



IoT·인공지능·빅데이터 개론 및 실습

Neural Networks

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- ① Artificial Neural Networks
- ② Elements of a Neural Network
- ③ Network Architecture

2. Training Neural Networks

- ① Core Concepts
- ② Backpropagation

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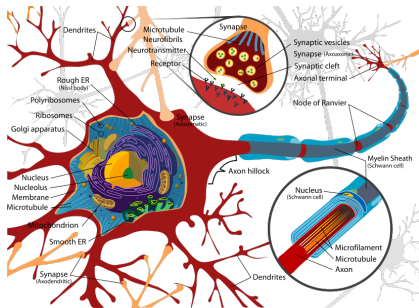
- ② Backpropagation

1 Artificial Neural Networks

(1) Neuron

▶ 신경세포

- electrically excitable cell that processes and transmits information through electrical and chemical signals



[출처] Wikipedia

1 Artificial Neural Networks



(2) Artificial neural networks (ANN)

► Computational models inspired by brain

- capable of machine learning and pattern recognition
- popular until early 90's; popularity then diminished
- renaissance: deep learning, AlphaGo, ...

► Traditionally most studied: feedforward neural net

- comprises multiple layers of logistic regression models
- also known as *multilayer perceptron* (MLP)

1 Artificial Neural Networks

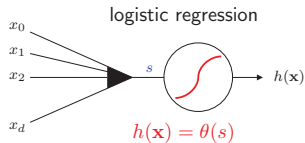
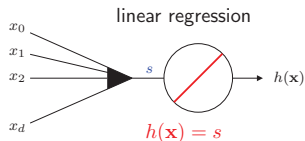
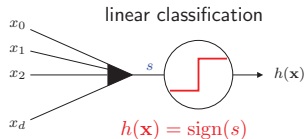
(3) Recall

► “signal”

$$s = \sum_{i=0}^d w_i x_i$$

► “activation”

- different



1 Artificial Neural Networks



(4) Multilayer perceptron

► Misnomer

- network of multiple *logistic* models (continuous nonlinearity)
- rather than multiple *perceptrons* (discontinuous nonlinearity)

► Central idea

- extract linear combinations of inputs as derived features
- model the target as nonlinear function of these features

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2 Elements of a Neural Network



(1) Models of a neuron

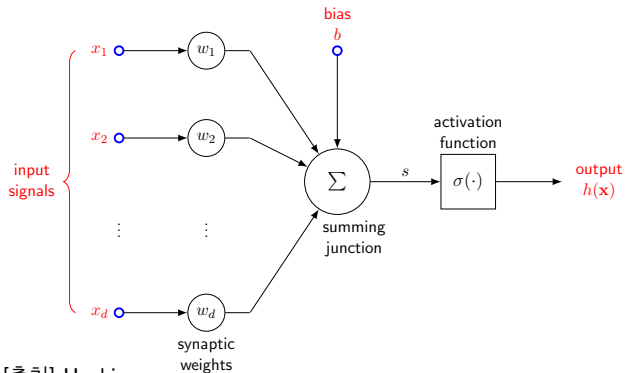
► Three basic elements

1. synapses (with weights)
2. adder (input vector \rightarrow scalar)
3. activation function (possibly nonlinear)

2 Elements of a Neural Network

(1) Models of a neuron

► Representation

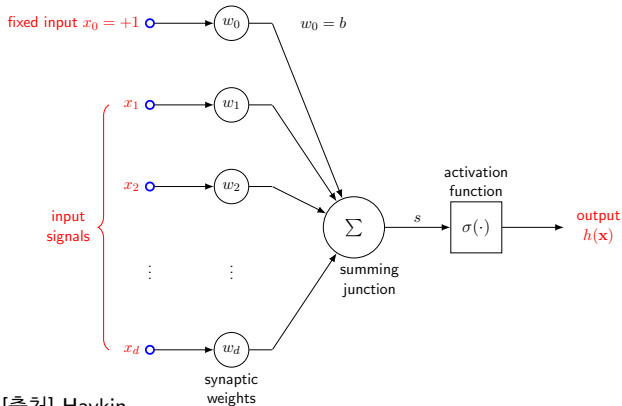


[출처] Haykin

2 Elements of a Neural Network

(1) Models of a neuron

► Alternative representation (w_0 for bias b)

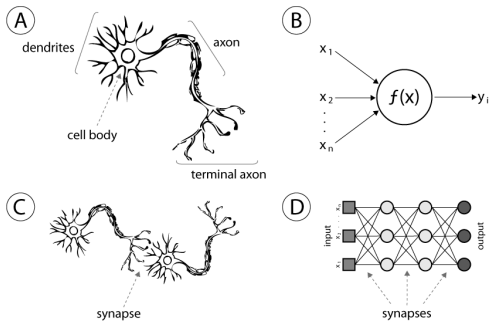


[출처] Haykin

2 Elements of a Neural Network

(1) Models of a neuron

► Human neuron vs ANN neuron

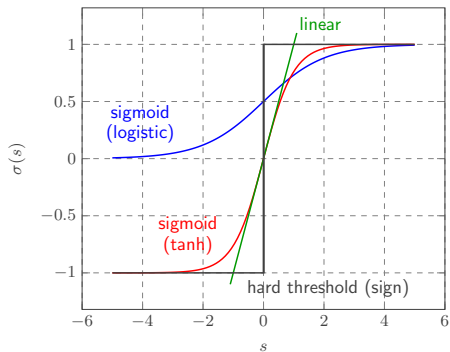


[출처] Matarollo (2013)

