

Broadcasting

numpy가 연산 중 다른 shape을 가진 배열을 처리하는 방법

$$\begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} + \begin{bmatrix} 100 \\ 100 \\ 100 \\ 100 \end{bmatrix} = \begin{bmatrix} 101 \\ 102 \\ 103 \\ 104 \end{bmatrix}$$

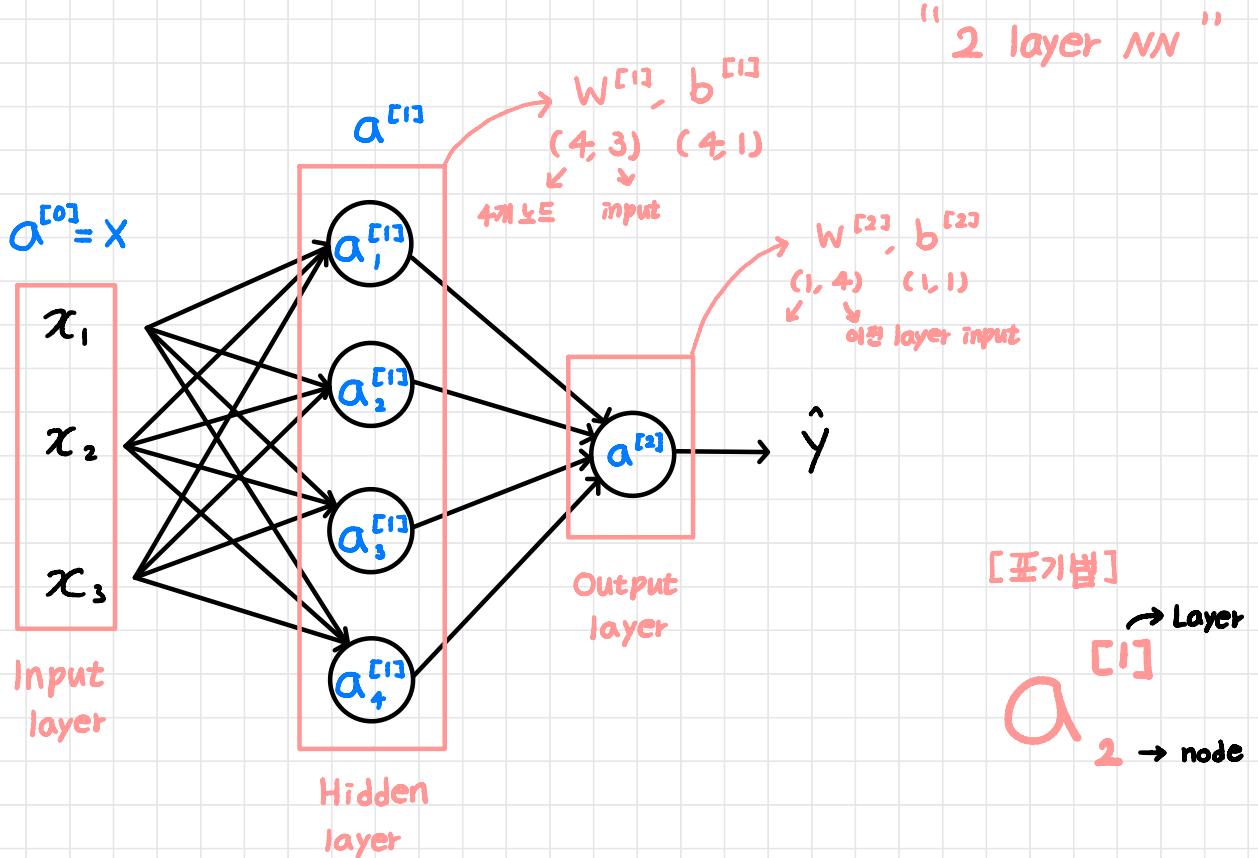
$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} + \begin{bmatrix} 100 & 200 & 300 \\ 100 & 200 & 300 \end{bmatrix} = \begin{bmatrix} 101 & 202 & 303 \\ 104 & 205 & 306 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} + \begin{bmatrix} 100 \\ 200 \end{bmatrix} = \begin{bmatrix} 101 & 102 & 103 \\ 204 & 205 & 206 \end{bmatrix}$$

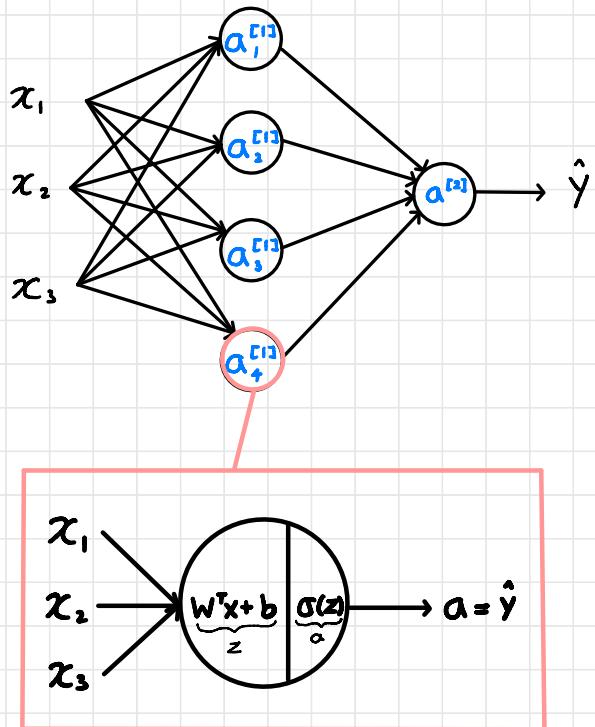
$$\begin{bmatrix} 100 & 100 & 100 \\ 200 & 200 & 200 \end{bmatrix}$$

numpy 연산 시 rank 1인
행렬은 사용하지 않기!
→ 오류가 발생할 수 있음

Neural Network representation



Neural Network representation



Given input X :

$$Z^{[1]} = W^{[1]}x + b^{[1]}$$

(4, 1) (4, 3) (3, 1) (4, 1)

$$a^{[1]} = \sigma(Z^{[1]})$$

(4, 1) (4, 1)

$$Z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$

(1, 1) (1, 4) (4, 1) (1, 1)

$$a^{[2]} = \sigma(Z^{[2]})$$

(1, 1) (1, 1)

