# Natural Language Processing

**Lecture 15**


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# Neural Nets Everywhere



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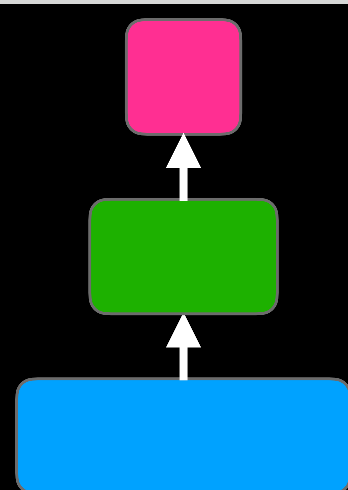
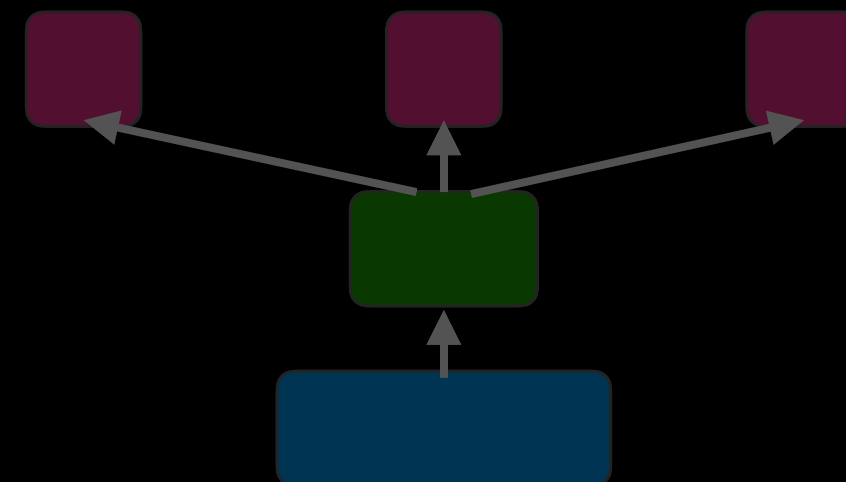
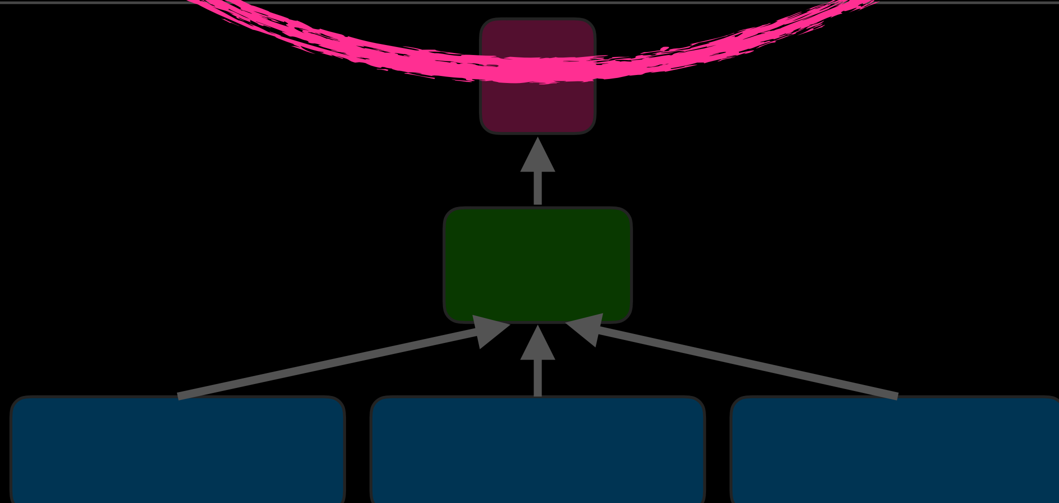
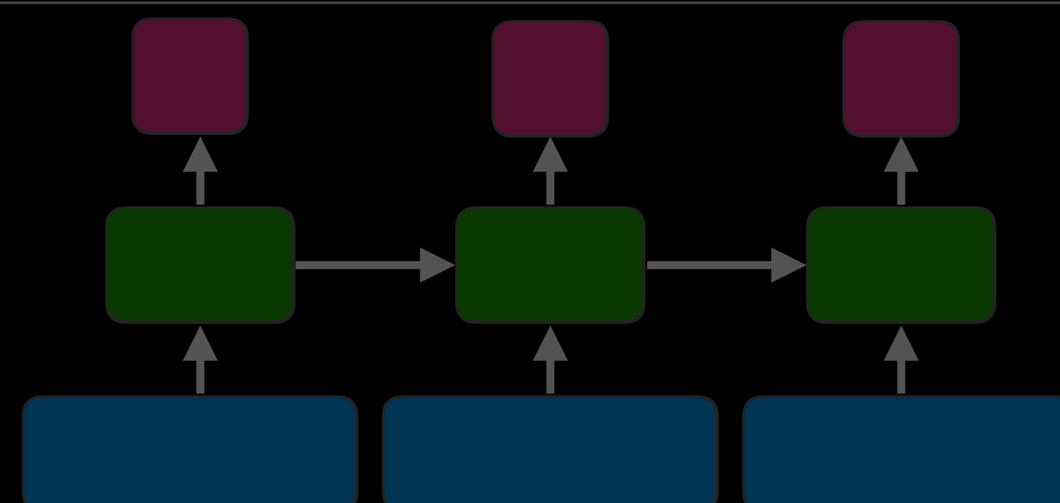
# Goals for Today

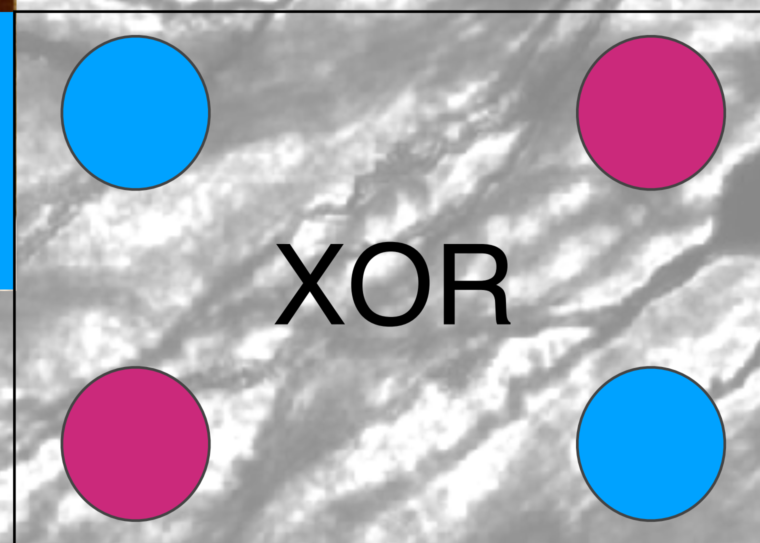
- Learn the basic difference between **neural architectures**
- Understand the **perceptron** as a basic element
- Understand training through **backpropagation**
- Learn about **dropout regularization**

# Types of Neural Models

| | Fixed length | Variable length |
|---|---|---|
| **Fixed length** |  Logistic Regression, Perceptron, Feed-Forward Network, Deep Belief Network… |  Multitask Learning, Decoder |
| **Variable length** |  Convolutional Neural Networks (CNN) |  Recurrent Neural Networks (RNN), Hidden Markov Models (HMM), Conditional Random Fields |


Frank Rosenblatt
(1928–1971)

The Perceptron can learn anything!!!

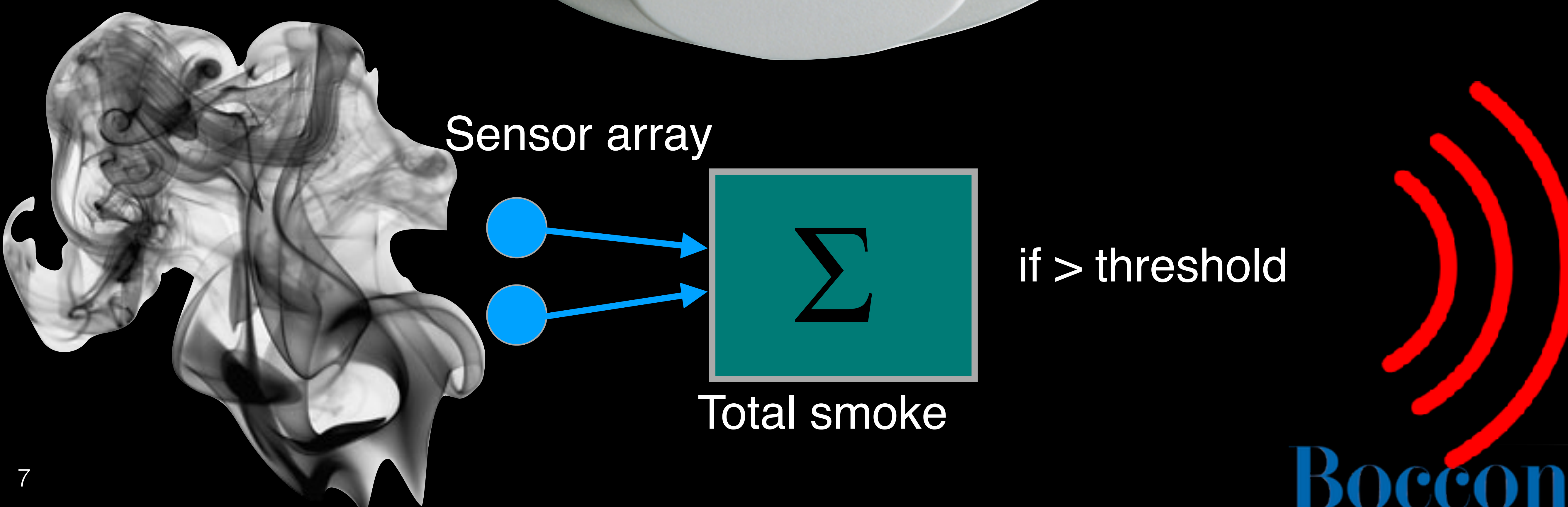



The Perceptron fails at learning even basic concepts

Marvin Minsky
(1927–2016)

