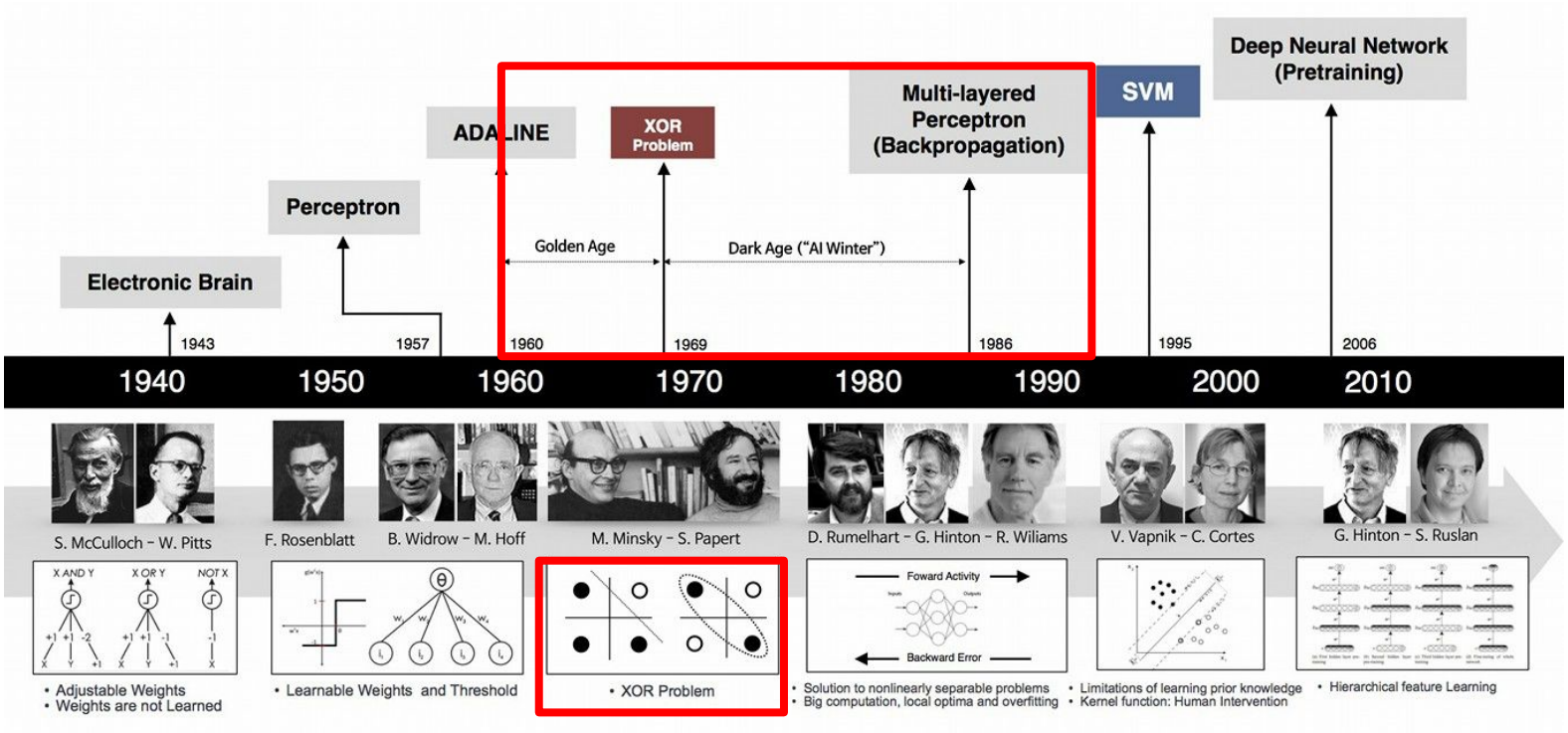
# Tensorflow day2

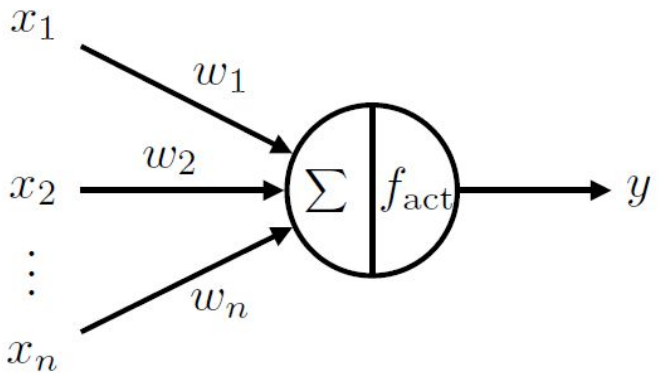
모두의연구소 Lab. Rubato
**소준섭**

# XOR Problem


Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch - W. Pitts
F. Rosenblatt
B. Widrow - M. Hoff
M. Minsky - S. Papert
D. Rumelhart - G. Hinton - R. Wiliams
V. Vapnik - C. Cortes
G. Hinton - S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

# Perceptron

- Frank Rosenblatt, 1957
- Neural network의 시초




- 몇 개의 binary inputs: $x_1, x_2, \cdots, x_n$
- 한 개의 binary output: $y$
- 가중치 (Weights): $w_1, w_2, \cdots, w_n$

$$\sum = w_1 x_1 + w_2 x_2 + \cdots w_n x_n$$

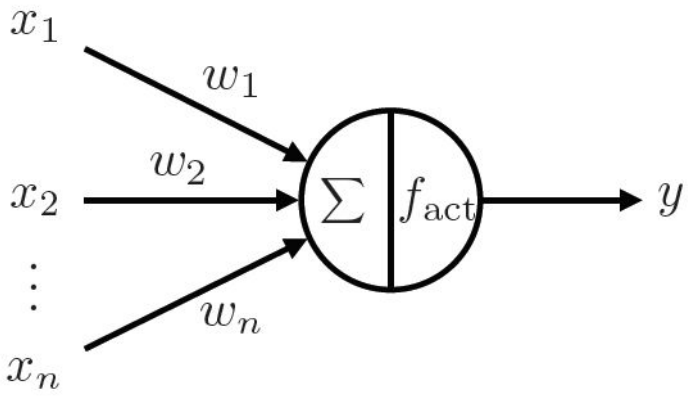
$f_{\text{act}}$: Heaviside step function

# Perceptron

- 작동 방식

$$y = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{threshold} \end{cases}$$

$$y = f_{\text{act}}\left(\sum_j w_j x_j - \text{threshold}\right)$$

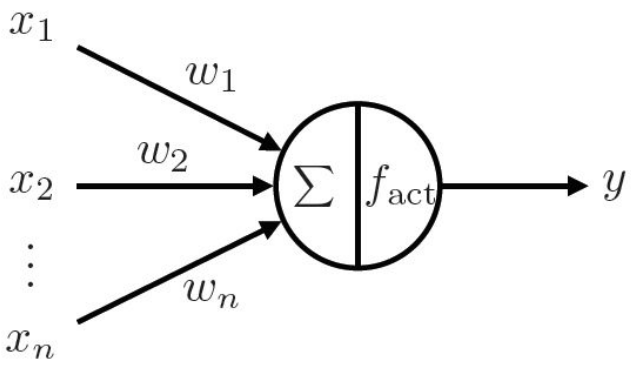



- 신호의 가중합(weighted sum)이 특정 임계값을 넘어서면 활성화(activation)
- 가중치(weights)는 각 입력값(inputs)의 영향력을 조절하는 요소

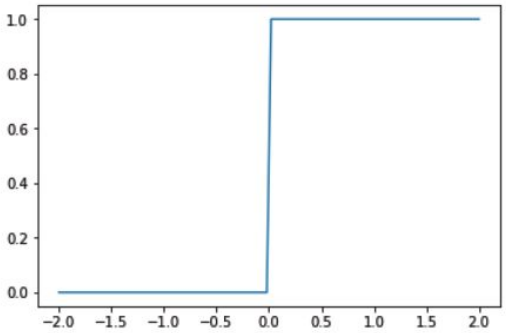
# Perceptron

- 활성화 함수 (activation function)

$$y = f_{\text{act}}\left(\sum_j w_j x_j + b\right)$$

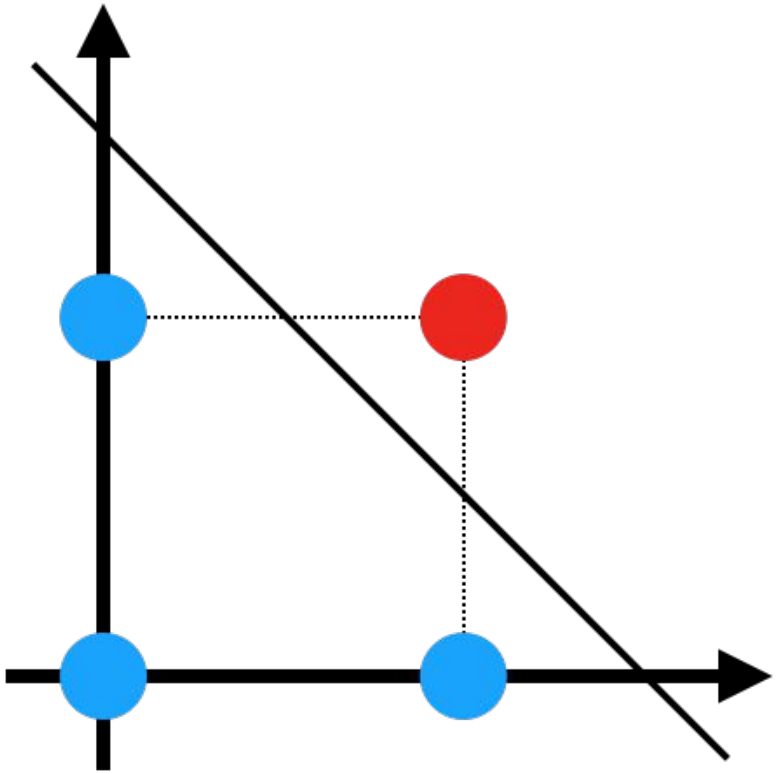



- Heaviside step function




activation function:
    Heaviside step function
bias:
    -threshold

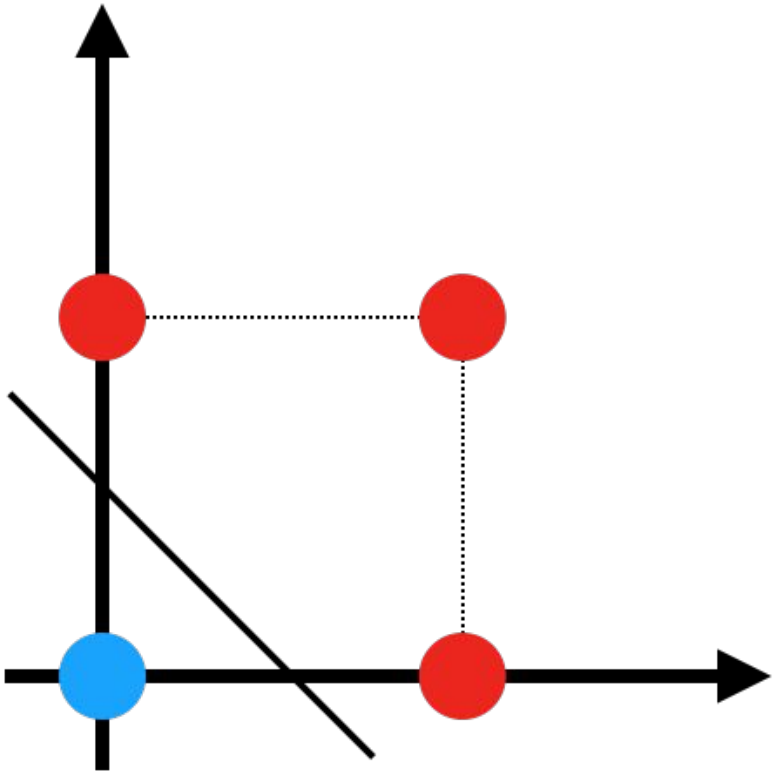
# XOR problem - AND Gate



$$w_1 = 2,\ w_2 = 2,\ b = -3$$

| $x_1$ | $x_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 0 | 0 | -3 | 0 |
| 0 | 1 | -1 | 0 |
| 1 | 0 | -1 | 0 |
| 1 | 1 | 1 | 1 |

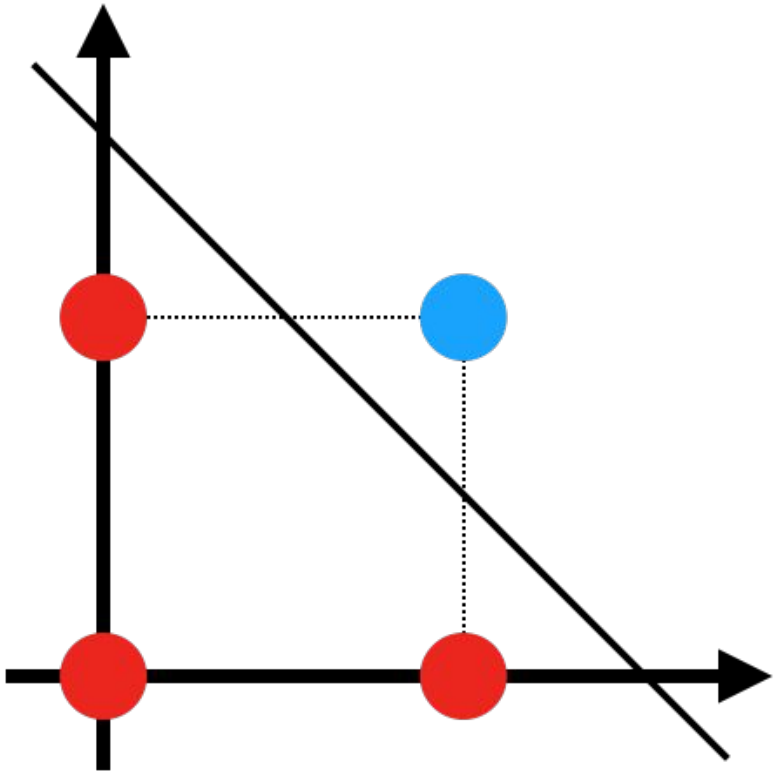
# XOR problem - OR Gate



$$w_1 = 2,\ w_2 = 2,\ b = -1$$

| $x_1$ | $x_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 0 | 0 | -1 | 0 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | 3 | 1 |

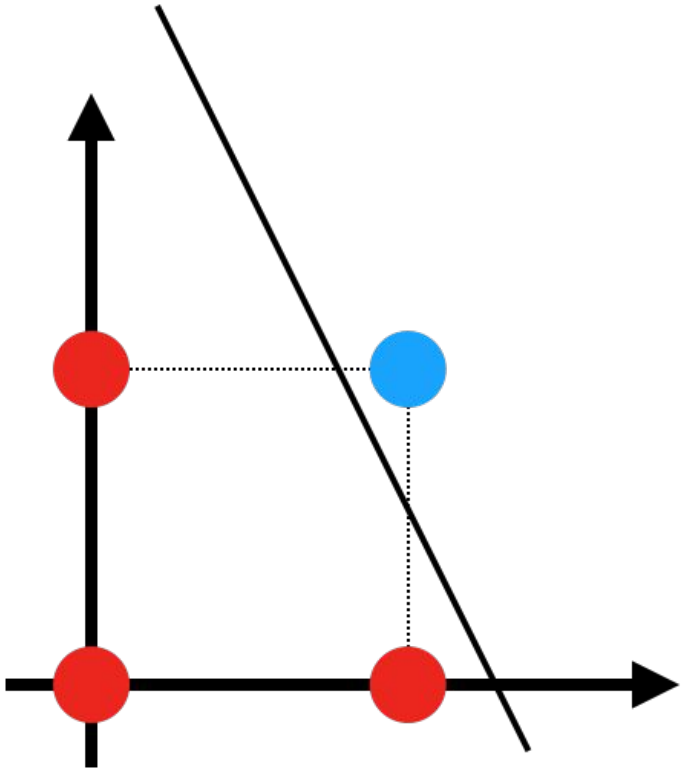
# XOR problem - NAND Gate



$$w_1 = -2,\ w_2 = -2,\ b = 3$$

| $x_1$ | $x_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 0 | 0 | 3 | 1 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | -1 | 0 |

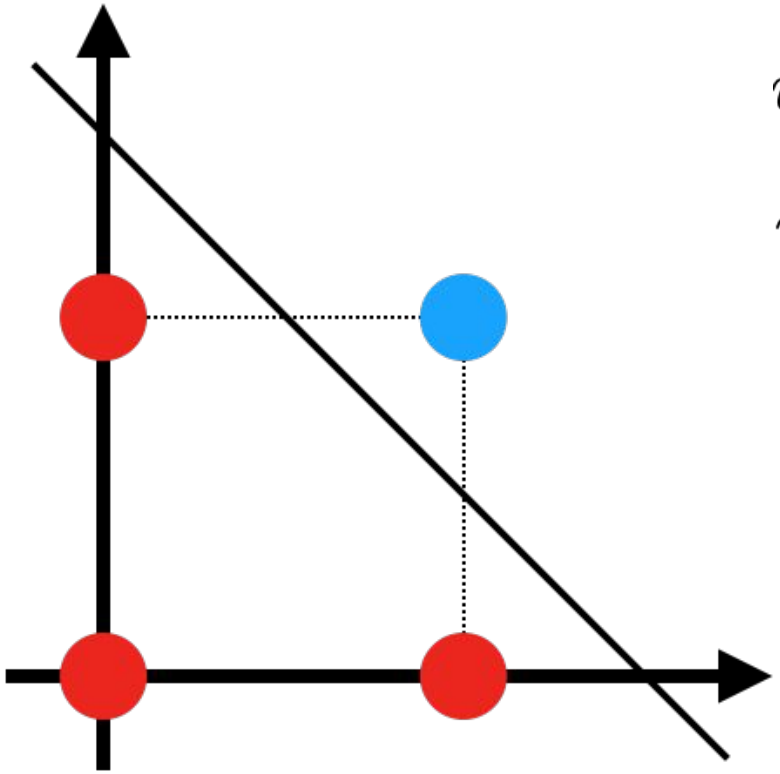
# XOR problem - NAND Gate



$$w_1 = -2,\ w_2 = -1,\ b = 2.5$$

| $x_1$ | $x_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 0 | 0 | 2.5 | 1 |
| 0 | 1 | 1.5 | 1 |
| 1 | 0 | 0.5 | 1 |
| 1 | 1 | -0.5 | 0 |

# XOR problem - NAND Gate

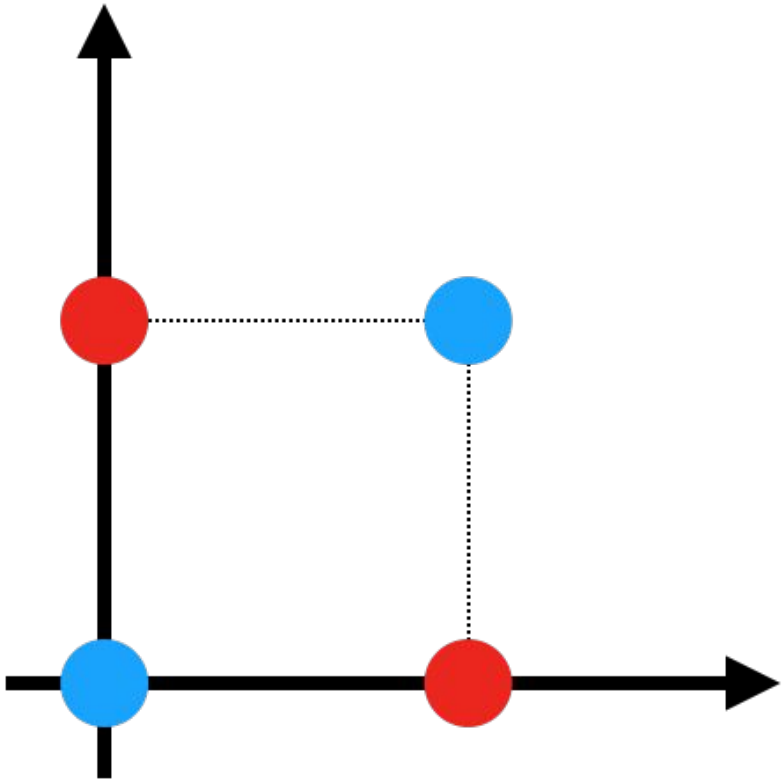


$$w_1 = -2,\ w_2 = -2,\ b = 3$$

$$w_1 = -2,\ w_2 = -1,\ b = 2.5$$

$$\vdots$$

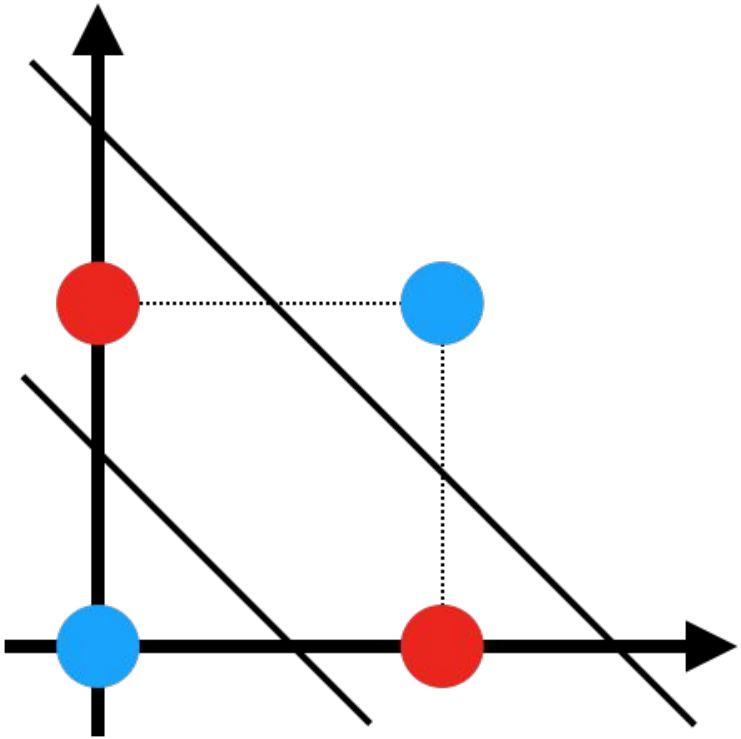
# XOR problem

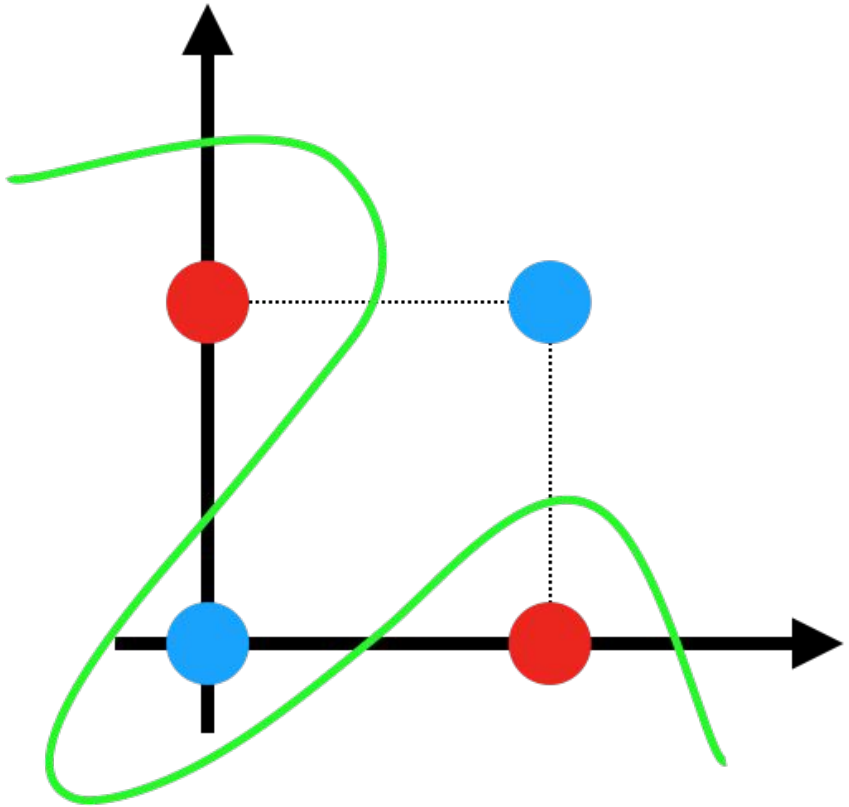


$$w_1 =?,\ w_2 =?,\ b =?$$

| $x_1$ | $x_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 0 | 0 | | 0 |
| 0 | 1 | | 1 |
| 1 | 0 | | 1 |
| 1 | 1 | | 0 |

# XOR problem





# XOR problem

$w_1 = -2,\ w_2 = -2,\ b = 3$

| $x_1$ | $x_2$ | $\sum$ | $s_1$ |
|---|---|---|---|
| 0 | 0 | 3 | 1 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | -1 | 0 |

$w_1 = 2,\ w_2 = 2,\ b = -1$

| $x_1$ | $x_2$ | $\sum$ | $s_2$ |
|---|---|---|---|
| 0 | 0 | -1 | 0 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | 3 | 1 |

