

# Fundamentals of Artificial Intelligence

## Chapter 02: Intelligent Agents

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# Outline

- 1 Agents and Environments
- 2 Rational Agents
- 3 Task Environments
- 4 Task-Environment Types
- 5 Agent Types
- 6 Environment States

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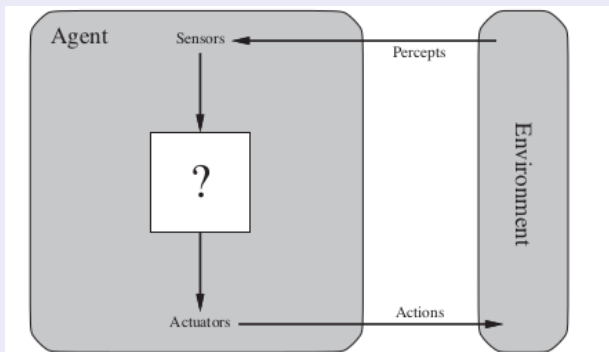
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# Agents and Environments

## Agents

An **agent** is any entity that can be viewed as:

- **perceiving** its environment through **sensors**, and
- **acting** upon that environment through **actuators**.



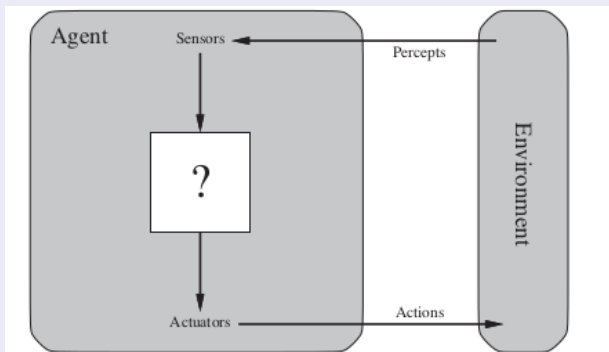
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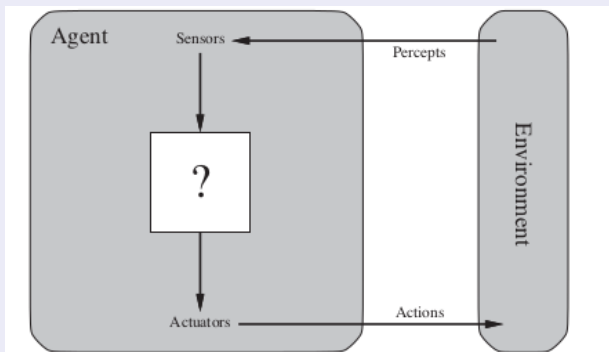
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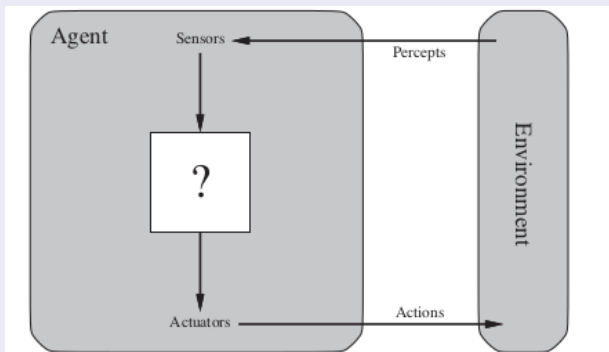
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# Agents and Environments [cont.]

## Agents

Agents include humans, robots, softbots, thermostats, etc.

- human:

perceives: with eyes, ears, nose, hands, ...

acts: with voice, hands, arms, legs, ...

- robot:

perceives: with video-cameras, infra-red sensors, radar, ...

acts: with wheels, motors,

- softbot:

perceives: receiving keystrokes, files, network packets, ...

acts: displaying on the screen, writing files, sending network packets

- thermostat:

perceives: with heat sensor, ...

acts: electric impulses to valves, devices, ...



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# Key concepts

## Percept and Percept sequences

- **percept**: the collection of agent's perceptual inputs at any given instant
- **percept sequence**: the 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
- does not depend on anything it hasn't perceived

## Remark

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## Key concepts [cont.]

### Agent function

An agent's behavior is described by the **agent function**  $f : P^* \mapsto A$  which **maps any given percept sequence into an action**.

- ideally, can be seen as a table [*percept sequence, action*]

### Agent program

Internally, the agent function for an artificial agent is implemented by an **agent program**.

