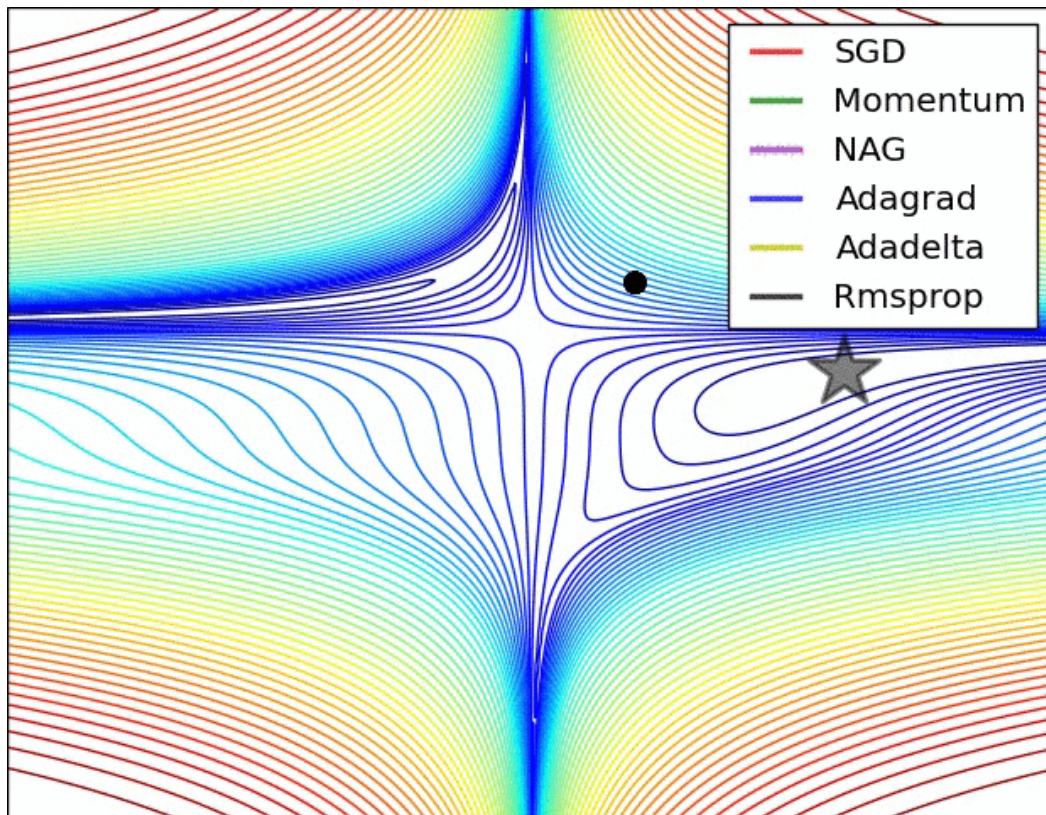


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$$w_{t+1} = w_t - \text{gradient} * \text{learning_rate}$$

계속 업데이트 하다 보면 optimal한 w 에 근접하게 된다.

Linear Regression



Linear Regression

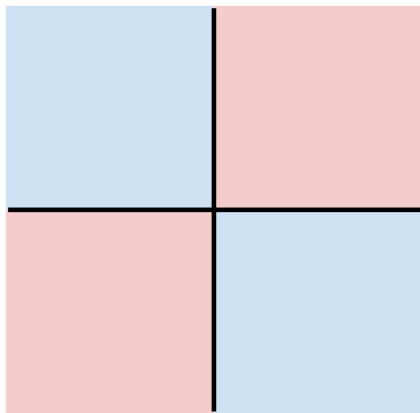
Hard cases for a linear classifier

Class 1:

number of pixels > 0 odd

Class 2:

number of pixels > 0 even

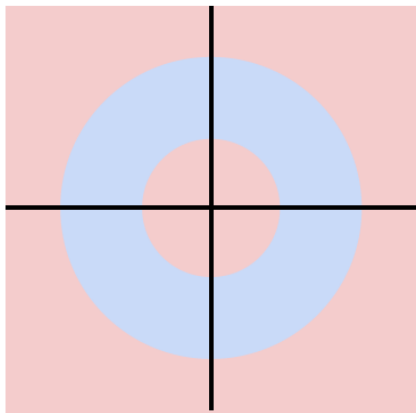


Class 1:

$1 \leq \text{L2 norm} \leq 2$

Class 2:

Everything else

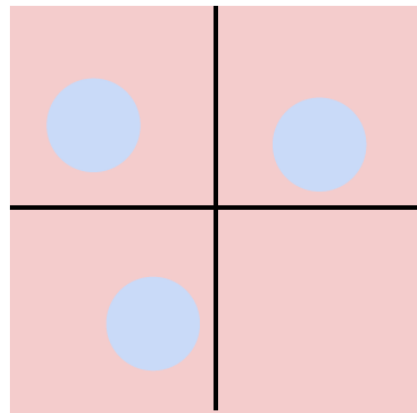


Class 1:

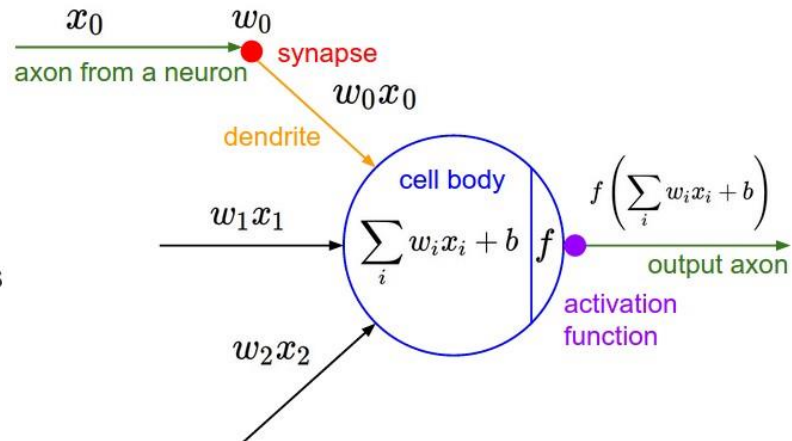
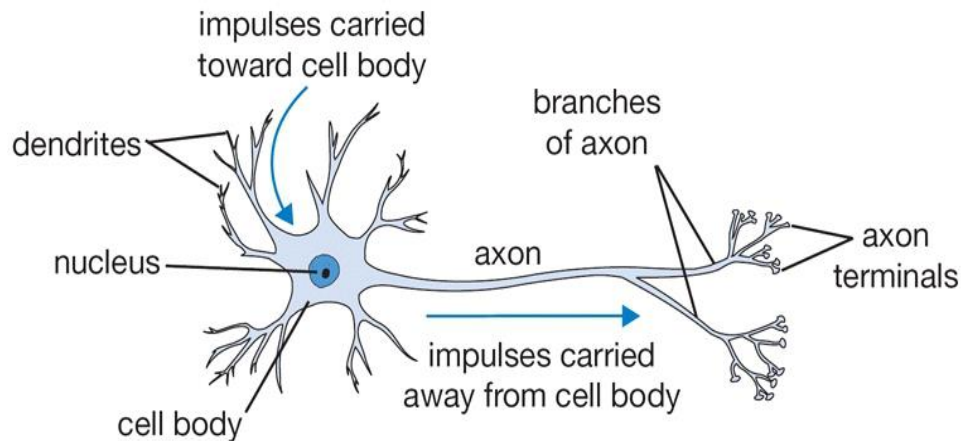
Three modes

Class 2:

Everything else



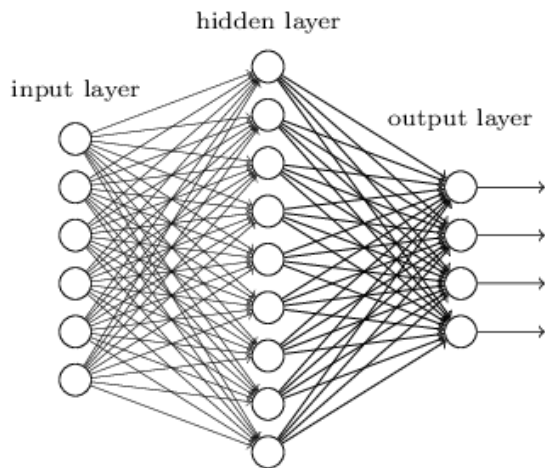
Neural Network



여러 자극이 들어오고 일정 기준을 넘으면 이를 다른 뉴런에 전달하는 구조

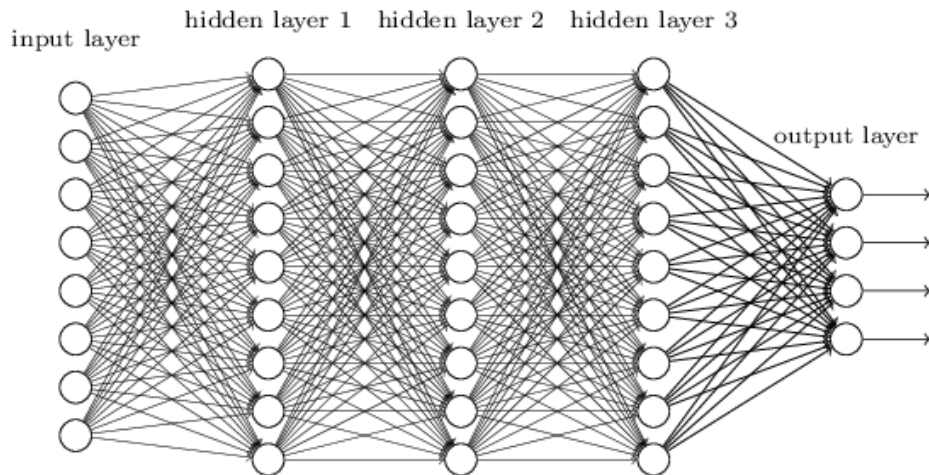
Neural Network

"Non-deep" feedforward neural network



$$y = w2(\text{act}(w1 * \text{input} + b1)) + b2$$

Deep neural network



$$y = w4(\text{act}(w3(\text{act}(w2(\text{act}(w1 * \text{input} + b1)) + b2)) + b3)) + b4$$

Neural Network

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

$$= \begin{bmatrix} x_{00} & x_{01} & \dots & \dots & \dots \\ x_{10} & x_{11} & & & \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & & & \vdots \\ \vdots & \vdots & & & \vdots \\ \vdots & \vdots & & & \vdots \\ x_{mn} & & & & \end{bmatrix} \begin{bmatrix} w_{00} & w_{01} & w_{02} & \dots & \dots \\ w_{10} & w_{11} & & & \\ w_{20} & & & & \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & & & \vdots \\ \vdots & \vdots & & & \vdots \\ \vdots & \vdots & & & \vdots \\ w_{nl} & & & & \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ b_m \end{bmatrix}$$

$m \times n$ $n \times l$ $m \times 1$

Neural Network

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

The diagram illustrates the matrix multiplication $W \cdot X$ and the addition of the bias vector b to produce the output Y .

