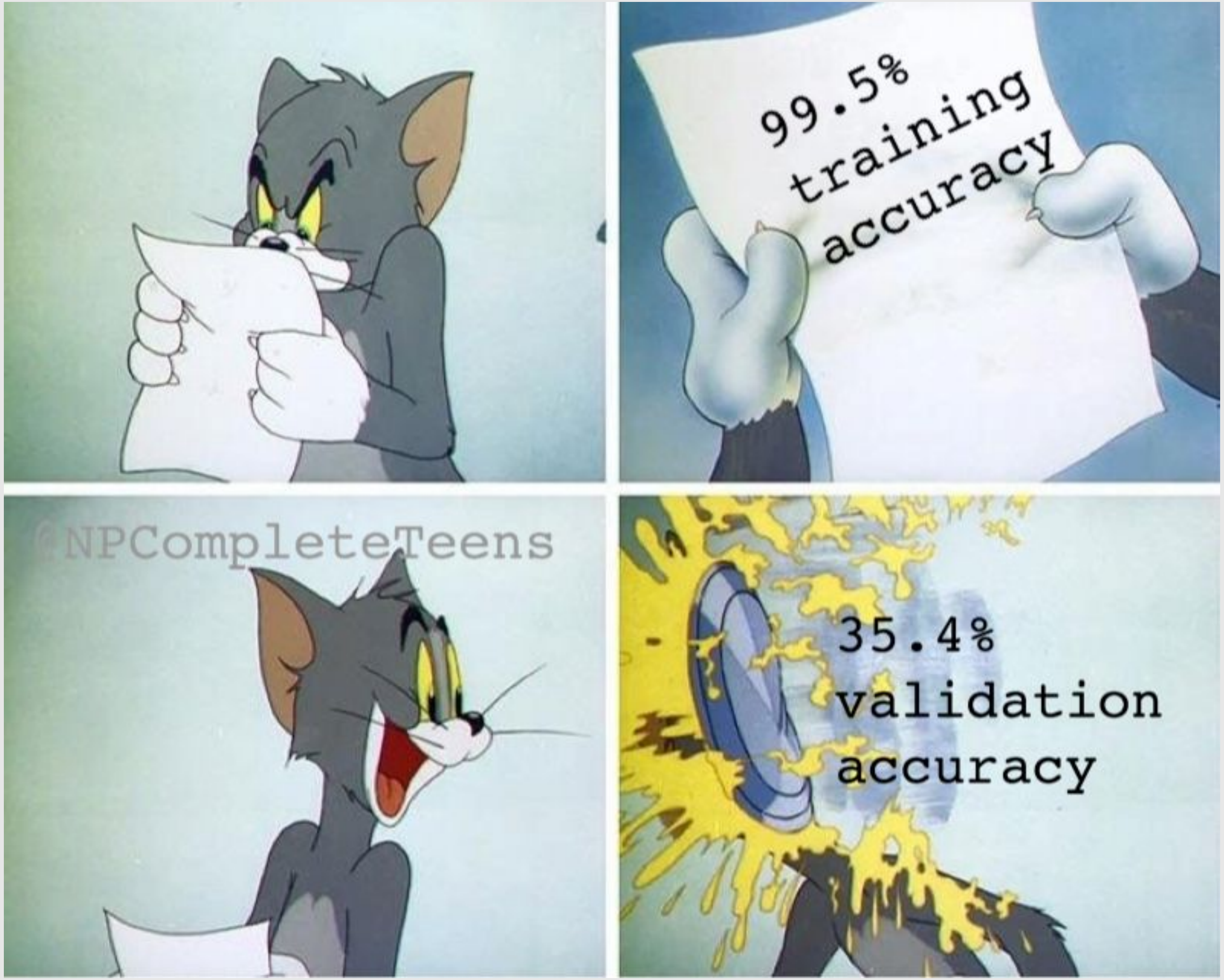

99.5% training accuracy
@NPCompleteTeens
35.4% validation accuracy

Artificial Neural Networks

Machine Learning

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

MC886, September 9, 2019

Many inventions were inspired by Nature ...

Birds inspired us to fly

https://i.pinimg.com/736x/18/4a/cc/184accf6b4d7980d2c2e8090ff295cd7--animal-tracks-friends.jpg

Many inventions were inspired by Nature …

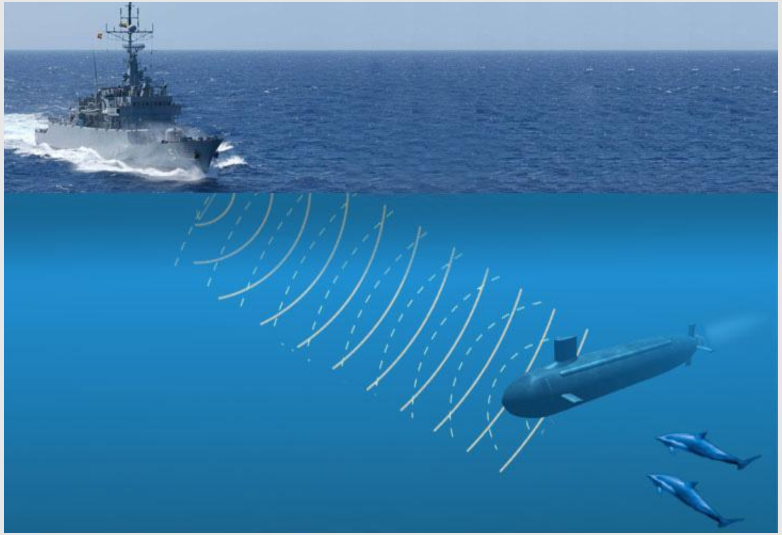
Burdock plants inspired velcro

http://www.youngworldclub.com/wp-content/uploads/2017/04/velcro.jpeg

https://c1.staticflickr.com/3/2887/12882961455_f2d6bee40c_b.jpg

Many inventions were inspired by Nature ...

Dolphins inspired sonar development



https://sites.google.com/site/echolocationkawproject/_/rsrc/1459209762464/sonars/image.jpeg

http://www.dolphinkind.com/images/dolphin_echolocation.jpg

Many inventions were inspired by Nature …

Dogs inspired …

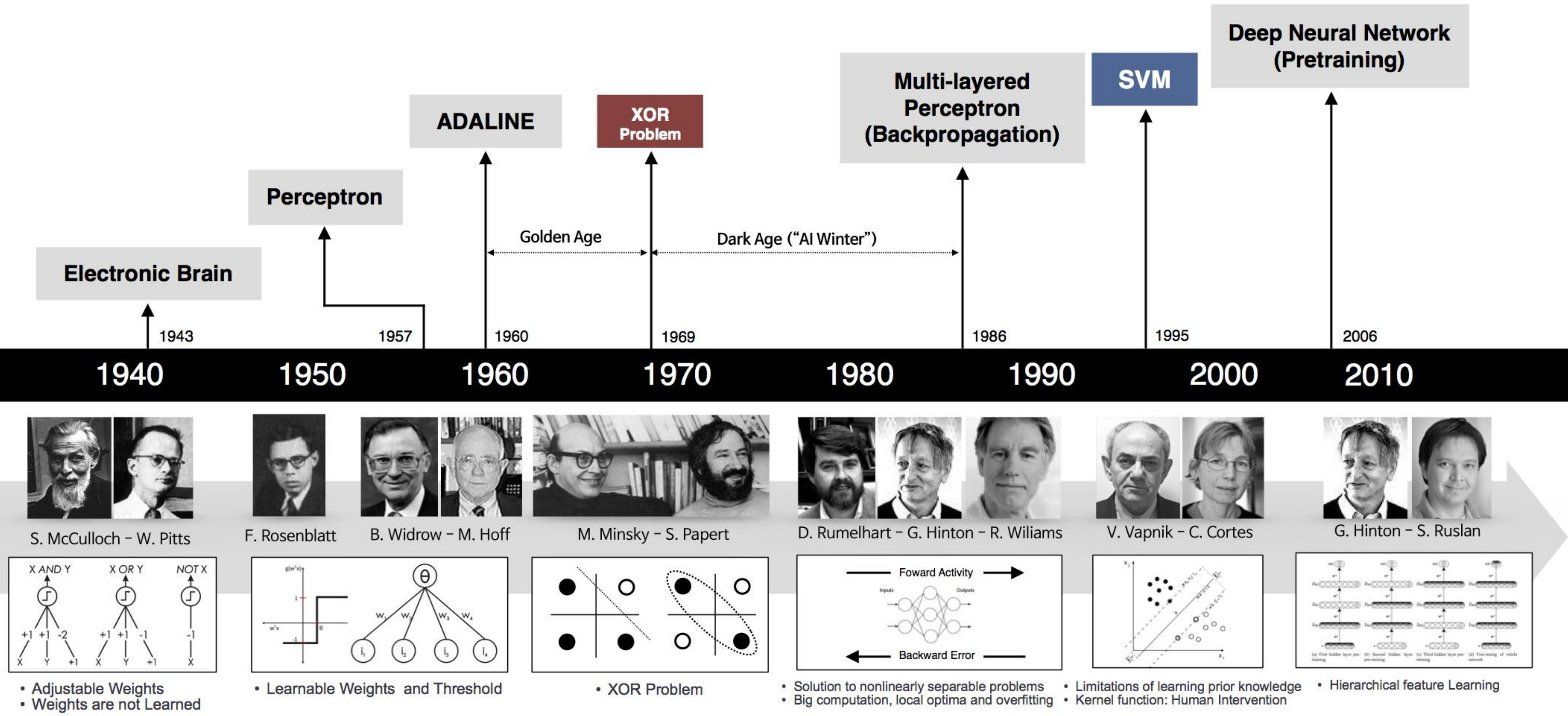
https://farm2.staticflickr.com/1586/24734777053_d1bdb8bba4_o.jpg

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

Today's Agenda

- Artificial Neural Networks
  - From Biological to Artificial Neurons
  - Biological Neurons
  - Logical Computations with Neurons
  - The Perceptron
  - Examples
  - Neural Network

From Biological to Artificial Neurons



Deep Neural Network (Pretraining)
SVM
Multi-layered Perceptron (Backpropagation)
XOR Problem
ADALINE
Perceptron
Electronic Brain
Golden Age
Dark Age ("AI Winter")
1943
1957
1960
1969
1986
1995
2006
1940
1950
1960
1970
1980
1990
2000
2010
S. McCulloch – W. Pitts
F. Rosenblatt
B. Widrow – M. Hoff
M. Minsky – S. Papert
D. Rumelhart – G. Hinton – R. Wiliams
V. Vapnik – C. Cortes
G. Hinton – S. Ruslan
X AND Y
X OR Y
NOT X
Foward Activity
Backward Error
• Adjustable Weights
• Weights are not Learned
• Learnable Weights and Threshold
• XOR Problem
• Solution to nonlinearly separable problems
• Big computation, local optima and overfitting
• Limitations of learning prior knowledge
• Kernel function: Human Intervention
• Hierarchical feature Learning

References

- “A logical calculus of the ideas immanent in nervous activity”, 1943: https://link.springer.com/content/pdf/10.1007%2FBF02478259.pdf
- “The Perceptron: A perceiving and recognizing automaton”, 1957 https://www.import.io/wp-content/uploads/2017/06/rosenblatt-1957.pdf
- “Perceptrons: An Introduction to Computational Geometry”, 1969
- “Learning representations by back-propagating errors”, 1986 https://www.nature.com/articles/323533a0

  https://web.stanford.edu/class/psych209a/ReadingsByDate/02_06/PDPVolIChapter8.pdf

IMAGENET

ILSVRC 2012 — Image Classification task

<table>
<tr><th>Rank</th><th>Name</th><th>Error Rate (%)</th><th>Description</th></tr>
<tr><td>1</td><td>University of Toronto</td><td></td><td>Deep Learning</td></tr>
<tr><td>2</td><td>University of Tokyo</td><td>26.2</td><td rowspan="3">Hand-crafted features and learning models</td></tr>
<tr><td>3</td><td>University of Oxford</td><td>26.9</td></tr>
<tr><td>4</td><td>Xerox/INRIA</td><td>27.0</td></tr>
</table>

Object recognition over 1,000,000 images and 1,000 categories (2 GPU)

“ImageNet classification with deep convolutional neural networks”. NIPS, 2012.

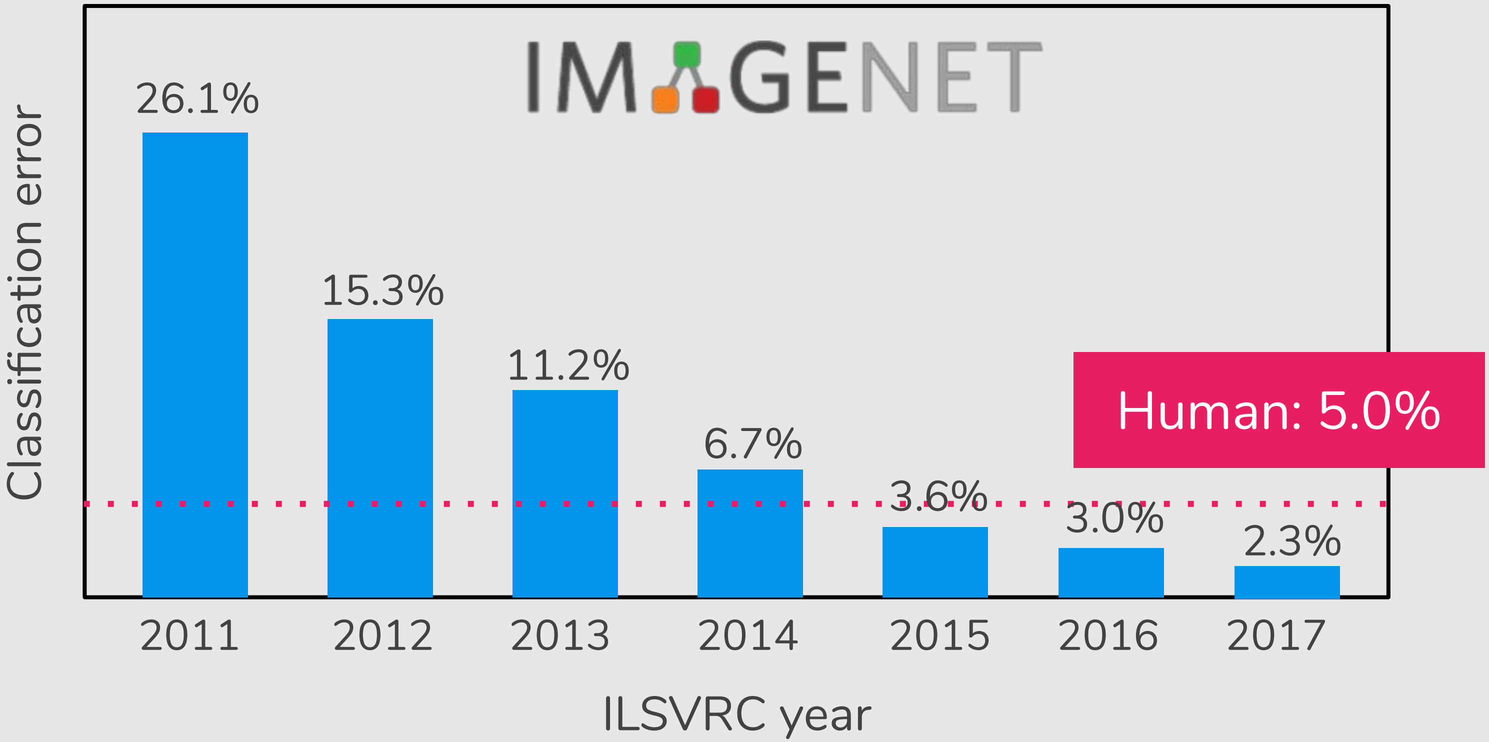
IMAGENET

ILSVRC 2012 — Image Classification task

Rank	Name	Error Rate (%)	Description
1	University of Toronto	**15.3**	Deep Learning
2	University of Tokyo	26.2	Hand-crafted features and learning models
3	University of Oxford	26.9	
4	Xerox/INRIA	27.0	

Object recognition over 1,000,000 images and 1,000 categories (2 GPU)

"ImageNet classification with deep convolutional neural networks". NIPS, 2012.



