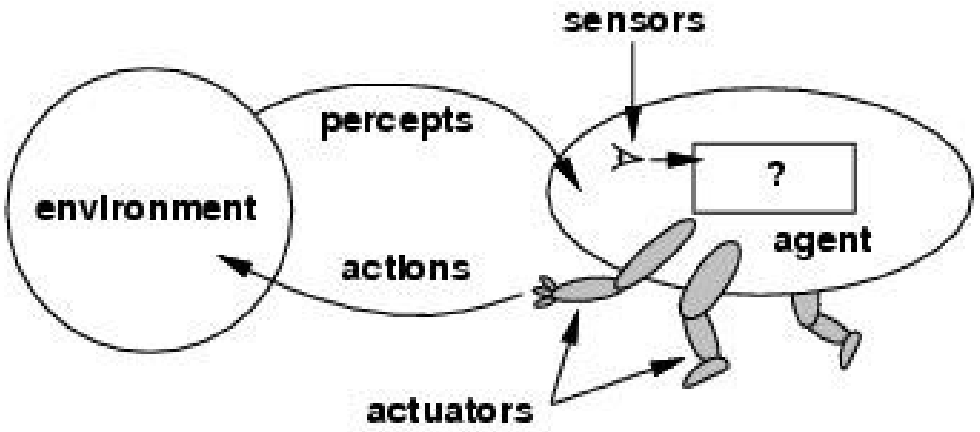
Agents

This course is about designing intelligent agents

- Agents and environments
  - The vacuum-cleaner world
- Rationality
  - The concept of rational behavior.
- Environment types
- Agent types

Agents

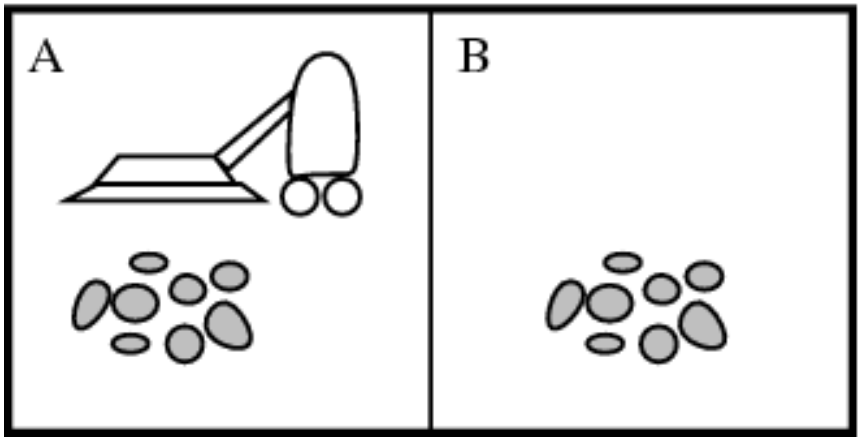
- An **agent** is an entity that perceives and acts in an environment
  - environment can be real or virtual



- An agent can always perceive its actions, but not necessarily their effects on the environment
- **Rational agent**: optimizes some performance criterion
  - For any given task and class of environments we seek the agent (or class of agents) with the best performance.
- Problem:
  - computational limitations make perfect rationality unachievable

The Vacuum-Cleaner world

- A robot-vacuum-cleaner that operates in a simple world



- **Environment:**
  - Virtual house with room A and room B
- **Percepts:**
  - The robot can sense pairs [<*location*>,<*status*>]
    - *Location:* whether it is in room *A* or *B*
    - *Status:* whether the room is *Clean* or *Dirty*
- **Actions:**
  - *Left, Right, Suck, NoOp*

Rational Agent – Performance Measure

- A rational agent is an agent that "does the right thing"
  - intuitively clear, but needs to be measurable in order to be useful for computer implementation
- Performance Measure:
  - a function that evaluates sequence of actions/environment states
  - obviously not fixed but task-dependent
- Vacuum-World performance measures:
  - reward for the amount of dust cleaned
    - one point per square cleaned up in time T
    - can be maximized by dumping dust on the floor again...
  - reward for clean floors
    - one point per clean square per time step
  - possibly with penalty for consumed energy
    - minus one per move?
- General rule:
  - design performance measure based on desired environment state
  - not on desired agent behavior

Rational Agent

> *A* **rational agent** *chooses whichever action maximizes the expected value of the performance measure given the percept sequence to date and prior environment knowledge.*

- Rational ≠ omniscient
  - An omniscient agent knows the actual outcome of its actions.
- Rational ≠ successful
  - Rationality maximizes expected performance
  - This may not be the optimal outcome
  - Example:
    - the expected monetary outcome of playing in the in the lottery/casino, etc. is negative (hence it is rational not to play)
    - but if you're lucky, you may win...