### Note: Agent function vs. agent program

- The **agent function** is an **abstract mathematical description**
  - possibly-infinite description
- The **agent program** is a **concrete implementation** of the agent function
  - finite description
  - runs on the physical architecture to produce the agent function  $f$



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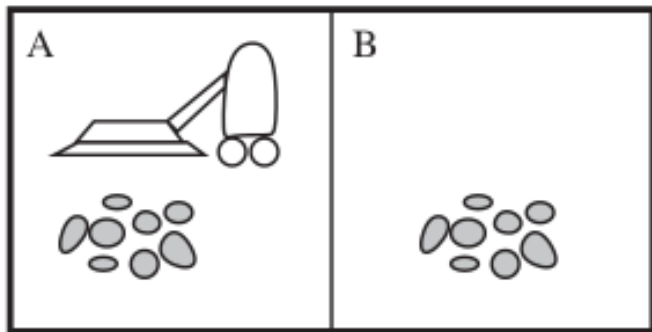
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# Example

## A very-simple vacuum cleaner

- Environment: squares A and B
- Percepts: location ( $\{A, B\}$ ) and content ( $\{\textit{Dirty}, \textit{Clean}\}$ )
  - e.g.  $[A, \textit{Dirty}]$
- Actions:  $\{\textit{left}, \textit{right}, \textit{suck}, \textit{no\_op}\}$



## Example [cont.]

### A simple agent function

If the current square is dirty, then suck;  
otherwise, move to the other square.

| Percept sequence                          | Action       |
|---|--------------|
| <i>[A, Clean]</i>                         | <i>Right</i> |
| <i>[A, Dirty]</i>                         | <i>Suck</i>  |
| <i>[B, Clean]</i>                         | <i>Left</i>  |
| <i>[B, Dirty]</i>                         | <i>Suck</i>  |
| <i>[A, Clean], [A, Clean]</i>             | <i>Right</i> |
| <i>[A, Clean], [A, Dirty]</i>             | <i>Suck</i>  |
| <i>⋮</i>                                  | <i>⋮</i>     |
| <i>[A, Clean], [A, Clean], [A, Clean]</i> | <i>Right</i> |
| <i>[A, Clean], [A, Clean], [A, Dirty]</i> | <i>Suck</i>  |
| <i>⋮</i>                                  | <i>⋮</i>     |

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Note: this agent function depends only on the last percept, not on the whole percept sequence.

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| <i>[B, Clean]</i>                         | <i>Left</i>  |
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| <i>[A, Clean], [A, Clean]</i>             | <i>Right</i> |
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## Example [cont.]

### Corresponding agent program

```
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
```

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- 1 Agents and Environments
- 2 Rational Agents**
- 3 Task Environments
- 4 Task-Environment Types
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# Main question

What is a **rational** agent?



# Rational Agents

- Intuition: a rational agent is one that “does the right thing”
  - i.e., every entry in the agent function-table is filled out correctly
- What is the right thing?
- Approximation: the most “successful” thing:
  - In a given environment, according to the percept sequence it receives, an agent generates a sequence of actions, ...
  - ... causing the environment to go through a sequence of states.
  - If such sequence is desirable, then the agent has performed well.

⇒ need a performance measure to evaluate any sequence of environment states

- Performance measure should be objective

Performance measure according to what is wanted in the environment, not to how the agents should behave

- e.g. “how clean the floor is” is a better measure than “the amount of dirt cleaned within a certain time”

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## Rational Agents [cont.]

What is rational 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 (from sensors)

Definition of a 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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# Rational Agents: Example

## The simple vacuum-cleaner agent

Under the following assumptions:

- **Performance measure:** one point for each clean square at each time step, over 1000 time steps
- **Environment knowledge:**
  - “geography” known a priori,
  - dirt distribution and agent initial location unknown
  - [clean squares cannot become dirty again ]
- **Perception:** self location, presence of dirt
- **Actions:** Left, Right, Suck

Is the agent rational?

⇒ **Yes!** (provided the given performance measure)

Beware: if a penalty for each move is given, the agent behaves poorly

⇒ better agent: do nothing once it is sure all the squares are clean

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  - “geography” known a priori,
  - dirt distribution and agent initial location unknown
  - [clean squares cannot become dirty again ]
- **Perception:** self location, presence of dirt
- **Actions:** Left, Right, Suck

Is the agent rational?

