# Foundations of Artificial Intelligence

## A4. Introduction: Rational Agents

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# Introduction: Overview

Chapter overview: introduction

- A1. Organizational Matters
- A2. What is Artificial Intelligence?
- A3. AI Past and Present
- A4. Rational Agents
- A5. Environments and Problem Solving Methods

# Systematic AI Framework

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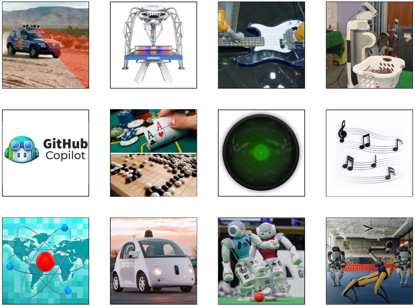
so far we have seen that:

- AI systems applied to wide variety of challenges



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so far we have seen that:

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| | |
|---|---|
| thinking like humans | thinking rationally |
| acting like humans | acting rationally |

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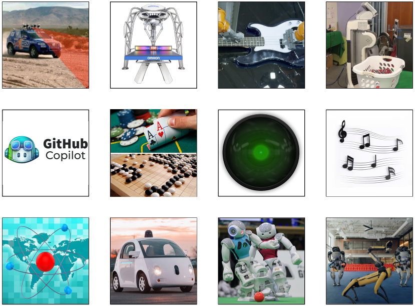

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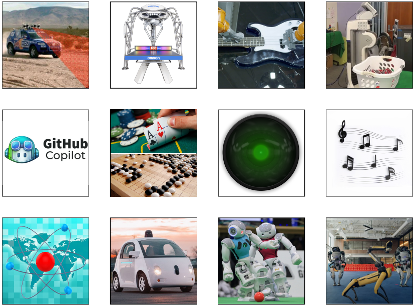

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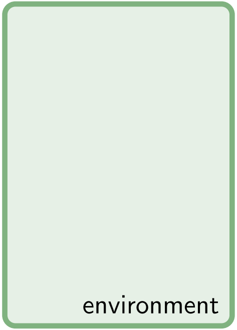

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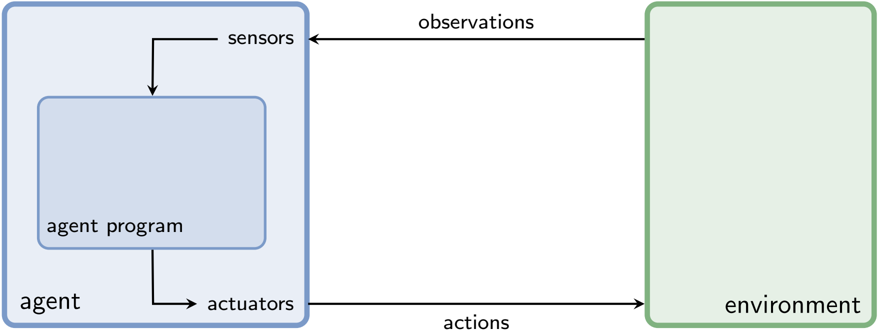

