Discussion

CS 5/7320 Artificial Intelligence

Intelligent Agents
AIMA Chapter 2

Slides by Michael Hahsler
with figures from the AIMA textbook.

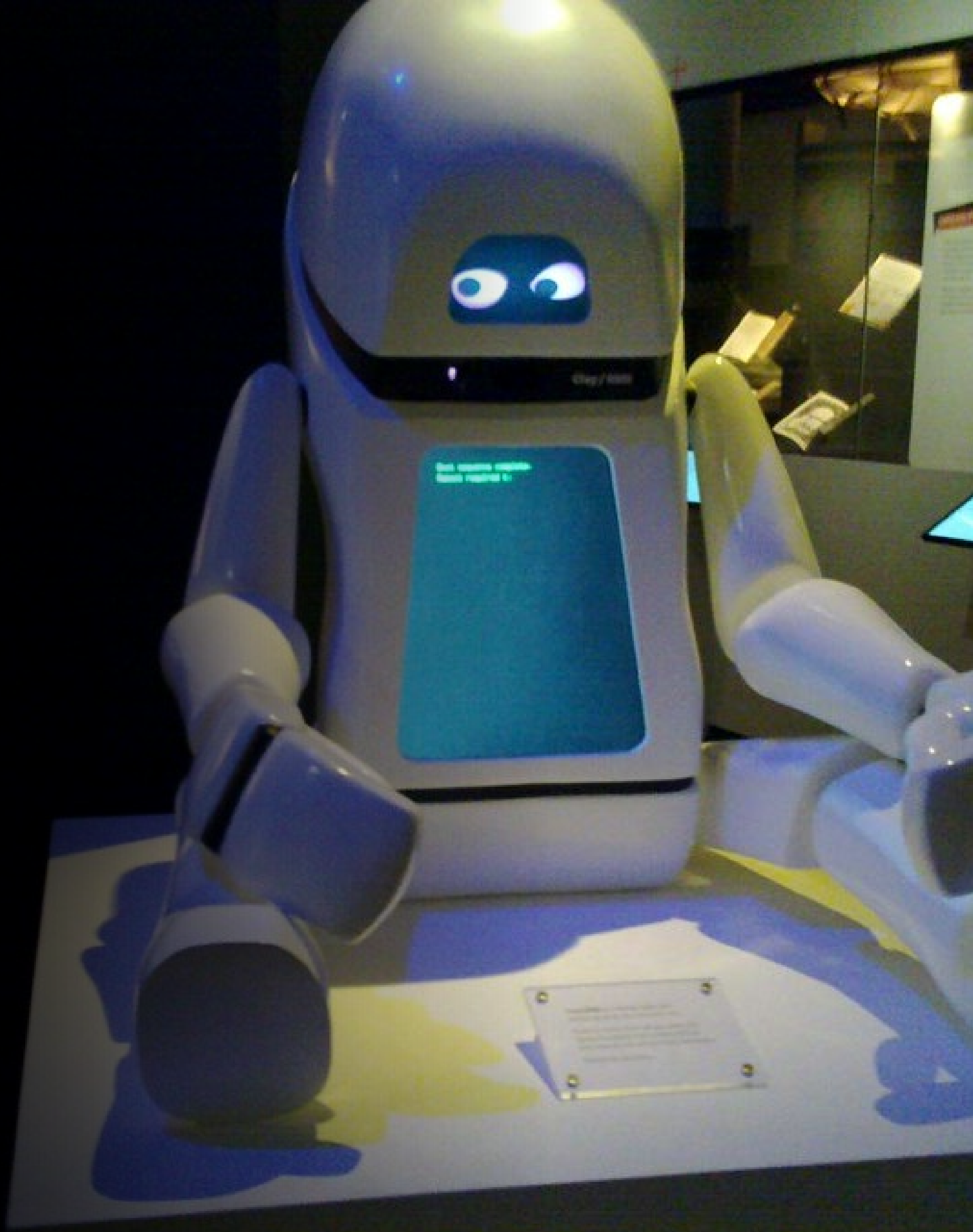
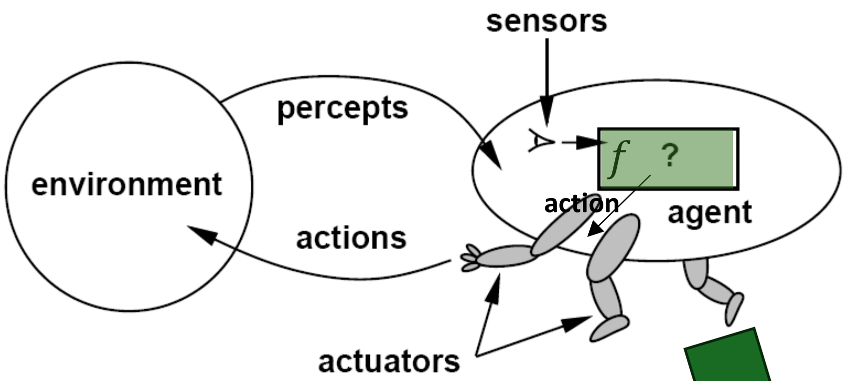