⇒ **Yes!** (provided the given performance measure)

Beware: if a penalty for each move is given, the agent behaves poorly

⇒ better agent: do nothing once it is sure all the squares are clean

# Rational Agents: Example

## The simple vacuum-cleaner agent

Under the following assumptions:

- **Performance measure:** one point for each clean square at each time step, over 1000 time steps
- **Environment knowledge:**
  - “geography” known a priori,
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⇒ better agent: do nothing once it is sure all the squares are clean



# Rationality vs. Omniscience vs. Perfection

## Remark

- Rationality  $\neq$  Omniscience!
  - An omniscient agent **knows for sure** the outcome of its actions  
 $\implies$  omniscience impossible in reality
  - A rational agent may only know “up to a reasonable confidence” (e.g., when crossing a road, what if something falling from a plane flattens you? if so, would you be considered irrational?)
- Rational behaviour is not perfect behaviour!
  - perfection maximizes **actual** performance
  - (given uncertainty) rationality maximizes **expected** performance

# Information Gathering, Learning, Autonomy

Rationality requires other important features

- **Information gathering/exploration:**
  - the rational choice depends only on the percept sequence to date  
⇒ **actions needed in order to modify future percepts**
  - Ex: **look both ways before crossing a busy road**
- **Learning:**
  - agent's prior knowledge of the environment incomplete  
⇒ **learning from percept sequences improves & augments it**
  - Ex: a baby learns from trial&errors the right movements to walk
- **Being Autonomous:**
  - prior knowledge may be partial/incorrect or evolving  
⇒ **learn to compensate for partial or incorrect prior knowledge**
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Information gathering, learning, autonomy play an essential role in AI.

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# Outline

- 1 Agents and Environments
- 2 Rational Agents
- 3 Task Environments**
- 4 Task-Environment Types
- 5 Agent Types
- 6 Environment States

# Task Environments

## PEAS Description of Task Environments

- To design a rational agent we must specify its **task environment**
  - i.e. the “problems” to which rational agents are the “solutions”
- Task environment described in terms of four elements (“PEAS”):
  - Performance measure
  - Environment
  - Actuators
  - Sensors

## Simple Example: Simple Vacuum Cleaner

- Performance measure: 1 point per clean square per time step
- Environment: squares A and B, possibly dirty
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# Task Environments [cont.]

## Complex Example: Autonomous Taxi

- **Performance measure:** safety, destination, profits, comfort, ...
- **Environment:** streets/freeways, other traffic, pedestrians, ...
- **Actuators:** steering, accelerator, brake, horn, speaker/display, ...
- **Sensors:** video, sonar, speedometer, engine sensors, GPS, ...

## Remark

Some goals to be measured may conflict!

- e.g. profits vs. safety, profits vs. comfort, ...  
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# Task Environments: Examples

| Agent Type                      | Performance Measure                 | Environment                      | Actuators   | Sensors   |
|---------------------------------|-------------------------------------|----------------------------------|---|---|
| Medical diagnosis system        | Healthy patient, reduced costs      | Patient, hospital, staff         | Display of questions, tests, diagnoses, treatments, referrals | Keyboard entry of symptoms, findings, patient's answers |
| Satellite image analysis system | Correct image categorization        | Downlink from orbiting satellite | Display of scene categorization                               | Color pixel arrays                                      |
| Part-picking robot              | Percentage of parts in correct bins | Conveyor belt with parts; bins   | Jointed arm and hand  | Camera, joint angle sensors                             |
| Refinery controller             | Purity, yield, safety               | Refinery, operators              | Valves, pumps, heaters, displays                              | Temperature, pressure, chemical sensors                 |
| Interactive English tutor       | Student's score on test             | Set of students, testing agency  | Display of exercises, suggestions, corrections                | Keyboard entry  |



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# Properties of Task Environments

Task environments can be categorized along six dimensions:

- Fully observable vs. partially observable
- Single-agent vs. multi-agent
- Deterministic vs. stochastic
- Episodic vs. sequential
- Static vs. dynamic
- Discrete vs. continuous

# Properties of Task Environments [cont.]

## Fully observable vs. partially observable

- A task environment is (effectively) **fully observable** iff the sensors detect **the complete state of the environment**
  - "relevant" depends on the performance measure
  - no need to maintain internal state to keep track of the environment
- A t.e. may be **partially observable** (Ex: **Taxi driving**):
  - noisy and inaccurate sensors
  - parts of the state are not accessible for sensors
- A t.e. might be even **unobservable** (no sensors)
  - e.g. fully-deterministic actions

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# Properties of Task Environments [cont.]

## Single-agent vs. multi-agent

- A task environment is **multi-agent** iff contains **other agents who are also maximizing some performance measure that depends on the current agent's actions**
  - latest condition essential
  - distinction between single- and multi-agent sometimes subtle
- Two important cases
  - competitive multi-agent environment: other agents' goals conflict with or oppose to the agent's goals
    - Ex: chess, war scenarios, taxi driving (compete for parking lot), ...
  - cooperative multi-agent environment: other agents' goals coincide in full or in part with the agent's goals
- different design problems for multi-agent wrt. single-agent
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# Properties of Task Environments [cont.]

