Agents and Environments

Lecture 2

How do we characterize environments?

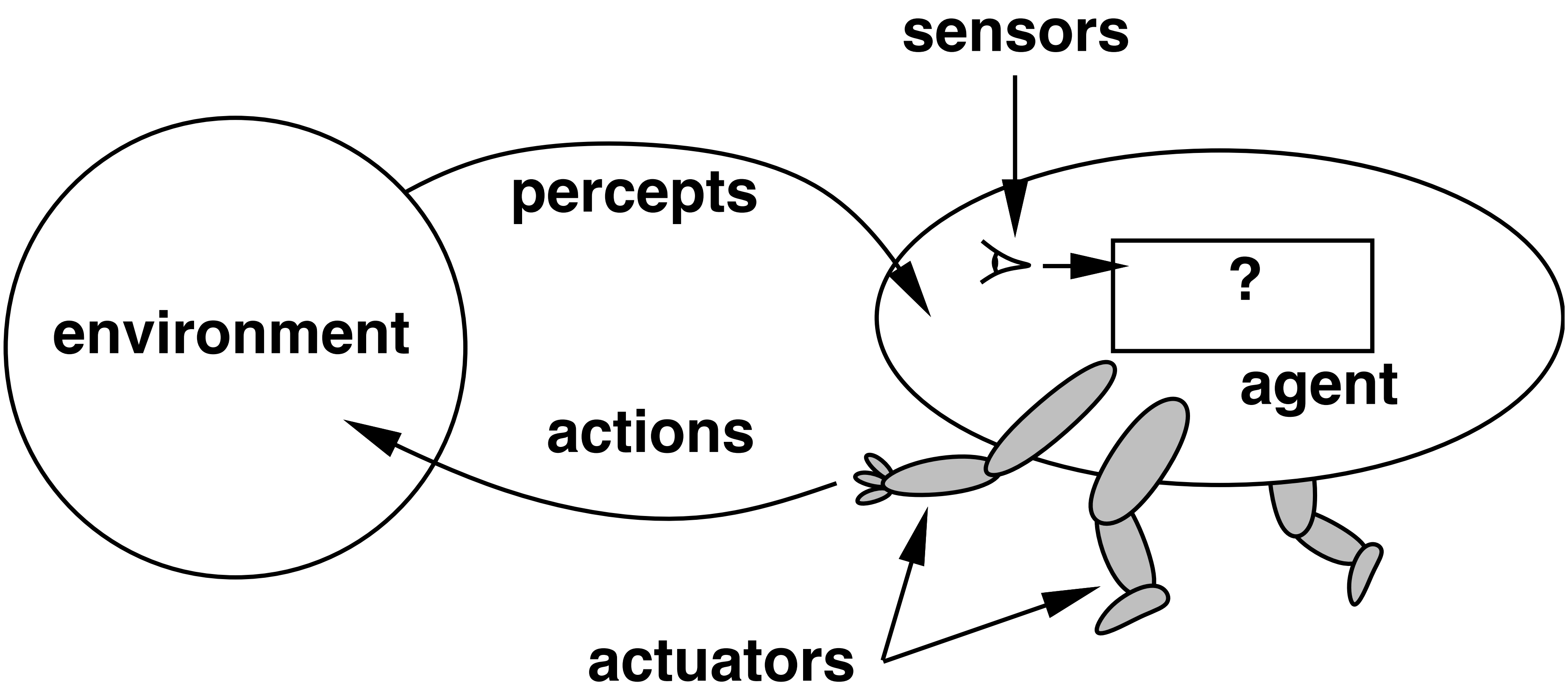
What is an agent?

What characterizes rational behavior?

