

# Artificial Neural Network: Perceptron

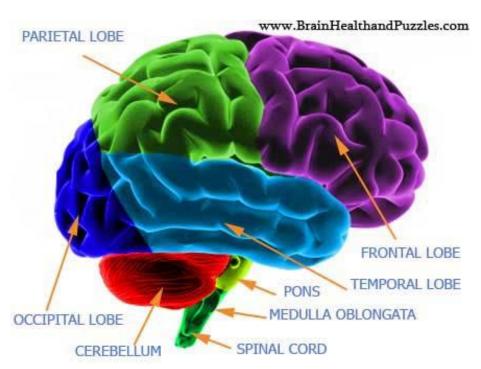
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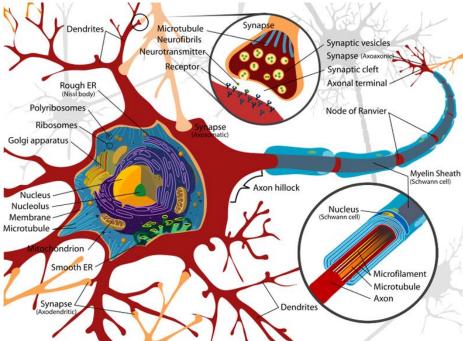
# AGENDA

- 01 Artificial Neural Networks: Perceptron
- 02 Multi-layer Perceptron (MLP)

### **Brain Structure**

- How our brain works...
  - ✓ Neurons transmit and analyze communication within the brain and other parts of the nervous system
  - ✓ A message within the brain is converted to electronic signs

