Natural Language Processing

Lecture 18

Dirk Hovy

dirk.hovy@unibocconi.it

@dirk_hovy

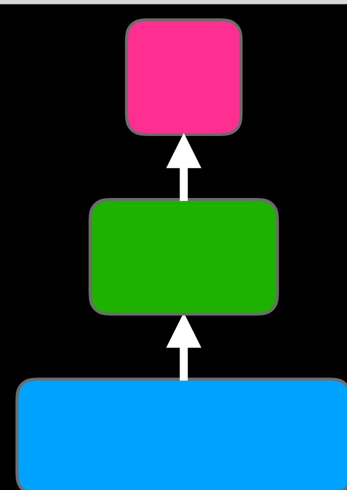
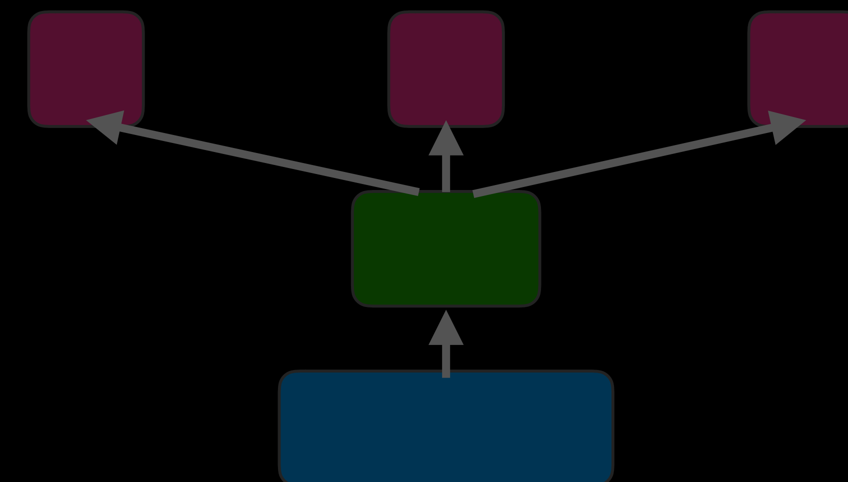
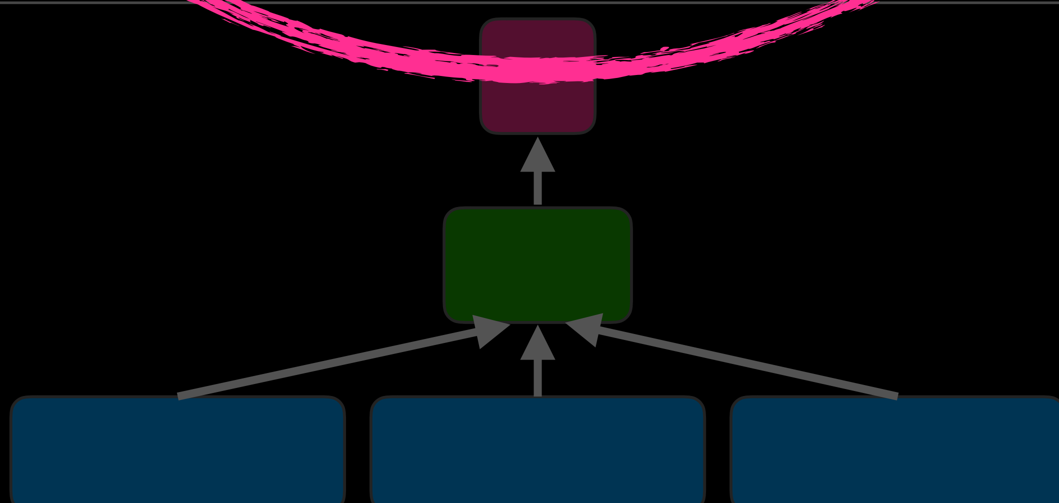
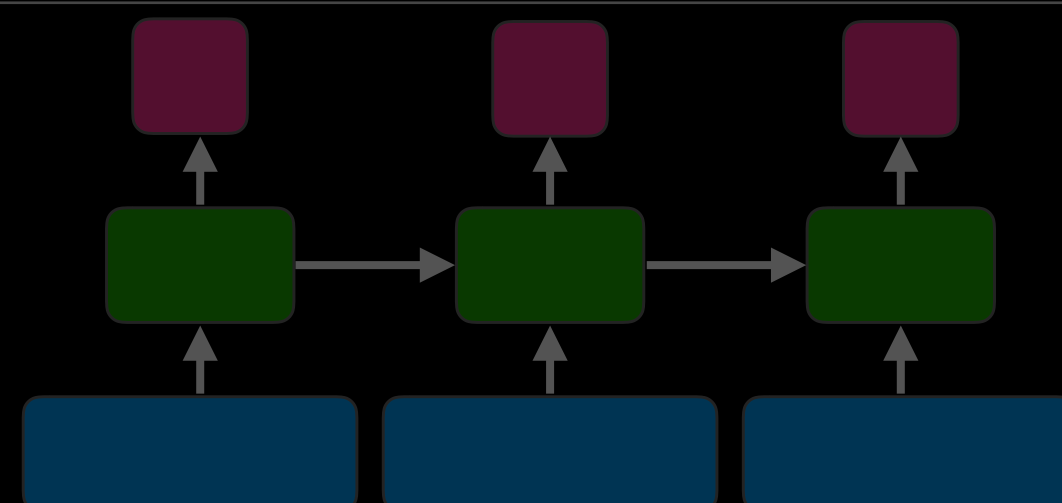
Bocconi

Neural Nets Everywhere

Goals for Today

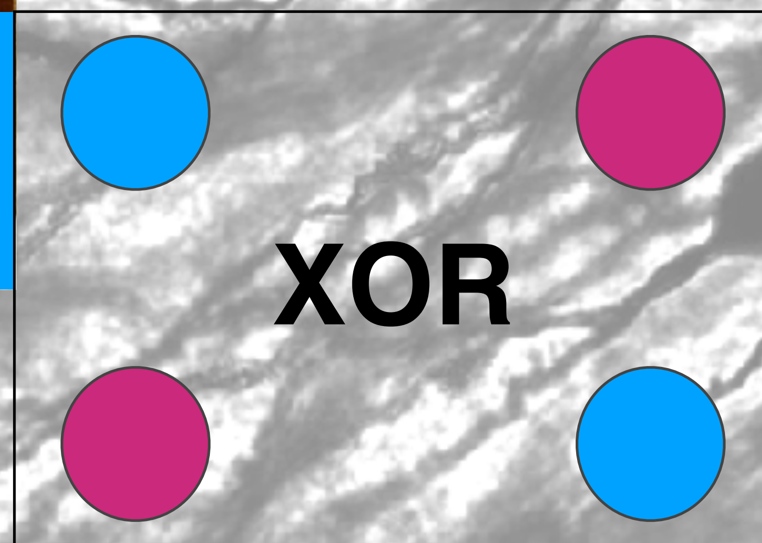
- Learn about **neural architectures**
- Understand the **perceptron** as basic element
- Understand training through **backpropagation**
- Learn about **dropout regularization**

