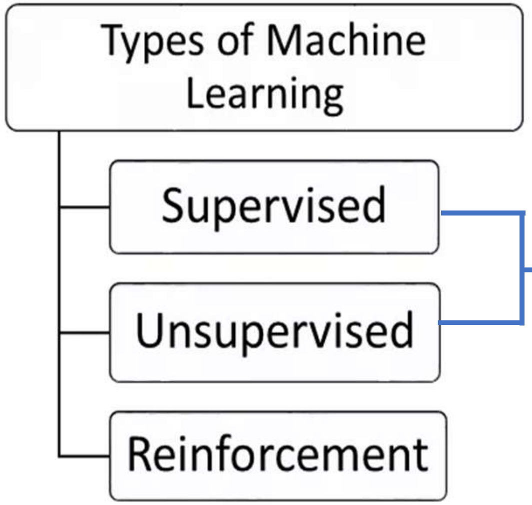
Neural Network
and
Deep Learning

Machine Learning 모델의 종류



전통적 ML	• Linear & Logistic Regression • KNN • Decision Tree • SVM • Ensembles • K-Means Clustering • PCA
Deep Learning (Neural Network)	• FC • CNN • RNN • Auto Encoder • GAN

전통적 Machine Learning 의 학습

전통적
Machine Learning

-. Hunan-crafted features
-. Great fit for data mining applications

컴퓨터가 이해할 수 있도록 Domain 지식 및 통계학적 지식을 바탕으로 Feature 를 잘 만들어서 Data 를 구성

80~90 % 의 비중

Domain 전문지식을 가진 석,박사급 인재 필요

알고리즘 학습

10~20% 의 비중

각 feature 의 weight 를 optimize

Deep Learning 의 학습

- 중요한 Feature 를 스스로 구분하여weight 를 부여
    - 사람이 manually 정해준 feature 는 over-specified, incomplete 위험성 있고 작성에 많은 시간 소요
- 여러 층에 걸친 내부 parameter 를 스스로 학습
    - 적용하기 쉽고 빠르다.
- Raw data 를 거의 그대로 사용 – computer vision, 언어처리 등 (ex, image, sound, characters, words)
- Unsupervised, supervised learning 모두 가능
- Great fit for hard vision, speech, language problem

Artificial Neuron (Perceptron)

구성요소:

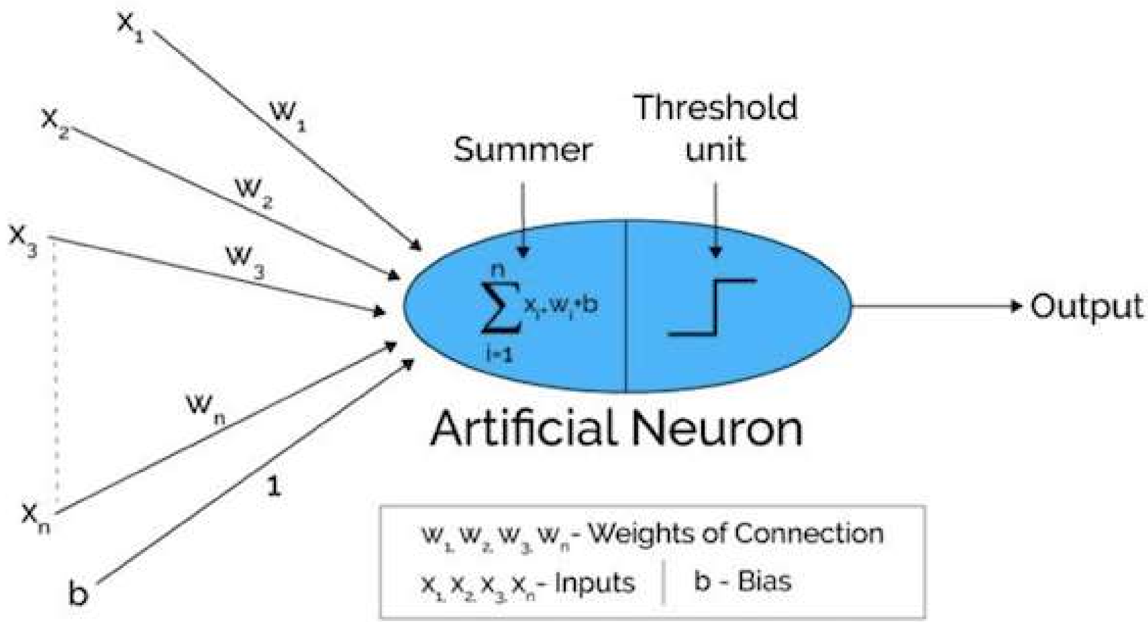
Pre-Activation :

a(x) = $b + \sum_i w_i x_i = b + w^T X$

Activation :

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

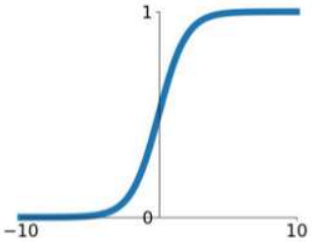
w : connection weights
b : bias
g : activation function



Activation Functions

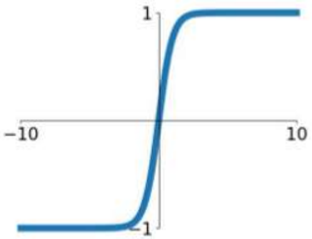
Sigmoid

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



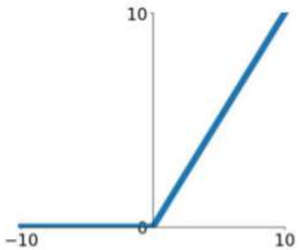
tanh

$\tanh(x)$



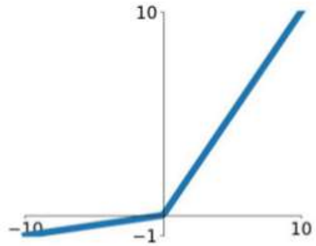
ReLU

$\max(0, x)$



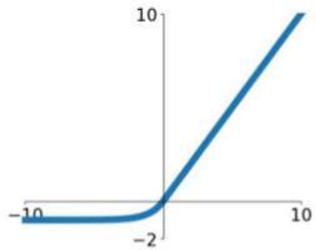
Leaky ReLU

$\max(0.1x, x)$



ELU

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

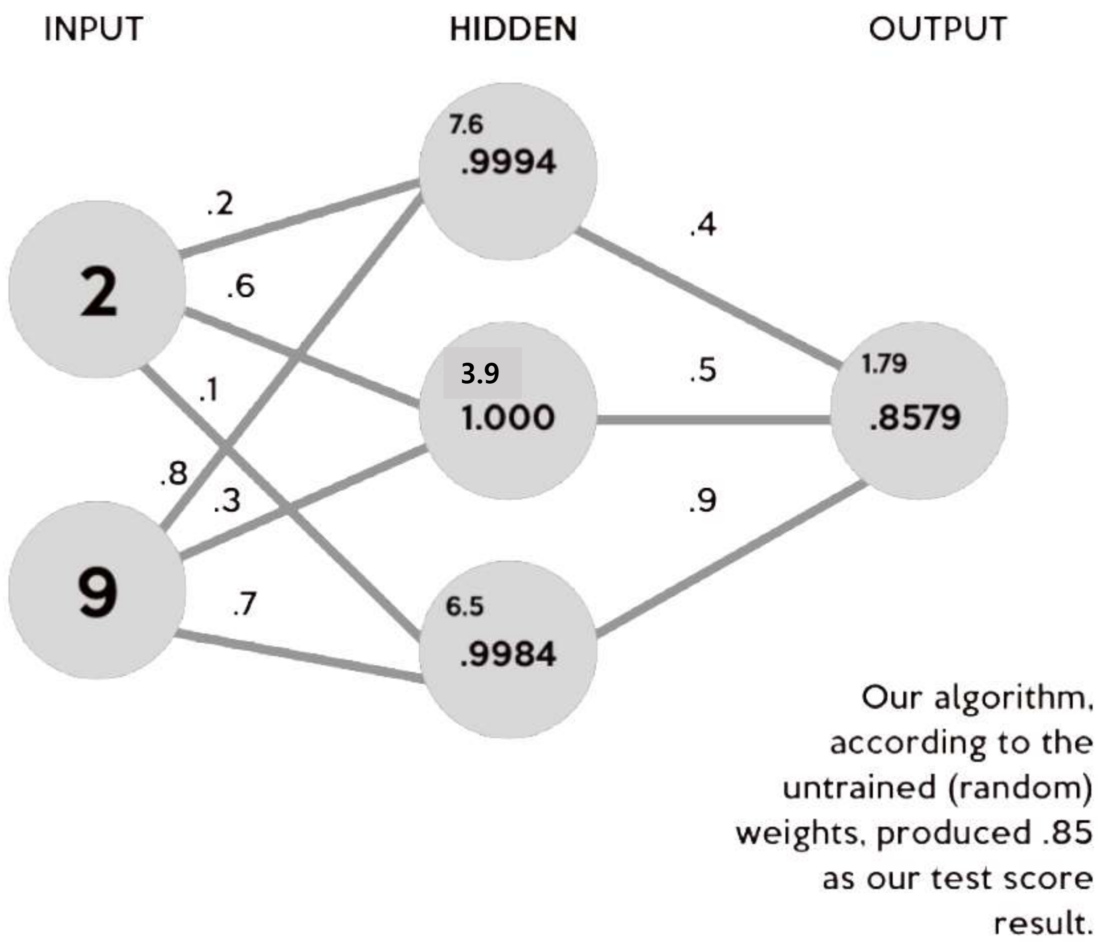


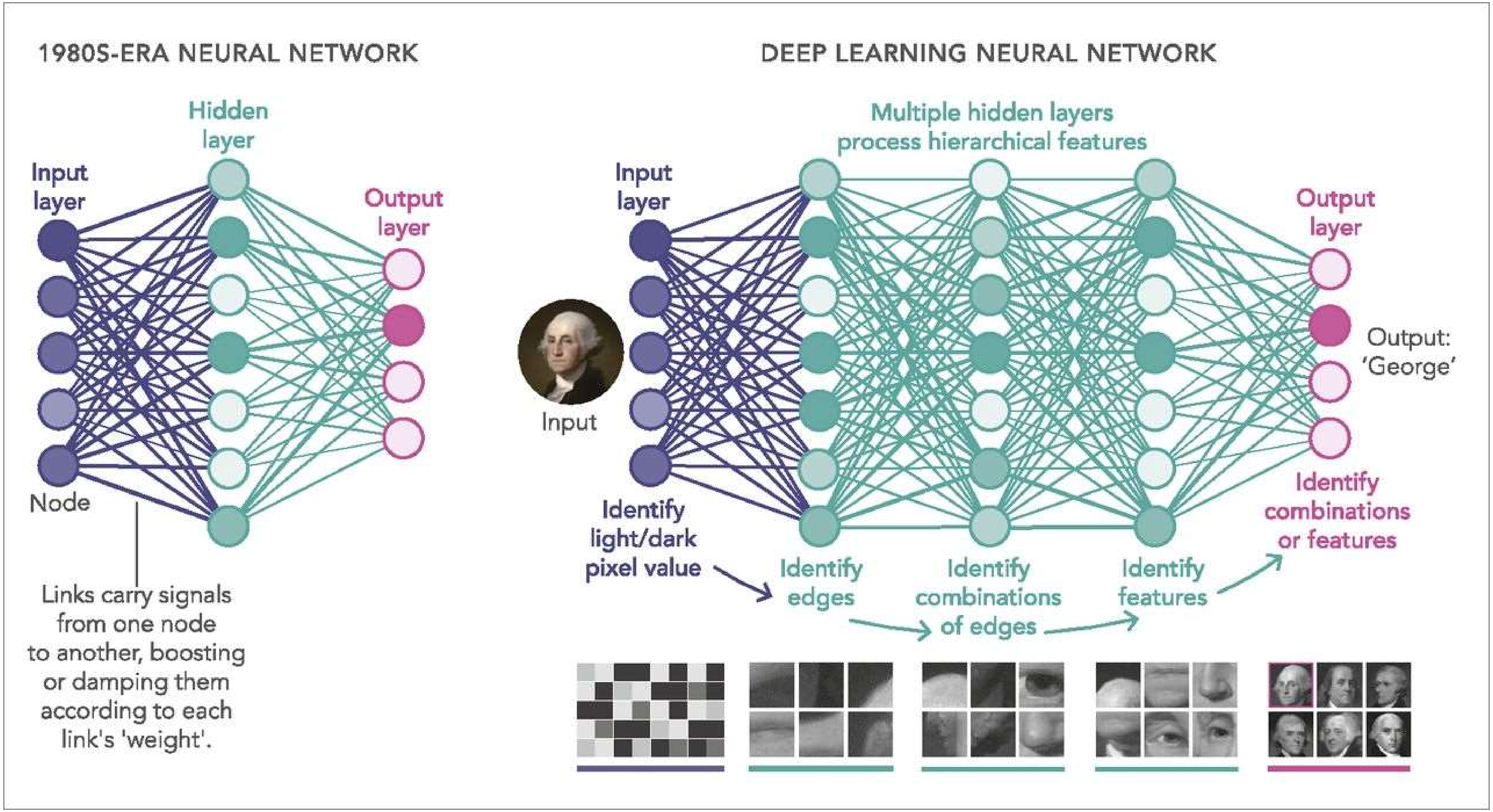
Softmax

- 출력값의 class 분류를 위하여 출력값에 대해 **정규화 → 확률 분포 출력**

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

Neural Network 의 작동 원리

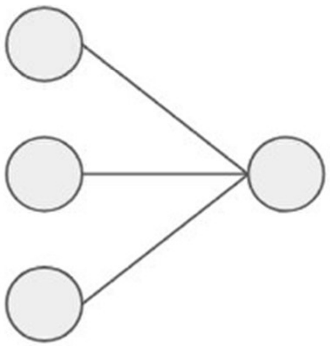



1980S-ERA NEURAL NETWORK
Hidden layer
Input layer
Output layer
Node
Links carry signals from one node to another, boosting or damping them according to each link's 'weight'.
DEEP LEARNING NEURAL NETWORK
Multiple hidden layers process hierarchical features
Input layer
Output layer
Input
Output: 'George'
Identify light/dark pixel value
Identify edges
Identify combinations of edges
Identify features
Identify combinations or features

