

T1. Compute the forward and backward pass of the following computation. Note that this is a simplified residual connection.

$$\begin{aligned}x_1 &= \text{ReLU}(x_0 * w_0 + b_0) \\y_1 &= x_1 * w_1 + b_1 \\z &= \text{ReLU}(y_1 + x_0)\end{aligned}$$

Let $x_0 = 1.0$, $w_0 = 0.3$, $w_1 = -0.2$, $b_0 = 0.1$, $b_1 = -0.3$. Find the gradient of z with respect to w_0 , w_1 , b_0 , and b_1 .

$$x_0 = 1.0 \quad w_0 = 0.3 \quad w_1 = -0.2 \quad b_0 = 0.1 \quad b_1 = -0.3$$

$$x_1 = \text{ReLU}(x_0 * w_0 + b_0)$$

$$= \text{ReLU}(1.0 * 0.3 + 0.1)$$

$$= \text{ReLU}(0.4)$$

$$= 0.4.$$

$$\begin{aligned}\frac{\partial z}{\partial w_0} &= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{dy_1}{dw_0} \\&= \text{ReLU}'(y_1 + x_0) \cdot \frac{d(x_0 * w_1 + b_1)}{dw_0} \\&= \text{ReLU}'(y_1 + x_0) \cdot w_1 \frac{d}{dw_0} \text{ReLU}(x_0 * w_0 + b_0). \\&= \text{ReLU}'(y_1 + x_0) \cdot w_1 \text{ReLU}'(x_0 * w_0 + b_0) x_0 \\&= (1)(-0.2)(1)(1.0) \\&= -0.2.\end{aligned}$$

$$\begin{aligned}\frac{\partial z}{\partial w_1} &= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{dy_1}{dw_1} \\&= \text{ReLU}'(y_1 + x_0) \cdot \frac{d(x_0 * w_1 + b_1)}{dw_1} \\&= \text{ReLU}'(y_1 + x_0) x_1 \\&= (1)(0.4) \\&= 0.4.\end{aligned}$$

$$\begin{aligned}y_1 &= x_1 * w_1 + b_1 \\&= (0.4)(-0.2) + 0.1 \\&= -0.7\end{aligned}$$

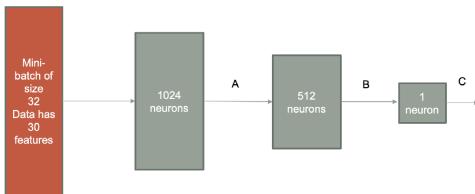
$$\begin{aligned}z &= \text{ReLU}(y_1 + x_0) \\&= \text{ReLU}(-0.7 + 1.0) \\&= \text{ReLU}(0.3) \\&= 0.3.\end{aligned}$$

$$\begin{aligned}\frac{\partial z}{\partial b_0} &= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{dy_1}{db_0} \\&= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{d(x_0 * w_1 + b_1)}{db_0} \\&= \text{ReLU}'(y_1 + x_0) w_1 \frac{d}{db_0} \text{ReLU}(x_0 * w_0 + b_0). \\&= \text{ReLU}'(y_1 + x_0) w_1 \text{ReLU}'(x_0 * w_0 + b_0) \\&= (1)(0.2)(1) \\&= 0.2.\end{aligned}$$

$$\begin{aligned}\frac{\partial z}{\partial b_1} &= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{dy_1}{db_1} \\&= \frac{d}{d} \text{ReLU}(y_1 + x_0) \frac{d(x_0 * w_1 + b_1)}{db_1} \\&= \text{ReLU}'(y_1 + x_0)\end{aligned}$$

$$= 1.$$

T2. Given the following network architecture specifications, determine the size of the output A, B, and C.



Minibatch's dimension 80×32

A^1 's dimension 1024×32 .

B^1 's dimension 512×32 .

C^1 's dimension 1×32 .

T3. What is the total number of learnable parameters in this network?
(Don't forget the bias term)

กำหนดให้ M_A, M_B, M_C คือ Matrix ที่ transform input ไปเป็น Output A, B, C ตามลำดับ.