“ImageNet classification with deep convolutional neural networks”. NIPS, 2012.

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

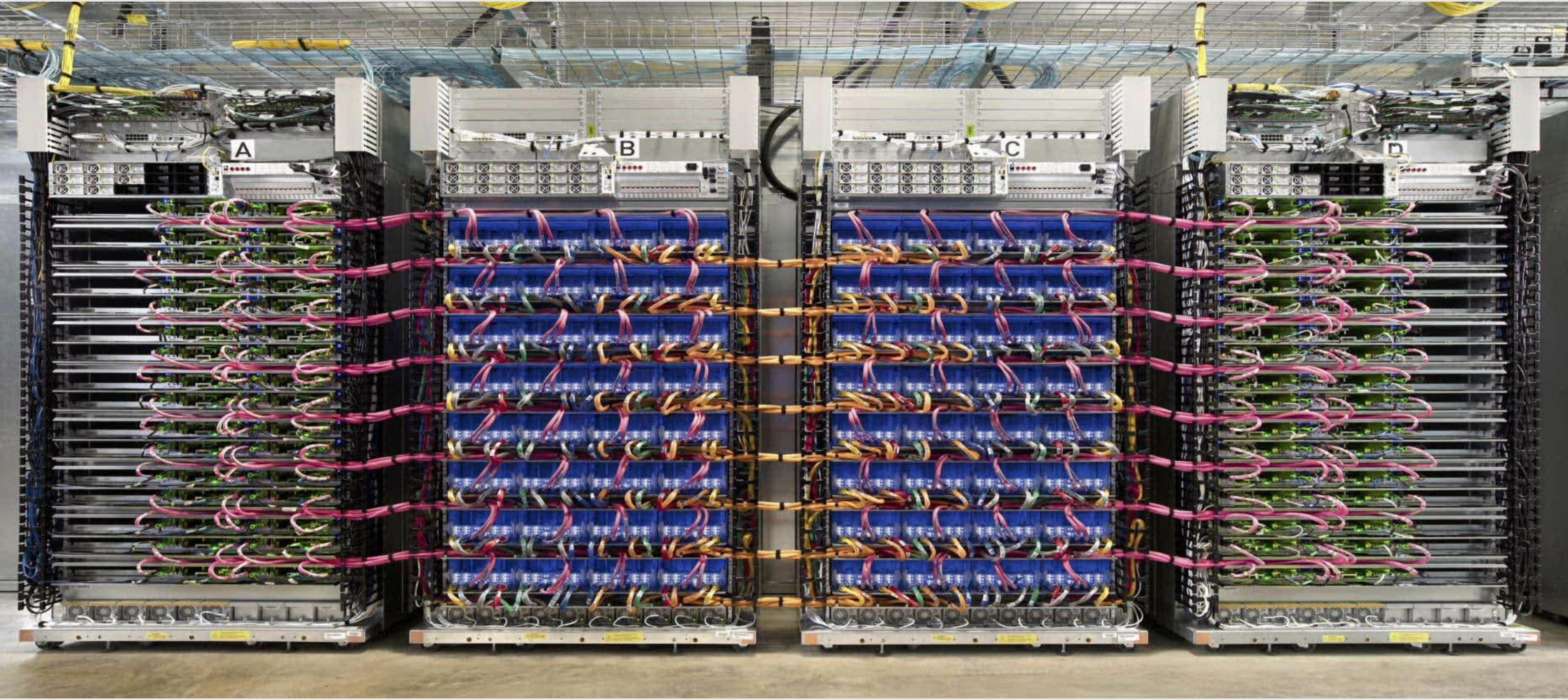
22K categories and 14M images

- Animals
  - 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

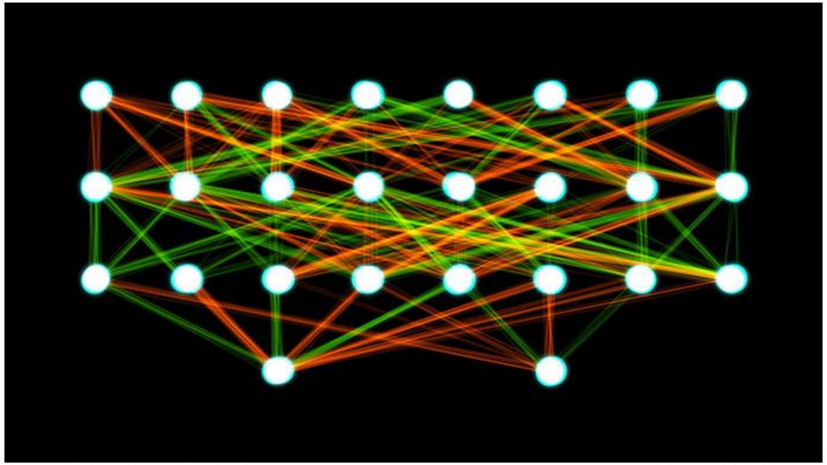
1. There is now a **huge quantity of data** available to train neural networks.
2. **Computing power** now makes it possible to train large neural networks in a reasonable amount of time.



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**.



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

Grad-CAM for cat

Grad-CAM for dog

“Grad-CAM++: Improved Visual Explanations for Deep Convolutional Networks”, https://arxiv.org/abs/1710.11063

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

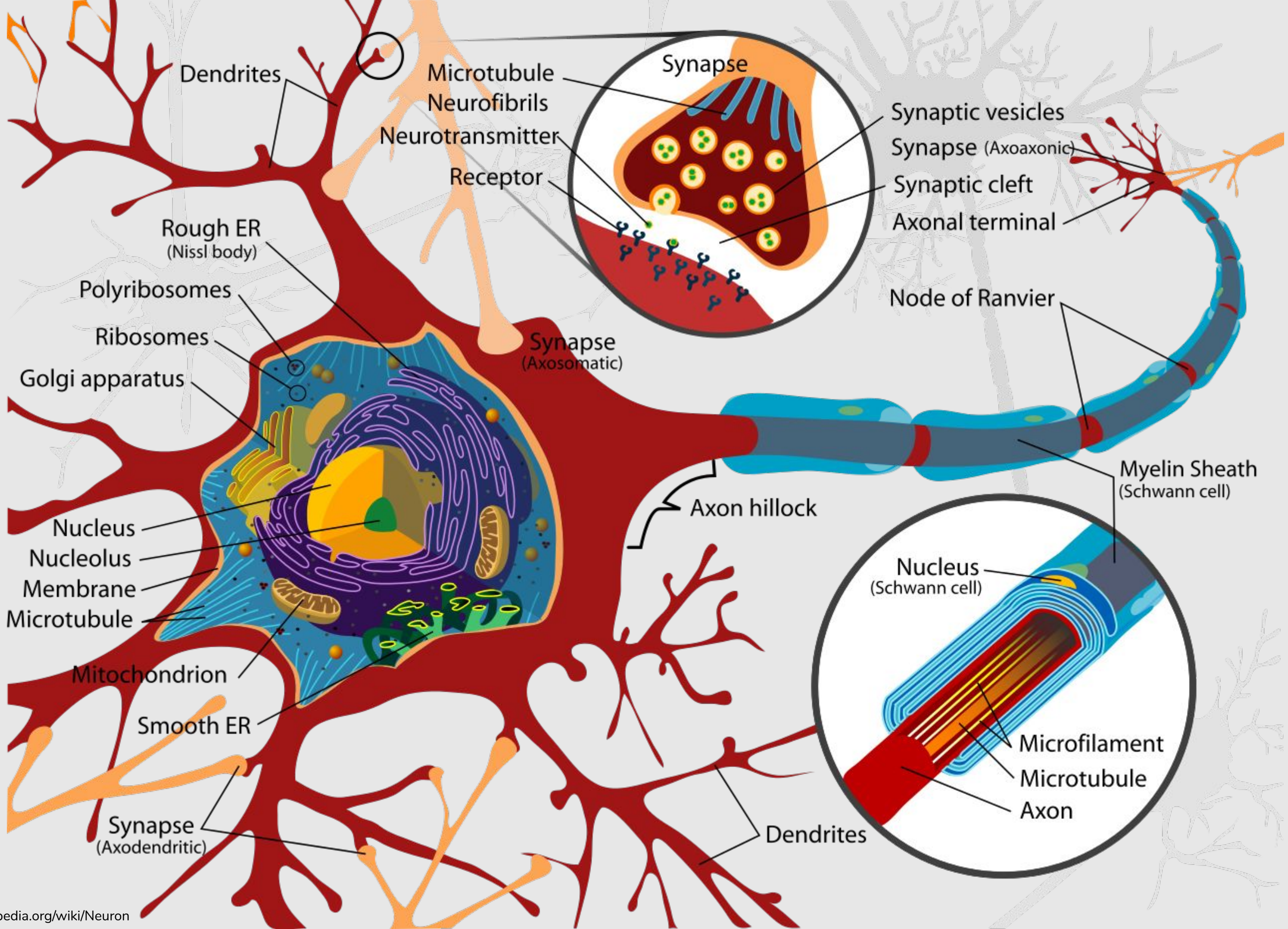
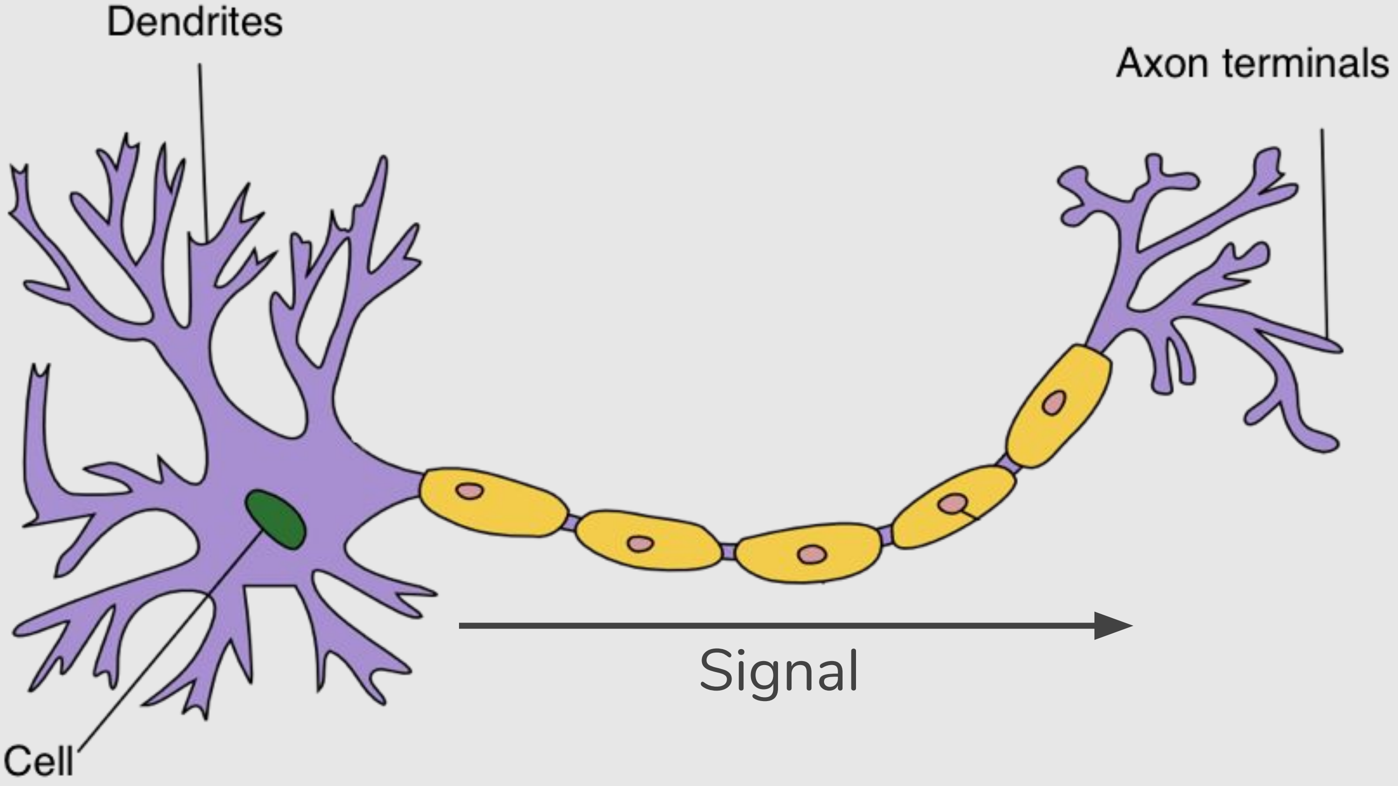
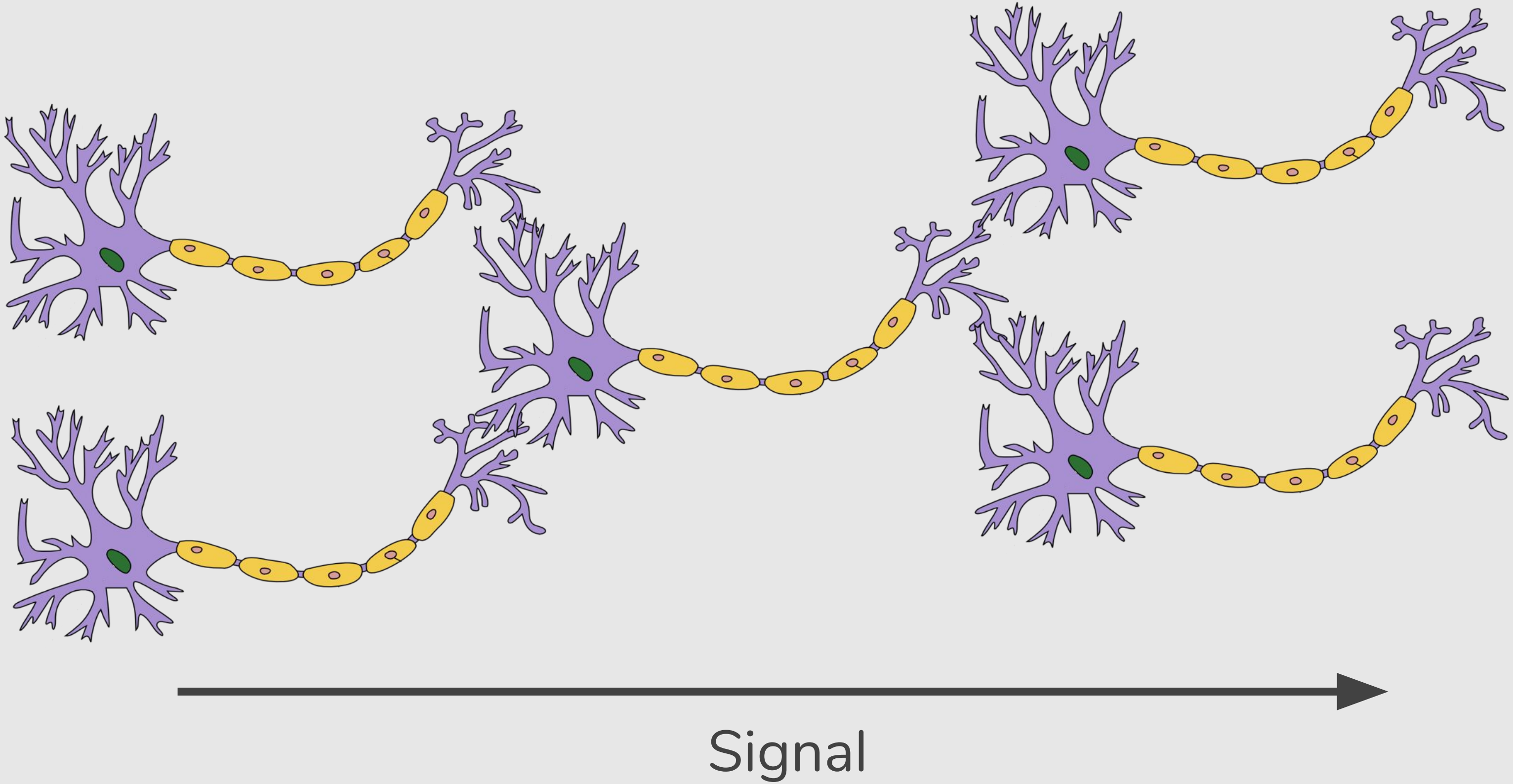