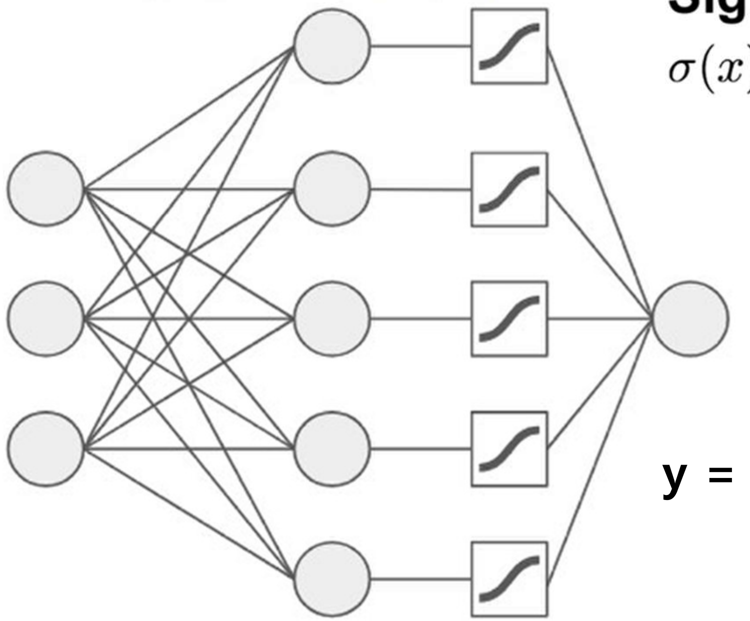
Regression (Linear / non-Linear)

A. Linear-regression model

y = Wx + b

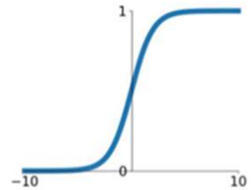


B. Two-layer neural network with nonlinear internal activation



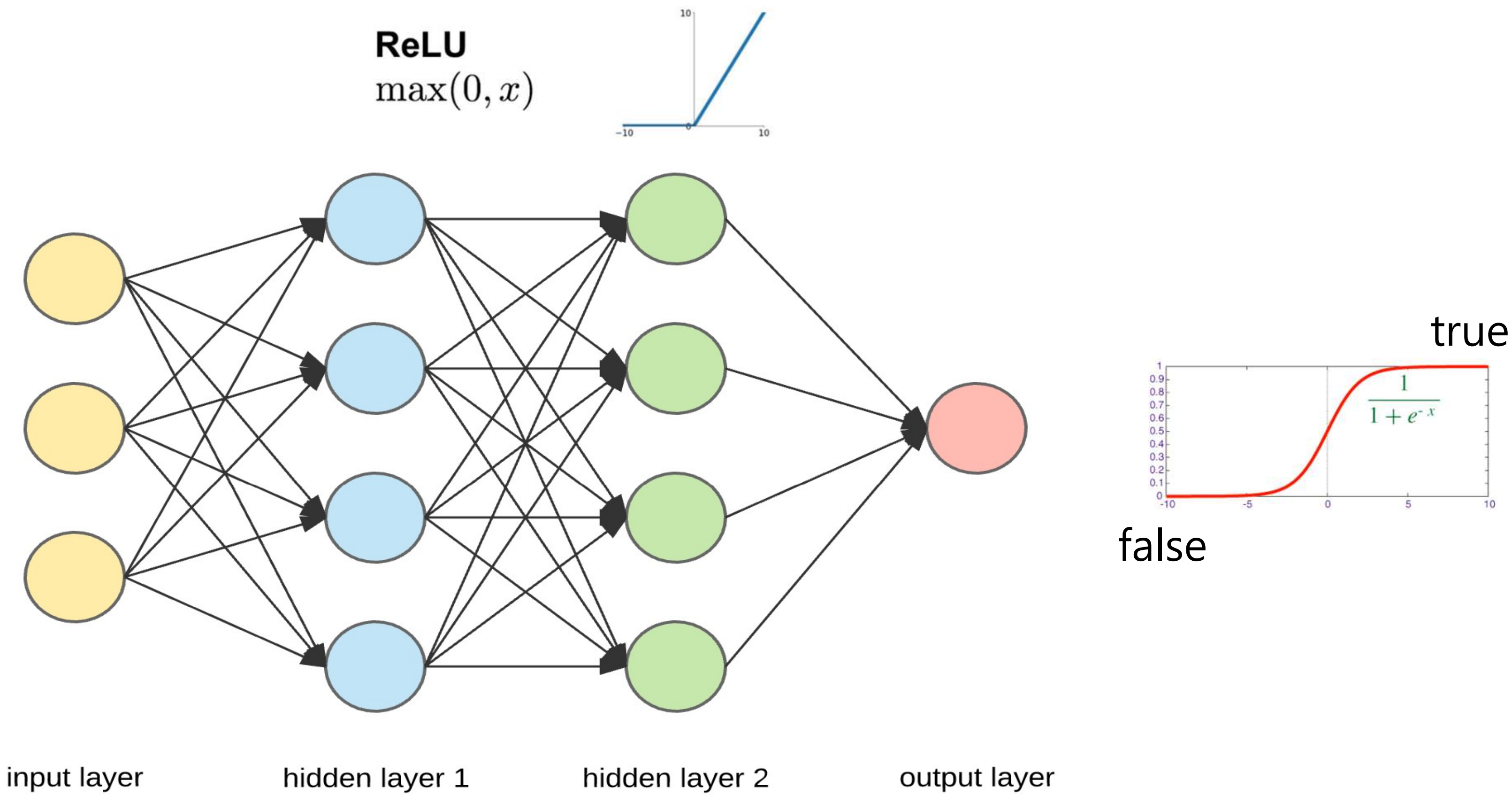
Sigmoid

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

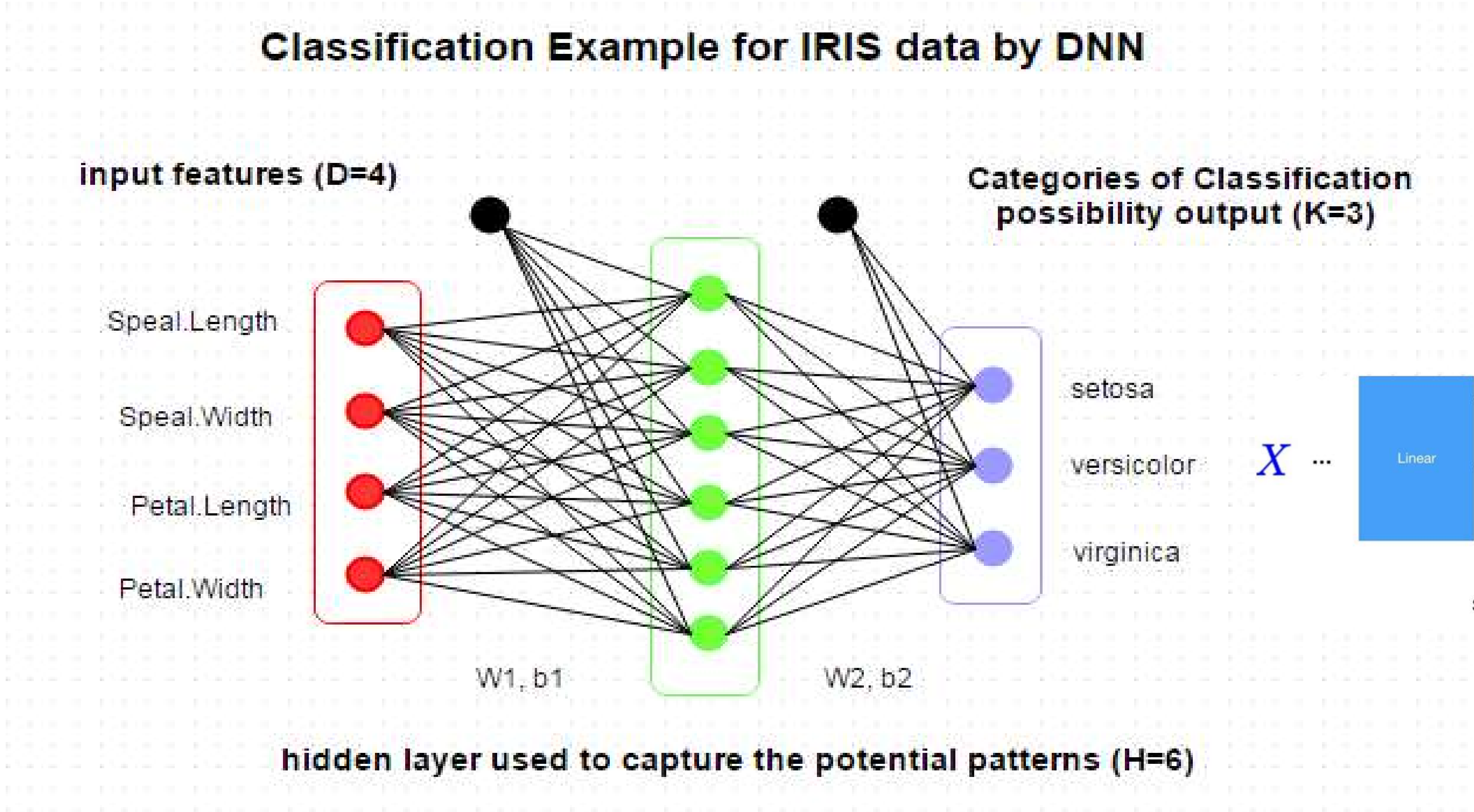


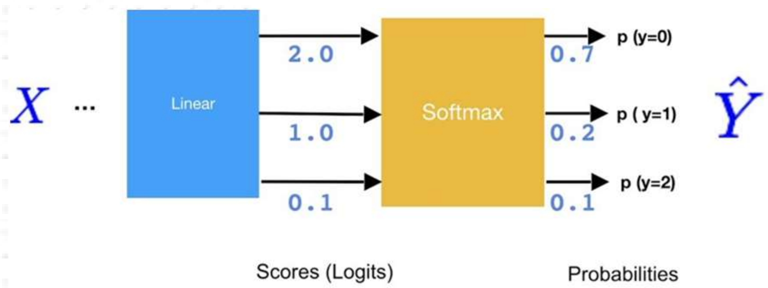
y = Wx + b

Binary Classification (Sigmoid)



Multi-Class Classification (Softmax)





Gradient Descent (경사하강법)

- Yhat = θX 의 θ 를 inference 하는 방법

  X = m x (n+1) matrix

  y = m dimensional vector

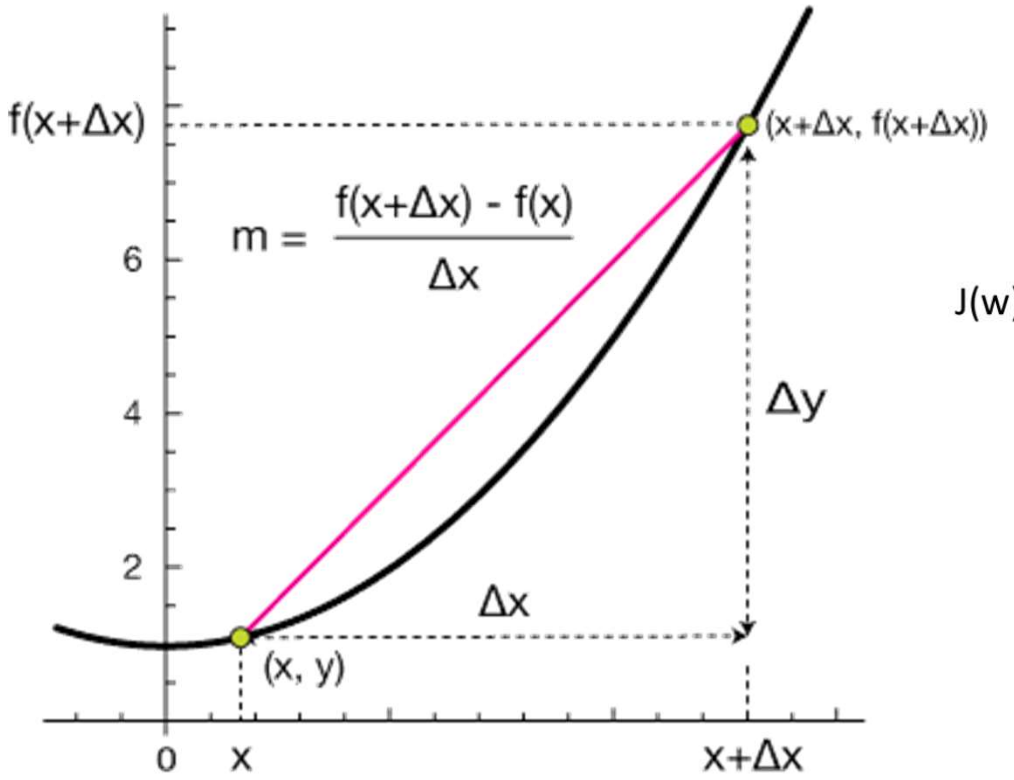
- OLS (Ordinary Least Squares) method 의 문제점

