

# Maximizing Sparsity in NN with MIP

## Research Archive

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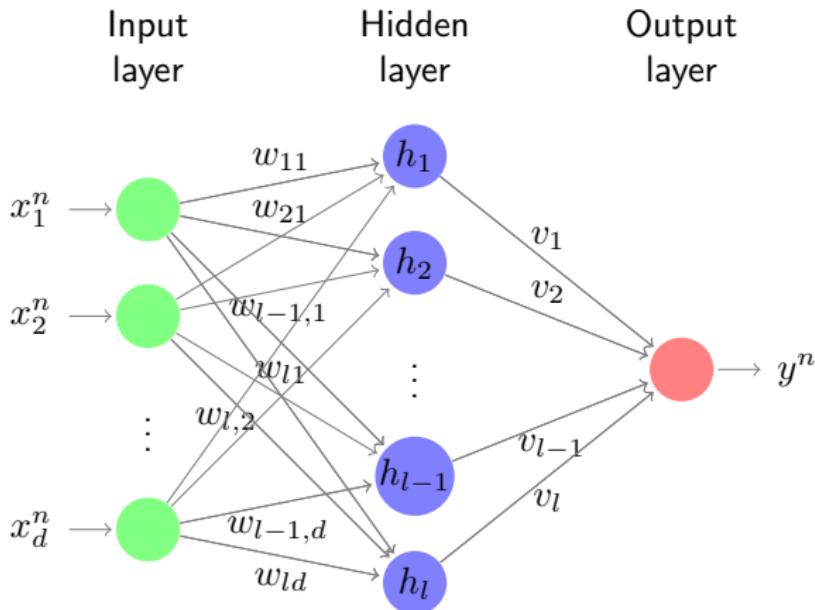
Motivated by *Rob Nowak, Fischetti and Jo*  
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# Problem Setting

- ① Given  $N$  datasets :  $(\mathbf{x}^1, y^1), (\mathbf{x}^2, y^2), \dots, (\mathbf{x}^N, y^N)$
- ② Input : 'd'-dimensional  
 $\mathbf{x}^n = (x_1^n, x_2^n, \dots, x_d^n) \in \mathbb{R}^d, \quad \forall n \in [N]$   
 $(\overline{\mathbf{x}^n} = (x_1^n, x_2^n, \dots, x_d^n, 1) \in \mathbb{R}^{d+1})$
- ③  $w$
- ④  $\mathbf{x}^n \rightarrow$  Affine Combination :  $w^k \overline{\mathbf{x}^n} \rightarrow$  Nonlinear Operator (ReLU) :  $\rightarrow$  Activation of Neuron  $k$

# NN Formulation



①  $h_i^1 = \max\{0, \mathbf{w} \cdot \mathbf{x}^n + b_i^1\} = \max\{0, \mathbf{w} \cdot \overline{\mathbf{x}^n}\}$

# MINLP Formulation 1

**Decision vars:**  $\mathbf{W} \in \mathbb{R}^{l_1 \times d} : w_{ij} \in \mathbb{R} (i = 1, \dots, l_1; j = 1, \dots, d),$