Image Credit: https://en.wikipedia.org/wiki/Neuron

https://www.youtube.com/watch?v=A9Xru1ReRwc



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



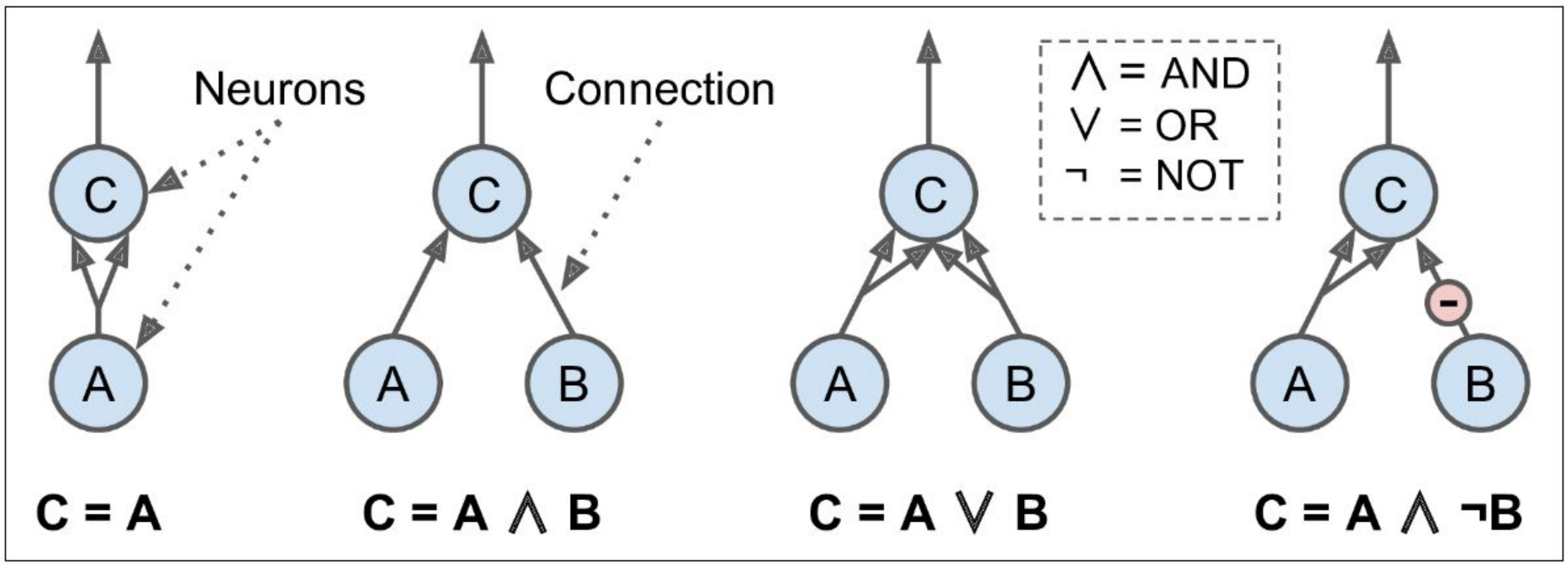
http://www.jeremyjordan.me/content/images/2017/06/Neuron_Hand-tuned.png

Logical Computations with Neurons

Logical Computations with Neurons

McCulloch and Pitts (1943) proposed a very simple model:

- It has one or more binary (on/off) inputs and one binary output.
- The artificial neuron **simply** activates its output when more than a certain number of its inputs are active.



Artificial Neural Networks performing simple logical computations

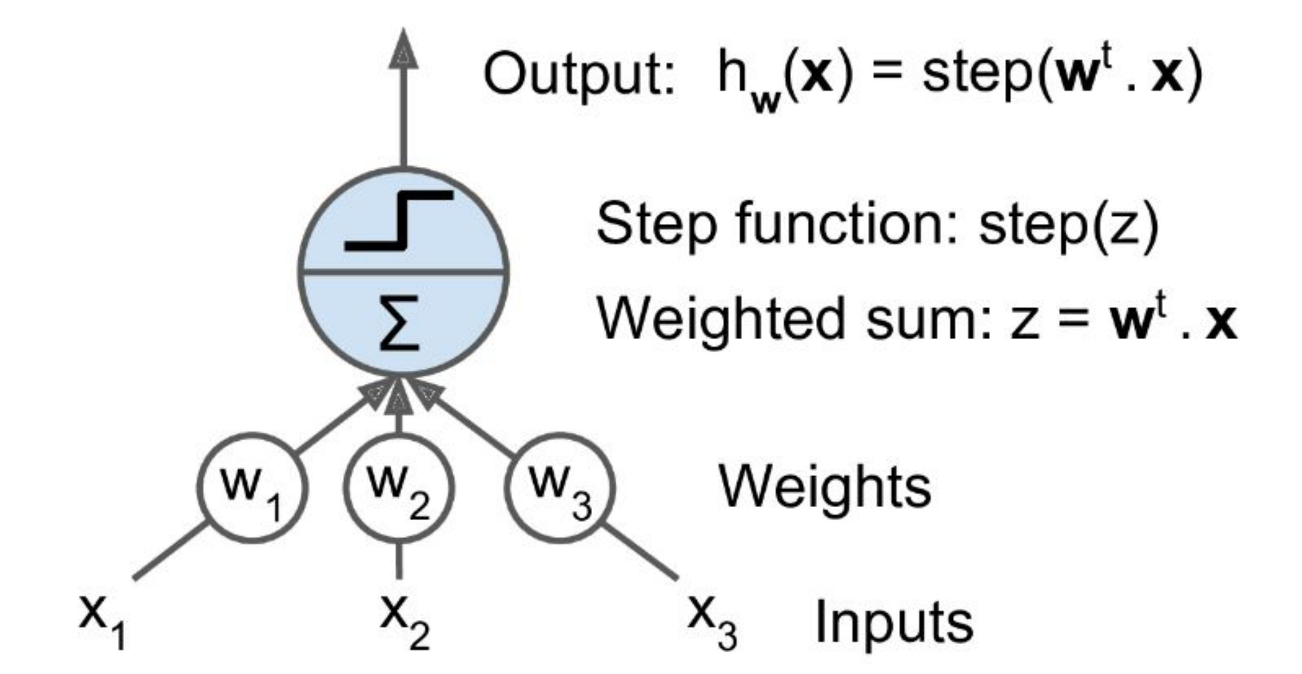
The Perceptron

The Perceptron

Invented in 1957 by Frank Rosenblatt.

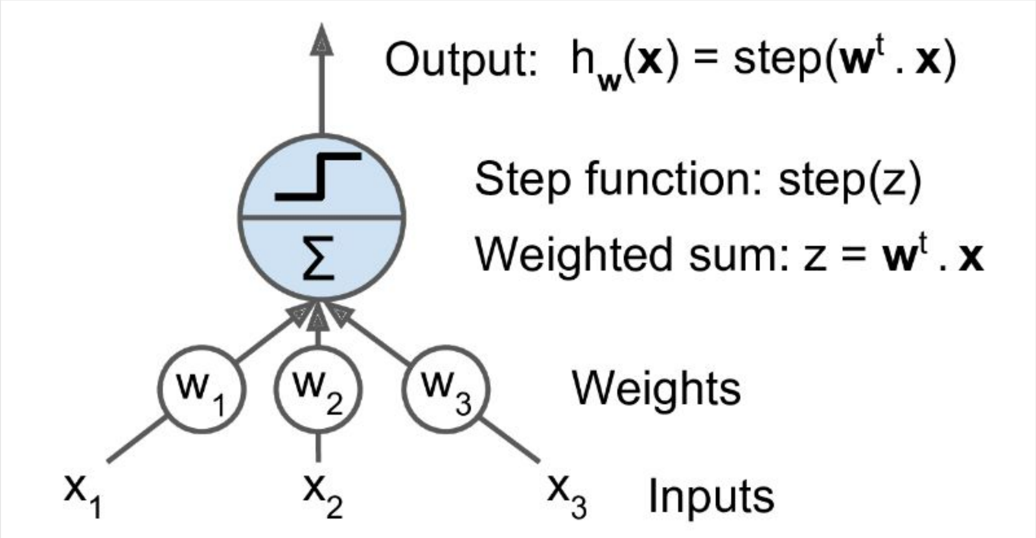
- It is based on a Linear Threshold Unit (LTU):
  - The inputs and output are now **numbers** (instead of binary on/off values) and each input connection is associated with a **weight**.
- The LTU computes a weighted sum of its inputs then it applies a step function to that sum and outputs the result.

The Perceptron



Linear Threshold Unit

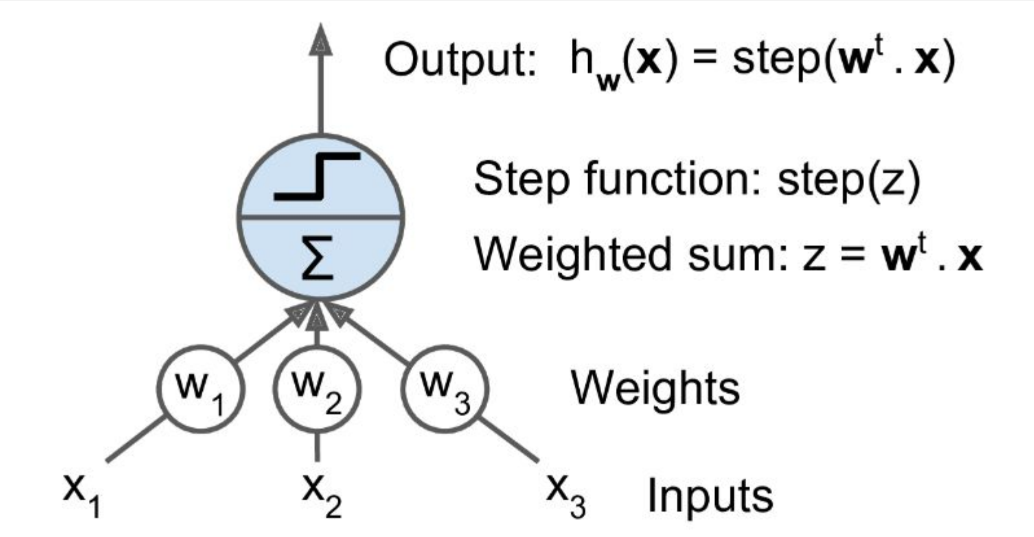
The Perceptron



Linear Threshold Unit

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

The Perceptron

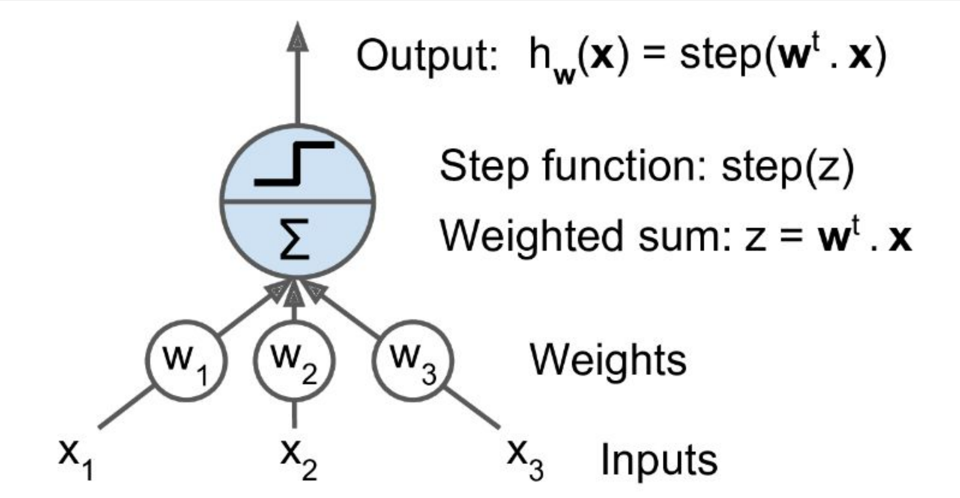


Linear Threshold Unit

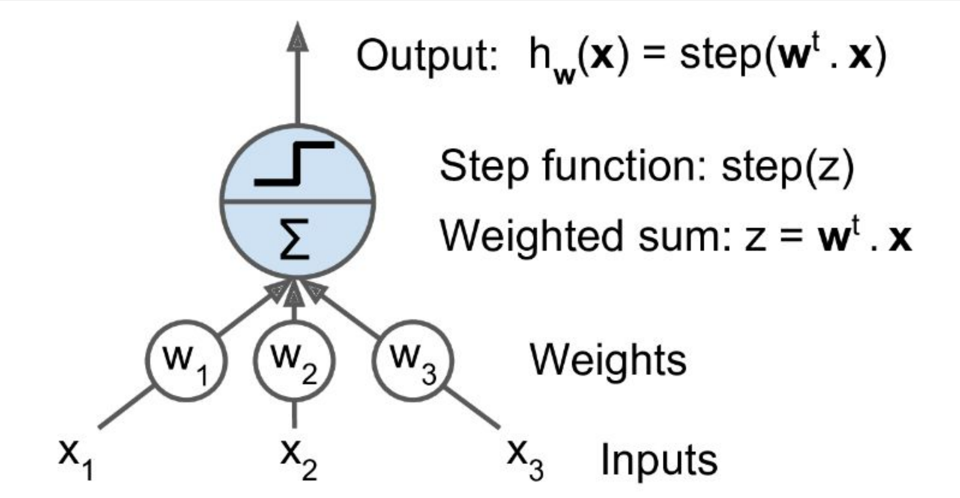
$$\text{heaviside}(z) = \begin{cases} 0 & \text{if } z < 0 \\ 1 & \text{if } z \geq 0 \end{cases}$$