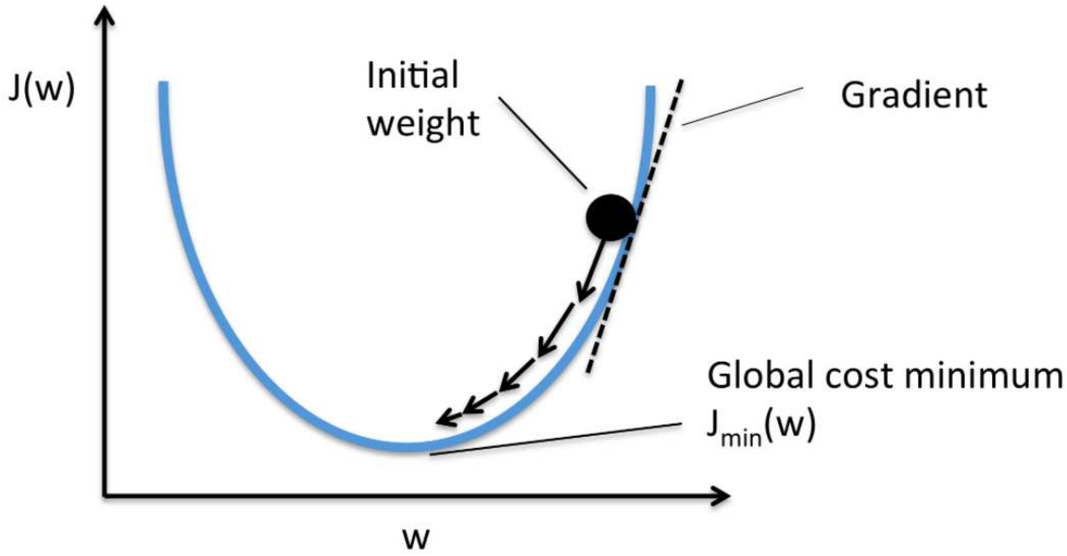
  1. OLS 는 Normal Equation 을 이용

     $\theta = (X^T X)^{-1} X^T y$

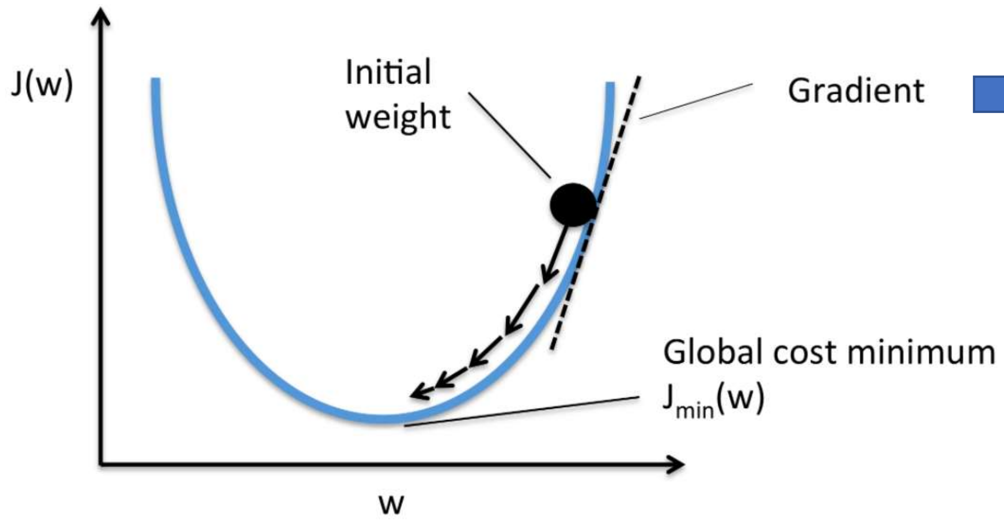
  2. O(n^3) 의 complexity 를 가진다. (n : feature 수)
  3. large data set, large # of features 에는 부적합
  4. Regularization term 을 추가할 수 없음
  5. N > n 만큼의 Data 필요 (N: data 개수)

Derivative (도함수, 미분, 접선의 기울기)





Gradient Descent (경사하강법) Optimization

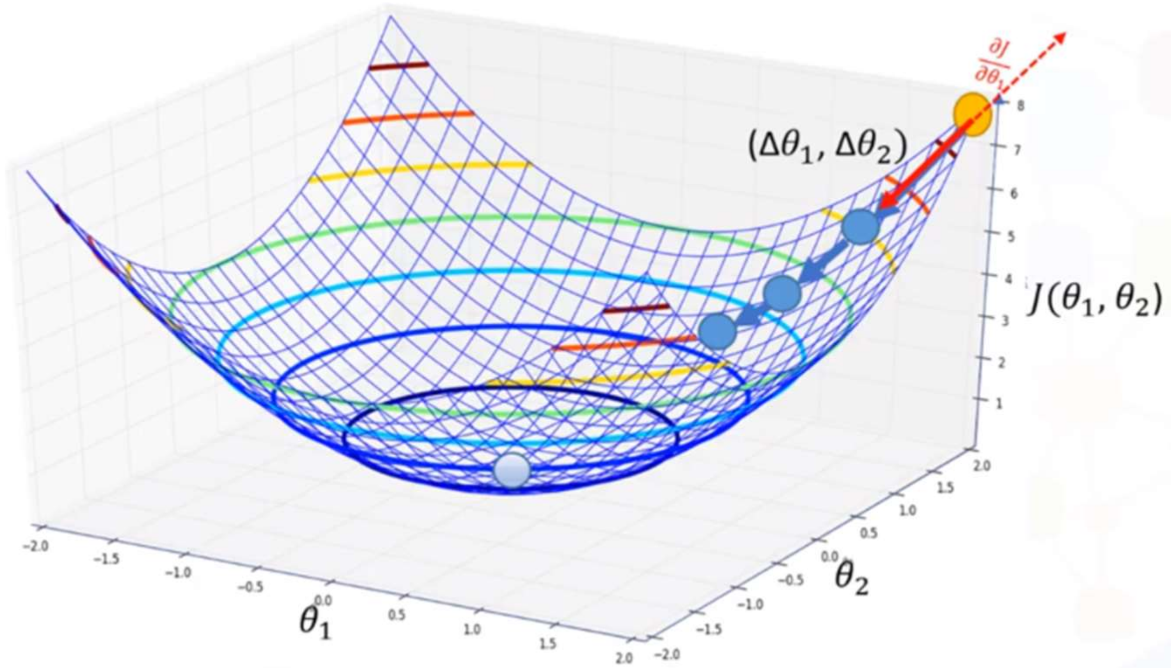


방향 – Gradient
(derivative of Cost Function)

이동 속도 – Learning Rate

New W = old W – (Learning Rate) * (Gradient)

Goal : Minimize $J(\theta_1, \theta_2)$, $y = \theta_1 X_1 + \theta_2 X_2$



$\hat{y} = \sigma(\theta_1 x_1 + \theta_2 x_2)$

$$J(\theta) = -\frac{1}{m}\sum_{i-1}^{m} y^i \log(\hat{y}^i) + (1 - y^i)\log(1 - \hat{y}^i)$$

1. Loss Function (손실함수) 의 derivative(slope) 계산
2. Step size (Learning Rate 계산) slope * learning rate
3. Update the parameter (batch)
4. Repeat until slope = 0

Gradient Descent for Linear Regression

- Hypothesis : $h_{\theta}(X) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \ldots.. + \theta_n x_n$
  $= \theta^T X$

$$\theta^T = [\theta_0, \theta_1, \ldots., \theta_n]$$

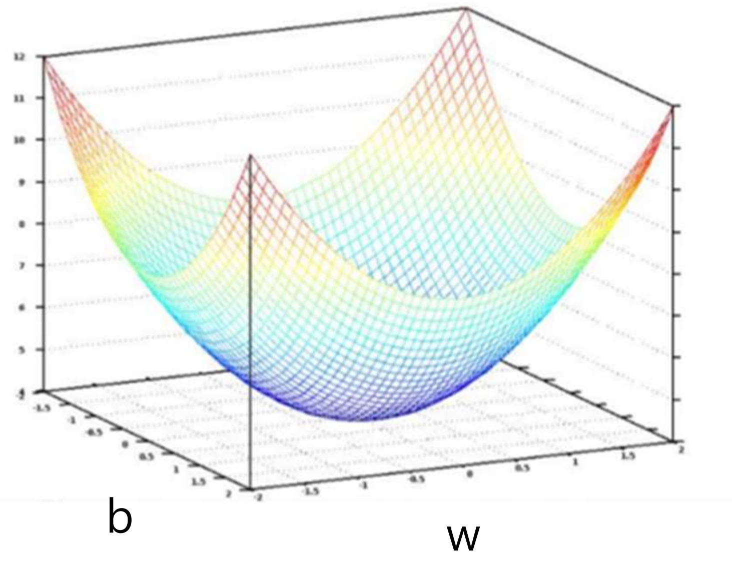
$$X = \begin{bmatrix} x_0 \\ x_1 \\ . \\ . \\ x_n \end{bmatrix} \qquad y = \begin{bmatrix} y_0 \\ y_1 \\ . \\ . \\ y_n \end{bmatrix}$$

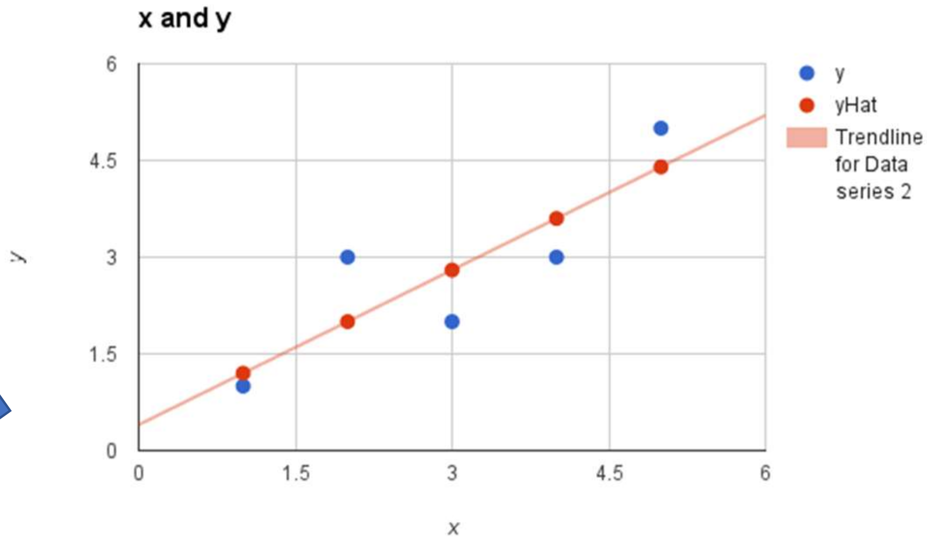
- Cost Function : $J(\theta) = \frac{1}{2m} \sum_{i=0}^{m} (h_{\theta}(x^{(i)}) - y^{(i)})^2$

➔ 미분 가능 / convex
½ 은 수학적 trick (계산의 간편성)

Cost Function - Linear Regression

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y_i} - Y_i)^2$$





y = Wx + b

MSE(Mean Squared Error) 를 최소화 하는 W 와 b 를 optimize

Loss Function 의 미분과 parameter update

- y = Wx + b = $\theta_0 + \theta_1 x$

- Loss Function $L(\theta_0, \theta_1) = \frac{1}{N}\sum_{i=0}^{m} \left(y_i - (\theta_0 + \theta_1 x_i)\right)^2$

- Gradient $\frac{\partial L(\theta_0,\theta_1)}{\partial \theta_0} = -2\frac{1}{N}\sum_{i=0}^{m}(y_i - (\theta_0 + \theta_1 x_i))$

  $\frac{\partial L(\theta_0,\theta_1)}{\partial \theta_1} = -2\frac{1}{N}\sum_{i=0}^{m} x_i(y_i - (\theta_0 + \theta_1 x_i))$

- Update $\theta_0 := \theta_0 + \alpha \frac{\partial L(\theta_0,\theta_1)}{\partial \theta_0}$

  $\theta_1 := \theta_1 + \alpha \frac{\partial L(\theta_0,\theta_1)}{\partial \theta_1}$

Gradient Descent for Logistic Regression

- Hypothesis : $\sigma(\theta^T X) = \frac{1}{1+e^{-\theta^T X}}$

$$\theta^T = [\theta_0, \theta_1, \ldots., \theta_n]$$

$$X = \begin{bmatrix} x_0 \\ x_1 \\ . \\ . \\ x_n \end{bmatrix} \qquad y = \begin{bmatrix} y_0 \\ y_1 \\ . \\ . \\ y_n \end{bmatrix}$$

- Cost Function : $J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} (y^{(i)} \log(\hat{y}^{(i)}) + \left(1 - y^{(i)}\right) \log(1 - \hat{y}^{(i)}))$

if y = 1 : $J(\theta) = -\log(\hat{y}^{(i)})$

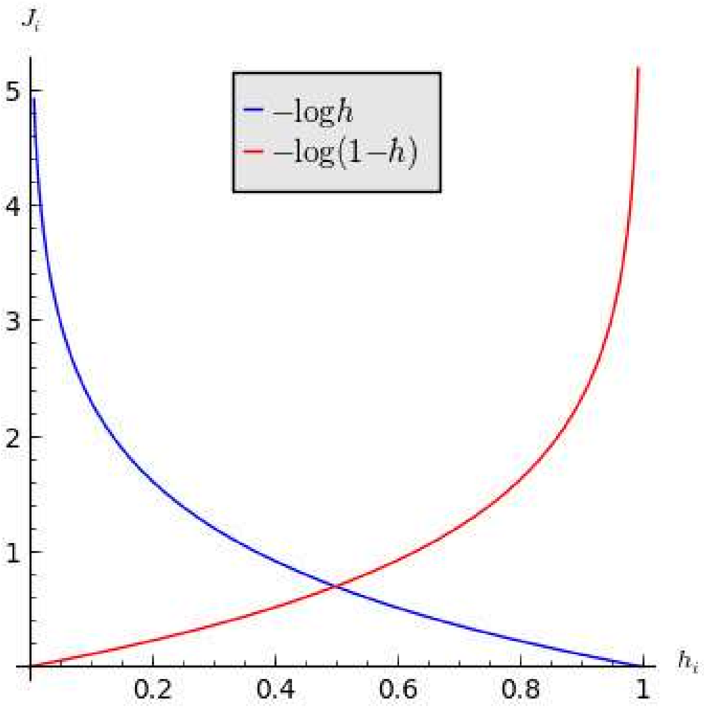
y = 0 : $J(\theta) = -\log(1 - \hat{y}^{(i)})$

Cost Function - Logistic Regression (Binary Cross-entropy)

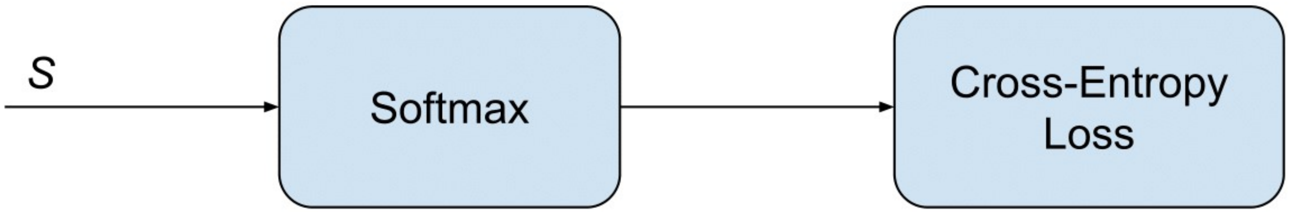
$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}(1-y^{(i)})\log(1-h_\theta(x^{(i)})) + y^{(i)}\log h_\theta(x^{(i)})\right]$$

