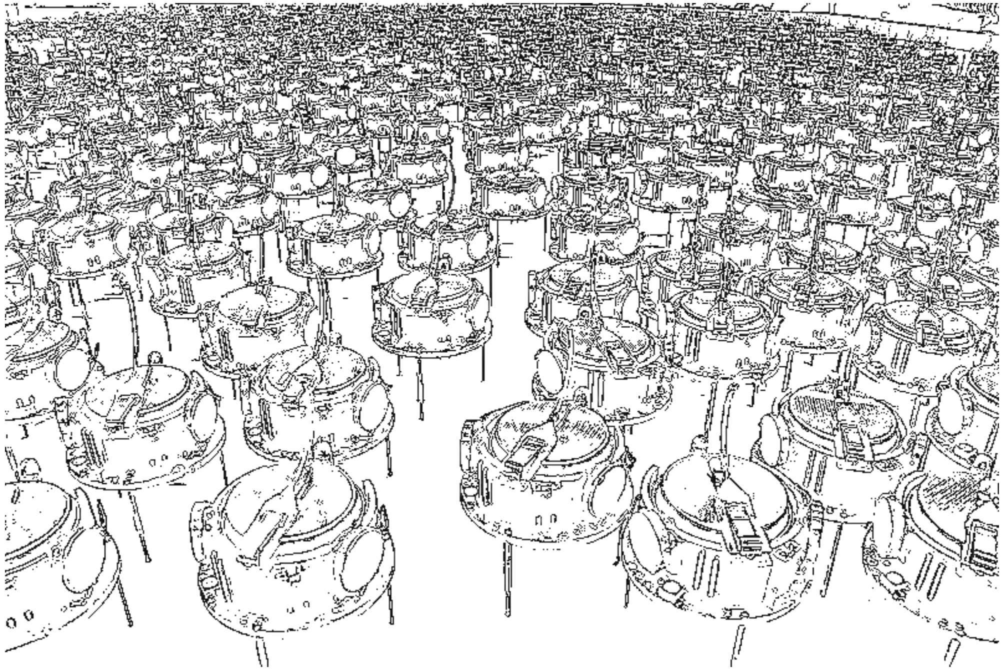
Intelligent Multi Agent Systems



Introduction to Multi Agent Systems

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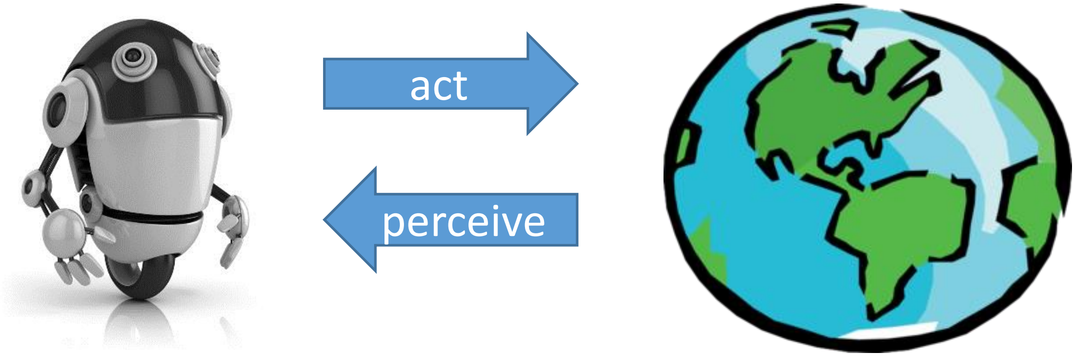
Agenda

- Characteristics of Multi-Agent Systems
- What is an agent?
- Utility Theory

Some definitions

Agent: anything that perceives and acts upon its environment.



➡Multiagent system (MAS): a collection of interacting agents.

➡Distributed AI (DAI): the subfield of AI that studies MAS.

Characteristics of MAS: Agent Design

- Agents are designed by different people.
- Hardware differences (soccer robots).
- Software differences (softbots on the Internet).
- Heterogeneous vs. homogeneous agents.
- Agent heterogeneity can affect perception, decision making, etc.