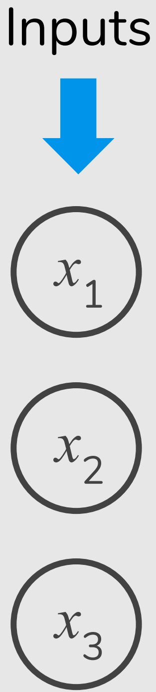
$$\text{sign}(z) = \begin{cases} -1 & \text{if } z < 0 \\ 0 & \text{if } z = 0 \\ +1 & \text{if } z > 0 \end{cases}$$

Neuron Model: Logistic Unit



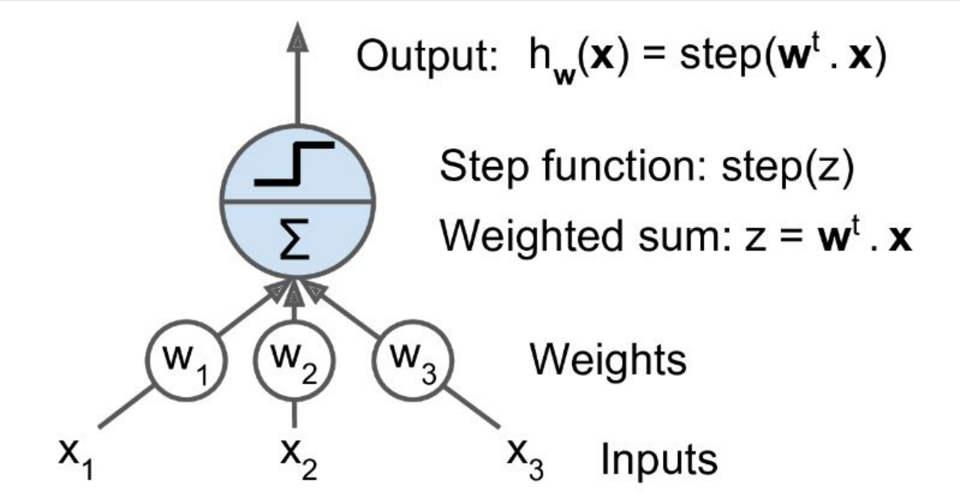
Neuron Model: Logistic Unit

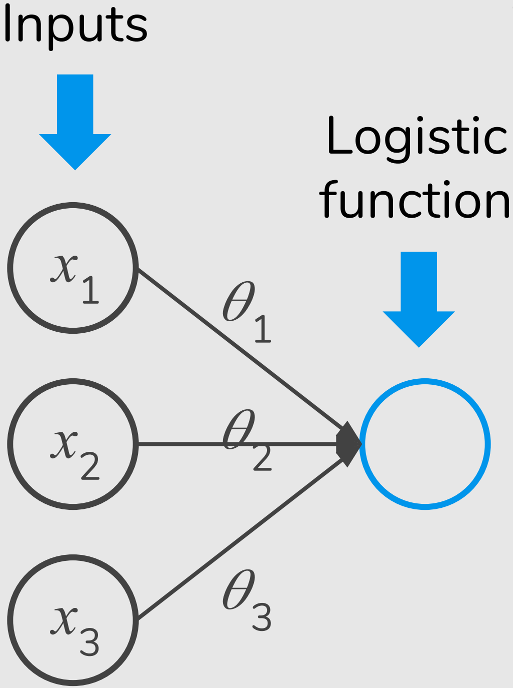




Neuron Model: Logistic Unit

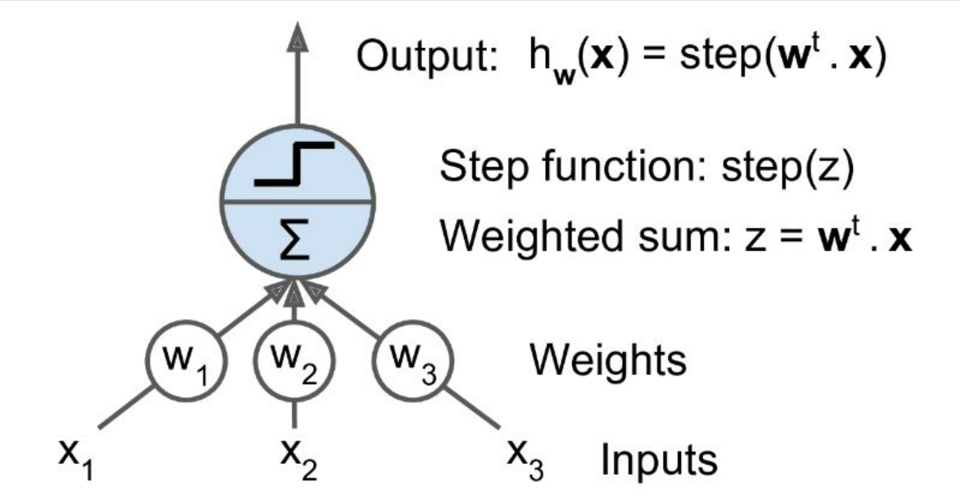
$$\frac{1}{1+e^{-\theta^T x}}$$

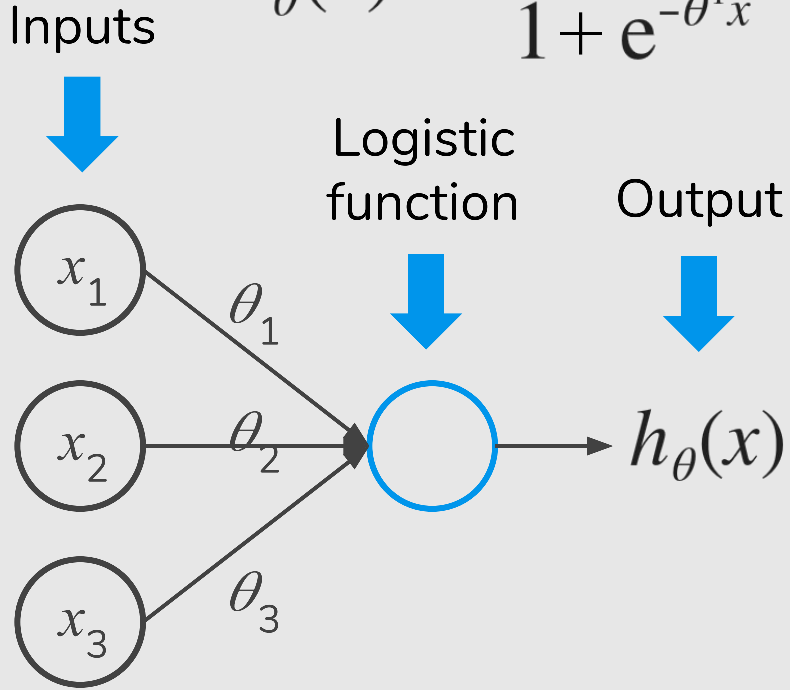




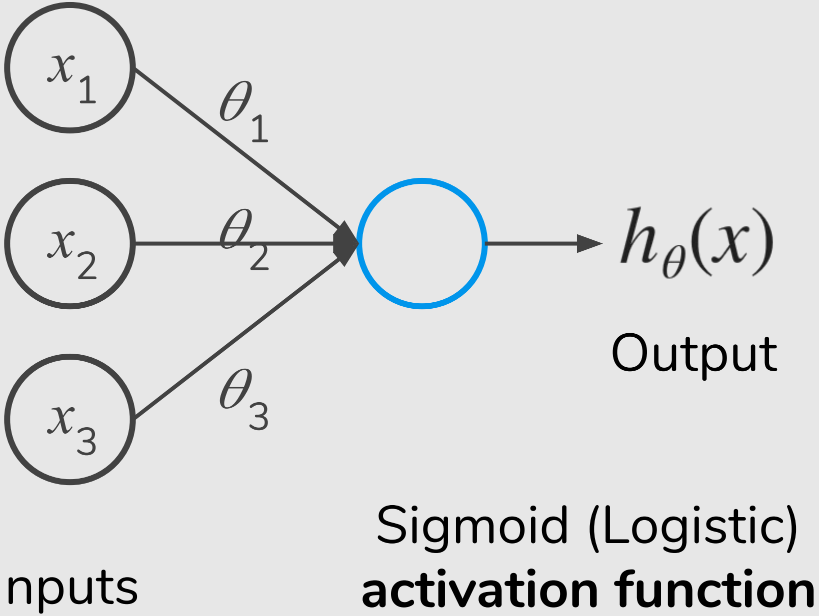
Neuron Model: Logistic Unit

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





Neuron Model: Logistic Unit



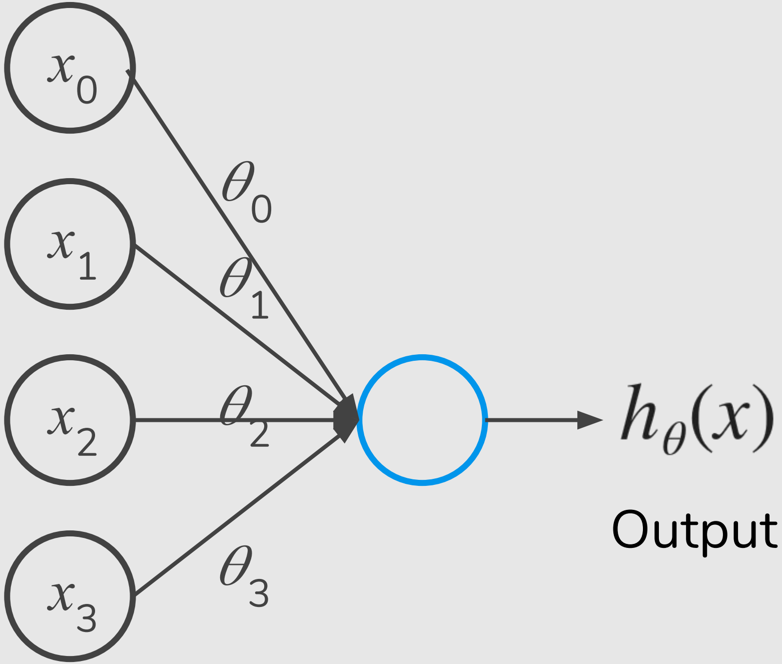
weights

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

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

weights

Neuron Model: Logistic Unit



Inputs

Sigmoid (Logistic)
activation function

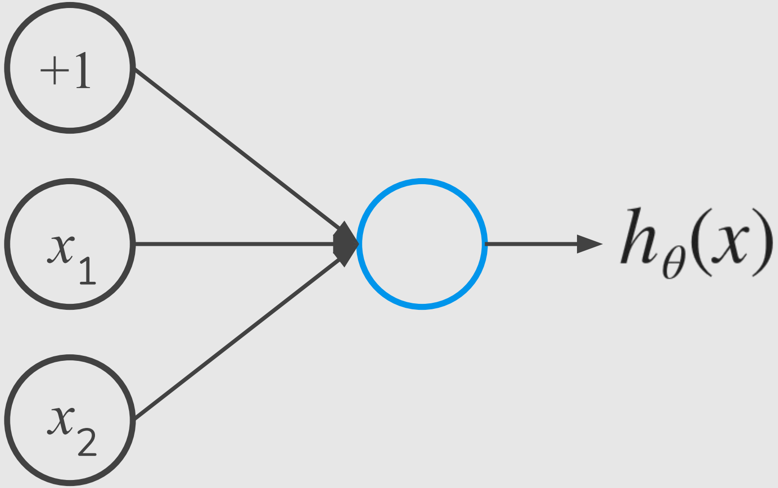
$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

