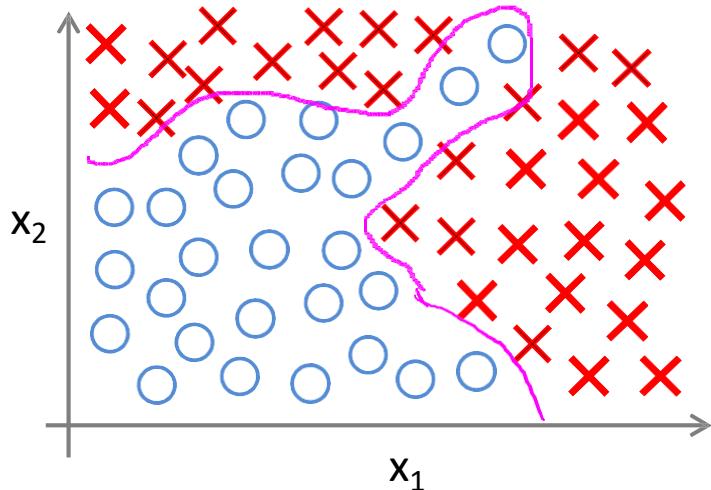


Machine Learning

Neural Networks: Representation Non-linear hypotheses

Non-linear Classification



x_1 = size

x_2 = # bedrooms

x_3 = # floors

x_4 = age

...

x_{100}

$\{ h=100 \}$

$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 x_2 + \theta_5 x_1^3 x_2 + \theta_6 x_1 x_2^2 + \dots)$$

$$\rightarrow \underline{x_1^2}, \underline{x_1 x_2}, \underline{x_1 x_3}, \underline{x_1 x_4} \dots \underline{x_1 x_{100}} \\ \underline{x_2^2}, \underline{x_2 x_3} \dots$$

≈ 5000 feature

$\mathcal{O}(n^2)$

$$\rightarrow \underline{x_1^2}, \underline{x_2^2}, \underline{x_3^2}, \dots, \underline{x_{100}^2}$$

$\frac{n^2}{2}$

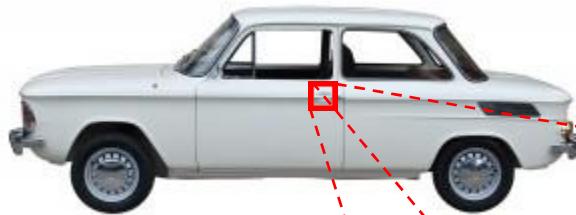
$$\rightarrow \underline{x_1 x_2 x_3}, \underline{x_1^2 x_2}, \underline{x_{10} x_{11} x_{12}}, \dots$$

$\mathcal{O}(n^3)$

170,000

What is this?

You see this:



But the camera sees this:

194	210	201	212	199	213	215	195	178	158	182	209
180	189	190	221	209	205	191	167	147	115	129	163
114	126	140	188	176	165	152	140	170	106	78	88
87	103	115	154	143	142	149	153	173	101	57	57
102	112	106	131	122	138	152	147	128	84	58	66
94	95	79	104	105	124	129	113	107	87	69	67
68	71	69	98	89	92	98	95	89	88	76	67
41	56	68	99	63	45	60	82	58	76	75	65
20	43	69	75	56	41	51	73	55	70	63	44
50	50	57	69	75	75	73	74	53	68	59	37
72	59	53	66	84	92	84	74	57	72	63	42
67	61	58	65	75	78	76	73	59	75	69	50

Computer Vision: Car detection



Cars

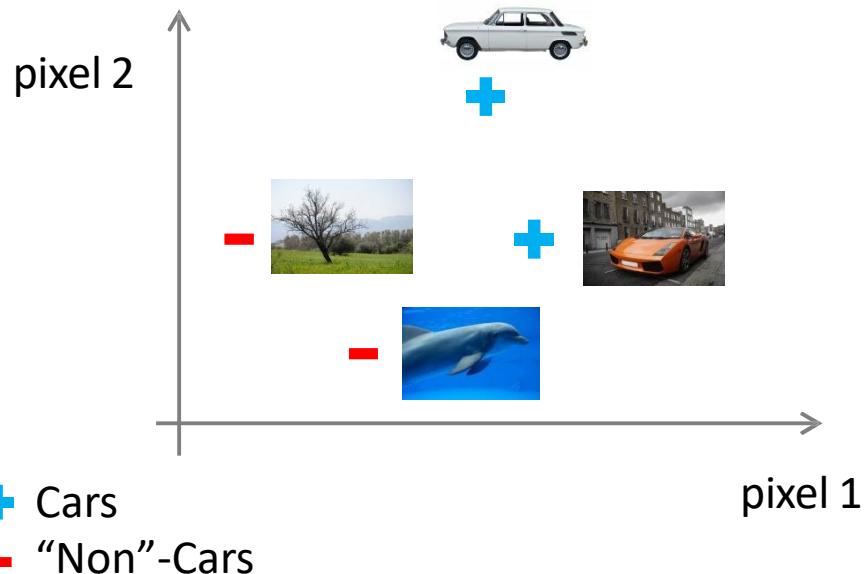
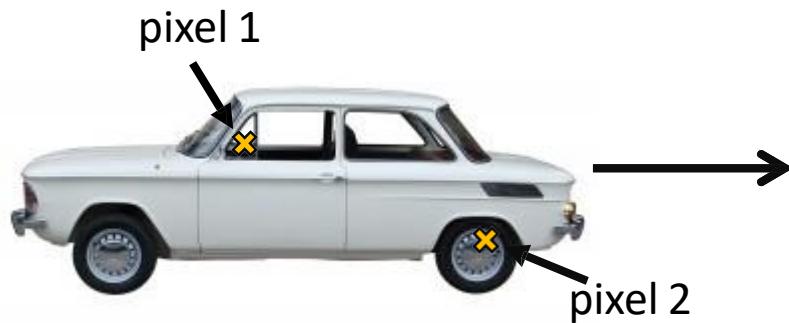


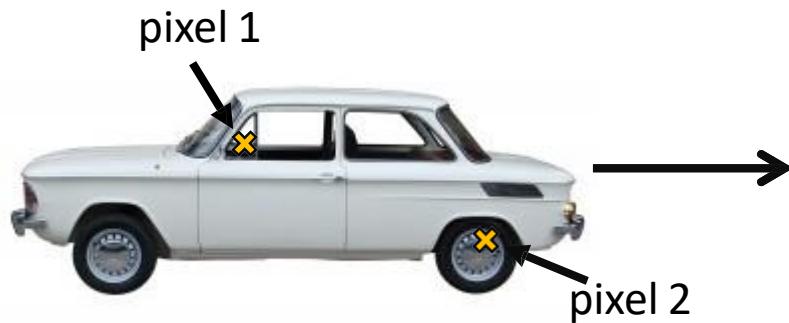
Not a car

Testing:

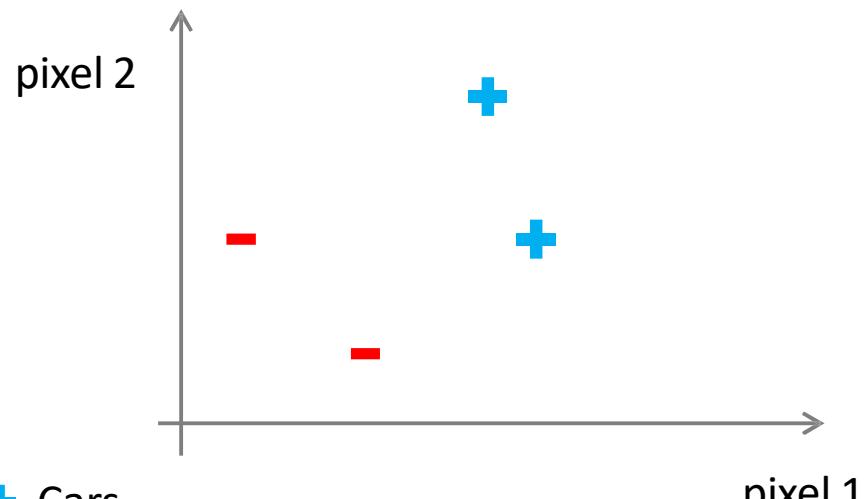


What is this?