Characteristics of MAS: Environments

- In traditional AI, an agent's environment is assumed static.
- In a MAS, the presence of multiple agents makes the environment dynamic.
- More agents -> more dimensions
- This complicates the mathematical analysis of algorithms.
- What should be treated as environment and what as agent?

Characteristics of MAS: Perception

- Sensor data are distributed:
  - Spatially, appear at different locations.
  - Temporally, arrive at different times.
  - Semantically, require different interpretations.
- The world state is partially observable to each agent.
- Sensor fusion is the problem of combining perceptions.

Characteristics of MAS: Control

- In a MAS, control is distributed.
- Each agent has to choose an action (more or less) by himself.
- Game theory studies distributed decision making,
- In a cooperative MAS the agents must coordinate their actions.
- Coordination ensures that individual actions result in good joint actions..

Characteristics of MAS: Interaction

- In a MAS, agents might interact
  - Cooperatively: Solve the same task together
  - Neutrally: Live in same world, solve different non-competitive task
  - Competitively: Opposing task objectives
- Optimize joint reward or individual reward functions
- Intensions/task of other agents might be unknown

Characteristics of MAS: Knowledge

- Each agent in a MAS can possess different amounts of knowledge.
- Moreover, each agent should know about the knowledge of the others.
- A fact is common knowledge if all agents know it, all agents know that they all know it, etc.
- Coordination, for instance, can be implemented based on certain common knowledge assumptions.

Characteristics of MAS: Communication

- Interaction is often associated with some form of communication.
- Coordinating and negotiating agents may use communication.
- What language should the agents speak?
- What protocols to use for message transmission?

Challenges

- Decompose problems into subtasks.
- Deal with distributed perception
- Implement decentralized control and coordination.
- Multiagent planning and learning.
- Represent knowledge.
- Develop communication languages and protocols.
- Enable agents to negotiate.
- Enable organizational structures, e.g., teams.
- Ensure stable system behavior.

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Definition of an Agent

There are many definitions of an intelligent agent, we adopt the following:

- An intelligent agent is a rational decision maker who is able to perceive some external environment and act autonomously upon it.

?

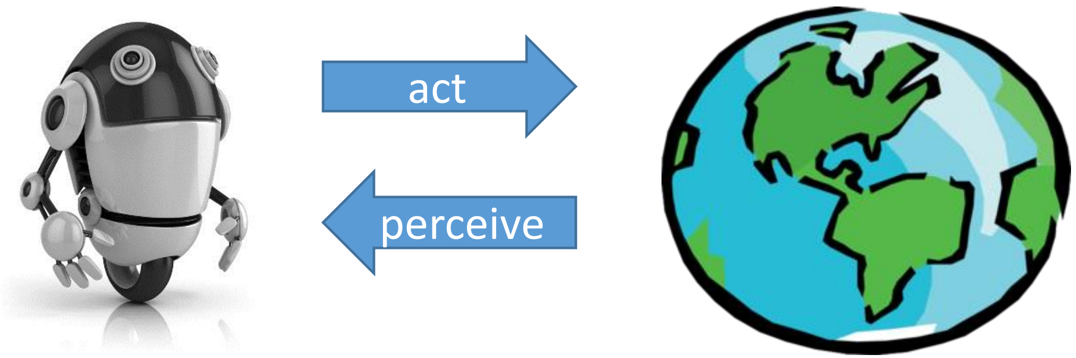
Important points:

- Rationality means optimizing a performance measure.
- Autonomy means using its own perception to guide behavior.
- We are mostly interested in rational autonomous agents.

Definition of an Agent

The agent acts in an environment...

- state $\boldsymbol{s}_t$: The current state of the environment
- observation $\boldsymbol{o}_t$: The perception of the agent (might be different from the state)
- action $\boldsymbol{a}_t$: Used to interact with the environment



Decision theory

Decision theory deals with the problem of optimal action selection.

- In each time *t* the agent has to decide on its current action a_t.
- There is an environment or world that is outside the agent, and that is affected by a_t.