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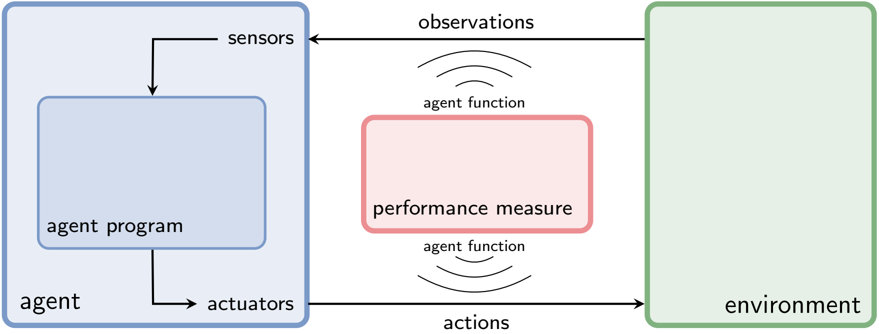
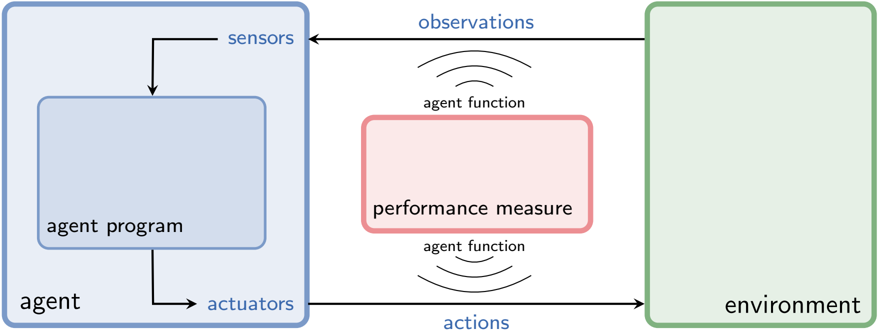


now: describe a systematic framework that

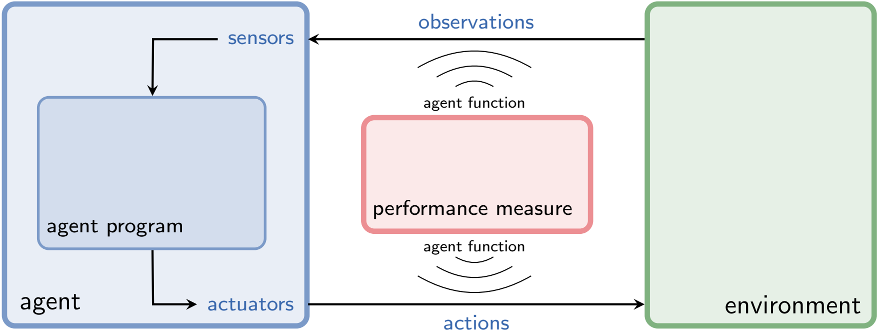
- captures this diversity of challenges
- includes an entity that acts in the environment
- determines if the agent acts rationally in the environment

# Agent-Environment Interaction



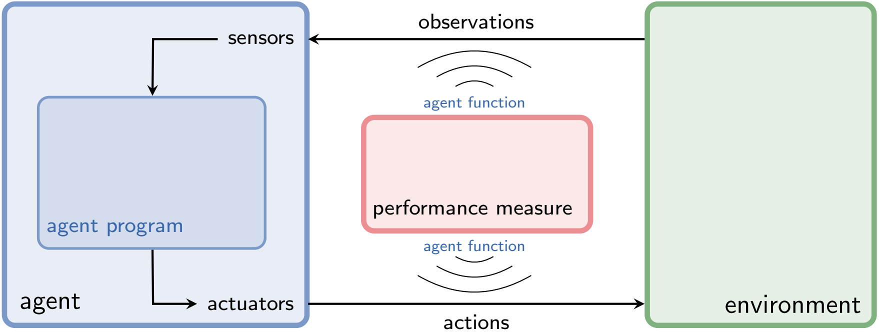
- sensors: physical entities that allow the agent to observe
- observation: data perceived by the agent's sensors
- actuators: physical entities that allow the agent to act
- action: abstract concept that affects the state of the environment

# Agent-Environment Interaction



- sensors and actuators are not relevant for the course (⇝ typically covered in courses on robotics)
- observations and actions describe the agent's capabilities (the agent model)