## Deterministic vs. stochastic

- A task environment is **deterministic** iff its next state is completely determined by its current state and by the action of the agent.  
(Ex: a crossword puzzle).
- If not so:
  - A t.e. is **stochastic** if uncertainty about outcomes is **quantified in terms of probabilities** (Ex: dice, poker game, component failure,...)
  - A t.e. is **nondeterministic** iff actions are characterized by their possible outcomes, but no probabilities are attached to them

In a multi-agent environment we ignore uncertainty that arises from the actions of other agents (Ex: **chess** is deterministic even though each agent is unable to predict the actions of the others).

A **partially observable** environment could **appear to be stochastic**.  
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# Properties of Task Environments [cont.]

## Episodic vs. sequential

- In an **episodic** task environment
  - the agent's experience is divided into **atomic episodes**
  - in each episode the agent receives a percept and then performs a single action
  - ⇒ **episodes do not depend on the actions taken in previous episodes, and they do not influence future episodes**
  - Ex: **an agent that has to spot defective parts on an assembly line,**
- In **sequential** environments the current decision could affect future decisions ⇒ actions can have long-term consequences
  - Ex: **chess, taxi driving, ...**
- Episodic environments **are much simpler** than sequential ones
  - No need to think ahead!

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# Properties of Task Environments [cont.]

## Static vs. dynamic

- The task environment is **dynamic** iff **it can change while the agent is choosing an action**, **static** otherwise
  - ⇒ **agent needs keep looking at the world while deciding an action**
    - Ex: crossword puzzles are static, taxi driving is dynamic
- The t.e. is **semidynamic** if the environment itself does not change with time, but **the agent's performance score does**
  - Ex: chess with a clock
- Static environments are easier to deal wrt. [semi]dynamic ones

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# Properties of Task Environments [cont.]

## Discrete vs. continuous

- The **state of the environment**, the way **time** is handled, and agents **percepts** & **actions** can be **discrete** or **continuous**
  - Ex: **Crossword puzzles**: discrete state, time, percepts & actions
  - Ex: **Taxi driving**: continuous state, time, percepts & actions
  - ...

# Properties of Task Environments [cont.]

## Note

- The simplest environment is fully observable, single-agent, deterministic, episodic, static and discrete.
  - Ex: simple vacuum cleaner
- Most real-world situations are partially observable, multi-agent, stochastic, sequential, dynamic, and continuous.
  - Ex: taxi driving

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# Properties of Task Environments [cont.]

## Note

- The simplest environment is **fully observable**, **single-agent**, **deterministic**, **episodic**, **static** and **discrete**.
  - Ex: **simple vacuum cleaner**
- Most real-world situations are **partially observable**, **multi-agent**, **stochastic**, **sequential**, **dynamic**, and **continuous**.
  - Ex: **taxi driving**

# Properties of Task Environments [cont.]

## Example properties of task Environments

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

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Several of the answers in the table depend on how the task environment is defined.

# Properties of the Agent's State of Knowledge

## Known vs. unknown

- Describes the agent's (or designer's) **state of knowledge** about the "laws of physics" of the environment
  - if the environment is **known**, then **the outcomes (or outcome probabilities if stochastic) for all actions are given.**
  - if the environment is **unknown**, then **the agent will have to learn how it works** in order to make good decisions
- Orthogonal wrt. task-environment properties

## Known $\neq$ Fully observable

- a known environment can be partially observable  
(Ex: a **solitaire card games**)
- an unknown environment can be fully observable  
(Ex: a **game I don't know the rules of**)



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# Outline

- 1 Agents and Environments
- 2 Rational Agents
- 3 Task Environments
- 4 Task-Environment Types
- 5 Agent Types**
- 6 Environment States

# Agents

## Agent = Architecture + Program

- AI Job: design an agent program implementing the agent function
- The agent program runs on some computing device with physical sensors and actuators: the agent architecture
- All agents have the same skeleton:
  - Input: current percepts
  - Output: action
  - Program: manipulates input to produce output

## Remark

- the agent function takes the entire percept history as input
  - the agent program takes only the current percept as input
- ⇒ if the actions need to depend on the entire percept sequence, the agent will have to remember the percepts

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# A trivial Agent Program

## The Table-Driven Agent

- The table represents explicitly the agent function
  - Ex: the simple vacuum cleaner

```
function TABLE-DRIVEN-AGENT(percept) returns an action
  persistent: 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
```

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Blow-up in table size  $\implies$  doomed to failure

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# Agent Types

## Four basic kinds of agent programs

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

All these can be turned into **learning** agents.

