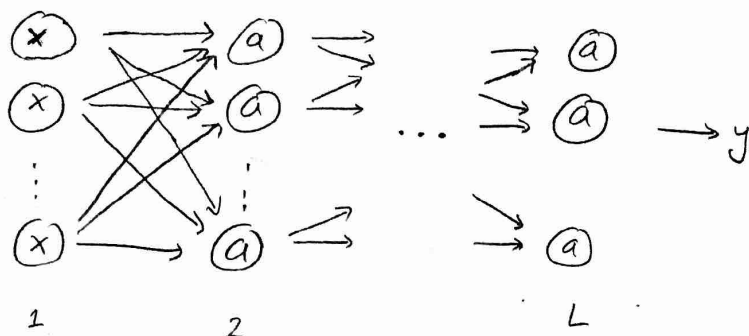
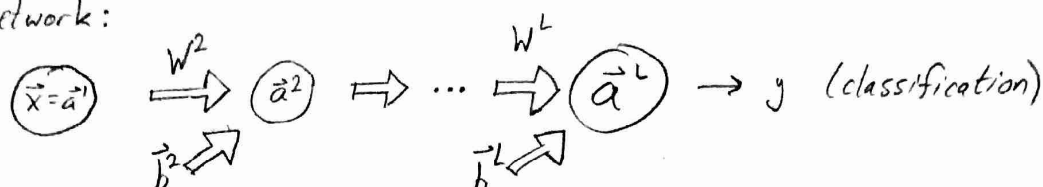


Feedforward algorithm derivation

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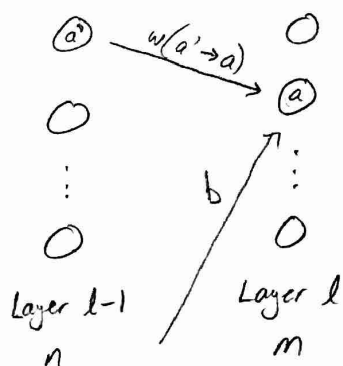
Network:



For each neuron in a layer, we weight the incoming activations from the previous layer and add a bias.

Formally, for a layer l , let n be the number of neurons in the previous layer $l-1$, and m be the number in this layer l . Let a denote activation values in this layer l , and a' denote values from the previous layer $l-1$. Finally, b denotes bias values and w denotes weights coming into this layer l . We will express w as $w(a' \rightarrow a_i)$ to indicate it is the weight applied to a'_i in computing a_i . (Don't worry much about indices; we'll see that they're not really necessary.)

Note: Layers are indexed 1 to L , ($L = \#$ layers).



Then for the i th neuron in this layer, we compute the activation as:

$$z_i = \sum_{a'} w(a' \rightarrow a_i) \cdot a' + b_i$$

$$a_i = \sigma(z_i)$$

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So, putting all of the activations a_i together $1 \leq i \leq m$, we get:

$$\vec{z} = \sum_{a'} \vec{w}(a' \rightarrow \vec{a}) \cdot a' + \vec{b} = W\vec{a}' + \vec{b} \quad \text{where } W \text{ is the matrix of column vectors in the sum.}$$

$$\vec{a} = \vec{\sigma}(\vec{z})$$

(Here I am defining the matrix W as the list of column vectors shown above, and I use the notation $\vec{\sigma}(\vec{z})$ to mean $(\sigma(z_1), \dots, \sigma(z_m))$).

To express this in terms of layer numbers (i.e. l), we'll use the superscript $\vec{a}^l, \vec{b}^l, W^l$, etc. to denote activations in layer l , and biases/weights coming into layer l . Then we translate the a/a' notation to:

$$\vec{z}^l = W^l \vec{a}^{l-1} + \vec{b}^l$$

$$\vec{a}^l = \vec{\sigma}(\vec{z}^l)$$

The classification chosen is therefore the index of the largest activation value in the last layer, that is:

$$y = \operatorname{argmax}_i \vec{a}^L \quad \text{where } i \text{ indexes values of } \vec{a}^L$$

The formal algorithm is on a separate page.