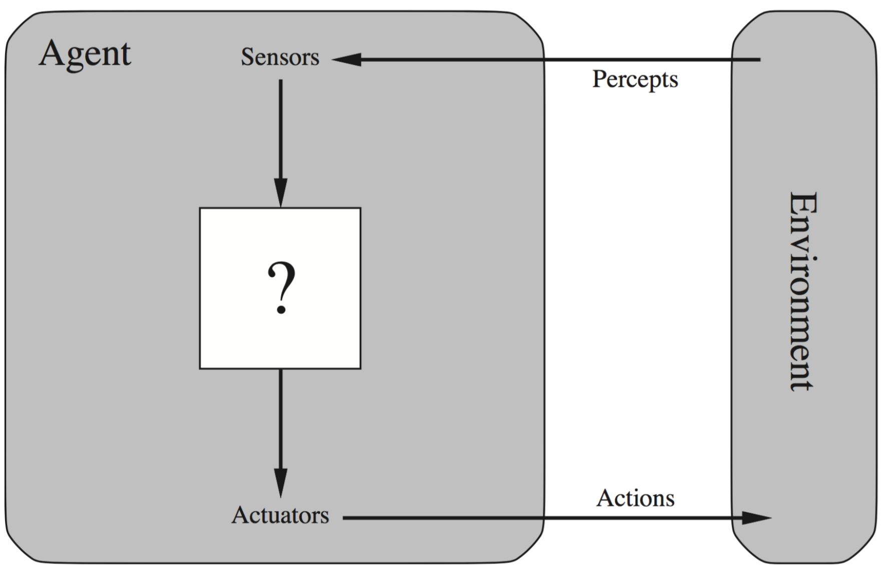
Agenda

- Interaction model
- Rationality
- Task environments
- Types of agents

Agent-Environment Interaction



Agent-Environment Interaction



- An **agent** is anything that perceives its environment through **sensors** and acts via **actuators**
  - In AI: non-trivial decision-making + significant computation
- **Percept** refers to sensor values at an instant; **percept sequence** is a complete history

