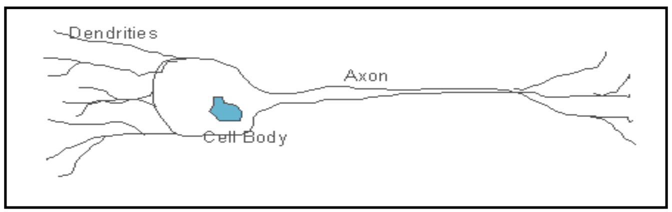
Neural Networks

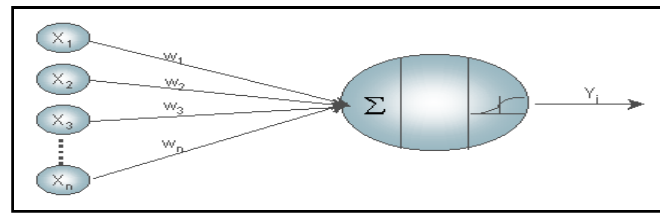
신경망(Neural Networks)의 개요

- 머신러닝 알고리즘 중 가장 많이 알려진 것이 신경망 분석이며, 보통 머신러닝에서 "신경망 분석 = 패턴을 찾아내는 것"이라고 연상할 만큼 잘 알려진 분석

- 인간 두뇌의 신경망(860억 개의 뉴런과 5000조 개의 시냅스로 구성)을 흉내 내어 데이터로부터의 반복적인 학습 과정을 거쳐 데이터에 숨어 있는 패턴을 찾아내는 모델링 기법



신경세포(neuron)

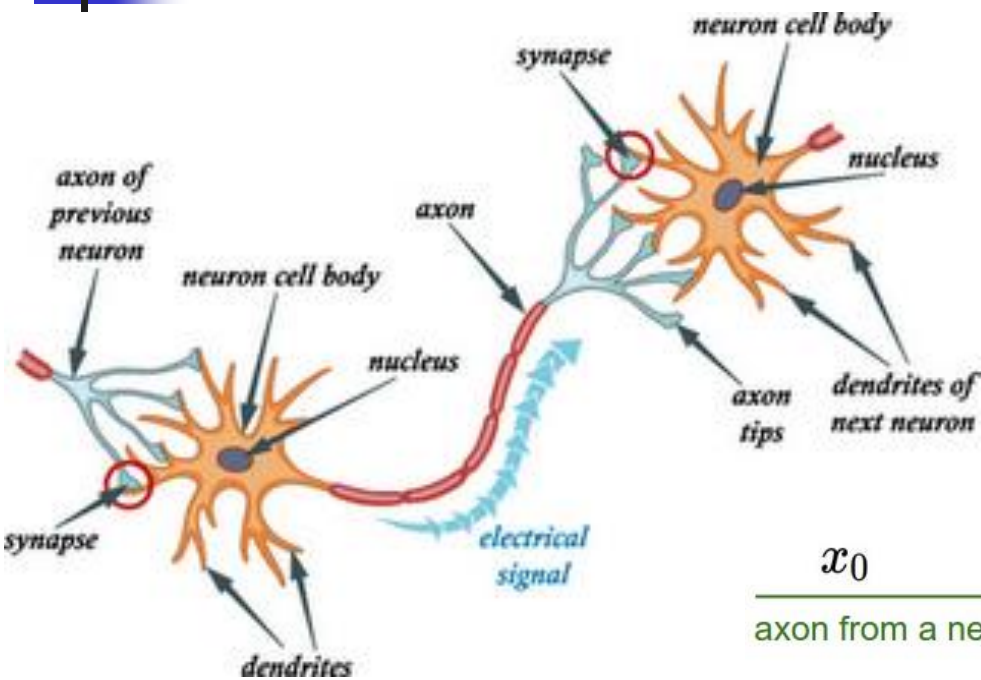


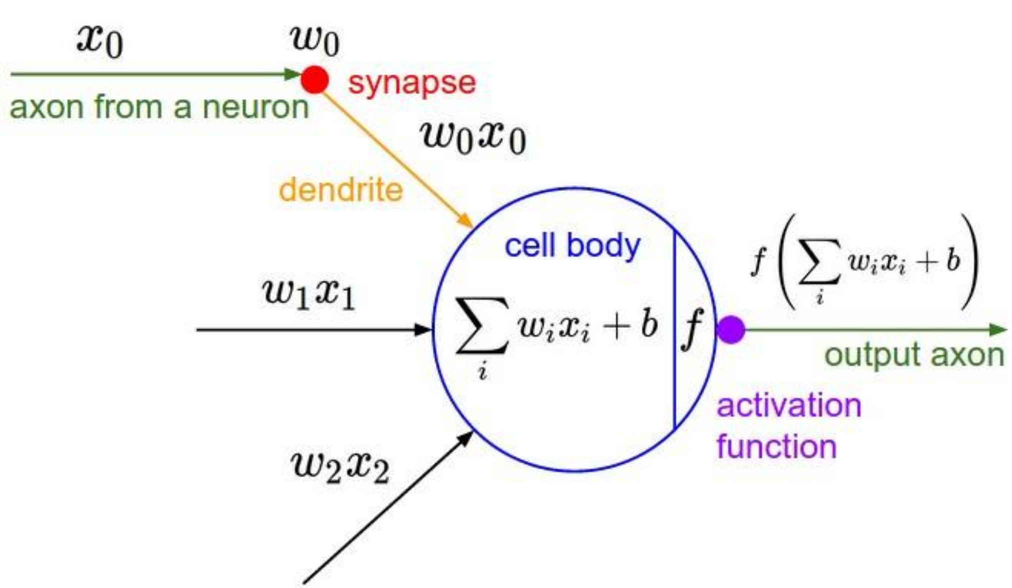
신경망(neural networks)

- 계층 구조를 갖는 수많은 프로세싱 요소로 이루어진 수학모형
  - 신경망 이론의 다양한 아키텍처를 기반으로 데이터로부터 패턴을 학습하여 최적해를 도출

- 장단점
  - 비선형 자료, 범주/연속형 혼합 자료 처리가 탁월하고 통계적 가정이 불필요
  - 설명변수들이 목표변수에 구체적으로 어떠한 영향을 주는지 해석하기 어렵고, Over-Fitting 가능성 높음

Biological vs. Artificial neural network

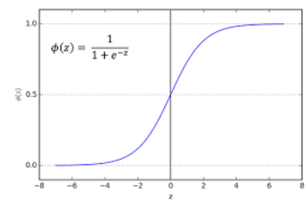




Source: http://cs231n.github.io/neural-networks-1/

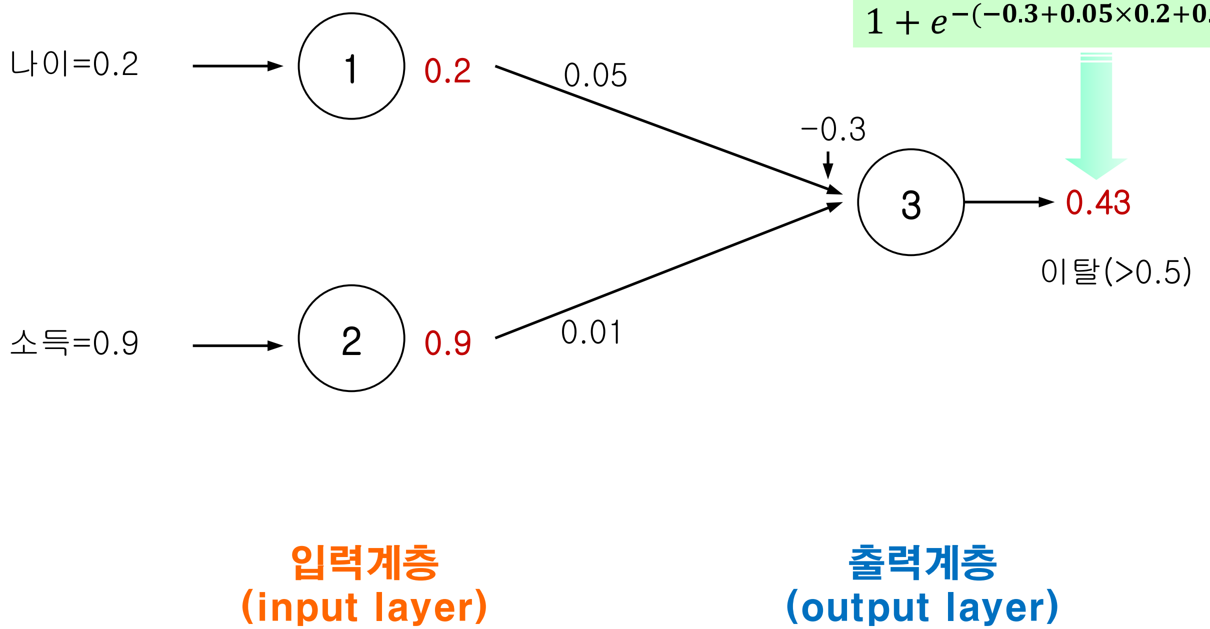
How neural networks work

- Single layer neural network



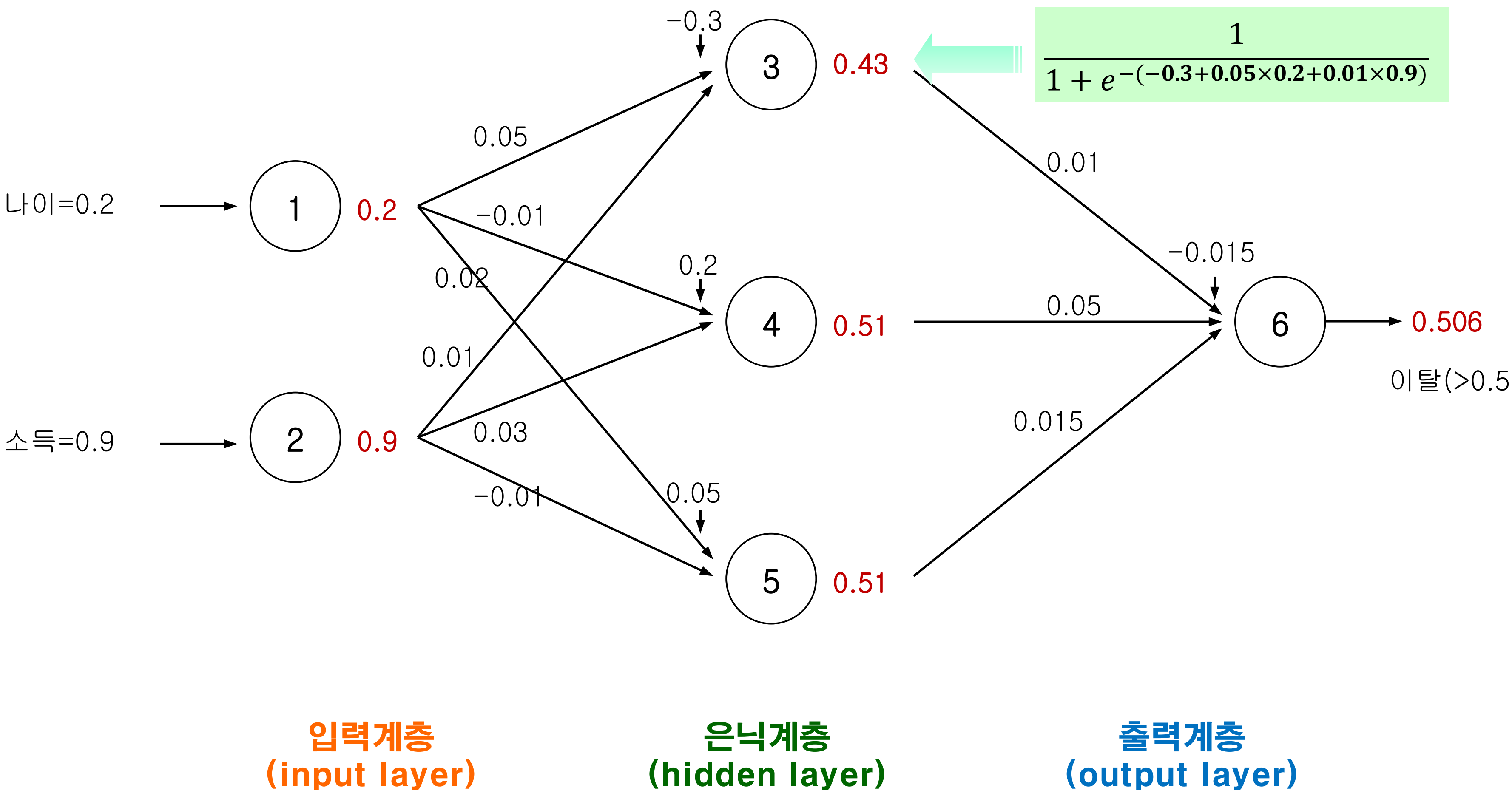
$$\frac{1}{1+e^{-(-0.3+0.05\times0.2+0.01\times0.9)}}$$

나이	소득	이탈
0.2	0.9	1
0.3	0.5	0
0.7	0.9	1
…	…	…
0.6	0.2	0



How neural networks work

- Multi-layer neural network



Mathematical notation

- Single layer neural network

  - Neuron pre-activation (or input activation):

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

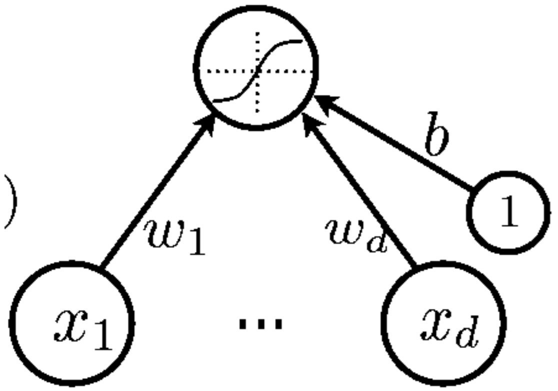
  - Neuron (output) activation

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

$\mathbf{w}$ are the connection weights

b is the neuron bias

$g(\cdot)$ is called the activation function



Source: *Neural Networks by Hugo Larochelle*

Mathematical notation

- Multi-layer neural network

  - Could have L hidden layers:
    - layer pre-activation for $k>0$ $(\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x})$

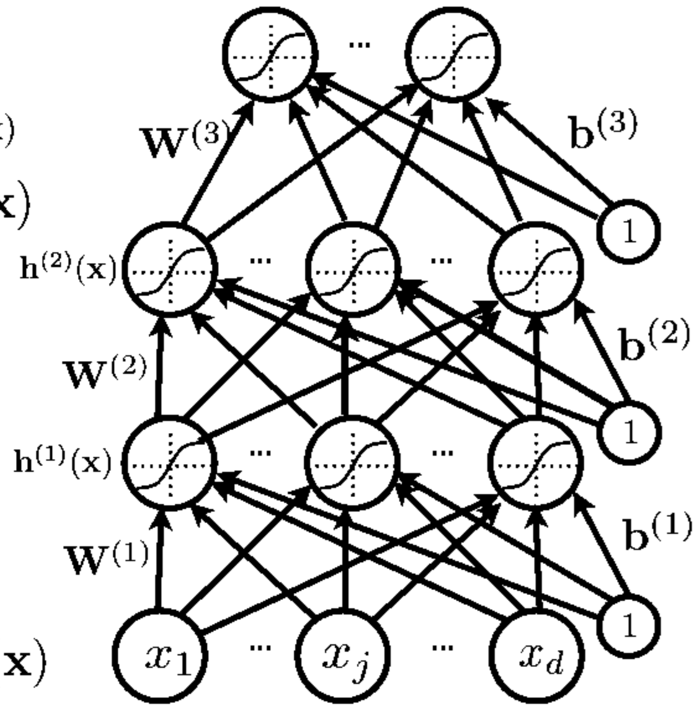
      $$\mathbf{a}^{(k)}(\mathbf{x}) = \mathbf{b}^{(k)} + \mathbf{W}^{(k)}\mathbf{h}^{(k-1)}(\mathbf{x})$$

