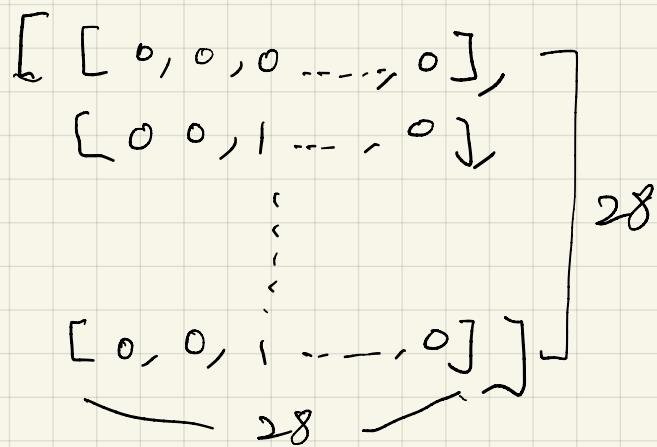
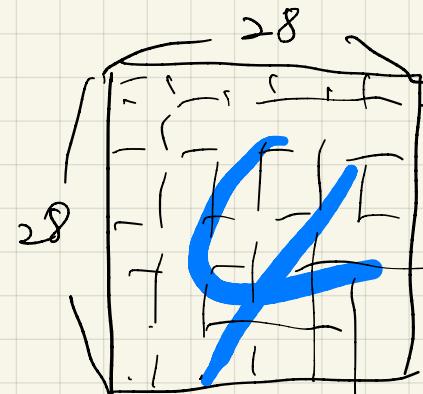
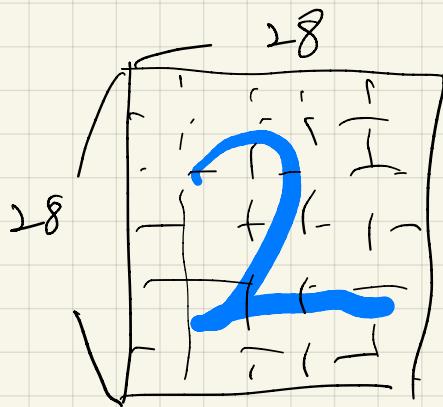


COSMAX AI class

- numpy 를 이용한

Logistic Regression 의 구현

Problem : MNIST image binary classification. (이진분류)



MNIST Dataset

0 ~ 9 \Rightarrow 10

"손글자" Data

2×2 Array로 구성되어 있음.

MNIST Dataset 9 73

$x\text{-train}\text{-shape} = (60000, 28, 28)$

28×28
60,000 $\frac{1}{2}$

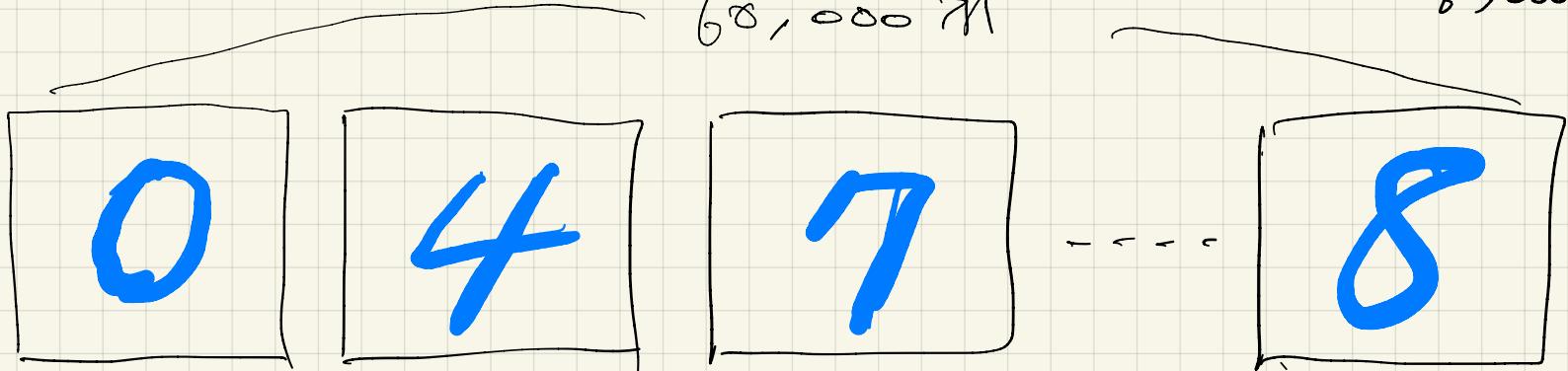
$y\text{-train}\text{-shape} = (60000, 1)$