Image: "Robot at the British Library Science Fiction Exhibition" by BadgerGravling

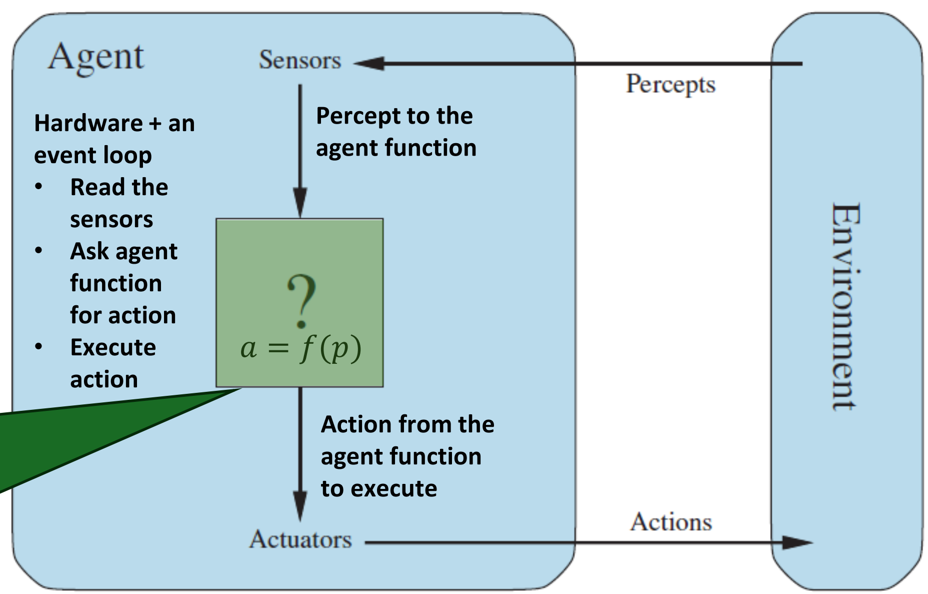
Module Review

Designing a Rational Agent



Remember the definition of a rational agent:

> *"For each possible percept sequence, a rational agent should select an* ***action*** *that* ***maximizes its expected performance measure****, given the evidence provided by the* ***percept sequence*** *and the* ***agent's built-in knowledge****."*



Agent Function

- Represents the "brain"
- Assess performance measure
- Remember percept sequence
- Built-in knowledge

Important: Everything outside the agent function represents the environment. This includes the physical robot, its sensors and its actuators, and event loop!

Rational Agents

Rule: Pick the action that maximize the expected utility

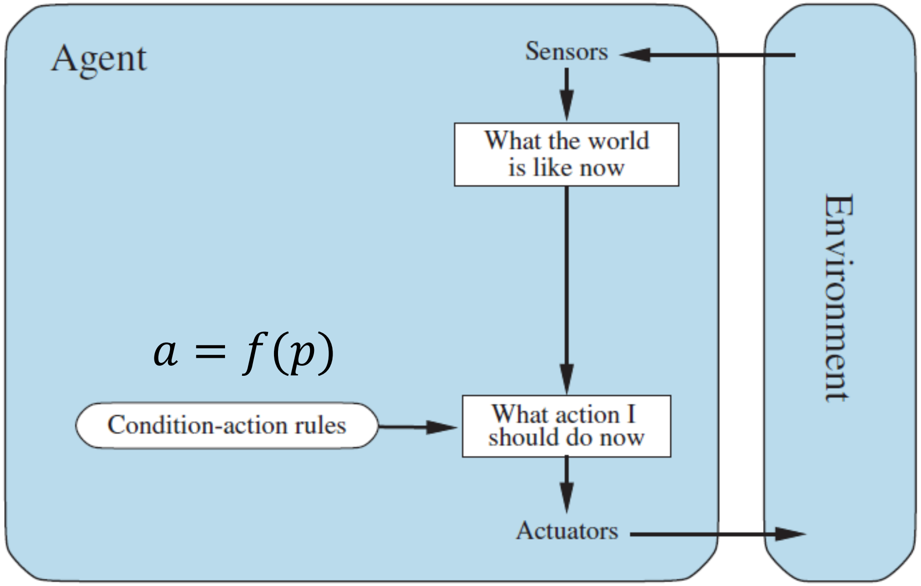
$$a = \text{argmax}_{a \in \mathrm{A}}\, E(U \mid a)$$