In principle, an optimal decision should depend on two things:

- The past: what the agent did before time *t*.
- The future: what is going to happen next.

How many perceptions are needed?

To behave rationally at any time step t, an agent must in general map its complete history of perceptions $o_{1:t}$ and actions $a_{1:t-1}$ to an optimal new action a_t:

$$\pi(\boldsymbol{o}_{1:t}, \boldsymbol{a}_{1:t-1}) = \boldsymbol{a}_t$$

➡The function is called the policy of the agent.

➡Is such a mapping feasible?

Reflex Policies

A reflex agent just maps its current perception o_t to a new action a_t, thus ignoring the past:

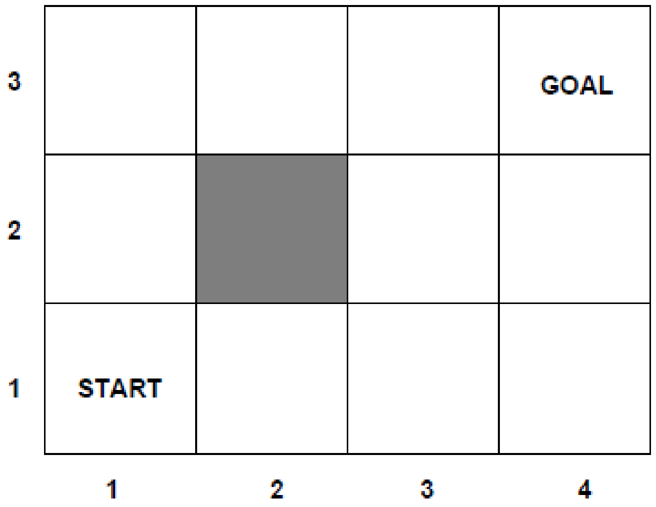
$$\pi(\boldsymbol{o}_t) = \boldsymbol{a}_t$$

- ➡ Such a policy is called reactive or memoryless.
- ➡ How successful such a reflex agent can be?

Discrete vs. continuous worlds

A discrete world consists of a finite number of states, e.g.,

$S = \{(1,1), (1,2), \ldots, (4,3)\}.$



A continuous world can have infinitely many states, e.g., for a translating-rotating robot on the plane holds $S = \mathbb{R}^3$.

Transition Models and the Markov Property

Each time step the agent can choose an action a from a set A of actions

A transition model specifies how the world changes when an action is executed.

An environment is markov, if its dynamics only depend on the current state $\boldsymbol{s}_t$ and on the action of the agent, but not on the history

$$p(\boldsymbol{s}_{t+1}|\boldsymbol{s}_{1:t}, \boldsymbol{a}_{1:t}) = p(\boldsymbol{s}_{t+1}|\boldsymbol{s}_t, \boldsymbol{a}_t)$$

➡The current state $\boldsymbol{s}_t$ captures all relevant statistics to predict the future

Stochastic vs. Determinstic Worlds

In a deterministic world, the transition model maps a state-action pair to a single new state:

$$(\boldsymbol{s}_t, \boldsymbol{a}_t) \to \boldsymbol{s}_{t+1}$$

In a stochastic world, the world model maps a state-action pair to a probability distribution over states:

$$(\boldsymbol{s}_t, \boldsymbol{a}_t) \to p(\boldsymbol{s}_{t+1} | \boldsymbol{s}_t, \boldsymbol{a}_t)$$

Observable vs. Partial Observable World

A world is called observable to an agent if the current perception o_t of the agent provides complete information about the current world state s_t:

$$\boldsymbol{o}_t = \boldsymbol{s}_t, \qquad \pi(\boldsymbol{o}_t) = \pi(\boldsymbol{s}_t)$$

➡ Reflex policies are sufficient to model optimal behavior

In a partially observable world the current perception o_t provides only partial information about the world state, in the form of a probability distribution over all world states:

$$\boldsymbol{o}_t \sim p(\boldsymbol{o}_t | \boldsymbol{s}_t) \ldots \text{ sampled from observation model}$$