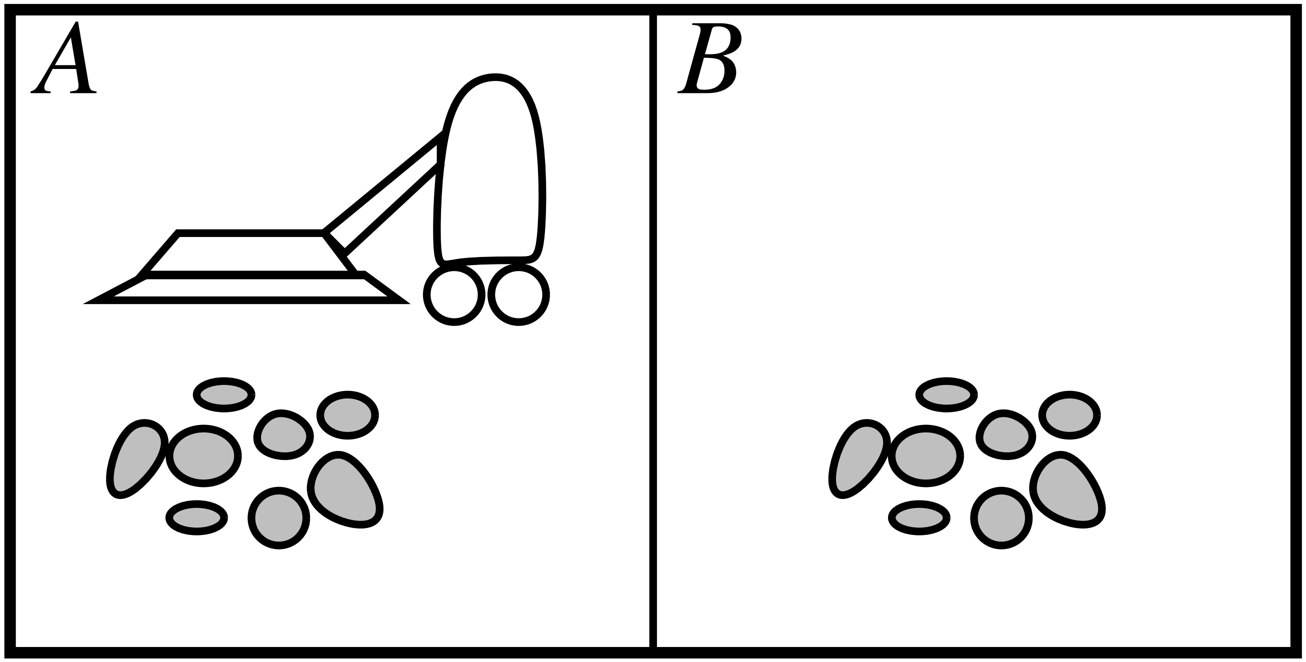
Agent Behavior

- Mathematically/externally, we consider the **agent function** as a mapping between an arbitrary percept sequence and an action

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

- As AI practitioners, we implement the function via an **agent program**

Example: `vacuum-cleaner` World



Percepts: [location, status] (e.g. [`A`, `Dirty`])

Actions: `Left`, `Right`, `Suck`, `NoOp`

Example `vacuum-cleaner` Agent

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

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** $Left$

What is the **right** function?

Evaluating Behavior

To evaluate agent behavior, we consider a **performance measure**

$$f : S_E^* \rightarrow V$$

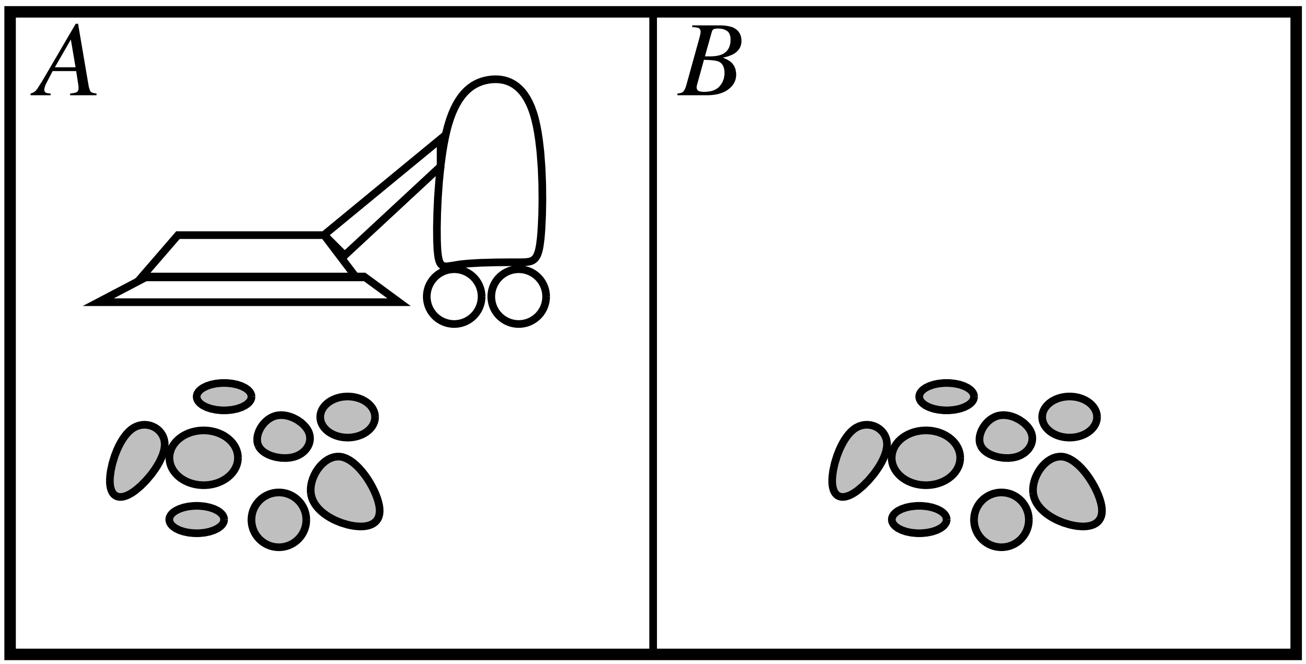
Notes:

- Evaluates environment states, not agent percepts (more on observability later) or states (i.e. no fooling ourselves)
- One of many, not always easy to specify
  - Should be based upon desired outcomes, not expected agent design/operation

Example Performance Measures

- One point per square cleaned
  - Penalize per move
  - Penalize for > *k* dirty squares

  …



Defining Rationality

For each *possible* percept sequence, a rational agent should…

select an action that is expected to maximize its performance measure, given…

1. the percept sequence, and
2. *a priori* (i.e. prior) knowledge.

Exercise

Provide a reasoned argument as to whether an agent executing the program below is rational given the following assumptions:

- One point for each clean square at each time step over 1000 time steps
- Geography is known, but initial environmental state is not; clean stays clean, cleaning always works
- Perception is always accurate

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*

Exercise

Provide a reasoned argument as to whether an agent executing the program below is rational given the following assumptions:

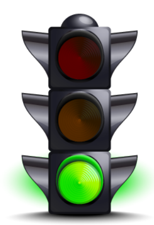
- One point for each clean square at each time step over 1000 time steps; **minus one point per move**
- Geography is known, but initial environmental state is not; clean stays clean, cleaning always works
- Perception is always accurate

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*

Rationality ≠ Omniscience

Knowing the actual outcome of one's actions.



Rationality ≠ Perfection

Rationality implies information gathering, exploration, and learning

- Agents that rely upon prior knowledge vs. percepts lacks **autonomy**

DungBeetle

PEAS Model

- Before designing an agent, we should fully specify the task environment (i.e. problem) it is to solve

- **P**erformance Measure
- **E**nvironment
- **A**ctuators
- **S**ensors

PEAS: Example

- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

- Safe, fast, legal, comfortable, profit!
- Roads, traffic, pedestrians, customers
- Steering, acceleration, brake, signal, horn, payment
- Camera, sonar, speedometer, GPS, odometer, accelerometer, engine

Properties of Task Environments (1)

- Observability
  - Partially vs. Fully
- Agents
  - Single vs. Multi (competitive/cooperative)
- Certainty
  - Stochastic vs. Deterministic

Properties of Task Environments (2)

- Temporal independence
  - Episodic vs. Sequential
- Environmental change [during deliberation]
  - Static vs. Dynamic
- Representation [of states, time, percepts/actions]
  - Discrete vs. Continuous
- A priori environmental model
  - Known vs. unknown

Environment: Example (1)

- Fully observable
- Single agent
- Deterministic
- Sequential
- Static
- Discrete
- Known

