LECTURE 2: INTELLIGENT AGENTS

An Introduction to Multiagent Systems

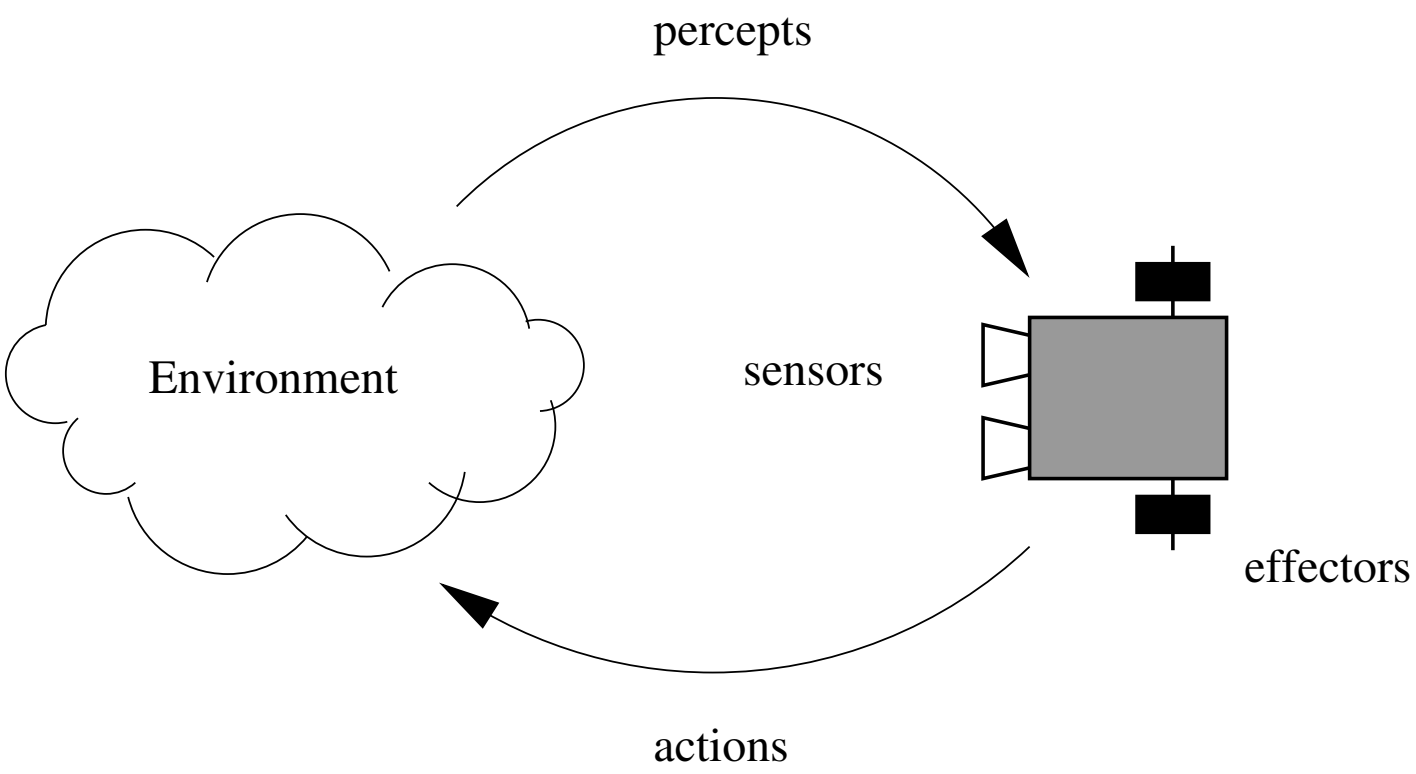
CIS 7412, Fall 2011

What is an Agent?

- The main point about agents is they are *autonomous*: capable of acting independently, exhibiting control over their internal state.

  An agent is a computer system that is *situated* in some *environment*, and that is capable of *autonomous action* in that environment in order to meet its delegated objectives.

- It is all about *decisions*
  - An agent has to choose *what* action to perform.
  - An agent has to decide *when* to perform an action.


percepts
Environment
sensors
effectors
actions

- There is a spectrum of autonomy.
  - Humans and other animals at one end
  - Word processors at the other.
- Autonomy is *adjustable*
  - Decisions handed to a higher authority when this is beneficial.

- Trivial (non-interesting) agents:
  - thermostat;
  - light switch;
  - UNIX daemon (e.g., biff).

- More interesting agents are *intelligent*.

- An *intelligent* agent is a computer system capable of *flexible* autonomous action in some environment.

  By *flexible*, we mean:

  – *reactive*;
  – *pro-active*;
  – *social*.

- All these properties make it able to respond to what is around it.

  (More on the next few slides).

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.

  Example of fixed environment: compiler.

- The real world is not like that: things change, information is incomplete.

  Many (most?) interesting environments are *dynamic*.

- Software is hard to build for dynamic domains: program must take into account possibility of failure — ask itself whether it is worth executing!

- 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 behaviour*.
- Pro-activeness = generating and attempting to achieve goals; not driven solely by events; taking the initiative.
- Also: recognising opportunities.

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 (for example, 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 of Agency Sometimes Discussed

- *Mobility*:

  The ability of an agent to move. For software agents this movement is around an electronic network.

- *Veracity*:

  Whether an agent will knowingly communicate false information.

- *Benevolence*:

  Whether agents have conflicting goals, and thus whether they are inherently helpful.

- *Rationality*:

  Whether an agent will act in order to achieve its goals, and will not deliberately act so as to prevent its goals being achieved.

- *Learning/adaption*:

  Whether 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.

- 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.

Objects do it for free. . .

- *Agents do it because they want to;*
- *Agents do it for money*.

Properties of Environments

- Since agents are in close contact with their environment, the properties of the environment affect agents.
  - Also have a big effect on those of us who build agents.
- Common to categorise environments along some different dimensions.

Fully observable versus partially observable

- A *fully observable* environment is one in which the agent can obtain complete, accurate, up-to-date information about the environment's state.
- Such an environment is also called *accessible*.
- Most moderately complex environments (including, for example, the everyday physical world and the Internet) are only *partially observable*.
- Such environments are also known as *non-accessible*
- The more observable an environment is, the simpler it is to build agents to operate in it.

Deterministic versus 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.
- We'll follow Russell and Norvig in calling environments *stochastic* if we quantify the non-determinism using probability theory.
- Non-deterministic environments present greater problems for the agent designer.