# Formalizing an Agent's Behavior



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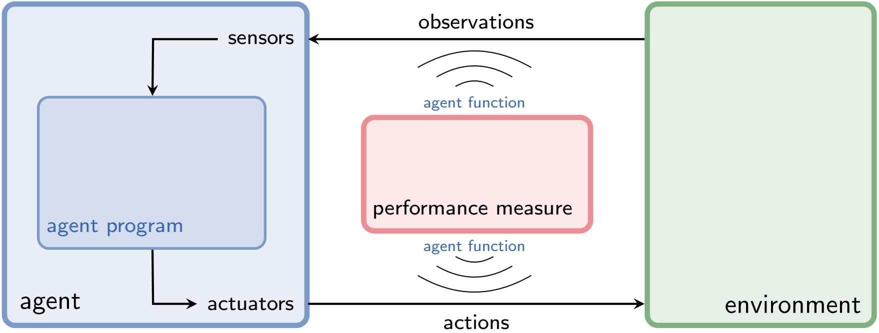
   - internal representation
   - specifics possibly unknown to outside
2. as agent function:
   - external characterization

# Formalizing an Agent's Behavior



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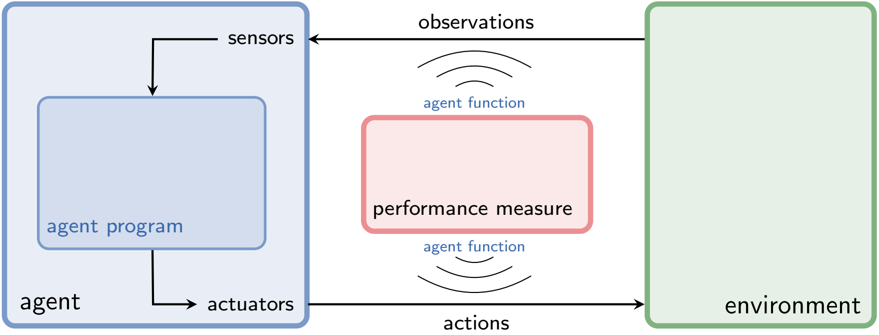
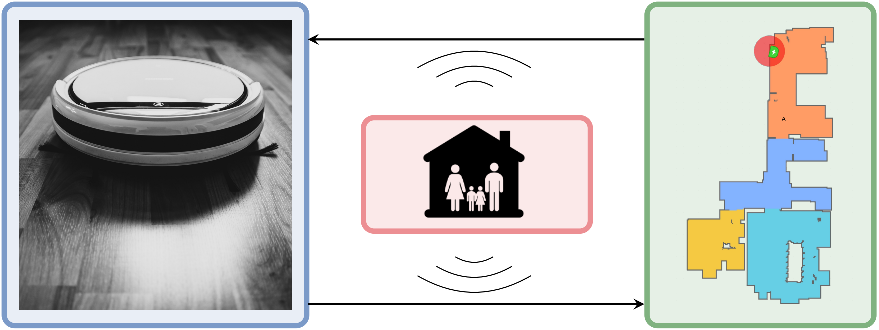


1. as agent program:
   - internal representation
   - specifics possibly unknown to outside
   - takes observation as input
   - outputs an action
   - computed on physical machine (the agent architecture)

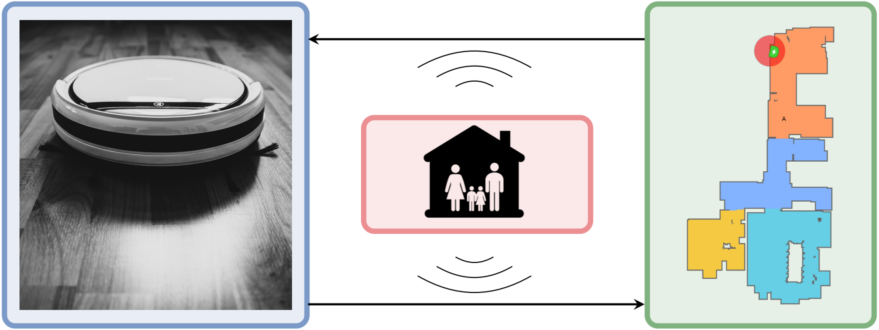
2. as agent function:
   - external characterization
   - maps sequence of observations to (probability distribution over) actions
   - abstract mathematical formalization