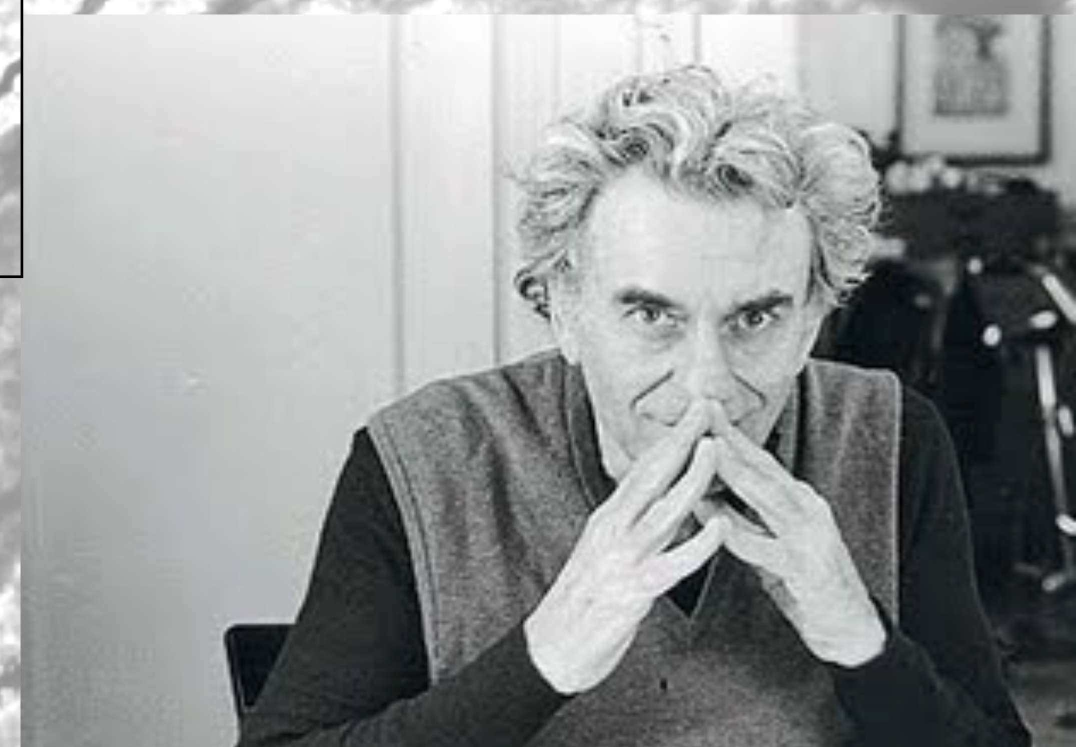
Types of Neural Models

	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!!!*



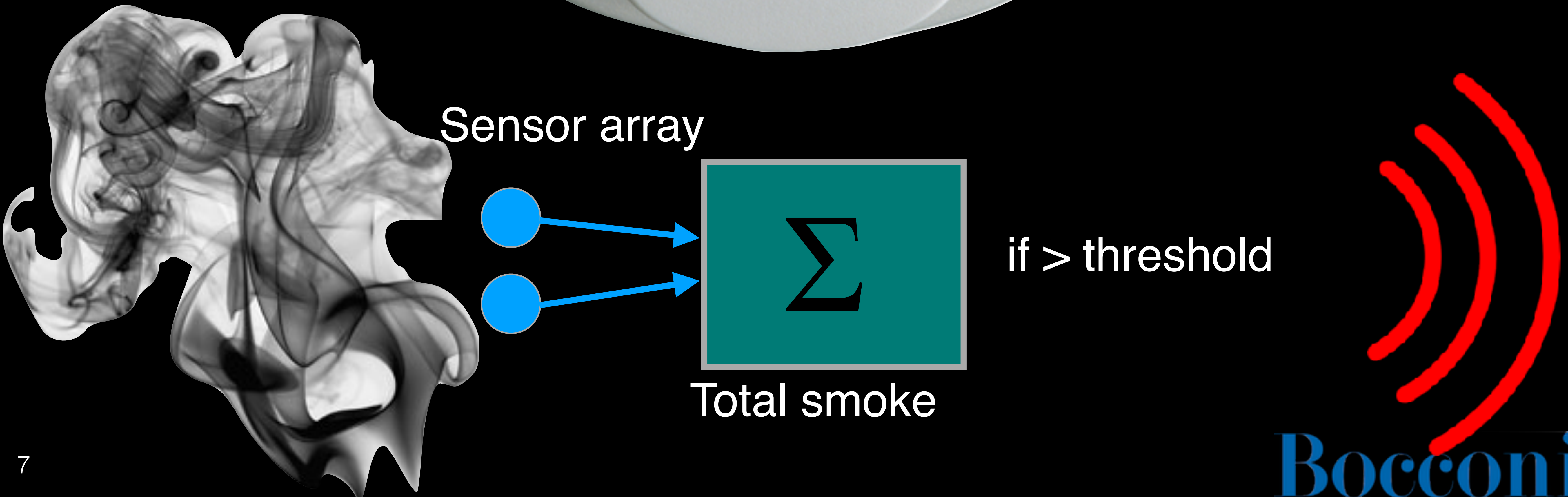


The Perceptron fails at learning even basic concepts

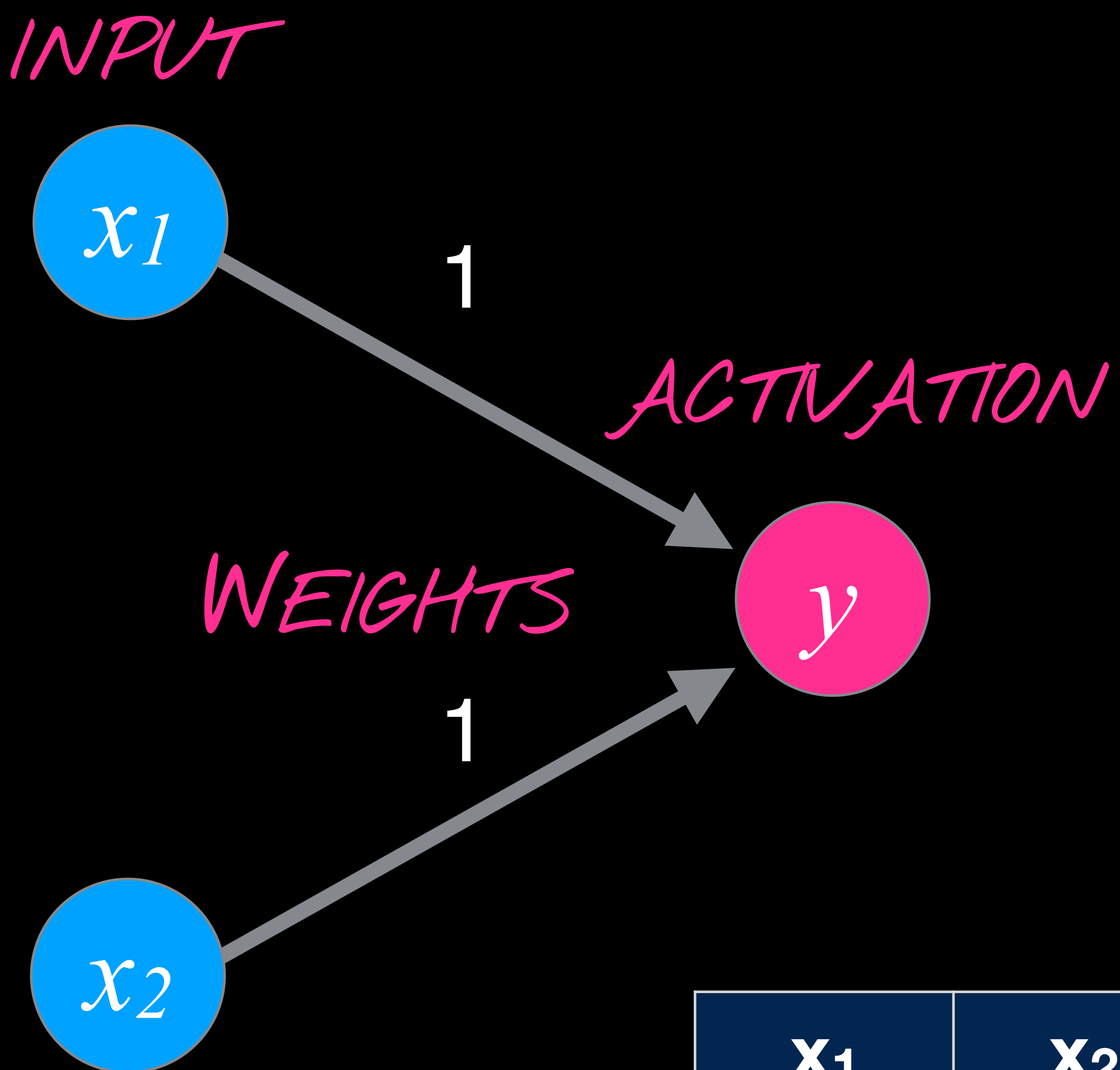
Marvin Minsky
(1927–2016)