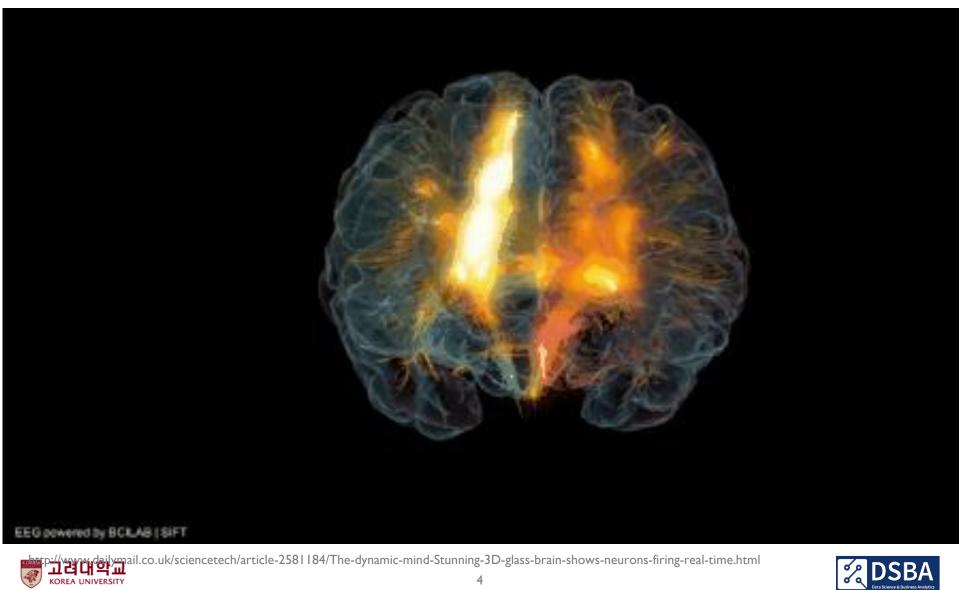






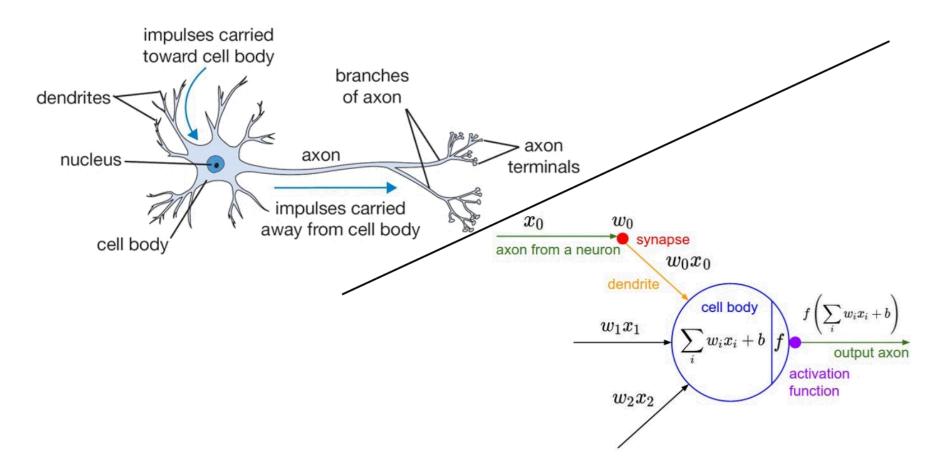


## Neuron Firing Off in Real-Time





### • Imitate a single neuron



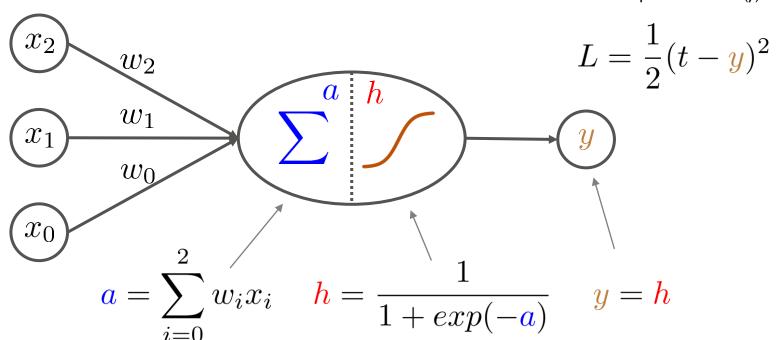




#### • Perceptron

√ An organism with only I neuron

Define the loss function as the squared difference between the desired value (t) and the predicted value (y)



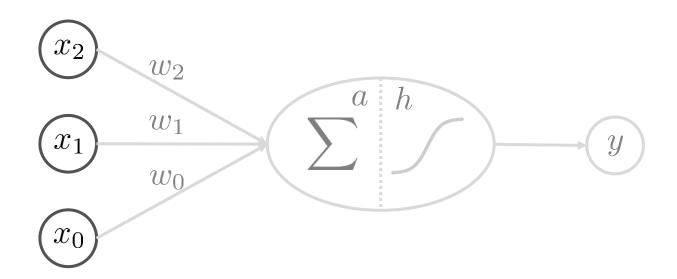
Take information from different sources

Decide the amount of information to be delivered (activation)





- Input node
  - ✓ Input (predictor, explanatory) variables

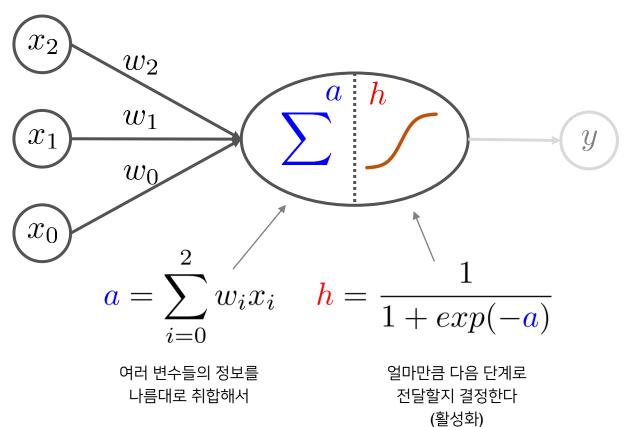






#### Hidden node

√ Take the weighted sum of input values and perform a non-linear activation





#### Role of activation

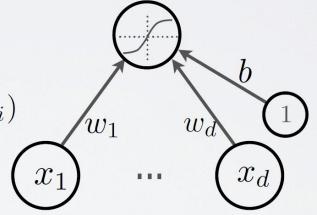
- ✓ Determine how much information from the previous layer is forward to the next layer
  - Neuron pre-activation (or input activation):

$$a(\mathbf{x}) = b + \sum_{i} w_i x_i = b + \mathbf{w}^{\top} \mathbf{x}$$

Neuron (output) activation

$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_{i} w_i x_i)$$

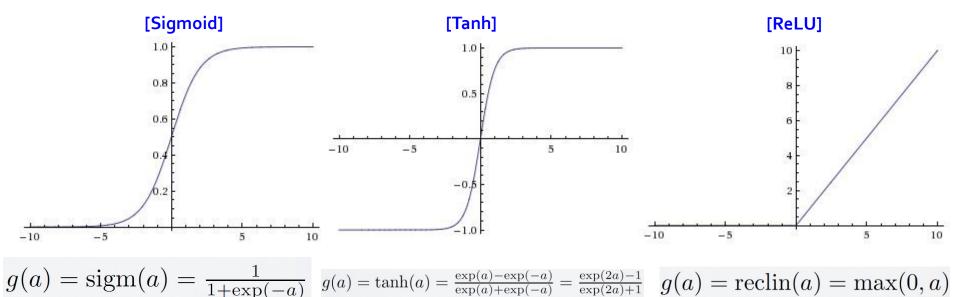
- W are the connection weights
- b is the neuron bias
- $g(\cdot)$  is called the activation function