Learning
Algorithm

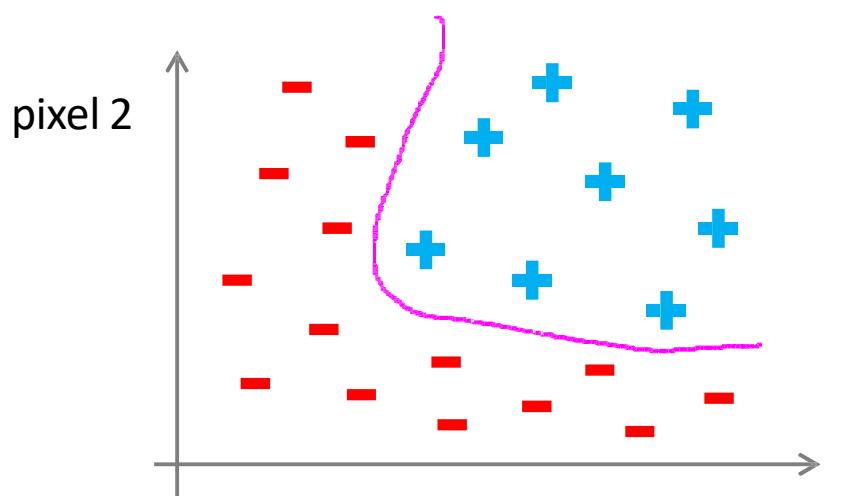
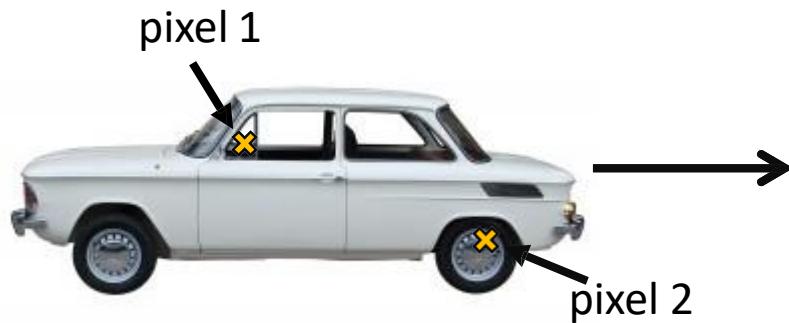


+

Cars

-

"Non"-Cars

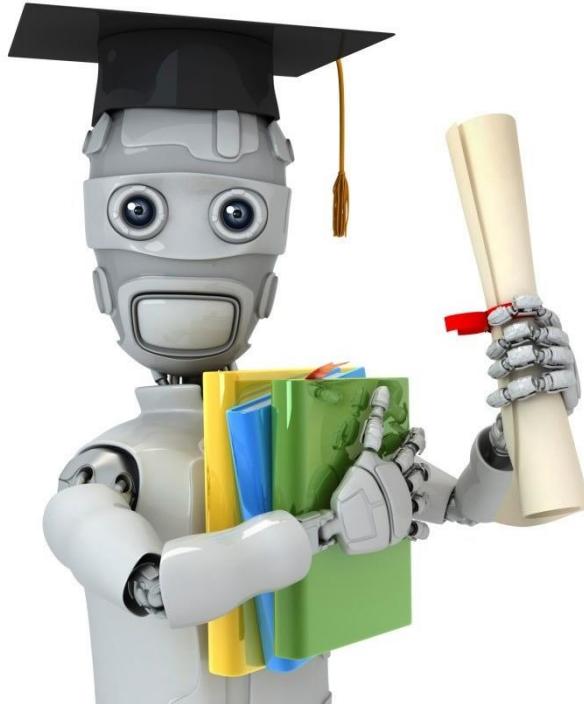


50×50 pixel images \rightarrow 2500 pixels
 $n = 2500$ (7500 if RGB)

$$x = \begin{bmatrix} \text{pixel 1 intensity} \\ \text{pixel 2 intensity} \\ \vdots \\ \text{pixel 2500 intensity} \end{bmatrix}$$

0-255

Quadratic features ($x_i \times x_j$): ≈ 3 million features



Machine Learning

Neural Networks: Representation

Neurons and the brain

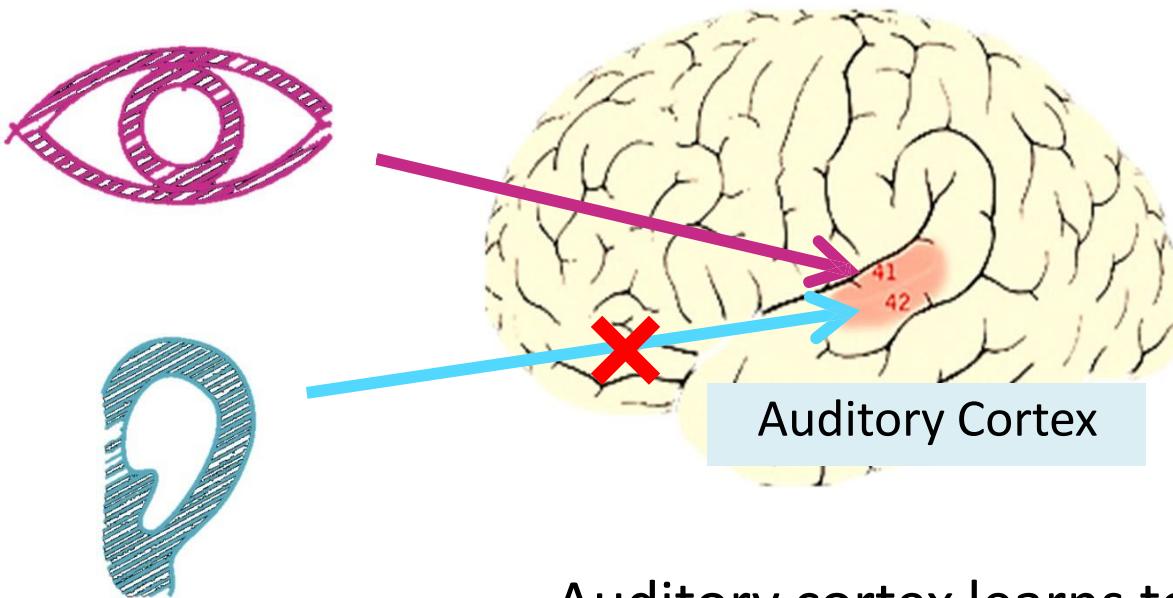
Neural Networks

Origins: Algorithms that try to mimic the brain.

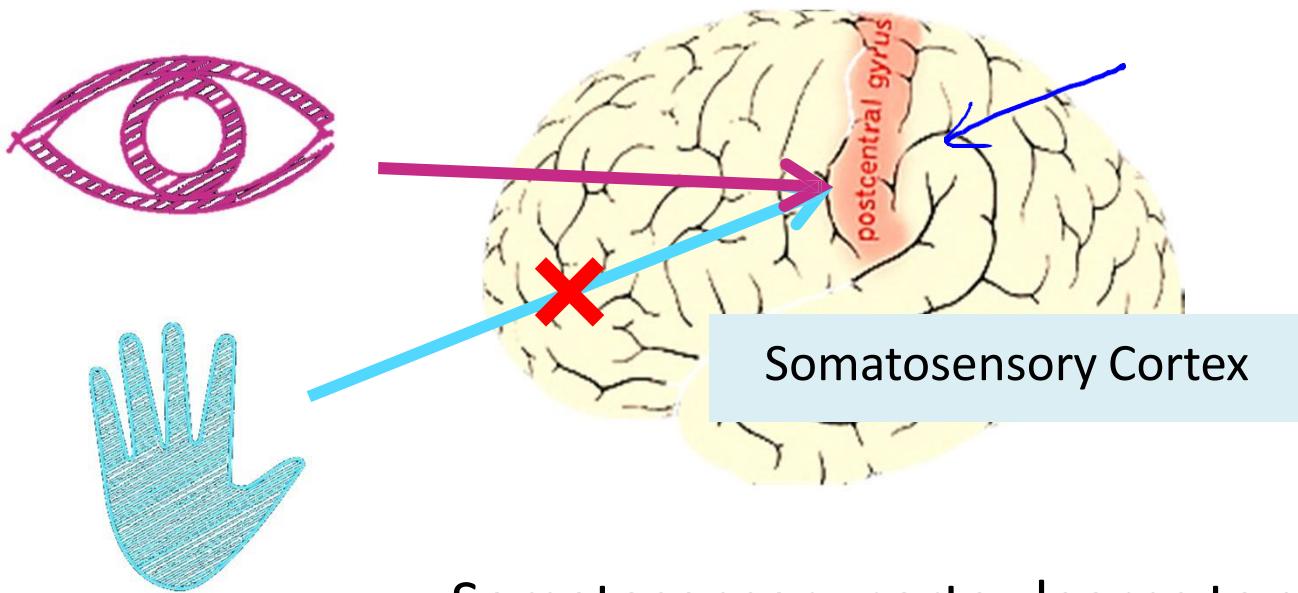
Was very widely used in 80s and early 90s; popularity diminished in late 90s.

Recent resurgence: State-of-the-art technique for many applications

The “one learning algorithm” hypothesis



The “one learning algorithm” hypothesis



Somatosensory cortex learns to see

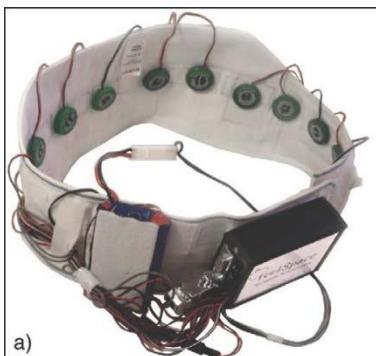
Sensor representations in the brain



Seeing with your tongue



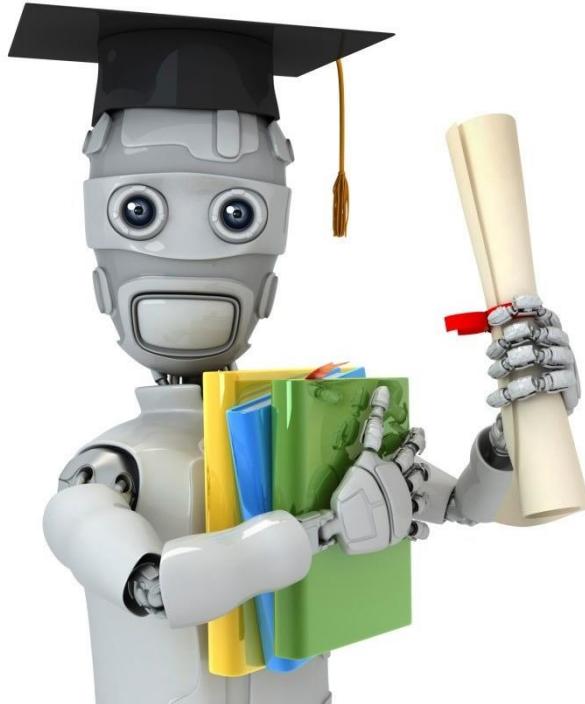
Human echolocation (sonar)



