## Machine Learning



# Neural Networks (Representation)

**Summary:** Non-linear hypothesis, neurons and the brain, model representation, and multi-class classification.

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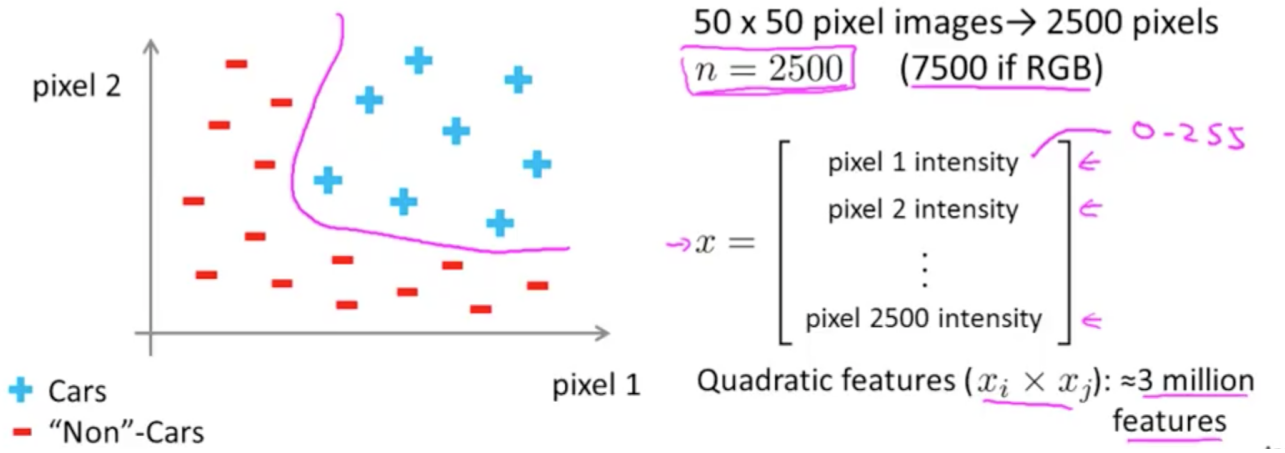
# 1. Motivations

I would like to give full credits to the respective authors as these are my personal python notebooks taken from deep learning courses from Andrew Ng, Data School and Udemy :) This is a simple python notebook hosted generously through Github Pages that is on my main personal notes repository on https://github.com/ritchieng/ritchieng.github.io. They are meant for my personal review but I have open-source my repository of personal notes as a lot of people found it useful.

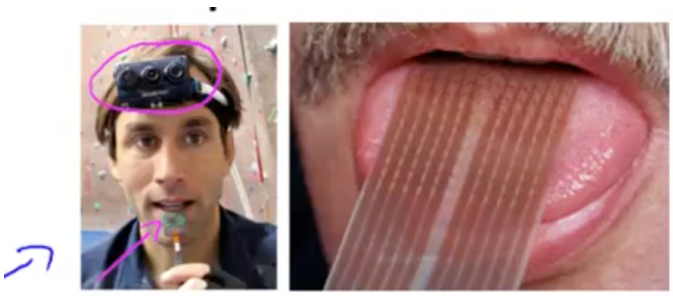
## 1a. Non-linear Hypothesis

- You can add more features
  - But it will be slow to process
- If you have an image with 50 x 50 pixels (greyscale, not RGB)
  - n = 50 x 50 = 2500
  - quadratic features = (2500 x 2500) / 2

- Neural networks are much better for a complex nonlinear hypothesis

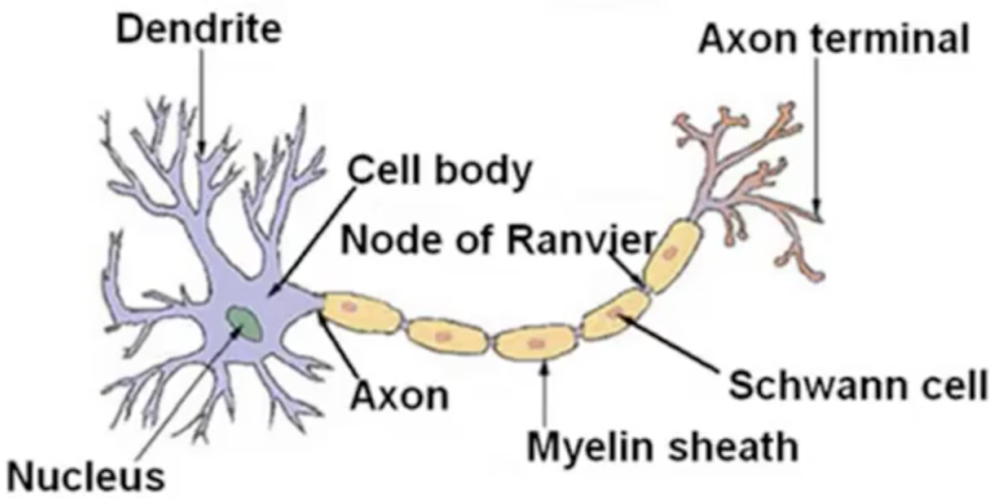
## 1b. Neurons and the Brain

- Origins
  - Algorithms that try to mimic the brain
- Was very widely used in the 80s and early 90's
  - Popularity diminished in the late 90's
- Recent resurgence
  - State-of-the-art techniques for many applications
- The "one learning algorithm" hypothesis
  - Auditory cortex handles hearing
    - Re-wire to learn to see
  - Somatosensory cortex handles feeling
    - Re-wire to learn to see
  - Plug in data and the brain will learn accordingly
- Examples of learning
  - 
    Seeing with your tongue
  - 
    Human echolocation (sonar)
  - 
    Haptic belt: Direction sense
  - 
    Implanting a 3rd eye

