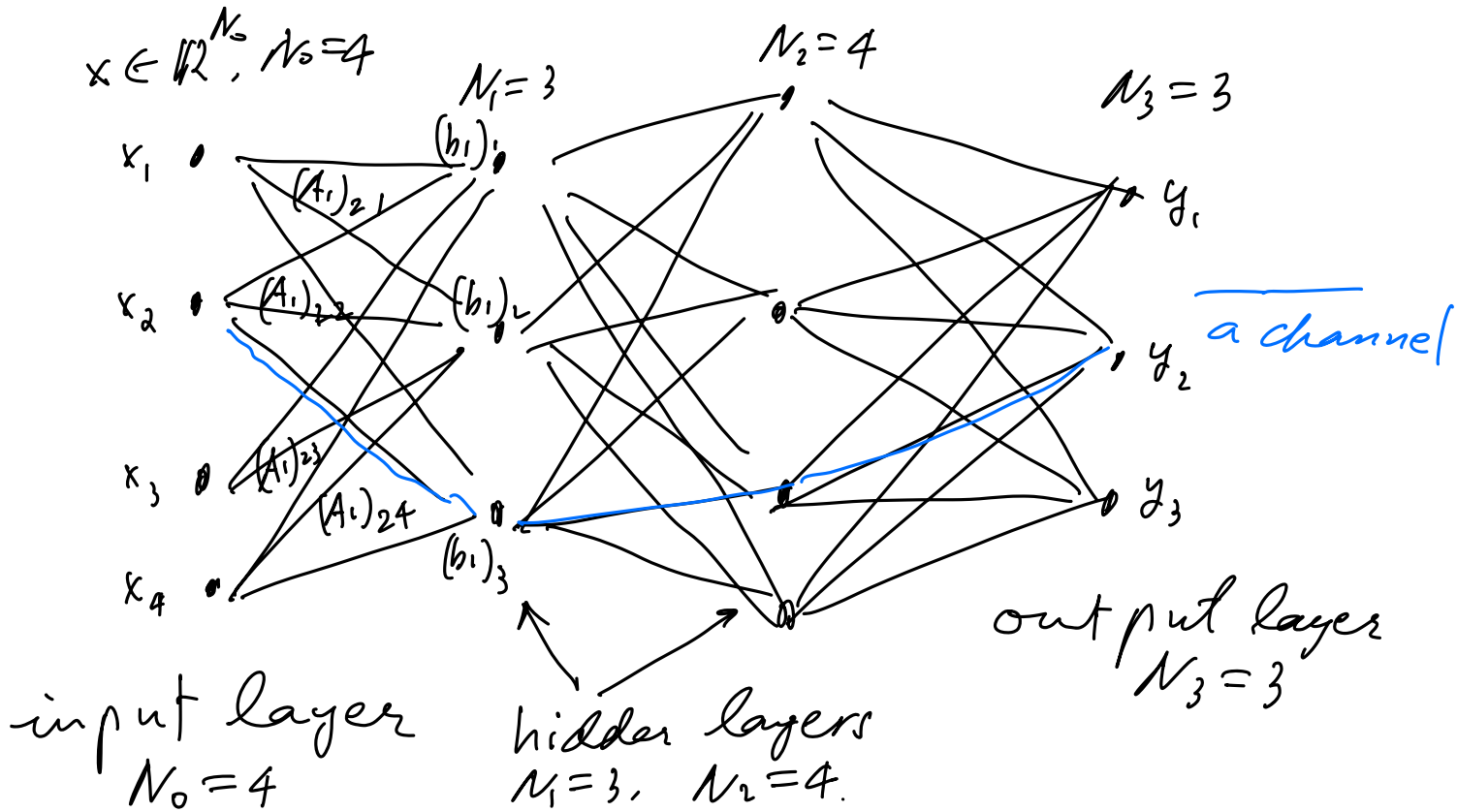


- Plan
- ① Some remarks on the definition of NNs
  - ② Simple operations / constructions of NNs