Haptic belt: Direction sense



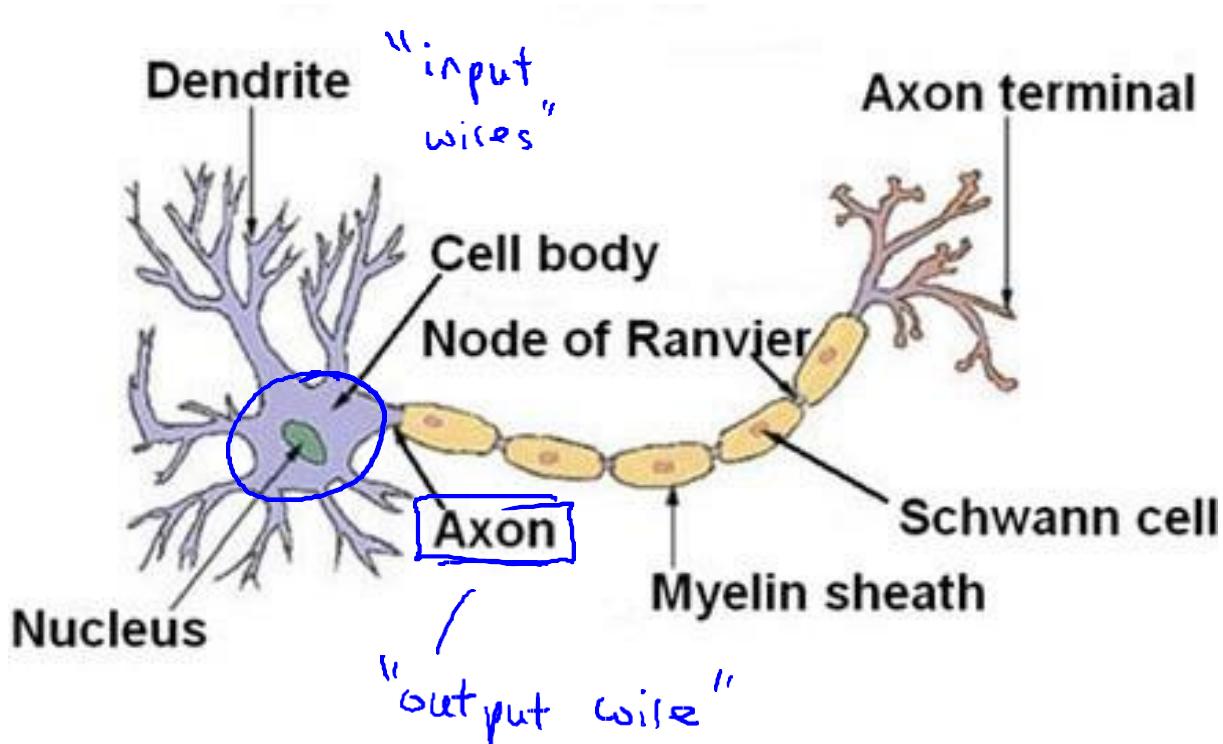
Implanting a 3rd eye



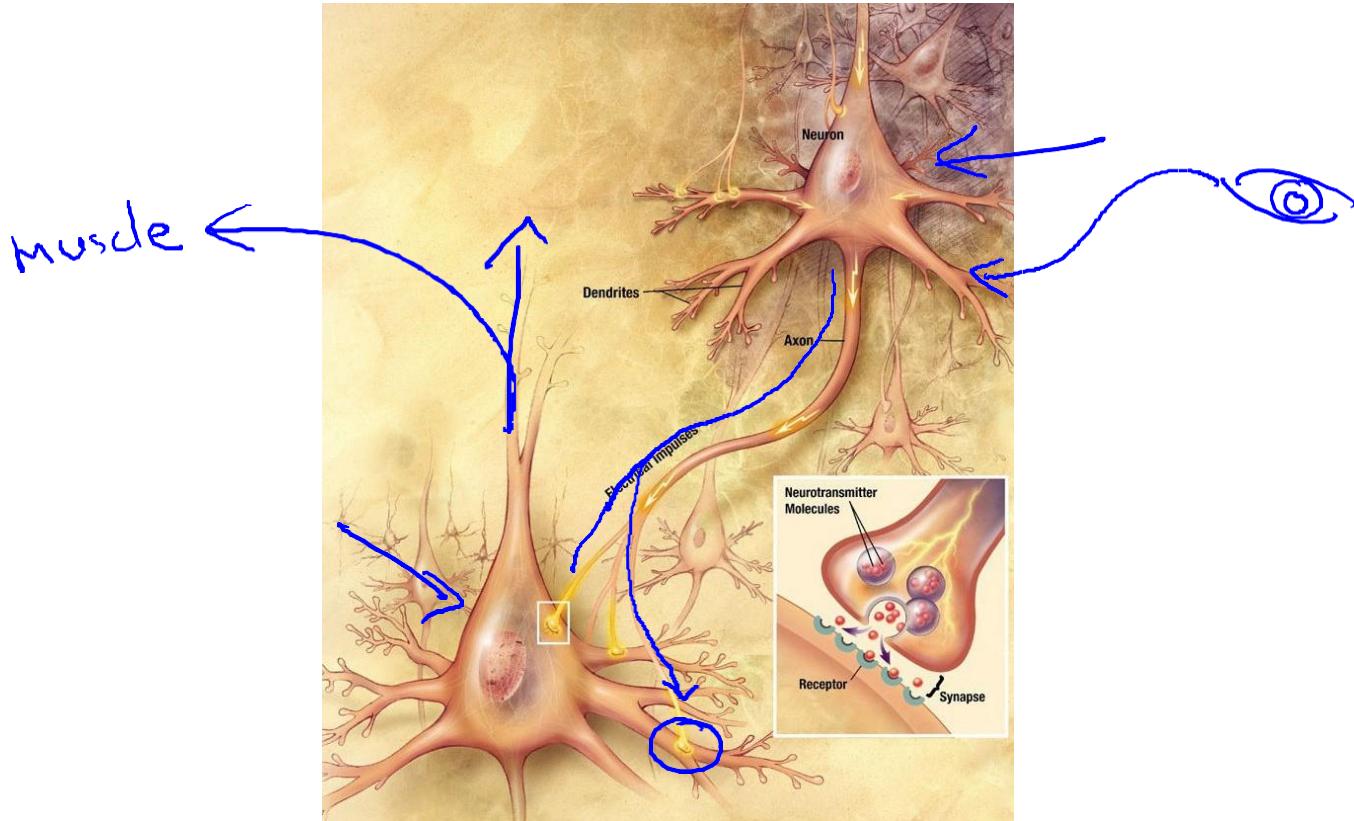
Machine Learning

Neural Networks: Representation Model representation I

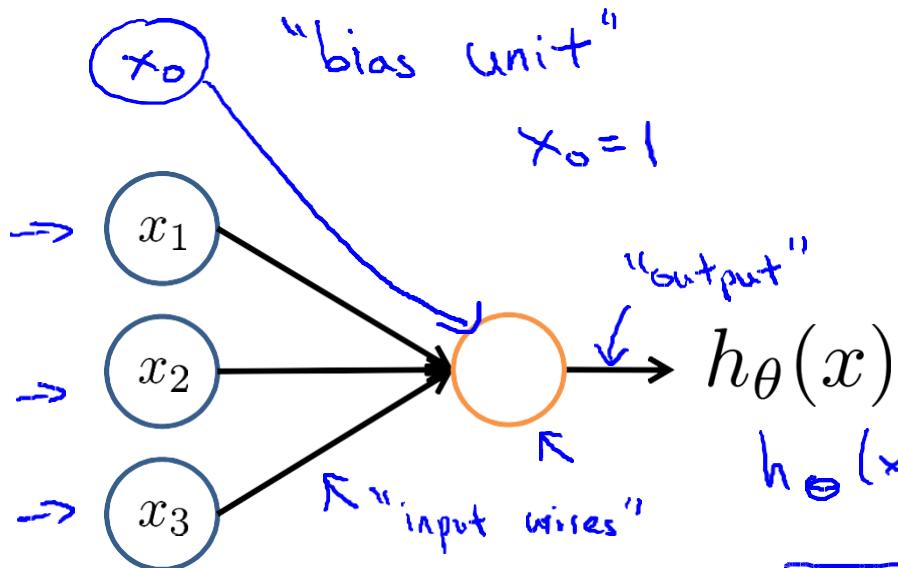
Neuron in the brain



Neurons in the brain



Neuron model: Logistic unit



$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

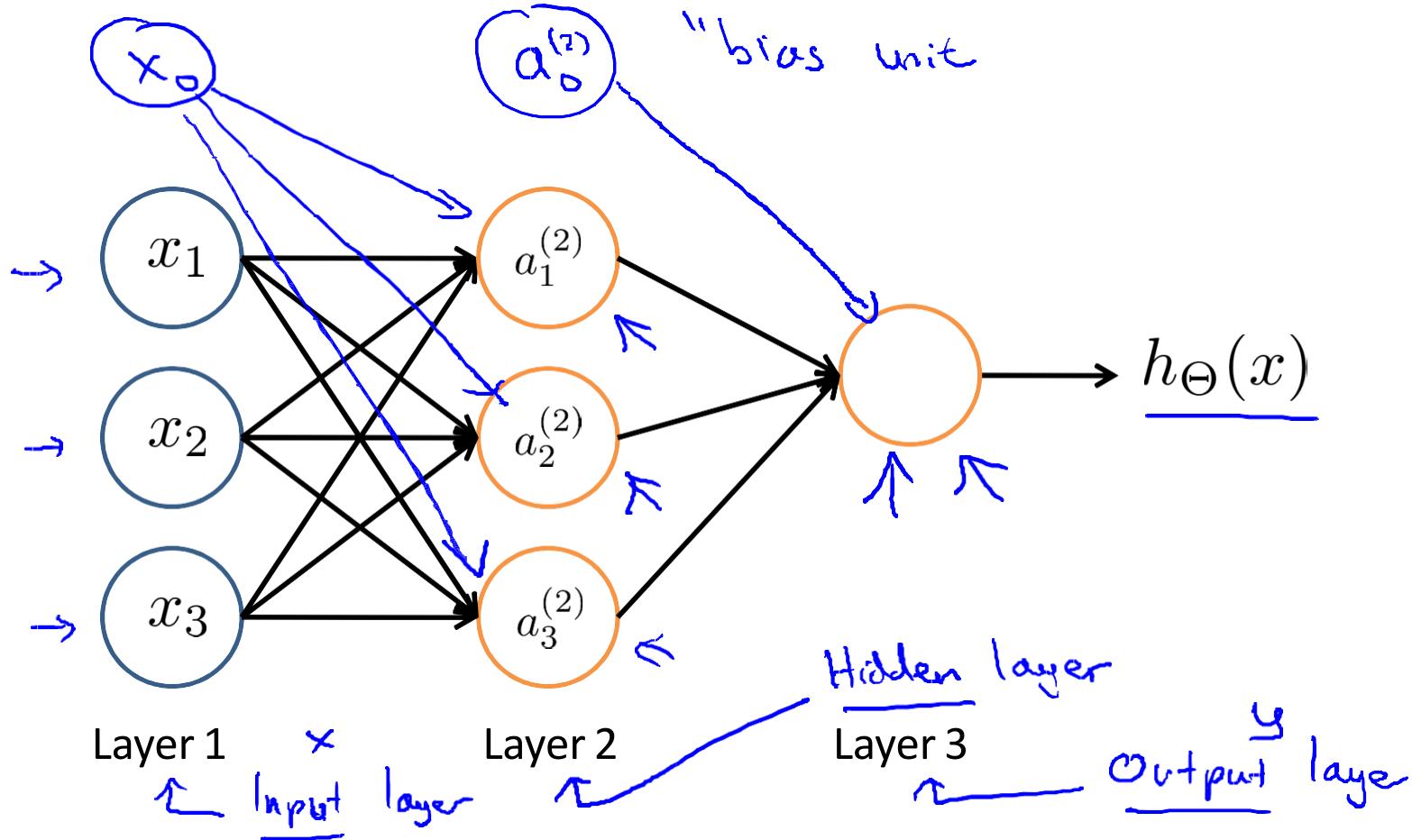
↑
"weights" ←
(parameters ←)

$$h_{\theta}(x) = \frac{1}{1+e^{-\theta^T x}}$$

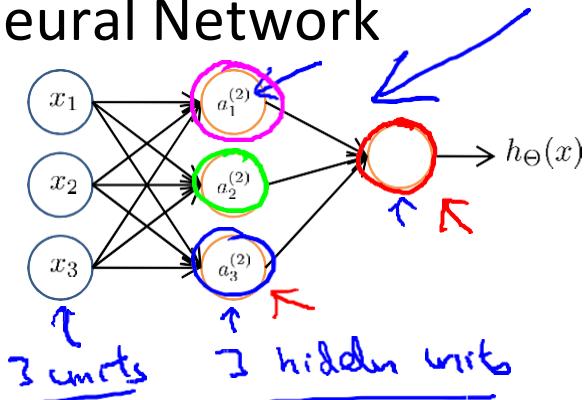
Sigmoid (logistic) activation function.

$$g(z) = \frac{1}{1+e^{-z}}$$

Neural Network



Neural Network



→ $a_i^{(j)}$ = “activation” of unit i in layer j

→ $\Theta^{(j)}$ = matrix of weights controlling function mapping from layer j to layer $j + 1$

