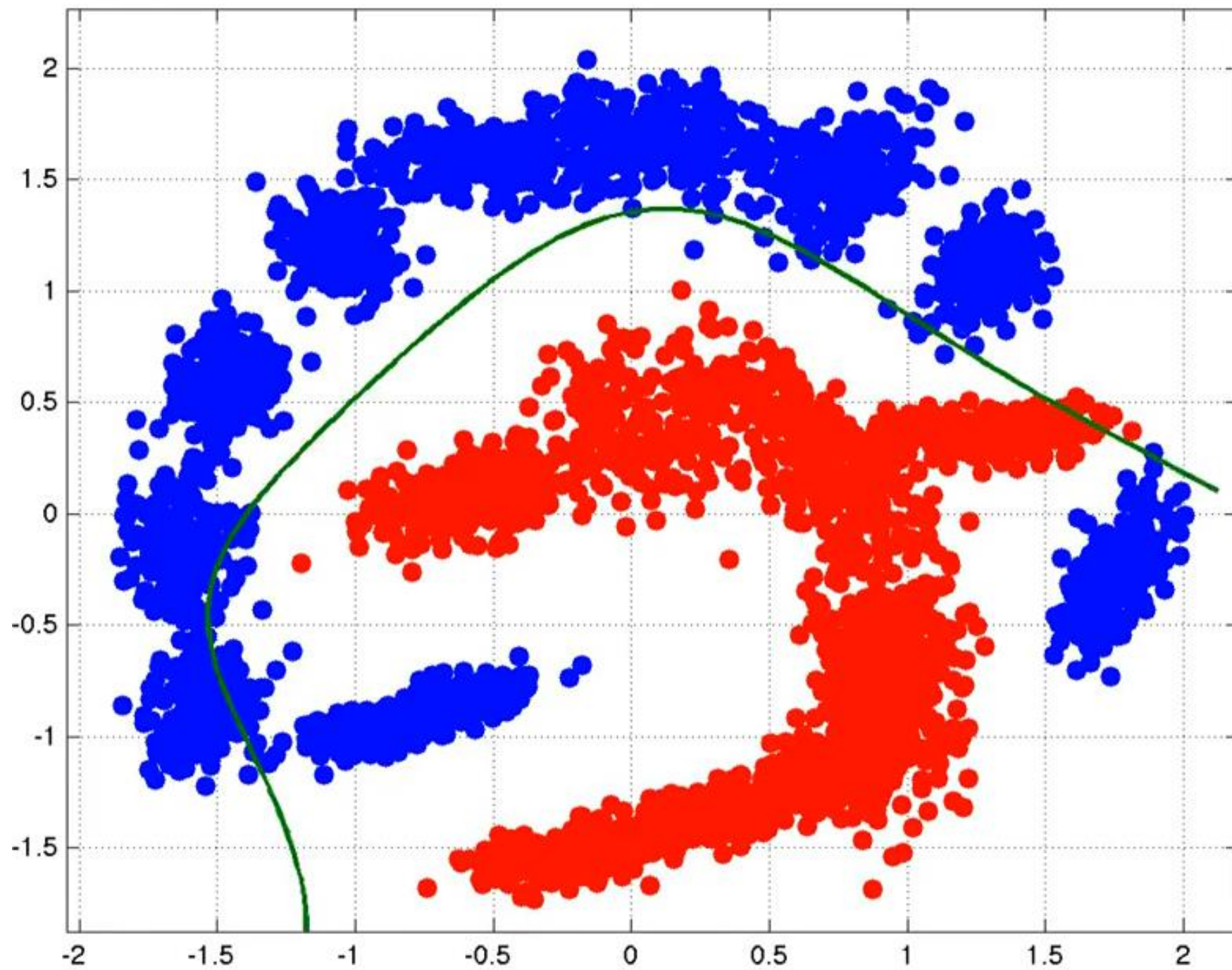


Introduction to Artificial neural networks.



