MATH 567: Introduction to Data Mining and Analysis
Introduction to Neural networks

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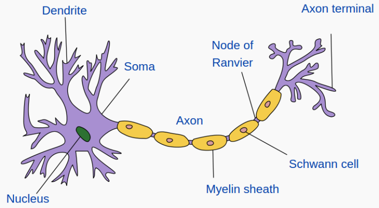
This lecture is based on the UFLDL tutorial (http://deeplearning.stanford.edu/)

Neurons



Neuron representation (Source: Wiki).

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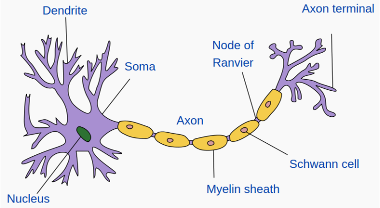

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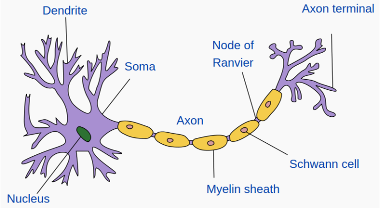

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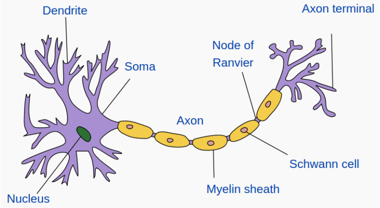

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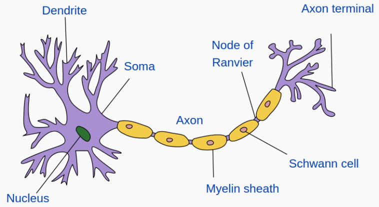

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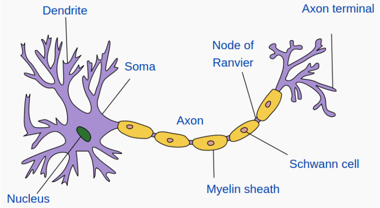

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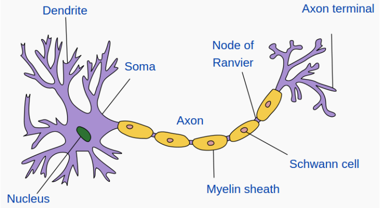

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- When a neuron fires, it starts a chain reaction that propagates information.
- There are *excitatory* and *inhibitory* synapses.

See Izenman (2013) for more details.

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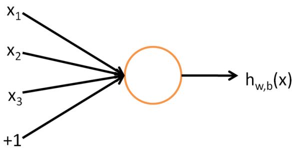
- Very popular in computer vision, natural language processing, and many other fields.
- Today, neural network models are often called *deep learning*.

Single neuron model:



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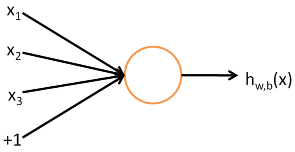

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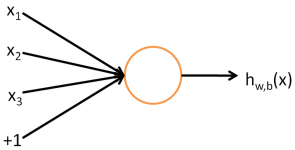

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Input: x_1, x_2, x_3 (and $+1$ intercept).
Output: $h_{W,b}(x) = f(W^T x) = f(W_1 x_1 + W_2 x_2 + W_3 x_3 + b)$, where f is the *sigmoid* function:

$$f(x) = \frac{1}{1 + e^{-x}}.$$

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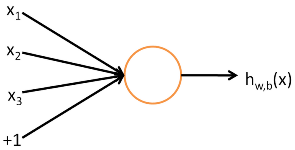

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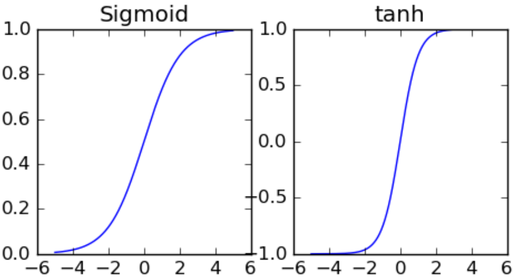
Other common choice for f:

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}.$$

Neural networks (cont.)