    - hidden layer activation (k from 1 to L):

      $$\mathbf{h}^{(k)}(\mathbf{x}) = \mathbf{g}(\mathbf{a}^{(k)}(\mathbf{x}))$$

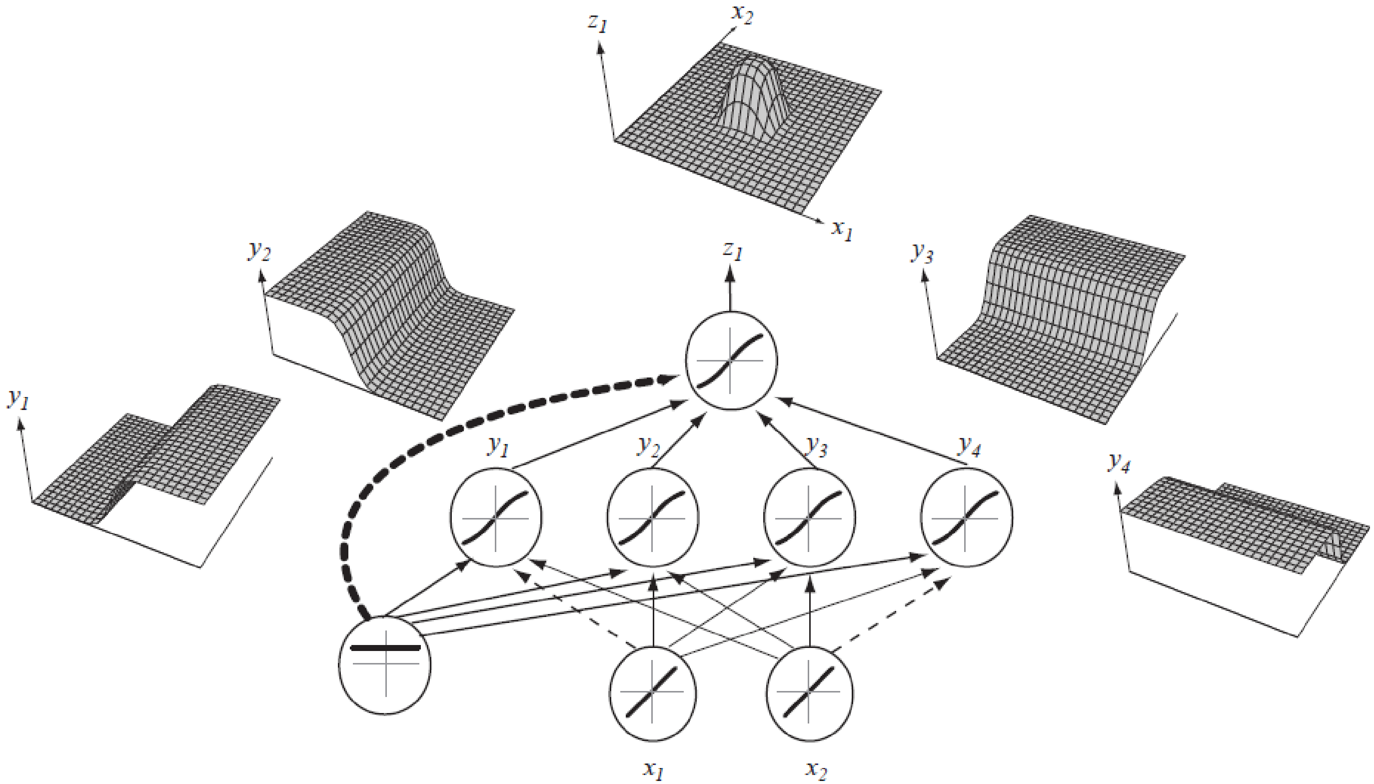
    - output layer activation ($k=L+1$):

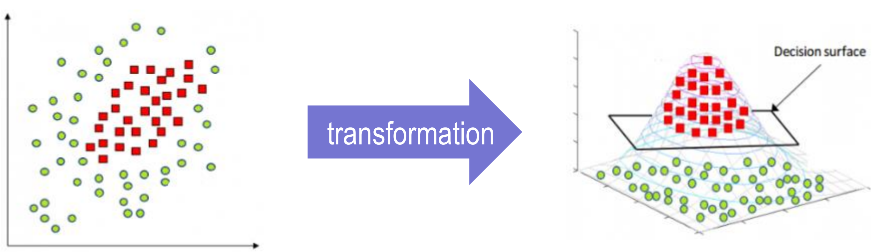
      $$\mathbf{h}^{(L+1)}(\mathbf{x}) = \mathbf{o}(\mathbf{a}^{(L+1)}(\mathbf{x})) = \mathbf{f}(\mathbf{x})$$



Source: Neural Networks by Hugo Larochelle

Capacity of neural network

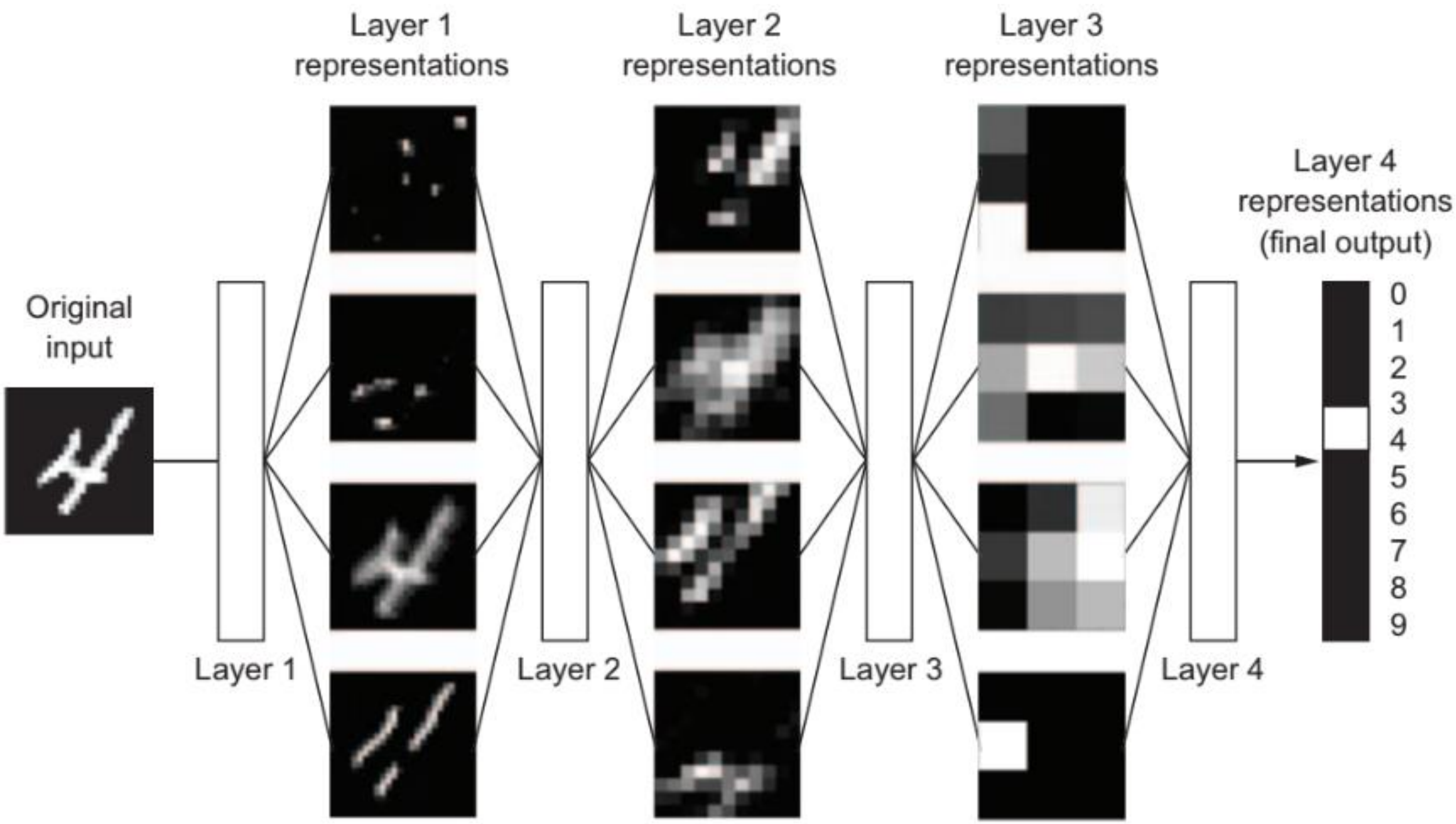




Source: Neural Networks by Hugo Larochelle

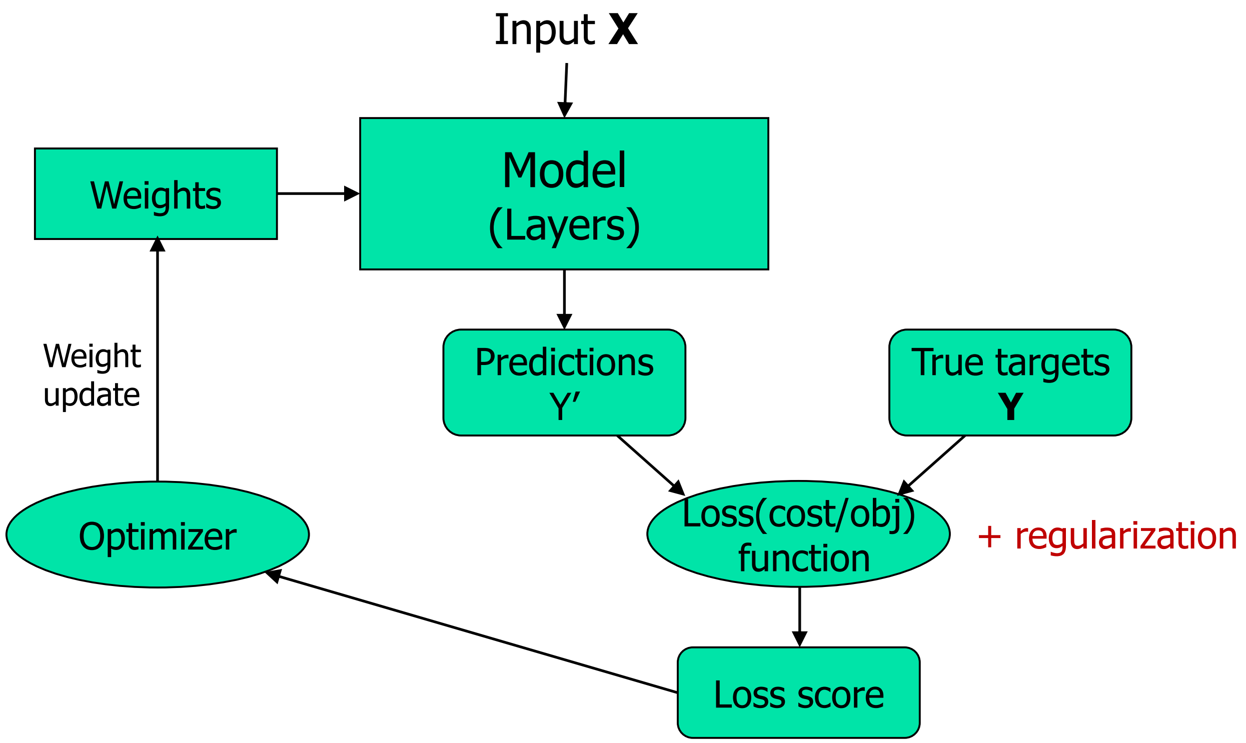
Capacity of neural network

- Neural networks do input–to–target mapping via a deep sequence of simple data transformations



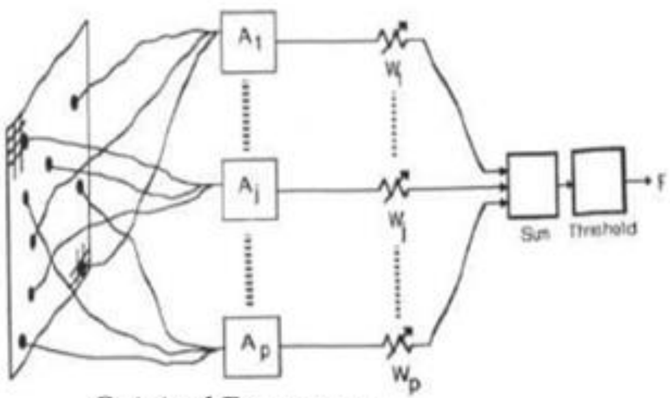
Source: Deep Learning with Python by François Chollet

Training loop in NN



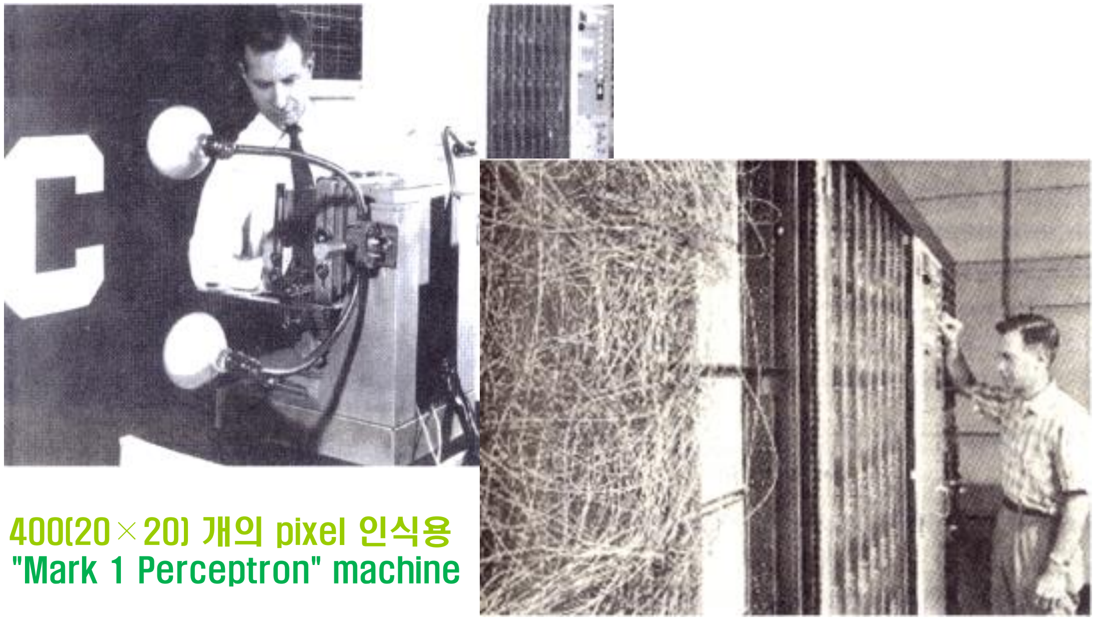
Perceptron: the simplest NN architecture

- 1943년, McCulloch와 Pitts는 인간의 두뇌를 수많은 신경세포들로 구성된 컴퓨터라 생각하고 최초로 신경망의 모델을 제안
- 1951년, Edmonds와 Minsky는 학습 기능을 갖는 최초의 신경망을 구축
- 1957년, Frank Rosenblatt는 Perceptron이라는 신경망모델을 제안하였는데, 이것은 패턴을 인식하기 위하여 학습 기능을 이용



Original Perceptron

Source: https://www.slideshare.net/roelofp/220115dlmeetup

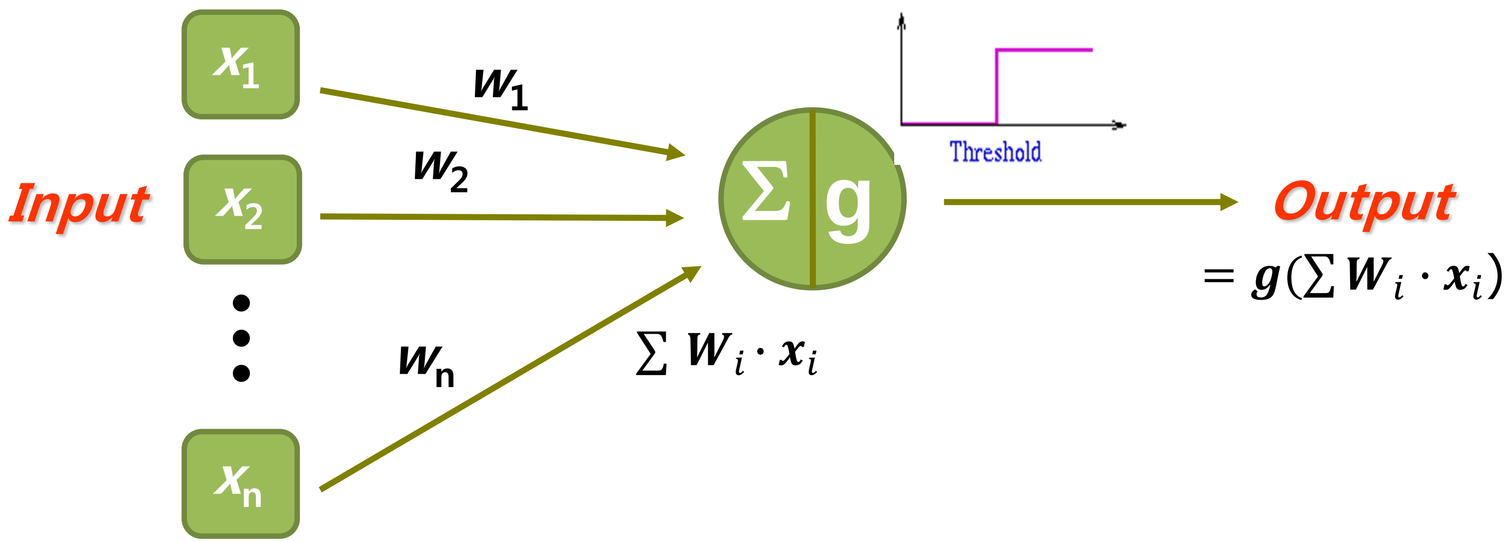


400(20×20) 개의 pixel 인식용
"Mark 1 Perceptron" machine

Source: http://www.aistudy.com/neural/model_kim.htm

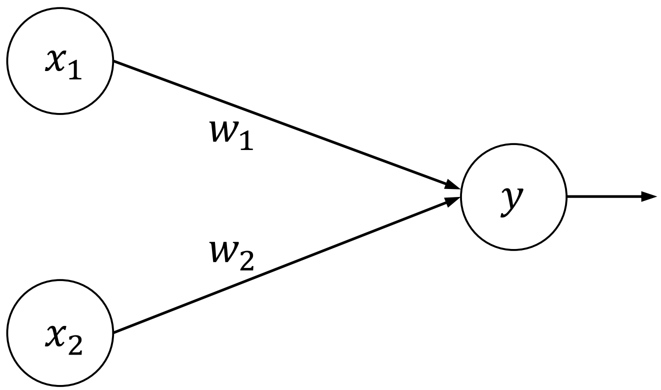
Perceptron

- 가중치(weight)
  - 입력신호의 강도를 표현: $\boldsymbol{W_1, W_2, \cdots, W_n}$
- 입력신호의 총합(total net input)
  - 각 입력신호에 해당 가중치를 곱하여 합한 값
  - $\boldsymbol{W_1 \cdot x_1 + W_2 \cdot x_2 + \cdots + W_n \cdot x_n = \sum W_i \cdot x_i}$
- 활성화 함수(activation/transfer function)
  - 입력신호의 총합이 활성화되는지(출력 값)를 결정하는 함수
  - 임계 값 $\boldsymbol{\theta}$를 갖는 Step Function 사용

