

# AMATH 840: Advanced Numerical Methods for Computational and Data Sciences

**Giang Tran**

Department of Applied Mathematics, University of Waterloo

Feb 13

~~Jan~~ 26, 2021

## Topic 2.2 Back propagation.

Example : Given  $\{(x_k, y_k)\}_{k=1}^m \subset \mathbb{R}^{d_{\text{in}}} \times \mathbb{R}^{d_{\text{out}}}$ ,

find a neural network :  $f_{\text{NN}}(x_k) \approx y_k$

$$\min_{\theta} \frac{1}{2m} \sum_{k=1}^m \|f_{\text{NN}}(x_k; \theta) - y_k\|_2^2 = \underline{\mathcal{L}(x_k; \theta)}$$

where  $\theta = \{\text{all weights \& bias of the neural network}\}$

For example :  $x_k = \text{a color image}$   
 $y_k = \text{"plane", "car", "bike"}$  | Classification

## Simplest method

Initialization:  $\theta_0$   
Update:  $\theta^{\text{new}} = \theta^{\text{old}} - \eta \frac{\partial L}{\partial \theta} (\theta^{\text{old}})$

More precisely,  
 $W_1^{\text{new}} = W_1^{\text{old}} - \eta \frac{\partial L}{\partial W_1} (W_1^{\text{old}})$

$W_2^{\text{new}} = W_2^{\text{old}} - \eta \frac{\partial L}{\partial W_2} (W_2^{\text{old}})$

⋮  
Need to compute  $\frac{\partial L}{\partial W_j}$ ,  $\frac{\partial L}{\partial \theta_j}$

Notation Einstein Jacobian formulation

$$\left( \frac{\partial y_i}{\partial x_j} \right)_{ij} := \frac{\partial y_i}{\partial x_j}$$

①  $y: \mathbb{R}^n \rightarrow \mathbb{R}^m$

$$(x_1, x_2, \dots, x_n) \mapsto (y_1, y_2, \dots, y_m)$$

$$\frac{\partial y}{\partial x} := \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \frac{\partial y_2}{\partial x_1} & \cdots & \frac{\partial y_2}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix} \in \mathbb{R}^{m \times n}$$

In particular,

Recall

$$\nabla y := \begin{pmatrix} \frac{\partial y}{\partial x_1} \\ \vdots \\ \frac{\partial y}{\partial x_n} \end{pmatrix}$$

① m=1 ,  $y: \mathbb{R}^n \rightarrow \mathbb{R}$

$$\frac{\partial y}{\partial x} = \left( \frac{\partial y}{\partial x_1}, \dots, \frac{\partial y}{\partial x_n} \right) \in \mathbb{R}^{1 \times n}$$

$$= (\nabla y)^T$$

② n=1 ,  $y: \mathbb{R} \rightarrow \mathbb{R}^m$  ,  $\frac{\partial y}{\partial x} = \left[ \begin{array}{c} \frac{\partial y_1}{\partial x} \\ \vdots \\ \frac{\partial y_m}{\partial x} \end{array} \right] \in \mathbb{R}^{m \times 1}$

③  $y = A x$   $\in \mathbb{R}^{m \times n} \times \mathbb{R}^{n \times 1}$  ,  $\frac{\partial y}{\partial x} \in \mathbb{R}^{m \times n}$  = A .

②  $y: \mathbb{R} \rightarrow \mathbb{R}^{m \times n}$

$$\frac{\partial y}{\partial x} := \begin{pmatrix} \frac{\partial y_{11}}{\partial x} & \frac{\partial y_{12}}{\partial x} & \cdots & \frac{\partial y_{1n}}{\partial x} \\ \frac{\partial y_{21}}{\partial x} & \frac{\partial y_{22}}{\partial x} & \cdots & \frac{\partial y_{2n}}{\partial x} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_{m1}}{\partial x} & \frac{\partial y_{m2}}{\partial x} & \cdots & \frac{\partial y_{mn}}{\partial x} \end{pmatrix} \in \mathbb{R}^{m \times n}$$

$$\left( \frac{\partial y}{\partial x} \right)_{ij} = \frac{\partial y_{ij}}{\partial x}$$

③  $y: \mathbb{R}^{n \times m} \rightarrow \mathbb{R}$

$$\frac{\partial y}{\partial x} := \begin{pmatrix} \frac{\partial y}{\partial x_{11}} & \frac{\partial y}{\partial x_{21}} & \cdots & \frac{\partial y}{\partial x_{n1}} \\ \frac{\partial y}{\partial x_{12}} & \frac{\partial y}{\partial x_{22}} & \cdots & \frac{\partial y}{\partial x_{n2}} \\ \vdots & \vdots & \ddots & \frac{\partial y}{\partial x_{nn}} \\ \frac{\partial y}{\partial x_{1m}} & \frac{\partial y}{\partial x_{2m}} & \cdots & \frac{\partial y}{\partial x_{nm}} \end{pmatrix} \in \mathbb{R}^{m \times n}$$

$$\left( \frac{\partial y}{\partial x} \right)_{ij} = \frac{\partial y}{\partial x_{ji}}$$

④  $y: \mathbb{R}^{n \times m} \rightarrow \mathbb{R}^N$

$$\frac{\partial y}{\partial x} := \boxed{\frac{\partial y}{\partial x}}$$

$$\left( \frac{\partial y}{\partial x} \right)_{ijk} := \frac{\partial y_i}{\partial x_{kj}}$$



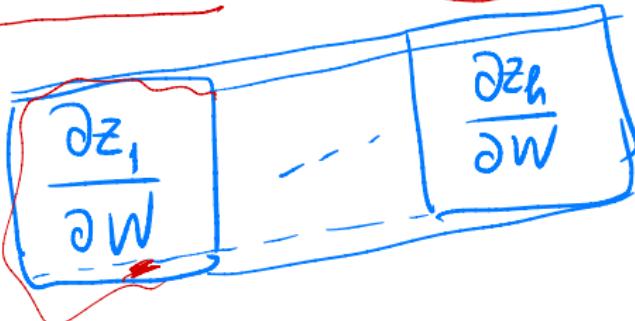
Example

$$z = \underline{Wx + b} \in \mathbb{R}$$

$R^{h \times d}$     $R^{d \times 1}$     $R^{h \times 1}$

See ④

$$\frac{\partial z}{\partial W} :=$$



$$z_i = (Wx + b)_i = w_i^T x + b_i$$

$$\frac{\partial z_i}{\partial w_{jk}} = \frac{\partial (\sum_{t=1}^d w_{it} x_t + b_i)}{\partial w_{jk}}$$

$$W = \begin{bmatrix} -w_1^T- \\ -w_2^T- \\ \vdots \\ -w_h^T- \end{bmatrix}$$

$$= \delta_{ij} x_k$$

$$\frac{\partial (Wx + b)}{\partial W} =$$

$$= I_h \circledast x$$

See note : AMATH840\_11\_Back propagation In Neural Networks