AGENTS

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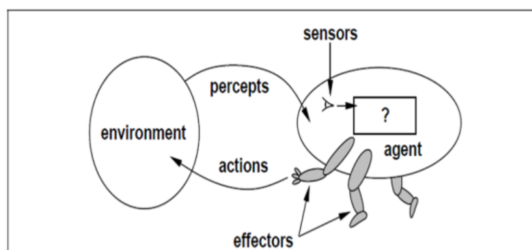
Outline

- Agents and environments
- Rationality
- PEAS (Performance measure, Environment, Actuators, Sensors)
- Environment types
- Agent types

Agents

An **agent** is anything that can be viewed as
– **perceiving** its environment through **sensors**
– **acting** upon that environment through **actuators**
Assumption:
Every agent can **perceive** its own actions (but not always the effects)

Agents



Agents interact with environments through sensors and effectors.

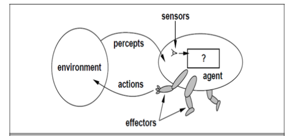
Agents

Human agent:
– eyes, ears, and other organs for sensors;
– hands, legs, mouth, and other body parts for actuators

Robotic agent:
– cameras and infrared range finders for sensors;
– various motors for actuators

Software agent:
– Keystrokes, file contents, received network packages as sensors
– Displays on the screen, files, sent network packets as actuators

Agents and environments



Agents interact with environments through sensors and effectors.

- **Percept**: agent's perceptual input at any given instant
- **Percept sequence**: complete history of everything the agent has ever perceived
- An agent's choice of action at any given instant can depend on the entire percept sequence observed to date

Agents and Environments

An agent's behavior is described by the **agent function** which maps from percept histories to actions:

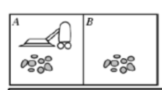
$$[f: P^* \rightarrow A]$$

The **agent function** can be tabulated that describes any given agent (**External characterization**)

Internally, the agent function will be implemented by an **agent program** which runs on the **physical architecture** to produce *f*

agent = **architecture** + **program**

Vacuum-Cleaner world



- Two locations: A and B
- Percepts: location and contents, e.g., [A,Dirty]
- Actions: *Left*, *Right*, *Suck*, *NoOp*

Percept sequence	Actions
[A,Clean]	Right
[A, Dirty]	Suck
[B,Clean]	Left
[B,Dirty]	Suck
[A,Clean],[A,Clean]	Right
[A,Clean],[A,Dirty]	Suck
…	…
[A,Clean],[A,Clean],[A,Clean]	Right
[A,Clean],[A,Clean],[A,Clean]	Suck

One simple function is :
if the current square is dirty then suck, otherwise move to the other square

Rational agents

An agent should strive to "**do the right thing**", based on what it can **perceive** and the **actions it** can perform.

The right action is the one that will cause the agent to be most successful.

Performance measure: An objective criterion for success of an agent's behavior

Rational agents

Performance measure of a vacuum-cleaner agent could be **amount of dirt** cleaned up, **amount of time** taken, **amount of electricity** consumed, **amount of noise** generated, etc.

As a general rule, it is better to **design performance measures** according to what one actually **wants** in the environment rather than according to how one thinks the agent should behave (amount of dirt cleaned vs a clean floor)

A more **suitable measure would reward the agent** for having a clean floor

Rationality

Rationality at any given time depends on four things

– The **performance measure** that 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

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.

Rational Agents

Rationality is distinct from omniscience (all-knowing with infinite knowledge)

Rationality maximizes expected performance while **perfection maximizes actual performance**

Agents can perform actions in order to **modify future percepts** so as to obtain useful information (information gathering, exploration)

An agent is **autonomous** if its behaviour is determined by its **own experience** (with ability to **learn** and **adapt**)

Vacuum-Cleaner Agent

Let's assume the following:

- The **performance measure** awards one point for each clean square at each time step, over a lifetime of 1000 time steps
- The geography of the environment is known ***apriori*** but the **dirt distribution** and the **initial location of the agent** are not.
- Clean squares stay clean and the sucking cleans the current square. The **Left** and **Right** actions move the agent left and right except when this would take the agent outside the environment, in which case the agent remains where it is.
- The only available actions are **Left**, **Right**, **Suck** and **NoOp**
- The agent correctly **perceives its location** and whether that **location contains dirt**

Vacuum cleaner agent

Same agent would be irrational under different circumstances:

- once all dirt is cleaned up it will oscillate needlessly back and forth.
- If the performance measure includes a penalty of one point for each movement left or right, the agent will fare poorly.
- A better agent for this case would do nothing once it is sure that all the squares are clean.
- Clean squares can become dirty again, thus the agent should occasionally check and clean them if needed.
- If the geography of the environment is unknown the agent will need to explore it rather than stick to squares A and B