- Representative activation functions
  - ✓ Sigmoid: the most commonly used activation, [0, 1] range, learning speed is relatively slow
  - √ Tanh: Similar to sigmoid but [-1, 1] range, learning speed is relatively fast.
  - ✓ ReLU (Rectified linear unit): very fast learning speed, easy to compute (without exponential function)

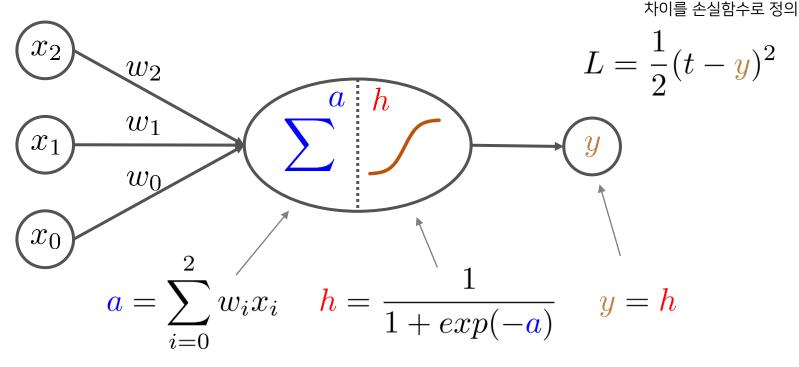






### Output node

- √ Take the value from the hidden node (Perceptron has only one hidden node)
- ✓ It takes a weighted sum of hidden nodes in a multi-layer perceptron 원하는 값(t)과 예측값(y)의



여러 변수들의 정보를 나름대로 취합해서 얼마만큼 다음 단계로 전달할지 결정한다 (활성화)





- Purpose of perceptron
  - √ Find the weight w that can best match the input (x) and the target (t)
- How do we know that the relationship is accurately found?
  - √ Use a loss function (how the output y is close to the target t)
    - Regression: squared loss is commonly used

$$L = \frac{1}{2}(t - y)^2$$

 Classification: cross-entropy is usually used (only binary classification is possible with perceptron)

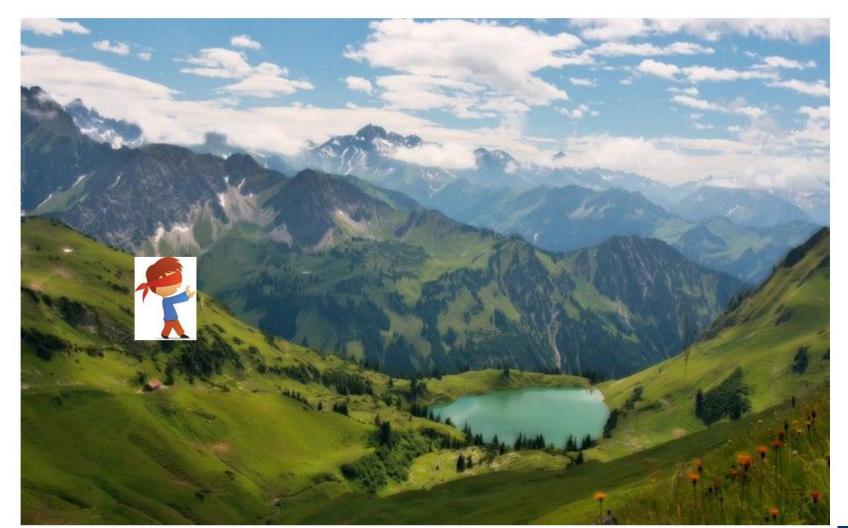
$$L = -\sum_{i} t_i \log p_i$$

- ✓ Cost function
  - Computes how inaccurate the current model is (the average of loss function values is commonly used)