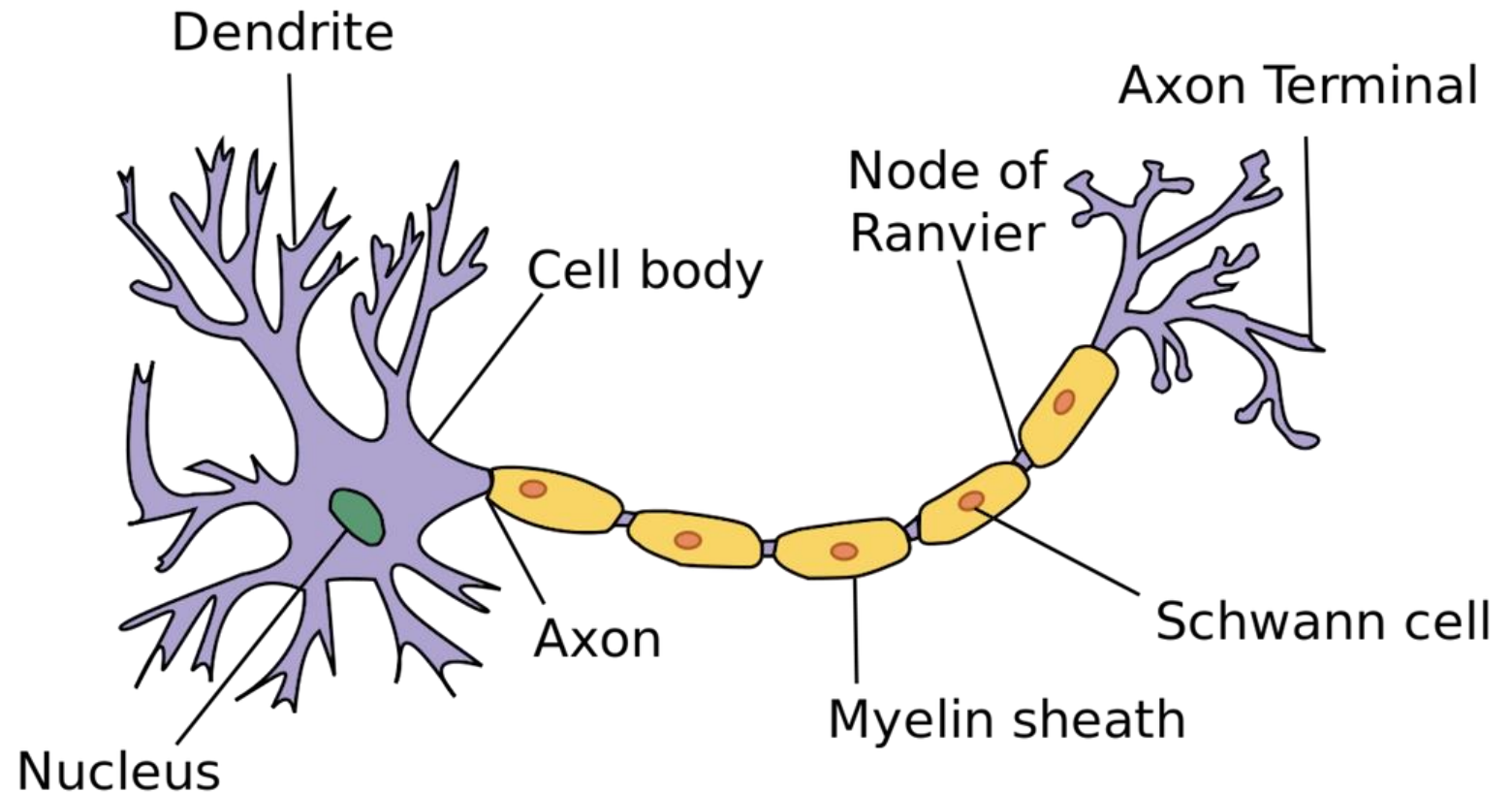
Introduction to biological neural

Dendrites: receives messages from other neurons

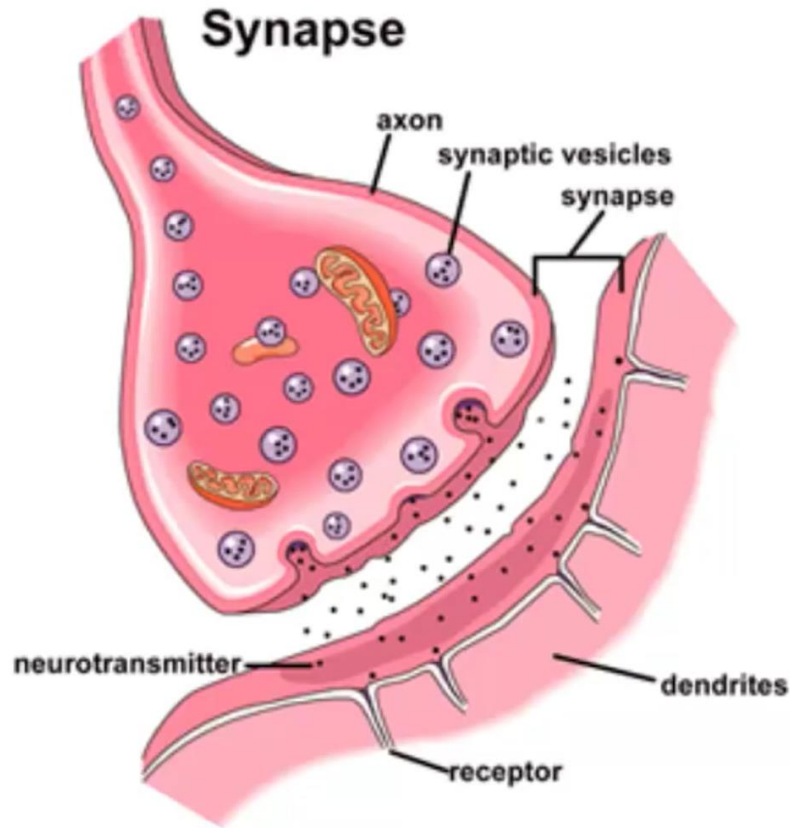
Nucleus:

Axon: send messages to other neurons

Synapse: when the axon connect other neuron's dendritic tree



How Synapse works & learning



When an impulse travel down the axon, it eventually reaches the axon terminal.

