Solutions for Chapter 2
Intelligent Agents

2.1 This question tests the student's understanding of environments, rational actions, and performance measures. Any sequential environment in which rewards may take time to arrive will work, because then we can arrange for the reward to be "over the horizon." Suppose that in any state there are two action choices, a and b, and consider two cases: the agent is in state s at time T or at time $T-1$. In state s, action a reaches state s' with reward 0, while action b reaches state s again with reward 1; in s' either action gains reward 10. At time $T-1$, it's rational to do a in s, with expected total reward 10 before time is up; but at time T, it's rational to do b with total expected reward 1 because the reward of 10 cannot be obtained before time is up.

Students may also provide common-sense examples from real life: investments whose payoff occurs after the end of life, exams where it doesn't make sense to start the high-value question with too little time left to get the answer, and so on.

The environment state can include a clock, of course; this doesn't change the gist of the answer—now the action will depend on the clock as well as on the non-clock part of the state—but it does mean that the agent can never be in the same state twice.

2.2 Notice that for our simple environmental assumptions we need not worry about quantitative uncertainty.

a. It suffices to show that for all possible actual environments (i.e., all dirt distributions and initial locations), this agent cleans the squares at least as fast as any other agent. This is trivially true when there is no dirt. When there is dirt in the initial location and none in the other location, the world is clean after one step; no agent can do better. When there is no dirt in the initial location but dirt in the other, the world is clean after two steps; no agent can do better. When there is dirt in both locations, the world is clean after three steps; no agent can do better. (Note: in general, the condition stated in the first sentence of this answer is much stricter than necessary for an agent to be rational.)

b. The agent in (a) keeps moving backwards and forwards even after the world is clean. It is better to do $NoOp$ once the world is clean (the chapter says this). Now, since the agent's percept doesn't say whether the other square is clean, it would seem that the agent must have some memory to say whether the other square has already been cleaned. To make this argument rigorous is more difficult—for example, could the agent arrange things so that it would only be in a clean left square when the right square

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was already clean? As a general strategy, an agent *can* use the environment itself as a form of **external memory**—a common technique for humans who use things like appointment calendars and knots in handkerchiefs. In this particular case, however, that is not possible. Consider the reflex actions for $[A, Clean]$ and $[B, Clean]$. If either of these is $NoOp$, then the agent will fail in the case where that is the initial percept but the other square is dirty; hence, neither can be $NoOp$ and therefore the simple reflex agent is doomed to keep moving. In general, the problem with reflex agents is that they have to do the same thing in situations that look the same, even when the situations are actually quite different. In the vacuum world this is a big liability, because every interior square (except home) looks either like a square with dirt or a square without dirt.

c. If we consider asymptotically long lifetimes, then it is clear that learning a map (in some form) confers an advantage because it means that the agent can avoid bumping into walls. It can also learn where dirt is most likely to accumulate and can devise an optimal inspection strategy. The precise details of the exploration method needed to construct a complete map appear in Chapter 4; methods for deriving an optimal inspection/cleanup strategy are in Chapter 21.

2.3

a. *An agent that senses only partial information about the state cannot be perfectly rational.*
False. Perfect rationality refers to the ability to make good decisions given the sensor information received.

b. *There exist task environments in which no pure reflex agent can behave rationally.*
True. A pure reflex agent ignores previous percepts, so cannot obtain an optimal state estimate in a partially observable environment. For example, correspondence chess is played by sending moves; if the other player's move is the current percept, a reflex agent could not keep track of the board state and would have to respond to, say, "a4" in the same way regardless of the position in which it was played.

c. *There exists a task environment in which every agent is rational.*
True. For example, in an environment with a single state, such that all actions have the same reward, it doesn't matter which action is taken. More generally, any environment that is reward-invariant under permutation of the actions will satisfy this property.

d. *The input to an agent program is the same as the input to the agent function.*
False. The agent function, notionally speaking, takes as input the entire percept sequence up to that point, whereas the agent program takes the current percept only.

e. *Every agent function is implementable by some program/machine combination.*
False. For example, the environment may contain Turing machines and input tapes and the agent's job is to solve the halting problem; there is an agent *function* that specifies the right answers, but no agent program can implement it. Another example would be an agent function that requires solving intractable problem instances of arbitrary size in constant time.