# 2. Neural Networks

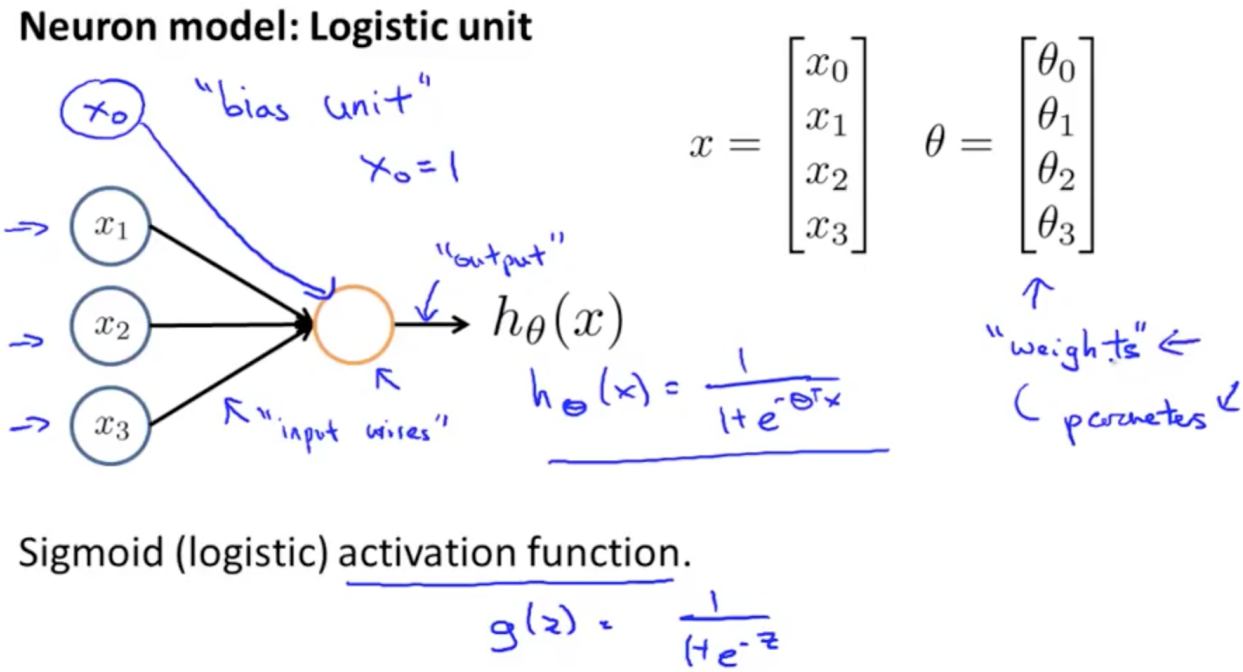
## 2a. Model Representation I

- Neuron in the brain
  - Many neurons in our brain
  - Dendrite: receive input
  - Axon: produce output
    - When it sends a message through the Axon to another neuron
    - It sends to another neuron's Dendrite



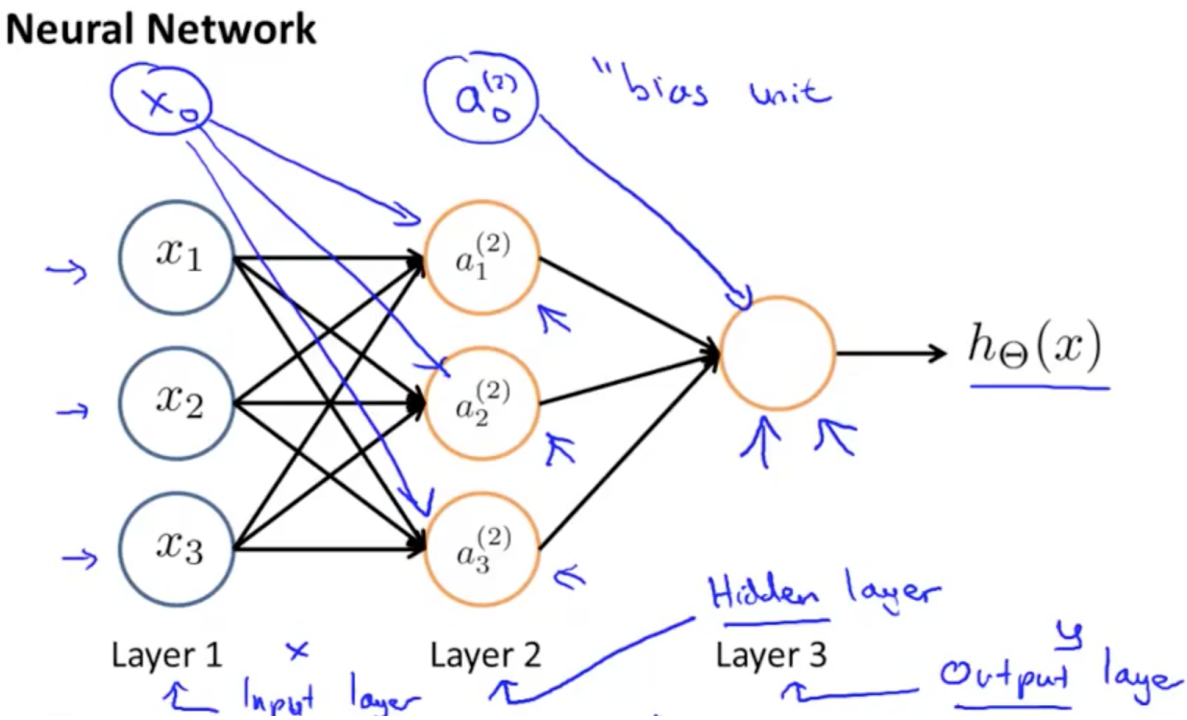

- Neuron model: logistic unit
  - Yellow circle: body of neuron
  - Input wires: dendrites