$w_1 = 2,\ w_2 = 2,\ b = -3$

| $s_1$ | $s_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 1 | 0 | -1 | 0 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 0 | 1 | -1 | 0 |

# XOR problem

$w_1 = -2,\ w_2 = -2,\ b = 3$

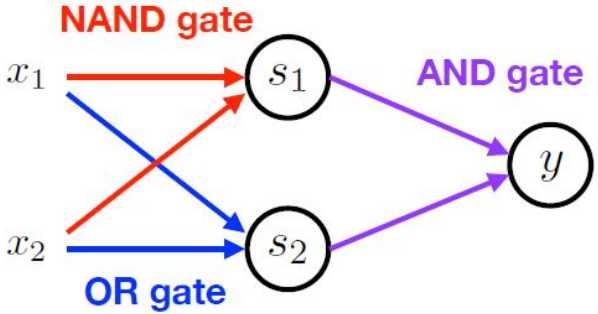
| $x_1$ | $x_2$ | $\sum$ | $s_1$ |
|---|---|---|---|
| 0 | 0 | 3 | 1 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | -1 | 0 |

$w_1 = 2,\ w_2 = 2,\ b = -1$

| $x_1$ | $x_2$ | $\sum$ | $s_2$ |
|---|---|---|---|
| 0 | 0 | -1 | 0 |
| 0 | 1 | 1 | 1 |
| 1 | 0 | 1 | 1 |
| 1 | 1 | 3 | 1 |

$w_1 = 2,\ w_2 = 2,\ b = -3$

| $s_1$ | $s_2$ | $\sum$ | $y$ |
|---|---|---|---|
| 1 | 0 | -1 | 0 |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 |
| 0 | 1 | -1 | 0 |

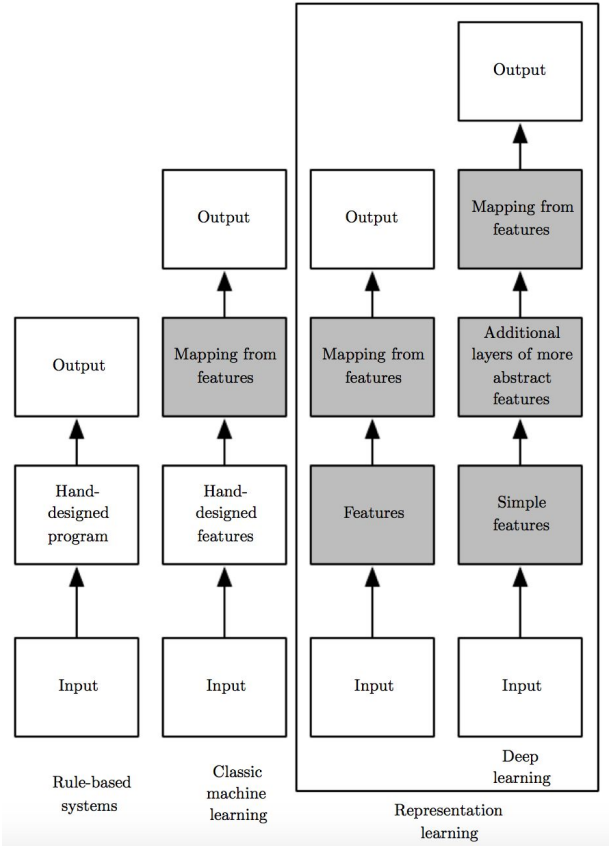



# XOR problem

to map space X to space Y

# Deep Neural Networks to Deep Learning

- Learning multiple levels of representation
- Representation / Feature learning
- Generally many layers
- From high dimensional vector to low dimensional vector (vice versa)
- F. Chollet's quotation: to map space X to space Y using a continuous geometric transform



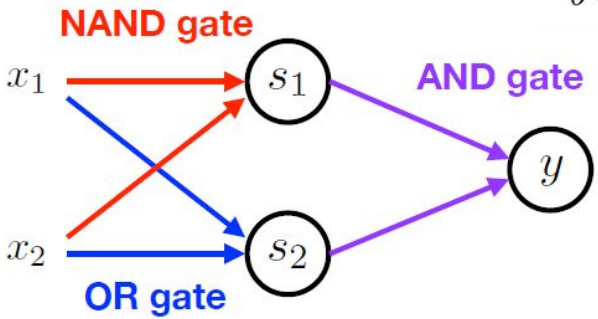
# XOR problem with NN

$$W = \begin{bmatrix} -2 \\ -2 \end{bmatrix}$$

$$b = -3$$

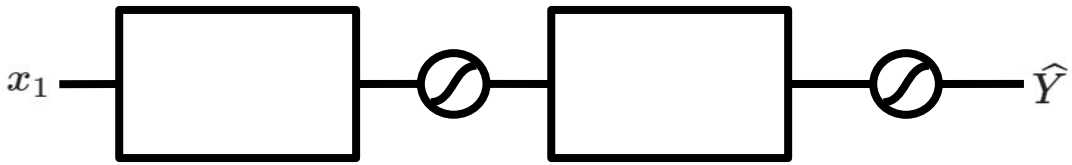
$$W = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

$$b = -3$$




$$W = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

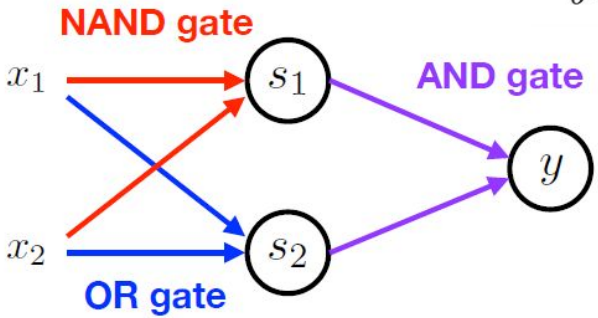
$$b = -1$$



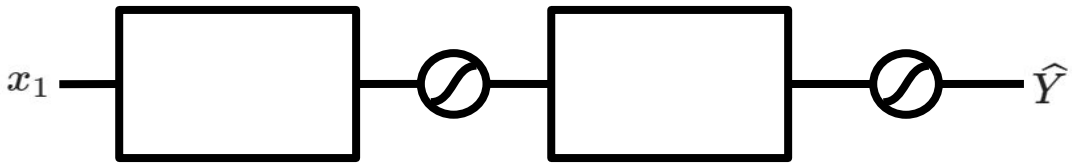
# XOR problem with NN

$$W = \begin{bmatrix} -2 \\ -2 \end{bmatrix} \qquad b = -3$$

$$W = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \qquad b = -3$$



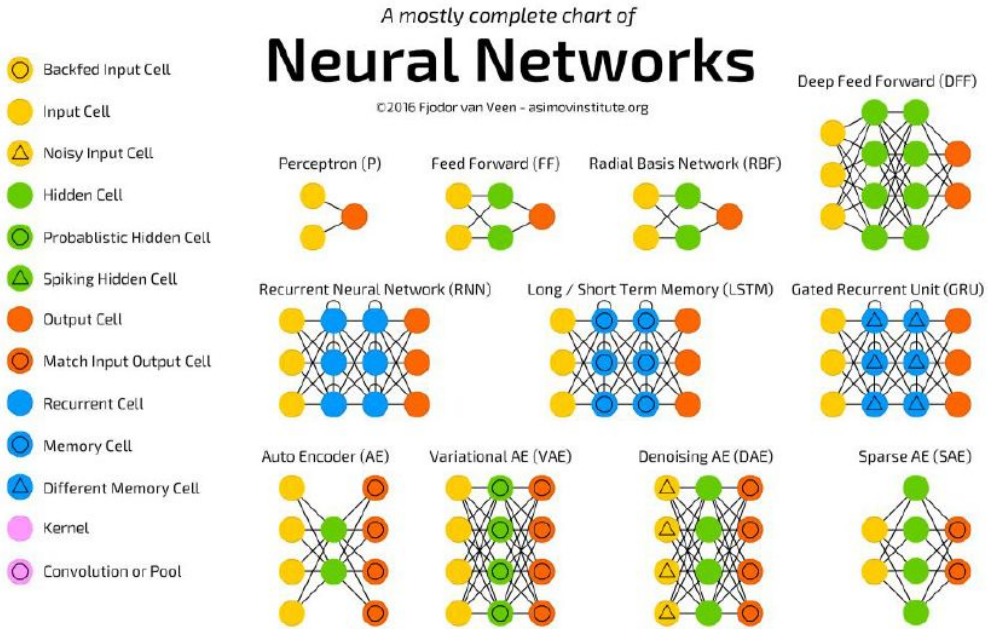

$$W = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \qquad b = -1$$

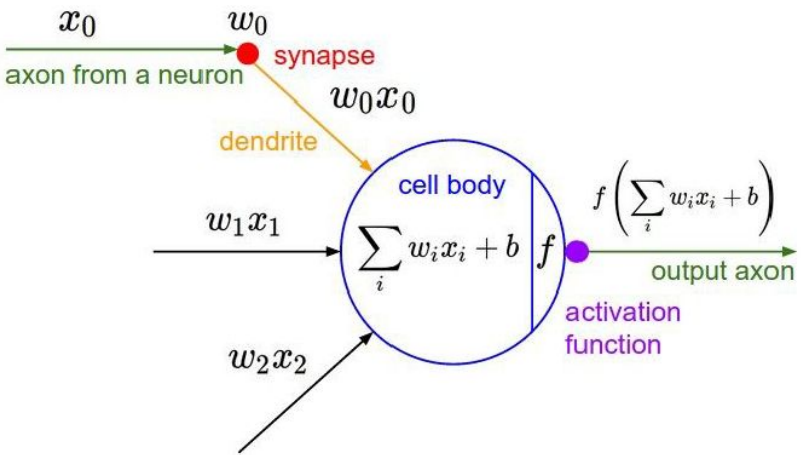



$$W = \begin{bmatrix} -2 & 2 \\ -2 & 2 \end{bmatrix} \qquad b = \begin{bmatrix} -3 & -1 \end{bmatrix}$$

$$W = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \qquad b = -3$$

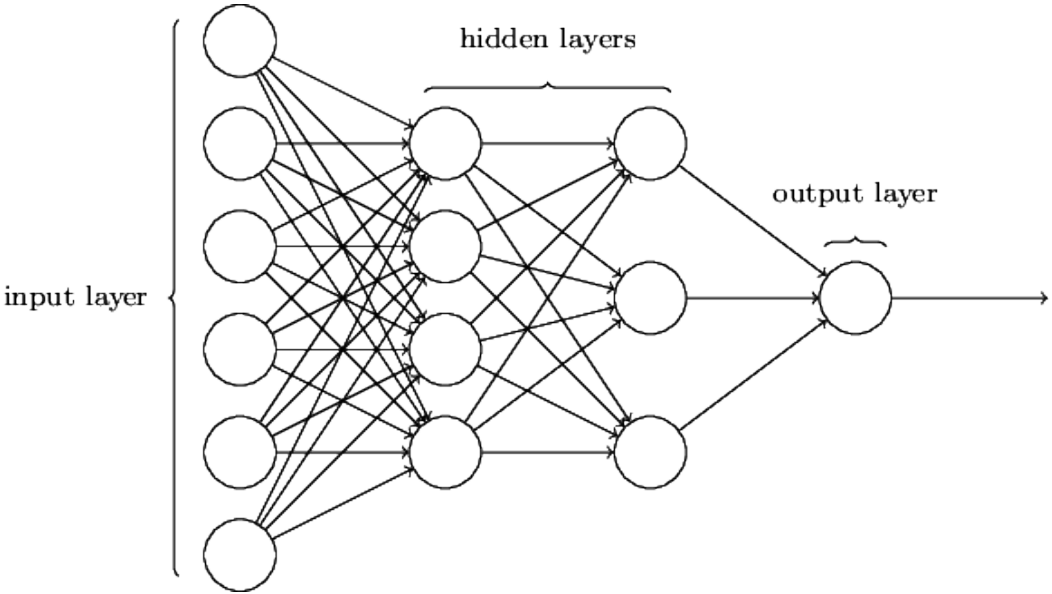
# Neural Networks



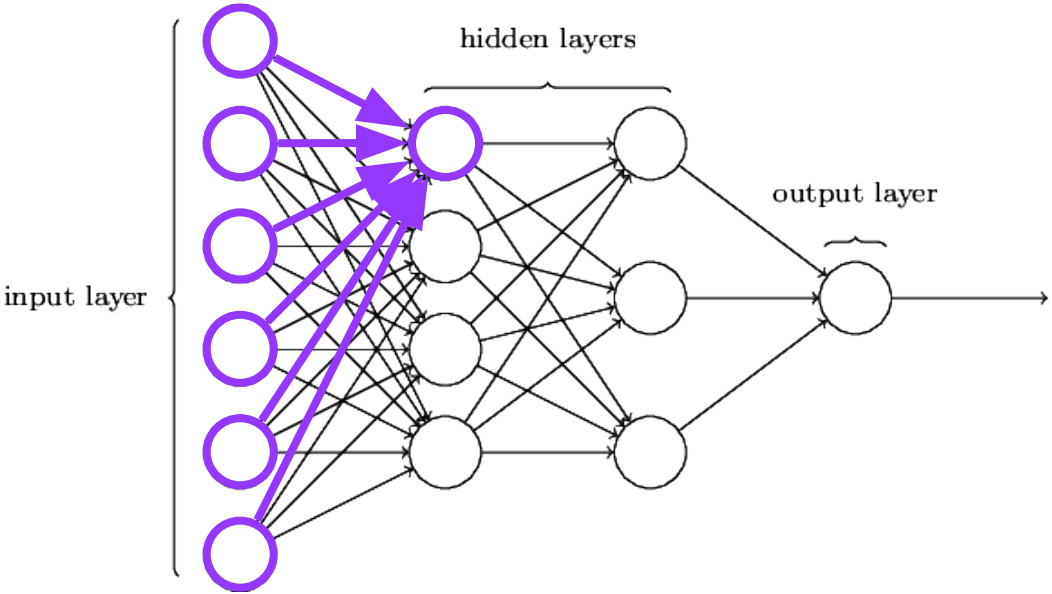

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

# Neural Networks




http://neuralnetworksanddeeplearning.com/chap2.html

# Neural Networks




$\mathbf{w}^1$: vectors

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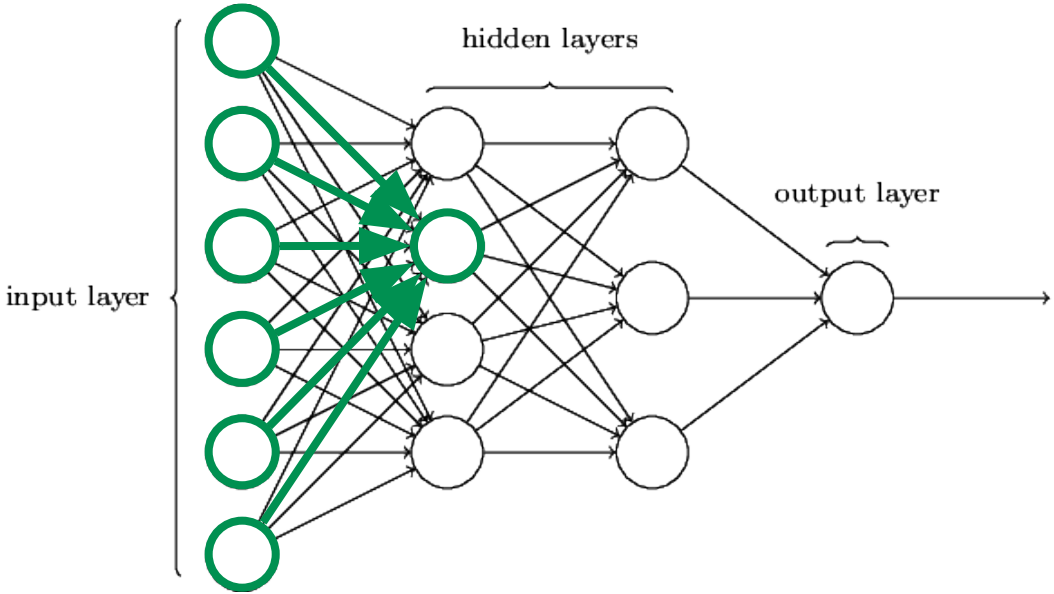
# Neural Networks




$\mathbf{w}^2$: vectors

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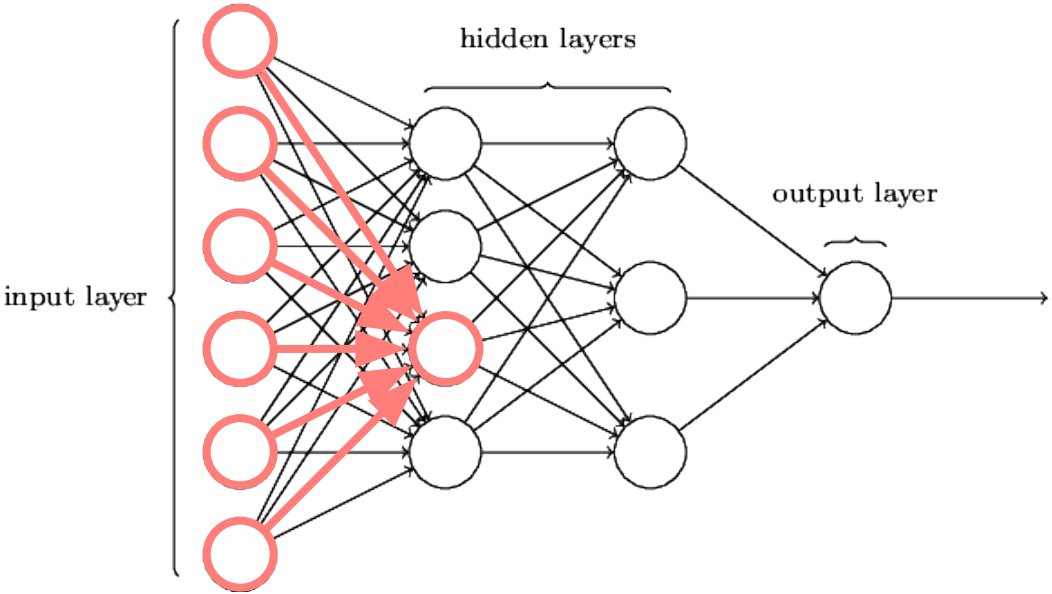
# Neural Networks




$\mathbf{w}^3$: vectors

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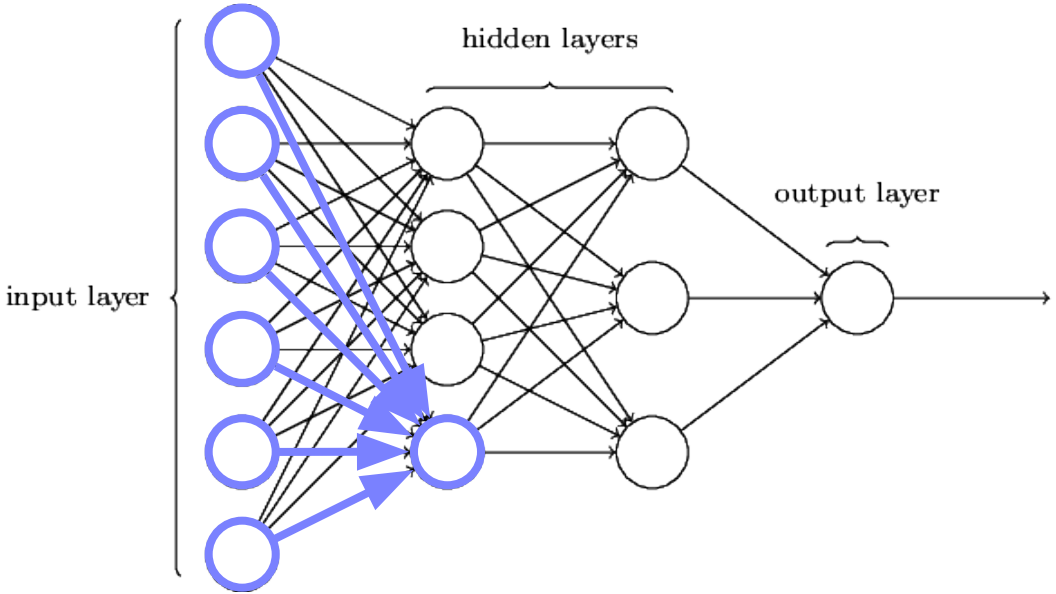
# Neural Networks




$\mathbf{w}^4$: vectors

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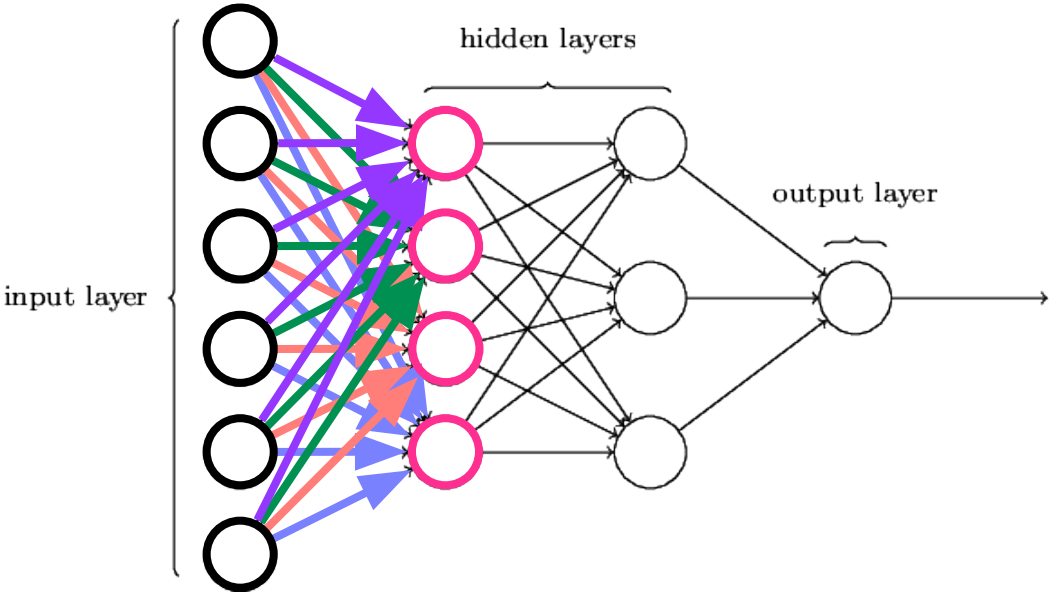
# Neural Networks




$\mathbf{x}$: vector $\mathbf{W}$: matrix $\mathbf{h}$: vector

$$\mathbf{h} = f_{\text{act}}\left(\mathbf{W}\mathbf{x} + \mathbf{b}\right)$$

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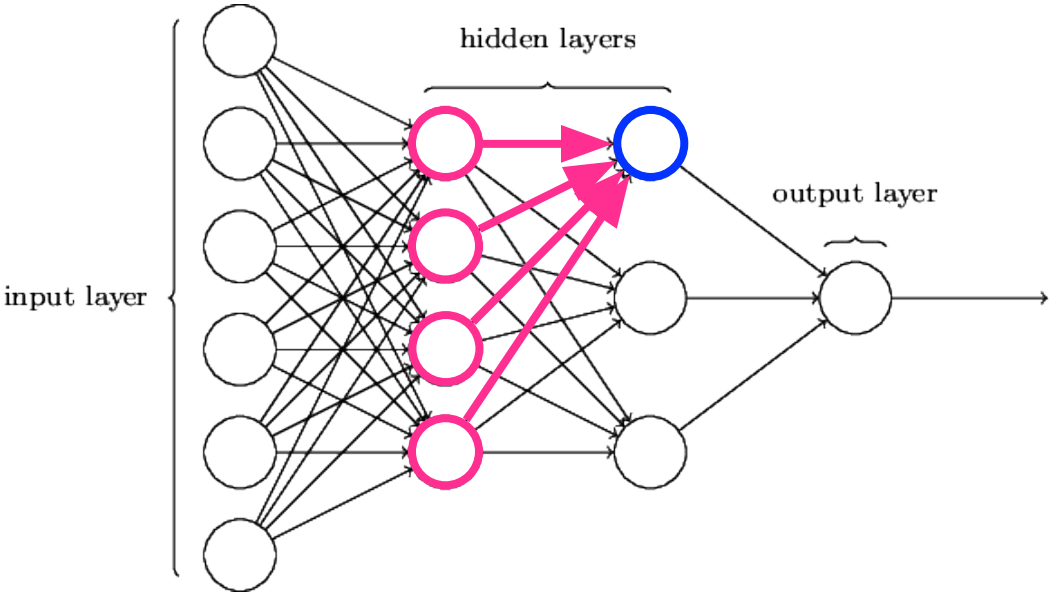
# Neural Networks