0 ~ 9 숫자
4자리수 [label]

60,000 개

60,000

$x\text{-train}:$



$y\text{-train}:$

0

4

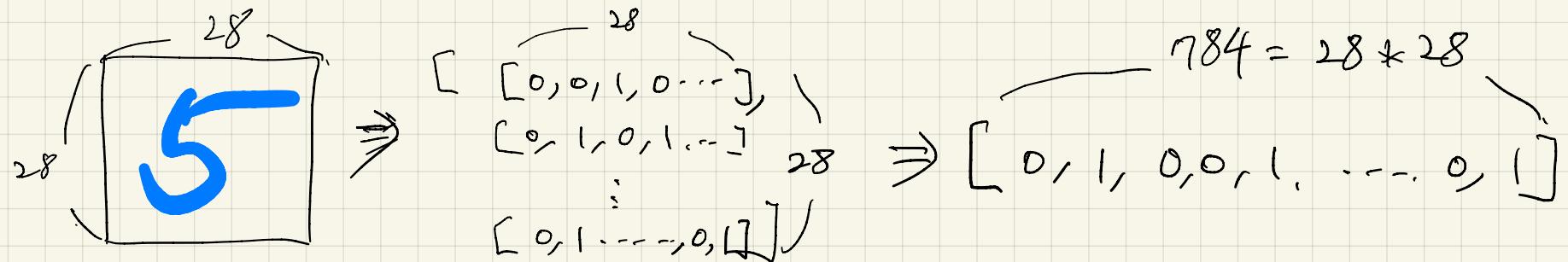
7

8

$x\text{-test. shape} (?)$

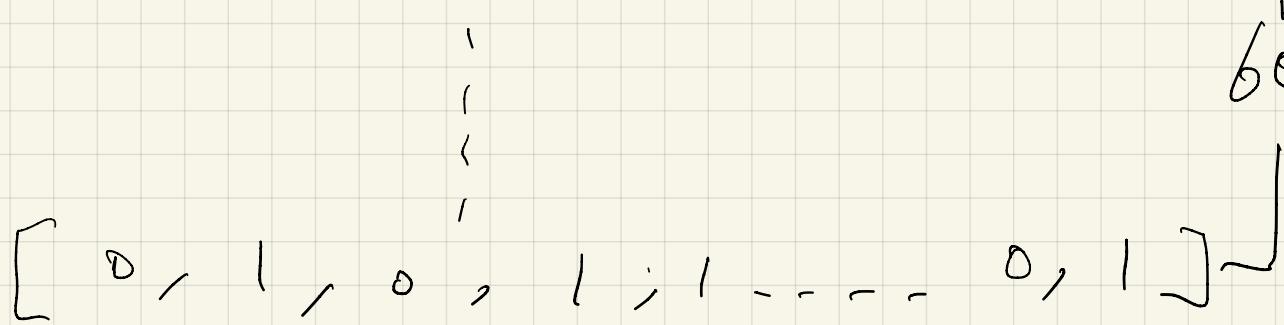
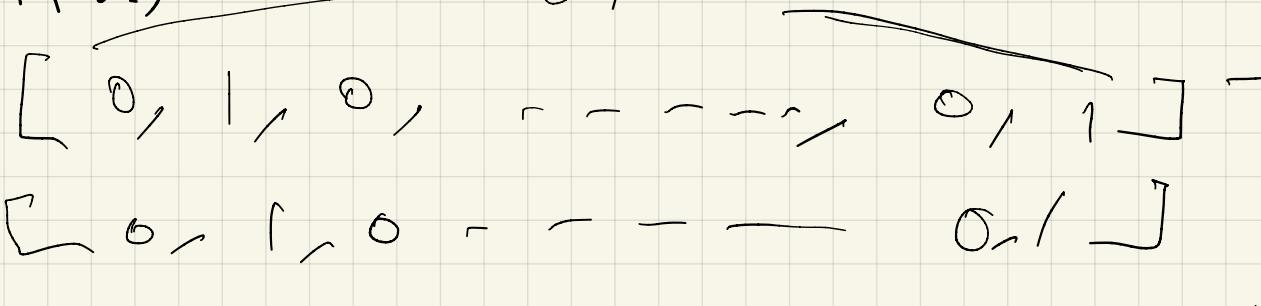
$y\text{-test. shape} (?)$

