Administrative

Every Monday, 4pm-6pm, @ Room 5, Institute of Computing

Lectures are non-exhaustive.
Read references for completeness.

Final Project

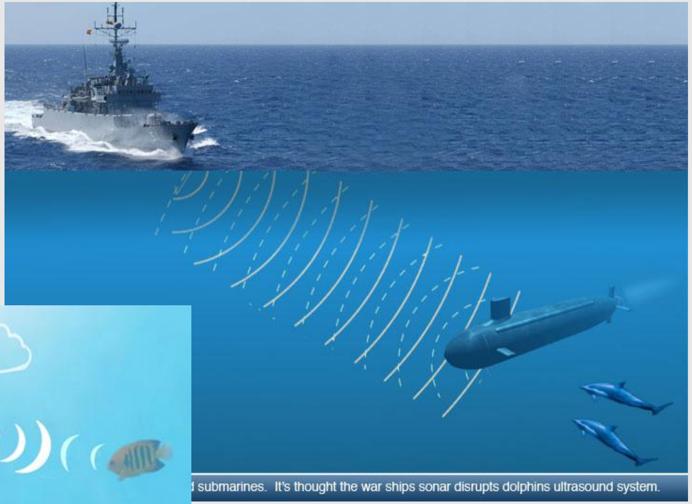
Artificial Neural Networks

Machine Learning and Pattern Recognition

Prof. Sandra Avila
Institute of Computing (IC/Unicamp)

MC886/MO444, September 12, 2017

Many inventions were inspired by Nature ...



It seems logical to look at the brain’s architecture for inspiration on how to build an intelligent machine.

From Biological to Artificial Neurons

From Biological to Artificial Neurons

- **1943:** Artificial Neural Networks (ANNs) were first introduced by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts.

  "A Logical Calculus of Ideas Immanent in Nervous Activity", Warren McCulloch and Walter Pitts. The bulletin of mathematical biophysics (1943).

From Biological to Artificial Neurons

- **Until the 1960s:** The early successes of ANNs led to the widespread belief that we would soon be conversing with truly intelligent machines.

- When it became clear that this promise would go unfulfilled funding flew elsewhere and ANNs entered a long dark era.

From Biological to Artificial Neurons

- **1980s:** There was a revival of interest in ANNs as new network architectures were invented and **better training techniques** were developed.

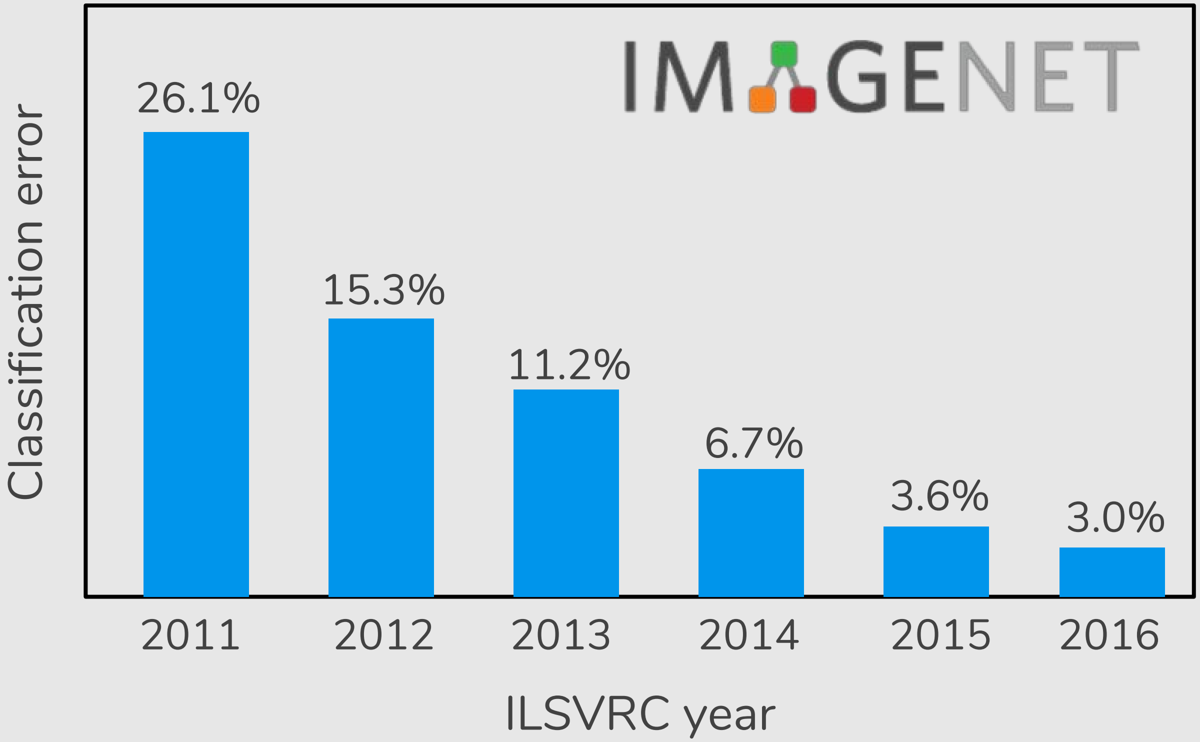
  "Learning representations by backpropagating errors". David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams. Nature (1986).

From Biological to Artificial Neurons

- **1990s:** **Powerful alternative Machine Learning techniques** such as Support Vector Machines were favored by most researchers, as they seemed to offer better results and stronger theoretical foundations.

From Biological to Artificial Neurons

- **2010s:** We are now witnessing yet another wave of interest in ANNs.



"ImageNet classification with deep convolutional neural networks". Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton. In: NIPS, 2012.

From Biological to Artificial Neurons

- **2010s:** We are now witnessing yet another wave of interest in ANNs.

Will this wave die out like the previous ones did?

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.

IMAGENET

www.image-net.org

22K categories and 14M images

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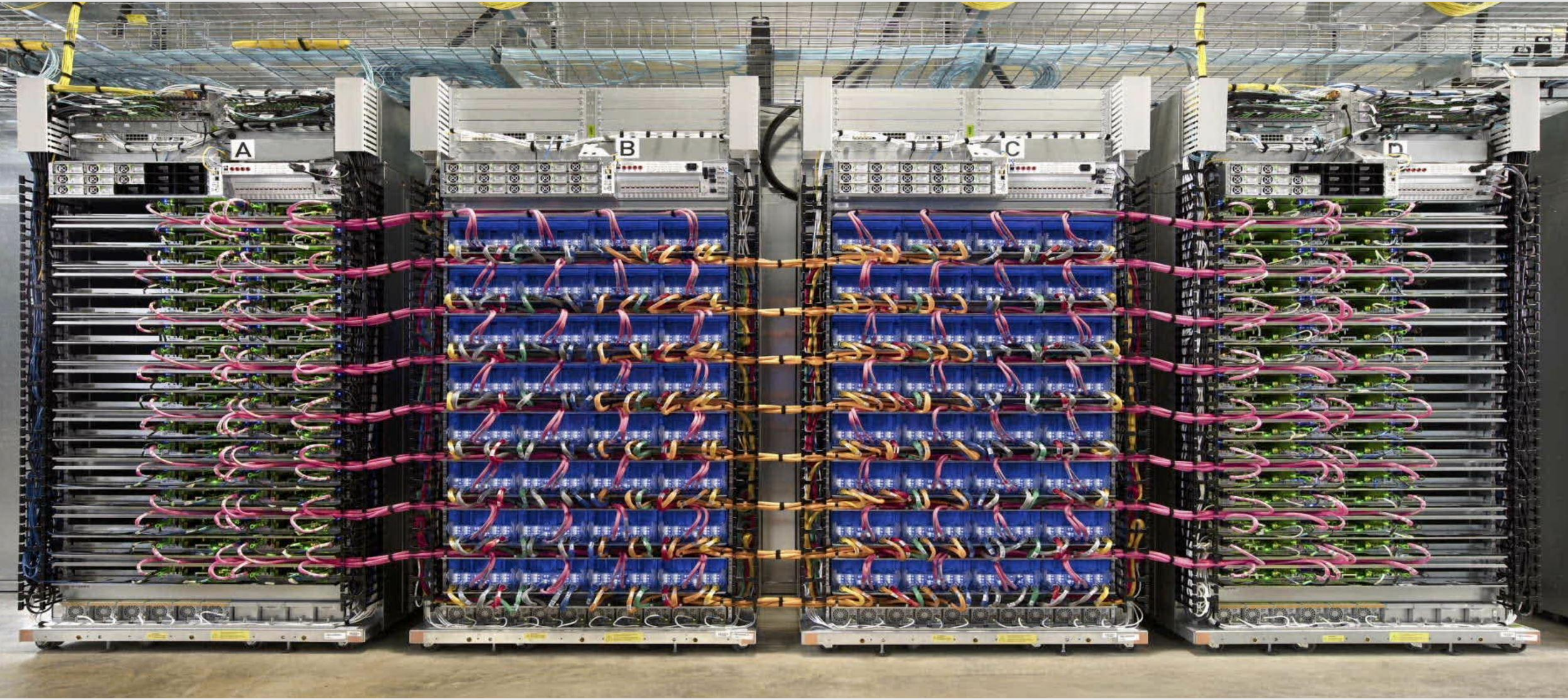
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
- Food
- Materials
- Structures
- Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geological Formations
- Sport Activities

Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.



http://www.tomshardware.com/news/google-automl-aritifical-intelligence-ai,34533.html

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.

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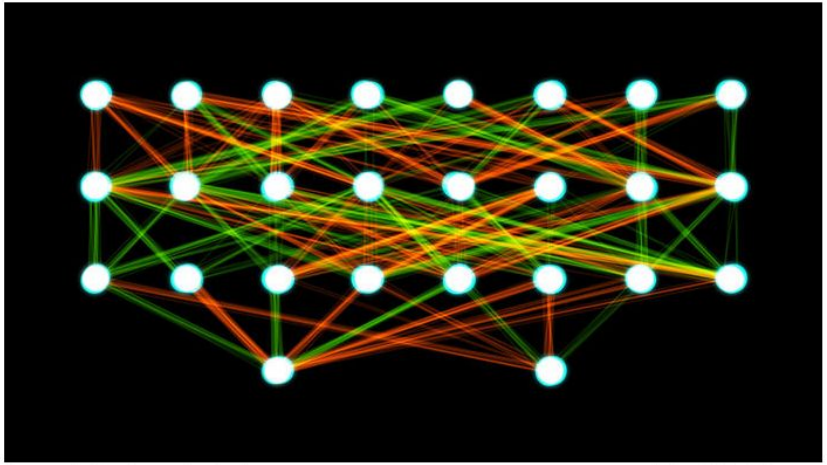


A representation of a neural network.

Akritasa/Wikimedia Commons

Brainlike computers are a black box. Scientists are finally peering inside

By Jackie Snow | Mar. 7, 2017 , 3:15 PM

Last month, Facebook announced software that could simply look at a photo and tell, for example, whether it was a picture of a cat or a dog. A related program identifies cancerous

http://www.sciencemag.org/news/2017/03/brainlike-computers-are-black-box-scientists-are-finally-peering-inside

From Biological to Artificial Neurons

1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.
3. The **training algorithms** have been **improved**.
4. ANNs seem to have entered a virtuous circle of funding and progress.

