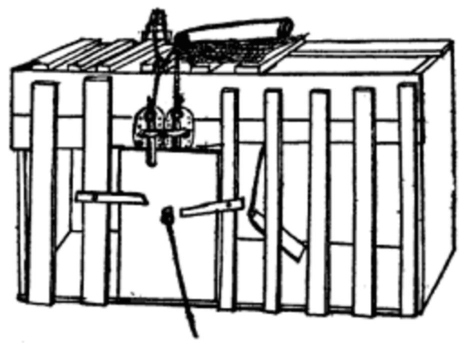

Figure 14.7: One of Thorndike's puzzle boxes. Reprinted from Thorndike, Animal Intelligence: An Experimental Study of the Associative Processes in Animals, *The Psychological Review, Series of Monograph Supplements*, II(4), Macmillan, New York, 1898.

These and other experiments (some with dogs, chicks, monkeys, and even fish) led Thorndike to formulate a number of "laws" of learning, the most influential being the *Law of Effect*, a version of which we quoted in Chapter 1. This law describes what is generally known as learning by trial and error. As mentioned in Chapter 1, many aspects of the Law of Effect have generated controversy, and its details have been modified over the years. Still the law—in one form or another—expresses an enduring principle of learning.

Essential features of reinforcement learning algorithms correspond to features of animal learning described by the Law of Effect. First, reinforcement learning algorithms are *selectional*, meaning that they try alternatives and select among them by comparing their consequences. Second, reinforcement learning algorithms are *associative*, meaning that the alternatives found by selection are associated with particular situations, or states, to form the agent's policy. Like learning described by the Law of Effect, reinforcement learning is not just the process of *finding* actions that produce a lot of reward, but also of *connecting* these actions to situations or states. Thorndike used the phrase learning by "selecting and connecting" (Hilgard, 1956). Natural selection in evolution is a prime example of a selectional process, but it is not associative (at least as it is commonly understood); supervised learning is associative, but it is not selectional because it relies on instructions that directly tell the agent how to change its behavior.

In computational terms, the Law of Effect describes an elementary way of combining *search* and *memory*: search in the form of trying and selecting among many actions in each situation, and memory in the form of associations linking situations with the actions found—so far—to work best in those situations. Search and memory are essential components of all reinforcement learning algorithms, whether memory takes the form of an agent's policy, value function, or environment model.

A reinforcement learning algorithm's need to search means that it has to explore in some way. Animals clearly explore as well, and early animal learning researchers disagreed about the degree of guidance an animal uses in selecting its actions in situations like Thorndike's puzzle boxes. Are actions the result of "absolutely random, blind groping" (Woodworth, 1938, p. 777), or is there some degree of guidance, either from prior learning, reasoning, or other means? Although some thinkers, including Thorndike, seem to have taken the former position, others favored more deliberate exploration. Reinforcement learning algorithms allow wide latitude for how much guidance an agent can employ in selecting actions. The forms of exploration we have used in the algorithms presented in this book, such as ϵ-greedy and upper-confidence-bound action selection, are merely among the simplest. More sophisticated methods are possible, with the only stipulation being that there has to be *some* form of exploration for the