2 Elements of a Neural Network

(2) Activation function σ

- Defines output of neuron in terms of signal s



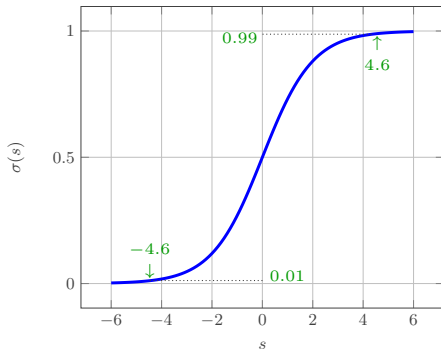
2 Elements of a Neural Network

(2) Activation function σ

► Simplifying assumption: all neurons use identical σ

- e.g. logistic sigmoid

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



2 Elements of a Neural Network

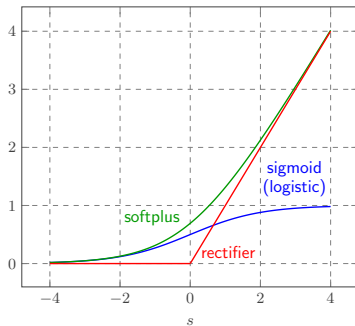
(2) Activation function σ

► ReLU (rectifier linear unit)

- very popular in deep neural nets

$$\sigma(s) = \max(0, s)$$

$\sigma(s)$



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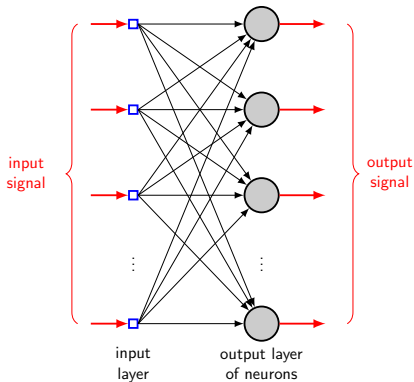
2. Training Neural Networks

- ① Core Concepts
- ② Backpropagation

3 Network Architecture

(1) Single-layer feedforward network

► Layered, feedforward

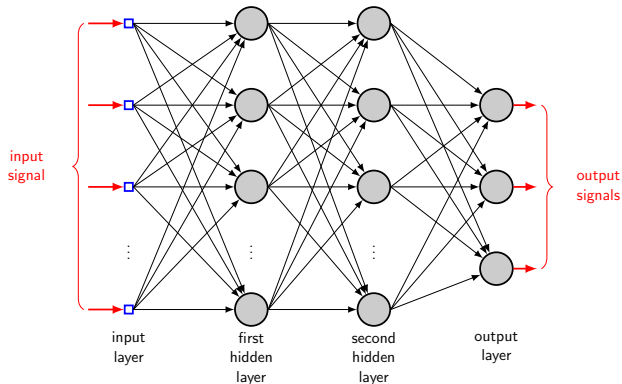


[출처] Haykin

3 Network Architecture

(2) Multi-layer feedforward network

- ▶ One or more hidden layers of neurons



[출처] Haykin

3 Network Architecture



(3) Softmax function

► Generalization of the logistic function

- final layer of a network for multi-class classification

► Given a K -dimensional vector $\mathbf{h} = (h_1, h_2, \dots, h_K)$

- softmax function $\sigma : \mathbb{R}^K \mapsto \mathbb{R}^K$ s.t.

$$\sigma(\mathbf{h})_j = \frac{e^{h_j}}{\sum_{k=1}^K e^{h_k}} \quad \text{for } j = 1, \dots, K$$

► Components of vector $\sigma(\mathbf{h})$

- sum to one and are all strictly between zero and one
- ⇒ represent a categorical probability distribution

3 Network Architecture



(4) Role of hidden neurons

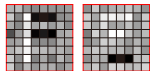
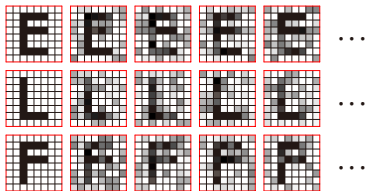
- ▶ **Play critical role in operation of MLP**
 - each layer corresponds to “distributed representation”
- ▶ **Hidden neurons act as feature detectors**
 - as learning goes on, they gradually “discover” salient features characterizing training data
 - they do so by performing nonlinear transformation on input data into new space called *feature space*
- ▶ **Increasing the number of hidden layers**
 - results in a more power model
 - but makes training more difficult