Specifying the task environment (PEAS)

- PEAS:
  - **Performance measure**,
  - **Environment**,
  - **Actuators**,
  - **Sensors**

In designing an agent, the first step must always be to **specify the task environment** (PEAS) as fully as possible

PEAS for an automated taxi driver

- **Performance measure**: Safe, fast, legal, comfortable trip, maximize profits
- **Environment**: Roads, other traffic, pedestrians, customers
- **Actuators**: Steering wheel, accelerator, brake, signal, horn
- **Sensors**: Cameras, sonar, speedometer, GPS, odometer, engine sensors, keyboard

PEAS for a medical diagnosis system

- **Performance measure**: Healthy patient, minimize costs, lawsuits
- **Environment**: Patient, hospital, staff
- **Actuators**: Screen display (questions, tests, diagnoses, treatments, referrals)
- **Sensors**: Keyboard (entry of symptoms, findings, patient's answers)

PEAS for a Satellite Image Analysis System

- **Performance measure**: correct image categorization
- **Environment**: downlink from orbiting satellite
- **Actuators**: display categorization of scene
- **Sensors**: color pixel arrays

PEAS for a Part-picking Robot

- **Performance measure**: Percentage of parts in correct bins
- **Environment**: Conveyor belt with parts, bins
- **Actuators**: Jointed arm and hand
- **Sensors**: Camera, joint angle sensors

PEAS for a Refinery Controller

- **Performance measure**: maximize purity, yield, safety
- **Environment**: refinery, operators
- **Actuators**: valves, pumps, heaters, displays
- **Sensors**: temperature, pressure, chemical sensors

PEAS for Interactive English Tutor

- **Performance measure**: Maximize student's score on test
- **Environment**: Set of students
- **Actuators**: Screen display (exercises, suggestions, corrections)
- **Sensors**: Keyboard

Environment Types

- Fully observable vs. Partially observable
- Deterministic vs. stochastic
- Episodic vs. Sequential
- Static vs. Dynamic
- Discrete vs. Continuous
- Single agent vs. Multi-agent

Environment Types

Fully observable vs. partially observable:

- An environment is fully observable if an agent's **sensors** give it access to the **complete state of the environment** at each point in time.
- Fully observable environments are **convenient**, because the **agent need not maintain any internal state** to keep track of the world
- An environment might be **partially observable** because of **noisy** and **inaccurate sensors** or because parts of the state are simply missing from the sensor data

- Examples: vacuum cleaner with local dirt sensor, taxi driver

Environment Types

Deterministic vs. Stochastic:

- The environment is **deterministic** if the next state of the environment is **completely determined by the current state** and **the action executed by the agent.**
- In principle, an agent need not worry about **uncertainty** in a **fully observable**, **deterministic** environment
- If the environment is **partially observable** then it could appear to be **stochastic**
- Examples: Vacuum world is deterministic while taxi driver is not
- If the environment is **deterministic** except for the actions of other agents, then the environment is **strategic**

Environment Types

Episodic vs. Sequential:
• In episodic environments, the agent's **experience is divided into atomic "episodes"** (each episode consists of the agent perceiving and then performing a single action), and the choice of action in each episode **depends only on the episode itself**.
Examples: classification tasks
• In sequential environments, the **current decision could affect all future decisions**
Examples: chess and taxi driver

Environment Types

Static vs. Dynamic:
- The environment is **unchanged** while an agent is deliberating.
- Static environments are **easy to deal** with because the agent need not keep looking at the world while it is deciding on the action or need it worry about the passage of time
- Dynamic environments **continuously ask** the agent what it wants to do
- The environment is **semi-dynamic** if the environment itself **does not change** with the passage of time but the agent's performance score does

Examples: taxi driving is dynamic, chess when played with a clock is semi-dynamic, crossword puzzles are static

Environment Types

Discrete vs. Continuous:
- A limited number of **distinct**, **clearly defined states**, **percepts** and **actions**.