# Agent Types

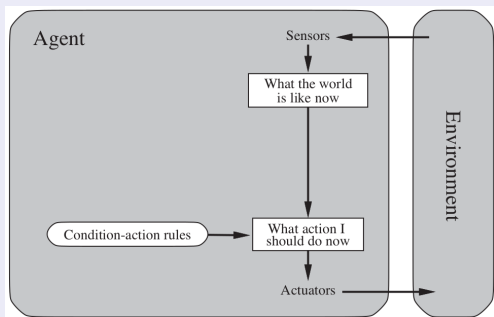
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# Agent Types: Simple-reflex agent

- Select action on the basis of **the current percept only**
  - Ex: **the simple vacuum-agent**
- Implemented through **condition-action rules**
  - Ex: **“if car-in-front-is-braking then initiate-braking”**
  - can be implemented, e.g., in a Boolean circuit
- **Large reduction in possible percept/action situations due to ignoring the percept history**



## Agent Types: Simple-reflex agent [cont.]

### Simple-reflex agent program

```
function SIMPLE-REFLEX-AGENT(percept) returns an action  
persistent: rules, a set of condition–action rules  
  
state ← INTERPRET-INPUT(percept)  
rule ← RULE-MATCH(state, rules)  
action ← rule.ACTION  
return action
```

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- very simple
  - may work **only if the environment is fully observable**
    - deadlocks or infinite loops may occur otherwise
- ⇒ limited applicability

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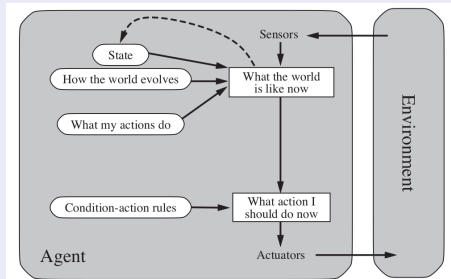
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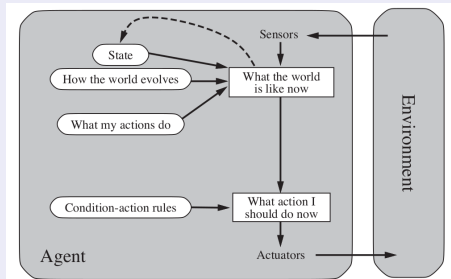
# Agent Types: Model-based agent

- Idea: To tackle partially-observable environments, **keeps track of the part of the world it can't see now**
  - Maintain **internal state** depending on the percept history
  - reflects at least some of the unobserved aspects of current state
- To update **internal state** the agent needs a **model of the world**:
  - **how the world evolves independently of the agent**
    - Ex: an overtaking car will soon be closer behind than it was before
  - **how the agent's own actions affect the world**
    - Ex: turn the steering wheel clockwise  $\implies$  the car turns to the right



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# Agent Types: Model-based Agent [cont.]

## Model-based Agent program

**function** MODEL-BASED-REFLEX-AGENT(*percept*) **returns** an action

**persistent:** *state*, the agent's current conception of the world state

*model*, a description of how the next state depends on current state and action

*rules*, a set of condition–action rules

*action*, the most recent action, initially none

*state* ← UPDATE-STATE(*state*, *action*, *percept*, *model*)

*rule* ← RULE-MATCH(*state*, *rules*)

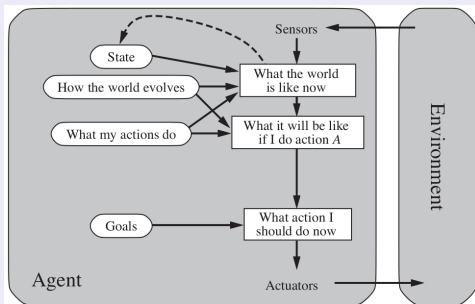
*action* ← *rule*.ACTION

**return** *action*

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# Agent Types: Goal-based agent

- The agent needs **goal information** describing **desirable situation**
  - Ex: **destination for a Taxi driver**
- Idea: **combine goal with the model to choose actions**
- Difficult if long action sequences are required to reach the goal  
⇒ Typically investigated in **search** and **planning** research.
- Major difference: **future is taken into account**
  - rules are simple condition-action pairs, do not target a goal



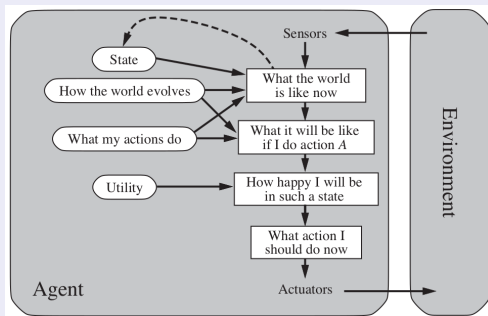
# Agent Types: Goal-based Agent [cont.]

