

Prig. Remark

cs 245a 021

Lab 07: complete

from-scratch-library

## Objective Function:

where:

$$\Rightarrow J = L + S \quad \frac{\partial J}{\partial L} = 1$$

$$\frac{\partial J}{\partial S} = 1$$

## Linear Layer

$$\Rightarrow \vec{z} = W\vec{x} + \vec{b} \quad (\text{forward propagation})$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial \vec{z}}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial W}, \frac{\partial J}{\partial \vec{b}}, \frac{\partial J}{\partial \vec{x}} \text{ (optional)}$$

$$i) \frac{\partial J}{\partial W} = \text{prod} \left( \frac{\partial J}{\partial \vec{z}}, \frac{\partial \vec{z}}{\partial W} \right) = \frac{\partial J}{\partial \vec{z}} \cdot \vec{x}^T$$

$$ii) \frac{\partial J}{\partial \vec{b}} = \text{prod} \left( \frac{\partial J}{\partial \vec{z}}, \frac{\partial \vec{z}}{\partial \vec{b}} \right) = \frac{\partial J}{\partial \vec{z}} \cdot 1 = \frac{\partial J}{\partial \vec{z}}$$

$$iii) \frac{\partial J}{\partial \vec{x}} = \text{prod} \left( \frac{\partial J}{\partial \vec{z}}, \frac{\partial \vec{z}}{\partial \vec{x}} \right) = \frac{\partial J}{\partial \vec{z}} \cdot W$$

EXAMPLE:

Given:

$$\vec{x} = \begin{bmatrix} 2 \\ 10 \\ 5 \end{bmatrix}_{2 \times 1}, \quad W = \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3}, \quad \vec{b} = \begin{bmatrix} 4 \\ 9 \end{bmatrix}_{2 \times 1}$$

$$\text{Assume: } \frac{\partial J}{\partial \vec{z}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{2 \times 1}$$

then:

(option-1)

$$\frac{\partial J}{\partial \vec{z}} = \frac{\partial J}{\partial \vec{z}} \cdot W$$

$$= W^T \cdot \frac{\partial J}{\partial \vec{z}}$$

$$= \begin{bmatrix} 1 & 3 \\ 2 & 5 \\ 7 & 4 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{2 \times 1} = \begin{bmatrix} (1)(1) + (3)(1) \\ (2)(1) + (5)(1) \\ (7)(1) + (4)(1) \end{bmatrix}_{3 \times 1}$$

$$\frac{\partial J}{\partial \vec{z}} = \begin{bmatrix} 4 \\ 7 \\ 11 \end{bmatrix}$$

$$\frac{\partial J}{\partial W} = \frac{\partial J}{\partial \vec{z}} \cdot \vec{x}^T$$

$$= \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{2 \times 1} \cdot \begin{bmatrix} 2 & 10 & 5 \end{bmatrix}_{1 \times 3} = \begin{bmatrix} (1)(2) & (1)(10) & (1)(5) \\ (1)(2) & (1)(10) & (1)(5) \end{bmatrix}$$

$$\frac{\partial J}{\partial W} = \begin{bmatrix} 2 & 10 & 5 \\ 2 & 10 & 5 \end{bmatrix}_{2 \times 3}$$

$$\frac{\partial J}{\partial \vec{b}} = \frac{\partial J}{\partial \vec{z}}$$

$$\frac{\partial J}{\partial \vec{b}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{2 \times 1}$$

step 1: GRADIENT DESCENT

Let  $\alpha = 0.1$

$$W^* = W - \alpha \frac{\partial J}{\partial W}$$

$$= \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3} - 0.1 \cdot \begin{bmatrix} 2 & 10 & 5 \\ 2 & 10 & 5 \end{bmatrix}_{2 \times 3}$$

$$= \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix} - \begin{bmatrix} 0.2 & 1.0 & 0.5 \\ 0.2 & 1.0 & 0.5 \end{bmatrix}$$

$$W^* = \begin{bmatrix} 0.8 & 4.0 & 6.5 \\ 2.8 & 1.0 & 3.5 \end{bmatrix}_{2 \times 3}$$

