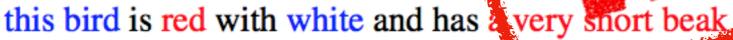
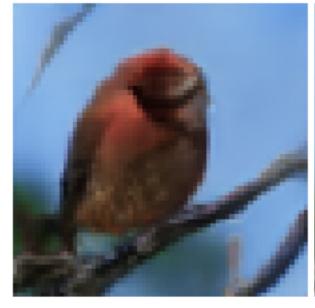
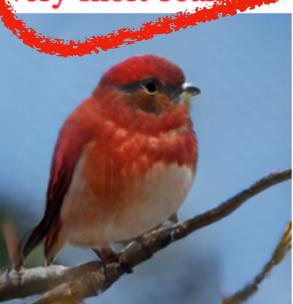
Neural Nets Everywhere











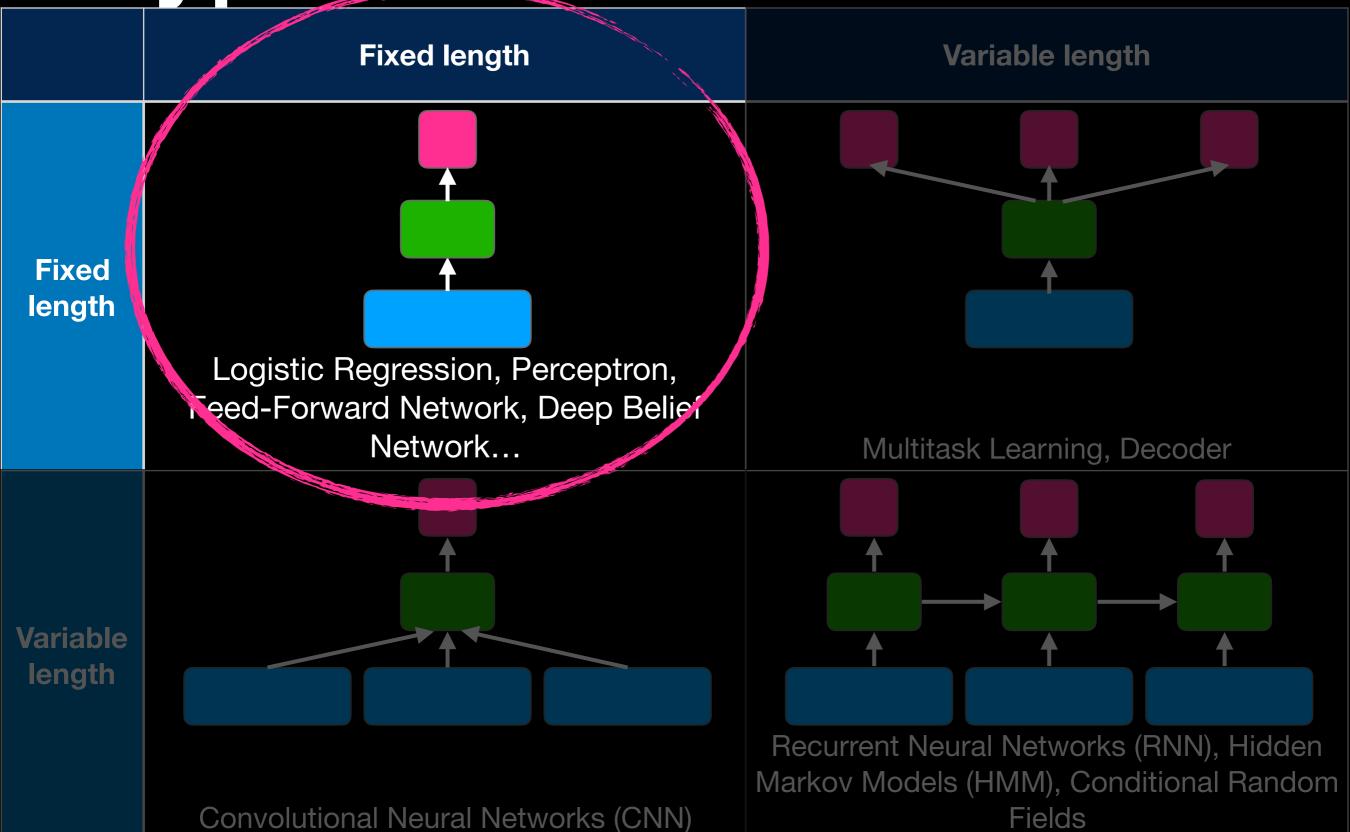


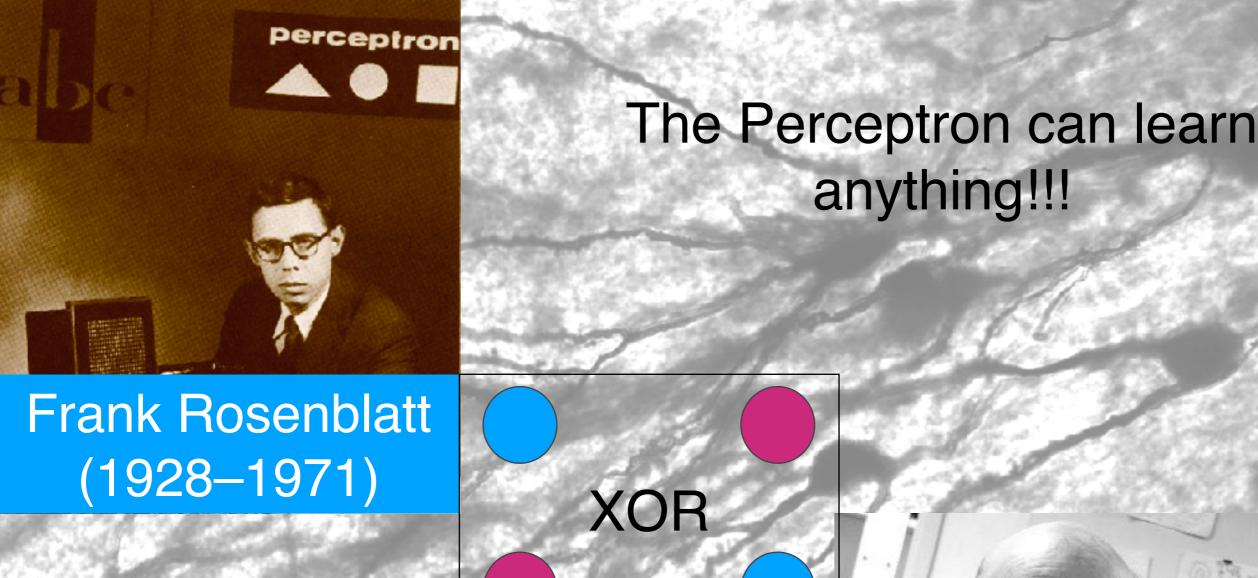
Goals for Today