PEAS

What is rational at a given time depends on four things:

- **P**: the performance measure that defines the success
- **E**: the agent's prior knowledge of the environment
- **A**: the actions that the agent can perform
- **S**: the agent's percept sequence to date

- *Example:* Fully automated Taxi

  - Performance
    - Safety, destination, profits, legality, comfort
  - Environment
    - Streets/freeways, other traffic, pedestrians, weather, …
  - Actuators
    - Steering, accelerating, brake, horn, speaker/display,…
  - Sensors
    - Video, sonar, speedometer, engine sensors, keyboard, GPS, …

PEAS

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- **S**: the agent's percept sequence to date

- *Example:* Internet Shopping Agent

  - Performance
    - price, quality, appropriateness, efficiency
  - Environment
    - the Web: current and future WWW sites, vendors, shippers
  - Actuators
    - display to user, follow URL, fill in form
  - Sensors
    - parsing of HTML pages (text, graphics, scripts)…

PEAS

What is rational at a given time depends on four things:

- **P**: the performance measure that defines the success
- **E**: the agent's prior knowledge of the environment
- **A**: the actions that the agent can perform
- **S**: the agent's percept sequence to date

- *Example:* Chess Program
  - Performance
    - number of games won, ELO rating,...
  - Environment
    - the chess board
  - Actuators
    - moves that can be performed
  - Sensors
    - placement of pieces in current position, whose turn is it?, ...

Environment Types

- *Fully observable*
  - the complete state of the environment can be sensed
  - at least the relevant parts
  - no need to keep track of internal states
- *Partially observable*
  - parts of the environment cannot be sensed

Task Environment	Observable
Sudoku Chess With a Clock	
Poker Backgammon	
Taxi driving Medical diagnosis	
Image Analysis Part-Picking Robot	
Refinery Controller Interactive Tutor	

Environment Types

- *Deterministic*
  - the next environment state is completely determined by the current state and the executed action
- *Strategic*
  - only the opponents' actions cannot be foreseen
- *Stochastic*

Task Environment	Observable	Deterministic
Sudoku	*Fully*	
Chess With a Clock	*Fully*	
Poker	*Partially*	
Backgammon	*Fully*	
Taxi driving	*Partially*	
Medical diagnosis	*Partially*	
Image Analysis	*Fully*	
Part-Picking Robot	*Partially*	
Refinery Controller	*Partially*	
Interactive Tutor	*Partially*	

Environment Types

- *Episodic*
  - the agent's experience can be divided into atomic steps
  - the agent perceives and then performs a single action
  - the choice of action depends only on the episode itself
- *Sequential*
  - the current decision could influence all future decision

Task Environment	Observable	Deterministic	Episodic
Sudoku	*Fully*	*Deterministic*	
Chess With a Clock	*Fully*	*Strategic*	
Poker	*Partially*	*Strategic*	
Backgammon	*Fully*	*Stochastic*	
Taxi driving	*Partially*	*Stochastic*	
Medical diagnosis	*Partially*	*Stochastic*	
Image Analysis	*Fully*	*Deterministic*	
Part-Picking Robot	*Partially*	*Stochastic*	
Refinery Controller	*Partially*	*Stochastic*	
Interactive Tutor	*Partially*	*Stochastic*	

Environment Types

- *Dynamic*
  - the environment may change while the agent deliberates
- *Static*
  - the environment does not change
- *Semidynamic*
  - the environment does not change, but the performance score may

Task Environment	Observable	Deterministic	Episodic	Static
Sudoku	*Fully*	*Deterministic*	*Sequential*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	
Poker	*Partially*	*Strategic*	*Sequential*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	

Environment Types

- *Discrete*
  - finite number of actions / environment states / percepts
- *Continuous*
  - actions, states, percepts are on a continuous scale
- this disctinction applies separately to actions, states, and percepts
  - can be mixed in individual tasks

Task Environment	Observable	Deterministic	Episodic	Static	Discrete
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*	
Poker	*Partially*	*Strategic*	*Sequential*	*Static*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	