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

Examples

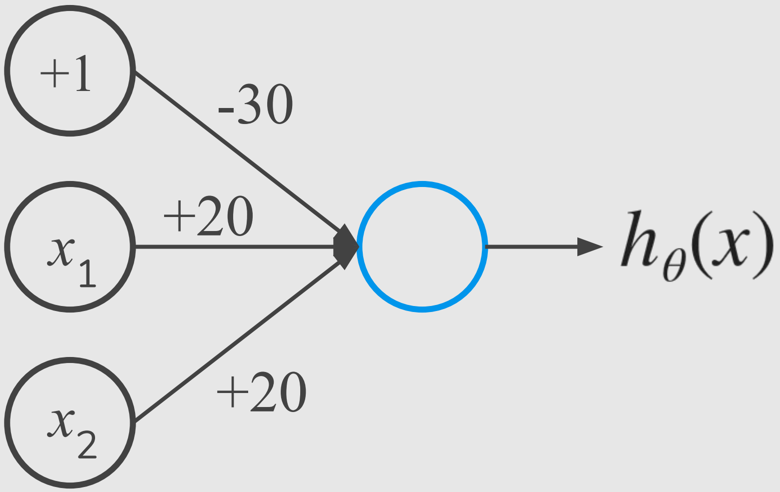
Simple Example: AND

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



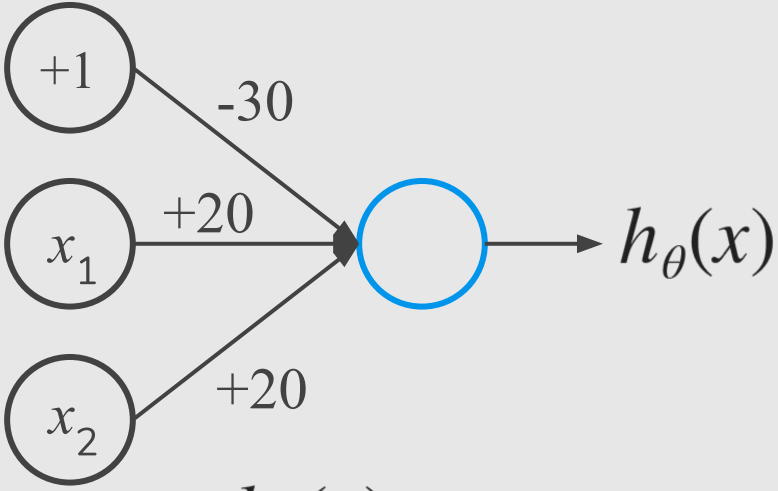
Simple Example: AND

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



Simple Example: AND

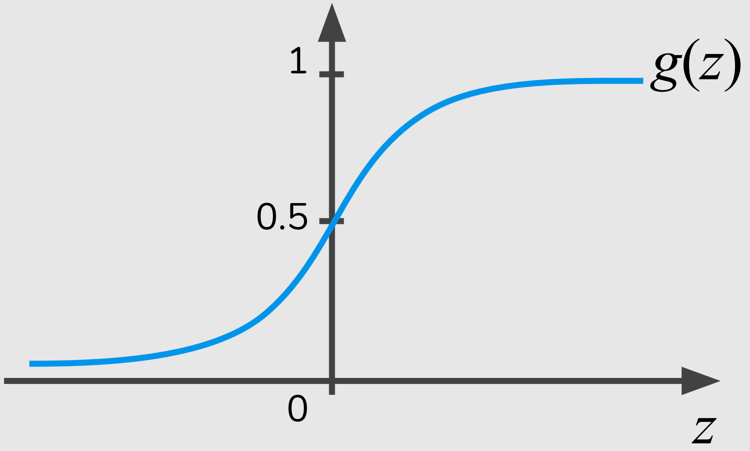
$x_1, x_2 \in \{0,1\}$ $y = x_1$ AND x_2

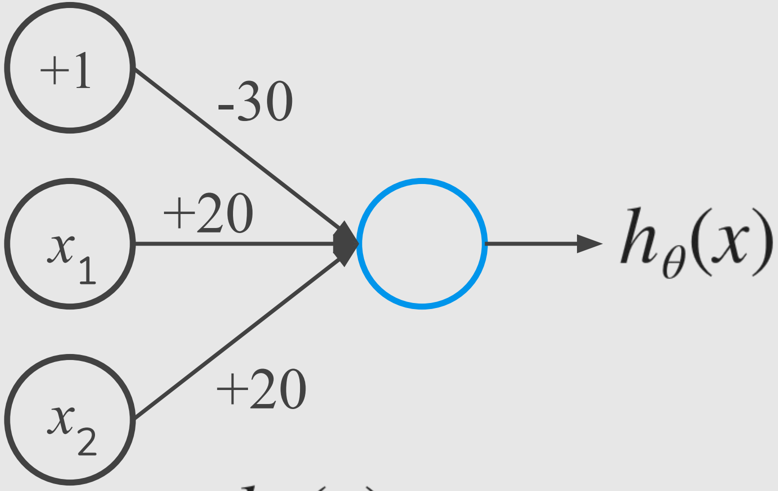


$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

Simple Example: AND

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



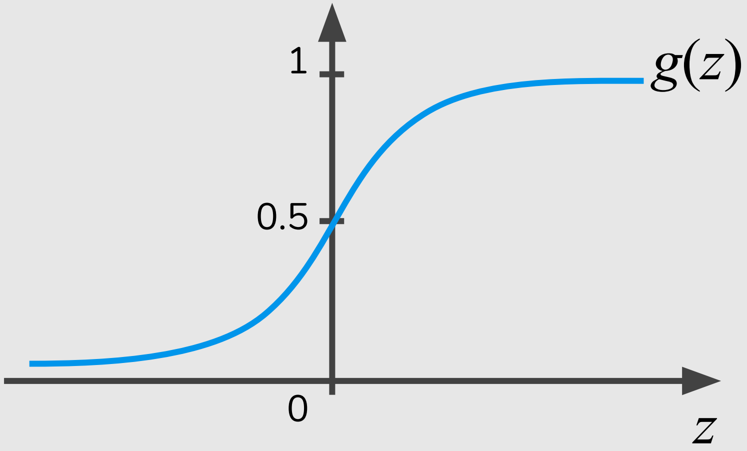


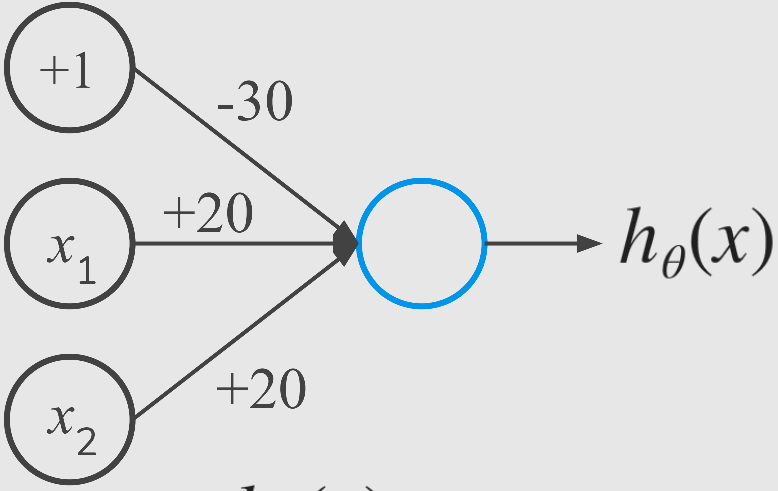
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

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

Simple Example: AND

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



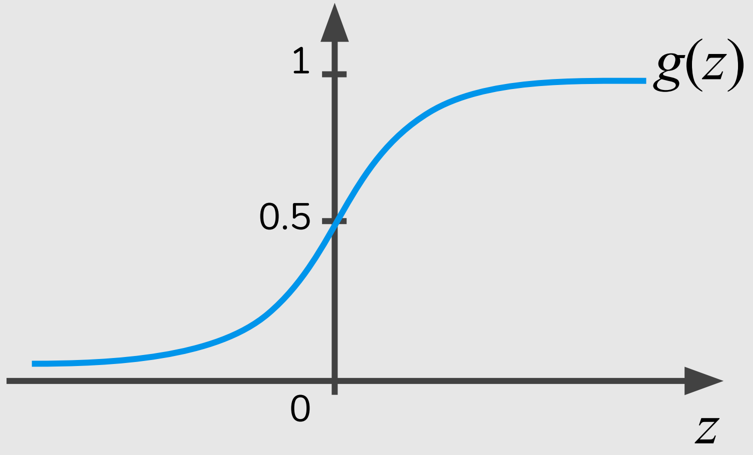


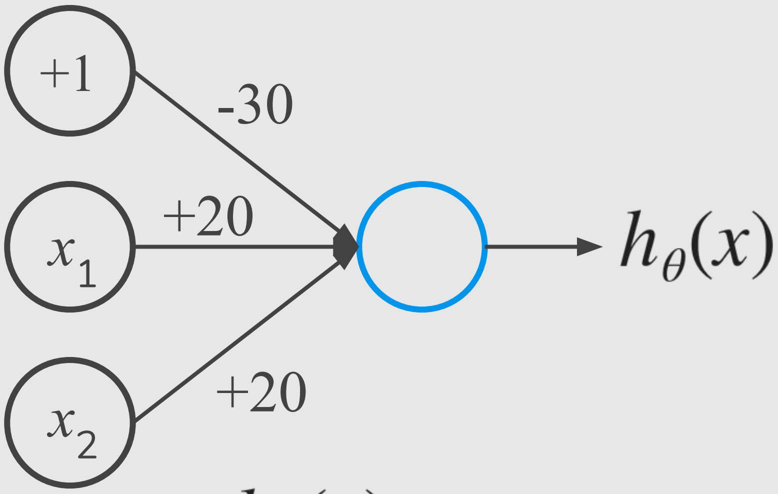
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	
1	0	
1	1	

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

Simple Example: AND

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



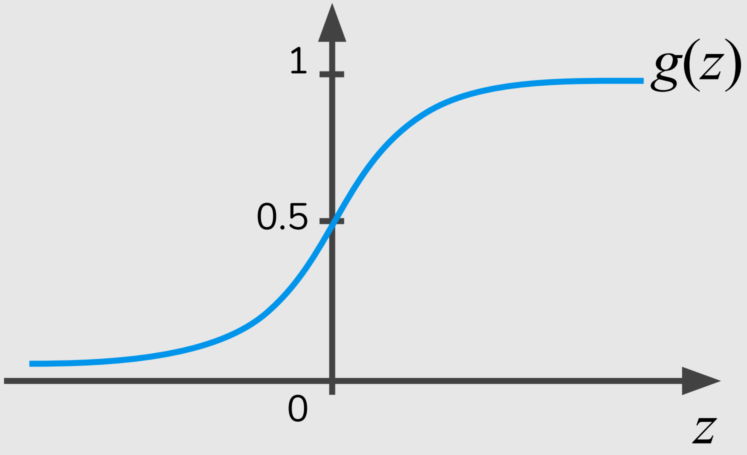


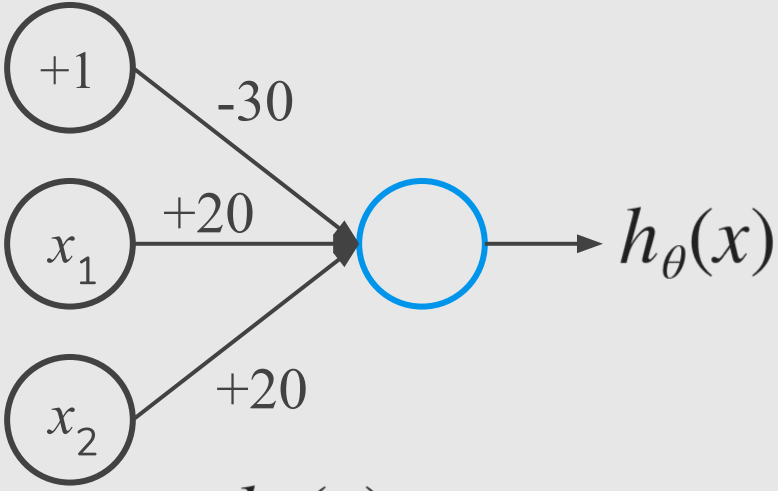
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	
1	1	

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

Simple Example: AND

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



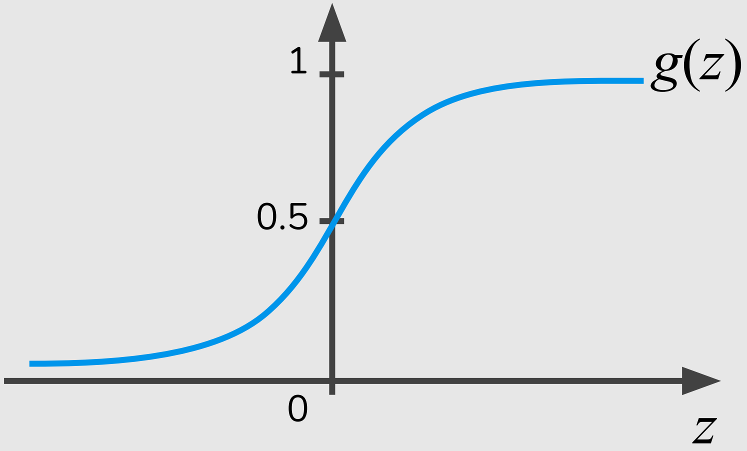


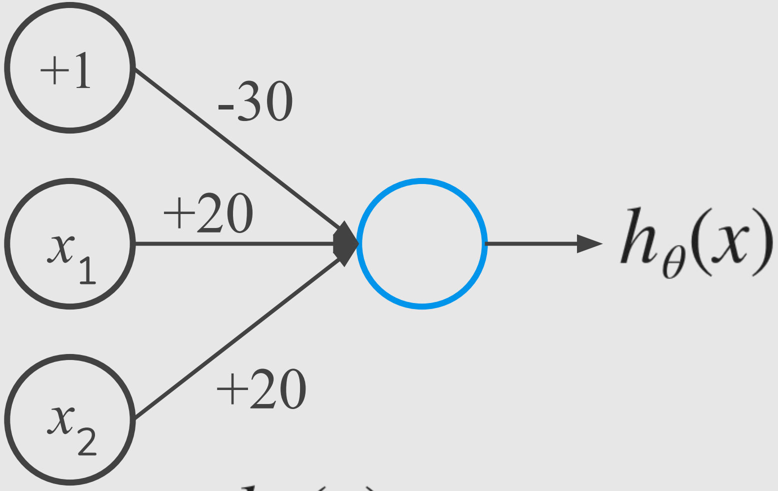
$$h_\theta(x) = g(-30 + 20x_1 + 20x_2)$$

