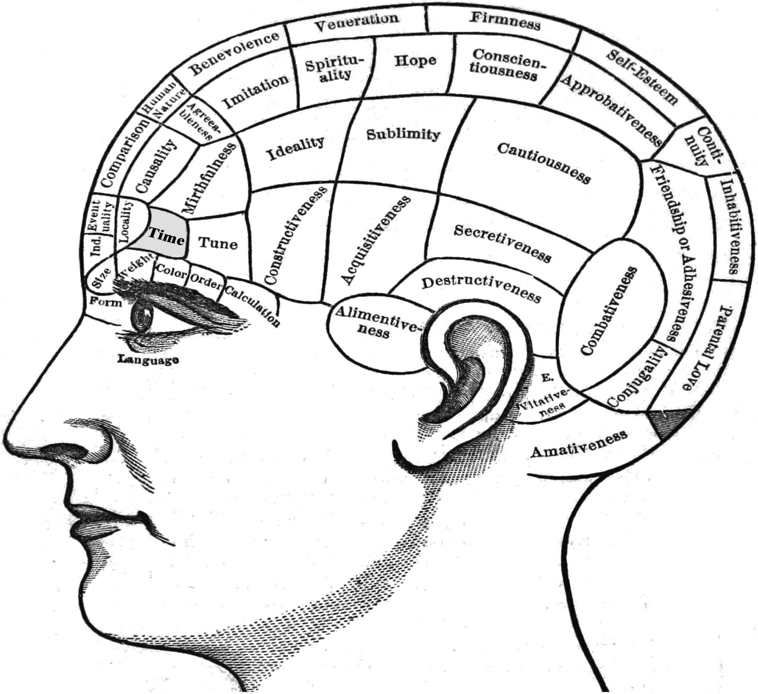

Figure 1.1: A phrenology chart from the nineteenth century.

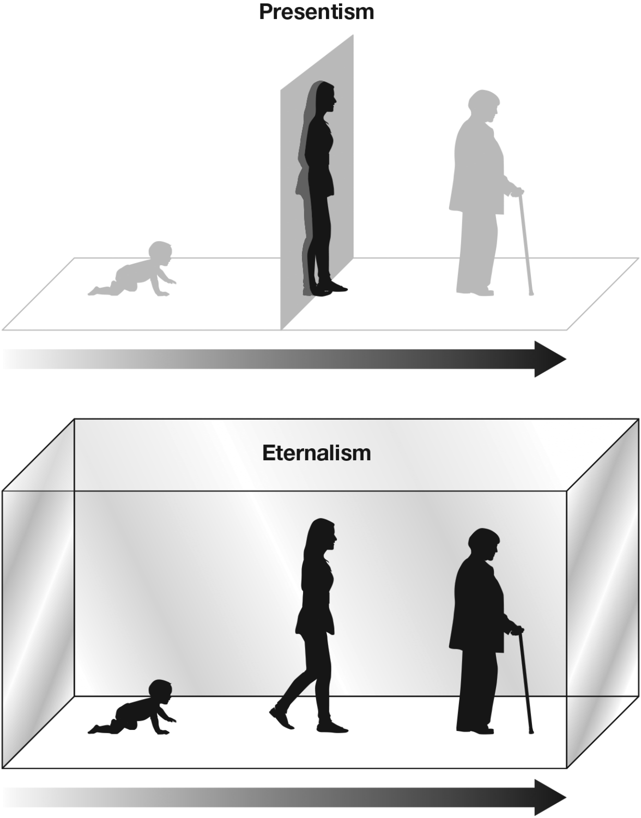

Figure 1.2: Two views of the nature of time: presentism versus eternalism.