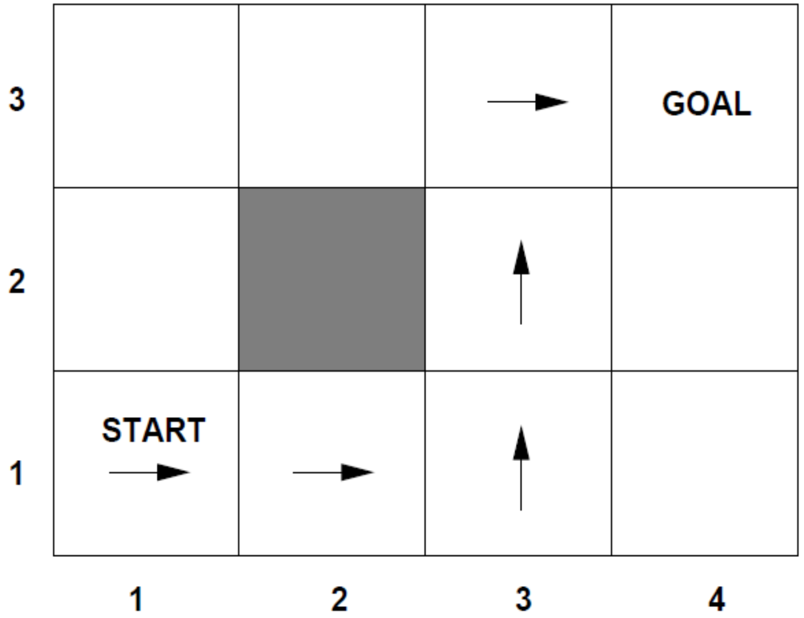
➡ We need to consider the history for modelling optimal behaviour

Goals and planning

A goal is a desired state of the world, e.g., $\boldsymbol{s}_{\text{goal}} = (4, 3)$

➡ Planning is a search through the state space for an optimal path to goal

➡ Classical graph search algorithms can be used, e.g., Dijkstra.



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Specification of the Task

We need a more flexible way to describe a task

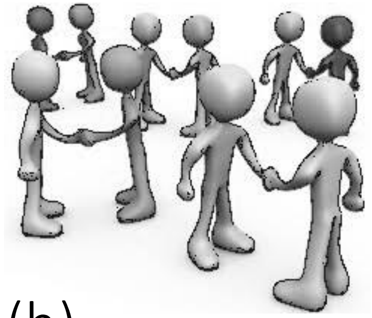
Utility theory:

- quantifies degree of preference across alternatives
- understand the impact of uncertainty on these preferences
- utility function: a mapping from states of the world to real numbers, indicating the agent's level of happiness with that state of the world
- Decision-theoretic rationality: take actions to maximize expected utility.

Often, we will further assume that agent‘s are self-interested

- Each agent has its own description of states of the world that it likes, and that its actions are motivated by this description

Friends and Annoying Persons



Alice has three options: club (c), movie (m), watching a video at home (h)

- On her own, her utility for these three outcomes is 100 for c, 50 for m and 50 for h
- However, Alice also cares about Bob (who she hates) and Carol (who she likes)
  - Bob is at the club 60% of the time, and at the movies otherwise
  - Carol is at the movies 75% of the time, and at the clubotherwise
- If Alice runs into Bob at the movies, she suffers disutility of 40; if she sees him at the club she suffers disutility of 90.
- If Alice sees Carol, she enjoys whatever activity she's doing 1.5 times as much as she would have enjoyed it otherwise (taking into account the possible disutility caused by Bob)

What should Alice do ?

What should Alice do?

$A = c$	$B = c$	$B = m$
$C = c$	15	150
$C = m$	10	100

$A = m$	$B = c$	$B = m$
$C = c$	50	10
$C = m$	75	15

Alice's expected utility for c:

$$0.25(0.6 \cdot 15 + 0.4 \cdot 150) + 0.75(0.6 \cdot 10 + 0.4 \cdot 100) = 51.75$$

Alice's expected utility for m:

$$0.25(0.6 \cdot 50 + 0.4 \cdot 10) + 0.75(0.6 \cdot 75 + 0.4 \cdot 15) = 46.75$$

Alice's expected utility for h:

$$50$$

Alice should go to the club despite that Bob is annoying her.