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	

Simple Example: AND

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



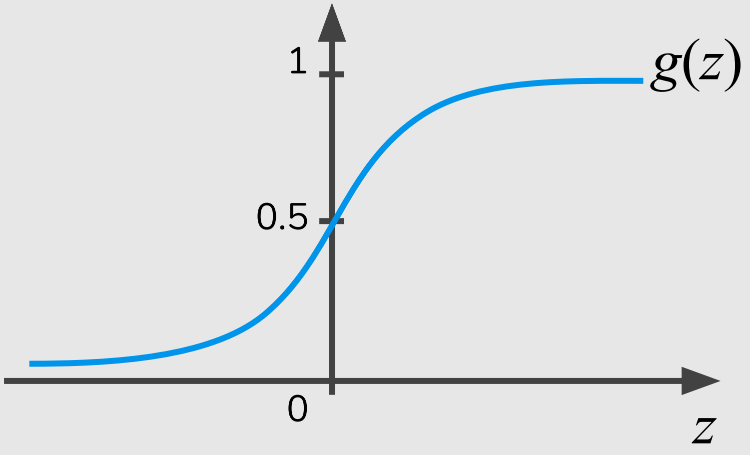


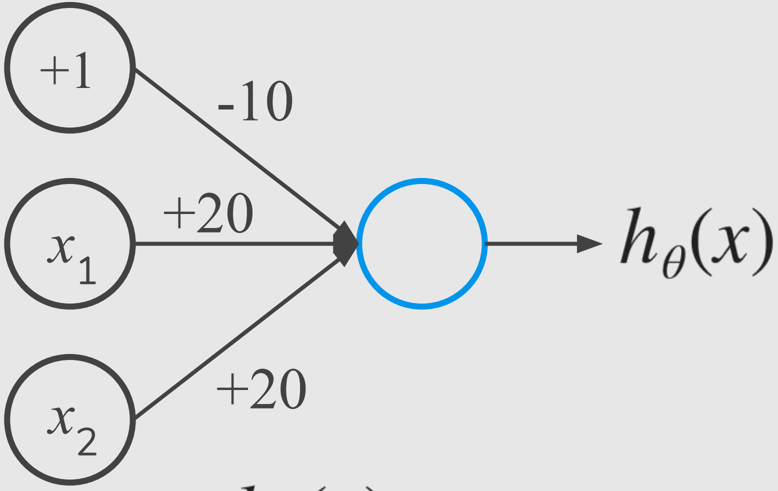
x_1	x_2	$h_\theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

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

Simple Example: OR

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



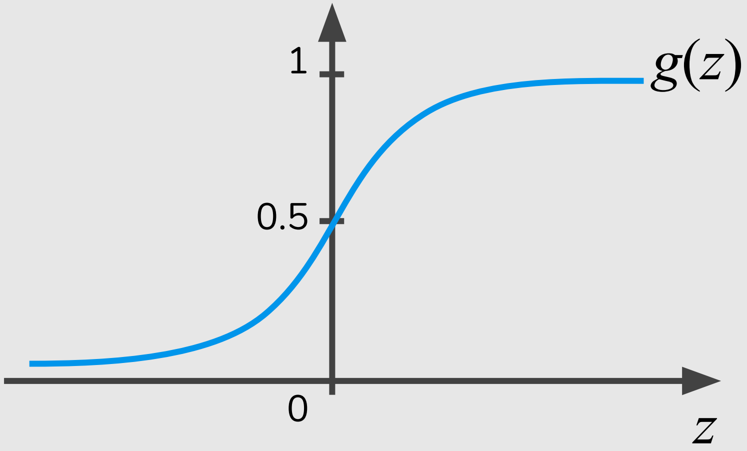


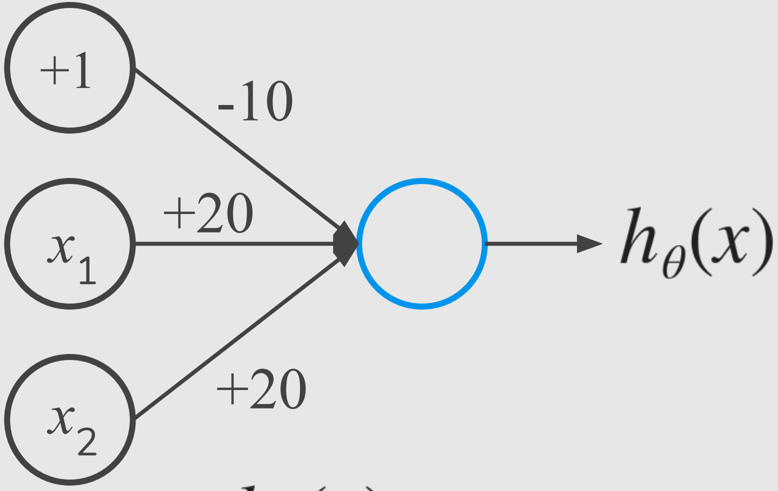
x_1	x_2	$h_\theta(x)$
0	0	
0	1	
1	0	
1	1	

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

Simple Example: OR

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



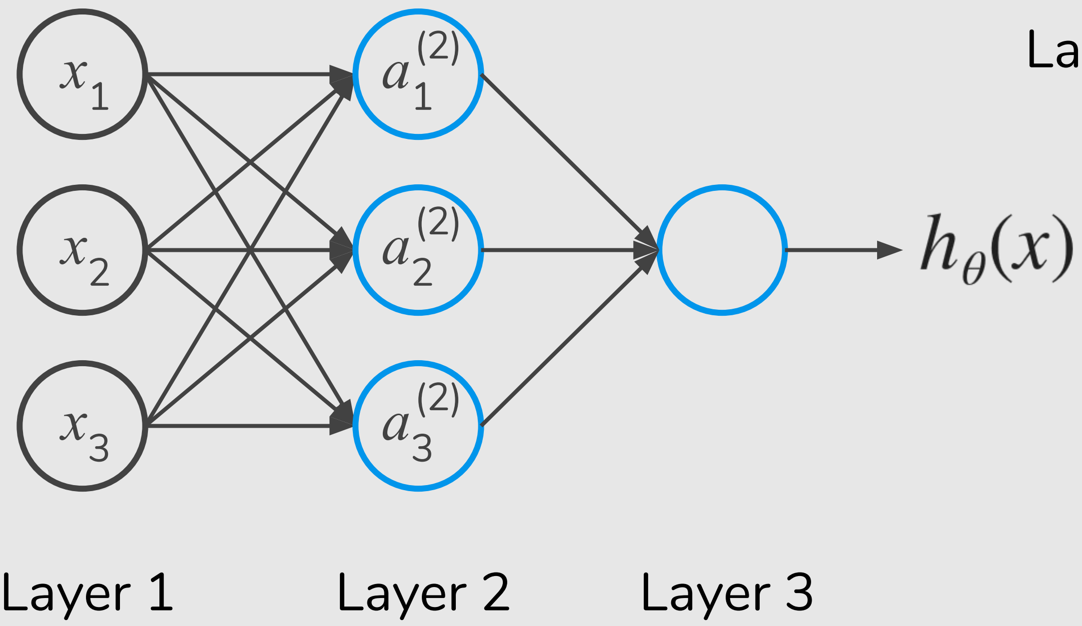


x_1	x_2	$h_\theta(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	$g(10) \approx 1$
1	1	$g(30) \approx 1$

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

Neural Network

Neural Network

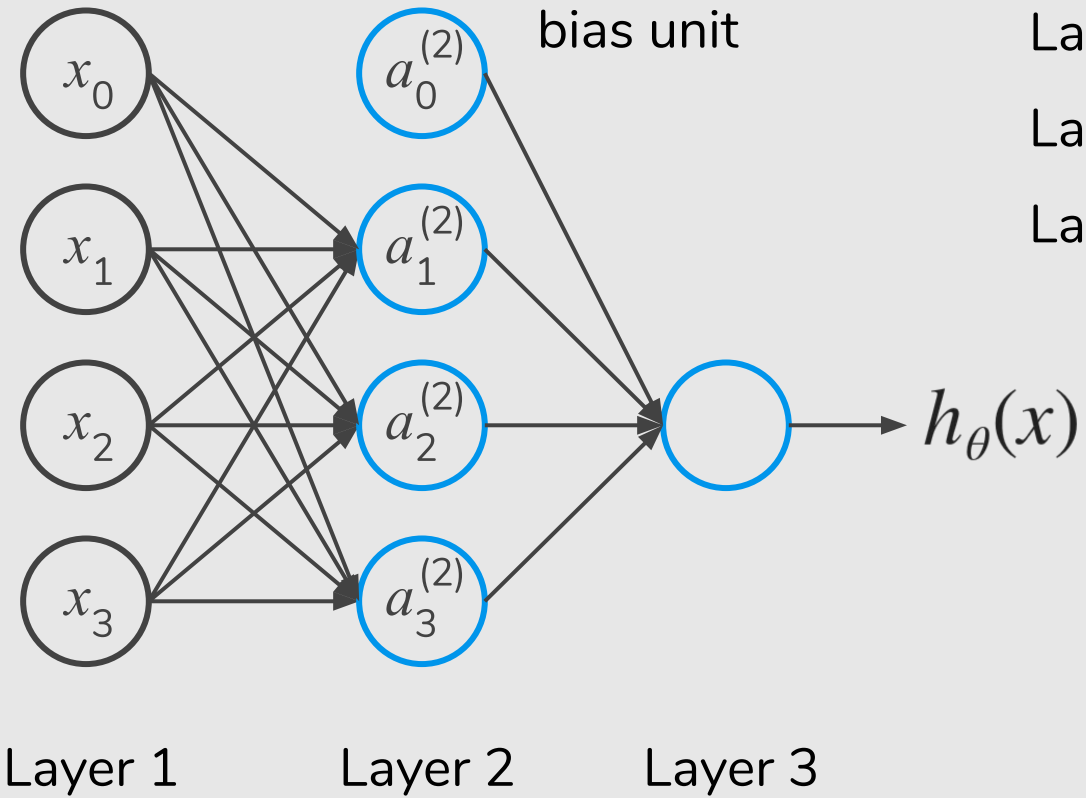


Layer 1 = Input layer

Layer 2 = Hidden layer

Layer 3 = Output layer

Neural Network

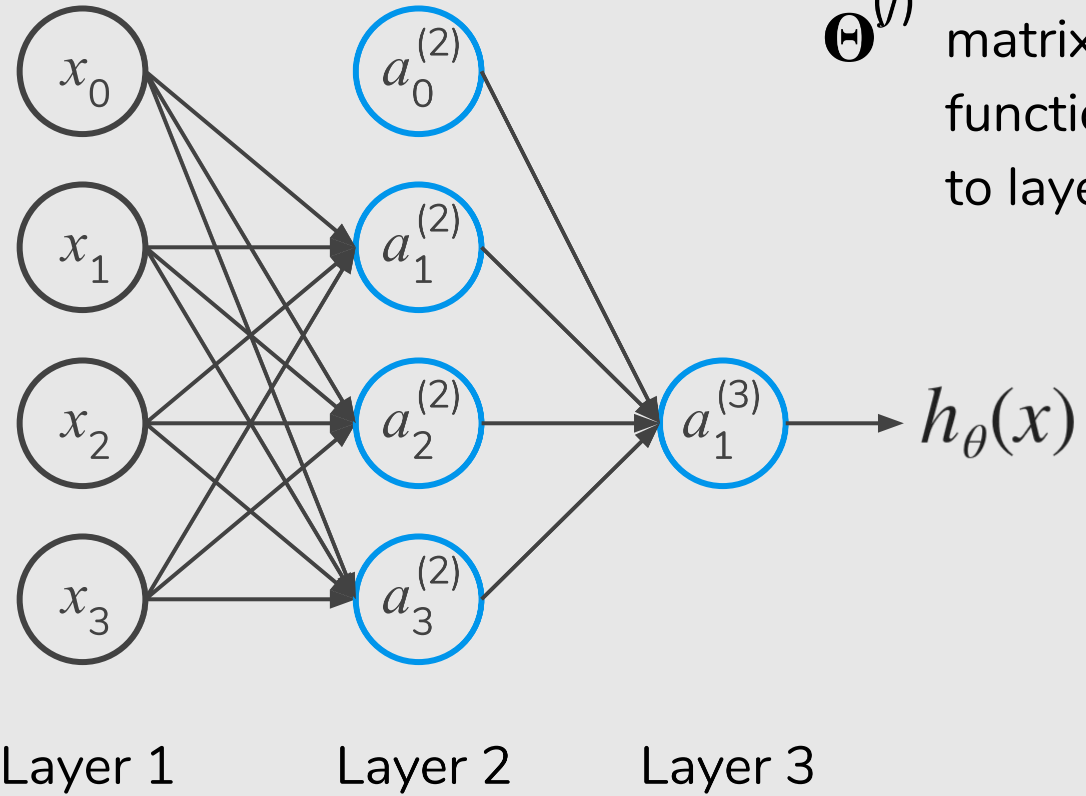


Layer 1 = Input layer

Layer 2 = Hidden layer

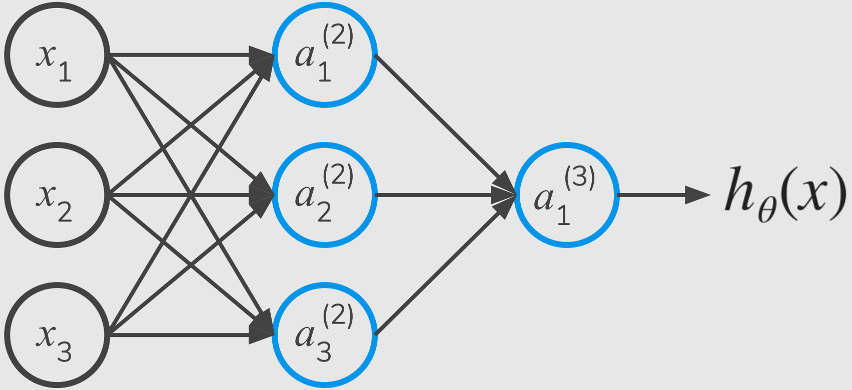
Layer 3 = Output layer

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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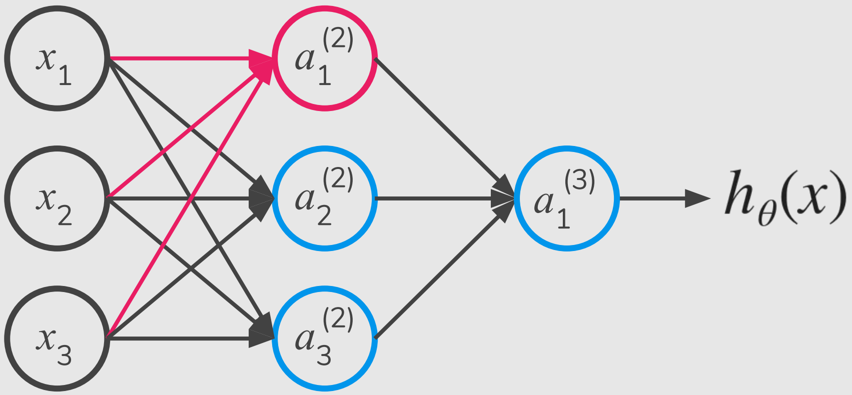
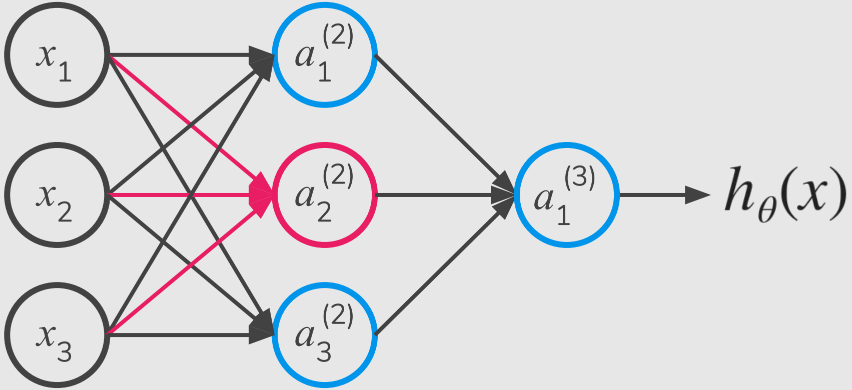