Training Set Prep



Flattened

$x\text{-train (?)}$: 784

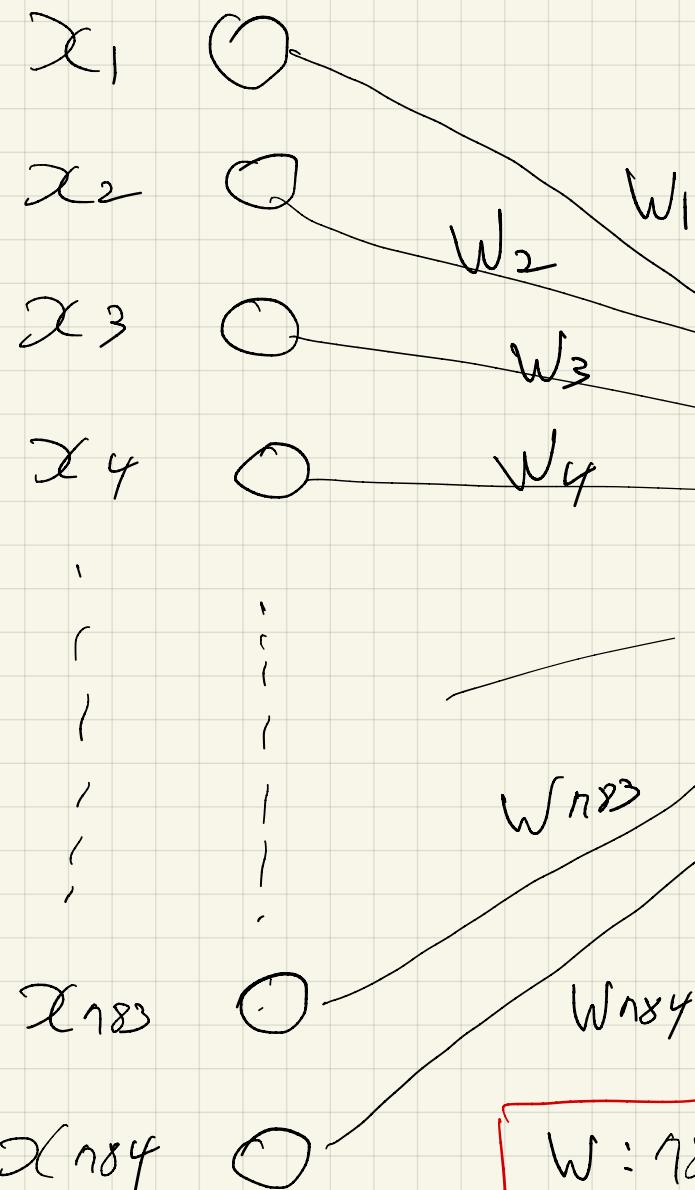


$x_1, x_2, x_3, x_4, \dots, x_{783}, x_{784}$

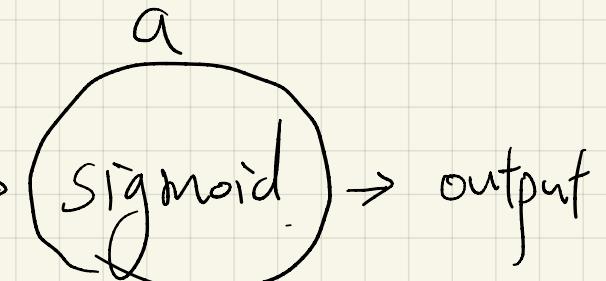
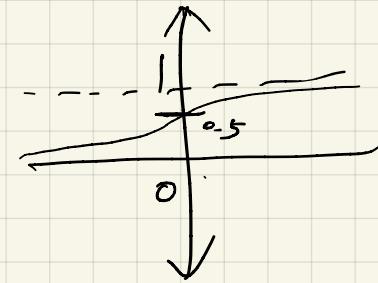
1D - Array flatten.