Definition of a NN  $\Phi: \mathbb{R}^{N_0} \rightarrow \mathbb{R}^{N_L}$  [MLP (multilayer perceptron), or feed forward NN]

$$y = \Phi(x) = (W_L \circ \sigma \circ W_{L-1} \circ \dots \circ W_2 \circ \sigma \circ W_1)(x)$$

$$W_k: \mathbb{R}^{N_{k-1}} \rightarrow \mathbb{R}^{N_k}, W_k(x) = A_k x + b_k, A_k \in \mathbb{R}^{N_k \times N_{k-1}}, b_k \in \mathbb{R}^{N_k}$$



$(A_k)_{ij}$  represents the weight associated with the edge between  $j$ th node in the  $(k-1)$ -th layer and the  $i$ th node in the  $k$ th layer.

$L(\Phi) = L$ : depth (#layers:  $L+1$ , #hidden layers:  $L-1$ ).

$W(\Phi) = \max_{0 \leq k \leq L} N_k$ : width

$M_c(\Phi) = \# \text{non zero weights}$  (entries of  $A_k, b_k$  for all  $k$ )  
connectivity

$B(\Phi) = \max_{1 \leq k \leq L} \max(\|A_k\|_{\infty}, \|b_k\|_{\infty})$ : weight magnitude

The NN architecture =  $\Phi: (N_0, \dots, N_L)$ .

Some remarks

○ Definition using iteration  
 $\Phi(x) = y \quad x \in \mathbb{R}^{N_0}, y \in \mathbb{R}^{N_L}$

$$\begin{cases} x_0 = x \\ x_k = \sigma(A_k x_{k-1} + b_k), \quad k=1, \dots, L-1 \\ x_L = A_L x_{L-1} + b_L \\ y = x_L \end{cases}$$

In general, we can allow  $\sigma$  to depend on  $k$ , i.e., we can replace  $\sigma$  by  $\sigma_k$  in the definition of  $x_k$ .

These NNs are called feed-forward NNs. More generally, they can be defined by directed acyclic graphs. Also called multi-layer perceptron (MLP).

Also:  $\mathcal{M}(\Phi) \leq \mathcal{L}(\Phi) W(\Phi) (W(\Phi) + 1)$

Why: # of entries of  $A_k \leq W(\Phi)^2$ .  
 # of entries of  $b_k \leq W(\Phi)$ .  
 $k=1, 2, \dots, L = \mathcal{L}(\Phi)$ .

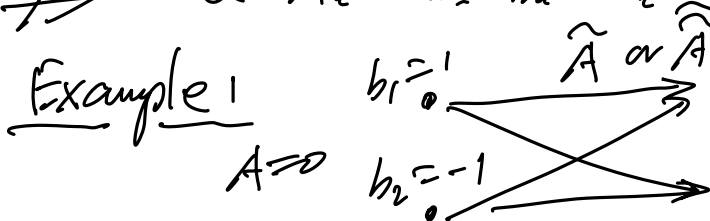
Add the def. of NNs using directed acyclic graphs

So,  $\mathcal{M}(\Phi) \leq \mathcal{L}(\Phi) W(\Phi)^2 + \mathcal{L}(\Phi) W(\Phi) = \mathcal{L}(\Phi) W(\Phi) (W(\Phi) + 1)$ .

○ We write  $\Phi = NN(\sigma, N_0, \dots, N_L, A_1, \dots, A_L, b_1, \dots, b_L)$ .  
 $\Phi$  is not uniquely determined by its weights!

$NN(\sigma, N_0, \dots, N_L, A_1, \dots, A_L, b_1, \dots, b_L) = NN(\sigma, N_0, \dots, N_L, \tilde{A}_1, \dots, \tilde{A}_L, \tilde{b}_1, \dots, \tilde{b}_L)$

$\Rightarrow$  all  $A_k = \tilde{A}_k, b_k = \tilde{b}_k \quad (1 \leq k \leq L)$ .



$\tilde{A} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$

$\hat{A} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix}$

$\tilde{A} b = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ .  $\hat{A} b = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ .

$\tilde{A} \neq \hat{A}$  but the output is always the same.