Episodic versus sequential

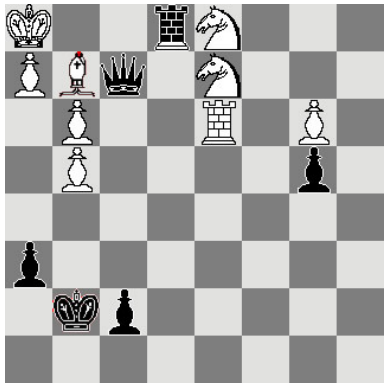
- In an *episodic* environment, the performance of an agent is dependent on a number of discrete episodes, with no link between the performance of an agent in different scenarios.
- An example of an episodic environment would be an assembly line where an agent had to spot defective parts.
- Episodic 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 that are not episodic are called either *non-episodic* or *sequential*. Here the current decision affects future decisions.
- Driving a car is sequential.

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.
- The physical world is a highly dynamic environment.
- One reason an environment may be dynamic is the presence of other agents.

Discrete *vs* continuous

- An environment is *discrete* if there are a fixed, finite number of actions and percepts in it.
- The textbook *gives* credits Russell and Norvig with using a chess game as an example of a discrete environment, and taxi driving as an example of a continuous one.



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 behaviour 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.

- The philosopher Daniel Dennett coined the term *intentional system* to describe entities 'whose behaviour 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'.

- Is it legitimate or useful to attribute beliefs, desires, and so on, to computer 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 behaviour, 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'.

- What objects can be described by the intentional stance?
- As it turns out, more or less anything can. . . consider a light switch:

  > 'It is perfectly coherent to treat a light switch as a (very cooperative) agent with the capability of transmitting current at will, who invariably transmits current when it believes that we want it transmitted and not otherwise; flicking the switch is simply our way of communicating our desires'. (Yoav Shoham)

- But most adults would find such a description absurd!

  Why is this?

- The answer seems to be that while the intentional stance description is consistent,

  > . . . it does not *buy us anything*, since we essentially understand the mechanism sufficiently to have a simpler, mechanistic description of its behaviour. (Yoav Shoham)

- Put crudely, the more we know about a system, the less we need to rely on animistic, intentional explanations of its behaviour.
- But with very complex systems, a mechanistic, explanation of its behaviour 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 behaviour of complex systems.
- Remember: most important developments in computing are based on new *abstractions*:
  - procedural abstraction;
  - abstract data types;
  - objects.

  Agents, and agents as intentional systems, represent a further, and increasingly powerful abstraction.
- So agent theorists start from the (strong) view of agents as intentional systems: one whose simplest consistent description requires the intentional stance.

- This *intentional stance* is an *abstraction tool* — a convenient way of talking about complex systems, which allows us to predict and explain their behaviour without having to understand how the mechanism actually works.
- Much of computer science is about finding abstraction mechanisms . . .

  So why not use the intentional stance as an abstraction tool in computing — to explain, understand, and, crucially, program *computer systems?*

- Other 3 points in favour of this idea . . .

Characterising Agents

- It provides us with a familiar, non-technical way of *understanding* and *explaining* agents.

Nested Representations

- It gives us the potential to specify systems that *include representations of other systems*.
- It is widely accepted that such nested representations are essential for agents that must cooperate with other agents.
- "If you think that Agent B knows x, then move to location L".

North By Northwest

- Eve Kendell knows that Roger Thornhill is working for the FBI. Eve believes that Philip Vandamm suspects that she is helping Roger. This, in turn, leads Eve to believe that Philip thinks she is working for the FBI (which is true). By pretending to shoot Roger, Eve hopes to convince Philip that she is not working for the FBI.

Post-Declarative Systems

- 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.

Abstract Architectures for Agents

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

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

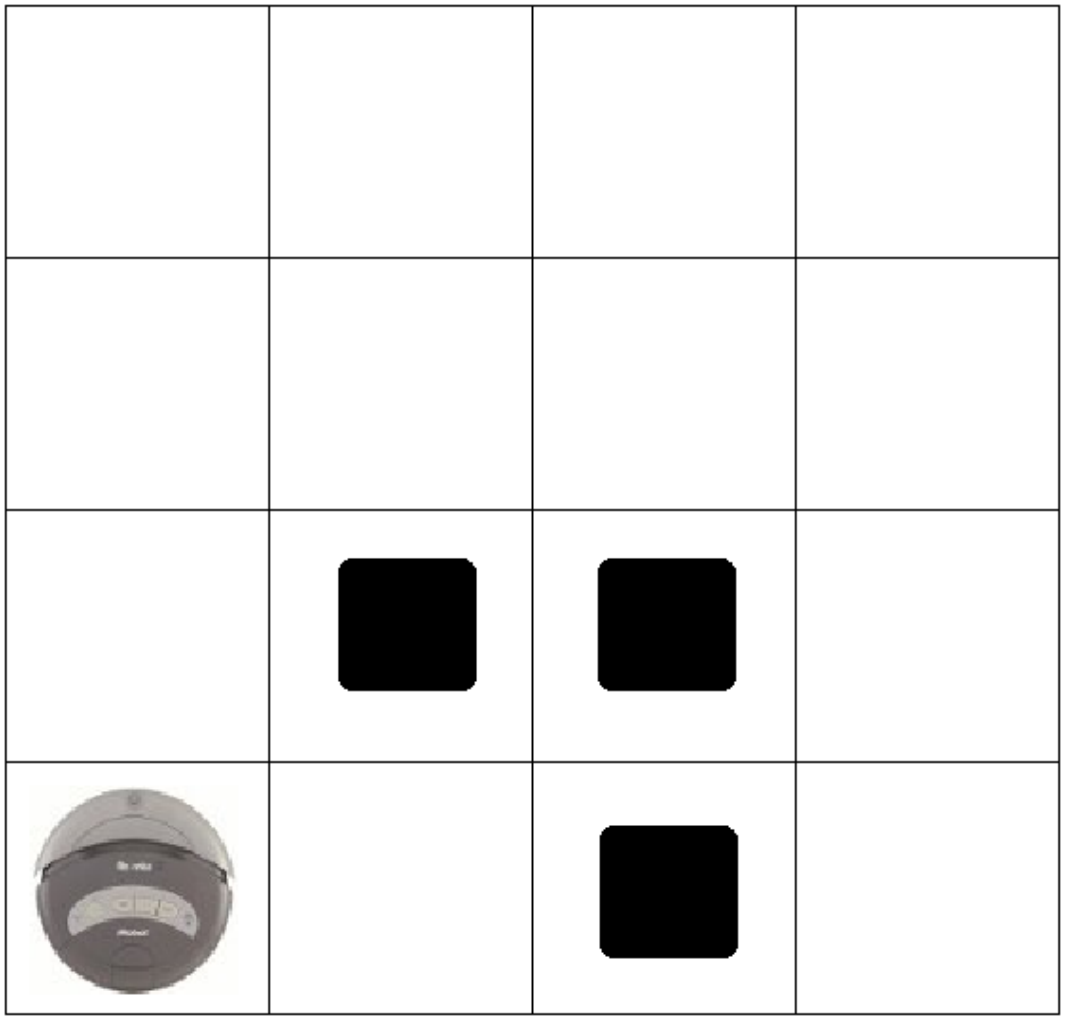
- Agents are assumed to have a repertoire of possible actions available to them, which transform the state of the world.