$$b^* = \vec{b} - \alpha \frac{\partial J}{\partial \vec{b}}$$

$$= \begin{bmatrix} 4 \\ 9 \end{bmatrix}_{2 \times 1} - 0.1 \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix}_{2 \times 1}$$

$$= \begin{bmatrix} 4 \\ 9 \end{bmatrix} - \begin{bmatrix} 0.1 \\ 0.1 \end{bmatrix}$$

$$b^* = \begin{bmatrix} 3.9 \\ 8.9 \end{bmatrix}_{2 \times 1}$$

## ReLU Layer

$$\Rightarrow \vec{h} = \text{relu}(\vec{v}) \quad (\text{forward propagation})$$

where:

$$\text{relu}(v_i) = \begin{cases} v_i, & \text{if } v_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial \vec{h}}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial \vec{v}}$$

$$\frac{\partial J}{\partial \vec{v}} = \text{prod} \left( \frac{\partial J}{\partial \vec{h}}, \frac{\partial \vec{h}}{\partial \vec{v}} \right) = \frac{\partial J}{\partial \vec{h}} \odot \text{relu}'(\vec{v})$$

where:

$$\text{relu}'(v_i) = \begin{cases} 1, & \text{if } v_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

EXAMPLE:

Given:

Assume:

$$\vec{v} = \begin{bmatrix} -4 \\ 10 \\ 5 \end{bmatrix}_{3 \times 1}, \quad \frac{\partial J}{\partial \vec{h}} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}_{3 \times 1}$$

then:

$$\frac{\partial J}{\partial \vec{v}} = \frac{\partial J}{\partial \vec{h}} \odot \text{relu}'(\vec{v}) = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \odot \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \rightarrow \begin{matrix} \text{relu}'(-4) \\ \text{relu}'(10) \\ \text{relu}'(5) \end{matrix}$$

$$\frac{\partial J}{\partial \vec{v}} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}_{3 \times 1}$$

## Regularization Layer

$$\Rightarrow S = \lambda \|W\|_F^2$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial S}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial W}$$

$$\frac{\partial J}{\partial W} = \text{prod} \left( \frac{\partial J}{\partial S}, \frac{\partial S}{\partial W} \right) = \frac{\partial J}{\partial S} \cdot \lambda W$$

EXAMPLE:

Given:

Assume:

$$W = \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3}, \quad \lambda = 0.1$$

$$\text{Assume: } \frac{\partial J}{\partial S} = 1 \quad (\text{scalar})$$

then:

$$\frac{\partial J}{\partial W} = \frac{\partial J}{\partial S} \cdot \lambda W$$

$$= 1 \cdot (0.1) \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}$$

$$\frac{\partial J}{\partial W} = \begin{bmatrix} 0.1 & 0.5 & 0.7 \\ 0.3 & 0.2 & 0.4 \end{bmatrix}_{2 \times 3}$$

## Sum Layer

$$\Rightarrow K = s_1 + s_2 \quad (\text{forward propagation})$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial K}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial s_1}, \frac{\partial J}{\partial s_2}$$

$$\frac{\partial J}{\partial s_1} = \text{prod} \left( \frac{\partial J}{\partial K}, \frac{\partial K}{\partial s_1} \right) = \frac{\partial J}{\partial K}$$

$$\frac{\partial J}{\partial s_2} = \text{prod} \left( \frac{\partial J}{\partial K}, \frac{\partial K}{\partial s_2} \right) = \frac{\partial J}{\partial K}$$

EXAMPLE:

Given:

Assume:

$$s_1 = 50, \quad s_2 = 5, \quad \frac{\partial J}{\partial K} = 1$$

then:

$$\frac{\partial J}{\partial s_1} = \frac{\partial J}{\partial K} \cdot \frac{\partial K}{\partial s_1}, \quad \frac{\partial J}{\partial s_2} = \frac{\partial J}{\partial K} \cdot \frac{\partial K}{\partial s_2}$$

$$= 1 \cdot 1, \quad = 1 \cdot 1$$

$$\frac{\partial J}{\partial s_1} = 1$$

$$\frac{\partial J}{\partial s_2} = 1$$

## L2 Loss Layer

$$\Rightarrow L = \frac{1}{2} \|\vec{o} - \vec{y}\|_2^2 \quad (\text{forward propagation})$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial \vec{h}}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial \vec{o}}$$

$$\frac{\partial J}{\partial \vec{o}} = \text{prod} \left( \frac{\partial J}{\partial \vec{h}}, \frac{\partial \vec{h}}{\partial \vec{o}} \right) = \frac{\partial J}{\partial \vec{h}} \cdot (\vec{o} - \vec{y})$$