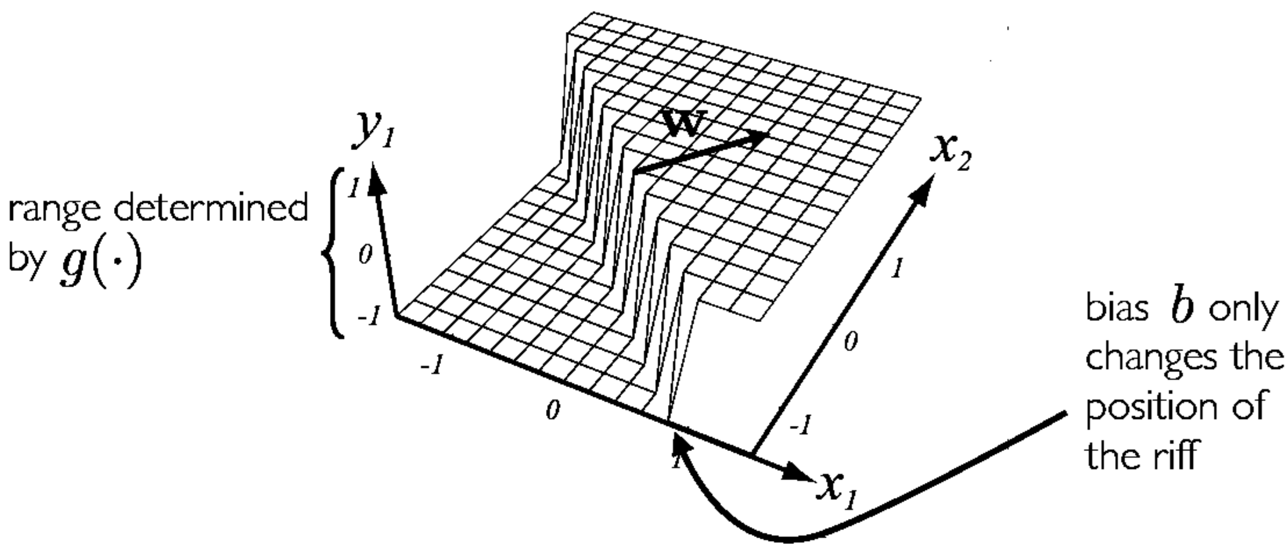


Perceptron

- How a perceptron works



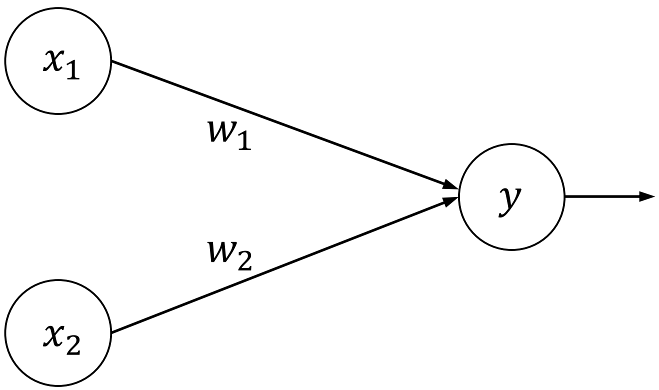
$$y = \begin{cases} 0 & (w_1 \cdot x_1 + w_2 \cdot x_2 \leq b) \\ 1 & (w_1 \cdot x_1 + w_2 \cdot x_2 > b) \end{cases}$$



Source: Neural Networks by Hugo Larochelle

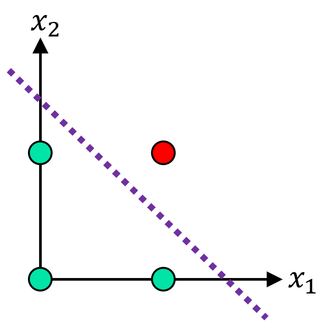
Perceptron

- Limitation of (single layer) perceptron



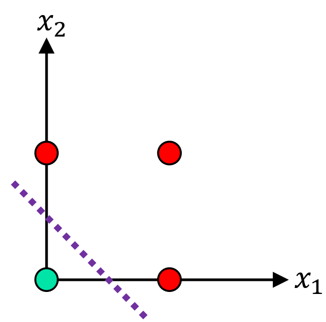
$$y = \begin{cases} 0 & (w_1 \cdot x_1 + w_2 \cdot x_2 \leq b) \\ 1 & (w_1 \cdot x_1 + w_2 \cdot x_2 > b) \end{cases}$$

AND



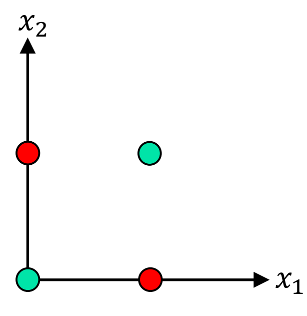
$w_1 = 1.0$
$w_2 = 1.0$
$b = 1.5$

OR



$w_1 = 1.0$
$w_2 = 1.0$
$b = 0.5$

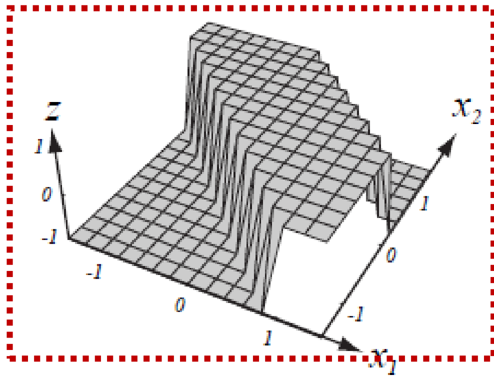
XOR

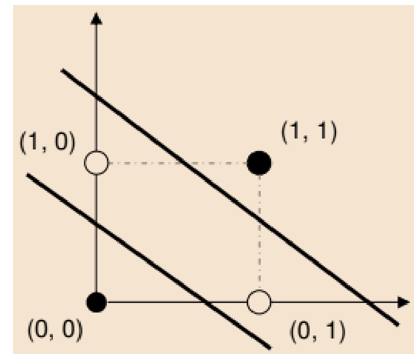


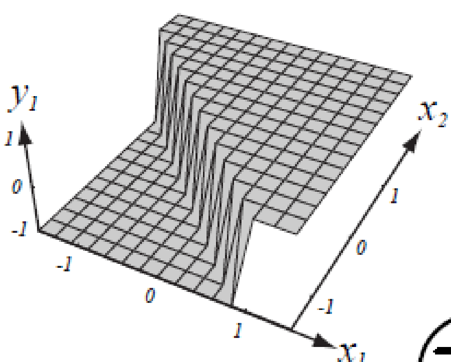
$w_1 = ?$
$w_2 = ?$
$\theta = ?$

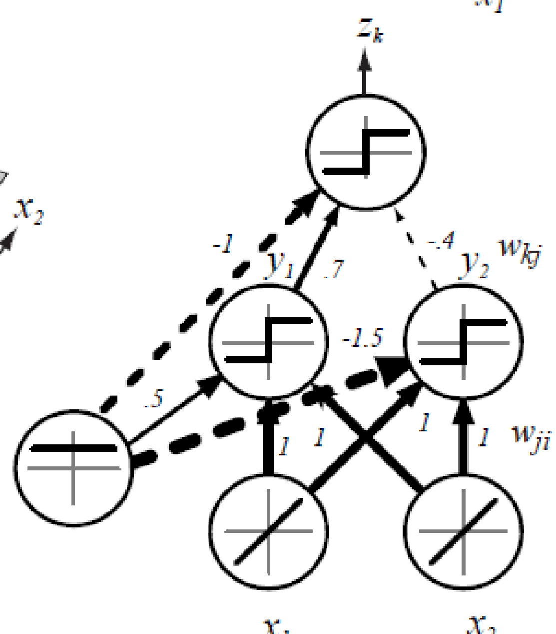
Perceptron

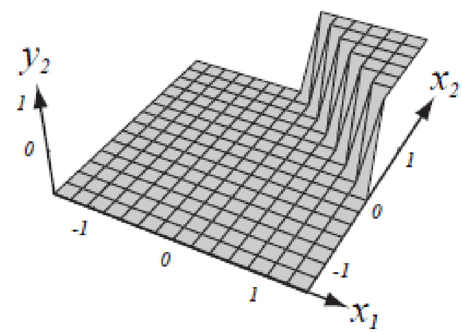
- Capacity of multi-layer perceptron









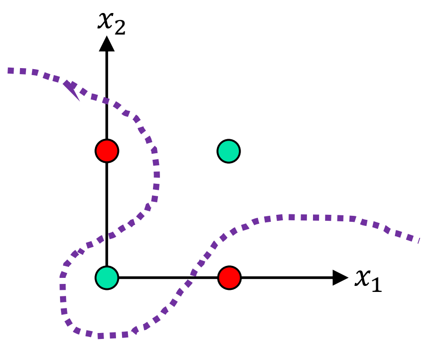


Source: Neural Networks by Hugo Larochelle

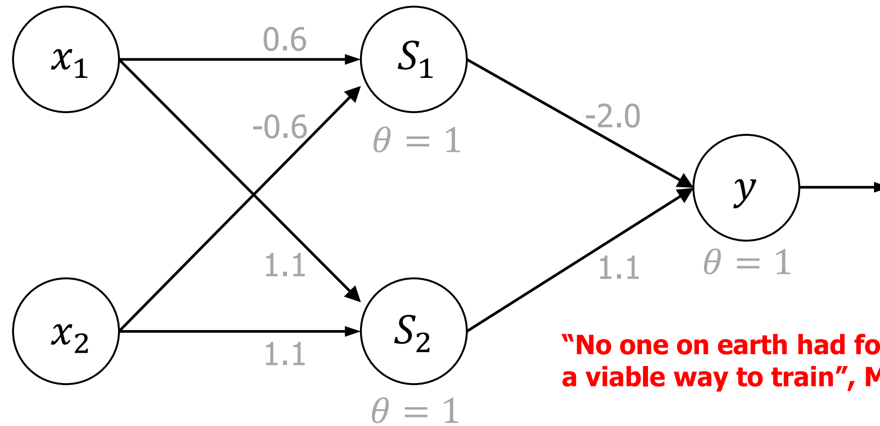
Perceptron

- 1969년, Minsky와 Papert가 그들의 저서 "Perceptrons"에서 퍼셉트론이 비선형 분리 문제를 풀 수 없음을 증명하여, <u>침체기에 들어감 (**1st AI winter**)</u>

XOR

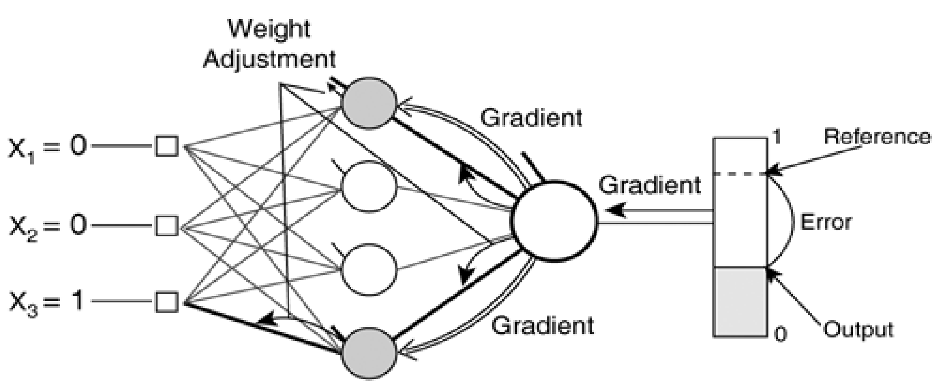


needs multi-layer perceptron (**MLP**)



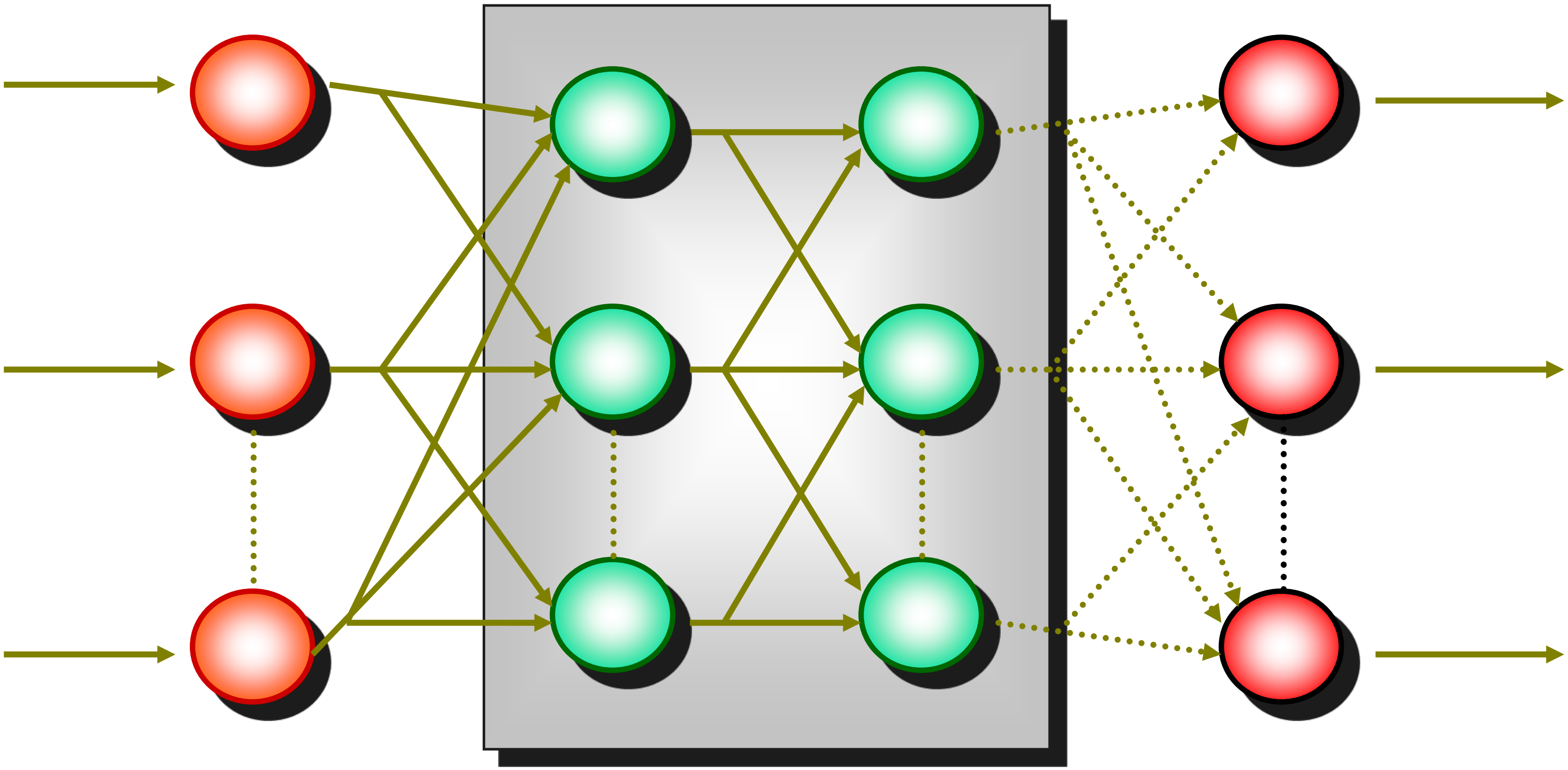
"No one on earth had found a viable way to train", Minsky

- 1986년, PDP그룹에 의해 <u>Back-Propagation 알고리즘을 사용하는 MLP가 탄생</u>되어 신경망의 다양한 분야에 대한 연구와 응용이 이루어짐.