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

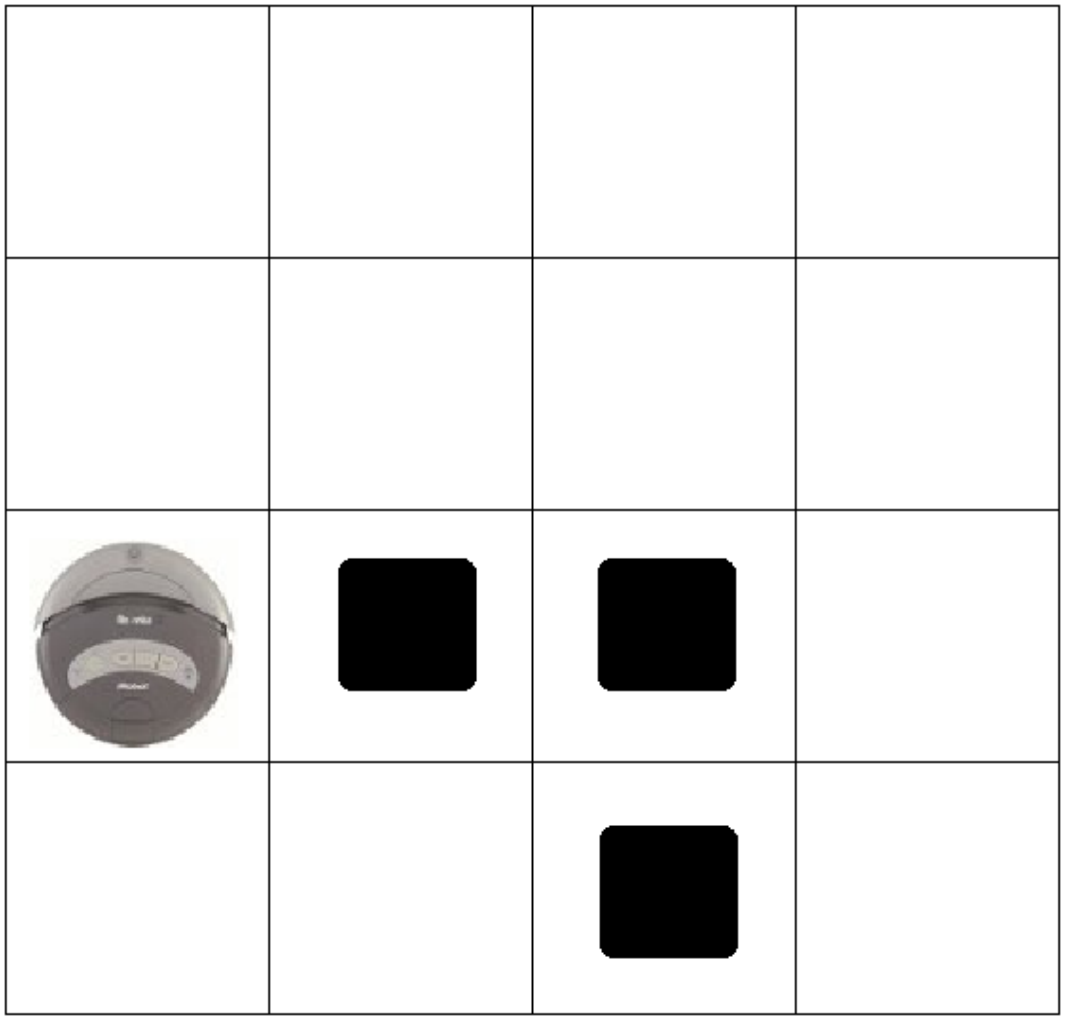
- Actions can be non-deterministic, but only one state ever results from and action.
- A *run*, r, of an agent in an environment is a sequence of interleaved world states and actions:

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

- When actions are deterministic each state has only one possible successor.
- A run would look something like the following:



North!



