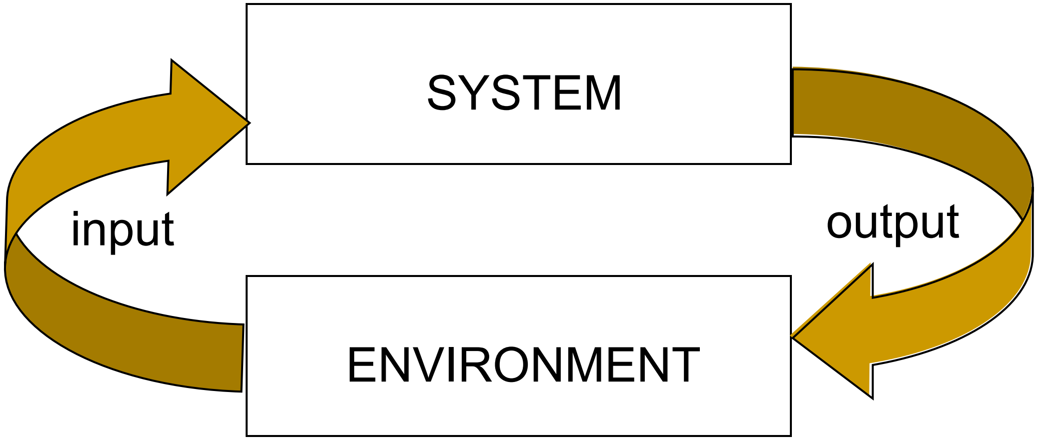
INTELLIGENT AGENTS

What is an Agent?

- The main point about agents is they are *autonomous*: capable of acting independently, exhibiting control over their internal state
- Thus: *an agent is a computer system capable of* autonomous action *in some environment in order to meet its* design objectives



What is an Agent?

- The effecrotic capability of an agent
- Trivial (non-interesting) agents:
  - thermostat
- *An* intelligent agent *is a computer system capable of* flexible *autonomous action in some environment*
- By *flexible*, we mean:
  - *reactive*
  - *pro-active*
  - *social*

Reactivity

- If a program's environment is guaranteed to be fixed, the program need never worry about its own success or failure – program just executes blindly
- The real world is not like that: things change, information is incomplete. Many (most?) interesting environments are *dynamic*
- A *reactive* system is one that maintains an ongoing interaction with its environment, and responds to changes that occur in it (in time for the response to be useful)

Proactiveness

- Reacting to an environment is easy (e.g., stimulus $\rightarrow$ response rules)
- But we generally want agents to *do things for us*
- Hence *goal directed behavior*
- Pro-activeness = generating and attempting to achieve goals; not driven solely by events; taking the initiative
- Recognizing opportunities

Balancing Reactive and Goal-Oriented Behavior

- We want our agents to be reactive, responding to changing conditions in an appropriate (timely) fashion
- We want our agents to systematically work towards long-term goals
- These two considerations can be at odds with one another
- Designing an agent that can balance the two remains an open research problem

Social Ability

- The real world is a *multi*-agent environment: we cannot go around attempting to achieve goals without taking others into account
- Some goals can only be achieved with the cooperation of others
- Similarly for many computer environments: witness the Internet
- *Social ability* in agents is the ability to interact with other agents (and possibly humans) via some kind of *agent-communication language*, and perhaps cooperate with others

Other Properties

- Other properties, sometimes discussed in the context of agency:
- *mobility*: the ability of an agent to move around an electronic network
- *veracity*: an agent will not knowingly communicate false information
- *benevolence*: agents do not have conflicting goals, and that every agent will therefore always try to do what is asked of it
- *rationality*: agent will act in order to achieve its goals, and will not act in such a way as to prevent its goals being achieved — at least insofar as its beliefs permit
- *learning/adaption*: agents improve performance over time

Agents and Objects

- Are agents just objects by another name?
- Object:
  - encapsulates some state
  - communicates via message passing
  - has methods, corresponding to operations that may be performed on this state

Agents and Objects

- Main differences:
  - *agents are autonomous:*
    agents embody stronger notion of autonomy than objects, and in particular, they decide for themselves whether or not to perform an action on request from another agent
  - *agents are smart:*
    capable of flexible (reactive, pro-active, social) behavior, and the standard object model has nothing to say about such types of behavior
  - *agents are active:*
    a multi-agent system is inherently multi-threaded, in that each agent is assumed to have at least one thread of active control

Intelligent Agents and AI

- Aren't agents just the AI project?
  Isn't building an agent what AI is all about?
- AI aims to build systems that can (ultimately) understand natural language, recognize and understand scenes, use common sense, think creatively, etc. — all of which are very hard
- So, don't we need to solve all of AI to build an agent…?