EXAMPLE:

Given:

Assume:

$$\vec{o} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}_{2 \times 1}, \quad \vec{y} = \begin{bmatrix} 11 \\ 5 \end{bmatrix}_{2 \times 1}, \quad \frac{\partial J}{\partial \vec{h}} = 1$$

then:

$$\frac{\partial J}{\partial \vec{o}} = \frac{\partial J}{\partial \vec{h}} \cdot (\vec{o} - \vec{y})$$

$$= 1 \cdot \begin{bmatrix} 10 \\ 5 \end{bmatrix} - \begin{bmatrix} 11 \\ 5 \end{bmatrix}$$

$$\frac{\partial J}{\partial \vec{o}} = \begin{bmatrix} -1 \\ 0 \end{bmatrix}_{2 \times 1}$$

## Softmax (+ cross-entropy) Layer

$$\Rightarrow \vec{o} = \text{softmax}(\vec{v}) \quad (\text{forward propagation})$$

$$L = \text{cross-entropy-loss}(\vec{o})$$

Backpropagation:

$$\rightarrow \text{lin: } \frac{\partial J}{\partial \vec{h}}$$

$$\rightarrow \text{goal: } \frac{\partial J}{\partial \vec{o}}$$

$$\frac{\partial J}{\partial \vec{o}} = \text{prod} \left( \frac{\partial J}{\partial \vec{h}}, \frac{\partial \vec{h}}{\partial \vec{o}} \right) = \frac{\partial J}{\partial \vec{h}} \cdot (\vec{o} - \vec{y})$$

EXAMPLE:

Given:

Assume:

$$\vec{v} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}_{2 \times 1}, \quad \vec{y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}_{2 \times 1}, \quad \frac{\partial J}{\partial \vec{h}} = 1$$

then:

→ here to calculate softmax of  $\vec{v}$  to get  $\vec{o}$

how I set up my tests

$$\vec{o} = \text{softmax}(\vec{v}) = \text{softmax} \left( \begin{bmatrix} 10 \\ 5 \end{bmatrix} \right)$$

$$\text{softmax}(10) = \frac{e^{10-10}}{e^{10-10} + e^{5-10}} = \frac{1}{1+e^{-5}} = \underline{0.985}$$

$$\text{softmax}(5) = \frac{e^{5-10}}{e^{10-10} + e^{5-10}} = \frac{e^{-5}}{1+e^{-5}} = \underline{0.007}$$

$$\vec{o} = \begin{bmatrix} 0.985 \\ 0.007 \end{bmatrix}_{2 \times 1} \quad \leftarrow \text{use for backprop}$$

$$\frac{\partial J}{\partial \vec{o}} = \frac{\partial J}{\partial \vec{h}} \cdot (\vec{o} - \vec{y})$$

$$= 1 \cdot \begin{bmatrix} 0.985 \\ 0.007 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\frac{\partial J}{\partial \vec{o}} = \begin{bmatrix} -0.007 \\ 0.007 \end{bmatrix}_{2 \times 1}$$

## ① LINEAR LAYER

where:

$$\vec{u} = W\vec{x} + \vec{b}$$

$$W \in \mathbb{R}^{m \times n}$$

$$\vec{x} \in \mathbb{R}^{n \times 1}$$

$$\vec{b}, \vec{u} \in \mathbb{R}^{m \times 1}$$

EXAMPLE:

$$W = \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3}, \quad \vec{x} = \begin{bmatrix} 2 \\ 10 \\ 5 \end{bmatrix}_{3 \times 1}$$

$$\vec{b} = \begin{bmatrix} 4 \\ 8 \end{bmatrix}_{2 \times 1}$$

$$\vec{u} = \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3} \begin{bmatrix} 2 \\ 10 \\ 5 \end{bmatrix}_{3 \times 1} + \begin{bmatrix} 4 \\ 8 \end{bmatrix}_{2 \times 1}$$