The Perceptron

A Threshold Unit



AND-Perceptron

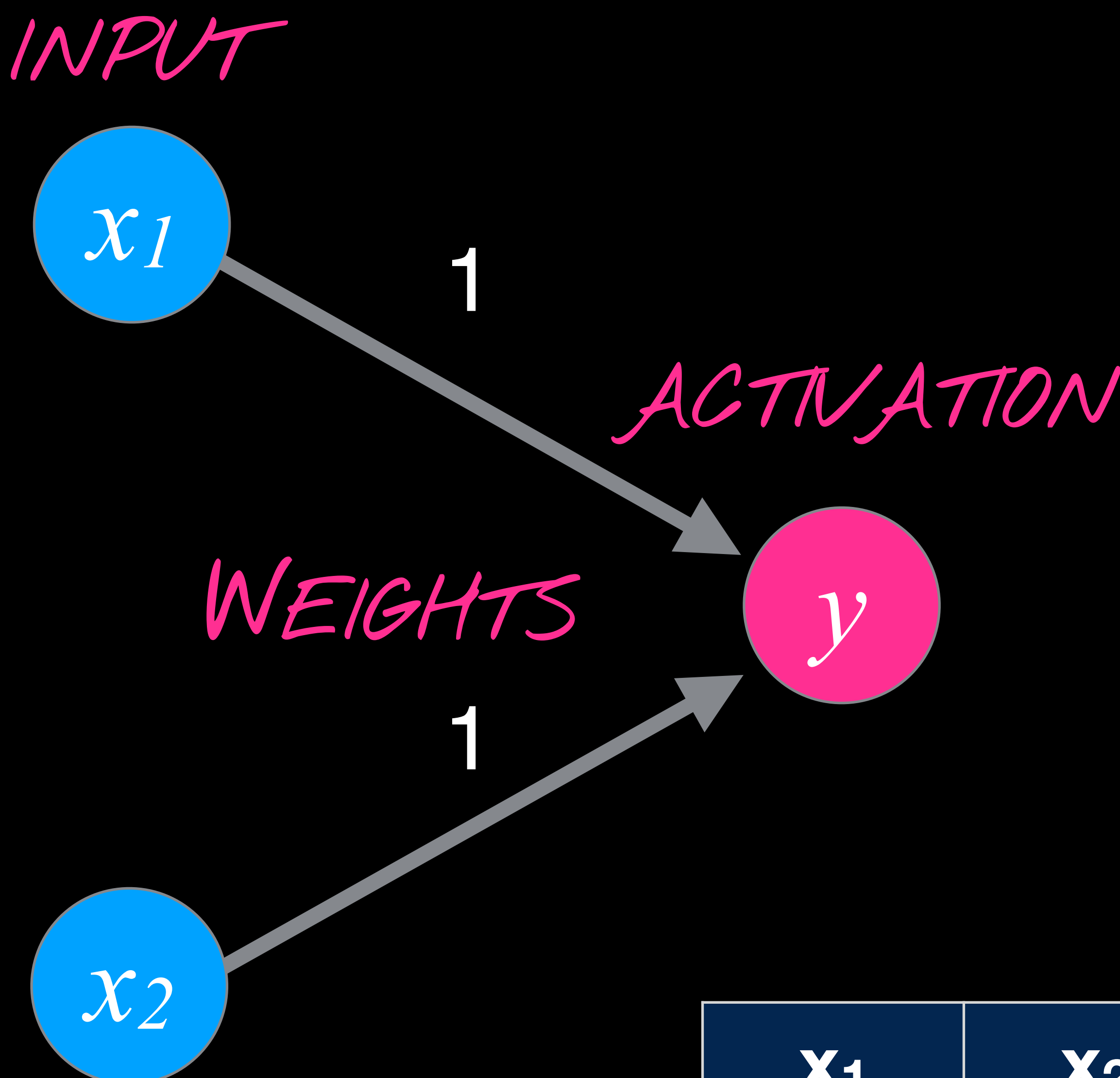


$$f(X) = w_1 x_1 + w_1 x_2$$

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

x_1	x_2	y
0	0	0
1	0	0
0	1	0
1	1	1

OR-Perceptron

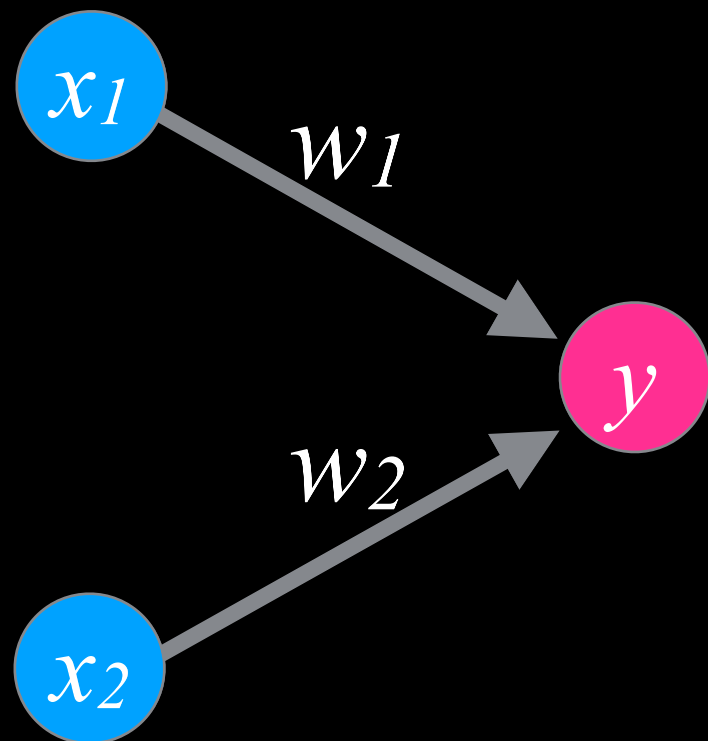


$$f(X) = w_1 x_1 + w_1 x_2$$

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

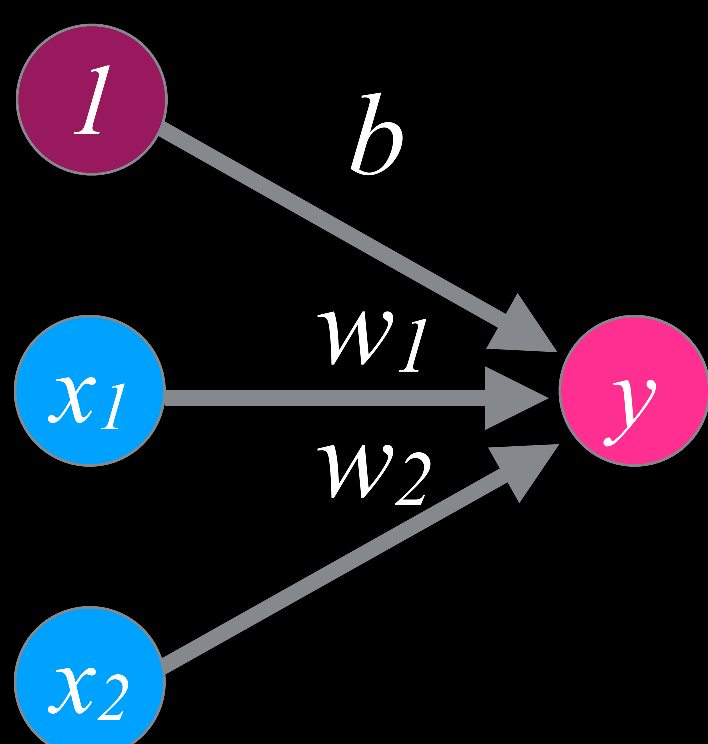
x_1	x_2	y
0	0	0
1	0	1
0	1	1
1	1	1

Learn the Threshold



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

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

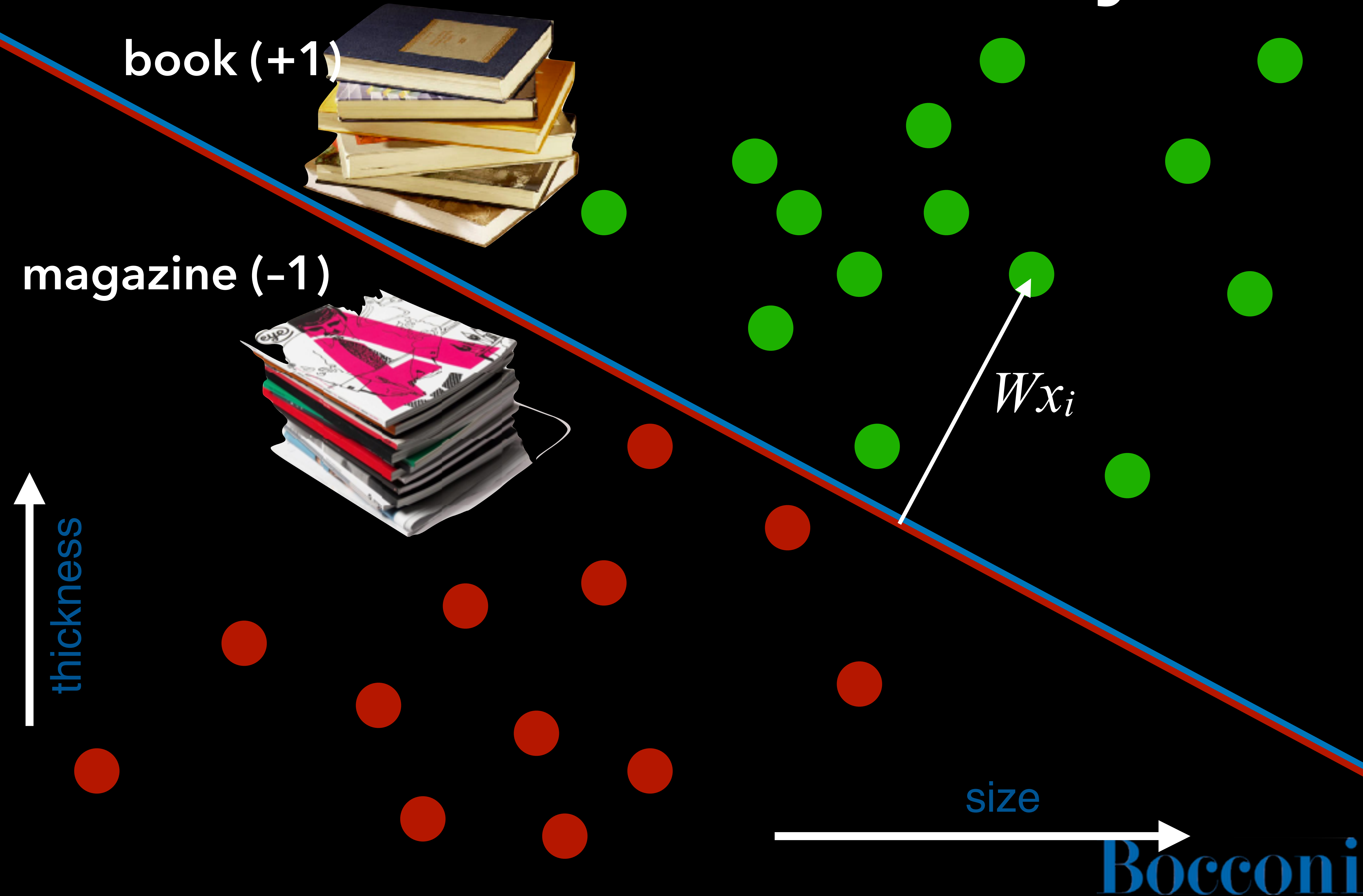


$$f(X) = w_1 x_1 + w_1 x_2 + \boldsymbol{b}$$

$$\hat{y} = \begin{cases} +1 & if\ \ y(X) \geq \boldsymbol{0} \\ -1 & otherwise \end{cases}$$