$\mathbf{b} \in \mathbb{R}^{l_1} : b_i \in \mathbb{R} (i = 1, \dots, l_1),$

$p_i^n, q_i^n \in \mathbb{R},$

$z_i^n \in \{0, 1\} \quad (n = 1, \dots, N; i = 1, \dots, l_1),$

$\mathbf{v} \in \mathbb{R}^{l_1} : v_i \in \mathbb{R} (i = 1, \dots, l_1),$

$s_{ij} \in \mathbb{R} \quad (i = 1, \dots, l_1; j = 1, \dots, d),$

$t_{ij} \in \{0, 1\} \quad (i = 1, \dots, l_1; j = 1, \dots, d),$

**Objective:**  $\min \sum_{i=1}^{l_1} \sum_{j=1}^d t_{ij}$

**Constraints:**  $\sum_{j=1}^d w_{ij} x_j^n + b_i = p_i^n - q_i^n, \quad \forall n \in [N], i \in [l_1]$

$p_i^n, q_i^n \geq 0, \quad \forall n \in [N], i \in [l_1]$

$p_i^n \leq M(1 - z_i^n), \quad \forall n \in [N], i \in [l_1]$

$q_i^n \leq Mz_i^n, \quad \forall n \in [N], i \in [l_1]$

$\sum_{i=1}^{l_1} p_i^n v_i = y^n, \quad \forall n \in [N]$

$s_{ij} = w_{ij} v_i, \quad \forall i \in [l_1], j \in [d]$

$-Mt_{ij} \leq s_{ij} \leq Mt_{ij}, \quad \forall i \in [l_1], j \in [d]$

# Normalization of Single-Layer ReLU Networks

*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  $\text{ReLU}(\mathbf{W}\mathbf{x}^n + \mathbf{b})^T \mathbf{v} = \text{ReLU}(\mathbf{W}'\mathbf{x}^n + \mathbf{b}')^T \mathbf{v}' = y^n$  for all dataset  
 $(\mathbf{x}^n, y)$ ,  $n \in [N]$   
and  $v'_i \in \{-1, 0, +1\} \quad \forall i \in [l]$ .



# MILP Formulation by Lemma 1

**Decision vars:**  $\mathbf{W} \in \mathbb{R}^{l \times d}$  :  $w_{ij} \in \mathbb{R}$  ( $i = 1, \dots, l$ ;  $j = 1, \dots, d$ ),

$\mathbf{b} \in \mathbb{R}^l$  :  $b_i \in \mathbb{R}$  ( $i = 1, \dots, l$ ),

$p_i^n, q_i^n \in \mathbb{R}$  ( $n = 1, \dots, N$ ;  $i = 1, \dots, l$ ),

$z_i^n \in \{0, 1\}$  ( $n = 1, \dots, N$ ;  $i = 1, \dots, l$ ),

$\mathbf{v} \in \{-1, 0, +1\}^l$  :  $v_i^{-1}, v_i^0, v_i^{+1} \in \{0, 1\}$  ( $i = 1, \dots, l$ ),

$t_{ij} \in \{0, 1\}$  ( $i = 1, \dots, l_1$ ;  $j = 1, \dots, d$ ),

**Objective:**  $\min \sum_{i=1}^{l_1} \sum_{j=1}^d t_{ij}$

**Constraints:**  $\sum_{j=1}^d w_{ij} x_j^n + b_i = p_i^n - q_i^n, \quad \forall n \in [N], i \in [l_1]$

$$p_i^n, q_i^n \geq 0, \quad \forall n \in [N], i \in [l_1]$$

$$p_i^n \leq M(1 - z_i^n), \quad \forall n \in [N], i \in [l_1]$$

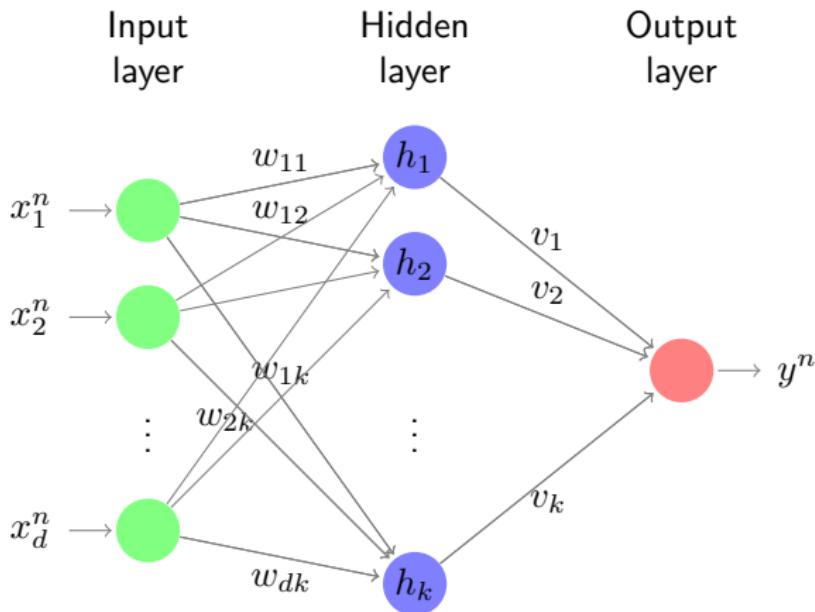
$$q_i^n \leq Mz_i^n, \quad \forall n \in [N], i \in [l_1]$$