# Example

# Vacuum Domain

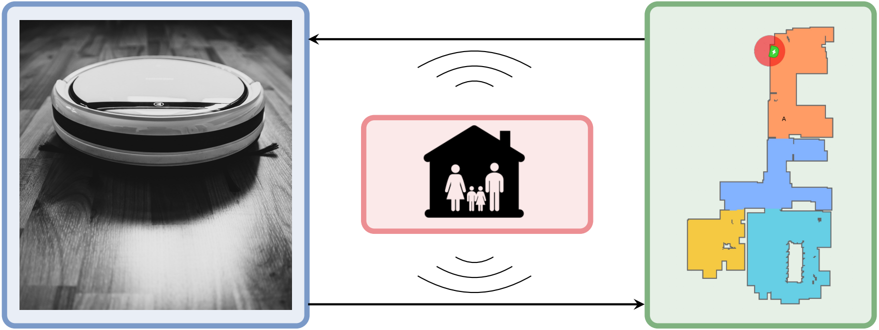


# Vacuum Agent: Sensors and Actuators



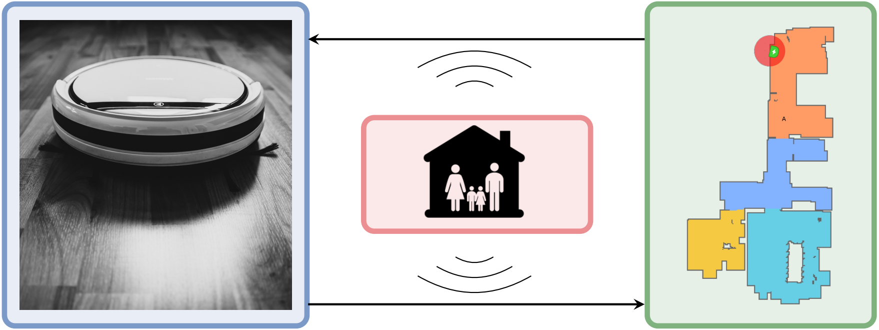
- sensors: cliff sensors, bump sensors, wall sensors, state of charge sensor, WiFi module
- actuators: wheels, cleaning system

# Vacuum Agent: Observations and Actions



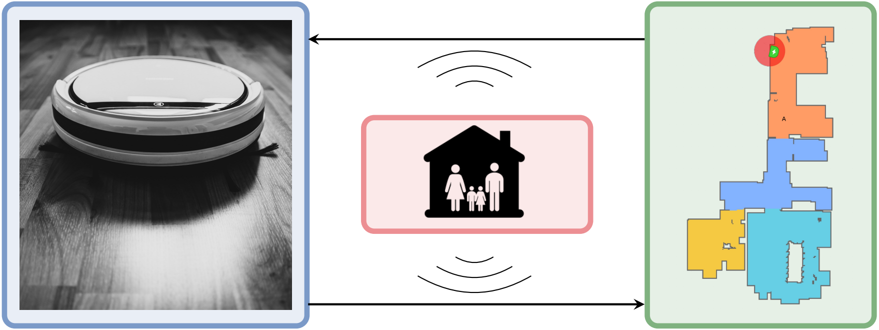
- observations: current location, dirt level of current room, presence of humans, battery charge
- actions: move-to-next-room, move-to-base, vacuum, wait

# Vacuum Agent: Agent Program



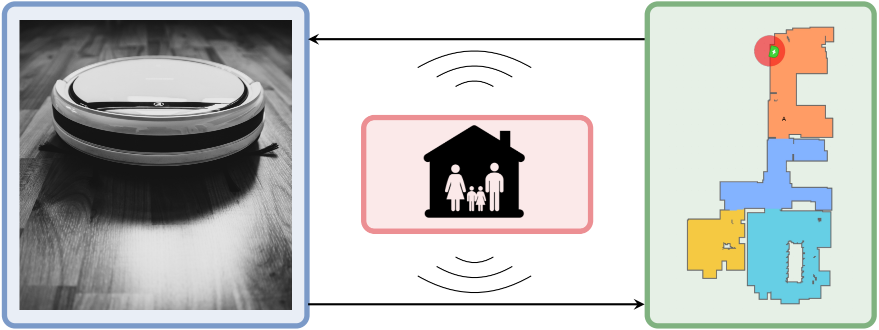
```
def vacuum-agent([$location$, $dirt\text{-}level$, $owner\text{-}present$, $battery$]):
    if $battery \leq 10\%$: return $move\text{-}to\text{-}base$
    else if $owner\text{-}present$ = True: return $move\text{-}to\text{-}next\text{-}room$
    else if $dirt\text{-}level$ = dirty: return $vacuum$
    else: return $move\text{-}to\text{-}next\text{-}room$
```