Matrix X (Input): A matrix of size $m \times n$. The top row is labeled $x_{00} \ x_{01} \ \dots$ and the bottom row is labeled $x_{m0} \ x_{m1} \ \dots$. The top row is highlighted with an orange box.

Matrix W (Weights): A matrix of size $n \times l$. The top row is labeled $w_{00} \ w_{01} \ w_{02} \ \dots$ and the bottom row is labeled $w_{n0} \ w_{n1} \ \dots$. The first column is highlighted with an orange box.

Vector b (Bias): A vector of size $m \times 1$. The top element is labeled b_0 and the bottom element is labeled b_m . The top element is highlighted with an orange box.

The equation is represented as:

$$= \begin{bmatrix} x_{00} & x_{01} & \dots & x_{m0} & x_{m1} & \dots \end{bmatrix} \begin{bmatrix} w_{00} & w_{01} & w_{02} & \dots & w_{n0} & w_{n1} & \dots \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_m \end{bmatrix}$$

The dimensions are indicated below the matrices:

- $m \times n$ for matrix X
- $n \times l$ for matrix W
- $m \times 1$ for vector b

Neural Network

$$y = \text{act}(wx + b)$$

$$= \text{activation} \left(\begin{bmatrix} wx + b \end{bmatrix} \right)$$

$m \times 1$

Neural Network

만약 activation function이 없다면 아래의 식은 결국 linear function.

$$y = w_4(\text{act}(w_3(\text{act}(w_2(\text{act}(w_1 * \text{input} + b_1)) + b_2)) + b_3)) + b_4$$

Neural Network

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activation function으로 non-linearity를 추가해야 함

Neural Network

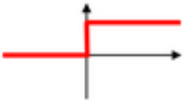
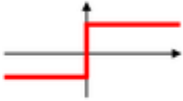

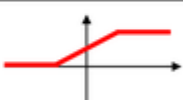


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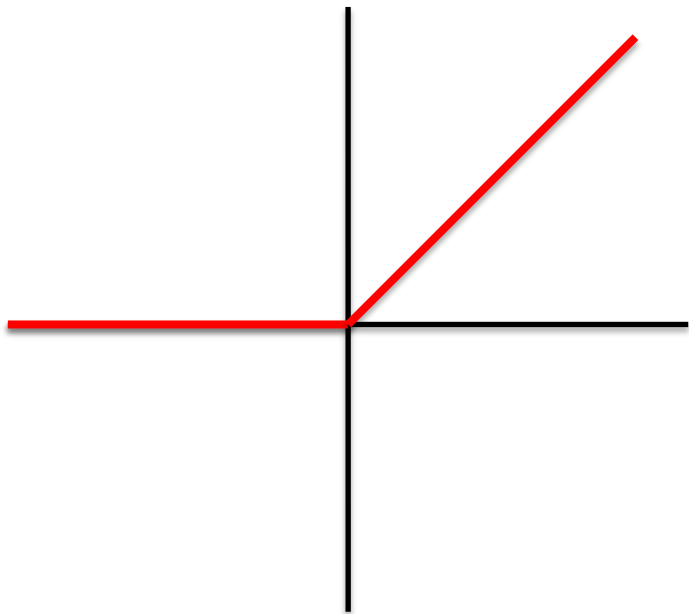
activation function으로 non-linearity를 추가해야 함

그렇다면 어떤 activation function을 써야 할까?

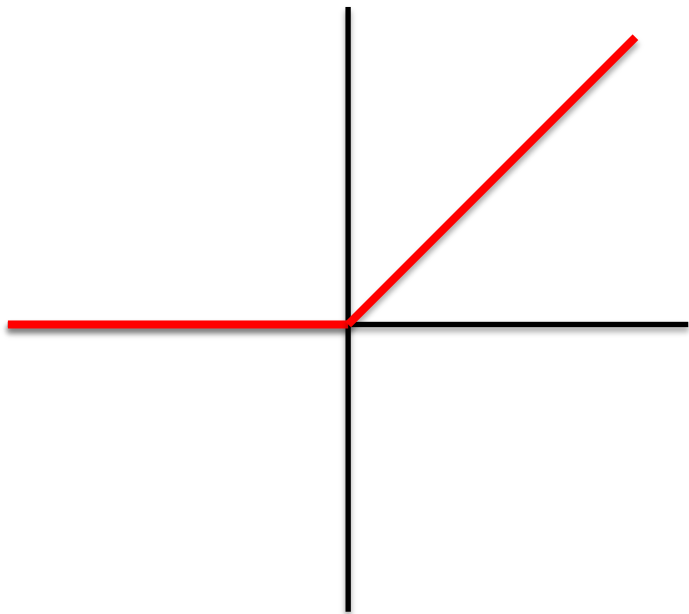
Neural Network

Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer NN	

Neural Network

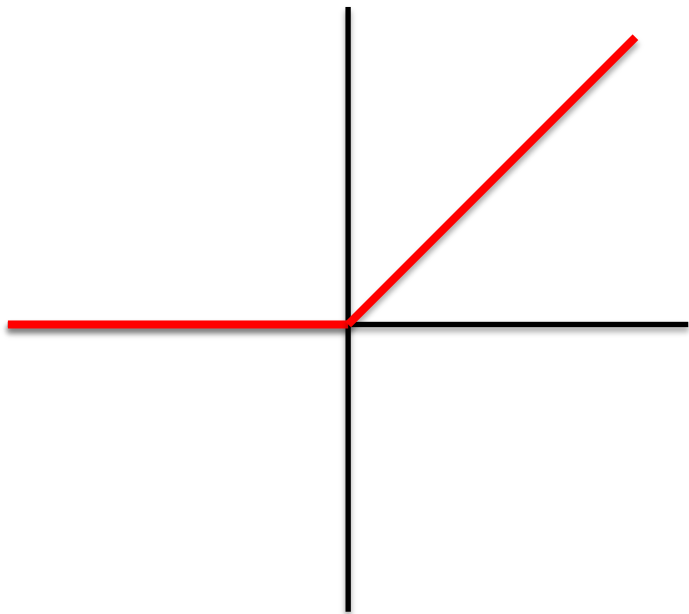


Neural Network



Rectified Linear Unit (ReLU)

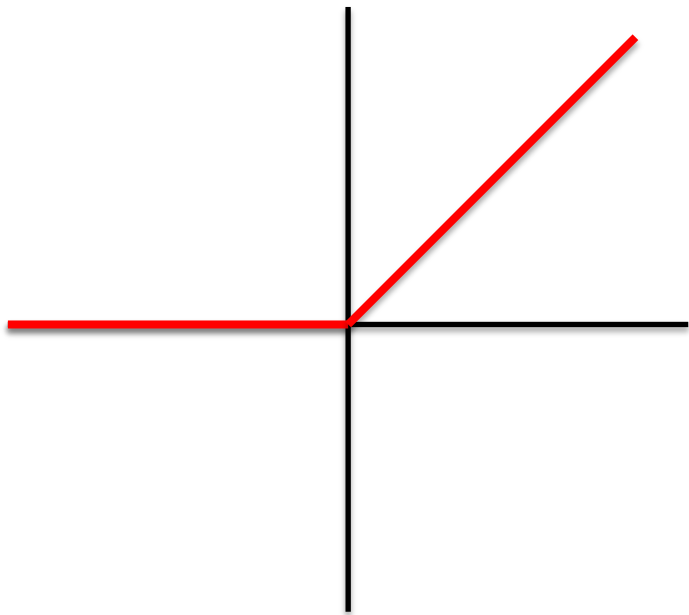
Neural Network



Rectified Linear Unit (ReLU)

$$f(x) = \max(0, x)$$

Neural Network

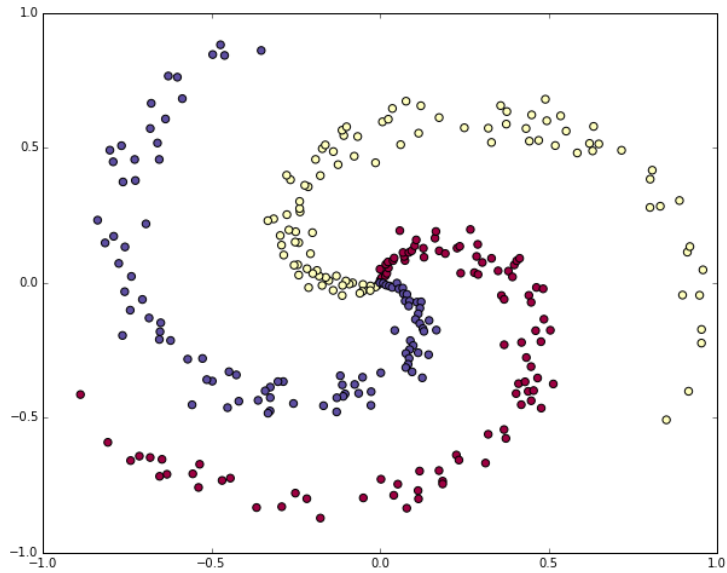


Rectified Linear Unit (ReLU)