$$\Theta^{(1)} \in \mathbb{R}^{3 \times 4}$$

$$h_{\Theta}(x)$$

$$\rightarrow a_1^{(2)} = g(\underline{\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3})$$

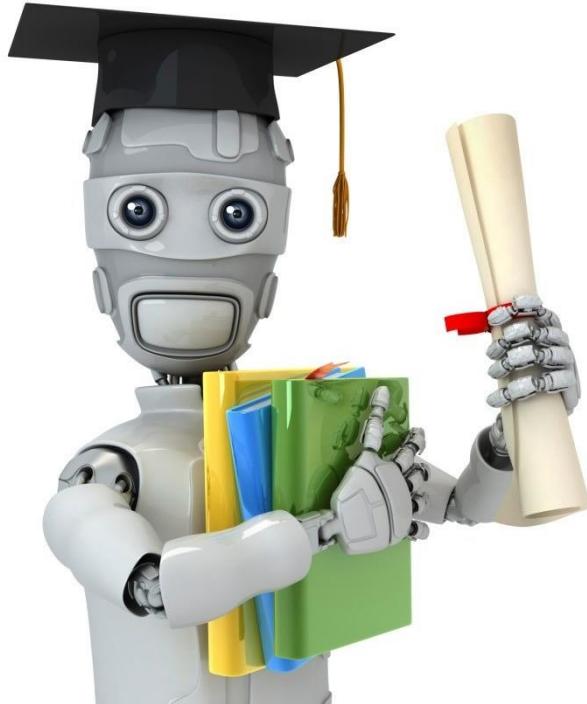
$$\rightarrow a_2^{(2)} = g(\underline{\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3})$$

$$\rightarrow a_3^{(2)} = g(\underline{\Theta_{30}^{(1)} x_0 + \Theta_{31}^{(1)} x_1 + \Theta_{32}^{(1)} x_2 + \Theta_{33}^{(1)} x_3})$$

$$\rightarrow h_{\Theta}(x) = \underline{a_1^{(3)}} = g(\underline{\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)}})$$

- If network has s_j units in layer j , s_{j+1} units in layer $j + 1$, then $\underline{\Theta^{(j)}}$ will be of dimension $\underline{s_{j+1} \times (s_j + 1)}$.

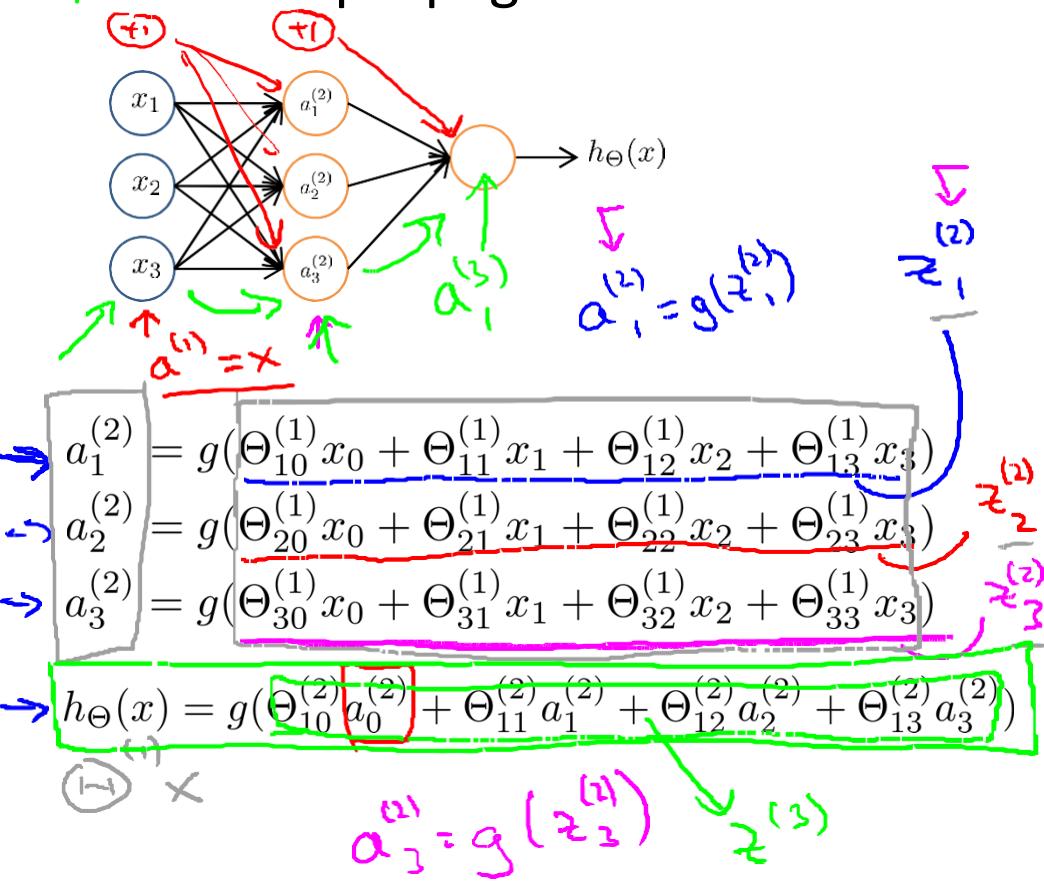
$$\underline{s_{j+1} \times (s_j + 1)}$$