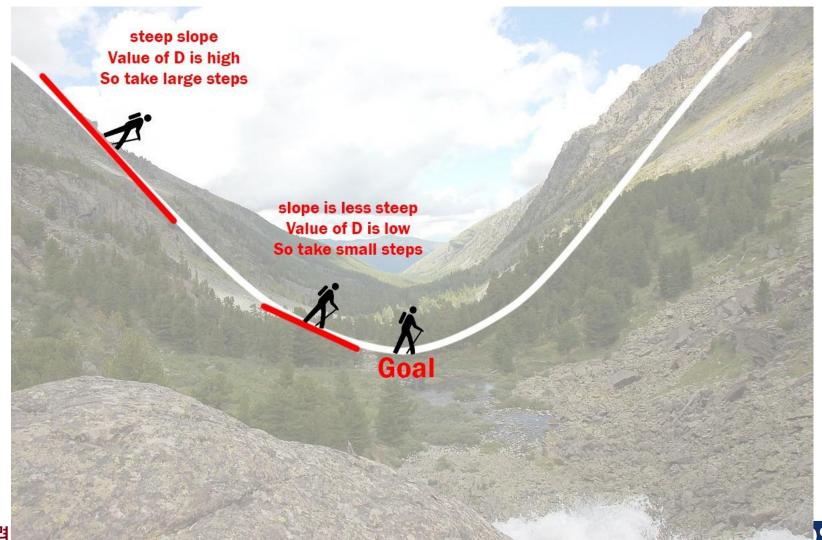
• Gradient Descent



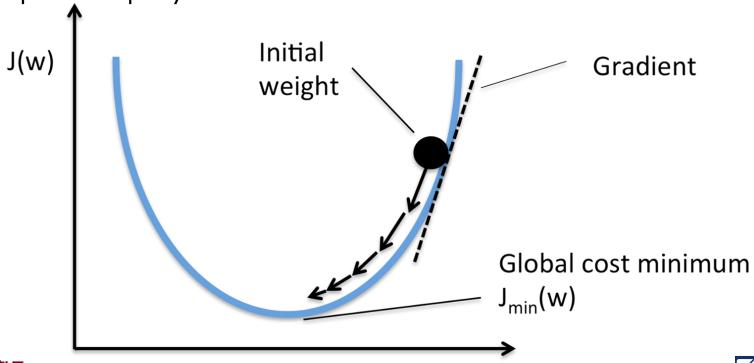




#### Gradient Descent



- Gradient Descent Algorithm
  - ✓ Blue line: the objective function to be minimized
  - ✓ Black circle: the current solution
  - ✓ Direction of the arrows: the direction that the current solution should move to improve the quality of solution







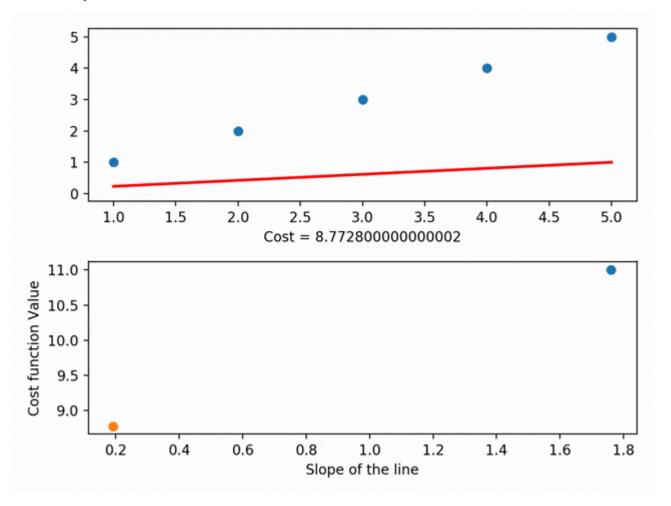
- Take the first derivative of the cost function w.r.t the current weight w
  - ✓ Is the gradient 0?
    - Yes: Current weights are the optimum! → end of learning
    - No: Current weights can be improved → learn more
  - ✓ How can we improve the current weights if the gradient is not 0?
    - Move the current weight toward to the opposite direction of the gradient
  - ✓ How much should the weights be moved?
    - Not sure
    - Move them a little and compute the gradient again
    - It will converge







### • Illustrative example





- Theoretical Background
  - √ Taylor expansion

$$f(w + \Delta w) = f(w) + \frac{f'(w)}{1!} \Delta w + \frac{f''(w)}{2!} (\Delta w)^2 + \cdots$$

✓ If the first derivative is not zero, we can decrease the function value by moving x toward the opposite direction of its first derivative

$$w_{new}=w_{old}$$
 -  $\alpha f'(w), \quad \text{where } 0<\alpha<1.$ 

 $\checkmark$  Then the function value of the new x is always smaller than that of the old x

$$f(w_{new}) = f(w_{old} - \alpha f'(w_{old})) \cong f(w_{old}) - \alpha |f'(w)|^2 < f(w_{old})$$