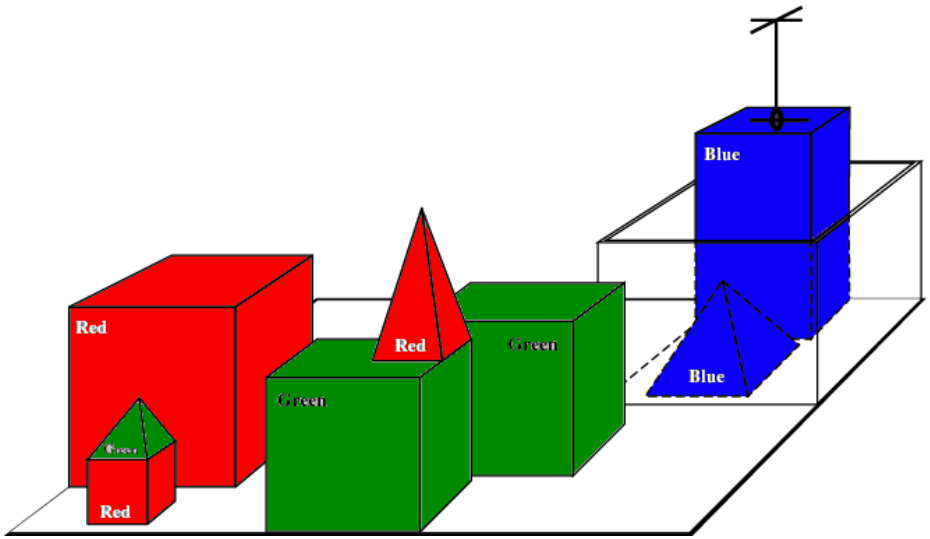
Environment Types

- *Single-Agent*
  - No other agents (other agents may be part of the environment)
- *Multi-Agent*
  - Does the environment contain other agents whose performance measure depends on my *actions?*
  - other agents may be *co-operative* or *competitive*

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*	*Discrete*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*	*Discrete*	
Poker	*Partially*	*Strategic*	*Sequential*	*Static*	*Discrete*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	*Discrete*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	*Continuous*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	*Continuous*	
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Discrete*	

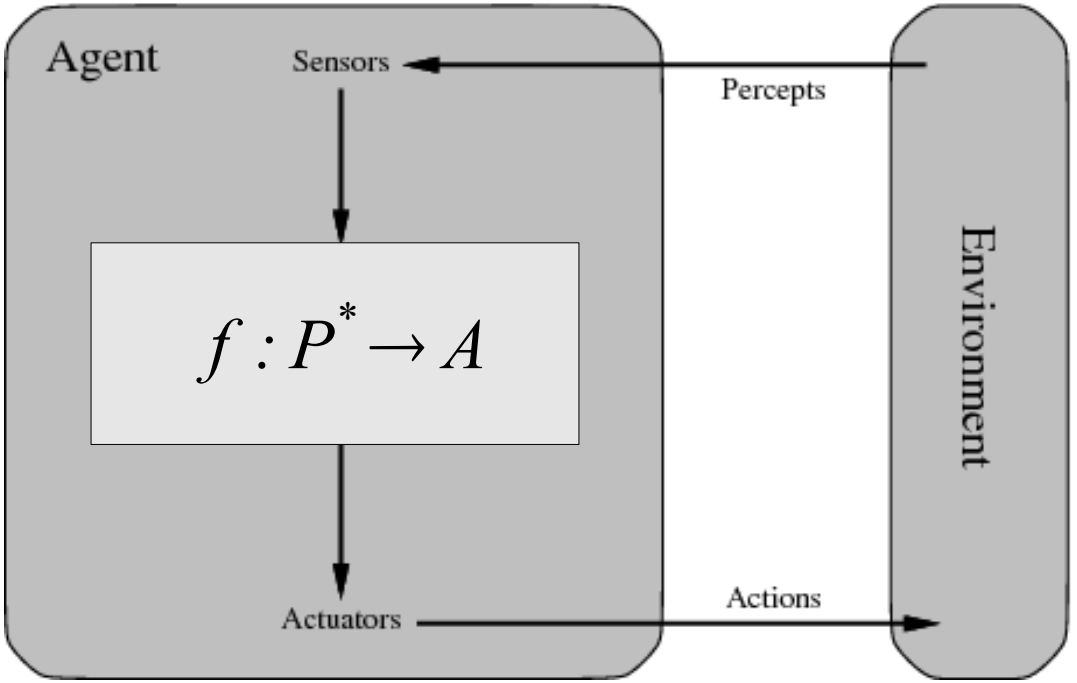
Environment Types

- The simplest environment is
  - fully observable
  - deterministic
  - episodic
  - static
  - discrete
  - single-agent
- Most real situations are
  - partially observable
  - stochastic
  - sequential
  - dynamic
  - continuous
  - multi-agent



Agent Function

- The agent function maps percept histories to actions



- The agent function will internally be represented by the agent program.
- The agent program runs on the physical architecture to produce f.

A Simple Vacuum Cleaner Agent

- Strategy

> "If current room is dirty then suck, otherwise move to the other room."

- As a tabulated function:

Percept sequence	Action
$[A, Clean]$	$Right$
$[A, Dirty]$	$Suck$
$[B, Clean]$	$Left$
$[B, Dirty]$	$Suck$
$[A, Clean], [A, Clean]$	$Right$
$[A, Clean], [A, Dirty]$	$Suck$
⋮	⋮

A Simple General Agent

function TABLE-DRIVEN-AGENT(*percept*) **returns** an action
  static: *percepts*, a sequence initially empty
    table, a table of actions, indexed by percept sequence

  append *percept* to the end of *percepts*
  action ← LOOKUP(*percepts*, *table*)
  return *action*

- has a table of all possible percept histories
- looks up the right response in the table
- Clearly infeasible:
  - if there are $|P|$ percepts and a life-time of T time steps, we need a look-up table of size $\sum_{t=1}^{T} |P^t|$
- For example: chess:
  - about 36 moves per position, average game-length 40 moves
    $\longrightarrow$ 510542600702905870089807077969822280652245065718862123259096 5

A Simple Vacuum Cleaner Agent

- Strategy

> "If current room is dirty then suck, otherwise move to the other room."

