

- Gradient :  $\nabla f(\mathbf{u}) \in \mathbb{R}^d$
- Jacobienne  $\partial F(\mathbf{u}) \in \mathbb{R}^{d \times p}$
- Transposé Adjoint  $A \rightarrow A^T$

$$f: \mathbb{R}^d \rightarrow \mathbb{R} \quad \nabla f(\mathbf{u}) = \begin{pmatrix} \frac{\partial f}{\partial x_1}(\mathbf{u}) \\ | \\ \frac{\partial f}{\partial x_d}(\mathbf{u}) \end{pmatrix} \in \mathbb{R}^d$$

$$f(\mathbf{u} + \varepsilon \delta) = f(\mathbf{u}) + \varepsilon \langle \nabla f(\mathbf{u}), \delta \rangle + o(\varepsilon)$$

$$F: \mathbb{R}^d \rightarrow \mathbb{R}^p$$

$$\partial F(\mathbf{u}): \mathbb{R}^d \xrightarrow{\text{Linéaire}} \mathbb{R}^{1^p} \quad = \quad \partial F(\mathbf{u}) \in \mathbb{R}^{p \times d}$$

$$F(\mathbf{u}) = \begin{bmatrix} F_1(\mathbf{u}) \\ \vdots \\ F_p(\mathbf{u}) \end{bmatrix}$$

$$\partial F(\mathbf{u}) \stackrel{\Delta}{=} \begin{bmatrix} \frac{\partial F_i}{\partial x_j}(\mathbf{u}) \end{bmatrix}_{\substack{i=1 \dots p \\ j=1 \dots d}}$$

$$F(x + \varepsilon \delta) = F(x) + \varepsilon \underbrace{\partial F(x)[\delta]}_{\partial F(x) \times \delta} + o(\varepsilon)$$

$$F: \mathbb{R}^d \rightarrow \mathbb{R} \quad p=1$$

$$\partial F(x) = \boxed{\phantom{00000}}$$

$$\nabla F(x) = \boxed{\phantom{000}} = \partial F(x)^+$$

$$A = (A_{ij})_{ij} \quad A^T = (A_{ji})_{ij}$$

$$\langle A[x], y \rangle \doteq \langle x, A^T[y] \rangle$$

$$\text{"} \partial(F \circ G) = \partial F \times \partial G \text{"}$$

$$\left[ \partial(F \circ G)(u) = \partial F(G(u)) \times \partial G(u) \right]$$

Q:  $\nabla f(u)$  calcul

code  $f(u)$   $\xrightarrow[\text{"BackProp"}]{\text{Meta}}$  code  $\nabla f(u)$

code calcul  $f(u)$  k opér°

→ coût calculer  $\nabla f(u)$  en ?? opér°

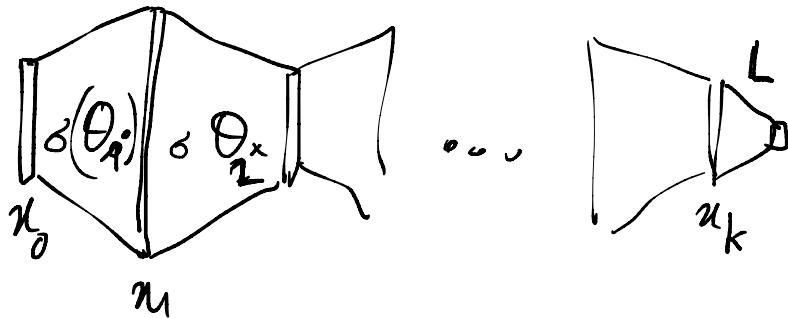
$$\begin{cases} f: \mathbb{R}^d \rightarrow \mathbb{R} \\ \nabla f: \mathbb{R}^d \rightarrow \mathbb{R}^d \end{cases}$$

$$Df(x) \simeq \left( -\frac{f(x) - f(x+\varepsilon d)}{\varepsilon}, \dots, \frac{f(x+kd) - f(x)}{\varepsilon} \right)^{(d+1)K}$$

Thm: Seppo Linnainmaa 1970  
 Baur-Strassen 1983  
 $O(M^{2.7}) \rightarrow \omega$