Examples:
Chess has finite number of discrete states, and has discrete set of percepts and actions.
Taxi driving has continuous states and actions

Environment Types

Single agent vs. Multi-agent:

• An agent **operating by itself in an environment** is single agent
Examples: Crossword is a single agent while chess is two-agents

Question: Does an agent A have to treat an object B, as an agent or can it be treated as a stochastically behaving object
• Whether B's behavior is best described by as maximizing a performance measure whose value depends on agent A's behaviour
Examples: Chess is a competitive multi-agent environment while taxi driving is a partially cooperative multi-agent environment

Environment Types

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Crossword puzzle	Fully	Deterministic	Sequential	Static	Discrete	Single
Chess with a clock	Fully	Strategic	Sequential	Semi	Discrete	Multi
Poker	Partially	Stochastic	Sequential	Static	Discrete	Multi
Backgammon	Fully	Stochastic	Sequential	Static	Discrete	Multi
Taxi driving	Partially	Stochastic	Sequential	Dynamic	Continuous	Multi
Medical Diagnosis	Partially	Stochastic	Sequential	Dynamic	Continuous	Single
Image Analysis	Fully	Deterministic	Episodic	Semi	Continuous	Single
Part-picking robot	Partially	Stochastic	Episodic	Dynamic	Continuous	Single
Refinery controller	Partially	Stochastic	Sequential	Dynamic	Continuous	Single
Interactive English Tutor	Partially	Stochastic	Sequential	Dynamic	Discrete	Multi

- The environment type largely determines the agent design
- The real world is (of course) partially observable, stochastic, sequential, dynamic, continuous, multi-agent

Agent functions and programs

- An agent is completely specified by the agent function mapping percept sequences to actions
- One agent function (or a small equivalence class) is rational
- Aim: find a way to implement the rational agent function concisely -> design an **agent program** Agent = agent program + architecture
- Architecture: some sort of computing device with physical sensors and actuators (PC, robotic car)

– should be appropriate: walk action requires legs

Agent functions and programs

- Agent program:

– Takes the current percept as input from the sensors

– Return an action to the actuators

– While agent function takes the whole percept history, agent program takes just the current percept as input which the only available input from the environment

– The agent need to remember the whole percept sequence, if it needs it

Table-lookup agent

A trivial agent program: keeps track of the percept sequence and then uses it to index into a table of actions to decide what to do

- The designers must construct the table that contains the appropriate action for every possible percept sequence

function TABLE-DRIVEN-AGENT(*percept*) **returns** an action
    static: *percepts*, a sequence, initially empty
        table, a table of actions, indexed by percept sequences, initially fully specified
    append *percept* to the end of *percepts*
    action <--LOOKUP(*percepts*, *table*)
    return *action*

Table-lookup agent

- Drawbacks:
– Huge table (P^T , P: set of possible percepts, T: lifetime)
- Space to store the table
- Take a long time to build the table
- No autonomy
- Even with learning, need a long time to learn the table entries

Agent types

- Rather than a table how we can produce rational behavior from a small amount of code

- Four basic types in order of increasing generality:
– Simple reflex agents
– Model-based reflex agents
– Goal-based agents
– Utility-based agents

Simple reflex agents

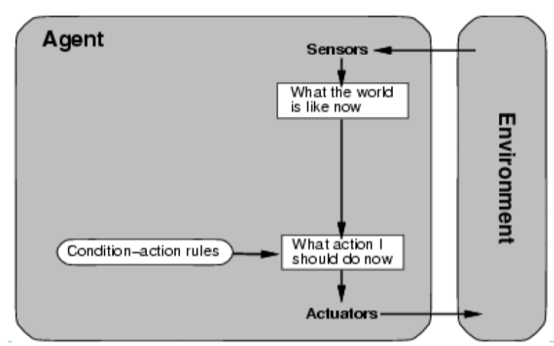
- Select actions on the basis of the **current percept** ignoring the rest of the percept history

- Example: simple reflex vacuum cleaner agent

```
function REFLEX-VACUUM-AGENT([location,status]) returns an action
    if status = Dirty then return Suck
    else if location = A then return Right
    else if location = B then return Left
```

- **Condition-action-rule**
- Example: **if** *car-in-front-is-breaking* **then** *initiate-breaking*

Simple reflex agents



Simple reflex agents

```
function SIMPLE-REFLEX-AGENT(percept) returns an action
    static: rules,  a set if condition-action rules
    state <-- INTERPRET_INPUT(percept)
    rule <-- RULE_MATCH(state, rules)
    action <-- RULE_ACTION[rule]
    return action
```

- Simple-reflex agents are simple, but they turn out to be of very limited intelligence
- The agent will work only if the correct decision can be made on the basis of the current percept –that is only if the environment is fully observable
- Infinite loops are often unavoidable – escape could be possible by randomizing

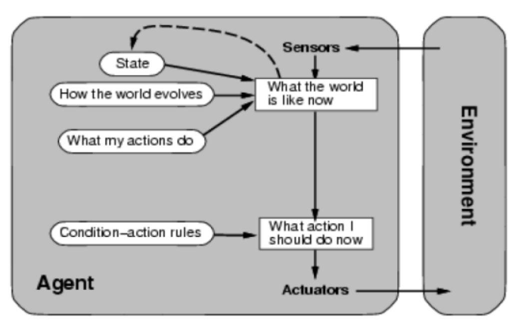
Model-based reflex agents

- The agent should keep track of the part of the world it can't see now
- The agent should maintain some sort of internal state that depends on the percept history and reflects at least some of the unobserved aspects of the current state

Model-based reflex agents contd..