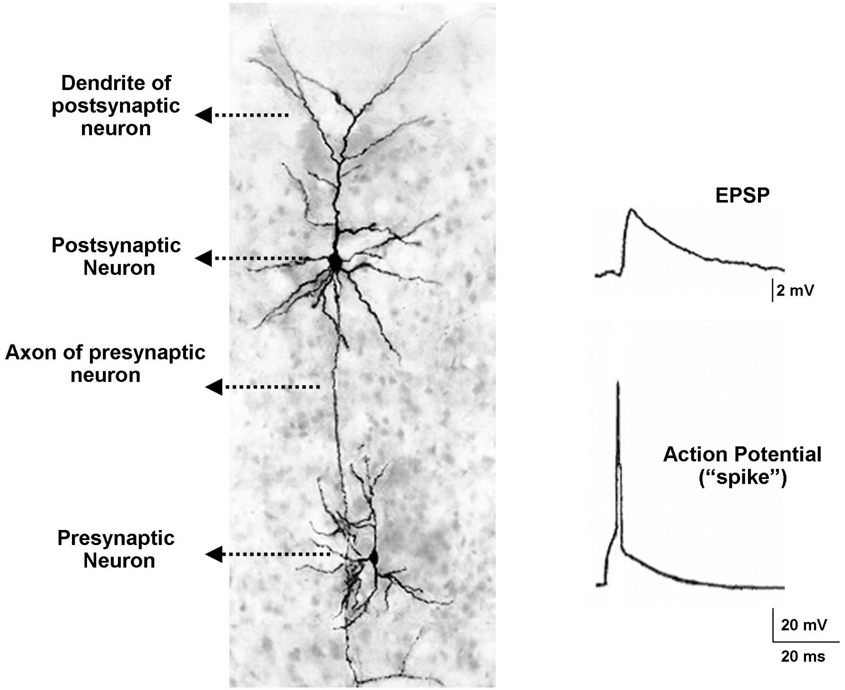

Figure 2.1: Neurons and synapses. Image of two cortical neurons. The axon of the lower, presynaptic neuron connects to a dendrite of the upper, postsynaptic neuron via a synapse (not visible). An action potential—a fast "spike" in the voltage—in the presynaptic neuron produces a small increase in the voltage of the postsynaptic neuron (called an excitatory postsynaptic potential, EPSP). (Modified with permission from Feldmeyer et al., 2002)

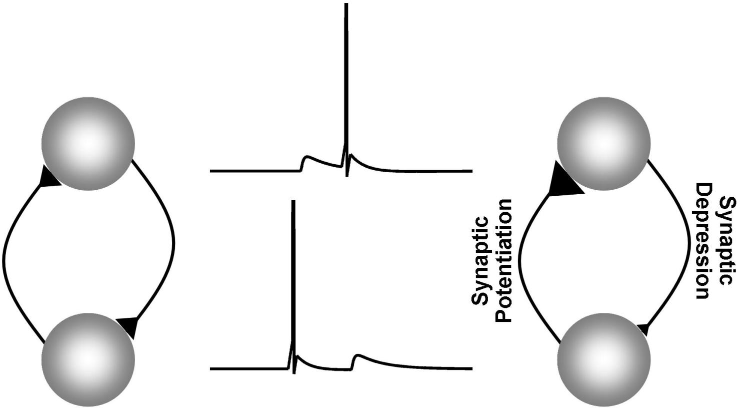

Figure 2.2: Spike-timing-dependent plasticity. Two neurons reciprocally connected to each other by two synapses (represented by the black triangles). If the lower neuron consistently fires before the upper one, the synapse from the lower to the upper neuron will get stronger (synaptic potentiation), and the synapse from the upper to lower neuron will get weaker (synaptic depression).