#### Use chain rule

$$\frac{\partial L}{\partial y} = y - t \qquad \frac{\partial y}{\partial h} = 1$$

$$\frac{\partial h}{\partial a} = \frac{exp(-a)}{(1 + exp(-a))^2} = \frac{1}{1 + exp(-a)} \cdot \frac{exp(-a)}{1 + exp(-a)} = h(1 - h)$$

$$\frac{\partial a}{\partial w_i} = x_i$$

#### Gradients for w and x

$$\frac{L}{\partial w_i} = \frac{L}{\partial y} \cdot \frac{\partial y}{\partial h} \cdot \frac{\partial h}{\partial a} \cdot \frac{\partial a}{\partial w_i} = (y - t) \cdot 1 \cdot h(1 - h) \cdot x_i$$

$$w_i^{new} = w_i^{old} - \alpha \times \frac{L}{\partial w_i} = w_i^{old} - \alpha \times (y - t) \cdot 1 \cdot h(1 - h) \cdot x_i$$





Weight update by Gradient Descent

$$w_i^{new} = w_i^{old} - \alpha \times (y - t) \cdot 1 \cdot h(1 - h) \cdot x_i$$

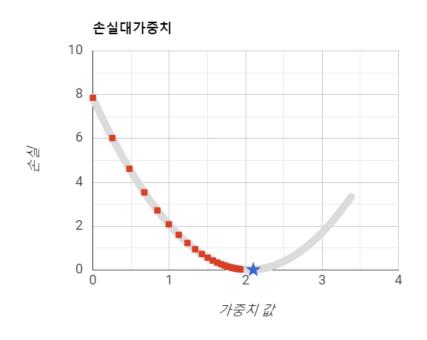
현재의 출력값(y)과 정답(t)이 차이가 많이 날 수록 가중치를 많이 업데이트 하라 대상 가중치와 연결된 입력 변수의 값이 클 수록 가중치를 많이 업데이트 하라





• The Effect of learning rate lpha

학습률 설정:	=	0.20	
한 단계 실행:	단계 22		
그래프 재설정:	재설정		

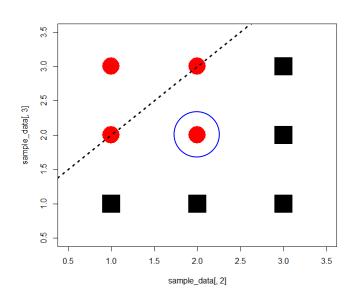


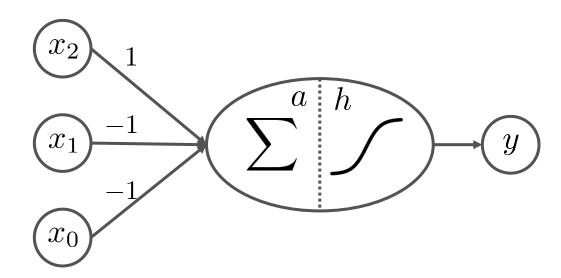




## Training Perceptron: Example I (alpha = I)

• Initialize and select the first training example  $(x_1=2, x_2=2, t=1)$ 



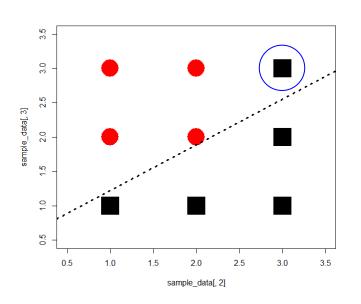


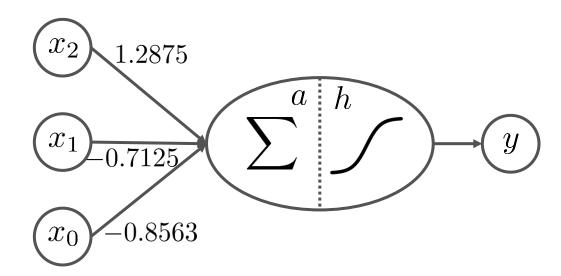




## Training Perceptron: Example I (alpha = I)

• Training result and selection of the second training example  $(x_1=3, x_2=3, t=0)$ 