This means:

- **Rationality is an ideal** – it implies that no one can build a better agent
- **Rationality ≠ Omniscience** – rational agents can make mistakes if percepts and knowledge do not suffice to make a good decision
- **Rationality ≠ Perfection** – rational agents maximize **expected** outcomes not actual outcomes
- **It is rational to explore and learn** – I.e., **use percepts** to supplement prior knowledge and become autonomous
- **Rationality is often bounded** by available memory, computational power, available sensors, etc.

Simple Reflex Agent

- Uses only built-in knowledge in the form of **rules** that select action only **based on the current percept.** This is typically very fast!
- The **agent does not know about the performance measure**! But well-designed rules can lead to good performance.
- The agent needs no memory and ignores all past percepts.

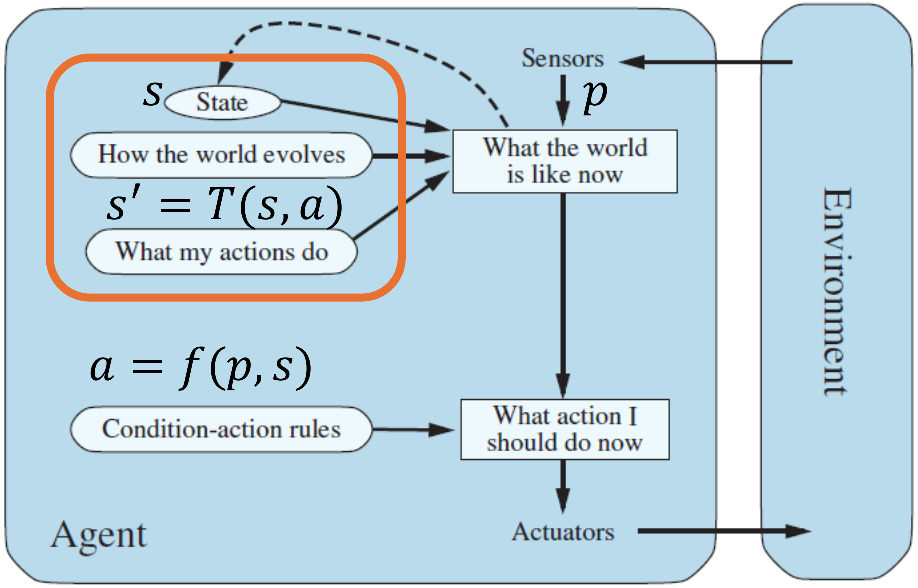


The interaction is a sequence: $p_0, a_0, p_1, a_1, p_2, a_2, \ldots p_t, a_t, \ldots$

Example: A simple vacuum cleaner that uses rules based on its current sensor input.

Model-based Reflex Agent

- Maintains a **state variable** to keeps track of aspects of the environment that cannot be currently observed. I.e., it has memory.
- It knows how the environment evolves over time given its last action. It updates the state using a **transition function** and the new percept.
- There is now more information for the **rules** to make better decisions.