# The Perceptron

# A Threshold Unit

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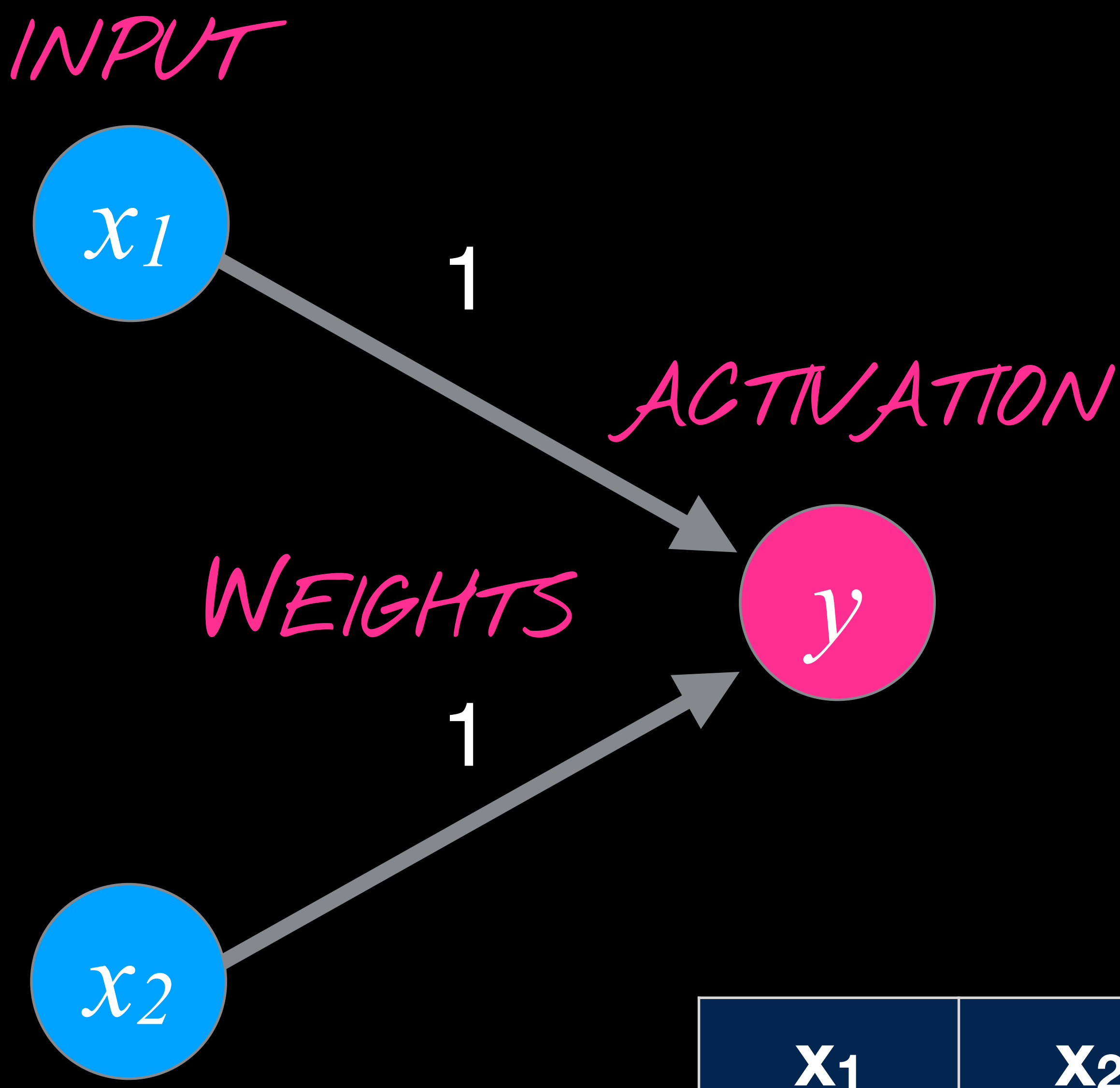
# OR-Perceptron

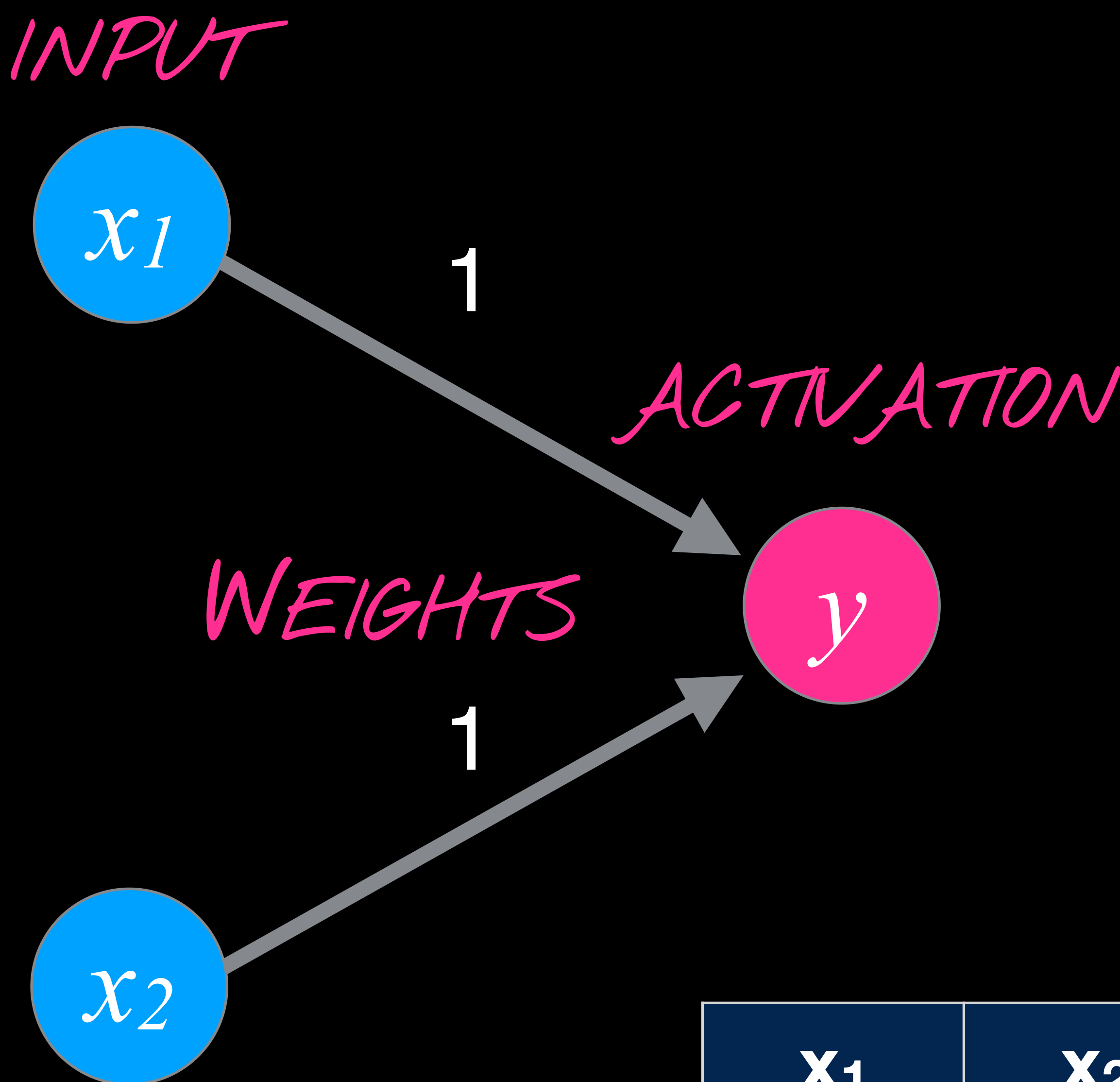



$$f(X) = w_1 x_1 + w_2 x_2$$

$$\hat{y} = \begin{cases} +1 & \text{if } f(X) \geq 1 \\ -1 & \text{otherwise} \end{cases}$$

| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | -1 |
| 1 | 0 | 1 |
| 0 | 1 | 1 |
| 1 | 1 | 1 |

# AND-Perceptron




$$f(X) = w_1 x_1 + w_2 x_2$$

$$\hat{y} = \begin{cases} +1 & \text{if } f(X) \geq 2 \\ -1 & \text{otherwise} \end{cases}$$

| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | -1 |
| 1 | 0 | -1 |
| 0 | 1 | -1 |
| 1 | 1 | 1 |

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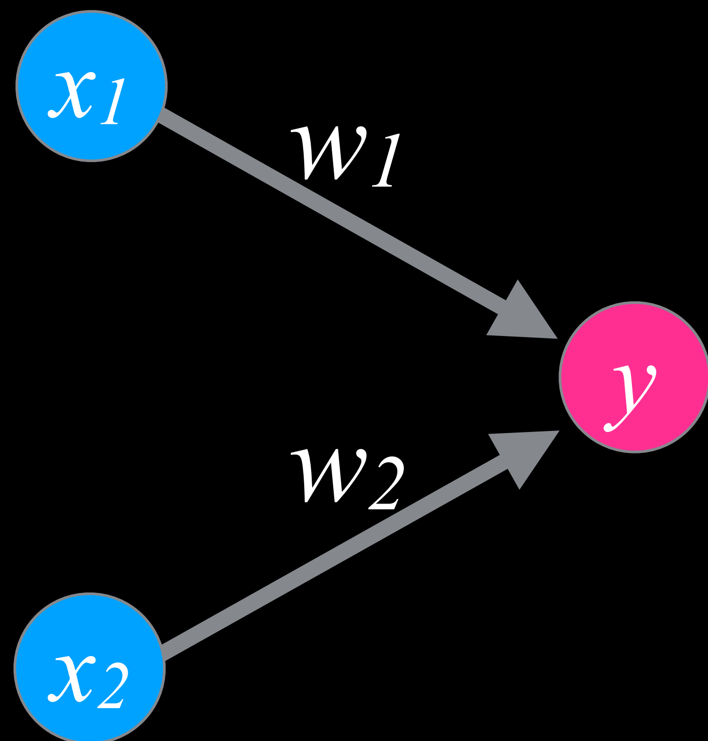
# Learn the Threshold




$$f(X) = w_1 x_1 + w_2 x_2$$

$$\hat{y} = \begin{cases} +1 & \text{if } f(X) \geq t \\ -1 & \text{otherwise} \end{cases}$$

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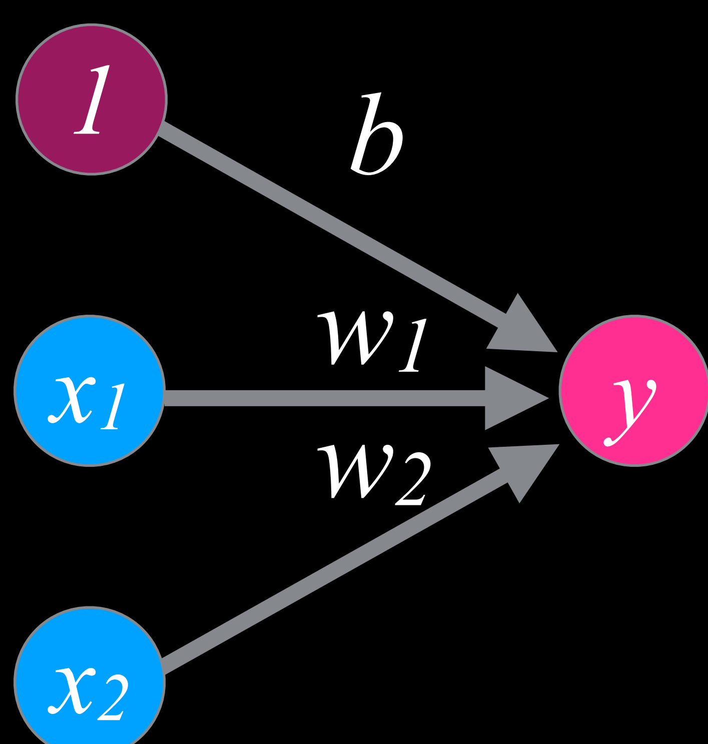


$$f(X) = w_1 x_1 + w_2 x_2 + \boldsymbol{b}$$

$$\hat{y} = \begin{cases} +1 & \text{if } f(X) \geq \mathbf{0.5} \\ -1 & \text{otherwise} \end{cases}$$