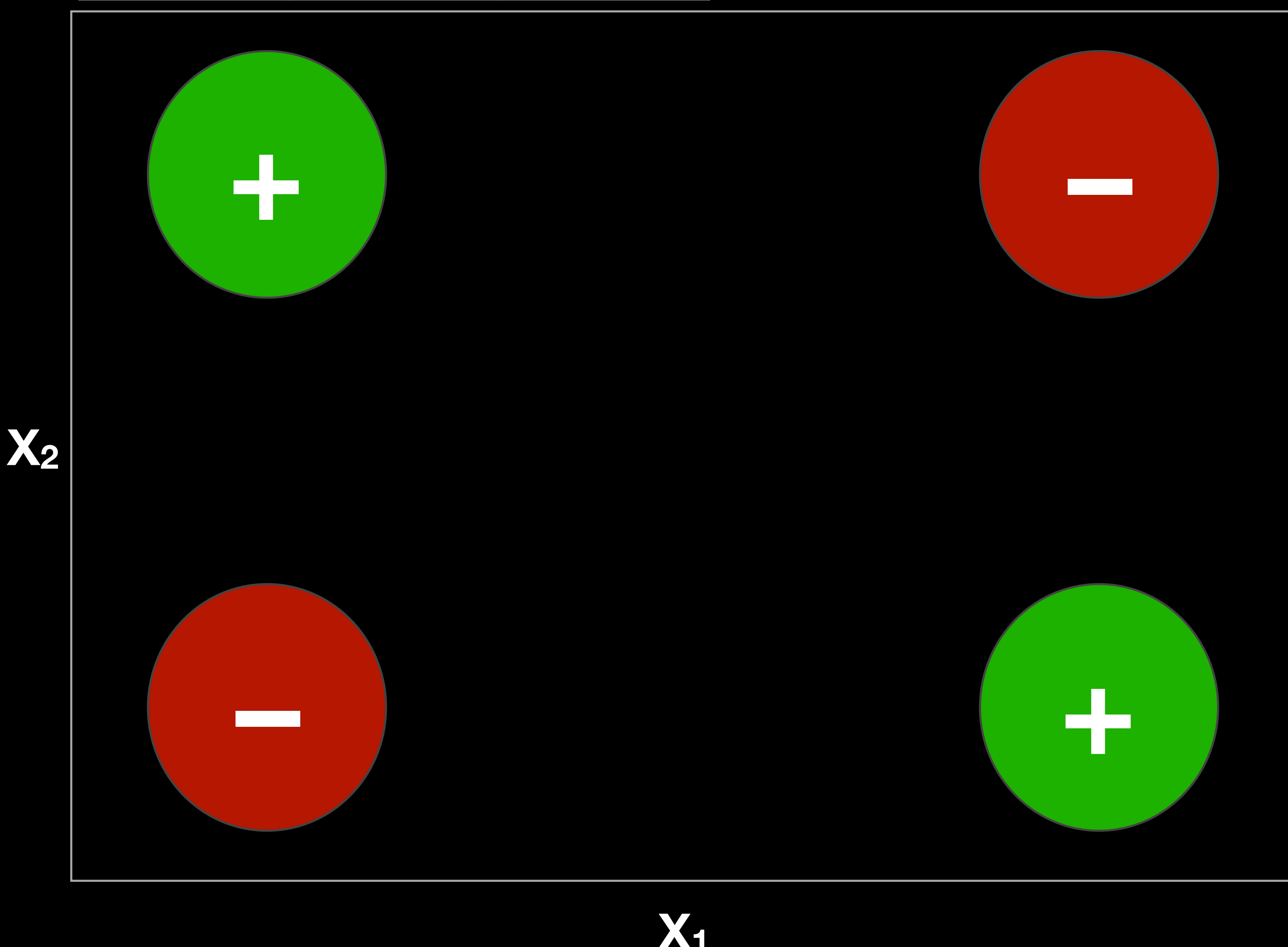
Bocconi

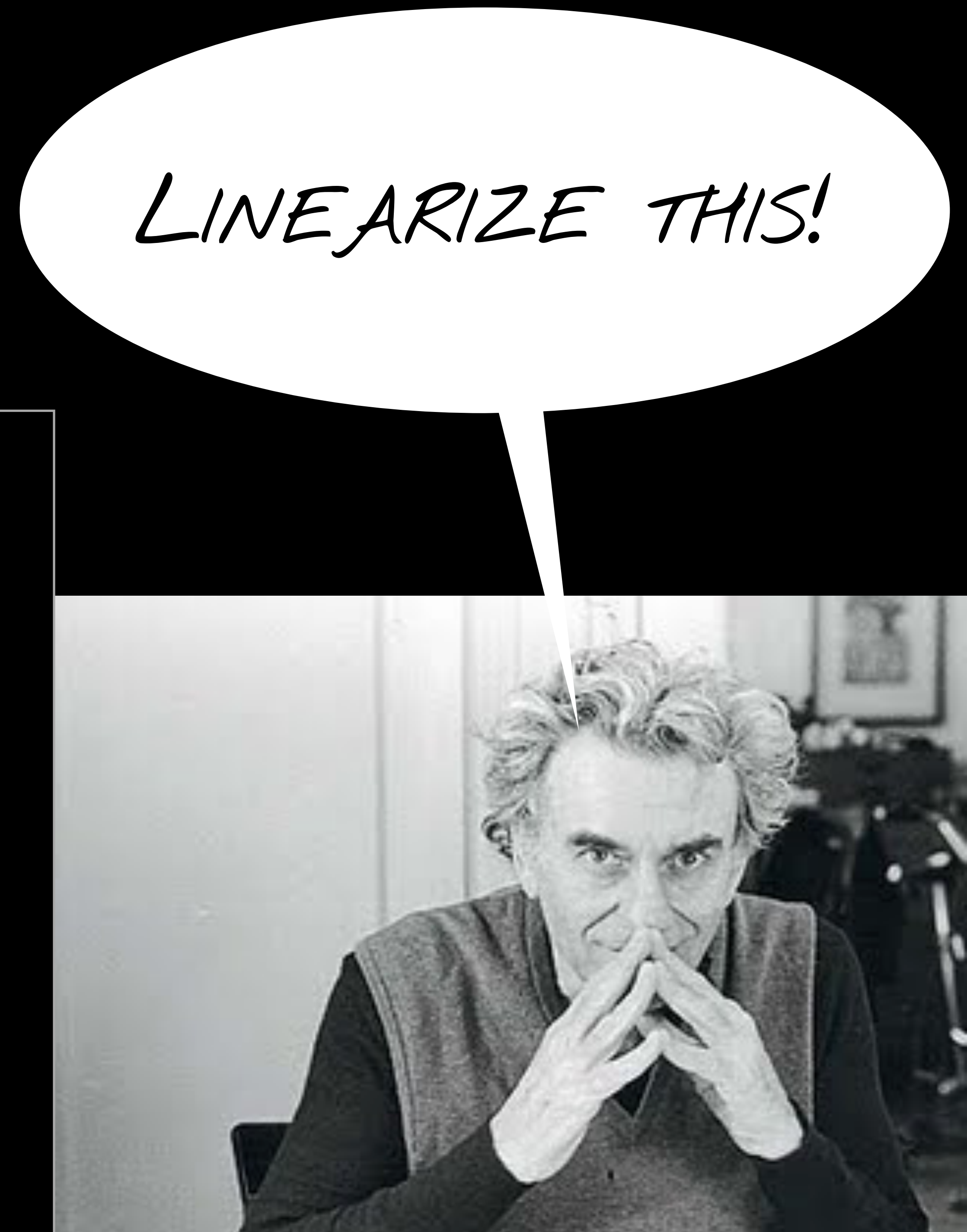
Decision Boundary



The XOR Limit

x_1	x_2	y
0	0	0
1	0	1
0	1	1
1	1	0

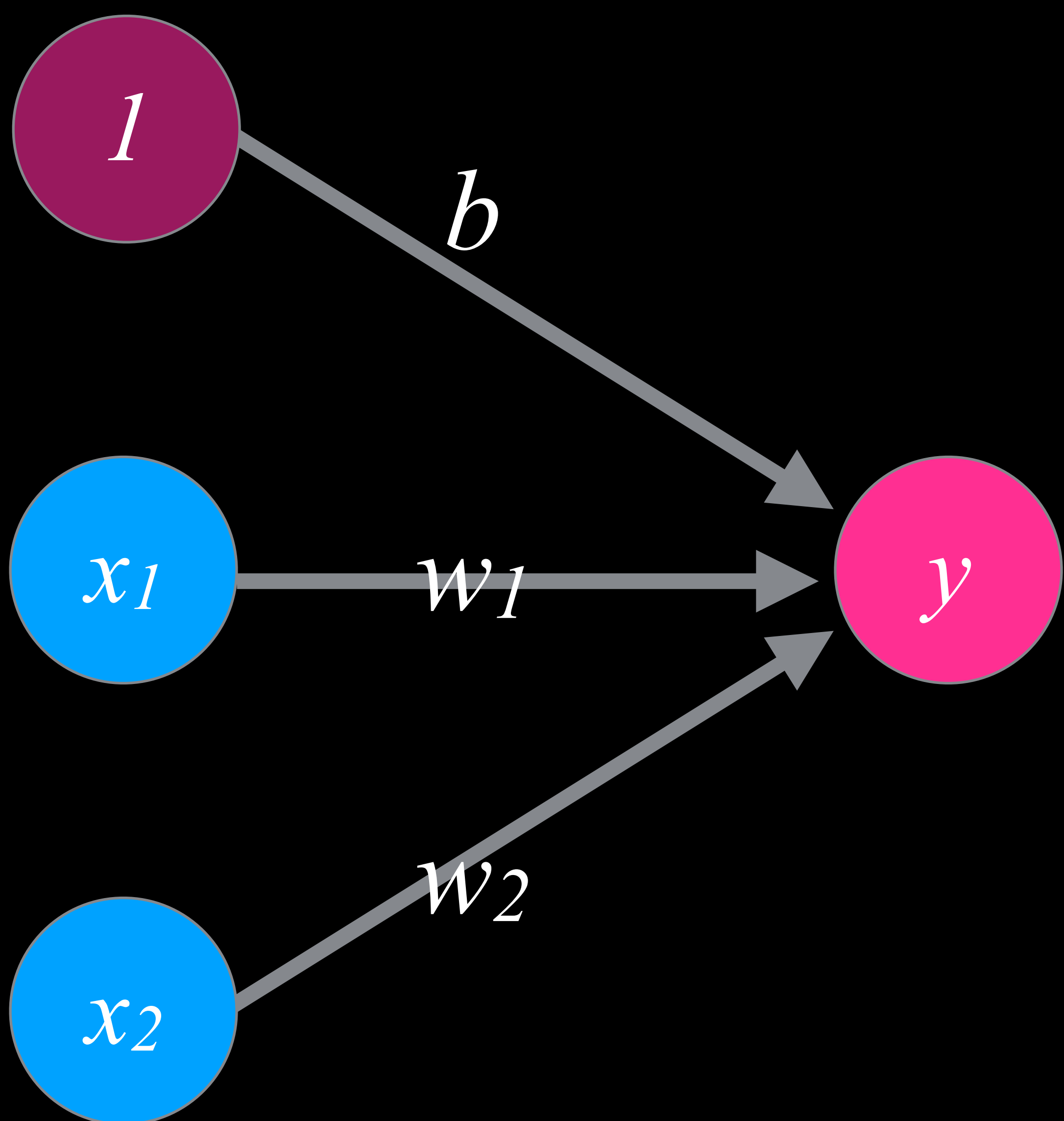




Marvin Minsky (1927–2016)