- As an 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
```

- Obvious Questions:
  - Is this the right agent?
  - Is this a good agent?
  - Is there a right agent?

Agent Programs

The key challenge for AI is to write programs that produce rational behavior from a small amount of code rather than a large number of table entries

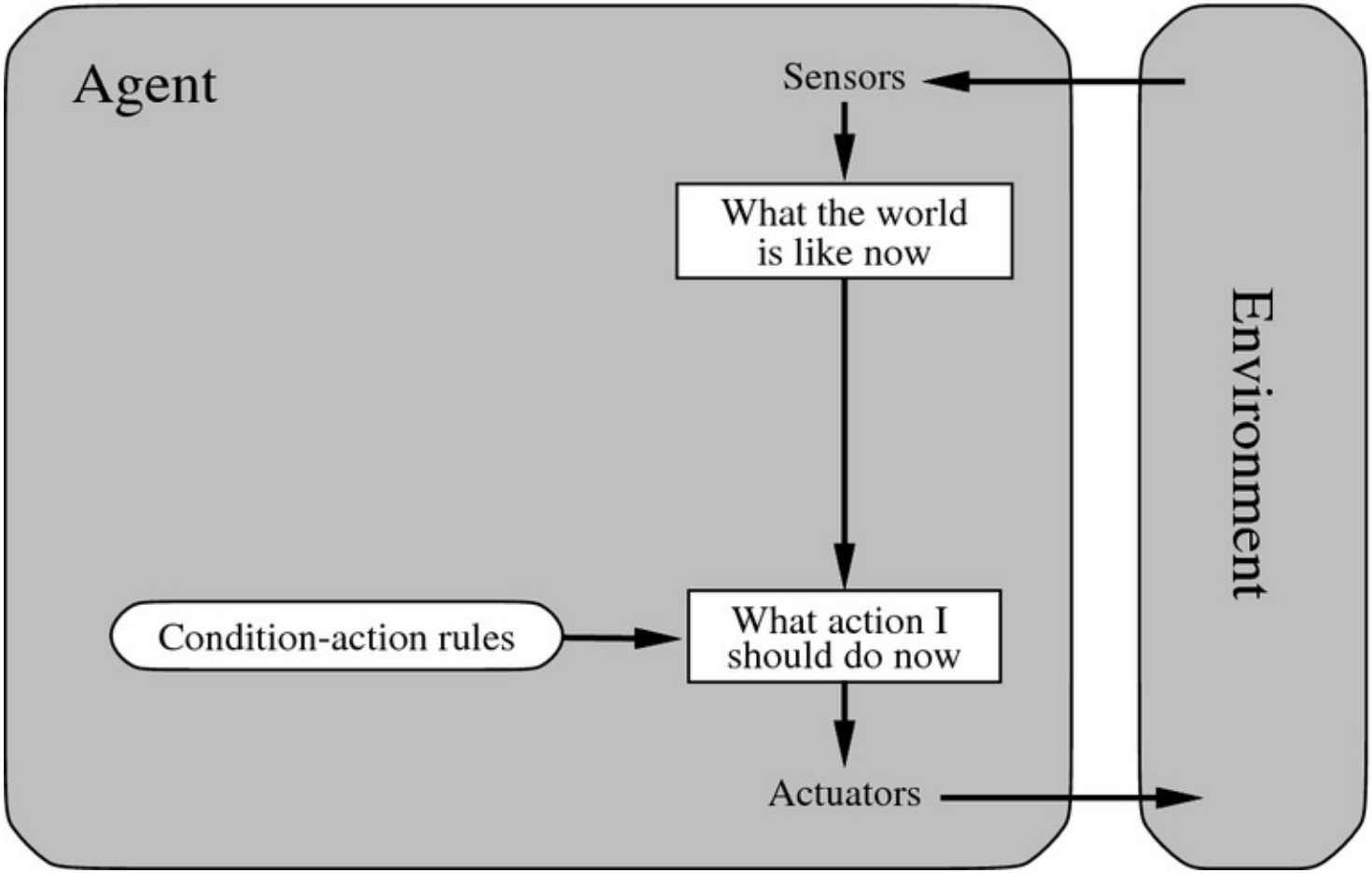
- Writing down the agent functions is not practical for real applications
- But feasibility is also important
  - you can write a perfect chess playing agent with a few lines of code
  - it will run forever, though...
- Agent = architecture + program

Agent Types

- Four basic kinds of agent programs will be discussed:
  - Simple reflex agents
  - Model-based reflex agents
  - Goal-based agents
  - Utility-based agents
- All these can be turned into learning agents.

Simple Reflex Agent

- Select action on the basis of only the current percept
  - ignores the percept history



Simple Reflex Agent

- Select action on the basis of only the current percept
  - ignores the percept history
- Implemented through condition-action rules
- Large reduction in possible percept/action situations
  - from $\sum_{t=1}^{T} |P^t|$ to $|P|$
- But will make a very bad chess player
  - does not look at the board, only at the opponent's last move
    (assuming that the sensory input is only the last move, no visual)

Example:

```
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
```

General Simple Reflex Agent

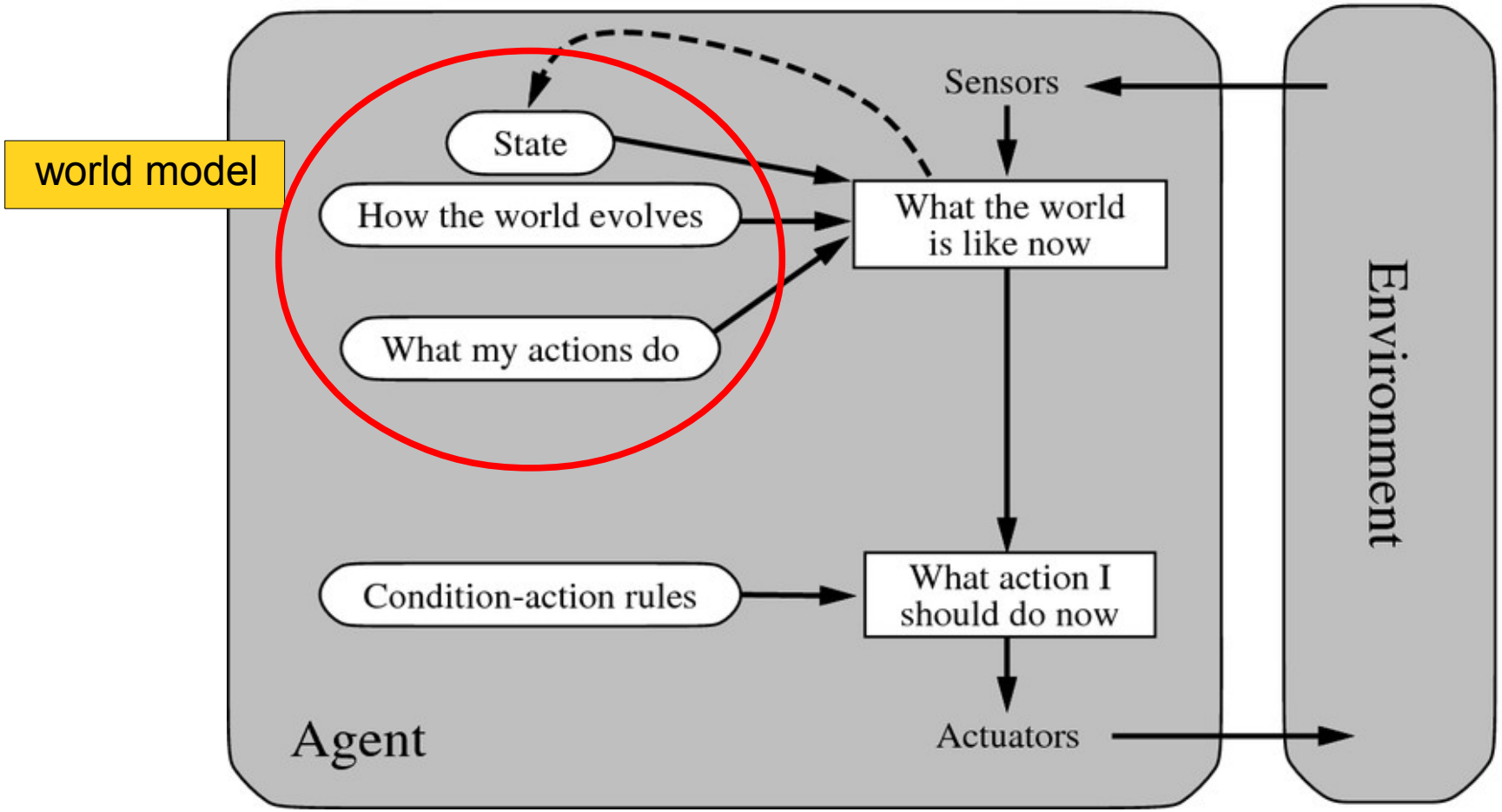
function SIMPLE-REFLEX-AGENT(*percept*) **returns** an action
  static: *rules*, a set of condition-action rules

  state ← INTERPRET-INPUT(*percept*)
  rule ← RULE-MATCH(*state*, *rule*)
  action ← RULE-ACTION[*rule*]
  return *action*

- Note that rules are just used as a concept
  - actual implementation could, e.g., be logical circuitry
- Will only work if the environment is *fully observable*
  - everything important needs to be determinable from the current sensory input
  - otherwise infinite loops may occur
    - e.g. in the vacuum world without a sensor for the room, the agent does not know whether to move right or left
    - possible solution: randomization

Model-Based Reflex Agent

- Keep track of the state of the world
  - better way to fight partial observability



General Model-Based Reflex Agent

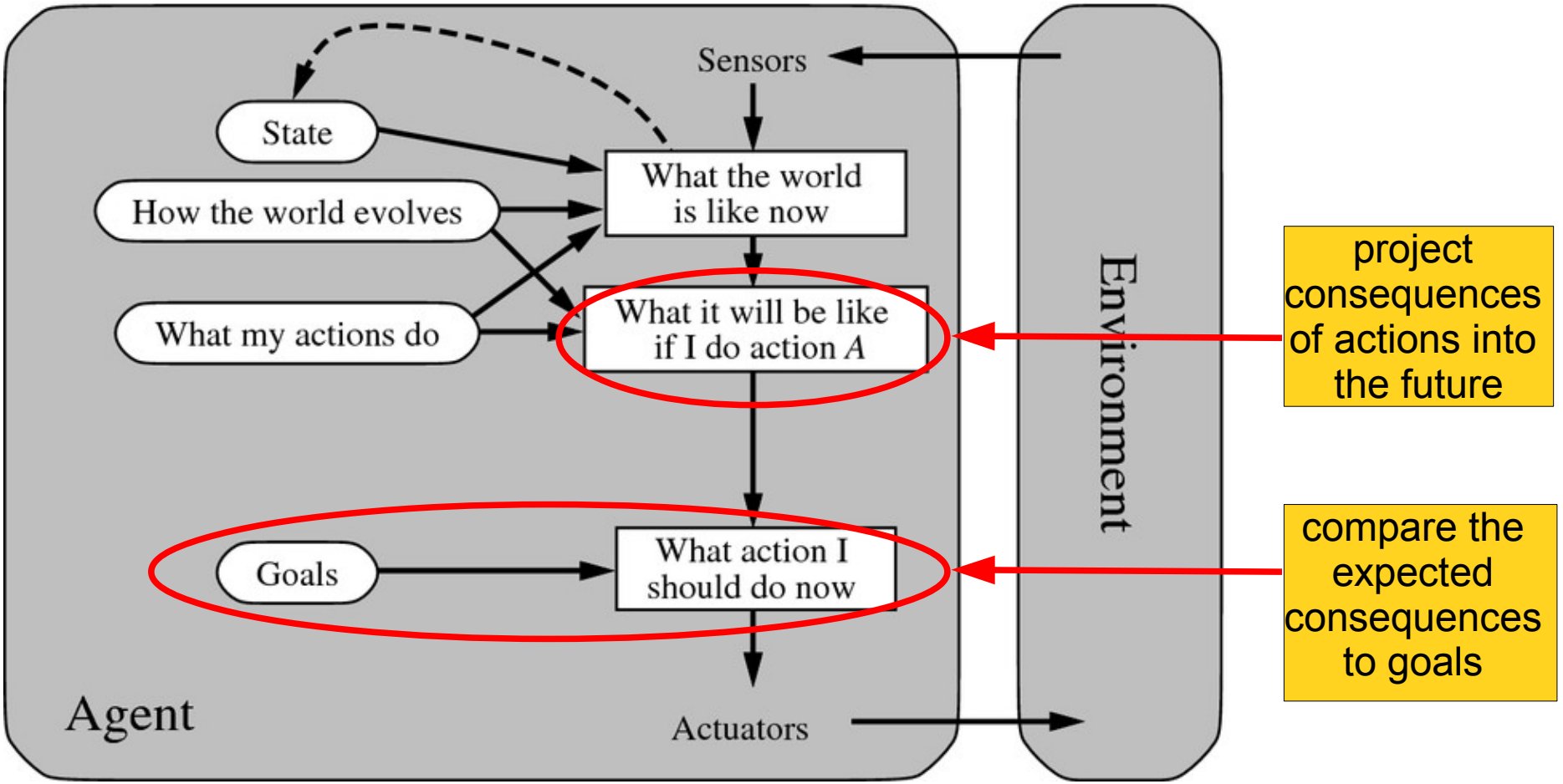
function REFLEX-AGENT-WITH-STATE(*percept*) **returns** an action
  static: *state*, a description of the current world state