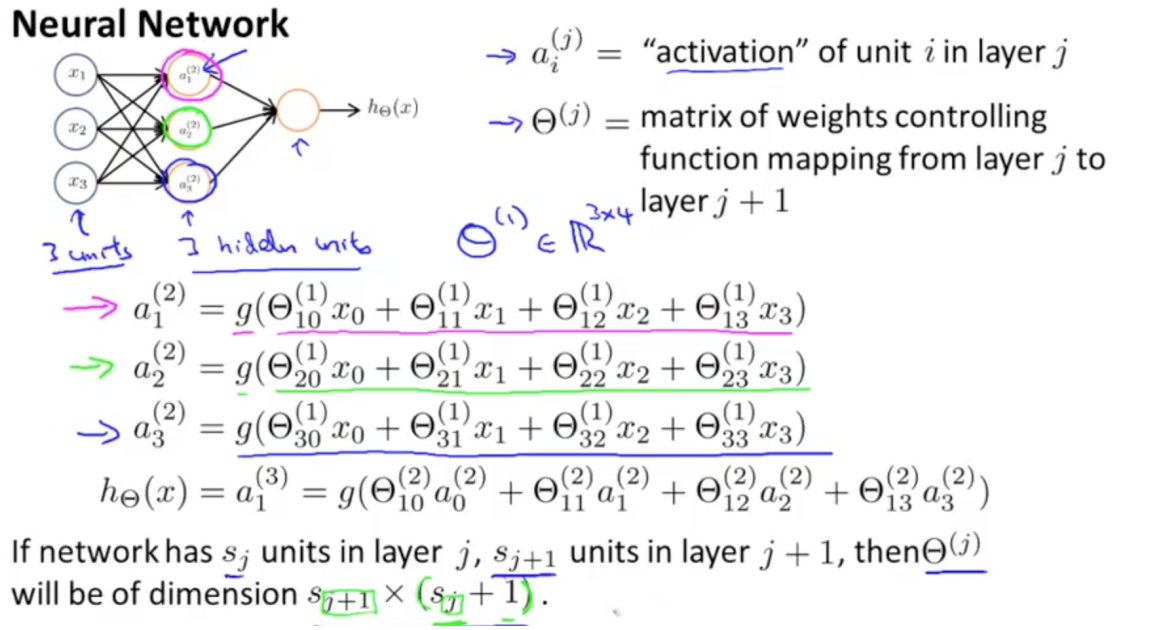
- Output wire: axon




- Neural Network
  - 3 Layers
    - 1 Layer: input layer
    - 2 Layer: hidden layer
      - Unable to observe values
      - Anything other than input or output layer

- 3 Layer: output layer

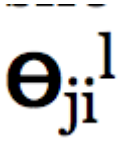



- We calculate each of the layer-2 activations based on the input values with the bias term (which is equal to 1)
  - i.e. x0 to x3
  - We then calculate the final hypothesis (i.e. the single node in layer 3) using exactly the same logic, except in input is not x values, but the activation values from the preceding layer
- The activation value on each hidden unit (e.g. a12 ) is equal to the sigmoid function applied to the linear combination of inputs

- Three input units
- Θ(1) is the matrix of parameters governing the mapping of the input units to hidden units
  - Θ(1) here is a [3 x 4] dimensional matrix

- Three hidden units
  - Then Θ(2) is the matrix of parameters governing the mapping of the hidden layer to the output layer
    - Θ(2) here is a [1 x 4] dimensional matrix (i.e. a row vector)

- Every input/activation goes to every node in following layer
  - Which means each “layer transition” uses a matrix of parameters with the following significance 
    - j (first of two subscript numbers)= ranges from 1 to the number of units in layer l+1
    - i (second of two subscript numbers) = ranges from 0 to the number of units in layer l
    - l is the layer you’re moving FROM

