INTELLIGENT AGENTS

Outline

- Agents and Environments
- Good Behavior and Rationality
- Nature of Environments
- Structure of Agents

Based on the textbook by Stuart Russell & Peter Norvig:

*Artificial Intelligence, A Modern Approach. (2nd Edition)*

Chapter 2

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1. AGENTS AND ENVIRONMENTS

Definition. Russell and Norvig define agents as follows:

“An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators.”

Examples

A physical robot

- Sensors: video camera, laser scanner, microphone, …
- Actuators: motor, switch, display, speaker, …

A software robot (softbot)

- Percepts: encoded bit strings
- Sensors and actuators:
  - calls to operating system, libraries or other programs
- Calls to sensor programs provide input for the agent.

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Mapping Percept Sequences to Actions

- Agent’s behavior depends only on its percept sequence to date.
- An agent can be designed by
  - “specifying which action an agent ought to take in response to any given percept sequence”:
- Such a mapping (agent function) can be represented as a table or as an agent program.

Example. Consider a calculator agent that computes square-roots of positive integers (accurate to 15 decimals).

Approach 1: store square roots in a very large table.
Approach 2: implement the ideal mapping as a program.

The latter approach is clearly more compact and flexible.

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**Example.** A vacuum-cleaner world with just two locations.

<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>

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**2. GOOD BEHAVIOR AND RATIONALITY**

- A **rational agent** should do the right thing, but how and when do we evaluate agent's success?
- A **performance measure** determines how successful an agent is (by an outside observer).

**Problems:**
- Self-deception: humans typically say they didn't really want something after they are unsuccessful at getting it.
- Malpractice if performance is measured only instantly.
- You get what you ask for!
- The measure should depend on effects on the environment.

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**Rational Agents**

Rationality depends on four things:
- The performance measure which defines the criterion of success.
- The agent's prior knowledge of the environment.
- The actions that the agent can perform.
- The agent's percept sequence to date (complete perceptual history).

**Definition.** (Rational agent)

For each possible percept sequence, a rational agent should select an action that is expected to **maximize its performance measure**, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.

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**Omniscience vs. Rationality**

An omniscient agent
- knows the actual outcomes of its actions and acts accordingly; and
- is impossible in reality.

**Example.** A person is crossing a street, as (s)he noticed a friend across the street and there is no traffic nearby.

Is this person acting rationally if (s)he is crashed by a cargo door falling off a passing airplane?

[ ☞ Rationality: expected success given what has been perceived. ]
Information Gathering

Example. Often begin rational requires performing actions in order to acquire information about the environment.

► For instance, crossing a street without looking is too risky.

Example. A clock can be thought as a simple (even degenerate) agent that keeps moving its hands (or displaying digits) in the proper way.

• This can be thought as rational action given what kind of functionality one expects from a clock in general.

• However, many clocks are unable to take changing time zones into account automatically. This is quite acceptable if the clock does not have a mechanism for perceiving time zones.

3. NATURE OF ENVIRONMENTS

► A task environment specifies a "problem" to which a rational agent is a "solution".

► Task environments can be roughly specified by giving a PEAS (Performance, Environment, Actuators, Sensors) description.

Example. Task environment for an automated taxi.

<table>
<thead>
<tr>
<th>Agent Type</th>
<th>Performance Measure</th>
<th>Environment</th>
<th>Actuators</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi driver</td>
<td></td>
<td></td>
<td></td>
<td>Camera, sonar, accelerometer, GPS, accelerometer, engine sensors, keyboard</td>
</tr>
</tbody>
</table>

Autonomy

► An agent lacks autonomy if its actions depend solely on its built-in knowledge about the environment.

► A system is autonomous to the extent that its behavior is determined by its own experience.

► Flexible operation in a variety of environments demands ability to learn (in addition to initial knowledge).

Example. After digging its nest and laying its eggs, a dung beetle fetches a ball of dung to plug the entrance.

► Even if the ball is removed from its grasp en route, the beetle continues and mimics the procedure to the very end.