$$= \begin{bmatrix} (1)(2) + (5)(10) + (7)(5) \\ (3)(2) + (2)(10) + (4)(5) \end{bmatrix} + \begin{bmatrix} 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 87 \\ 46 \end{bmatrix} + \begin{bmatrix} 4 \\ 8 \end{bmatrix}$$

$$\boxed{\vec{u} = \begin{bmatrix} 91 \\ 54 \end{bmatrix}_{2 \times 1}}$$

## ② RELU LAYER

where:

$$\vec{h} = \text{ReLU}(\vec{u})$$

$$\vec{h}, \vec{u} \in \mathbb{R}^{m \times 1}$$

NOTE:

$$\text{ReLU}(u_i) = \begin{cases} u_i, & \text{if } u_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

EXAMPLE:

$$\vec{u} = \begin{bmatrix} -4 \\ 10 \\ 5 \end{bmatrix}_{3 \times 1}$$

$$\vec{h} = \text{ReLU}(\vec{u})$$

$$= \text{ReLU} \left( \begin{bmatrix} -4 \\ 10 \\ 5 \end{bmatrix} \right)$$

$$\text{ReLU}(-4) = 0$$

$$\text{ReLU}(10) = 10$$

$$\text{ReLU}(5) = 5$$

$$\boxed{\vec{h} = \begin{bmatrix} 0 \\ 10 \\ 5 \end{bmatrix}_{3 \times 1}}$$

## ③ REGULARIZATION LAYER

$$S = \frac{\lambda}{2} \|W\|_F^2$$

where:

$$= \frac{\lambda}{2} \sum_{i=1}^m \sum_{j=1}^n (w_{ij})^2$$

$$W \in \mathbb{R}^{m \times n}$$

$$\lambda, S \in \mathbb{R}$$

EXAMPLE:

$$W = \begin{bmatrix} 1 & 5 & 7 \\ 3 & 2 & 4 \end{bmatrix}_{2 \times 3}, \quad \lambda = 0.1$$

$$S = \frac{\lambda}{2} \|W\|_F^2$$

$$= \frac{0.1}{2} (1)^2 + (5)^2 + (7)^2 + (3)^2 + (2)^2 + (4)^2$$

$$= \frac{0.1}{2} (104)$$

$$= 0.05 (104)$$

$$\boxed{S = 5.2}$$

## ④ SUM LAYER

$$s = s_1 + s_2$$

where:

$$s, s_1, s_2 \in \mathbb{R}$$

EXAMPLE:

$$s_1 = 50 \quad s_2 = 5$$

$$s = 50 + 5$$

$$\boxed{s = 55}$$

## ⑤ L<sub>2</sub> LOSS LAYER (MSE)

$$L = \frac{1}{2} \|\vec{o} - \vec{y}\|_2^2$$

where:

$$= \frac{1}{2} [(o_1 - y_1)^2 + \dots + (o_m - y_m)^2]$$

$$\vec{o}, \vec{y} \in \mathbb{R}^{m \times 1}$$

$$L \in \mathbb{R}$$

EXAMPLE

$$\vec{o} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}_{2 \times 1}$$

$$\vec{y} = \begin{bmatrix} 11 \\ 5 \end{bmatrix}_{2 \times 1}$$

$$L = \frac{1}{2} \left\| \begin{bmatrix} 10 \\ 5 \end{bmatrix} - \begin{bmatrix} 11 \\ 5 \end{bmatrix} \right\|_2^2$$

$$= \frac{1}{2} \cdot [(10-11)^2 + (5-5)^2]$$

$$= \frac{1}{2} (1+0)$$

$$\boxed{L = 0.5}$$

## ⑥ SOFTMAX LAYER

$$\vec{o} = \text{softmax}(\vec{v})$$

where:

$$\vec{o}, \vec{v} \in \mathbb{R}^{d \times 1}$$

NOTE:

$$\text{softmax}(v_i) = \frac{e^{(v_i - \max(\vec{v}))}}{\sum_{j=1}^d e^{(v_j - \max(\vec{v}))}}$$

! cross-entropy loss: L

$$L = \text{CE}(\vec{o}, \vec{y}) = -\frac{1}{N} \sum_{j=1}^d (y_j \cdot \log(o_j))$$