Machine Learning

Neural Networks: Representation Model representation II

Forward propagation: Vectorized implementation



Vectorized Implementation:

$$z^{(2)} = \Theta^{(1)}x + a^{(1)}$$

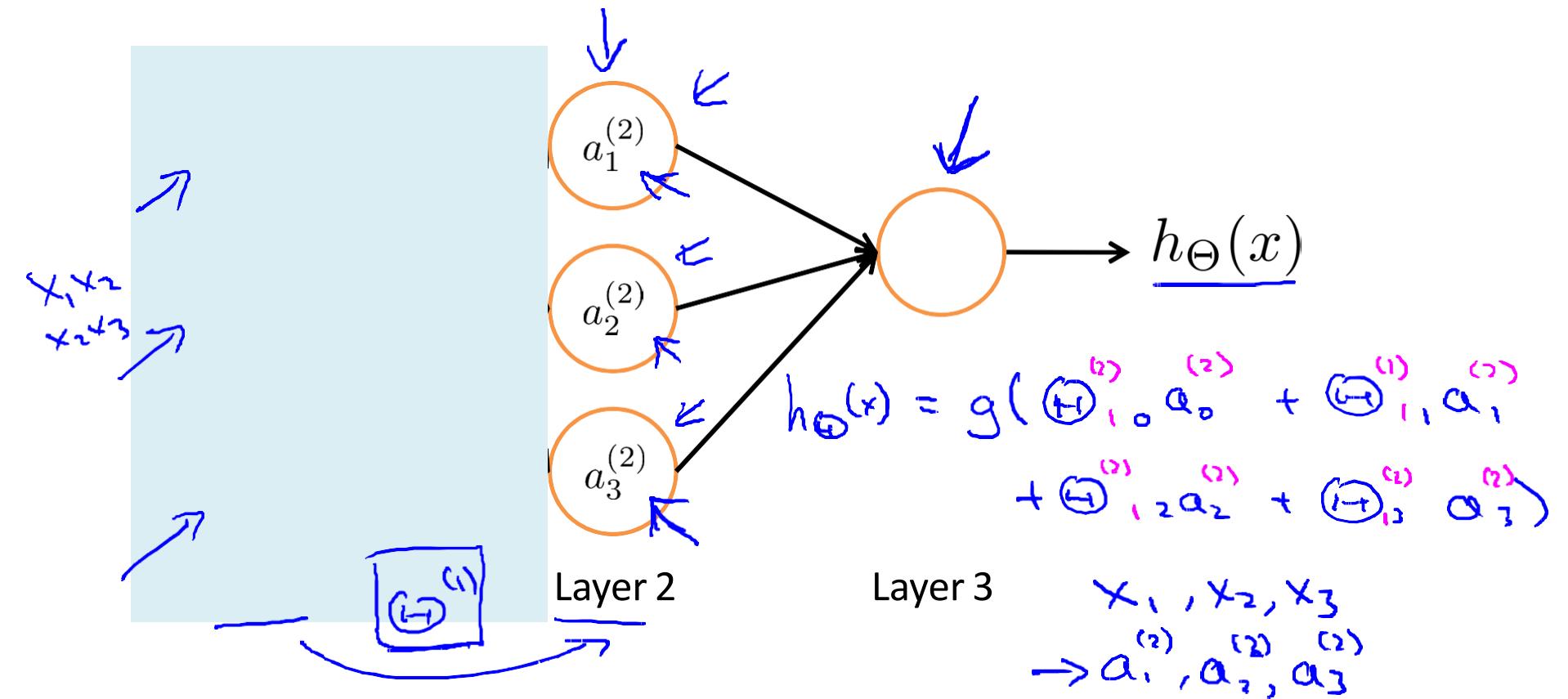
$$a^{(2)} = g(z^{(2)})$$

$$\text{Add } a_0^{(2)} = 1. \rightarrow a^{(2)} \in \mathbb{R}^4$$

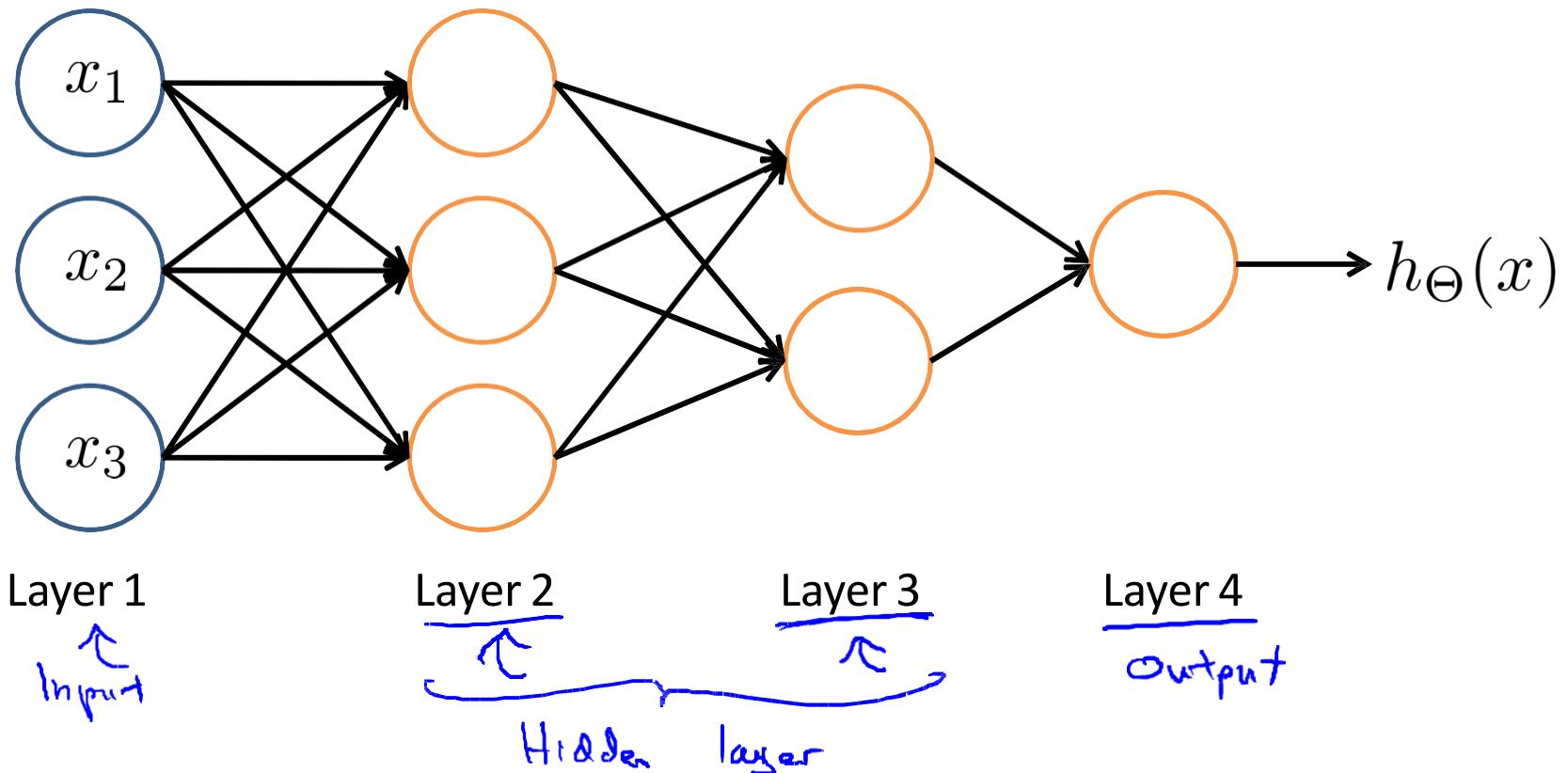
$$z^{(3)} = \Theta^{(2)}a^{(2)}$$

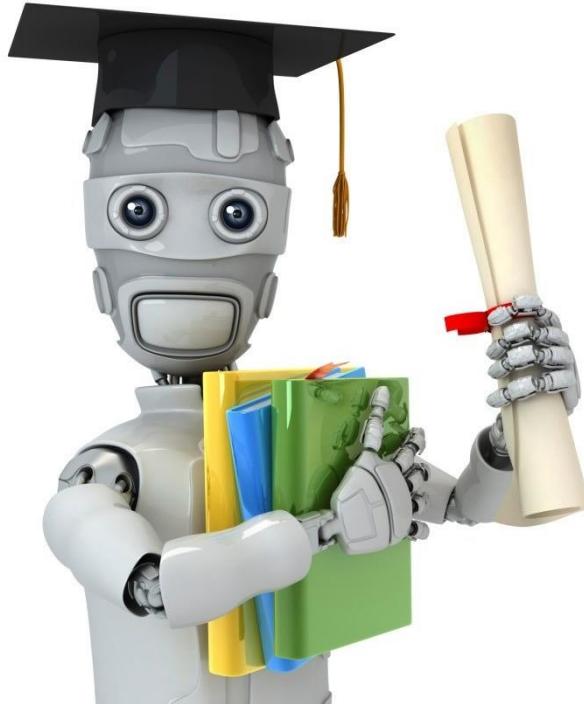
$$h_{\Theta}(x) = a^{(3)} = g(z^{(3)})$$

