

# Example of Python code optimization

✗ MM - matrix multiplication

$$A \times B = C, \quad A \in \mathbb{R}^{N \times k}, \quad B \in \mathbb{R}^{k \times M}$$
$$C \in \mathbb{R}^{N \times M}$$

$$C_{ij} = \sum_k a_{ik} \cdot b_{kj} \quad - \text{3 for loops}$$

1) Get rid of loop over  $k$ :

$$C_{ij} = (a_{i,:} * b_{:,j}).\text{sum}()$$

↑  
element wise operation

2) Get rid of loop over  $j$ :

We gonna use Broadcasting

$$a_{i,:} = (a_{i1} \dots a_{ik}) \in \mathbb{R}^k \quad - \text{shape} = k$$

First we are gonna squeeze new dimension  $(a[:, \text{None}])$ . This will give us  $(a_{i1} \dots a_{ik})^T \in \mathbb{R}^{k \times 1}$

Broadcasting will give us:

$a_{i1}$	$a_{i1} \dots a_{i1}$
$\vdots$	$\vdots$
$a_{ik}$	$a_{ik} \dots a_{ik}$

$$\begin{matrix} k & & \\ & * B = & \end{matrix} \begin{pmatrix} b_{11}a_{i1} & \dots & b_{1M}a_{i1} \\ \vdots & & \vdots \\ b_{k1}a_{ik} & \dots & b_{kM}a_{ik} \end{pmatrix}$$

↑  
elem-wise

$M$

Sum over  $\leftarrow$   
rows equals to  $C_{i,:}$

$$= C_{i,:}$$

Resulting expression :

$$C_{i,:} = (a[i, \text{None}] * B) . \text{sum}(\text{dim}=0)$$

## Chain Rule

$$y = f(g(x))$$

$$\frac{\partial y}{\partial x} = \frac{\partial y}{\partial f} \cdot \frac{\partial f}{\partial g} \cdot \frac{\partial g}{\partial x}$$

$$x \xrightarrow{g} h \xrightarrow{f} y$$

$g(x) \quad f(h)$



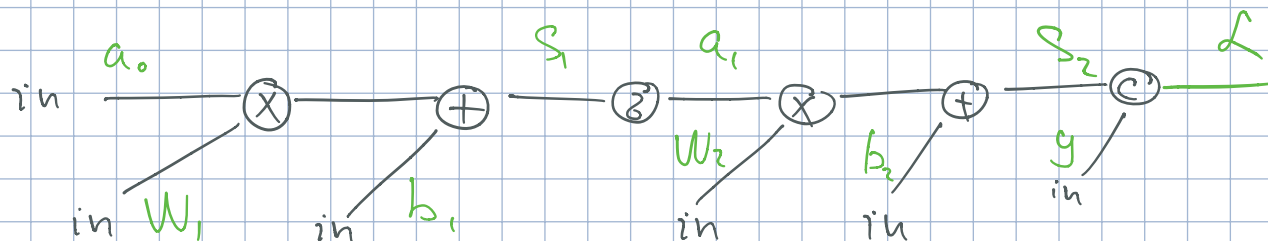
## Forward Pass

$$S_1 = a_0 \cdot W_1 + b_1, \quad a_1 = \text{relu}(S_1), \quad a_0 = X \in \mathbb{R}^{1 \times n}$$

$$\text{out} = S_2 = a_1 \cdot W_2 + b_2, \quad L = (S_2 - y)^2 \in \mathbb{R}$$

$$W_1 \in \mathbb{R}^{n \times m}, \quad a_1 \in \mathbb{R}^{1 \times m}, \quad W_2 \in \mathbb{R}^{m \times 1}$$

$$b_1 \in \mathbb{R}^{1 \times m}, \quad b_2 \in \mathbb{R}^{1 \times 1}$$



## Backward Pass

$$\frac{\partial L}{\partial W_1} = \frac{\partial L}{\partial S_2} \frac{\partial S_2}{\partial a_1} \frac{\partial a_1}{\partial S_1} \frac{\partial S_1}{\partial W_1}$$

$\xrightarrow{\hspace{10em}}$   
order of calculation

$$\frac{\partial y}{\partial x} = \dots$$

$\downarrow$   
input

$$\frac{\partial \mathcal{L}}{\partial s_2} = 2(s_2 - y) \rightarrow \text{inp. grad}$$

Shape

$1 \times 1$

$$\frac{\partial s_2}{\partial a_1} = W_2^T$$

$1 \times m$

$$\frac{\partial a_1}{\partial s_1} = \mathbb{1}\{s_1 > 0\}$$

$1 \times m$

$$\frac{\partial s_1}{\partial w_1} = a_0 \quad ?$$

$1 \times n$

$(m \times n?)$

$$\frac{\partial s_1}{\partial b_1} = \mathbb{1} \quad ?$$

$1 \times m$

$\frac{\partial \mathcal{L}}{\partial w_1}$  should have shape as  $W_1$ , i.e.  $n \times m$   
or  $1 \times m$  for  $b_1$