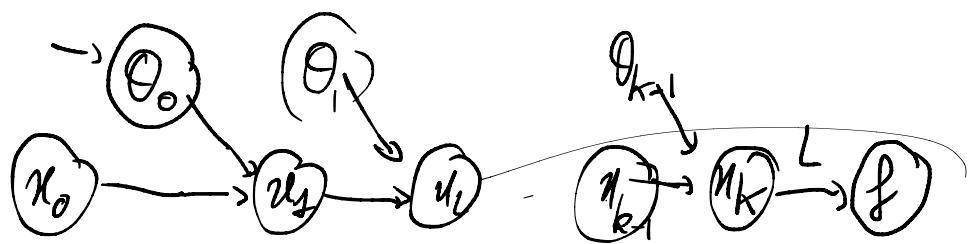
calcular  $Df(u)$  3K óptimal

MLP:



$$f(\theta) = L(u_k)$$

$$u_{k+1} = \sigma(\theta_k @ u_k)$$



Composición  $f(u) = f_k \circ f_{k-1} \circ \dots \circ f_0(u)$

$$\partial f(u) = \underbrace{\partial f_k(u_k)}_{\substack{u_k \in \mathbb{R}^d}} \times \underbrace{\partial f_{k-1}(u_{k-1})}_{\substack{u_{k-1} \in \mathbb{R}^d}} \times \dots \times \underbrace{\partial f_0(u_0)}_{\substack{u_0 \in \mathbb{R}^d}}$$

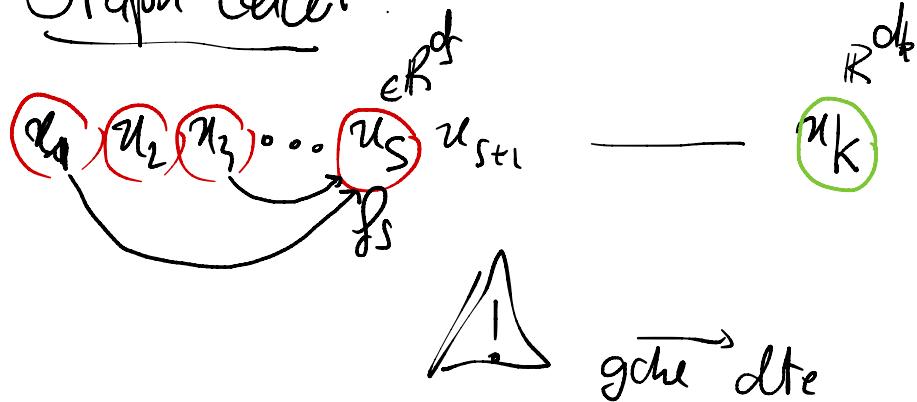
$$= \overbrace{\quad \quad \quad}^{\text{FWD}} \underbrace{\square \times \square \times \square \times \dots \times \square}_{\substack{d^2 \\ d^2 \\ \vdots \\ d^2}} \overbrace{\quad \quad \quad}^{\text{BWD}}$$

$$\left. \begin{array}{l} \Leftarrow Kd^3 \\ \Rightarrow Kd^2/d \end{array} \right] \underbrace{d^2}_{d^2}$$

Check Pointing  
[Invertible Neural Net]

"RaNet"

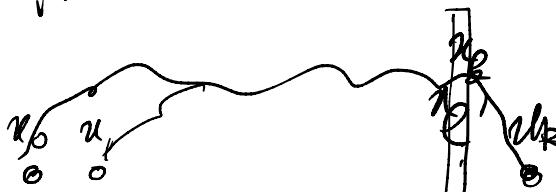
## Graph model



$$x_k = f_k(x_{k-1}, x_{k-2} - x_1)$$

DAG directed acyclic graph  
In<sup>o</sup> topo

# Dif. auto. FWDP:



$$u_k = f$$

$$\frac{\partial u_k}{\partial x_0} \in \mathbb{R}^{d_k \times d_0} \quad \text{Parent}(k)$$

$$u_k = f_k \left( (x_0)_{\text{Parent}} \right)$$

Prop:

$$\frac{\partial u_k}{\partial x_0} = \sum_{l \in \text{Parent}(k)} \left[ \frac{\partial u_k}{\partial x_l} \right]_{\text{III}} \times \frac{\partial x_l}{\partial x_0} \quad \text{II}$$