$$\sum_{i=1}^l p_i^n (-v_i^{-1} + v_i^{+1}) = y^n, \quad \forall n \in [N]$$

$$v_i^{-1} + v_i^0 + v_i^{+1} = 1, \quad \forall i \in [l]$$

$$-Mt_{ij} \leq w_{ij} \leq Mt_{ij}, \quad \forall i \in [l_1], j \in [d]$$

# Normalized $v$ Formulation



①  $h_i^1 = \max\{0, \mathbf{w} \cdot \mathbf{x}^n + b_i^1\} = \max\{0, \mathbf{w} \cdot \overline{\mathbf{x}^n}\}$

# New MILP Formulation

**Given:**  $(\mathbf{x}^n, y^n)_{n=1}^N \in (\mathbb{R}^d \times \mathbb{R})^N : \mathbf{x}_i^n, y^n \in \mathbb{R}$  ( $n \in [N], i \in [d]$ )  
 $d, N, K \in \mathbb{N}$

**Decision vars:**  $\theta := \{\mathbf{w}_k, b_k, v_k\}_{k=1}^K \in (\mathbb{R}^d \times \mathbb{R} \times \mathbb{R})^K$

**weight 1:**  $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_K] \in \mathbb{R}^{d \times K} : w_{ik} \in \mathbb{R}$  ( $i \in [d], k \in [K]$ )

**bias:**  $\mathbf{b} \in \mathbb{R}^K : b_k \in \mathbb{R}$  ( $k \in [K]$ )

**weight 2:**  $\mathbf{v} \in \{-1, +1\}^K : v_k \in \{-1, 1\}$  ( $v'_k \in \{0, 1\}, v_k = 2v'_k - 1$ ) ( $k \in [K]$ )

**Output of linear combination**  $(\mathbf{w}_k^T \mathbf{x}^n + b_k)(\text{pos/neg}) : p_k^n, q_k^n \in \mathbb{R}$  ( $n \in [N], k \in [K]$ )

**Nonnegativity of Neuron(Y/N)** :  $z_k^n \in \{0, 1\}$  ( $n \in [N], k \in [K]$ )

**Nonzero Weight Path(Y/N)** :  $t_{ik} \in \{0, 1\}$  ( $i \in [d], k \in [K]$ )

# New MILP Formulation (Cont'd)

**Objective(Sparsity):**  $\min \sum_{i=1}^d \sum_{k=1}^K t_{ik}$

**Constraints:** **Output of linear combination**

$$\sum_{i=1}^d w_{ik} x_i^n + b_k = p_k^n - q_k^n, \quad \forall n \in [N], k \in [K]$$