### Example 2

$$\begin{array}{ccc}
 x \in \mathbb{R}^p & y \in \mathbb{R}^q & z \in \mathbb{R}^r \\
 \bullet & \bullet y_1 & \\
 & \parallel & \\
 \bullet & \bullet y_2 & \bullet \\
 & & \\
 \bullet & \bullet & \bullet \\
 & \bullet & \\
 & \bullet & 
 \end{array}$$

$y = Ax + b, z = By + c$ . Choose row 1 of  $A =$  row 2 of  $A$ ,

$b = \begin{bmatrix} b_1 \\ \vdots \\ b_q \end{bmatrix}, b_1 = b_2$ . Then  $y_1 = y_2$ .

$$z = By + c = \begin{bmatrix} B_{11} & B_{12} & \dots & B_{1q} \\ B_{21} & B_{22} & \dots & B_{2q} \\ \dots & \dots & \dots & \dots \\ B_{r1} & B_{r2} & \dots & B_{rq} \end{bmatrix} \begin{bmatrix} y_1 \\ y_1 \\ y_3 \\ \vdots \\ y_q \end{bmatrix} + \begin{bmatrix} c_1 \\ \vdots \\ c_r \end{bmatrix}$$

$$= \begin{bmatrix} (B_{11} + B_{12})y_1 + \dots \\ (B_{21} + B_{22})y_1 + \dots \\ (B_{31} + B_{32})y_3 + \dots \\ \dots \\ (B_{r1} + B_{r2})y_1 + \dots \end{bmatrix} + \begin{bmatrix} c_1 \\ \vdots \\ c_r \end{bmatrix}$$

where all  $\dots$  are indep. of  $B_{i1}, B_{i2}$  ( $1 \leq i \leq r$ ) and  $y_1, y_2$ .

So, if  $B$  and  $\tilde{B}$  have the same first 2 columns then  $(A, b), (B, c)$  and  $(A, b), (\tilde{B}, c)$  define 2 NNs that are the same map. But  $B \neq \tilde{B}$  possible.

This example is from C. Fefferman (1994) where the concept and conditions of isomorphic sets of parameters are given, and where it is proven that under generic conditions, sets of parameters defining the same NN (as function) are isomorphic. More recent works (Berner et al. NeurIPS 2019 & Petersen et al. Found. Comp. Math 2021) study the related issues, e.g. the inverse stability  $\Phi(\Theta) \rightarrow \Phi(\tilde{\Theta}) \Rightarrow \Theta \rightarrow \tilde{\Theta}$ , and the structures of NN functions generated by parameters of same size.

# Some simple operations / constructions of NNs [4]

Concatenation / Composition. Let  $\Phi^1$  and  $\Phi^2$  be two NNs with the same activation function  $\sigma$ :

$$\Phi^1 = \text{NN}(\sigma, N_0^{(1)}, \dots, N_{L_1}^{(1)}, (A_1^{(1)}, b_1^{(1)}), \dots, (A_{L_1}^{(1)}, b_{L_1}^{(1)})),$$

$$\Phi^2 = \text{NN}(\sigma, N_0^{(2)}, \dots, N_{L_2}^{(2)}, (A_1^{(2)}, b_1^{(2)}), \dots, (A_{L_2}^{(2)}, b_{L_2}^{(2)})).$$

