

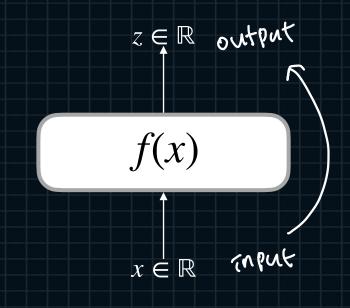
Forward Propagation Of Neural Networks

Lecture.1
Artificial Neurons

ex)

- Parametric Functions > output 2

OUTPUT ?



$$f(x; \theta)$$

$$x \in \mathbb{R} \quad \text{exp} \quad \theta = 5$$

 $z \in \mathbb{R}$

$$z = e^{x}$$

$$z = log(x)$$

$$\vdots$$

$$(z) = \underbrace{x + \theta}_{z = \varphi_{x}} = \underbrace{x + \xi}_{z = \varphi_{x}}$$

$$\vdots$$

- Hierarchy of Tensor Computations

L Scalar, vector, matrix,...

Scalar

Zeroth-order First-order

Tensor Operations

$$a,b \in \mathbb{R}$$

$$a+b: \mathbb{R} \times \mathbb{R} \to \mathbb{R}$$

$$a \cdot b : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$$

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Tensor Operations

$$a \in \mathbb{R}$$

$$\overrightarrow{u}, \overrightarrow{v} \in \mathbb{R}^n$$

$$a\overrightarrow{u}: \mathbb{R} \times \mathbb{R}^n \to \mathbb{R}^n$$

$$\overrightarrow{u} + \overrightarrow{v} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n$$

$$\overrightarrow{u} \bigcirc \overrightarrow{v} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n$$

$$(\overrightarrow{u})^T \cdot \overrightarrow{v} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$$

$$\begin{pmatrix} 2 \\ 3 \\ 4 \end{pmatrix} \circ \begin{pmatrix} 10 \\ 20 \\ 30 \end{pmatrix} = \begin{pmatrix} 20 \\ 60 \\ 120 \end{pmatrix}$$

Second-order 7 Max

Tensor Operations

$$a \in \mathbb{R} \quad \overrightarrow{u} \in \mathbb{R}^n$$
$$M, N \in \mathbb{R}^{m \times n}, O \in \mathbb{R}^{n \times o}$$

$$aM: \mathbb{R} \times \mathbb{R}^{m \times n} \to \mathbb{R}^{m \times n}$$

$$M+N: \mathbb{R}^{m\times n} \times \mathbb{R}^{m\times n} \to \mathbb{R}^{m\times n}$$

$$M\bigcirc N: \mathbb{R}^{m\times n} \times \mathbb{R}^{m\times n} \to \mathbb{R}^{m\times n}$$

$$M \cdot \overrightarrow{u} : \mathbb{R}^{m \times n} \times \mathbb{R}^n \to \mathbb{R}^m$$

$$MO: \mathbb{R}^{m \times n} \times \mathbb{R}^{n \times o} \to \mathbb{R}^{m \times o}$$

Third-order

Tensor Operations

$$a \in \mathbb{R}$$
$$M, N \in \mathbb{R}^{m \times n \times o}$$

 $aM: \mathbb{R} \times \mathbb{R}^{m \times n \times o} \to \mathbb{R}^{m \times n \times o}$

$$M + N : \mathbb{R}^{m \times n \times o} \times \mathbb{R}^{m \times n \times o} \to \mathbb{R}^{m \times n \times o}$$

$$M\bigcirc N: \mathbb{R}^{m\times n\times o}\times \mathbb{R}^{m\times n\times o}\to \mathbb{R}^{m\times n\times o}$$

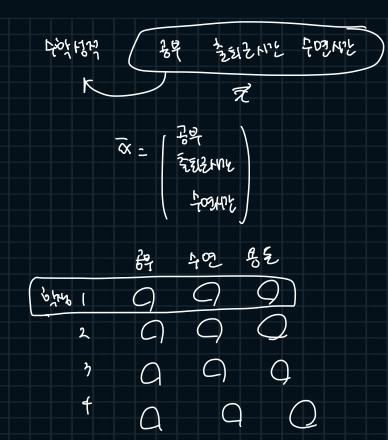
- Dataset(X Data)

$$\overrightarrow{x}^T = \left[(x_1 \quad x_2 \quad \dots \quad x_{l_I}) \right]$$

$$(\overrightarrow{x}^{(1)})^T = \begin{pmatrix} x_1^{(1)} & x_2^{(1)} & \dots & x_{l_I}^{(1)} \end{pmatrix}$$

$$\left(\overrightarrow{x}^{(2)}\right)^T = \begin{pmatrix} x_1^{(2)} & x_2^{(2)} & \dots & x_{l_I}^{(2)} \end{pmatrix}$$

