

# Normalization of Single-Layer ReLU Networks

Consider a single-hidden layer ReLU Neural Network:  $ReLU(\mathbf{W}\mathbf{x} + \mathbf{b})^T \mathbf{v} = y$

Where

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix} \in \mathbb{R}^d, \quad y \in \mathbb{R}$$

and

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1d} \\ w_{21} & w_{22} & \cdots & w_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ w_{l1} & w_{l2} & \cdots & w_{ld} \end{bmatrix} \in \mathbb{R}^{l \times d}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_l \end{bmatrix} \in \mathbb{R}^l, \quad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_l \end{bmatrix} \in \mathbb{R}^l.$$

**Lemma 1.** *For any given NN weights/biases  $\mathbf{W}, \mathbf{b}, \mathbf{v}$ , there exists an (unique) alternate weights/biases  $\mathbf{W}', \mathbf{b}', \mathbf{v}'$  such that  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})^T \mathbf{v} = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')^T \mathbf{v}' = y^n$  for all dataset  $(\mathbf{x}^n, y)$ ,  $n \in [N]$  and  $v'_i \in \{-1, 0, +1\} \quad \forall i \in [l]$ .*

*Proof.* For a given  $\mathbf{v}$ , let  $I \subseteq [l]$  be the index set where  $v_i = 0 \quad \forall i \in I$  and  $v_i \neq 0 \quad \forall i \in [l]/I$ .

Let  $\mathbf{v}'$  be  $v'_i = 0 \quad \forall i \in I$  and  $v'_i = \frac{v_i}{|v_i|} \in \{-1, +1\} \quad \forall i \in [l]/I$ .

Let  $\mathbf{W}'$  be  $w'_{ij} = w_{ij} \quad \forall i \in I, \forall j \in [d]$  and  $w'_{ij} = \frac{w_{ij}}{|v_i|} \quad \forall i \in [l]/I, \forall j \in [d]$ .

Let  $\mathbf{b}'$  be  $b'_i = b_i \quad \forall i \in I$  and  $b'_i = \frac{b_i}{|v_i|} \quad \forall i \in [l]/I$ .

Then for an arbitrary dataset  $(\mathbf{x}^n, y^n)$ ,

$(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i = (\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i \quad \forall i \in I$  and therefore  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i \quad \forall i \in I$ .  
Then  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i v_i = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i v'_i = 0 \quad \forall i \in I$ .

$(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i = |v_i|(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i \quad \forall i \in [l]/I$ .

If  $(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i > 0$  then  $|v_i|(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i > 0$  and  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i$  and therefore  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i \quad \forall i \in [l]/I$ .

Then  $ReLU(\mathbf{W}\mathbf{x}^n + \mathbf{b})_i v_i = ReLU(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')_i v'_i = 0 \quad \forall i \in [l]/I$ .

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