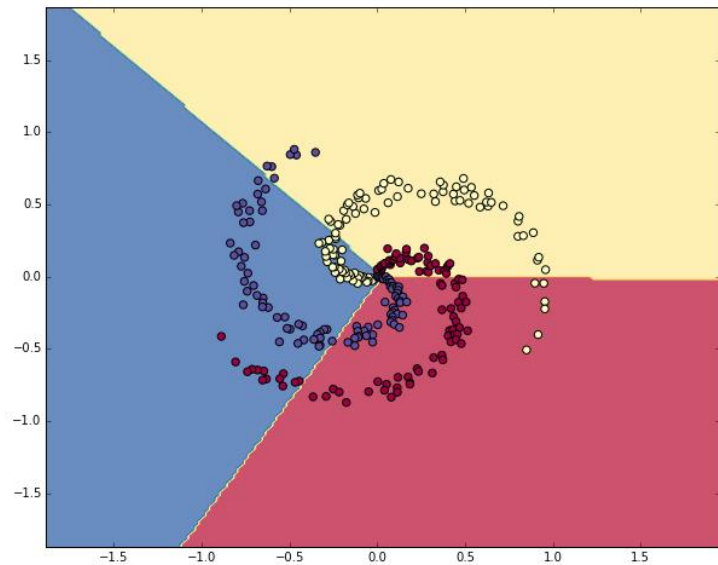
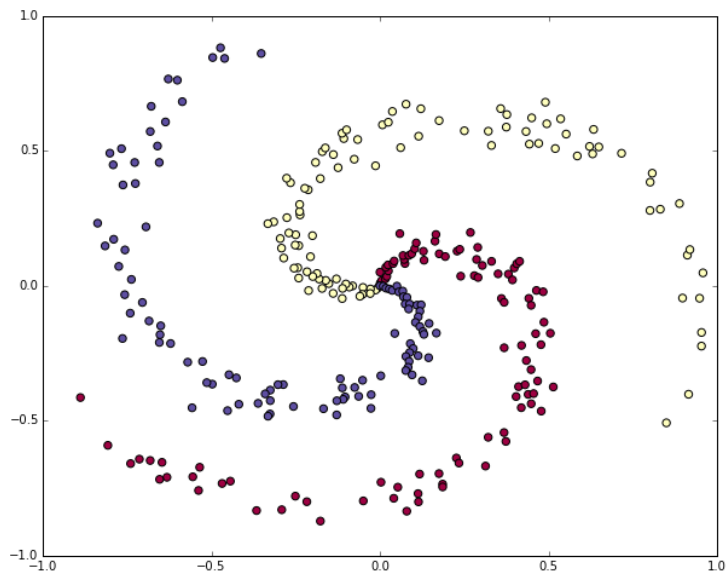
$$f(x) = \max(0, x)$$

기존의 sigmoid와 tanh로는
학습이 잘 안됐었는데 relu는
gradient의 전달이 좋아서
default로 사용되고 있음

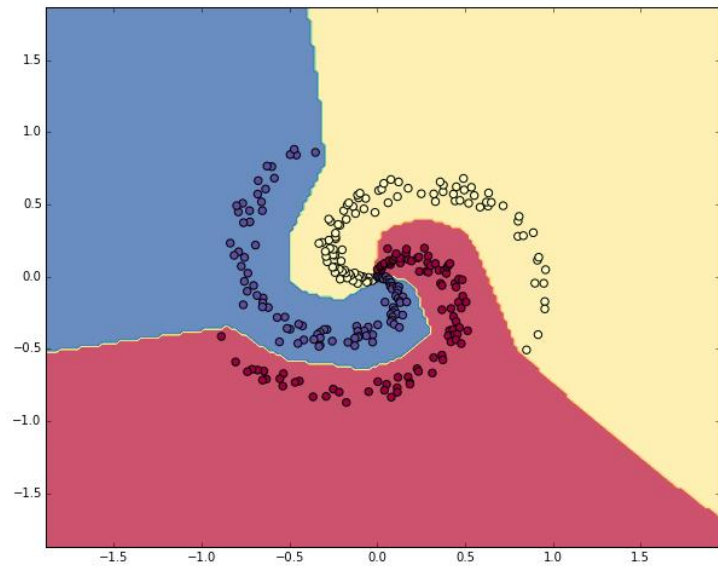
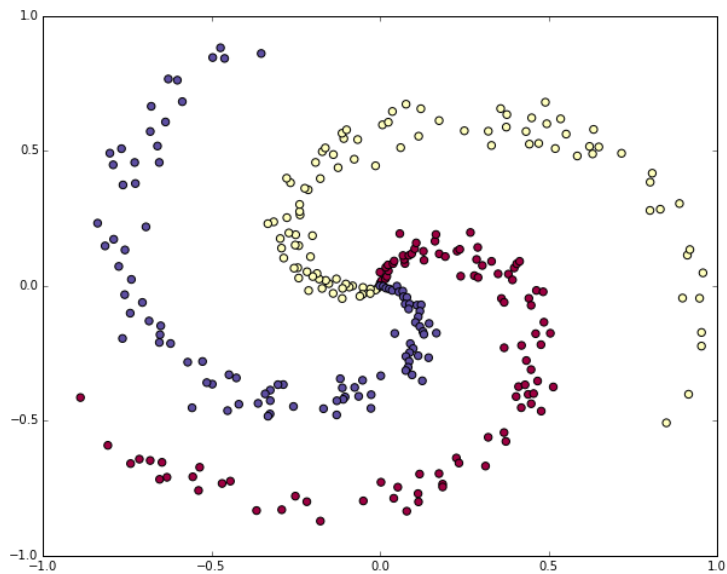
Neural Network



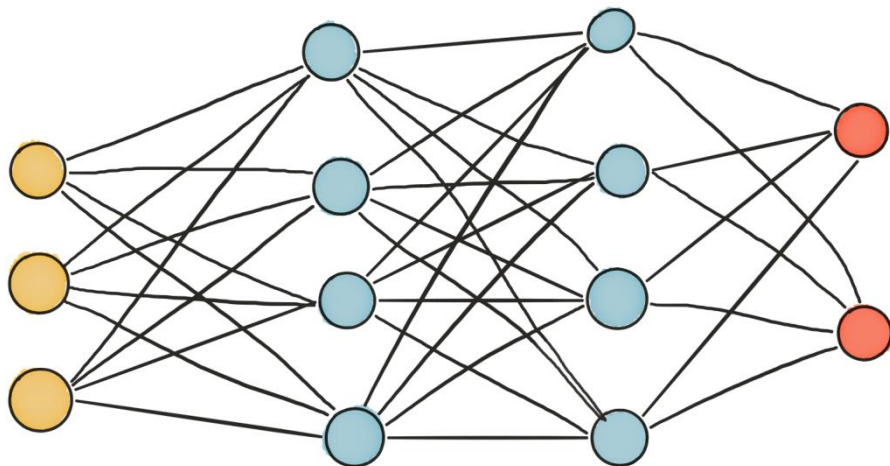
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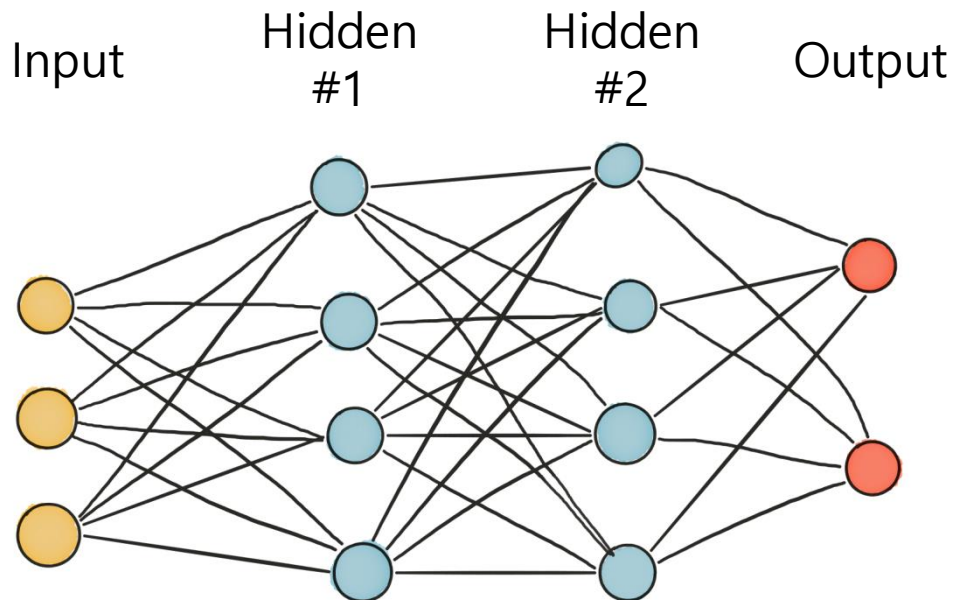
Neural Network



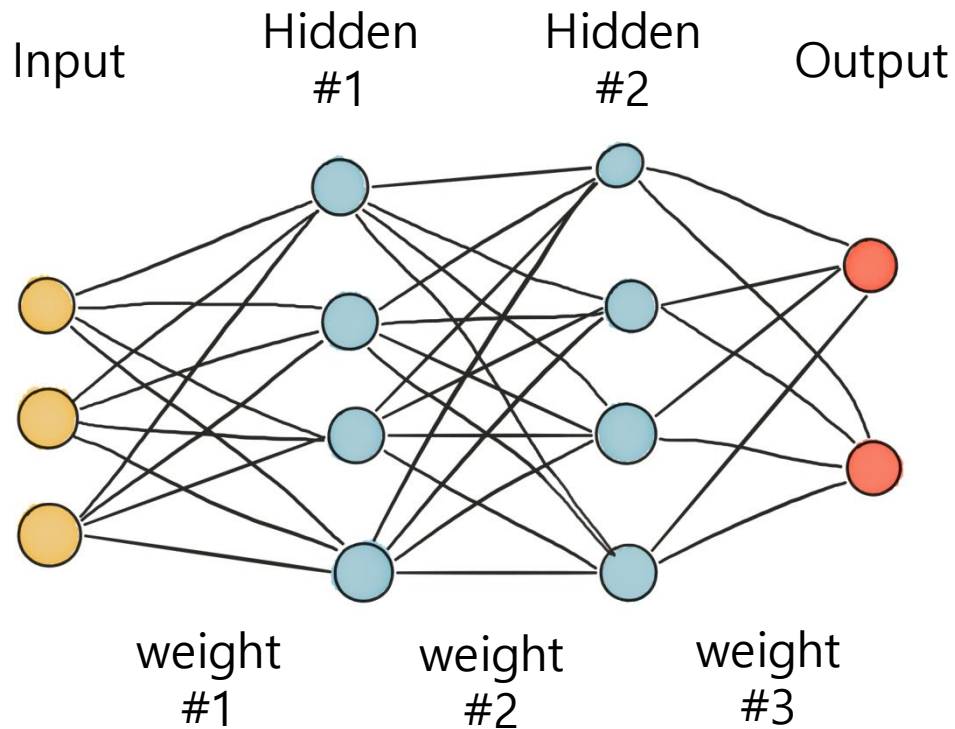
Forward & Back Prop.