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



Types of Neural Models





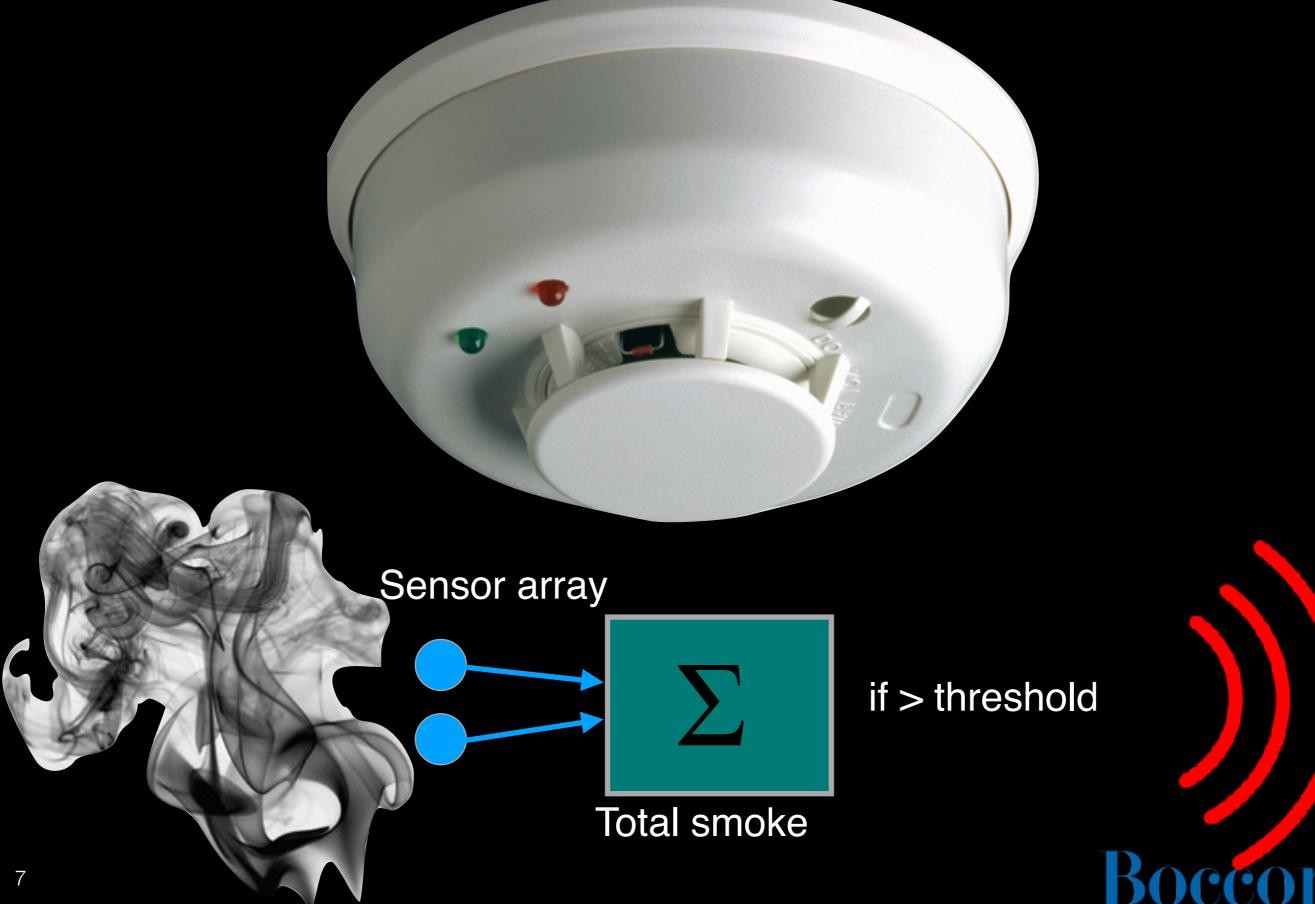


The Perceptron fails at learning even basic concepts

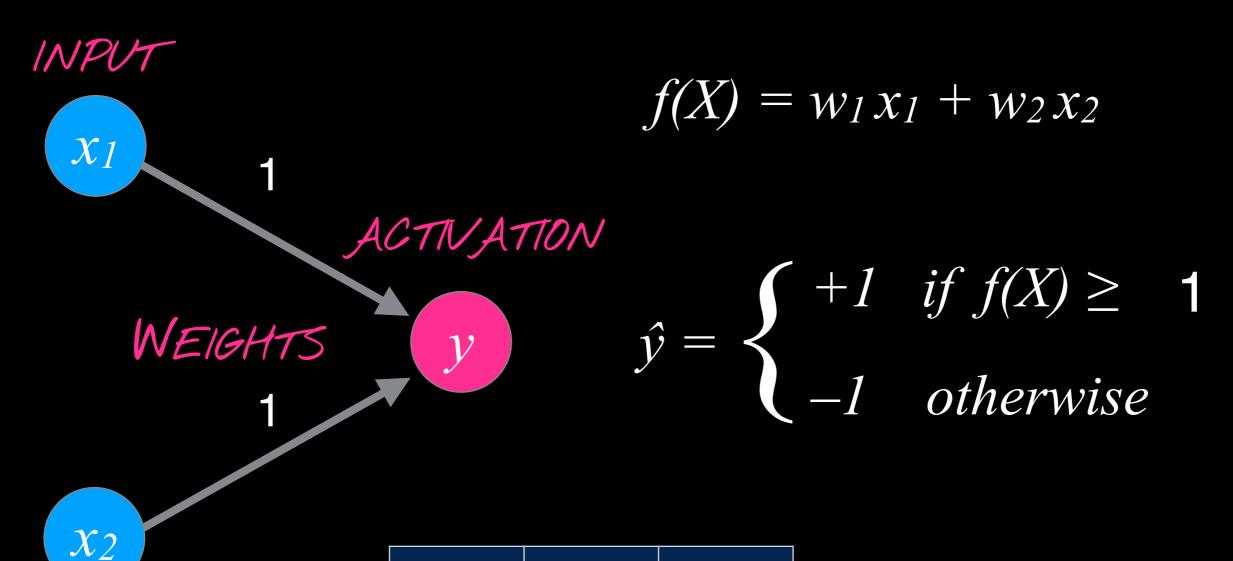
Marvin Minsky (1927–2016)

