From: https://medium.com/swlh/learning-a-xor-function-with-feedforward-neural-networks-74ba3841f1c0

Finding the XOR weights:

First take the regression equation:

$$\hat{y} = w^T x + b - \text{eq-1}$$

And the inputs:
$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}$$
 and their corresponding outputs:
$$\begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix}$$

Plugging the values to eq-1 gives:

First input
$$[0 \ 0] -> 0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} w^T + b -> b = 0$$

Second input
$$\begin{bmatrix} 0 \\ 1 \end{bmatrix} \longrightarrow 1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} w^T + 0 \longrightarrow w_2 = 1$$

Third input
$$\begin{bmatrix} 1 & 0 \end{bmatrix} \longrightarrow 1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} w^T + 0 \longrightarrow w_1 = 1$$

For the final output we have to keep b to see the issue with linear regression on a nonlinear function.

Final input
$$\begin{bmatrix} 1 & 1 \end{bmatrix} -> 0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} w^T + b -> b + 2 = 0$$
; Now taking $b=0$ makes the equation

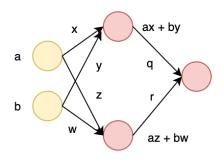
invalid. This shows how the linear regression cannot approximate a nonlinear function such as XOR. Therefore lets take the final input and give it to a simple neural network model

$$xW = \begin{bmatrix} a & b \end{bmatrix} \begin{bmatrix} x & z \\ y & w \end{bmatrix} = \begin{bmatrix} ax + by & az + bw \end{bmatrix}$$
 -eq-2

Since we know $w_1 = 1, w_2 = 1$ works for the first Three inputs, We can replicate and set it here

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}.$$
From eq-2
$$\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 2 \end{bmatrix}.$$
 Then the rest of the inputs.

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



So we have now the input mapping in the representation space (The hidden layer)

$$\begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 1 \\ 2 & 2 \end{bmatrix}$$

Now it is clear that the first 3 rows of the representation space outputs has the expected pattern

of the output space $\begin{bmatrix} 0\\1\\1\\0 \end{bmatrix}$. So the idea is to find a vector that would:

- 1. Keep the first column as it is (Since the fist 3 elements are the expected output)
- 2. Adjust the last column so that we can find a pair of output weights to map the 2 -> 0 and keep the rest of the elements as they are.

Take $c = \begin{bmatrix} 0 & -1 \end{bmatrix}$ and extend now the equation 2 with the new bias term c

$$\begin{bmatrix} 0 & 0 \\ 1 & 1 \\ 1 & 1 \\ 2 & 2 \end{bmatrix} - \begin{bmatrix} 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

Now we must handle the -1 case (Otherwise the output mapping would not be easy) by using a ReLU layer.

$$\begin{bmatrix} 0 & -1 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix} - \text{ReLU} -> \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 1 & 0 \\ 2 & 1 \end{bmatrix}$$

Finally we can select a pair of weights to handle the last row of the representation space as follows

$$\begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} q \\ r \end{bmatrix} = 0$$

Which gives q=1, r=-2. Also these weights map the first three elements to their corresponding outputs.

For the rest of the representation space

$$\begin{bmatrix} 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} = 0$$

$$\begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} = 1$$

$$\begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix} = 1$$