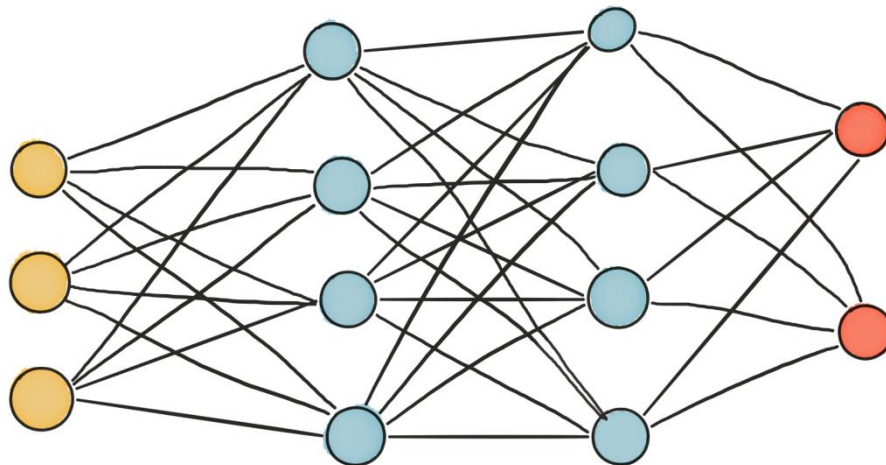
Forward & Back Prop.



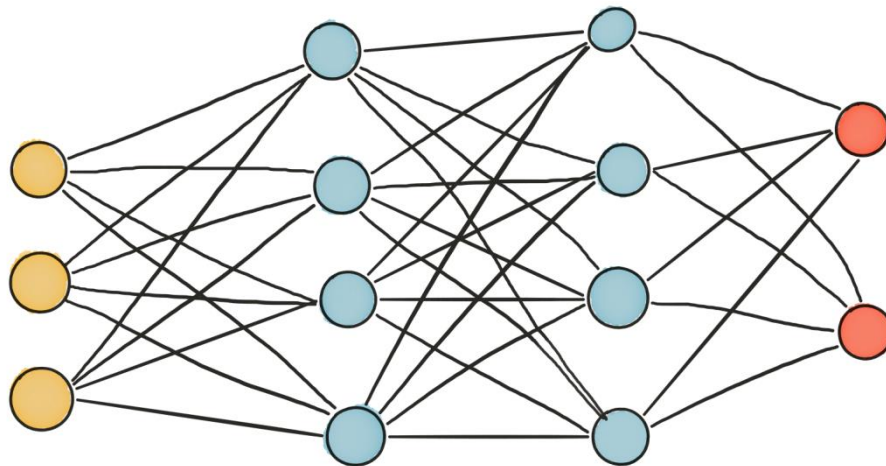
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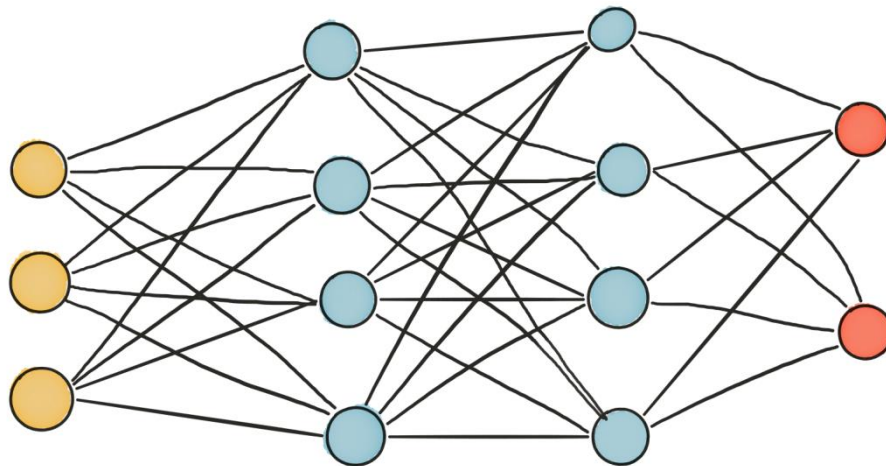


Forward & Back Prop.



$$\begin{bmatrix} w_{00} & w_{01} & w_{02} & w_{03} \\ w_{10} & w_{11} & w_{12} & w_{13} \\ w_{20} & w_{21} & w_{22} & w_{23} \end{bmatrix} \times \begin{bmatrix} w_{00} & w_{01} & w_{02} & w_{03} \\ w_{10} & w_{11} & w_{12} & w_{13} \\ w_{20} & w_{21} & w_{22} & w_{23} \\ w_{30} & w_{31} & w_{32} & w_{33} \end{bmatrix} \times \begin{bmatrix} w_{00} & w_{01} \\ w_{10} & w_{11} \\ w_{20} & w_{21} \\ w_{30} & w_{31} \end{bmatrix}$$

Forward & Back Prop.

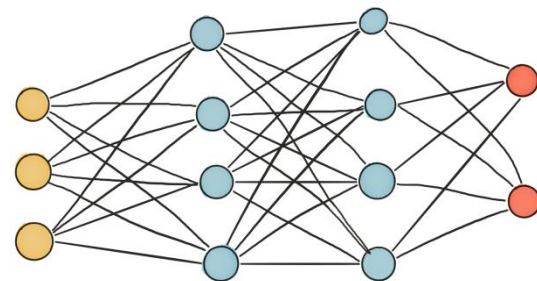


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$3 \times 4 \qquad \qquad \qquad 4 \times 4 \qquad \qquad \qquad 4 \times 2$

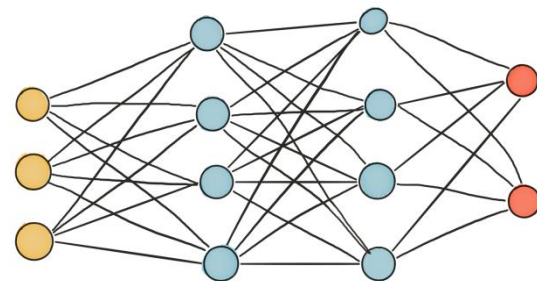
Forward & Back Prop.

$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$



쉽게 이해되도록
loss = 예측값-실제로 설정

Forward & Back Prop.

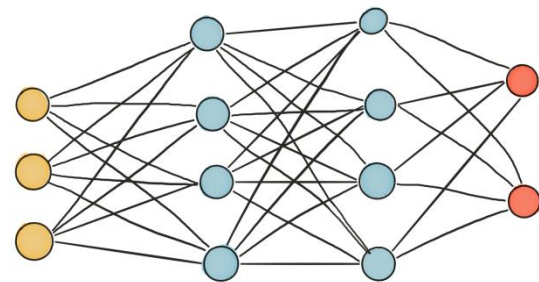


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loss = 예측값 - 실제로 설정

$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$

$$\begin{aligned} loss &= y^* - y \\ &= w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3 - y \end{aligned}$$

Forward & Back Prop.



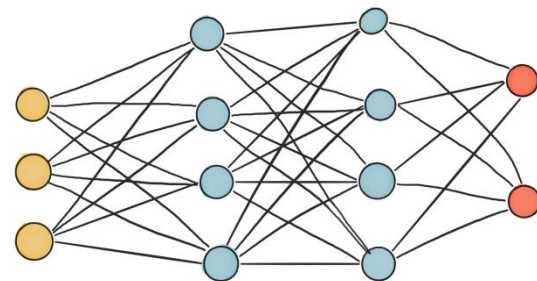
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$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$

$$\begin{aligned} loss &= y^* - y \\ &= w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3 - y \end{aligned}$$

$$\frac{\partial loss}{\partial w3} = sig(w2 * sig(w1 * x + b1) + b2)$$

Forward & Back Prop.



쉽게 이해되도록
loss = 예측값-실제로 설정

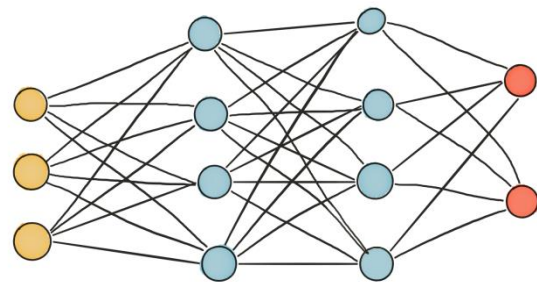
$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$

$$\begin{aligned} loss &= y^* - y \\ &= w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3 - y \end{aligned}$$

$$\frac{\partial loss}{\partial w3} = sig(w2 * sig(w1 * x + b1) + b2)$$

$$\frac{\partial loss}{\partial b3} = 1$$

Forward & Back Prop.



