Rational Agents (Ch. 2)
Teaching Assistant

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Rational agent

An agent/robot must be able to perceive and interact with the environment.

A rational agent is one that always takes the best action (possibly expected best).

Agent = Player → Watching → Thinking → Pushing → Videogame → Displaying → Computing → Inputing
Rational agent

Consider the case of a simple vacuum agent

Environment: [state A] and [state B], both possibly with dirt that does not respawn
Actions: [move left], [move right] or [suck]
Perception: current location, [dirty or clean]
Rational agent

An agent's **percept** is the sequence of perceptions that it has seen up to this point.

For the vacuum agent, one percept might be: [A, Dirty], [A, Clean], [B, Dirty]
There are two ways to describe an agent's action using the percept:

1. Agent function = directly map a percept to action
2. Agent program = logic dictating next action (percept as an input to logic)

The agent function is basically a look-up table, and is typically much larger.
Rational agent

An agent function for vacuum agent:

<table>
<thead>
<tr>
<th>Percept sequence</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>[A, Clean]</td>
<td>Right</td>
</tr>
<tr>
<td>[A, Dirty]</td>
<td>Suck</td>
</tr>
<tr>
<td>[B, Clean]</td>
<td>Left</td>
</tr>
<tr>
<td>[B, Dirty]</td>
<td>Suck</td>
</tr>
<tr>
<td>[A, Clean], [A, Clean]</td>
<td>Right</td>
</tr>
<tr>
<td>[A, Clean], [A, Dirty]</td>
<td>Suck</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

A corresponding agent program:

if [Dirty], return [Suck]
if at [state A], return [move right]
if at [state B], return [move left]
In order to determine if the vacuum agent is rational I need a performance measure.

Under which of these metrics is the agent program on the previous slide rational?

1. Have a clean floor in A and B
2. Have a clean floor as fast as possible
3. Have a clean floor with moving as little as possible
4. Maximize the amount of time sucking
Rational agent

You want to express the performance measure in terms of the environment not the agent.

For example, if we describe a measure as: “Suck up the most dirt”

A rational vacuum agent would suck up dirt then dump it back to be sucked up again...

This will not lead to a clean floor.
Rational agent

Let our performance measure be: “-5 points per time step a state is dirty and -1 point per move”

Is our agent rational (with the proposed agent program) if...

1. Dirt does not reappear
2. Dirt always reappears the next time step
3. Dirt has a 30% chance of reappearing
4. Dirt reappears but at an unknown rate
Rational agent

If we do not know how often dirt will reappear, a rational agent might need to learn.

Learning can use prior knowledge to estimate how often dirt tends to reappear, but should value actual observations more (its percept).

The agent might need to explore and take sub-optimal short-term actions to find a better long-term solution.
Rational agent

In short a rational agent depends on:
1. Performance measure
2. Prior knowledge of the environment
3. Actions available
4. Percept to current time

Suppose a large vacuum agent existed that could suck both states A and B at the same time.

This does not change the rationality of our agent.
Rational agent

To fully specify the situation we need to know about the task environment as well (also abbreviated PEAS)
Performance measure
Environment
Actuators
Sensors
# Rational agent

<table>
<thead>
<tr>
<th>Agent type</th>
<th>Performance</th>
<th>Environment</th>
<th>Actuators</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vacuum</td>
<td>time to clean</td>
<td>A, B, dirt</td>
<td>suck, move, move</td>
<td>dust sensor</td>
</tr>
<tr>
<td>Student</td>
<td>GPA, honors</td>
<td>campus, dorm</td>
<td>do HW, take test</td>
<td>eye, ear, hand</td>
</tr>
<tr>
<td>Particles</td>
<td>time alive</td>
<td>boarder, red balls</td>
<td>move mouse</td>
<td>screen-shot</td>
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</table>
Environment classification

Environments can be further classified on the following characteristics:

1. Fully vs. partially observable
2. Single vs. multi-agent
3. Deterministic vs. stochastic
4. Episodic vs. sequential
5. Static vs. dynamic
6. Discrete vs. continuous
7. Known vs. unknown
Environment classification

In a **fully observable** environment, agents can see every part.

Agents can only see part of the environment if it is **partially observable**.
Environment classification

If your agent is the only one, the environment is a **single agent** environment.

More than one is a **multi-agent** environment (possibly cooperative or competitive).
Environment classification

If your state+action has a known effect in the environment, it is deterministic.