$$\frac{\partial u_k}{\partial x_l} \quad \text{I}$$

$$x_0 \leftarrow \text{init}$$

$$x_1 \leftarrow \text{init}$$

$$x_s \leftarrow \text{init}$$

$$\Rightarrow$$

$$\text{for } k=s+1 \dots K \\ u_k = f_k(\text{---})$$

$$\equiv$$

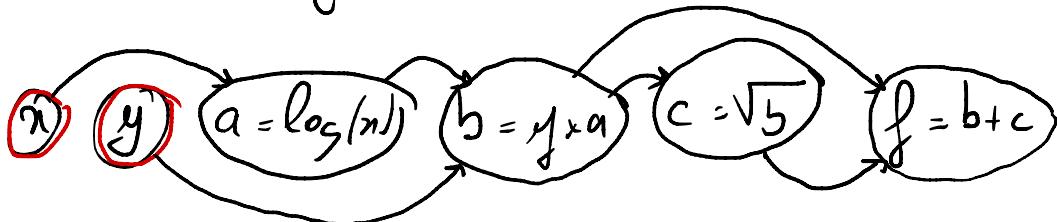
$$\text{for } k=s+1 \dots K \\ \frac{\partial u_k}{\partial x_0} = \text{Chain} \oplus$$

$$\frac{\partial u_0}{\partial x_0} = \text{Id}$$

$$\frac{\partial u_1}{\partial x_0}$$

$$\frac{\partial u_1}{\partial x_0} = 0 \dots = 0$$

$$f(n, y) = y \log(n) + \sqrt{y \log(n)}$$



$$\frac{\partial z}{\partial xy} = 1 \rightarrow 0$$

$$\frac{\partial y}{\partial xy} = 0 \rightarrow 1$$

$$\frac{\partial a}{\partial xy} = \left[ \frac{\partial a}{\partial n} \right] \times \frac{\partial n}{\partial xy} = \frac{1}{n} \times \frac{\partial n}{\partial xy}$$

$$\frac{\partial b}{\partial xy} = \left[ \frac{\partial b}{\partial a} \right] \times \frac{\partial a}{\partial xy} + \left[ \frac{\partial b}{\partial y} \right] \times \frac{\partial y}{\partial xy} = y \frac{\partial a}{\partial n} + a \frac{\partial y}{\partial n}$$

$$\frac{\partial c}{\partial xy} = \left[ \frac{\partial c}{\partial b} \right] \times \frac{\partial b}{\partial xy} = \frac{1}{2\sqrt{b}} \times \frac{\partial b}{\partial xy}$$

$$\frac{\partial f}{\partial x} = \left[ \frac{\partial f}{\partial b} \right] \times \frac{\partial b}{\partial xy} + \left[ \frac{\partial f}{\partial c} \right] \times \frac{\partial c}{\partial xy} = \frac{\partial b}{\partial x} + \frac{\partial c}{\partial x}$$

(16) — (15) — ...



$$\frac{\partial \mathcal{L}}{\partial u_k}$$

$$u_k = f_k(\dots, u_{k-1}, \dots)$$

Prop:

$$\frac{\partial \mathcal{L}}{\partial u_k} = \sum_{l \in \text{Files}(k)} \frac{\partial \mathcal{L}}{\partial u_l} \times \left[ \frac{\partial u_l}{\partial u_k} \right]$$
$$\frac{\partial f_l}{\partial u_k}$$

Algo calc f

$u_1, \dots, u_s$  input

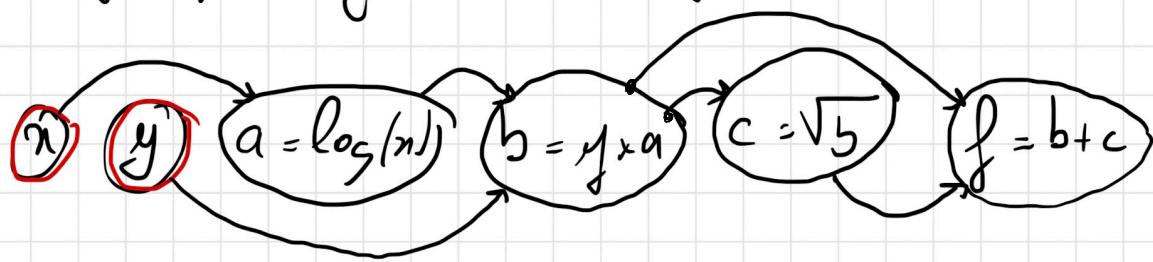
for  $k = s+1, \dots, K$

$$u_k = f_k(\dots)$$

$$\frac{\partial \mathcal{L}}{\partial u_k} = \text{fd}$$

for  $k = K \dots 1$

$$\frac{\partial \mathcal{L}}{\partial u_k} = \sum \dots$$



$$\frac{\partial f}{\partial x} = 1$$

$$\textcircled{1} \quad \frac{\partial f}{\partial c} = \frac{\partial f}{\partial x} \times \left[ \frac{\partial f}{\partial c} \right] = \frac{\partial f}{\partial x} \times 1$$