The Perceptron

A Threshold Unit



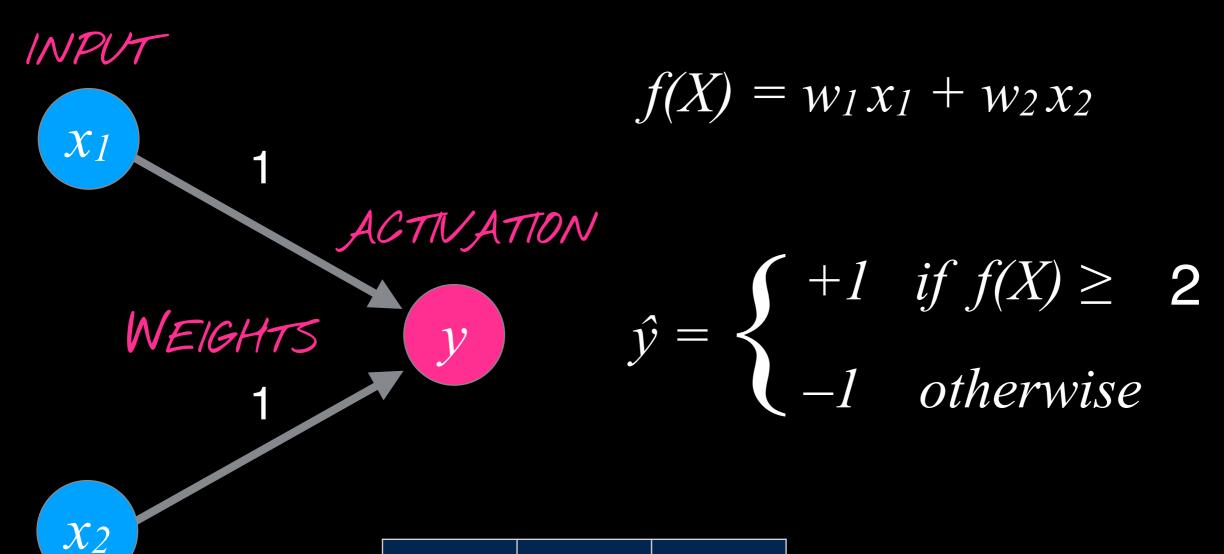
OR-Perceptron



X1	X 2	у
0	0	-1
1	0	1
0	1	1
1	1	1



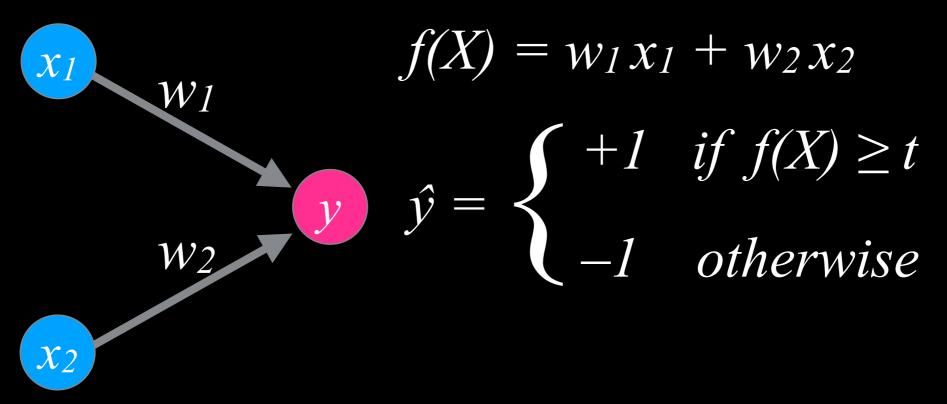
AND-Perceptron

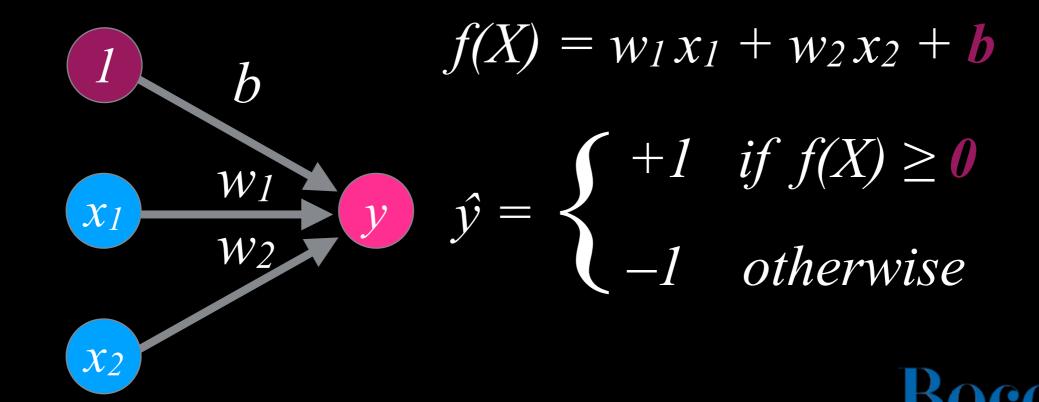


X ₁	X 2	у
0	0	-1
1	0	-1
0	1	-1
1	1	1



Learn the Threshold





Learning to Distinguish

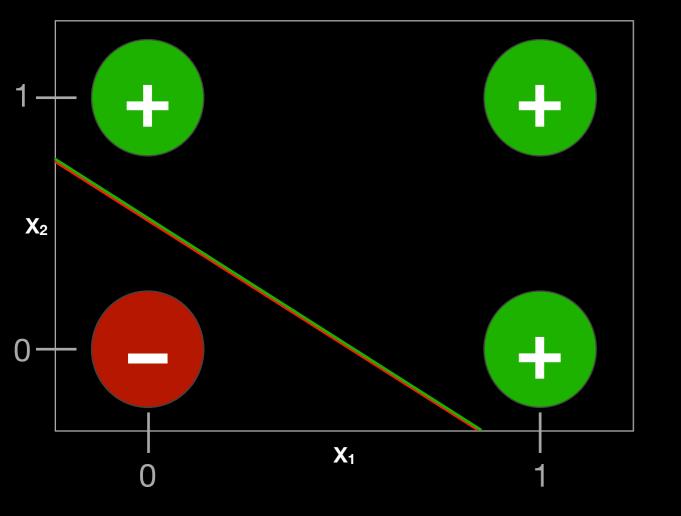
$$f(X) = 1 x_1 + 1 x_2 - 1$$

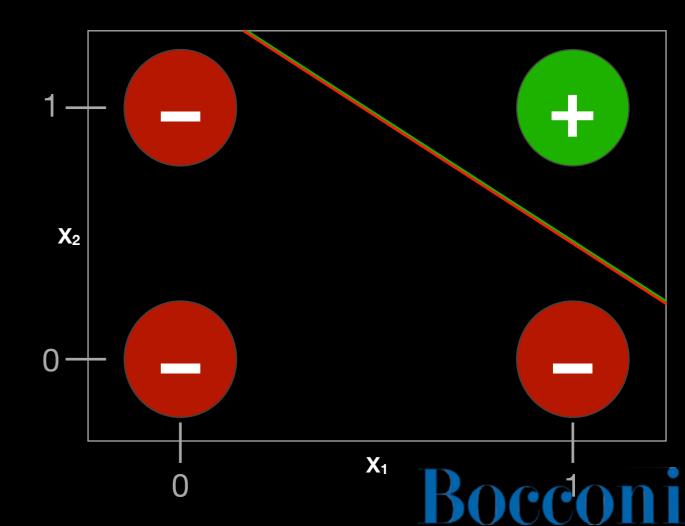
1	X ₁	X 2	У
	0	0	-1
	1	0	1
	0	1	1
	1	1	1