EXAMPLE

$$\vec{v} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}_{2 \times 1}$$

softmax:

$$\vec{o} = \text{softmax}(\vec{v})$$

where:

$$\text{softmax}(v_i) = \frac{e^{(v_i - \max(\vec{v}))}}{\sum_{j=1}^d e^{(v_j - \max(\vec{v}))}}$$

$$\vec{o} = \text{softmax} \left( \begin{bmatrix} 10 \\ 5 \end{bmatrix} \right)$$

$$\text{softmax}(10) = \frac{e^{10-10}}{e^{10-10} + e^{5-10}} = \frac{1}{1 + e^{-5}} = \underline{0.993}$$

$$\text{softmax}(5) = \frac{e^{5-10}}{e^{10-10} + e^{5-10}} = \frac{e^{-5}}{1 + e^{-5}} = \underline{0.007}$$

$$\boxed{\vec{o} = \begin{bmatrix} 0.993 \\ 0.007 \end{bmatrix}_{2 \times 1}}$$

check:

→ should sum to 1

$$0.993 + 0.007 = 1 \checkmark$$

cross-entropy loss:

$$\vec{o} = \begin{bmatrix} 0.993 \\ 0.007 \end{bmatrix}_{2 \times 1}, \quad \vec{y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}_{2 \times 1}$$

$$L = \text{CE}(\vec{o}, \vec{y}) = -\frac{1}{N} \sum_{j=1}^d (y_j \cdot \log(o_j))$$

$$= -\frac{1}{2} \sum_{j=1}^2 y_j \cdot \log(o_j)$$

$$= -\frac{1}{2} [(1) \cdot \log(0.993) + (0) \cdot \log(0.007)]$$

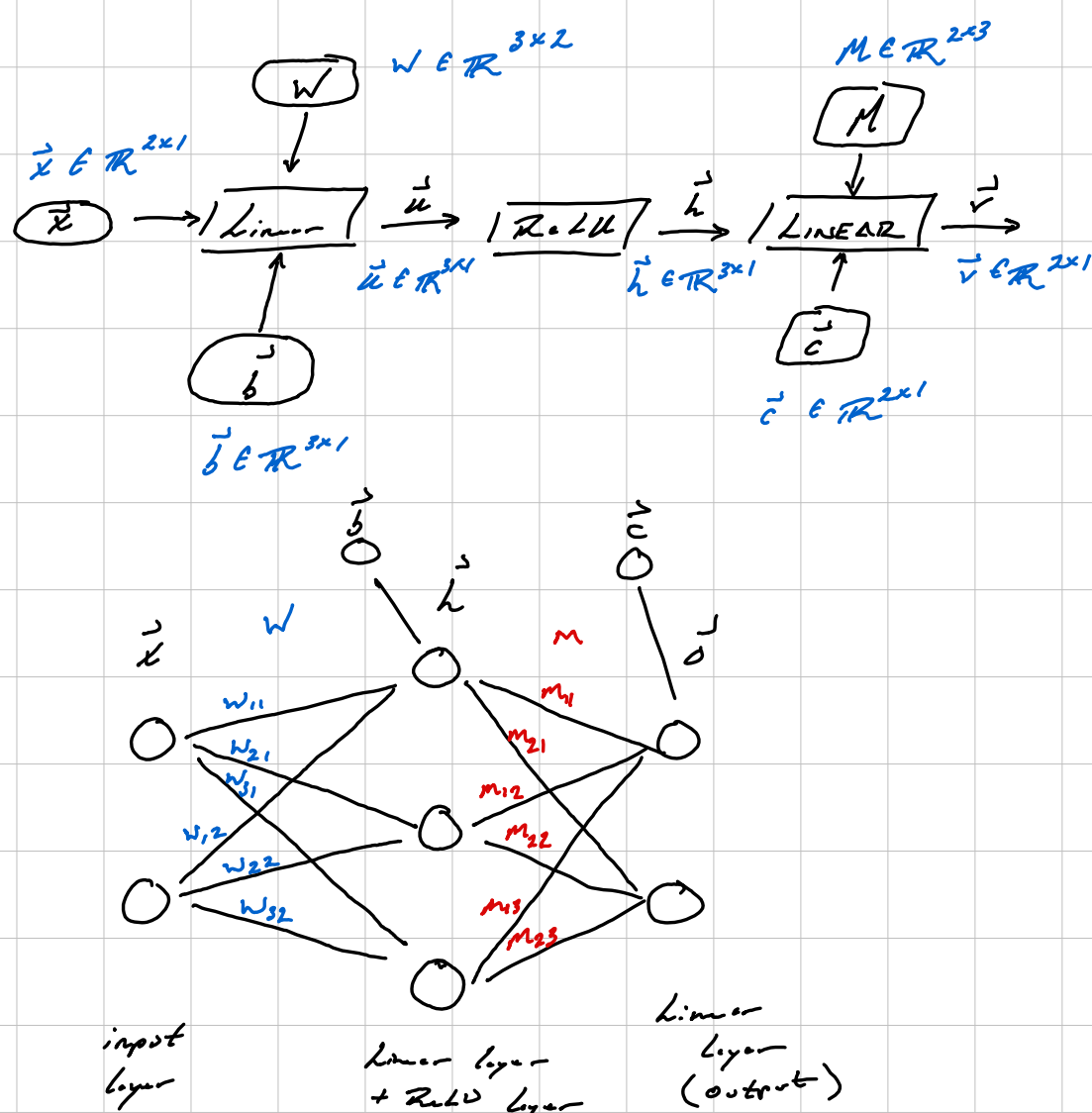
$$= -\frac{1}{2} [-0.00472] = \underline{0.00236}$$