Biological Neurons

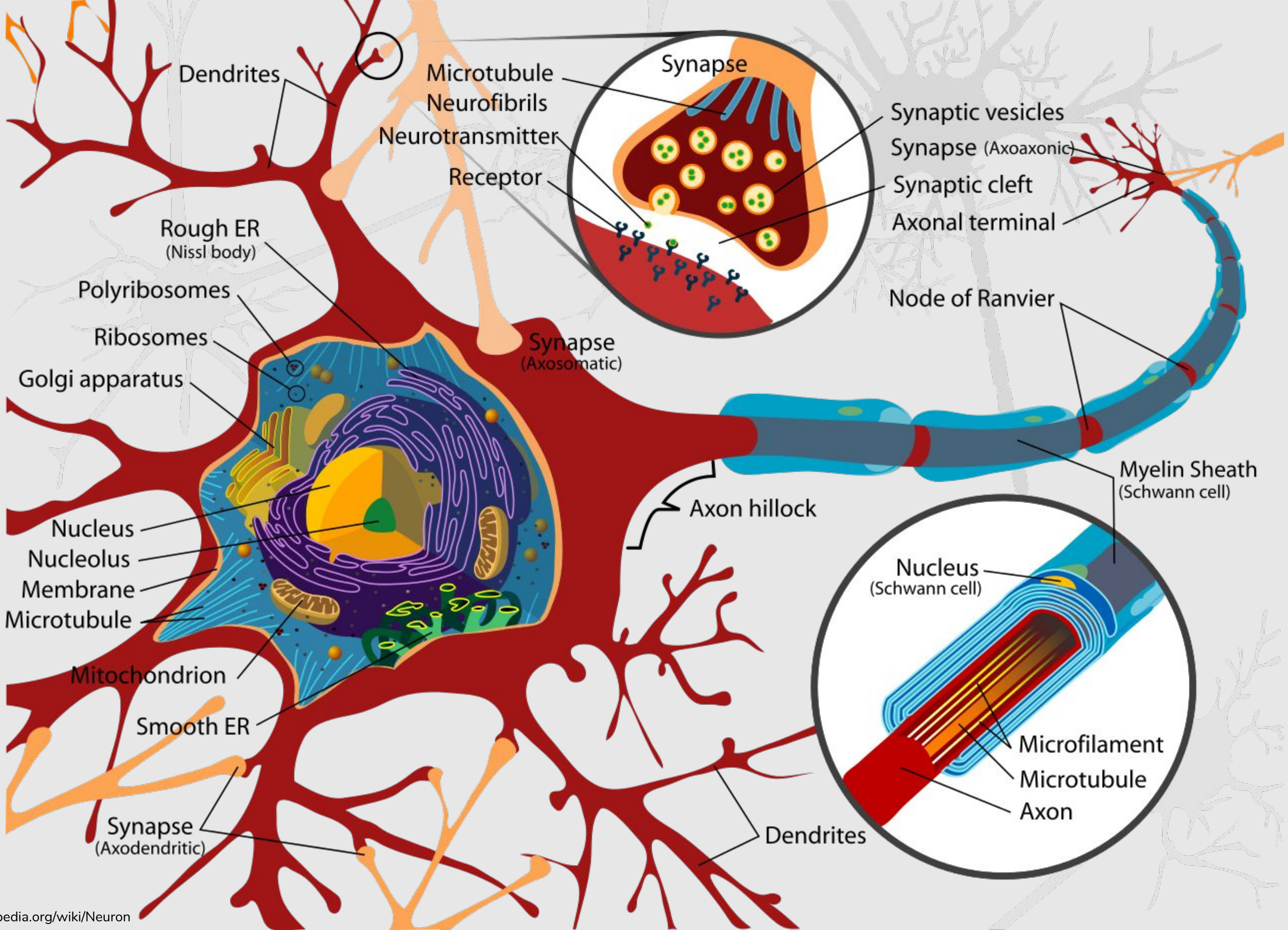
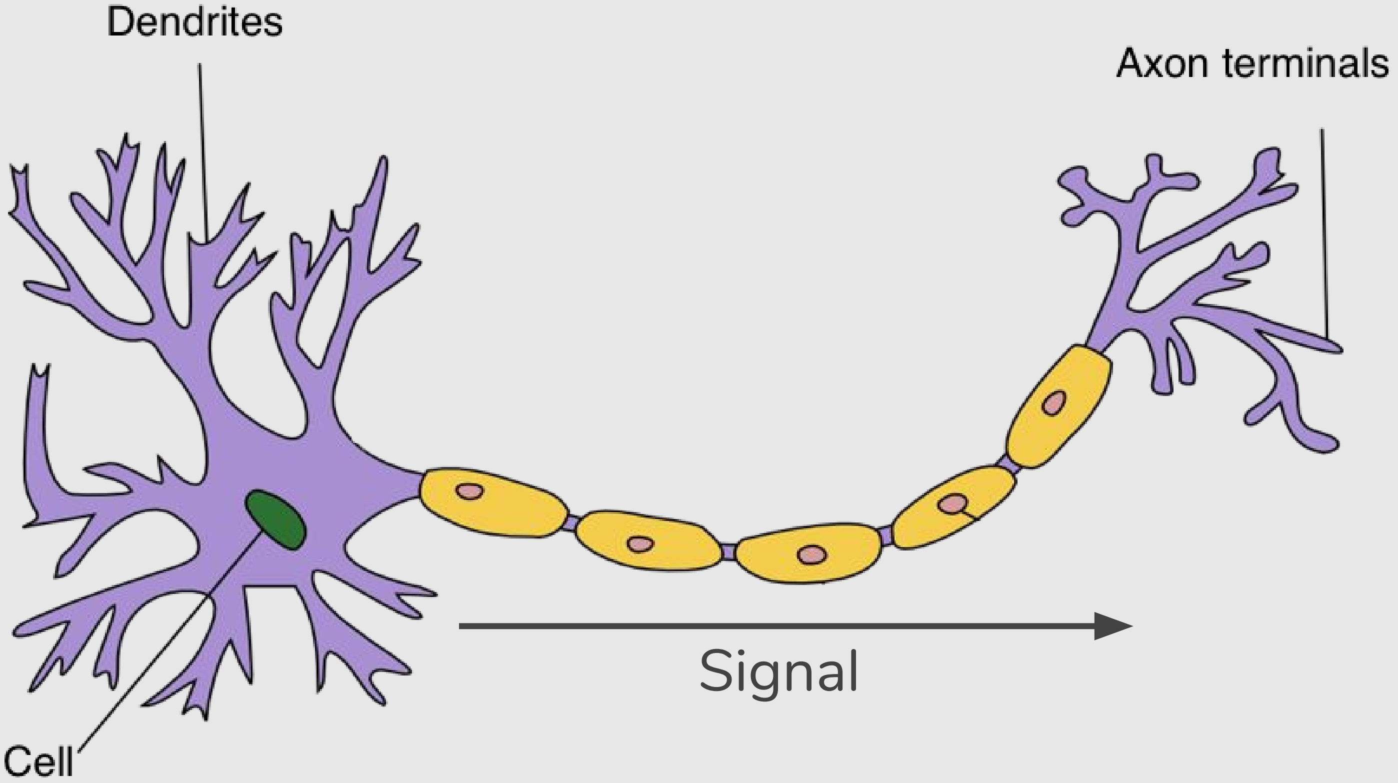


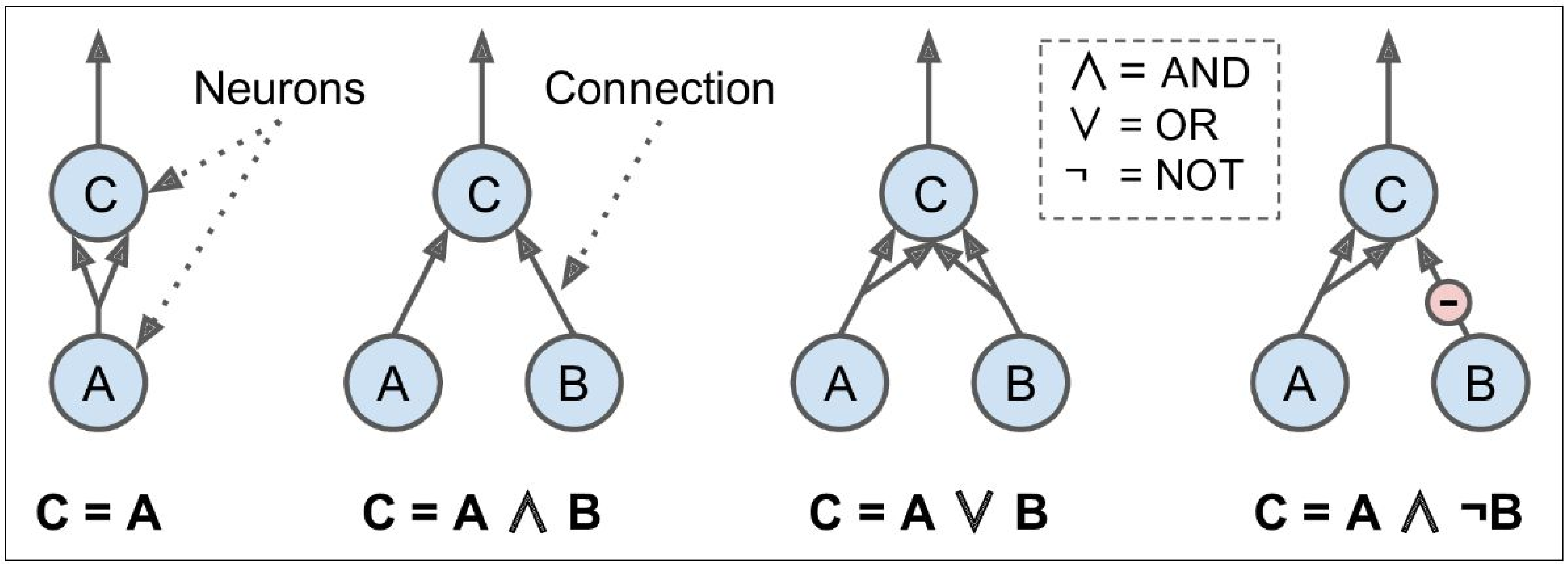
Image Credit: https://en.wikipedia.org/wiki/Neuron



http://www.jeremyjordan.me/content/images/2017/06/Neuron_Hand-tuned.png

Logical Computations with Neurons

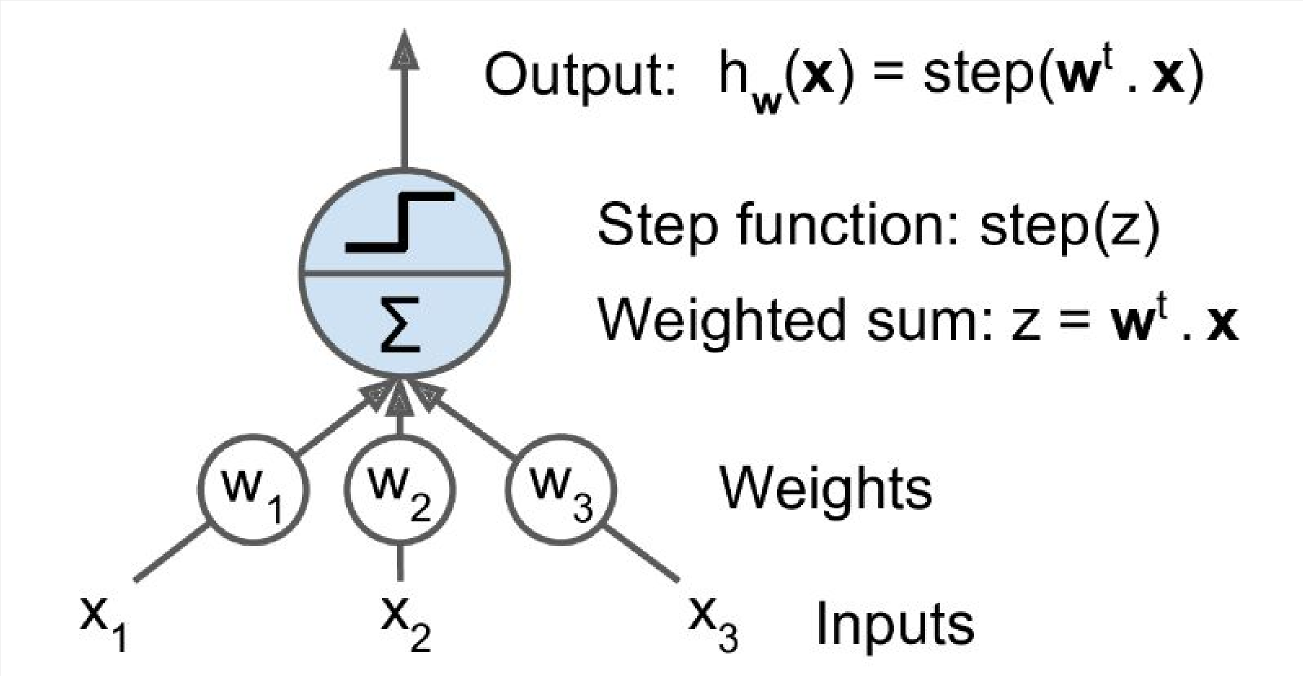
McCulloch and Pitts (1943)



Artificial Neural Networks performing simple logical computations

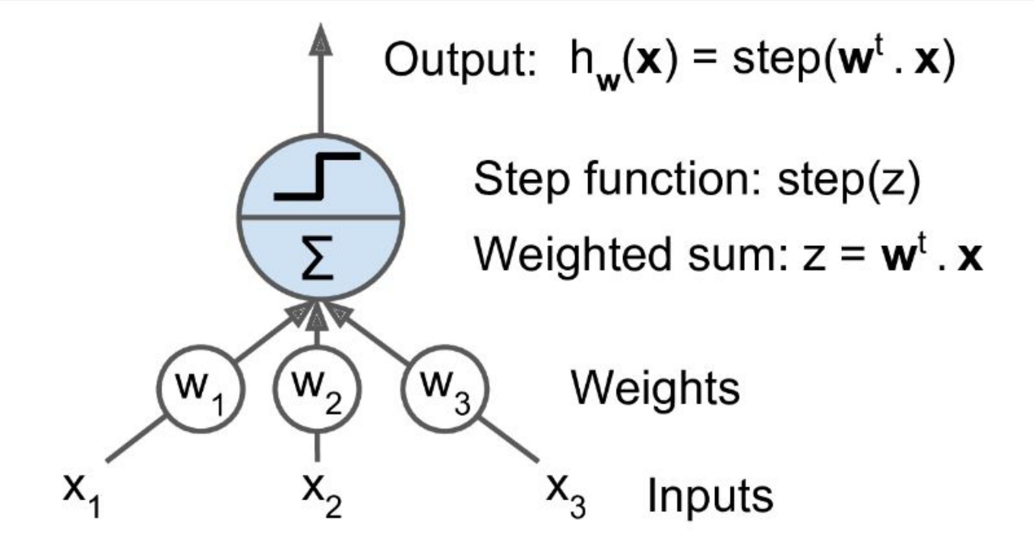
The Perceptron

The Perceptron



Linear Threshold Unit, Frank Rosenblatt (1957)

The Perceptron

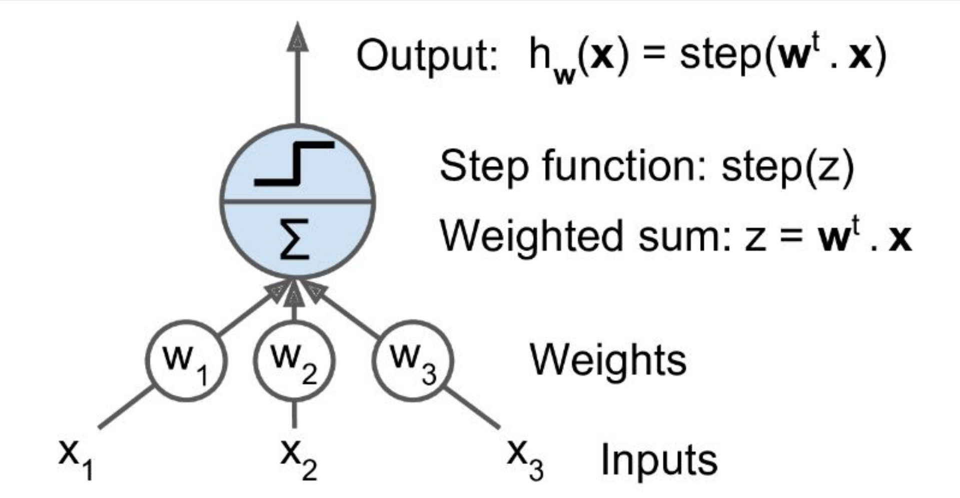


Linear Threshold Unit

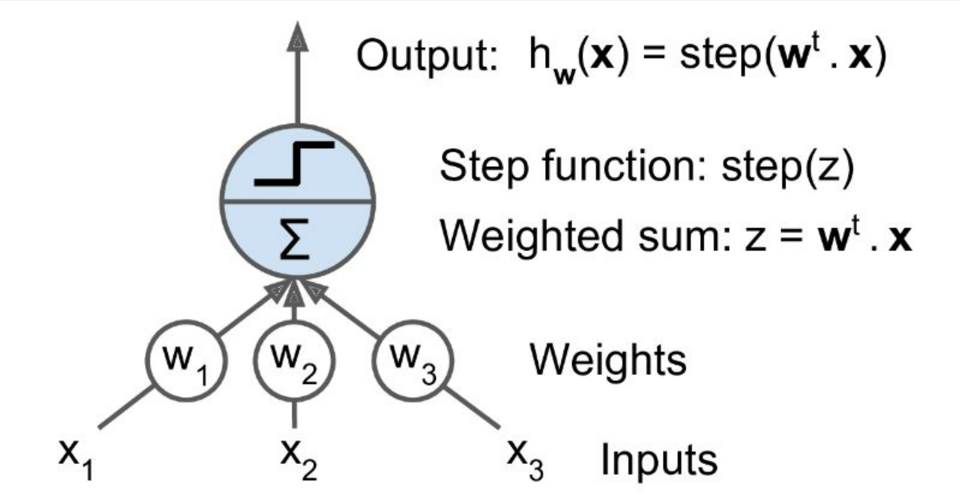
$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