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

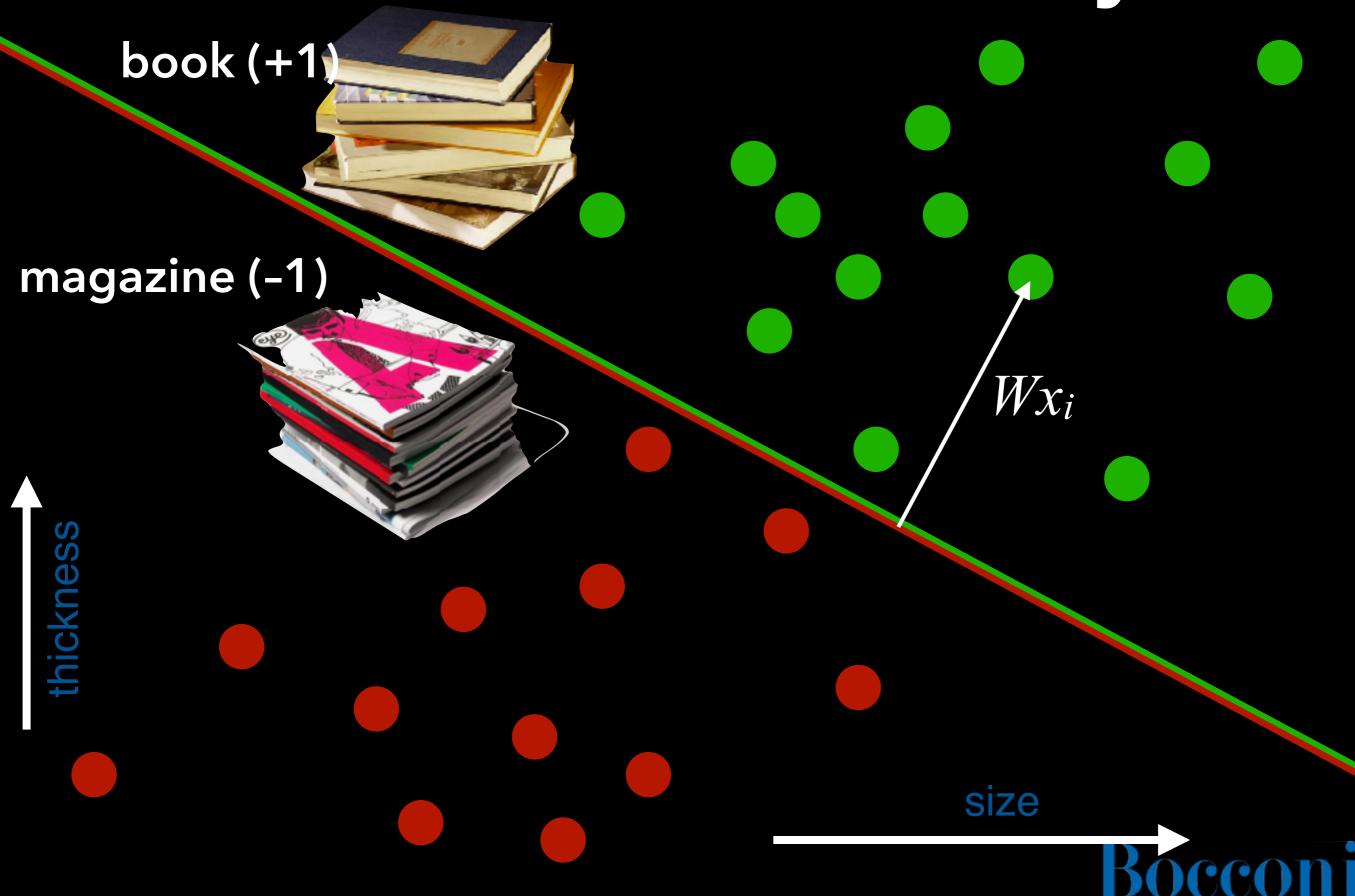
A	D

X 1	X 2	У
0	0	-1
1	0	-1
0	1	-1
1	1	1





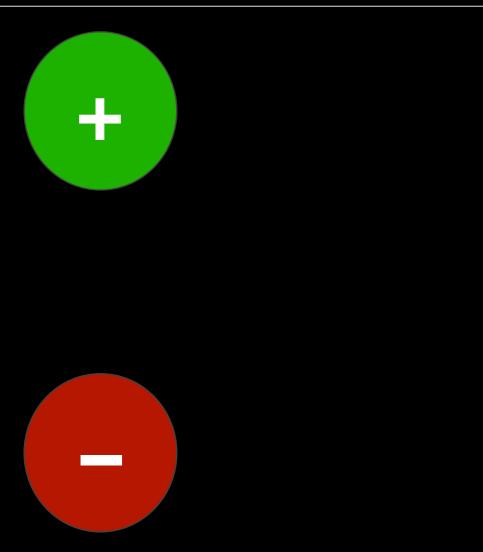
Decision Boundary



The XOR Limit

X 1	X 2	у
0	0	-1
1	0	1
0	1	1
1	1	-1





 X_1

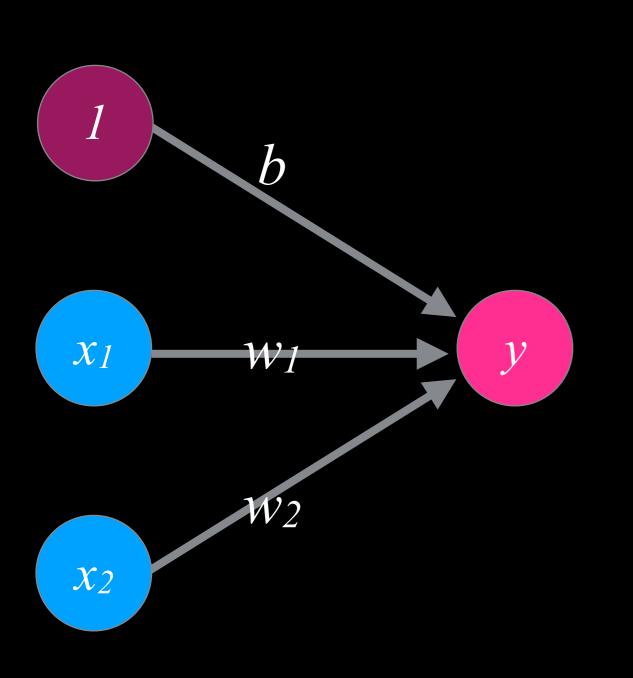




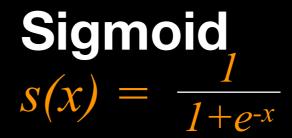
Marvin Minsky (1927–2016)