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# Learning to Distinguish

$$f(X) = 1\,x_1 + 1\,x_2 - 1$$

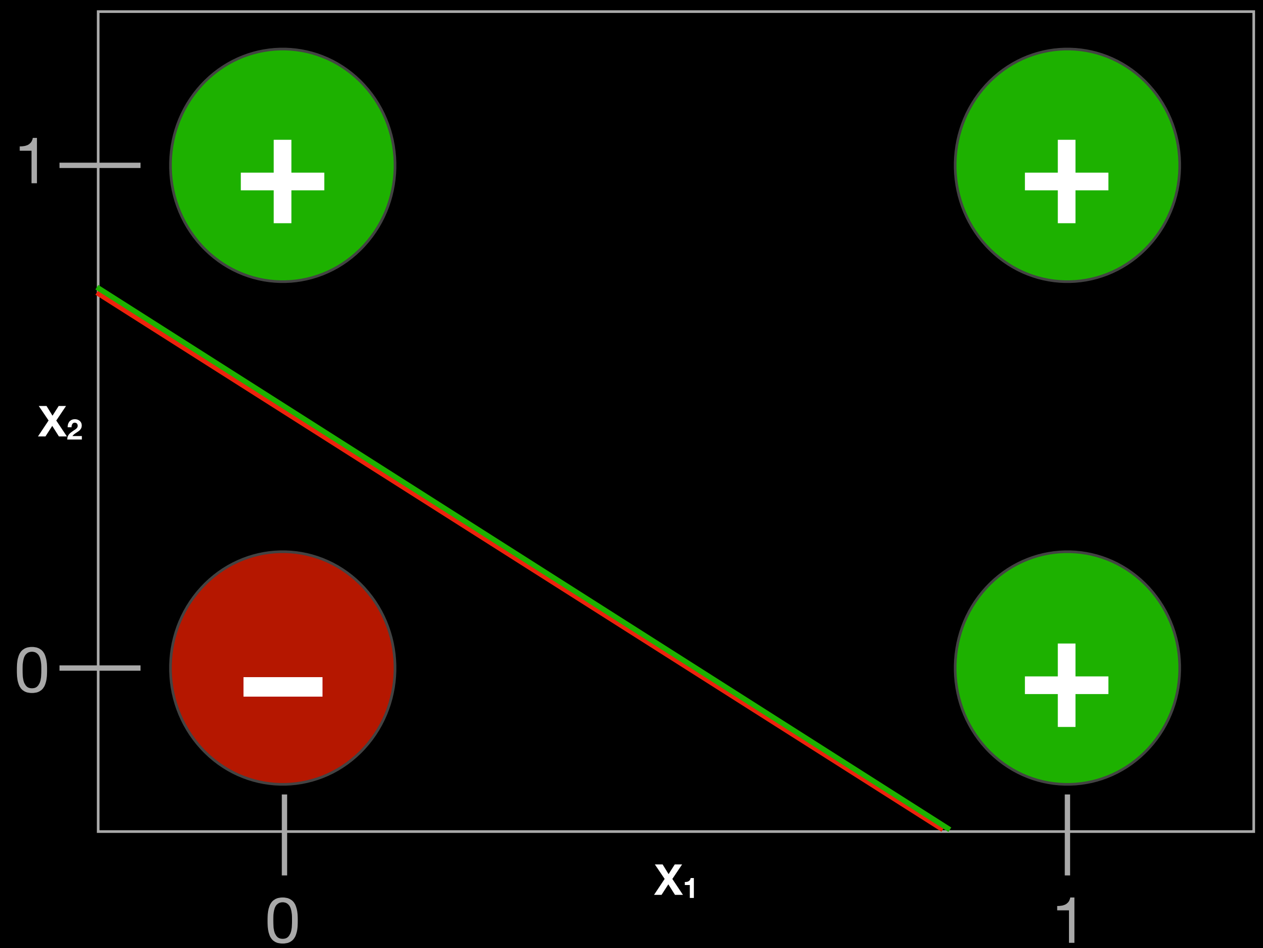
**OR**

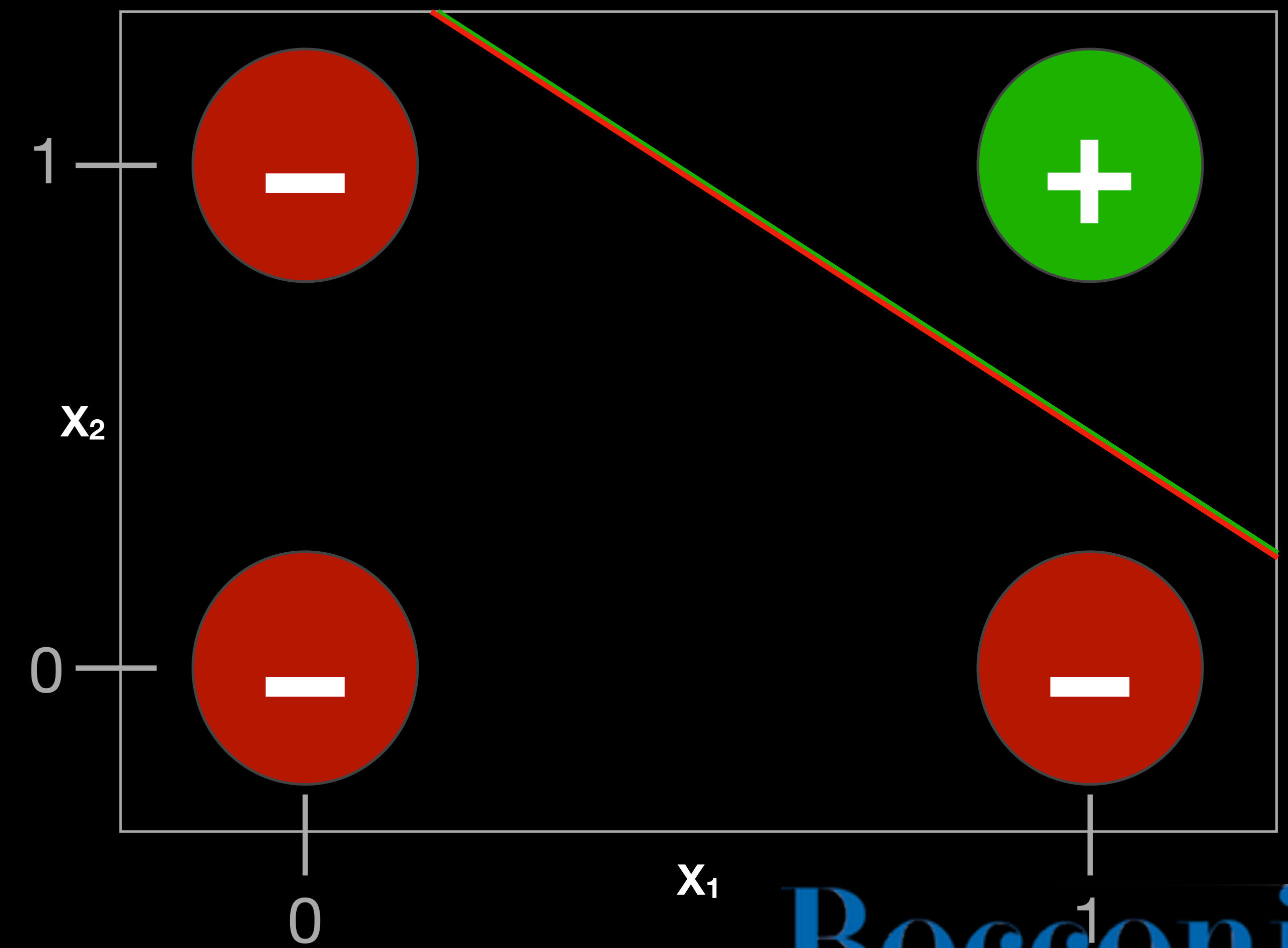
| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | -1 |
| 1 | 0 | 1 |
| 0 | 1 | 1 |
| 1 | 1 | 1 |

$$f(X) = 1\,x_1 + 1\,x_2 - 2$$

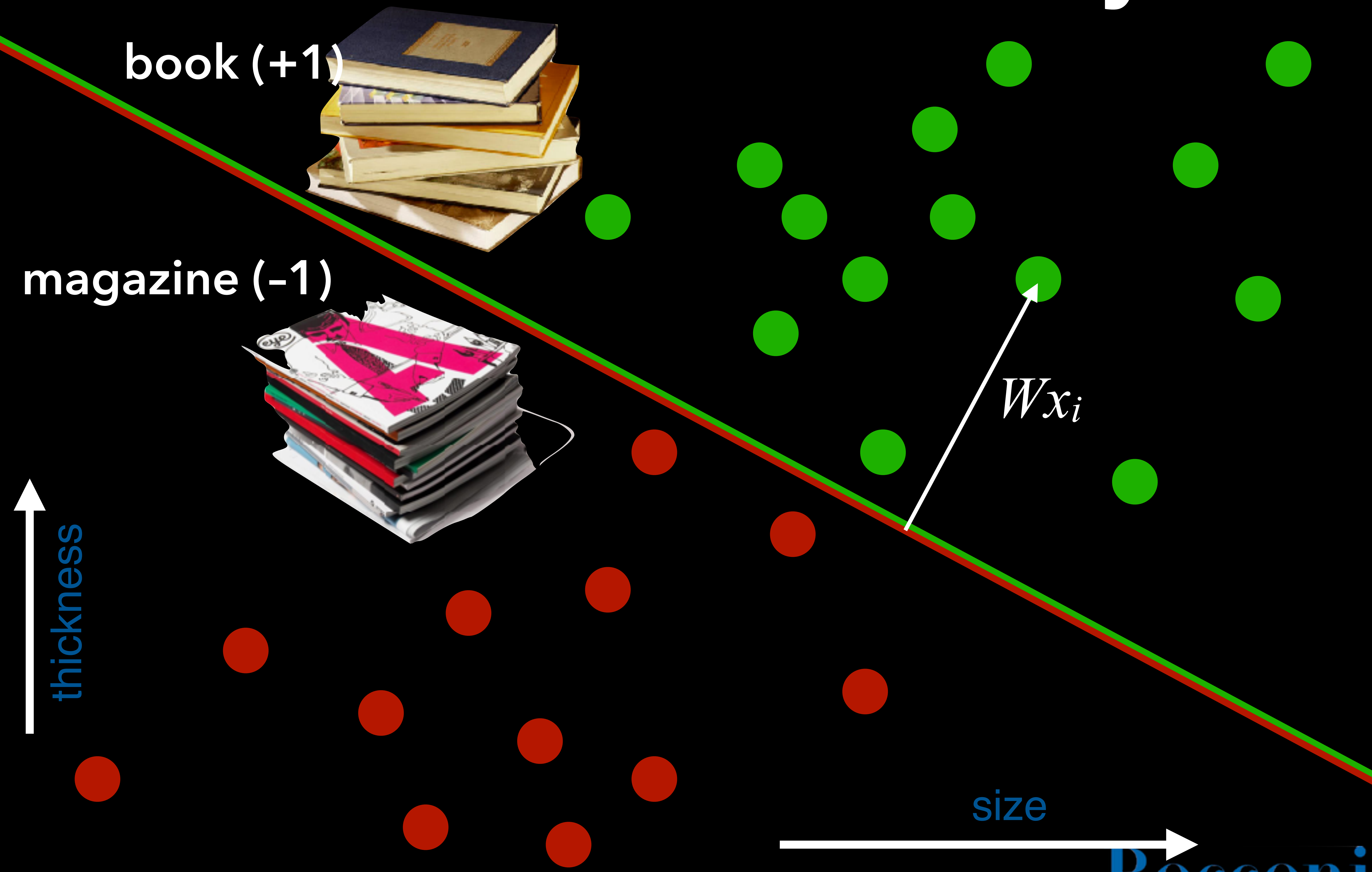
**AND**

| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | -1 |
| 1 | 0 | -1 |
| 0 | 1 | -1 |
| 1 | 1 | 1 |