$a_i^{(j)}$ "activation" of unit i in layer j

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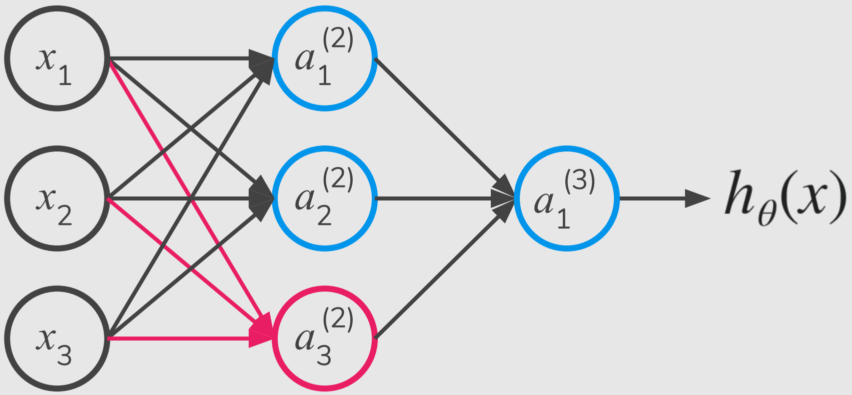
$$a_2^{(2)} = g(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3)$$



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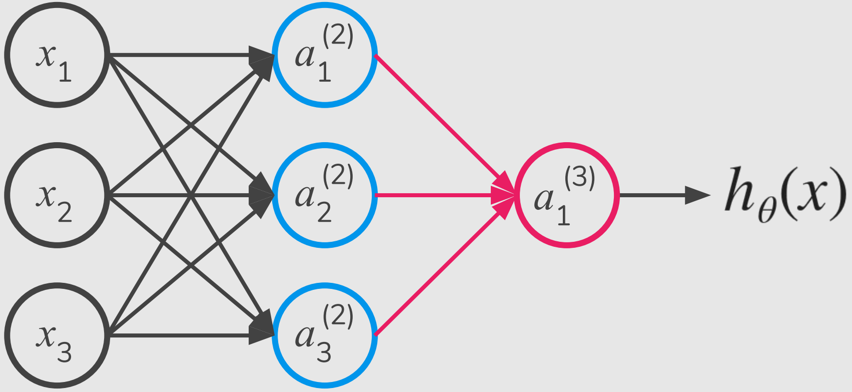
$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$



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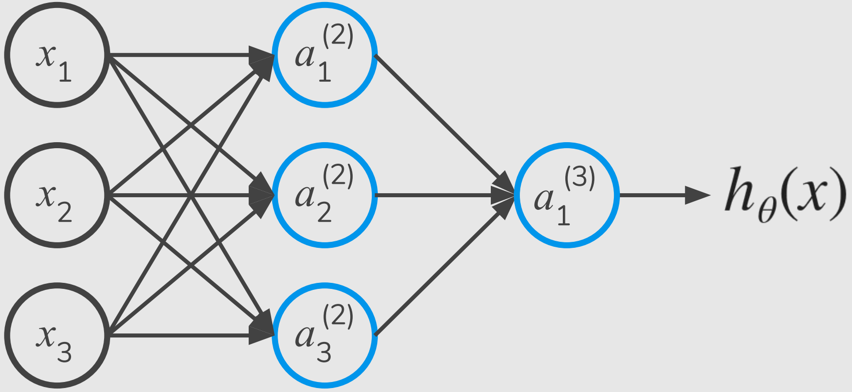
$$a_3^{(2)} = g(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3)$$

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



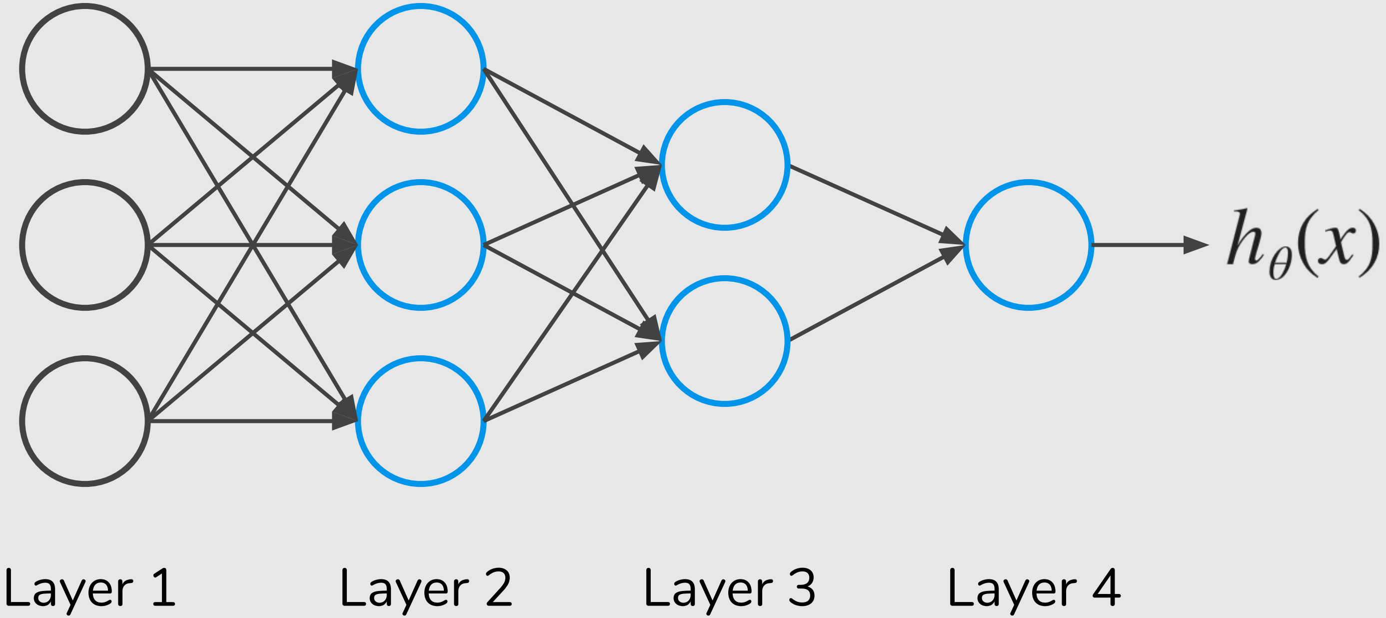
$a_i^{(j)}$ "activation" of unit i in layer j

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

Feedforward Neural Network (forward propagating)

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

Other Network Architectures



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

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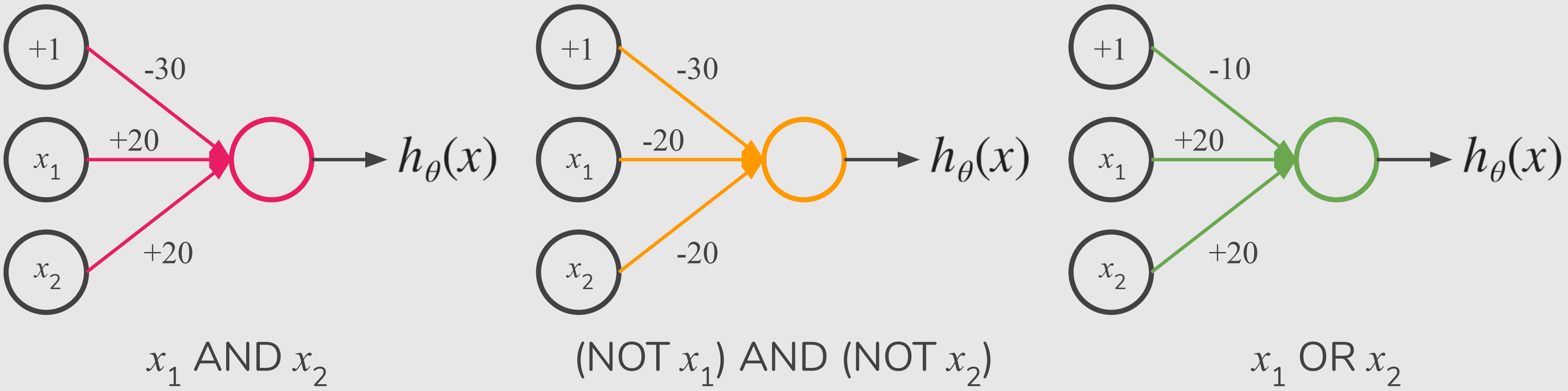
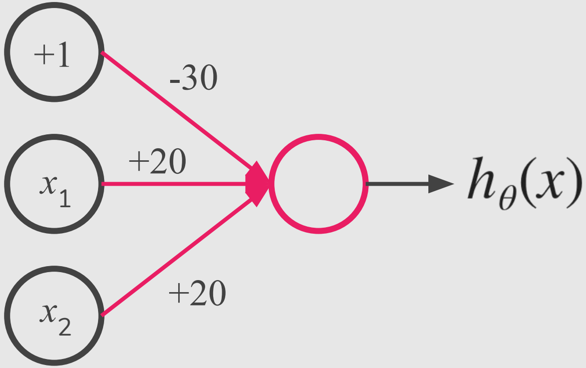
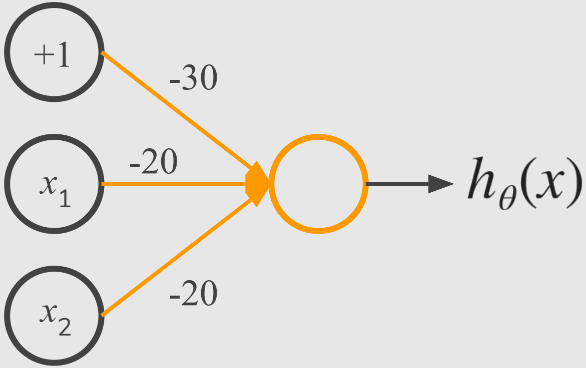


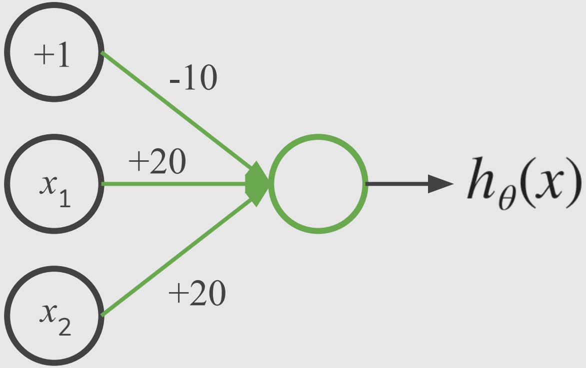
Example: XNOR $x_1, x_2 \in \{0,1\}$ $y = x_1$ XNOR x_2



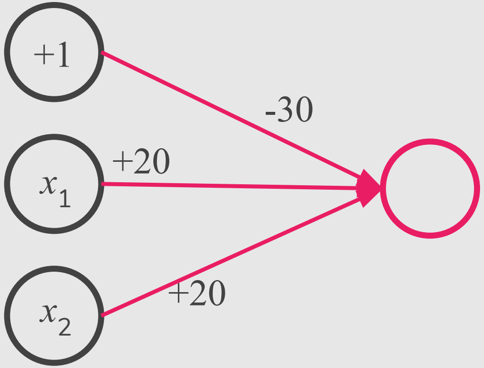
x_1 AND x_2



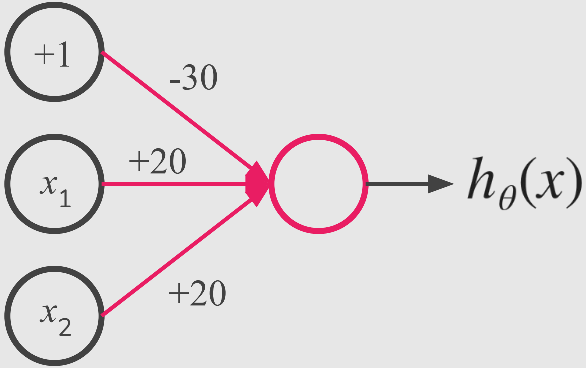
(NOT x_1) AND (NOT x_2)



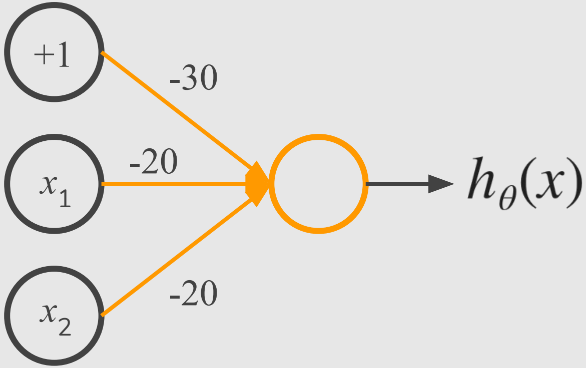
x_1 OR x_2



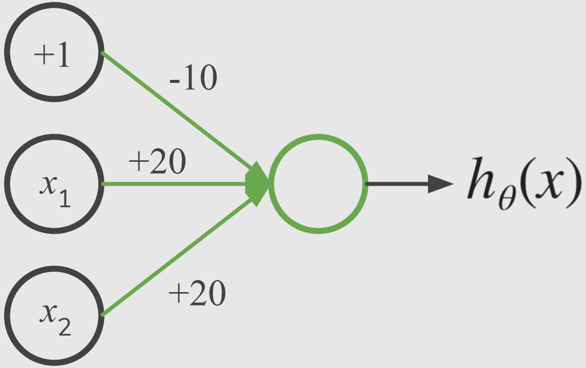
Example: XNOR $x_1, x_2 \in \{0,1\}$ $y = x_1 \text{ XNOR } x_2$



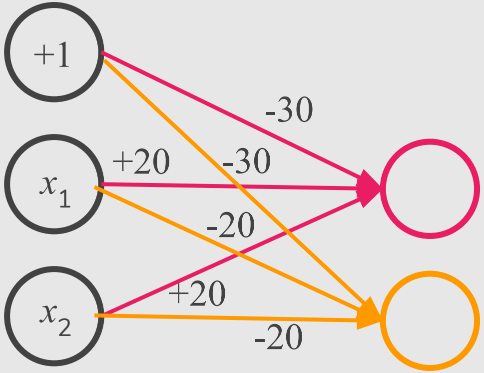
x_1 AND x_2



(NOT x_1) AND (NOT x_2)