If $y^{(i)} = 1$: J(θ) $= -log\ h_\theta\ (x^{(i)})$
where $h_\theta\ (x^{(i)})$ should be close to 1

If $y^{(i)} = 0$: J(θ) $= -\log(1 - h_\theta\ (x^{(i)}))$
where $h_\theta\ (x^{(i)})$ should be close to 0



Cost Function - Categorical Crossentroy (Softmax Loss)



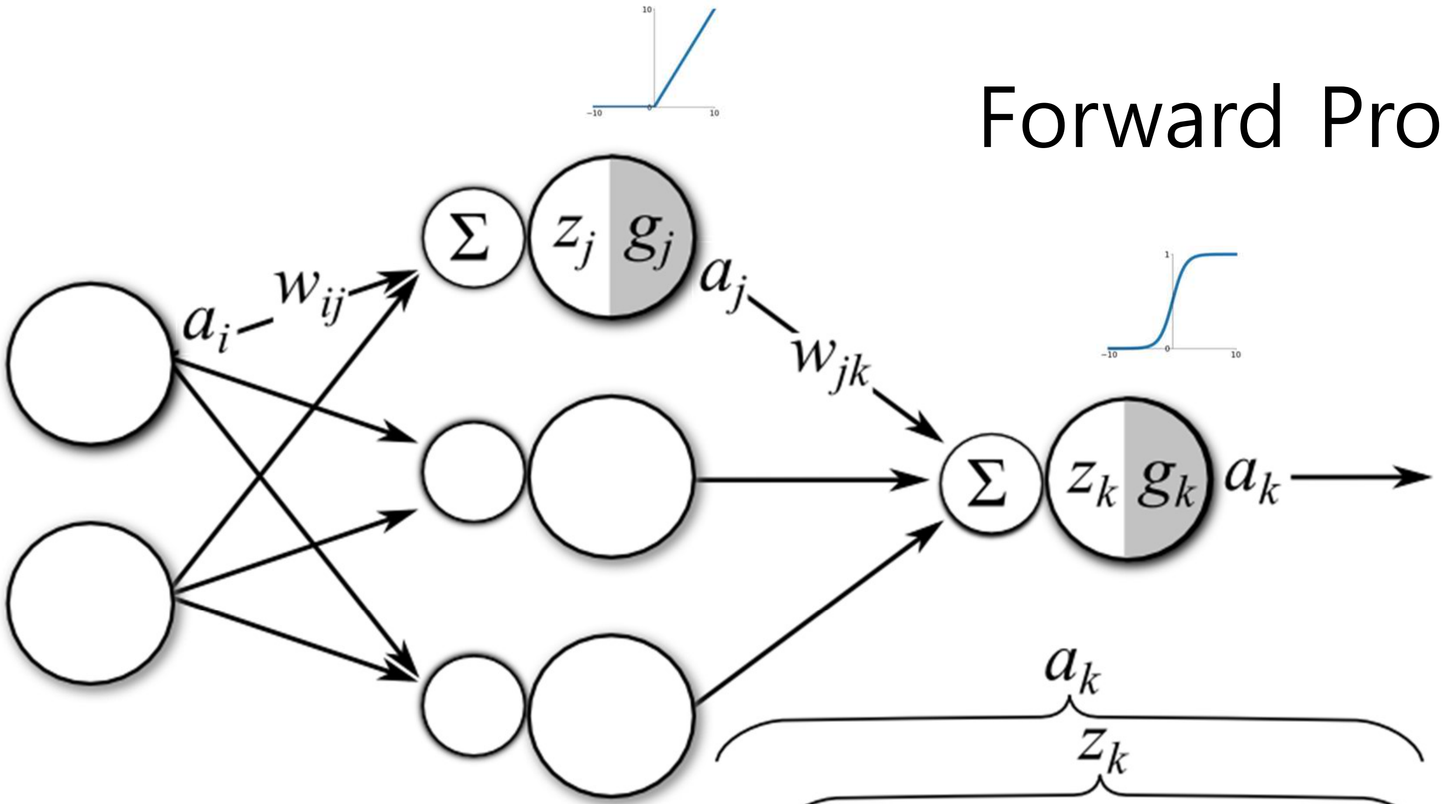
$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \qquad CE = -\sum_i^C t_i log(f(s)_i)$$

t_i : 0 이 아닌 target
(one-hot encoded
되어 있으므로
multi-class 중 오직
1 개만 1)

C : multi-classes

Index	0	1	2	3	4	5	6	7	8	9
True Label	0	0	0	0	0	0	0	**1**	0	0
Prediction	0.1	0.01	0.01	0.01	0.20	0.01	0.01	**0.60**	0.03	0.02

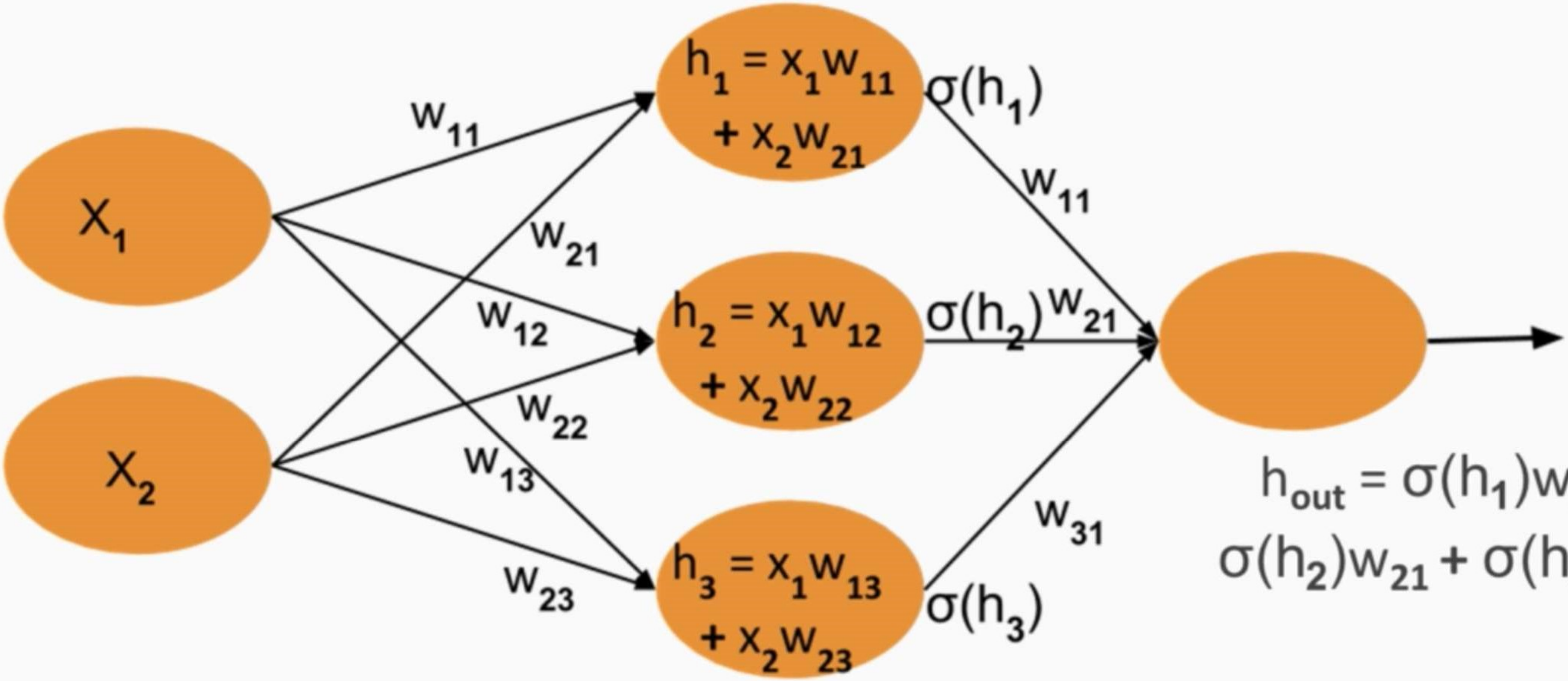
Forward Propagation



$$\overbrace{a_k = g_k(b_k + \Sigma_j g_j \underbrace{(b_j + \Sigma_i a_i w_{ij})}_{z_j} w_{jk})}^{z_k}$$

$$a_k = g_k\Big(\overbrace{b_k + \Sigma_j \underbrace{g_j(b_j + \Sigma_i a_i w_{ij})}_{a_j} w_{jk}}^{z_k}\Big)$$

- Forward Propagation



$h_{out} = \sigma(h_1)w_{11} + \sigma(h_2)w_{21} + \sigma(h_3)w_{31}$

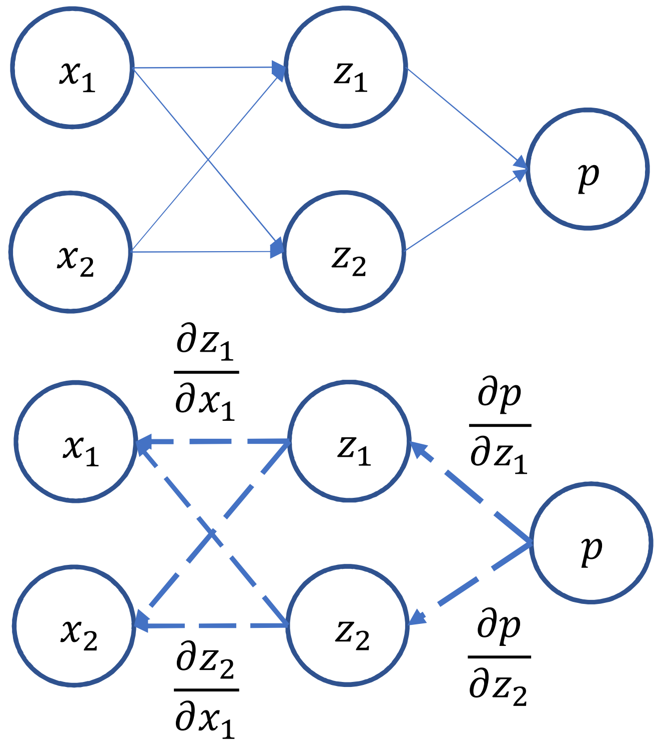
Backward Propagation 기초 공식

- 기본 함수의 도함수 (derivative) : $\frac{dx^2}{dx} = 2\mathrm{x}$, $\frac{de^x}{dx} = \mathrm{e}^{\mathrm{x}}$, $\frac{d\ln(x)}{dx} = \frac{1}{x}$

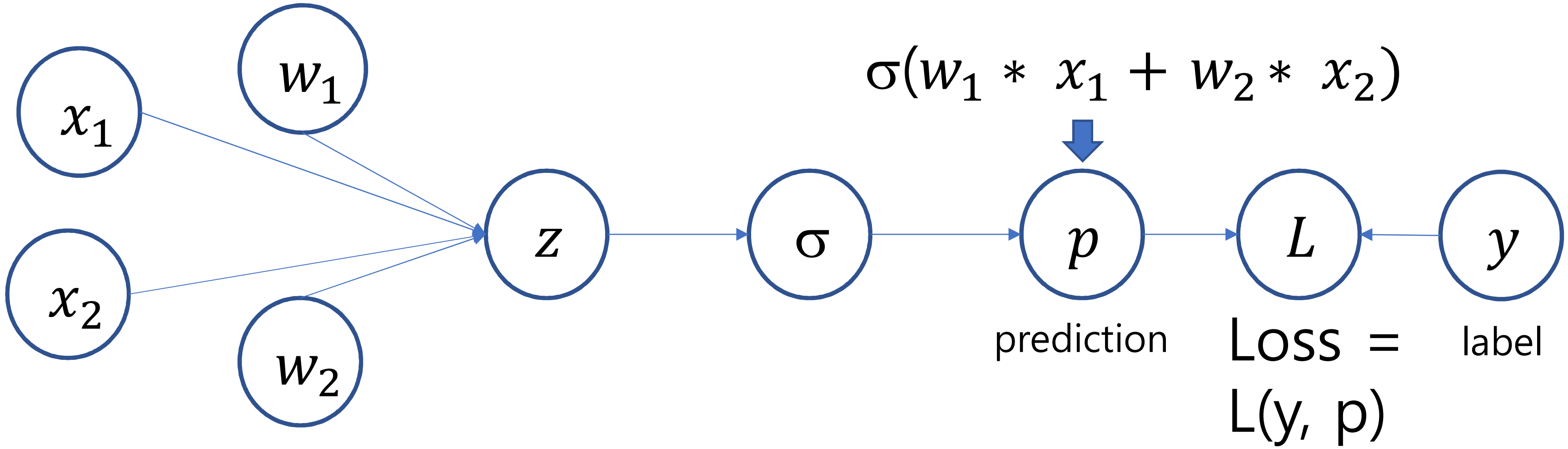
- Chain Rule :