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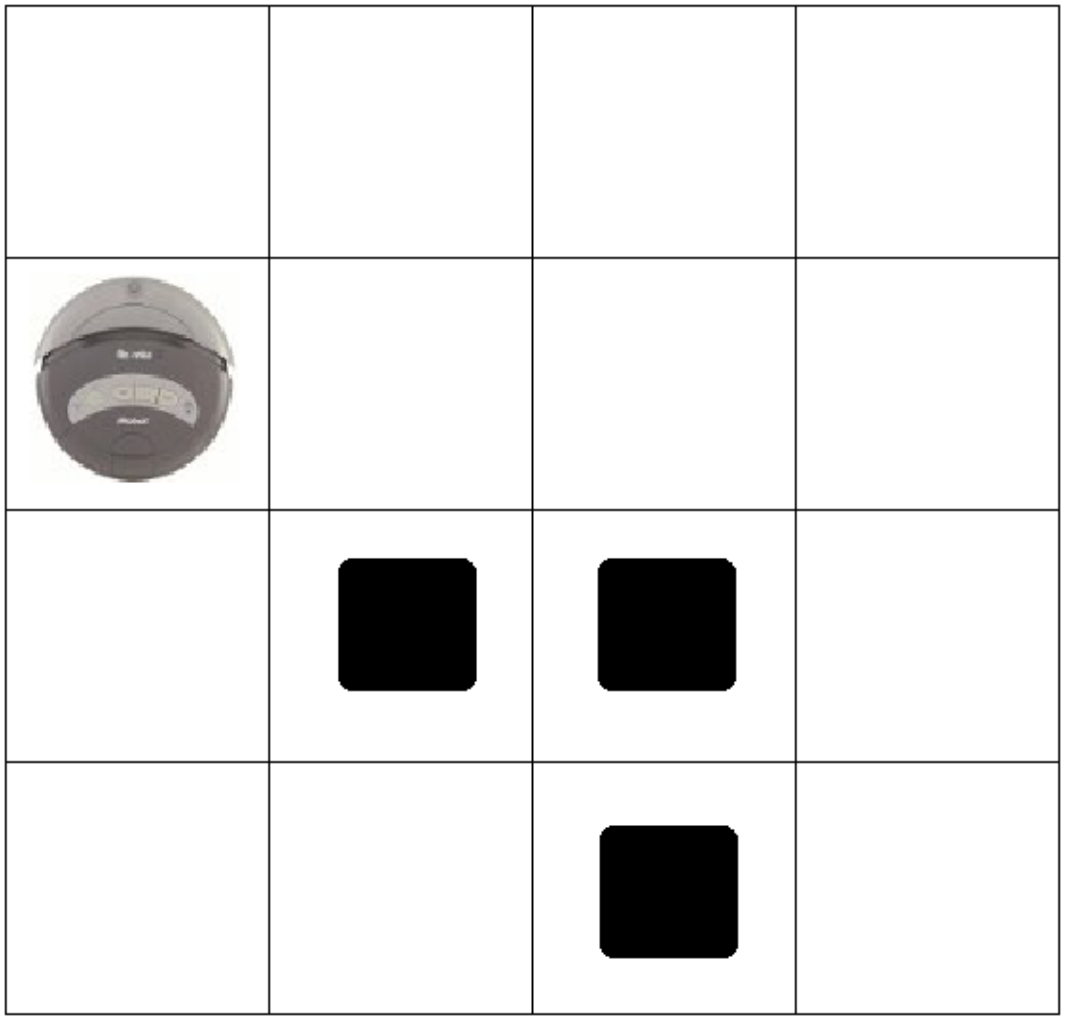
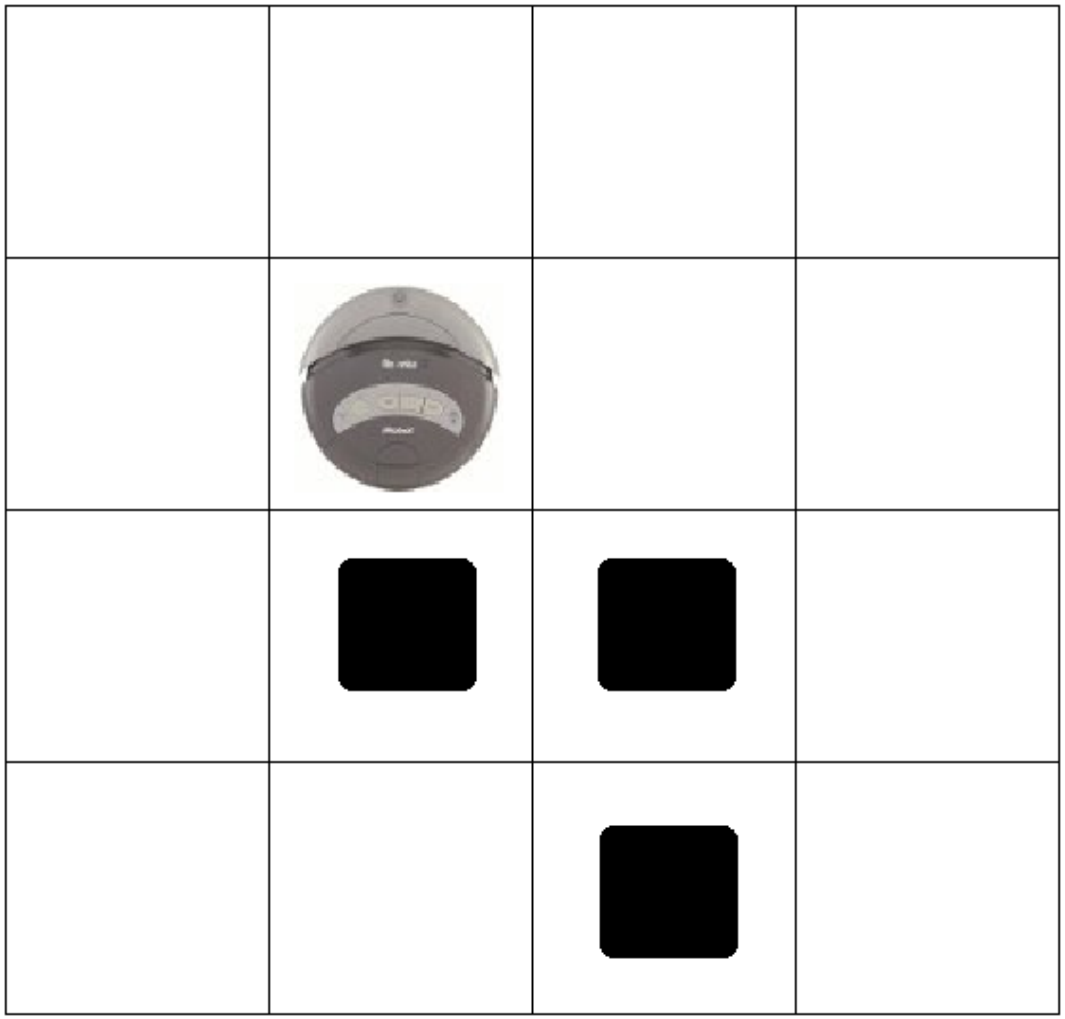
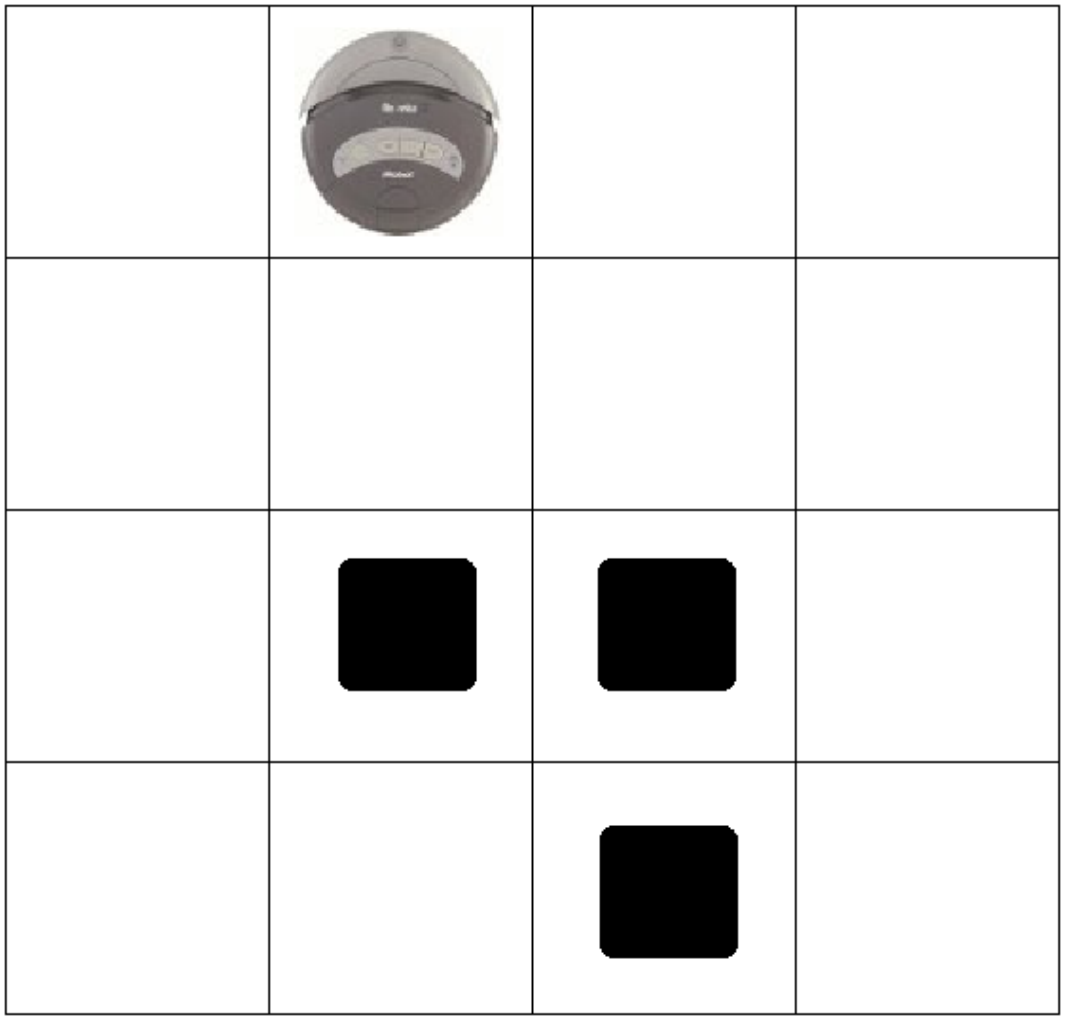