f. *Suppose an agent selects its action uniformly at random from the set of possible actions. There exists a deterministic task environment in which this agent is rational.*
True. This is a special case of (c); if it doesn't matter which action you take, selecting randomly is rational.

g. *It is possible for a given agent to be perfectly rational in two distinct task environments.*
True. For example, we can arbitrarily modify the parts of the environment that are unreachable by any optimal policy as long as they stay unreachable.

h. *Every agent is rational in an unobservable environment.*
False. Some actions are stupid—and the agent may know this if it has a model of the environment—even if one cannot perceive the environment state.

i. *A perfectly rational poker-playing agent never loses.*
False. Unless it draws the perfect hand, the agent can always lose if an opponent has better cards. This can happen for game after game. The correct statement is that the agent's expected winnings are nonnegative.

2.4 Many of these can actually be argued either way, depending on the level of detail and abstraction.

A. Partially observable, stochastic, sequential, dynamic, continuous, multi-agent.

B. Partially observable, stochastic, sequential, dynamic, continuous, single agent (unless there are alien life forms that are usefully modeled as agents).

C. Partially observable, deterministic, sequential, static, discrete, single agent. This can be multi-agent and dynamic if we buy books via auction, or dynamic if we purchase on a long enough scale that book offers change.

D. Fully observable, stochastic, episodic (every point is separate), dynamic, continuous, multi-agent.

E. Fully observable, stochastic, episodic, dynamic, continuous, single agent.

F. Fully observable, stochastic, sequential, static, continuous, single agent.

G. Fully observable, deterministic, sequential, static, continuous, single agent.

H. Fully observable, strategic, sequential, static, discrete, multi-agent.

2.5 The following are just some of the many possible definitions that can be written:

- *Agent*: an entity that perceives and acts; or, one that *can be viewed* as perceiving and acting. Essentially any object qualifies; the key point is the way the object implements an agent function. (Note: some authors restrict the term to *programs* that operate *on behalf of* a human, or to programs that can cause some or all of their code to run on other machines on a network, as in **mobile agents**.)

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- *Agent function*: a function that specifies the agent's action in response to every possible percept sequence.
- *Agent program*: that program which, combined with a machine architecture, implements an agent function. In our simple designs, the program takes a new percept on each invocation and returns an action.

- *Rationality*: a property of agents that choose actions that maximize their expected utility, given the percepts to date.
- *Autonomy*: a property of agents whose behavior is determined by their own experience rather than solely by their initial programming.
- *Reflex agent*: an agent whose action depends only on the current percept.
- *Model-based agent*: an agent whose action is derived directly from an internal model of the current world state that is updated over time.
- *Goal-based agent*: an agent that selects actions that it believes will achieve explicitly represented goals.
- *Utility-based agent*: an agent that selects actions that it believes will maximize the expected utility of the outcome state.
- *Learning agent*: an agent whose behavior improves over time based on its experience.

2.6 Although these questions are very simple, they hint at some very fundamental issues. Our answers are for the simple agent designs for *static* environments where nothing happens while the agent is deliberating; the issues get even more interesting for dynamic environments.

a. Yes; take any agent program and insert null statements that do not affect the output.

b. Yes; the agent function might specify that the agent print $true$ when the percept is a Turing machine program that halts, and $false$ otherwise. (Note: in dynamic environments, for machines of less than infinite speed, the rational agent function may not be implementable; e.g., the agent function that always plays a winning move, if any, in a game of chess.)

c. Yes; the agent's behavior is fixed by the architecture and program.

d. There are 2^n agent programs, although many of these will not run at all. (Note: Any given program can devote at most n bits to storage, so its internal state can distinguish among only 2^n past histories. Because the agent function specifies actions based on percept histories, there will be many agent functions that cannot be implemented because of lack of memory in the machine.)

e. It depends on the program and the environment. If the environment is dynamic, speeding up the machine may mean choosing different (perhaps better) actions and/or acting sooner. If the environment is static and the program pays no attention to the passage of elapsed time, the agent function is unchanged.