Source: http://www.yaldex.com/game-development/1592730043_ch20lev1sec5.html

MLP: multi-layer perceptron



입력계층
(input layer)

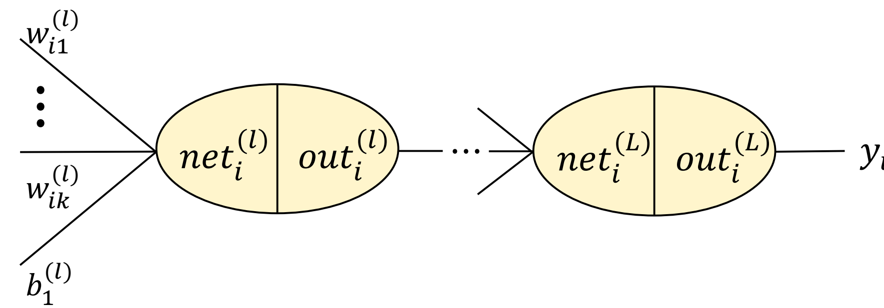
은닉계층
(hidden layer)

출력계층
(output layer)

MLP

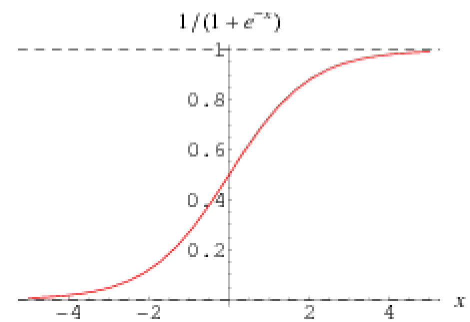
- Total net input에 편향(bias) 추가

$$net_i^{(l)} = \sum_{j=1}^{k} w_{ij}^{(l)} \cdot out_j^{(l-1)} + b_1^{(l)}$$



- Activation 함수
  - Hidden Node: 주로 시그모이드(sigmoid / logistic) 함수 사용

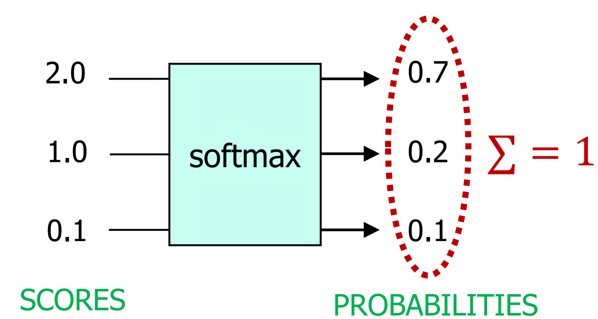
$$out_i^{(l)} = \frac{1}{1+\exp(-net_i^{(l)})}$$



  - Output Node
    - 추정(y가 연속형) 문제에는 항등(identity) 함수 사용. 즉, $y = net^{(L)}$
    - 분류 문제에는 소프트맥스(softmax) 함수 사용

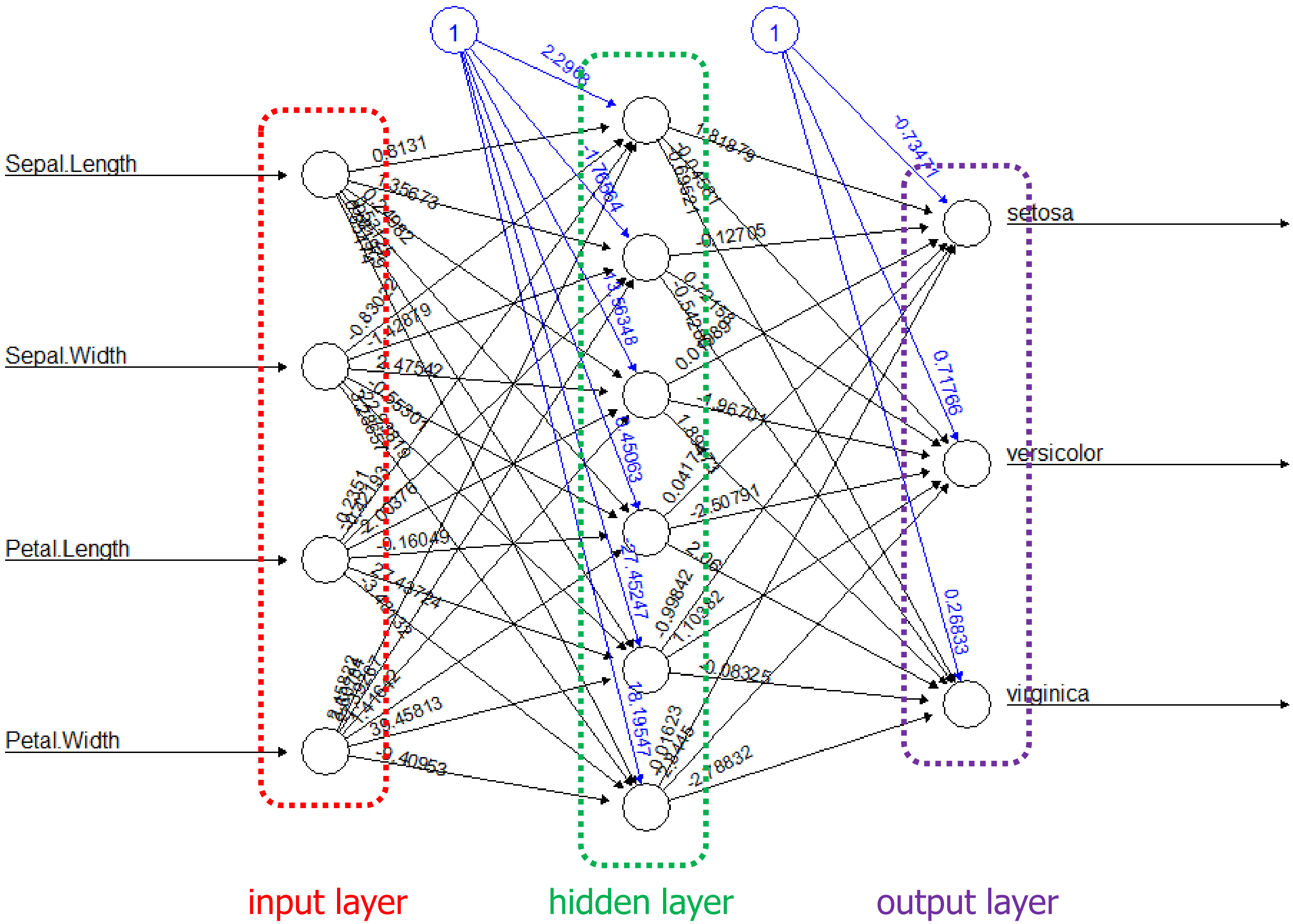
$$y_n = \frac{\exp(net_n^{(L)})}{\sum_{i=1}^{N} \exp(net_i^{(L)})}$$

N: 출력층의 뉴런 수, $0 \le y_n \le 1$



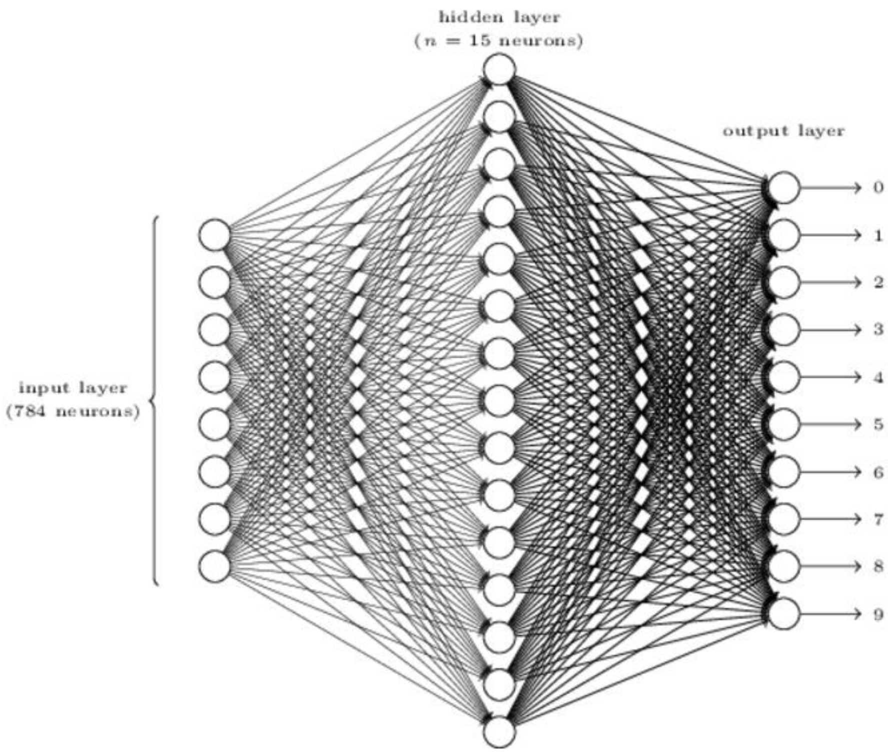
MLP

- Classification Example for IRIS data by MLP

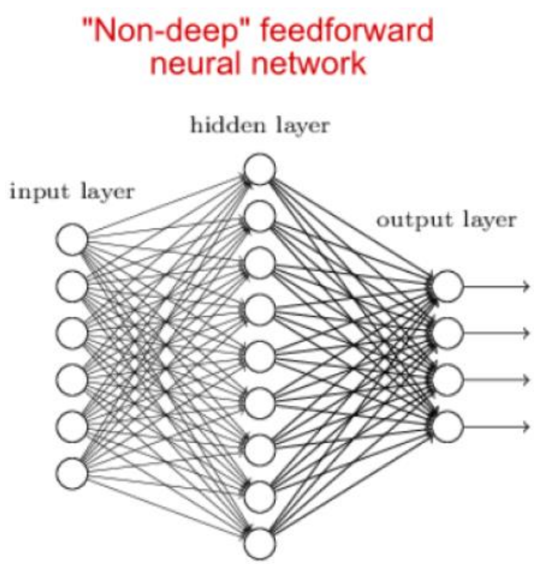


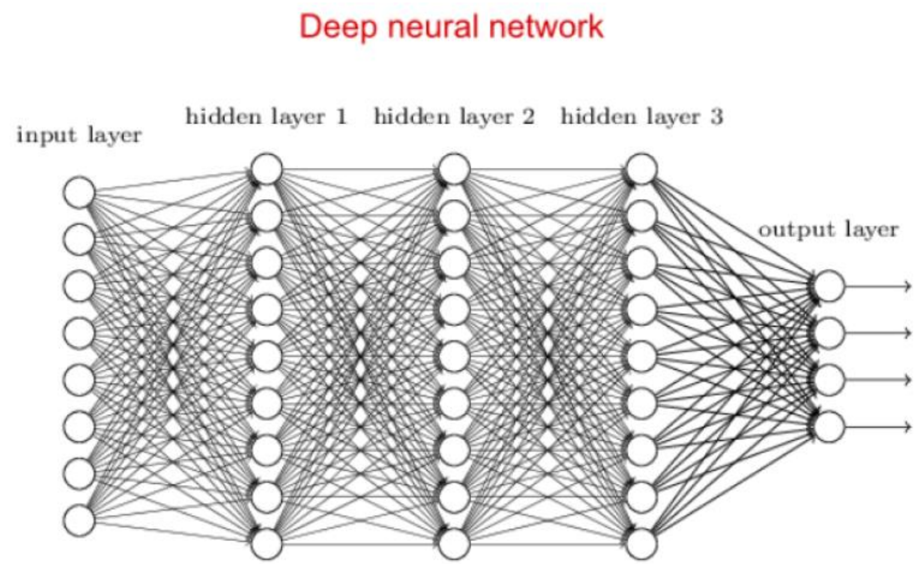
MLP

- A simple network to classify handwritten digits
  - Training data: 28X28(784) pixel, greyscale(0.0~1.0)



Shallow NN vs. Deep NN



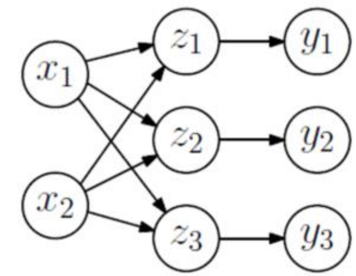


- Input layer: 6개의 input neuron으로 구성 (dimension = 6)
- Hidden layer: 1개 layer, 9개 neuron(unit)
- Output layer: 4개 unit

- Input layer: 8개의 input neuron으로 구성 (dimension = 8)
- Hidden layer: 3개 layer, 각 9개 unit
- Output layer: 4개 unit

Learning algorithm

- Error(cost) function
  - Mean squared error: $E(\boldsymbol{W}) = \frac{1}{2}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$
  - Cross entropy error: $E(\boldsymbol{W}) = -\sum_{i=1}^{N} y_i log(\hat{y}_i)$



$$z_1 = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 + b_1$$
$$z_2 = w_{21}x_1 + w_{22}x_2 + w_{23}x_3 + b_2$$
$$z_3 = w_{31}x_1 + w_{32}x_2 + w_{33}x_3 + b_3$$

Z=Wb

$$y_i = \sigma(z_i)$$

- Learning network
  - adjusting weights to minimize error (E)
  - Iterative numerical procedure

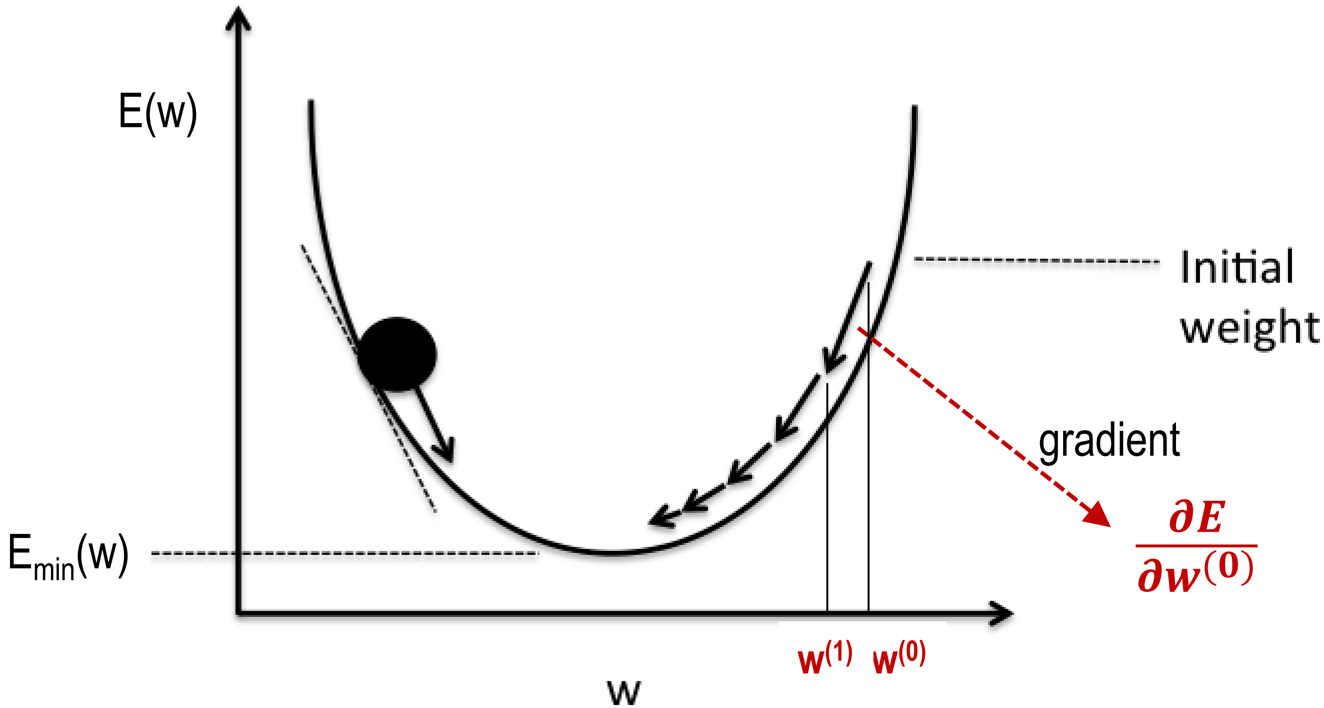
$$\boldsymbol{W}^{(t+1)} = \boldsymbol{W}^{(t)} + \nabla\boldsymbol{W}^{(t)}$$

- Gradient descent optimization

$$\boldsymbol{W}^{(t+1)} = \boldsymbol{W}^{(t)} - \eta\frac{\partial E(\boldsymbol{W}^{(t)})}{\partial \boldsymbol{W}^{(t)}} \qquad \eta\text{: learning rate } (0 \sim 1)$$

- Mini-batch stochastic gradient descent (mini-batch SGD)
  - Instead of the entire training data, work with mini-batch of m examples in each iteration (*note: epoch*)

Schematics of gradient descent



$$w^{(1)} = w^{(0)} - \eta \frac{\partial E}{\partial w^{(0)}}$$

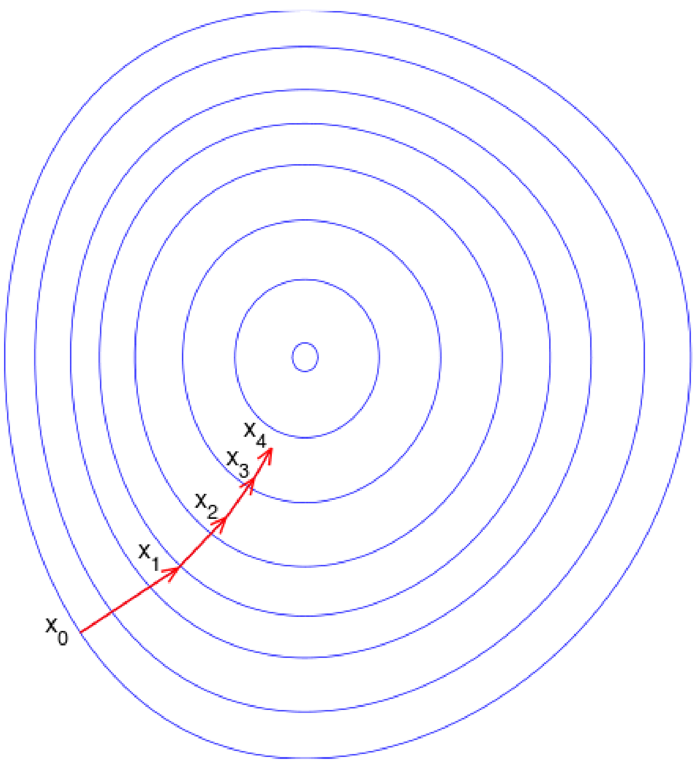
Source: http://sebastianraschka.com/Articles/2015_singlelayer_neurons.html