# Decision Boundary

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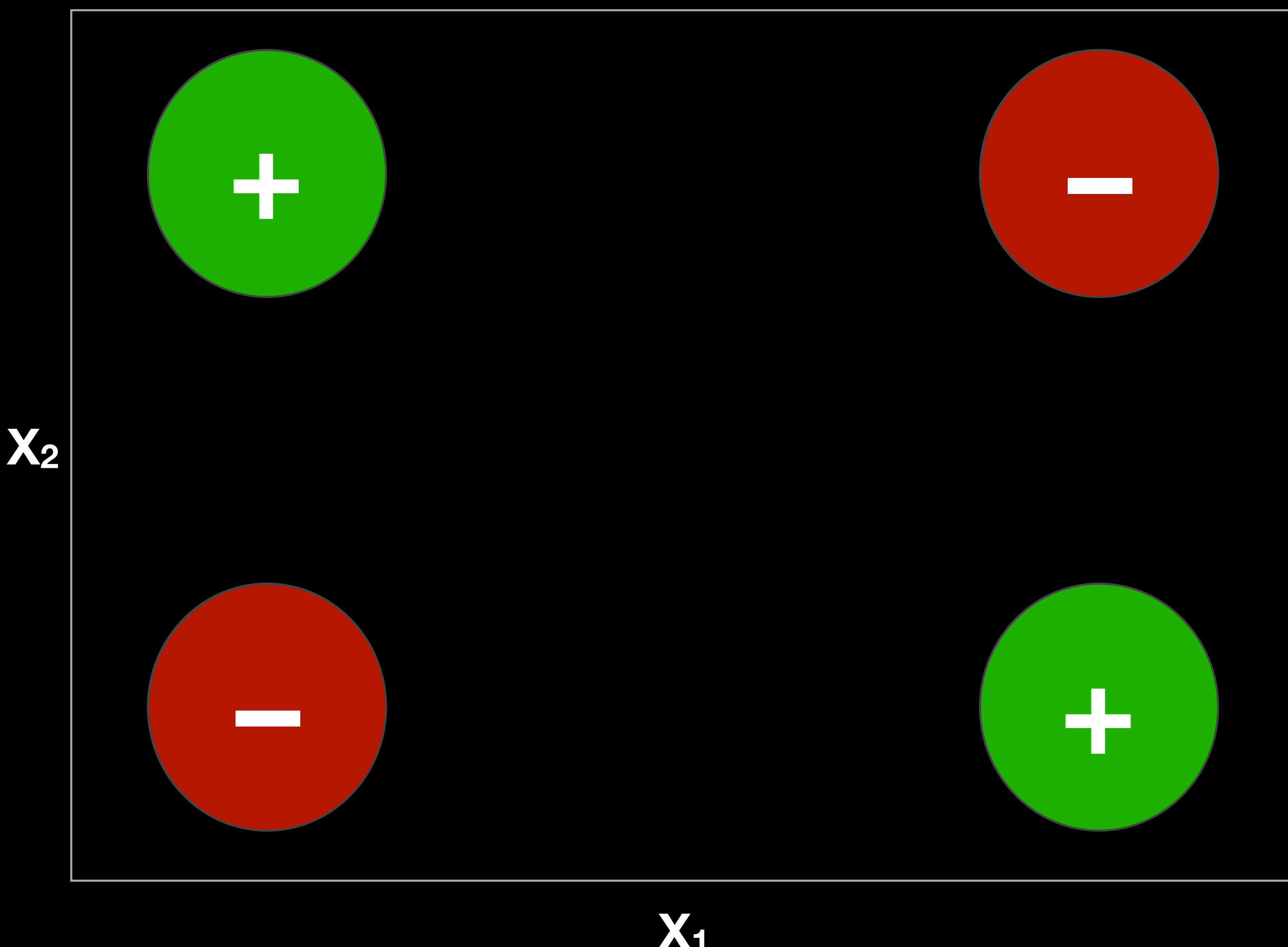
# The XOR Limit

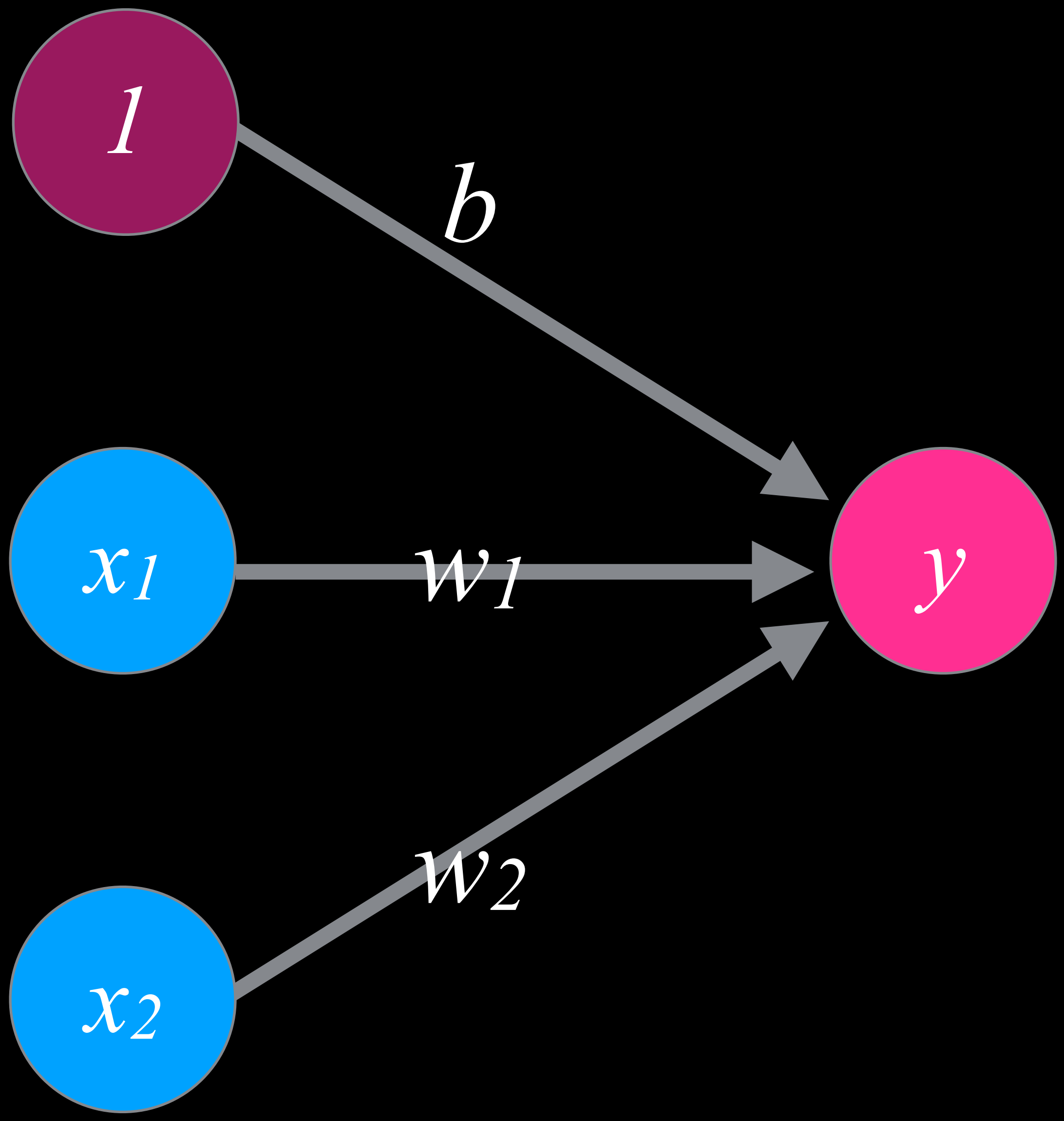
| $x_1$ | $x_2$ | y |
|---|---|---|
| 0 | 0 | -1 |
| 1 | 0 | 1 |
| 0 | 1 | 1 |
| 1 | 1 | -1 |




# Step 1:
# Non-Linearity

# Nonlinear Activation Functions

$$f(X) = a(w_1 x_1 + w_2 x_2 + b)$$




SIGMOID (S-LIKE)