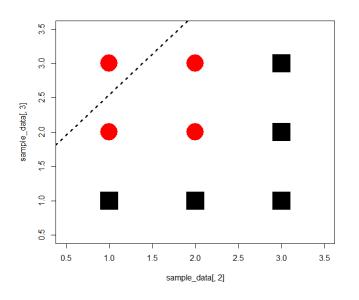


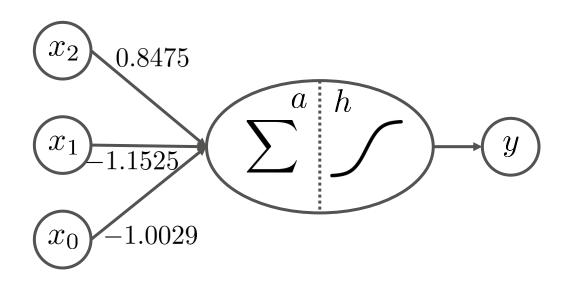




## Training Perceptron: Example I (alpha = I)

### • Training result



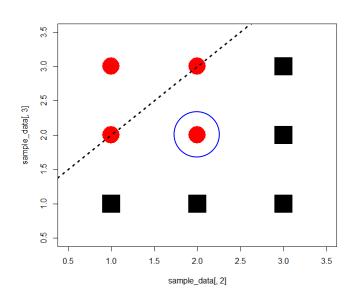


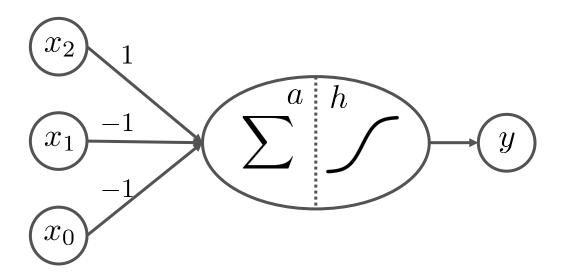




## Training Perceptron: Example 1 (alpha = 0.5)

• Initialize and select the first training example  $(x_1=2, x_2=2, t=1)$ 



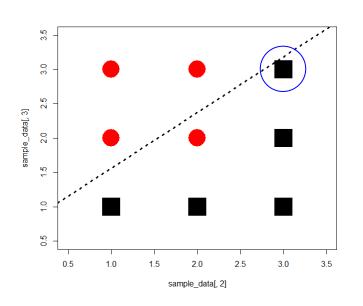


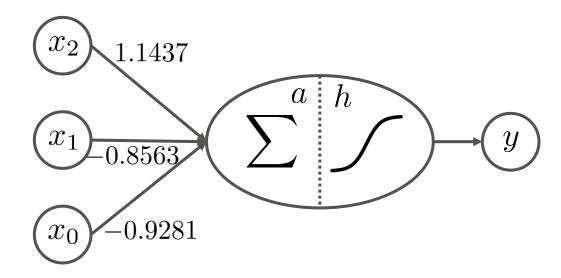




## Training Perceptron: Example 1 (alpha = 0.5)

• Training result and selection of the second training example  $(x_1=3, x_2=3, t=0)$ 