$$\textcircled{2} \quad \frac{\partial f}{\partial b} = \frac{\partial f}{\partial x} \times \left[ \frac{\partial c}{\partial b} \right] + \frac{\partial f}{\partial c} \times \left[ \frac{\partial c}{\partial b} \right] = \frac{\partial f}{\partial x} \frac{1}{2\sqrt{b}} + \frac{\partial f}{\partial c} \times 1$$

$$\textcircled{3} \quad \frac{\partial f}{\partial a} = \frac{\partial f}{\partial x} \frac{\partial b}{\partial a} = \frac{\partial f}{\partial b} \times y$$

$$\boxed{\textcircled{4}} \quad \frac{\partial f}{\partial y} = \frac{\partial f}{\partial b} \times \left[ \frac{\partial b}{\partial y} \right] - \frac{\partial f}{\partial a} \times a$$

$$\boxed{\textcircled{5}} \quad \frac{\partial f}{\partial x} = \frac{\partial f}{\partial a} \times \left[ \frac{\partial a}{\partial x} \right] = \frac{\partial f}{\partial a} \times \frac{1}{u}$$

Back Prop en mode grad

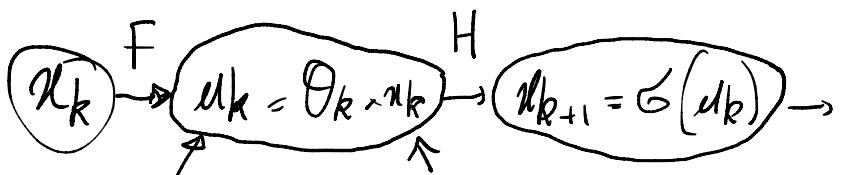
$$\frac{\partial L}{\partial u_k} = \sum_{l \in \text{Fls}(k)} \frac{\partial L}{\partial u_l} \times \frac{\partial \phi_l}{\partial u_k}$$

$$\nabla_{u_k} L = \sum_{l \in \text{Fls}(k)} \underbrace{\left[ \frac{\partial \phi_l}{\partial u_k} \right]^T}_{\text{JVP}} (\nabla_{u_l} L)$$

$$(AB)^T = B^T A^T$$

JVP

"Jacobien Vector Product"



$\nabla_{u_{k+1}} L = \text{calculé}$

$$\nabla_{u_k} L = \left[ \frac{\partial H(u_k)}{\partial u_k} \right]^T (\nabla_{u_k} L) = \boxed{\sigma'(u) * \nabla_u L}$$

$$\nabla_{\theta_k} L = \left[ \frac{\partial F(\mathbf{u}_k, \boldsymbol{\theta}_k)}{\partial \theta_k} \right]^T (\nabla_{\mathbf{u}_k} L) = \boxed{\boldsymbol{\theta}_k^T \odot \nabla_{\mathbf{u}_k} L}$$

$$\nabla_{\theta_k} L = \left[ \frac{\partial F(\mathbf{u}_k, \boldsymbol{\theta}_k)}{\partial \theta_k} \right]^T (\nabla_{\mathbf{u}_k} L) + \boxed{\nabla_{\mathbf{u}_k} L \odot u^+}$$

$$H(u) = \sigma(u) = (\sigma(u[i])),$$

$$\partial H(u) = \text{diag}(\sigma'(u[i])),$$

$$\sigma = \text{ReLU}$$

$$\sigma' = \text{PI}_{R^+}$$

$$\partial H(u)^T = \text{diag}(\sigma'(u))$$

$$F(\mathbf{u}, \boldsymbol{\theta}) = \boldsymbol{\theta} \odot \underline{\mathcal{L}}$$

$$\partial_u F(\mathbf{u}, \boldsymbol{\theta})[z] = \underline{\boldsymbol{\theta}} \odot z$$

$$\partial_\theta F(\mathbf{u}, \boldsymbol{\theta})[w] = w \odot \underline{\boldsymbol{\theta}}$$

$$\sigma'$$

$$\partial_n F^T \rightarrow \underbrace{\langle \theta @ z, w \rangle}_{\sim} = \langle z, \theta^T @ w \rangle$$

$$\underbrace{\langle w @ n, z \rangle}_{\sim} = \langle w, z @ u^T \rangle$$