**Logistic**

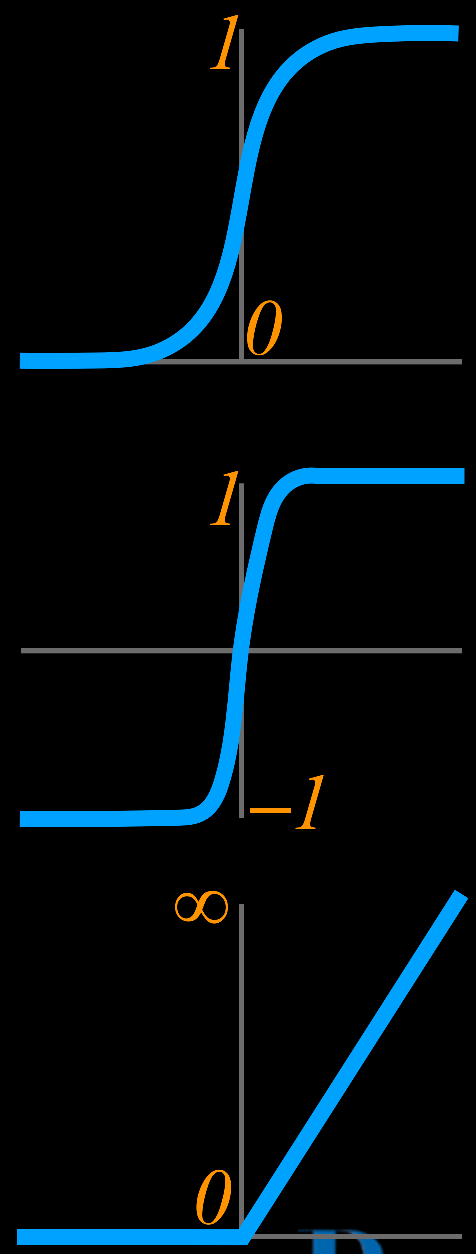
$s(x) = \frac{1}{1+e^{-x}}$

**tanh**

$tanh(x)$

**ReLU**

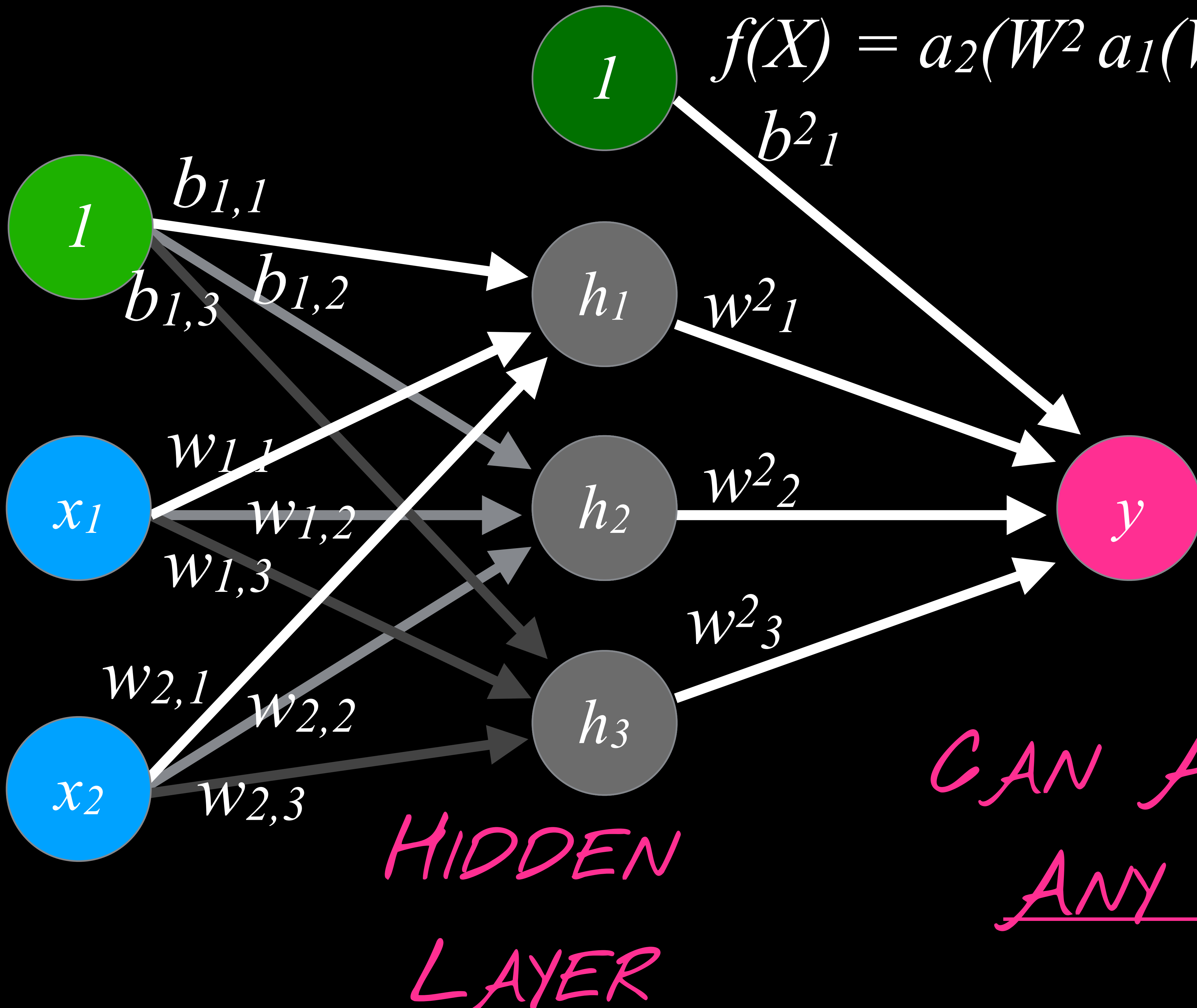
$max(0, x)$



# Step 2:
# Going Deep –
# The Multilayer Perceptron

# Multilayer Perceptron

$$f(X) = a_2(W^2\, a_1(W^1X + b^1) + b^2))$$




- How many perceptrons do you see?
- How many parameters?

CAN APPROXIMATE ANY FUNCTION!

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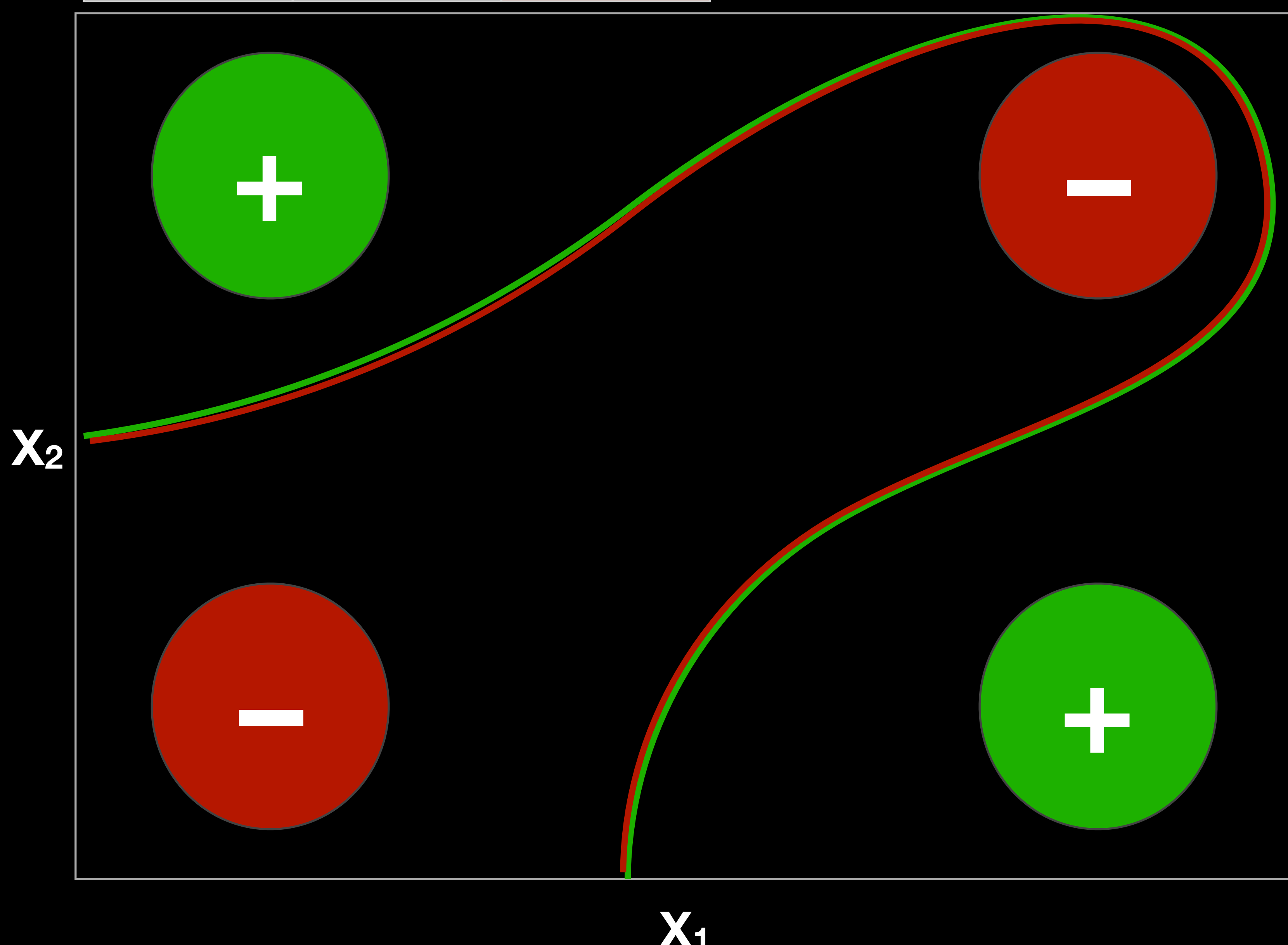
# The XOR Limit

| $x_1$ | $x_2$ | |
|---|---|---|
| 0 | | |
| 1 | | |
| 0 | 1 | |
| 1 | 1 | -1 |

THERE YOU GO...

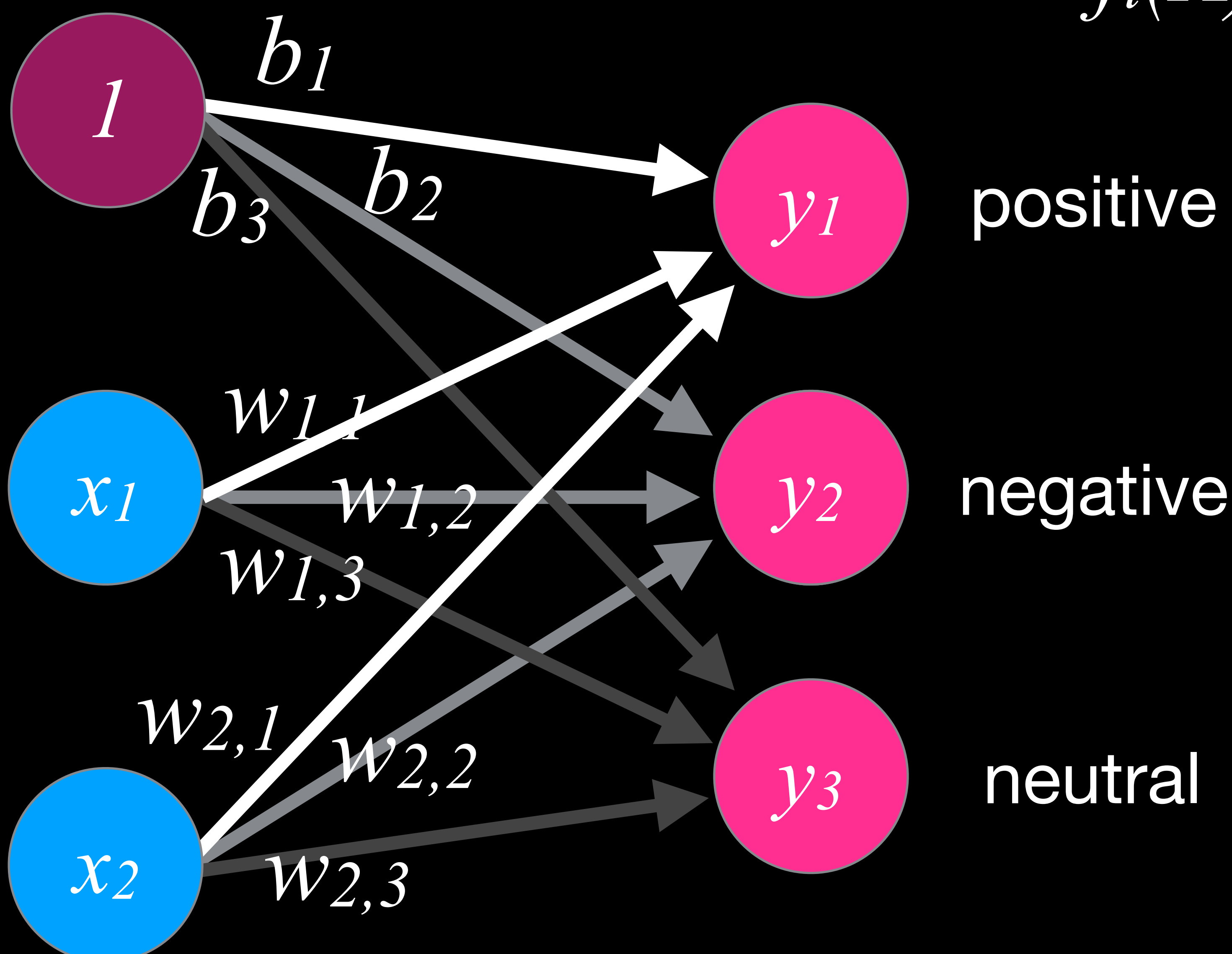
LINEARIZE THIS!




