

belief state, consisting of the first few states examined, is also unsolvable. In some cases, this leads to a speedup proportional to the size of the belief states, which may themselves be as large as the physical state space itself.

#### 4.4.2 Searching in partially observable environments

Many problems cannot be solved without sensing. For example, the sensorless 8-puzzle is impossible. On the other hand, a little bit of sensing can go a long way: we can solve 8-puzzles if we can see just the upper-left corner square. The solution involves moving each tile in turn into the observable square and keeping track of its location from then on.

For a partially observable problem, the problem specification will specify a  $\text{PERCEPT}(s)$  function that returns the percept received by the agent in a given state. If sensing is non-deterministic, then we can use a  $\text{PERCEPTS}$  function that returns a set of possible percepts. For fully observable problems,  $\text{PERCEPT}(s) = s$  for every state  $s$ , and for sensorless problems  $\text{PERCEPT}(s) = \text{null}$ .

Consider a local-sensing vacuum world, in which the agent has a position sensor that yields the percept  $L$  in the left square, and  $R$  in the right square, and a dirt sensor that yields *Dirty* when the current square is dirty and *Clean* when it is clean. Thus, the  $\text{PERCEPT}$  in state 1 is  $[L, \text{Dirty}]$ . With partial observability, it will usually be the case that several states produce the same percept; state 3 will also produce  $[L, \text{Dirty}]$ . Hence, given this initial percept, the initial belief state will be  $\{1, 3\}$ . We can think of the transition model between belief states for partially observable problems as occurring in three stages, as shown in Figure 4.15:

- The **prediction** stage computes the belief state resulting from the action,  $\text{RESULT}(b, a)$ , exactly as we did with sensorless problems. To emphasize that this is a prediction, we use the notation  $\hat{b} = \text{RESULT}(b, a)$ , where the “hat” over the  $b$  means “estimated,” and we also use  $\text{PREDICT}(b, a)$  as a synonym for  $\text{RESULT}(b, a)$ .
- The **possible percepts** stage computes the set of percepts that could be observed in the predicted belief state (using the letter  $o$  for observation):

$$\text{POSSIBLE-PERCEPTS}(\hat{b}) = \{o : o = \text{PERCEPT}(s) \text{ and } s \in \hat{b}\}.$$

- The **update** stage computes, for each possible percept, the belief state that would result from the percept. The updated belief state  $b_o$  is the set of states in  $\hat{b}$  that could have produced the percept:

$$b_o = \text{UPDATE}(\hat{b}, o) = \{s : o = \text{PERCEPT}(s) \text{ and } s \in \hat{b}\}.$$

The agent needs to deal with *possible* percepts at planning time, because it won’t know the *actual* percepts until it executes the plan. Notice that nondeterminism in the physical environment can enlarge the belief state in the prediction stage, but each updated belief state  $b_o$  can be no larger than the predicted belief state  $\hat{b}$ ; observations can only help reduce uncertainty. Moreover, for deterministic sensing, the belief states for the different possible percepts will be disjoint, forming a *partition* of the original predicted belief state.

Putting these three stages together, we obtain the possible belief states resulting from a given action and the subsequent possible percepts:

$$\text{RESULTS}(b, a) = \{b_o : b_o = \text{UPDATE}(\text{PREDICT}(b, a), o) \text{ and } o \in \text{POSSIBLE-PERCEPTS}(\text{PREDICT}(b, a))\}. \quad (4.5)$$