(training example)

Logistic Regression Model



$$\text{sigmoid}(z) = \frac{1}{1+e^{-z}}$$



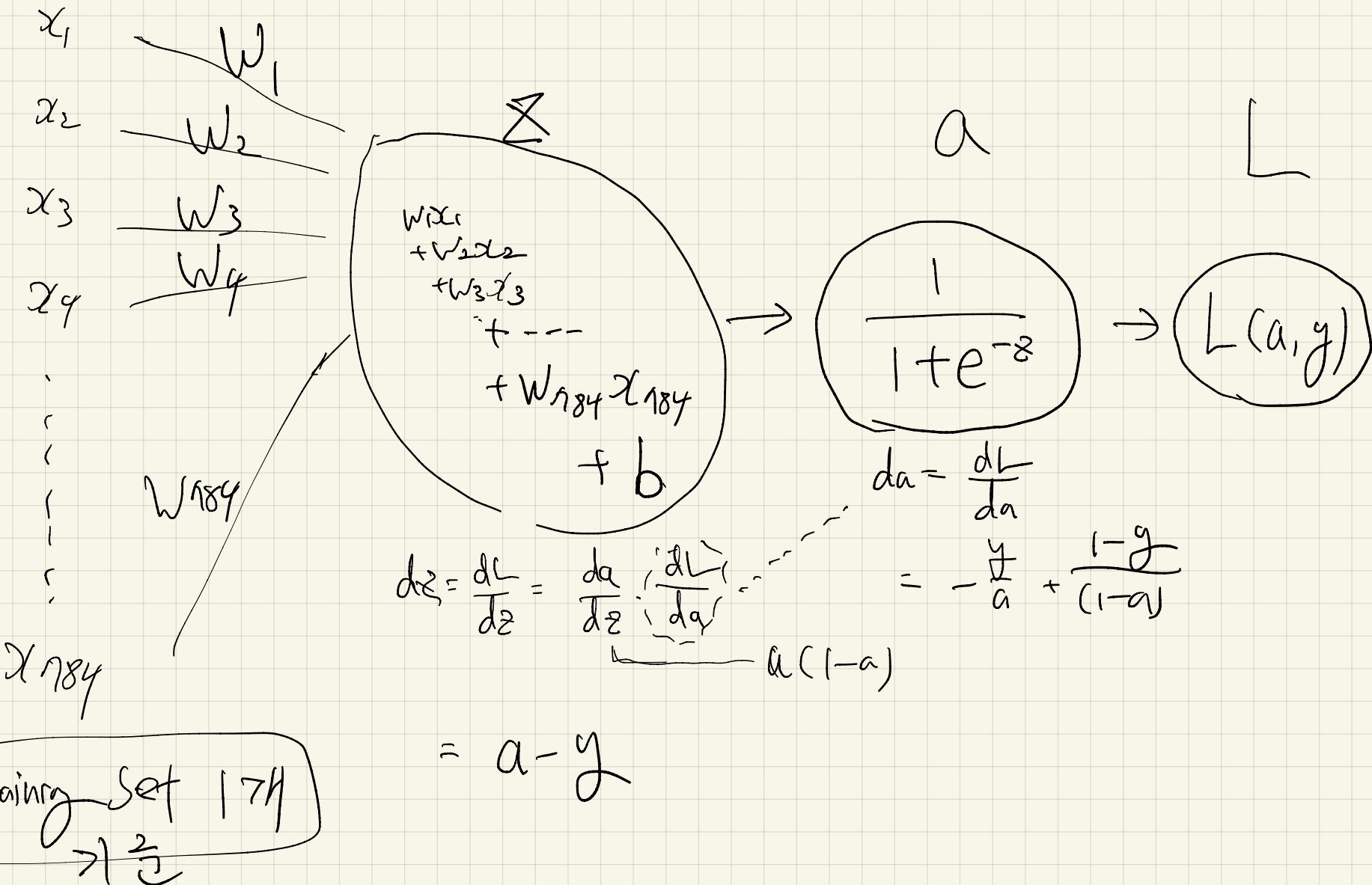
Activation
function.

$$h(x) = \sum w_i x_i + b$$

$w: 184 \times 1$ $b: 1 \times 1$

trainable - parameter.

Logistic Regression Basic Algorithm



학습의 training set 올 대해 G

$$z = \underbrace{Wx}_{\text{data}} + b \quad \text{계산}$$

trainable
parameter.

$$a = \sigma(z) \quad \text{계산}$$

$$L = h(a, y) \quad \text{계산}$$

$\underbrace{y}_{\text{true label}}$

$$\frac{dL}{dw_1} = dw_1 = x_1 \cdot dz$$

$$\frac{dL}{dw_2} = dw_2 = x_2 \cdot dz$$

$$\dots \frac{dL}{dw_{184}} = dw_{184} = x_{184} \cdot dz$$

$$\frac{dL}{db} = db = dz$$

$$w_1 := w_1 - \alpha dw_1 \quad w_2 := w_2 - \alpha dw_2 \quad \dots$$

$$b := b - \alpha db$$

$$w_{184} := w_{184} - \alpha dw_{184}$$

$$J(w, b) = \frac{1}{m} \sum_{i=1}^m L(a^{(i)}, y^{(i)}) : \text{cost function.}$$