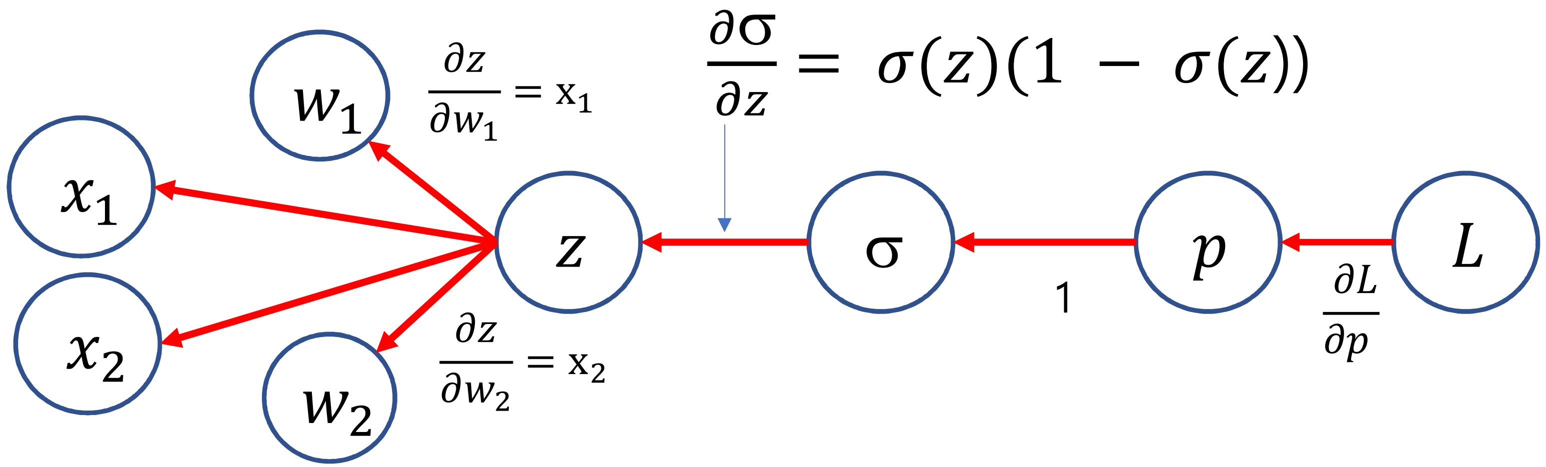
$$p = f(z_1, z_2)$$
$$z_1 = f(x_1, x_2)$$
$$z_2 = f(x_1, x_2)$$

$$\boxed{\begin{aligned} \frac{\partial p}{\partial x_1} &= \frac{\partial p}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial z_2}\frac{\partial z_2}{\partial x_1} \\ \frac{\partial p}{\partial x_2} &= \frac{\partial p}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial z_2}\frac{\partial z_2}{\partial x_2} \end{aligned}}$$



Example : 2 개의 feature 를 가진 1 layer + sigmoid activation





경사하강법 적용을 위해 $\frac{\partial L}{\partial W_1}$ 과 $\frac{\partial L}{\partial W_2}$ 필요

$$
\begin{aligned}
\boxed{\frac{d}{dx}\sigma(x)} &= \frac{d}{dx}\left[\frac{1}{1+e^{-x}}\right] \\
&= \frac{d}{dx}\left(1+\mathrm{e}^{-x}\right)^{-1} \\
&= -(1+e^{-x})^{-2}(-e^{-x}) \\
&= \frac{e^{-x}}{\left(1+e^{-x}\right)^{2}} \\
&= \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}} \\
&= \frac{1}{1+e^{-x}} \cdot \frac{(1+e^{-x})-1}{1+e^{-x}} \\
&= \frac{1}{1+e^{-x}} \cdot \left(\frac{1+e^{-x}}{1+e^{-x}} - \frac{1}{1+e^{-x}}\right) \\
&= \frac{1}{1+e^{-x}} \cdot \left(1 - \frac{1}{1+e^{-x}}\right) \\
&= \boxed{\sigma(x) \cdot (1-\sigma(x))}
\end{aligned}
$$

Backpropagation (Chain Rule 적용)

* 같은 색으로 표시된 부분은 한번 계산하면 여러 번 reuse

We will need these for GD

3: $\frac{\partial p}{\partial h_1}$ $\quad$ $\frac{\partial p}{\partial h_2}$

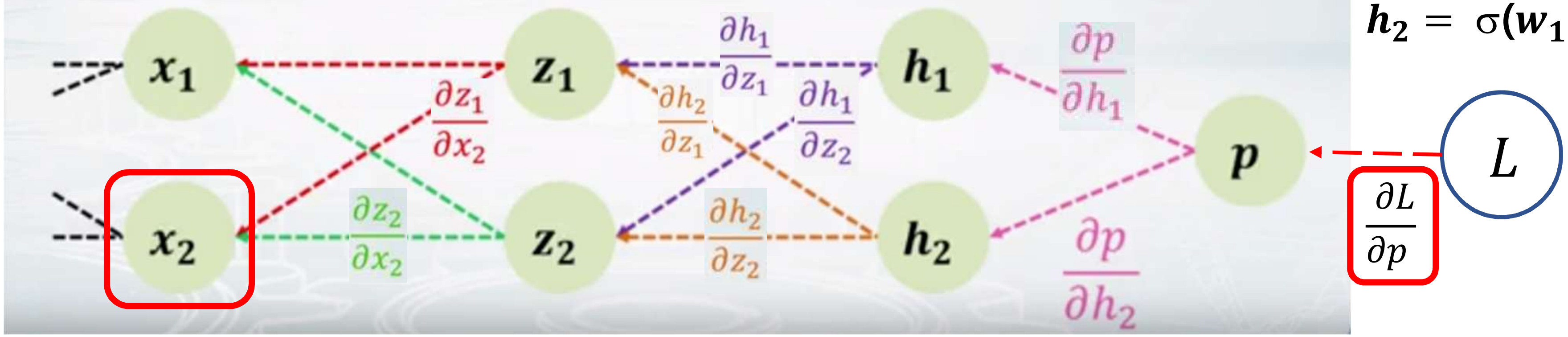
2: $\frac{\partial p}{\partial z_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}$ $\qquad$ $\frac{\partial p}{\partial z_2} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}$

1:

$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_1} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_1} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_1}$$

$$\boxed{\frac{\partial p}{\partial x_2}} = \boxed{\frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_1}\frac{\partial z_1}{\partial x_2} + \frac{\partial p}{\partial h_1}\frac{\partial h_1}{\partial z_2}\frac{\partial z_2}{\partial x_2} + \frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial z_2}\frac{\partial z_2}{\partial x_2}}$$

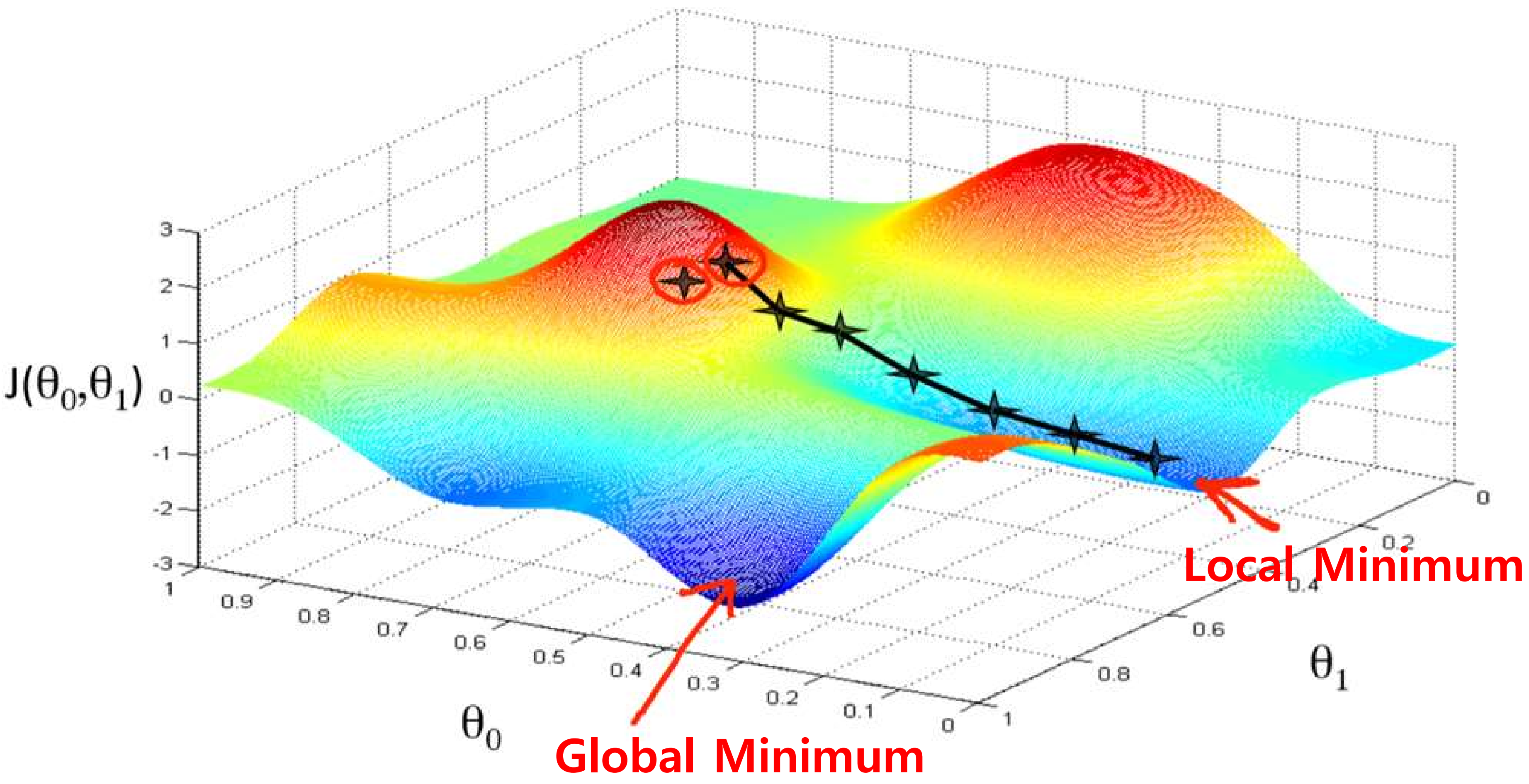
$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial p}\frac{\partial p}{\partial w_1} = \frac{\partial L}{\partial p}\frac{\partial p}{\partial h_2}\frac{\partial h_2}{\partial w_1}$$



$$h_2 = \sigma(w_1 * x_1 + w_2 * x_2)$$

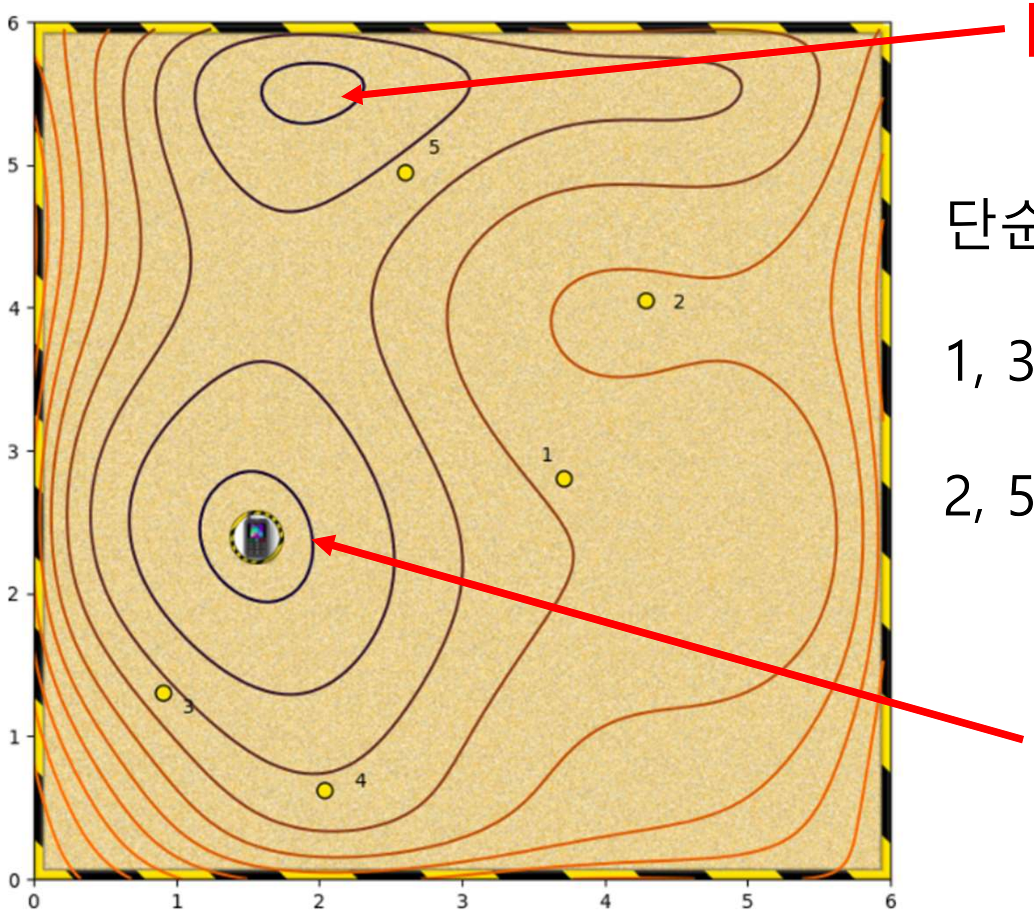
Backpropagation 요약

- 각각의 input data 에 대하여,
- 각 layer 별로 forward pass output 값을 계산
- Output layer 의 cost function 값을 계산
- Backpropagation 을 통해 cost function 의 derivative 를 전단계의 layer 로 전달
- Error term 의 값에 따라 각 layer 의 weight 를 update



J(θ0,θ1)
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ0
0
0.2
0.4
0.6
0.8
1
θ1
Local Minimum
Global Minimum

