Chapter 2
INTELLIGENT AGENTS

- ✓ Introduction
- ✓ Intelligent Agents
- ✓ Agents and Objects
- ✓ Agents and Expert Systems
- ✓ Agents as Intentional Systems

1. Abstract Archtectures for Intelligent Agents
2. How to Tell an Agent What to Do
3. Synthesizing Agents

Abstract Architecture for Agents

- Assume the environment may be in any of a finite set E of discrete, instantaneous states:

$$E = \{e, e', \ldots\}.$$

- Agents are assumed to have a repertoire of possible actions available to them, which transform the state of the environment:

$$Ac = \{\alpha, \alpha', \ldots\}$$

- A *run*, r, of an agent in an environment is a sequence of interleaved environment states and actions:

$$r : e_0 \xrightarrow{\alpha_0} e_1 \xrightarrow{\alpha_1} e_2 \xrightarrow{\alpha_2} e_3 \xrightarrow{\alpha_3} \cdots \xrightarrow{\alpha_{u-1}} e_u$$

Abstract Architecture for Agents

- Let:
  - R be the set of all such possible finite sequences (over E and Ac)
  - R^{Ac} be the subset of these that end with an action
  - R^{E} be the subset of these that end with an environment state

State Transformer Functions

- A *state transformer* function represents behavior of the environment: $\tau : \mathcal{R}^{Ac} \to \wp(E)$
- Note that environments are…
  - *history dependent*
  - *non-deterministic*
- If $\tau(r)=\emptyset$, then there are no possible successor states to r. In this case, we say that the system has *ended* its run
- Formally, we say an environment Env is a triple $Env = \langle E, e_0, \tau \rangle$ where: E is a set of environment states, $e_0 \in E$ is the initial state, and τ is a state transformer function

Agents

- **<u>Agent</u>** is a function which maps runs to actions:

$$Ag : \mathcal{R}^E \to Ac$$

  An agent makes a decision about what action to perform based on the history of the system that it has witnessed to date.

- Let AG be the set of all agents

Systems

- A *system* is a pair containing an agent and an environment
- Any system will have associated with it a set of **possible runs**; we denote the set of runs of agent Ag in environment Env by $\mathbf{R}(Ag, Env)$
- (We assume $R(Ag, Env)$ contains only *terminated* runs)

Systems

- Formally, a sequence

$$(e_0, \alpha_0, e_1, \alpha_1, e_2, \ldots)$$

represents a run of an agent Ag in environment $Env = \langle E, e_0, \tau \rangle$ if:

1. e_0 is the initial state of Env
2. $\alpha_0 = Ag(e_0)$; and
3. For $u > 0$, $e_u \in \tau((e_0, \alpha_0, \ldots, \alpha_{u-1}))$ where $\alpha_u = Ag((e_0, \alpha_0, \ldots, e_u))$

Purely Reactive Agents

- Some agents decide what to do without reference to their history — they base their decision making entirely on the **present**, with no reference at all to the past
- We call such agents *purely reactive*:

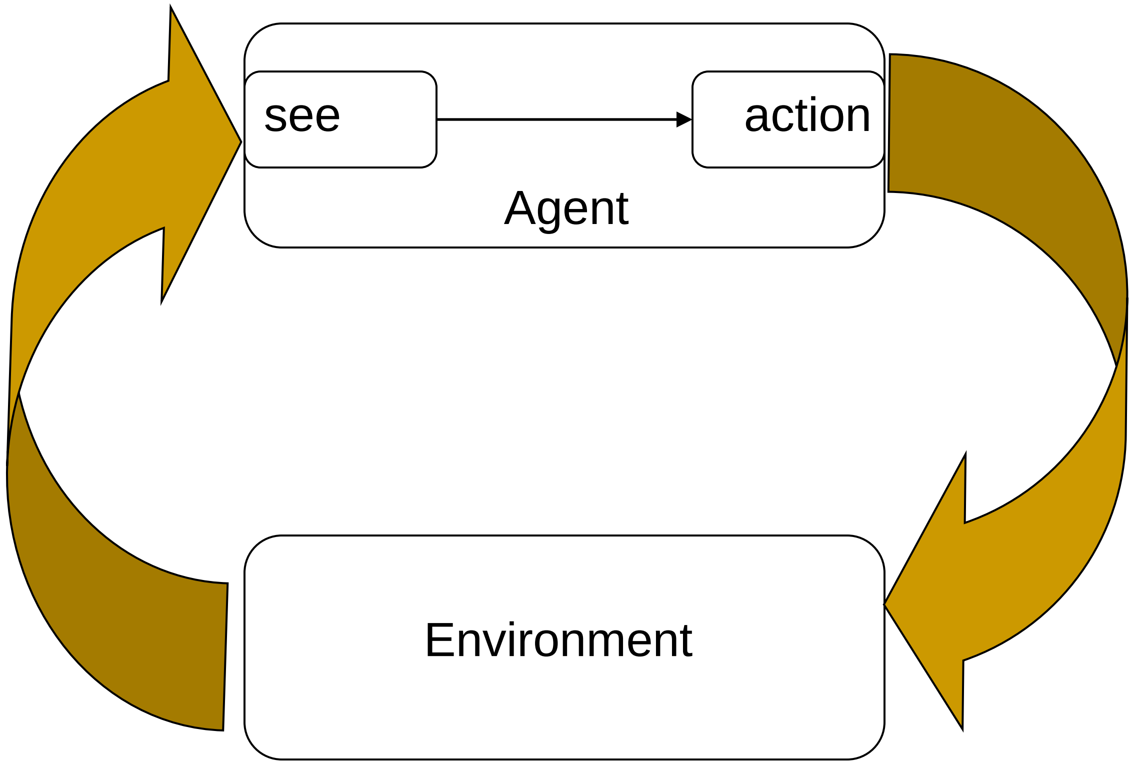
$$action : E \to Ac$$

- A thermostat is a purely reactive agent

$$action(e) = \begin{cases} \text{off} & \text{if } e = \text{temperature OK} \\ \text{on} & \text{otherwise.} \end{cases}$$

Perception

- Now introduce *perception* system:



Perception

- The *see* function is the agent’s ability to observe its environment, whereas the *action* function represents the agent’s decision making process
- *Output* of the *see* function is a *percept*:

$$see : E \to Per$$

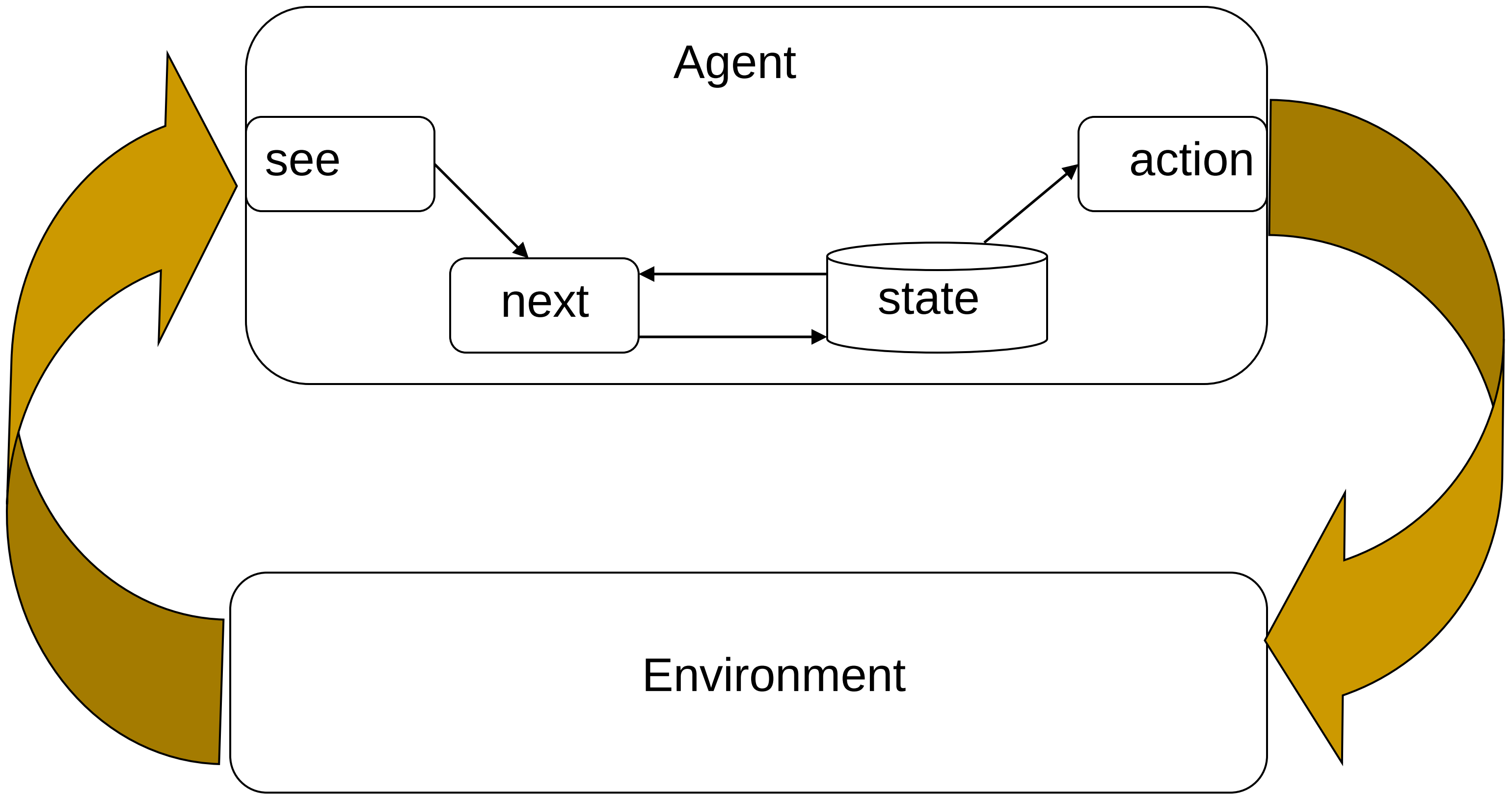
which maps environment states to percepts, and *action* is now a function