แล้ว b_A, b_B, b_C คือ กำหนดค่า bias ที่ใช้ในการบวกกับผลลัพธ์ของ matrix ที่ transform ไปเป็น Output A, B, C ตามลำดับ.

M_A มี Dimension 30×1024 b_A มี Dimension 1024×1

M_B มี Dimension 1024×512 b_B มี Dimension 512×1

M_C มี Dimension 512×1 b_C มี Dimension 1×1

\therefore จำนวน Network ที่มีจำนวน Learnable Parameters ทั้งหมด 357,057 ตัว.

T4. Prove that the derivative of the loss with respect to h_i is $P(y=i) - y_i$.
 In other words, find $\frac{\partial L}{\partial h_i}$ for $i \in \{0, \dots, N-1\}$ where N is the number of classes.

$$\begin{aligned}
 L &= -\sum_j y_j \log P(y=j). \\
 &= -\sum_j y_j \log \frac{\exp(h_j)}{\sum_k \exp(h_k)}. \\
 &= -\sum_j [y_j \log \exp(h_j) - \log \sum_k \exp(h_k)]. \\
 &= -\sum_j [y_i h_i - \log \sum_k \exp(h_k)]
 \end{aligned}$$

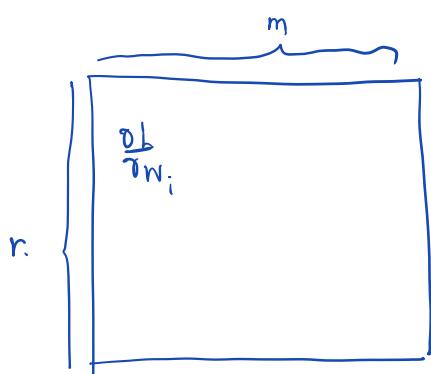
$$\begin{aligned}
 \frac{\partial L}{\partial h_i} &= -\frac{\partial}{\partial h_i} \sum_j [y_j h_j - \log \sum_k \exp(h_k)]. \\
 &= -[y_i - \frac{\partial}{\partial h_i} \log \sum_k \exp(h_k)]. \\
 &= -[y_i - \frac{\partial \log \sum_k \exp(h_k)}{\partial \sum_k \exp(h_k)} \frac{\partial \sum_k \exp(h_k)}{\partial h_i}] \\
 &= -[y_i - \frac{\exp(h_i)}{\sum_k \exp(h_k)}]. \\
 &= \frac{\exp(h_i)}{\sum_k \exp(h_k)} - y_i \\
 &= P(y=i) - y_i
 \end{aligned}$$

Gradient

$$L = -\sum_j \sum_i \underbrace{y_{ji} \log(P_j=1)}_D + \frac{\lambda}{2} \sum_i w_i^2$$

$$Y = \begin{bmatrix} \\ \vdots \\ N \end{bmatrix}$$

w_1 $n = \# \text{input}$ $m = \# \text{neuron}$



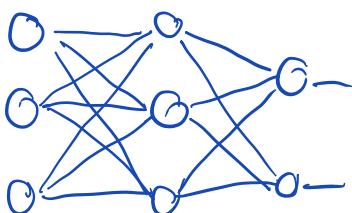
$$\frac{\partial L}{\partial w_i}$$

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

$$w_1 \in \mathbb{R}^{D \times H}$$

$$x_1 = Xw_1 + b \in \mathbb{R}^H$$

$$x_2 = x_1 w_2 + b \in \mathbb{R}^C$$



Sigmoid

$$P(X_j=1) = \frac{e^{w_2 x_2 + b_2}}{\sum e^{w_2 x_2 + b_2}}$$

$$h = w_2 x_2 + b_2$$

$$\frac{\partial L}{\partial h} \cdot \frac{\partial h}{\partial w_2}$$

$$P(X_j=1) = \dots \in \mathbb{R}^C$$

$$\frac{\partial L}{\partial h} = \begin{bmatrix} \frac{\partial L}{\partial h_{i1}} & \frac{\partial L}{\partial h_{i2}} & \frac{\partial L}{\partial h_{i3}} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \end{bmatrix}_{N^x C} = \begin{bmatrix} P(y_{i1}=1) - y_{i1} & P(y_{i2}=2) - y_{i2} & P(y_{i3}=1) - y_{i3} \end{bmatrix}$$