Schematics of gradient descent

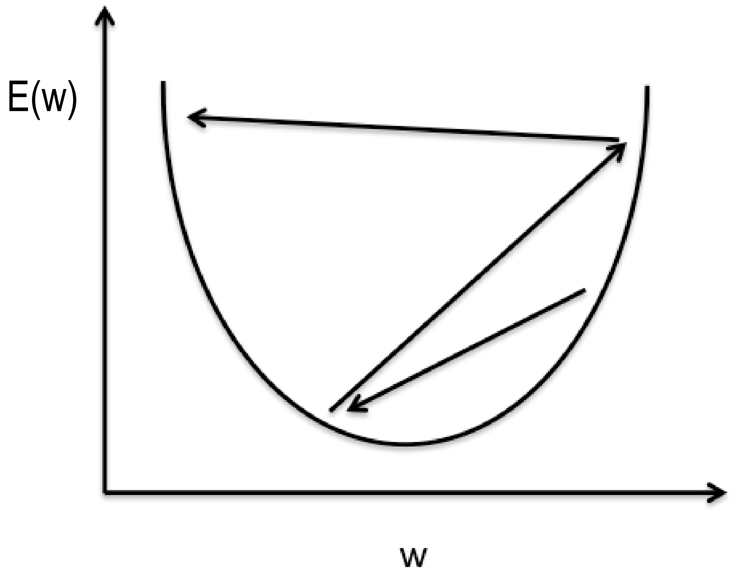
- $x \in \mathbb{R}^n$
- 현재값 $\boldsymbol{x}^{(k)}$에서 가장 빠르게 $f(\boldsymbol{x})$를 감소시키는 방향 $-\nabla f(\boldsymbol{x}^{(k)})$ 으로 α만큼씩 이동

$$\begin{bmatrix} x_1^{(k+1)} \\ x_2^{(k+1)} \\ \vdots \\ x_n^{(k+1)} \end{bmatrix} = \begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \\ \vdots \\ x_n^{(k)} \end{bmatrix} - \alpha \begin{bmatrix} \frac{\partial}{\partial x_1} f(x_1^{(k)}) \\ \frac{\partial}{\partial x_2} f(x_2^{(k)}) \\ \vdots \\ \frac{\partial}{\partial x_n} f(x_n^{(k)}) \end{bmatrix}$$

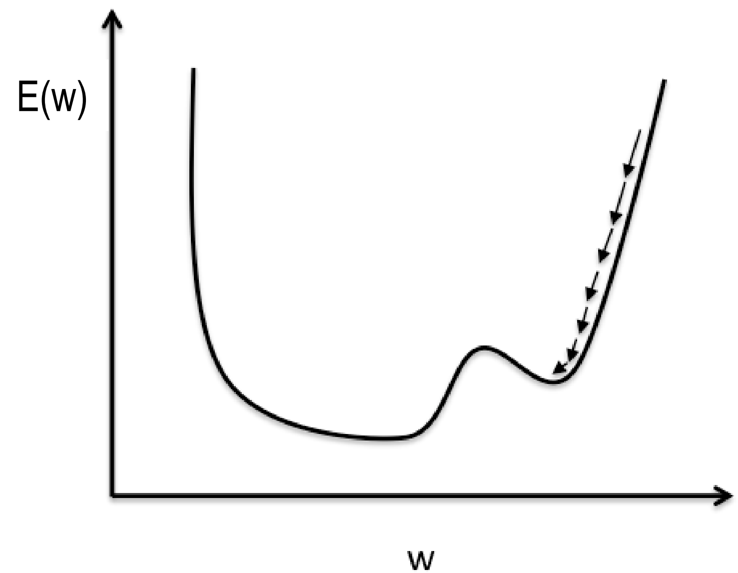
$$\boldsymbol{x}^{(k+1)} = \boldsymbol{x}^{(k)} - \alpha \left\{ \nabla f\left(\boldsymbol{x}^{(k)}\right) \right\}^T$$



Learning rate



Large learning rate: Overshooting.

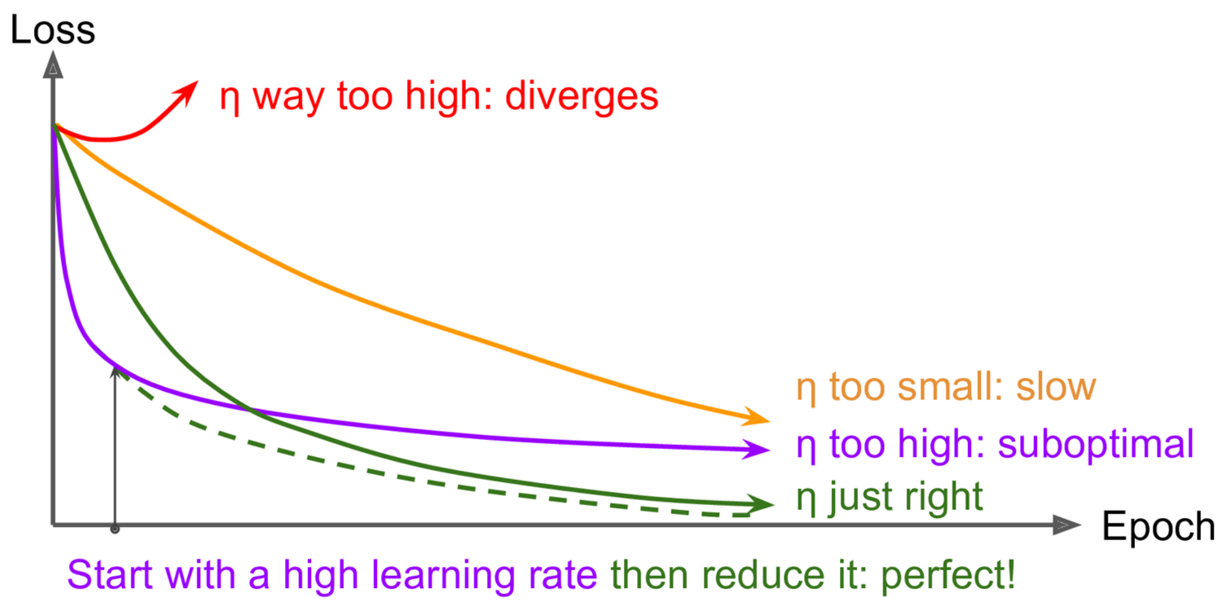


Small learning rate: Many iterations until convergence and trapping in local minima.

☞ recommended learning rate ≈ 0.01~0.001

Source: http://sebastianraschka.com/Articles/2015_singlelayer_neurons.html

Learning rate Scheduling



- 미리 정의된 개별적인 고정 학습률
- 성능 기반 스케줄링
- 지수 기반 스케줄링 (Exponential Scheduling) *
- 거듭제곱 기반 스케줄링 (Power Scheduling)

Source: Hands-On Machine Learning with Scikit-Learn & TensorFlow

Computing the gradient

- Numerical gradient
  - computes the partial derivative of each weight using the finite difference approximation

$$\frac{\partial \boldsymbol{E}}{\partial w_{ji}} = \frac{\boldsymbol{E}(w_{ji}+\epsilon)-\boldsymbol{E}(w_{ji})}{\epsilon} + O(\epsilon)$$

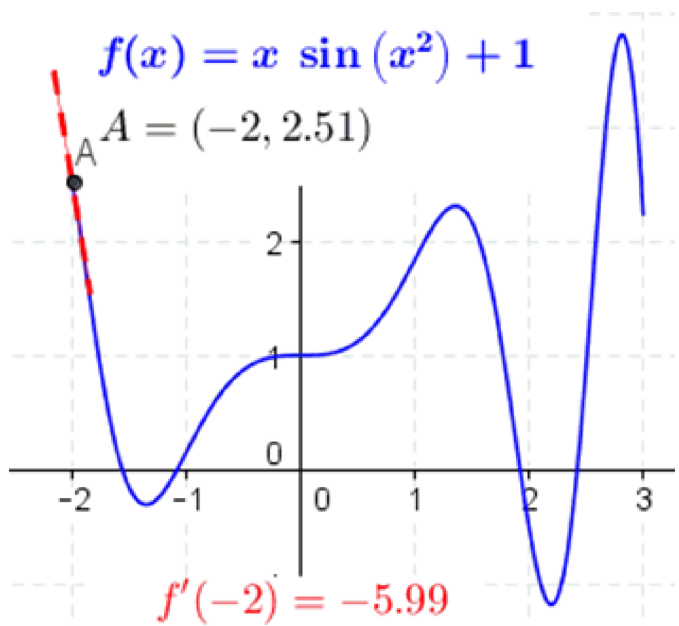
  - is very simple, but approximate and very computationally expensive; $O(W^2)$
- Back-propagation
  - enables us to compute the gradients very efficiently; $O(W)$
  - uses the chain rule for gradient decent
  - consists of a two-pass procedure:
    - forward pass: fix weights, evaluate y from x
    - backward pass: compute the error E and back propagate it

[Ref] Scalar Differentiation

- 미분의 정의
  - 함수 $y = f(x)$의 정의역에서 임의의 x에서 미분은 다음과 같이 정의된다.

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

  - 점 x에서 f가 변하는 순간 변화율



[Ref] Scalar Differentiation: Formulas

- 많이 사용되는 미분 공식

$$\frac{d}{dx}(x^n) = nx^{n-1} \qquad \frac{d}{dx}(\ln x) = \frac{1}{x}$$

$$\frac{d}{dx}(e^x) = e^x \qquad \frac{d}{dx}(\sin x) = \cos x$$

$$\frac{d}{dx}(\cos x) = -\sin x \qquad \frac{d}{dx}(\tanh x) = 1 - \tanh^2 x$$

$$\frac{d}{dx}\left(\frac{1}{1+\exp(-x)}\right) = \left(\frac{1}{1+\exp(-x)}\right)\left(1 - \frac{1}{1+\exp(-x)}\right)$$

[Ref] Scalar Differentiation: Rules

- Sum rule

$$(f(x)+g(x))' = f'(x) + g'(x) = \frac{df}{dx} + \frac{dg}{dx}$$

- Product rule

$$(f(x)g(x))' = f'(x)g(x) + f(x)g'(x) = \frac{df}{dx}g(x) + f(x)\frac{dg}{dx}$$

- Chain rule

$$\boxed{(g \circ f)'(x) = (g(f(x)))' = g'(f(x))f'(x) = \frac{dg}{df}\frac{df}{dx}}$$

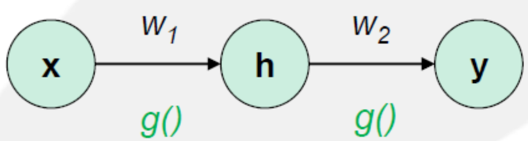
[Ref] Scalar Differentiation: Chain Rule

- Example

$$g(z) = \tanh(z)$$
$$z = f(x) = x^n$$
$$(g \circ f)'(x) = \underbrace{\left(1 - \tanh^2(x^n)\right)}_{dg/df} \underbrace{n x^{n-1}}_{df/dx}$$

Backpropagation (an easy case)

$$\boldsymbol{y = g(h \cdot w_2) = g(g(x \cdot w_1) \cdot w_2)}$$



$E(\mathbf{w}) = \frac{1}{2}(\mathrm{y} - y_i)^2, where\ y_i\ is\ a\ real\ value.$

$g' = g(1-g), when\ g\ is\ a\ sigmod\ ft.$

$$\frac{\partial \boldsymbol{E(w)}}{\partial \boldsymbol{w_2}} = (\mathrm{y} - y_i) \cdot \frac{\partial y}{\partial w_2}$$

$$= (\mathrm{y} - y_i) \cdot \frac{\partial g(h \cdot w_2)}{\partial w_2}$$

$$= (\mathrm{y} - y_i) \cdot g(h \cdot w_2) \cdot (1 - g(h \cdot w_2)) \times \frac{\partial (h \cdot w_2)}{\partial w_2}$$

$$= \boldsymbol{(\mathrm{y} - y_i) \cdot y \cdot (1 - y) \cdot h = E_y \cdot h}$$

$$\frac{\partial \boldsymbol{E(w)}}{\partial \boldsymbol{w_1}} = (\mathrm{y} - y_i) \cdot \frac{\partial y}{\partial w_1}$$

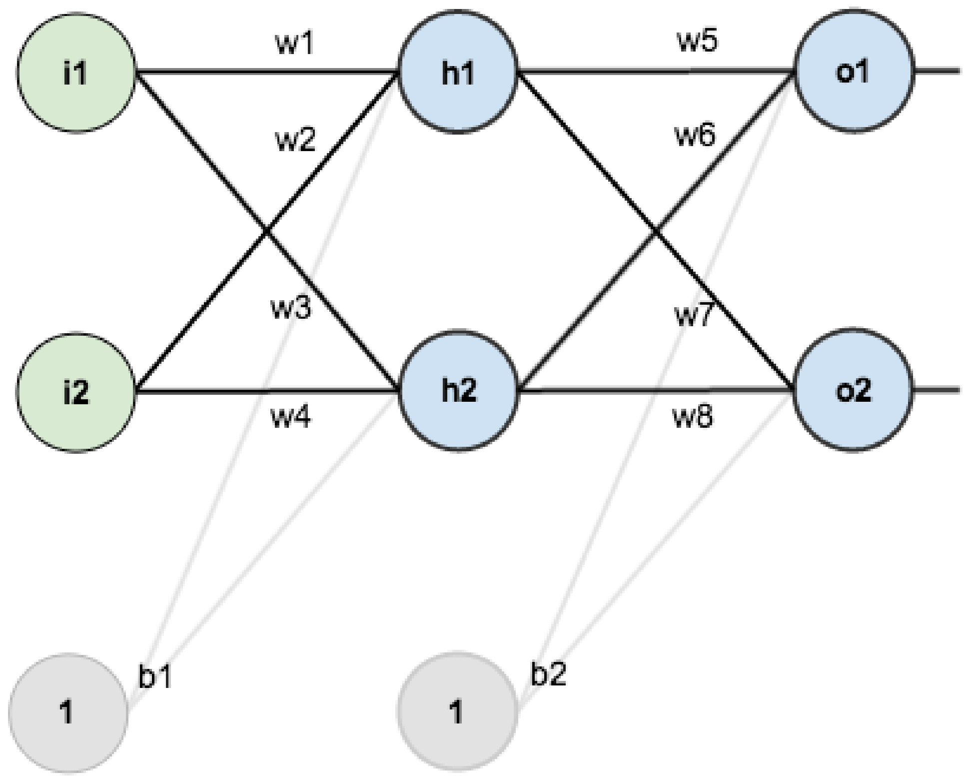
$$= (\mathrm{y} - y_i) \cdot y \cdot (1 - y) \cdot \frac{\partial (h \cdot w_2)}{\partial w_1}$$

$$= (\mathrm{y} - y_i) \cdot y \cdot (1 - y) \cdot w_2 \cdot \frac{\partial h}{\partial w_1}$$

$$= (\mathrm{y} - y_i) \cdot y \cdot (1 - y) \cdot w_2 \cdot h \cdot (1 - h) \cdot \frac{\partial (x \cdot w_1)}{\partial w_1}$$

$$= \boxed{\boldsymbol{(\mathrm{y} - y_i) \cdot y \cdot (1 - y)}} \cdot \boldsymbol{w_2 \cdot h \cdot (1 - h) \cdot x = E_h \cdot x}$$