Assume  $N_0^{(2)} = N_{L_1}^{(1)}$ , i.e.,

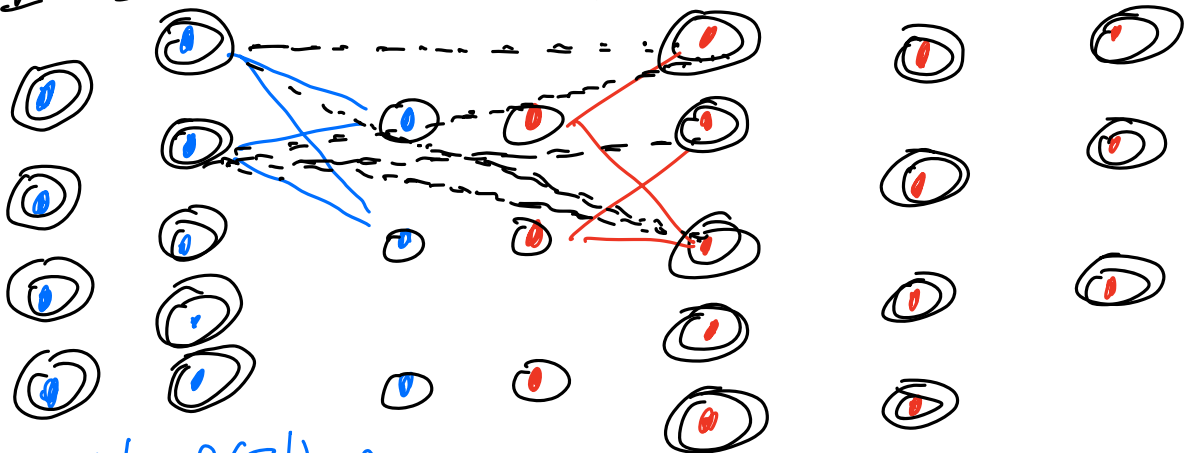
the input dim. of  $\Phi^2 =$  the output dim. of  $\Phi^1$ .

Define

$$\Phi^2 \circ \Phi^1 = \text{NN}(\sigma, N_0^{(1)}, \dots, N_{L_1-1}^{(1)}, N_1^{(2)}, \dots, N_{L_2}^{(2)}, (A_1^{(1)}, b_1^{(1)}), \dots, (A_{L_1-1}^{(1)}, b_{L_1-1}^{(1)}), (A_1^{(2)}, b_1^{(2)}), (A_2^{(2)}, b_2^{(2)}), \dots, (A_{L_2}^{(2)}, b_{L_2}^{(2)})).$$

Then, this is a NN with the same activation function  $\sigma$  and with the depth  $\mathcal{L}(\Phi^2 \circ \Phi^1) = \mathcal{L}(\Phi^1) + \mathcal{L}(\Phi^2) - 1$ .

Call  $\Phi^2 \circ \Phi^1$  the concatenation of  $\Phi^1$  and  $\Phi^2$ .



$\Phi^1$   $\mathcal{L}(\Phi^1) = 2$

$\Phi^2$ ,  $\mathcal{L}(\Phi^2) = 3$

o  $\Phi^2 \circ \Phi^1$   $\mathcal{L}(\Phi^2 \circ \Phi^1) = \mathcal{L}(\Phi^1) + \mathcal{L}(\Phi^2) - 1$

o Remove the output layer of  $\Phi^1$  and the input layer of  $\Phi^2$  since they are not activated (no application of  $\sigma$ )

We have

$$\Phi^2 \circ \Phi^1 = \Phi^2 \circ \Phi^1,$$

i.e., concatenation = composition. This follows from the fact that for any  $x^{(L-1)} \in \mathbb{R}^{N_{L-1}^{(1)}}$ ,

$$A_1^{(2)} A_{L_1}^{(1)} x^{(L-1)} + A_1^{(2)} b_{L_1}^{(1)} + b_1^{(2)} = A_1^{(2)} \underbrace{(A_L^{(1)} x^{(L-1)} + b_{L_1}^{(1)})}_{\in \mathbb{R}^{N_{L_1}^{(1)}} = \mathbb{R}^{N_0^{(2)}}} + b_1^{(2)} \in \mathbb{R}^{N_0^{(2)}}.$$

## Parallelization

Given two  $\sigma$ -NNs

$$\Phi^1 = \text{NN}(\sigma, N_0^{(1)}, \dots, N_{L_1}^{(1)}, (A_1^{(1)}, b_1^{(1)}), \dots, (A_{L_1}^{(1)}, b_{L_1}^{(1)})),$$