쉽게 이해되도록
loss = 예측값-실제로 설정

$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$

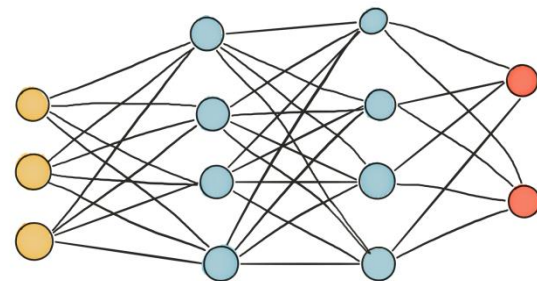
$$\begin{aligned} loss &= y^* - y \\ &= w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3 - y \end{aligned}$$

$$\frac{\partial loss}{\partial w3} = sig(w2 * sig(w1 * x + b1) + b2)$$

$$\frac{\partial loss}{\partial b3} = 1$$

$$\frac{\partial loss}{\partial w2} = ??$$

Forward & Back Prop.



쉽게 이해되도록
loss = 예측값-실제로 설정

$$y^* = w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3$$

$$\begin{aligned} loss &= y^* - y \\ &= w3 * sig(w2 * sig(w1 * x + b1) + b2) + b3 - y \end{aligned}$$

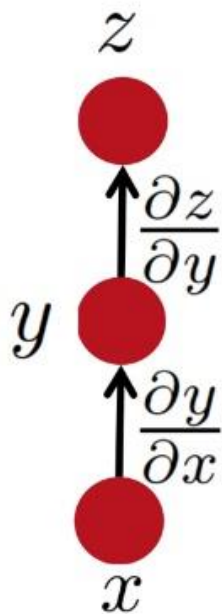
$$\frac{\partial loss}{\partial w3} = sig(w2 * sig(w1 * x + b1) + b2)$$

$$\frac{\partial loss}{\partial b3} = 1$$

$$\frac{\partial loss}{\partial w2} = chain\ rule!!$$

Forward & Back Prop.

Simple Chain Rule



$$\Delta z = \frac{\partial z}{\partial y} \Delta y$$

$$\Delta y = \frac{\partial y}{\partial x} \Delta x$$

$$\Delta z = \frac{\partial z}{\partial y} \frac{\partial y}{\partial x} \Delta x$$

$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial y} \frac{\partial y}{\partial x}$$

Forward & Back Prop.

Backpropagation: a simple example

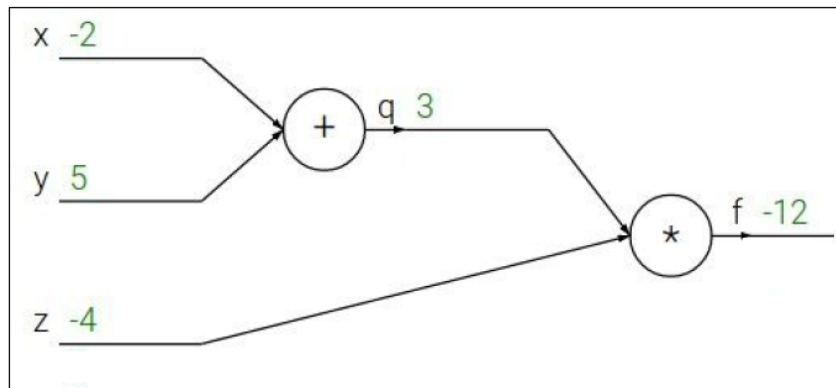
$$f(x, y, z) = (x + y)z$$

e.g. $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



Forward & Back Prop.

Backpropagation: a simple example

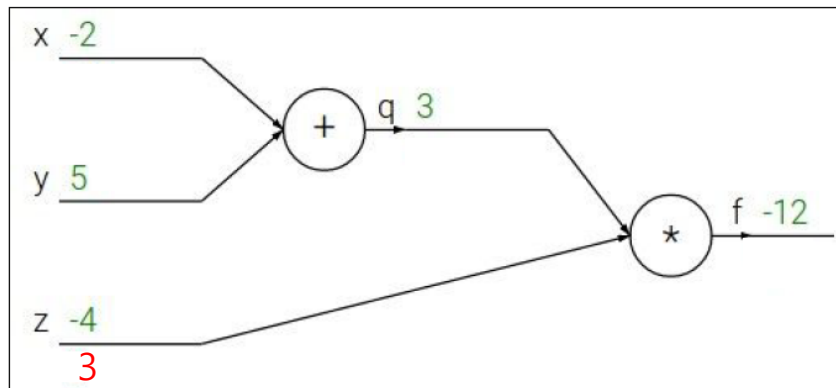
$$f(x, y, z) = (x + y)z$$

e.g. $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



$$\frac{\partial f}{\partial z} = q = x + y = -2 + 5 = 3$$

Forward & Back Prop.

Backpropagation: a simple example

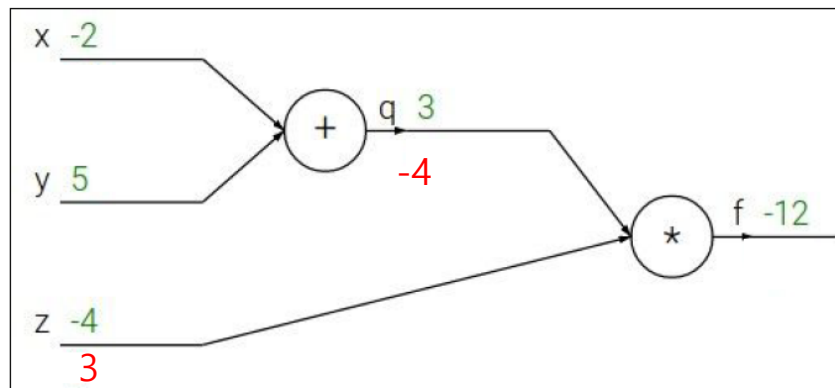
$$f(x, y, z) = (x + y)z$$

e.g. $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



$$\frac{\partial f}{\partial z} = q = x + y = -2 + 5 = 3$$

$$\frac{\partial f}{\partial q} = z = -4$$

Forward & Back Prop.

Backpropagation: a simple example

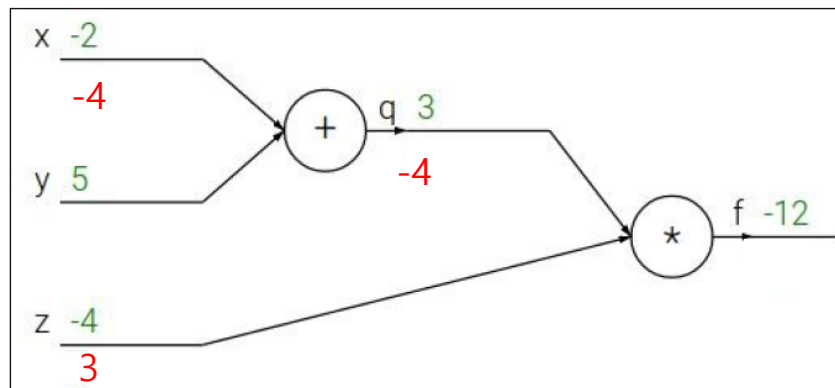
$$f(x, y, z) = (x + y)z$$

e.g. $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



$$\frac{\partial f}{\partial z} = q = x + y = -2 + 5 = 3$$

$$\frac{\partial f}{\partial q} = z = -4 \quad \frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x} = -4 * 1 = -4$$

Forward & Back Prop.

Backpropagation: a simple example

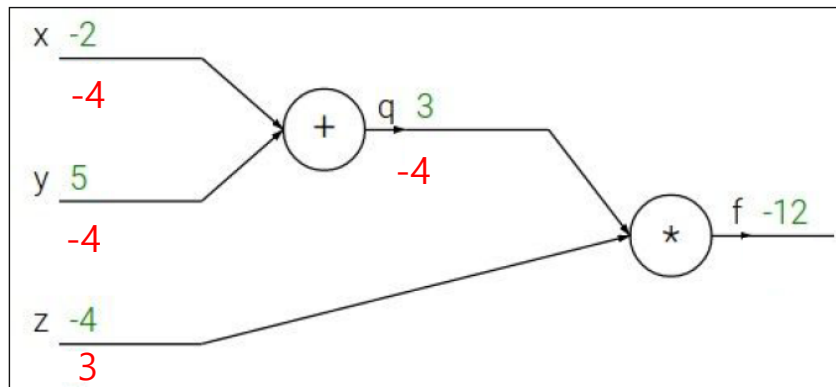
$$f(x, y, z) = (x + y)z$$

e.g. $x = -2, y = 5, z = -4$

$$q = x + y \quad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \quad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$

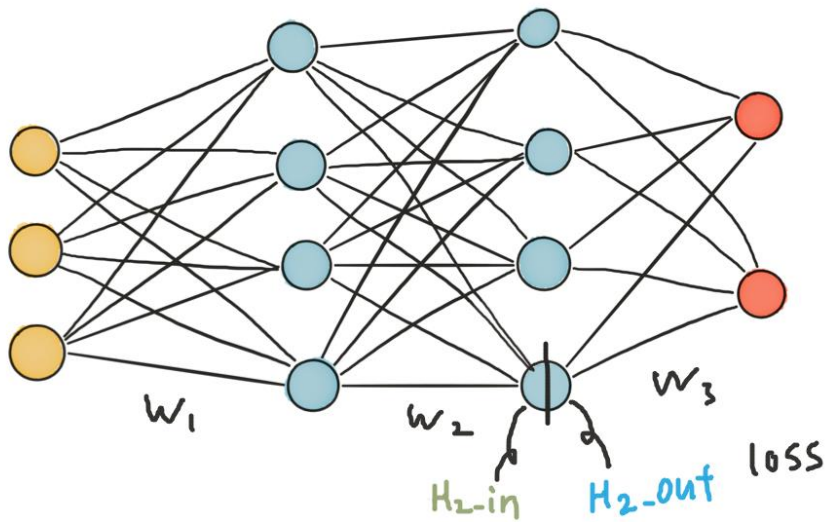


$$\frac{\partial f}{\partial z} = q = x + y = -2 + 5 = 3$$

$$\frac{\partial f}{\partial q} = z = -4 \quad \frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x} = -4 * 1 = -4$$

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y} = -4 * 1 = -4$$

Forward & Back Prop.