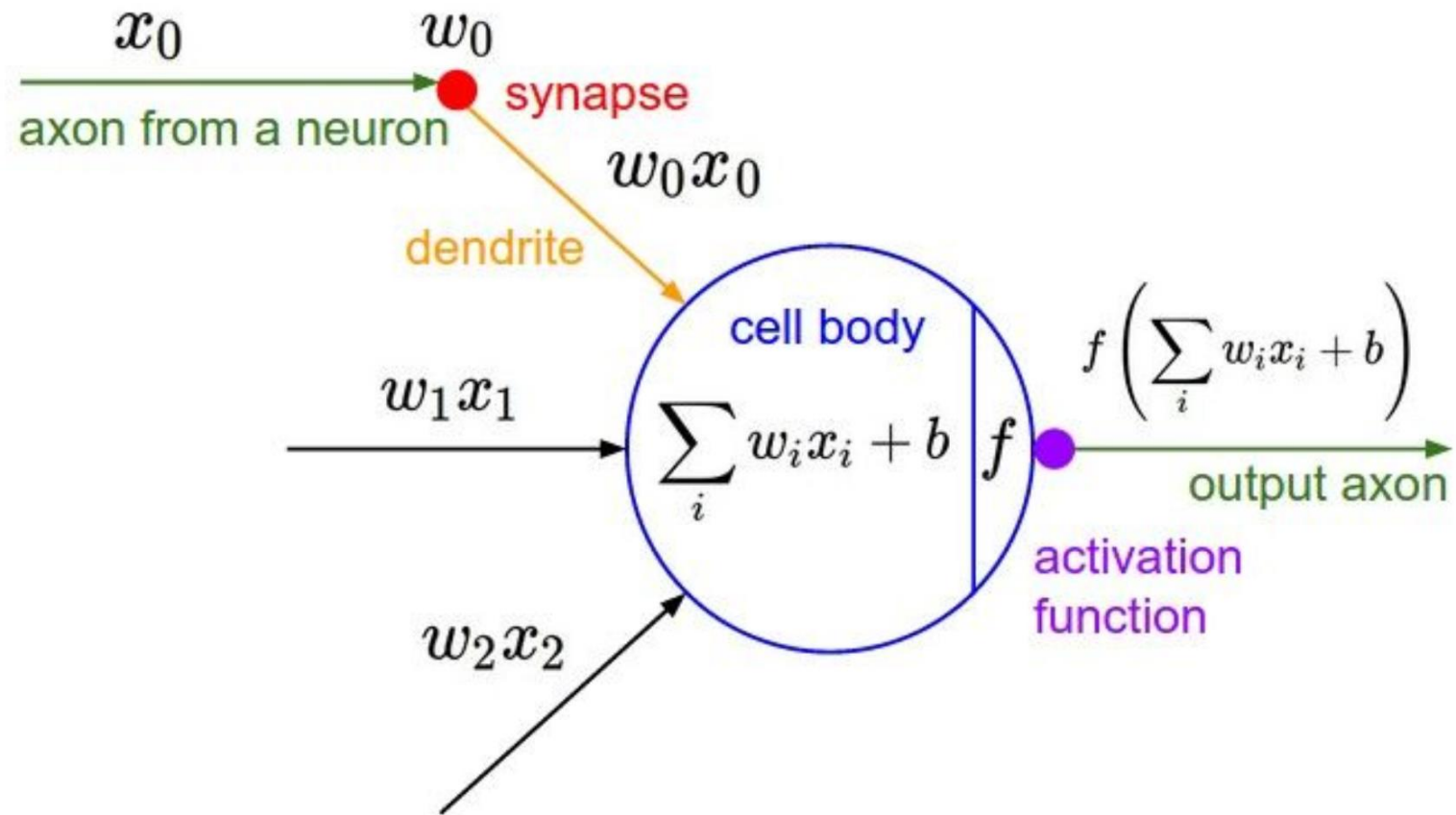
When it reach the terminal, the change in electrical charge triggers biochemical reactions that lead to the release of neurotransmitter.

They can adapt by varying the number of vesicles of transmitter.