# Vacuum Domain: Agent Function



| observation sequence | action |
|---|---|
| ⟨[blue, clean, False, 100%]⟩ | *move-to-next-room* |
| ⟨[blue, dirty, False, 100%]⟩ | *vacuum* |
| ⟨[blue, clean, True, 100%]⟩ | *move-to-next-room* |
| ... | ... |
| ⟨[blue, clean, False, 100%], [blue, clean, False, 90%]⟩ | *move-to-next-room* |
| ⟨[blue, clean, False, 100%], [blue, dirty, False, 90%]⟩ | *vacuum* |
| ... | ... |

# Vacuum Domain: Performance Measure



potential influences on performance measure:

- dirt levels
- noise levels
- energy consumption
- safety

# Rationality

# Evaluating Agent Functions

What is the right agent function?

# Rationality

rationality of an agent depends on performance measure (often: utility, reward, cost) and environment

## Perfect Rationality

- for each possible observation sequence
- select an action which maximizes
- expected value of future performance
- given available information on observation history
- and environment

# Perfect Rationality of Our Vacuum Agent

Is our vacuum agent perfectly rational?

# Perfect Rationality of Our Vacuum Agent

Is our vacuum agent perfectly rational?

depends on performance measure and environment, e.g.:

- Do actions reliably have the desired effect?
- Do we know the initial situation?
- Can new dirt be produced while the agent is acting?

# Performance Measure

- specified by designer
- sometimes clear,
  sometimes not so clear
- significant impact on
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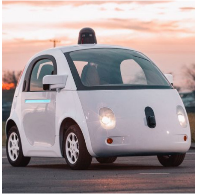

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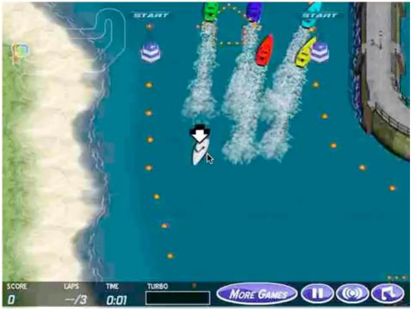

# Perfect Rationality of Our Vacuum Agent

consider performance measure:

- $+1$ utility for cleaning a dirty room

consider environment:

- actions and observations reliable
- world only changes through actions of the agent

our vacuum agent is perfectly rational

# Perfect Rationality of Our Vacuum Agent

consider performance measure:

- $-1$ utility for each dirty room in each step

consider environment:

- actions and observations reliable
- yellow room may spontaneously become dirty

our vacuum agent is not perfectly rational

# Rationality: Discussion

- perfect rationality $\neq$ omniscience
  - incomplete information (due to limited observations) reduces achievable utility
- perfect rationality $\neq$ perfect prediction of future
  - uncertain behavior of environment (e.g., stochastic action effects) reduces achievable utility
- perfect rationality is rarely achievable
  - limited computational power $\leadsto$ bounded rationality

# Summary

# Summary (1)

common metaphor for AI systems: rational agents

agent interacts with environment:

- sensors perceive observations about state of the environment
- actuators perform actions modifying the environment
- formally: agent function maps observation sequences to actions

# Summary (2)

rational agents:

- try to maximize performance measure (utility)
- perfect rationality: achieve maximal utility in expectation given available information
- for "interesting" problems rarely achievable
  $\rightsquigarrow$ bounded rationality