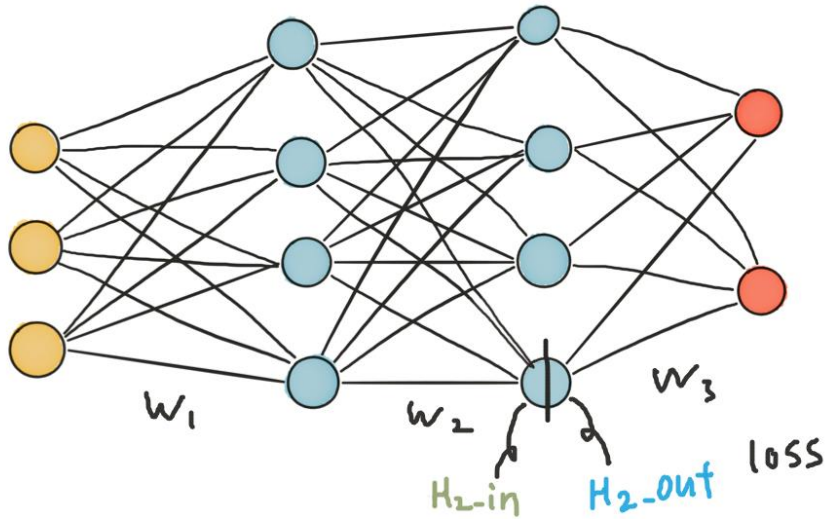
$$loss = w_3 \times \text{sig}(\underbrace{w_2 \times \text{sig}(w_1 x + b_1)}_{H_{2-in}} + b_2)$$

H_{2-out}

$$\frac{\partial loss}{\partial w_2} = \frac{\partial loss}{\partial H_{2-out}} \times \frac{\partial H_{2-out}}{\partial H_{2-in}} \times \frac{\partial H_{2-in}}{\partial w_2}$$

$\frac{\partial loss}{\partial w_2}$: $loss$ 의 w_2 에 대한 편도함수
 $\frac{\partial H_{2-out}}{\partial H_{2-in}}$: H_{2-out} 의 H_{2-in} 에 대한 편도함수
 $\frac{\partial H_{2-in}}{\partial w_2}$: H_{2-in} 의 w_2 에 대한 편도함수

Forward & Back Prop.



$$loss = w_3 \times \text{sig}(\underbrace{w_2 \times \text{sig}(w_1 x + b_1)}_{H_{2-in}} + b_2)$$

H_{2-out}

$$\frac{\partial loss}{\partial w_2} = \frac{\partial loss}{\partial H_{2-out}} \times \frac{\partial H_{2-out}}{\partial H_{2-in}} \times \frac{\partial H_{2-in}}{\partial w_2}$$

$\frac{\partial loss}{\partial w_2}$: $loss$ 의 w_2 에 대한 편도함수
 $\frac{\partial H_{2-out}}{\partial H_{2-in}}$: H_{2-out} 의 H_{2-in} 에 대한 편도함수
 $\frac{\partial H_{2-in}}{\partial w_2}$: H_{2-in} 의 w_2 에 대한 편도함수

$$\frac{\partial loss}{\partial w_2} = w_3 * \text{sigmoid}'(h2_in) * \text{sigmoid}(w_1 * x + b)$$

Forward & Back Prop.

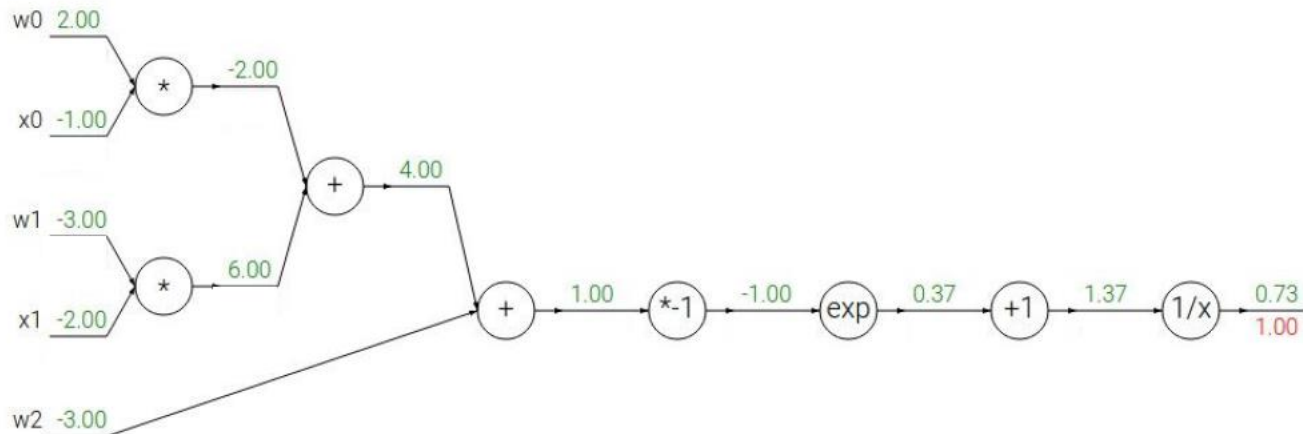
(참고) sigmoid 함수의 미분

$$\sigma(x)' = \frac{\delta\{1+e^{-x}\}^{-1}}{\delta x} = -(1+e^{-x})^{-2} \cdot e^{-x} = \frac{e^{-x}}{(1+e^{-x})^2}$$

$$\sigma(x)(1-\sigma(x)) = \frac{1}{1+e^{-x}} \left(1 - \frac{1}{1+e^{-x}}\right) = \frac{1}{1+e^{-x}} \left(\frac{e^{-x}}{1+e^{-x}}\right) = \frac{e^{-x}}{(1+e^{-x})^2}$$

Forward & Back Prop.

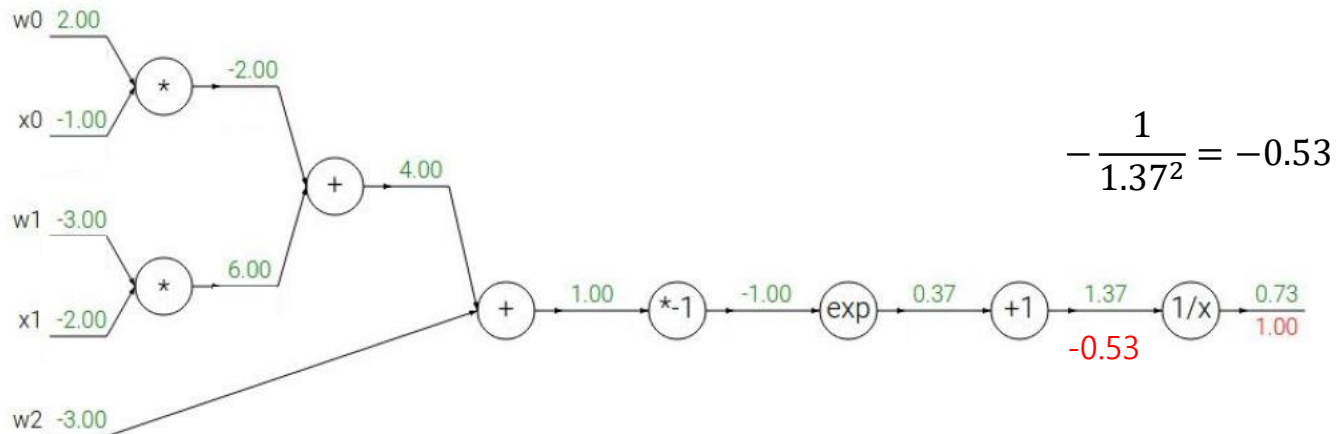
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	\rightarrow	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	\rightarrow	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	\rightarrow	$\frac{df}{dx} = a$		$f_c(x) = c + x$	\rightarrow	$\frac{df}{dx} = 1$

Forward & Back Prop.

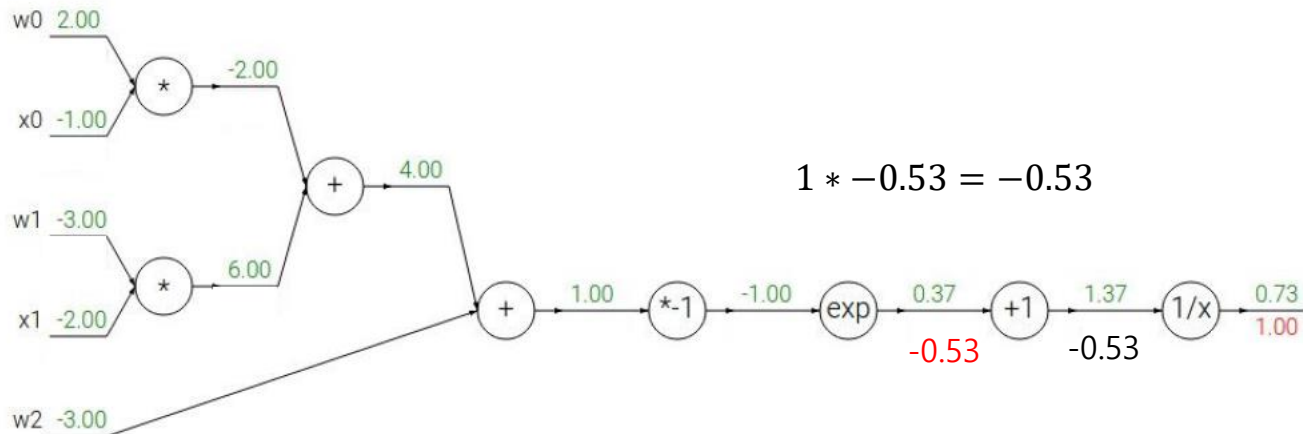
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



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Forward & Back Prop.