Examples of PEAS Descriptions

<table>
<thead>
<tr>
<th>Agent Type</th>
<th>Performance Measure</th>
<th>Environment</th>
<th>Actuators</th>
<th>Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical diagnosis system</td>
<td>Healthy patient minima costs, lives</td>
<td>Patient, hospital staff</td>
<td>Display questions, test, diagnose, treatments</td>
<td>Keyboard entry of symptoms, findings, patient's answers</td>
</tr>
<tr>
<td>Satellite image analysis system</td>
<td>Correct image categorization</td>
<td>Downlink from orbiting satellite</td>
<td>Display categorization of scenes</td>
<td>Color pixel arrays</td>
</tr>
<tr>
<td>Part-picking robot</td>
<td>Percentage of parts in correct bins</td>
<td>Conveyor belt with parts, bins</td>
<td>Jointed arm and hand</td>
<td>Canvas, joint angle sensors</td>
</tr>
<tr>
<td>Refrigerator controller</td>
<td>Maintains purity, yield, safety</td>
<td>Refrigerator, operators</td>
<td>Valves, pumps, heaters, displays</td>
<td>Temperature, pressure, chemical sensors</td>
</tr>
<tr>
<td>Interactive English tutor</td>
<td>Maximize student's score on test</td>
<td>Set of students, testing agency</td>
<td>Display exercises, suggestions, corrections</td>
<td>Keyboard entry</td>
</tr>
</tbody>
</table>
Properties of Task Environments

Environments can be categorized by several aspects such as

- Fully vs. partially observable state of the environment
  Also: effectively fully observable
- Deterministic vs. stochastic outcomes of agent’s actions
- Episodic vs. sequential
- Static vs. dynamic
  Also: semidynamic (performance degrades over time)
- Discrete vs. continuous
- Single agent vs. multiagent (competitive or cooperative)

Examples. Analyzing properties of a number of familiar environments.

<table>
<thead>
<tr>
<th>Environment</th>
<th>Accessible</th>
<th>Deterministic</th>
<th>Episodic</th>
<th>Static</th>
<th>Discrete</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chess with a clock</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Semi</td>
<td>Yes</td>
</tr>
<tr>
<td>Chess without a clock</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Poker</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Backgammon</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Taxi driving</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Medical diagnosis system</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Image-analysis system</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Semi</td>
<td>No</td>
</tr>
<tr>
<td>Part-picking robot</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Refinery controller</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Interactive English tutor</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

- Some of the properties are dependent on how the environments and agents are conceptualized.

Agent Programs

A skeleton for agent programs:

- A single percept is obtained as input.
- Memory is used for storing the percept history (if necessary).
- The program chooses and outputs an action to be executed next.

function SKELETON AGENT (percept) returns action
  static memory, the agent’s memory of the world
  memory ← UPDATE MEMORY (memory, percept)
  action ← CHOOSE BEST ACTION (memory)
  memory ← UPDATE MEMORY (memory, action)
  return action

- The performance measure is not a part of the program.
Using Lookup Tables

- An agent program that looks up the action from a table:

```python
function TABLE-DRIVEN-AGENT1(percept) returns action
    static: percepts, a sequence, initially empty
    table, a table, indexed by percept sequences, initially fully specified
    append percept to the end of percepts
    action = LOOKUP(percepts, table)
    return action
```

- Drawbacks of lookup table agents:
  1. The lookup table becomes easily very large
     (a chess playing agent would need a table with $35^{100}$ entries).
  2. The table is difficult to build and maintain.
  3. The resulting agent does not have autonomy at all.
  4. It would take forever to learn the right values for all entries.

Simple Reflex Agents

- Condition-action rules provide a way to represent common regularities appearing in input/output associations:
  ```
  if car-in-front-is-braking then initialize-braking
  ```
- It is even possible to learn such rules on the fly.
- Humans also have many such connections some of which are learned responses and some of which are innate reflexes (such as eye blinking in order to protect the eye).
- Mimicking reflexes of living creatures, a reflex agent chooses the next action on the basis of the current percept.
- No track of the world/environment is kept.

Different Kinds of Agent Programs

In the sequel, we will consider four kinds of agent programs:

- Simple reflex agents
- Model-based reflex agents
- Goal-based agents
- Utility-based agents

Then we discuss a general way to incorporate learning into these.

The structure of a simple reflex agent as a schematic diagram and the corresponding skeletal agent program:

```python
function SIMPLE-REFLEX-AGENT1(percept) returns action
    static: rules, a set of condition-action rules
    rule = INTERPRET-INPUT(percept)
    action = RULE-ACTION(rule)
    return action
```

- Rules provide an efficient representation, but one problem is that decision making is seldom possible on the basis of a single percept.
**Model-based Reflex Agents**

- The choice of actions may depend on the entire percept history.
- Sensors do not necessarily provide access to the complete state of the environment.
- The agent keeps track of the world by extracting relevant information from percepts and storing it in its memory.
- Using a model of the environment, the agent may try to estimate
  1. how the environment evolves in the (near) future, and
  2. how the environment is affected by the agent’s actions.