Vectorizing across multiple examples

for $i=1$ to m :

$$z^{[1](i)} = W^{[1]}x^{(i)} + b^{[1]}$$

$$\alpha^{[1](i)} = \sigma(z^{[1](i)})$$

$$z^{[2](i)} = W^{[2]}\alpha^{[1](i)} + b^{[2]}$$

$$\alpha^{[2](i)} = \sigma(z^{[2](i)})$$

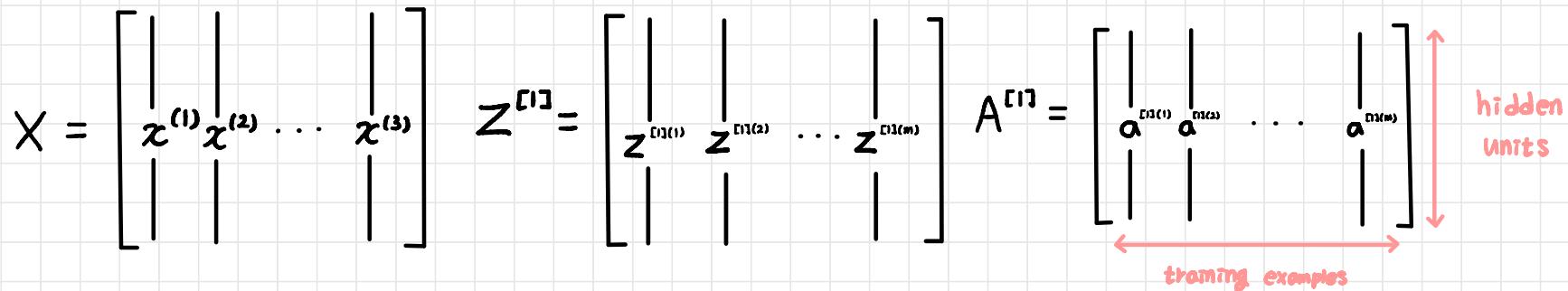


$$Z^{[1]} = W^{[1]}X + b^{[1]}$$

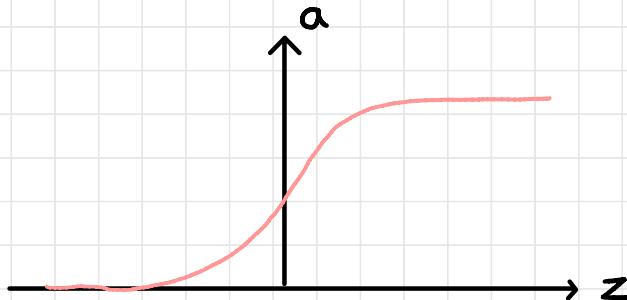
$$A^{[1]} = \sigma(Z^{[1]})$$

$$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$$

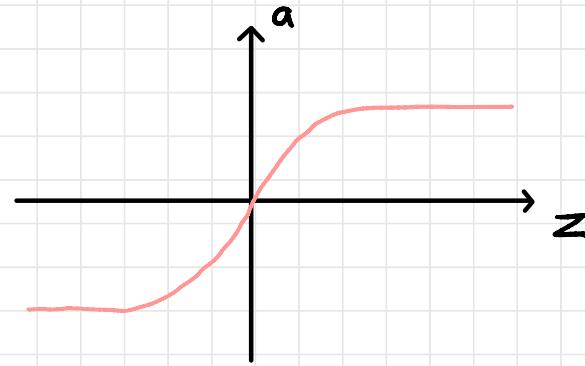
$$A^{[2]} = \sigma(Z^{[2]})$$



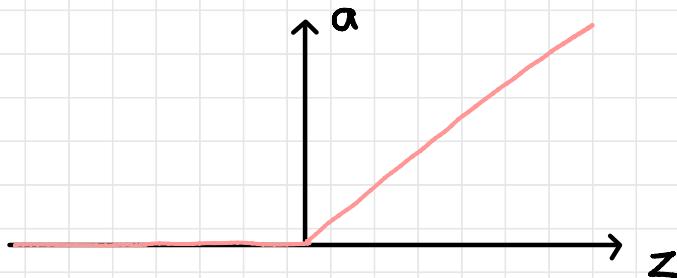
Pros and cons of activation functions



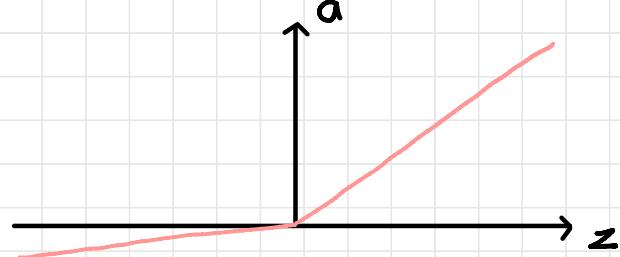
$$\text{Sigmoid: } a = \frac{1}{1 + e^{-z}}$$



$$\tanh: a = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$



$$\text{ReLU: } a = \max(0, z)$$



$$\text{Leaky ReLU: } a = \max(0.01z, z)$$