    rules, a set of condition-action rules
    action, the most recent action, initially none

  state ← UPDATE-STATE(*state*, *action*, *percept*)
  rule ← RULE-MATCH(*state*, *rule*)
  action ← RULE-ACTION[*rule*]
  return *action*

- Input is not only interpreted, but mapped into an internal state description (a world model)
  - a chess agent could keep track of the current board situation when its percepts are only the moves
- Internal state is also used for interpreting subsequent percepts
- The world model may include effects of own actions!

Goal-Based Agent

- the agent knows what states are desirable
  - it will try to choose an action that leads to a desirable state

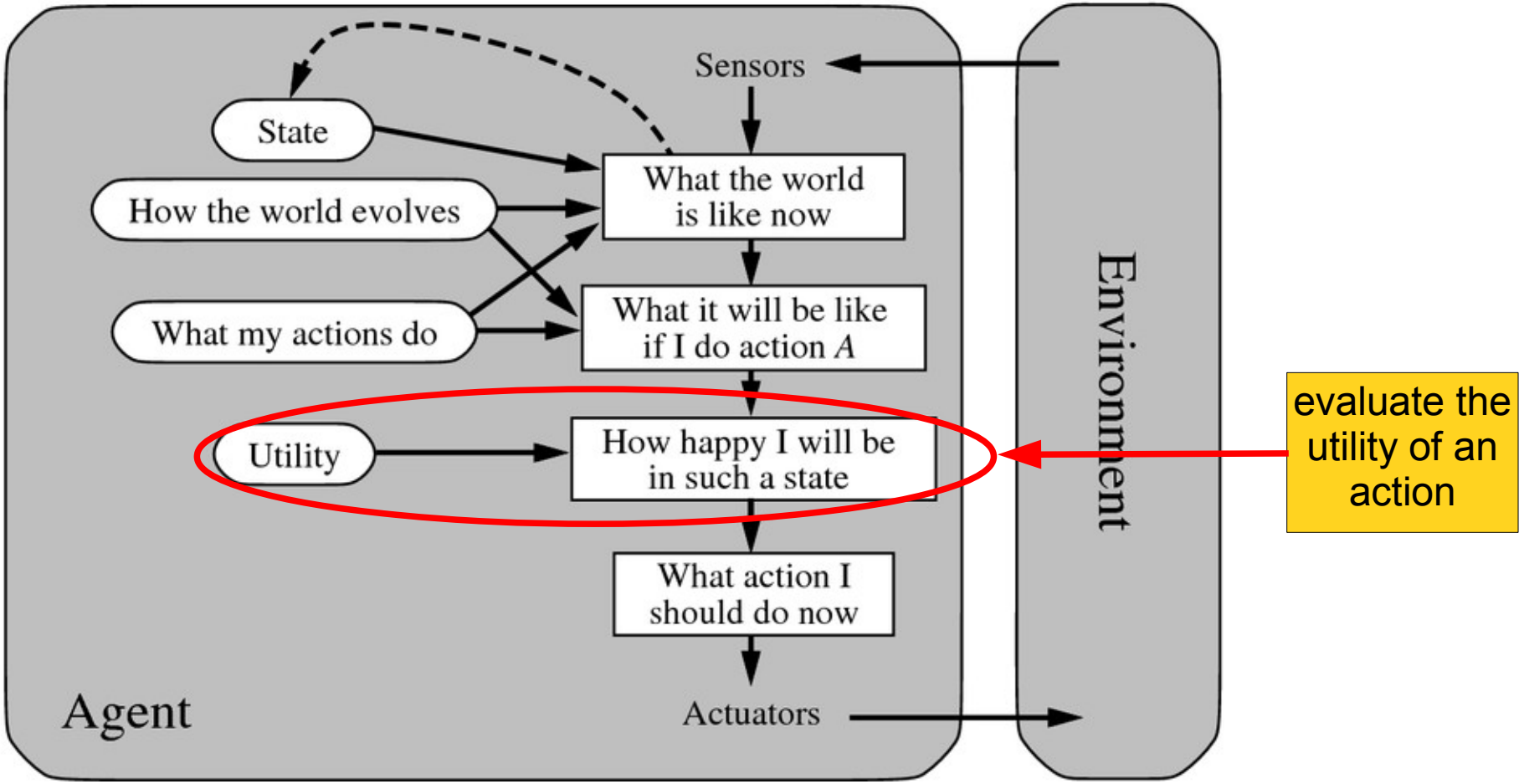


Goal-Based Agent

- the agent knows what states are desirable
  - it will try to choose an action that leads to a desirable state
- things become difficult when long sequences of actions are required to find the goal
  - typically investigated in search and planning research
- main difference to previous approaches
  - decision-making takes future into account
    - “What will happen if I do such-and-such?”