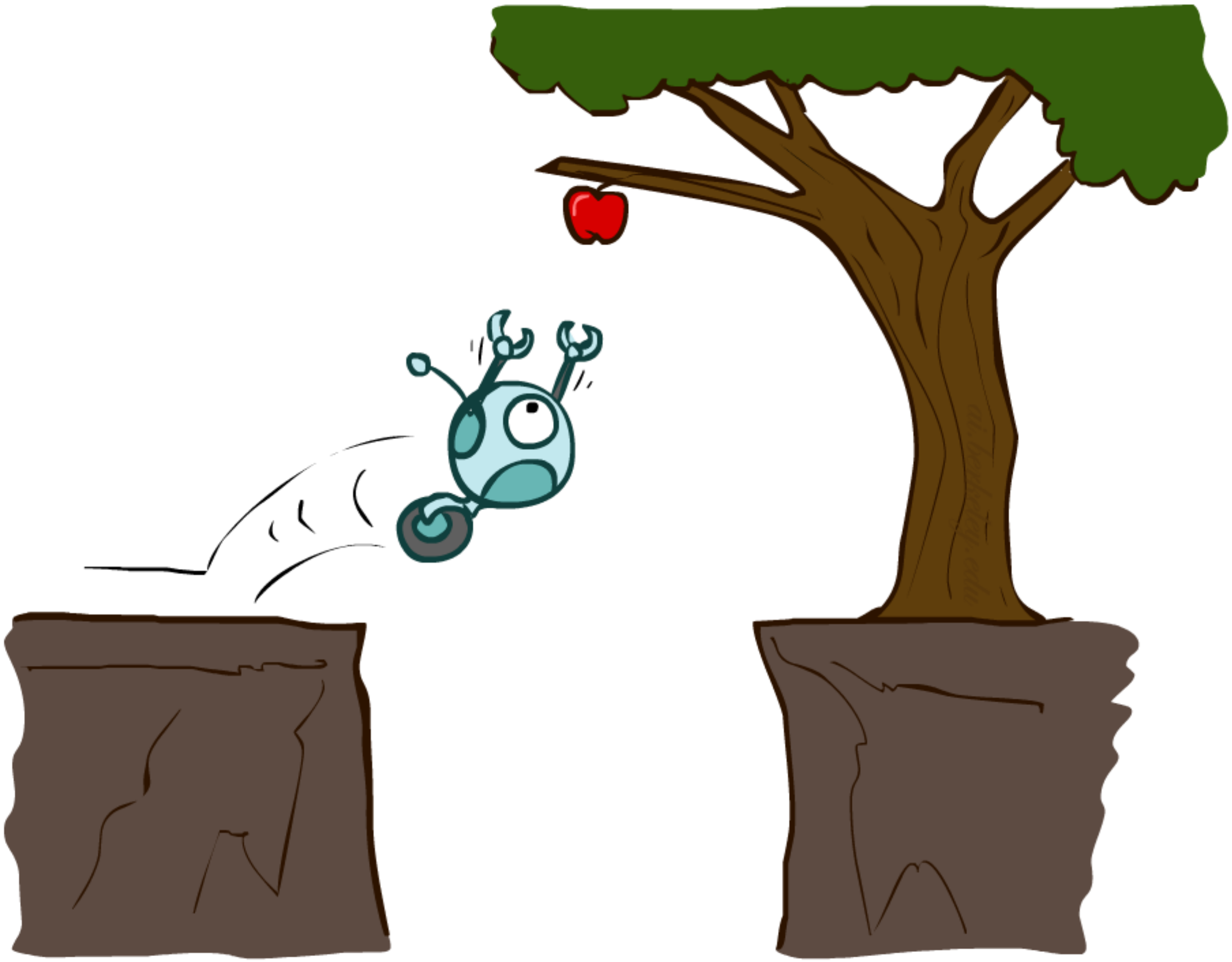
Environment: Example (2)

- Partially observable
- Multi-agent, semi-cooperative
- Stochastic
- Sequential
- Dynamic
- Continuous
- Known

Agent Structure

- agent = architecture + program
- The key challenge for AI is to write [smallish] programs that produce rational behavior given complex environments
- We now examine 4 representative agent architectures