Environments – *Accessible* vs. *inaccessible*

- An accessible environment is one in which the agent can obtain complete, accurate, up-to-date information about the environment's state
- Most moderately complex environments (including, for example, the everyday physical world and the Internet) are inaccessible
- The more accessible an environment is, the simpler it is to build agents to operate in it

Environments – *Deterministic* vs. *non-deterministic*

- A deterministic environment is one in which any action has a single guaranteed effect — there is no uncertainty about the state that will result from performing an action
- The physical world can to all intents and purposes be regarded as non-deterministic
- Non-deterministic environments present greater problems for the agent designer

Environments - *Episodic* vs. *non-episodic*

- In an episodic environment, the performance of an agent is dependent on a number of discrete episodes, with no link between the performance of an agent in different scenarios
- Episodic environments are simpler from the agent developer's perspective because the agent can decide what action to perform based only on the current episode — it need not reason about the interactions between this and future episodes

Environments - *Static* vs. *dynamic*

- A static environment is one that can be assumed to remain unchanged except by the performance of actions by the agent
- A dynamic environment is one that has other processes operating on it, and which hence changes in ways beyond the agent’s control
- Other processes can interfere with the agent’s actions (as in concurrent systems theory)
- The physical world is a highly dynamic environment

Environments – *Discrete* vs. *continuous*

- An environment is discrete if there are a fixed, finite number of actions and percepts in it
- Russell and Norvig give a chess game as an example of a discrete environment, and taxi driving as an example of a continuous one
- Continuous environments have a certain level of mismatch with computer systems
- Discrete environments could *in principle* be handled by a kind of "lookup table"

Agents as Intentional Systems

- When explaining human activity, it is often useful to make statements such as the following:

  Janine took her umbrella because she *believed* it was going to rain.

  Michael worked hard because he *wanted* to possess a PhD.

- These statements make use of a *folk psychology*, by which human behavior is predicted and explained through the attribution of *attitudes*, such as believing and wanting (as in the above examples), hoping, fearing, and so on
- The attitudes employed in such folk psychological descriptions are called the *intentional* notions

Agents as Intentional Systems

- The philosopher Daniel Dennett coined the term *intentional system* to describe entities 'whose behavior can be predicted by the method of attributing belief, desires and rational acumen'
- Dennett identifies different 'grades' of intentional system:
  'A *first-order* intentional system has beliefs and desires (etc.) but no beliefs and desires *about* beliefs and desires. …A *second-order* intentional system is more sophisticated; it has beliefs and desires (and no doubt other intentional states) about beliefs and desires (and other intentional states) — both those of others and its own'

Agents as Intentional Systems

- Is it legitimate or useful to attribute beliefs, desires, and so on, to computer systems?

Agents as Intentional Systems

- McCarthy argued that there are occasions when the *intentional stance* is appropriate:

'To ascribe *beliefs*, *free will*, *intentions*, *consciousness*, *abilities*, or *wants* to a machine is *legitimate* when such an ascription expresses the same information about the machine that it expresses about a person. It is *useful* when the ascription helps us understand the structure of the machine, its past or future behavior, or how to repair or improve it. It is perhaps never *logically required* even for humans, but expressing reasonably briefly what is actually known about the state of the machine in a particular situation may require mental qualities or qualities isomorphic to them. Theories of belief, knowledge and wanting can be constructed for machines in a simpler setting than for humans, and later applied to humans. Ascription of mental qualities is *most straightforward* for machines of known structure such as thermostats and computer operating systems, but is *most useful* when applied to entities whose structure is incompletely known'.

Agents as Intentional Systems

- The more we know about a system, the less we need to rely on animistic, intentional explanations of its behavior
- But with very complex systems, a mechanistic, explanation of its behavior may not be practicable
- *As computer systems become ever more complex, we need more powerful abstractions and metaphors to explain their operation — low level explanations become impractical. The intentional stance is such an abstraction*
- The intentional notions are thus *abstraction tools*, which provide us with a convenient and familiar way of describing, explaining, and predicting the behavior of complex systems

  Agents, and agents as intentional systems, represent a further, and increasingly powerful abstraction

