

# La propagation avant en tant que matrice

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# Références

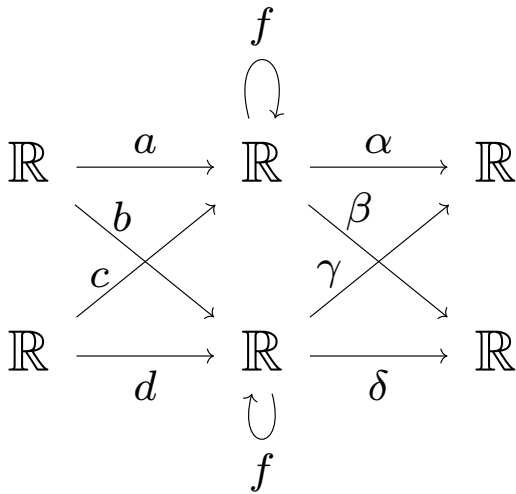
- i. Marco ARMENTA et Pierre-Marc JODOIN. “The Representation Theory of Neural Networks”. In : *Mathematics* 9.24 (2021)
- ii. Marco ARMENTA, Thomas BRÜSTLE, Souheila HASSOUN et Markus REINEKE. “Double Framed Moduli Spaces of Quiver Representations”. In : *Linear Algebra and its Applications* 650 (2022), p. 98-131
- iii. Marco ARMENTA, Thierry JUDGE, Nathan PAINCHAUD, Youssef SKANDARANI, Carl LEMAIRE, Gabriel GIBEAU SANCHEZ, Philippe SPINO et Pierre-Marc JODOIN. “Neural Teleportation”. In : *Mathematics* 11.2 (2023)
- iv. L., Aiky RASOLOMANANA et Marco ARMENTA. *Hidden Activations Are Not Enough : A General Approach to Neural Network Predictions*. 2024. arXiv : 2409.13163 [cs.LG]

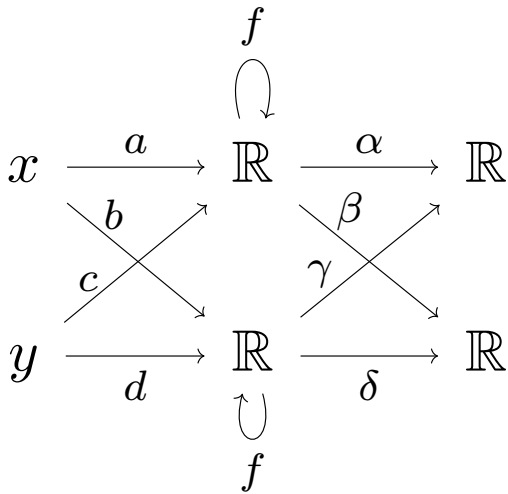
$$\mathcal{D} = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

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But : Trouver  $\psi$  telle que  $\psi(x_i) = y_i$ .

$$\Psi(W, f) = \begin{pmatrix} \alpha & \gamma \\ \beta & \delta \end{pmatrix} \circ \begin{pmatrix} f \\ f \end{pmatrix} \circ \begin{pmatrix} a & c \\ b & d \end{pmatrix}$$