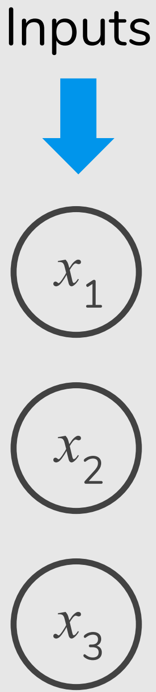
$$\text{sign}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$

Neuron Model: Logistic Unit



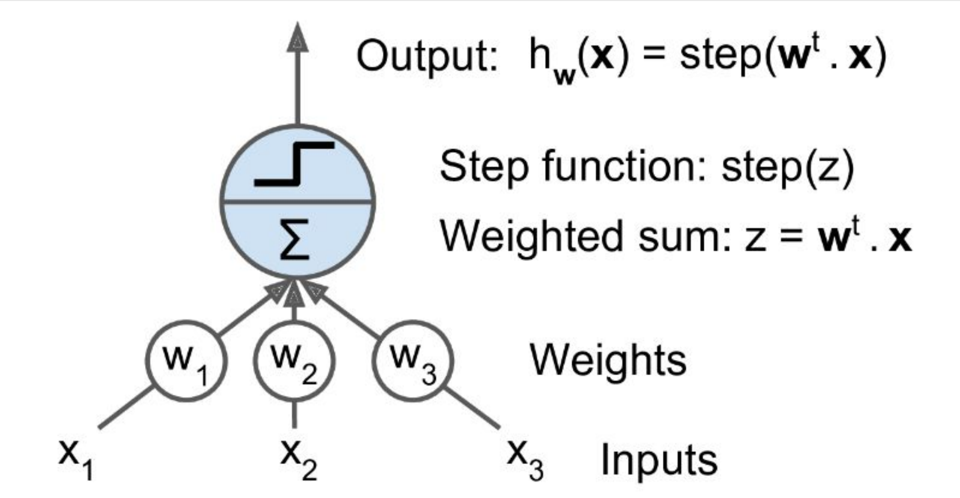
Neuron Model: Logistic Unit

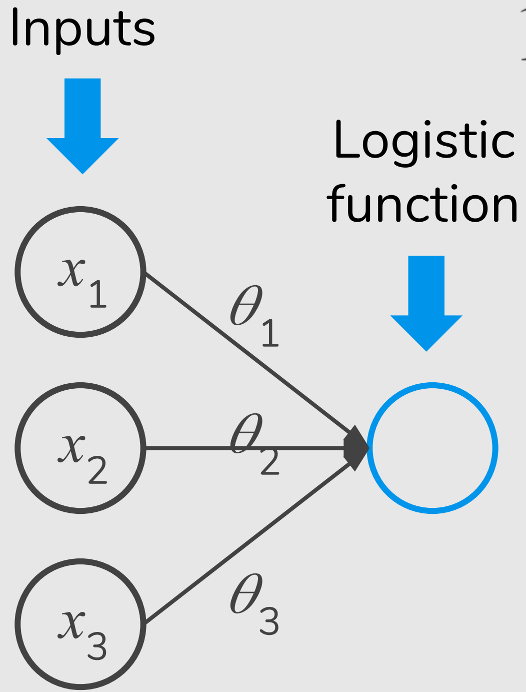




Neuron Model: Logistic Unit

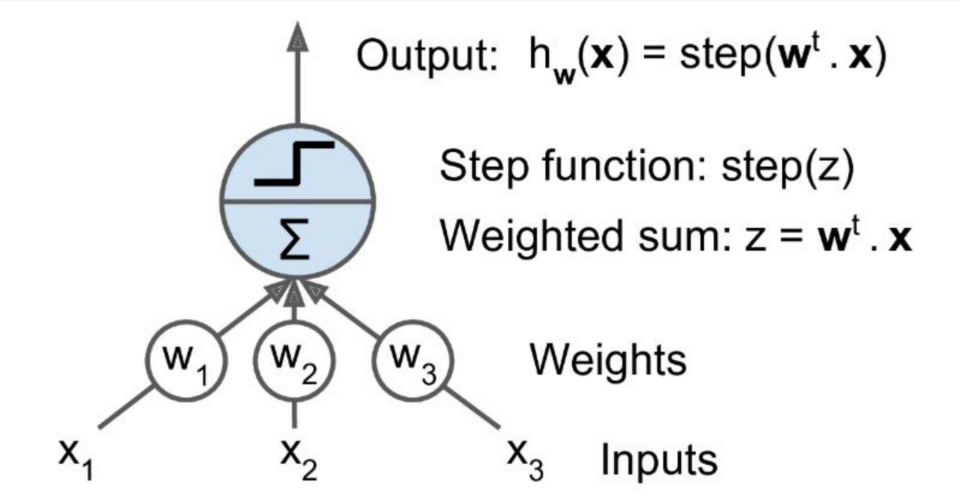
$$\frac{1}{1 + e^{-\theta^T x}}$$

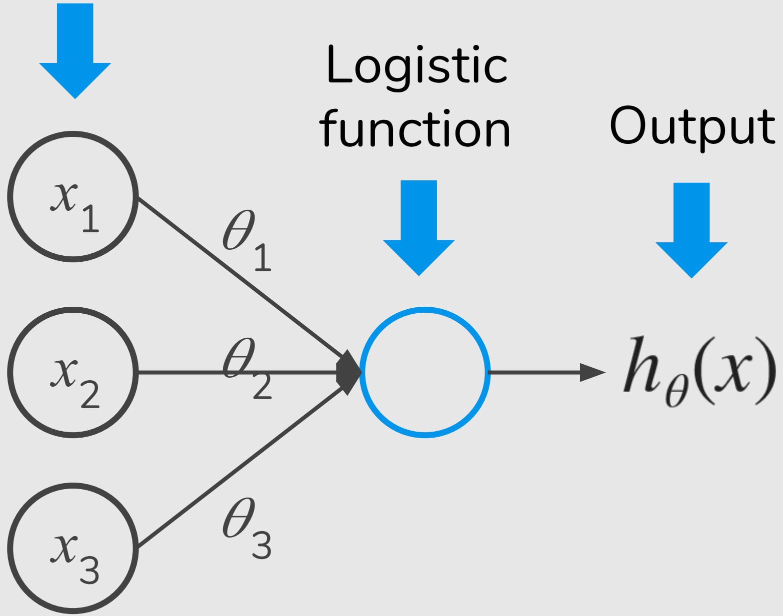




Neuron Model: Logistic Unit

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

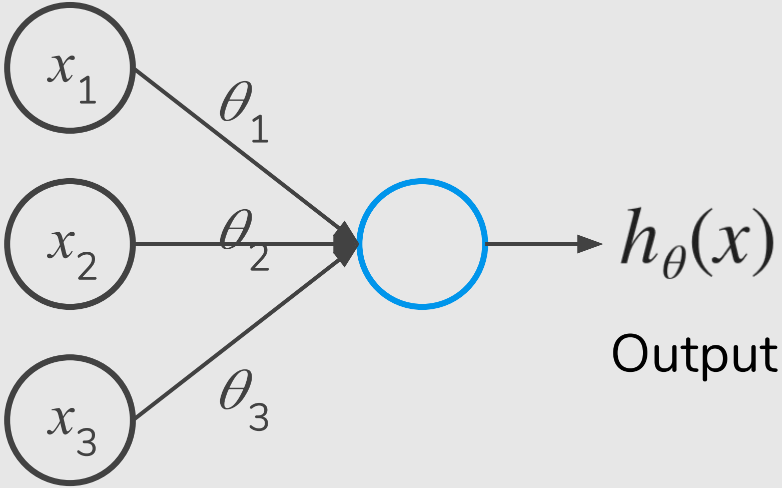




Neuron Model: Logistic Unit

weights

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$



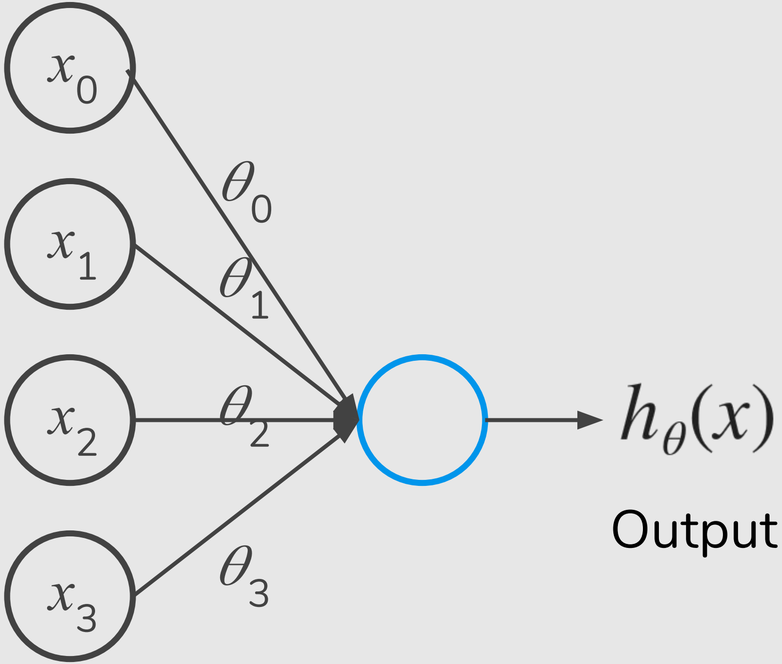
Output

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

Sigmoid (Logistic)
activation function

Inputs

Neuron Model: Logistic Unit



Output

Inputs

Sigmoid (Logistic)
activation function

weights

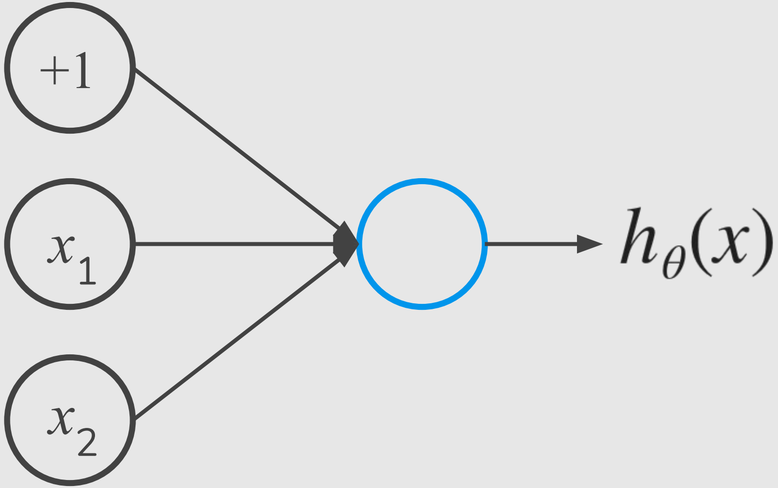
$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

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

Examples

Simple Example: AND

$x_1, x_2 \in \{0,1\}$ $\quad y = x_1 \text{ AND } x_2$



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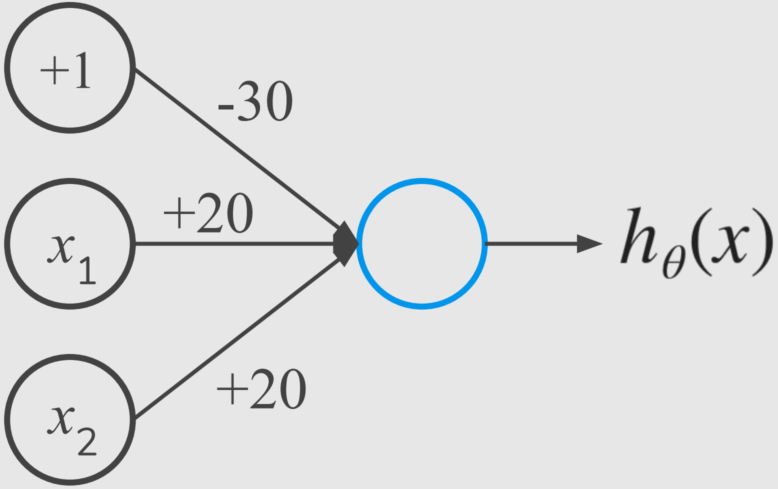