Why utilities?

Why would anyone argue with the idea that an agent's preferences could be described using a utility function as wejust did?

➡why should a single-dimensional function be enough to explain preferences over an arbitrarily complicated set of alternatives?

➡Why should an agent's response to uncertainty be captured purely by the expected value of his utility function?

It turns out that the claim that an agent has a utility function is substantive.

Preferences over Outcomes

If o_1 and o_2 are outcomes

- $o_1 \succeq o_2$ means o_1 is at least as desirable as o_2.
  - read this as "the agent weakly prefers o_1 to o_2"
- $o_1 \sim o_2$ means $o_1 \succeq o_2$ and $o_2 \succeq o_1$.
  - read this as "the agent is indifferent between o_1 and o_2."
- $o_1 \succ o_2$ means $o_1 \succeq o_2$ and $o_2 \not\succeq o_1$
  - read this as "the agent strictly prefers o_1 to o_2"

Lottery

An agent may not know the outcomes of his actions, but may instead only have a probability distribution over the outcomes.

Definition (lottery):

A lottery is a probability distribution over outcomes. We will write it as $[p_1 : o_1, p_2 : o_2, \ldots, p_k : o_k]$

We will consider lotteries to be outcomes.

Lotteries can be stacked $[p_1 : o_1, p_2 : [p_{21} : o_1, p_{22} : o_2], \ldots]$

Preference Axioms

- Completeness: A preference relationship must be defined between every pair of outcomes

$$\forall o_1 \forall o_2 \; o_1 \succeq o_2 \text{ or } o_2 \succeq o_1$$

- Transitivity: All preferences must be transitive

$$\text{if } o_1 \succeq o_2 \text{ and } o_2 \succeq o_3 \text{ then } o_1 \succeq o_3$$

- Monotonicity: An agent prefers a larger chance of getting a better outcome to a smaller chance:

$$\text{if } o_1 \succ o_2 \text{ and } p > q \text{ then } [p : o_1, 1-p : o_2] \succ [q : o_1, 1-q : o_2]$$

Preference Axioms

- Decomposability: Let $P_l(o_i)$ denote the probability that outcome o_i is selected by lottery *l*. If $\forall o_i \in O,\ P_{\ell_1}(o_i) = P_{\ell_2}(o_i)$ then $\ell_1 \sim \ell_2$.
  - „No fun in gambling“
  - For example, if $\ell = [0.3 : o_1; 0.7 : [0.8 : o_2; 0.2 : o_1]]$ then $P_\ell(o_1) = 0.44$ and $P_\ell(o_3) = 0$
- Substitutability: If $o_1 \sim o_2$ then

  $$[p : o_1, p_3 : o_3, \ldots, p_k : o_k] \sim [p : o_2, p_3 : o_3, \ldots, p_k : o_k]$$

- Continuity:

  If $o_1 \succ o_2$ and $o_2 \succ o_3$, then there exists a $p \in [0, 1]$ such that $o_2 \sim [p : o_1, 1 - p : o_3]$

Preferences and utility functions

Theorem (von Neumann and Morgenstern, 1944)

If an agent's preference relation satisfies the axioms Completeness, Transitivity, Decomposability, Substitutability, Monotonicity and Continuity then there exists a function $u : O \rightarrow [0, 1]$ with the properties that:

- $u(o_1) \geq u(o_2)$ iff the agent prefers o_1 to o_2; and
- when faced about uncertainty about which outcomes it will receive, the agent prefers outcomes that maximize the expected value of *u*.

Summary

- Charecteristics of MAS: Heterogeneous vs. homogeneous agents, dynamic environments, full vs. partial observability, cooperative vs. competative agents, what is common knowledge?
- Agent: perceive and act autonomously
- Utility Theory:
  - a single-dimensional function
  - Uncertainty in outcome: use expectation