$\Theta_{13}^{1}$ = means

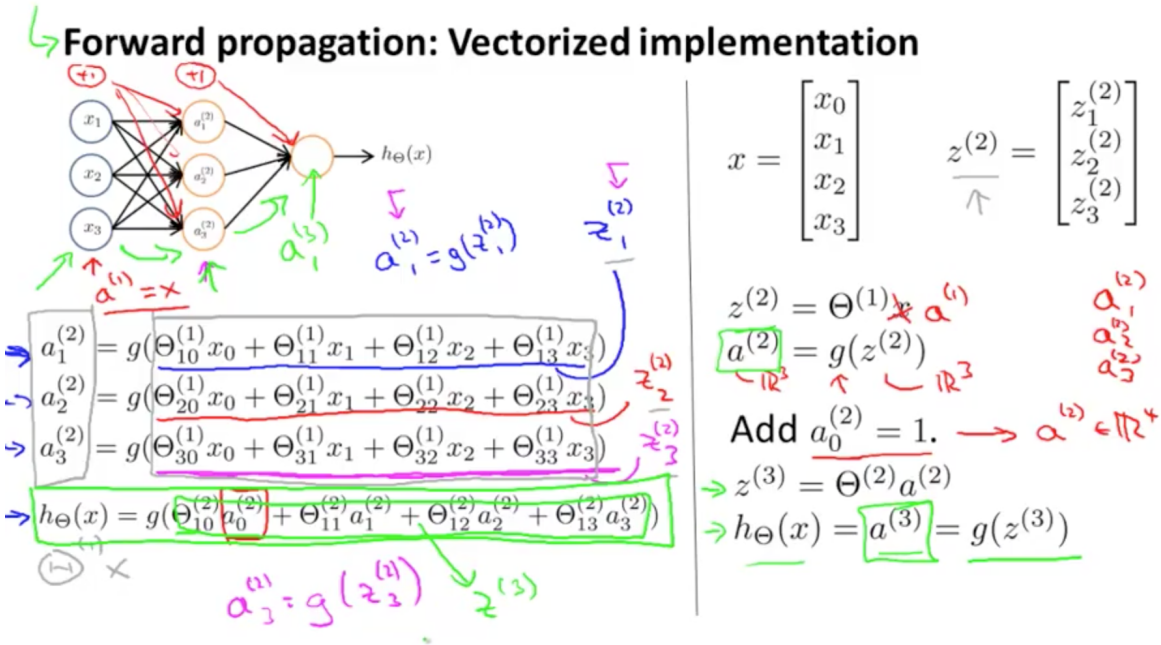
- 1 - we're mapping to node 1 in layer l+1
- 3 - we're mapping from node 3 in layer l
- 1 - we're mapping from layer 1

- Notation
  - **$a_i^{(j)}$ - activation of unit *i* in layer *j***
    - So, $a_1^2$ - is the **activation** of the 1st unit in the second layer
    - By activation, we mean the value which is computed and output by that node
  - **$\Theta^{(j)}$ - matrix of parameters controlling the function mapping from layer *j* to layer *j* + 1**
    - Parameters for controlling **mapping** from one layer to the next
    - If network has
      - $s_j$ units in layer *j* and
      - $s_{j+1}$ units in layer j + 1
      - Then $\Theta^j$ will be of dimensions $[s_{j+1} \times s_j + 1]$
        - Because
          - $s_{j+1}$ is equal to the number of units in layer (j + 1)
          - is equal to the number of units in layer j, plus an additional unit
    - Looking at the $\Theta$ matrix
      - Column length is the number of units in the following layer
      - Row length is the number of units in the current layer + 1 (because we have to map the bias unit)
      - So, if we had two layers - 101 and 21 units in each
        - Then $\Theta^j$ would be = [21 x 102]

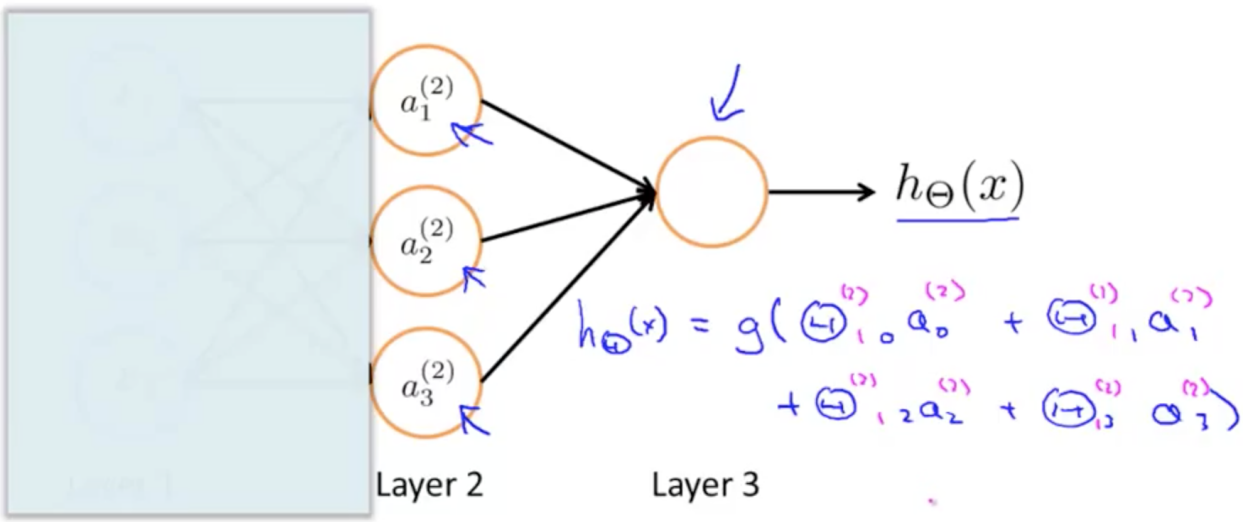
## 2a. Model Representation II

- Here we'll look at how to carry out the computation efficiently through a vectorized implementation. We'll also consider why neural networks are good and how we can use them to learn complex non-linear things
- Forward propagation: vectorized implementation
  - g applies sigmoid-function element-wise to z
  - This process of calculating H(x) is called forward propagation
    - Worked out from the first layer
    - Starts off with activations of input unit