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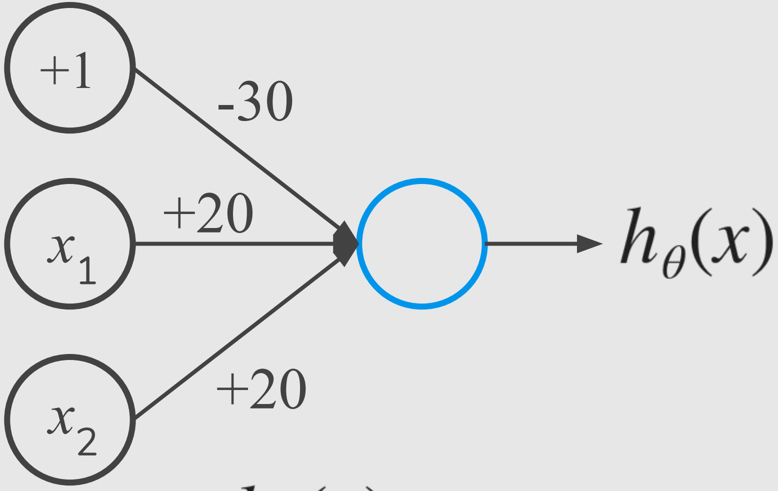
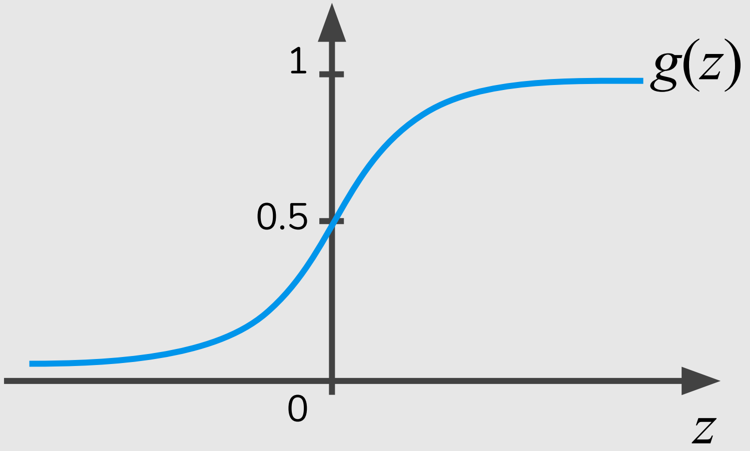
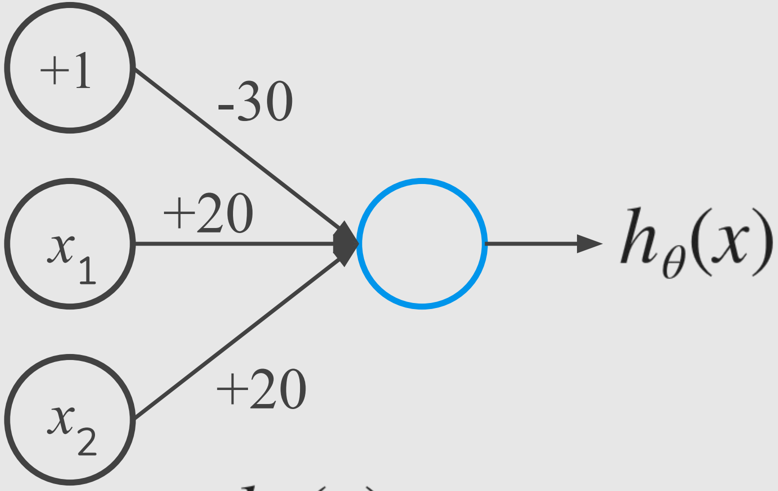


$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND

$x_1, x_2 \in \{0,1\}$ $\quad y = x_1 \text{ AND } x_2$





x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND

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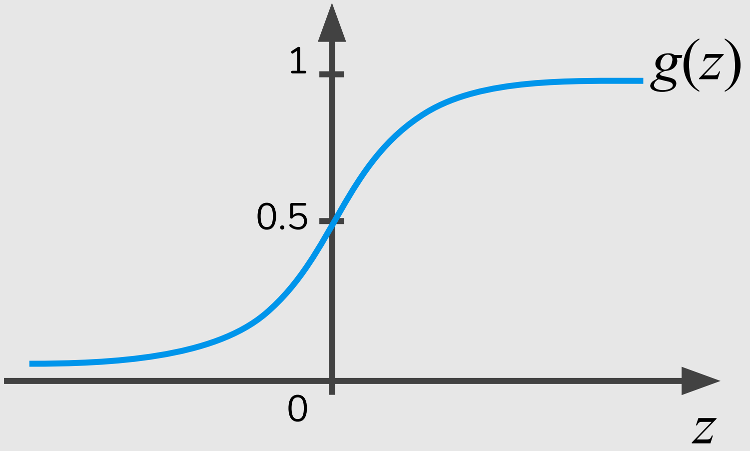
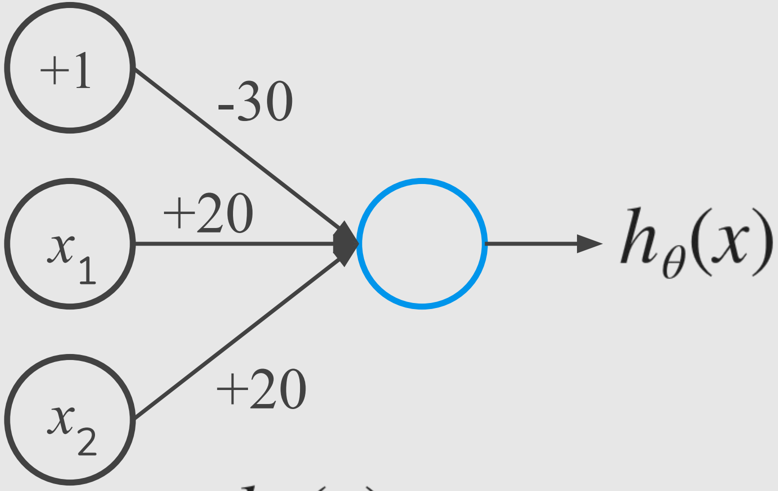


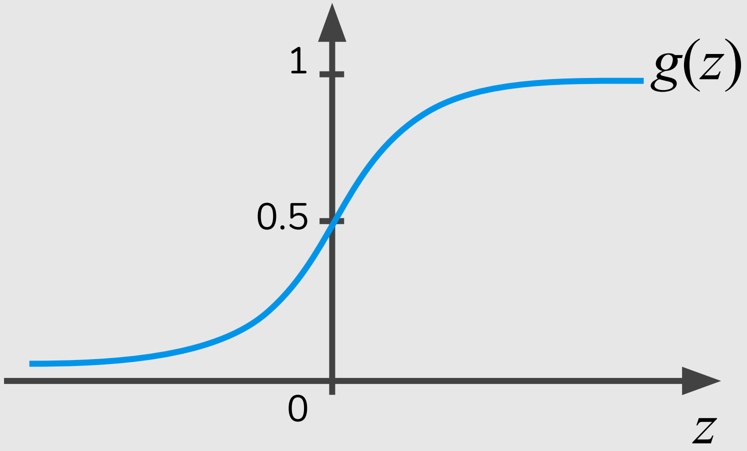


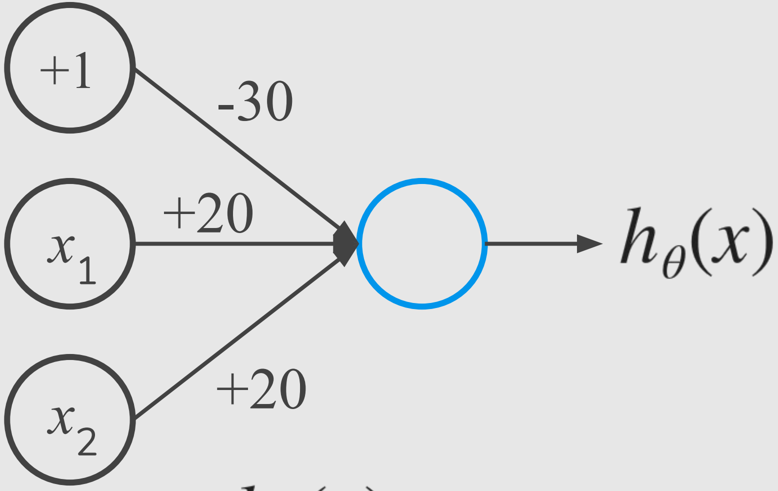
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	
1	0	
1	1	

$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND

$x_1, x_2 \in \{0,1\}$ $\quad$ $y = x_1 \text{ AND } x_2$



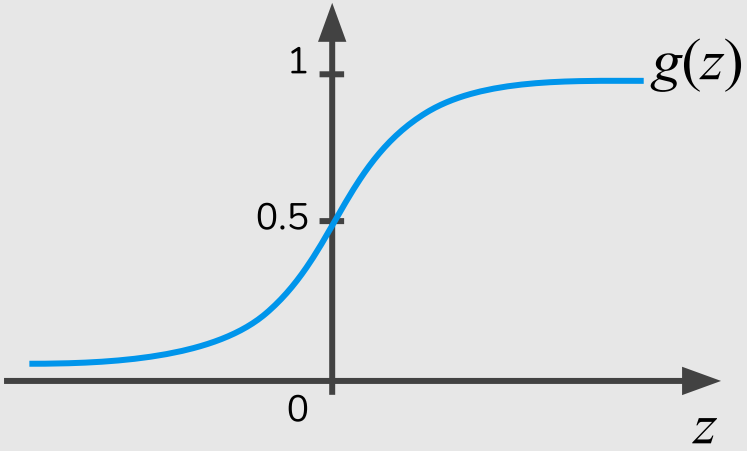


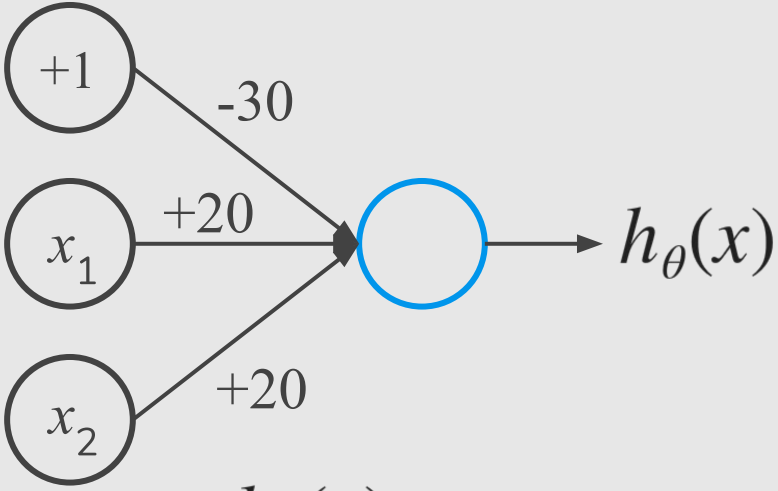
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	
1	1	

$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND

$x_1, x_2 \in \{0,1\}$ $y = x_1 \text{ AND } x_2$

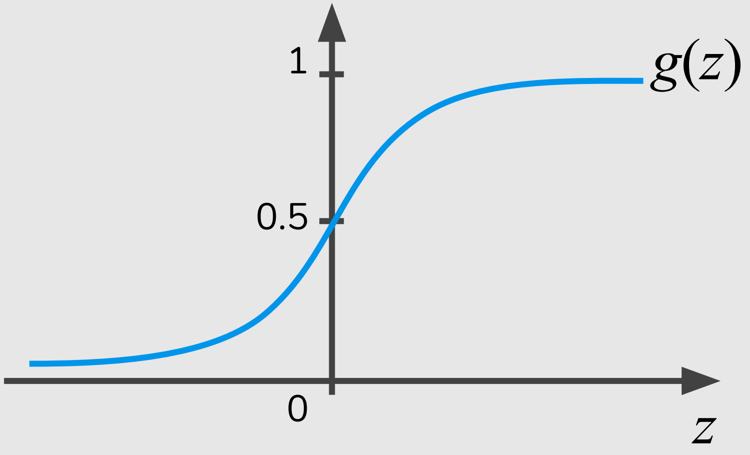




x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	

$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND



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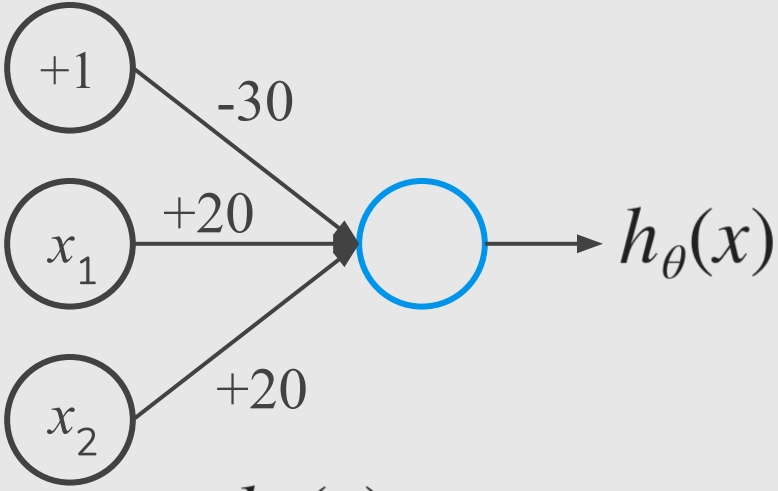
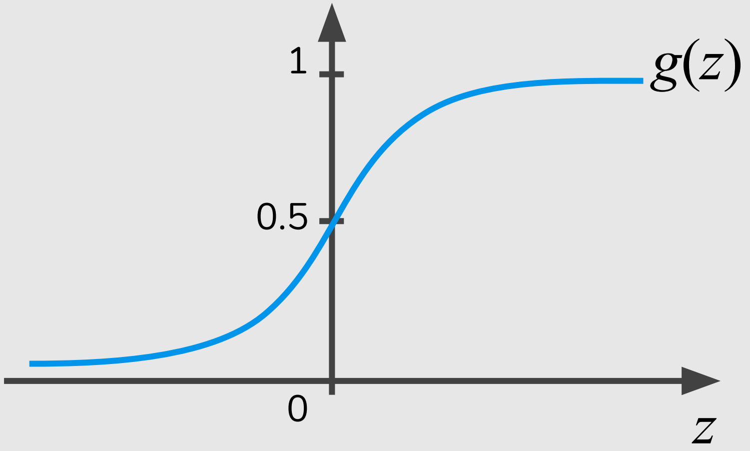