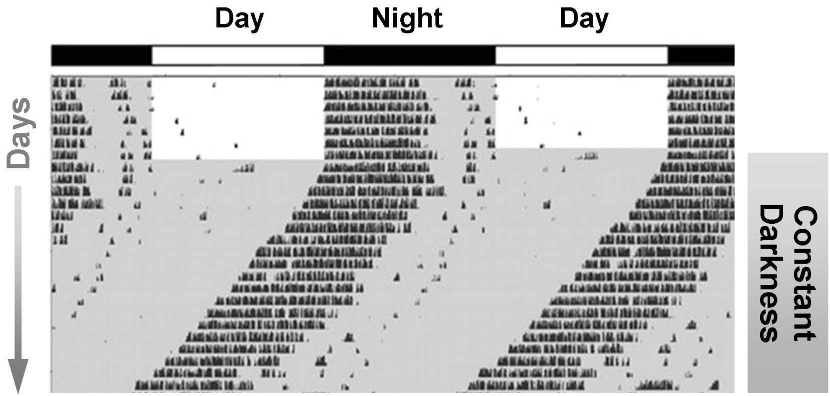

Figure 3.1: Running wheels and actograms. The nocturnal activity of a mouse is indicated by the black tick marks, which represent the revolutions of a running wheel. If mice are kept in constant darkness, their circadian rhythm continues with a period of approximately 23.5 hours, resulting in a progressive leftward shift of the activity pattern. Actograms are double- plotted, meaning that the same 24-hour period is represented at the end of a row and the beginning of the row below it.
(Modified from Yang et al., 2012 under CC BY license)

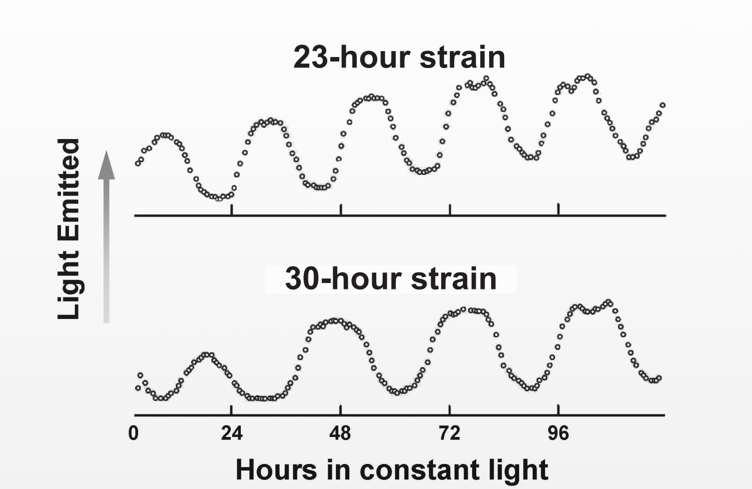

Figure 3.2: Fast and slow circadian rhythms in cyanobacteria. The circadian rhythms of two strains of cyanobacteria with periods of approximately 23 and 30 hours. The bacteria were genetically engineered to emit light in a manner proportional to the concentration of a specific protein. When these strains are forced to compete with each other for resources in an environment with a 23-hour light-dark, the 23-hour strain will win; in contrast, if they are placed in a 30-hour light-dark cycle, the 30-hour strain will win. (Adapted with permission from Johnson et al., 1998)

Figure 4.1: (Paul Noth/The New Yorker Collection/The Cartoon Bank)

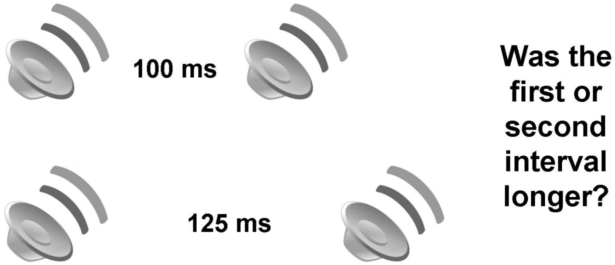

Figure 5.1: Interval Discrimination Task.