Backpropagation

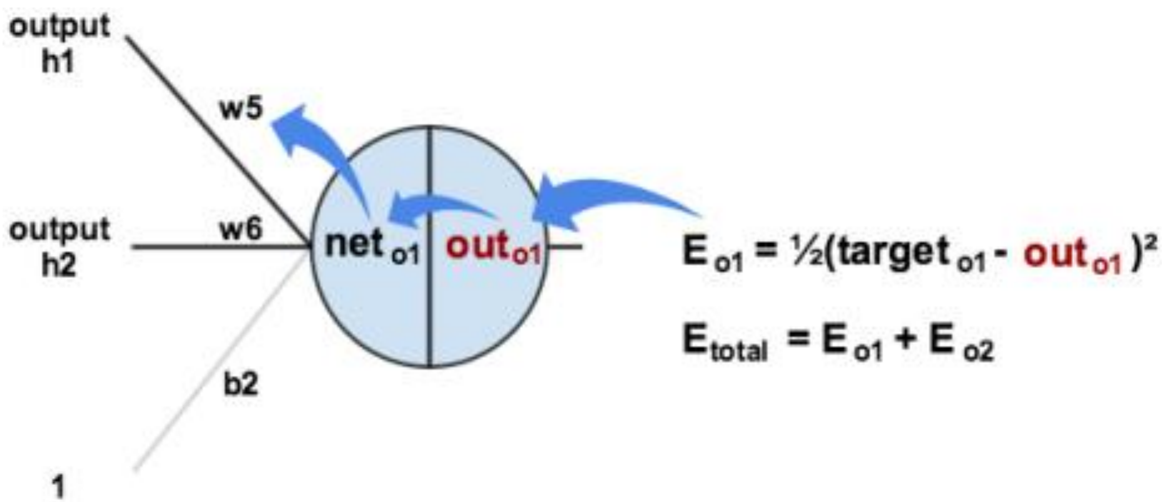


Assume the hidden and output neurons use the sigmoid function for activation

Source: https://mattmazur.com/2015/03/17/

Backpropagation

- Output layer



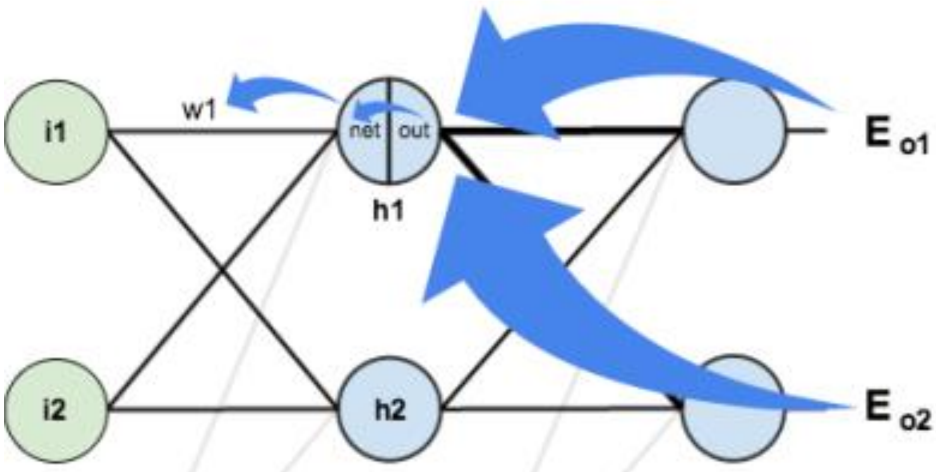
$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{01}}{\partial out_{01}} \times \frac{\partial out_{01}}{\partial net_{01}} \times \frac{\partial net_{01}}{\partial w_5}$$

$$= \boxed{-(target_{01} - out_{01})} \times \boxed{out_{01}(1 - out_{01})} \times \boxed{out_{h1}}$$

$$= \delta_{01} \times out_{h1}$$

Backpropagation

- Hidden layer



$E_{total} = E_{o1} + E_{o2}$

$$\frac{\partial E_{total}}{\partial w_1} = \frac{\partial E_{total}}{\partial out_{h1}} \times \frac{\partial out_{h1}}{\partial net_{h1}} \times \frac{\partial net_{h1}}{\partial w_1}$$

$$\boxed{\frac{\partial E_{total}}{\partial out_{h1}} = \frac{\partial E_{01}}{\partial out_{h1}} + \frac{\partial E_{02}}{\partial out_{h1}}}$$

$$\boxed{\frac{\partial E_{01}}{\partial out_{h1}} = \frac{\partial E_{01}}{\partial net_{01}} \times \frac{\partial net_{01}}{\partial out_{h1}}}$$

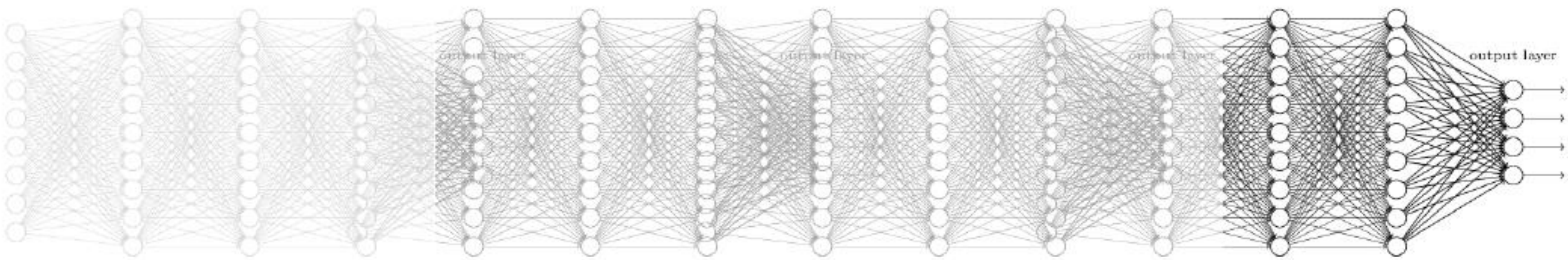
$$= \left(\sum_o \frac{\partial E_o}{\partial out_o} \times \frac{\partial out_o}{\partial net_o} \times \frac{\partial net_o}{\partial out_{h1}}\right) \times \frac{\partial out_{h1}}{\partial net_{h1}} \times \frac{\partial net_{h1}}{\partial w_1}$$

$$\boxed{\frac{\partial E_{01}}{\partial net_{01}} = \frac{\partial E_{01}}{\partial out_{01}} \times \frac{\partial out_{01}}{\partial net_{01}}}$$

$$= \boxed{\left(\sum_o \delta_o \times w_{ho}\right)} \times \boxed{out_{h1}(1 - out_{h1})} \times \boxed{i_1}$$

Source: https://mattmazur.com/2015/03/17/

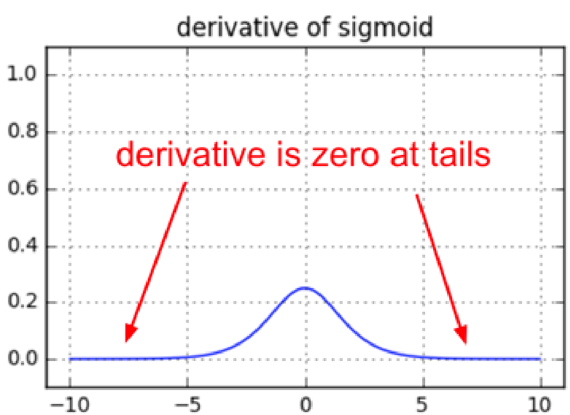
Vanishing gradient problem

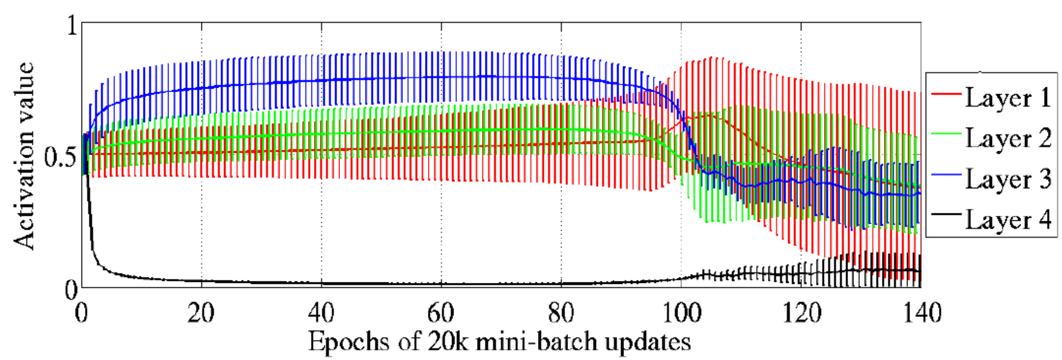


Source: http://hunkim.github.io/ml/

- meaning that the gradient (error signal) decreases exponentially with *n* and the front layers train very slowly.
- why?
  - Initializing the weights in a stupid way
  - Using wrong type of non-linearity

2nd AI winter

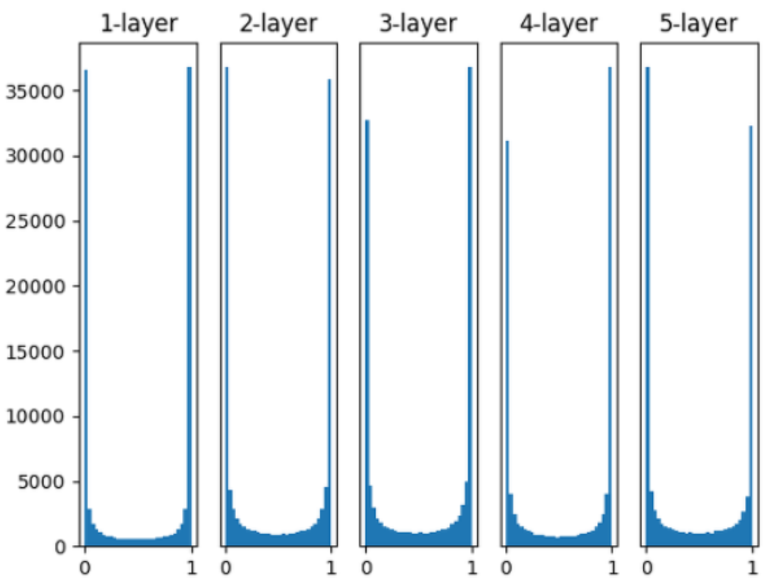




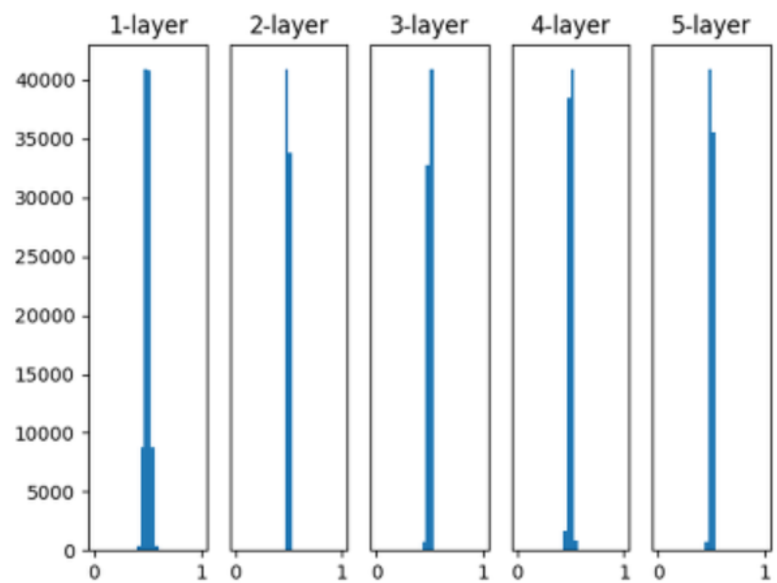
Source: Understanding the difficulty of training deep feedforward neural networks

초기 가중치에 따른 활성화 값 분포

- Activation function = sigmoid, init. W ~ N(0, 1)



- Activation function = sigmoid, init. W ~ N(0, 0.01)

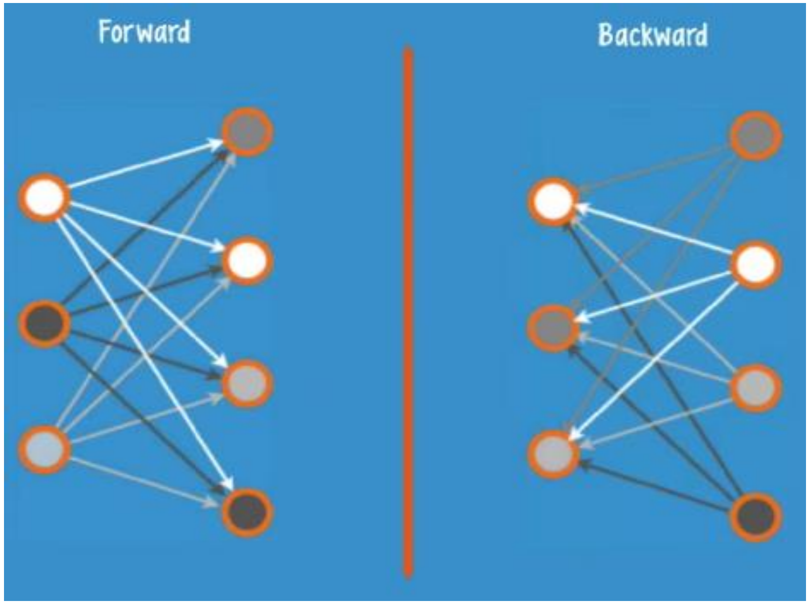


Source: "밑바닥부터 시작하는 딥러닝", 사이토 고키

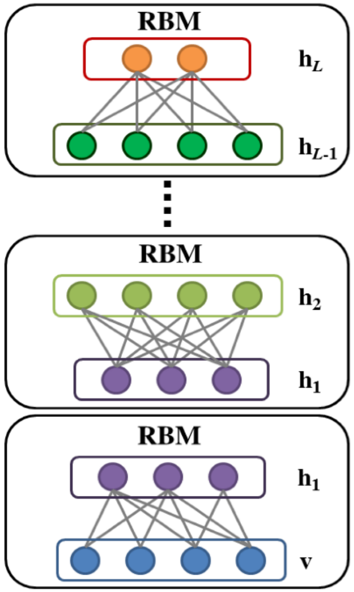
 # 단순한 신경망일수록 초기 가중치에 민감하다.

Deep learning begins

- 2006년, Geoffrey Hinton에 의해 RBM 기반의 pre-training으로 Deep Neural Network의 학습이 가능해 지면서 "Deep Learning"이라는 새로운 이름으로 다시 주목을 받기 시작함.
- Deep Belief Networks
  - Hinton et al. (2006) "A Fast Learning Algorithm for Deep Belief Nets”
  - Apply the RBM idea on adjacent two layers as a pre-training step, and continue the first process to all layers => This will initialize good weight values !



RBM(Restricted Boatman Machine) structure



DBN

Source: http://hunkim.github.io/ml/

Source: Maximum Entropy Learning with Deep Belief Networks

Modern weight value initialization

Makes sure the weights are 'just right', not too small, not too big

- Xavier initialization
  - Glorot & Bengio (2010) "Understanding the difficulty of training deep feedforward neural networks"
  - initializes the weights by drawing them from a distribution with zero mean and a specific variance,

$$Var(\boldsymbol{W}) = \frac{1}{n_{in}}$$

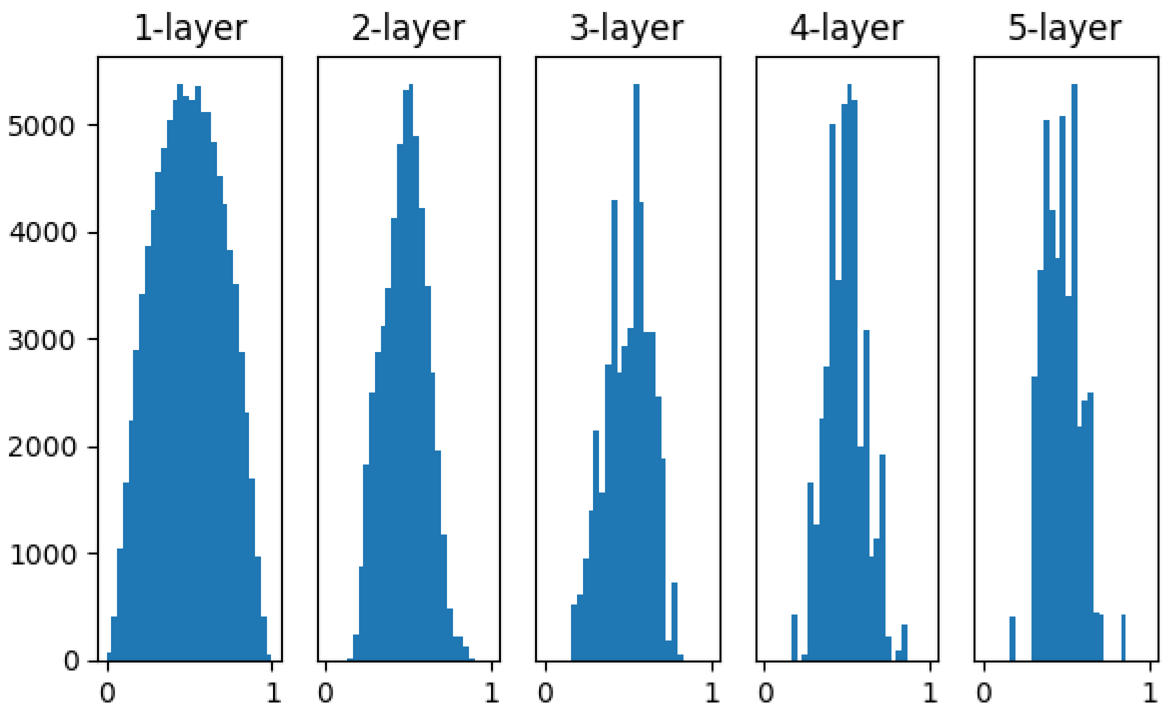
  where W is the initialization distribution for the neuron in question, and n_{in} is the number of neurons feeding into it. The distribution used is typically Gaussian or uniform.