    - “Will this make me happy?”
- is more flexible since knowledge is represented explicitly and can be manipulated
  - changing the goal does not imply changing the entire set of condition-action rules

Utility-Based Agent

- Goals provide just a binary happy/unhappy disctinction
  - utility functions provide a continuous scale



Utility-Based Agent

- Goals provide just a binary happy/unhappy disctinction
  - utility functions provide a continuous scale
- Certain goals can be reached in different ways.
  - “Alle Wege führen nach Rom”
  - Some ways are quicker, safer, more reliable, cheaper, ...

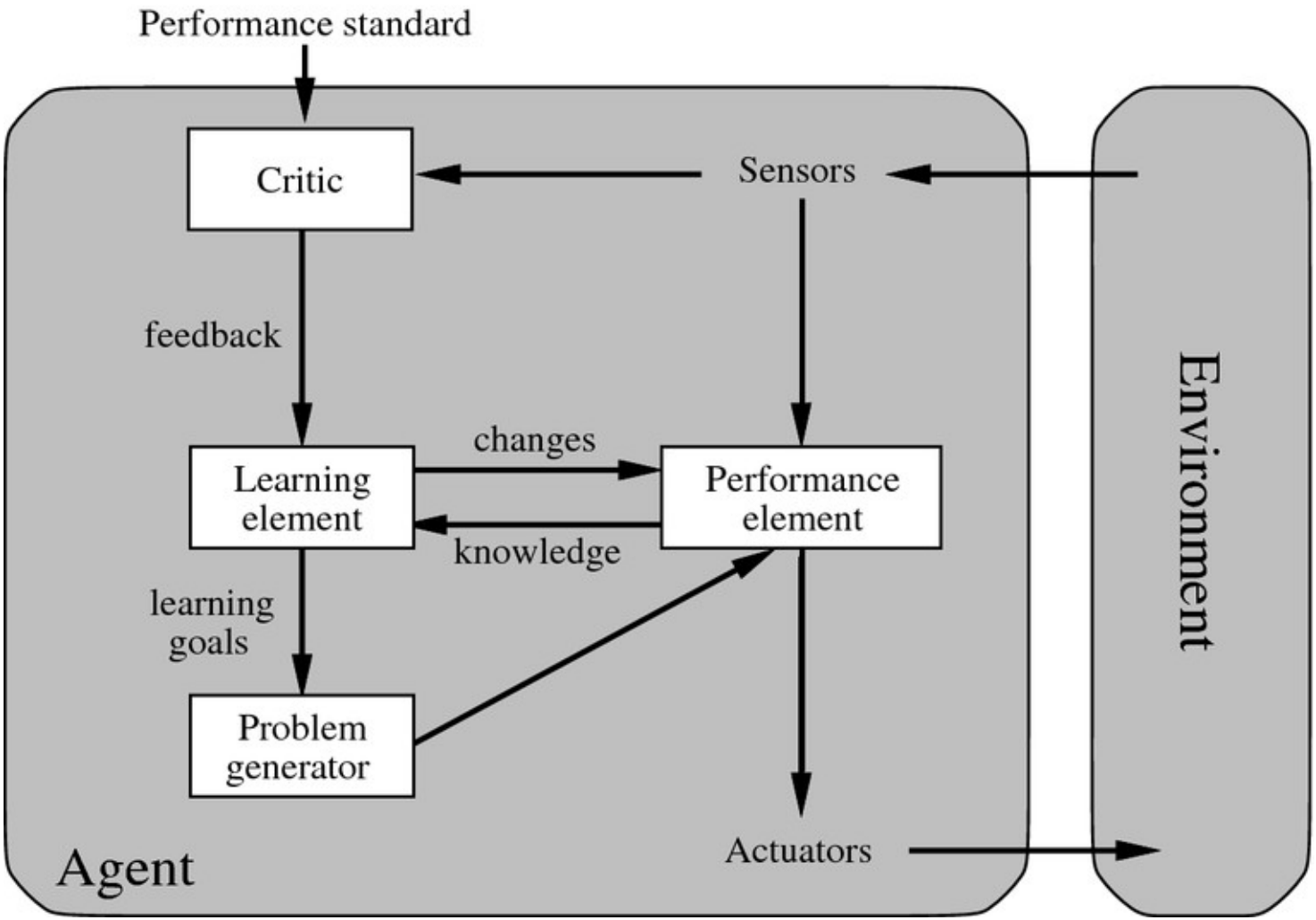
  → have a higher utility
- Utility function
  - maps a state (or a sequence of states) onto a real number
- Improves on goals:
  - selection between conflicting goals (e.g., speed and safety)
  - selection between goals based on trade-off between likelihood of success and importance of goal

Learning

- All previous agent-programs describe methods for selecting actions
  - yet they do not explain the origin of these programs.
- Learning mechanisms can be used for acquiring programs
  - teach them instead of instructing them
- Advantage
  - robustness of the program toward initially unknown environments.
- Every part of the previous agents can be improved with learning

> *Learning in intelligent agents can be summarized as a process of modification of each component of the agent to bring the components into closer agreement with the available feedback information, thereby improving the overall performance of the agent.*

Learning Agent



Learning Agent

- Performance element
  - makes the action selection (as usual)
- Critic
  - decides how well the learner is doing with respect to a fixed *performance standard*
  - necessary because the percepts do not provide any indication of the agent's success
    - e.g., it needs to know that checkmate is bad
- Learning element
  - improves the performance element
  - its design depends very much on the performance element
- Problem generator
  - responsible for *exploration* of new knowledge
    - sometimes try new, possibly suboptimal actions to acquire knowledge about their consequences
  - otherwise only *exploitation* of (insufficient) current knowledge