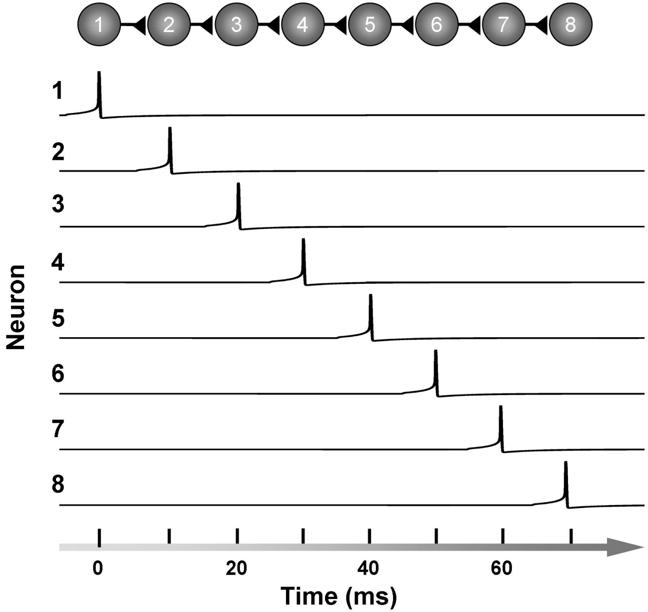

Figure 5.2: Synfire Chain. In a synfire chain model individual neurons (or groups of neurons) are connected in a feed-forward fashion. Activity—action potentials represented by "spikes" in voltage—propagates throughout the network much like a pattern of falling dominos. Time from the activation of the first neuron in the chain can be encoded by which neuron is currently active.

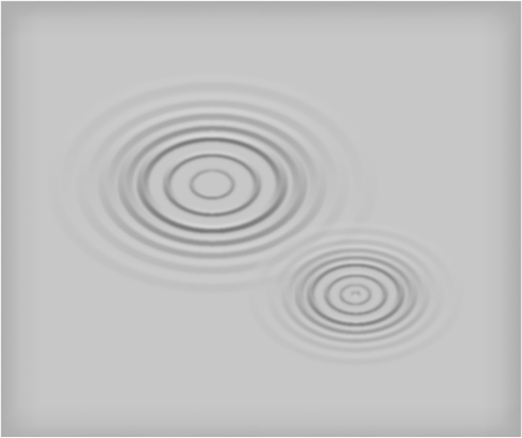

Figure 6.1: Ripples. Time is naturally encoded in the state of dynamical systems. Here it is clear which raindrop fell first, and it would be possible to estimate the interval between the raindrops.

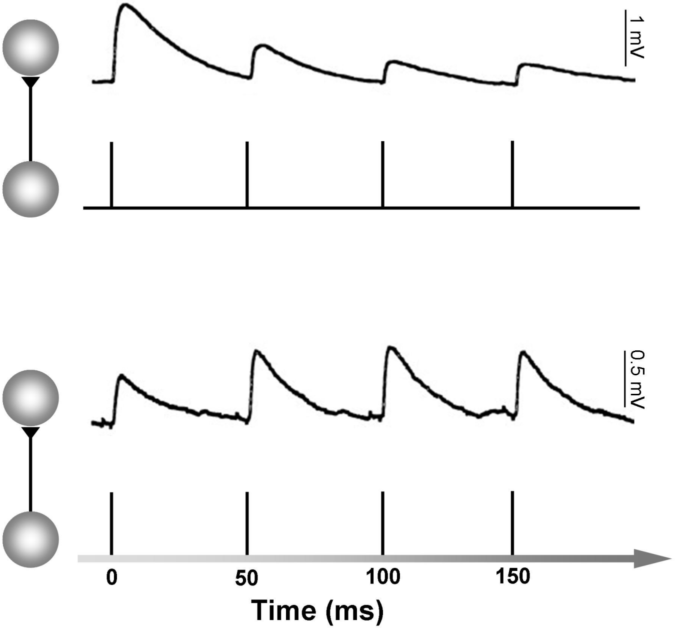

Figure 6.2: Short-term synaptic plasticity. On the time scale of milliseconds the strength of a synapse can undergo short-term depression (above) or short-term synaptic facilitation (below). (Traces from Reyes and Sakmann, 1999)