$$a^{(i)} = \hat{y}^{(i)} = \sigma(z^{(i)}) = \sigma(w^T x^{(i)} + b)$$

$$(x^{(i)}, y^{(i)}) = [d w_1^{(i)}, d w_2^{(i)}, \dots, d w_{184}^{(i)}] \rightarrow \boxed{d b^{(i)}} \quad |> h$$

$$\frac{d}{d w_1} J(w, b) = \frac{d}{d w_1} J(w, b)$$

$$= \frac{1}{m} \sum_{i=1}^m \frac{\partial}{\partial w_1} L(a^{(i)}, y^{(i)})$$

— 다 합해서 평균을 낸다 —

Algorithm

$$J=0, \quad dw_1=0 \dots dw_{784}=0, \quad db=0 \dots$$

For $i=1 \dots m \rightarrow$ One Epoch

$$z^{(i)} = w^T x^{(i)} + b$$

$$a^{(i)} = \text{sigmoid}(z^{(i)})$$

$$J += -[L(a^{(i)}, y^{(i)})]$$

$$= - (y^{(i)} \log a^{(i)} + (1-y^{(i)}) \log (1-a^{(i)}))$$

$$dz^{(i)} = a^{(i)} - y^{(i)}$$

$$dw_1 += x_1^{(i)} \cdot dz^{(i)} \quad | \quad \text{Gradient } w_1$$

$$dw_{784} += x_{784}^{(i)} \cdot dz^{(i)} \quad |$$

$$db += dz^{(i)} \quad |$$

$$J/m, \quad dw_1/m, \dots, dw_{784}/m, \quad db/m$$

$$w_1 = w_1 - \alpha \cdot dw_1 \quad |$$

$$w_2 = w_2 - \alpha \cdot dw_2 \quad |$$

$$b = b - \alpha \cdot db \quad |$$

- Gradient update

Training Set Vectorized
184 Representation

$$X_1 = [0, 0, 0, 1, 0 \quad \cdots \quad 0, 1] \}$$

$$X_2 = [0, 0, 0, 1 \quad \cdots \quad 0, 1] \}$$

⋮

60000

$$X_{60000} = [0, 0, 1, 0 \quad \cdots \quad 0, 1]$$

$n_x = 184$: Number of features

m = number of training set

60,000 개의 training image data 를 하나의
Matrix 로 표시하면 (?)

$$X = \begin{bmatrix} | & | & | & | \\ X_1 & X_2 & X_3 & \cdots & X_m \\ | & | & | & & | \end{bmatrix} \quad n_x = 784$$

m

$$X.\text{shape} = (n_x, m) = (784, 60000)$$

Label Vectorized Form

$$Y = [0, 2, 4, 8, \dots, 7, 9]^T \in \mathbb{R}^{60,000 \times 1}$$

m

$$Y.\text{shape} = (1, m)$$

$$\boxed{X \in \mathbb{R}^{n \times m}}$$
$$\boxed{Y \in \mathbb{R}^{1 \times m}}$$

$$X = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \cdots & x_m \\ | & | & & | \end{bmatrix} \underbrace{\quad}_{m} \quad \underbrace{n_x}$$

$$Y = [0, 4, 1, \dots, 8] \underbrace{\quad}_m$$

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_{n_x} \end{bmatrix}$$

$$b = b$$

"real
number"

cf. numpy broadcast

$$Z = W^T X + b \rightarrow Z = [Z^{(1)}, Z^{(2)}, \dots, Z^{(m)}]$$

$$A = \text{sigmoid}(Z) \quad A = [A^{(1)}, A^{(2)}, \dots, A^{(m)}]$$

$$L = L(A, Y) \quad L = [L^{(1)}, L^{(2)}, \dots, L^{(3)}]$$

Vectorized Implementation

• m 개의 training set (1-epoch)
을 단 "한번"에 계산!

$$Z = W^T X + b$$

$$A = \text{sigmoid}(Z)$$

$$L = \text{loss}(A, Y)$$

$$dZ = A - Y$$

$$dW = \frac{1}{m} \cdot X \cdot dZ^T = \frac{1}{m} * \text{np.dot}(X, dZ^T)$$

$$db = \frac{1}{m} \cdot \text{np.sum}(dZ)$$

$$W = W - \alpha \cdot dW \quad \cdots \text{vector}$$

$$b = b - \alpha \cdot db \quad \cdots \text{scalar}$$