 $\left(\overrightarrow{x}^{(N)}\right)^T = \left(x_1^{(N)} \quad x_2^{(N)} \quad \dots \quad x_{l_I}^{(N)}\right)$



- Dataset(X Data)

$$X^{T} = \begin{pmatrix} x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(N)} \end{pmatrix}$$

$$\in \mathbb{R}^{N \times}$$

$$\overrightarrow{x}^{T} = (x_{1} \quad x_{2} \quad \dots \quad x_{l_{I}})$$

$$X^{T} = \begin{pmatrix} \leftarrow & (\overrightarrow{x}^{(1)})^{T} & \longrightarrow \\ \leftarrow & (\overrightarrow{x}^{(2)})^{T} & \longrightarrow \\ \vdots & \vdots & \ddots & \vdots \\ \leftarrow & (\overrightarrow{x}^{(N)})^{T} & \longrightarrow \end{pmatrix} = \begin{pmatrix} x_{1}^{(1)} & x_{2}^{(1)} & \dots & x_{n_{I}}^{(1)} \\ x_{1}^{(2)} & x_{2}^{(2)} & \dots & x_{n_{I}}^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1}^{(N)} & x_{2}^{(N)} & \dots & x_{n_{I}}^{(N)} \end{pmatrix}$$

$$\boldsymbol{\in} \mathbb{R}^{N \times l_{I}}$$

$$(\overrightarrow{\chi})^{T} = (\chi_{1}, \chi_{2}, \chi_{3}, \dots, \chi_{L_{I}})$$

$$(\overrightarrow{\chi}^{(1)})^{T} = (\chi_{1}^{(1)}, \chi_{2}^{(1)}, \chi_{3}^{(1)}, \dots, \chi_{L_{I}}^{(1)})$$

$$(\overrightarrow{\chi}^{(2)})^{T} = (\chi_{1}^{(1)}, \chi_{2}^{(1)}, \chi_{3}^{(2)}, \dots, \chi_{L_{I}}^{(2)})$$

$$(\overrightarrow{\chi}^{(N)})^{T} = (\chi_{1}^{(N)}, \chi_{2}^{(N)}, \dots, \chi_{L_{I}}^{(N)})$$

$$(\overrightarrow{\chi}^{(N)})^{T} = (\chi_{1}^{(N)}, \chi_{2}^{(N)}, \dots, \chi_{L_{I}}^{(N)})$$

- Affine Functions with One Feature

Weighted Sum

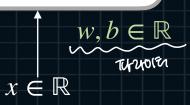
$$z = x\underline{w}$$

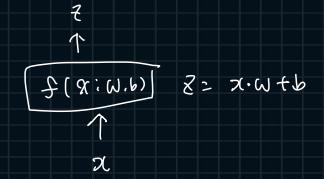
Affine Transformation

$$z = x\underline{w} + \underline{b}$$



f(x; w, b)





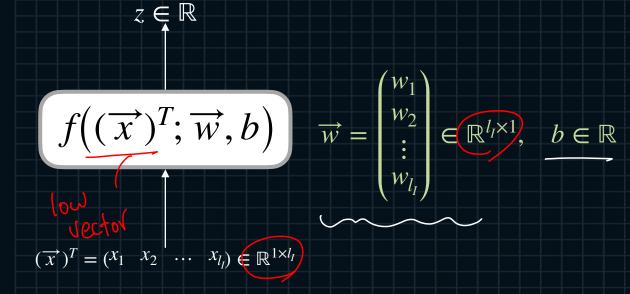
- Affine Functions with n Features

Weighted Sum

Weighted Sum
$$z = w_1 x_1 + w_2 x_2 + \dots + w_n x_n = (\overrightarrow{w})^T \overrightarrow{x} = (\overrightarrow{x})^T \overrightarrow{w}$$
 Affine Transformation