If actions have a distribution (probability) of possible effects, it is stochastic.

deterministic  ---  stochastic
Environment classification

An **episodic** environment is where the previous action does not effect the next observation (i.e. independent)

If there is the next action depends on the previous, the environment is **sequential**
Environment classification

If the environment only changes when you make an action, it is **static**

A **dynamic** environment can change while your agent is thinking or observing.
Environment classification

**Discrete** = separate/distinct (events)
**Continuous** = fluid transition (between events)

This classification can applies: agent's percept and actions, environment's time and states

- discrete (state)
- continuous (state)
Environment classification

**Known** = agent's actions have known effects on the environment

**Unknown** = the actions have an initially unknown effect on the environment (can learn)

→ **know rules** = known

→ **do not know rules** = unknown
Environment classification

Pick a game/hobby/sport/pastime/whatever and describe both the PEAS and whether the environment/agent is:
1. Fully vs. partially observable
2. Single vs. multi-agent
3. Deterministic vs. stochastic
4. Episodic vs. sequential
5. Static vs. dynamic
6. Discrete vs. continuous
7. Known vs. unknown
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Fully observable, single agent, deterministic, sequential (mouse) or episodic (touch pad), dynamic, continuous (time, state, action, and percept), known (to me!)
Agent models

Can also classify agents into four categories:

1. Simple reflex
2. Model-based reflex
3. Goal based
4. Utility based

Top is typically simpler and harder to adapt to similar problems, while bottom is more general representations
Agent models

A simple reflex agents acts only on the most recent part of the percept and not the whole history.

Our vacuum agent is of this type, as it only looks at the current state and not any previous.

These can be generalized as:
“if state = _____ then do action _____”
(often can fail or loop infinitely)
Agent models

A model-based reflex agent needs to have a representation of the environment in memory (called internal state)

This internal state is updated with each observation and then dictates actions

The degree that the environment is modeled is up to the agent/designer (a single bit vs. a full representation)
Agent models

This internal state should be from the agent's perspective, not a global perspective.

A state might be indistinguishable from the global perspective, yet unique from the agent's.

For example, you always eat when you get home, so your dinner robot learns to prepare food then. However, one day you do not have an appetite (sick) and the robot is wrong.
Agent models

For the vacuum agent if the dirt does not reappear, then we do not want to keep moving.

The simple reflex agent program cannot do this, so we would have to have some memory (or model)

This could be as simple as a flag indicating whether or not we have checked the other state.
Agent models

The goal based agent is more general than the model-based agent

In addition to the environment model, it has a goal indicating a desired configuration

Abstracting to a goal agent programs to solve a wider set of problems (for example, a model-based agent could solve one maze, but a goal can solve any maze)
Agent models

A utility based agent maps the sequence of states (or actions) to a real value.

Goals can describe general terms as “success” or “failure”, but there is no degree of success.

In the maze example, a goal based agent can find the exit. But a utility based agent can find the shortest path to the exit.
Agent models

What is the agent model of particles?

Think of a way to improve the agent and describe what model it is now.
Agent learning

For many complicated problems (facial recognition, high degree of freedom robot movement), it would be too hard to explicitly tell the agent what to do.

Instead, we build a framework to learn the problem and let the agent decide what to do.

This is less work and allows the agent to adapt if the environment changes.
Agent learning

There are four main components to learning:
1. Critic = evaluates how well the agent is doing and whether it needs to change actions (similar to performance measure)
2. Learning element = incorporate new information to improve agent
3. Performance element = selects action agent will do (exploit known best solution)
4. Problem generator = find new solutions (explore problem space for better solution)
States can be generalized into three categories:

1. Atomic (Ch. 3-5, 15, 17)
2. Factored (Ch. 6-7, 10-11, 13-16, 18, 20-21)
3. Structured (Ch. 8-9, 12, 14, 19, 22-23)

(Top are simpler, bottom are more general)

Occam's razor = if two results are identical, use the simpler approach
An **atomic** state has no sub-parts and acts as a simple unique identifier.

An example is an elevator:
Elevator = agent (actions = up/down)
Floor = state

In this example, when someone requests the elevator on floor 7, the only information the agent has is what floor it currently is on.
State structure

A factored state has a fixed number of variables/attributes associated with it.

Our simple vacuum example is factored, as each state has an id (A or B) along with a “dirty” property.

In particles, each state has a set of red balls with locations along with the blue ball location.
Structured states simply describe objects and their relationship to others.

Suppose we have 3 blocks: A, B and C. We could describe: A on top of B, C next to B.

A factored representation would have to enumerate all possible configurations of A, B and C to be as representative.