Agents as Intentional Systems

- **Post-Declarative Systems**:
  - This view of agents leads to a kind of post-declarative programming:
    - In procedural programming, we say exactly *what* a system should do
    - In declarative programming, we state something that we want to achieve, give the system general info about the relationships between objects, and let a built-in control mechanism (e.g., goal-directed theorem proving) figure out what to do
    - With agents, we give a very abstract specification of the system, and let the control mechanism figure out what to do, knowing that it will act in accordance with some built-in theory of agency (e.g., the well-known Cohen-Levesque model of intention)

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 $\tau(r)=\varnothing$, 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

- Agent 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 $\mathcal{R}(Ag, Env)$
- (We assume $\mathcal{R}(Ag, Env)$ 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 $u > 0$,

$$e_u \in \tau((e_0, \alpha_0, \ldots, \alpha_{u-1})) \quad \text{where}$$
$$\alpha_u = Ag((e_0, \alpha_0, \ldots, e_u))$$

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*:

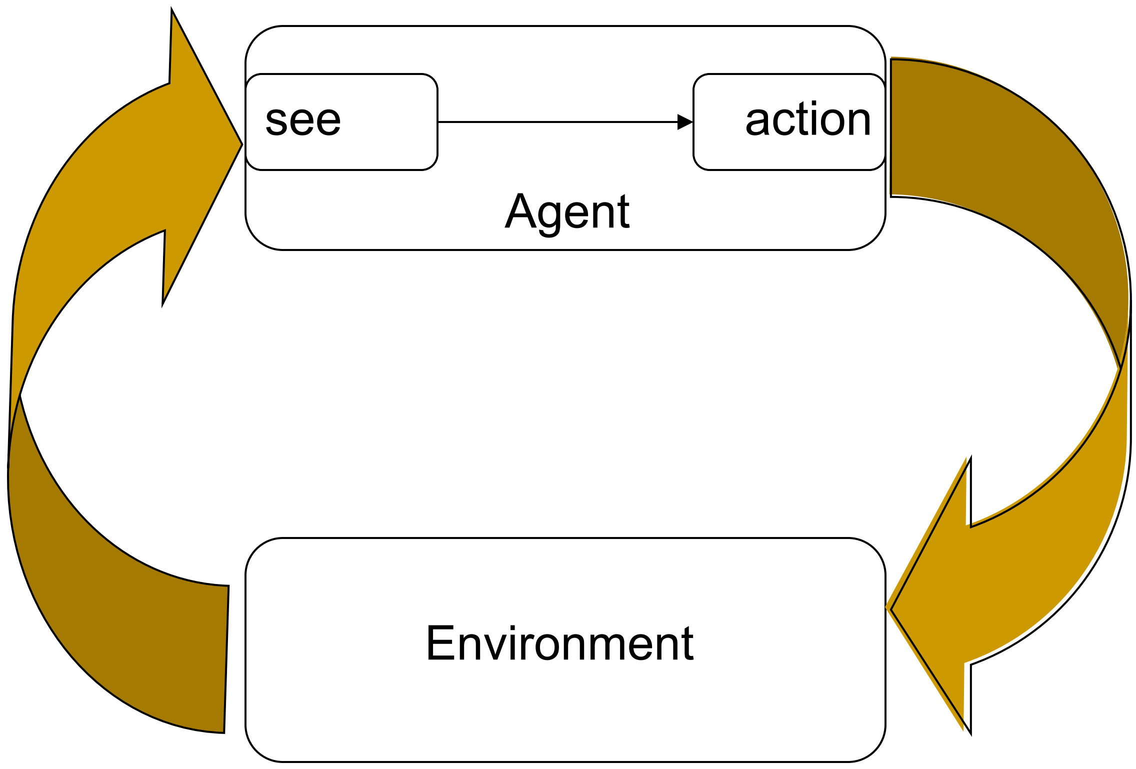
$$action : E \to Ac$$

- 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*:

$$see : E \to Per$$

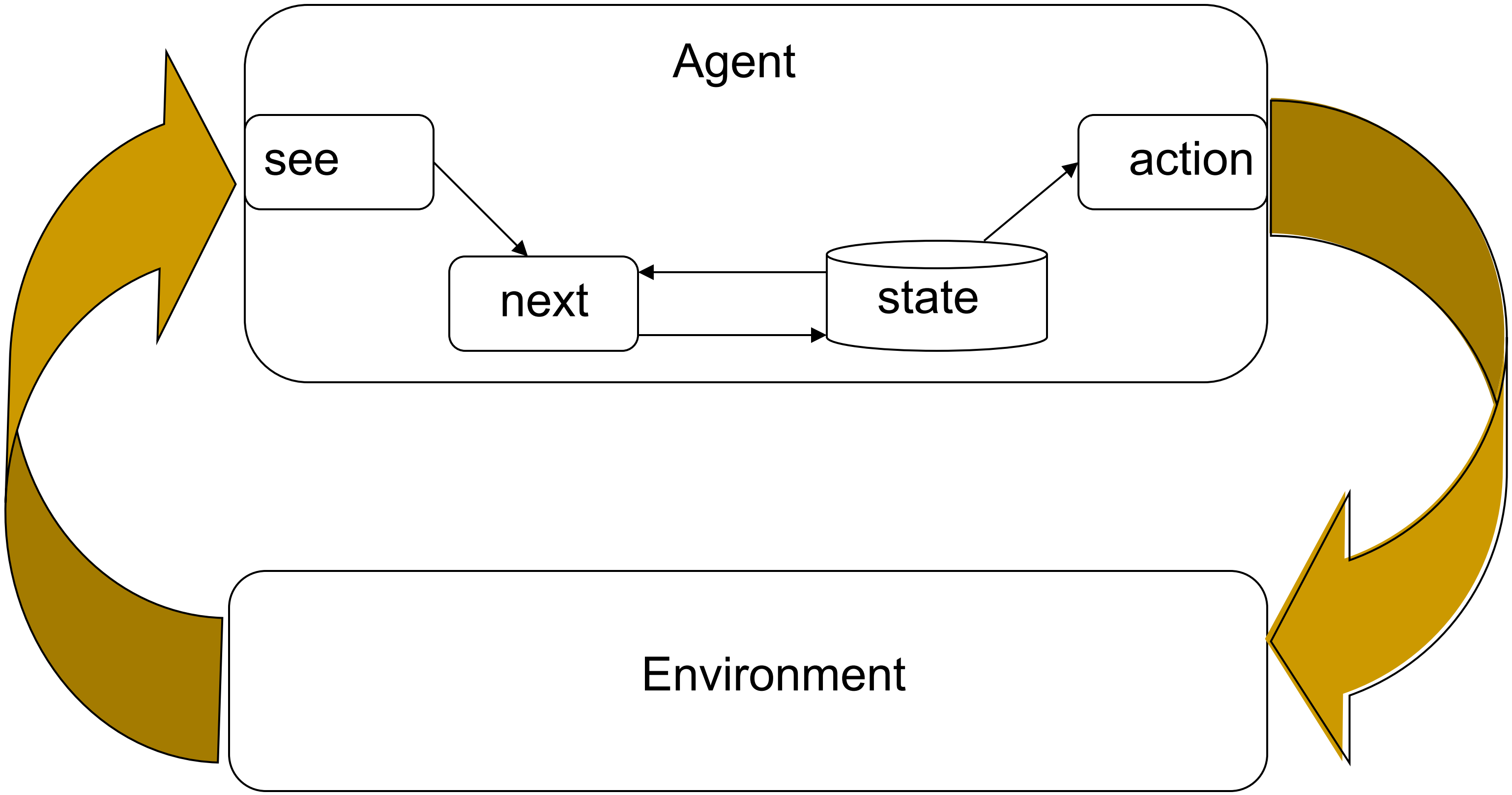
which maps environment states to percepts, and *action* is now a function

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

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

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
  (One possibility: a *discount* for states later on.)

Utilities over Runs

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

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

- 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?
  - we don’t think in terms of utilities!
  - 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:

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

The Tileworld, Some Examples

- From Goldman and Rosenschein, AAAI-94:

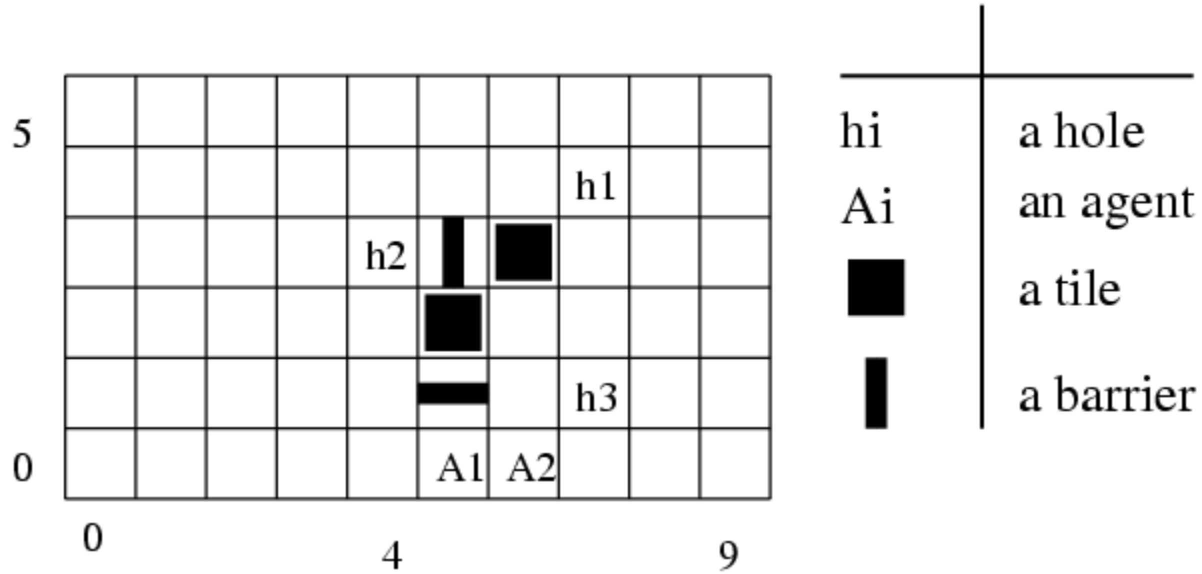


Figure 1: Strongly-Coupled Interactions

The Tileworld, Some Examples

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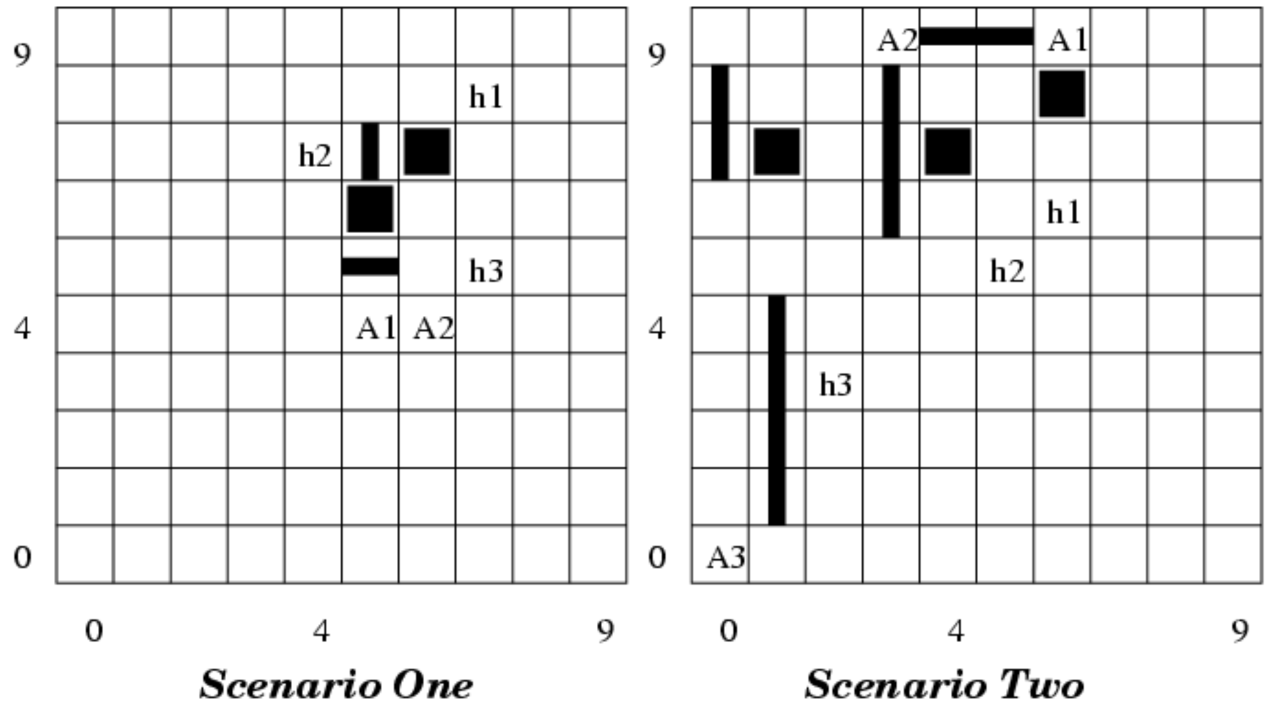

Figure 2: Simulations

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

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

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

Task Environments

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

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

is a predicate over runs.
Let 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 $\mathcal{R}_\Psi(Ag, Env)$ 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:

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

  (Think of $\perp$ 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:

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

and complete if:

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