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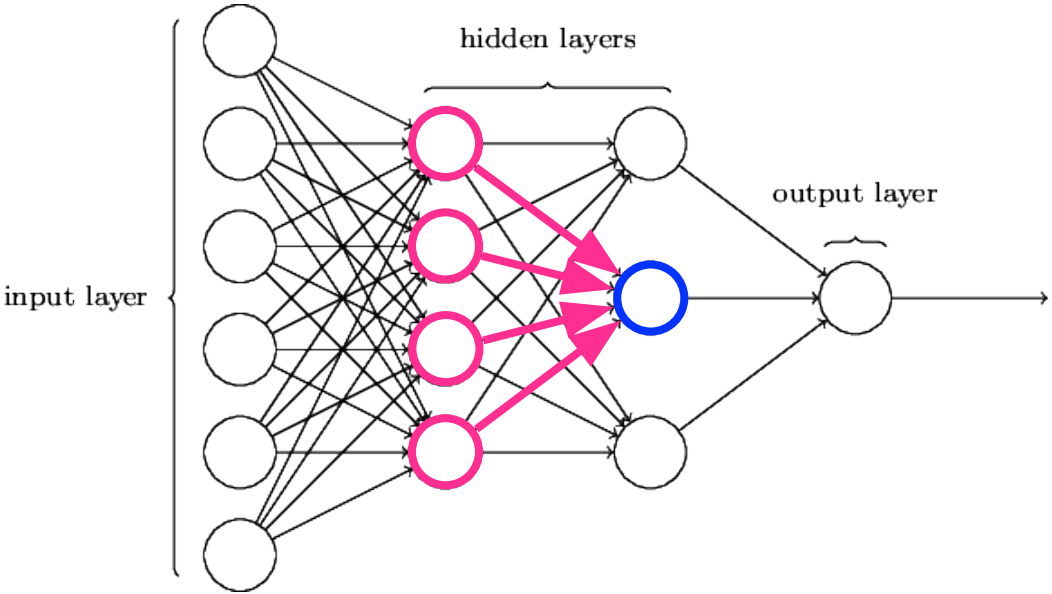
# Neural Networks

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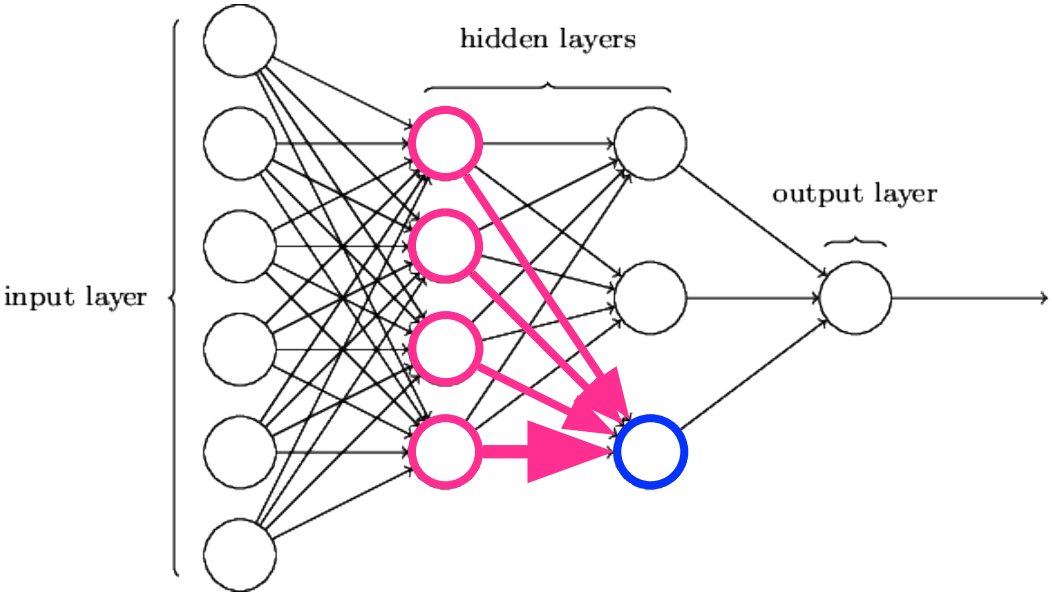
# Neural Networks

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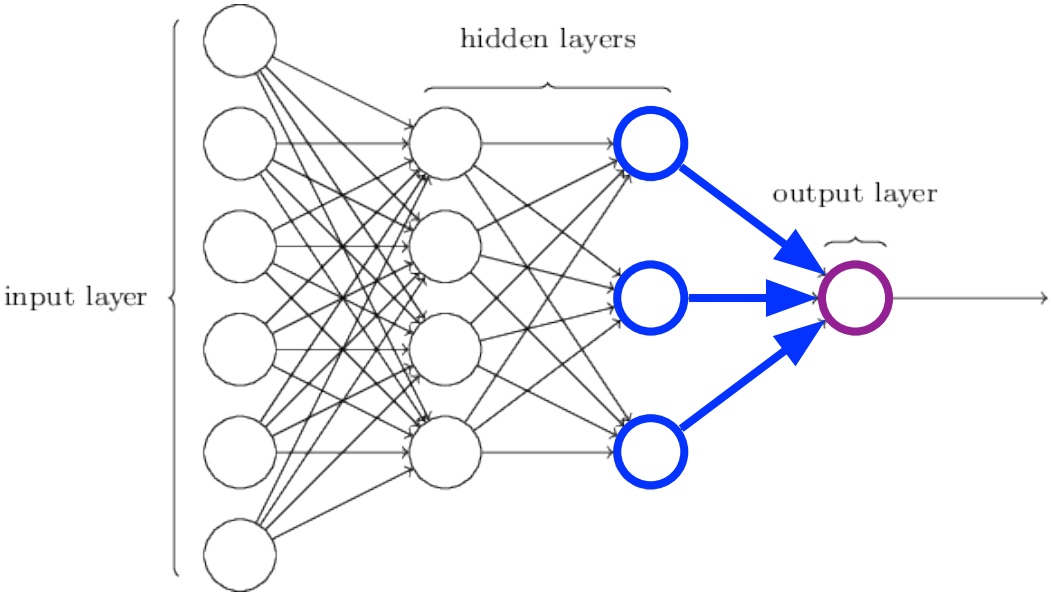
# Neural Networks

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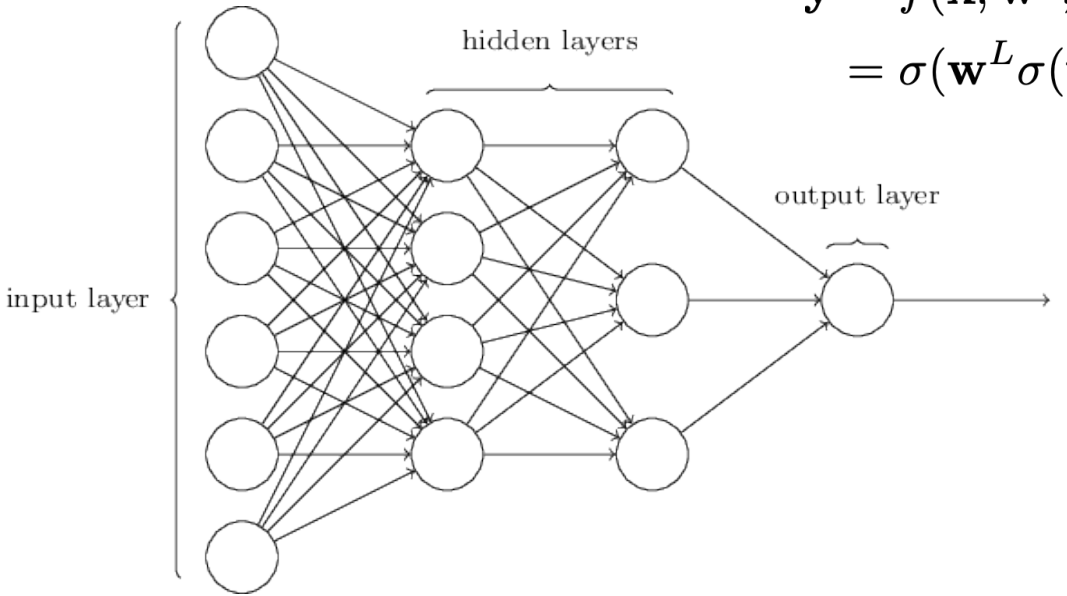
# Neural Networks



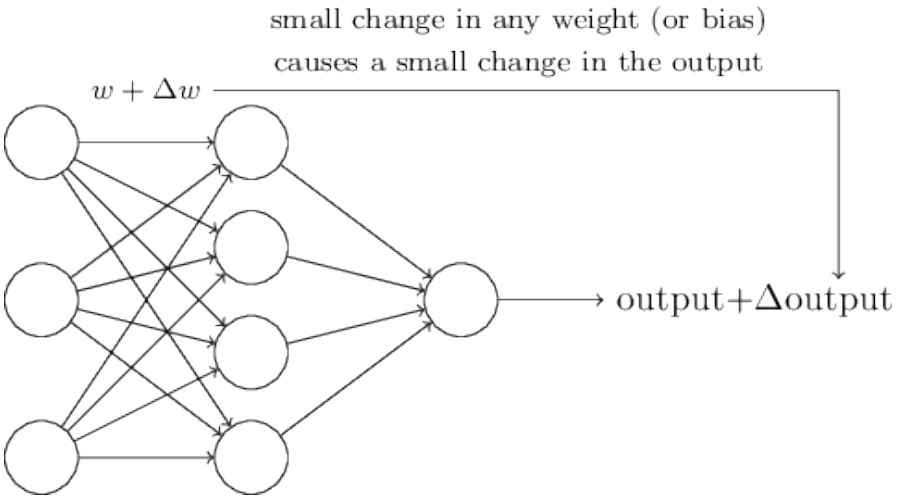

$$\hat{\mathbf{y}} = f(\mathbf{x}; \mathbf{w}^1, \cdots, \mathbf{w}^L, \mathbf{b}^1, \cdots, \mathbf{b}^L)$$
$$= \sigma(\mathbf{w}^L \sigma(\mathbf{w}^{L-1} \cdots \sigma(\mathbf{w}^1 \mathbf{x} + \mathbf{b}^1) \cdots) + \mathbf{b}^L)$$

activation function:
sigmoid function

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

http://neuralnetworksanddeeplearning.com/chap2.html

# Activation Function

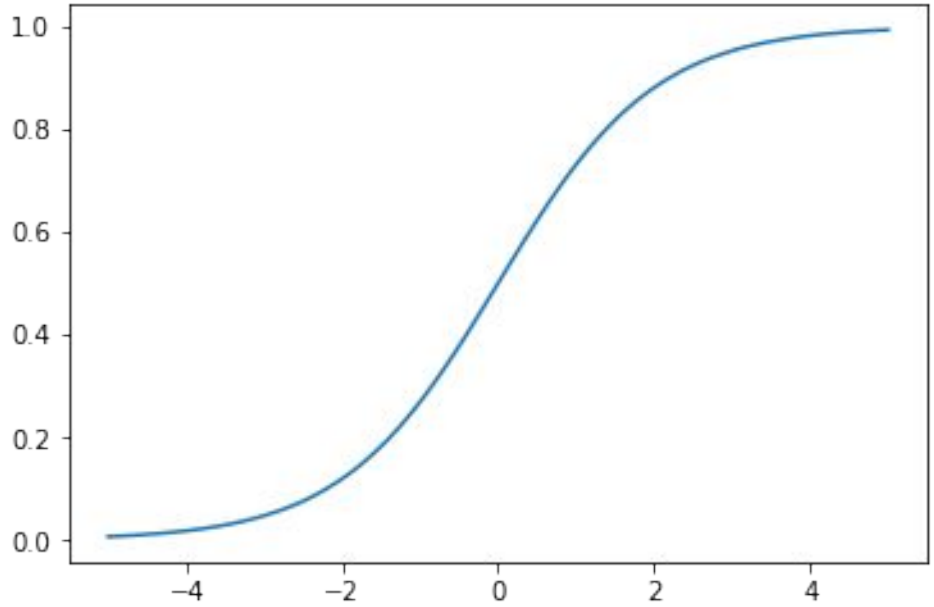



- 네트워크의 가중치를 약간만 변경했을때 출력도 조금만 변하게 하고 싶다
- 가중치를 조금씩 (반복하여) 변화시켜 더 좋은 출력(output)을 내도록 한다
- 퍼셉트론은 가중치가 변해도 출력이 잘 변하지 않음
- Sigmoid neuron을 사용

http://neuralnetworksanddeeplearning.com/chap2.html

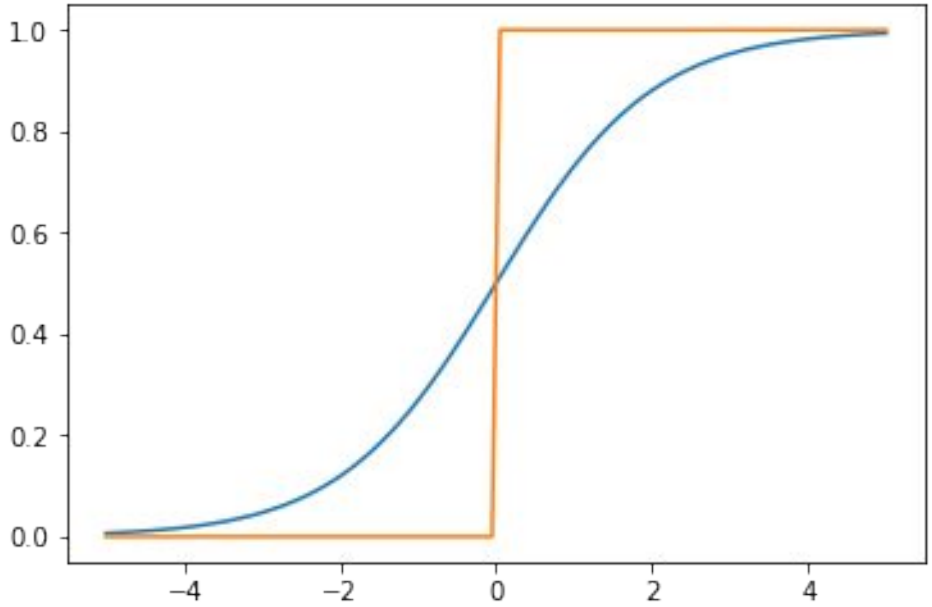
# Sigmoid Function

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}$$

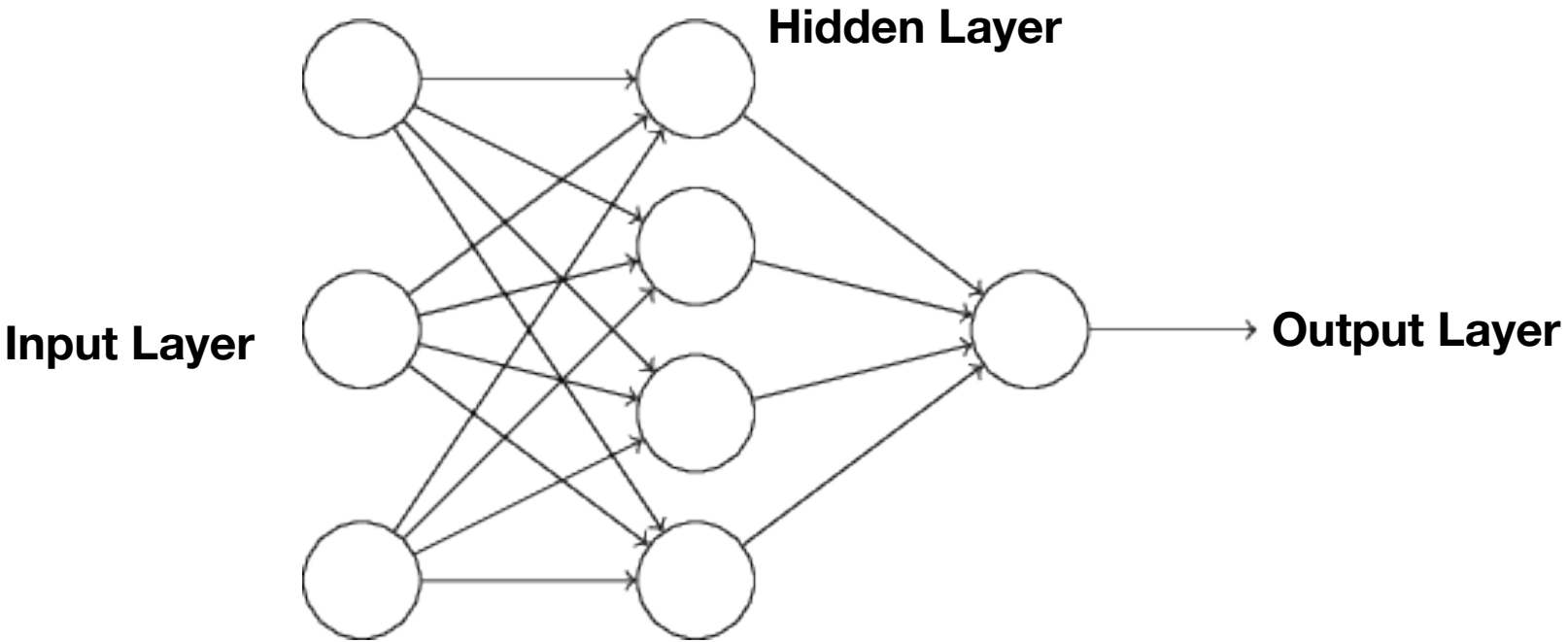


# Sigmoid vs Step Function

- 비슷한 점
  - Sigmoid function은 입력값이 크면 1에 가깝고 작으면 0에 가까워져서 step function과 비슷하다
  - 둘 다 [0, 1] 사이의 값을 갖는다
- 차이점
  - Sigmoid function은 부드러운 곡선을 갖는 (smoothed) step function이다
  - Sigmoid의 매끄러움 때문에 작은 가중치 변화로 작은 출력값의 변화가 생긴다

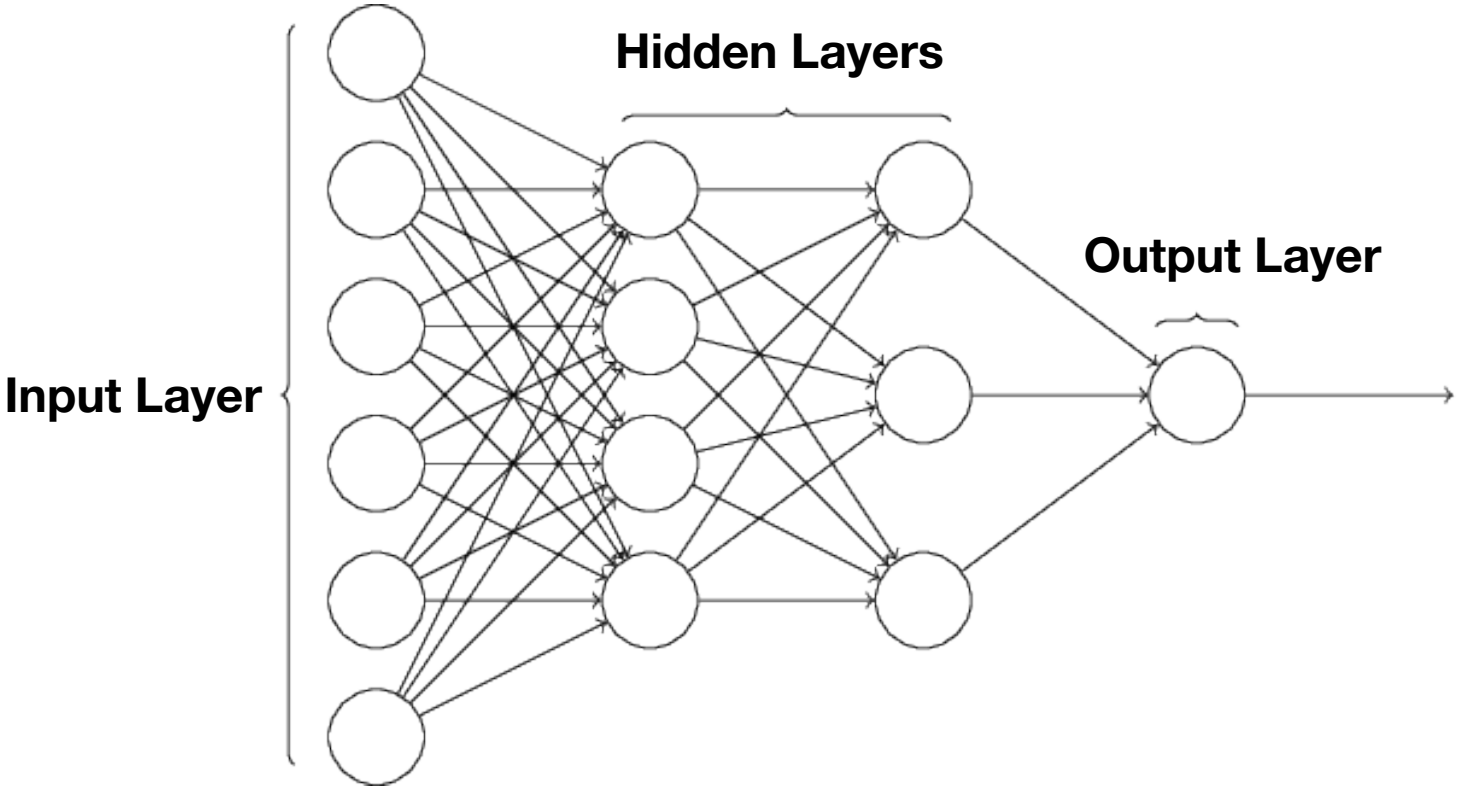


# Structures of Neural Networks



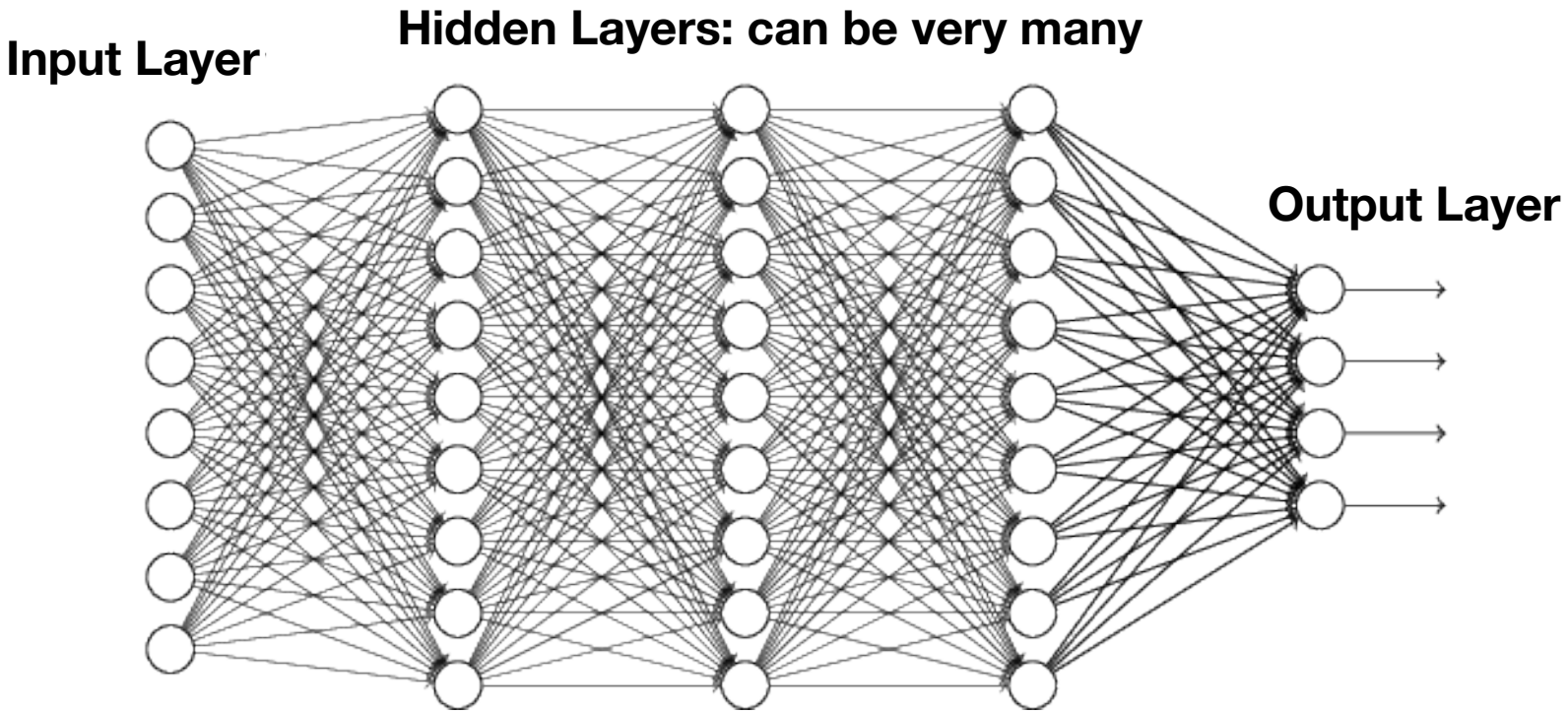

http://neuralnetworksanddeeplearning.com/chap2.html

# Structures of Neural Networks




http://neuralnetworksanddeeplearning.com/chap2.html

# Structures of Neural Networks




http://neuralnetworksanddeeplearning.com/chap5.html

# Optimizer

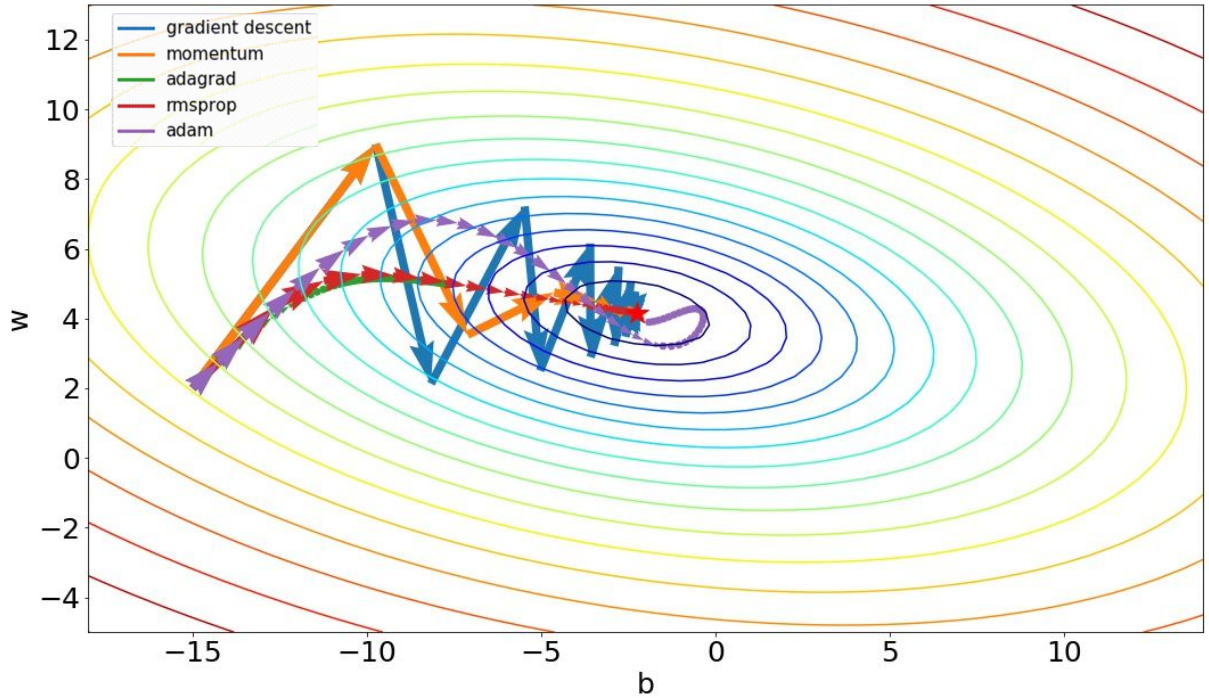
$$w^{+} = w - \eta * \frac{\partial E}{\partial w}$$