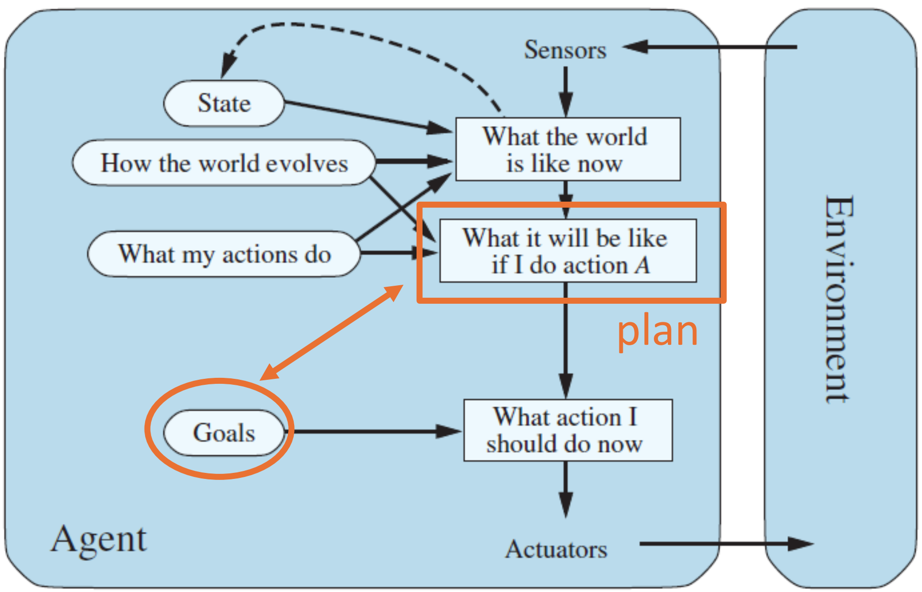


The interaction is a sequence: $p_0, s_0, a_0, p_1, s_1, a_1, p_2, s_2, a_2, p_3, \dots, p_t, s_t, a_t, \dots$

Example: A vacuum cleaner that remembers were it has already cleaned.

Goal-based Agent

- The agent has the task of reaching a defined **goal state** and is then finished.
- The agent needs to move towards the goal. As special type is a **planning agent** that uses **search algorithms** to plan a sequence of actions that leads to the goal.
- Performance measure: the **cost to reach the goal**.



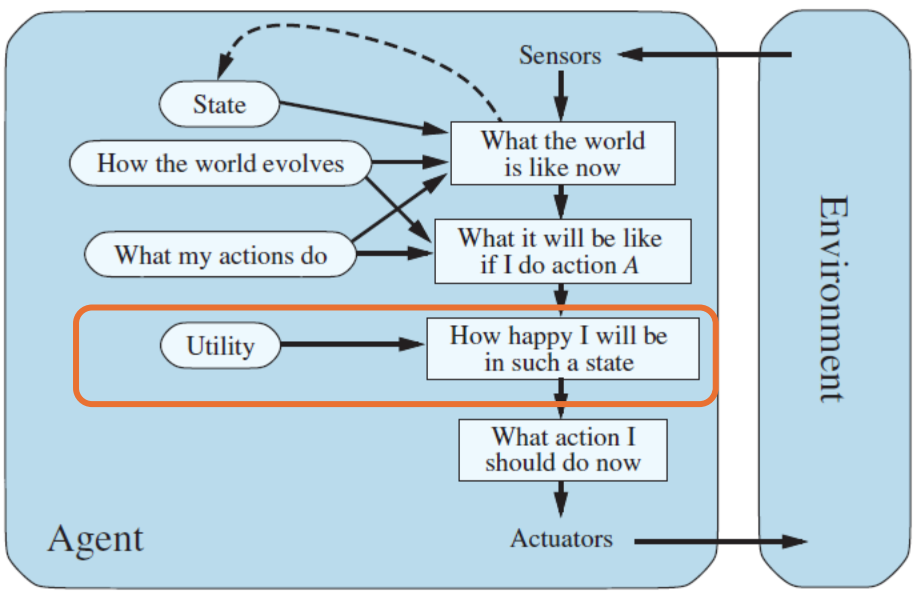
$$a = \operatorname{argmin}_{a_0 \in A} \underbrace{\left[\sum_{t=0}^{T} c_t \,\middle|\, s_T \in S^{goal} \right]}_{\text{Sum of the cost of a planed sequence of actions that leads to a goal state}}$$

The interaction is a sequence: $\underbrace{p_0, s_0, a_0, p_1, s_1, a_1, p_2, s_2, a_2, \dots, s^{goal}}_{\text{cost}}$

Example: Solving a puzzle. What action gets me closer to the solution?

Utility-based Agent

- The agent uses a utility function to evaluate the **desirability of each possible states.** This is typically expressed as the reward of being in a state $R(s)$.
- Choose actions to stay in desirable states.
- Performance measure: The discounted sum of **expected utility over time**.



$$a = \mathrm{arg}max_{a_0 \in \mathrm{A}} E \underbrace{\left[\sum_{t=0}^{\infty} \gamma^t r_t \,|a_0 \right]}_{\text{Implements rational behavior: Utility is the expected future discounted reward}}$$

Techniques: Markov decision processes, reinforcement learning

The interaction is a sequence: $\underbrace{p_0, s_0, a_0, p_1, s_1, a_1. p_2, s_2, a_2, \ldots}_{\text{reward}}$

Example: An autonomous Mars rover prefers states where its battery is not critically low.