## Goal-based Agents

- **more flexible:**
  - the knowledge that supports its decisions **is represented explicitly**
  - **such knowledge can be modified**
    - ⇒ all of the relevant behaviors to be altered to suit the new conditions
      - Ex: **If it rains, the agent can update its knowledge of how effectively its brakes operate**
  - **the goal can be modified/updated** ⇒ modify its behaviour
    - no need to rewrite all rules from scratch
- more complicated to implement
- **may require expensive computation** (search, planning)

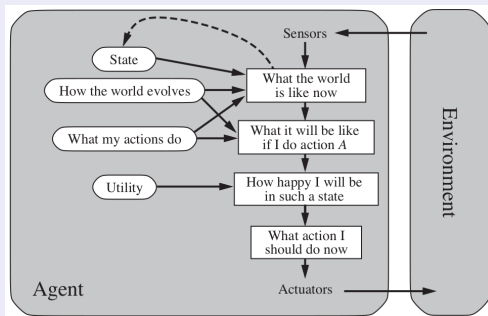
# Agent Types: Utility-based agent

- Goals alone often not enough to generate high-quality behaviors
    - Certain goals can be reached in different ways, of different quality
    - Ex: some routes are quicker, safer, or cheaper than others
  - Idea: Add utility function(s) to drive the choice of actions
    - maps a (sequence of) state(s) onto a real number
      - ⇒ actions are chosen which maximize the utility function
    - under uncertainty, maximize the expected utility function
- ⇒ utility function = internalization of performance measure



# Agent Types: Utility-based agent

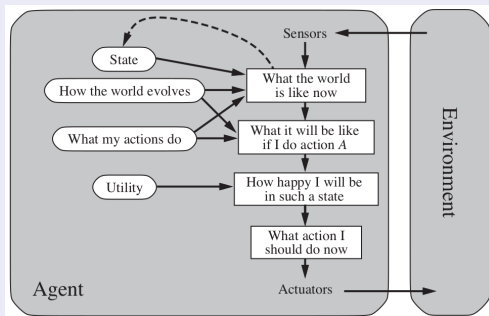
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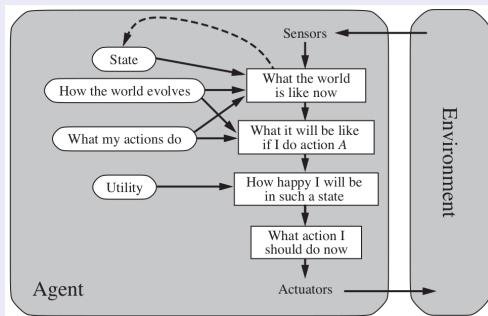
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# Agent Types: Utility-based Agent [cont.]

## Utility-based Agents

- advantages wrt. goal-based:
  - with **conflicting goals**, utility specifies and appropriate tradeoff
  - with **several goals none of which can be achieved with certainty**, utility selects proper tradeoff between importance of goals and likelihood of success
- still complicate to implement
- require sophisticated perception, reasoning, and learning
- **may require expensive computation**

# Agent Types: Learning

## Problem

- Previous agent programs describe methods for **selecting actions**
  - How are these agent programs programmed?
  - Programming by hand **inefficient** and **ineffective!**
  - Solution: build **learning machines** and then **teach** them (rather than **instruct** them)
  - Advantage: **robustness** of the agent program toward initially-unknown environments

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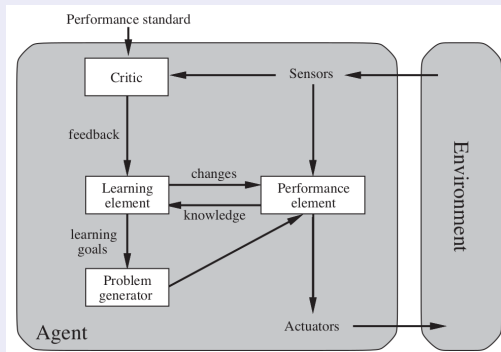
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# Agent Types: Learning

## Learning Agent Types: components

Performance element: **selects actions based on percepts**

- Corresponds to the previous agent programs



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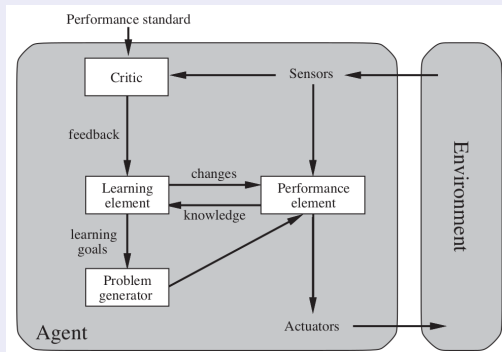