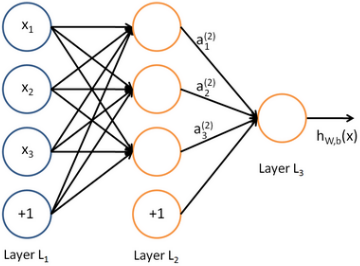
The function f acts as an **activation** function.



Idea: Depending on the input of the neuron and the *strength* of the links, the neuron “fires” or not.

Neural network models

A **neural networks model** is obtained by hooking together many neurons so that the output of one neuron becomes the input of another neuron.



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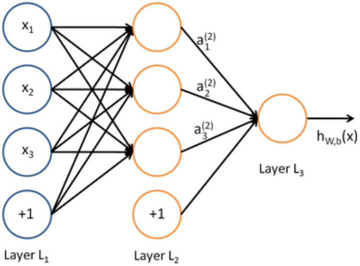

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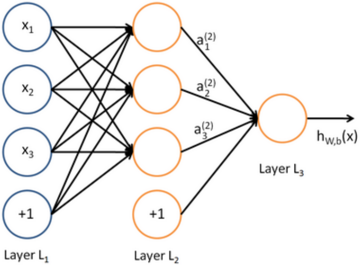

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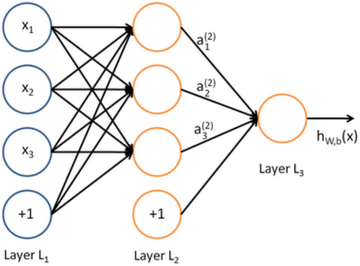

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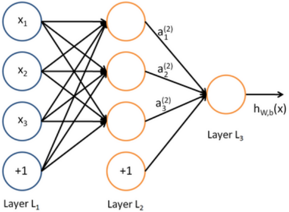
We will let n_l denote the **number of layers** in our model ($n_l = 3$ in the above example).

Notation



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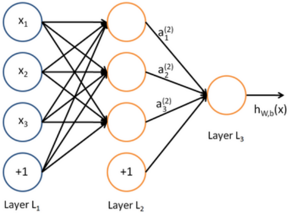

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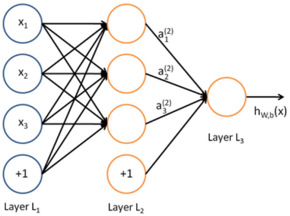

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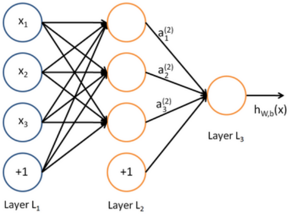

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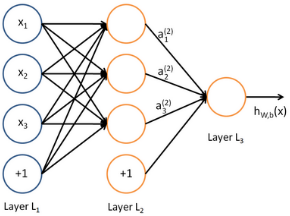

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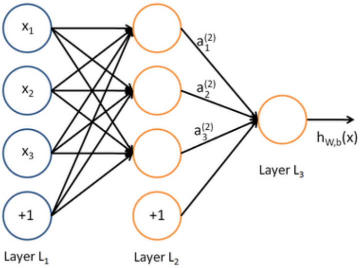
In above example: $(W, b) = (W^{(1)}, b^{(1)}, W^{(2)}, b^{(2)})$. Here $W^{(1)} \in \mathbb{R}^{3\times3}$, $W^{(2)} \in \mathbb{R}^{1\times3}$, $b^{(1)} \in \mathbb{R}^3$, $b^{(2)} \in \mathbb{R}$.