- Propagate forward and calculate the activation of each layer sequentially

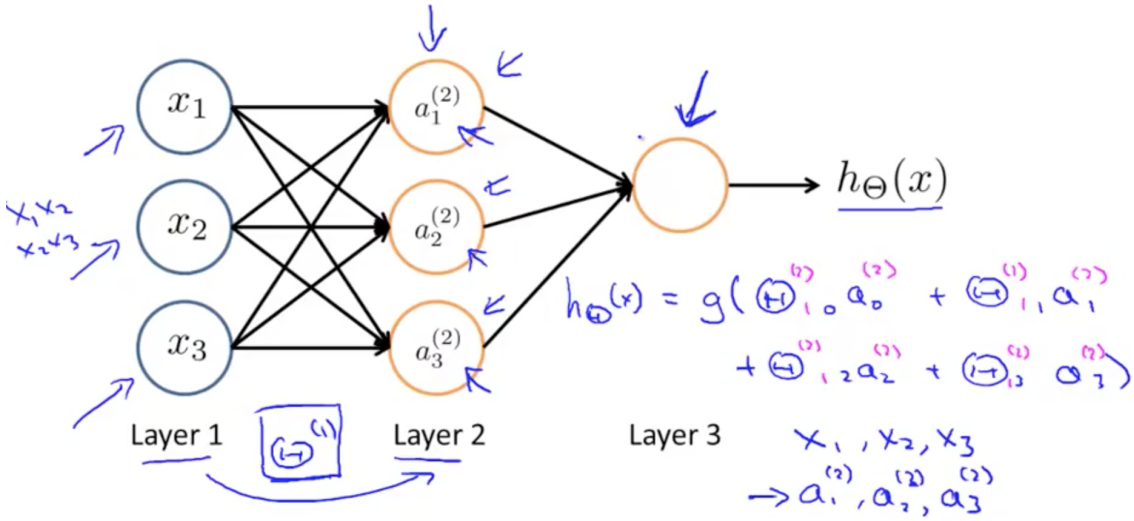



- Similar to logistic regression if you leave out the first layer
  - Only second and third layer
  - Third layer resembles a logistic regression node
  - The features in layer 2 are calculated/learned, not original features

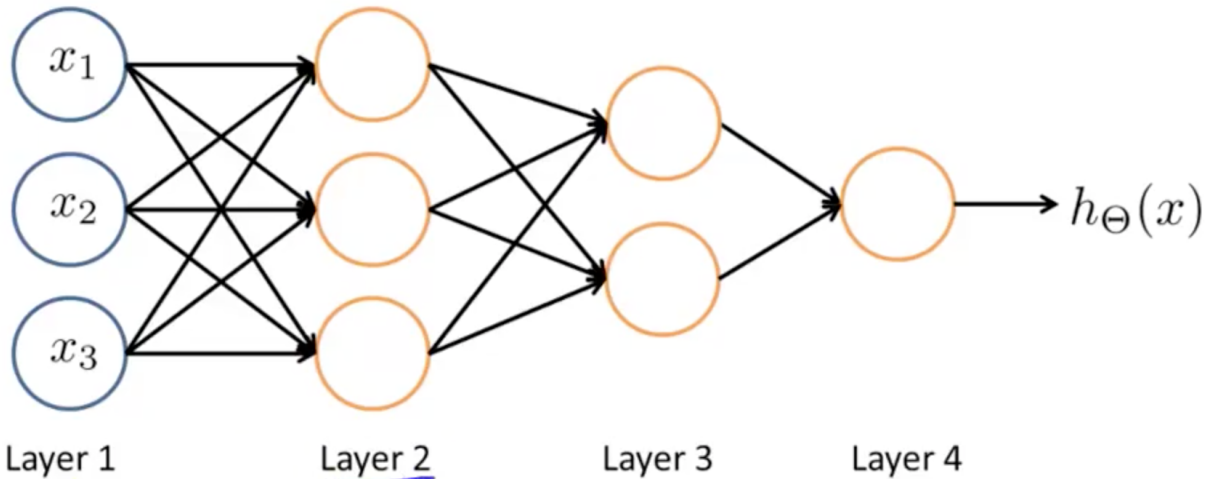



  - Neural network, learns its own features
    - The features a's are learned from x's
    - It learns its own features to feed into logistic regression
    - Better hypothesis than if we were constrained with just x1, x2, x3
    - We can have whatever features we want to feed to the final logistic regression function