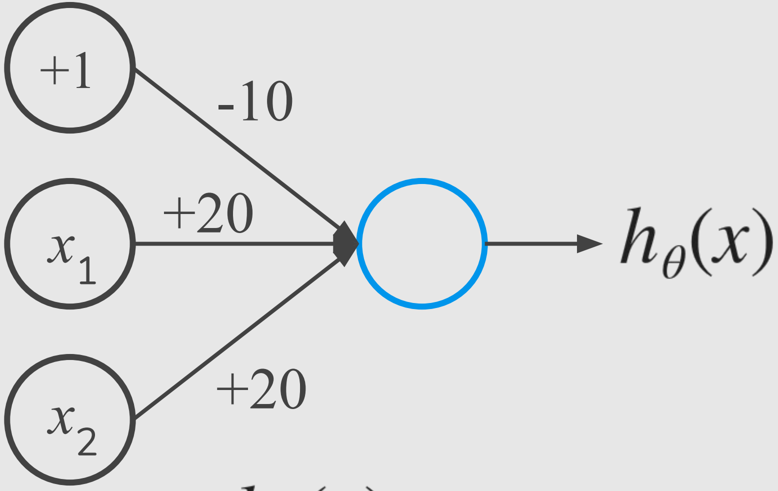
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: OR



$x_1, x_2 \in \{0,1\}$ $\qquad$ $y = x_1 \text{ OR } x_2$

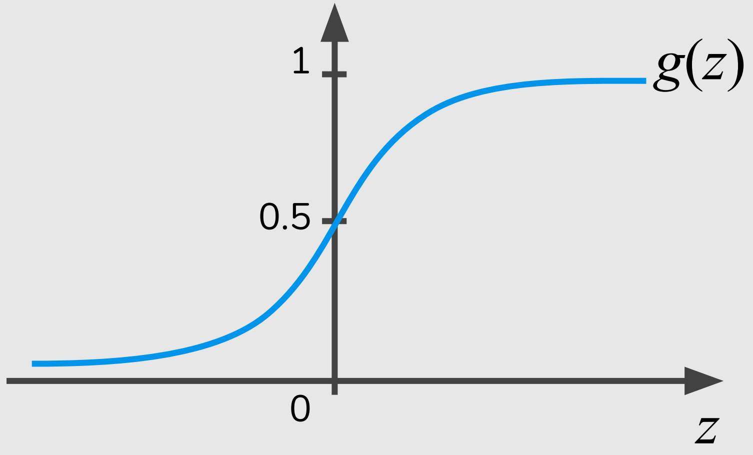


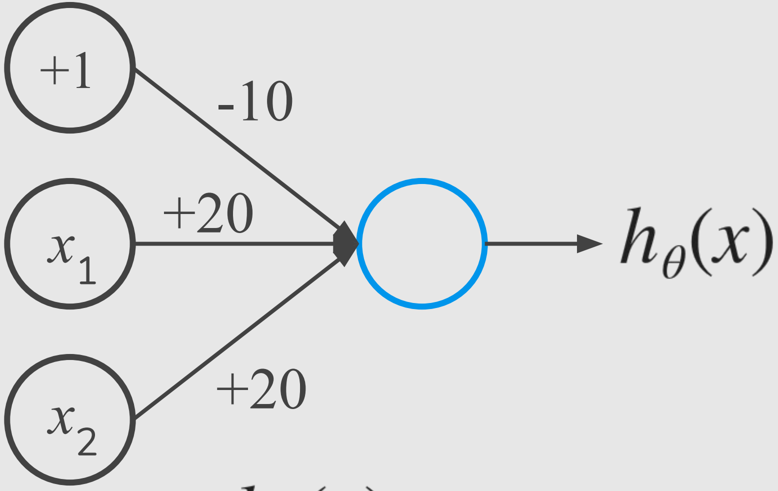
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

$$h_\theta(x) = g(-10 + 20x_1 + 20x_2)$$

Simple Example: OR

$x_1, x_2 \in \{0,1\}$ $\quad$ $y = x_1 \text{ OR } x_2$





x_1	x_2	$h_\theta(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	$g(10) \approx 1$
1	1	$g(30) \approx 1$

$$h_\theta(x) = g(-10 + 20x_1 + 20x_2)$$

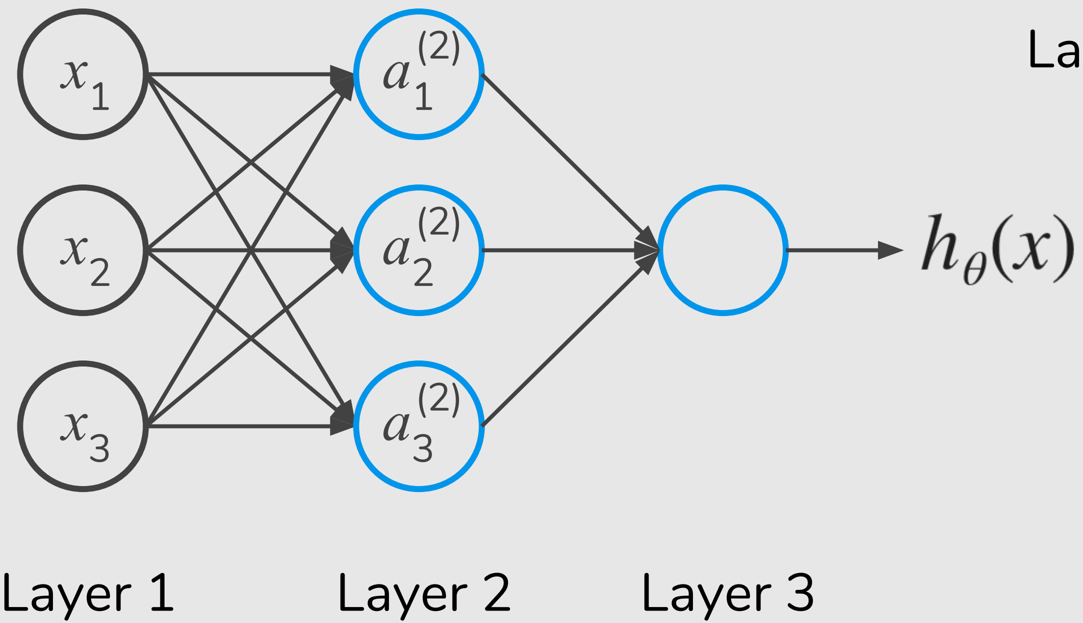
Neural Network

Neural Network

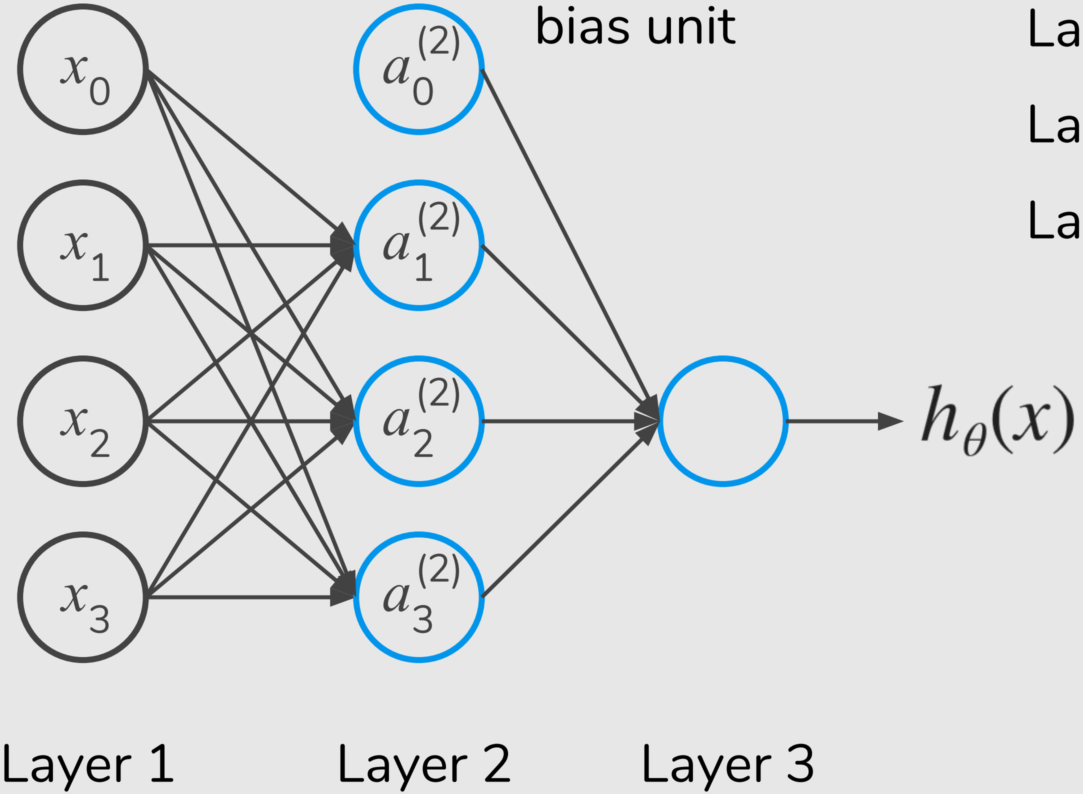
Layer 1 = Input layer

Layer 2 = Hidden layer

Layer 3 = Output layer



Neural Network



Layer 1 = Input layer

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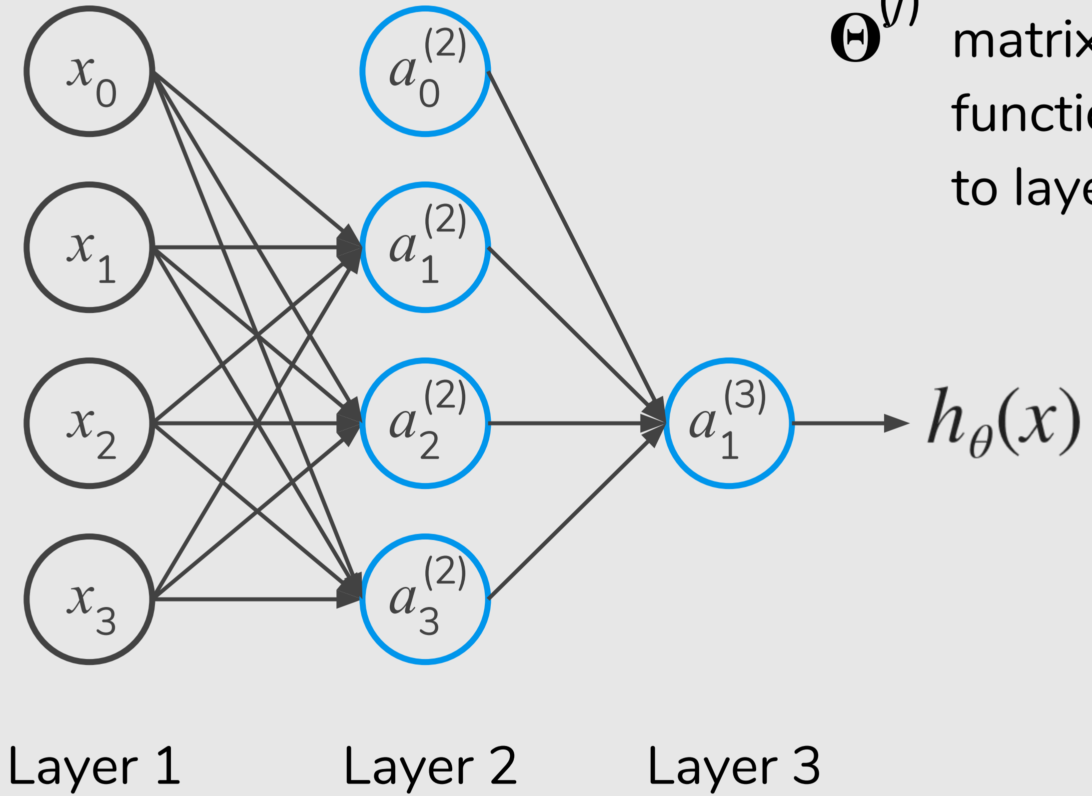
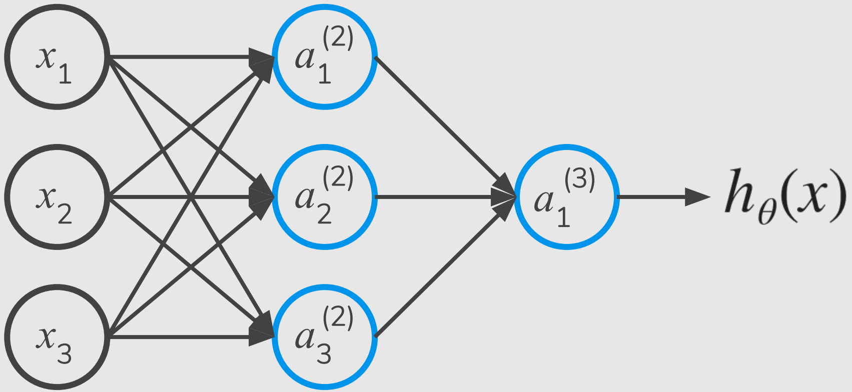
Neural Network