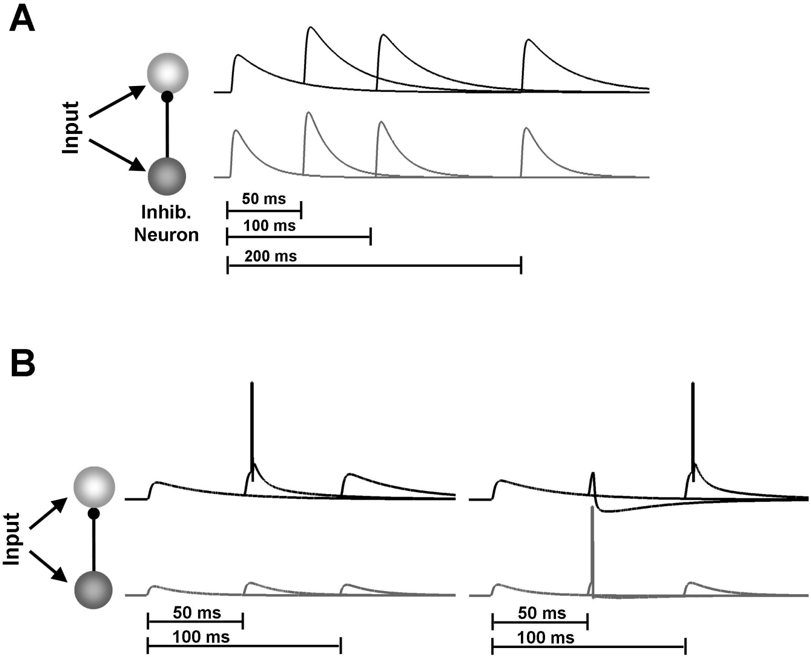

Figure 6.3: Interval selectivity based on short-term synaptic plasticity.
A. In this simulation of a simple neural circuit, a single input neuron contacts an excitatory (top) and inhibitory (bottom) neuron. The traces capture the voltage deflections in response to three different intervals: the input neuron fires two spikes separated by 50, 100, or 200 ms. The synapses from the input onto both neurons undergo short-term facilitation—for example, the amplitude of the voltage signal in response to the second spike of a 50 ms stimulus is larger than the voltage deflection caused by the first spike.
B. Depending on the strength of the synapses from the input to the excitatory and inhibitory neurons, the excitatory neuron can selectively respond to a 50 (left) or 100 ms (right) interval—thus the excitatory neuron in this simple circuit can, in a sense, tell time.

Time	Window #1	Window #2	Window #3
0	0	0	0
1	0	1	1
2	1	1	1
3	1	0	0
4	0	1	0
5	1	1	0

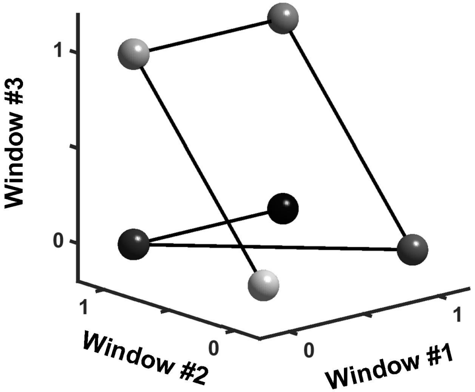

Figure 6.4: Encoding time in the changing states of the windows of a building. The states of the three windows at each point in time (shown in the table on the left) are equivalently represented as a trajectory in 3D space (right).

Perhaps our bank of Christmas lights has two switches, one controlled by Alice and one by Bob. Perhaps Alice's switch activates the following spatial patterns of lights at 1 sec intervals (where each number represents the position of the light in the chain):

t=1	5 10 15 20
t=2	6 12 18 24
t=3	7 14 21 28

. . .

whereas Bob's switch produces the following sequence of illumination (note that in this example each pattern follows a specific algorithm):

t=1	1 2 3 4
t=2	1 4 6 8
t=3	1 6 9 12

. . .