learning rate :
**한번에 얼마나 학습할지**

gradient :
**어떤 방향으로 학습할지**

https://github.com/ilguyi/optimizers.numpy

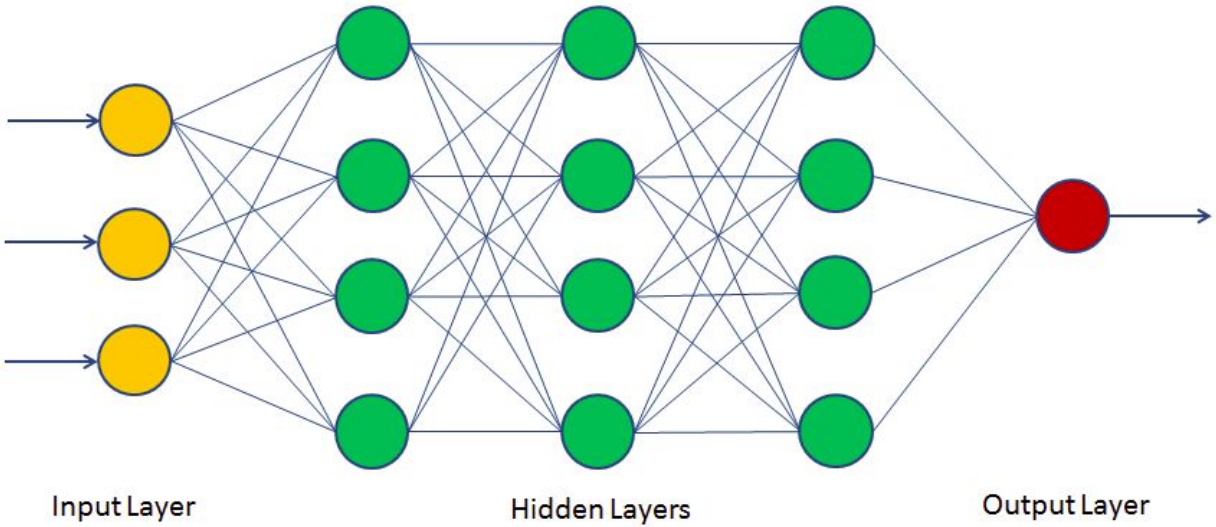
# Optimizer




Optimization of Linear Regression using Various Gradient Descent Algorithms

https://github.com/ilguyi/optimizers.numpy

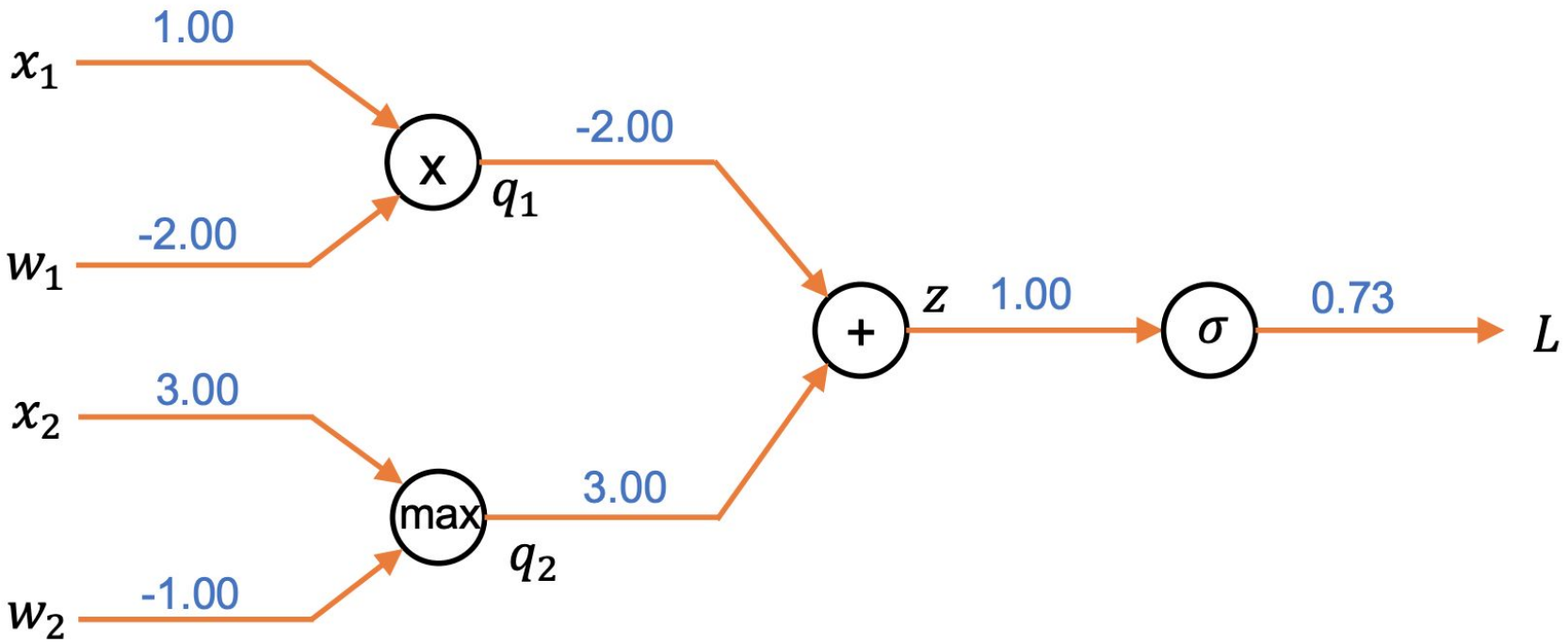
# Backpropagation




$$\frac{\partial L(\theta)}{\partial W_{ij}^{(1)}} \leftarrow \frac{\partial L(\theta)}{\partial W_{ij}^{(2)}} \leftarrow \frac{\partial L(\theta)}{\partial W_{ij}^{(3)}} \leftarrow \frac{\partial L(\theta)}{\partial W_{ij}^{(4)}}$$

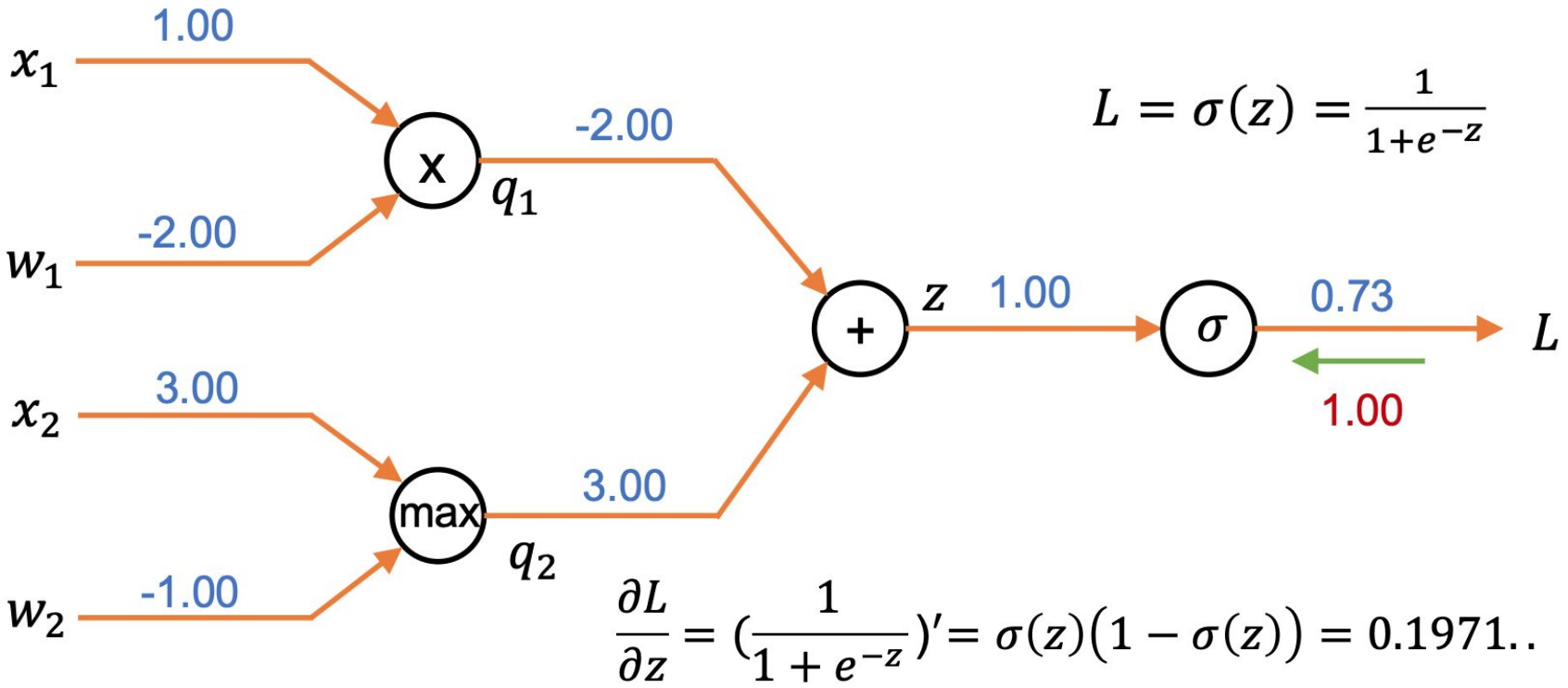
https://www.datacamp.com/community/tutorials/neural-network-models-r

# Backpropagation




http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

# Backpropagation

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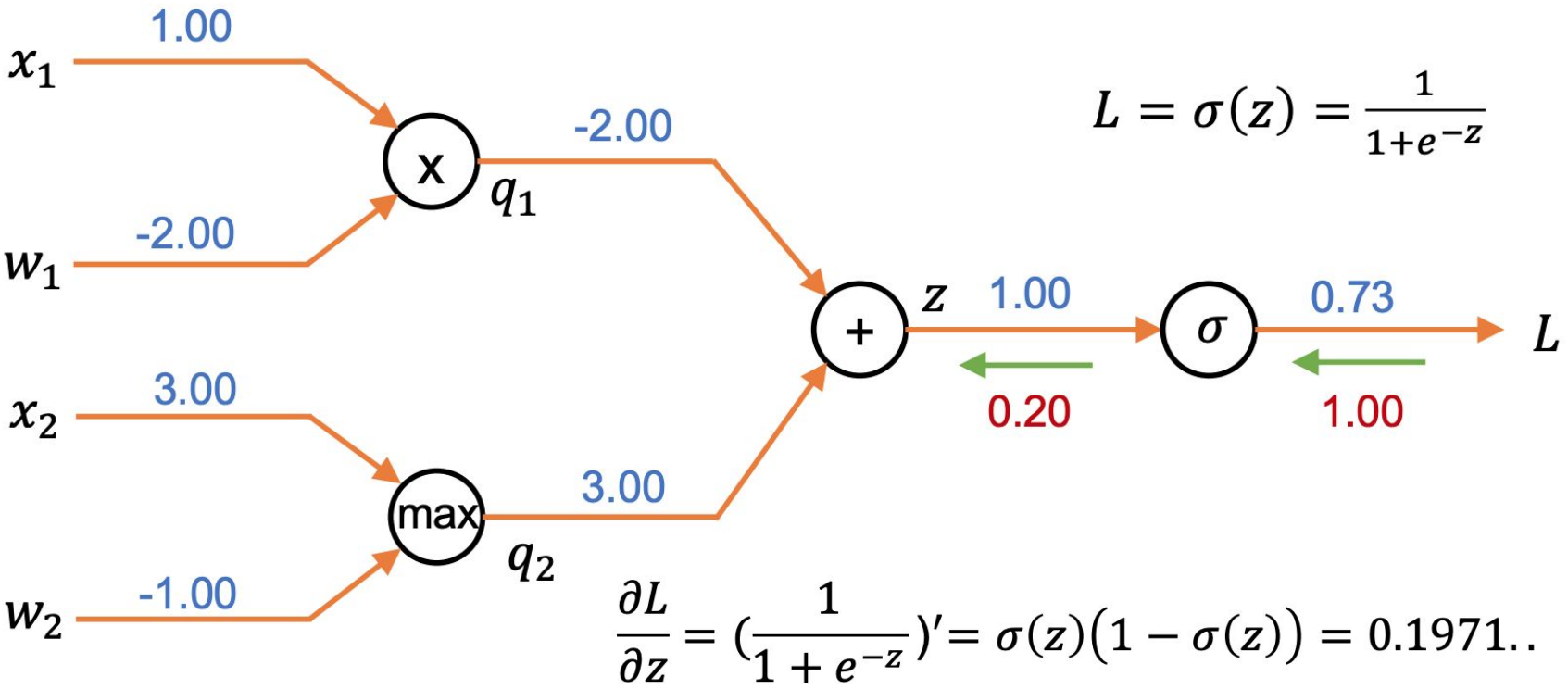
# Backpropagation

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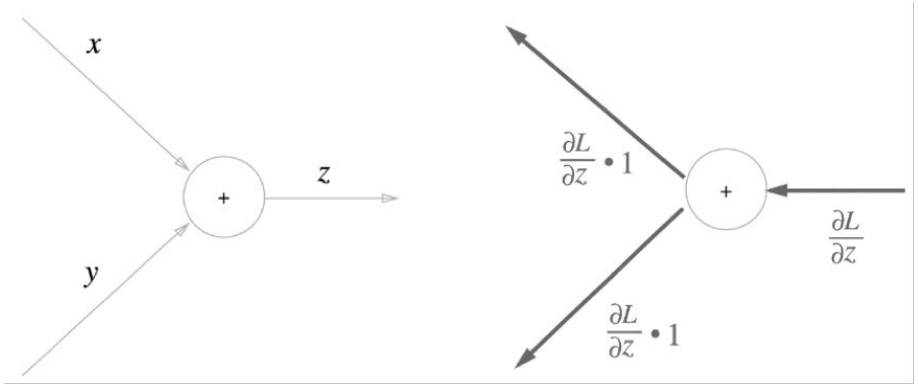
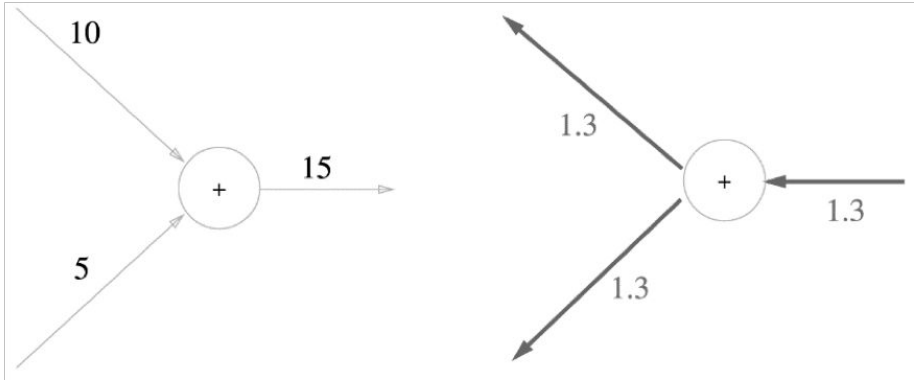
# Backpropagation

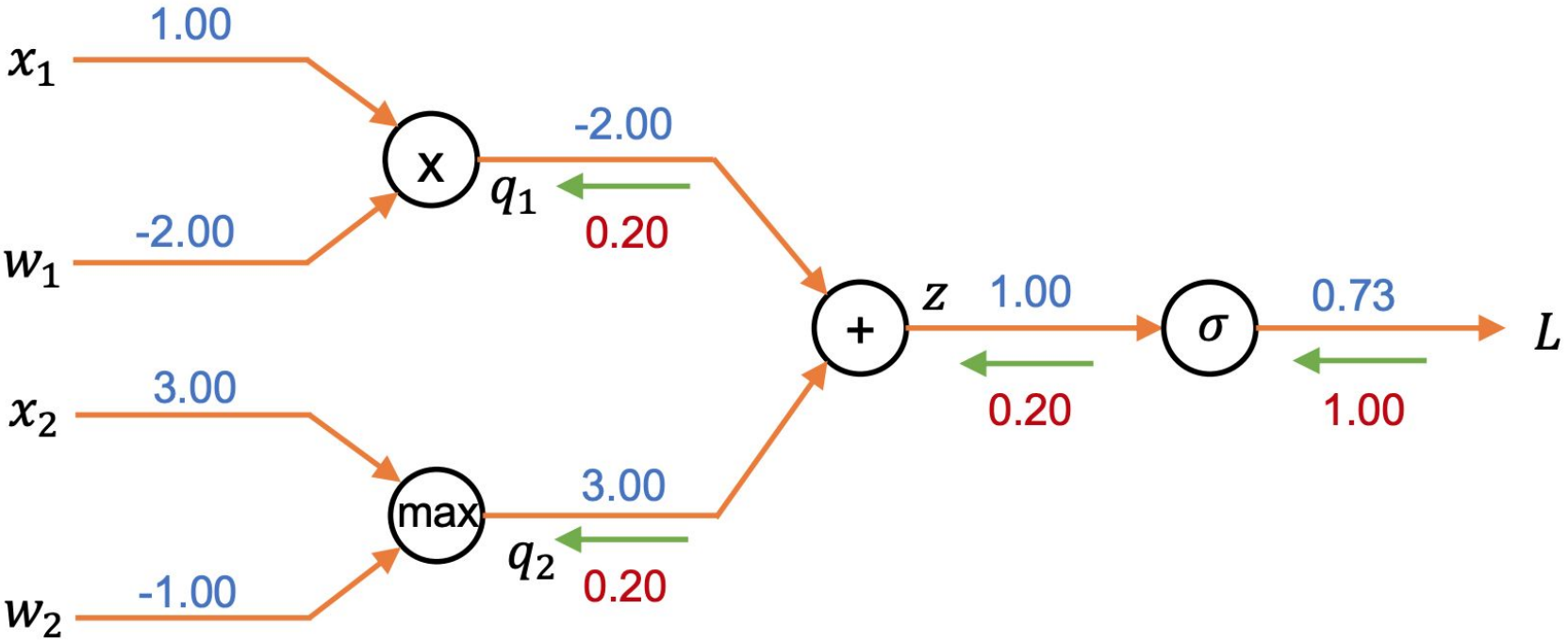



$$z = x + y \Rightarrow \begin{cases} \frac{\partial z}{\partial x} = 1 \\ \frac{\partial z}{\partial y} = 1 \end{cases}$$



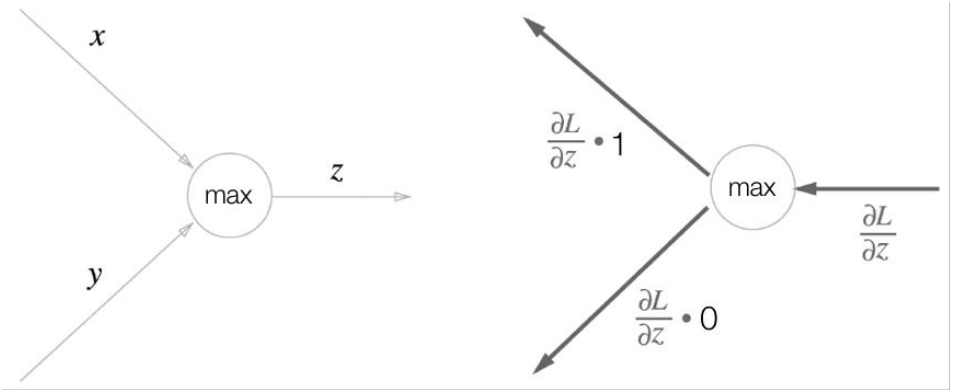

**gradient distributor**

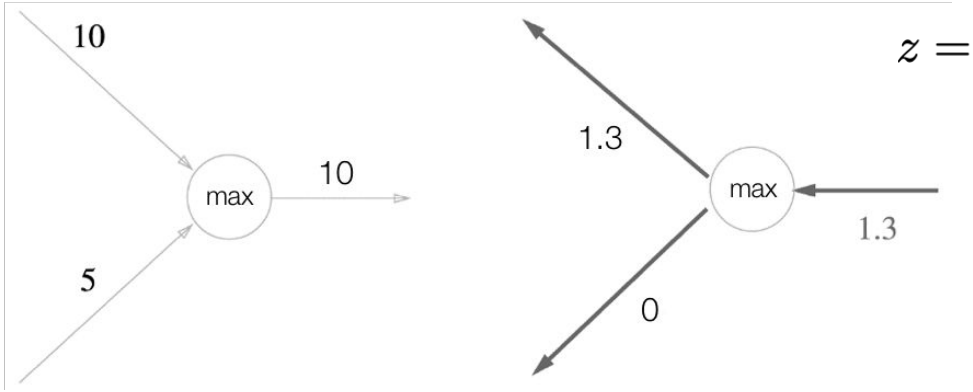
# Backpropagation




http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

# Backpropagation

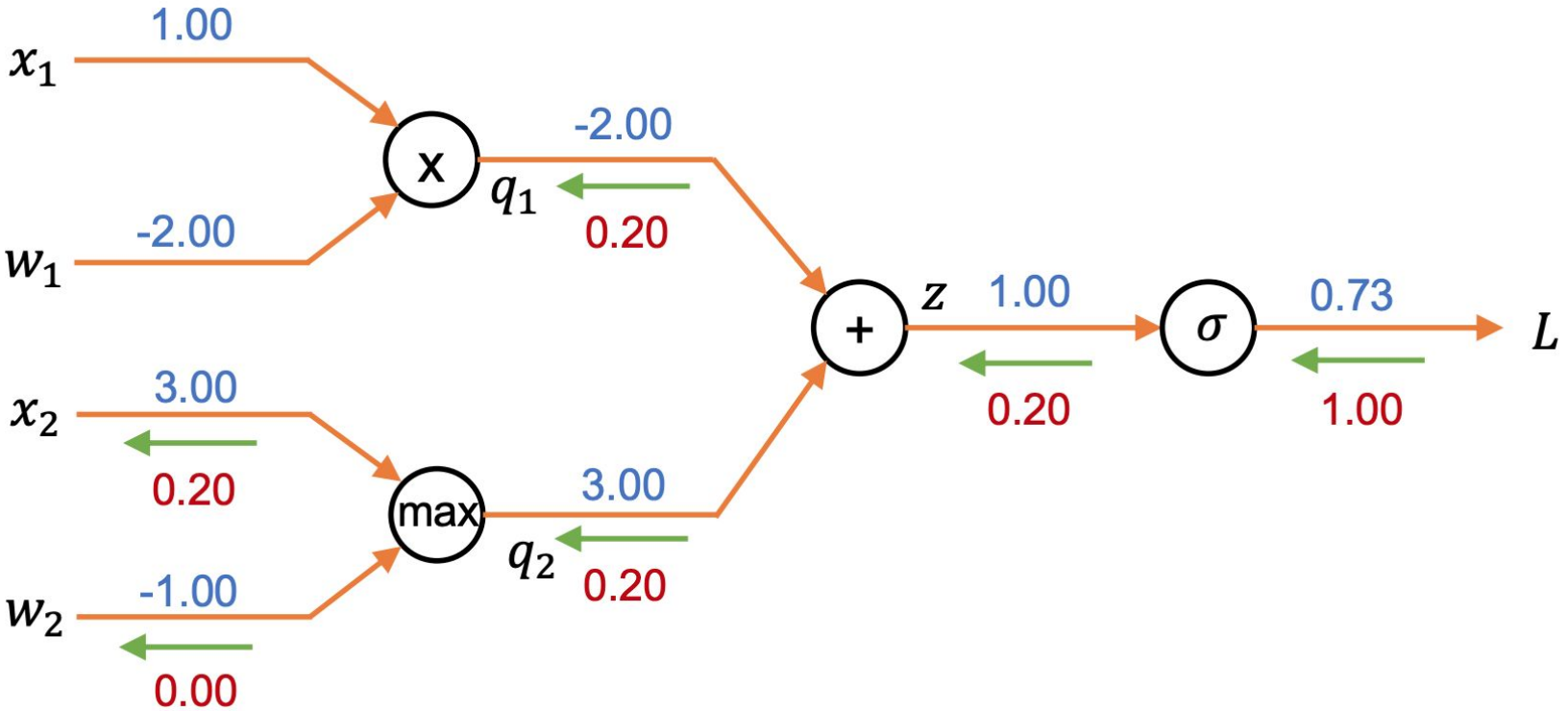



**gradient router**

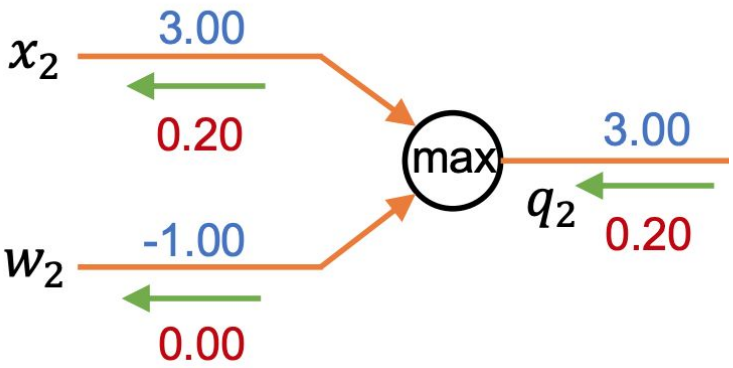
$$z = \max(x, y) \Rightarrow \begin{cases} \text{if } x > y \begin{cases} \frac{\partial z}{\partial x} = 1 \\ \frac{\partial z}{\partial y} = 0 \end{cases} \\ \text{if } x < y \begin{cases} \frac{\partial z}{\partial x} = 0 \\ \frac{\partial z}{\partial y} = 1 \end{cases} \end{cases}$$