$a_i^{(j)}$ "activation" of unit i in layer j

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



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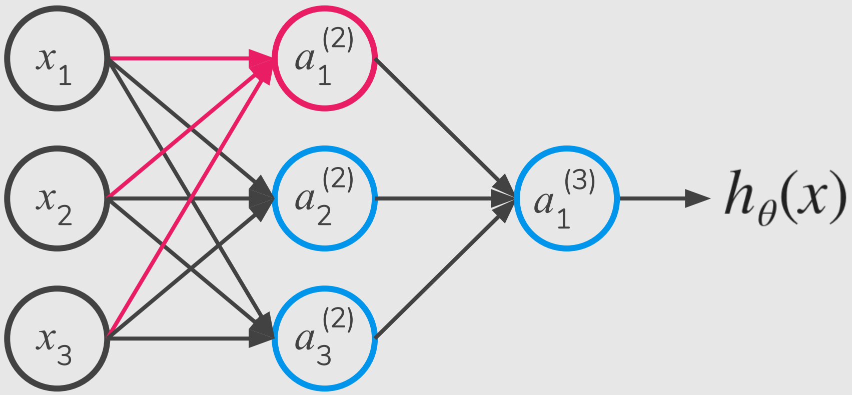
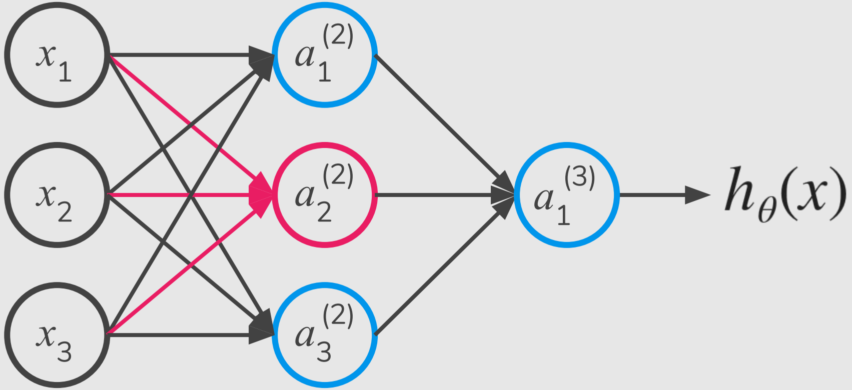


$a_i^{(j)}$ "activation" of unit i in layer j

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

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



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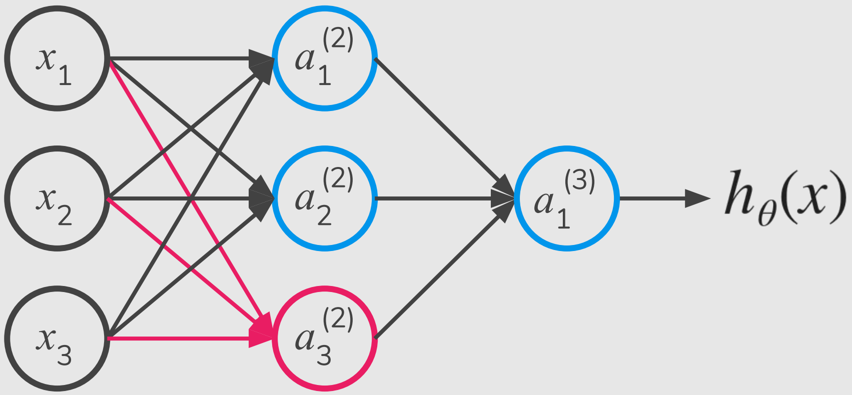
$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$

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



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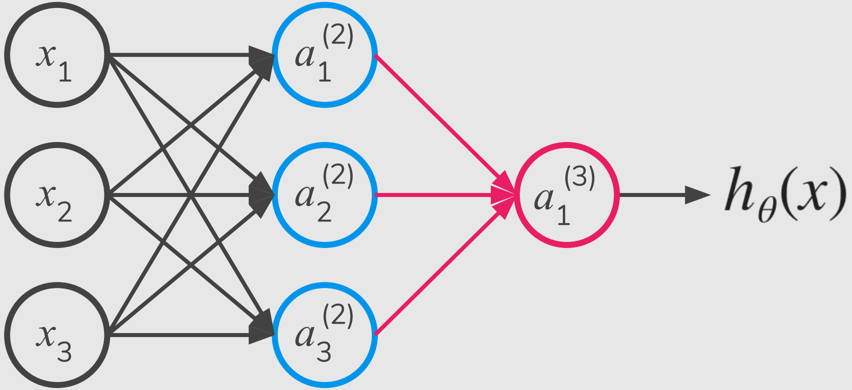
$$a_1^{(2)} = g(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3)$$
$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$
$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$



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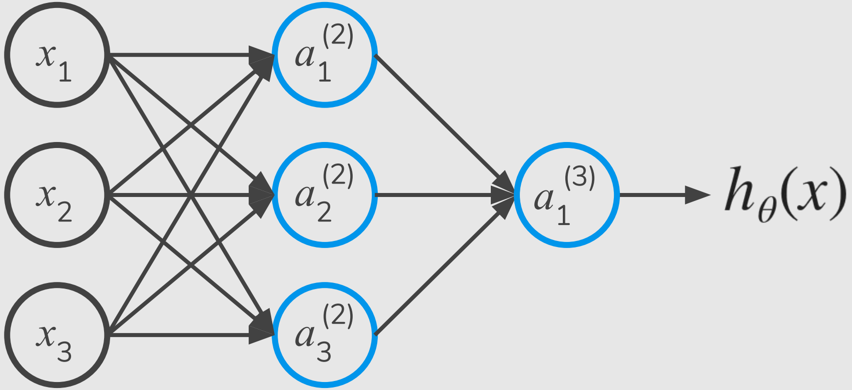
$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$

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



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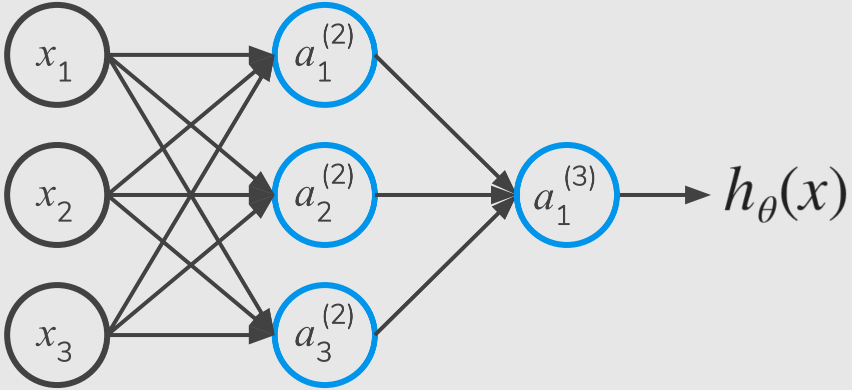
$\Theta^{(j)}$ matrix of weights controlling function mapping from layer j to layer $j+1$

Feedforward Neural Network (forward propagating)

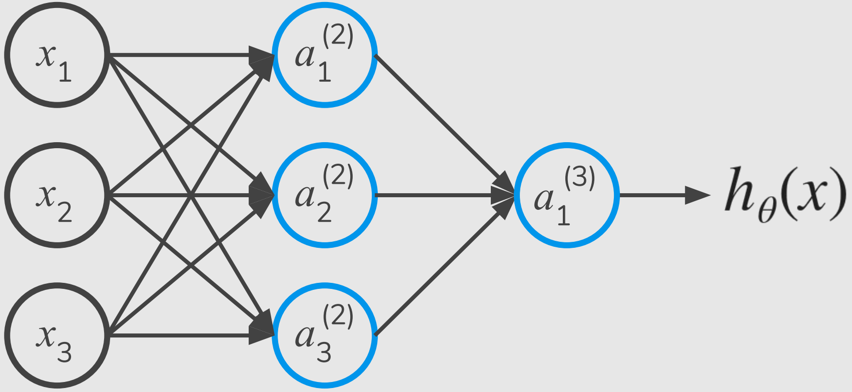
$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)})$$



$a_i^{(j)}$ "activation" of unit i in layer j

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

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



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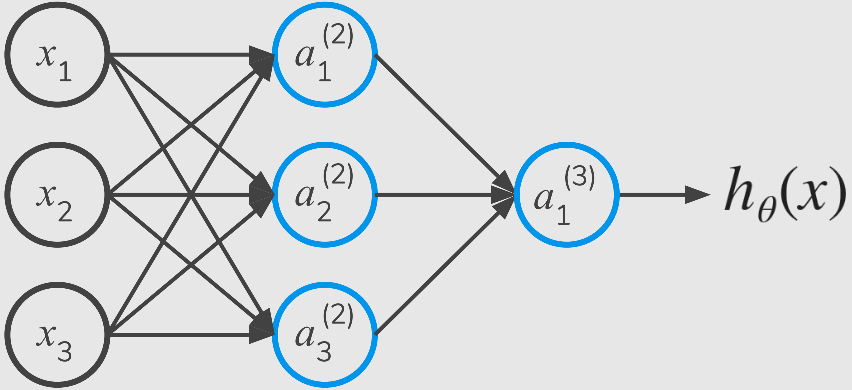
E.g.: If layer 1 has 2 input nodes and layer 2 has 4 activation nodes,



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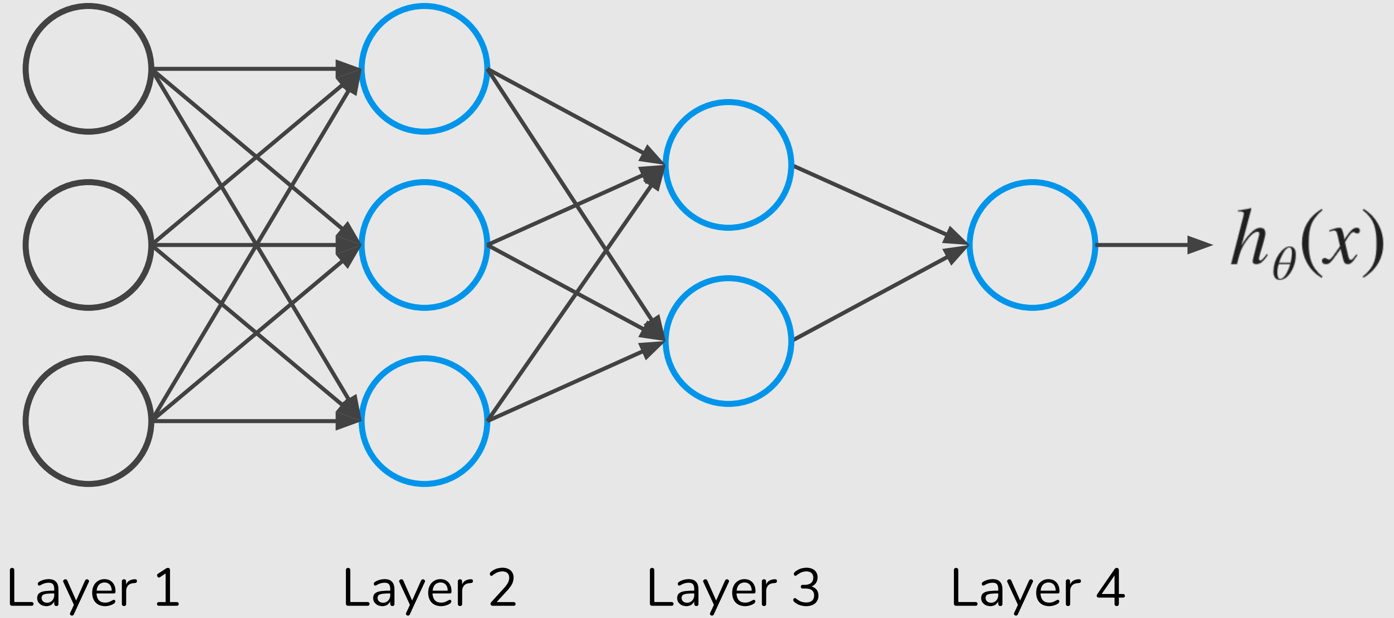
E.g.: If layer 1 has 2 input nodes and layer 2 has 4 activation nodes, dimension of $\Theta^{(1)}$ is going to be 4×3 where $s_j = 2$ and $s_{j+1} = 4$, so $s_{j+1} \times (s_j + 1) = 4 \times 3$.

Other Network Architectures



Example: XNOR $x_1, x_2 \in \{0,1\}$ $y = x_1 \text{ XNOR } x_2$

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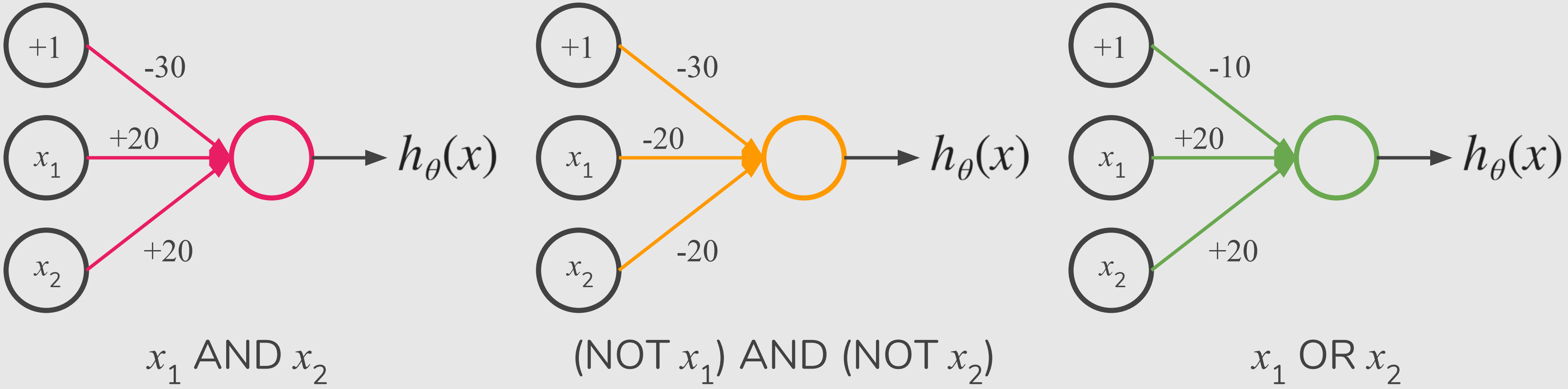