**Example.** In our taxi driving example, actions may depend on the state, e.g. the position of an overtaking car.

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**Goal-based agents**

- Knowing about the current state of the environment is not necessarily enough for deciding what to do.
- In addition, the agent may need **goals** to distinguish which situations are desirable and which are not.
- Goal information can be combined with the agent’s knowledge about the results of possible actions in order to choose an action leading to a goal.
- Problem: goals are not necessarily achievable by a single action.
- **Search** and **planning** are subfields of AI devoted to finding actions sequences that achieve the agent’s goals.

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**A schematic diagram and a skeletal agent program for a model-based reflex agent:**

```
function REFLEX-AGENT(WHAT-IT-SEES, percept) returns action
state := WHAT-IT-SEES
rules := a set of condition-action rules
state := UPDATE-STATE(state, percept)
rule := RULE-MATCH(state, rules)
action := RULE-ACTION(state, rule)
return action
```

---

**A schematic diagram for a goal-based agent:**

- Additional flexibility compared to previous designs: the behavior of a goal-based agent can be changed by changing its goal(s).
Utility-based agents

- Goals alone are not sufficient for decision making if there are several ways of achieving them.
- Further problem: agents may have several conflicting goals that cannot be achieved simultaneously.
- If an agent prefers one world state to another state then the former state has higher utility for the agent.
- Utility is a function that maps a state onto a real number.
- A utility function can be used for (i) choosing the best plan, (ii) resolving conflicts among goals, and (iii) estimating the success the of actions are uncertain.

Learning Agents

- A learning element is responsible for improving the performance element, which corresponds to an entire agent.
- The learning element gets feedback from a critic on the performance of the agent.
- A problem generator suggests actions that will lead to new and informative experiences.
- Sometimes the percepts of the agent include rewards or penalties (such as pain and hunger) that can be utilized in learning.
### Programs Simulating Environments

**procedure** RUN-ENVIRONMENT(state, UPDATE-FN, agents, termination)

**inputs**
- state, the initial state of the environment
- UPDATE-FN, function to modify the environment
- agents, a set of agents
- termination, a predicate to test when we are done

**repeat**
**for each** agent in agents **do**
  PERCEPT[agent] ← GET-PERCEPT(agent, state)
**end**

**for each** agent in agents **do**
  ACTION[agent] ← PROGRAM[agent](PERCEPT[agent])
**end**

**state** ← UPDATE-FN(actions, agents, state)
**until** termination(state)

- Agents are typically designed to work correctly in a class of environments (that has to be covered by a simulator somehow).
- Agent programs should not have other access than percepts to the state of the program simulating their environment!

**function** RUN-EVAL-ENVIRONMENT(state, UPDATE-FN, agents, termination, PERFORMANCE-FN) **returns** scores

**local variables**:
- scores, a vector the same size as agents, all 0

**repeat**
**for each** agent in agents **do**
  PERCEPT[agent] ← GET-PERCEPT(agent, state)
**end**

**for each** agent in agents **do**
  ACTION[agent] ← PROGRAM[agent](PERCEPT[agent])
**end**

**state** ← UPDATE-FN(actions, agents, state)
**scores** ← PERFORMANCE-FN(scores, agents, state)
**until** termination(state)
**return** scores  
/* change */

---

**SUMMARY**

- An agent program maps a percept (sequence) to an action.
- Agent = architecture + agent program.
- A rational agent tries to maximize its performance measure.
- Task environments can be described by PEAS descriptions.
- Various agent types: reflex agents with(out) internal state, goal-based agents, utility-based agents.
- Important aspects of agent program design: efficiency, compactness, flexibility.

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**QUESTIONS**

- Analyze soccer playing agents by writing down
  1. a PEAS description and
  2. the main properties of the environment.

- Consider the following designs for soccer playing agents:
  1. Simple reflex agent
  2. Model-based reflex agent
  3. Agent with explicit goals
  4. Utility-based agent
  5. Learning agent

What kind of functionality can be implemented in terms of these?