Global Minima / Local Minima

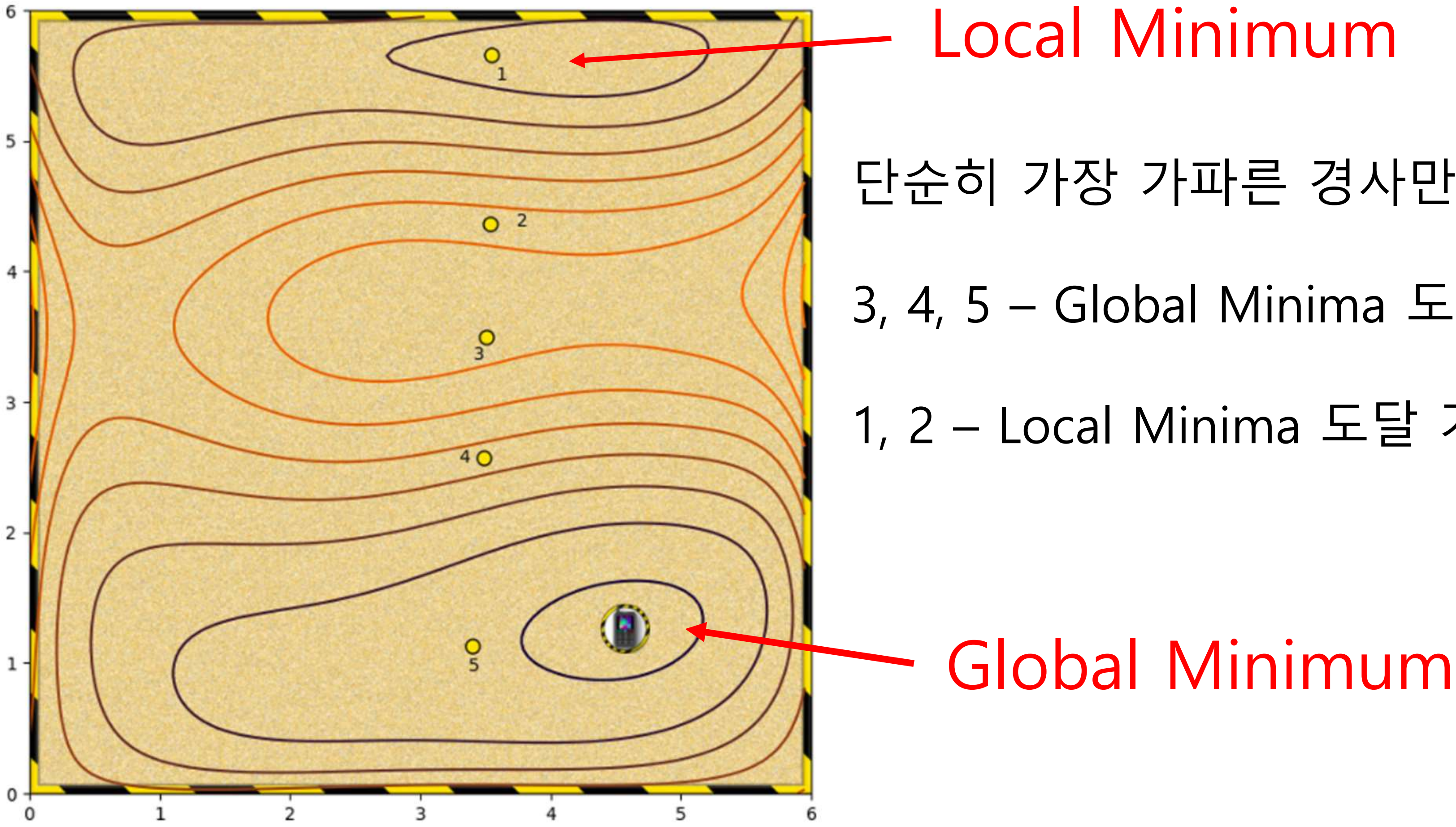


단순히 가장 가파른 경사만을 따라갈 경우,

1, 3, 4 – Global Minima 도달 가능

2, 5 – Local Minima 도달 가능

Global Minima / Local Minima



단순히 가장 가파른 경사만을 따라갈 경우,

3, 4, 5 – Global Minima 도달 가능

1, 2 – Local Minima 도달 가능

Learning Rate (α)

- Step size

- Range : 1e-6 ~ 1.0 (default 0.01)

  - High learning rate – fast learning, may overshoot the target
  - Low learning rate – slow learning, may take long time

- Adaptive Learning Rates
  초기값을 크게 주고 학습 진행에 따라 slow down

Optimizers

- Stochastic Gradient Descent Optimizer

- RMSProp Optimzer

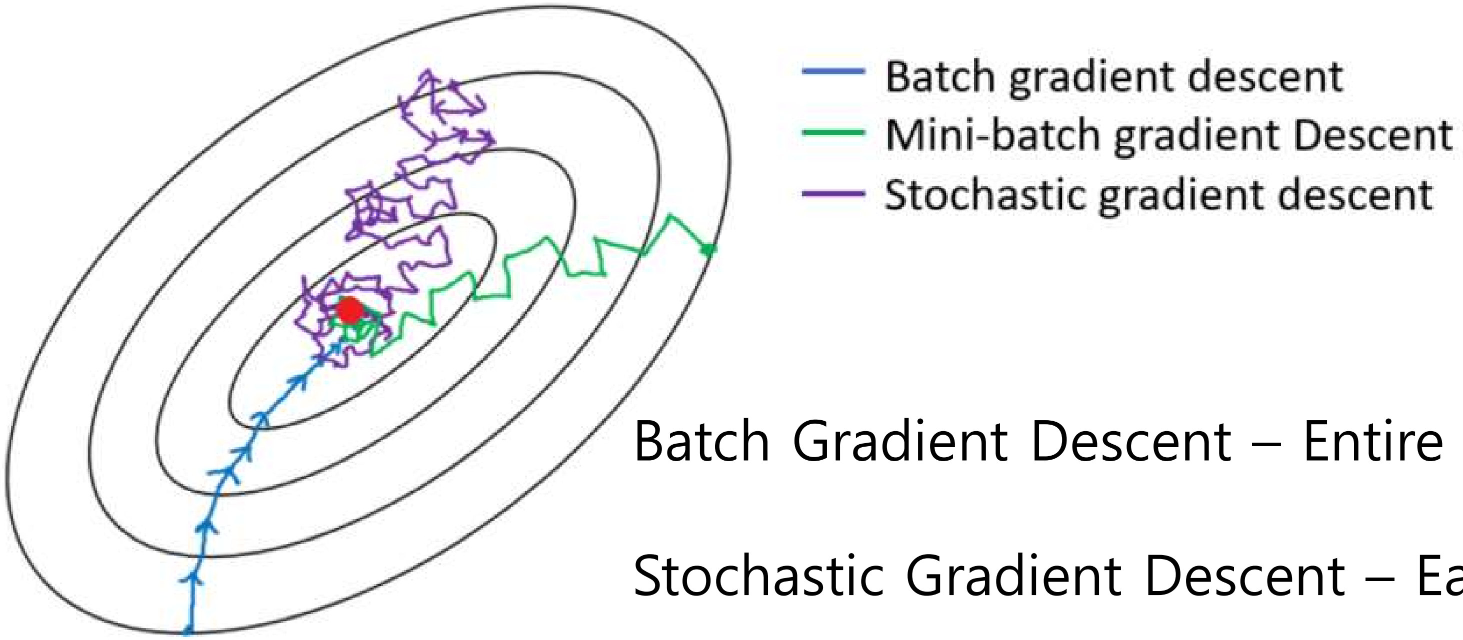
- Adagrad Optimizer

- Adam Optimizer, etc

http://ruder.io/content/images/2016/09/contours_evaluation_optimizers.gif

http://ruder.io/content/images/2016/09/saddle_point_evaluation_optimizers.gif

Stochastic Gradient Descent (확률적 경사하강법)

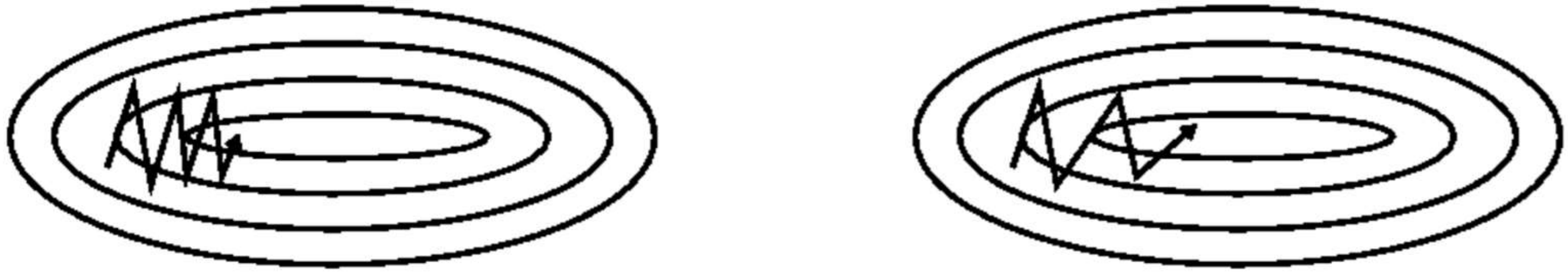


Batch Gradient Descent – Entire samples

Stochastic Gradient Descent – Each sample (size 1)

Mini-batch Gradient Descent – small size of samples

Momentum (β) : 방향성을 유지하며 가속

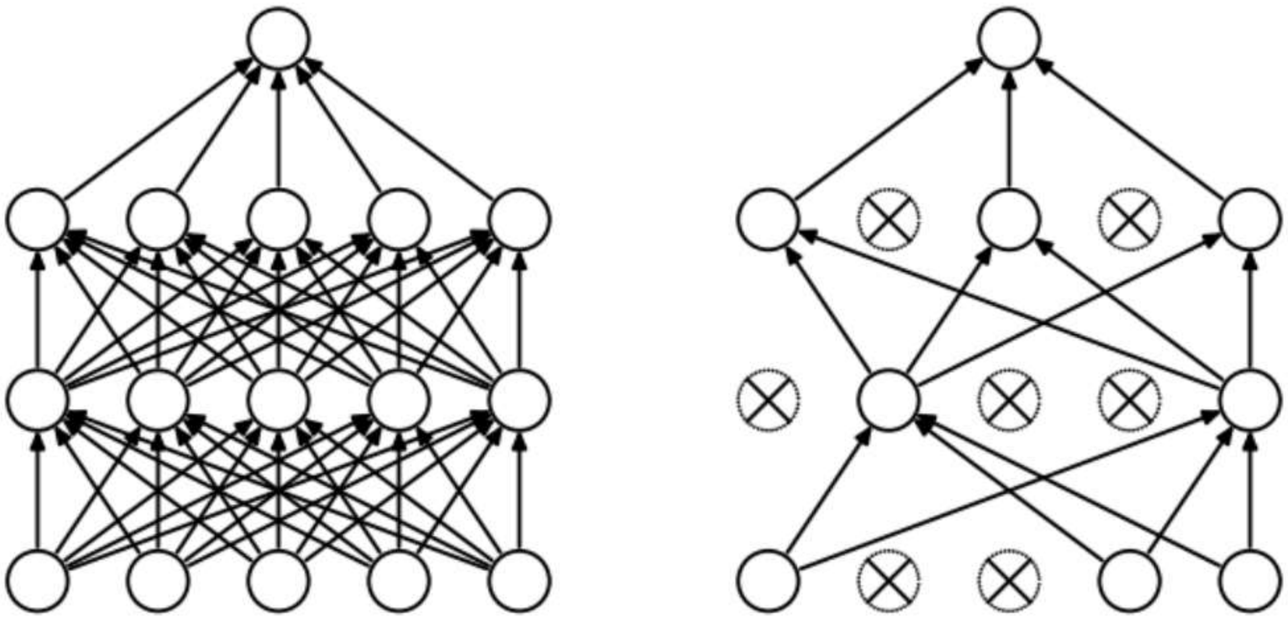


(a) SGD without momentum (b) SGD with momentum

Global minimum 에 빨리 도달하기 위해 vertically 는 변화가 적고 horizontally 는 변화가 크도록 parameter 조절

Dropout regularization

Random 한 drop out 을 통한 과적합 방지 (특정 feature 의존 방지)



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

epoch

- 정의 – 전체 dataset 이 neural network 을 통해 한번 처리된 것
- Epoch 은 model 의 training 시에 hyperparameter 로 횟수 지정
- 하나의 epoch 은 한번에 처리하기 어려운 size 이므로 여러 개의 batch 로 나누어 처리
- Parameter training 을 위해서는 여러 번 epoch 을 반복해야 한다.
- One epoch 내에서의 iteration 횟수는 total sample size / batch size
- Ex) 1 epoch = 4 iterations = 2000 training example / 500 batches

Hyper-parameters

- α - Learning Rate
- β - momentum term
- # of layers
- Dropout rate
- # of epochs
- Batch size

Network Layer 와 Neuron 의 개수는 어떻게 결정하는가 ?

- **정해진 rule 이 없음** : Empirical Try and See

  → Too few : 과소적합, Too many : 과대적합

- Input 및 output node 고려
- Training data 의 volume 고려
- Function 의 복잡도 고려
- Training algorithm 고려

Hyper-parameter 값은 어떻게 정하는가 ?

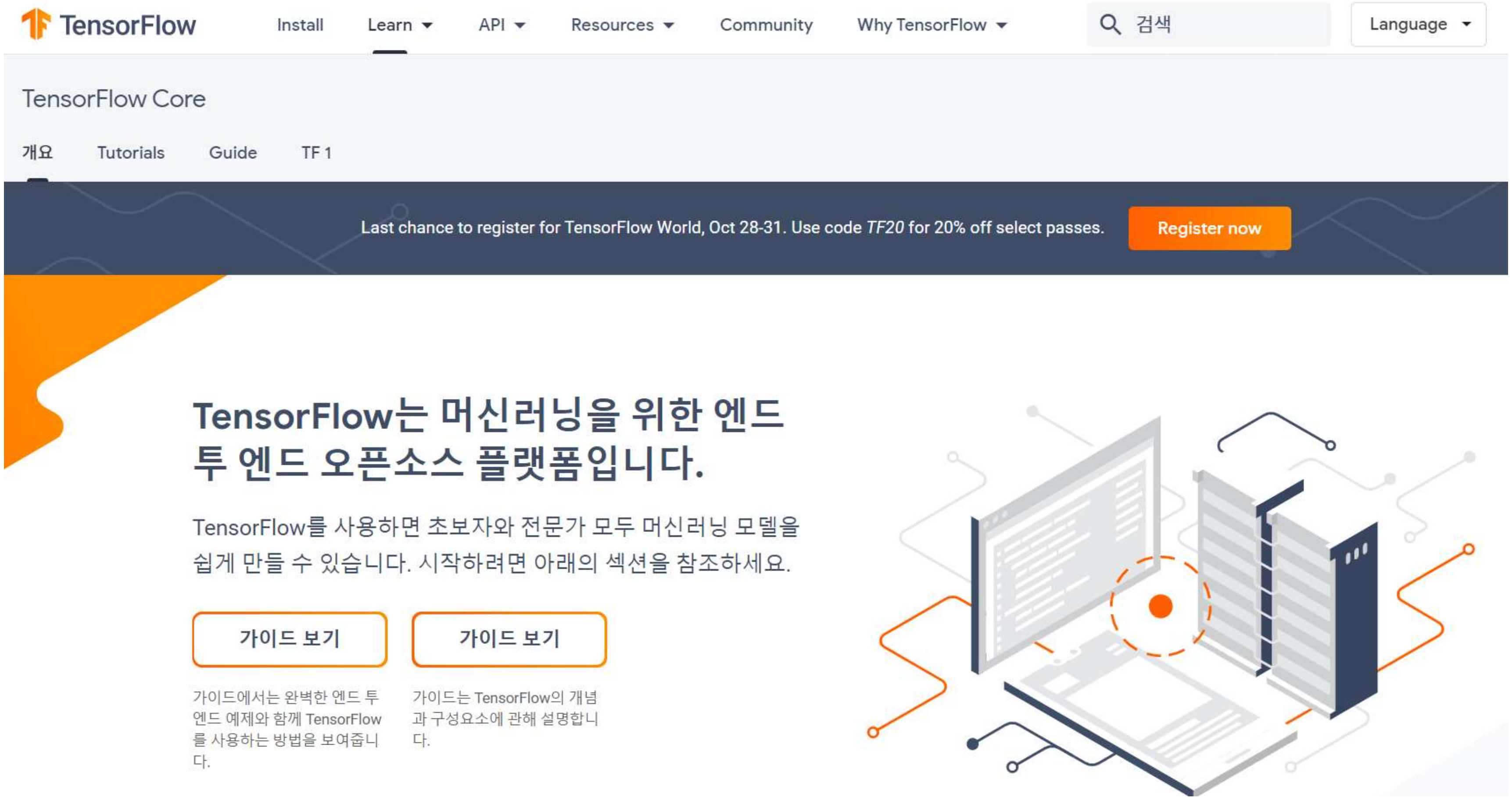
- 정해진 RULE 이 없음
- 유사한 model 참조
- 경험에 의한 guessing
- Grid search – computationally expensive

Open Source Libraries for Deep Learning

- Scikit-Learn – 2007, Python Library based on Matplotlib, NumPy, SciPy
- Theano - 2007, Open Source Python Library
- Tensorflow – 2015, Google. Open Source Machine Learning Framework
- Keras – 2015, Open Source Python Library
  (working on top of Tensorflow, Theano, CNTK)
- Microsoft Cognitive Tool – 2016, CNTK
- Caffe – 2017, Berkeley AI Research
- Pytorch – 2016, Facebook
- H2O – 2011, Open Source Big Data platform on Apache Hadoop

Tensorflow 2.0

What is Tensorflow ?