Some Environment Types Revisited

Fully observable: The agent's sensors always show the whole **state**.

vs.

Partially observable: The agent only perceives part of the **state** and needs to remember or infer the rest.

Deterministic:

a) **Percepts** are 100% reliable.

b) Changes in the environment are completely determined by the current **state** of the environment and the agent's **action**.

vs.

Stochastic:

a) **Percepts** are unreliable (noise distribution, sensor failure probability, etc.). This is called a stochastic sensor model.

b) The **transition function** is stochastic leading to transition probabilities and a Markov process.

Known: The agent knows the **transition function**.

vs.

Unknown: The needs to **learn the transition function** by trying actions.

We will spend the whole course on discussing algorithms that can deal with environments that have different combinations of these three properties.

Case Study: Self-Driving Cars

Self-driving Cars

SAE Automation Levels

- Level 1 - Driver Assistance (“hands on”)
- Level 2 - Partial Automation (“hands off”)
- Level 3 - Conditional Automation
- Level 4 - High Automation
- Level 5 - Full Automation (“steering wheel optional”)

Components

- Sensing
- Maps
- Path planning
- Controlling the vehicle

Why is this so hard?

A Self-Driving Car as a Rational Agents

Rule: Pick the action that maximize the expected utility

$$a = \text{argmax}_{a \in \text{A}}\, E(U \mid a)$$

Answer the following questions:

- If we have two cars and one provides more (expected) utility.
  Which car is rational?
- Can a rational self-driving car be involved in an accident?
- How would a self-driving car explore and learn?
- What does bounded rationality mean for a self-driving car?

PEAS Description of the Environment of a Self-Driving Car

Complete the PEAS description.

Performance measure	Environment	Actuators	Sensors

Percepts and States: Self-Driving Car

Describe percepts and states.

Percepts	**States**

State Representation: Self-Driving Car

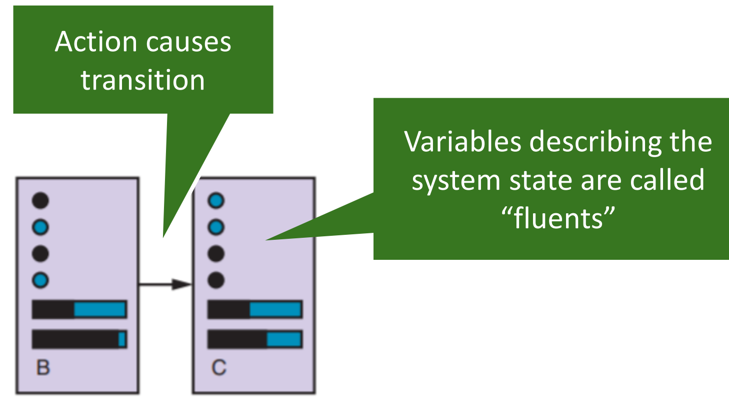
States help to keep track of the environment and the agent in the environment.

Design a structured representation for the state of a self-driving car.

a) What fluents should it contain?

b) What actions can cause transitions?

c) Draw a small transition diagram.



(b) Factored

Environment for a Self-Driving Car

☐ **Fully observable:** The agent's sensors always show the whole **state**.

vs.

☐ **Partially observable:** The agent only perceives part of the **state** and needs to remember or infer the test.

Deterministic:

☐ **a)** **Percepts** are 100% reliable

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☐ **a)** **Percepts** are unreliable (noise distribution, sensor failure probability, etc.). This is called a stochastic sensor model.

☐ b) The **transition function** is stochastic leading to transition probabilities and a Markov process.

☐ **Known:** The agent knows the **transition function**.

vs.

☐ **Unknown:** The needs to **learn the transition function** by trying actions.

☑ Check what applies and explain what it means for a self-driving car.

What Type of Intelligent Agent is a Self-Driving Car?

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

☐ Is it learning?

Does it collect utility over time? How would the utility for each state be defined?

Does it have a goal state?

Does it store state information. How would they be defined (atomic/factored)?

Does it use simple rules based on the current percepts?

☑ Check what applies

Why is this so hard?

- Self-driving cars operate in a very complicated partially observable, stochastic, and dynamic environment.
- Can only use bounded rationality because of limits with sensors and computational power.
- Require a set of different agents that cooperate.