$$action : Per^* \to A$$

which maps **sequences of percepts** to actions

Agents with State

- We now consider agents that *maintain state*:



Agents with State

- These agents have some internal data structure, which is typically used to **record** information about the environment state and history.
  Let I be the set of all internal states of the agent.
- The perception function *see* for a state-based agent is unchanged:

$$see : E \to Per$$

The action-selection function *action* is now defined as a mapping

$$action : I \to Ac$$

from internal states to actions. An additional function *next* is introduced, which maps an internal state and percept to an internal state:

$$next : I \times Per \to I$$

Agent Control Loop

1. Agent starts in some initial internal state i_0
2. Observes its environment state e, and generates a percept $see(e)$
3. Internal state of the agent is then updated via $next$ function, becoming $next(i_0, see(e))$
4. The action selected by the agent is $action(next(i_0, see(e)))$
5. Goto 2

Tasks for Agents

- We build agents in order to carry out *tasks* for us
- The task must be *specified* by us…
- But we want to tell agents what to do *without* telling them how to do it

How to Tell an Agent What to Do

Utility Functions over States

- One possibility: associate ***utilities*** with individual states — the task of the agent is then to bring about states that maximize **utility**
- A task specification is a function

$$u : E \to \mathbb{R}$$

which associates a real number with every environment state

Utility Functions over States

- But what is the value of a *run*…
  - minimum utility of state on run?
  - maximum utility of state on run?
  - sum of utilities of states on run?
  - average?
- Disadvantage: difficult to specify a *long term* view when assigning utilities to individual states

Utilities over Runs

- Another possibility: assigns a utility not to individual states, but to **runs** themselves:

$$u : R \rightarrow \mathbb{R}$$

- Such an approach takes an inherently *long term* view
- Other variations: incorporate probabilities of different states emerging
- Difficulties with utility-based approaches:
  - where do the numbers come from?
  - hard to formulate tasks in these terms

Utility in the Tileworld

- Simulated two dimensional grid environment on which there are agents, tiles, obstacles, and holes
- An agent can move in four directions, up, down, left, or right, and if it is located next to a tile, it can push it
- Holes have to be filled up with tiles by the agent. An agent scores points by filling holes with tiles, with the aim being to fill as many holes as possible
- TILEWORLD changes with the random appearance and disappearance of holes
- Utility function defined as follows:

$$u(r) \hat{=} \frac{\text{number of holes filled in } r}{\text{number of holes that appeared in } r}$$

Expected Utility & Optimal Agents

- Write $P(r \mid Ag, Env)$ to denote probability that run r occurs when agent Ag is placed in environment Env

  Note:
  $$\sum_{r \in \mathcal{R}(Ag, Env)} P(r \mid Ag, Env) = 1.$$

- Then optimal agent Ag_{opt} in an environment Env is the one that *maximizes expected utility*:

$$Ag_{opt} = \arg\max_{Ag \in \mathcal{AG}} \sum_{r \in \mathcal{R}(Ag, Env)} u(r) P(r \mid Ag, Env). \qquad (1)$$