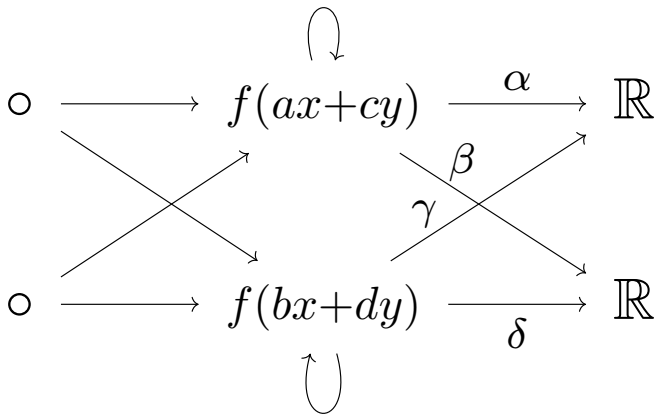


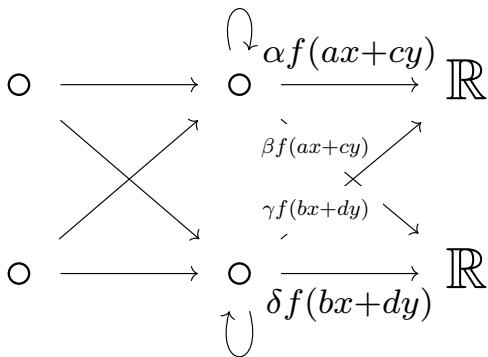


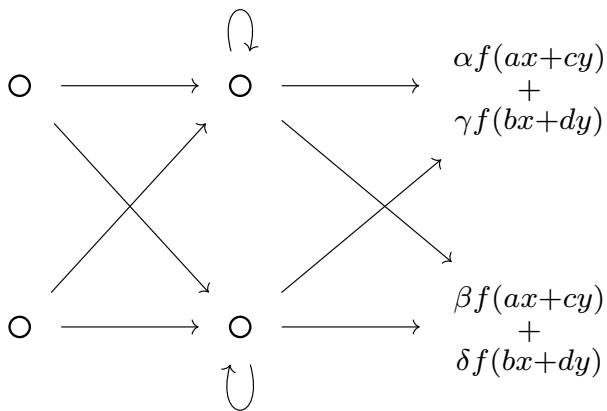
$$\begin{array}{ccccc}
 & & f & & \\
 & & \circlearrowright & & \\
 \circ & \xrightarrow{ax} & \mathbb{R} & \xrightarrow{\alpha} & \mathbb{R} \\
 & \searrow bx & & \nearrow \beta & \\
 & cy & & \nwarrow \gamma & \\
 \circ & \xrightarrow{dy} & \mathbb{R} & \xrightarrow{\delta} & \mathbb{R} \\
 & & \circlearrowleft & & \\
 & & f & & 
 \end{array}$$



$$\begin{array}{ccccc}
 & & f & & \\
 & & \cap & & \\
 \circ & \longrightarrow & ax+cy & \xrightarrow{\alpha} & \mathbb{R} \\
 & \searrow & & \nearrow \beta & \\
 & & & \gamma & \\
 \circ & \longrightarrow & bx+dy & \xrightarrow{\delta} & \mathbb{R} \\
 & \nearrow & & \searrow & \\
 & & f & & 
 \end{array}$$







$$\mathbb{R}^2 \xrightarrow{\Psi(W,f)} \mathbb{R}^2$$

$$\begin{array}{ccc}
 \mathbb{R}^2 & \xrightarrow{\Psi(W,f)} & \mathbb{R}^2 \\
 \varphi(W,f) \downarrow & \nearrow \Psi(\cdot,1)(1) & \\
 \text{Rep}Q / \cong & & 
 \end{array}$$

$$\begin{array}{ccc}
 \mathbb{R}^2 & \xrightarrow{\Psi(W,f)} & \mathbb{R}^2 \\
 \varphi(W,f) \downarrow & & \uparrow \text{ev}_1 \\
 \text{Rep}Q / \cong & \xrightarrow{\pi} & \text{Mat}_{2 \times 2}(\mathbb{R})
 \end{array}$$

$$\begin{array}{ccc}
 \mathbb{R}^2 & \xrightarrow{\Psi(W,f)} & \mathbb{R}^2 \\
 \varphi(W,f) \downarrow & \searrow \mathbb{M}(W,f) & \uparrow \text{ev}_1 \\
 \text{Rep}Q / \cong & \xrightarrow{\pi} & \text{Mat}_{2 \times 2}(\mathbb{R})
 \end{array}$$



# Attaques adversariales



Figure 1: Visual illustration of adversarial examples crafted by EAD (Algorithm 1). The original example is an ostrich image selected from the ImageNet dataset (Figure 1 (a)). The adversarial examples in Figure 1 (b) are classified as the target class labels by the Inception-v3 model.

Pin-Yu CHEN, Yash SHARMA, Huan ZHANG, Jinfeng YI et Cho-Jui HSIEH. "EAD : Elastic-Net Attacks to Deep Neural Networks via Adversarial Examples". In : AAAI Press, 2018. URL : <https://arxiv.org/abs/1709.04114>

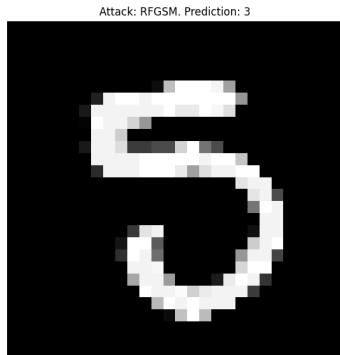
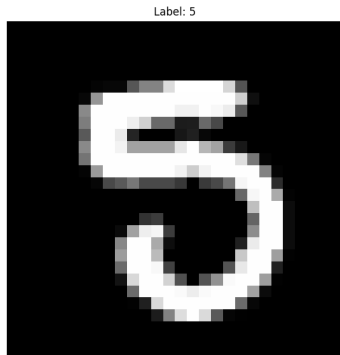
# Attaques adversariales



Figure 8. Real-life example of a backdoored stop sign near the authors' office. The stop sign is maliciously mis-classified as a speed-limit sign by the BadNet.

# MNIST — Exemple d'une détection d'attaque

Le réseau  $(W, f)$  a été entraîné jusqu'à  $\approx 98\%$  de précision.



Si on note par  $\mathbb{M}_3$  la matrice moyenne de la classe 3,  $\Psi_3$  le vecteur de sortie moyen de la classe 3 et  $x$  l'image attaquée, alors

$$\|\mathbb{M}(W, f)(x) - \mathbb{M}_3\|_\infty \approx 84 \text{ et } \|\Psi(W, f)(x) - \Psi_3\|_\infty \approx 4.$$

CODE : *simple\_adversarial\_detection*. [https://github.com/samueleblanc/simple\\_adversarial\\_detection](https://github.com/samueleblanc/simple_adversarial_detection). 2024