$$\frac{\partial L_2}{\partial w_1} = \begin{bmatrix} \frac{\partial L_2}{\partial w_1} \\ \vdots \end{bmatrix}_{D^x H} \quad \frac{\partial L_2}{\partial w_2} = \begin{bmatrix} \frac{\partial L_2}{\partial w_2} \\ \vdots \end{bmatrix}_{H^x C.}$$

$$h = x_1 w_2 + b_2$$

$$\frac{\partial h}{\partial w_2} = \begin{bmatrix} x_1 & \dots & \dots & \dots \\ \vdots & & & \end{bmatrix}_{N^x H.}$$

$$\frac{\partial h}{\partial b_2} = \begin{bmatrix} 1 & \dots & \dots & \dots \\ \vdots & & & \end{bmatrix}_{N^x 1.}$$

$$x_1 = \text{ReLU}(x_1 w_1 + b_1) \text{ and } x' = \text{ReLU}(x_1 w_1 + b_1)$$

$$\frac{d x_1}{d w_1} = \begin{cases} \text{is more than } (x_1 w_1) & \dots \\ \dots & \dots \end{cases} \quad \frac{d h}{d x_1} = \begin{bmatrix} w_2 & \dots & \dots \\ \vdots & & \end{bmatrix}_{H^x C.}$$

$$\frac{d x_1}{d b_1} = \begin{cases} \text{is more than } 0 (x_1) & \dots \\ \dots & \dots \end{cases} \quad \frac{d H}{d x_1} = \begin{bmatrix} x_1 & \dots & \dots \\ \vdots & & \end{bmatrix}_{N^x H.}$$

$$L = - \sum_j \sum_i y_{ji} \log(P_{j,i}) + \frac{\lambda}{2} \sum_i w_i^2$$

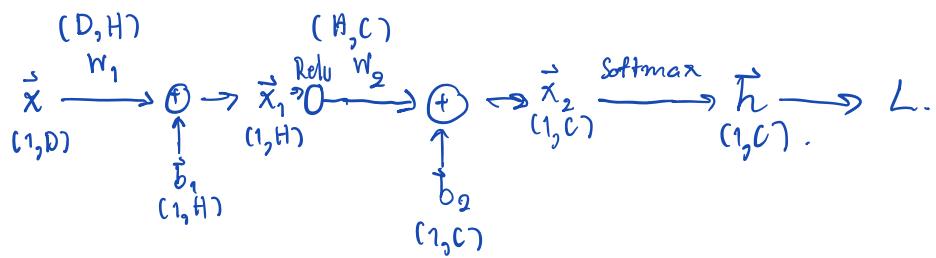
$$= - \sum_j \sum_i y_{ji} (\log \exp(h_{ji}) - \log \sum_i \exp(h_{ji})) + \frac{\lambda}{2} \sum_i w_i^2$$

$$h = x_1 w_2 + b_2$$

$$x_1 = x w_1 + b_1$$

$$\frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial w_2}$$

$$\frac{\partial L}{\partial w_2}_{ij} = \frac{\partial L}{\partial h} \frac{\partial h}{\partial w_2}_{ij}$$



$$\frac{\partial L}{\partial b_{2i}} = \frac{\partial L}{\partial \vec{h}} \frac{\partial \vec{h}}{\partial \vec{z}_2} \frac{\partial \vec{z}_2}{\partial b_{2i}}$$

$$\frac{\partial L}{\partial \vec{h}}$$

$$\begin{aligned} L &= -\sum_j y_j \log(P_j = i) + \frac{\lambda}{2} \sum_i w_i^2 \\ &= -\sum_i y_j \log h + \frac{\lambda}{2} \sum_i w_i^2 \end{aligned}$$