2.7

The design of goal- and utility-based agents depends on the structure of the task environment. The simplest such agents, for example those in chapters 3 and 10, compute the agent's entire future sequence of actions in advance before acting at all. This strategy works for static and deterministic environments which are either fully-known or unobservable

For fully-observable and fully-known static environments a policy can be computed in advance which gives the action to by taken in any given state.

```
function GOAL-BASED-AGENT(percept) returns an action
  persistent: state, the agent's current conception of the world state
              model, a description of how the next state depends on current state and action
              goal, a description of the desired goal state
              plan, a sequence of actions to take, initially empty
              action, the most recent action, initially none

  state ← UPDATE-STATE(state, action, percept, model)
  if GOAL-ACHIEVED(state,goal) then return a null action
  if plan is empty then
plan ← PLAN(state,goal,model)
  action ← FIRST(plan)
  plan ← REST(plan)
  return action
```

Figure S2.1 A goal-based agent.

For partially-observable environments the agent can compute a conditional plan, which specifies the sequence of actions to take as a function of the agent's perception. In the extreme, a conditional plan gives the agent's response to every contingency, and so it is a representation of the entire agent function.

In all cases it may be either intractable or too expensive to compute everything out in advance. Instead of a conditional plan, it may be better to compute a single sequence of actions which is likely to reach the goal, then monitor the environment to check whether the plan is succeeding, repairing or replanning if it is not. It may be even better to compute only the start of this plan before taking the first action, continuing to plan at later time steps.

Pseudocode for simple goal-based agent is given in Figure S2.1. GOAL-ACHIEVED tests to see whether the current state satisfies the goal or not, doing nothing if it does. PLAN computes a sequence of actions to take to achieve the goal. This might return only a prefix of the full plan, the rest will be computed after the prefix is executed. This agent will act to maintain the goal: if at any point the goal is not satisfied it will (eventually) replan to achieve the goal again.

At this level of abstraction the utility-based agent is not much different than the goal-based agent, except that action may be continuously required (there is not necessarily a point where the utility function is "satisfied"). Pseudocode is given in Figure S2.2.

2.8 The file `"agents/environments/vacuum.lisp"` in the code repository implements the vacuum-cleaner environment. Students can easily extend it to generate different shaped rooms, obstacles, and so on.

2.9 A reflex agent program implementing the rational agent function described in the chapter is as follows:

```
(defun reflex-rational-vacuum-agent (percept)
  (destructuring-bind (location status) percept
```

function UTILITY-BASED-AGENT($percept$) **returns** an action
  persistent: $state$, the agent's current conception of the world state
    $model$, a description of how the next state depends on current state and action
    $utility - function$, a description of the agent's utility function
    $plan$, a sequence of actions to take, initially empty
    $action$, the most recent action, initially none

$state \leftarrow$ UPDATE-STATE($state$, $action$, $percept$, $model$)
if $plan$ is empty **then**
$plan \leftarrow$ PLAN($state$,$utility - function$,$model$)
$action \leftarrow$ FIRST($plan$)
$plan \leftarrow$ REST($plan$)
return $action$

Figure S2.2 A utility-based agent.

```
(cond ((eq status 'Dirty) 'Suck)
      ((eq location 'A) 'Right)
      (t 'Left))))
```

For states 1, 3, 5, 7 in Figure 4.9, the performance measures are 1996, 1999, 1998, 2000 respectively.

2.10

a. No; see answer to 2.4(b).

b. See answer to 2.4(b).

c. In this case, a simple reflex agent can be perfectly rational. The agent can consist of a table with eight entries, indexed by percept, that specifies an action to take for each possible state. After the agent acts, the world is updated and the next percept will tell the agent what to do next. For larger environments, constructing a table is infeasible. Instead, the agent could run one of the optimal search algorithms in Chapters 3 and 4 and execute the first step of the solution sequence. Again, no internal state is *required*, but it would help to be able to store the solution sequence instead of recomputing it for each new percept.

2.11

a. Because the agent does not know the geography and perceives only location and local dirt, and cannot remember what just happened, it will get stuck forever against a wall when it tries to move in a direction that is blocked—that is, unless it randomizes.

b. One possible design cleans up dirt and otherwise moves randomly:

```
(defun randomized-reflex-vacuum-agent (percept)
  (destructuring-bind (location status) percept
    (cond ((eq status 'Dirty) 'Suck)
          (t (random-element '(Left Right Up Down))))))
```

