

# Learning objectives

At the end of the class you should be able to:

- characterize simplifying assumptions made in building AI systems
- determine what simplifying assumptions particular AI systems are making
- suggest what assumptions to lift to build a more intelligent system than an existing one

# Dimensions

- Research proceeds by making simplifying assumptions, and gradually reducing them.
- Each simplifying assumption gives a dimension of complexity
  - ▶ multiple values in a dimension: from simple to complex
  - ▶ simplifying assumptions can be relaxed in various combinations

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- **Example:** Planning a trip from here to a see the Mona Lisa in Paris.
- Flat representations are adequate for simple systems.
- Complex biological systems, computer systems, organizations are all hierarchical
- A flat description is either continuous or discrete. Hierarchical reasoning is often a hybrid of continuous and discrete.

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- **Infinite stage:** the agent plans for going on forever (process oriented)

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- **Individuals** and **relations**
  - ▶ There is a feature for each relationship on each tuple of individuals.
  - ▶ Often an agent can reason without knowing the individuals or when there are infinitely many individuals.

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- **Perfect rationality:** the agent can determine the best course of action, without taking into account its limited computational resources.
- **Bounded rationality:** the agent must make good decisions based on its perceptual, computational and memory limitations.



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- Learning is impossible without prior knowledge (bias).

# Uncertainty

There are two dimensions for uncertainty. In each dimension an agent can have

- **No uncertainty:** the agent knows what is true
- **Disjunctive uncertainty:** there is a set of states that are possible
- **Probabilistic uncertainty:** a probability distribution over the worlds.

# Why probability?

- Agents need to act even if they are uncertain.
- Predictions are needed to decide what to do:
  - ▶ definitive predictions: you will be run over tomorrow
  - ▶ disjunctions: be careful or you will be run over
  - ▶ point probabilities: probability you will be run over tomorrow is 0.002 if you are careful and 0.05 if you are not careful

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- Acting is gambling: agents who don't use probabilities will lose to those who do.
- Probabilities can be learned from data and prior knowledge.

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Whether an agent can determine the state from its stimuli:

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Whether an agent can determine the state from its stimuli:

- **Fully-observable**: the agent can observe the state of the world.
- **Partially-observable**: there can be a number states that are possible given the agent's stimuli.

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The dynamics can be:

- **Deterministic**: the resulting state is determined from the action and the state
- **Stochastic**: there is uncertainty about the resulting state.

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# Preference

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**Examples:** coffee delivery robot, medical doctor

# Number of agents

Are there multiple reasoning agents that need to be taken into account?

- **Single agent** reasoning: any other agents are part of the environment.
- **Multiple agent** reasoning: an agent reasons strategically about the reasoning of other agents.

Agents can have their own goals: cooperative, competitive, or goals can be independent of each other

When does the agent reason to determine what to do?

- **reason offline**: before acting
- **reason online**: while interacting with environment

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# State-space search

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# Deterministic planning

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# Decision networks

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# Markov decision processes (MDPs)

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# Decision-theoretic planning

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# Reinforcement learning

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# Classical game theory

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# Humans

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# The dimensions interact in complex ways

- Partial observability makes multi-agent and indefinite horizon reasoning more complex
- Modularity interacts with uncertainty and succinctness: some levels may be fully observable, some may be partially observable
- Three values of dimensions promise to make reasoning simpler for the agent:
  - ▶ Hierarchical reasoning
  - ▶ Individuals and relations
  - ▶ Bounded rationality