NOTE:

$$\log \rightarrow \ln$$

# FORWARD PROPAGATIONS FULL NETWORK

network :



Given :

$$\vec{x} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}_{2 \times 1}, \quad W = \begin{bmatrix} 1 & 2 \\ 2 & 5 \\ 7 & 3 \end{bmatrix}_{3 \times 2}, \quad \vec{b} = \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix}_{3 \times 1}$$

$$\vec{c} = \begin{bmatrix} 5 \\ 1 \end{bmatrix}_{2 \times 1}, \quad M = \begin{bmatrix} 4 & 1 & 2 \\ 3 & 4 & 1 \end{bmatrix}_{2 \times 3}$$

(1) Linear Layer (hidden layer)

$$\vec{z} = W\vec{x} + \vec{b}$$

$$\vec{z} = \begin{bmatrix} 1 & 2 \\ 2 & 5 \\ 7 & 3 \end{bmatrix} \begin{bmatrix} 10 \\ 5 \end{bmatrix} + \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} (1)(10) + (2)(5) \\ (2)(10) + (5)(5) \\ (7)(10) + (3)(5) \end{bmatrix}_{3 \times 1} + \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix}_{3 \times 1}$$

$$= \begin{bmatrix} 20 \\ 45 \\ 85 \end{bmatrix} + \begin{bmatrix} 4 \\ 2 \\ 1 \end{bmatrix}$$

$$\vec{z} = \begin{bmatrix} 24 \\ 47 \\ 86 \end{bmatrix}_{3 \times 1}$$

ReLU :

$$\vec{h} = \text{ReLU}(\vec{z})$$

$$= \text{ReLU} \left( \begin{bmatrix} 24 \\ 47 \\ 86 \end{bmatrix} \right)$$

$$\text{ReLU}(24) = 24$$

$$\text{ReLU}(47) = 47$$

$$\text{ReLU}(86) = 86$$

$$\vec{h} = \begin{bmatrix} 24 \\ 47 \\ 86 \end{bmatrix}_{3 \times 1}$$

(2) Linear Layer (output layer)

$$\vec{o} = M\vec{h} + \vec{c}$$

$$\vec{o} = \begin{bmatrix} 4 & 1 & 2 \\ 3 & 4 & 1 \end{bmatrix} \begin{bmatrix} 24 \\ 47 \\ 86 \end{bmatrix} + \begin{bmatrix} 5 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} (4)(24) + (1)(47) + (2)(86) \\ (3)(24) + (4)(47) + (1)(86) \end{bmatrix} + \begin{bmatrix} 5 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 315 \\ 440 \end{bmatrix} + \begin{bmatrix} 5 \\ 1 \end{bmatrix}$$

$$\vec{o} = \begin{bmatrix} 320 \\ 441 \end{bmatrix}_{2 \times 1}$$