# Agent Types: Learning

## Learning Agent Types: components

Learning element: **introduces improvements**

- uses feedback from the **critic** on how the agent is doing
- determines improvements for the performance element

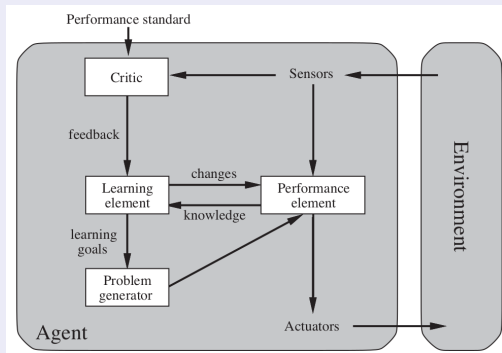


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# Agent Types: Learning

## Learning Agent Types: components

Critic tells how the agent is doing wrt. performance standard



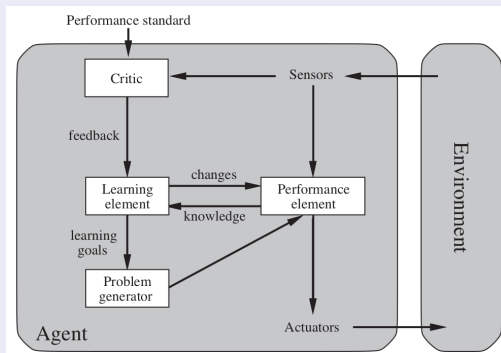
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# Agent Types: Learning

## Learning Agent Types: components

**Problem generator:** suggests actions that will lead to new and informative experiences

- forces exploration of new stimulating scenarios



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# Learning Agent Types: Example

## Taxi Driving

- After the taxi makes a quick left turn across three lanes, the **critic** observes the shocking language used by other drivers.
- From this experience, the **learning element** formulates a rule saying this was a bad action.
- The **performance element** is modified by adding the new rule.
- The **problem generator** might identify certain areas of behavior in need of improvement, and suggest trying out the brakes on different road surfaces under different conditions.

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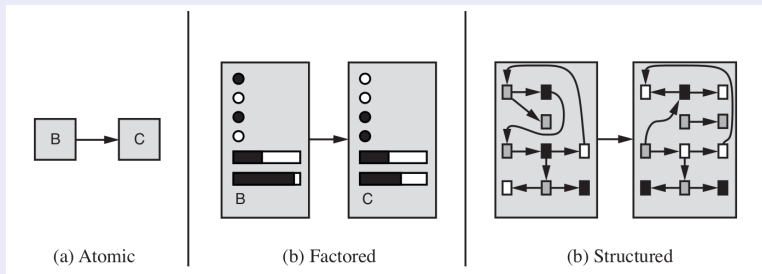
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# Representations