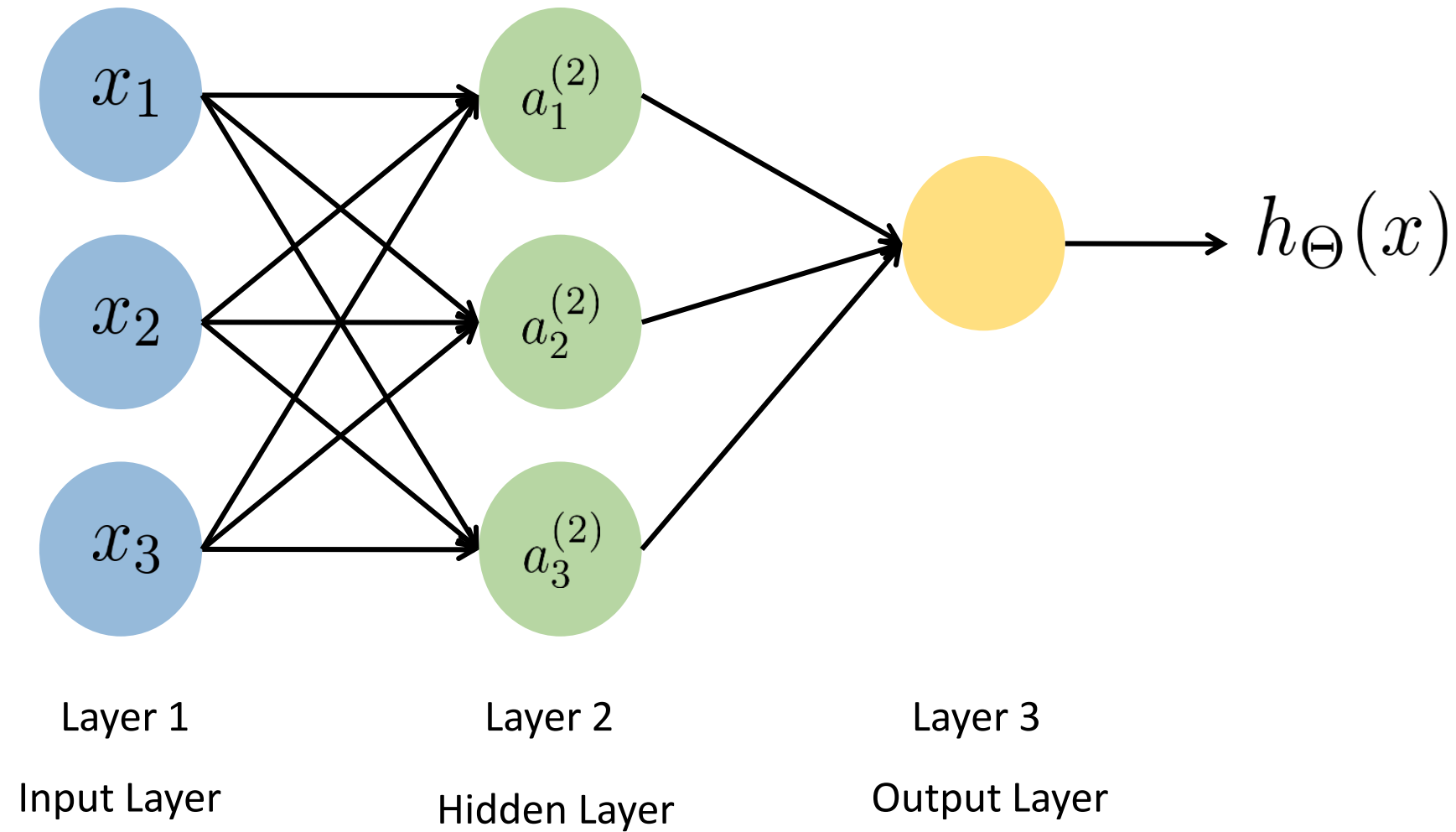
They can adapt by varying the number of receptor molecules.

How Synapse works

Artificial neural



Neural network



Neuron model: Activation Functions

Sigmoid: $\sigma(x) = \frac{1}{1 + e^{-x}}$

LeakyReLU:

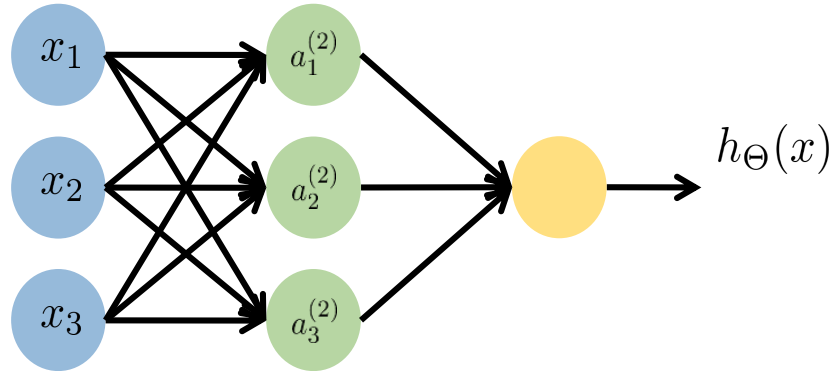
tanh: $\tanh(x)$

Maxout:

ReLU: $\max(x, 0)$

ELU:

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 $j + 1$.