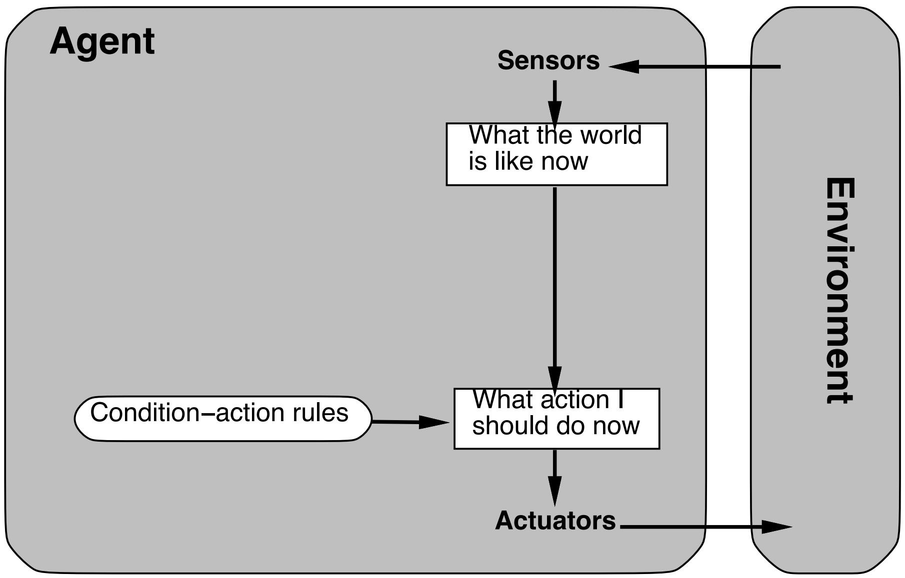
Reflexive Action



Simple Reflex Agents

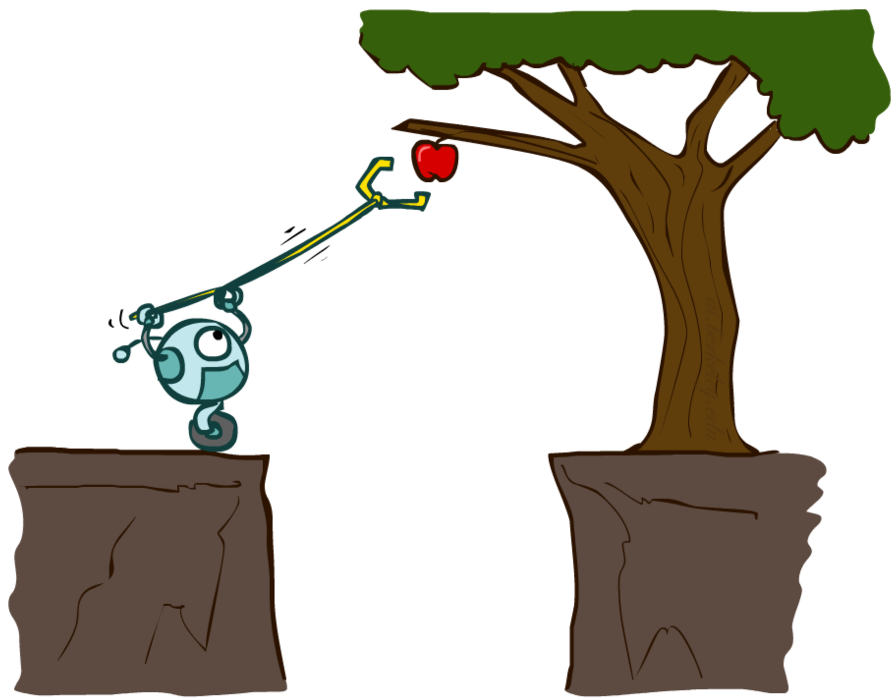
- Select actions based upon the current percept, ignoring history