Neural Network learning its own features



Other network architectures





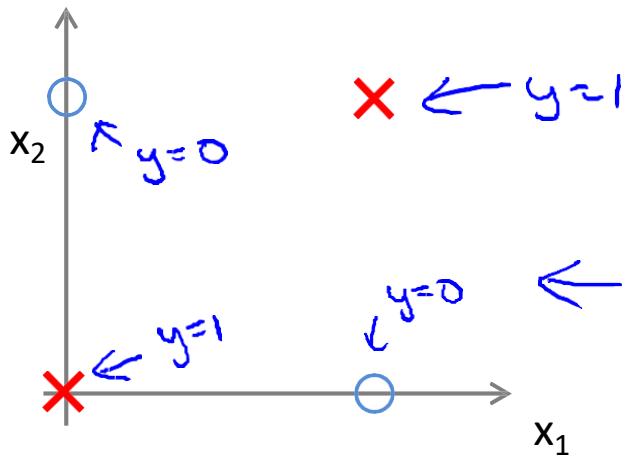
Machine Learning

Neural Networks: Representation

Examples and intuitions I

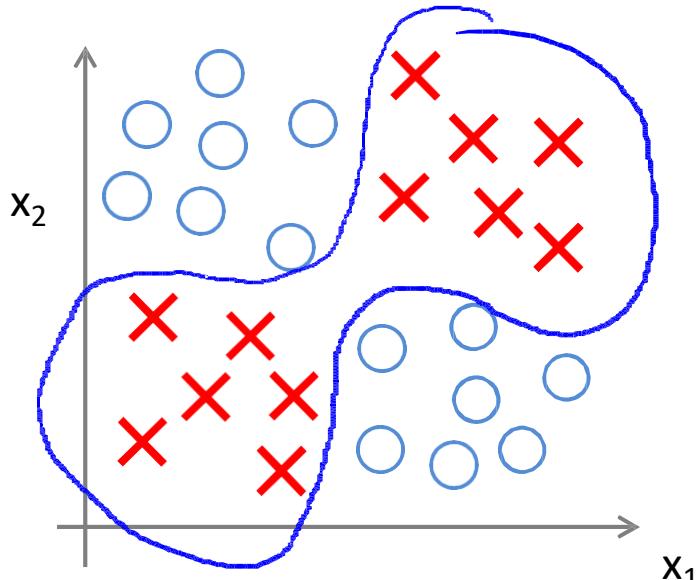
Non-linear classification example: XOR/XNOR

→ x_1, x_2 are binary (0 or 1).



$$y = \underline{x_1 \text{ XOR } x_2}$$

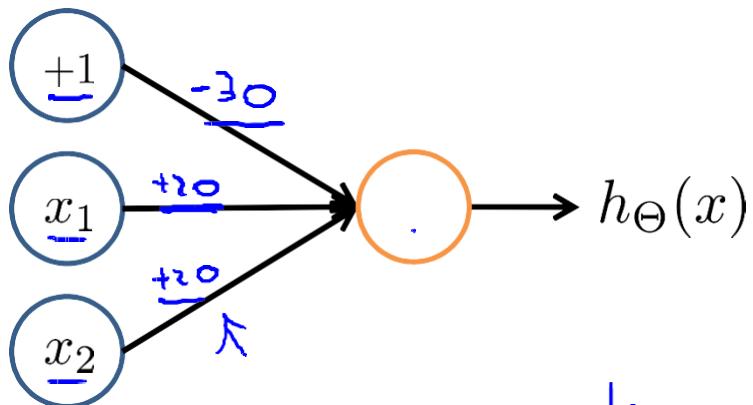
→ $\underline{x_1 \text{ XNOR } x_2}$ ←
→ NOT (x₁ XOR x₂)



Simple example: AND

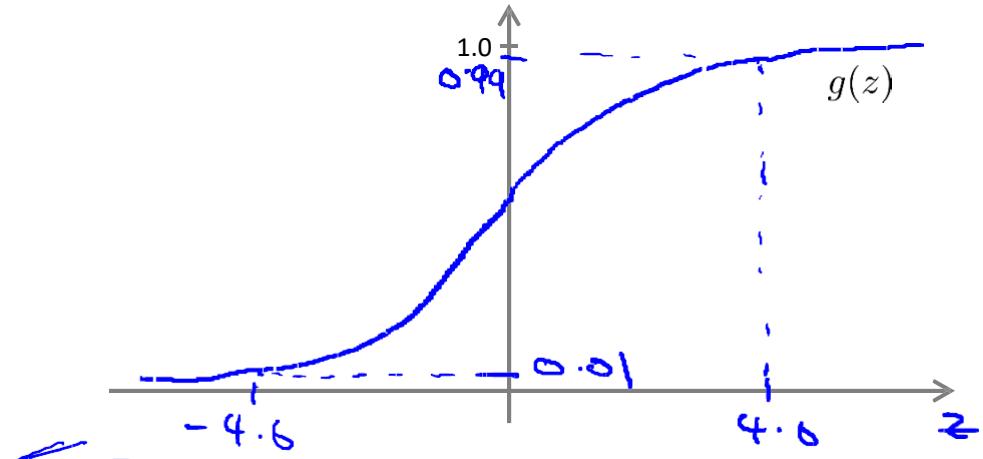
$$\rightarrow x_1, x_2 \in \{0, 1\}$$

$$\rightarrow y = x_1 \text{ AND } x_2$$



$$\rightarrow h_{\Theta}(x) = g\left(\frac{-30}{\pi} + \frac{20}{\pi}x_1 + \frac{20}{\pi}x_2\right)$$

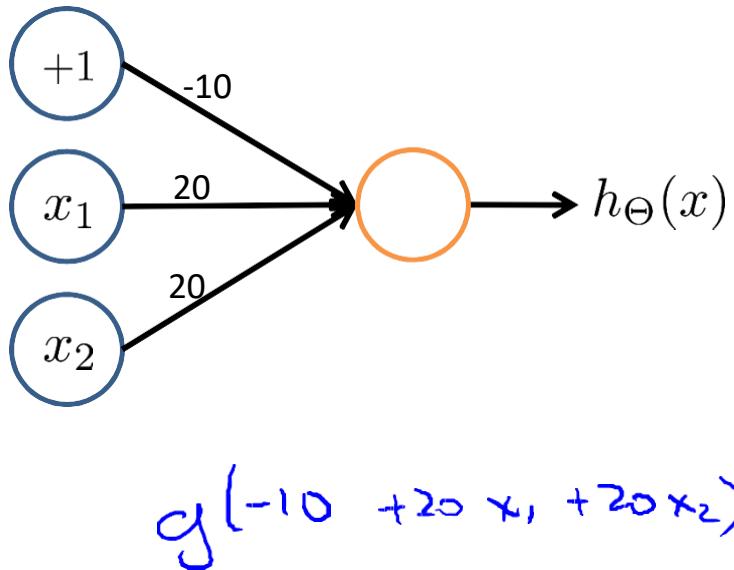
Θ_{10} Θ_{11} Θ_{12}



x_1	x_2	$h_{\Theta}(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

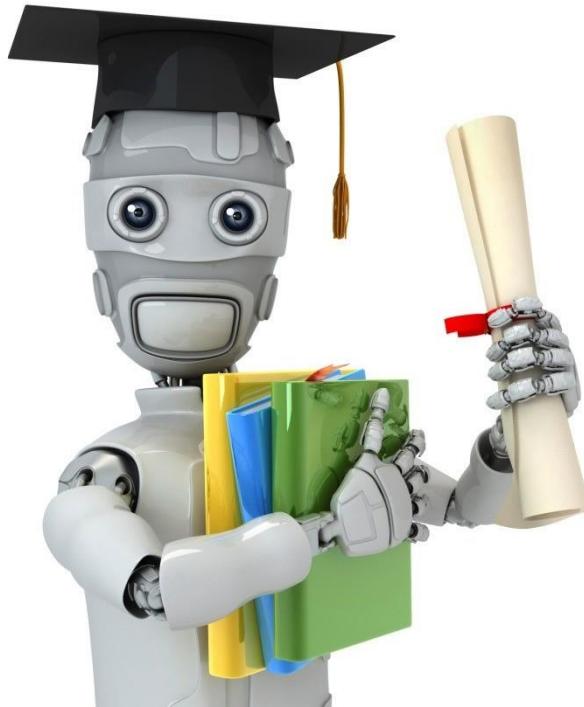
$h_{\Theta}(x) \approx x_1 \text{ AND } x_2$

Example: OR function



x_1	x_2	$h_{\Theta}(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	≈ 1
1	1	≈ 1

The table shows the output of the function $h_{\Theta}(x)$ for all combinations of x_1 and x_2 . The values are approximated by handwritten blue text. A pink hand-drawn bracket highlights the boundary where the output is approximately 1, which corresponds to the region where either x_1 or x_2 is 1.



