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Solutions discussed with Strijan Sood, Karon Shah and Nupur Chatterji

1-1 The general strategy is to write inequalities corresponding to each now of the truth table, and choose w and b such that all the inequalities are satisfied.

AND: $O \cdot W_1 + O \cdot W_2 + \cdots + O \cdot W_1$ Let $W = [W_1, W_2]$

0.w, +0.w2 +b <0 i.e. b <0

0. w, +1. w2+b<0

i.e. W2+b < 0 ______ (2)

 $1.w_1 + 0.w_2 + b < 0$

1.e. W1+p < 0 _______ 3

1.w, +1.w2+b>0

re. W1+W2+b≥0 — (f)

The inequalities above suggest that b should be negative, and w. and W2 should be possitive but lesser in magnitude than b. Let's choose w and b as follows (there are many possible solutions):

w=[1,1],b=-2

b<0

W2+b=1-2=-1<0

Wi+b=1-2=-1 <0

w,+w2+b=1+1-2=0≥0

Thus, the inequalities above are satisfied

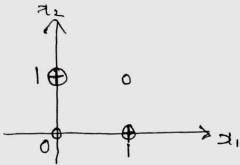
 $\Rightarrow \boxed{W_{AND} = [1,1]}$ $b_{AND} = -2$

1 Let's write down the inequalities like we did in part 1. 0.w, +0.w2+b <0 i.e. b <0 -0. W, +1. W2+b =0 i.e. W2+p >0 -1. w, + 0. w2 + b = 0 i.e. W,+b≥0 1.w,+1.w2+b ≥0 i-e. W1+ W2+ b >0 The inequalities above suggest that be should be negative and w, and We should be positive with a greater absolute value than that of b. Let's choose w and b as tollows (there are many possible solutions): w=[1,1], b=-1 b<0 $W_2+b=|-|=0\geq 0$ wi+b = 1-1 = 0 ≥ 0 $W_1+W_2+b=1+1-1=1\geq 0$

Thus, the inequalities above are satisfied.

$$\Rightarrow \boxed{W_{OR} = [1,1]}$$

$$b_{OR} = -1$$



As we can see above, there's no linear boundary that can separate the examples. Let's prove this analytically.

We will stort by writing down the inequalities as in part 1 and prove that they are inconsistent.

$$0.w_1 + 1.w_2 + b \geq 0$$

$$1.w_1 + 1.w_2 + b \ge 0$$

$$W_1 + W_2 + 2b \ge 0$$
 — (5)

From @ and @, we can see that there is a contradiction.

⇒ XOR connot be represented using a linear model with the same form as (1) in the question.

$$h(x) = W^{(0)}x + b^{(0)} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} = \begin{bmatrix} 0.52 \\ 0.53 + 1 \end{bmatrix}$$

$$a_1(x) = \max\{0, W^{(i)}x + b^{(i)}\} = \begin{cases} 0.5x \\ 0.5x + 1 \end{cases}$$
 as $x > 0$

$$h_{2}(x) = W^{(2)}\alpha_{1}(x) + b^{(2)} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0.5x \\ 0.5x + 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} x+1 \\ x+1 \end{bmatrix}$$

$$Q_2(x) = \max \{0, h_2(x)\} = \begin{bmatrix} x+1 \\ x+1 \end{bmatrix} \quad \text{os} \quad x > 0$$

$$h(x) = W^{(3)}a_2(x) + b^{(3)} = [1 \quad 1] [x+1] + 1 = 2x+3$$

$$\Rightarrow W=2$$

$$b=3$$

$$\frac{dh}{dx} = W = 2$$

$$h_{1}(x) = W^{(1)}x + b^{(1)} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.5x \\ 0.5x + 1 \end{bmatrix} = \begin{bmatrix} -0.5 \\ 0.5 \end{bmatrix}$$