- Sees the world as it is, does not consider future consequences



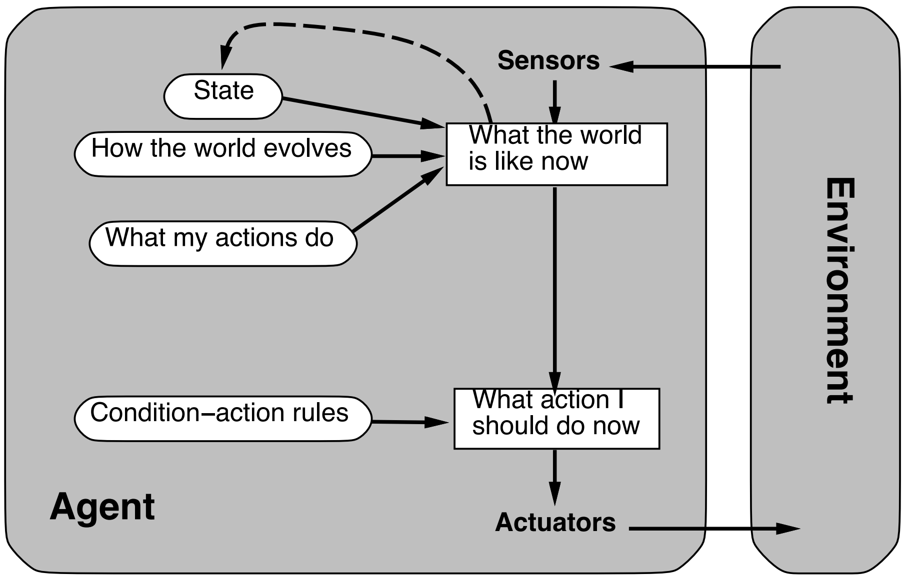
Adding Planning

- To handle partial observability, the agent needs to maintain **internal state**
  - Information it can't presently sense
- Updating requires **models** of the world
  - How the world evolves
  - Results of actions