Marvin Minsky
(1927–2016)

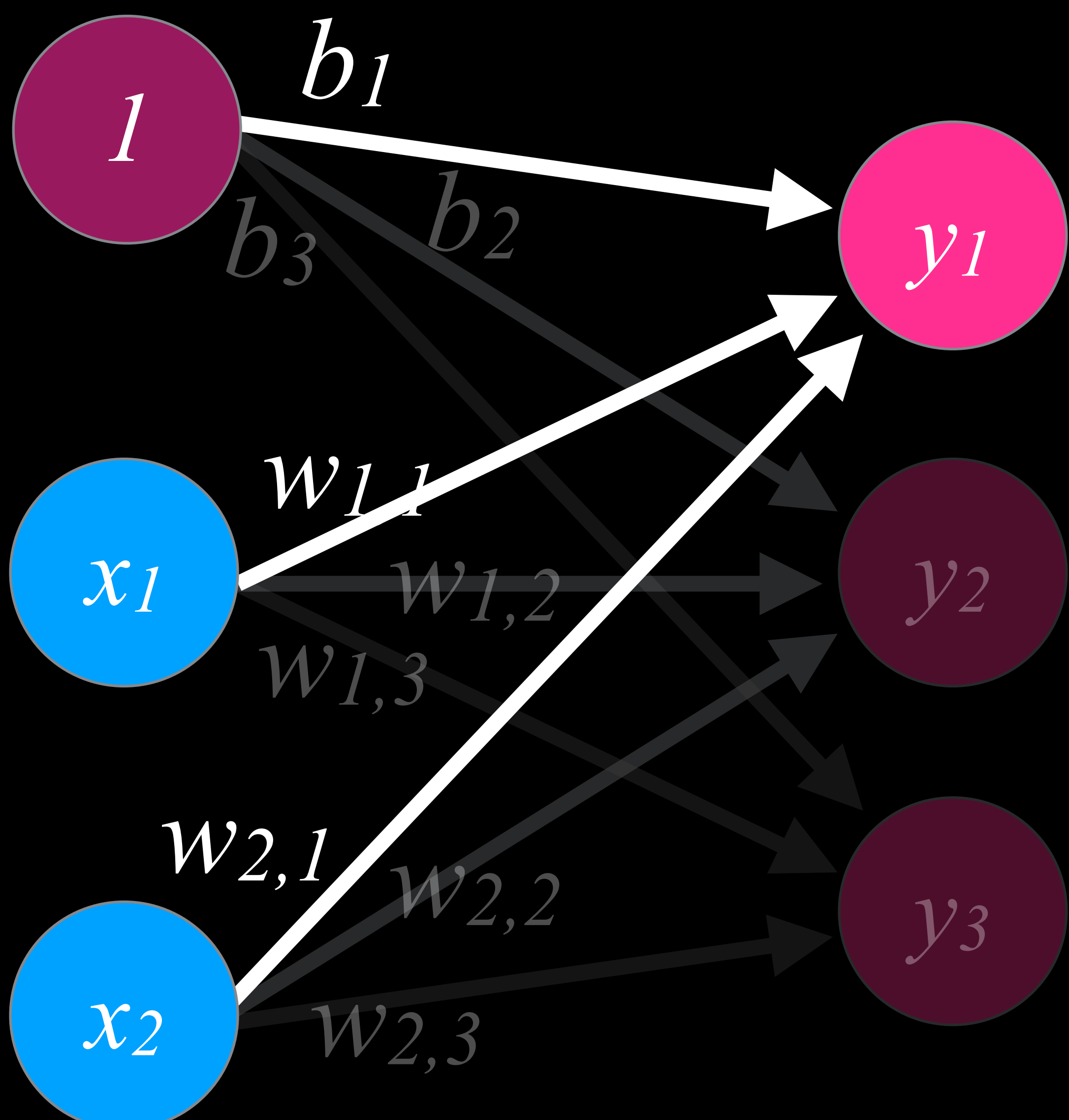
# Multi-Class Output

$$f_i(X) = a(w_{1,i}x_1 + w_{2,i}x_2 + b_i)$$




$$\hat{y} = \underset{i}{argmax}\, f_i(X)$$

# Enter the Matrix



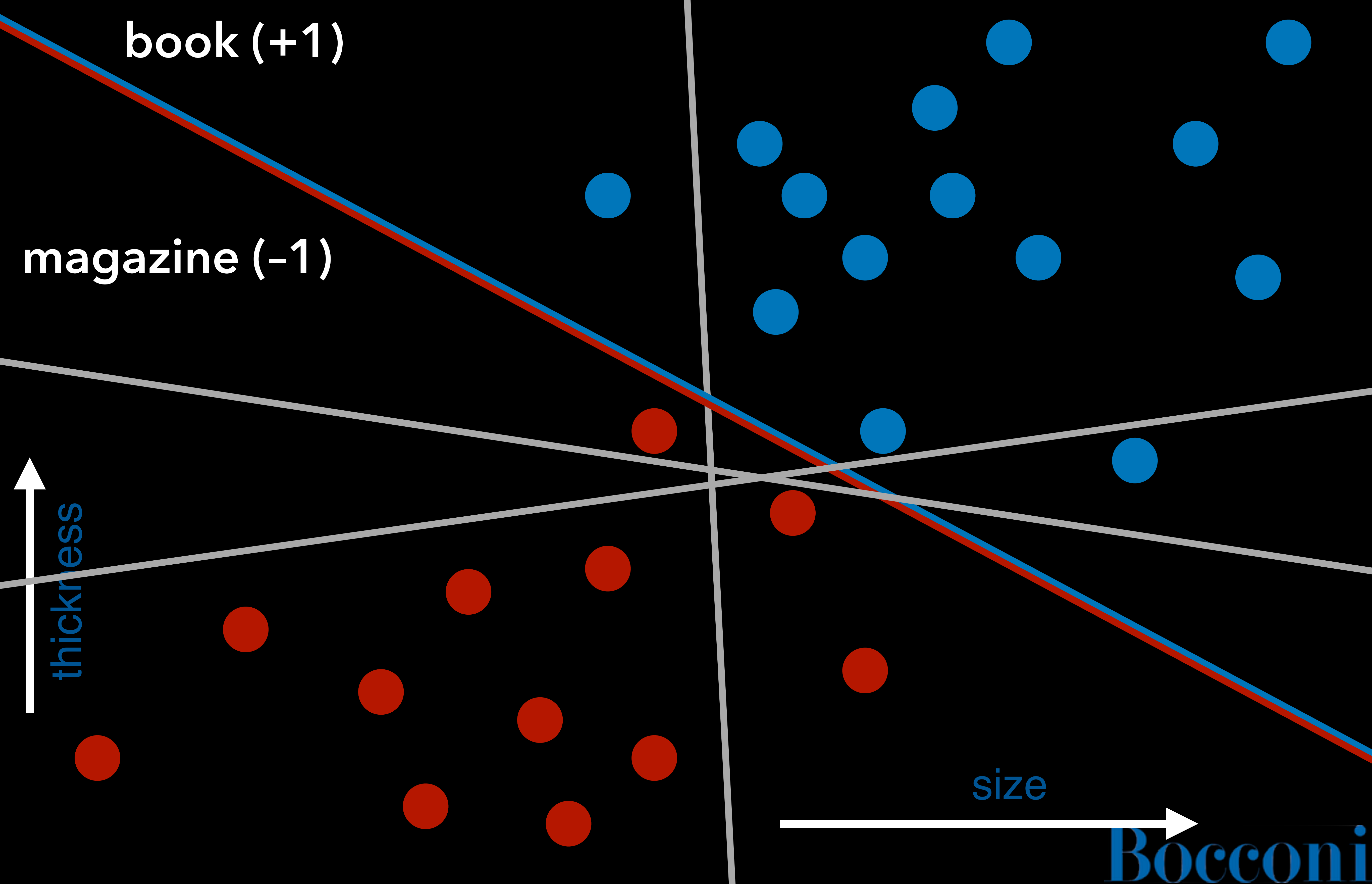

$$y_i = a(w_{1,i}x_1 + w_{2,i}x_2 + b_i)$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} \quad \begin{bmatrix} w_{1,1} & w_{2,1} \\ w_{2,1} & w_{2,2} \\ w_{3,1} & w_{3,2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