Affine Transformation

$$z = w_1 x_1 + w_2 x_2 + \dots + w_n x_n + b = (\overrightarrow{x})^T \overrightarrow{w} + b$$



- Activation Functions

#activation function

Sigmoid

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

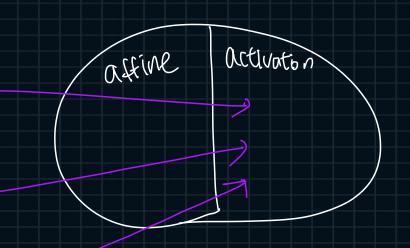
-Tanh

$$g(x) = tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

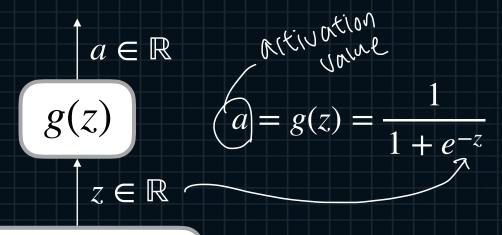
ReLU

$$g(x) = ReLU(x) = max(0, x)$$

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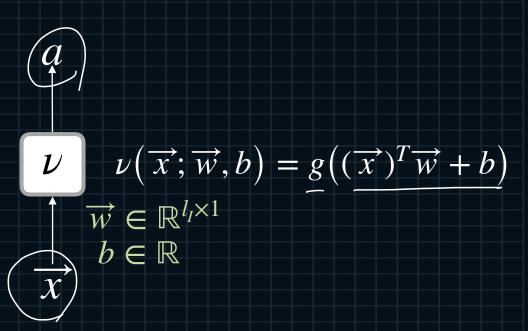
- Artificial Neurons



$$f((\overrightarrow{x})^T; \overrightarrow{w}, b) \qquad z = (\overrightarrow{x})^T \overrightarrow{w} + b$$

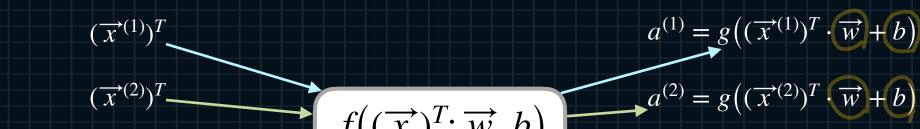
$$\overrightarrow{w} \in \mathbb{R}^{l_l \times 1}$$

$$b \in \mathbb{R}$$



- Minibatch in Artificial Neurons





$$\rightarrow (N) \setminus T$$

$$a^{(N)} = g((\overrightarrow{x}^{(N)})^T \cdot \overrightarrow{w} + b)$$

$$X^{T} = \begin{pmatrix} \longleftarrow & (\overrightarrow{x}^{(1)})^{T} & \longrightarrow \\ \longleftarrow & (\overrightarrow{x}^{(2)})^{T} & \longrightarrow \\ \vdots & & \vdots \\ \longleftarrow & (\overrightarrow{x}^{(N)})^{T} & \longrightarrow \end{pmatrix}$$

$$\boldsymbol{\in} \mathbb{R}^{N \times l_{I}}$$

$$f(X^{T}; \overrightarrow{w}, b) \longrightarrow A = \begin{bmatrix} a^{(1)} \\ a^{(2)} \\ \vdots \\ a^{(N)} \end{bmatrix}$$

$$(\in (x^{(N)})^{T} \longrightarrow A = \begin{bmatrix} a^{(1)} \\ a^{(2)} \\ \vdots \\ a^{(N)} \end{bmatrix}$$

$$\left(\begin{array}{c}
\left(\chi^{(u)}\right)^{T} \\
\left(\chi^{(u)}\right)^{T} \\
\left(\chi^{(u)}\right)^{T}
\end{array}\right)
\left(\begin{array}{c}
W_{1} \\
W_{2} \\
\vdots \\
W_{N}
\end{array}\right)
+ b = \begin{pmatrix}
Q \\
Q \\
\vdots \\
Q
\end{pmatrix}$$