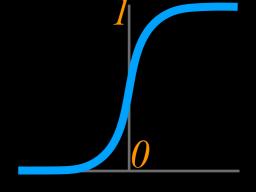
Step 1: Non-Linearity

Nonlinear Activation Functions

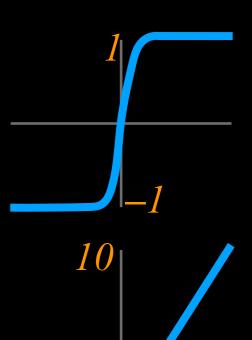


$$f(X) = a(w_1x_1 + w_2x_2 + b)$$





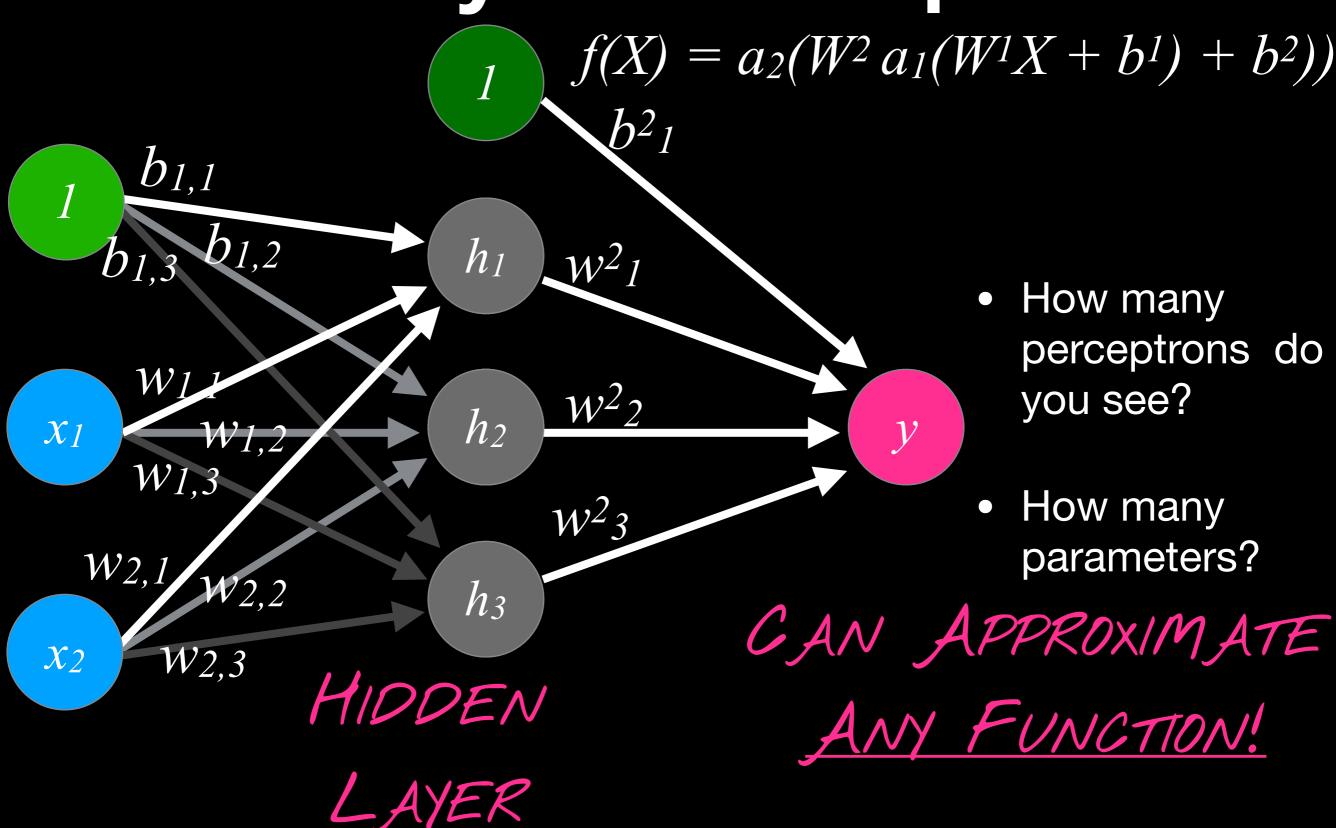
tanh
tanh(x)



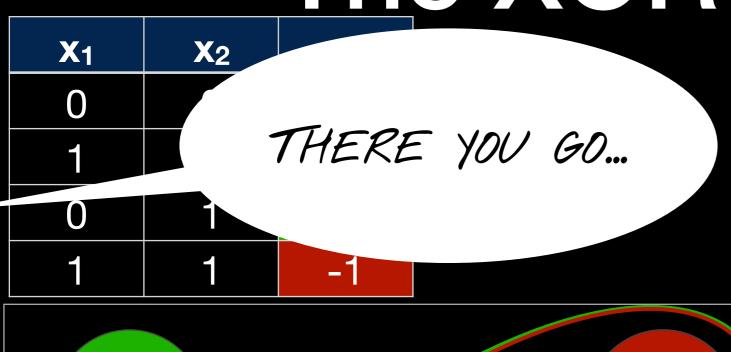
ReLU max(0, x)

Step 2: Going Deep – The Multilayer Perceptron

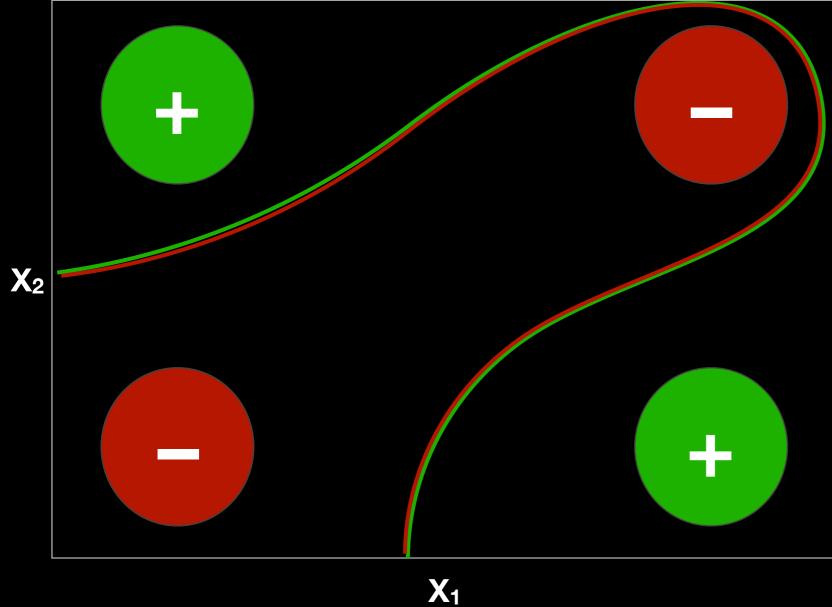
Multilayer Perceptron



The XOR Limit



LINEARIZE THIS!





Marvin Minsky (1927–2016)

Multi-Class Output

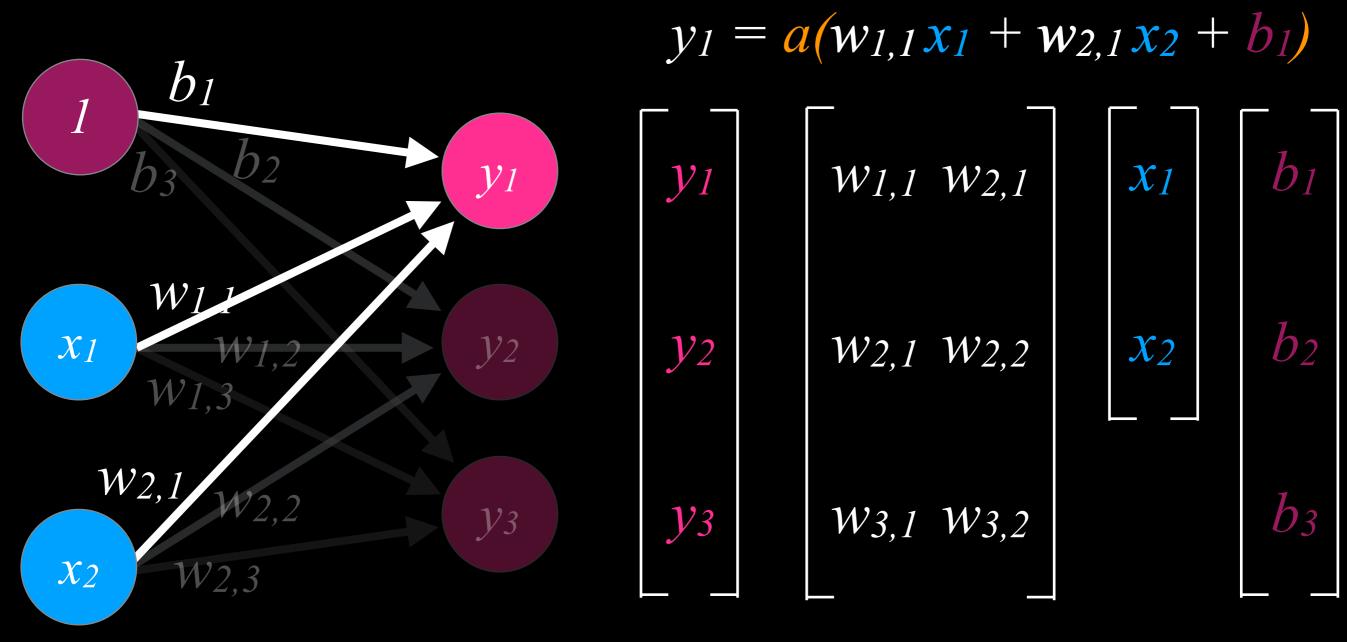
$$f_i(X) = a(w_{1,i}x_1 + w_{2,i}x_2 + b_i)$$