$$Y = a(W^i X + b^i)$$

# Learning

# Decision Boundary

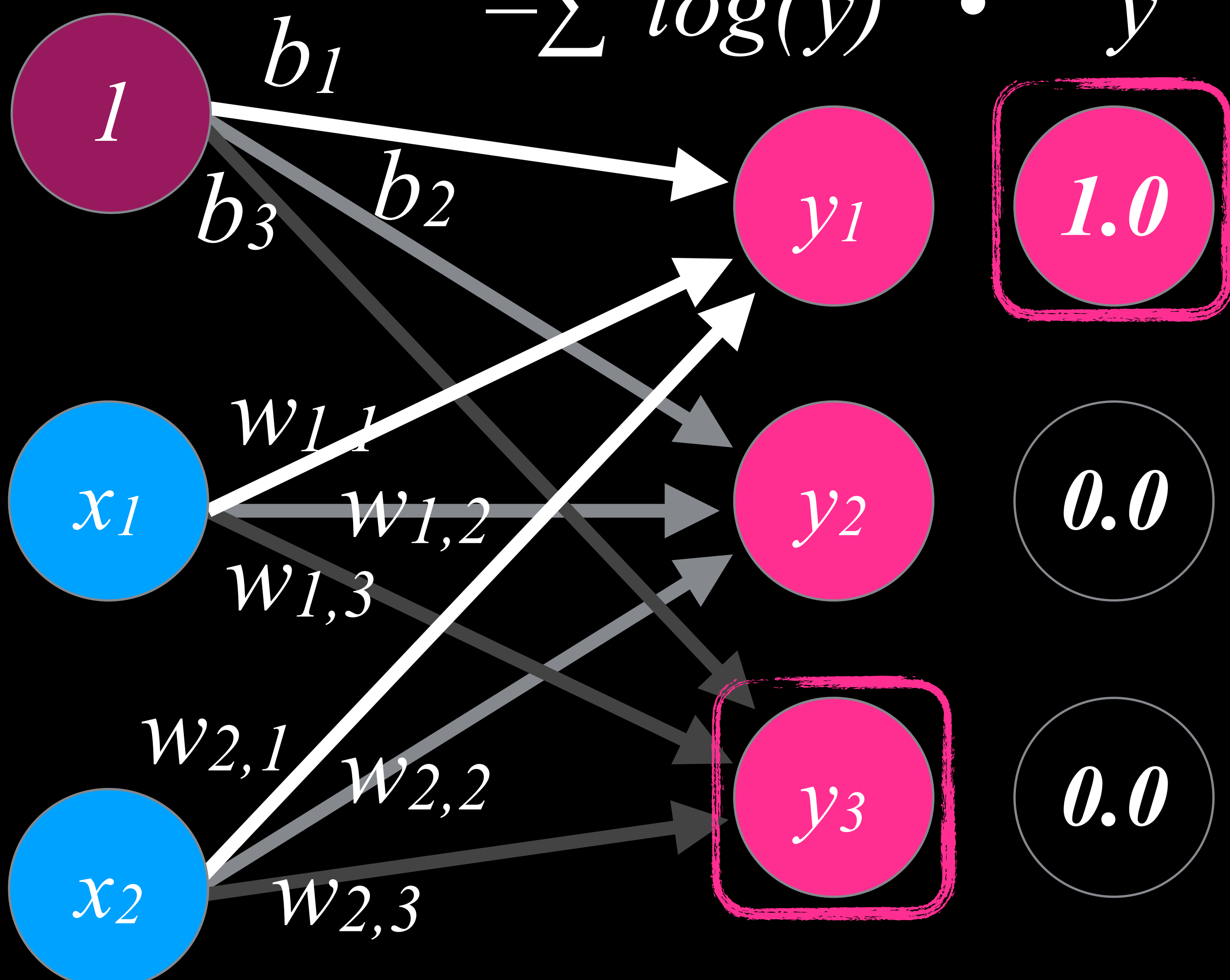


# Error!

neutral positive

$$-\sum \log(\hat{y}) \cdot y$$

HOW FAR OFF ARE WE?




–1.2

+

0.0

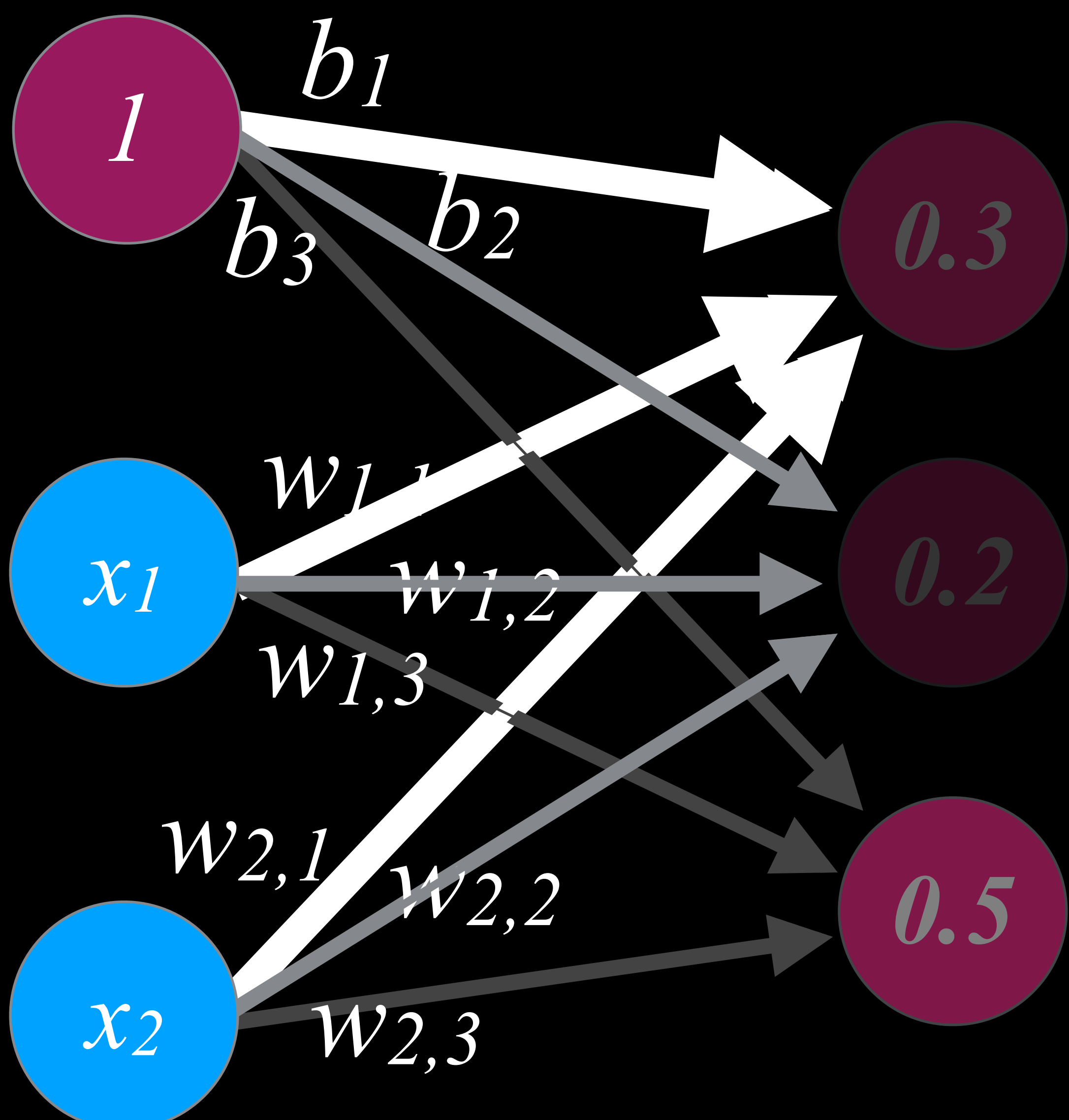
+

0.0

= 1.2

CROSS-ENTROPY

# Backpropagation




1.2

- Adjust weights/bias proportionately to change, using **Stochastic Gradient Descent**
- In deeper networks: compute effect on previous layer activation, then adjust *their* incoming weights accordingly, using **Chain Rule**
- If input layer is adjusted as well = learning representations

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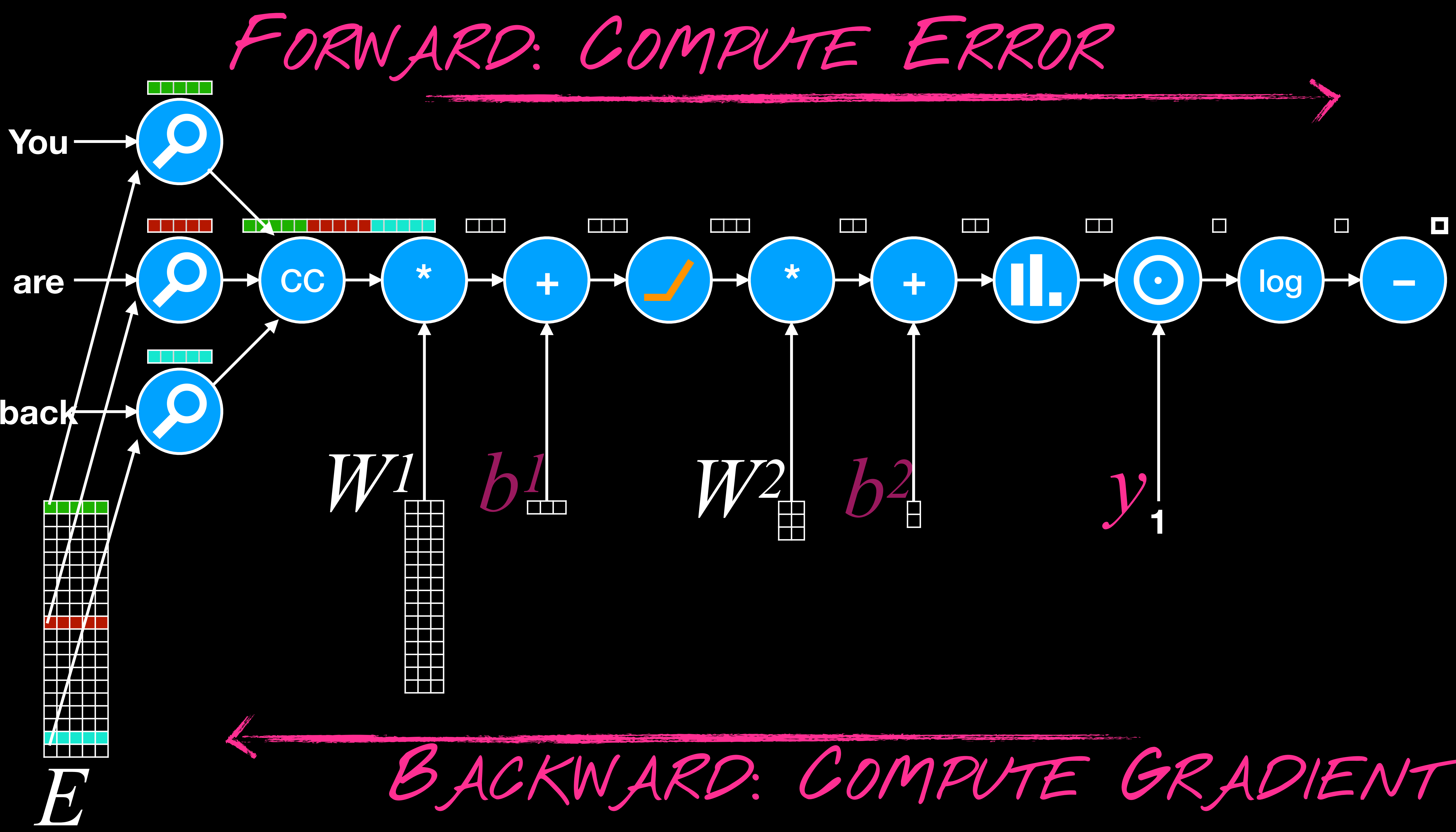
# Computational Graph

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# Regularization with Dropout

# Overfitting


- ALVINN autonomous vehicle, trained on a particular stretch of road
- Drove off the road when turned around => focused on having a ditch on one side
- Idea: randomly remove nodes to avoid over-reliance