Tensorflow Installation

- pip install --upgrade tensorflow

- import tensorflow as tf
- tf.__version__

일반용 – Sequential API

```python
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])

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

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

전문가용 – Subclassing API

```python
class MyModel(tf.keras.Model):
  def __init__(self):
    super(MyModel, self).__init__()
    self.conv1 = Conv2D(32, 3, activation='relu')
    self.flatten = Flatten()
    self.d1 = Dense(128, activation='relu')
    self.d2 = Dense(10, activation='softmax')

  def call(self, x):
    x = self.conv1(x)
    x = self.flatten(x)
    x = self.d1(x)
    return self.d2(x)
model = MyModel()

with tf.GradientTape() as tape:
  logits = model(images)
  loss_value = loss(logits, labels)
grads = tape.gradient(loss_value, model.trainable_variable
optimizer.apply_gradients(zip(grads, model.trainable_varia
```

Sequential API

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

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

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```
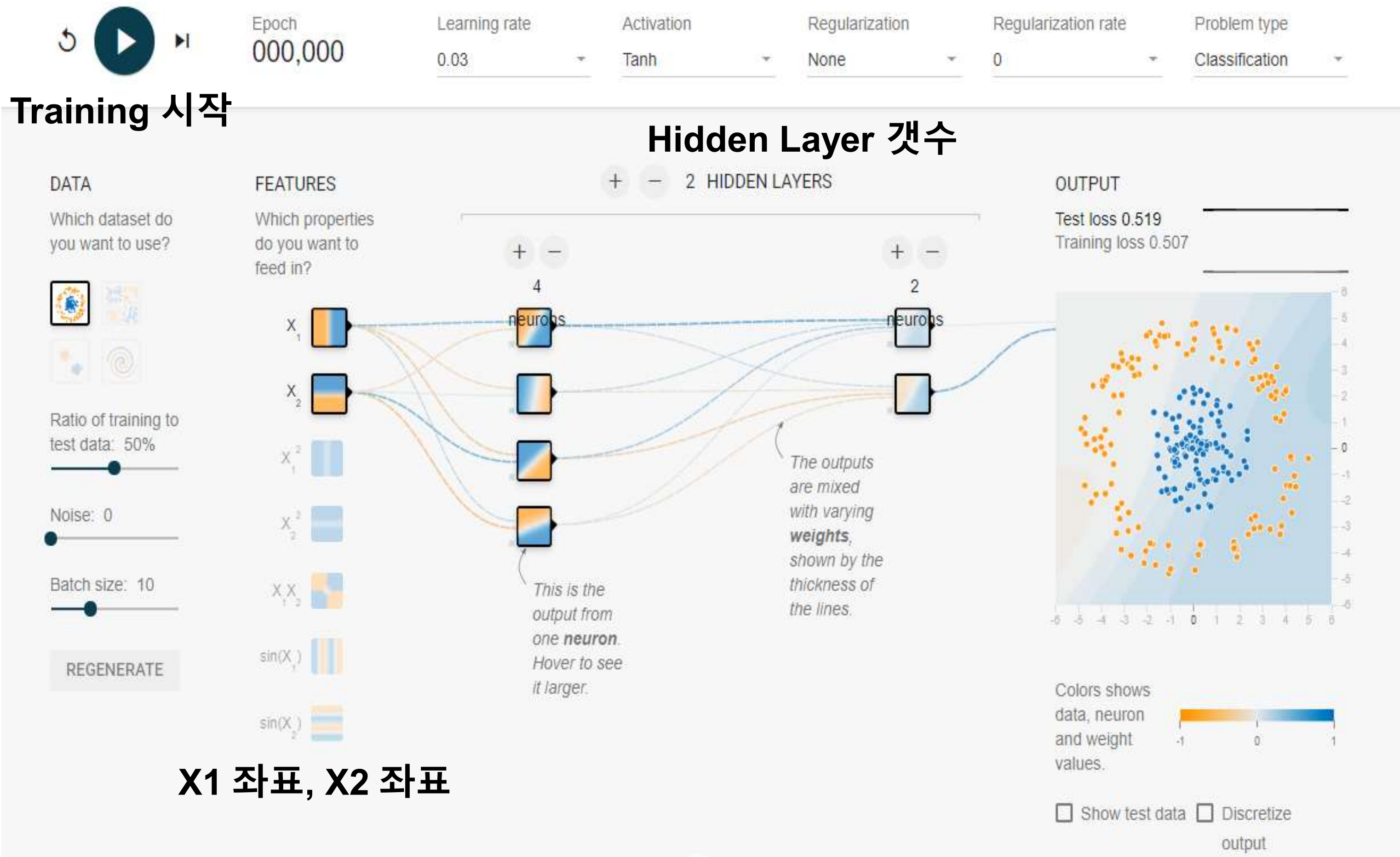

→ **Data Loading**
→ **Data Normalization**
→ **Model 정의**
→ **Model Compile**
→ **Model Train**
→ **Model 평가**

Deep Learning

Models

Tensorflow Playground



Basic Neural Network

실습: 비선형회귀 (Polynomial Regression)

- Data : X = np.random.rand() 를 이용한 random data 생성

- Data 변환 : poly_features = PolynomialFeatures(degree=2, include_bias=False)
  poly_features.fit_transform(X)
- Target : y = 0.5 * X**2 + X + 2 + np.random.randn(m, 1)

- Sequential API 를 사용한 2 layer Neural Network 구성
- Loss 함수 : MSE

- 평가 : matplotlib 을 이용한 시각화

실습 : Simple Logistic Regression

1. Hidden Layer 없는 Simple Logistic Regression Neural Network

   ➔ Shallow Neural Network

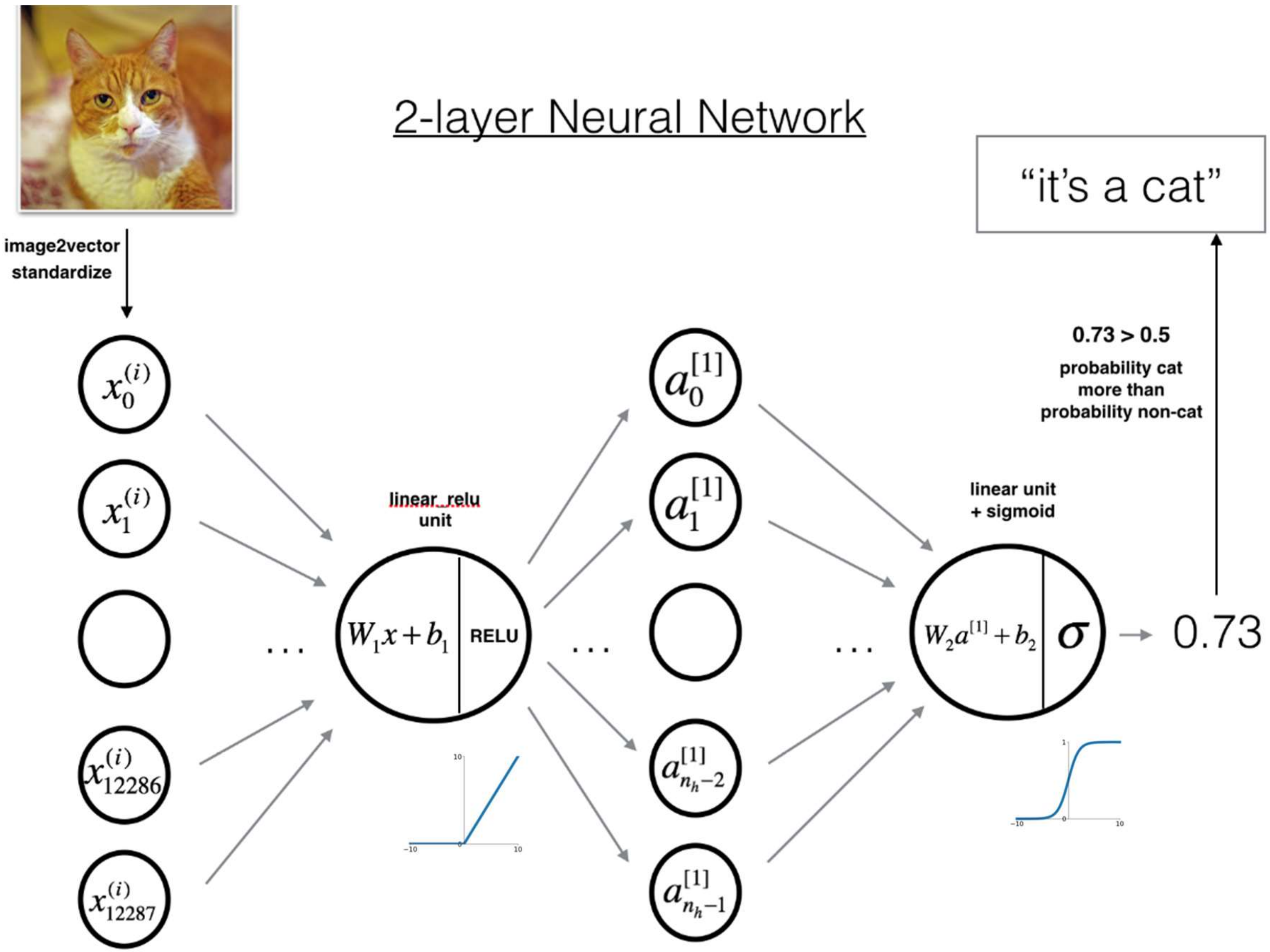
2. 입력된 image 가 고양이인지 여부 판별

3. Image 자료 시각화

4. Neural Network Model 구성 및 Compile

5. Model Train

6. Performance Evaluation



2-layer Neural Network
image2vector
standardize
$x_0^{(i)}$
$x_1^{(i)}$
$x_{12286}^{(i)}$
$x_{12287}^{(i)}$
linear_relu unit
W_1x+b_1
RELU
$a_0^{[1]}$
$a_1^{[1]}$
$a_{n_h-2}^{[1]}$
$a_{n_h-1}^{[1]}$
linear unit + sigmoid