FORWARD

$$s_1 = \text{lin}(a_0, W_1, b_1)$$

$$a_1 = \text{relu}(s_1)$$

$$s_2 = \text{lin}(a_1, W_2, b_2)$$

$$\text{out} = \text{mse}(s_2, y)$$

BACKWARD

in. out.

$$\text{mse-grad}(s_2, y)$$

$$\text{lin-grad}(a_1, s_2)$$

$$\text{relu-grad}(s_1, a_1)$$

$$\text{lin-grad}(a_0, s_1)$$

$$\text{mse-grad}(\text{inp}, \text{target}) :$$

$$\text{inp.g} = 2(\text{inp} - \text{target})$$

$$\text{inp.g} \triangleq \frac{\partial \mathcal{L}}{\partial \text{inp}}$$

$$\text{inp.g.shape} = \text{inp.shape}$$

$$\text{lin-grad}(\text{inp}, \text{out}, W, b) : \text{out.g} - \text{already computed}$$

$$\text{inp.g} = \text{out.g} @ W^T$$

$$W.g = \frac{\partial \mathcal{L}}{\partial W}$$

$$b.g = \frac{\partial \mathcal{L}}{\partial b} =$$

relu-grad(inp, out)

$$\text{inp.g} = \text{out.g} * (\text{inp} > 0)$$

$$s_2.g = 2(s_2 - y) \in \mathbb{R}$$

$$a_1.g = s_2.g W_2^T \in \mathbb{R}^{1 \times m}$$

$$s_1.g = a_1.g * \underline{1}[\{s_1 > 0\}] \in \mathbb{R}^{1 \times m}$$

$$\underbrace{a_o.g}_x = s_1.g W_1^T \in \mathbb{R}^{1 \times n}$$

$$1) \quad S = a W$$

$$a \in \mathbb{R}^{1 \times n}$$

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

$$a) \quad \frac{\partial S}{\partial a} = W^T$$

$$S \in \mathbb{R}^{1 \times m}$$

$$S = [s_1 \ s_2 \ \dots \ s_m] = [ \quad ] \begin{bmatrix} 1 \\ 1 \\ \vdots \end{bmatrix}$$

$$s_k = \sum_{i=1}^n a_i \cdot W_{ik}$$

$$s_k = s_k(a_1, a_2, \dots, a_n)$$

$$J_s = \begin{bmatrix} \frac{\partial s_1}{\partial a_1} & \frac{\partial s_1}{\partial a_2} & \dots & \frac{\partial s_1}{\partial a_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial s_m}{\partial a_1} & \frac{\partial s_m}{\partial a_2} & \dots & \frac{\partial s_m}{\partial a_n} \end{bmatrix}$$

$$\frac{\partial s_k}{\partial a_i} = W_{ik}$$

$$= \begin{bmatrix} W_{11} & W_{21} & \dots & W_{n1} \\ W_{12} & W_{22} & \dots & W_{n2} \\ \vdots & \vdots & & \vdots \\ W_{1m} & W_{2m} & \dots & W_{nm} \end{bmatrix} = W^T$$

b) ?

$$\frac{\partial S}{\partial W} =$$

$$s_k = s_k(W_{1k}, W_{2k}, \dots, W_{nk})$$

$$J_s = \begin{bmatrix} \frac{\partial s_1}{\partial W_{11}} & \frac{\partial s_1}{\partial W_{21}} & \dots & \frac{\partial s_1}{\partial W_{n1}} \\ \vdots & \vdots & & \vdots \\ \frac{\partial s_m}{\partial W_{1m}} & \frac{\partial s_m}{\partial W_{2m}} & \dots & \frac{\partial s_m}{\partial W_{nm}} \end{bmatrix}$$

$$\frac{\partial s_k}{\partial W_{ik}} = a_i$$

$$= \begin{bmatrix} a_1 & a_2 & \dots & a_n \\ a_1 & a_2 & \dots & a_n \\ \vdots & \vdots & & \vdots \\ a_1 & a_2 & \dots & a_n \end{bmatrix}$$

$$z) \quad a = \text{relu}(s) = [\text{relu}(s_1) \dots \text{relu}(s_m)]$$

$$\frac{\partial a}{\partial s} = \left[ \frac{\partial}{\partial s_1} \text{relu}(s_1) \dots \frac{\partial}{\partial s_m} \text{relu}(s_m) \right]$$

$$\frac{\partial \text{relu}(x)}{\partial x} = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases}$$

$$\frac{\partial a}{\partial s} = \underline{1} \{s > 0\} \quad (\text{elementwise})$$