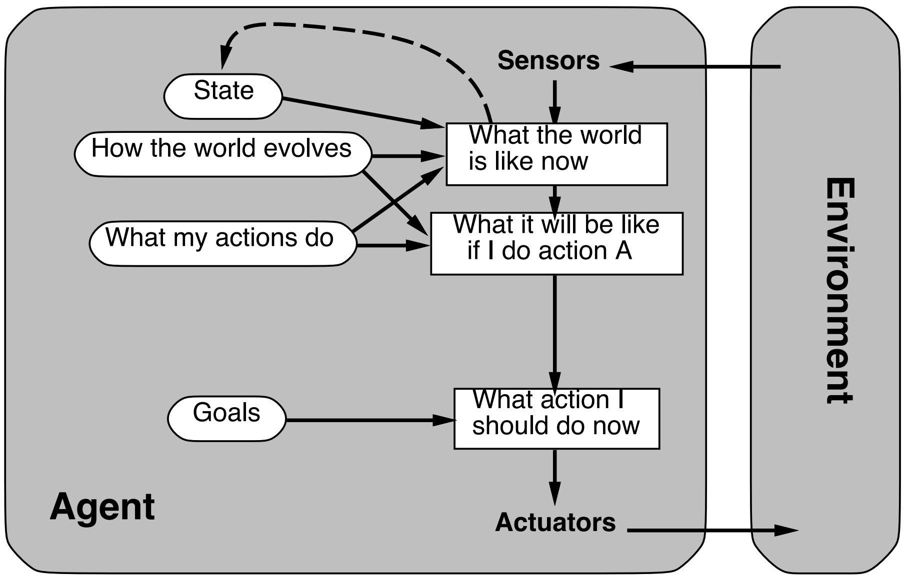
Model-based Reflex Agents

- Agent uses model + state to expand inputs to rules



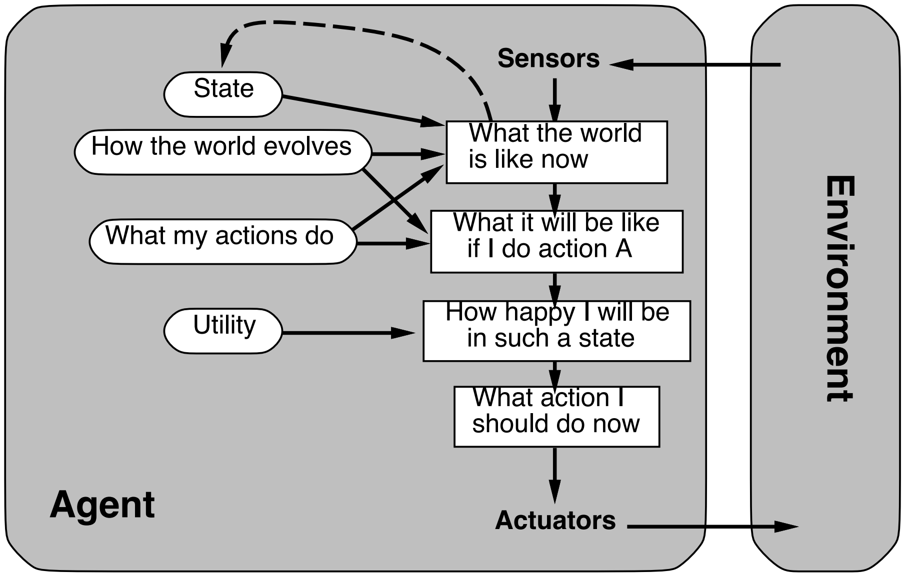
Goal-based Agents

- Incorporates both what the world is like, and goals are to be achieved
- More flexibility than rules: as long as new information relates to goals, can adapt



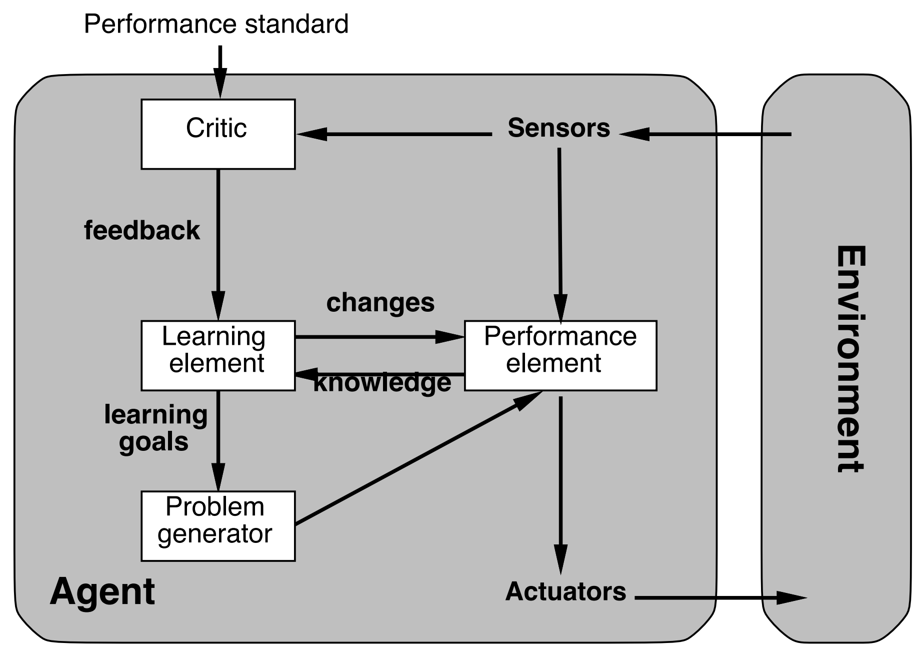
Utility-based Agents

- Utility: internalized performance measure
- Expands binary nature of goals
- A rational agent **<u>must</u>** behave *as if* it possesses a utility function whose expected value it tries to maximize



Learning Agents

- Performance element converts percepts into actions
- Learning element improves over time
- Critic converts percepts into good/bad (**reward/penalty**)
- Problem generator suggests actions to lead to "informative" experiences



Summary (1)

- **Agents** interact with **environments** through **sensors** and **actuators**
- The **agent function** describes what the agent *does* in all circumstances; the **agent program** is an actual *implementation*
- The **performance measure** evaluates the environment sequence; a **rational agent** maximizes *expected performance*

Summary (2)

- **PEAS** descriptions define task environments
  - Environments are described along numerous dimensions (observability, agents, certainty, temporal independence, environmental change, representation)

- Agent = architecture + program
  - Architectures: **reflexive** (with model]), **goal-based**, **utility-based**, **learning**