Bounded Optimal Agents

- Some agents cannot be implemented on some computers
(A function $Ag : \mathcal{R}^E \to Ac$ may need more than available memory to implement)
- Write $\mathcal{AG}_m$ to denote the agents that can be implemented on machine (computer) m:

$$\mathcal{AG}_m = \{Ag \mid Ag \in \mathcal{AG} \text{ and } Ag \text{ can be implemented on } m\}.$$

- We can replace equation (1) with the following, which defines the *bounded optimal* agent Ag_{opt}:

$$Ag_{opt} = \arg \max_{Ag \in \mathcal{AG}_m} \sum_{r \in \mathcal{R}(Ag, Env)} u(r) P(r \mid Ag, Env). \qquad (2)$$

Predicate Task Specifications

- A special case of assigning utilities to histories is to assign 0 (false) or 1 (true) to a run
- If a run is assigned 1, then the agent succeeds on that run, otherwise it fails
- Call these *predicate task specifications*
- Denote predicate task specification by Ψ. Thus $\Psi : \mathcal{R} \rightarrow \{0, 1\}$.

Task Environments

- A *task environment* is a pair $\langle Env, \Psi \rangle$ where Env is an environment,

$$\Psi : \mathcal{R} \rightarrow \{0, 1\}$$

is a predicate over runs.
Let $\mathcal{TE}$ be the set of all task environments.

- A task environment specifies:
  - the properties of the system the agent will inhabit
  - the criteria by which an agent will be judged to have either failed or succeeded

Task Environments

- Write $R_\Psi(Ag, Env)$ to denote set of all runs of the agent Ag in environment Env that satisfy Ψ:

$$\mathcal{R}_\Psi(Ag, Env) = \{r \mid r \in \mathcal{R}(Ag, Env) \text{ and } \Psi(r) = 1\}.$$

- We then say that an agent Ag succeeds in task environment $\langle Env, \Psi \rangle$ if

$$\mathcal{R}_\Psi(Ag, Env) = \mathcal{R}(Ag, Env)$$

The Probability of Success

- Let $P(r \mid Ag, Env)$ denote probability that run r occurs if agent Ag is placed in environment Env
- Then the probability $P(\Psi \mid Ag, Env)$ that Ψ is satisfied by Ag in Env would then simply be:

$$P(\Psi \mid Ag, Env) = \sum_{r \in \mathcal{R}_\Psi(Ag, Env)} P(r \mid Ag, Env)$$

Achievement & Maintenance Tasks

- Two most common types of tasks are *achievement tasks* and *maintenance tasks*:

1. *Achievement tasks* are those of the form “achieve state of affairs ϕ”
2. *Maintenance tasks* are those of the form “maintain state of affairs ψ”

Achievement & Maintenance Tasks

- An achievement task is specified by a set G of "good" or "goal" states: $G \subseteq E$
  The agent succeeds if it is guaranteed to bring about at least one of these states (we do not care which one — they are all considered equally good).
- A maintenance goal is specified by a set *B* of "bad" states: $B \subseteq E$
  The agent succeeds in a particular environment if it manages to *avoid* all states in B — if it never performs actions which result in any state in B occurring

Agent Synthesis

- *Agent synthesis* is automatic programming: goal is to have a program that will take a task environment, and from this task environment automatically generate an agent that succeeds in this environment:

$$syn : \mathcal{TE} \to (\mathcal{AG} \cup \{\bot\}).$$

(Think of $\bot$ as being like `null` in Java.)

- Synthesis algorithm is:
  - *sound* if, whenever it returns an agent, then this agent succeeds in the task environment that is passed as input
  - *complete* if it is guaranteed to return an agent whenever there exists an agent that will succeed in the task environment given as input

Agent Synthesis

- Synthesis algorithm *syn* is sound if it satisfies the following condition:

$syn(\langle Env, \Psi \rangle) = Ag$ implies $\mathcal{R}(Ag, Env) = \mathcal{R}_{\Psi}(Ag, Env)$.

and complete if:

$\exists Ag \in \mathcal{AG}$ s.t. $\mathcal{R}(Ag, Env) = \mathcal{R}_{\Psi}(Ag, Env)$ implies $syn(\langle Env, \Psi \rangle) \neq \perp$.