$$h = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

$$\frac{\partial L}{\partial \vec{h}} = \begin{bmatrix} -\frac{y_1}{h_1} & -\frac{y_2}{h_2} & -\frac{y_3}{h_3} \end{bmatrix}.$$

$$\frac{\partial L}{\partial w_{2i}} = \frac{\partial L}{\partial \vec{h}} \frac{\partial \vec{h}}{\partial \vec{z}_2} \frac{\partial \vec{z}_2}{\partial w_{2i}}$$

$$\vec{z}_2 = \underbrace{\vec{x}_1 w_1 + \vec{b}}_{\text{1H HC. 1C}} \quad \underbrace{\begin{bmatrix} w_{11} \\ w_1 \\ \vdots \\ w_{1H} \end{bmatrix}}_{\text{H}}$$

$$\begin{aligned} \nabla_{w_{ij}}(\vec{z}_2) &= \begin{bmatrix} 0 & 0 & 0 & x & 0 & 0 & 0 & 0 \end{bmatrix}. \\ &\quad \downarrow i \quad \downarrow j \quad \downarrow C \end{aligned}$$

$$\frac{\partial L}{\partial h_j} = \begin{bmatrix} P(y=1) - y_1 & P(y=2) - y_2 & P(y=3) - y_3 \\ \vdots & \vdots & \vdots \end{bmatrix},$$

C^k 1.

$$\frac{\partial \vec{h}}{\partial \vec{x}_2} = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \dots & \frac{\partial h_1}{\partial x_c} \\ \vdots & \vdots & \vdots \\ \frac{\partial h_c}{\partial x_1} & \dots & \frac{\partial h_c}{\partial x_c} \end{bmatrix} = \frac{\partial e^{x_1}}{\partial x_1} \cdot \frac{\sum e^{x_i} e^{x_1} - e^{x_1} e^{x_1}}{(\sum e^{x_i})^2} = \frac{\partial e^{x_1}}{\partial x_2} = \frac{-e^{x_1} e^{x_2}}{(\sum e^{x_i})^2}$$

$$\frac{\partial \vec{x}_2}{\partial b_{2i}} = \begin{bmatrix} 1 & 0 & \dots \end{bmatrix} \quad x_2 = \vec{x}_1 w_2 + \vec{b}_2$$

$b_{21} \quad b_{22} \quad b_{23}$

$$\frac{\partial L}{\partial h} = \frac{1}{N} \sum_j \frac{\partial L_j}{\partial b_{2i}}$$

$$\begin{matrix} \vec{x}_1 & \dots & \vec{x}_c \\ b_1 & & b_c \end{matrix} \quad \begin{matrix} x_1 \\ b_1 \\ \vdots \\ b_c \end{matrix}$$

$$\frac{\partial L_j}{\partial x_{2i}} = \frac{\partial \vec{x}_2}{\partial x_{2i}} \cdot \frac{\partial \vec{h}}{\partial \vec{x}_2} \cdot \frac{\partial L_j}{\partial h}$$

x_2
 b_1

(1xC) (CxC) (Cx1).

$$\frac{\partial L}{\partial x_{1i}} = \frac{\partial L}{\partial h} \cdot \frac{\partial h}{\partial \vec{x}_2} \cdot \frac{\partial \vec{x}_2}{\partial x_{1i}}$$

$$\begin{matrix} \frac{\partial x_{11}}{\partial x_{21}} \\ \frac{\partial x_{11}}{\partial x_{22}} \\ \vdots \\ \frac{\partial x_{11}}{\partial x_{2c}} \end{matrix} \quad \begin{matrix} x_c \\ b_1 \\ \vdots \\ b_c \end{matrix}$$

(1xH^Tdim) (1xC) (CxC) (C, 1)

$$\frac{\partial L}{\partial b_{2i}} = \frac{\partial L}{\partial \vec{x}_1} \cdot \frac{\partial \vec{x}_1}{\partial b_{1i}}$$

1xH^TH^T1.