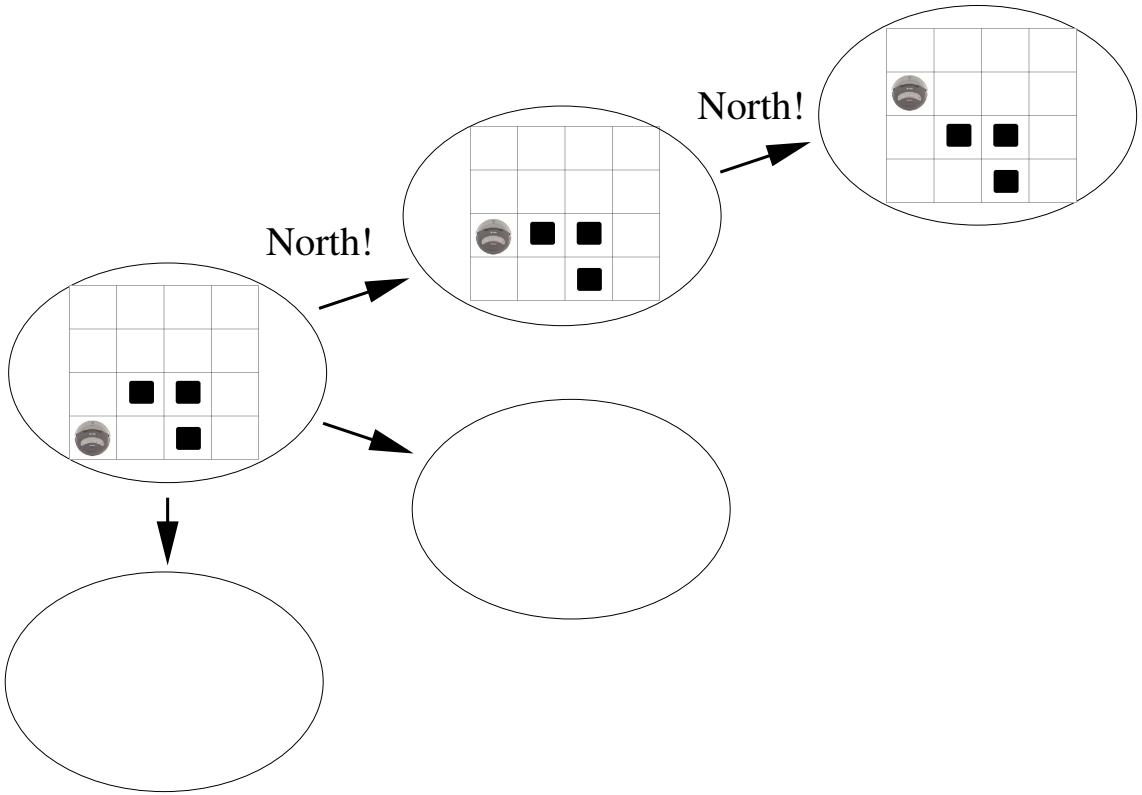
East!



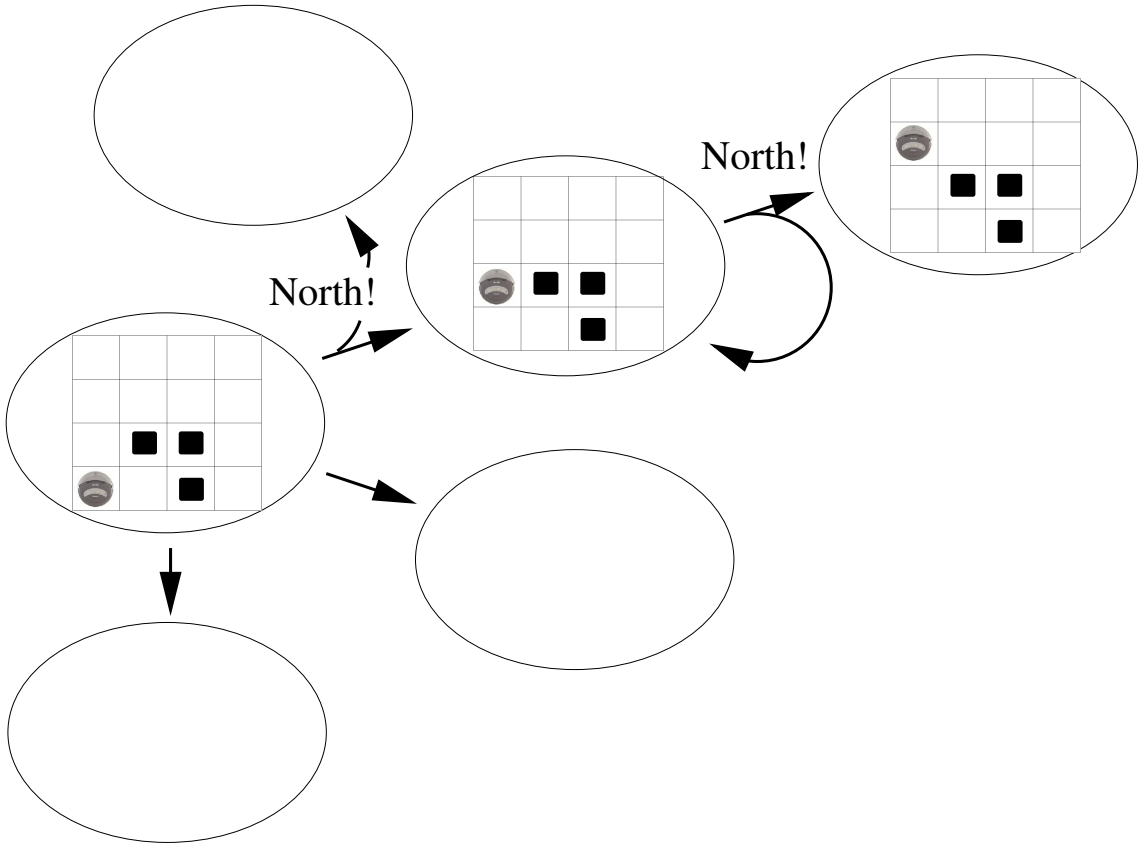
North!