Machine Learning

Neural Networks: Representation

Examples and intuitions II

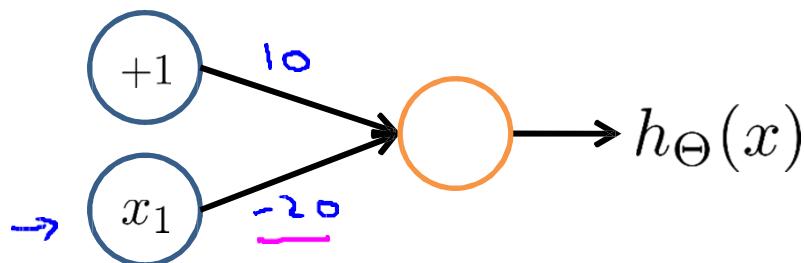
$\rightarrow x_1 \text{ AND } x_2$

$\rightarrow x_1 \text{ OR } x_2$

$\{0, 1\}$.

Negation:

NOT x_1



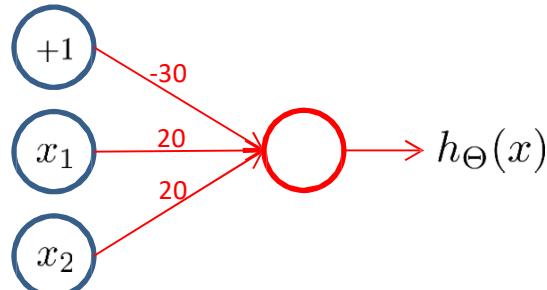
x_1	$h_{\Theta}(x)$
0	$g(10) \approx 1$
1	$g(-20) \approx 0$

$$h_{\Theta}(x) = g(10 - 20x_1)$$

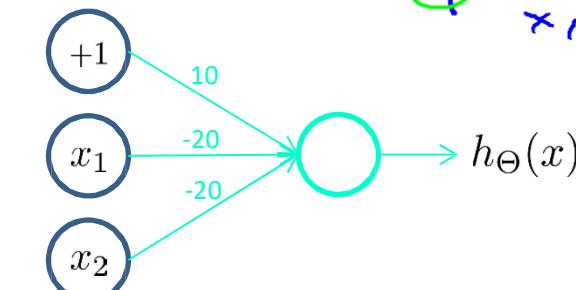
$\rightarrow (\text{NOT } x_1) \text{ AND } (\text{NOT } x_2)$