Time Step	Run 1	Run 2
1	0.9900	0.99001
2	0.0386	0.0386
3	0.1448	0.1446
4	0.4829	0.4825
5	0.9739	0.9738
6	0.0993	0.0995
7	0.3488	0.3494
8	0.8859	0.8866
9	0.3943	0.3922
10	0.9314	0.9296
11	0.2492	0.2551
12	0.7296	0.7410
13	0.7694	0.7484
14	0.6920	0.7343
15	0.8313	0.7609
16	0.5471	0.7095
17	0.9664	0.8038
18	0.1268	0.6150

$$\mathbf{x}_{t+1} = 3.9\mathbf{x}_t(1-\mathbf{x}_t)$$

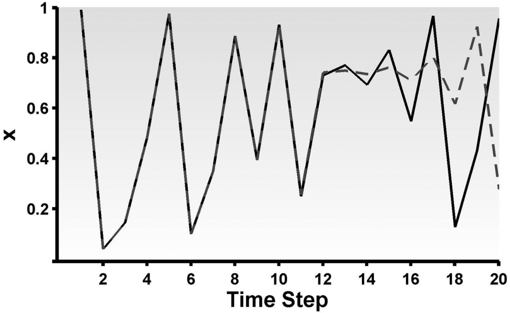

Figure 6.5: Example of an equation that exhibits chaos. In this equation the value of x at each subsequent time step (t+1) is determined by the value of x at the current time step (t). Even when starting with two close values of x in Run 1 and Run 2 (0.99 and 0.99001, respectively), the values of x will diverge over time, as shown in the table and graph. The divergence will be imperceptible at first, but after eighteen steps or so the values of x in both runs will be unrelated to each other.

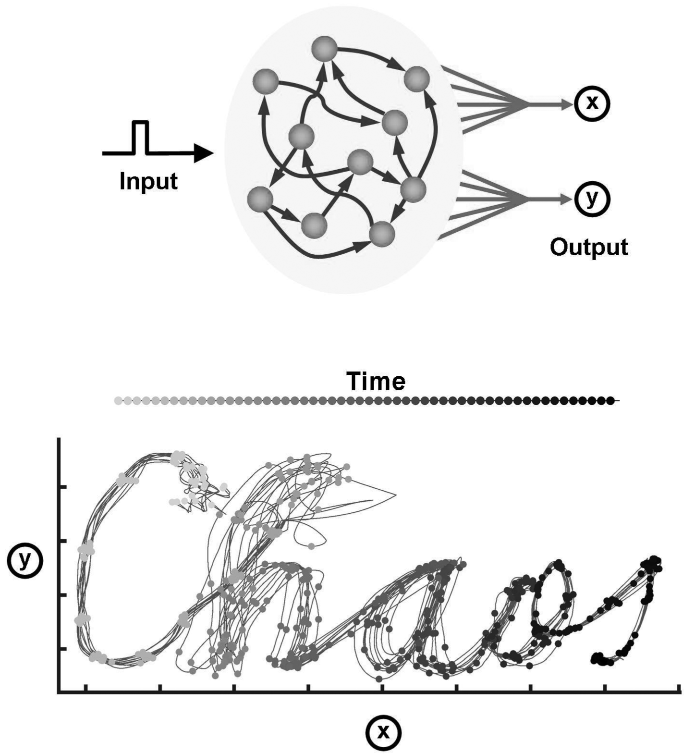

Figure 6.6: A recurrent network that generates a time-varying motor pattern. In this simulation a recurrent neural network is composed of interconnected units representing neurons (schematized in the middle of the top panel). The units in the recurrent network receive a brief input signal, and contact two output units. The activity in these two output units corresponds to the positions of a pen on the X and Y axes of a graph. Training consists of tuning the weights of the connections of the recurrent units onto the output units with a learning rule. After training, in response to a brief input the recurrent network generates a complex pattern of activity that drives the outputs in a manner that writes the word "Chaos." Motor patterns, such as handwritten digits, are inherently temporal, so the network also encodes time. The shaded dots imposed on the lines represent time. The network is not chaotic, as demonstrated by the fact that the motor pattern recovers after perturbing the recurrent network during the upswing of the "h" (ten trials are overlaid). (Modified from Laje and Buonomano, 2013)