# Backpropagation




http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

# Backpropagation




$$\frac{\partial q_2}{\partial x_2} = \mathbf{1}(x_2 > w_2)$$

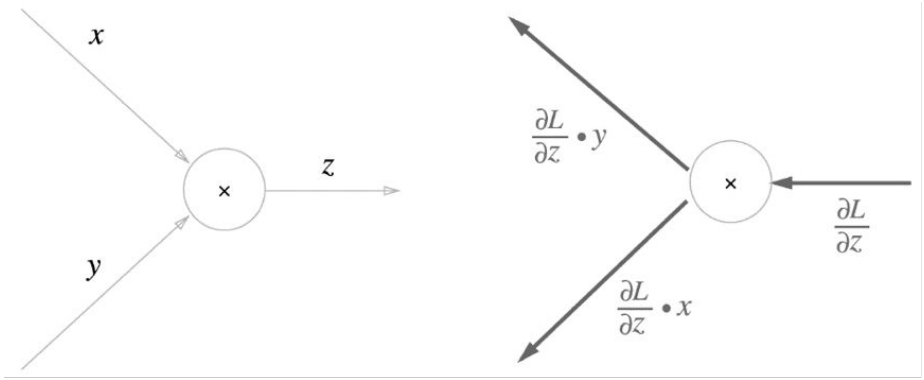
$$\frac{\partial L}{\partial x_2} = \frac{\partial L}{\partial q_2} \cdot \frac{\partial q_2}{\partial x_2} = 0.20 * 1.00 = 0.20$$

$$\frac{\partial q_2}{\partial w_2} = \mathbf{1}(w_2 > x_2)$$

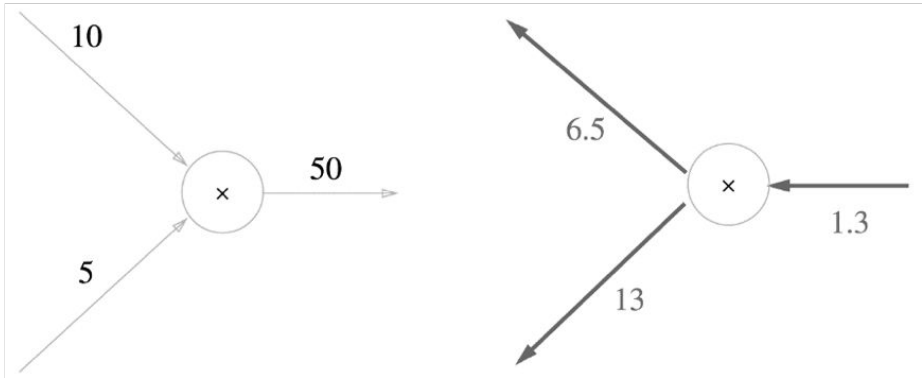
$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial q_2} \cdot \frac{\partial q_2}{\partial w_2} = 0.20 * 0.00 = 0.00$$

http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

# Backpropagation

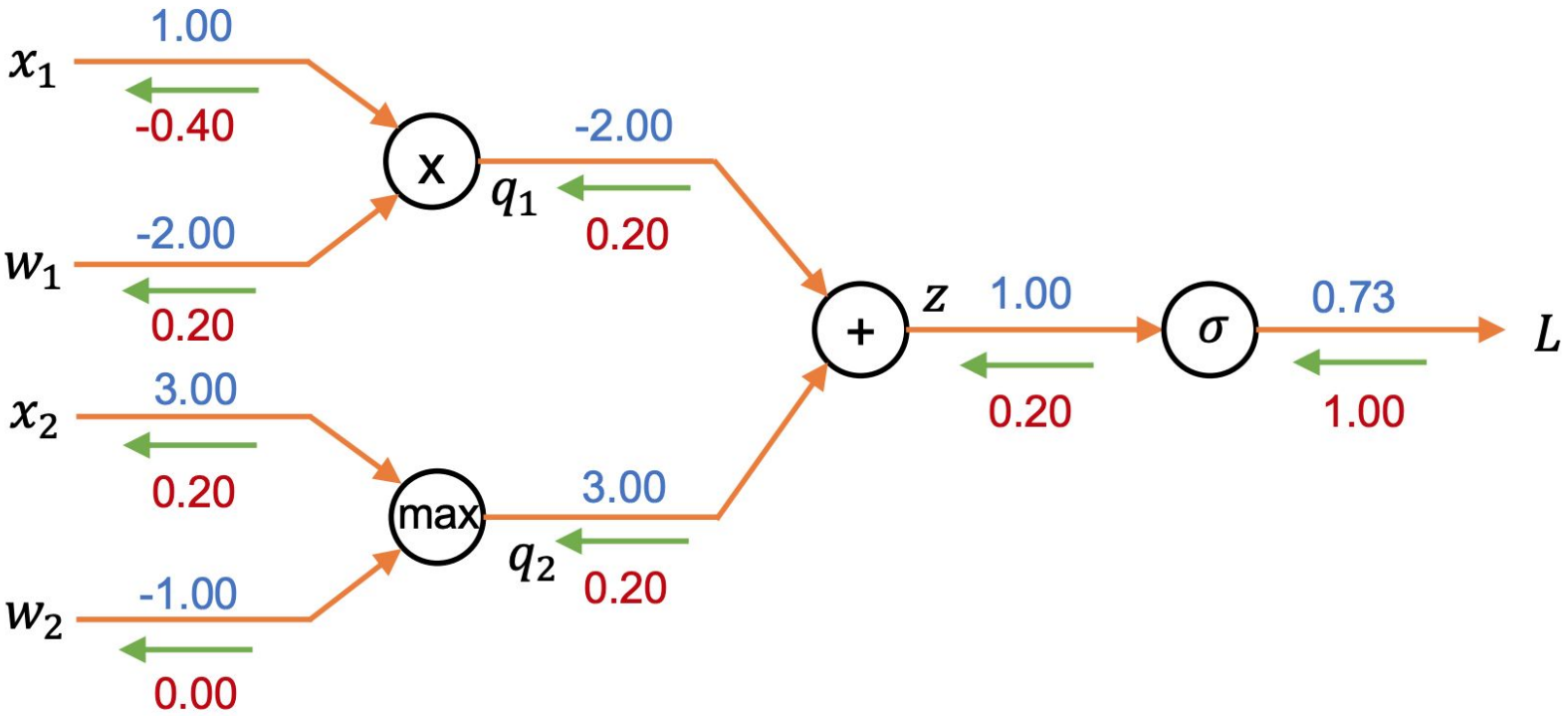



$$z = xy \Rightarrow \begin{cases} \dfrac{\partial z}{\partial x} = y \\ \dfrac{\partial z}{\partial y} = x \end{cases}$$



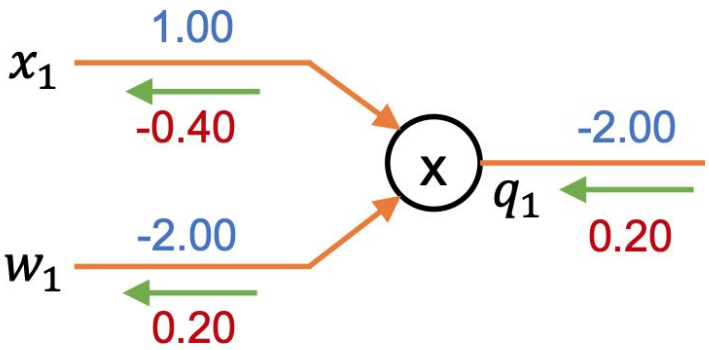

**gradient switcher**

# Backpropagation




http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

# Backpropagation




$$\frac{\partial q_1}{\partial x_1} = w_1$$

$$\frac{\partial L}{\partial x_1} = \frac{\partial L}{\partial q_1} \cdot \frac{\partial q_1}{\partial x_1} = 0.20 * (-2.00) = -0.40$$

$$\frac{\partial q_1}{\partial w_1} = x_1$$

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial q_1} \cdot \frac{\partial q_1}{\partial w_1} = 0.20 * 1.00 = 0.20$$

http://mac.kaist.ac.kr/~juhan/gct634/slides/06-deep_learning_intro.pdf

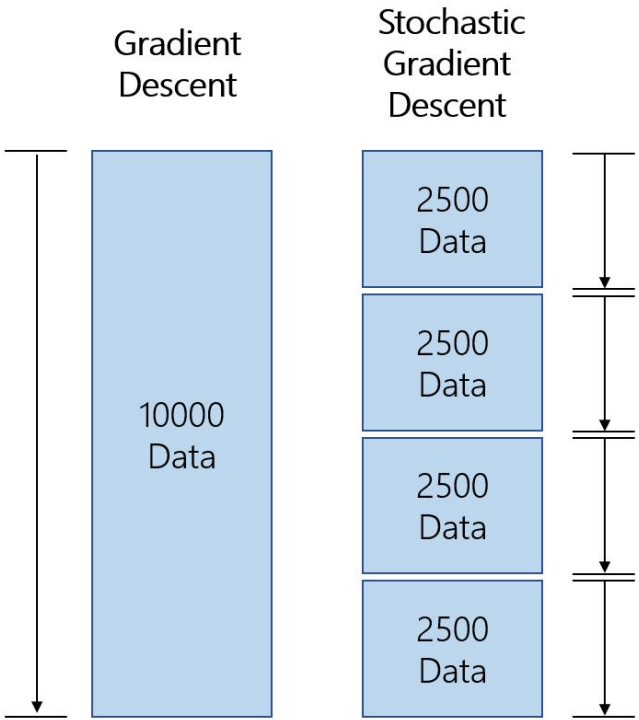
# Backpropagation

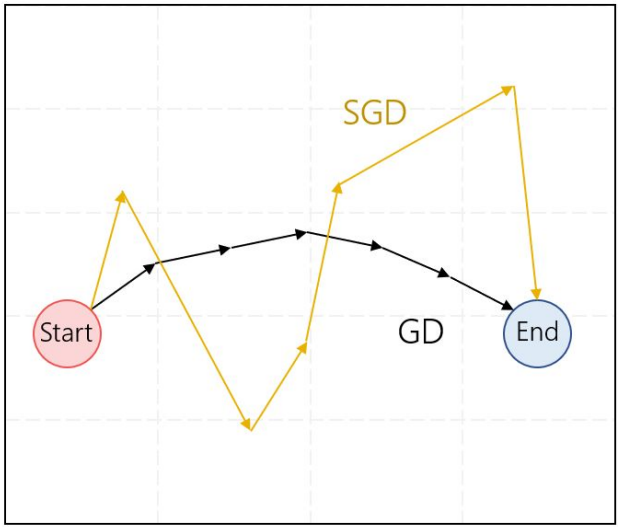
$$w^{+} = w - \eta * \frac{\partial E}{\partial w}$$

learning rate :
**한번에 얼마나 학습할지**

gradient :
**어떤 방향으로 학습할지**

# Optimizer

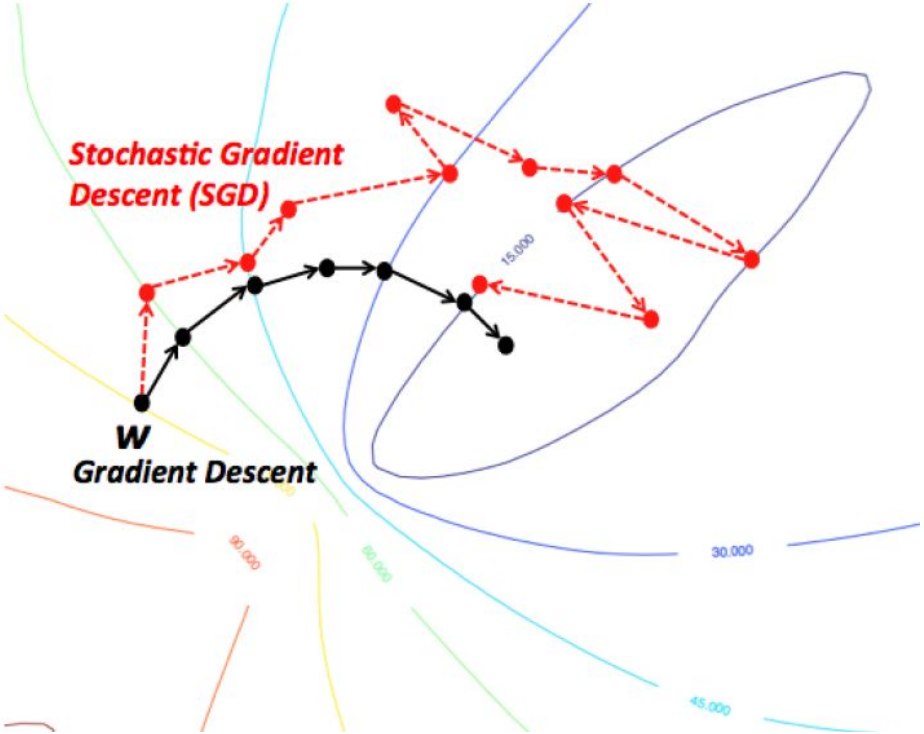



더 비틀비틀 가는 것 같지만
기존 보다 더 빠르게 학습합니다

https://github.com/ilguyi/optimizers.numpy

# Optimizer

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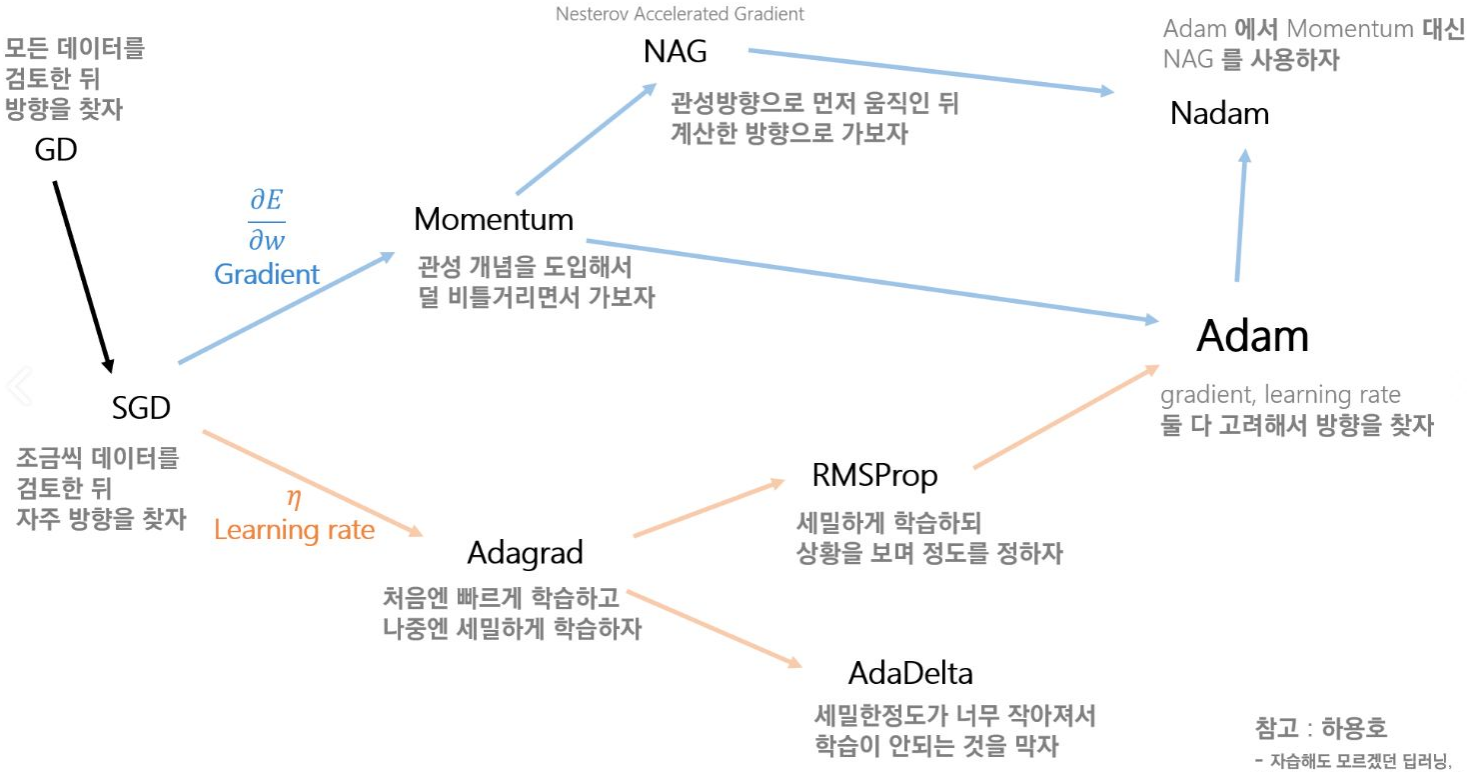
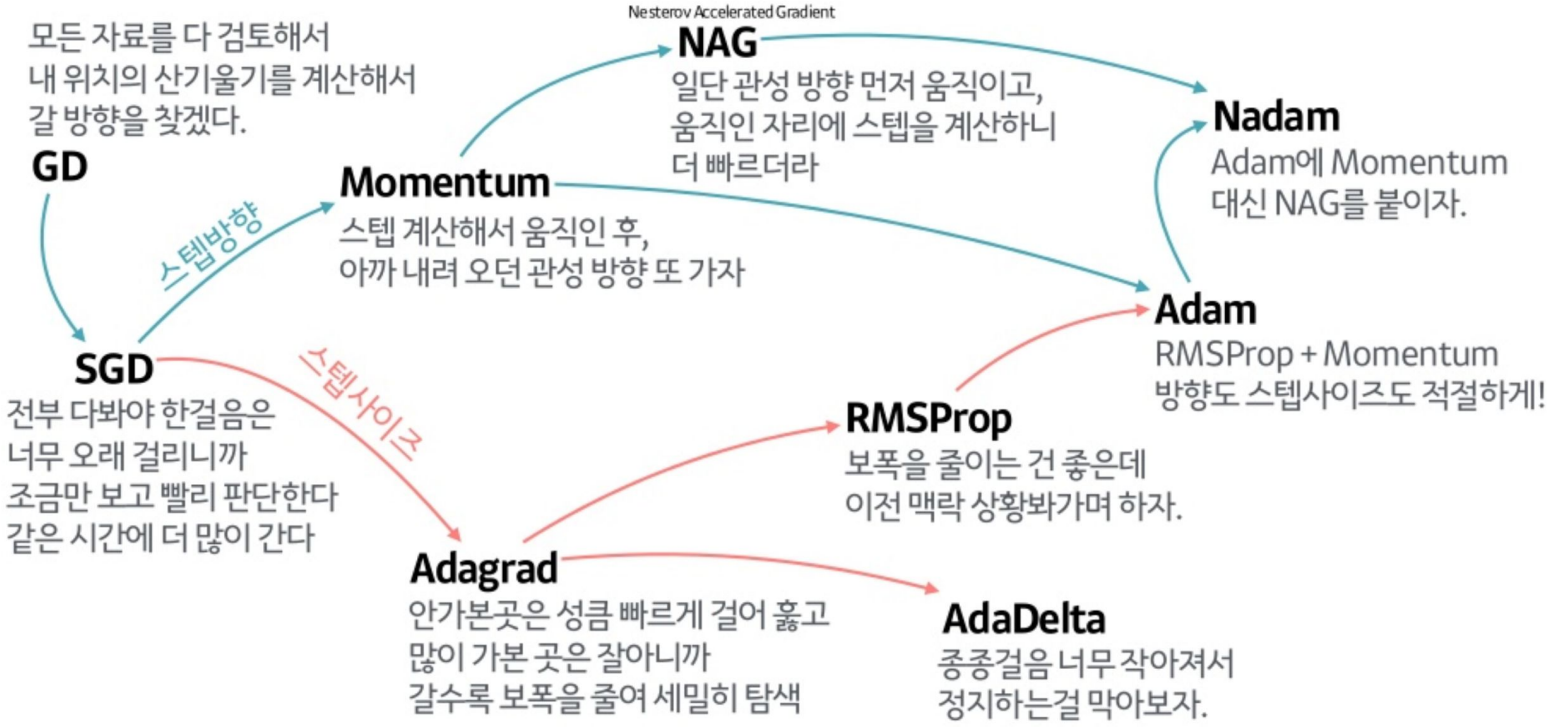
# Optimizer




https://gomguard.tistory.com/187

# Optimizer




https://seamless.tistory.com/38

# Training Process - MNIST

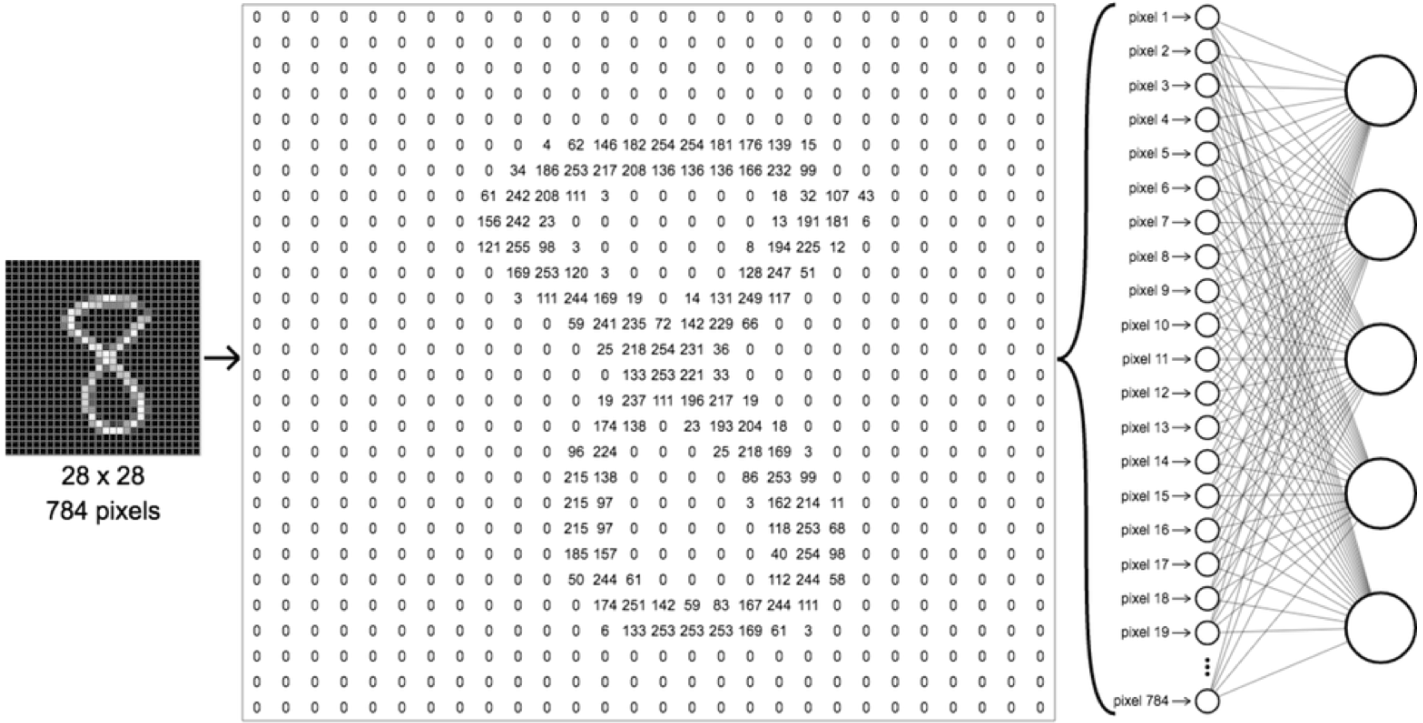
- MNIST dataset
- 0 ~ 9의 손 글씨 데이터
- 28 x 28 grayscale 이미지
- 6만장 학습 데이터, 1만장 테스트 데이터