Step 1:
Non-Linearity

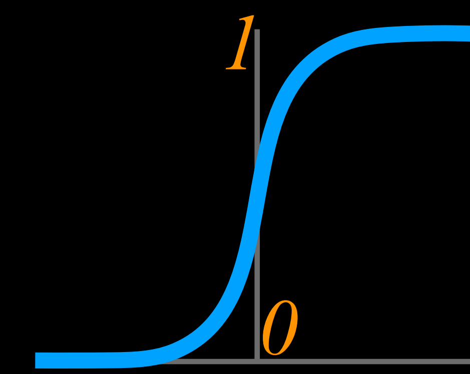
Nonlinear Activation Functions



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

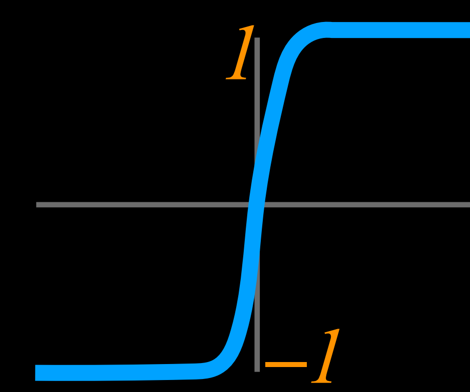
Sigmoid

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



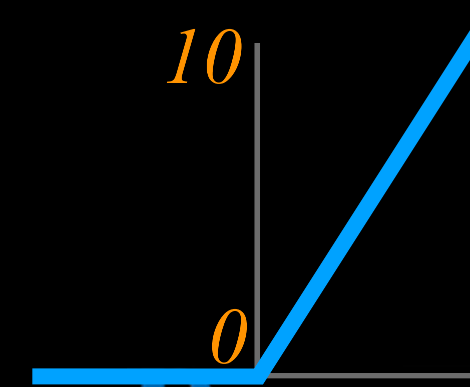
tanh

$tanh(x)$



ReLU

$max(0, x)$

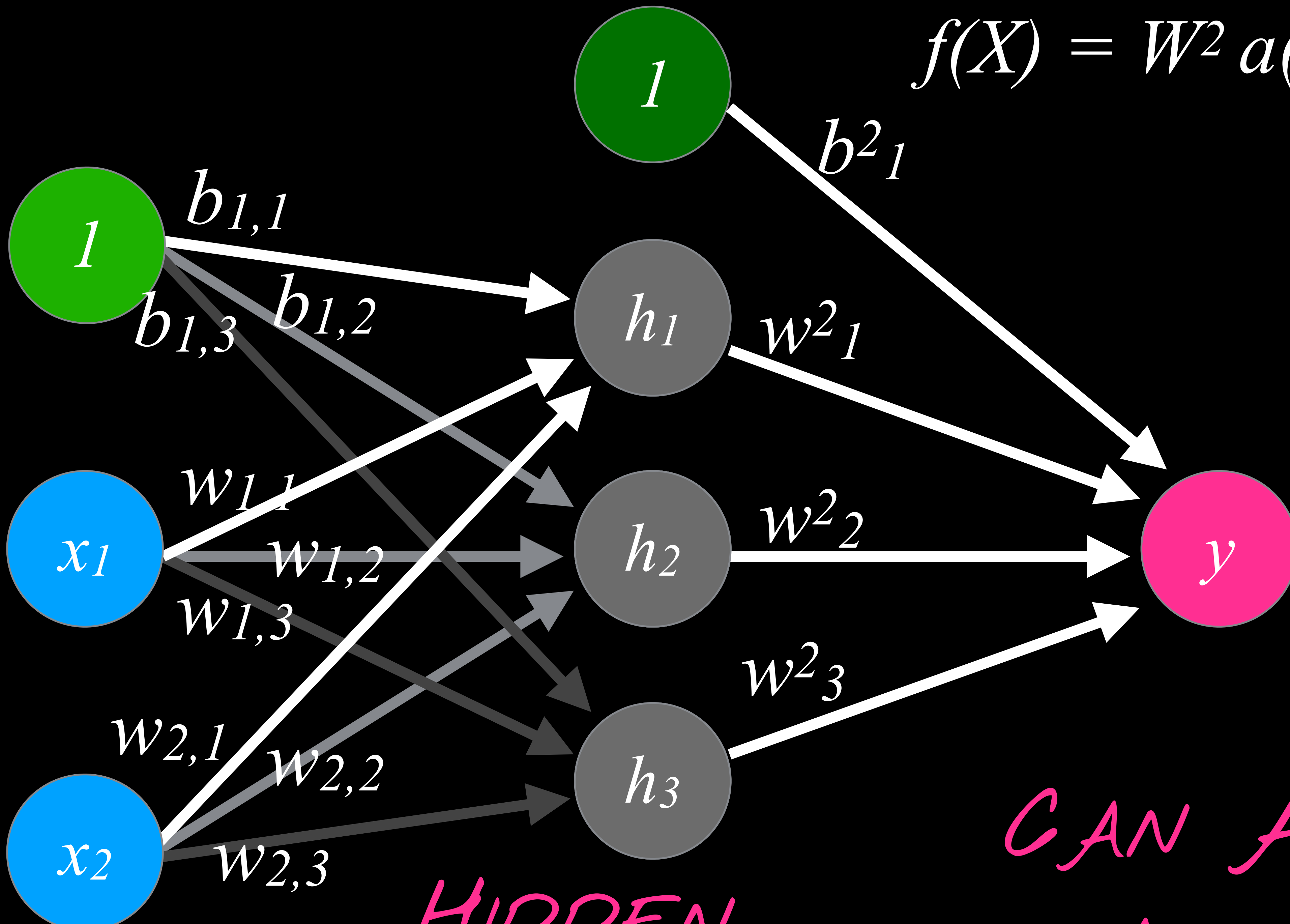


Bocconi

Step 2:
Going Deep –
The Multilayer Perceptron

Multilayer Perceptron

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



HIDDEN LAYER

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

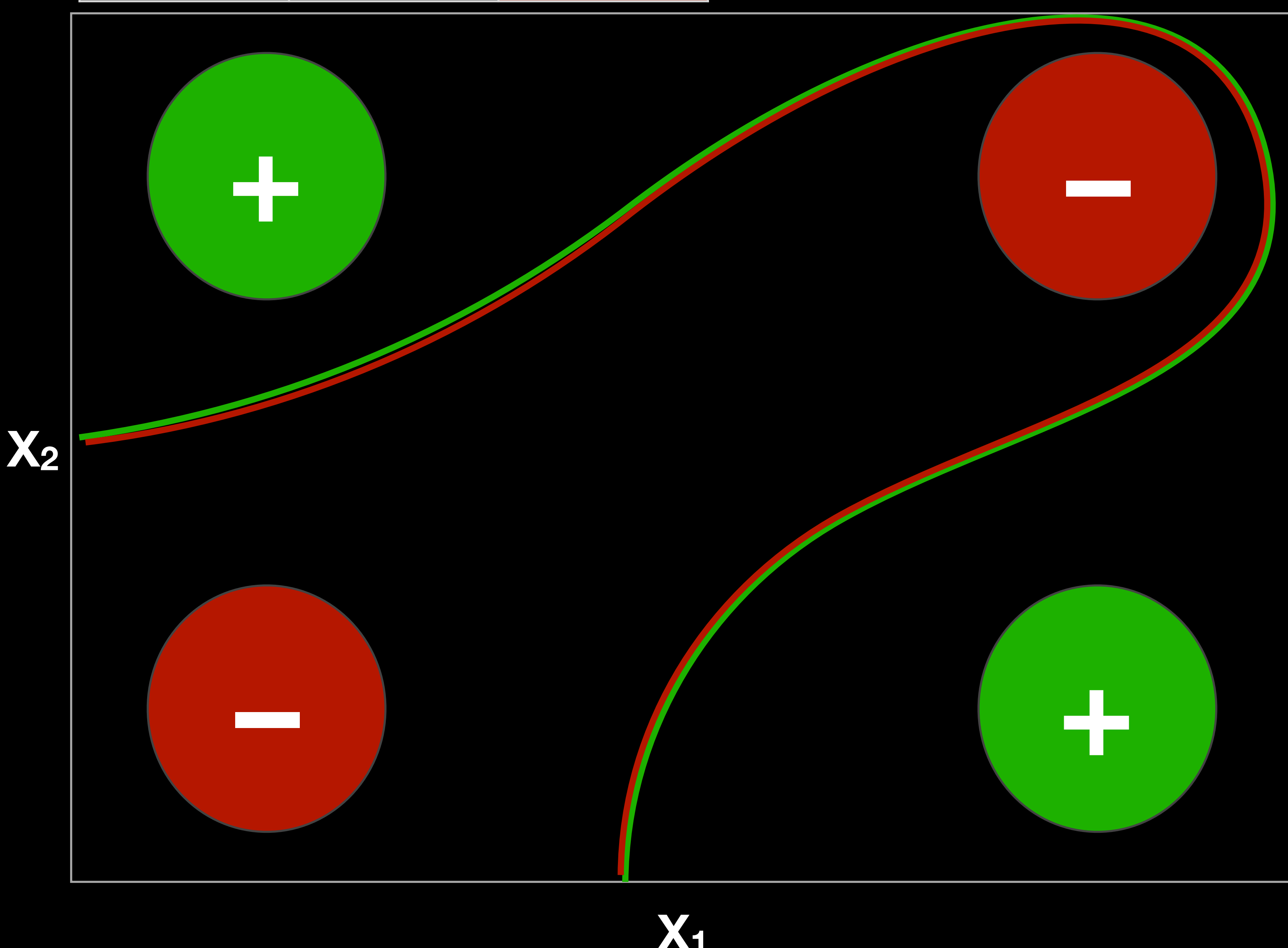
CAN APPROXIMATE ANY FUNCTION!

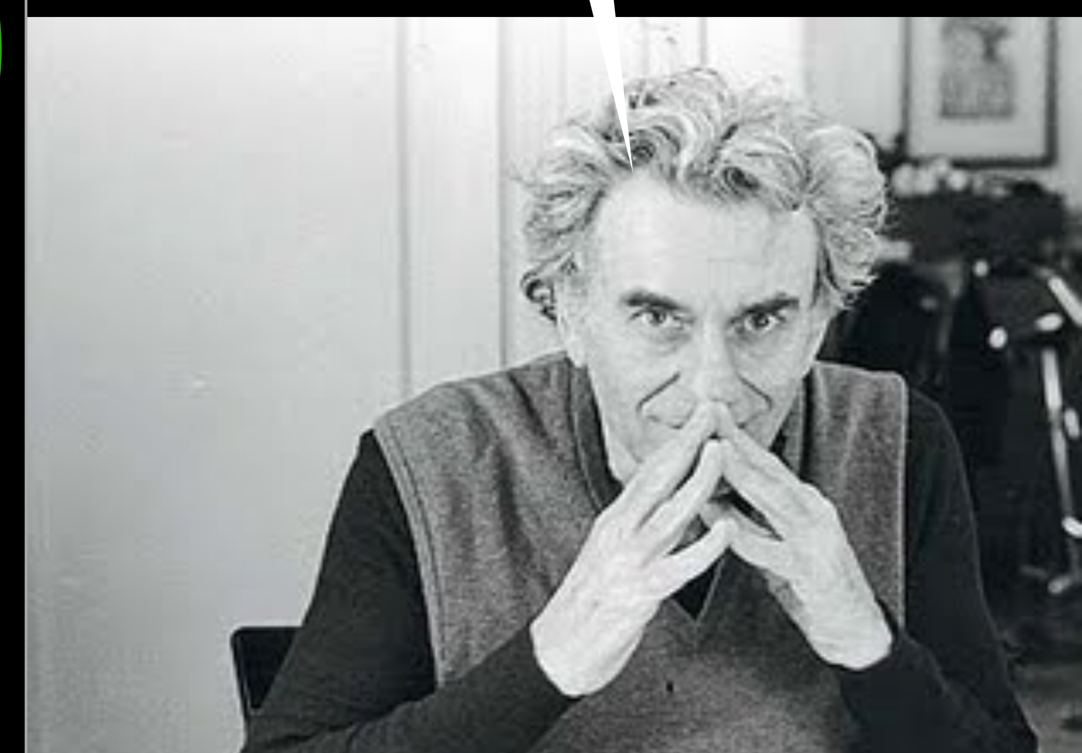
The XOR Limit

x_1	x_2	[illegible]
0	[illegible]	[illegible]
1	[illegible]	[illegible]
0	1	[illegible]
1	1	0

THERE YOU GO...

LINEARIZE THIS!

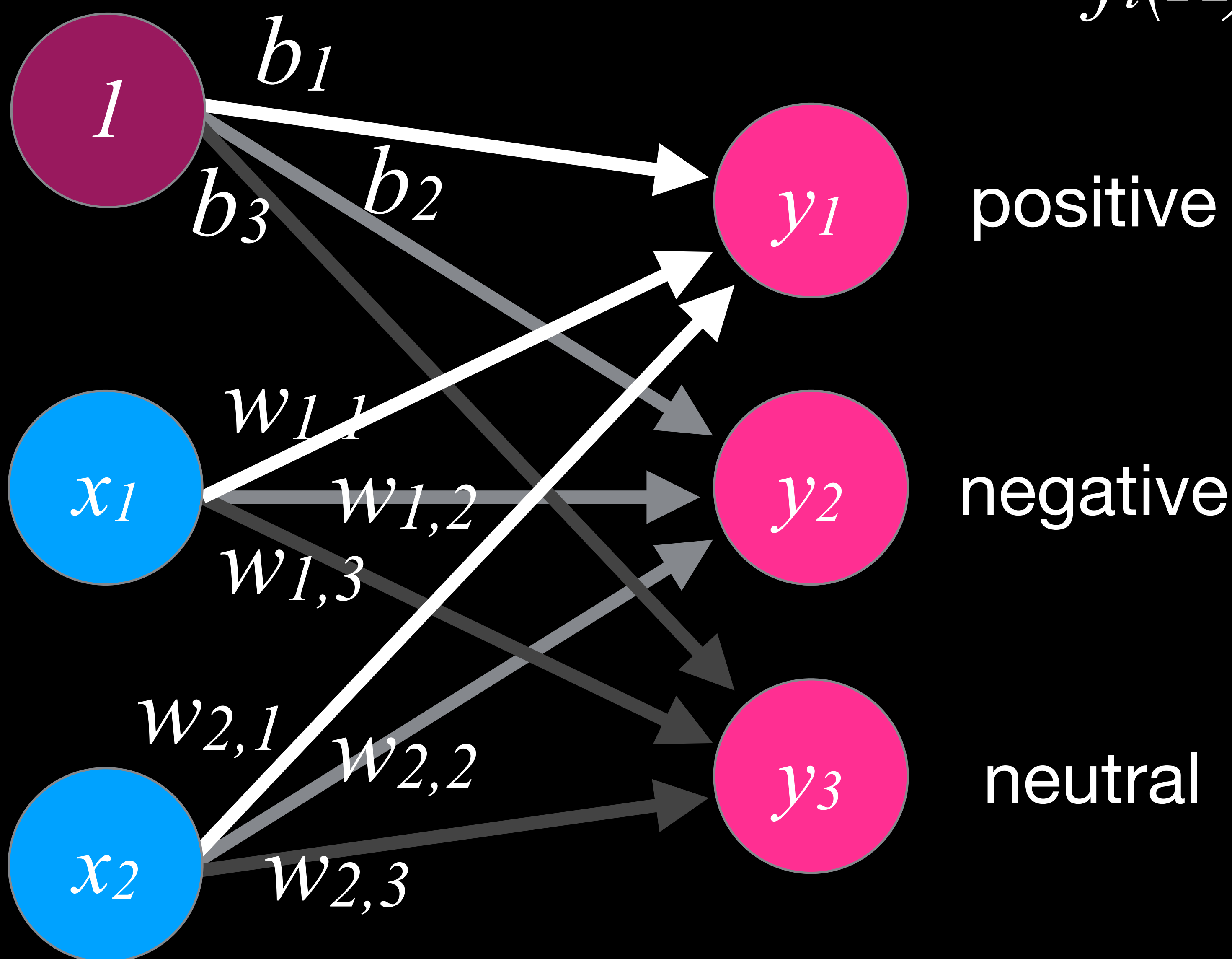




Marvin Minsky (1927–2016)