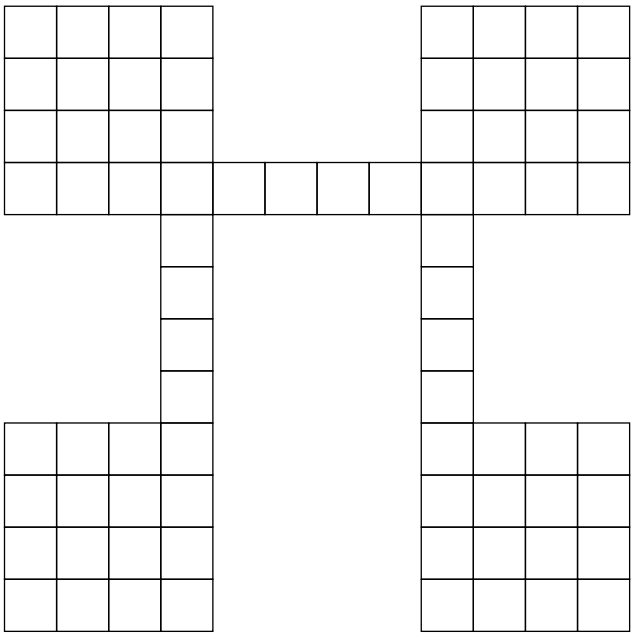

Figure S2.3 An environment in which random motion will take a long time to cover all the squares.

This is fairly close to what the Roomba^{TM} vacuum cleaner does (although the Roomba has a bump sensor and randomizes only when it hits an obstacle). It works reasonably well in nice, compact environments. In maze-like environments or environments with small connecting passages, it can take a very long time to cover all the squares.

c. An example is shown in Figure S2.3. Students may also wish to measure clean-up time for linear or square environments of different sizes, and compare those to the efficient online search algorithms described in Chapter 4.

d. A reflex agent with state can build a map (see Chapter 4 for details). An online depth-first exploration will reach every state in time linear in the size of the environment; therefore, the agent can do much better than the simple reflex agent.

The question of rational behavior in unknown environments is a complex one but it is worth encouraging students to think about it. We need to have some notion of the prior probability distribution over the class of environments; call this the initial **belief state**. Any action yields a new percept that can be used to update this distribution, moving the agent to a new belief state. Once the environment is completely explored, the belief state collapses to a single possible environment. Therefore, the problem of optimal exploration can be viewed as a search for an optimal strategy in the space of possible belief states. This is a well-defined, if horrendously intractable, problem. Chapter 21 discusses some cases where optimal exploration is possible. Another concrete example of exploration is the Minesweeper computer game (see Exercise 7.22). For very small Minesweeper environments, optimal exploration is feasible although the belief state

update is nontrivial to explain.

2.12 The problem appears at first to be very similar; the main difference is that instead of using the location percept to build the map, the agent has to "invent" its own locations (which, after all, are just nodes in a data structure representing the state space graph). When a bump is detected, the agent assumes it remains in the same location and can add a wall to its map. For grid environments, the agent can keep track of its (x, y) location and so can tell when it has returned to an old state. In the general case, however, there is no simple way to tell if a state is new or old.

2.13

a. For a reflex agent, this presents no *additional* challenge, because the agent will continue to $Suck$ as long as the current location remains dirty. For an agent that constructs a sequential plan, every $Suck$ action would need to be replaced by "$Suck$ until clean." If the dirt sensor can be wrong on each step, then the agent might want to wait for a few steps to get a more reliable measurement before deciding whether to $Suck$ or move on to a new square. Obviously, there is a trade-off because waiting too long means that dirt remains on the floor (incurring a penalty), but acting immediately risks either dirtying a clean square or ignoring a dirty square (if the sensor is wrong). A rational agent must also continue touring and checking the squares in case it missed one on a previous tour (because of bad sensor readings). it is not immediately obvious how the waiting time at each square should change with each new tour. These issues can be clarified by experimentation, which may suggest a general trend that can be verified mathematically. This problem is a partially observable Markov decision process—see Chapter 17. Such problems are hard in general, but some special cases may yield to careful analysis.

b. In this case, the agent must keep touring the squares indefinitely. The probability that a square is dirty increases monotonically with the time since it was last cleaned, so the rational strategy is, roughly speaking, to repeatedly execute the shortest possible tour of all squares. (We say "roughly speaking" because there are complications caused by the fact that the shortest tour may visit some squares twice, depending on the geography.) This problem is also a partially observable Markov decision process.