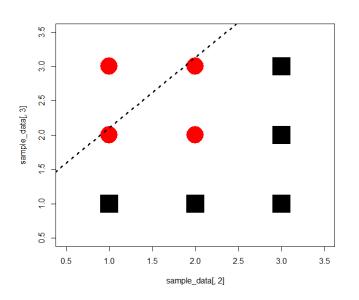


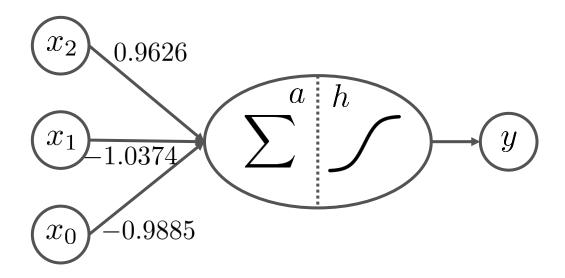




## Training Perceptron: Example I (alpha = 0.5)

### • Training result

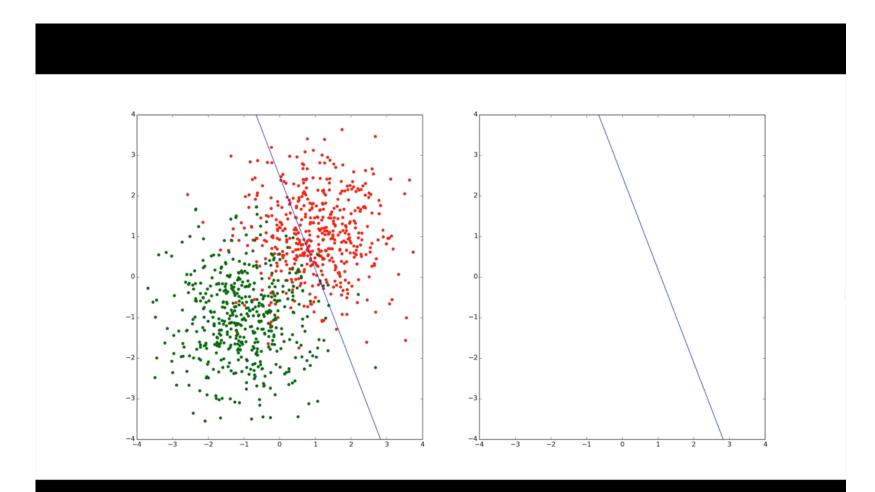








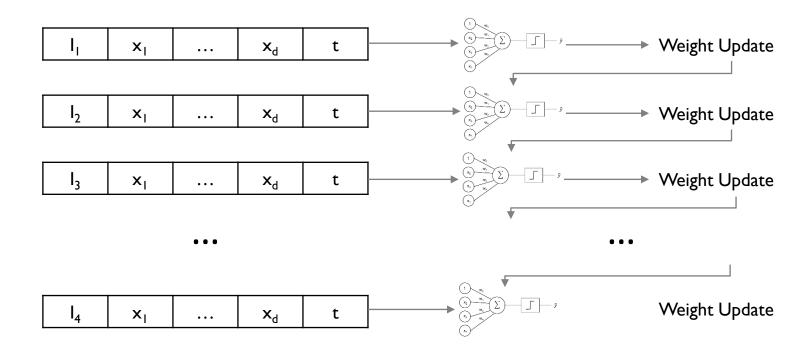
### • Training Perceptron







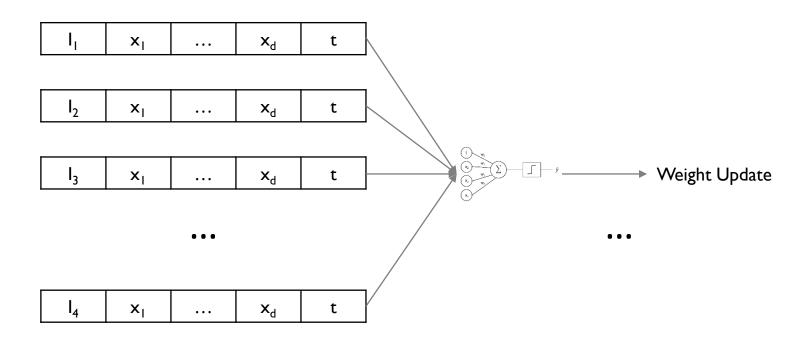
- Issue I: How frequently should the weights be updated?
  - √ Stochastic Gradient Descent (SGD)
    - Compute the loss function for an individual training example and update the gradients







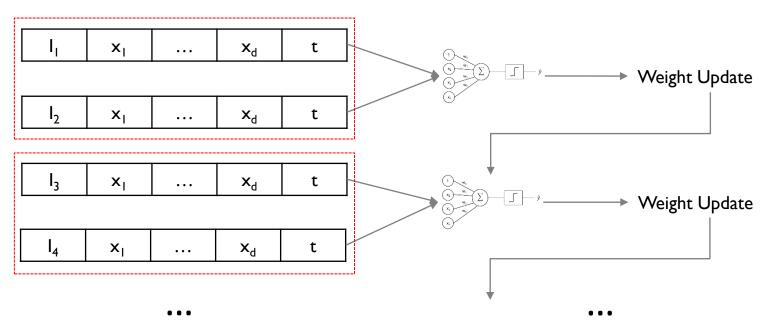
- Issue I: How frequently should the weights be updated?
  - √ Batch Gradient Descent (BGD)
    - Fix the network weights, compute the cost function using all training examples, compute the gradient, and update the weights







- Issue I: How frequently should the weights be updated?
  - √ Mini-Batch Gradient Descent
    - A strategy between SGD and BGD
    - Construct a mini-batch with n examples from N training examples and compute the gradient using the n examples (when the mini-batch size is set to 2)

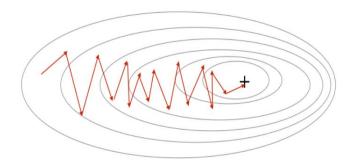




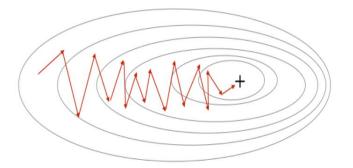


• Issue I: How frequently should the weights be updated?