Activation



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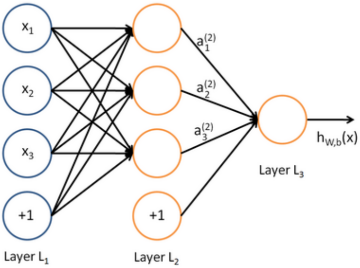

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We have:

$$\begin{aligned}
a_1^{(2)} &= f(W_{11}^{(1)}x_1 + W_{12}^{(1)}x_2 + W_{13}^{(1)}x_3 + b_1^{(1)}) \\
a_2^{(2)} &= f(W_{21}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{23}^{(1)}x_3 + b_2^{(1)}) \\
a_3^{(2)} &= f(W_{31}^{(1)}x_1 + W_{32}^{(1)}x_2 + W_{33}^{(1)}x_3 + b_3^{(1)}) \\
h_{W,b} = a_1^{(3)} &= f(W_{11}^{(2)}a_1^{(2)} + W_{12}^{(2)}a_2^{(2)} + W_{13}^{(2)}a_3^{(2)} + b_1^{(2)}).
\end{aligned}$$

Compact notation

- In what follows, we will let $z_i^{(l)}$ = total weighted sum of inputs to unit i in layer l (including the bias term):

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Using the above notation, we have:

$$\begin{aligned} z^{(2)} &= W^{(1)} x + b^{(1)} \\ a^{(2)} &= f(z^{(2)}) \\ z^{(3)} &= W^{(2)} a^{(2)} + b^{(2)} \\ h_{W,b} &= a^{(3)} = f(z^{(3)}). \end{aligned}$$

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- Can use different **architectures** (i.e., pattens of connectivity between neurons).
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- In that case, we obtain a **feedforward neural network** (no directed loops or cycles).

Multiple outputs

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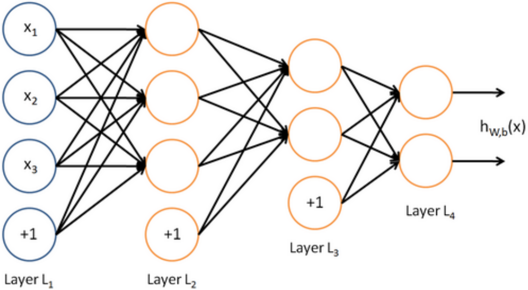

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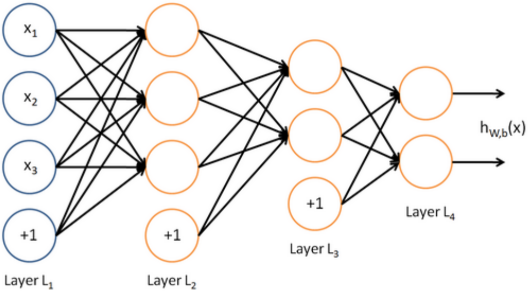

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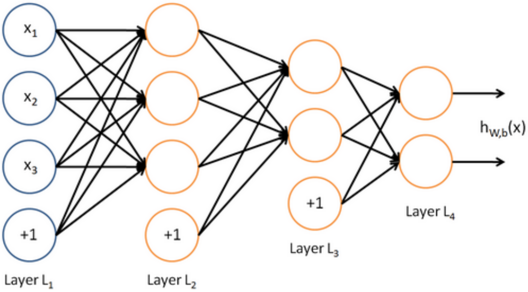

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- Useful for applications where the output is multivariate (e.g. medical diagnosis application where output is whether or not a patient has a list of diseases).

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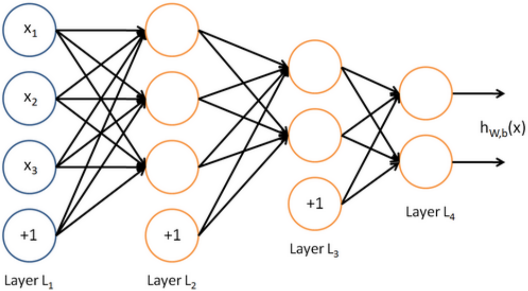

Source: UFLDL tutorial

- To train this network, we need observations $(x^{(i)}, y^{(i)})$ with $y^{(i)} \in \mathbb{R}^2$.
- Useful for applications where the output is multivariate (e.g. medical diagnosis application where output is whether or not a patient has a list of diseases).
- Useful to *encode* or *compress* information.

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Example: Let f be any continuous function defined on the unit cube $[0,1]^3$. Then for every $\epsilon > 0$, there exists a feedforward neural network $f_{W,b}$ with one layer such that

$$|f(x) - f_{W,b}(x)| < \epsilon \qquad \forall x \in [0,1]^3.$$