## Recurrent Neurons

Up to now we have mostly looked at feedforward neural networks, where the activations flow only in one direction, from the input layer to the output layer (except for a few networks in Appendix E). A recurrent neural network looks very much like a feedforward neural network, except it also has connections pointing backward. Let's look at the simplest possible RNN, composed of just one neuron receiving inputs, producing an output, and sending that output back to itself, as shown in Figure 14-1 (left). At each *time step t* (also called a *frame*), this *recurrent neuron* receives the inputs $\mathbf{x}_{(t)}$ as well as its own output from the previous time step, $y_{(t-1)}$. We can represent this tiny network against the time axis, as shown in Figure 14-1 (right). This is called *unrolling the network through time*.

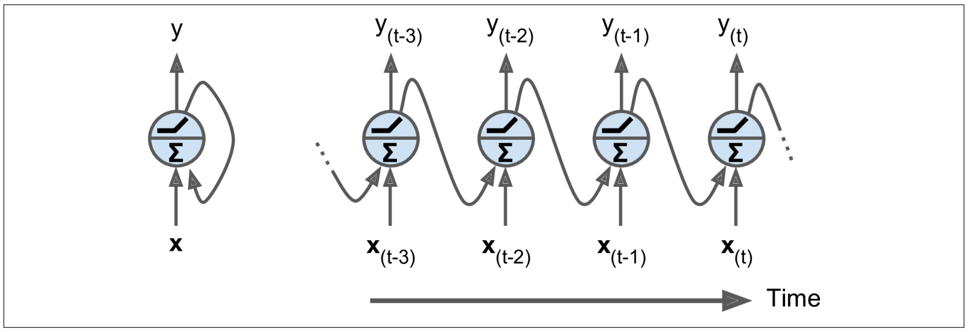


*Figure 14-1. A recurrent neuron (left), unrolled through time (right)*

You can easily create a layer of recurrent neurons. At each time step $t$, every neuron receives both the input vector $\mathbf{x}_{(t)}$ and the output vector from the previous time step $\mathbf{y}_{(t-1)}$, as shown in Figure 14-2. Note that both the inputs and outputs are vectors now (when there was just a single neuron, the output was a scalar).

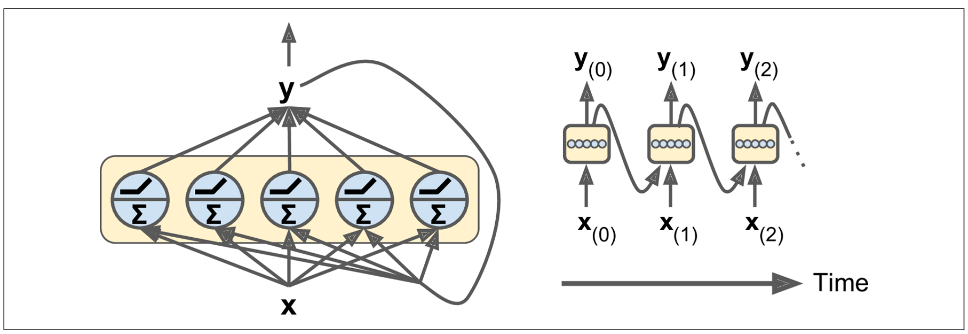


*Figure 14-2. A layer of recurrent neurons (left), unrolled through time (right)*

Each recurrent neuron has two sets of weights: one for the inputs $\mathbf{x}_{(t)}$ and the other for the outputs of the previous time step, $\mathbf{y}_{(t-1)}$. Let's call these weight vectors $\mathbf{w}_x$ and $\mathbf{w}_y$.