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

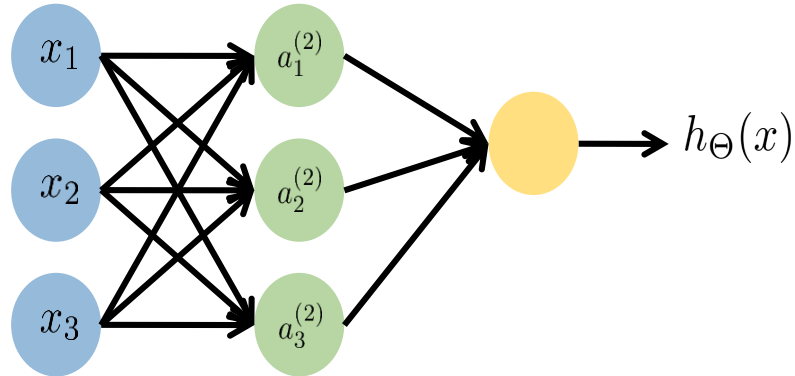
$$a_2^{(2)} = g(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3)$$

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

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

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

Neural network forward propagation



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

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

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

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

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad z^{(2)} = \begin{bmatrix} z_1^{(2)} \\ z_2^{(2)} \\ z_3^{(2)} \end{bmatrix}$$