1,000 +

40 +

1,000 +

30 +

1,000 +

20 +

1,000 +

10

$$t^{me} = \frac{t^{you}}{\sqrt{1 - \frac{v^2}{c^2}}}$$

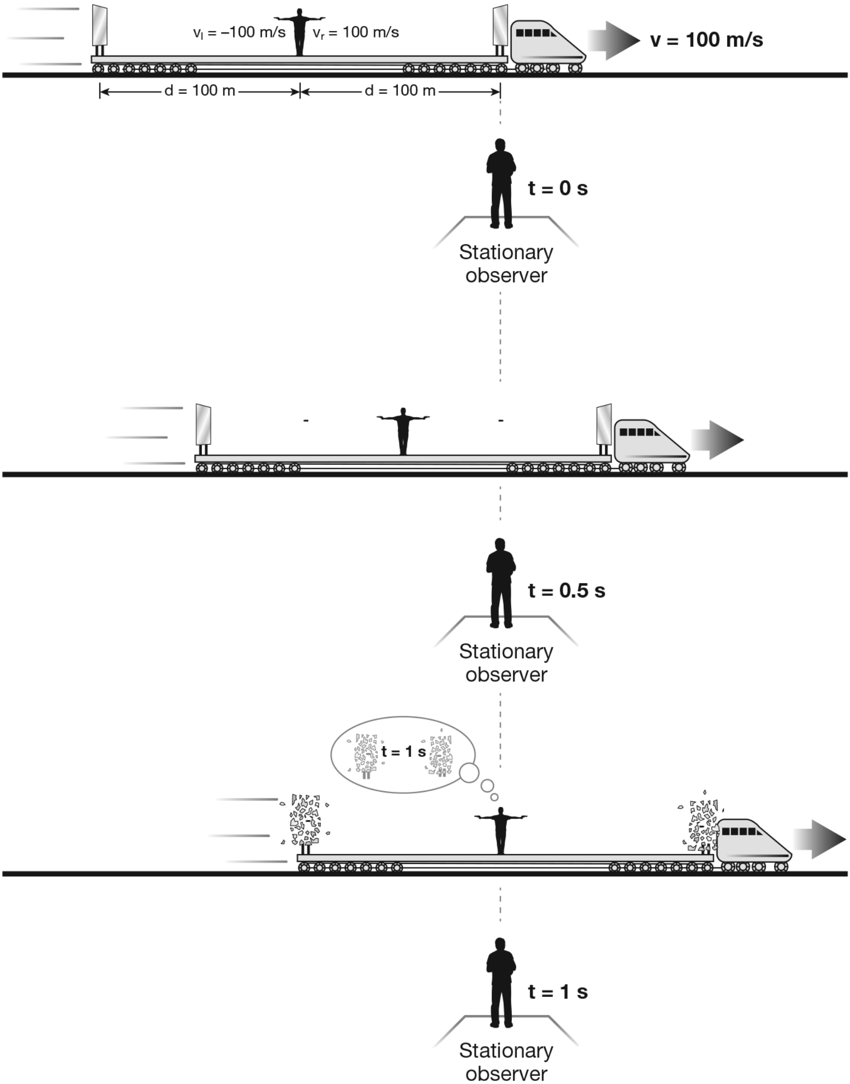

Figure 9.1: Newton's Train. Under Newton's laws, if an observer in the middle of a moving train shoots two bullets in opposite directions (t = 0), the panes in the front and back of the train will break simultaneously for all observers at t = 1 second.