**Output of ReLu Activation**

$$p_k^n, q_k^n \geq 0, \quad \forall n \in [N], k \in [K]$$

$$p_k^n \leq M z_k^n, \quad \forall n \in [N], k \in [K]$$

$$q_k^n \leq M(1 - z_k^n), \quad \forall n \in [N], k \in [K]$$

**Exact Data fitting**

$$\sum_{k=1}^K p_k^n (2v'_k - 1) = y^n, \quad \forall n \in [N]$$

**Nonzero Weight Path Indicator**

$$-M t_{ik} \leq w_{ik} \leq M t_{ik} \quad \forall i \in [d], k \in [K]$$



# McCormick Constraints

**Bilinear Constraints:**  $\sum_{k=1}^K p_k^n (2v'_k - 1) = y^n, \quad \forall n \in [N]$

$$\sum_{k=1}^K 2p_k^n v'_k - p_k^n = y^n, \quad \forall n \in [N]$$

**Auxiliary Variables:**  $r_k^n \in \mathbb{R} \quad (r_k^n = p_k^n v'_k) \quad \forall n \in [N], \forall k \in [K]$

**McCormick Constraints:**  $(\because 0 \leq p_k^n \leq M, v'_k \in \{0, 1\})$

$$0 \leq r_k^n \leq M v'_k \quad \forall n \in [N], \forall k \in [K]$$

$$p_k^n - M(1 - v'_k) \leq r_k^n \leq p_k^n \quad \forall n \in [N], \forall k \in [K]$$

# New MILP Formulation

**Given:**  $(\mathbf{x}^n, y^n)_{n=1}^N \in (\mathbb{R}^d \times \mathbb{R})^N : \mathbf{x}_i^n, y^n \in \mathbb{R}$  ( $n \in [N], i \in [d]$ )  
 $d, N, K \in \mathbb{N}$

**Decision vars:**  $\theta := \{\mathbf{w}_k, b_k, v_k\}_{k=1}^K \in (\mathbb{R}^d \times \mathbb{R} \times \mathbb{R})^K$

**weight 1:**  $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_K] \in \mathbb{R}^{d \times K} : w_{ik} \in \mathbb{R}$  ( $i \in [d], k \in [K]$ )

**bias:**  $\mathbf{b} \in \mathbb{R}^K : b_k \in \mathbb{R}$  ( $k \in [K]$ )

**weight 2:**  $\mathbf{v} \in \{-1, +1\}^K : v_k \in \{-1, 1\}$  ( $v'_k \in \{0, 1\}, v_k = 2v'_k - 1$ ) ( $k \in [K]$ )

**Output of linear combination**  $(\mathbf{w}_k^T \mathbf{x}^n + b_k)(\text{pos/neg}) : p_k^n, q_k^n \in \mathbb{R}$  ( $n \in [N], k \in [K]$ )

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**Nonzero Weight Path(Y/N)** :  $t_{ik} \in \{0, 1\}$  ( $i \in [d], k \in [K]$ )

**Auxiliary Variable** :  $r_k^n \in \mathbb{R}$  ( $r_k^n = p_k^n v'_k$ ) ( $\forall n \in [N], \forall k \in [K]$ )

# New MILP Formulation (Cont'd)

**Objective(Sparsity):**  $\min \sum_{i=1}^d \sum_{k=1}^K t_{ik}$

**Constraints:** **Output of linear combination**

$$\sum_{i=1}^d w_{ik} x_i^n + b_k = p_k^n - q_k^n, \forall n \in [N], k \in [K]$$

**Output of ReLu Activation**

$$p_k^n, q_k^n \geq 0, \quad \forall n \in [N], k \in [K]$$

$$p_k^n \leq M z_k^n, \quad \forall n \in [N], k \in [K]$$

$$q_k^n \leq M(1 - z_k^n), \quad \forall n \in [N], k \in [K]$$

**Exact Data fitting**

$$\sum_{k=1}^K 2r_k^n - p_k^n = y^n, \quad \forall n \in [N]$$

**McCormick Constraints**

$$0 \leq r_k^n \leq M v'_k \quad \forall n \in [N], \forall k \in [K]$$

$$p_k^n - M(1 - v'_k) \leq r_k^n \leq p_k^n \quad \forall n \in [N], \forall k \in [K]$$

**Nonzero Weight Path Indicator**

$$-M t_{ik} \leq w_{ik} \leq M t_{ik} \quad \forall i \in [d], k \in [K]$$

# Symmetry Handling

**Permutations:**  $\min \sum_{i=1}^d \sum_{k=1}^K t_{ik}$



# References I