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












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

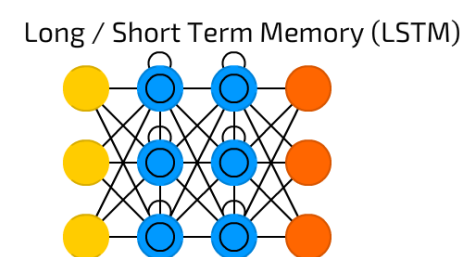
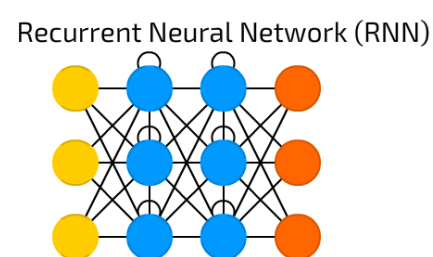
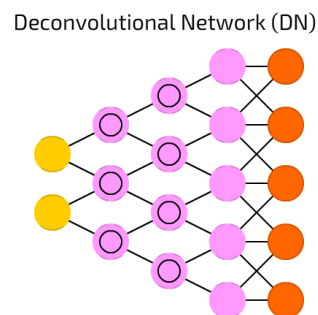
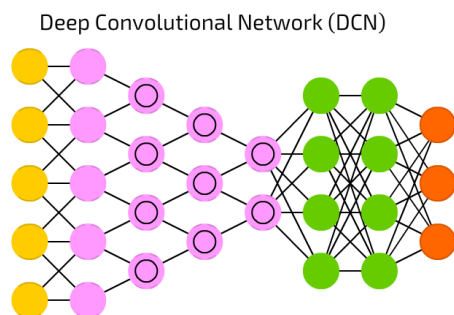
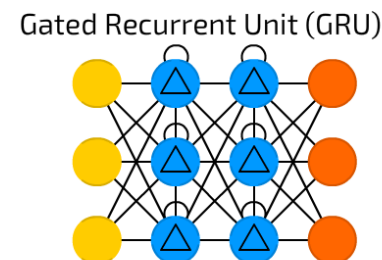
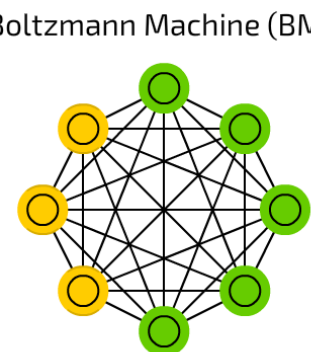
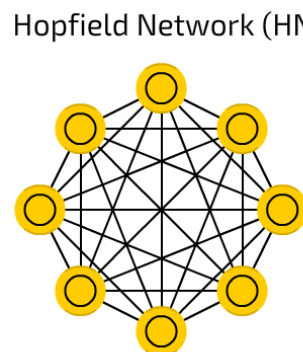
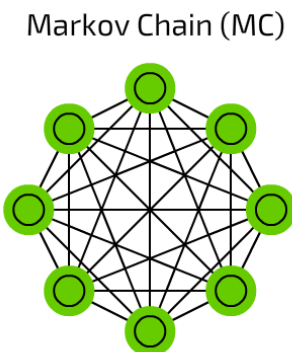
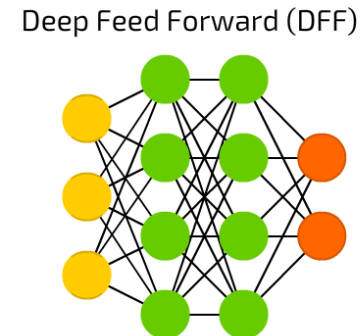
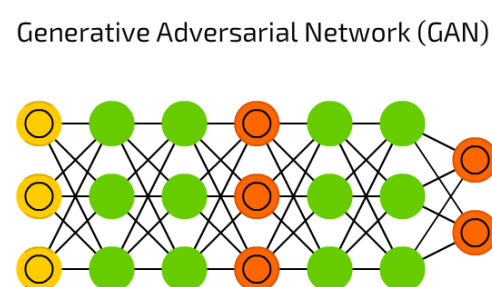
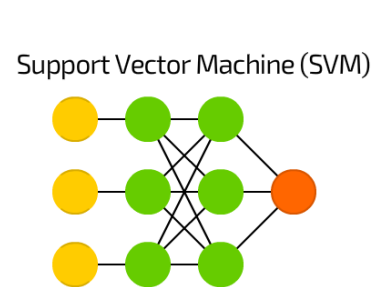
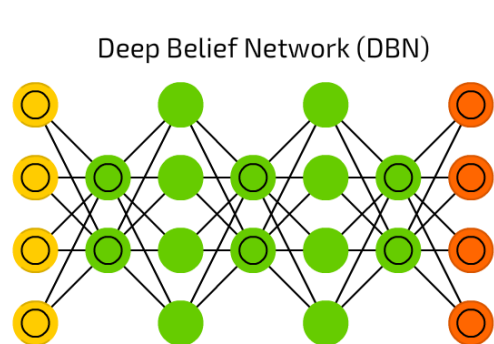
$$\text{Add } a_0^{(1)} = 1.$$