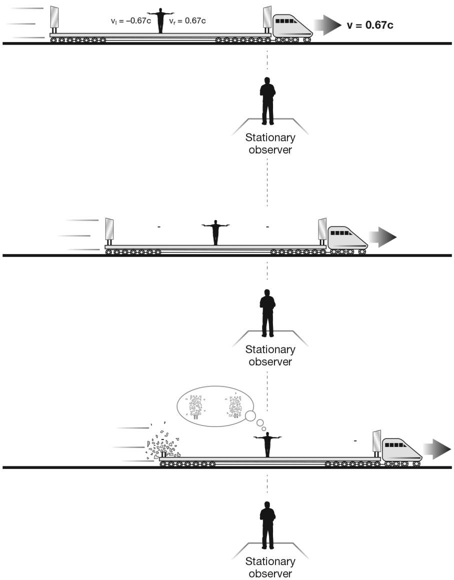

Figure 9.2: Einstein's Train. At high speeds special relativity tells us that different observers will experience space and time differently (making it very tricky to make figures about space and time). The clocks in both the train and platform frames are set to read t = 0 when the front pane of glass reaches the observer on the platform. When the observers on the train and platform are in front of each other, the observer in the train will witness both panes breaking simultaneously, but for the observer on the platform the back pane will have already broken and the front pane will still be intact.

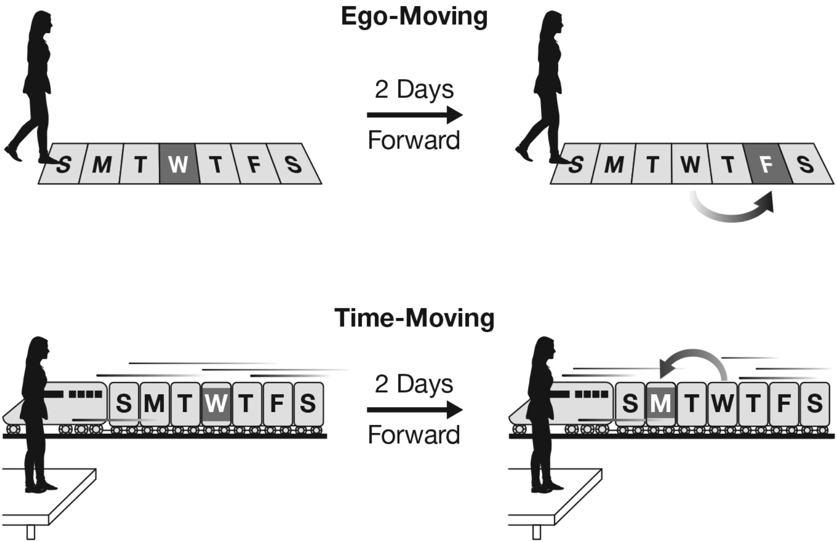

Figure 10.1: Ego-Moving and Time-Moving Perspectives.

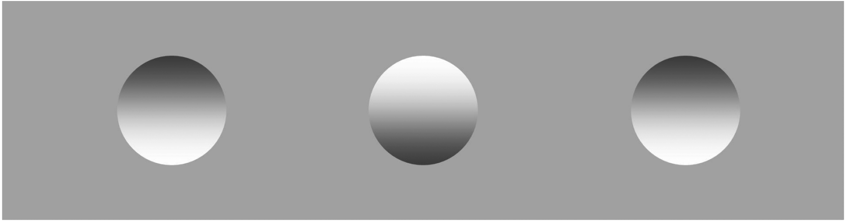

Figure 10.2: Concave-Convex Illusion. We see the middle circle with a dark lower edge as convex (popping out of the page) and the circles with dark upper edges as concave because the brain assumes light comes from above.