$$\in \mathbb{R}^{N \times 1}$$

- Minibatch in Artificial Neurons

Minibatch Input

Weight/Bias

Affine Function

Activation Function

$$(\overrightarrow{x}^{(1)})^T \in \mathbb{R}^{1 \times l_I}$$

$$(\overrightarrow{x}^{(2)})^T \in \mathbb{R}^{1 \times l_I}$$

$$(\overrightarrow{x}^{(N)})^T \in \mathbb{R}^{1 \times l_I}$$

$$(\overrightarrow{x}^{(1)})^T \in \mathbb{R}^{1 \times l_I}$$

$$(\overrightarrow{x}^{(2)})^T \in \mathbb{R}^{1 \times l_I}$$

$$\vdots$$

$$z^{(1)} = (\overrightarrow{x}^{(1)})^T \cdot \overrightarrow{w} + b$$

$$z^{(1)} = (\overrightarrow{x}^{(1)})^T \cdot \overrightarrow{w} + b$$

$$z^{(2)} = (\overrightarrow{x}^{(2)})^T \cdot \overrightarrow{w} + b$$

$$z^{(2)} = (\overrightarrow{x}^{(2)})^T \cdot \overrightarrow{w} + b$$

$$z^{(2)} = (\overrightarrow{x}^{(2)})^T \cdot \overrightarrow{w} + b$$

$$\vdots$$

$$b \in \mathbb{R}$$

$$z^{(1)} = (\overrightarrow{x}^{(1)})^T \cdot \overrightarrow{w} + b$$

$$z^{(2)} = (\overrightarrow{x}^{(2)})^T \cdot \overrightarrow{w} + b$$

$$z^{(N)} = (\overrightarrow{x}^{(N)})^T \cdot \overrightarrow{w} + \ell$$

$$a^{(1)} = g((\overrightarrow{x}^{(1)})^T \cdot \overrightarrow{w} + b)$$

$$a^{(2)} = g((\overrightarrow{x}^{(2)})^T \cdot \overrightarrow{w} + b)$$

$$z^{(N)} = (\overrightarrow{x}^{(N)})^T \cdot \overrightarrow{w} + b \qquad a^{(N)} = g((\overrightarrow{x}^{(N)})^T \cdot \overrightarrow{w} + b)$$

$$X^{T} = \begin{pmatrix} \longleftarrow & (\overrightarrow{x}^{(1)})^{T} & \longrightarrow \\ \longleftarrow & (\overrightarrow{x}^{(2)})^{T} & \longrightarrow \\ \vdots & & \vdots \\ \longleftarrow & (\overrightarrow{x}^{(N)})^{T} & \longrightarrow \end{pmatrix}$$

$$X^{T} = \begin{pmatrix} \longleftarrow & (\overrightarrow{x}^{(1)})^{I} & \longrightarrow \\ \longleftarrow & (\overrightarrow{x}^{(2)})^{T} & \longrightarrow \\ \vdots & \vdots & \ddots & \vdots \\ \longleftarrow & (\overrightarrow{x}^{(N)})^{T} & \longrightarrow \end{pmatrix} \quad \overrightarrow{z} = X^{T} \overrightarrow{w} + b \quad Z = \begin{pmatrix} z^{(1)} \\ z^{(2)} \\ \vdots \\ z^{(N)} \end{pmatrix}$$

$$\in \mathbb{R}^{N \times l_{I}} \quad \in \mathbb{R}^{N \times 1}$$

$$A = \begin{pmatrix} a^{(1)} \\ a^{(2)} \\ \vdots \\ a^{(N)} \end{pmatrix}$$

$$\in \mathbb{R}^{N \times 1}$$

- Minibatch in Artificial Neurons

$$f(X^{T}; \overrightarrow{w}, b)$$

$$Z \in \mathbb{R}^{N \times 1}$$

$$z \in \mathbb{R}^{l_{l} \times 1}$$

$$b \in \mathbb{R}$$

$$X^{T} \in \mathbb{R}^{N \times l_{l}}$$

$$Z = \begin{cases} g((\overrightarrow{x}^{(1)})^{T} \cdot \overrightarrow{w} + b) \\ g((\overrightarrow{x}^{(2)})^{T} \cdot \overrightarrow{w} + b) \\ (\overrightarrow{x}^{(2)})^{T} \cdot \overrightarrow{w} + b \\ (\overrightarrow{x}^{(2)})^{T} \cdot \overrightarrow{w} + b \\ (\overrightarrow{x}^{(N)})^{T} \cdot \overrightarrow{w} + b \end{cases}$$

$$(\overline{x})^{T}.\overline{w}+b$$

$$x^{T}.\overline{w}+b$$