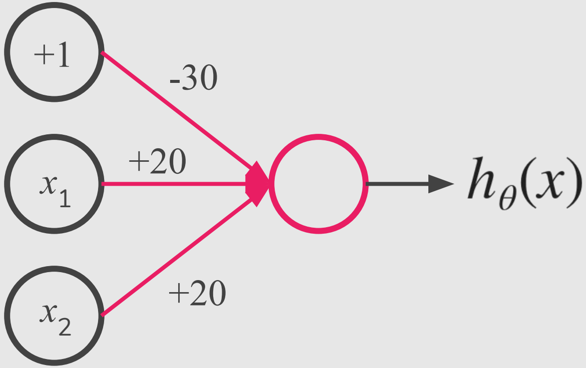


x_1 OR x_2

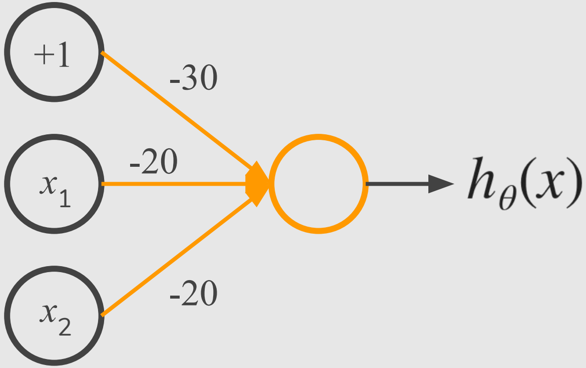


Example: XNOR

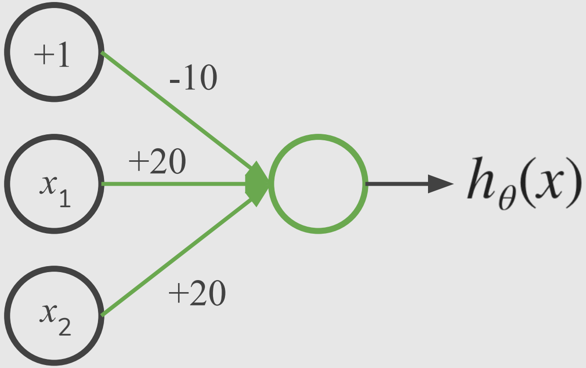
$x_1, x_2 \in \{0,1\}$ $y = x_1 \text{ XNOR } x_2$



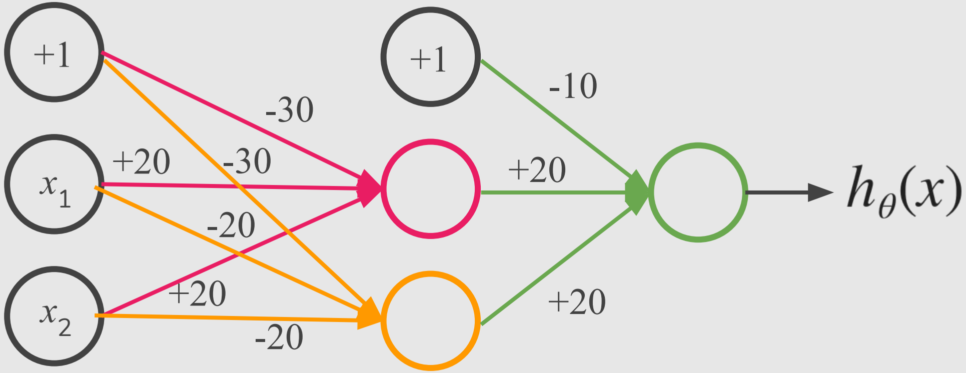
x_1 AND x_2



(NOT x_1) AND (NOT x_2)

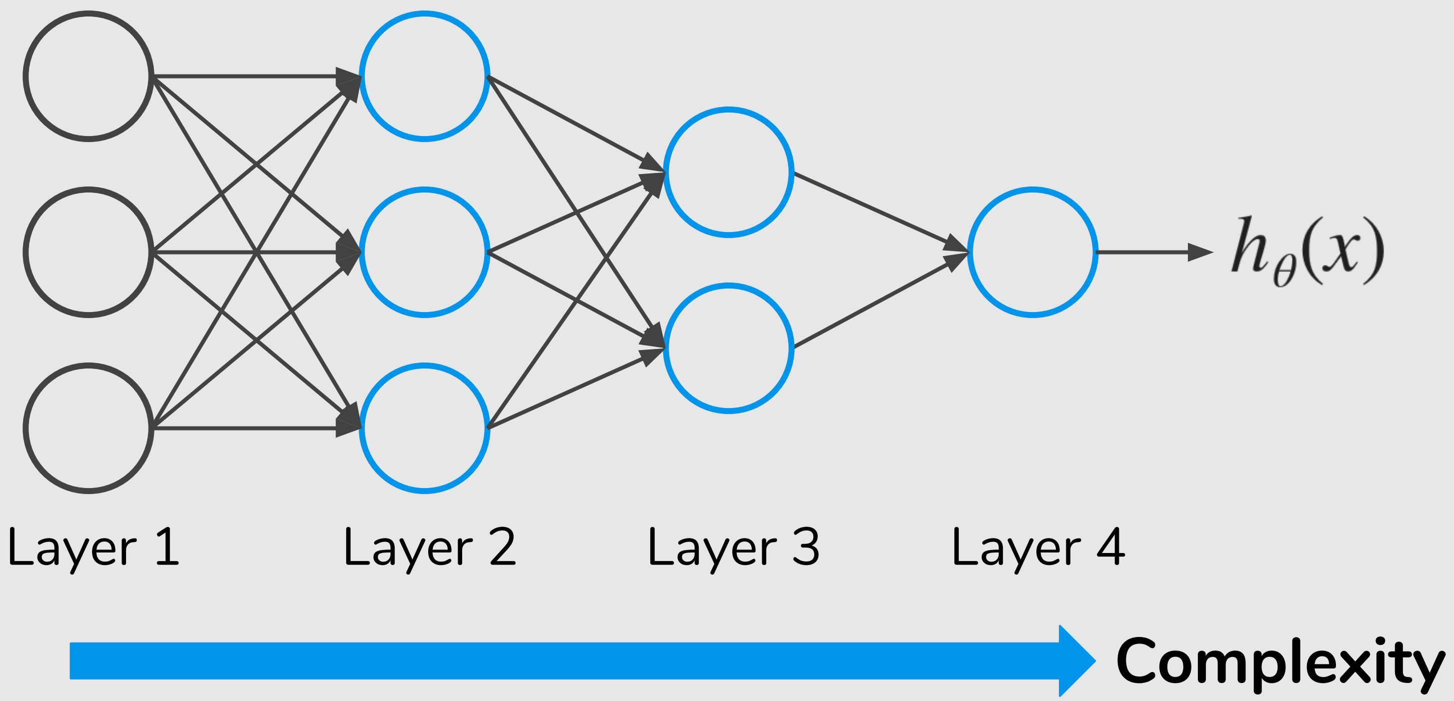


x_1 OR x_2



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

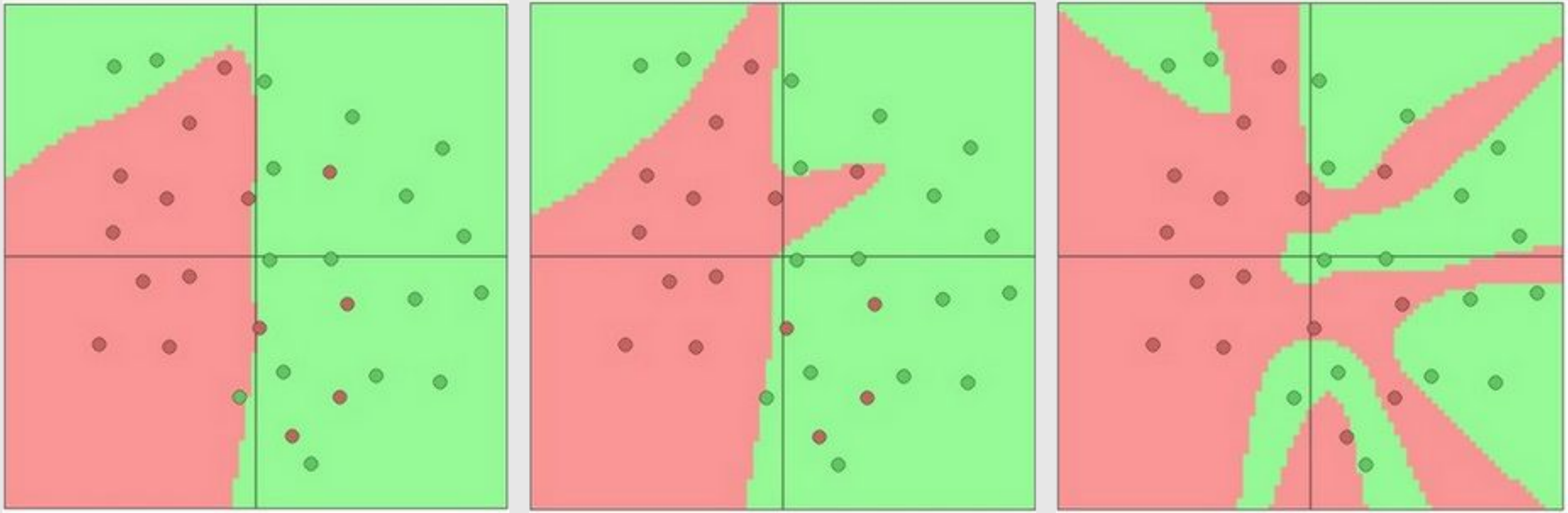
Neural Network Intuition



Neural Network Intuition

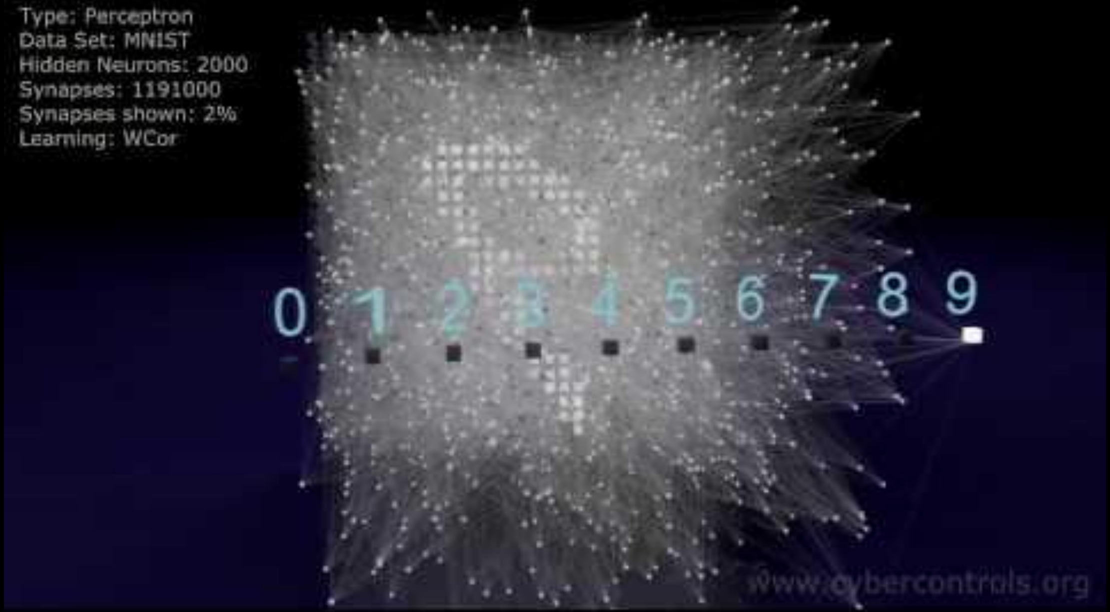
Toy 2d classification with 2-layer neural network

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



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

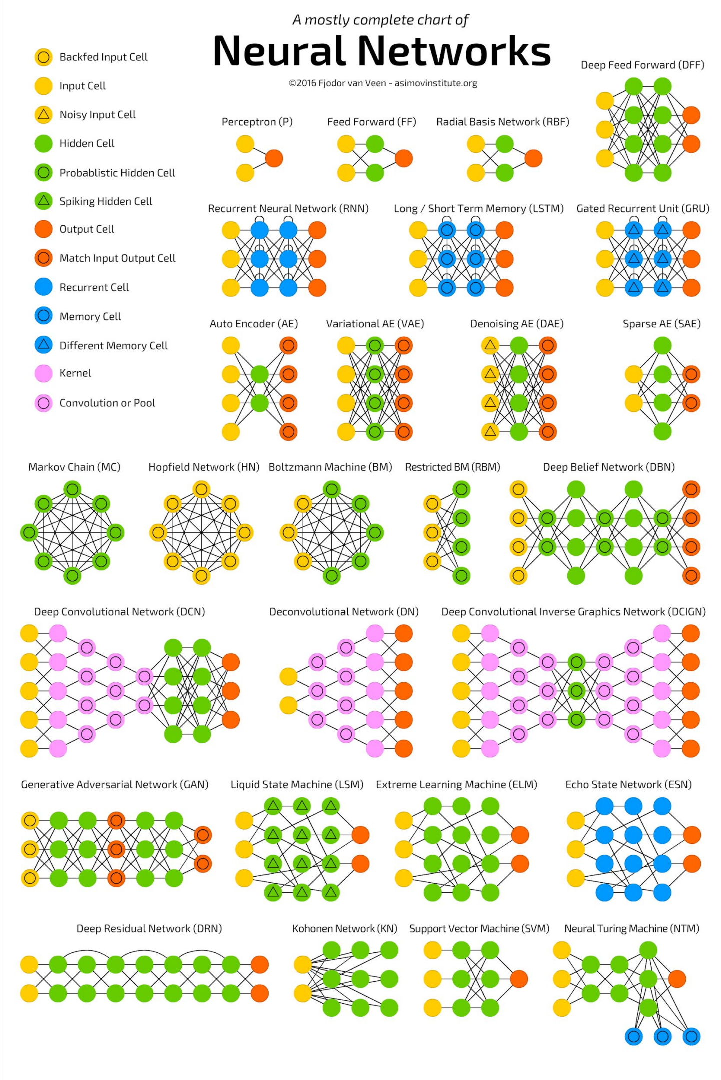
3 hidden neurons | 6 hidden neurons | 20 hidden neurons



https://youtu.be/3JQ3hYko51Y

Neural Network Zoo

http://www.asimovinstitute.org/neural-network-zoo/



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