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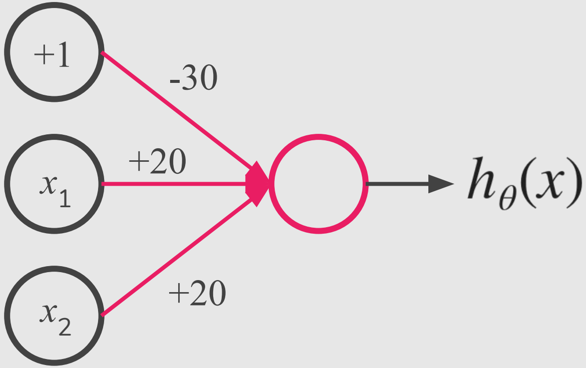
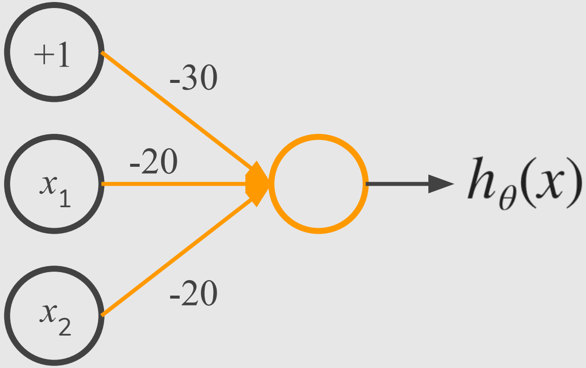
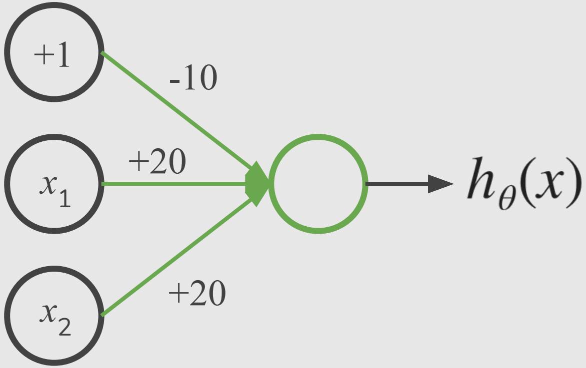


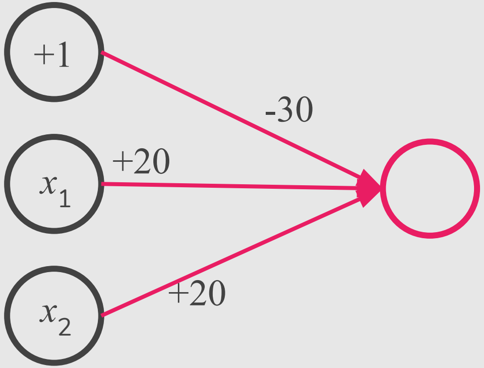
x_1 AND x_2



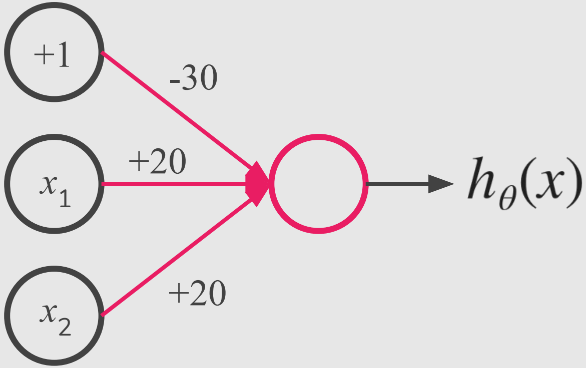
(NOT x_1) AND (NOT x_2)



x_1 OR x_2



Example: XNOR $x_1, x_2 \in \{0,1\}$ $y = x_1 \text{ XNOR } x_2$



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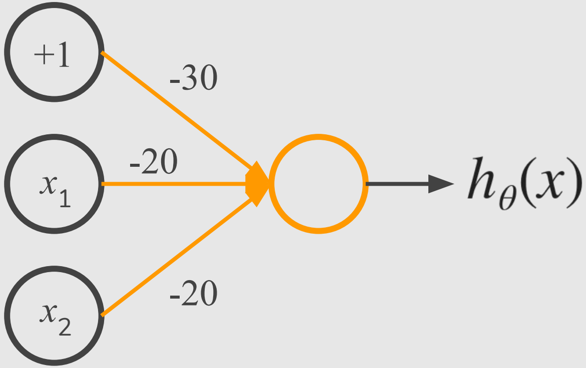

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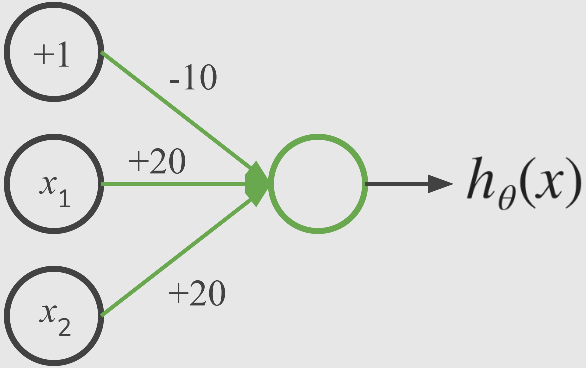
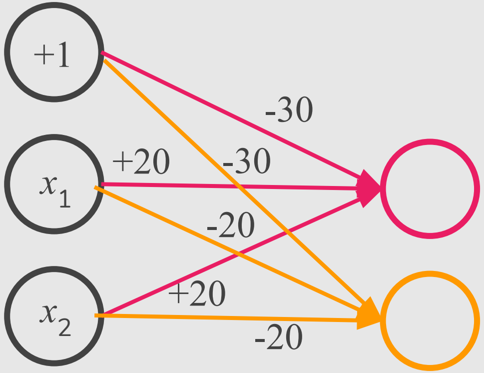


x_1 OR x_2



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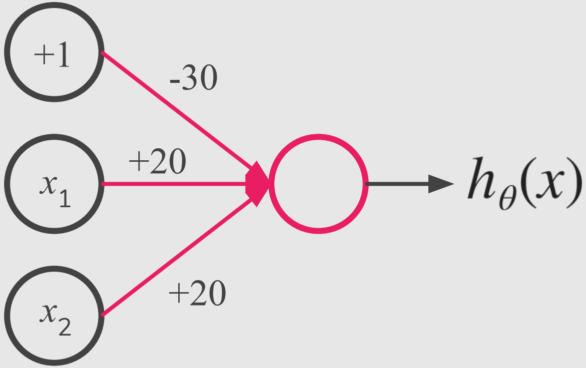

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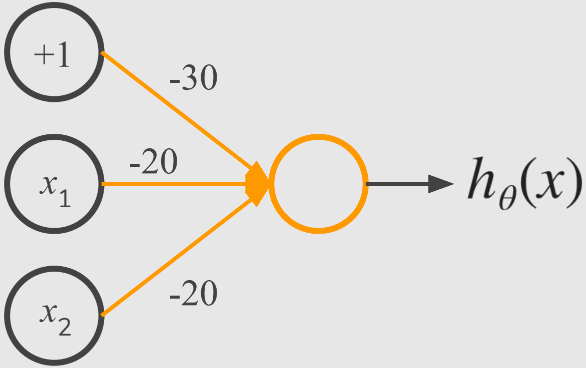

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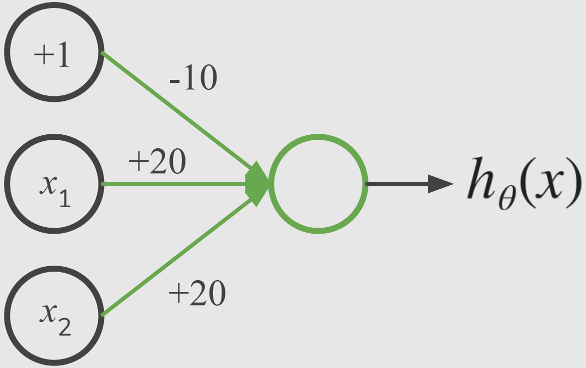
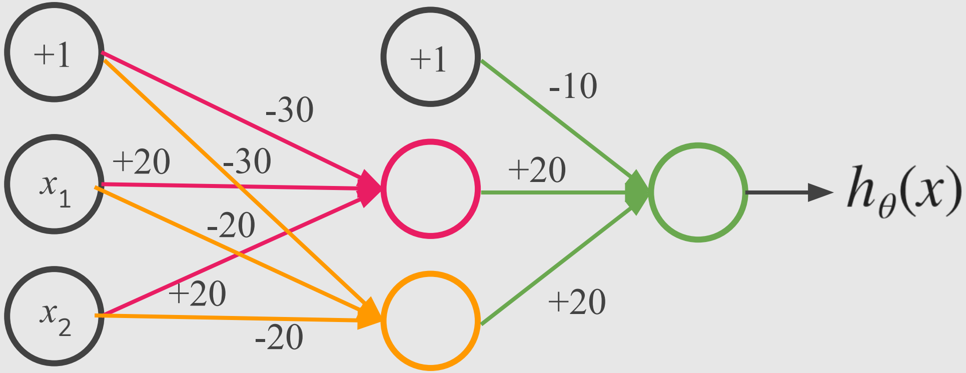
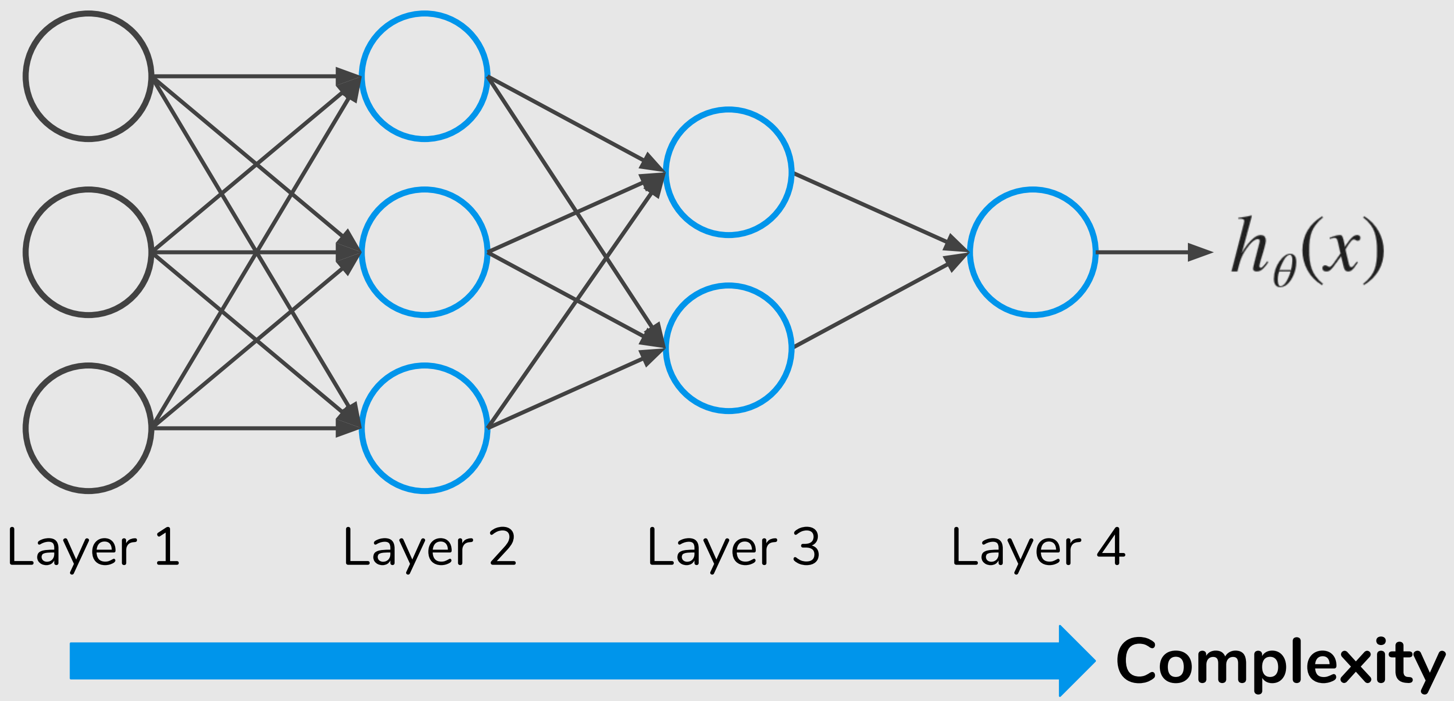


x_1 OR x_2



x_1	x_2	$h_\theta(x)$
0	0	1
0	1	0
1	0	0
1	1	1

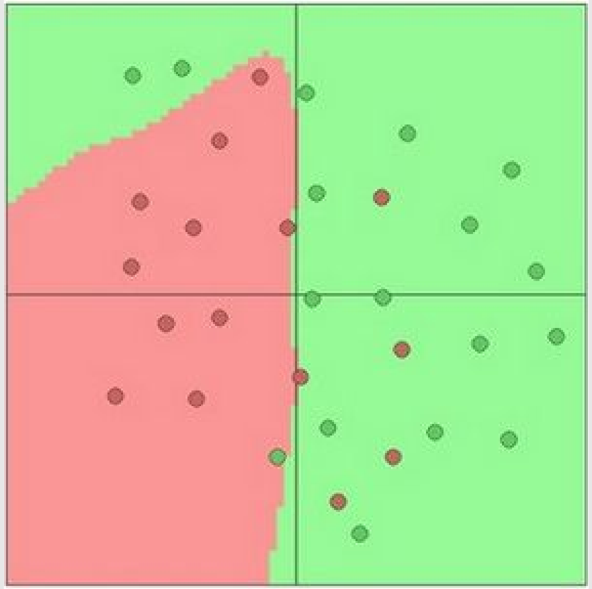
Neural Network Intuition



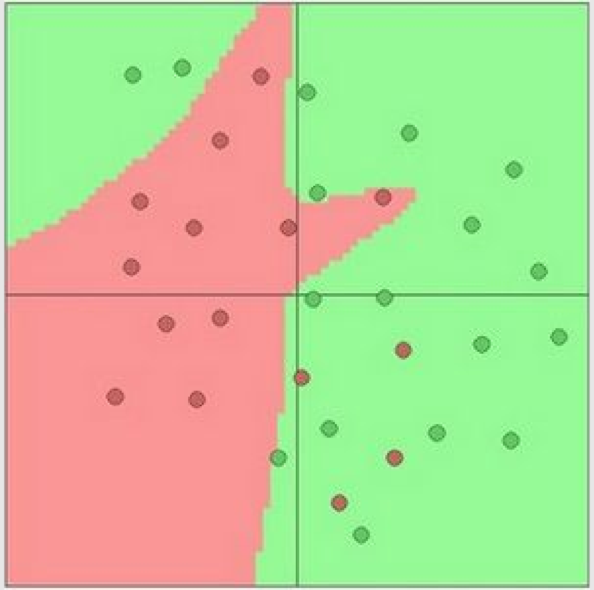
Neural Network Intuition

Toy 2d classification with 2-layer neural network

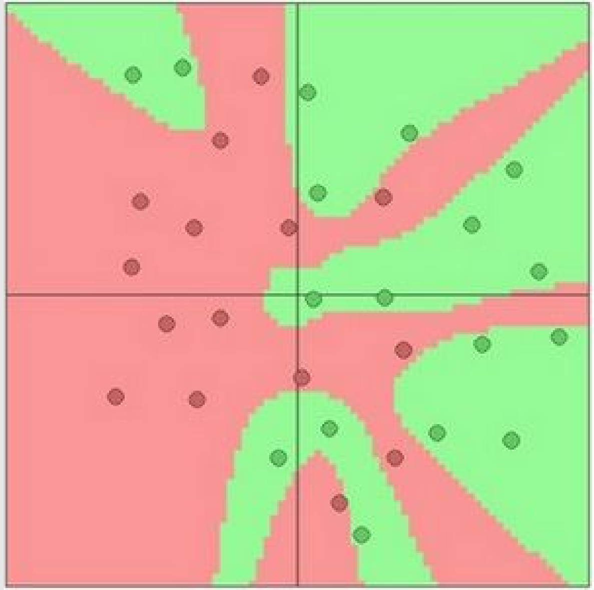
http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html