Stochastic Gradient Descent

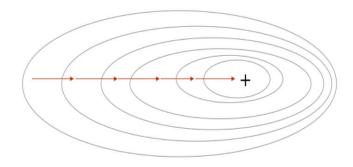


Stochastic Gradient Descent

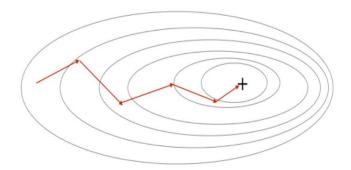


http://pengcheng.tech/2017/09/28/gradient-descent-momentum-and-adam/

**Gradient Descent** 



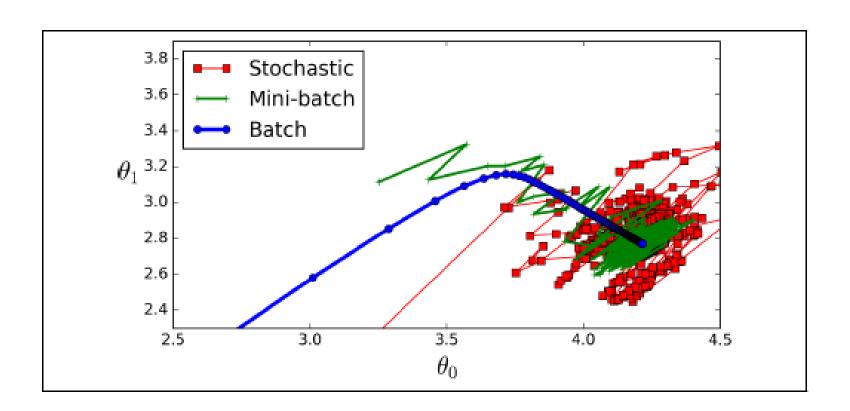
Mini-Batch Gradient Descent







• Issue I: How frequently should the weights be updated?



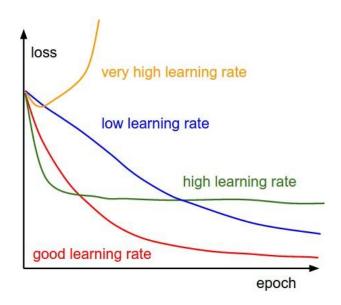




- Issue 2: How much should the weights be updated?
  - √ A problem of deciding learning rate

$$w_{new} = w_{old} - \alpha f'(w)$$

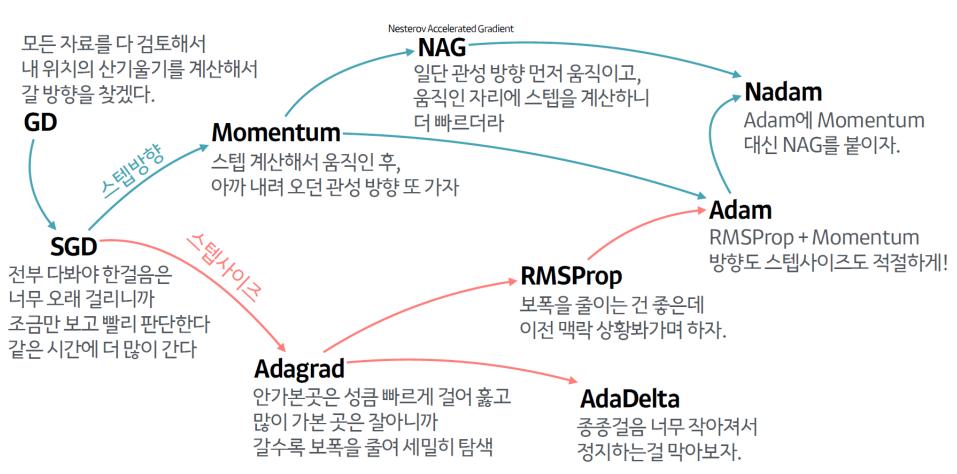
- If the learning rate is too large, the network will not converge
- If the learning rate is too small, it takes too long time to converge
- √ An appropriate (?) learning rate is required







Issue 2: How much should the weights be updated?

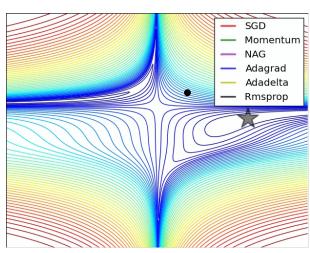


하용호. 자습해도 모르겠던 딥러닝, 머리속에 인스톨 시켜드립니다. (https://www.slideshare.net/yongho/ss-79607172)

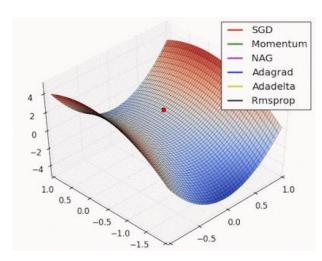




• Issue 2: How much should the weights be updated?



Beale's function



Long valley

SGD

Momentum

NAG

Adagrad

Adadelta

Rmsprop

-2

-4

1.0

0.5

0.0

0.5

1.0<sup>-1.0</sup>