## Representations of states and transitions

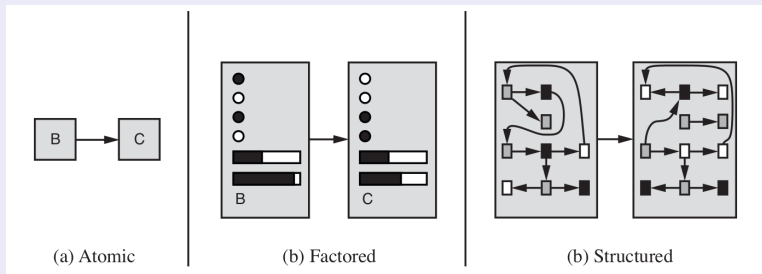
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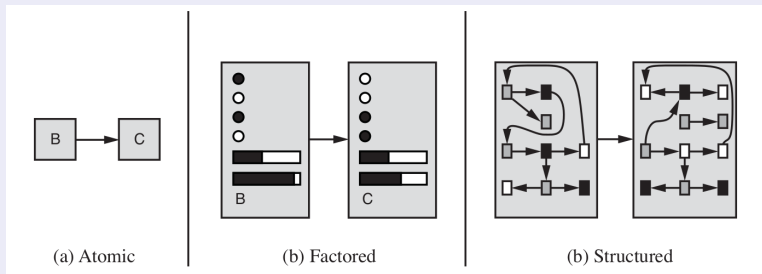
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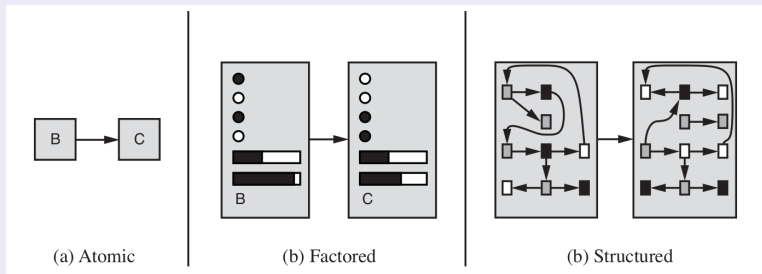
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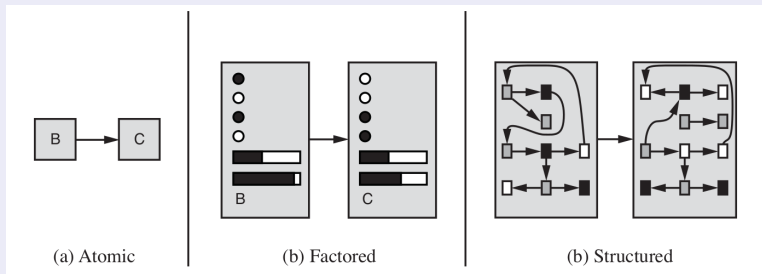
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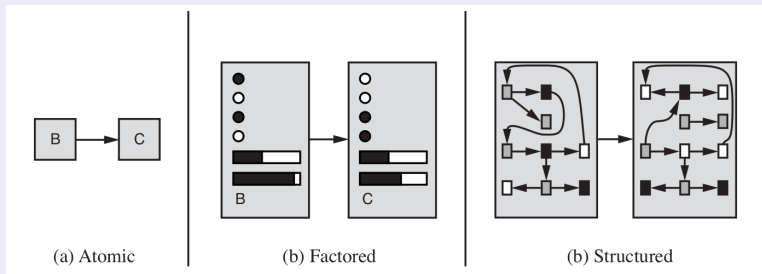
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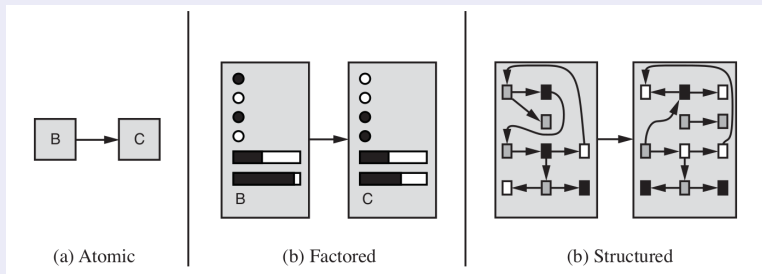
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  - **structured**: a state **includes objects**, each of which may have **attributes** of its own as well as **relationships** to other objects
- increasing **expressive power** and **computational complexity**
- reality represented at **different levels of abstraction**





# Representations [cont.]

## Atomic Representations

- each state of the world is **indivisible**
  - no internal structure
- state: one among a **collection of discrete state values**
  - Ex: find driving routes: {*Trento*, *Rovereto*, *Verona*, ...}

⇒ only property: be identical to or different from another state
- **very high level of abstraction**

⇒ lots of details ignored
- The algorithms underlying
  - **search** and **game-playing**
  - **hidden Markov models**
  - **Markov decision processes**

all work with atomic representations (or treat it as such)

# Representations [cont.]

## Factored Representation

- Each state represented in terms of **a vector of attribute values**
  - Ex:  $\langle \text{zone}, \{\text{dirty}, \text{clean}\} \rangle$ ,  $\langle \text{town}, \text{speed} \rangle$
- State: **combination of attribute values**
  - Ex:  $\langle A, \text{dirty} \rangle$ ,  $\langle \text{Trento}, 40\text{kmh} \rangle$
- Distinct states may share the values of some attribute
  - Ex:  $\langle \text{Trento}, 40\text{kmh} \rangle$  and  $\langle \text{Trento}, 47\text{kmh} \rangle$
  - identical iff all attribute have the same values  
 $\implies$  must differ for at least one value to be different
- **Can represent uncertainty** (e.g., ignorance about the amount of gas in the tank represented by leaving that attribute blank)
- **Lower level of abstraction**  $\implies$  less details ignored
- Many areas of Ai based on factored representations
  - **constraint satisfaction** and **propositional logic**
  - **planning**
  - **Bayesian networks**
  - (most of) **machine learning**

# Representations [cont.]

## Structured Representation

- States represents in terms of **objects** and **relations** over them
  - $\text{Ex } \forall x. (\text{Men}(x) \rightarrow \text{Mortal}(x)),$   
 $\text{Woman}(\text{Maria}), \text{Mother} \equiv \text{Woman} \cap \exists \text{hasChild. Person}$
- **Lowest level of abstraction**  $\implies$  can represent reality in details
- Many areas of Ai based on factored representations
  - relational databases
  - first-order logic
  - first-order probability models
  - knowledge-based learning
  - natural language understanding