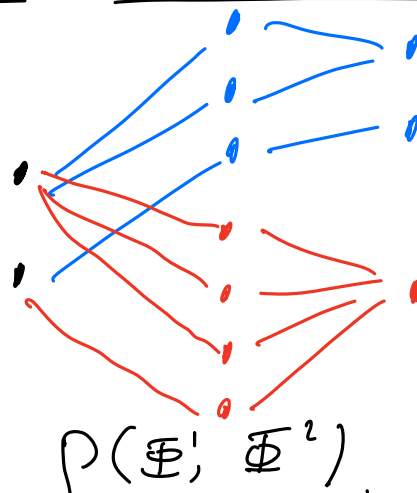
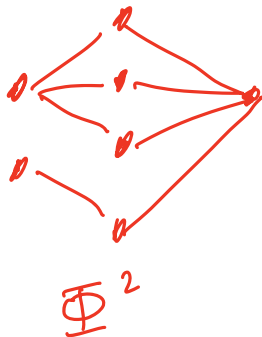
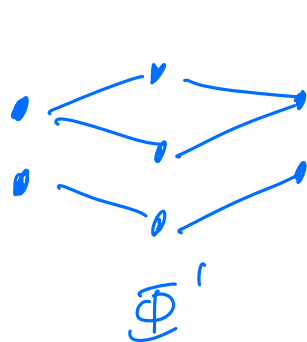
$$\Phi^2 = \text{NN}(\sigma, N_0^{(2)}, \dots, N_{L_2}^{(2)}, (A_1^{(2)}, b_1^{(2)}), \dots, (A_{L_2}^{(2)}, b_{L_2}^{(2)})).$$

Assume  $L_1 = L_2 = L$  and  $N_0^{(1)} = N_0^{(2)} = N_0$  (i.e., same depth and same input dim.). Define

$$\underline{\Phi} = \rho(\Phi^1, \Phi^2) = \text{NN}(\sigma, N_0, N_1^{(1)} + N_1^{(2)}, \dots, N_1^{(L)} + N_2^{(L)}, \left( \begin{bmatrix} A_1^{(1)} \\ A_1^{(2)} \end{bmatrix}, \begin{bmatrix} b_1^{(1)} \\ b_1^{(2)} \end{bmatrix} \right), \dots, \left( \begin{bmatrix} A_L^{(1)} & 0 \\ 0 & A_L^{(2)} \end{bmatrix}, \begin{bmatrix} b_L^{(1)} \\ b_L^{(2)} \end{bmatrix} \right)).$$

Then  $\underline{\Phi}$  is a  $\sigma$ -NN with  $\mathcal{L}(\underline{\Phi}) = L$ . (check it!)

Call  $\underline{\Phi}$  the parallelization of  $\Phi^1$  and  $\Phi^2$  with shared inputs.



We have

$$\rho(\Phi^1, \Phi^2)(x) = \begin{bmatrix} \Phi^1(x) \\ \Phi^2(x) \end{bmatrix} \quad \forall x \in \mathbb{R}^{N_0}.$$

Given two  $\sigma$ -NNs  $\Phi^1$  and  $\Phi^2$  as above.

Assume  $L_1 = L_2 =: L$ . Define

$$\Phi = \text{FP}(\Phi^1, \Phi^2) = \text{NN}(\sigma, N_0^{(1)} + N_0^{(2)}, \dots, N_{L-1}^{(1)} + N_{L-1}^{(2)}, N_L^{(1)} + N_L^{(2)},$$

$$\left( \left[ \begin{array}{c|c} A_1^{(1)} & 0 \\ \hline 0 & A_2^{(1)} \end{array} \right], \left[ \begin{array}{c} b_1^{(1)} \\ b_1^{(2)} \end{array} \right] \right), \dots, \left( \left[ \begin{array}{c|c} A_L^{(1)} & 0 \\ \hline 0 & A_L^{(2)} \end{array} \right], \left[ \begin{array}{c} b_L^{(1)} \\ b_L^{(2)} \end{array} \right] \right).$$

Then  $\Phi$  is a  $\sigma$ -NN with  $L(\Phi) = L$ , the input dimension  $N_0^{(1)} + N_0^{(2)}$ , and the output dimension  $N_L^{(1)} + N_L^{(2)}$ . We call  $\Phi$  the parallelization of