3 Network Architecture

(4) Role of hidden neurons

► Example

(a) sample training patterns



(b) learned input-to-hidden weights

[출처] Duda, Hart, Stork (2001)

3 Network Architecture



(5) Deep learning

► Based on deep neural nets

- a neural network with many hidden layers
- conventionally considered very difficult to train
(major reason: vanishing/exploding gradient problem)
- recent success: effective training of deep neural nets

► Popular deep neural nets

- convolutional neural net (CNN)
- recurrent neural net (RNN)
- autoencoder (AE)
- generative adversarial net (GAN)

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1 Core Concepts

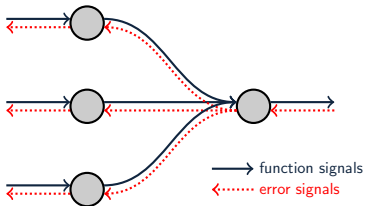
(1) Types of signals in neural nets

► Function signals: forward propagation

- input signal comes in at input
- propagates forward through network, and
- emerges at output

► Error signals: back(ward) propagation

- originates at an output neuron, and
- propagates backward



[출처] Haykin

1 Core Concepts

(2) Computations at hidden/output layer

► Each neuron performs two types of computations:

1. function signal appearing at neuron output
 - continuous nonlinear function of input and synaptic weights
2. estimate of gradient vector needed for back pass
 - gradients of error surface with respect to weights:
 $\nabla \mathcal{E}(\mathbf{w})$

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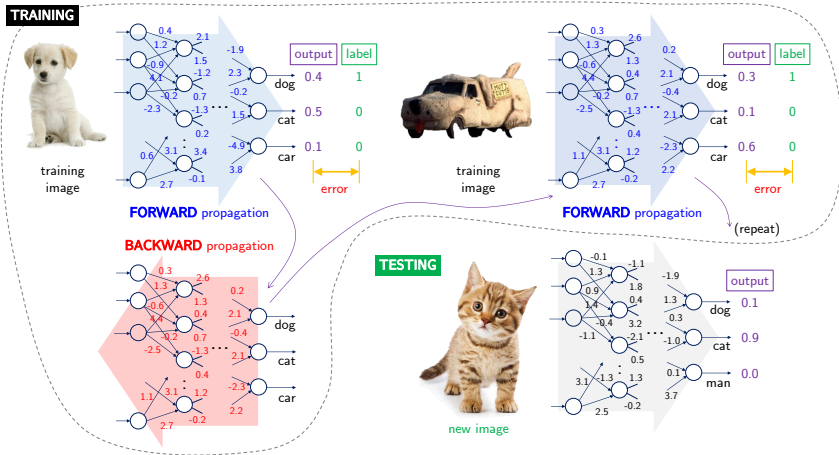
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2 Backpropagation

(2) Example: training by forward/backward prop



2 Backpropagation

(3) Credit assignment problem

► For output layer

- explicit 'teacher' (correct output y) exists for h
- error signal can be evaluated directly: $e = h - y$
- it is straightforward to find how output (thus error) depends on hidden-to-output weights

⇒ hidden-to-output 'sensitivity' $\frac{\partial \mathcal{E}}{\partial w}$: easy to evaluate

2 Backpropagation

(3) Credit assignment problem

► For hidden layer

- no teacher to tell what hidden unit's output should be
- this is called *credit assignment* problem

⇒ input-to-hidden sensitivity $\frac{\partial \mathcal{E}}{\partial w}$: difficult to evaluate

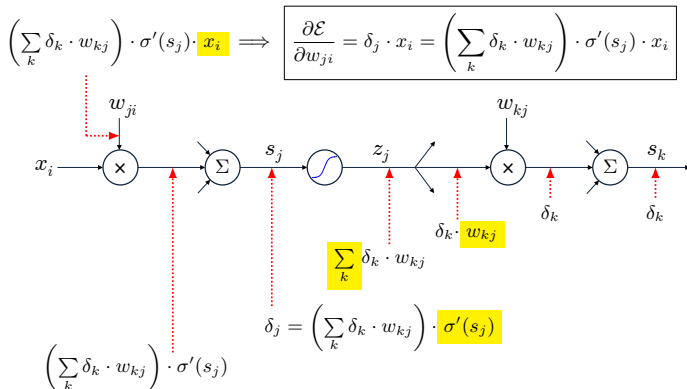
► Power of back-propagation

- it allows us to calculate error for each hidden unit
- we can derive learning rule for input-to-hidden weights

2 Backpropagation

(4) More details of backprop

▶ 실습을 통해 학습



Summary

► Neural network: universal function approximator

- neuron: synapse (weights), adder, activation functions
- conventional: feed-forward multilayer perceptrons
- recent: deep neural networks (“deep learning”)

► Hidden layers act as feature detectors

- # hidden layers $\uparrow \Rightarrow$ intelligence \uparrow
but training difficulty \uparrow
- practical solutions exist for deep neural nets

► Two types of signals for training MLP

1. function signals: forward propagation
2. error signals: backward propagation

► Backpropagation algorithm

- Popular method for training neural networks