- Which we might picture as so:



- When actions are non-deterministic a run (or *trajectory*) is the same, but the set of possible runs is more complex.



- In fact it is more complex still, because all of the runs we pictured start from the same state.
- Let:
  - $\mathcal{R}$ be the set of all such possible finite sequences (over E and Ac);
  - $\mathcal{R}^{Ac}$ be the subset of these that end with an action; and
  - $\mathcal{R}^{E}$ be the subset of these that end with a state.
- We will use $r, r', \ldots$ to stand for the members of $\mathcal{R}$
- These sets of runs contain *all* runs from *all* starting states.

Environments

- A *state transformer* function represents behaviour of the environment:

$$\tau : \mathcal{R}^{Ac} \rightarrow \wp(E)$$

- Note that environments are...
  - *history dependent*.
  - *non-deterministic*.
- If $\tau(r) = \emptyset$, there are no possible successor states to r, so we say the run has *ended*. ("Game over.")
- An environment Env is then a triple $Env = \langle E, e_0, \tau \rangle$ where E is set of states, $e_0 \in E$ is initial state; and τ is state transformer function.

Agents

- We can think of an agent as being a function which maps runs to actions:

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

- Thus an agent makes a decision about what action to perform based on the history of the system that it has witnessed to date.
- Let $\mathcal{AG}$ 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 $\mathcal{R}(Ag, Env)$.
- Assume $\mathcal{R}(Ag, Env)$ contains only runs that have ended.

- 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 $u > 0$,

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

- Why do we bother with all this notation?
- Well, it allows us to get a precise handle on some ideas about agents.
- For example, we can tell when two agents are the same.
- Of course, there are different meanings for “same”. Here is one specific one.
- Two agents are said to be *behaviorally equivalent* with respect to Env iff $\mathcal{R}(Ag_1, Env) = \mathcal{R}(Ag_2, Env)$.
- We won’t be able to tell two such agents apart by watching what they do.

Purely Reactive Agents

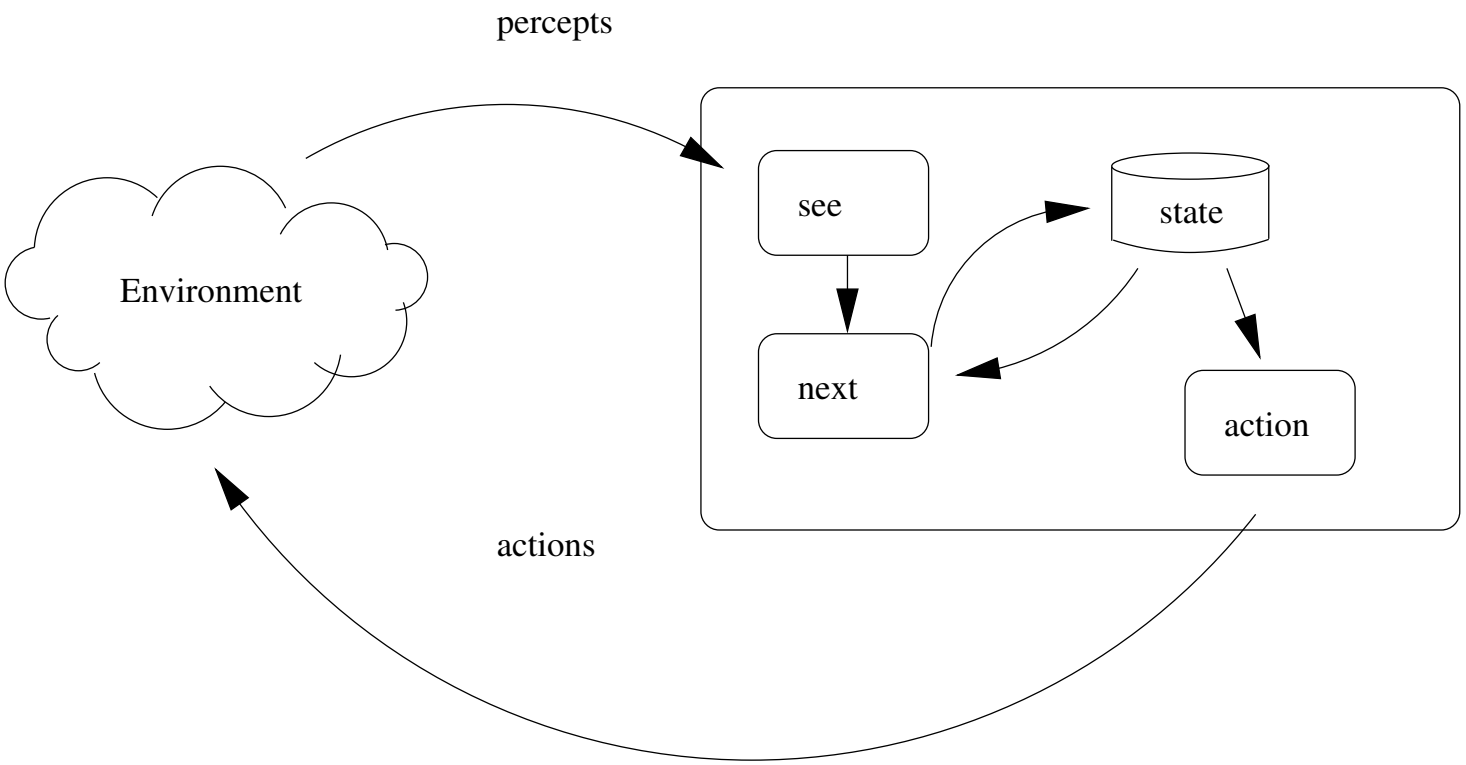
- Some agents decide what to do without reference to their history — they base their decision making entirely on the present, with no reference at all to the past.
- We call such agents *purely reactive*:

$$action : E \rightarrow Ac$$

- A thermostat is a purely reactive agent.