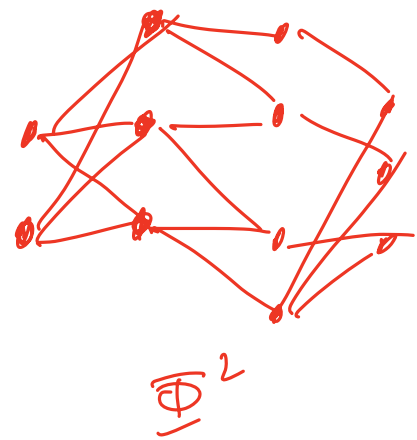
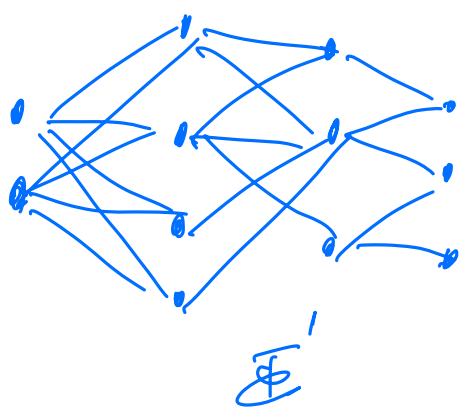
$\Phi^1$  and  $\Phi^2$  without shared inputs. We have

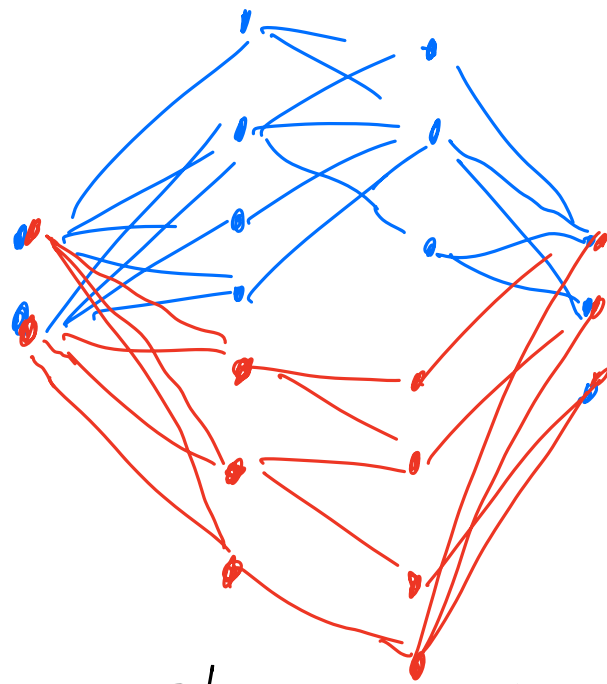
$$\text{FP}(\Phi^1(x), \Phi^2(y)) = (\Phi^1(x), \Phi^2(y)) \quad \forall (x, y) \in \mathbb{R}^{N_0^{(1)}} \times \mathbb{R}^{N_0^{(2)}}.$$

We denote by  $\text{NN}(\sigma, L, N_0, N_L)$  the class of all NNs with the activation function  $\sigma$ , the depth  $L$ , the input dimension  $N_0$ , and the output dimension  $N_L$ .

Parallelization again. Let  $\Phi^i \in \text{NN}(\sigma, L, N_0, N_L)$  be

given by  $\Phi^i = \text{NN}(\sigma, N_0^{(i)}, N_1^{(i)}, \dots, N_L^{(i)}, (A_1^{(i)}, b_1^{(i)}), \dots, (A_L^{(i)}, b_L^{(i)}))$ ,  $i=1, 2$ , with  $N_0^{(1)} = N_0^{(2)} = N_0$ ,  $N_L^{(1)} = N_L^{(2)} = N_L$ . We construct  $\Phi^1 \oplus \Phi^2 \in \text{NN}(\sigma, L, N_0, N_L)$  so that  $(\Phi^1 \oplus \Phi^2)(x) = \Phi^1(x) + \Phi^2(x) \quad \forall x \in \mathbb{R}^{N_0}$ .