$$a_1(x) = \max\{0, h_1(x)\} = \begin{bmatrix} 0 \\ 0.5x+1 \end{bmatrix}$$

$$b_{2}(x) = W^{(2)}a_{1}(x) + b^{(2)} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0.5x+1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0.5x+1 \end{bmatrix} = \begin{bmatrix} 0.5 \end{bmatrix}$$

$$=\begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}$$

$$a_2(x) = \max\{0, h_2(x)\} = \begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix}$$

$$h(x) = W^{(3)}a_2(x) + b^{(3)} = [1 \ 1] \begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix} +]$$

$$\Rightarrow \boxed{W=1}$$

$$b=3$$

$$\frac{dh}{dx} = W = 1$$

$$h_1(x) = W^{(1)}x + b^{(1)} = \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.5x \\ 0.5x + 1 \end{bmatrix} = \begin{bmatrix} -0.25 \\ 0.75 \end{bmatrix}$$

$$a_1(x) = \max\{0, h_1(x)\} = \begin{bmatrix} 0 \\ 0.5x + 1 \end{bmatrix}$$

$$h_{2}(x) = W^{(2)}(x) + b^{(2)} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0.5x + 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix} = \begin{bmatrix} 0.75 \\ 0.75 \end{bmatrix}$$

$$a_2(x) = \max\{0, h_2(x)\} = \begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix}$$

$$h(x) = W^{(3)}a_2(x) + b^{(3)} = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 0.5x + 1 \\ 0.5x + 1 \end{bmatrix} + 1 = x + 3$$

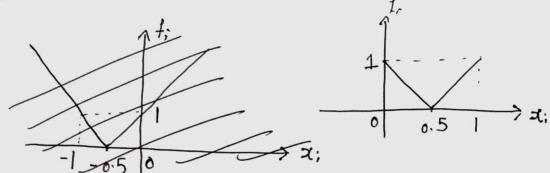
$$\Rightarrow \boxed{W=1}$$

$$b=3$$

$$\frac{dh}{dx} = W = 1$$

As W is a diagonal model, $W^{(i)}x + b = 2\pi i + 2x - 1$ $\Rightarrow f_{i}(x) = |2\pi i + 1| |2x - 1|$ As $x \in \mathbb{R}^{d}$, $f_{i}(x) \in \mathbb{R}^{d}$. Let f_{i} be the g_{i} element of $f_{i}(x)$ $(i \in \{1,2,...d\})$ $f_{i} = |2x_{i} + 1| \text{ where } x_{i} \text{ is the } i^{th} \text{ element } o^{t} \text{ input } x.$ $= \begin{cases} 2x_{i} + 1 & \text{if } x_{i} \geq +0.5 \\ -2x_{i} + 1 & \text{otherwise} \end{cases}$

Thus, it we consider a single dimension of the output, it identities the imput in 2 regions of the input. This is shown in the figure below:



The 2 regions are $R_1 = \{(-\frac{1}{4}, +0.5), (0.5, \bullet)\}$ for z_i . This applies to each dimension of the output. For every dimension, we can pick one of the two regions identified based on the value of the input in that dimension. This will result in a total of $2^{\frac{1}{4}}$ regions of the input that are identified onto $0 = (0,1)^{\frac{1}{4}}$ by $f_i(\cdot)$. We can combine the regions of the input for each dimension in this way as they are independent of each other, i.e. f_i depends only on z_i .

3-2 According to the definition, given g(to), it con an output value of g, say go, it could have come from any of the ng regions identified by it. In the composition, the output of g(·) is the input to f(·). Given an output value of fog(·), the input to f(·) could have come from any of the mx regions identified by f(·). Each of these inputs in turn could have come from any of the mx regions identified by g(·). Thus, fog(·) identifies mxng regions of its input.

3-3 As proved in part 2, composition of 2 functions, we the number of regions in the input identified is equal to the product of the number of regions identified by each of them. In the case of L layers, L functions are composed. As proved in part 1, each of them identifies 2d regions of the input. Thus, the number of regions identified by $f(x) = h_L$ is $T 2^d = 2^{Ld}$.