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

Agents with State



- 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*:

$$see : E \rightarrow Per$$

  which maps environment states to percepts.
- The agent has 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 action-selection function $action$ is now defined as a mapping

$$action : I \rightarrow Ac$$

  from internal states to actions.

- An additional function $next$ is introduced, which maps an internal state and percept to an internal state:

$$next : I \times Per \rightarrow I$$

- This says how the agent updates its view of the world when it gets a new percept.

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 $action(next(i_0, see(e)))$. This action is then performed.
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 can we make this happen.
- One idea: associated rewards with states that we want agents to bring about.

Utility Functions

- We associate *utilities* with individual states — the task of the agent is then to bring about states that maximise utility.
- A task specification is then a function

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

which associates a real number with every environment state.

- 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. This is what we do in *reinforcement learning*.

Utilities over Runs

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

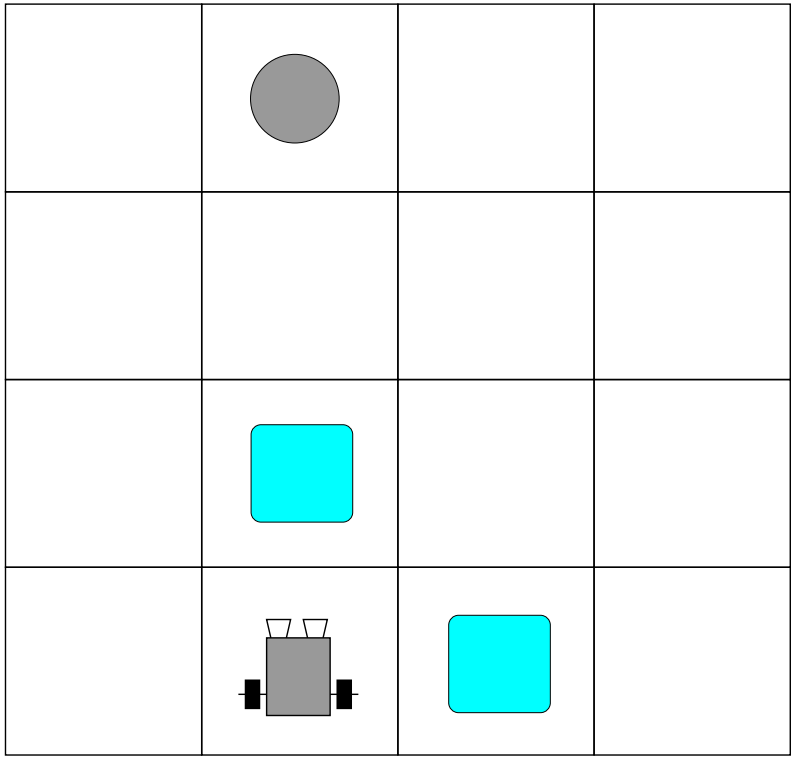
$$u : \mathcal{R} \rightarrow \mathbb{R}$$

- Such an approach takes an inherently *long term* view.
- Other variations: incorporate probabilities of different states emerging.
- To see where utilities might come from, let's look at an example.

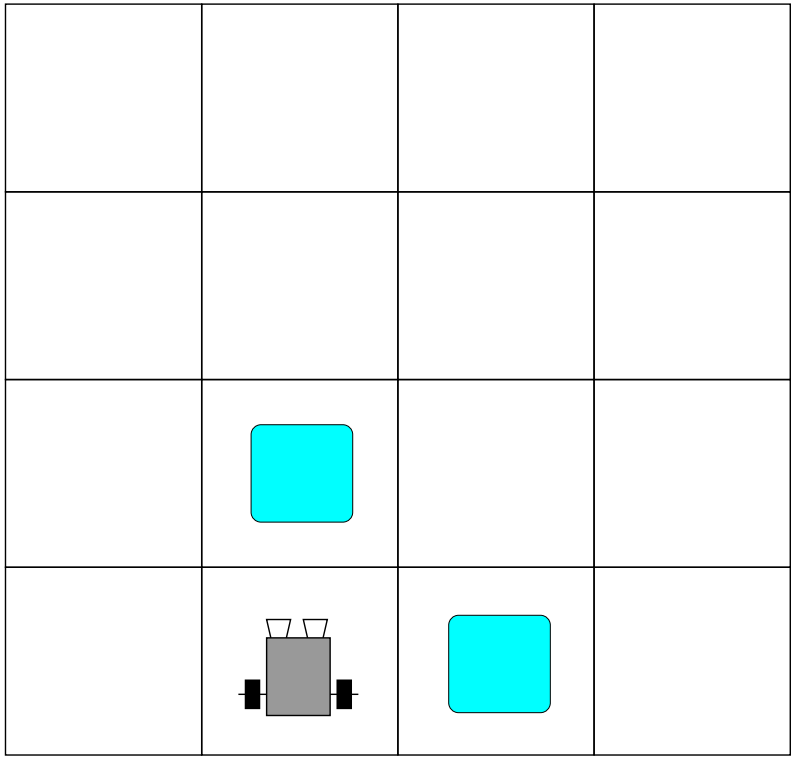
Utility in the Tileworld

- 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.