3 hidden neurons

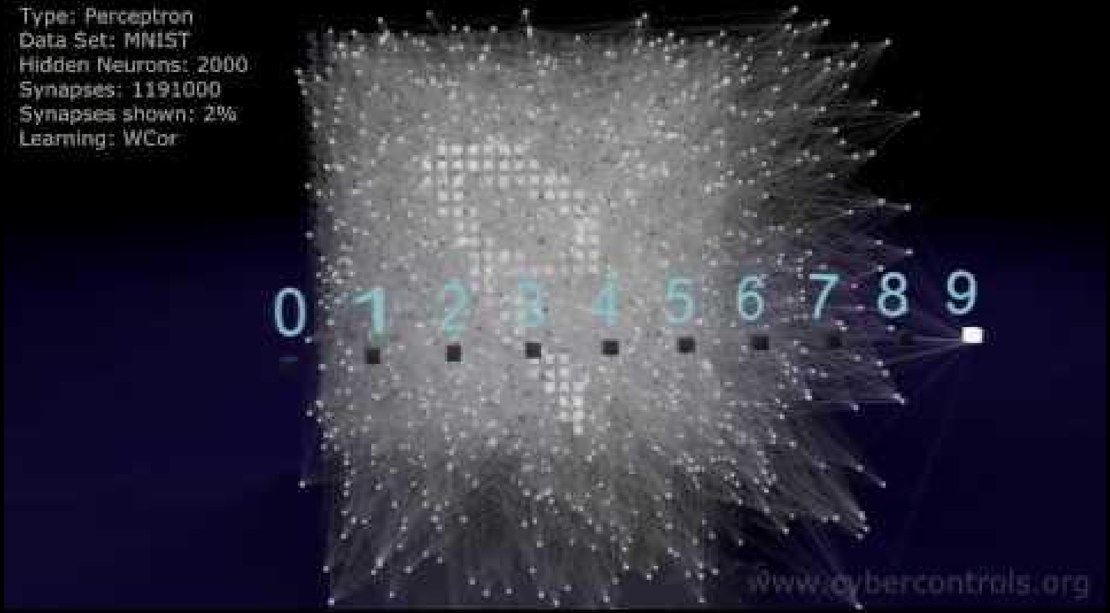


6 hidden neurons



20 hidden neurons

http://cs231n.github.io/assets/nn1/layer_sizes.jpeg



https://youtu.be/3JQ3hYko51Y

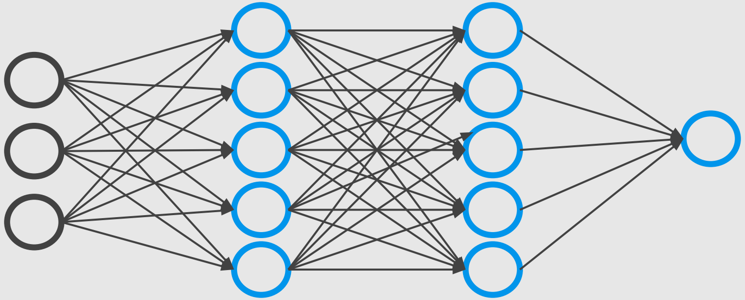
Multi-class Classification

Cat

Dog

Frog

Car

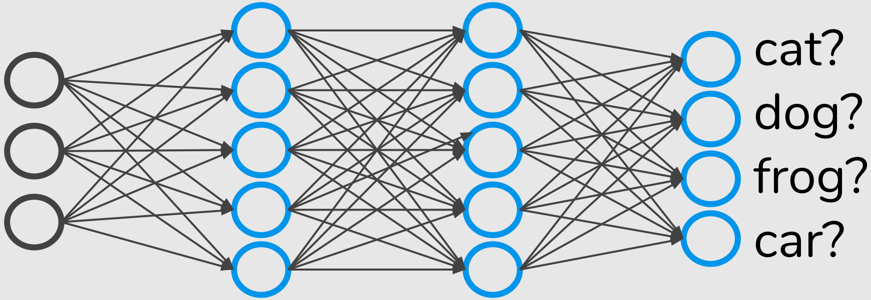


Cat

Dog

Frog

Car

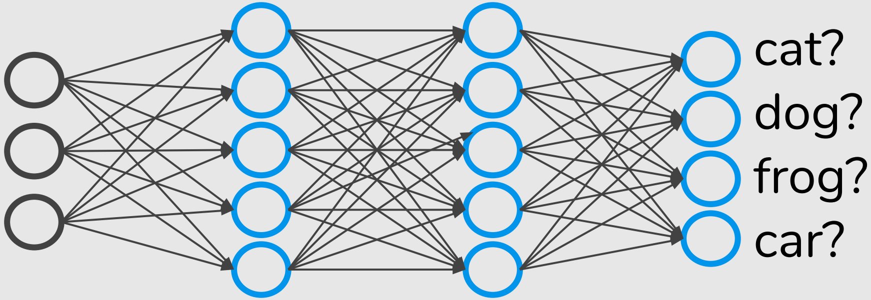


Cat

Dog

Frog

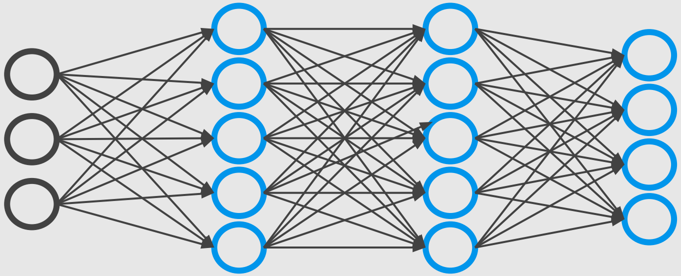
Car



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

when cat when dog when frog when car

Multiple Output Units



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when cat, when dog, when frog, when car

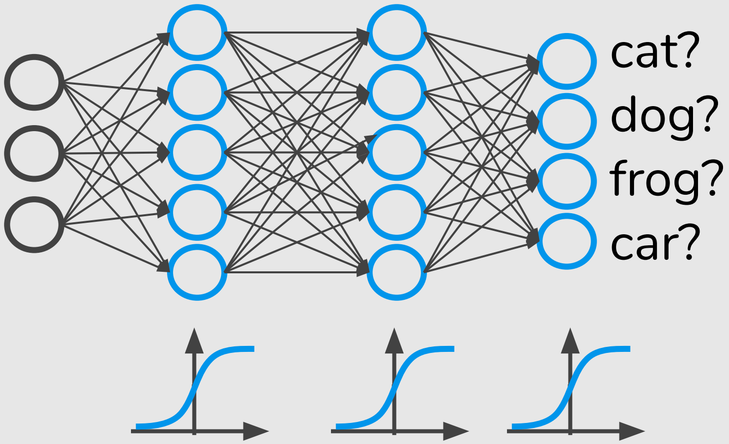
Training Set: $(x^{(1)}, y^{(1)}),\ (x^{(2)}, y^{(2)}),\ \ldots,\ (x^{(m)}, y^{(m)})$

$y^{(i)}$ one of $\begin{bmatrix}1\\0\\0\\0\end{bmatrix}, \begin{bmatrix}0\\1\\0\\0\end{bmatrix}, \begin{bmatrix}0\\0\\1\\0\end{bmatrix}, \begin{bmatrix}0\\0\\0\\1\end{bmatrix}$

Softmax Classification

Softmax Classification

The **output layer** is typically modified **by replacing** the individual activation functions **by a shared softmax** function.



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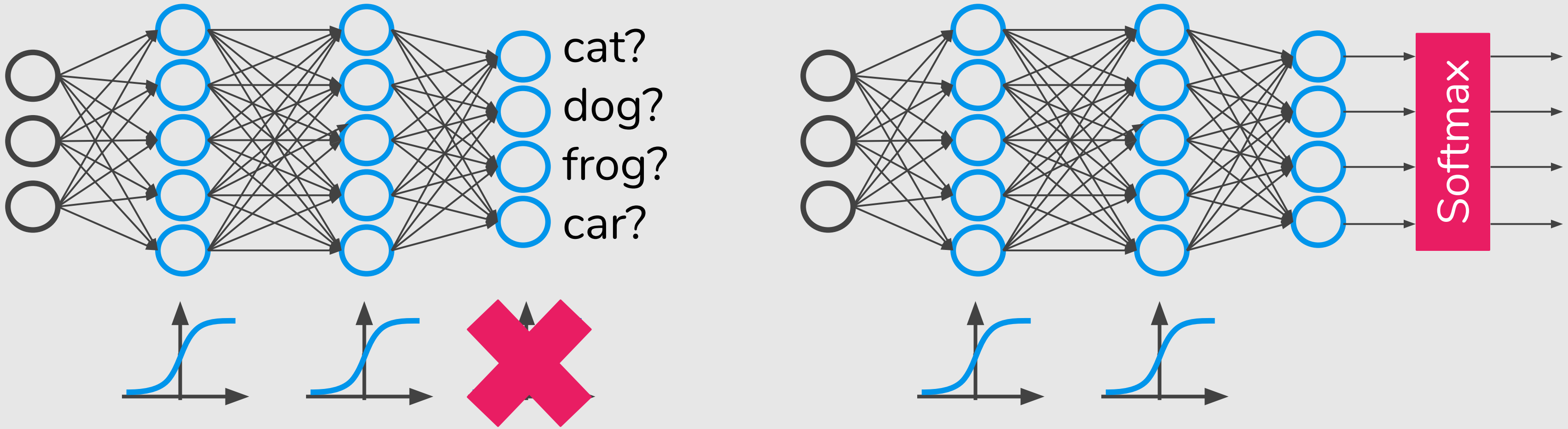

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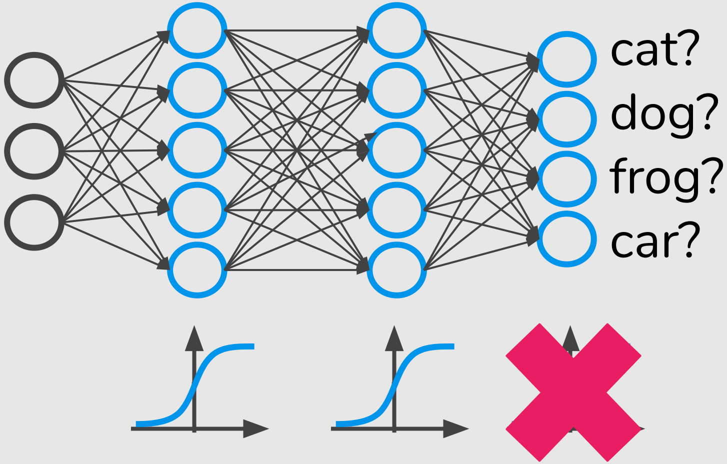

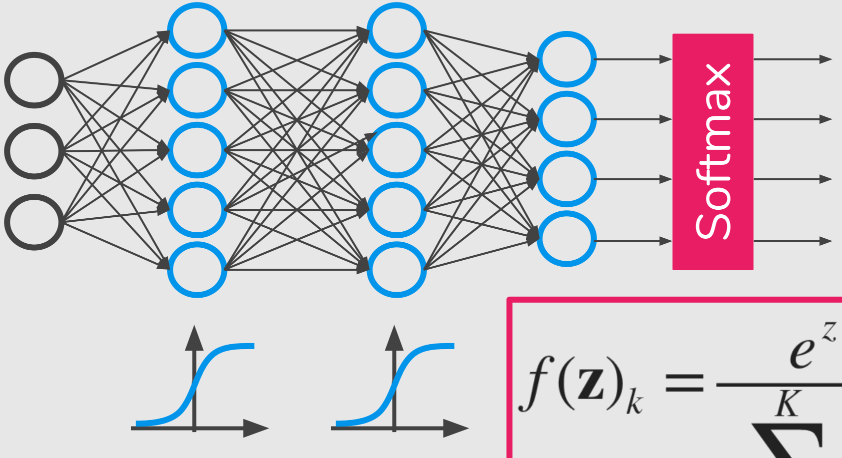

$$f(\mathbf{z})_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

To be continued ...

References

Machine Learning Books

- Hands-On Machine Learning with Scikit-Learn and TensorFlow, Chap. 10
- Pattern Recognition and Machine Learning, Chap. 5
- Pattern Classification, Chap. 6
- Free online book: http://neuralnetworksanddeeplearning.com

Machine Learning Courses

- https://www.coursera.org/learn/machine-learning, Week 4 & 5
- https://www.coursera.org/learn/neural-networks