$$y_i \qquad positive$$

$$w_{1,2} \qquad y_2 \qquad negative \qquad \hat{y} = \underset{i}{argmax} f_i(X)$$

$$w_{2,1} \qquad w_{2,2} \qquad y_3 \qquad neutral$$

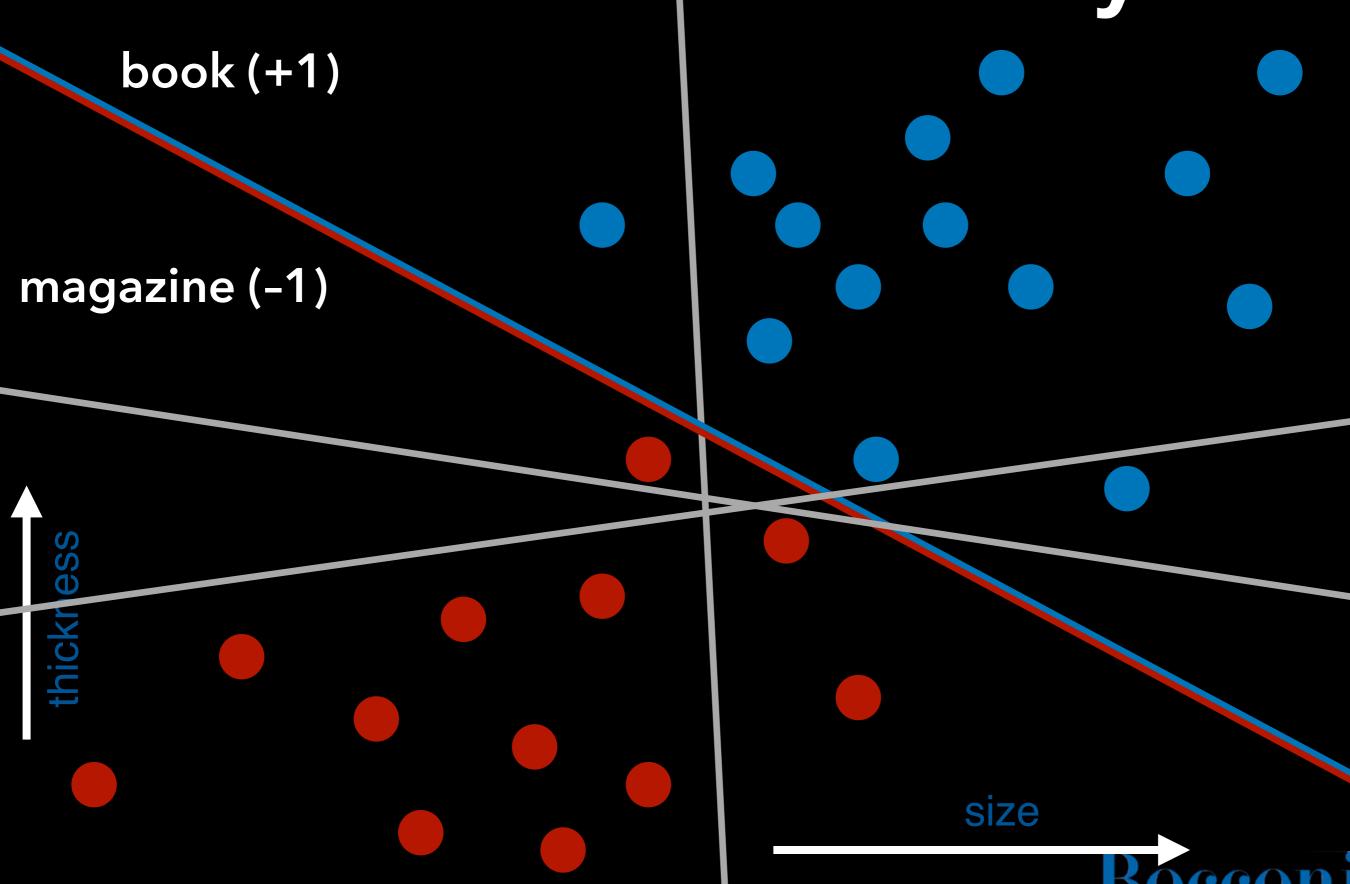
Enter the Matrix



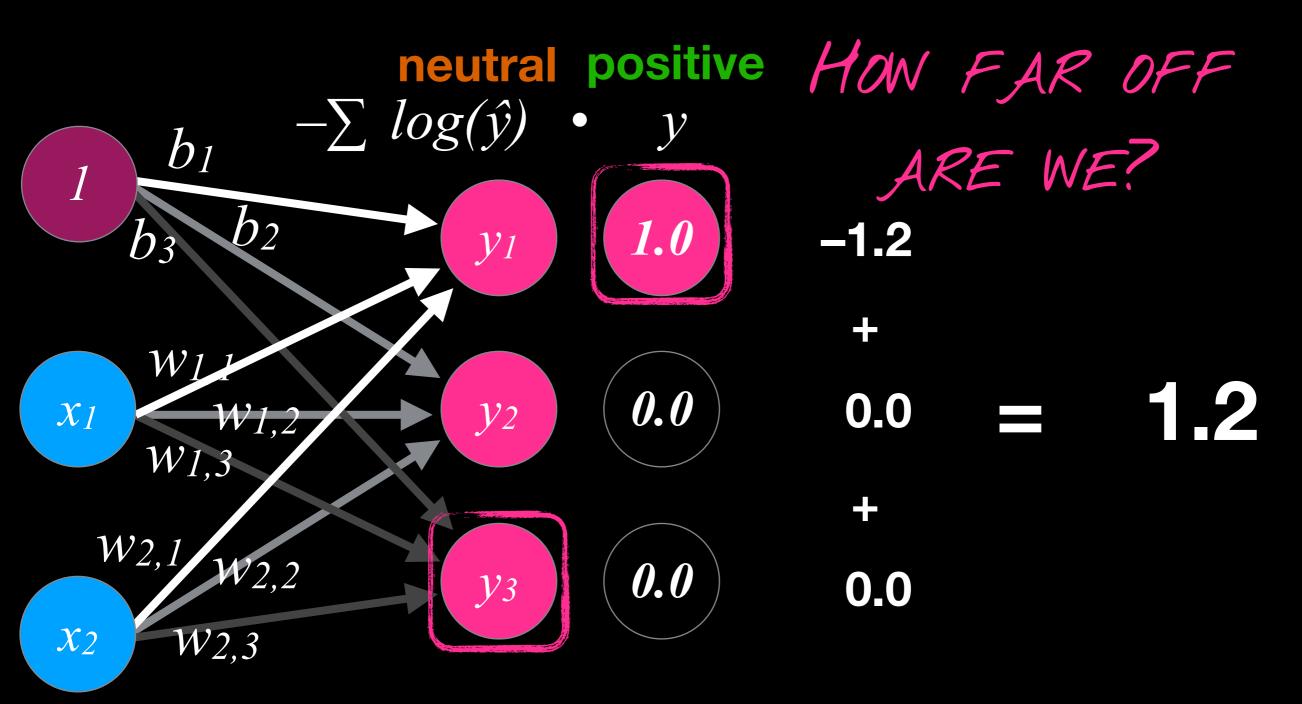