\Leftrightarrow if and only if
 $\rightarrow x_1 = x_2 = 0$

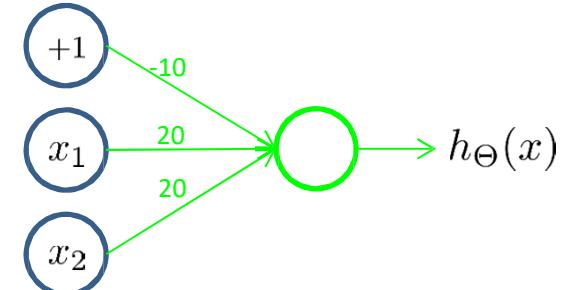
Putting it together: x_1 XNOR x_2



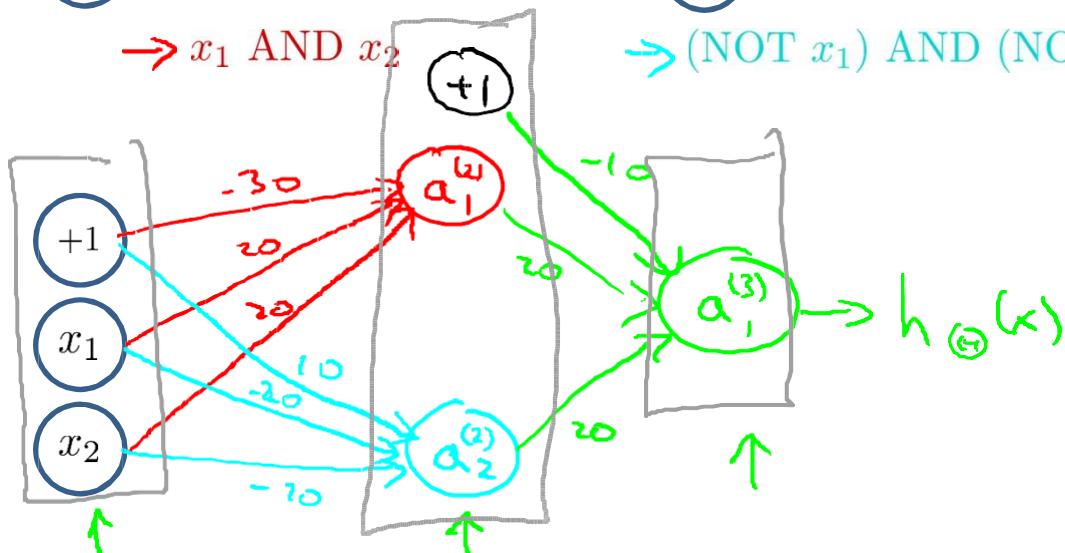
$\rightarrow x_1 \text{ AND } x_2$



$\rightarrow (\text{NOT } x_1) \text{ AND } (\text{NOT } x_2)$

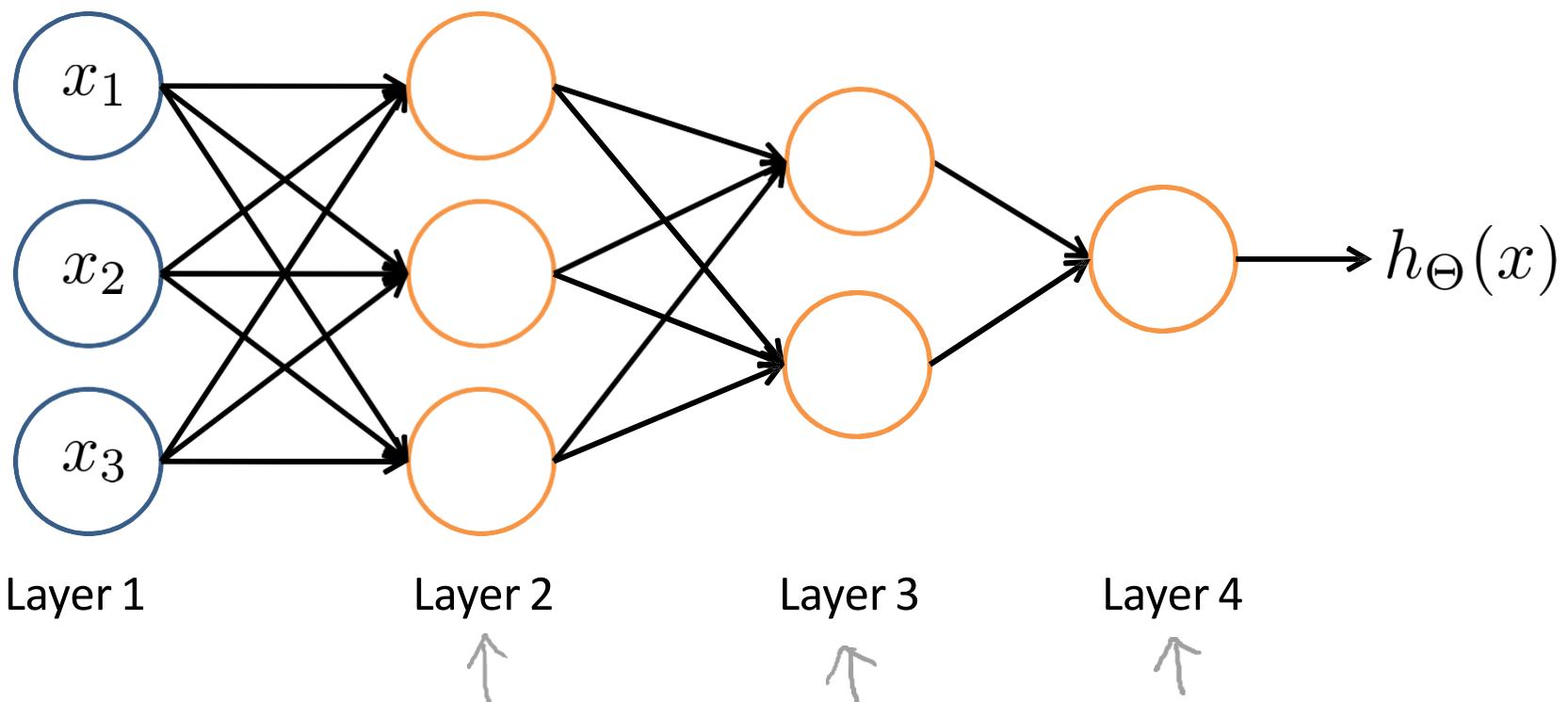


$\rightarrow x_1 \text{ OR } x_2$

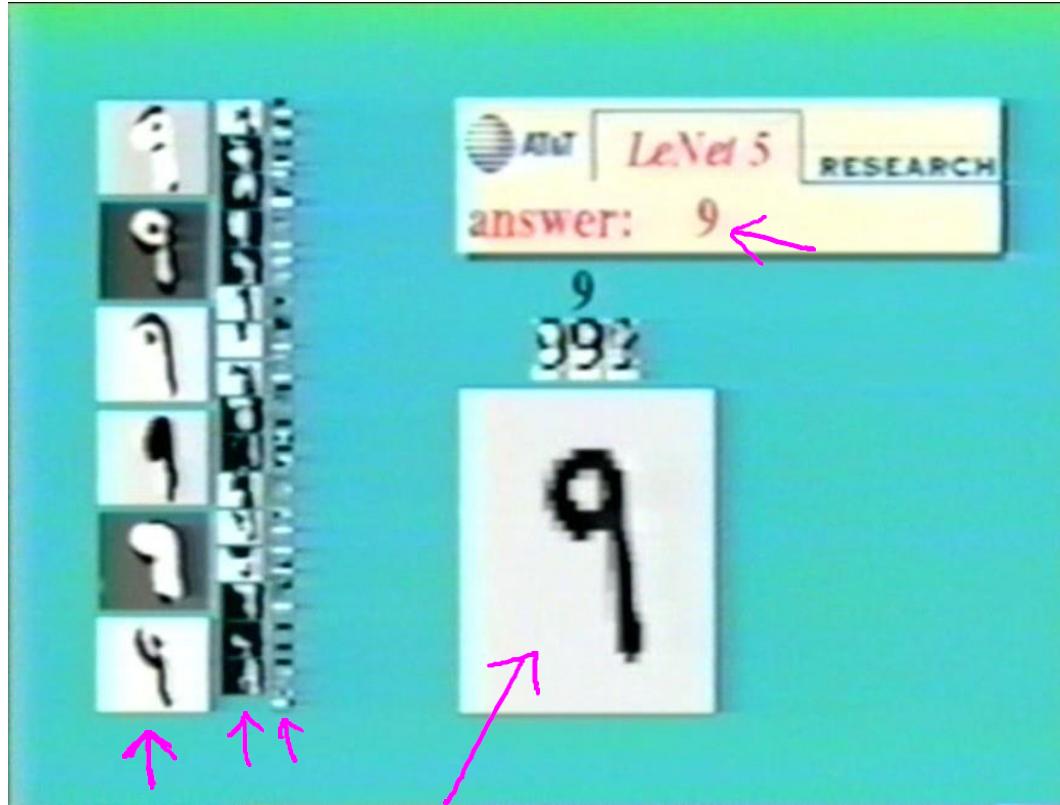


x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_{\Theta}(x)$
0	0	1	1	1 ←
0	1	1	0	0
1	0	0	1	0
1	1	0	0	1 ←

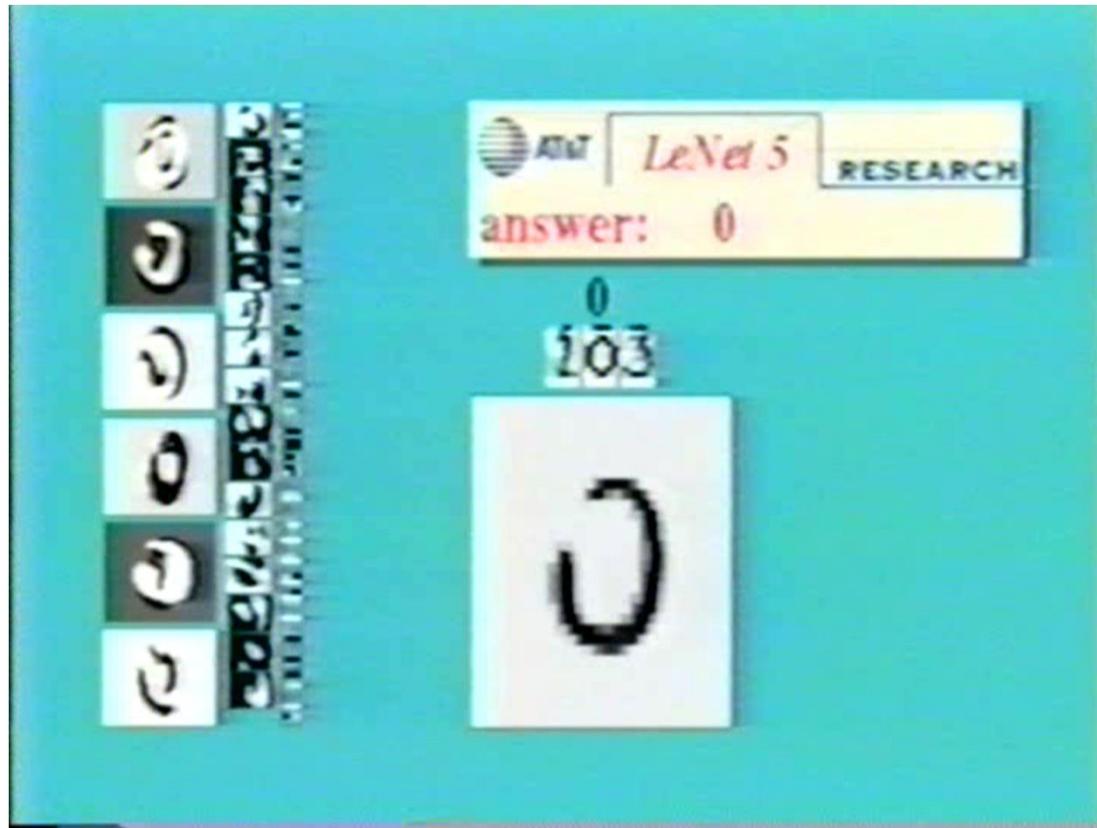
Neural Network intuition

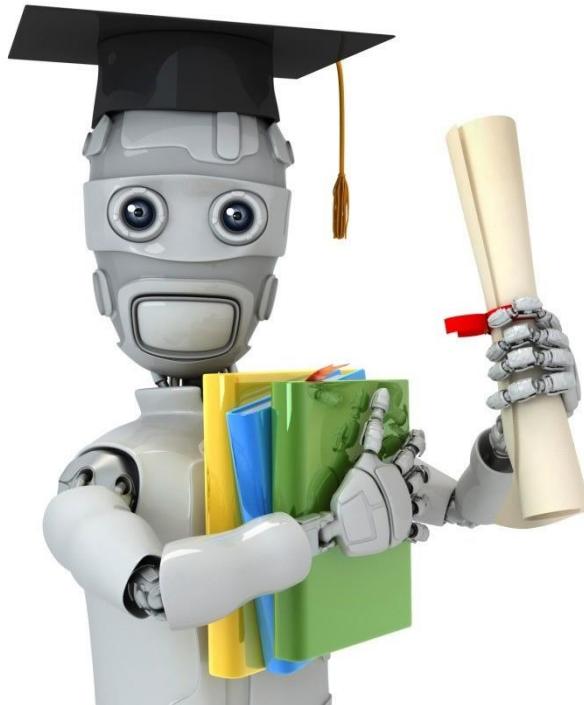


Handwritten digit classification



Handwritten digit classification





Machine Learning

Neural Networks: Representation

Multi-class classification

Multiple output units: One-vs-all.



Pedestrian



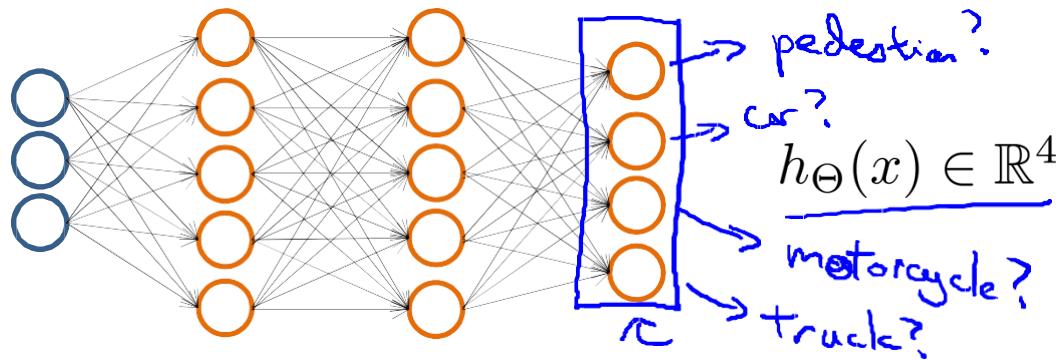
Car



Motorcycle



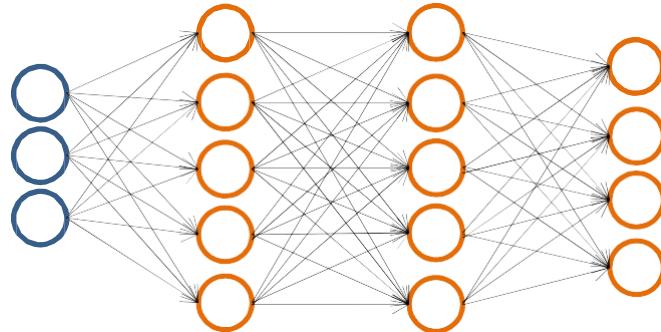
Truck



Want $h_{\Theta}(x) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_{\Theta}(x) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $h_{\Theta}(x) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, etc.

when pedestrian when car when motorcycle

Multiple output units: One-vs-all.



$$h_{\Theta}(x) \in \mathbb{R}^4$$

Want $h_{\Theta}(x) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $h_{\Theta}(x) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $h_{\Theta}(x) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, etc.
 when pedestrian when car when motorcycle

Training set: $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \dots, (x^{(m)}, y^{(m)})$

$\rightarrow y^{(i)}$ one of
 $\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$, $\begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$
 pedestrian car motorcycle truck

~~Previously~~
 $y \in \{1, 2, 3, 4\}$
 $h_{\Theta}(x^{(i)}) \approx y^{(i)}$
 $\in \mathbb{R}^4$