Multi-Class Output

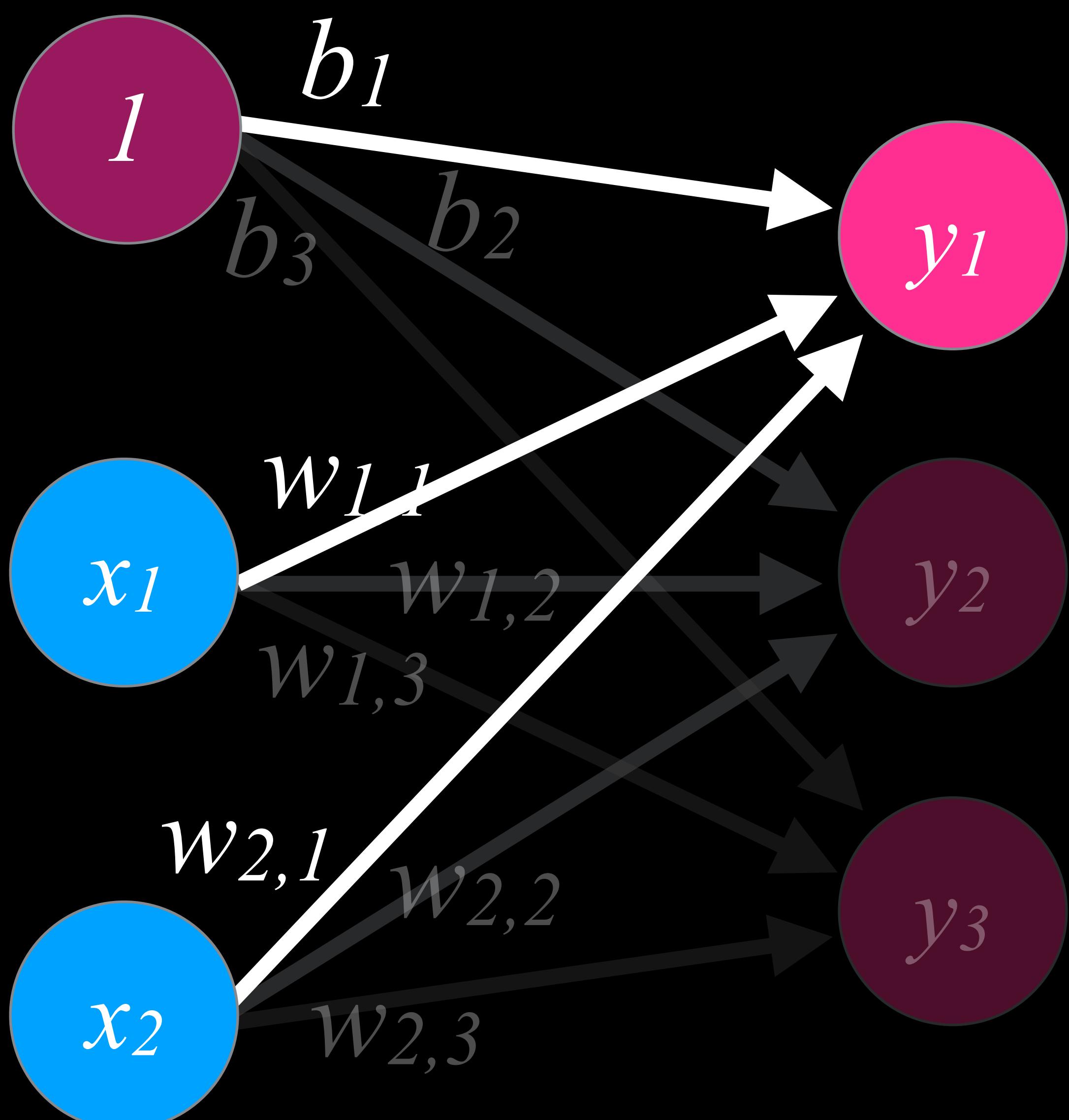
$$f_i(X) = a(w_{1,i}x_1 + w_{2,i}x_2 + b_i)$$



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

Bocconi

Enter the Matrix



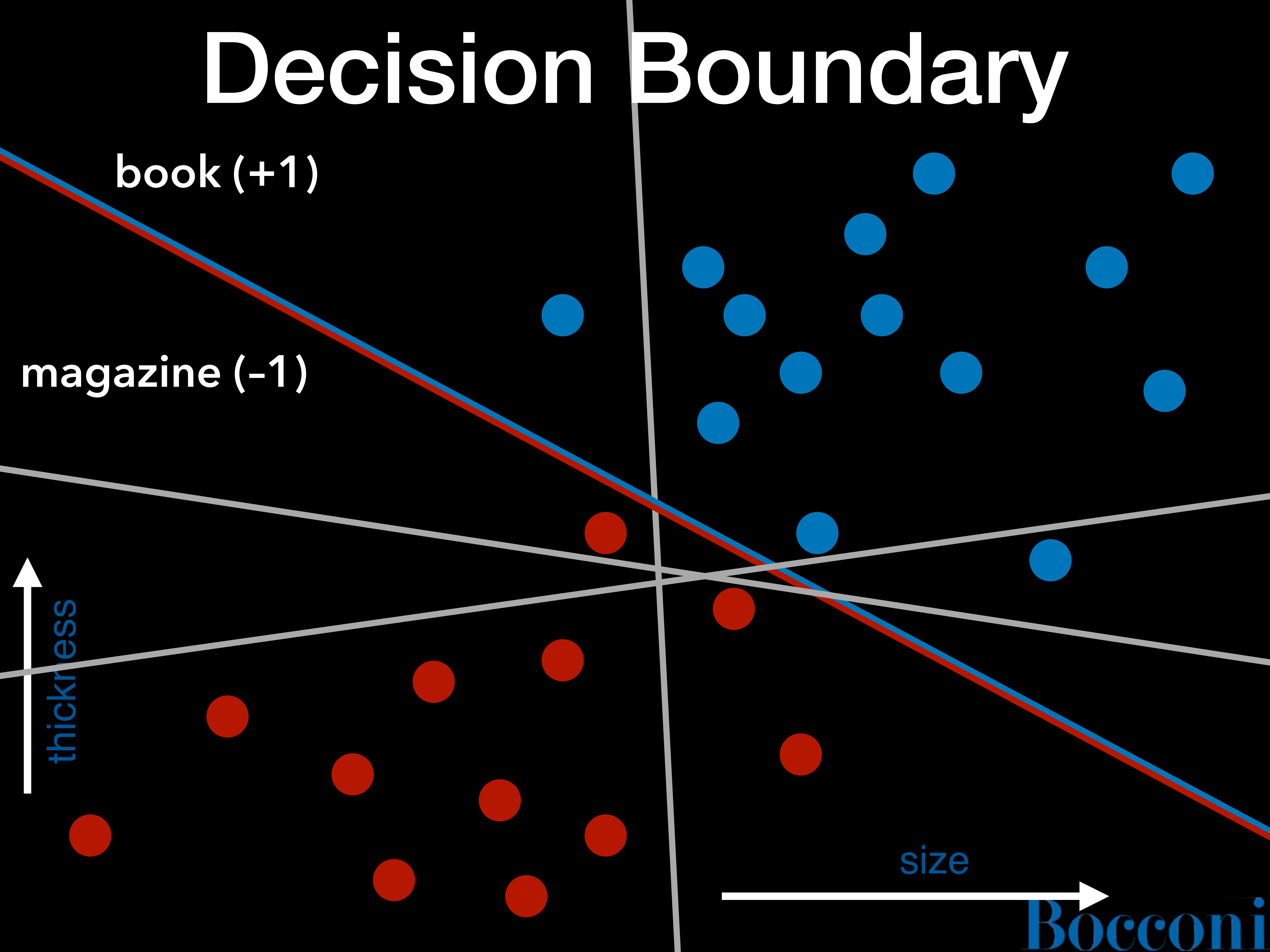
$$y_1 = a(w_{1,1}x_1 + w_{2,1}x_2 + b_1)$$