$$\underline{\Phi}^1 \oplus \underline{\Phi}^2 = \underline{\Phi}^1 + \underline{\Phi}^2$$

We define

$$\underline{\Phi}^1 \oplus \underline{\Phi}^2 = \mathcal{NN}(\sigma, N_0, N_1^{(1)} + N_1^{(2)}, \dots, N_{L-1}^{(1)} + N_{L-1}^{(2)}, N_L, (\hat{A}_1, \hat{b}_1), \dots, (\hat{A}_L, \hat{b}_L)),$$

where

$$\hat{A}_1 = \begin{bmatrix} A_1^{(1)} \\ A_2^{(1)} \end{bmatrix}, \quad \hat{b}_1 = \begin{bmatrix} b_1^{(1)} \\ b_1^{(2)} \end{bmatrix}$$

$$\hat{A}_j = \begin{bmatrix} A_j^{(1)} & 0 \\ 0 & A_j^{(2)} \end{bmatrix}, \quad \hat{b}_j = \begin{bmatrix} b_j^{(1)} \\ b_j^{(2)} \end{bmatrix}, \quad j=2, \dots, L-1 \text{ (if } L \geq 3)$$

$$\hat{A}_L = [A_L^{(1)} \quad A_L^{(2)}] \quad \hat{b}_L = b_L^{(1)} + b_L^{(2)}$$

One verifies that  $(\underline{\Phi}^1 \oplus \underline{\Phi}^2)(x) = \underline{\Phi}^1(x) + \underline{\Phi}^2(x) \quad \forall x \in \mathbb{R}^{N_0}$ .

We denote by  $\mathcal{NN}(\sigma, N_0, \dots, N_L)$  the class of  $\sigma$ -NNs with depth  $L$  and dimension of the layers  $N_0, \dots, N_L$ .

Shifted dilates Given a NN  $\underline{\Phi} \in \mathcal{NN}(\sigma, N_0, \dots, N_L)$ .

Also, given  $\alpha \in \mathbb{R}$  and  $\xi \in \mathbb{R}^{N_0}$ . Define  $T(x) = S(\alpha x + \xi) \quad \forall x \in \mathbb{R}^{N_0}$ . Then  $T$  is also a NN. To see this, assume

$\Phi = NN(\sigma, N_0, \dots, N_L, (A_1, b_1), \dots, (A_L, b_L))$ . Define 8

$\hat{A}_1 = \alpha A_1$ ,  $\hat{b}_1 = A_1 \bar{z} + b_1$ , and  $\hat{A}_k = A_k$ ,  $b_k = b_k$ ,  $k=2, \dots, L$ .

Then  $T = NN(\sigma, N_0, \dots, N_L, (\hat{A}_1, \hat{b}_1), \dots, (\hat{A}_L, \hat{b}_L))$ .

From the above constructions, we have:

Proposition  $NN(\sigma, L, N_0, N_L)$  is a vector space, a subspace of the vector space of all maps from  $\mathbb{R}^{N_0}$  to  $\mathbb{R}^{N_L}$ . Q.E.D.

Note: If we fix the architecture,  $NN(\sigma, L, N_0, \dots, N_L)$  is not a vector space, as in general the addition is not closed. (Find an example!)

Question:

$NN(\sigma, L, N_0=d, N_L=m) \subseteq NN(\sigma, L+1, N_0=d, N_{L+1}=m)$ ?

Question: Let  $\Phi^1, \Phi^2$  be two NNs with the same activation function  $\sigma$ , the same input dimension  $N_0$ , and the same 1-dimensional output  $N_L=1$ . Then, is there a NN with  $\sigma, N_0, N_L=1$  such that it is the same as  $\Phi^1(x) \cdot \Phi^2(x) \forall x \in \mathbb{R}^{N_0}$ ?

Note: if  $\sigma = \text{ReLU}$ , then we have more operations. In particular, Augmentation!