$W_2a^{[1]}+b_2$
σ
0.73
0.73 > 0.5
probability cat
more than
probability non-cat
"it's a cat"

실습 : Boston 주택가격 Regreesion

1. Boston House Price Dataset
   - sklearn.datasets.load_boston 이용

2. 보스턴 시의 주택 가격에 대한 데이터
   - 주택의 여러가진 요건들과 주택의 가격 정보가 포함.
   - 주택의 가격에 영향을 미치는 요소를 이용하여 회귀분석

3. 13 개의 종속변수와 1 개의 독립변수 (주택가격 중앙값) 으로 구성

- Feature 설명

CRIM 자치시(town) 별 1인당 범죄율,

ZN 25,000 평방피트를 초과하는 거주지역의 비율

INDUS 비소매상업지역이 점유하고 있는 토지의 비율

CHAS 찰스강에 대한 더미변수(강의 경계에 위치한 경우는 1, 아니면 0)

NOX 10ppm 당 농축 일산화질소

RM 주택 1가구당 평균 방의 개수

AGE 1940년 이전에 건축된 소유주택의 비율

DIS 5개의 보스턴 직업센터까지의 접근성 지수

RAD 방사형 도로까지의 접근성 지수

TAX 10,000 달러 당 재산세율

PTRATIO 자치시(town)별 학생/교사 비율

B 1000(Bk-0.63)^2, 여기서 Bk는 자치시별 흑인의 비율을 말함

LSTAT 모집단의 하위계층의 비율(%)

MEDV 본인 소유의 주택가격(중앙값) (단위: $1,000)

Deep Neural Network

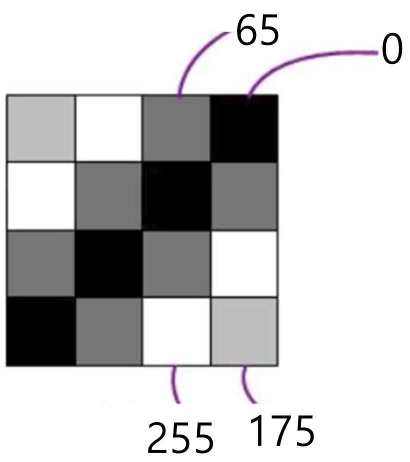
Mnist Dataset 소개

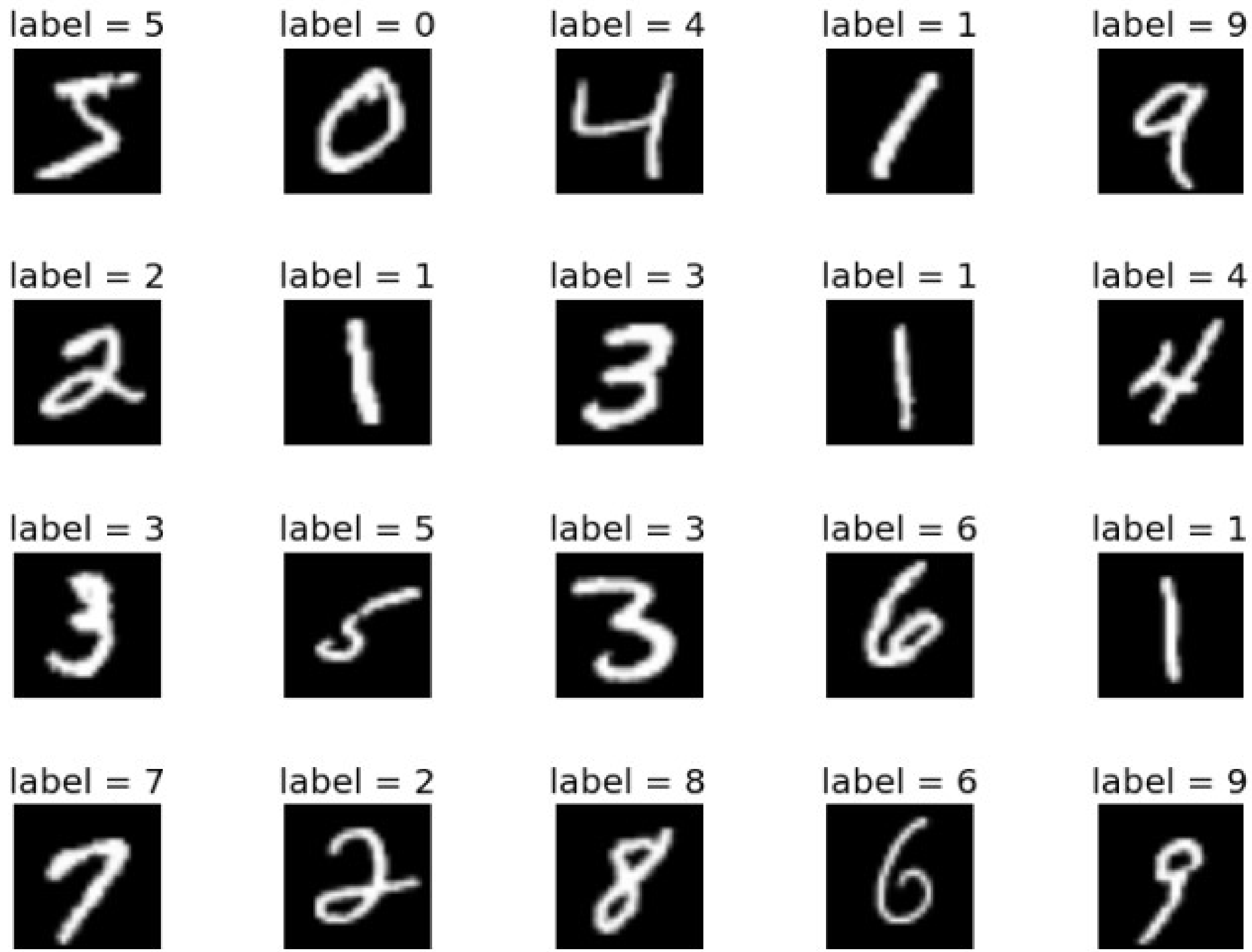
- Mixed National Institute of Standards and Technology

- 0 ~ 9 의 10 개 숫자 손글씨 image dataset
- 28 x 28 pixel 의 gray scale image
- 각 image 마다 0 to 9 의 label 로 쌍을 이루고 있음
- Train set 60,000 / Test set 10,000
- Machine Learning 의 Hello World 에 해당

Pixel 의 구성

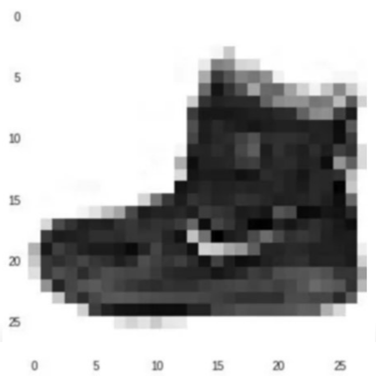
0 – black
255 - white

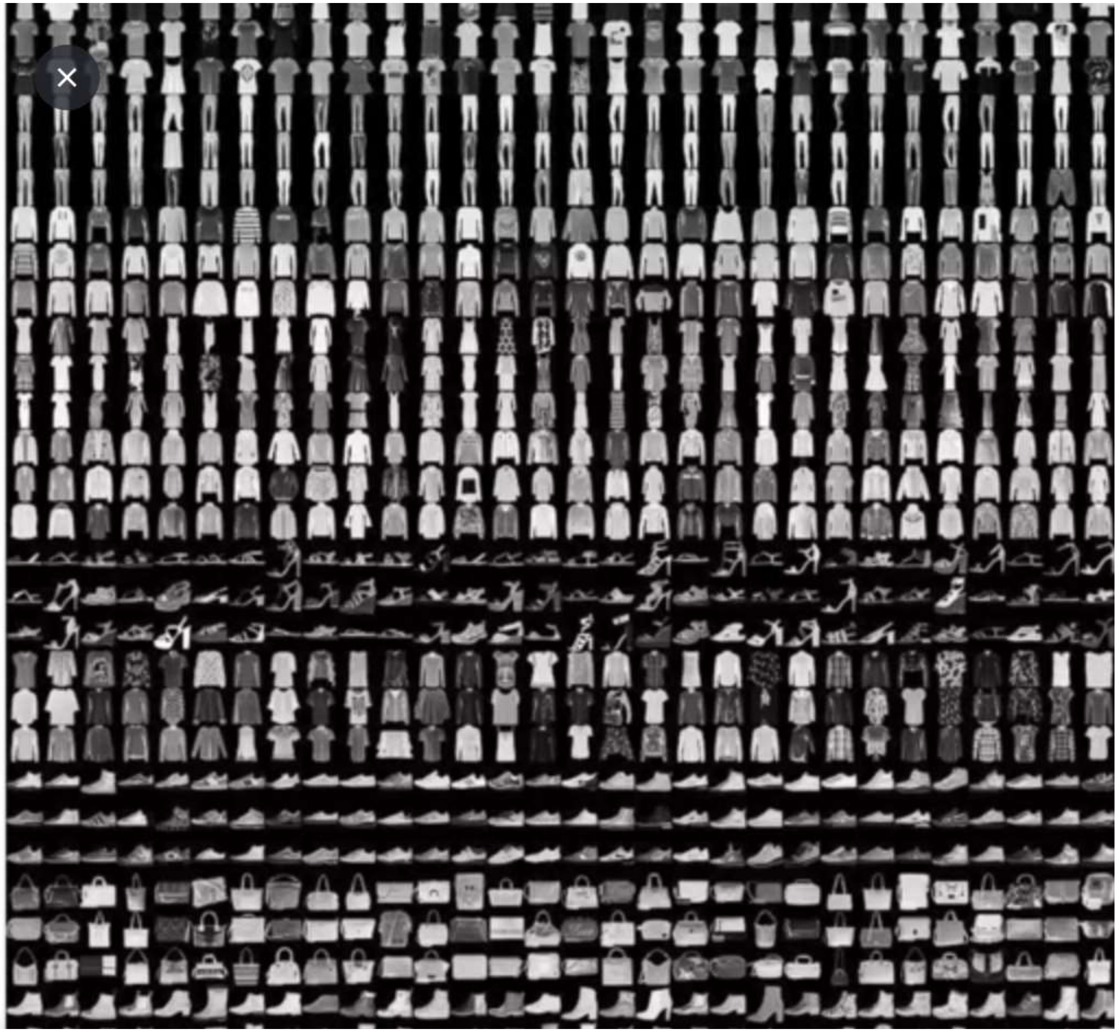




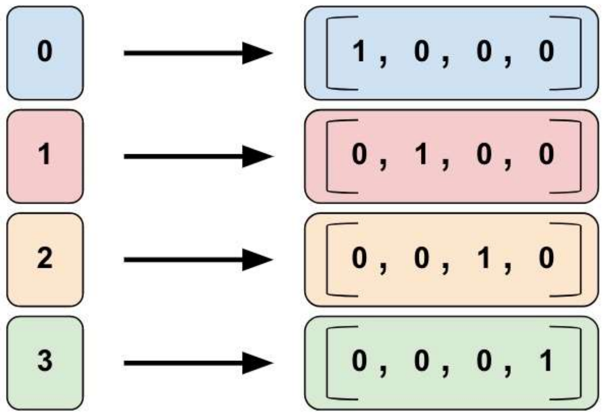
Fashion MNIST

- 70k Images
- 10 Categories
- Images are 28x28
- Can train a neural net!

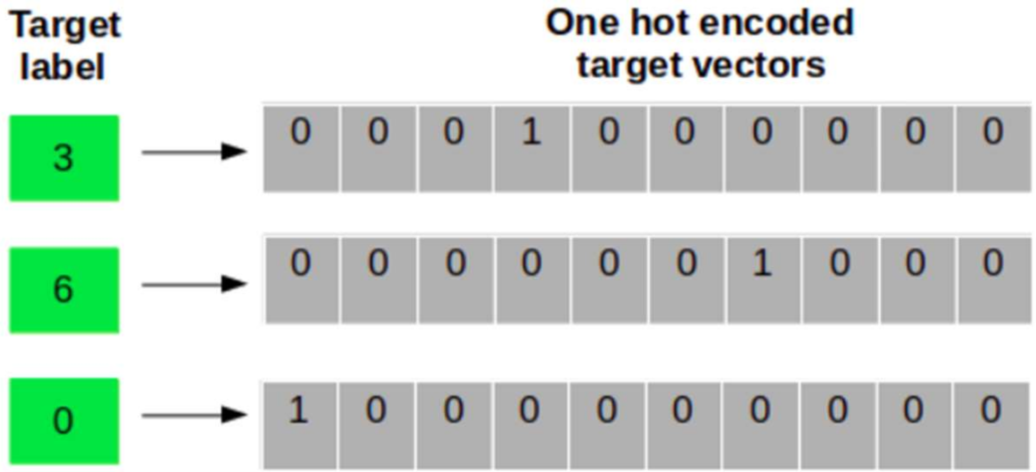




One-Hot encoding



color	color_red	color_blue	color_green
red	1	0	0
green	0	0	1
blue	0	1	0
red	1	0	0

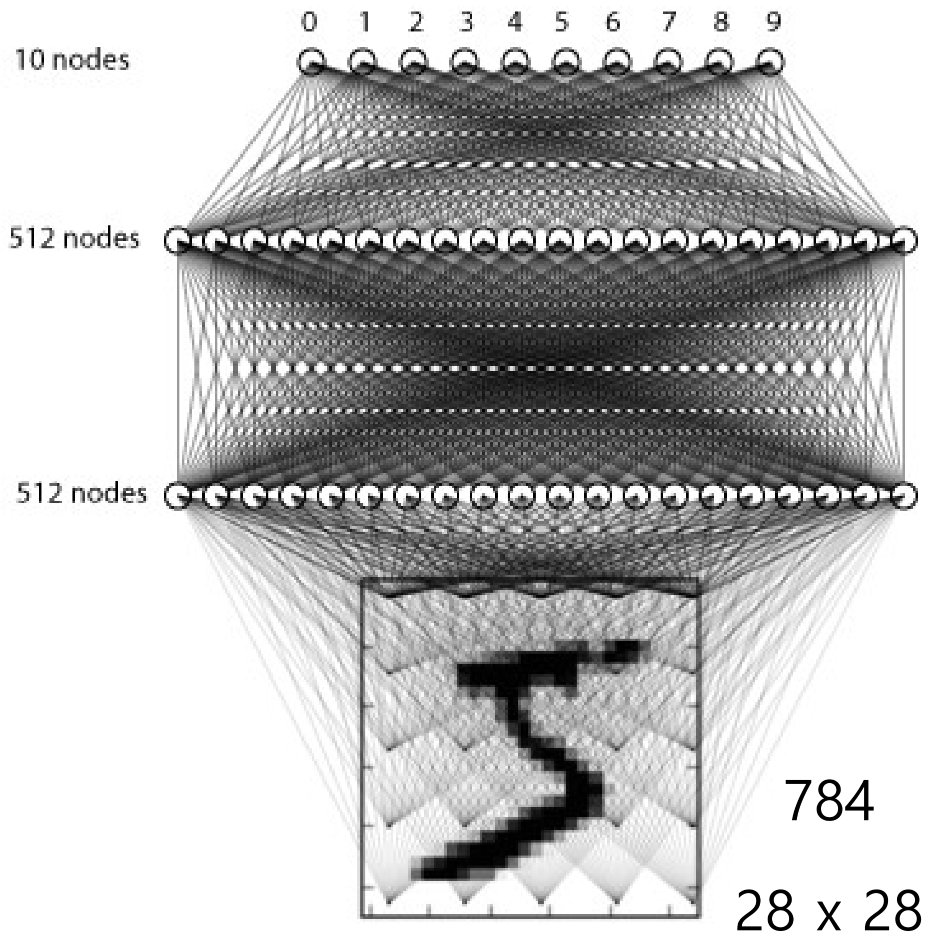


Output Layer - softmax

Output Layer

2nd Hidden Layer

1st Hidden Layer



784

28 x 28

실습 : Mnist set 을 이용한 손글씨 인식

1. 2-Layer 이상의 Fully Connected(Dense) Neural Network
2. Input reshaping and scaling
3. One-hot encoding
4. Neural Network Model 구성 및 Compile
5. Model Train
6. Performance Evaluation

실습 : Hyper-parameter Tunning 을 이용한 손글씨 인식 성능 개선

	Model 1	Model 2	Model 3	Model 4	Model 5
# of Hidden Layers	0	2	2	2	3
# of Hidden neurons	128	128	128	512	?+?+?
# of epochs	10	10	10	10	10/15/20
Dropout	0	0	0.2	0.2	0.2/0.3
Batch size	128	128	512	512	256/512
accuracy	92.6	97.4	98.01	98.06	98.40

Hyperparameter tuning 을 통해 98.4 % 의 정확도 달성

Enough ? ➔ No ! ➔ CNN