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

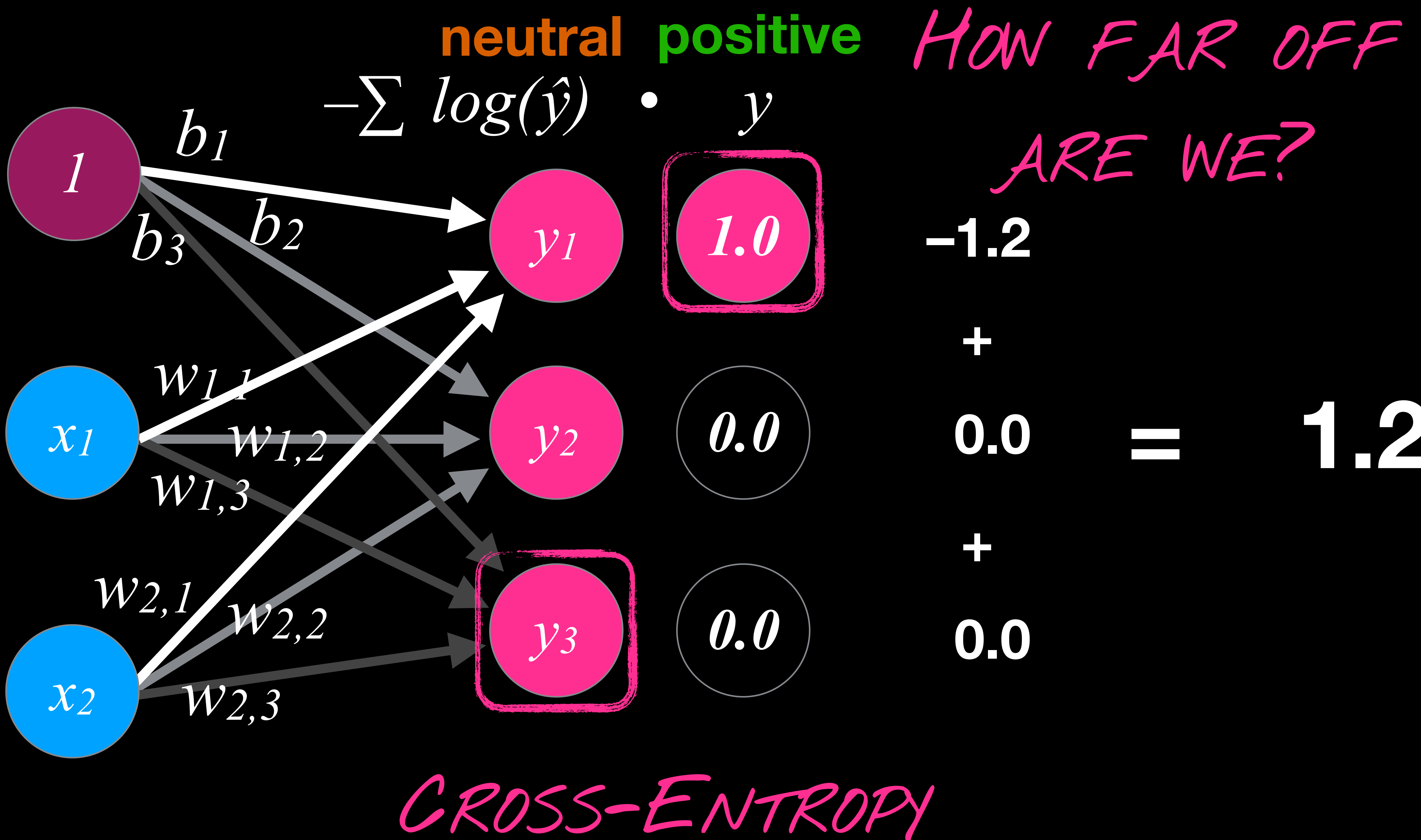
$$Y = a(W^i \quad X + b^i)$$

Learning

Decision Boundary

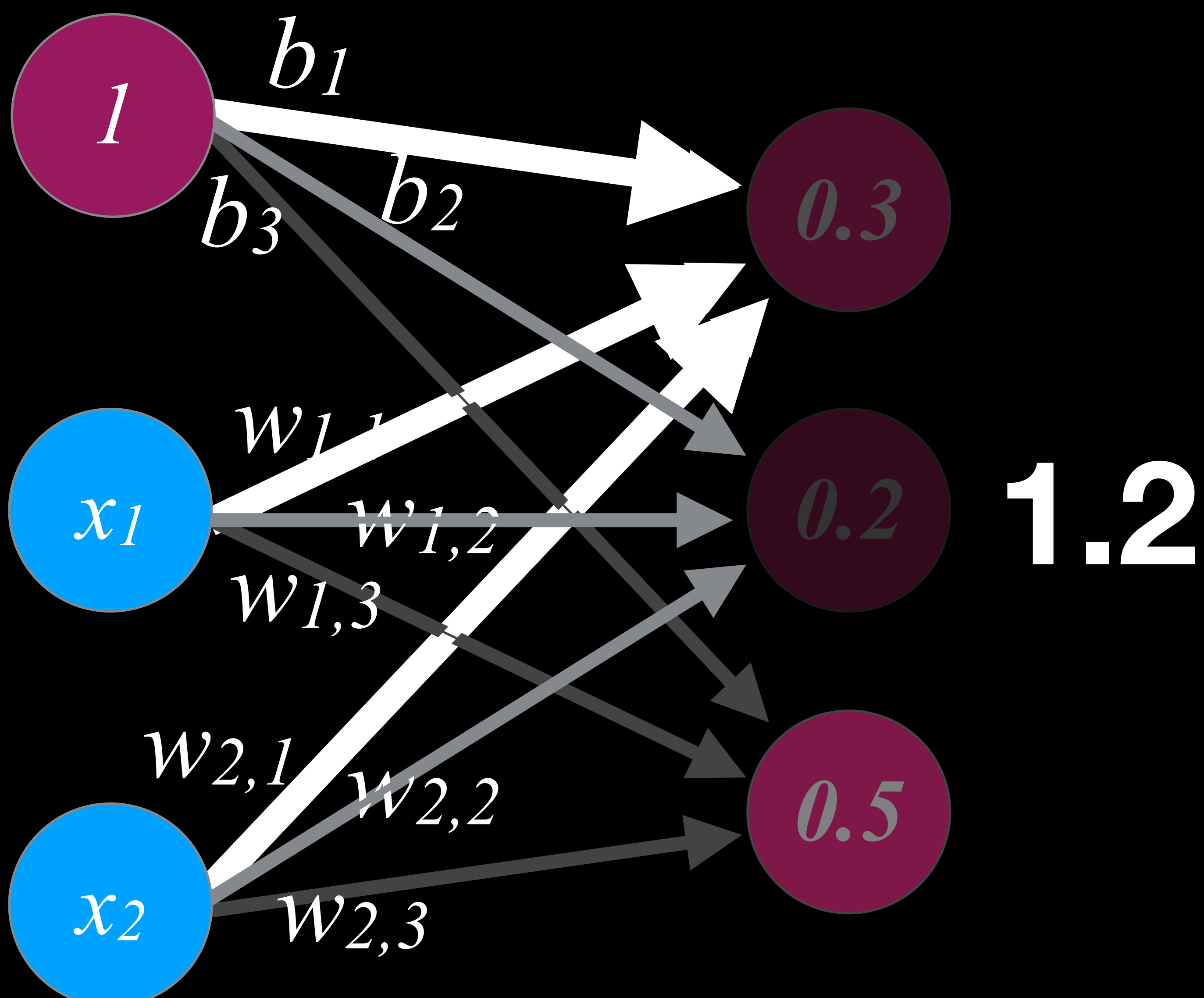


Error!



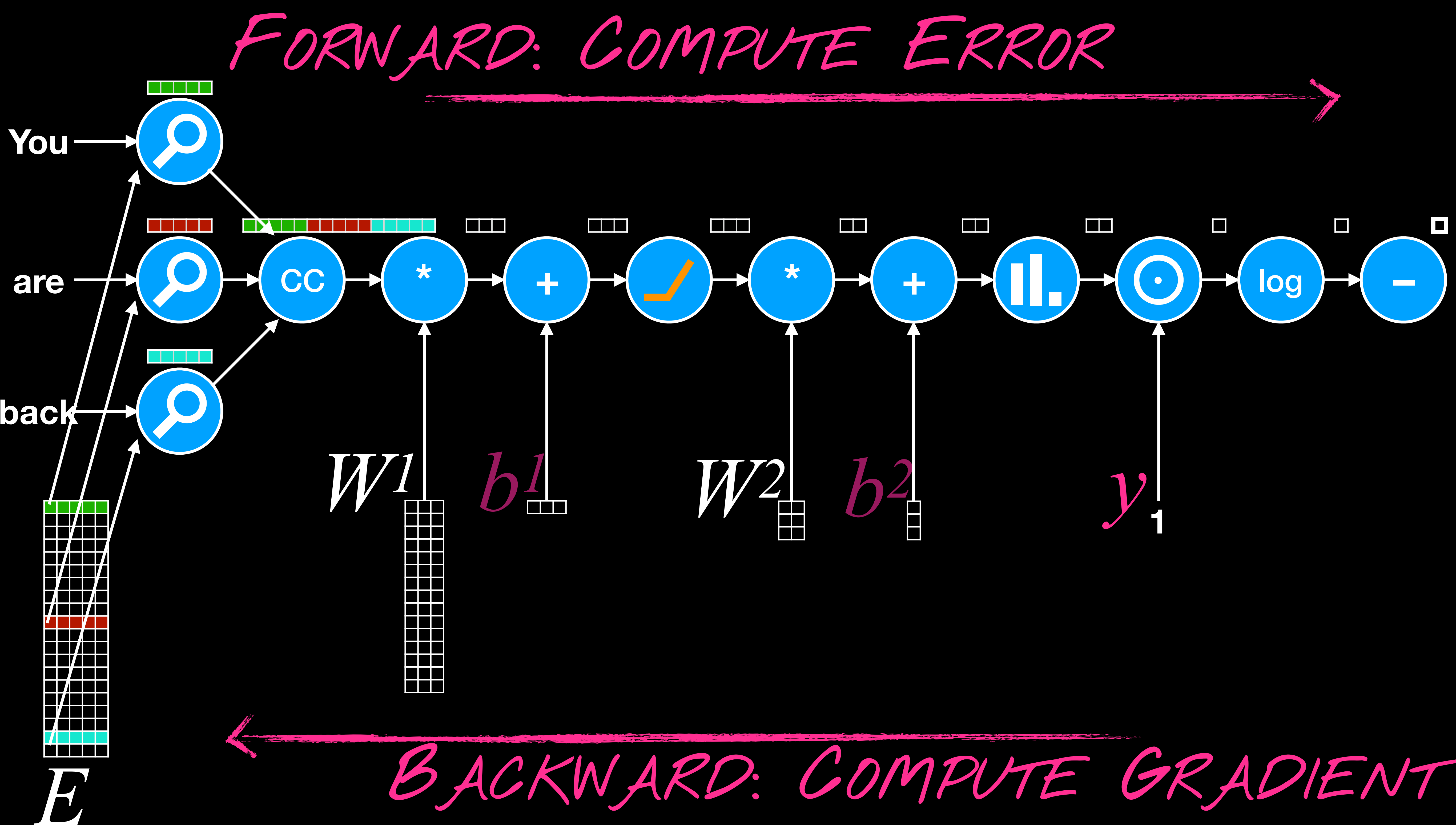
neutral
positive
$-\sum log(\hat{y}) \bullet y$
How far off are we?
1
b_1
b_2
b_3
x_1
x_2
$w_{1,1}$
$w_{1,2}$
$w_{1,3}$
$w_{2,1}$
$w_{2,2}$
$w_{2,3}$
y_1
y_2
y_3
1.0
0.0
0.0
–1.2
+
0.0
+
0.0
= 1.2
Cross-Entropy