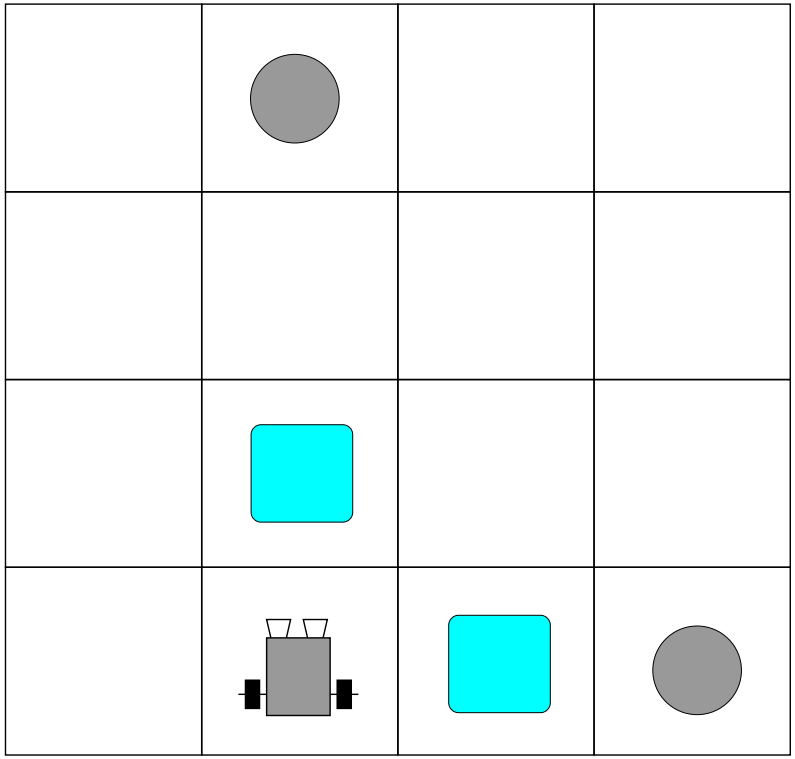
- The agent starts to push a tile towards the hole.



- The hole disappears. . .



- A more convenient hole appears . . .



- TILEWORLD changes with the random appearance and disappearance of holes.
- Utilities are associated over runs, so that more holes filled is a higher utility.
- Utility function defined as follows:

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

- TILEWORLD captures the need for *reactivity* and for the advantages of exploiting opportunities.

Expected Utility

- Write $P(r \mid Ag, Env)$ to denote probability that run r occurs when agent Ag is placed in environment Env.
- In a non-deterministic environment, for example, this can be computed from the probability of each step.
- For a run $r = (e_0, \alpha_0, e_1, \alpha_1, e_2, \ldots)$:

$$\Pr(r \mid Ag, Env) = \Pr(e_1, \mid e_0, \alpha_0) \Pr(e_2 \mid e_1, \alpha_1) \ldots$$

and clearly:

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

- The *expected utility* of agent Ag in environment Env (given P, u), is then:

$$EU(Ag, Env) = \sum_{r \in \mathcal{R}(Ag, Env)} u(r) P(r \mid Ag, Env).$$

- That is, for each run we compute the utility and multiply it by the probability of the run.
- The expected utility is then the sum of all of these.

An Example

Consider the environment $Env_1 = \langle E, e_0, \tau \rangle$ defined as follows:

$$E = \{e_0, e_1, e_2, e_3, e_4, e_5\}$$

$$\tau(e_0 \xrightarrow{\alpha_0}) = \{e_1, e_2\}$$

$$\tau(e_0 \xrightarrow{\alpha_1}) = \{e_3, e_4, e_5\}$$

There are two agents possible with respect to this environment:

$$Ag_1(e_0) = \alpha_0$$

$$Ag_2(e_0) = \alpha_1$$

The probabilities of the various runs are as follows:

$$P(e_0 \xrightarrow{\alpha_0} e_1 \mid Ag_1, Env_1) = 0.4$$

$$P(e_0 \xrightarrow{\alpha_0} e_2 \mid Ag_1, Env_1) = 0.6$$

$$P(e_0 \xrightarrow{\alpha_1} e_3 \mid Ag_2, Env_1) = 0.1$$

$$P(e_0 \xrightarrow{\alpha_1} e_4 \mid Ag_2, Env_1) = 0.2$$

$$P(e_0 \xrightarrow{\alpha_1} e_5 \mid Ag_2, Env_1) = 0.7$$

Assume the utility function u_1 is defined as follows:

$$u_1(e_0 \xrightarrow{\alpha_0} e_1) = 8$$

$$u_1(e_0 \xrightarrow{\alpha_0} e_2) = 11$$

$$u_1(e_0 \xrightarrow{\alpha_1} e_3) = 70$$

$$u_1(e_0 \xrightarrow{\alpha_1} e_4) = 9$$

$$u_1(e_0 \xrightarrow{\alpha_1} e_5) = 10$$

What are the expected utilities of the agents for this utility function?

Optimal Agents

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

$$Ag_{opt} = \arg \max_{Ag \in \mathcal{AG}} EU(Ag, Env) \quad (1)$$

- Of course, the fact that an agent is optimal does not mean that it *will* be best; only that *on average*, we can expect it to do best.

Optimal Agents

- To see the difference between these two ideas, recall the Patriots 4th down and 2 against the Colts during the 2009 season.

- Also note that though we can characterise an optimal agent as the MEU agent, it does not tell us how to build it.

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 m:

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

- The *bounded optimal* agent, Ag_{bopt}, with respect to m is then...

$$Ag_{bopt} = \arg \max_{Ag \in \mathcal{AG}_m} EU(Ag, Env) \tag{2}$$

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:

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

Task Environments

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

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

  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.

- 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

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

- In other words, an agent succeeds if every run satisfies the specification of the agent.

- We might write this as:

$$\forall r \in \mathcal{R}(Ag, Env), \text{we have} \Psi(r) = 1$$

- This is a bit pessimistic.
- If the agent fails on a single run, we say it has failed overall.
- A more optimistic idea of success is:

$$\exists r \in \mathcal{R}(Ag, Env), \text{we have} \Psi(r) = 1$$

which counts an agent as successful as soon as it completes a single successful run.

The Probability of Success

- If the environment is non-deterministic, the τ returns a *set* of possible states.
- We can define a probability distribution across the set of states.
- 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

- The idea of a predicate task specification is admittedly abstract.
- It generalises two common types of tasks: *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".

- 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.
- (For now we do not care which one — they are all considered equally good).
- We can think of the agent playing *a game against nature*.
- The agent succeeds if it can force the environment into one of the goal states $g \in G$.

- 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.
- In terms of games, the agent succeeds in a maintenance task if it ensures that it is never forced into one of the fail states $b \in B$.

Agent Synthesis

- *Agent synthesis* is automatic programming.
- The 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:

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

(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; and
  - *complete* if it is guaranteed to return an agent whenever there exists an agent that will succeed in the task environment given as input.

- 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:

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

- If syn is sound and complete, it will only output $\bot$ for $\langle Env, \Psi \rangle$ if there is no agent that will succeed for $\langle Env, \Psi \rangle$.

Summary

- This lecture has looked in detail at what constitutes an intelligent agent.
- We looked at the properties of an intelligent agent and the properties of the environents in which it may operate.
- We introduced the intentional stance and discussed its use.
- We looked at abstract architectures for agents of different kinds; and
- Finally we discussed what kinds of task an agent might need to carry out.
- In the next lecture, we will start to look at how one might program an agent.