- Implemention in Octave for a2
  - `a2 = sigmoid (Theta1 * x);`




- Other network architectures
  - Layer 2 and 3 are hidden layers

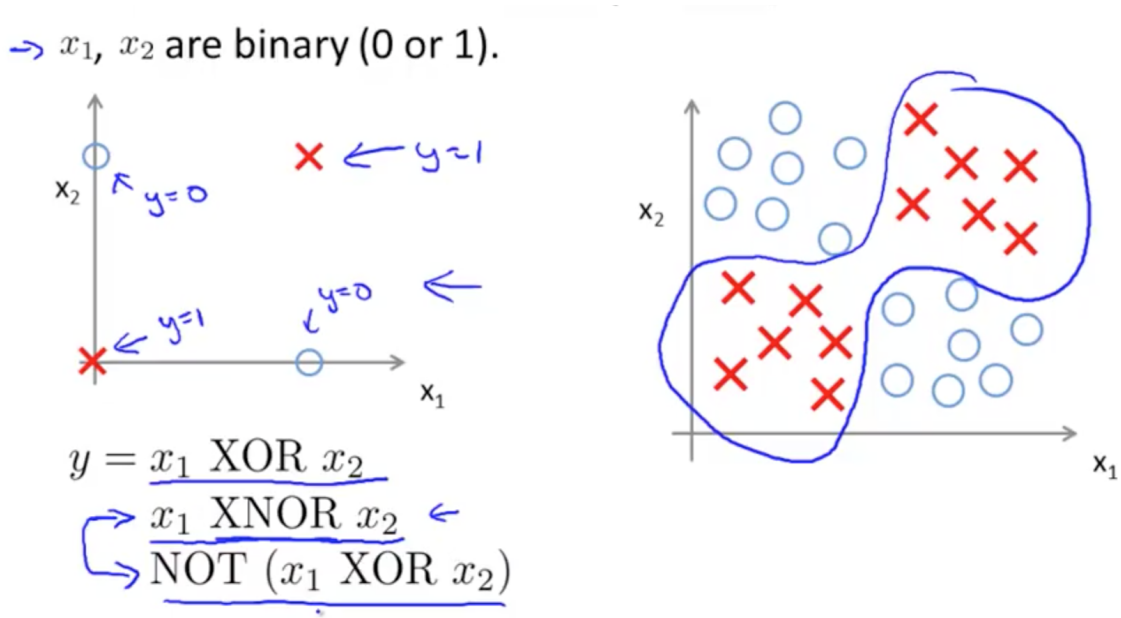


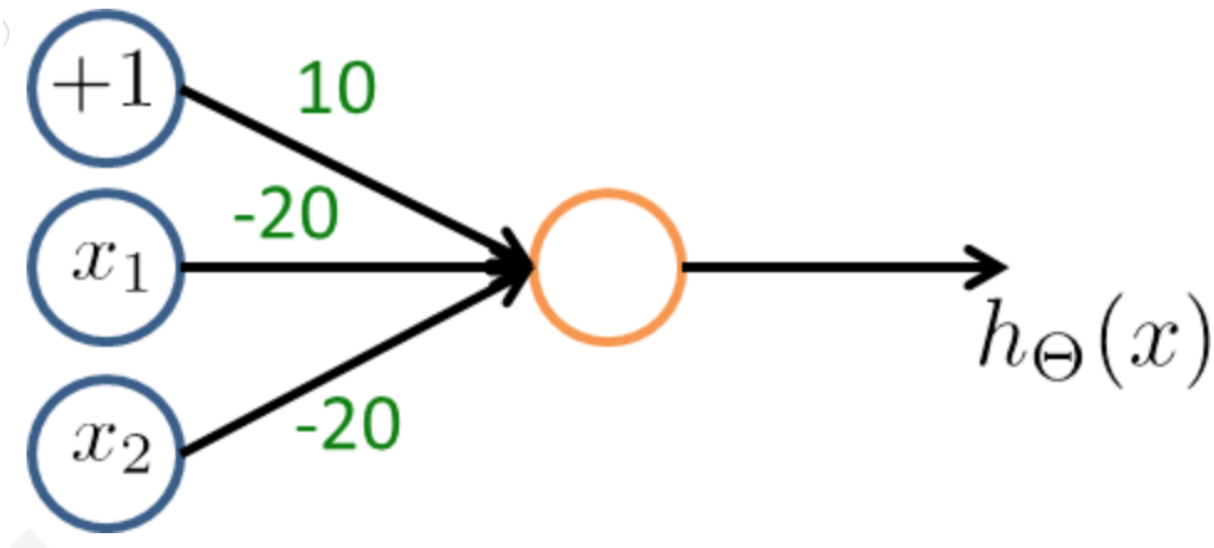

# 2. Neural Network Application

## 2a. Examples and Intuitions I

- XOR/XNOR
  - XOR: or

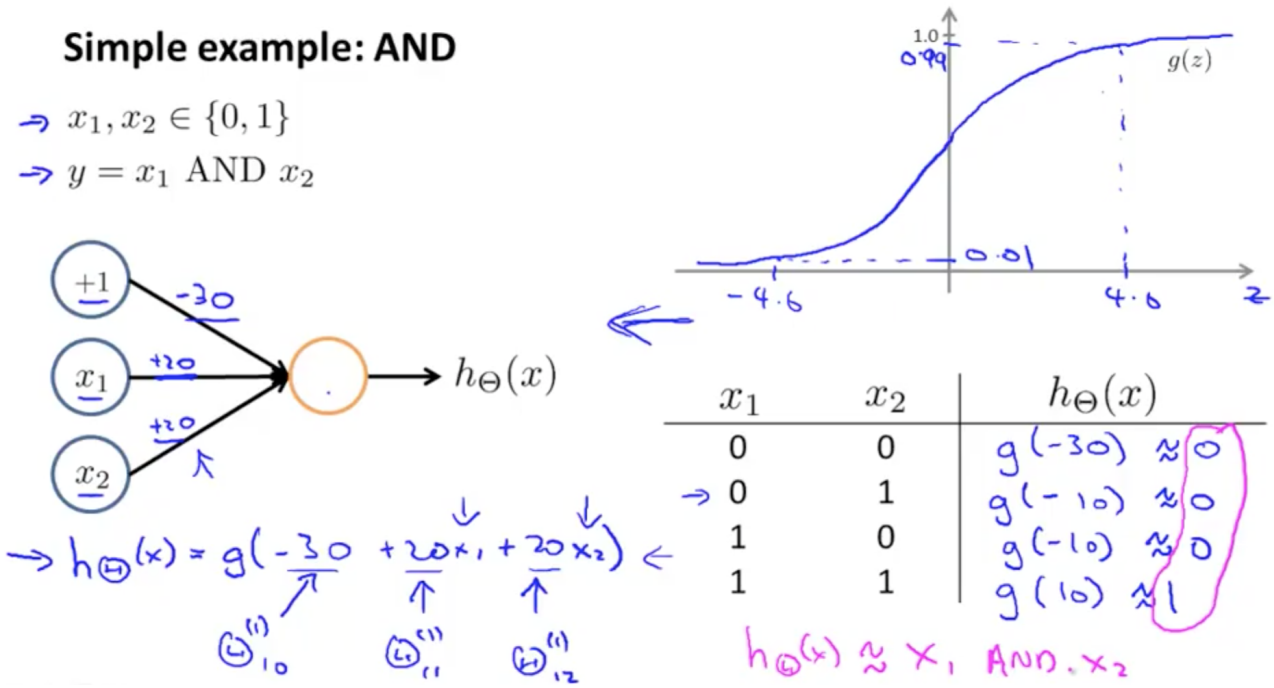
- XNOR: not or



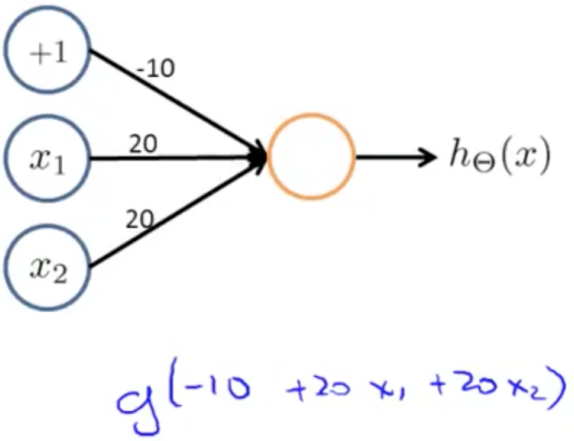

- AND function
  - Outputs 1 only if x1 and x2 are 1

- Draw a table to determine if OR or AND




- NAND function
  - NOT AND