Backpropagation



- 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

Computational Graph



Bocconi

Regularization with Dropout

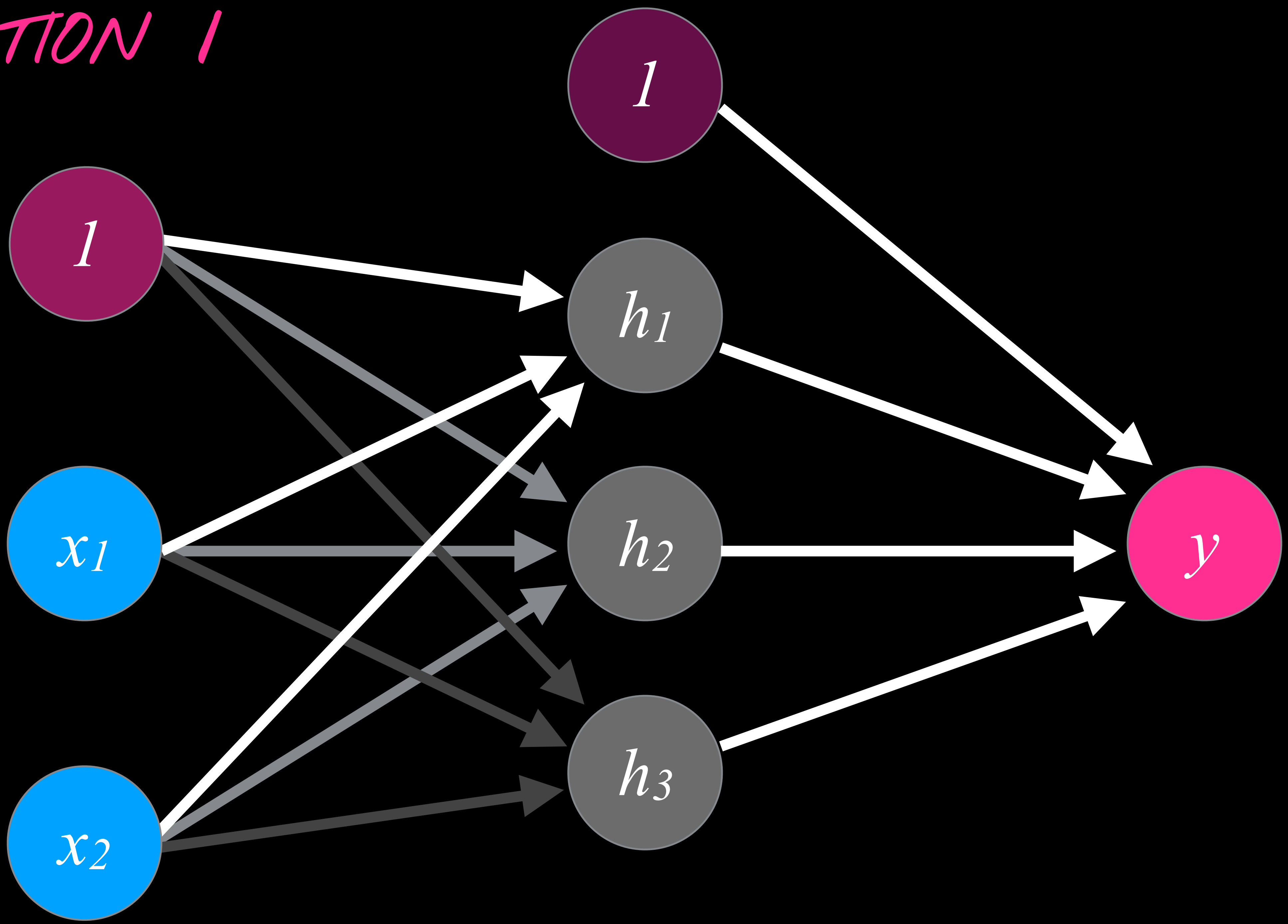
Overfitting

- 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

Bocconi

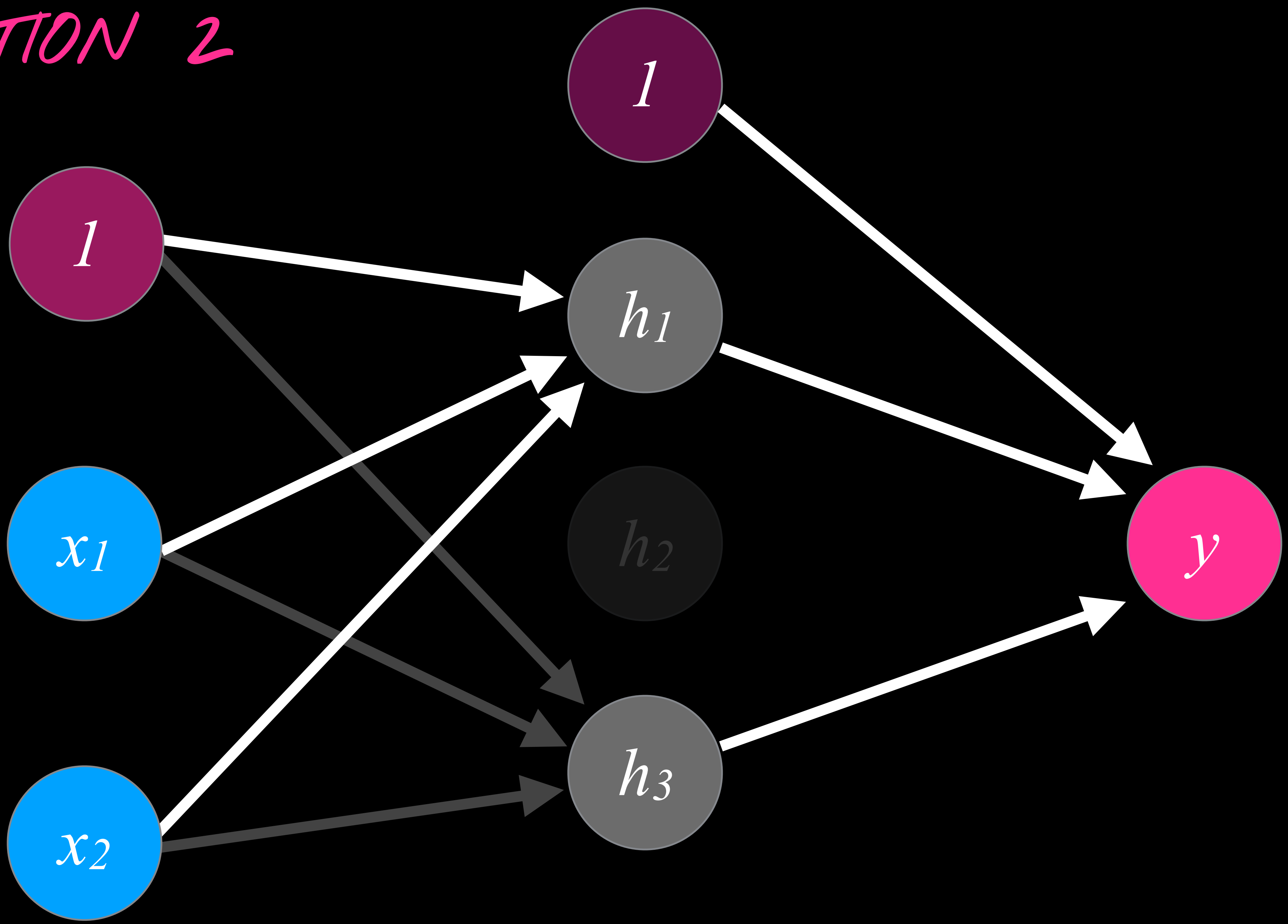
Dropout

Iteration 1



Dropout

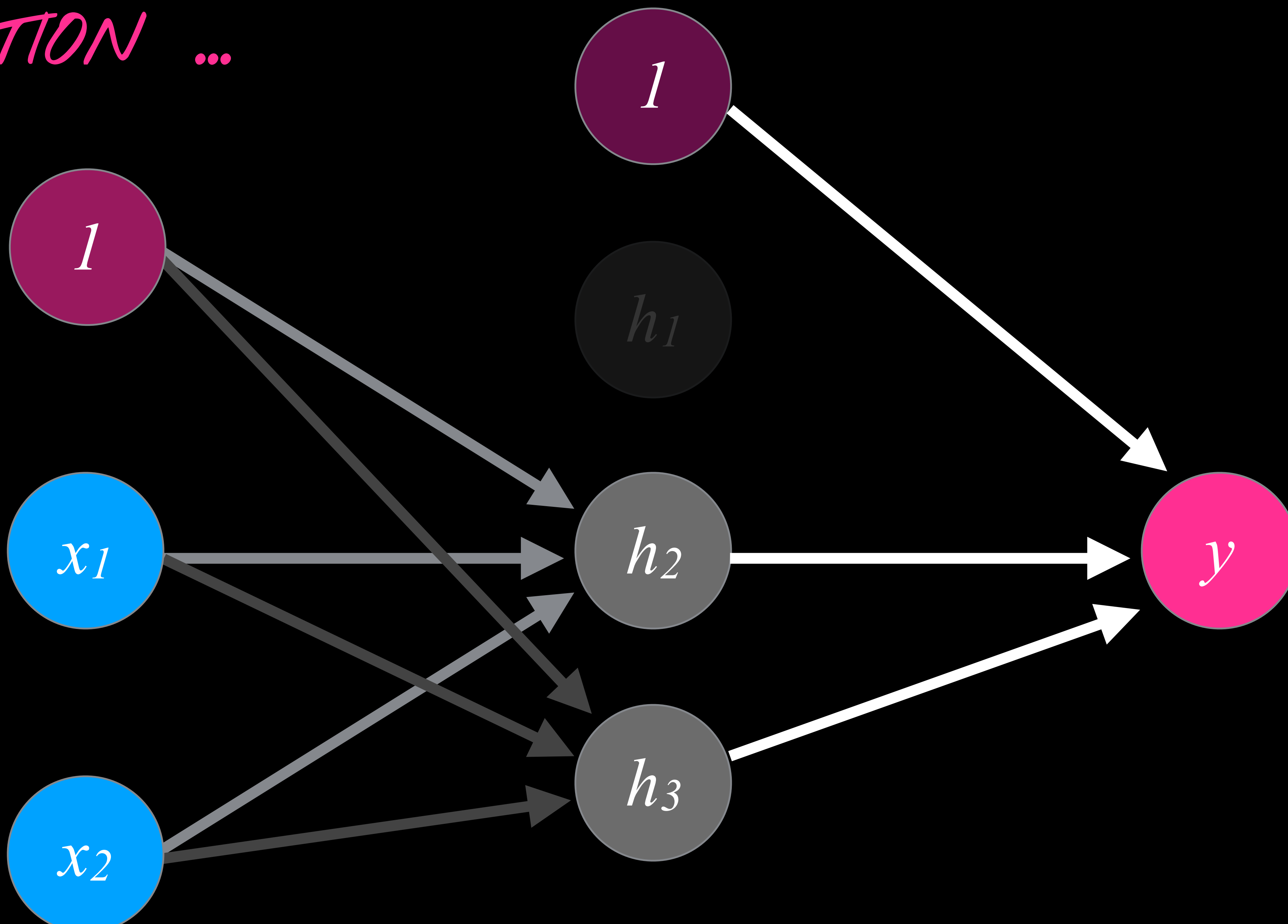
ITERATION 2



Bocconi

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