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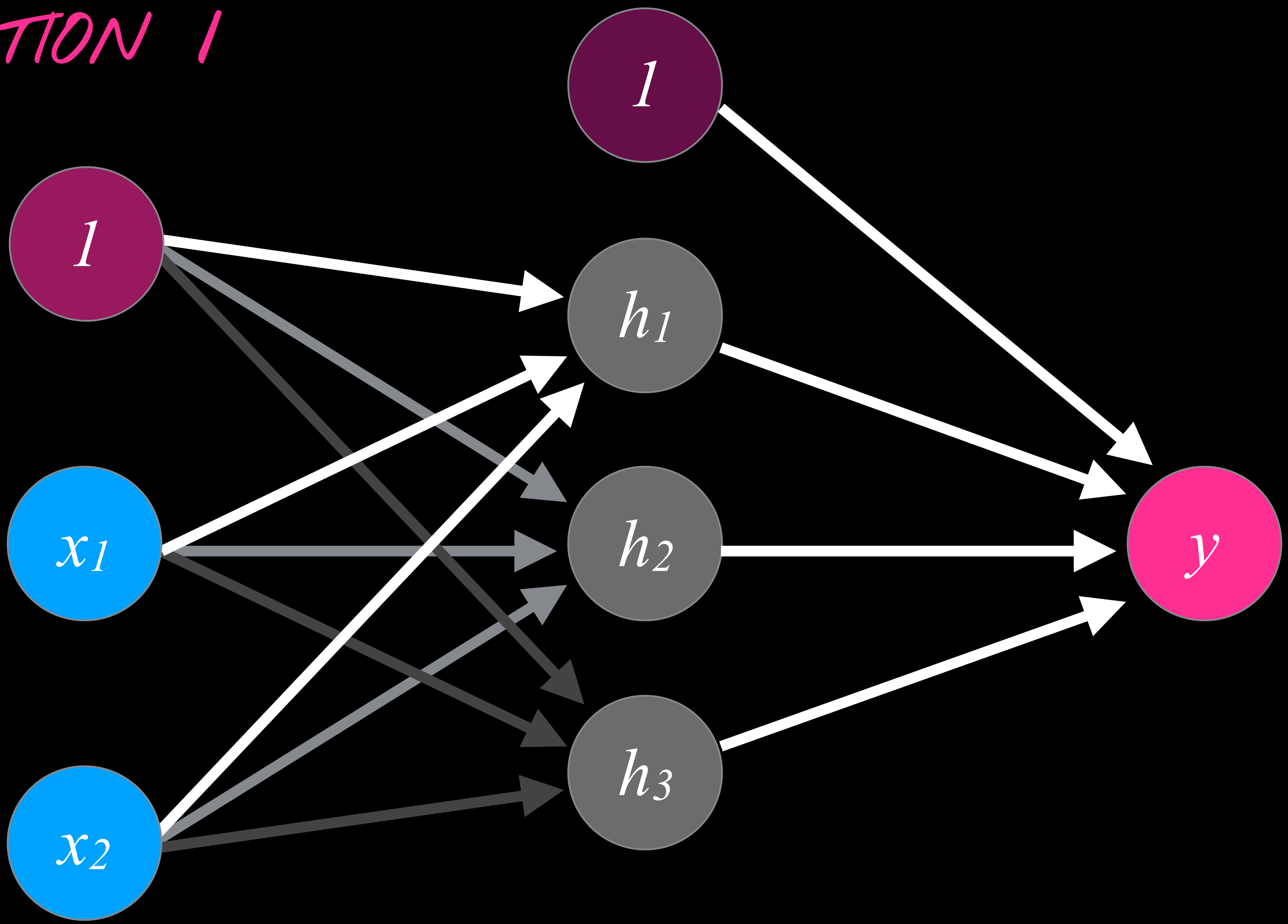
# Dropout

ITERATION 1

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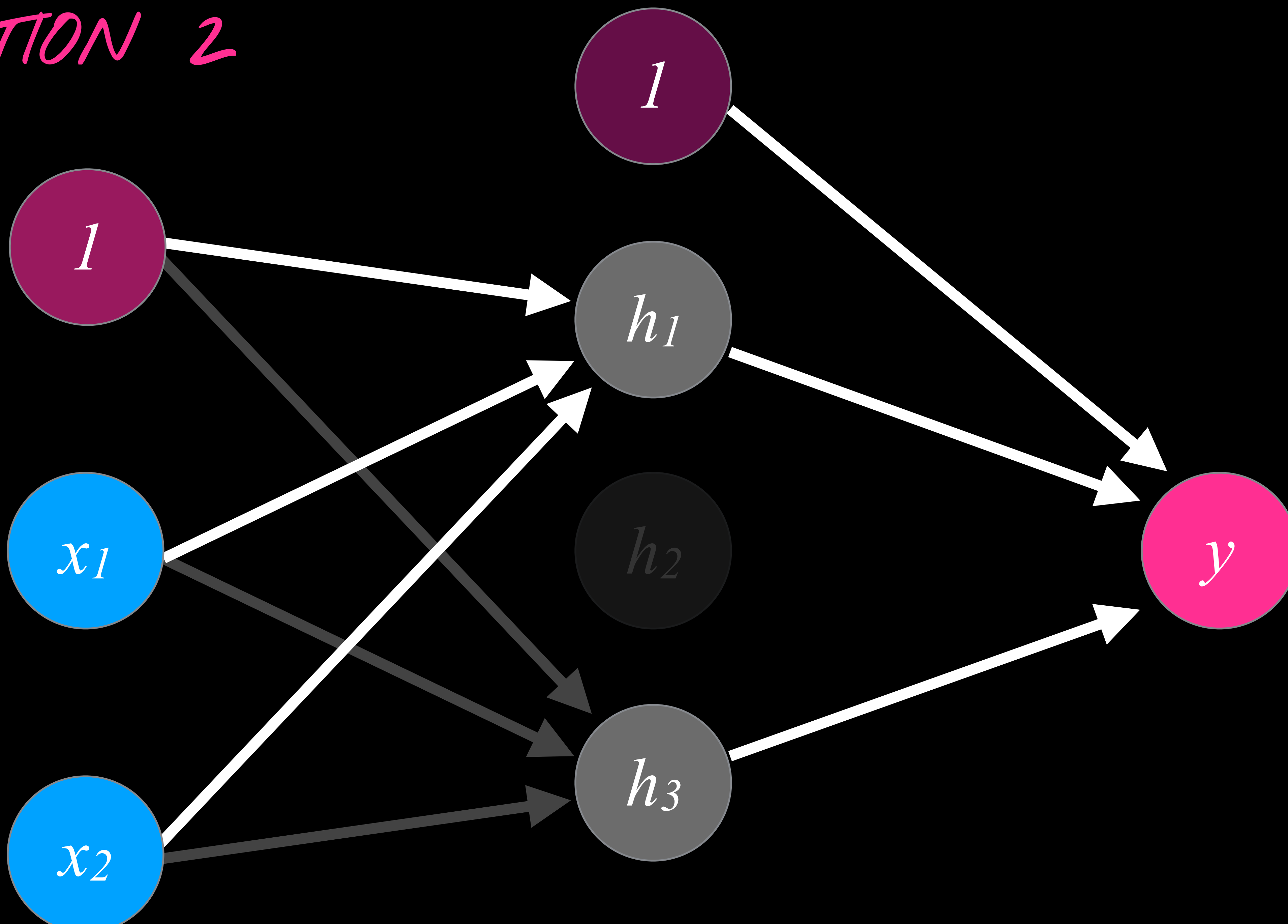
# Dropout

ITERATION 2

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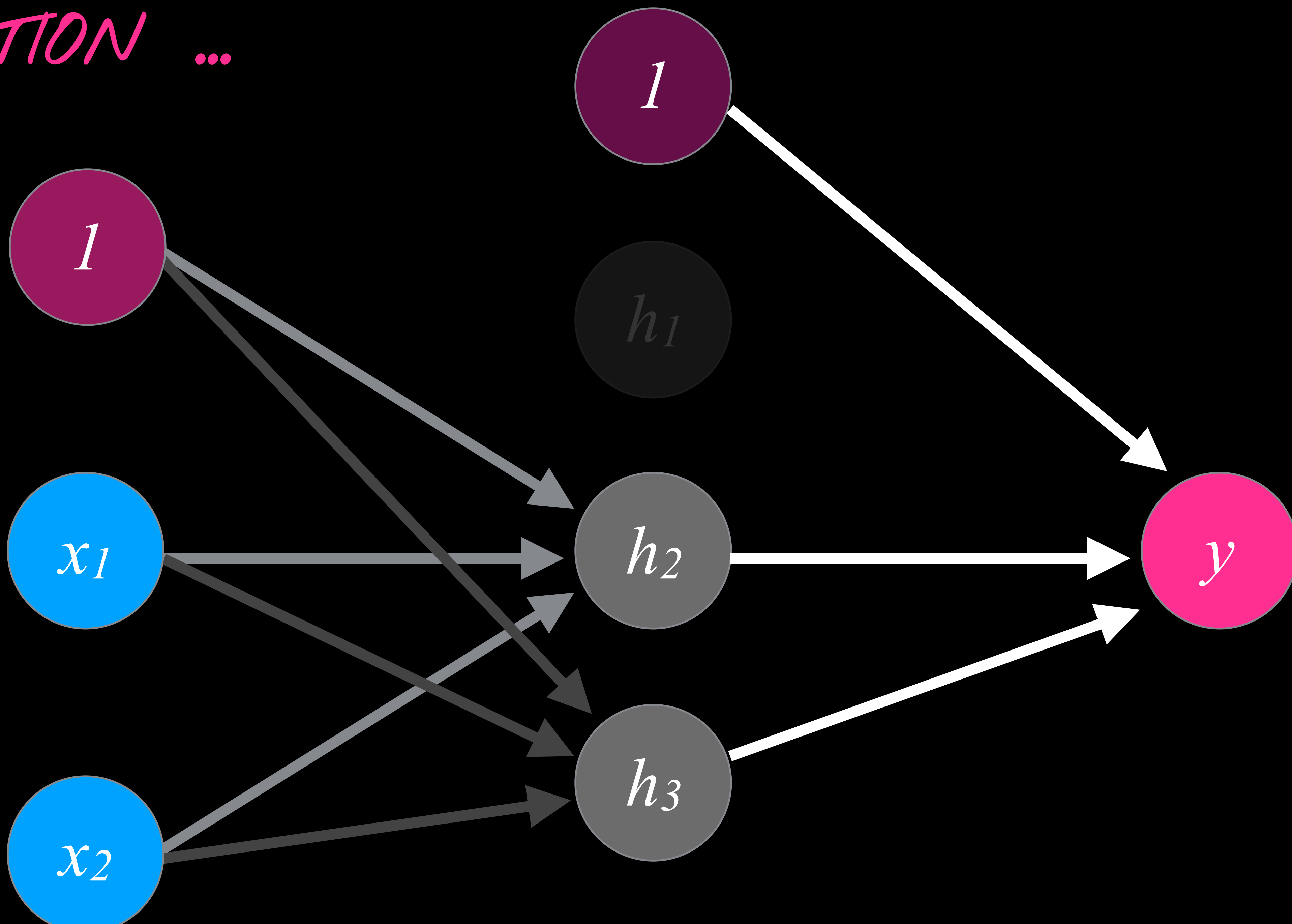
# Dropout

ITERATION ...



# Wrapping up

# Take Home Points

- The **perceptron** is the basic building block of NNs
- Several perceptrons are a **Multilayer Perceptron** or **Feedforward Network**
- Each layer is matrix multiplication wrapped in an **activation function** (usually **ReLU**)
- Training **backpropagates** an error through the network to change weights
- **Dropout** helps regularize networks by randomly deleting nodes

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# Moar Sources

- 3Blue1Brown: https://www.youtube.com/playlist?list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi
- Yoav Goldberg Primer: https://arxiv.org/pdf/1510.00726.pdf
- The Keras book
- …

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