- He's initialization
  - He et al. (2015) "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification"
  - For ReLU, it is recommended using

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

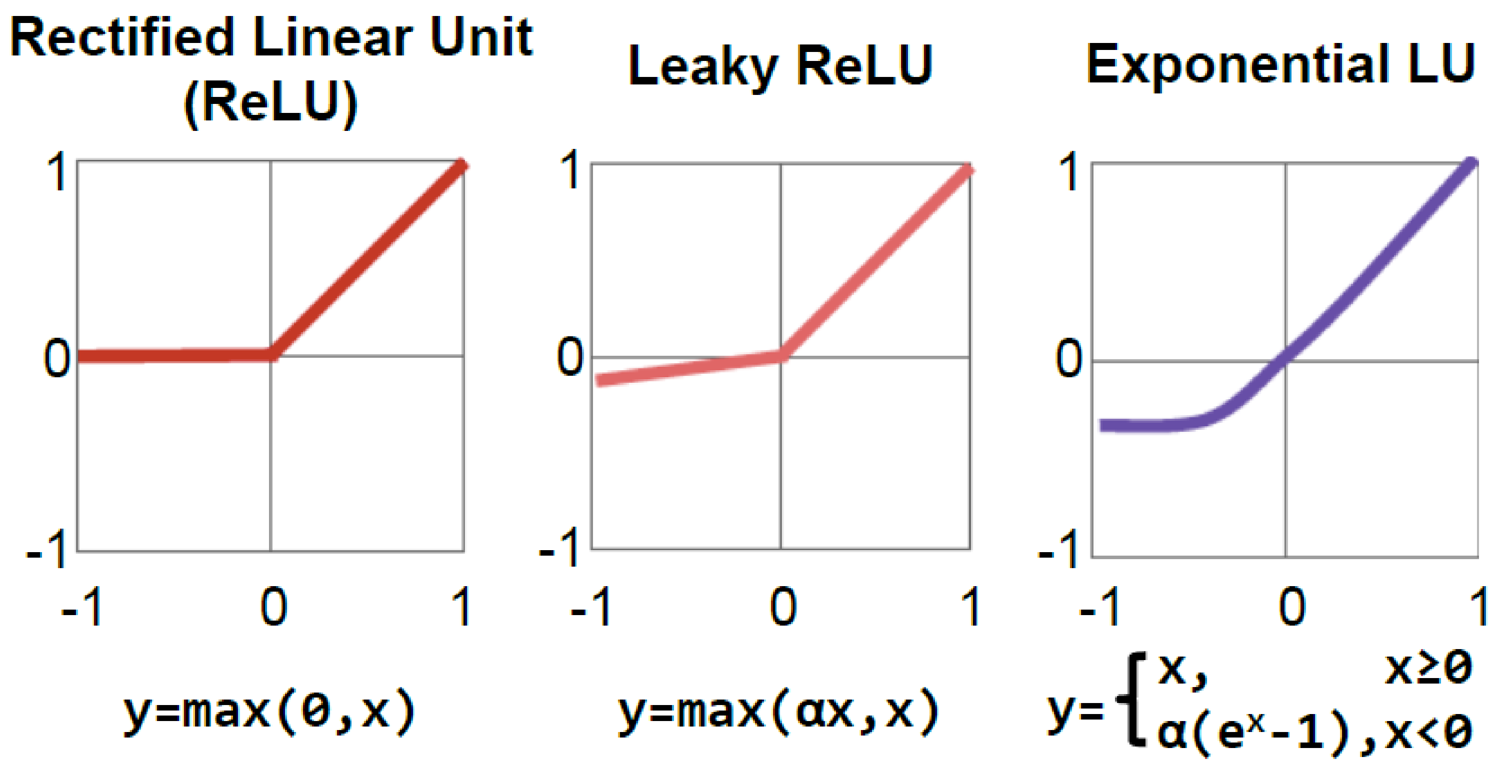
Modern weight value initialization

- Xavier initialization 적용 시의 활성화 값 분포



Modern activation functions

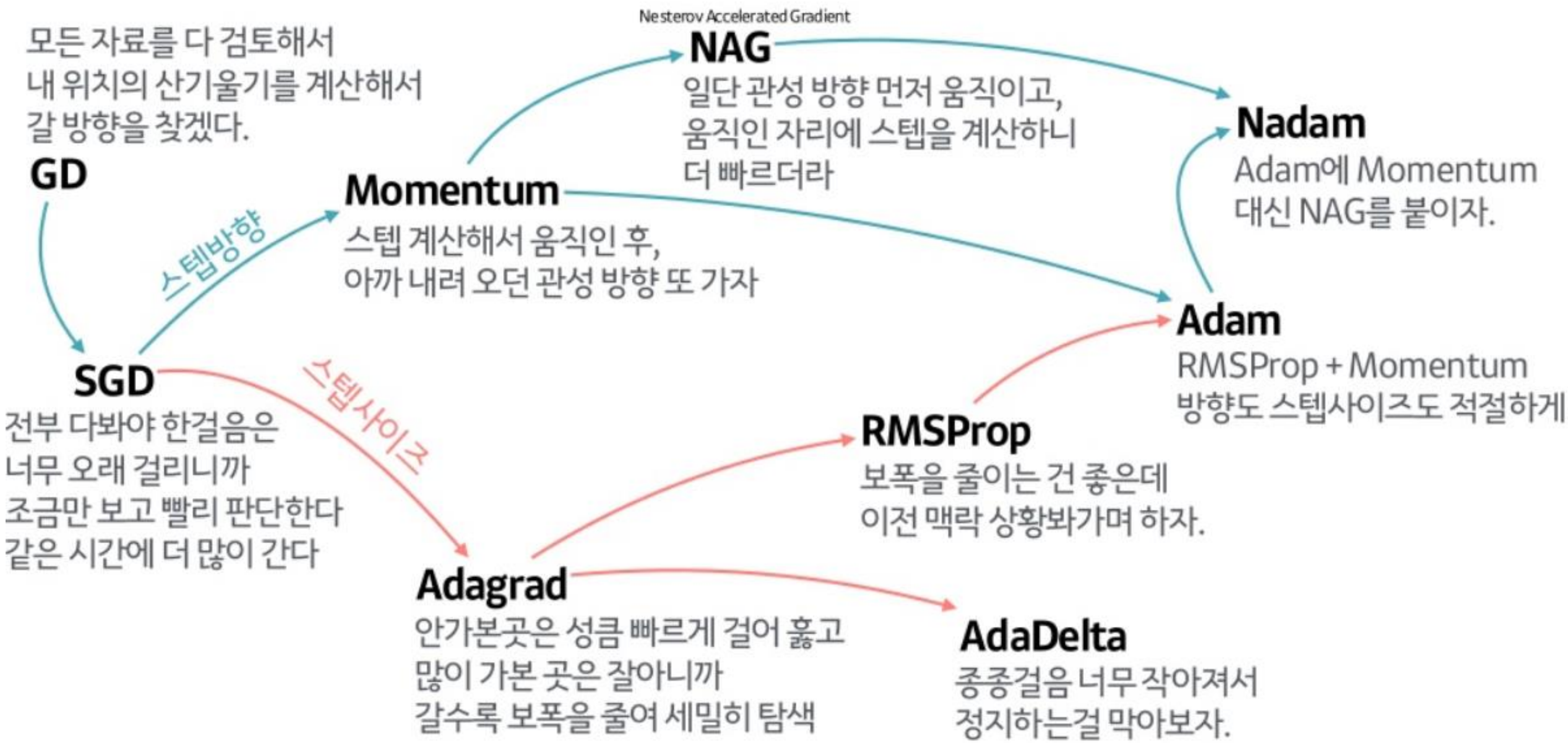
Source: Efficient Processing of Deep Neural Networks: A Tutorial and Survey



 # scikit-learn에서는 relu(기본값), logistic, tanh, identity를 지원

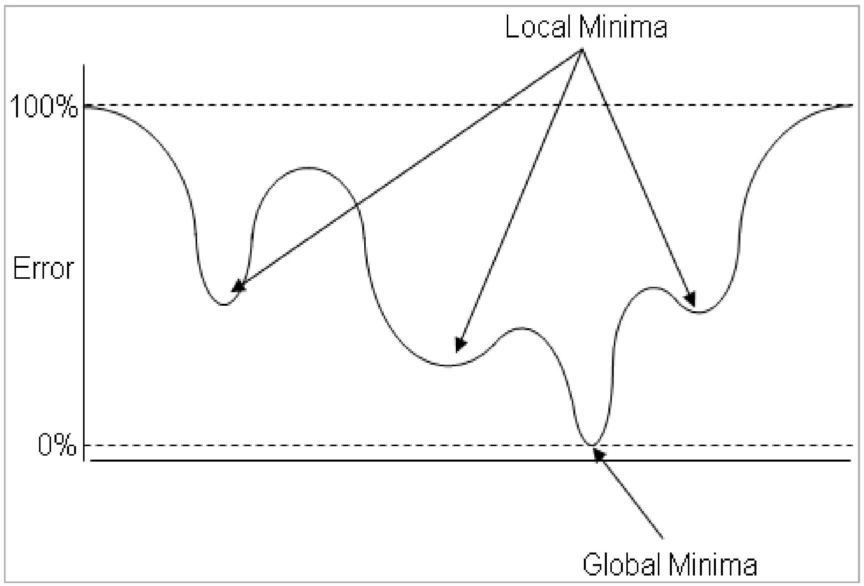
Optimization techniques

Source: https://www.slideshare.net/yongho/ss-79607172

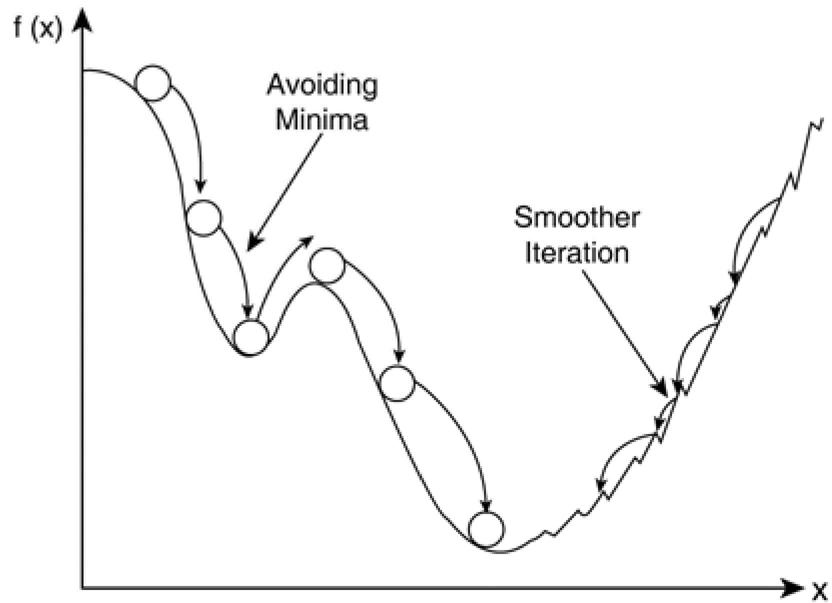


 # scikit-learn에서는 adam(기본값), sgd, lbfgs를 지원

Momentum



Source: http://mnemstudio.org/neural-networks-backpropagation.htm



Source: http://www.yaldex.com

기존 업데이트에 사용했던 기울기의 일정 비율을 남겨서 현재의 기울기와 더하여 업데이트함.

$$\boldsymbol{v}^{(t+1)} = \alpha \boldsymbol{v}^{(t)} + \eta \frac{\partial E}{\partial \boldsymbol{W}^{(t)}}$$

$$\boldsymbol{W}^{(t+1)} = \boldsymbol{W}^{(t)} - \boldsymbol{v}^{(t+1)}$$

☞ recommended $\alpha \approx 0.9$

Modern optimizers

- Adagrad
  (Adaptive Gradient)

$$G_t = G_{t-1} + (\nabla_\theta J(\theta_t))^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

- RMSProp

$$G = \gamma G + (1-\gamma)(\nabla_\theta J(\theta_t))^2$$

$$\theta = \theta - \frac{\eta}{\sqrt{G + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

- Adam
  (Adaptive Moment Estimation)

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta J(\theta)$$ ← Momentum

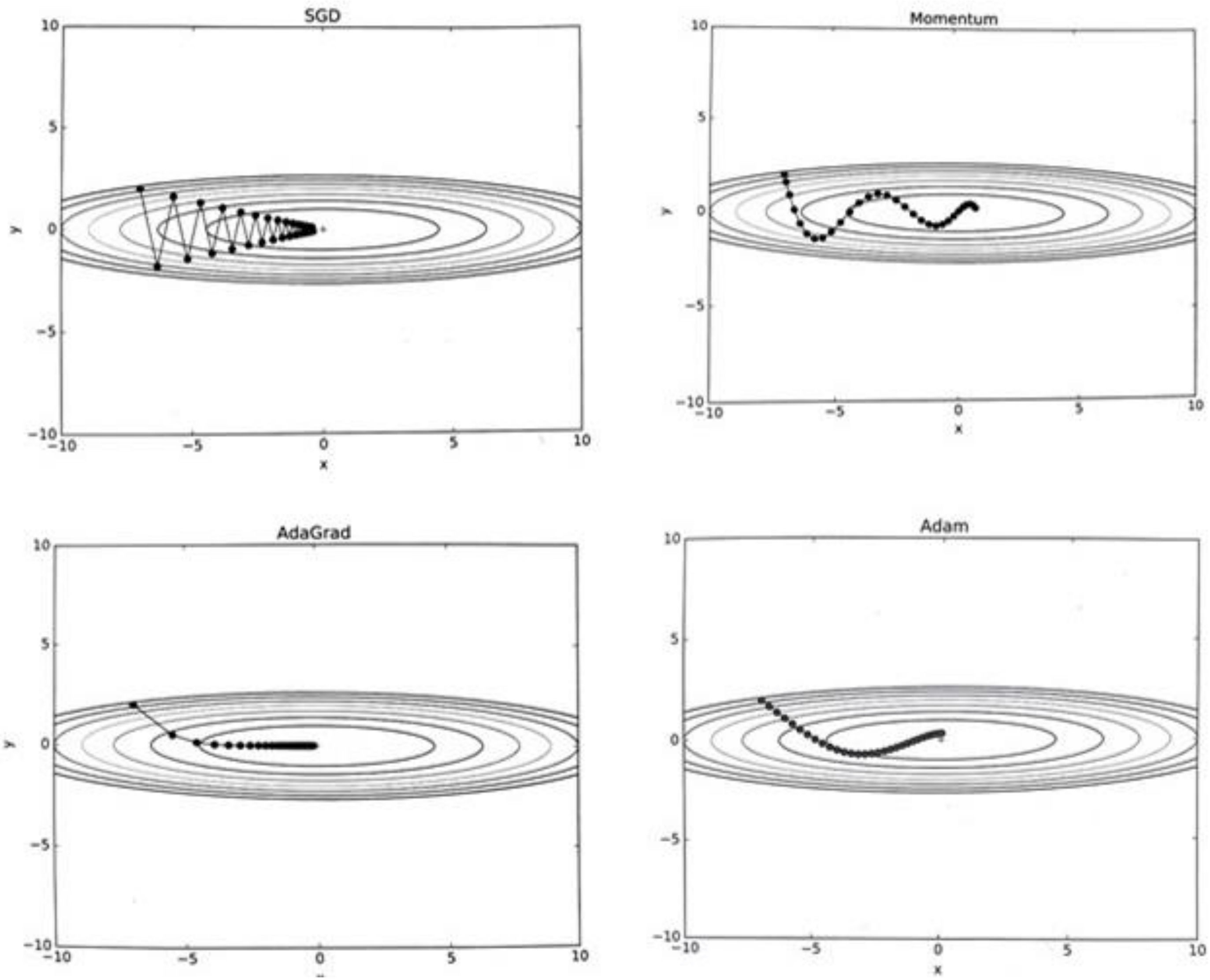
$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\theta J(\theta))^2$$ ← RMSProp

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta = \theta - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

Optimizer Comparison



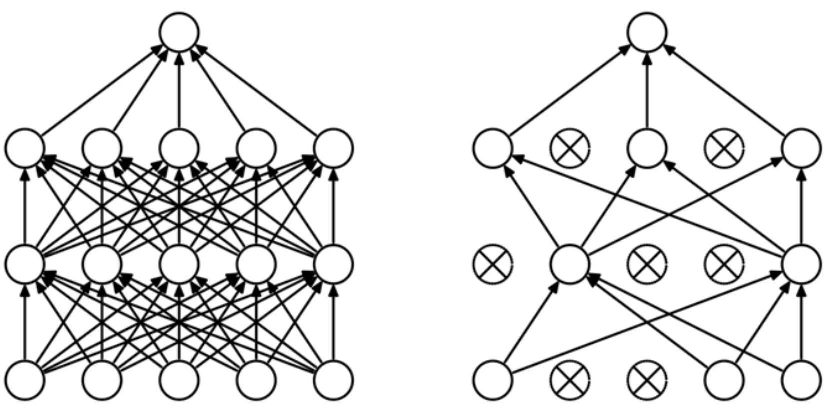
Source: "밑바닥부터 시작하는 딥러닝", 한빛미디어, 2017.

Solutions for overfitting

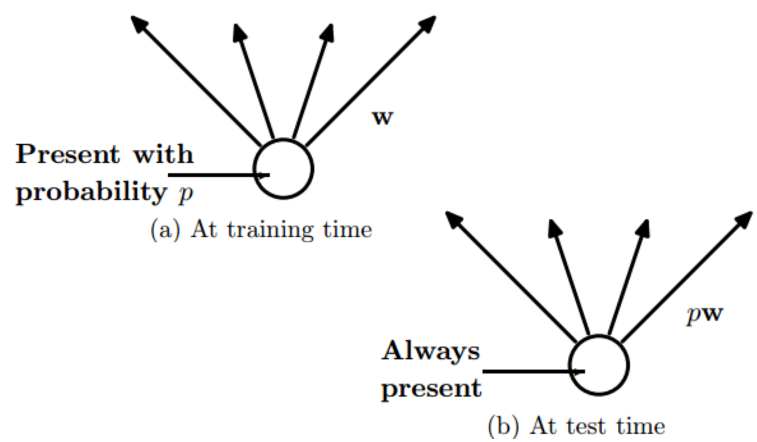
- Regularization (L2 penalty)
  - Let's not have too big numbers in the weight

$$\boldsymbol{E(W) + \frac{1}{2}\lambda W^2}$$

- Dropout
  - Srivastava et al. (2014) "Dropout: A Simple Way to Prevent Neural Networks from Overfitting"
  - randomly selected neurons are ignored during training
  - If a unit is retained with probability p during training, the outgoing weights of that unit are multiplied by p at test time



(a) Standard Neural Net (b) After applying dropout.