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

# Training Process - MNIST

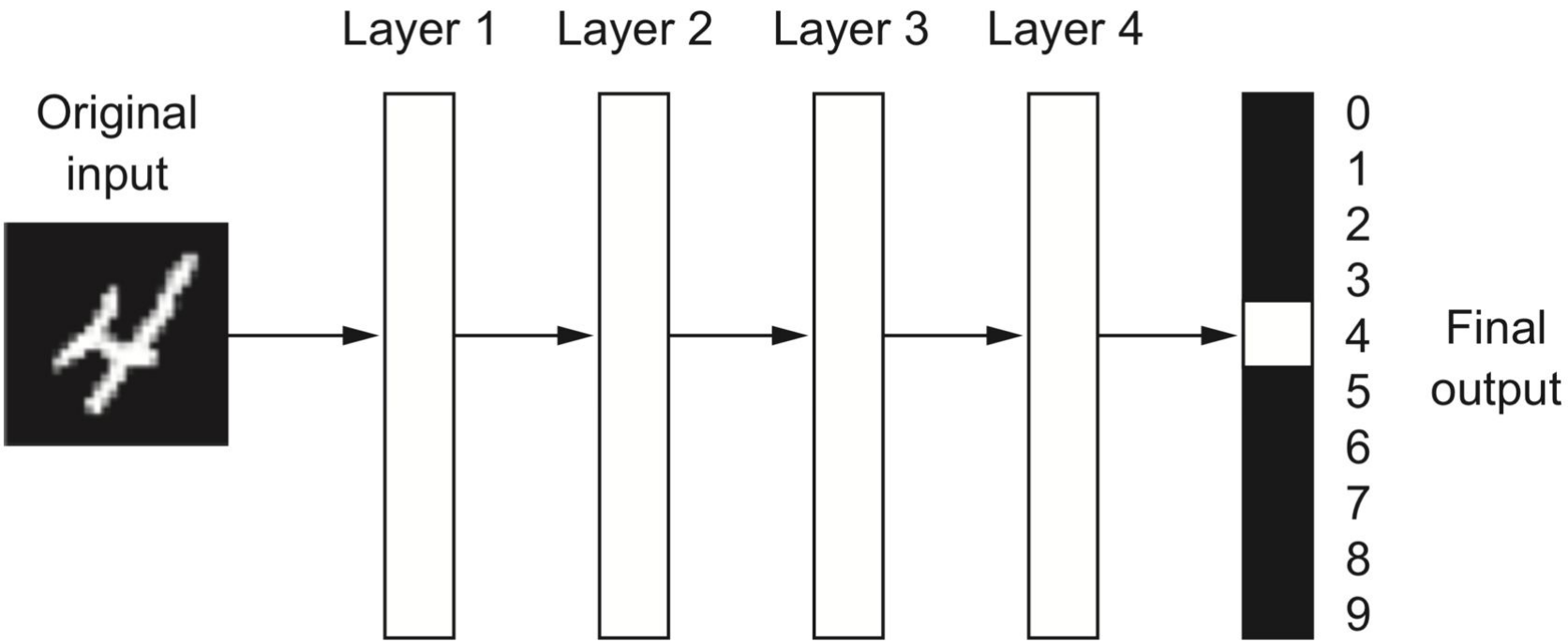
- 입력 ($x$ )
  - 28 x 28 = 784 dimensional vector
- 출력 ($y = y(x)$ )
  - 10 dimensional vector
  - ex) 숫자 6 : $y(x) = (0, 0, 0, 0, 0, 0, 1, 0, 0, 0)^T$

# Training Process - MNIST




https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

# Training Process - MNIST

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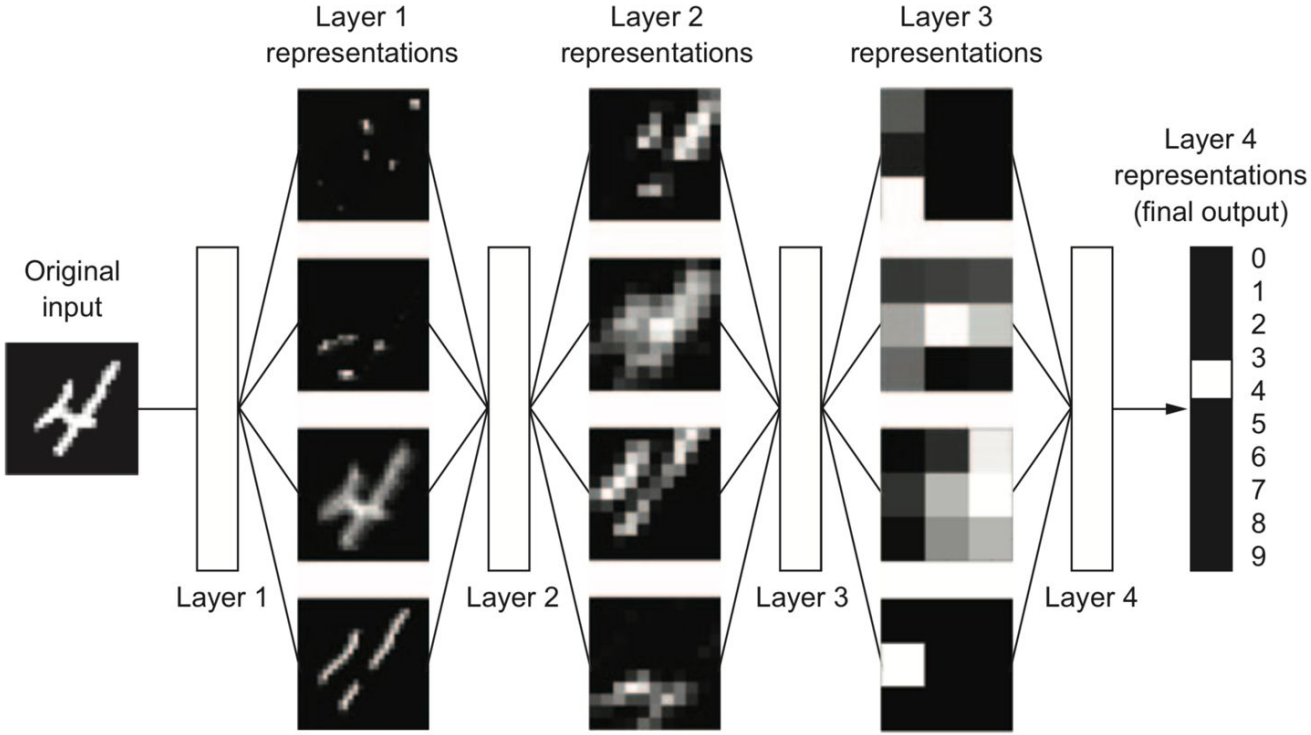
# Training Process - MNIST

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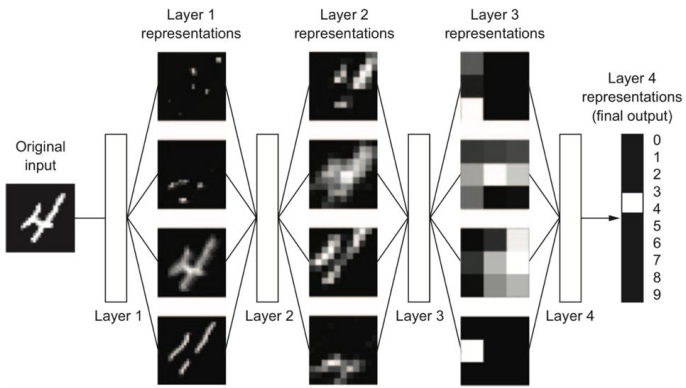
# Training Process - MNIST




| logits: $\mathbf{z}$ |
|---|
| -2.1 |
| -0.3 |
| 0.8 |
| 0.9 |
| 4.2 |
| -0.4 |
| 1.2 |
| 2.0 |
| -1.8 |
| -0.8 |

$$a_i = \frac{e^{z_i}}{\sum_k e^{z_k}},$$

$$\text{where } z_i = \sum_j W_{ij} x_j + b_i$$

| softmax: $\mathbf{a}$ |
|---|
| 0.0015 |
| 0.0088 |
| 0.026 |
| 0.029 |
| 0.79 |
| 0.008 |
| 0.039 |
| 0.088 |
| 0.002 |
| 0.0053 |

Francois Chollet, Deep Learning with Pyhont (2018), chap. 1, p. 9

# Training Process - MNIST

| prediction | label |
|---|---|
| 0.0015 | 0 |
| 0.0088 | 0 |
| 0.026 | 0 |
| 0.029 | 0 |
| 0.79 | 1 |
| 0.008 | 0 |
| 0.039 | 0 |
| 0.088 | 0 |
| 0.002 | 0 |
| 0.0053 | 0 |

**Mean Squared Error (MSE)**

$$\mathcal{L} \equiv \frac{1}{2N}\sum_i ||\hat{\mathbf{y}}_i - \mathbf{y}_i||^2 = \frac{1}{2N}\sum_i \sum_k (\hat{y}_{ik} - y_{ik})^2$$

**Cross Entropy Loss**

$$\mathcal{L} \equiv -\frac{1}{N}\sum_i \mathbf{y}_i \log \hat{\mathbf{y}}_i = -\frac{1}{N}\sum_i \sum_k y_{ik} \log \hat{y}_{ik}$$

label: $y$
prediction: $\hat{y}$
dimension: $k$

Francois Chollet, Deep Learning with Pyhont (2018), chap. 1, p. 9

# Training Process - MNIST

- 주어진 loss function $\mathcal{L}$을 **최소화** 하는 parameters $\Theta$를 찾는 것

$$\arg\min_{\Theta} \mathcal{L} \qquad \Theta = \{\mathbf{w}_1, \cdots, \mathbf{b}_1, \cdots\}$$

- 간단하게 말하면 굉장히 복잡한 함수를 잘 **fitting** 하는 것

## How to?

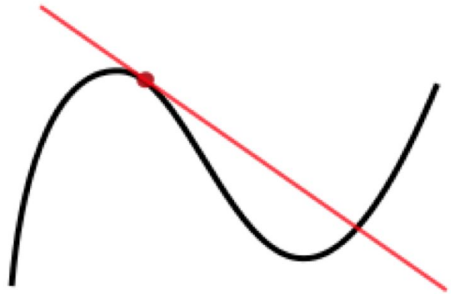
현재 위치에서 **가장 가파른 (내리막) 방향**으로 **조금씩 이동**하자

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

# Training Process - MNIST

- **미분**을 하면 된다

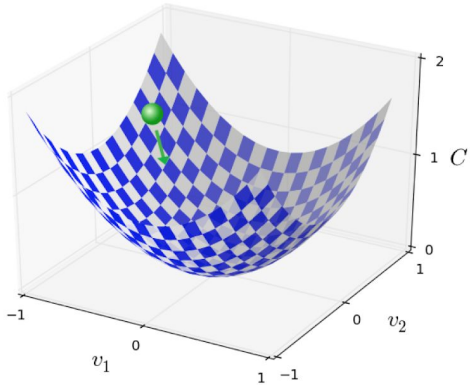
$$\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$



- 방향이 두 (또는 여러) 방향 : 편미분

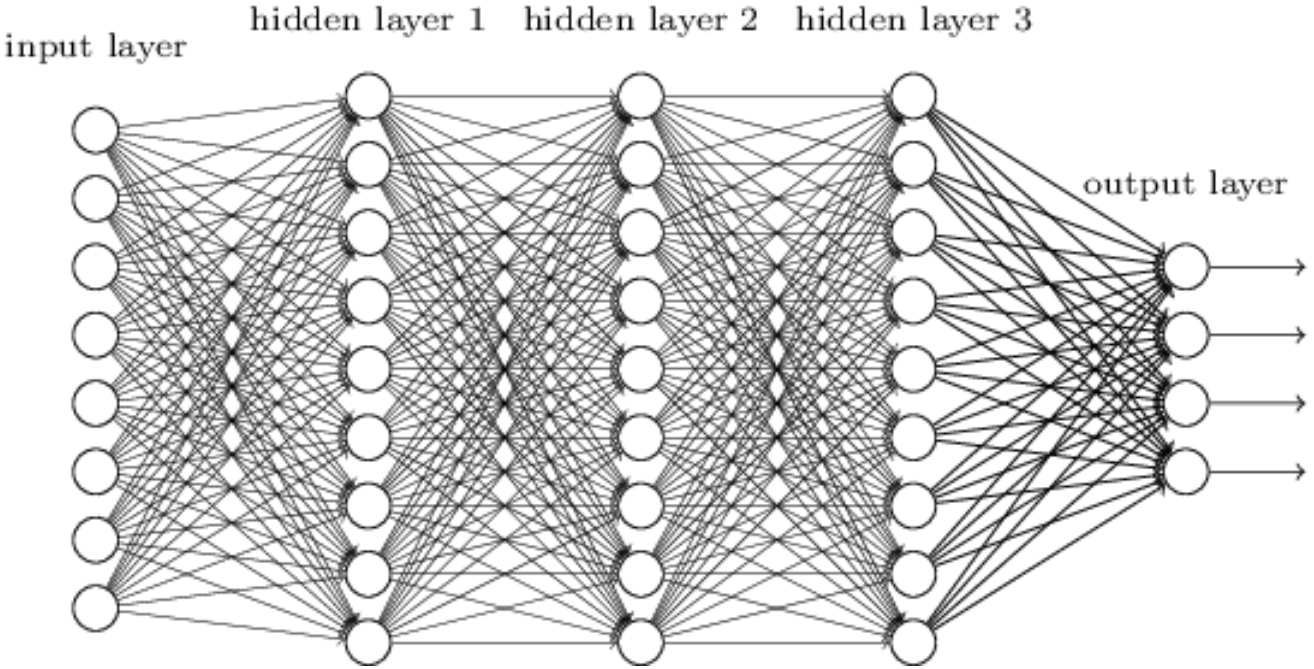
$$\frac{\partial f(x,y)}{\partial x} = \lim_{h \to 0} \frac{f(x+h,y) - f(x,y)}{h}$$

$$\frac{\partial f(x,y)}{\partial y} = \lim_{h \to 0} \frac{f(x,y+h) - f(x,y)}{h}$$




https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/neural_networks.html

# Vanishing Gradient

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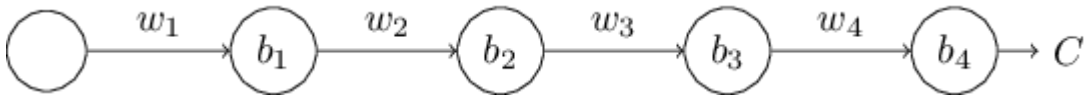
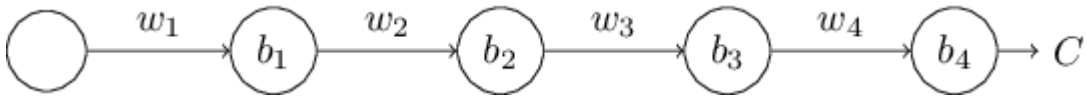
# Vanishing Gradient




$$W := W - \alpha \frac{\partial}{\partial W} cost(W)$$

http://neuralnetworksanddeeplearning.com/chap5.html

# Vanishing Gradient




$$W := W - \alpha \frac{\partial}{\partial W} cost(W)$$

## Chain rule

$$\frac{\partial C}{\partial b_1} = \left(\frac{\partial C}{\partial a_4}\frac{\partial a_4}{\partial z_4}\right)\left(\frac{\partial z_4}{\partial a_3}\frac{\partial a_3}{\partial z_3}\right)\left(\frac{\partial z_3}{\partial a_2}\frac{\partial a_2}{\partial z_2}\right)\left(\frac{\partial z_2}{\partial a_1}\frac{\partial a_1}{\partial z_1}\frac{\partial z_1}{\partial b_1}\right)$$

http://neuralnetworksanddeeplearning.com/chap5.html

# Vanishing Gradient

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$


## Chain rule

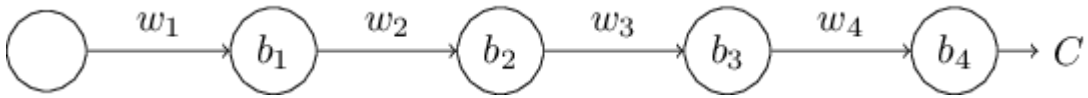
$$\frac{\partial C}{\partial b_1} = \left(\frac{\partial C}{\partial a_4}\frac{\partial a_4}{\partial z_4}\right)\left(\frac{\partial z_4}{\partial a_3}\frac{\partial a_3}{\partial z_3}\right)\left(\frac{\partial z_3}{\partial a_2}\frac{\partial a_2}{\partial z_2}\right)\left(\frac{\partial z_2}{\partial a_1}\frac{\partial a_1}{\partial z_1}\frac{\partial z_1}{\partial b_1}\right)$$

$$a_l = \sigma(z_l) \Rightarrow \frac{\partial a_l}{\partial z_l} = \sigma'(z_l) \qquad z_l = w_l a_{l-1} + b_l \Rightarrow \frac{\partial z_l}{\partial a_{l-1}} = w_l$$

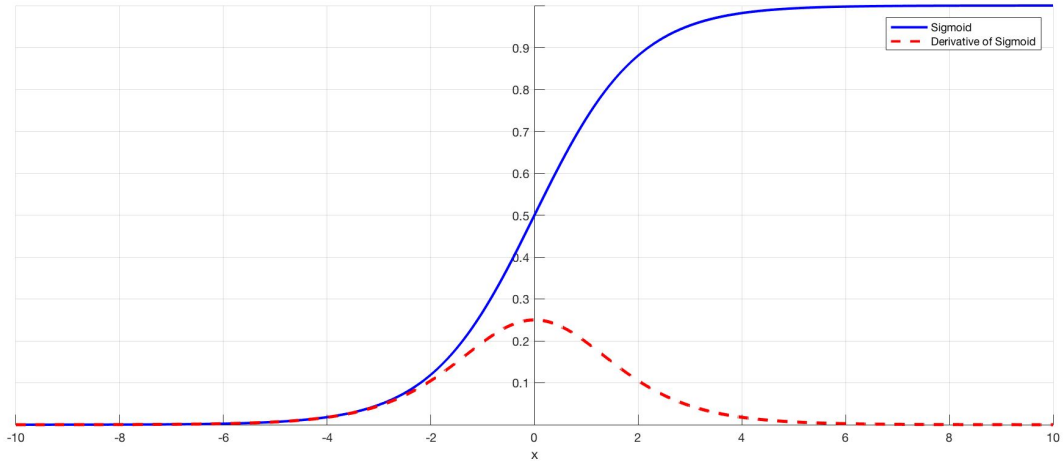
$$\frac{\partial C}{\partial b_1} = \frac{\partial C}{\partial a_4}\sigma'(z_4) \times w_4\sigma'(z_3) \times w_3\sigma'(z_2) \times w_2\sigma'(z_1)$$

http://neuralnetworksanddeeplearning.com/chap5.html

# Vanishing Gradient

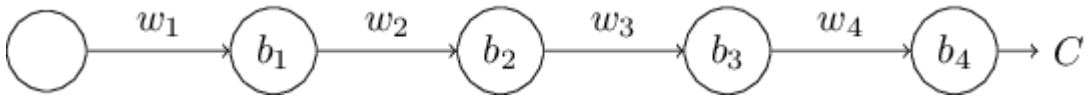


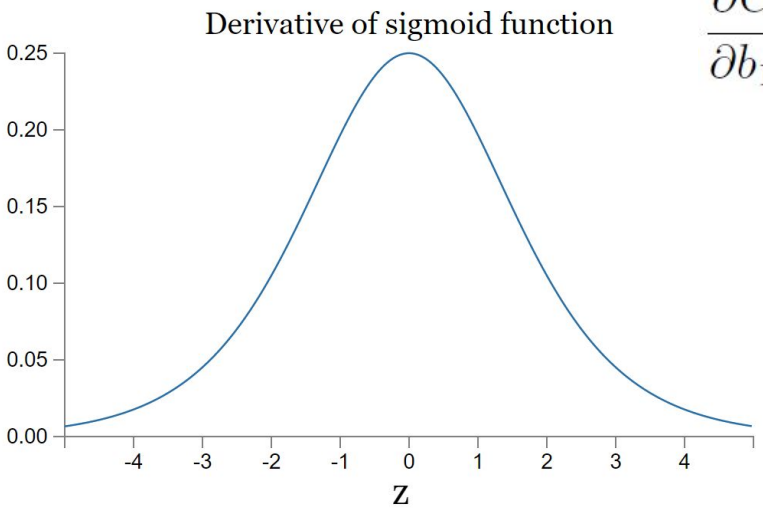

sigmoid function




http://neuralnetworksanddeeplearning.com/chap5.html

# Vanishing Gradient




$$\frac{\partial C}{\partial b_1} = \frac{\partial C}{\partial a_4}\sigma'(z_4) \times w_4\sigma'(z_3) \times w_3\sigma'(z_2) \times w_2\sigma'(z_1)$$

generally $|w_l| < 1$

$\therefore |w_l\sigma'(z_l)| < 1/4$

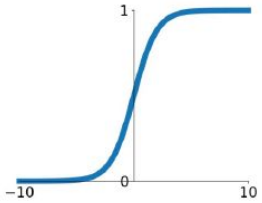
아래쪽 layer는
학습이 잘 안됨

http://neuralnetworksanddeeplearning.com/chap5.html

# Activation Function

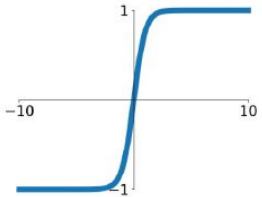
**Sigmoid**

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



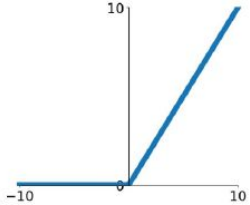

**tanh**

$$\tanh(x)$$



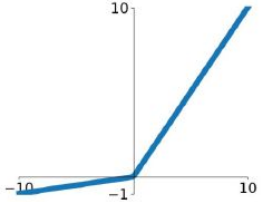

**ReLU**

$$\max(0, x)$$




**Leaky ReLU**

$$\max(0.1x, x)$$

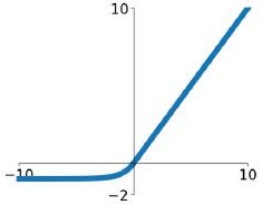



**Maxout**

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

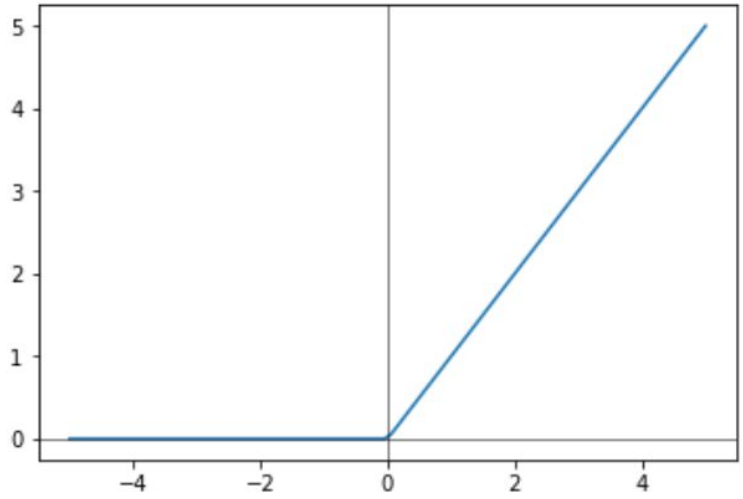
**ELU**

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



# Rectified Linear Unit (ReLU)

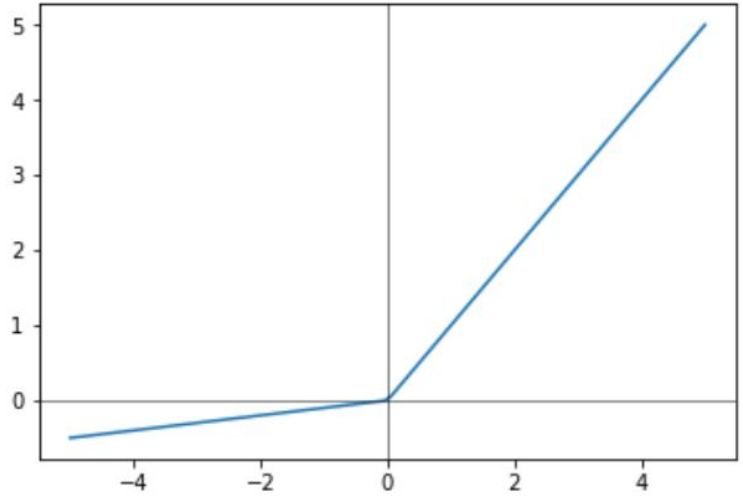
1. Gradient가 죽지 않는다
2. 계산량이 적다 (exponential에 비해)
3. 학습이 빠르게 수렴한다
    1. sigmoid, tanh에 비해 6배 정도 (실험적으로)
4. 실제로는 sigmoid보다 ReLU가 더 생물학적 뉴런에 더 가깝다




$$f_{\text{act}}(x) = \max(x, 0)$$

# Leaky ReLU

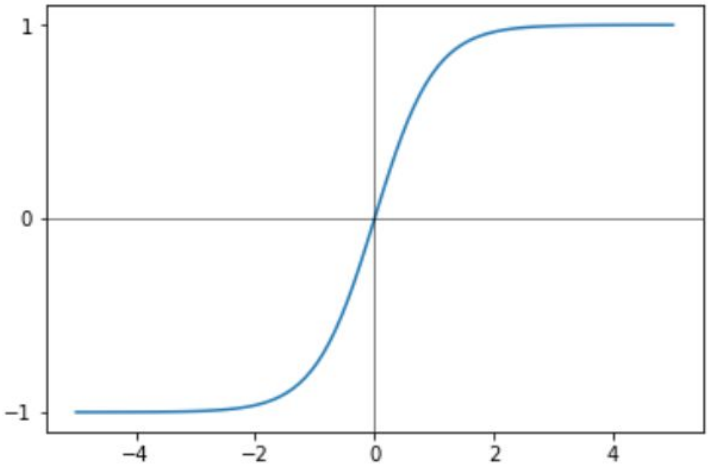
1. Gradient가 죽지 않는다
2. 계산량이 적다 (exponential에 비해)
3. 학습이 빠르게 수렴한다
    1. sigmoid, tanh에 비해 6배 정도 (실험적으로)
4. 노드가 죽지 않는다 ( output != 0 )




$$f_{\text{act}}(x) = \max(x, 0.01x)$$

# Tanh Activation Function

1. 출력값 범위 : [-1, 1]
2. 양끝의 뉴런들은 미분값(gradient)이 0에 가깝다
   - vanishing gradient 원인
3. 출력값이 zero-centered (해결)




$$f_{\text{act}}(x) = \tanh(x)$$

# Activation Function

- ReLU를 쓰자
  - Learning rate를 잘 조절하자
- Leaky ReLU / Maxout / ELU 등을 시도해보자
- Sigmoid / tanh 는 쓰지 말자