$$Y = a(Wi X + bi)$$

Learning

Decision Boundary

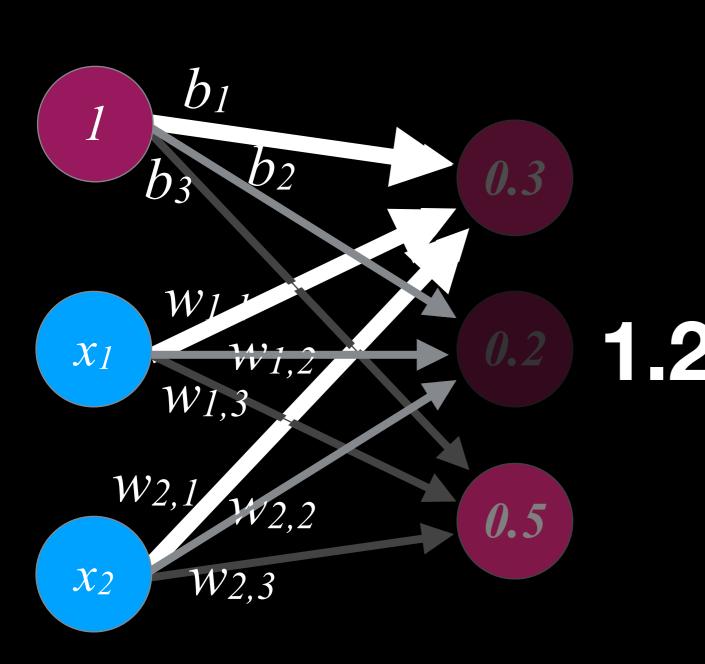


Error!



CROSS-ENTROPY

Backpropagation



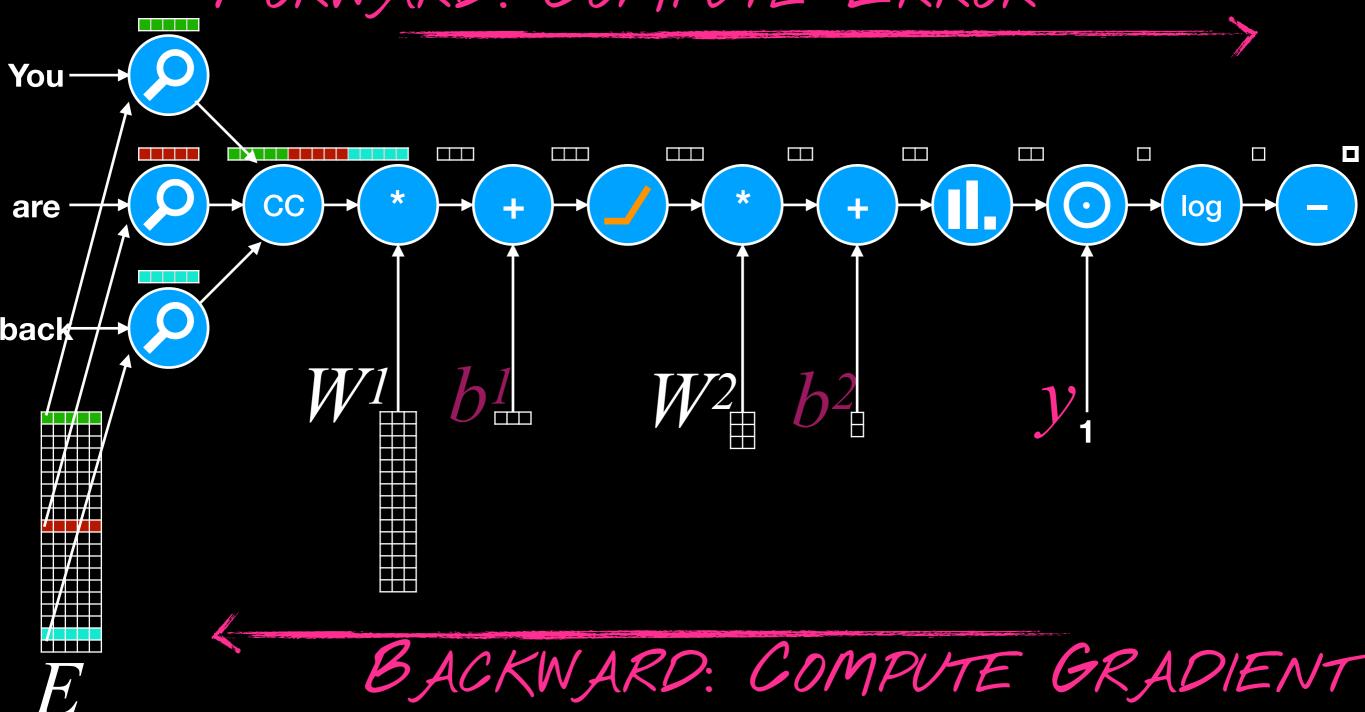
 Adjust weights/bias proportionately to change, using Stochastic Gradient Descent