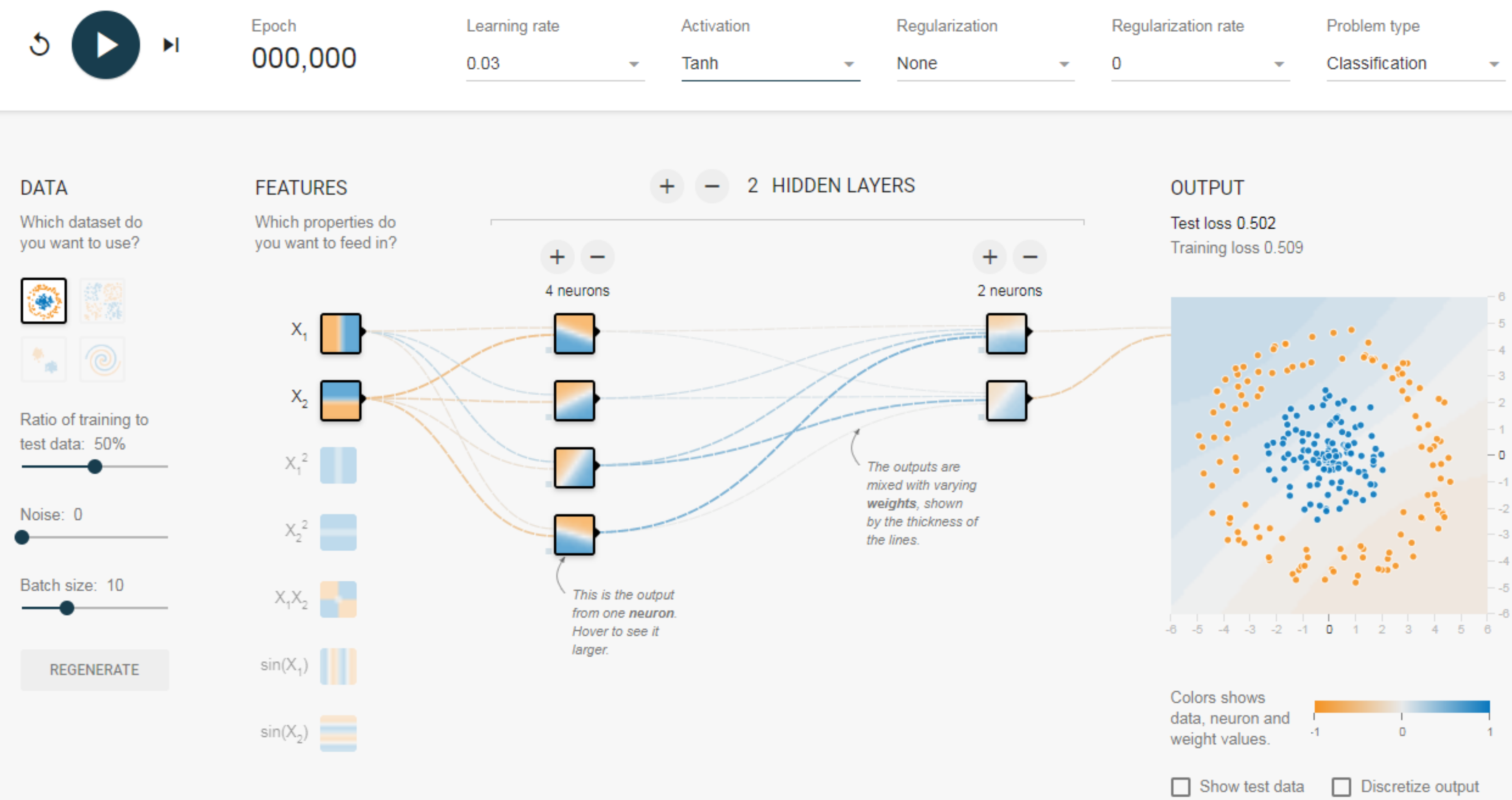


How to tune hyperparameter

- 주요 파라미터
  - 은익층과 은익노드의 개수
  - 활성화함수
  - Regularization
  - 최적화 기법
  - 가중치 초기화 방식
  - learning rate와 mini-batch size

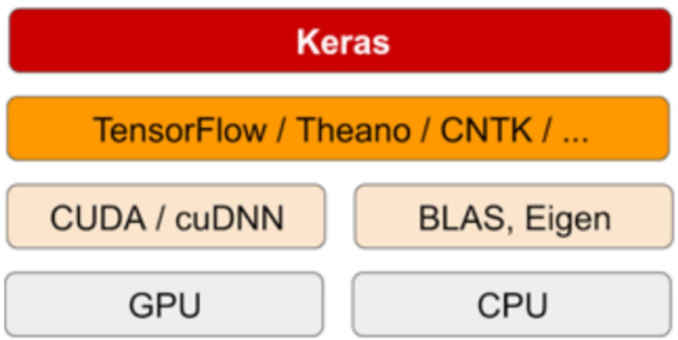
- 일반적인 방법
  - 'Stretch pants' 접근법
    - 충분히 과적합되어 원하는 성능이 나올만한 복잡한 모델을 만든 후 신경망 구조를 줄이거나 regularization을 강화하여 일반화 성능을 향상
    - Deep network이 shallow network 보다 파라미터 효율성이 좋음 – 훨씬 적은 수의 뉴런 사용
    - 최근에는 고려할 hyperparameter의 수를 줄이기 위해 모든 은익층에서 같은 수의 은익노드를 갖는 추세
  - Random Search 활용
    - CV를 통해 적절한 hyperparameter를 찾고자 할 때 grid search 보다 random search가 더 효율적

Neural Network Playground: An interactive tool for learning neural networks

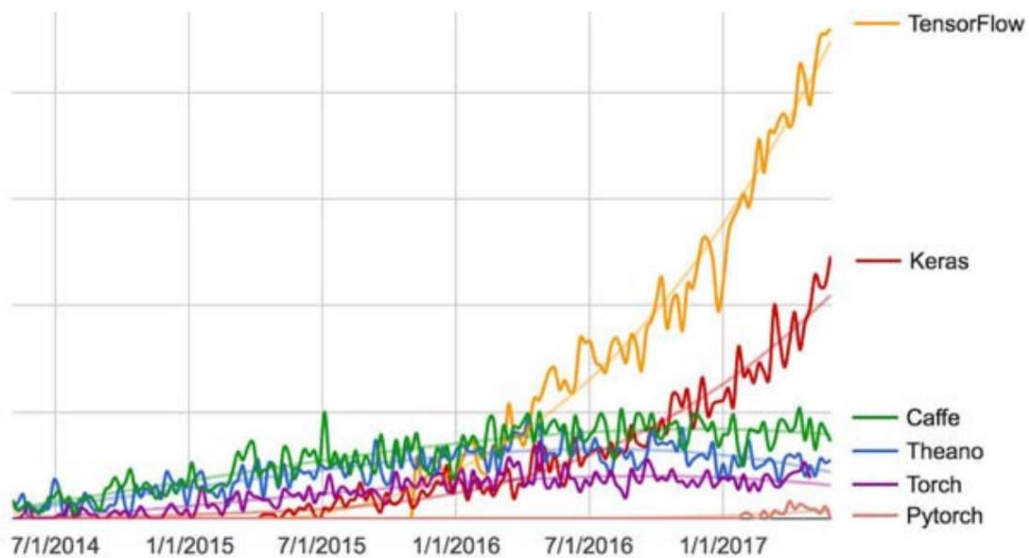


Keras Framework

- What is Keras
  - Tensorflow, CNTK, Theano를 사용하기 편하게 만들어 놓은 high-level API
  - Documentation: http://keras.io/



Source: Deep Learning with Python by François Chollet



Model building steps (Sequential API)

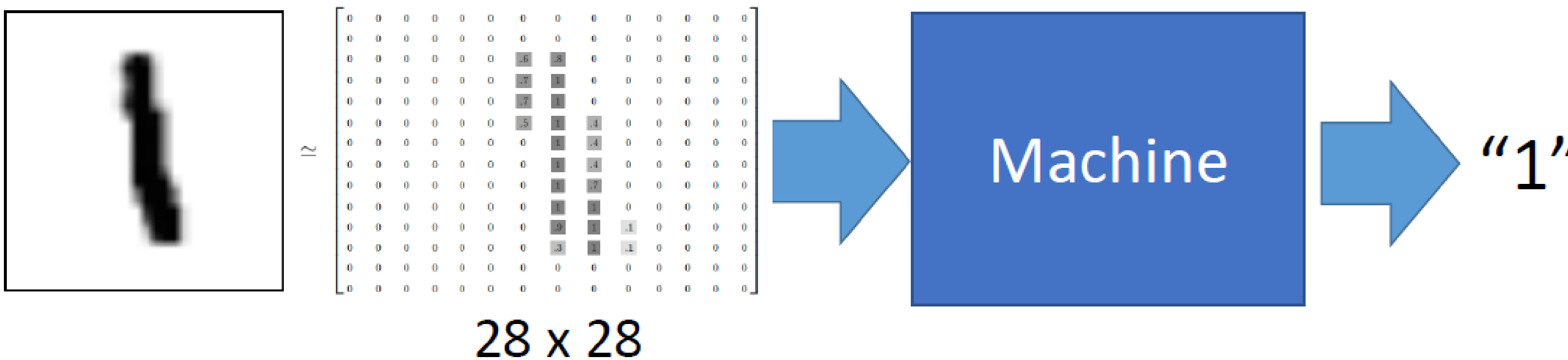
- Specify Architecture
  - model = Sequential(): 모형 생성
  - model.add(): 레이어 추가
- Compile
  - model.compile(): 목적함수 및 최적화 방법 지정
- Fit
  - model.fit(): 입력, 출력 데이터를 사용하여 가중치 계산
- Predict
  - model.predict()

Core layers

- Dense()
- Activation()
  - softmax(): multi-category output
  - sigmoid(): binary output
- Dropout()

Training DNN with keras

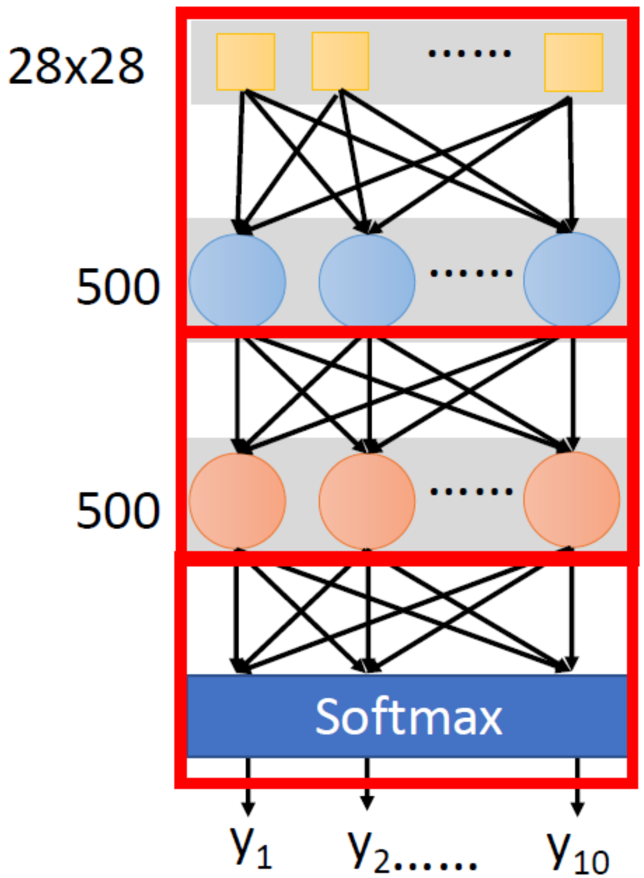
Application – Handwriting Digit Recognition



Source: Deep Learning Toolkit: Keras

Training DNN with keras

Step 1. define a model




```
model = Sequential()
```

```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

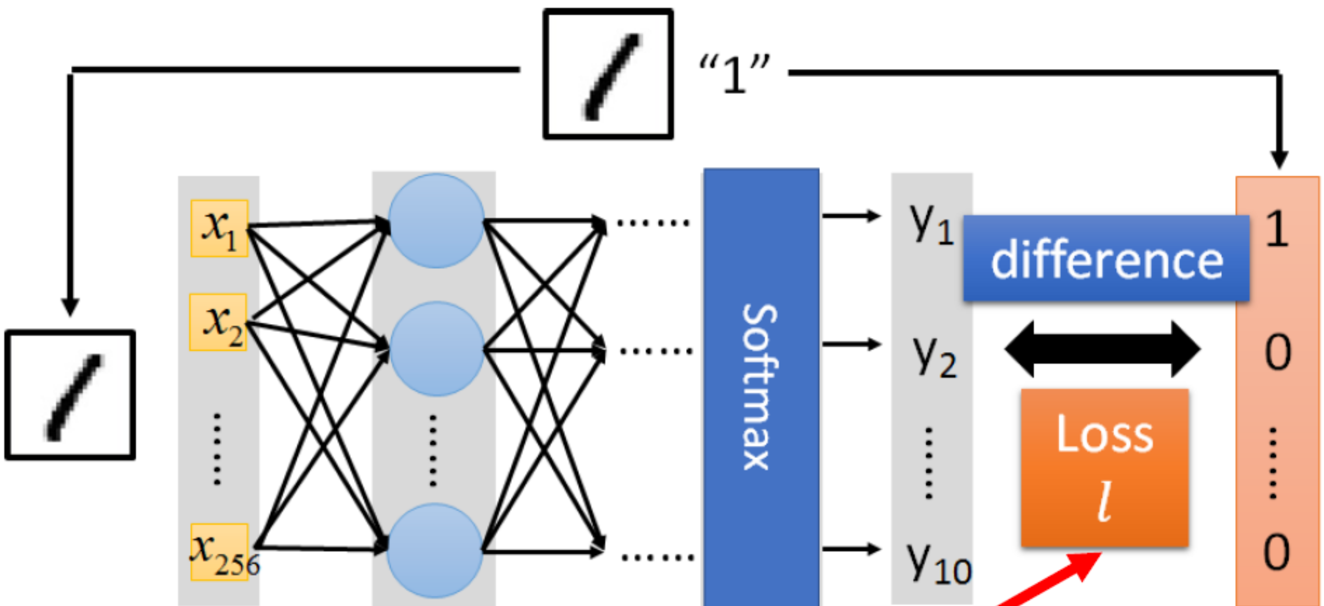
softplus, softsign, relu, tanh, hard_sigmoid, linear

```
model.add( Dense( output_dim=500 ) )
model.add( Activation('sigmoid') )
```

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

Training DNN with keras

Step 2. configure the learning process



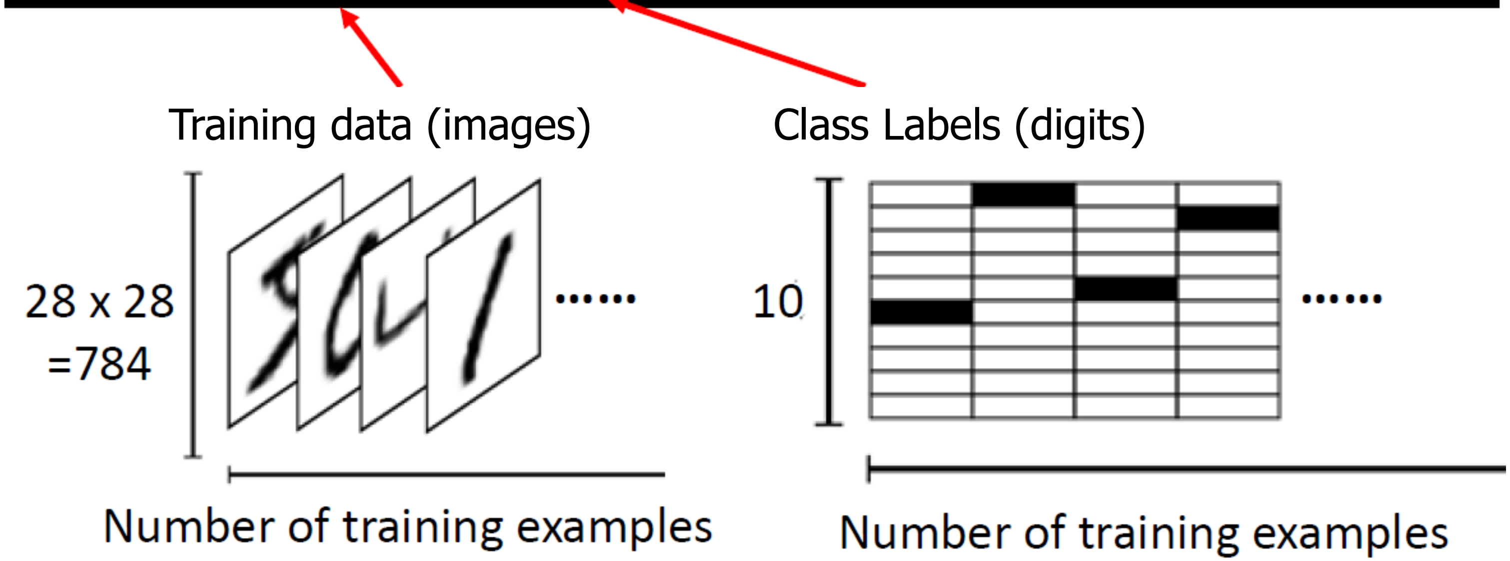

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

Source: Deep Learning Toolkit: Keras

Training DNN with keras

Step 3. iterate on the training data

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```



Training DNN with keras

Step 4. evaluate & use the model

```
score = model.evaluate(x_test,y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

```
result = model.predict(x_test)
```