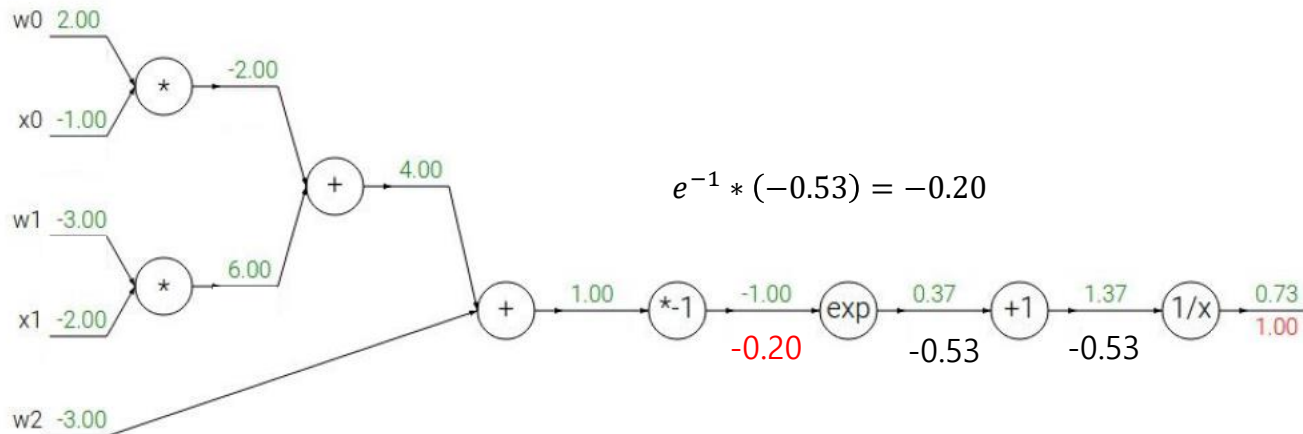
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	\rightarrow	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	\rightarrow	$\frac{df}{dx} = -1/x^2$
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Forward & Back Prop.

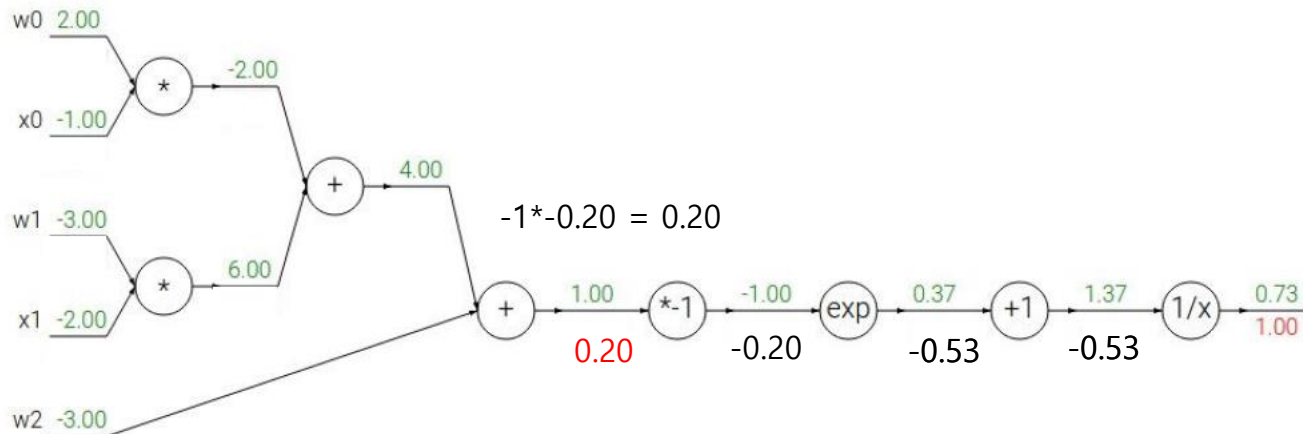
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	→	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	→	$\frac{df}{dx} = -1/x^2$
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Forward & Back Prop.

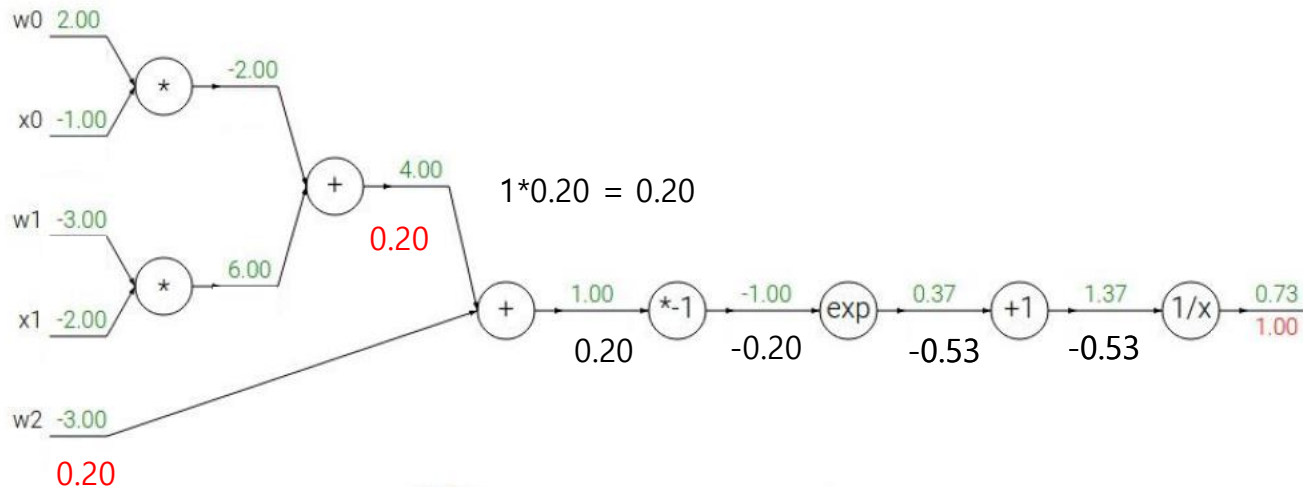
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	→	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	→	$\frac{df}{dx} = -1/x^2$
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Forward & Back Prop.

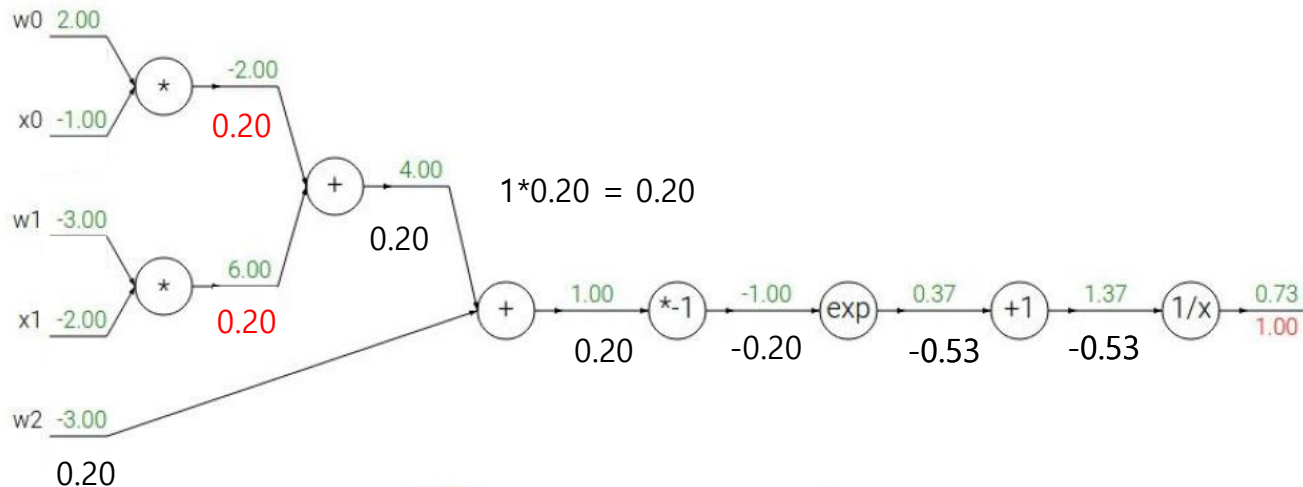
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	\rightarrow	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	\rightarrow	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	\rightarrow	$\frac{df}{dx} = a$		$f_c(x) = c + x$	\rightarrow	$\frac{df}{dx} = 1$

Forward & Back Prop.

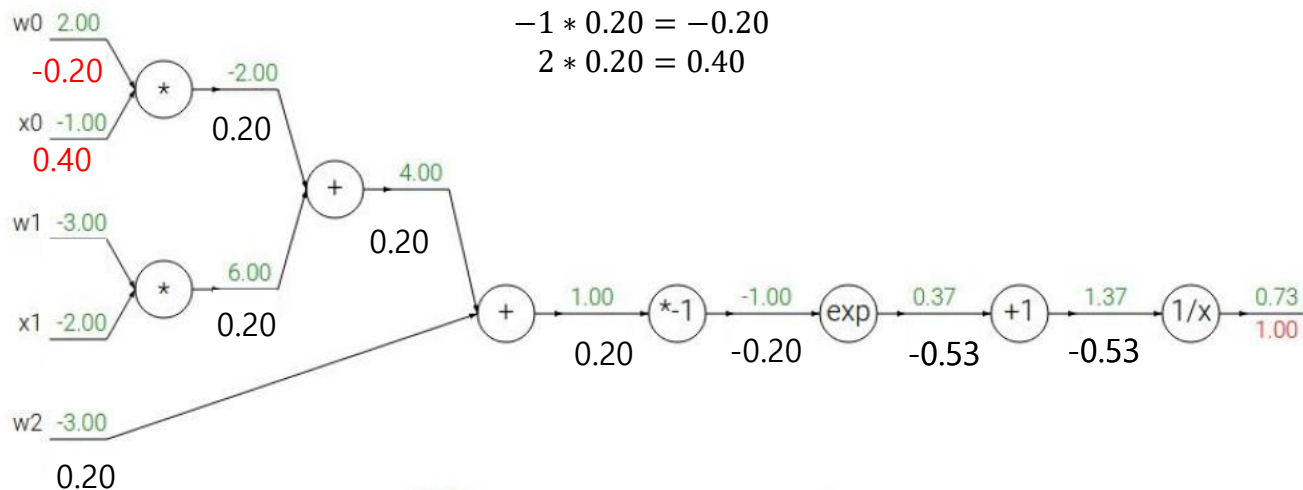
Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$f(x) = e^x$	\rightarrow	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	\rightarrow	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	\rightarrow	$\frac{df}{dx} = a$		$f_c(x) = c + x$	\rightarrow	$\frac{df}{dx} = 1$

Forward & Back Prop.

Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2)}}$



$$\begin{aligned} -1 * 0.20 &= -0.20 \\ 2 * 0.20 &= 0.40 \end{aligned}$$

$$f(x) = e^x$$

→

$$\frac{df}{dx} = e^x$$

$$f(x) = \frac{1}{x}$$

→

$$\frac{df}{dx} = -1/x^2$$

$$f_a(x) = ax$$

→

$$\frac{df}{dx} = a$$

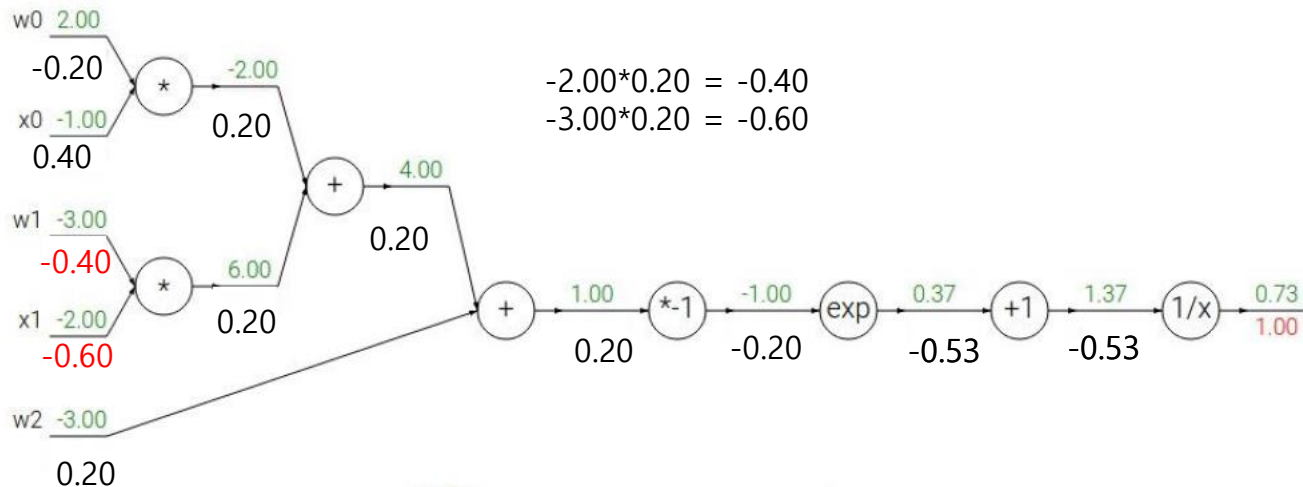
$$f_c(x) = c + x$$

→

$$\frac{df}{dx} = 1$$

Forward & Back Prop.

Another example: $f(w, x) = \frac{1}{1 + e^{-(w_0x_0 + w_1x_1 + w_2x_2)}}$



$f(x) = e^x$	\rightarrow	$\frac{df}{dx} = e^x$		$f(x) = \frac{1}{x}$	\rightarrow	$\frac{df}{dx} = -1/x^2$
$f_a(x) = ax$	\rightarrow	$\frac{df}{dx} = a$		$f_c(x) = c + x$	\rightarrow	$\frac{df}{dx} = 1$

Forward & Back Prop.

$$y = \frac{1}{1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}} = [1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}]^{-1}$$

$$\text{loss} = \hat{y} - y$$

$$= [1 + e^{-(w_0 x_0 + w_1 x_1 + w_2)}]^{-1} - y$$

$\alpha = -1$
 $\beta = 0.37$
 $\sigma = 1.37$

$$w_0 = 2$$

$$w_1 = -3$$

$$w_2 = -3$$

$$x_0 = -1$$

$$x_1 = -2$$

$$\frac{\partial \text{loss}}{\partial r} = (r^{-1})' = -\frac{1}{r^2} = -0.5327$$

$$\frac{\partial r}{\partial \beta} = 1$$

$$\frac{\partial \beta}{\partial \alpha} = (e^{\alpha})' = e^{\alpha} = 0.3678$$

$$\frac{\partial \alpha}{\partial w_0} = -x_0 = 1$$

$$\text{loss} = r^{-1} - y$$

$$r = 1 + \beta$$

$$\beta = e^{\alpha}$$

$$\frac{\partial \text{loss}}{\partial w_0} = \frac{\partial \text{loss}}{\partial r} \times \frac{\partial r}{\partial \beta} \times \frac{\partial \beta}{\partial \alpha} \times \frac{\partial \alpha}{\partial w_0}$$




$$= -0.5327 \times 1 \times 0.3678 \times 1$$

$$= -0.1959 \approx -0.2$$

Neural Network

A mostly complete chart of Neural Networks

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-  Backfed Input Cell
-  Input Cell
-  Noisy Input Cell
-  Hidden Cell
-  Probablistic Hidden Cell
-  Spiking Hidden Cell
-  Output Cell
-  Match Input Output Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Kernel
-  Convolution or Pool

Perceptron (P)



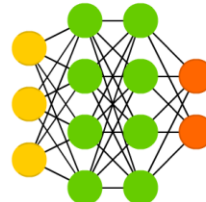
Feed Forward (FF)



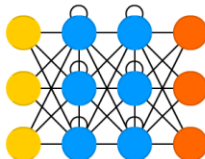
Radial Basis Network (RBF)



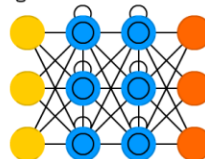
Deep Feed Forward (DFF)



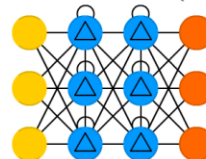
Recurrent Neural Network (RNN)



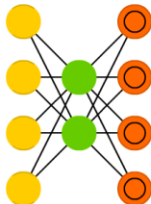
Long / Short Term Memory (LSTM)



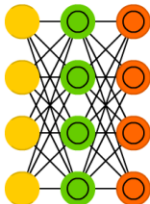
Gated Recurrent Unit (GRU)



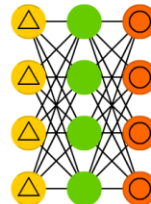
Auto Encoder (AE)



Variational AE (VAE)



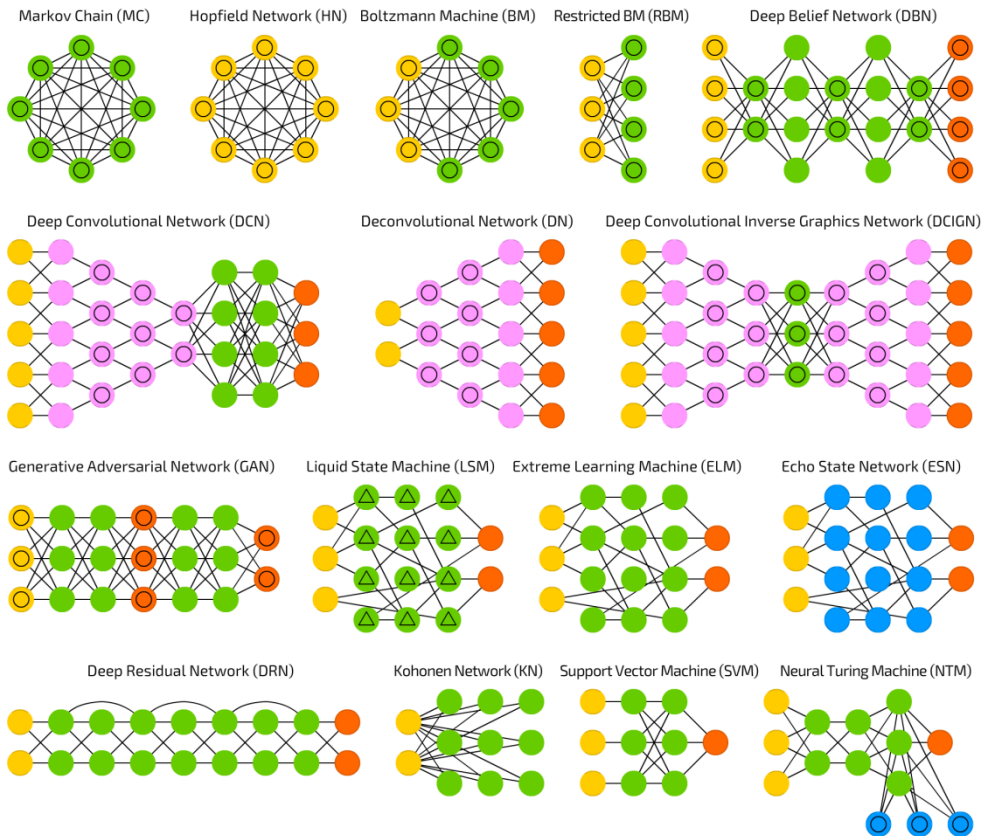
Denosing AE (DAE)



Sparse AE (SAE)



Neural Network



Q&A