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

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

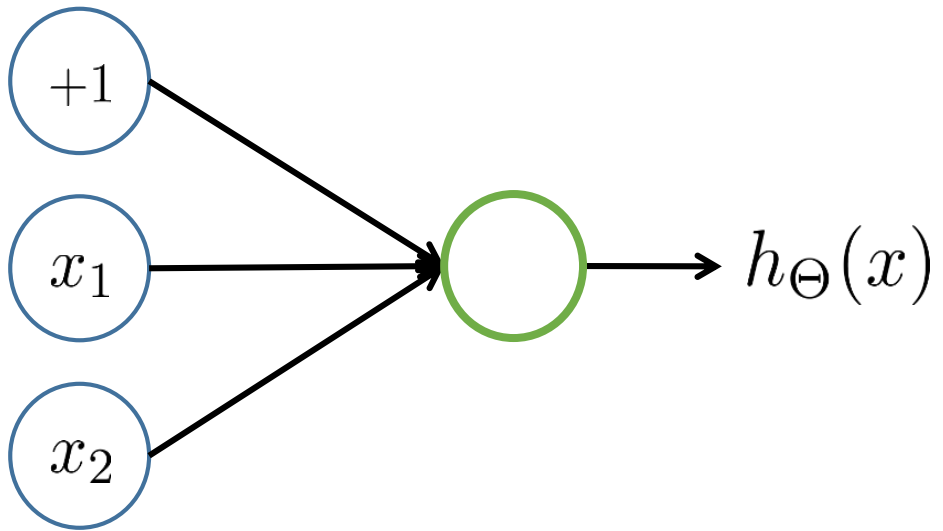
Neural network zoo

-  Backfed Input Cell
-  Input Cell
-  Noisy Input Cell
-  Hidden Cell
-  Probablistic Hidden Cell
-  Spiking Hidden Cell
-  Output Cell
-  Match Input Output Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Kernel
-  Convolution or Pool