 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

FORWARD: COMPUTE ERROR



Regularization with Dropout

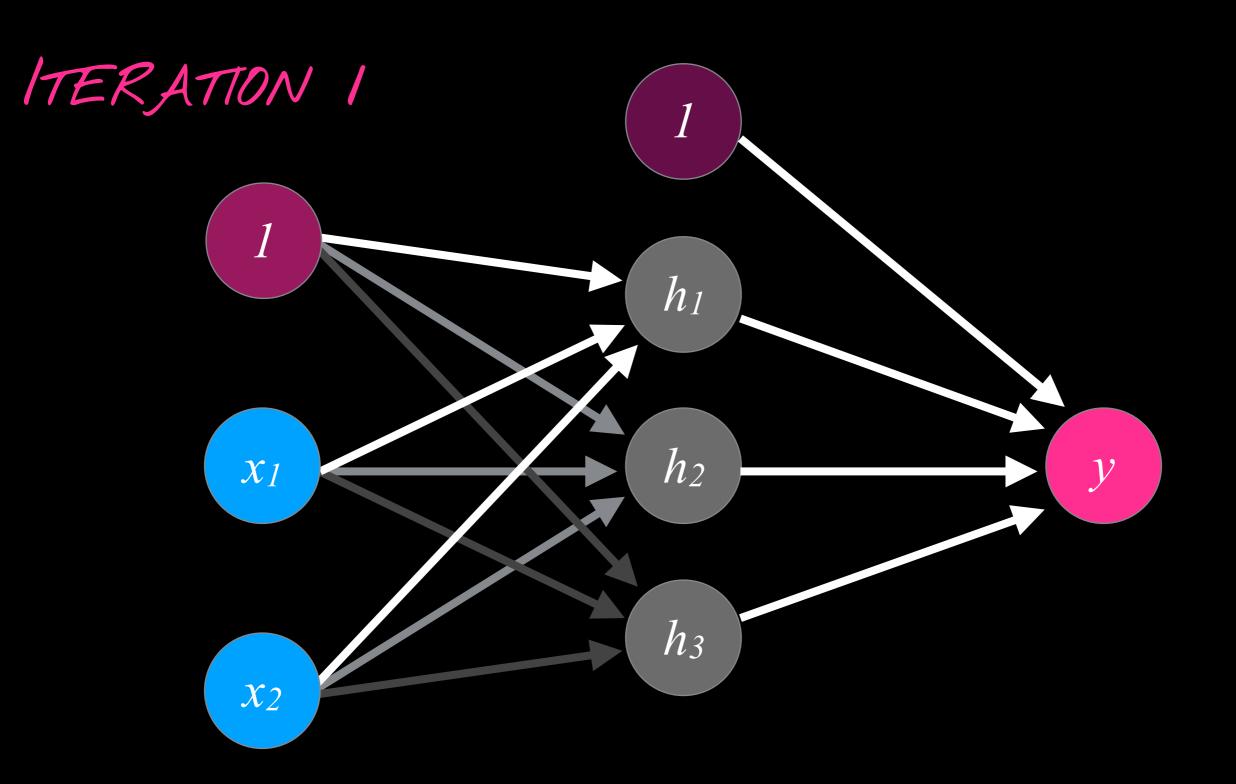


 ALVINN autonomous vehicle, trained on a particular stretch of road

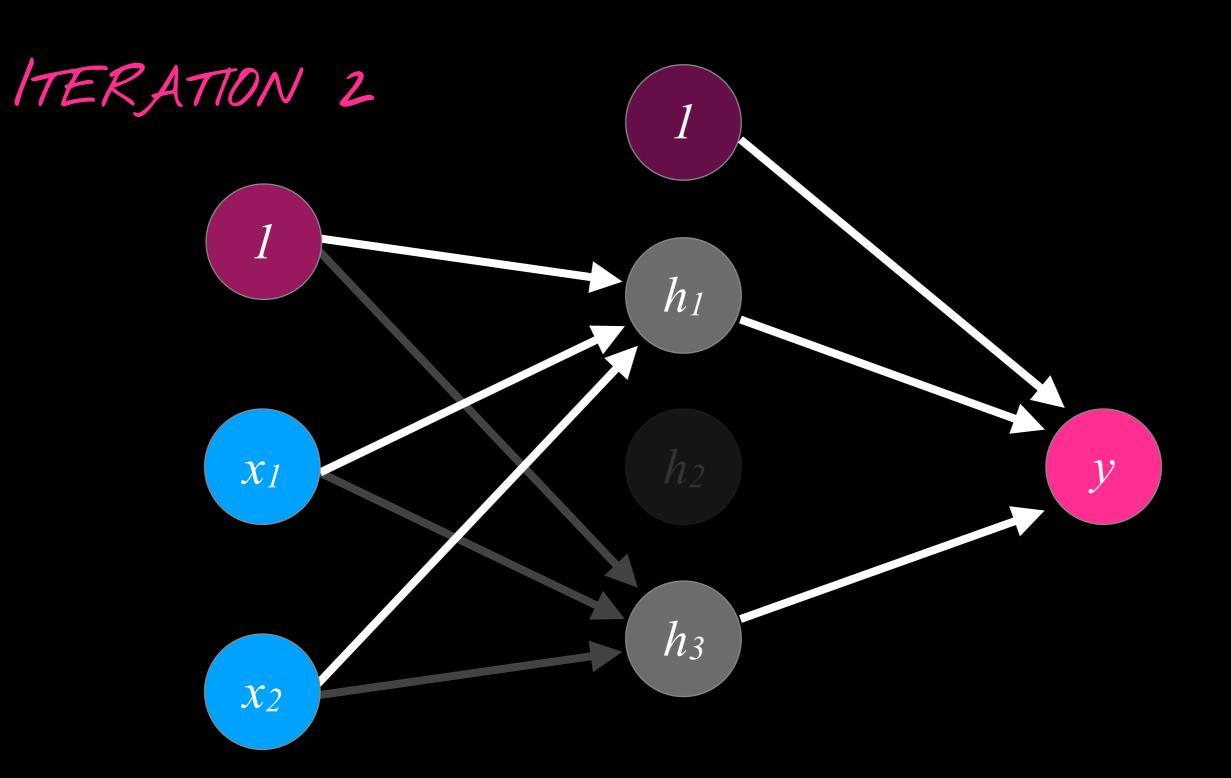
 Drove off the road when turned around => focused on having a ditch on one side

 Idea: randomly remove nodes to avoid over-reliance

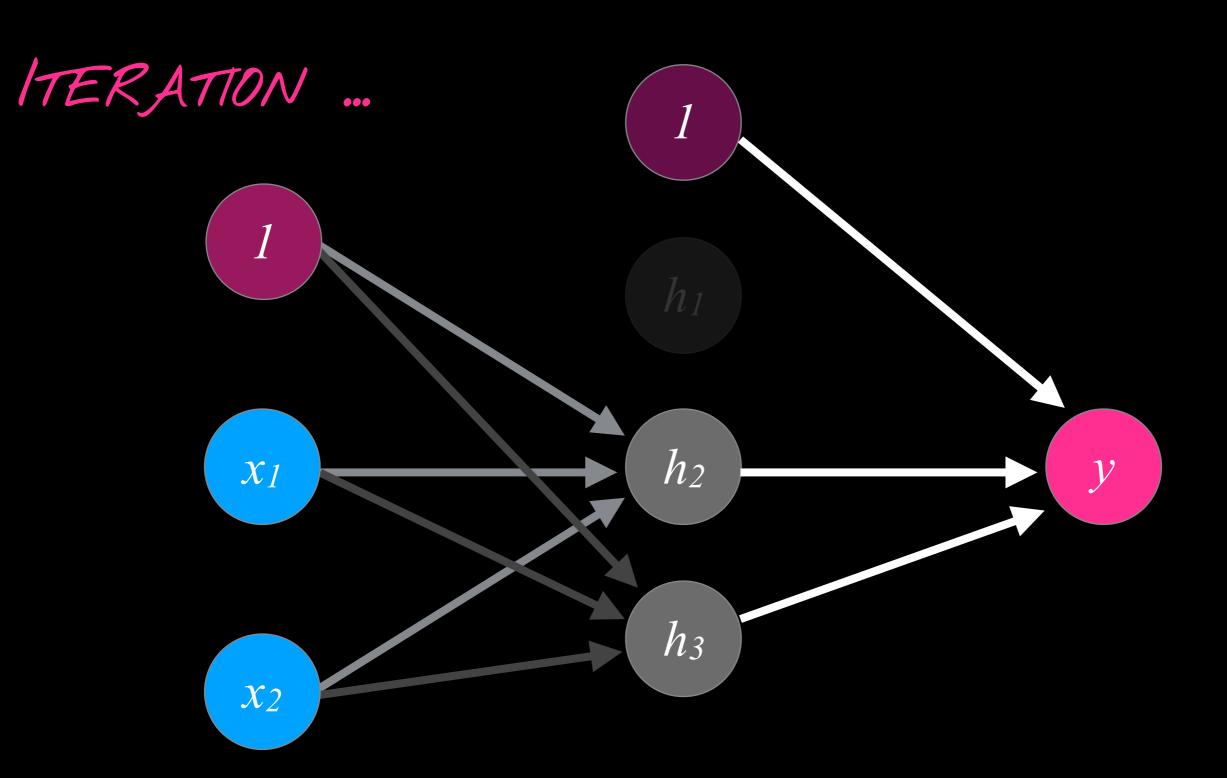
Dropout



Dropout



Dropout



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



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

•