# Preparing Datasets

**Idea #1**: Choose hyperparameters that work best on the data


**Idea #2**: Split data into **train** and **test**, choose hyperparameters that work best on test data

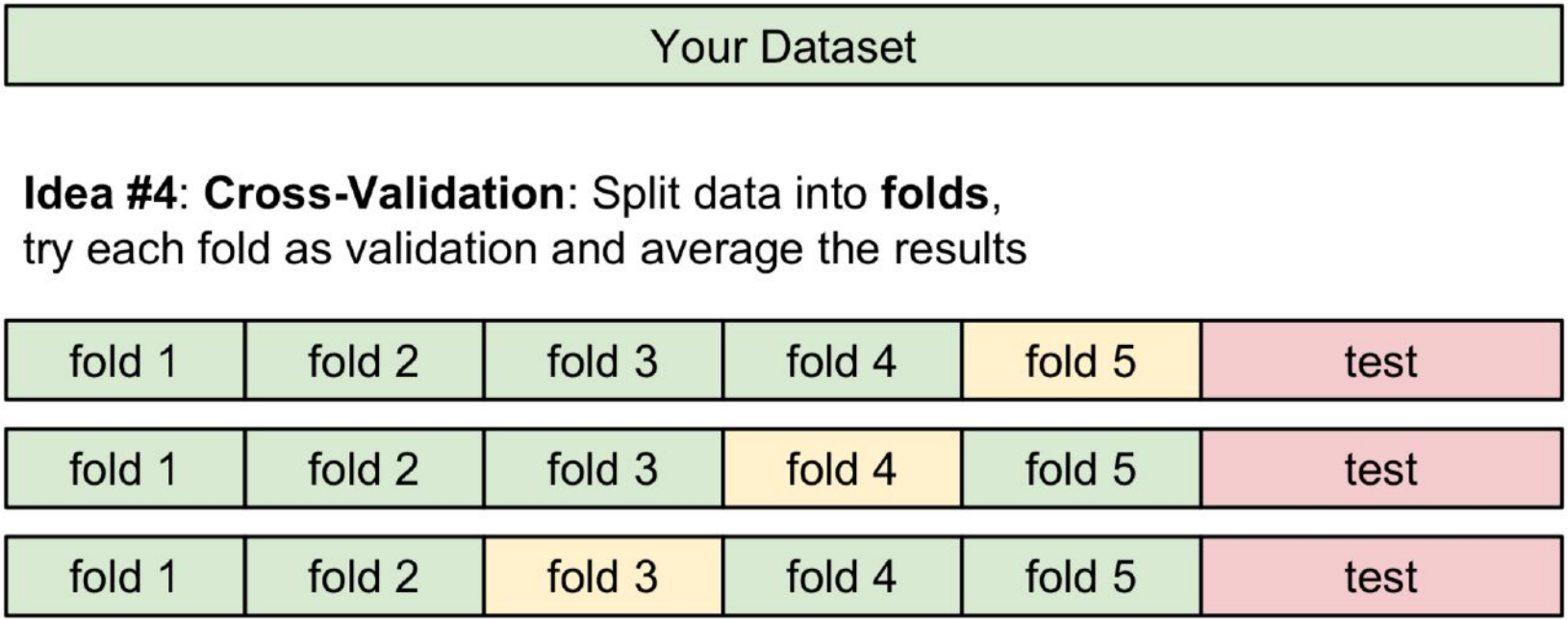
**BAD**: No idea how algorithm will perform on new data


**Idea #3**: Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

**Better!**

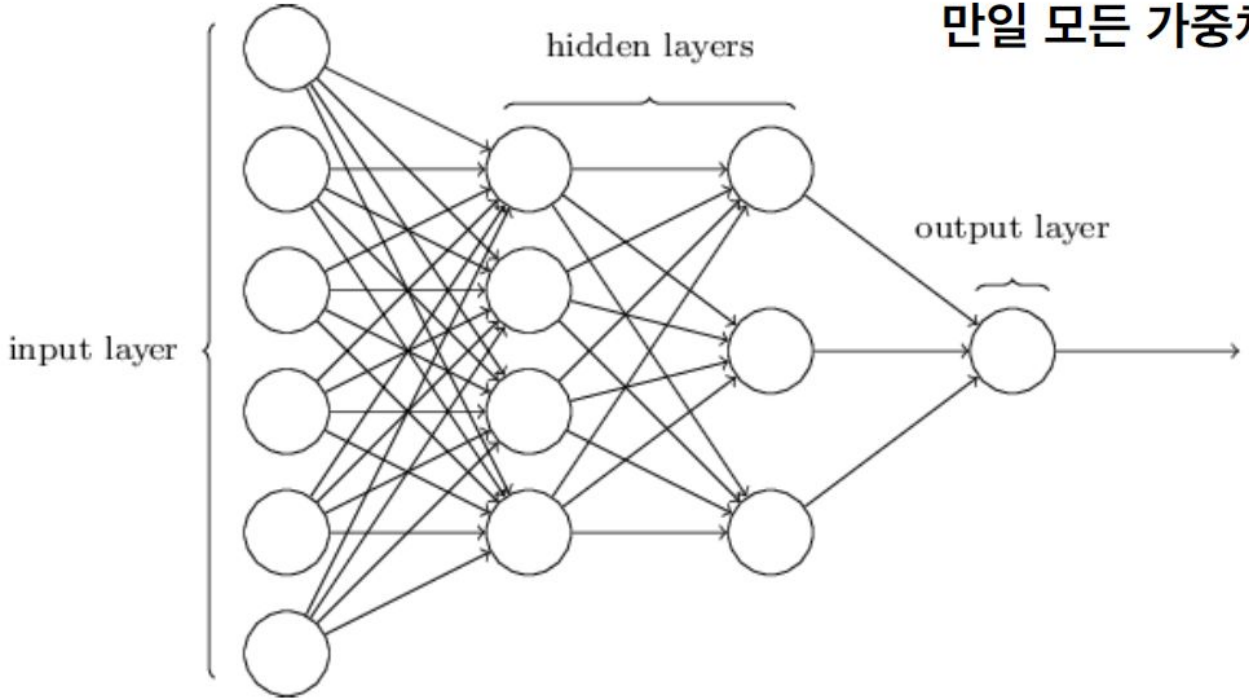

http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture02.pdf

# Preparing Datasets




http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture02.pdf

# Weight Initialization




만일 모든 가중치가 0이라면?

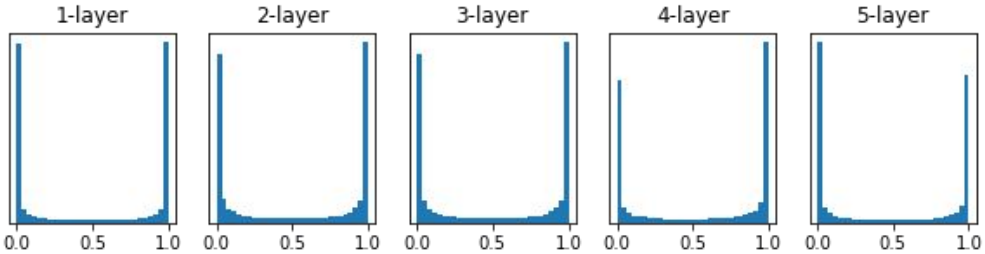
http://neuralnetworksanddeeplearning.com/chap2.html

# Weight Initialization

- 초깃값의 변화에 따라 은닉층의 활성화 값 분포가 어떻게 변할까?
  - Test
    - 5개의 layers, 각 100개 Nodes
    - 1000개의 무작위 입력 데이터
    - Activation Function - sigmoid, relu
    - 표준편차를 다르게 해서 실험

# Weight Initialization - Sigmoid

- 가중치를 표준편차가 1인 정규분포로 초기화

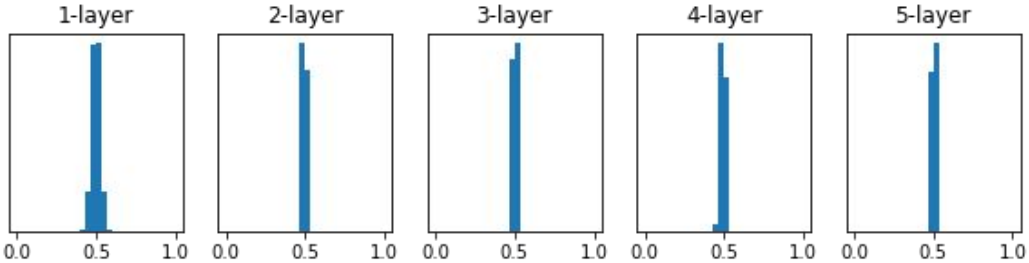



- 값이 0과 1에 치우침
- sigmoid 함수의 gradient가 죽는 현상이 일어남 (vanishing gradient)
- 네트워크가 깊어질수록 문제가 심해짐

https://sacko.tistory.com/43

# Weight Initialization - Sigmoid

- 가중치를 표준편차가 0.01인 정규분포로 초기화

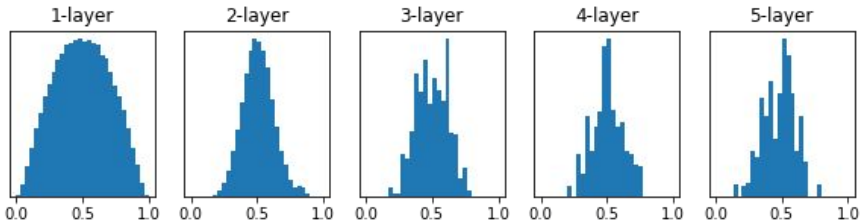



- 값이 0.5근처에 집중 : gradient가 죽지 않음
- 하지만 값이 몰려 있음 : 표현력이 제한 되어 있는 문제가 생김
  - 많은 뉴런이 같은 값을 출력한다는 것은 100개의 뉴런이 사실상 1개의 뉴런과 같음

https://sacko.tistory.com/43

# Weight Initialization - Sigmoid

- Xavier Normal Initialization



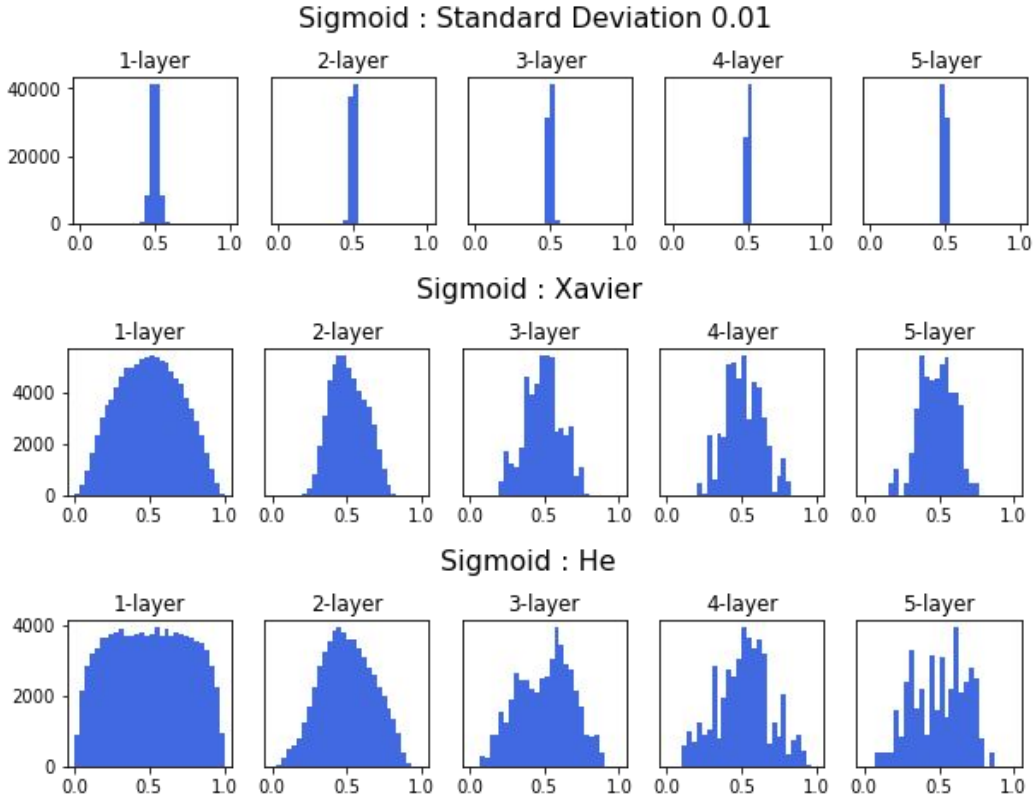

$$W \sim N(0, Var(W))$$

$$Var(W) = \sqrt{\frac{2}{n_{in} + n_{out}}}$$

($n_{in}$ : 이전 layer(input)의 노드 수, $n_{out}$ : 다음 layer의 노드 수)

https://reniew.github.io/13/

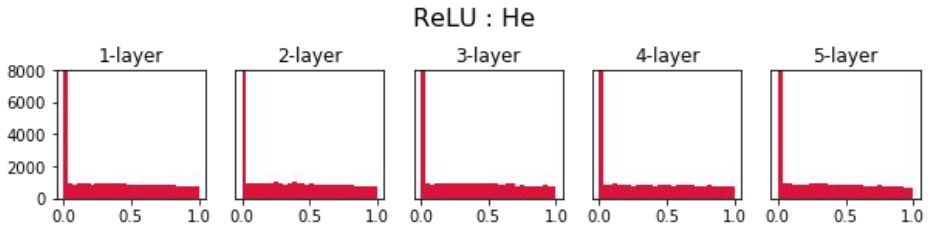
# Weight Initialization - Sigmoid




https://sacko.tistory.com/43

# Weight Initialization - ReLU

- He Normal Initialization



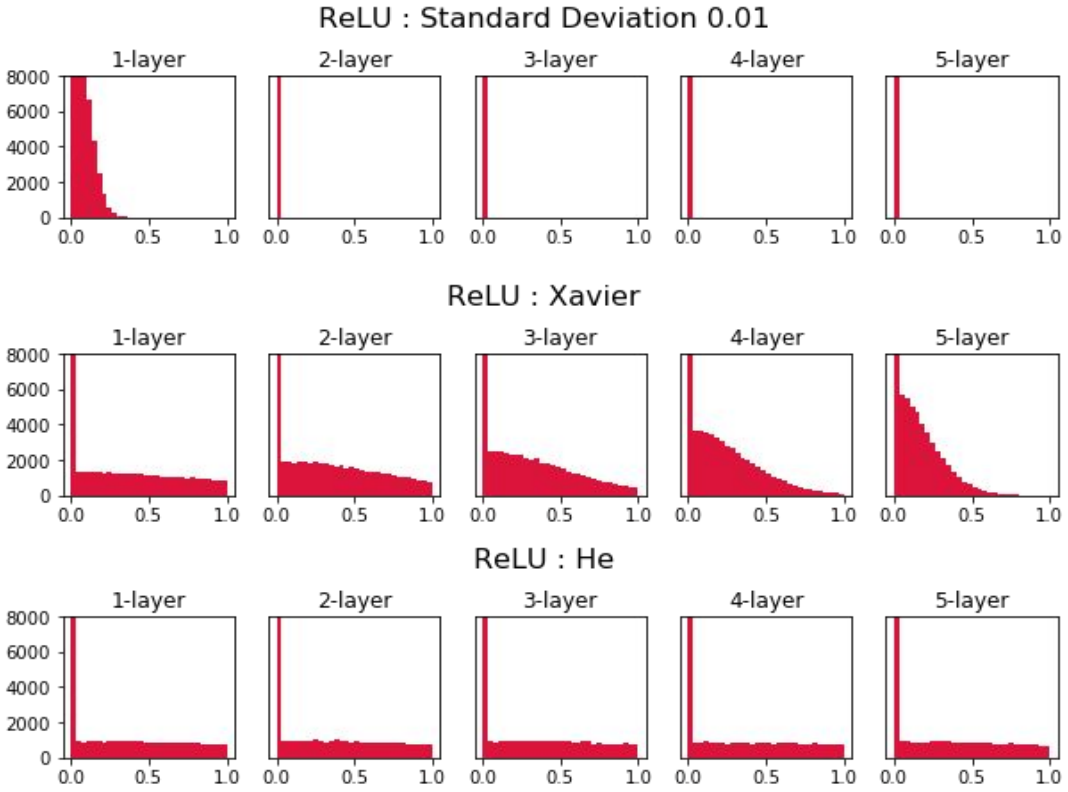

$$W \sim N(0, Var(W))$$

$$Var(W) = \sqrt{\frac{2}{n_{in}}}$$

($n_{in}$ : 이전 layer(input)의 노드 수)

https://sacko.tistory.com/43

# Weight Initialization - ReLU




https://sacko.tistory.com/43

# Weight Initialization

- Activation Function - sigmoid, tanh
  - Xavier initialization
- Activation Function - ReLU
  - He initialization

- Xavier init - default initializer in tf.contrib.layers

http://neuralnetworksanddeeplearning.com/chap2.html

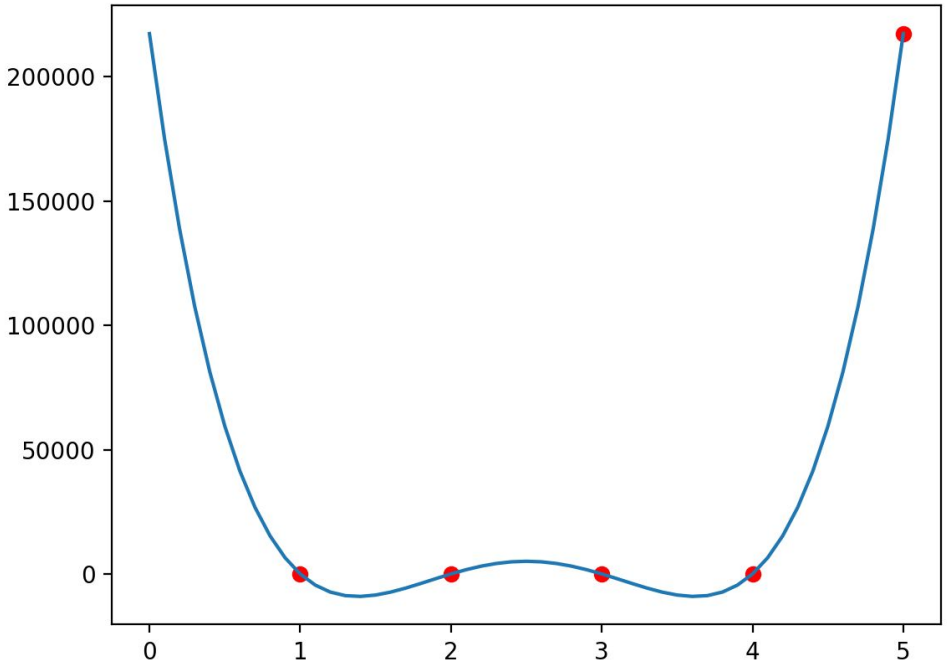
# Regularization

- 예측해 봅시다

1, 3, 5, 7, ?