- Updating the internal state information as time goes by requires two kinds of knowledge to be encoded in the agent program
– Information about how the world evolves independently of the agent
– Information about how the agent's own actions affects the world
- Model of the world – model based agents

Model-based reflex agents



Model-based reflex agents

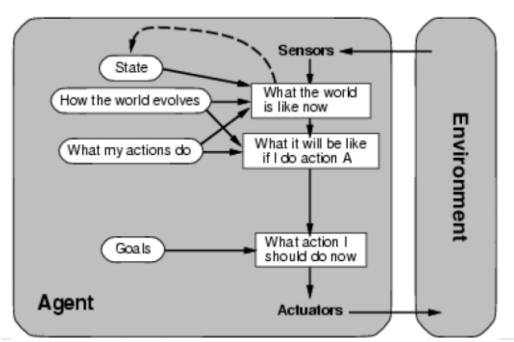
```
function REFLEX-AGENT-WITH-STATE(percept) returns an action
    static:  state, a description of the current world state
             rules, a set of condition-action rules
             action, the most recent action, initially none

    state <-- UPDATE_INPUT(state, action, percept)
    rule <-- RULE_MATCH(state, rules)
    action <-- RULE_ACTION[rule]
    return action
```

Goal-based agents

- Knowing about the current state of the environment is not always enough to decide what to do (e.g. decision at a road junction)
- The agent needs some sort of goal information that describes situations that are desirable
- The agent program can combine this with information about the results of possible actions in order to choose actions that achieve the goal
- Usually requires search and planning

Goal-based agents



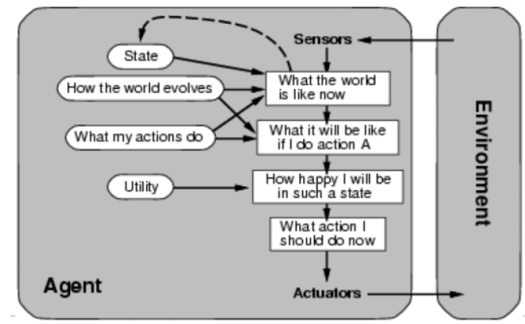
Goal-based agents vs reflex-based agents

- Although goal-based agents appears less efficient, it is more flexible because the knowledge that supports its decision is represented explicitly and can be modified
- On the other hand, for the reflex-agent, we would have to rewrite many condition-action rules
- The goal based agent's behavior can easily be changed
- The reflex agent's rules must be changed for a new situation

Utility-based agents

- Goals alone are not really enough to generate high quality behavior in most environments – they just provide a binary distinction between happy and unhappy states
- A more general performance measure should allow a comparison of different world states according to exactly how happy they would make the agent if they could be achieved
- Happy – Utility (the quality of being useful)
- A utility function maps a state onto a real number which describes the associated degree of happiness

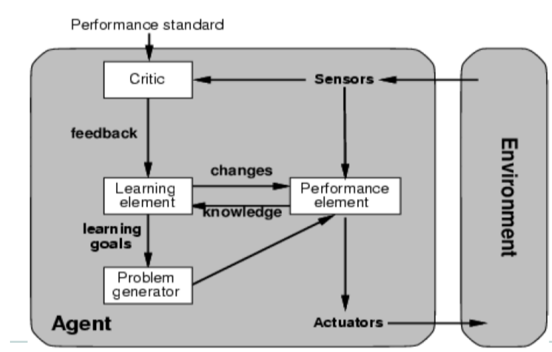
Utility-based agents



Learning agents

- Turing – instead of actually programming intelligent machines by hand, which is too much work, build learning machines and then teach them
- Learning also allows the agent to operate in initially unknown environments and to become more competent than its initial knowledge alone might allow

Learning agents



Learning agents

- Learning element – responsible for making improvements
- Performance element – responsible for selecting external actions (it is what we had defined as the entire agent before)
- Learning element uses feedback from the critic on how the agent is doing and determines how the performance element should be modified to do better in the future
- Problem generator is responsible for suggesting actions that will lead to a new and informative experiences