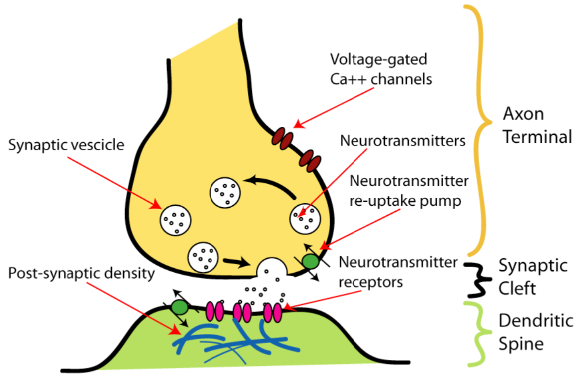
Synapses



Communication between cells happens at **synapses**, which are not a part of neurons themselves, but are the junctions between neurons, tiny clefts, where an axon almost touches a dendrite.

When an **action potential** reaches the axon terminal of the pre-synaptic neuron, chemicals called neuro-transmitters are released into the synapse. These neurotransmitters are housed in water-balloon-like containers called vesicles, which fuse in to the cell membrane to release their neurotransmitters into the synaptic cleft. The neurotransmitters bind to receptors on the post-synaptic dendrite (often on to an outgrowth called a "spine"). This is like a key being fit in to a keyhole – the neurotransmitters are the keys and the receptors are the keyholes which, when opened, let ions (charged particles) flow in to the post-synaptic dendrite.

There are **different kinds** of synapses. Some synapses have neurotransmitters which open post-synaptic channels which raise the voltage post-synaptically; they are "**excitatory synapses**". Some have neurotrans-mitters which result in the voltage being lowered post-synaptically: they are "**inhibitory synapses**".

Synapses are modifiable, and this is believed to be the basis of **learning**. In certain situations – for example, when a synapse transmits information repeatedly in a short time – the ability of the synapse to transmit information changes. It is not known how precisely this occurs. In fact, there are several mechanisms which seem to allow for this. One is the recruitment of additional receptors to the post-synaptic dendrite, so that when the neurotransmitters are released more receptors open and more ions are allowed in to the post-synaptic cell.

Learning as Weight Change

Learning in a neural network corresponds to adjustment of its weights by application of a "**learning rule**". A learning rule is a method for updating the weights of a neural network over time. Intuitively, this corresponds to the fact that as weights change, the way a network responds to stimuli changes as well.

For now, we define learning rules at the level of individual weights (this can be extended to weight "vectors" and "matrices"). A learning rule is a technique for updating the state of a weight over time. At the level of an individual weight $\mathbf{w_{ij}}$ we write this as a delta value, $\mathbf{\Delta w_{ij}}$, meaning "change in weight". At any time step, you simply add the current $\mathbf{\Delta w_{ij}}$ to the weight's current strength. We can write this as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t)$$

We will often drop explicit reference to time in what follows. For example, if $\mathbf{\Delta w_{1,4}}$ is **4**, and $\mathbf{w_{1,4}}$ is currently **-1**, then at the next time step **t+1** $\mathbf{w_{1,4} = -1 + 4 = 3}$.

Hebbian Learning

Hebbian learning is perhaps the oldest and simplest learning algorithm for neural networks. It is biologically plausible, but has limitations which prevent it from being widely used. The basic idea of Hebbian learning is that neurons which are connected, and which are both active at the same time, will strengthen their connection. As it is sometimes said, "neurons which fire together, wire together." The original formulation of this rule is due to Donald Hebb, who proposed the idea in the 1940's, before there was experimental support for the idea. As he put it:

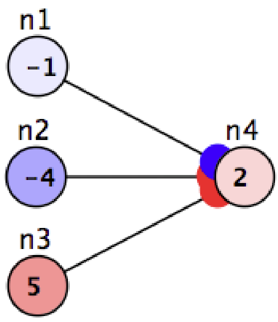
> *"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased" (Hebb, 1962).*

Today it is known that something like Hebbian learning occurs in the brain, called "**Long Term Potentiation**", though how precisely this works is still being debated.

Psychologically, this was thought to correspond roughly to building up association between ideas. If I always hear bells when I see meat, then those ideas are associated in my mind. Hebbian learning proposes one idea about how this happens in the brain. In fact there are even older proposals of roughly this sort (in *Bain*, and even in the philosopher *Descartes*) , according to which the association of ideas corresponds to strengthening of some sort of connection in the brain.

Hebb Rule

For the Hebb rule, the change in a weight is equal to the product of a learning rate epsilon, the source activation, and the target activation. Epsilon controls the rate of weight change over time. If you set it to **0.5**, then weights will change at half the rate as they would if it was set to **1**. For this reason epsilon is also called a "learning rate," and sometimes a "momentum."



Load the network from the last lab. It is called **“Feedforw.xml”** and its weights are $\mathbf{w_{1,4} = -1, w_{2,4}=1, w_{3,4} = 1}$. **Clamp** the neurons by clicking **.**

Now set the epsilon to **1**. What will the new values of the weights be on each time step? (Verify the calculation below by instantiating the network twice).

Remember, $\mathbf{w(t+1) = w(t) + \Delta w}$

In this case, $\mathbf{\Delta w = \varepsilon * a\ i * a,}$

so $\mathbf{\Delta w_{1,4} = 1 * -1 * 2 = -2}$

$\mathbf{\Delta w_{2,4} = 1 * -4 * 2 = -8}$

$\mathbf{\Delta\ w_{3,4} = 1 * 5 * 2 = 10}$

Applying this rule, at the next time step:

$\mathbf{w_{1,4} = -1 + -2 = -3}$

$\mathbf{w_{2,4} = 1 + -8 = -7}$

$\mathbf{w_{3,4} = 1 + 10 = 11}$

For the next time step, we have:

$$\mathbf{w_{1,4} = -3 + -2 = -5}$$

$$\mathbf{w_{2,4} = -7 + -8 = -15}$$

$$\mathbf{w_{3,4} = 11 + 10 = 21}$$

You can see that without clipping these weights will just head towards extreme values. This is the problem with Hebbian learning, it tends to push weights towards extreme values.

One way to slow this down is to use a smaller value for epsilon. Suppose in the example above epsilon was set to **0.01**. Now what would the new weight values be at each time step?