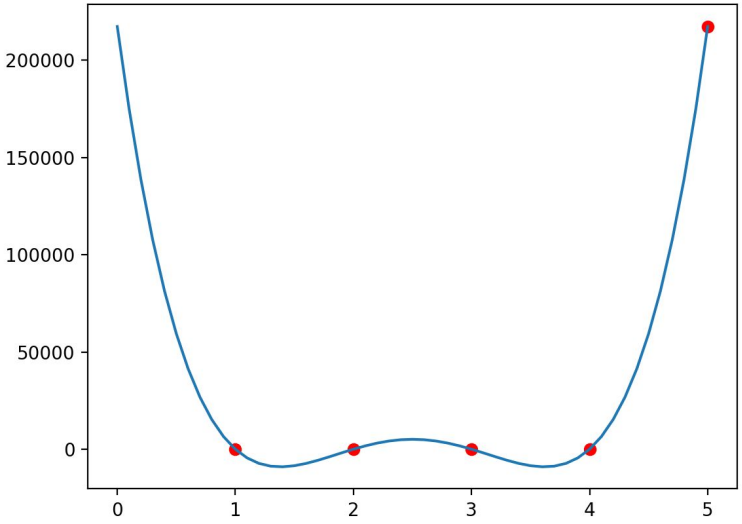
# Regularization

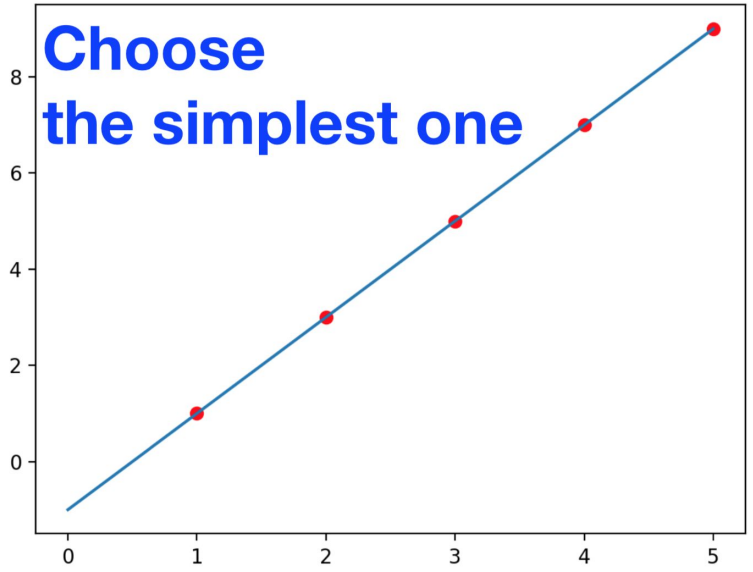
# Regularization



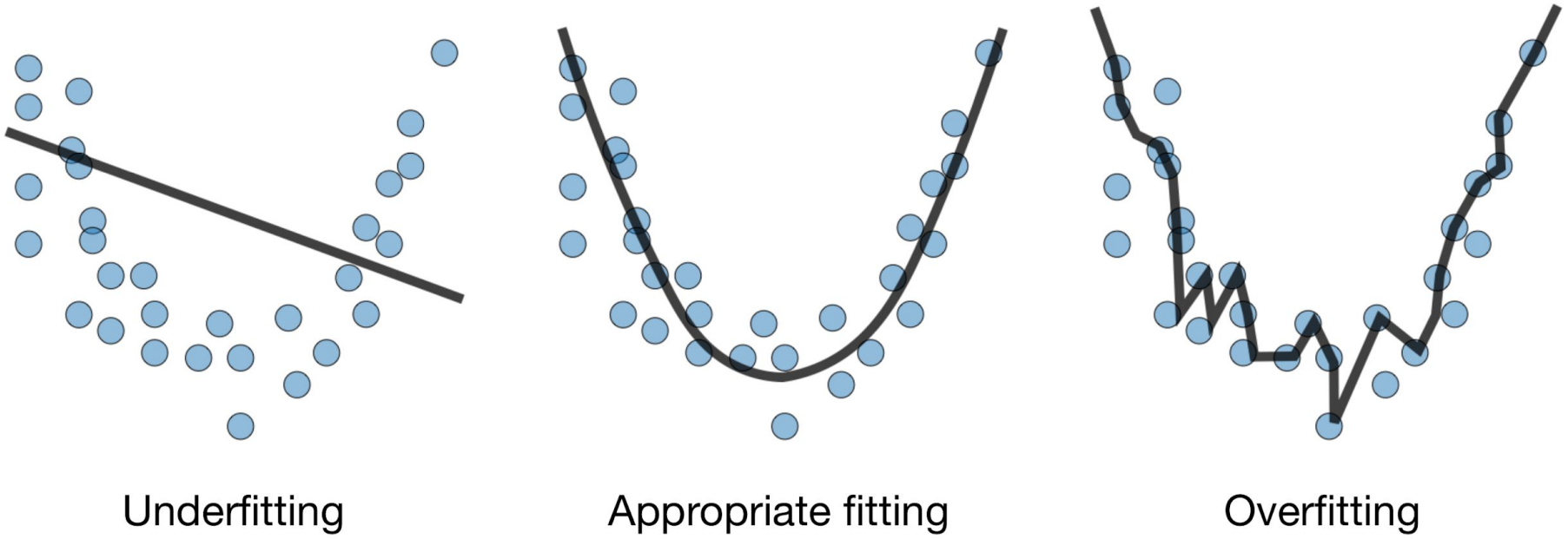

217341

# Regularization



# Overfitting and Underfitting



Underfitting

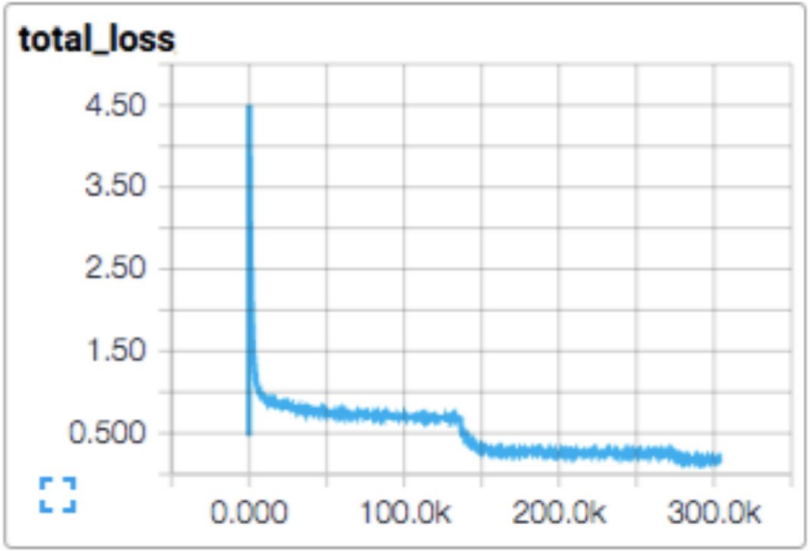
Appropriate fitting

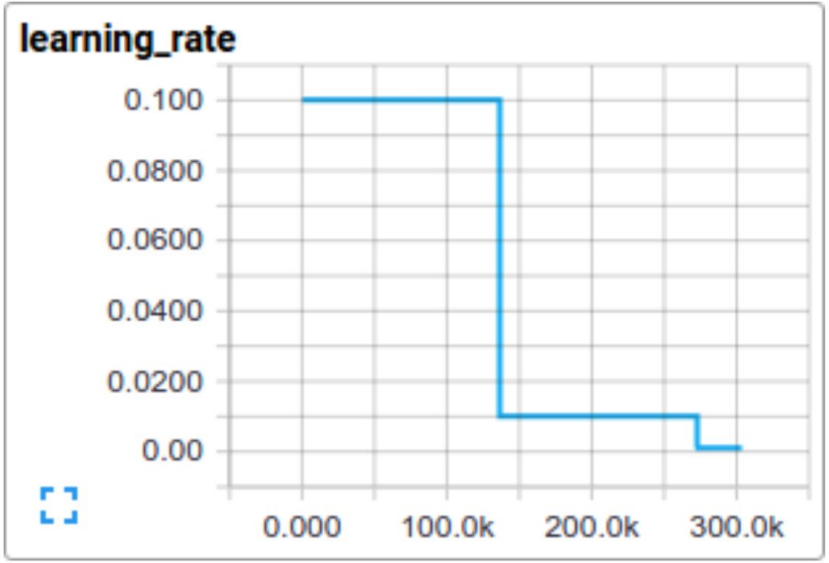
Overfitting

# Overfitting

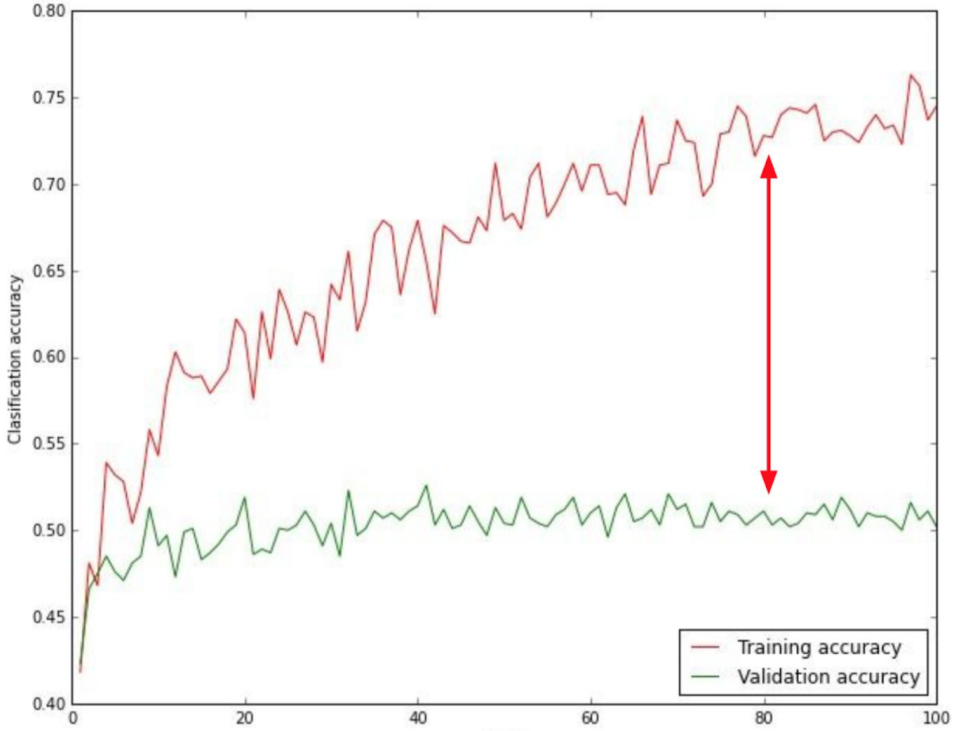
- 훈련 데이터(training data)에만 너무 과하게 학습되어 테스트에서 결과가 좋지 않음
  - 일반화 능력이 떨어진다
- 발생 원인?
  - 모델이 너무 복잡할때
  - 데이터가 너무 적을때
  - 혹은 둘 다

# Monitoring Overfitting



# Monitoring Overfitting




big gap = overfitting

=> increase regularization strength?

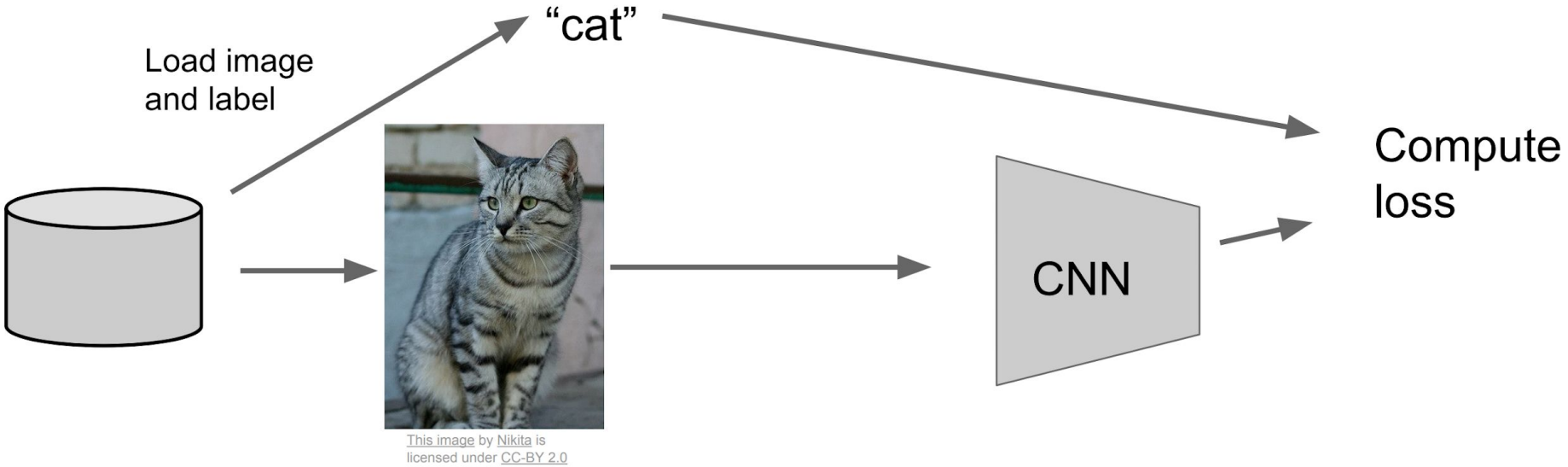
no gap

=> increase model capacity?

# Regularization

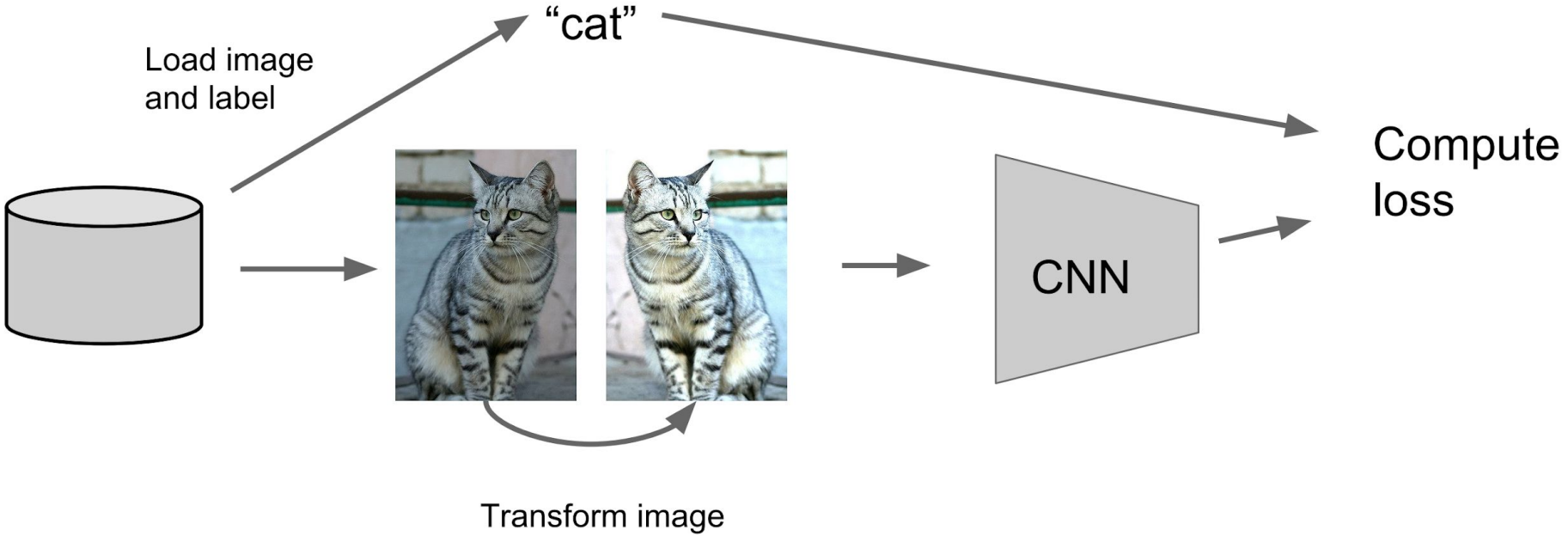
- 오버피팅이 발생한다면 어떻게 조정할 수 있을까?

# Data Augmentation




http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

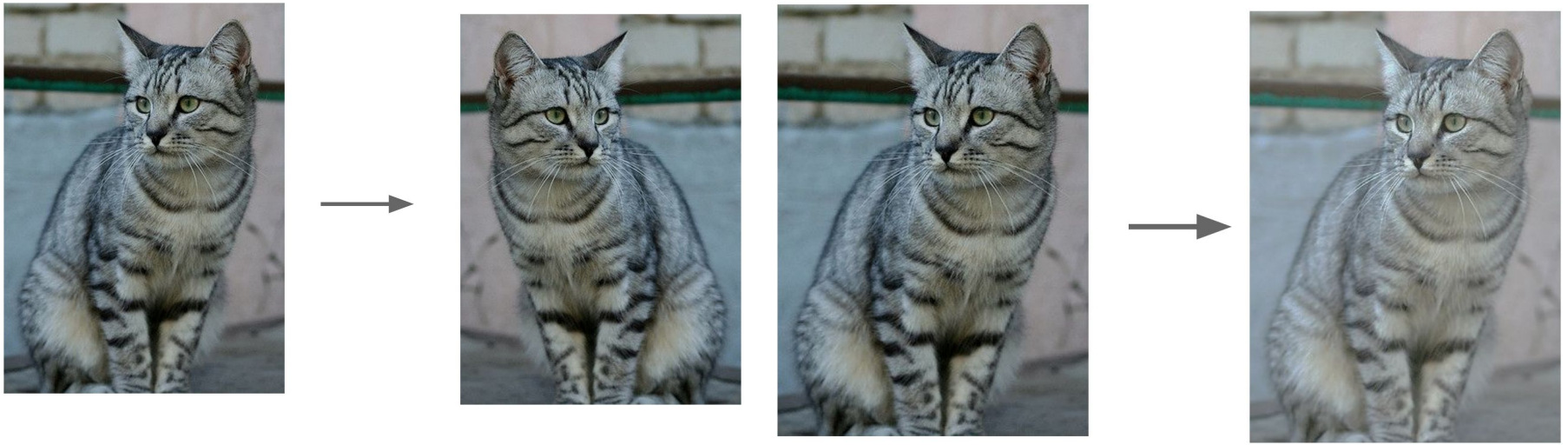
# Data Augmentation




http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Data Augmentation

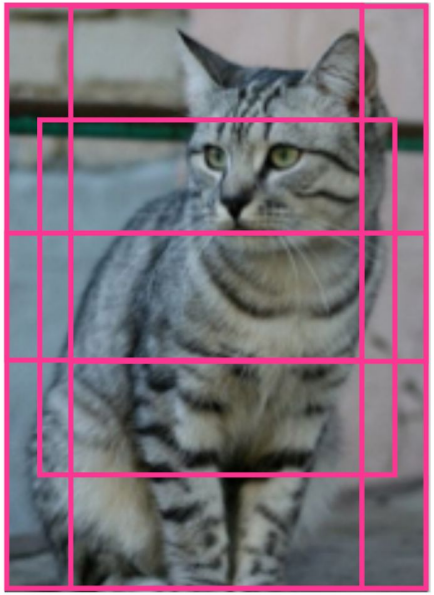
Simple: Randomize contrast and brightness



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Data Augmentation

- Training (Inception-V3)
  - aspect_ratio_range: [0.75, 1.33]
  - area_range: [0.05, 1.0]
  - resize: 299 x 299
- Testing (ResNet)
  - Resize image at 5 scales: {224, 256, 384, 480, 640}
  - For each size, use 10 224 x 224 crops: (4 corners + center) x flips



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Data Augmentation

- **Image data**
  - translation
  - rotation
  - stretching
  - shearing
  - lens distortions
  - and so on
- **Voice or music data**
  - add white noise
  - pitch shift
  - time expanding
  - and so on

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Weight regularization

$$\mathcal{L} = \frac{1}{2N} \sum_i ||\mathbf{y}_i - \hat{\mathbf{y}}_i||^2 + \lambda R(\mathbf{w})$$

regularization strength

- 자주 사용하는 방법

| | | |
|---|---|---|
| **L2 regularization** | $R(\mathbf{w}) = \sum_i \sum_j w_{ij}^2$ | (weight decay) |
| L1 regularization | $R(\mathbf{w}) = \sum_i \sum_j \lvert w_{ij} \rvert$ | |
| Elastic net (L1 + L2) | $R(\mathbf{w}) = \sum_i \sum_j \beta w_{ij}^2 + \lvert w_{ij} \rvert$ | |

# L2 regularization

전체 Loss

$$\mathcal{L} = \mathcal{L}_0 + \lambda \sum_w w^2$$

전체 Loss의 미분

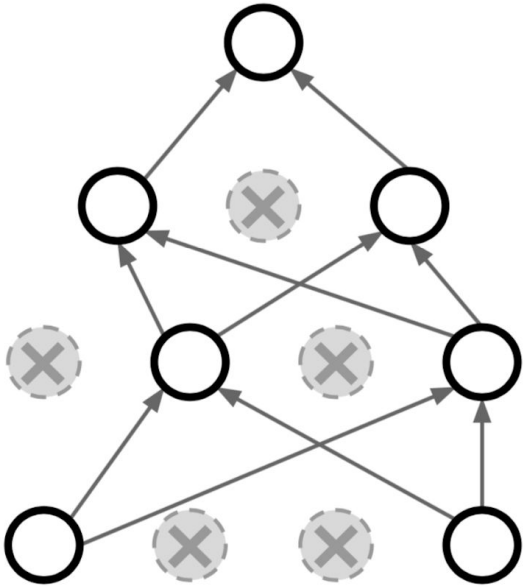
$$\frac{\partial \mathcal{L}}{\partial w} = \frac{\partial \mathcal{L}_0}{\partial w} + 2\lambda w$$

**가중치 업데이트**

$$w \to w - \eta \frac{\partial \mathcal{L}_0}{\partial w} - 2\eta\lambda w$$

$$= \underbrace{(1 - 2\eta\lambda)\, w}_{\text{Weight Decay}} - \eta \frac{\partial \mathcal{L}_0}{\partial w}$$

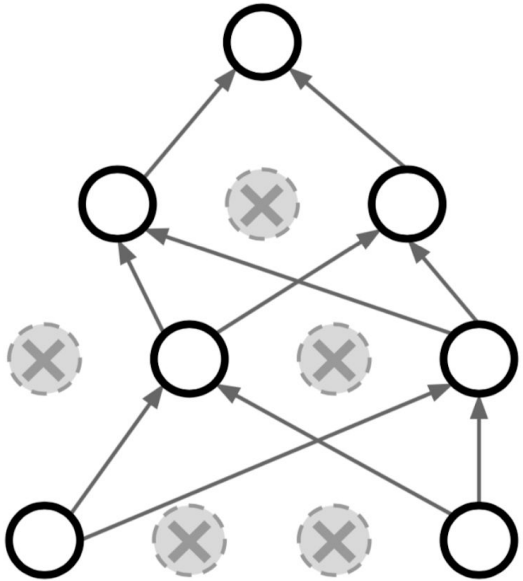
# Dropout



Forces the network to have a redundant representation;
Prevents co-adaptation of features


http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Dropout



Another interpretation:

Dropout is training a large **ensemble** of models (that share parameters).

Each binary mask is one model

An FC layer with 4096 units has $2^{4096} \sim 10^{1233}$ possible masks!
Only $\sim 10^{82}$ atoms in the universe...

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

# Batch Normalization

- 장점
  - 학습을 빨리 진행할 수 있다
  - 초기값에 크게 의존하지 않는다
  - Overfitting을 억제한다
  - Dropout 의 필요성이 감소한다

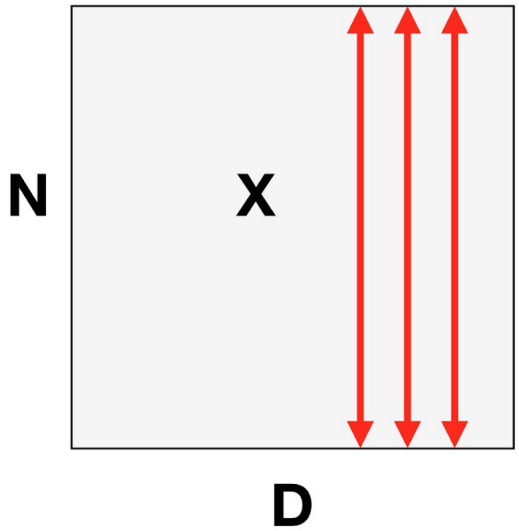
- 각 층에서 활성화 값이 정규분포가 되도록 조정한다

Ioffe et. al., Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (2015)

# Batch Normalization

- 각 레이어의 input을 정규분포로 만들어보자

$$\hat{x}^{(k)} = \frac{x^{(k)} - \mathbb{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$




Ioffe et. al., Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (2015)

# Batch Normalization

Vanilla Normalization

$$\hat{x}^{(k)} = \frac{x^{(k)} - \mathbb{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

Scaling and Transformation

$$\hat{y}^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)}$$

$\gamma^{(k)}, \beta^{(k)}$ 는 학습되는 파라미터

$$\gamma^{(k)} = \sqrt{\mathrm{Var}[x^{(k)}]}$$

$$\beta^{(k)} = \mathbb{E}[x^{(k)}]$$

Ioffe et. al., Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (2015)

# Batch Normalization

- BatchNorm layer at test time
  - 테스트 배치에 대해서 mean/std를 계산하지 않는다
  - 대신 트레이닝 하는 동안 single fixed empirical mean/std를 사용한다
  - 실제로는 트레이닝 시 mean/std의 moving average를 계산하여 미니배치 통계량으로 사용한다

**Input:** Values of $x$ over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: $\gamma, \beta$
**Output:** $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

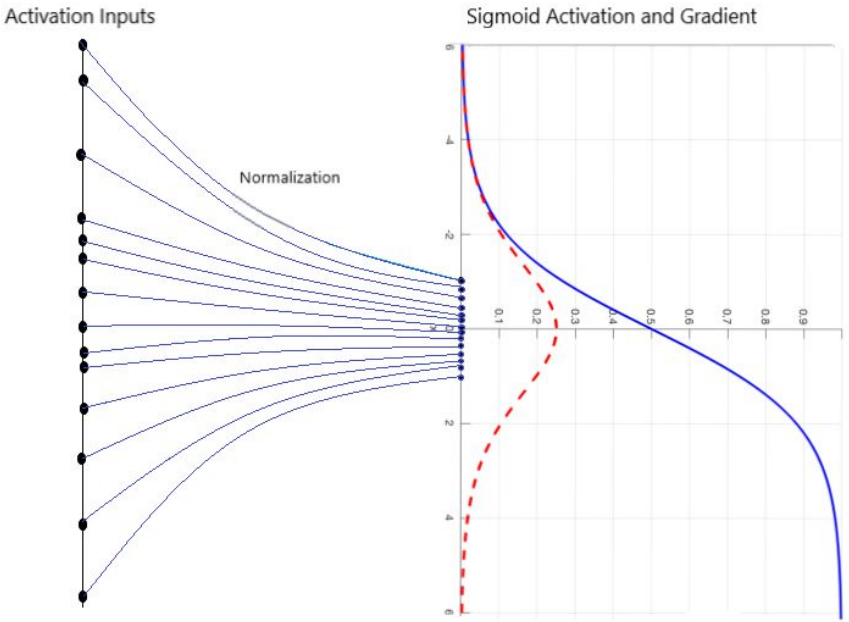
$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Ioffe et. al., Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (2015)

# Batch Normalization




Ioffe et. al., Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (2015)

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  https://www.edwith.org/boostcourse-dl-tensorflow/joinLectures/22150

- 모두의연구소 이일구님 강의 자료
  https://github.com/ilguyi

- KAIST MAC Lab. 남주한 교수님 강의 자료
  http://mac.kaist.ac.kr/~juhan/gct634/