- OR function



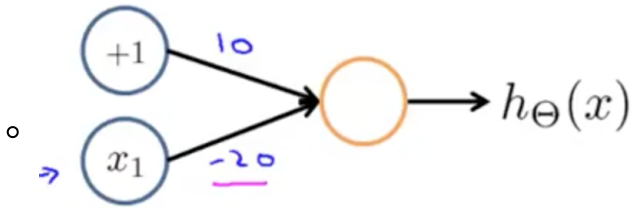

| $x_1$ | $x_2$ | $h_\Theta(x)$ |
|---|---|---|
| 0 | 0 | $g(-10) \approx 0$ |
| 0 | 1 | $g(10) \approx 1$ |
| 1 | 0 | $\approx 1$ |
| 1 | 1 | $\approx 1$ |

## 2b. Examples and Intuitions II

- NOT function

**Negation:**

NOT $x_1$




| $x_1$ | $h_\Theta(x)$ |
|---|---|
| 0 | $g(10) \approx 1$ |
| 1 | $g(-10) \approx 0$ |

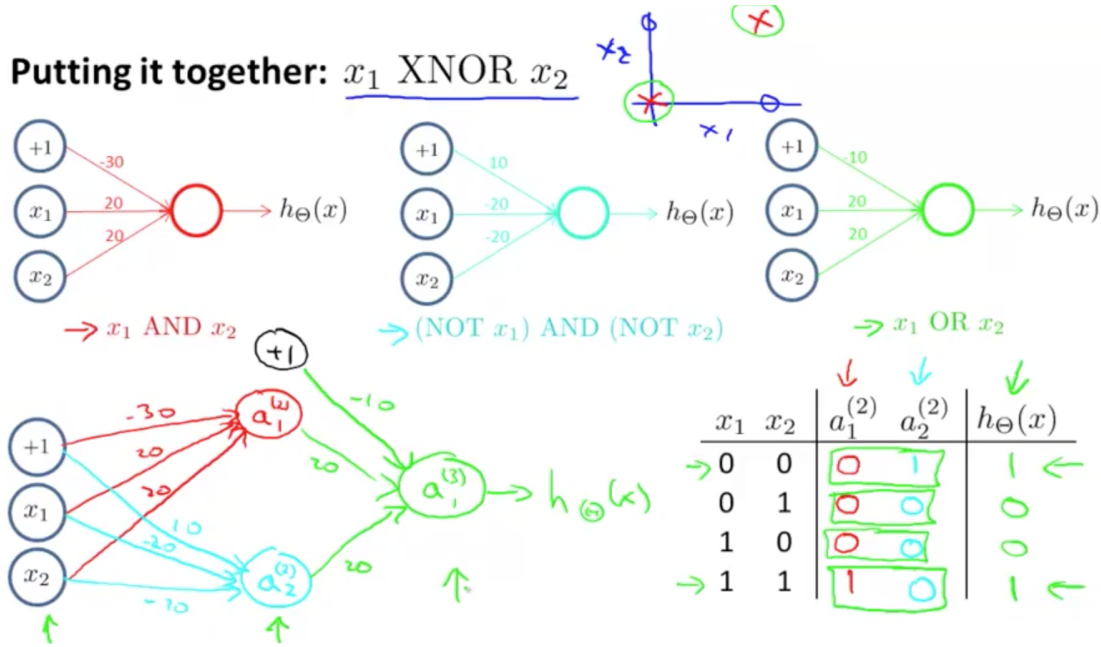
$h_\Theta(x) = g(10 - 20x_1)$

$\rightarrow$ (NOT $x_1$) AND (NOT $x_2$)

(=1 if and only if $\rightarrow x_1 = x_2 = 0$)