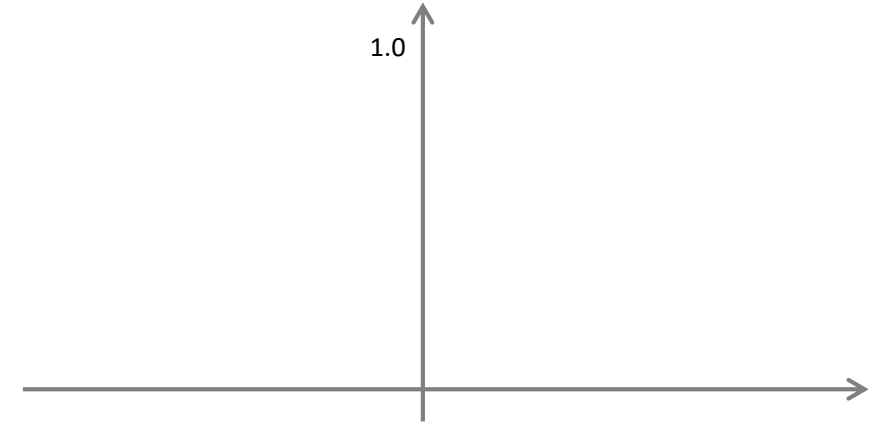
Simple example: AND

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



Example: OR function

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



x_1	x_2	$h_{\Theta}(x)$
0	0	
0	1	
1	0	
1	1	

Multi-class classification



Pedestrian



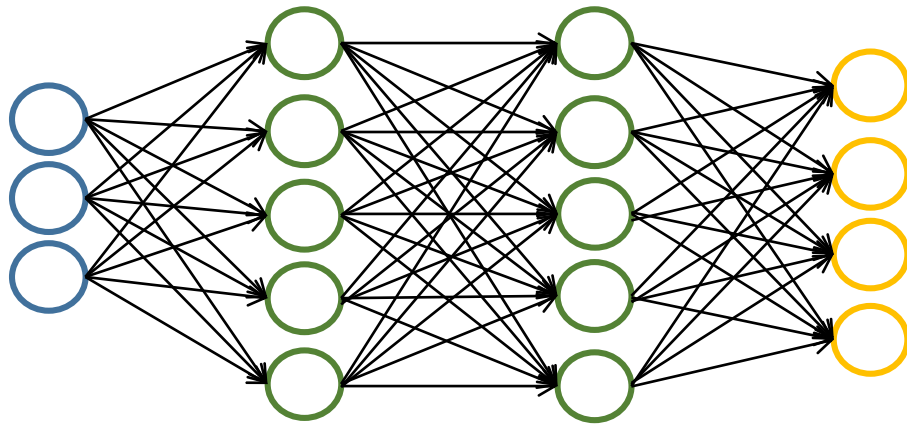
Car



Motorcycle



Truck



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

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

Neural network learning:

Cost function

Logistic regression:

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m y_i (\log(h_{\theta}(x_i))) + (1 - y_i) \log(1 - h_{\theta}(x_i))$$

Neural network:

$$h_{\Theta}(x) \in \mathbb{R}^K \quad (h_{\Theta}(x))_i = i^{th} \text{ output}$$

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m \sum_{k=1}^K y_k^{(i)} \log \left((h_{\theta}(x^{(i)}))_k \right) + \left(1 - y_k^{(i)} \right) \log \left(1 - (h_{\theta}(x^{(i)}))_k \right)$$



ANACONDA®