$$L = -\sum_j y_j \log P(y=j) \quad (2)$$

where y_j is 1 if y is class j , and 0 otherwise.

$$\frac{\partial L}{\partial b_2} = \frac{\partial h}{\partial b_2} \frac{\partial L}{\partial h}$$

$$h = [- \dots - \dots] \quad h \in N^C \quad L \in \mathbb{R}$$

$$b \in N^C \quad h \in N^C$$

$$L = -\sum_i^c y_i \log P(X_i=j) + \frac{\lambda}{2} \sum_k w_k^2$$

$$L = L_1 + L_2$$

$$\frac{\partial L}{\partial b_{2i}} = \frac{\partial L}{\partial h} \cdot \frac{\partial h}{\partial b_{2i}} \quad 1^C$$

$$= \frac{\partial \vec{x}_2}{\partial b_{2i}} \frac{\partial h}{\partial \vec{x}_2} \cdot \frac{\partial L}{\partial h}$$

$$N^C \times C \quad C^C \quad C^C \quad C^1 \quad \vec{x}_2 = \text{ReLU}(\vec{y}_2)$$

$$\frac{\partial L}{\partial b_{2i}} = \frac{1}{N} \sum_j \frac{\partial L}{\partial b_{2i}}$$

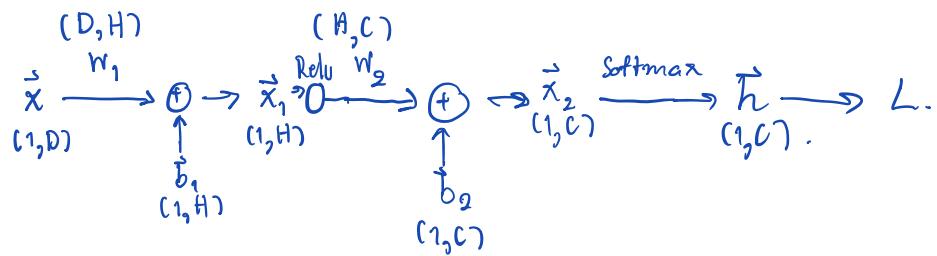
$$\vec{x}_2 = \text{ReLU}(x_1 w_2 + b_2) \quad \begin{bmatrix} x_1 \\ 1 \end{bmatrix} \times H \quad (1, H) \times C \quad (1, C)$$

$$\begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}$$

$$\frac{\partial \vec{x}_2}{\partial x_1} = \left[\overbrace{\frac{\partial \vec{x}_{21}}{\partial x_{11}} \quad \dots \quad \frac{\partial \vec{x}_{21}}{\partial x_{1j}}}^{\vec{x}_2} \right] \quad \left\{ \begin{array}{l} \frac{\partial \vec{x}_2}{\partial x_{11}} = 0 \\ \frac{\partial \vec{x}_{2i}}{\partial x_{1j}} = w_{ji} \cdot \text{sign}(x_{1j}) \end{array} \right.$$

$$\frac{\partial \vec{x}_2}{\partial x_1} = \frac{\partial \vec{x}_2}{\partial \text{ReLU}} \frac{\partial \text{ReLU}}{\partial x_1} = \text{ReLU}'(x_1)$$

$$\frac{\partial \vec{x}_2}{\partial x_1} = \frac{\partial \vec{x}_2}{\partial \vec{y}_1} \frac{\partial \vec{y}_1}{\partial x_1}$$



$$\frac{\partial l}{\partial \hat{x}_2} = N, 1, C$$

$$\frac{\partial l}{\partial b_2} = C, N, 1, 1 \quad b \in C.$$

$$\frac{\partial l}{\partial w_2}$$

$$\frac{\partial l}{\partial b_1} = \frac{\partial l}{\partial \hat{x}_1} \circ \frac{\partial \hat{x}_1}{\partial b_1}$$

$$\frac{\partial l}{\partial w_1} = \frac{\partial l}{\partial \hat{x}_1} \circ \cancel{\frac{\partial \hat{x}_1}{\partial w_1}}$$