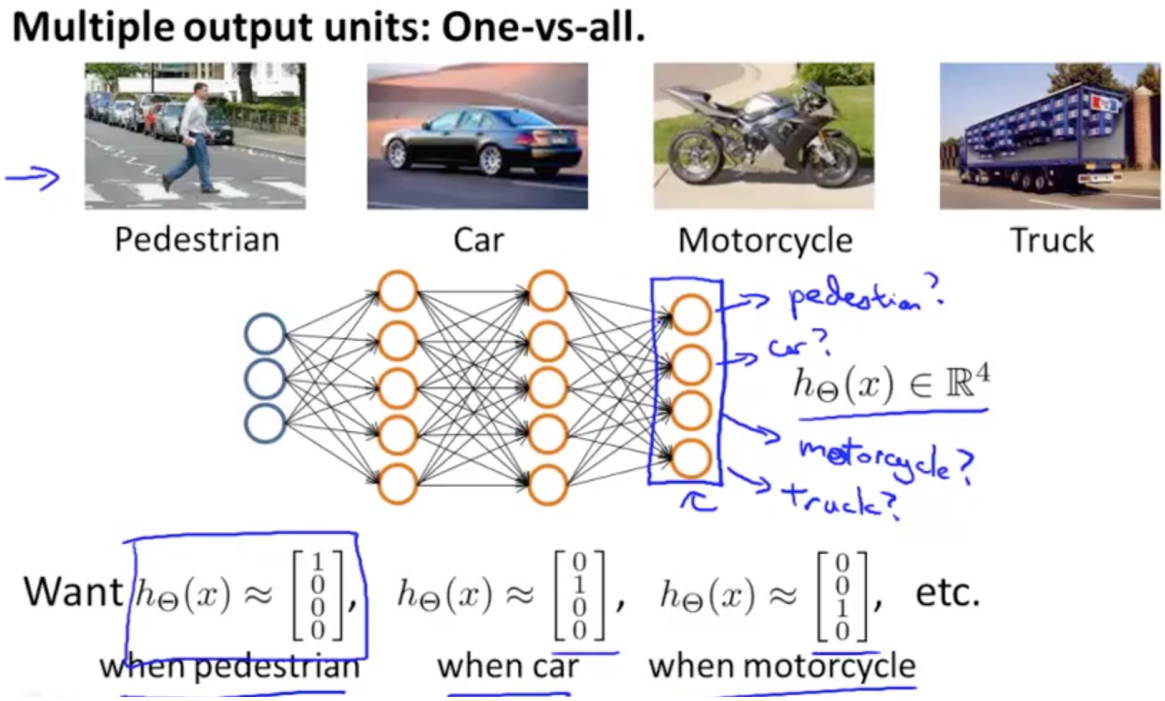
- XNOR function
  - NOT XOR
  - NOT an exclusive or
    - Hence we would want
      - AND

- Neither



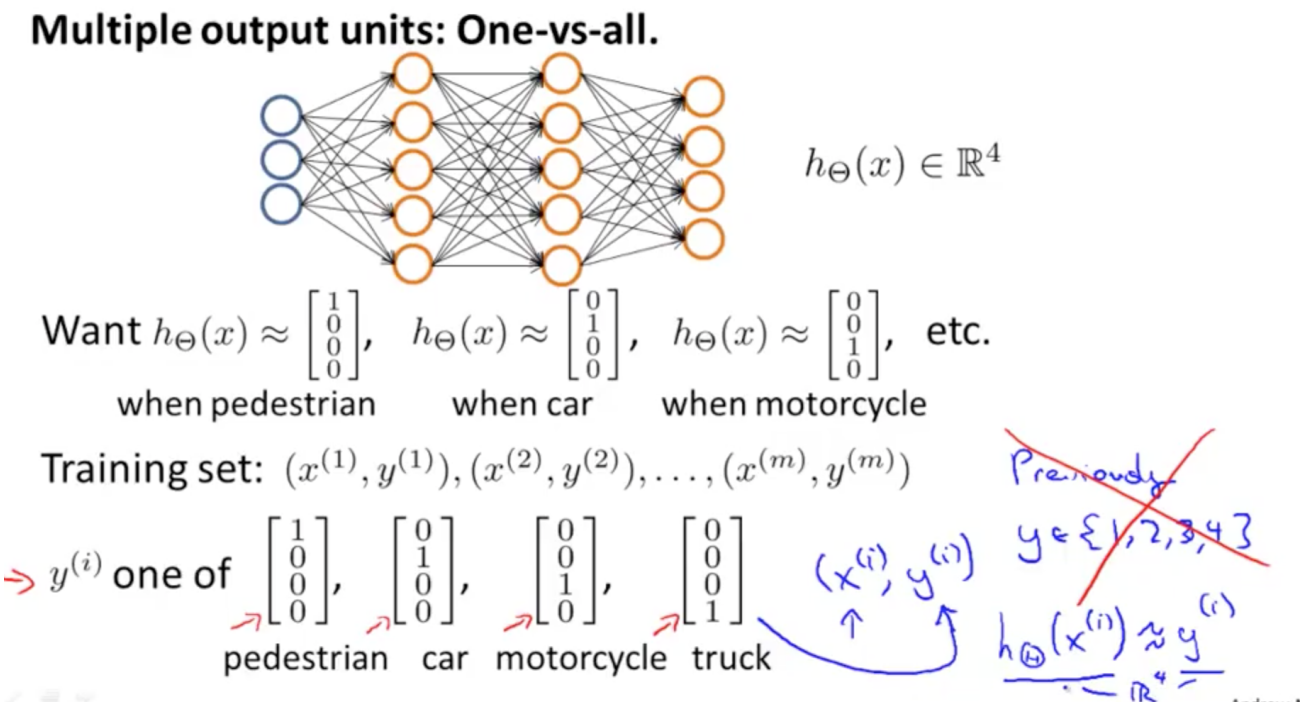

## 2c. Multi-class Classification

- Example: identify 4 classes
  - You would want a 4 x 1 vector for h_theta(X)
  - 4 logistic regression classifiers in the output layer




  - There will be 4 output

- y would be a 4 x 1 vector instead of an integer

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