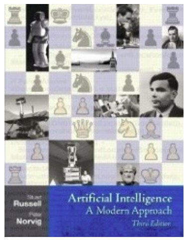
Agents

- This course is about designing intelligent agents

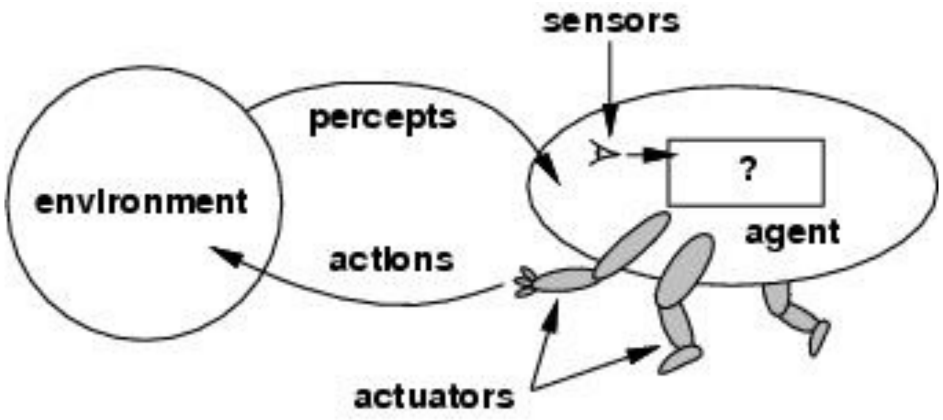
- Agents and environments
  - The vacuum-cleaner world
- Rationality
  - The concept of rational behavior.
- Environment types
- Agent types



Many slides based on Russell & Norvig's slides [Artificial Intelligence: A Modern Approach]

Agents

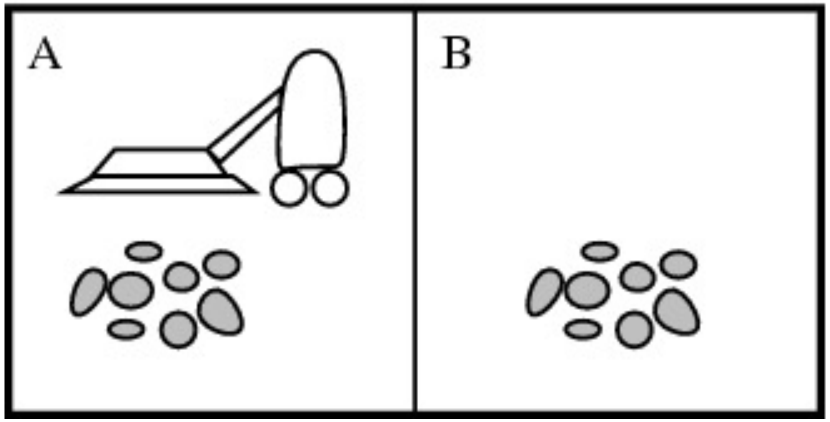
- An **agent** is an entity that perceives and acts in an environment
  - environment can be real or virtual



- An agent can always perceive its actions, but not necessarily their effects on the environment
- **Rational agent**: optimizes some performance criterion
  - For any given task and class of environments we seek the agent (or class of agents) with the best performance.
- Problem:
  - computational limitations make perfect rationality unachievable

The Vacuum-Cleaner world

- A robot-vacuum-cleaner that operates in a simple world



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
…	

- **Environment:**
  - Virtual house with room A and room B
- **Percepts:**
  - The robot can sense pairs [<*location*>,<*status*>]
    - *Location:* whether it is in room *A* or *B*
    - *Status:* whether the room is *Clean* or *Dirty*
- **Actions:**
  - *Left, Right, Suck, NoOp*

Rational Agent – Performance Measure

- A rational agent is an agent that "does the right thing"
  - intuitively clear, but needs to be measurable in order to be useful for computer implementation
- Performance Measure:
  - a function that evaluates sequence of actions/environment states
  - obviously not fixed but task-dependent
- Vacuum-World performance measures:
  - reward for the amount of dust cleaned
    - one point per square cleaned up in time T
    - can be maximized by dumping dust on the floor again...
  - reward for clean floors
    - one point per clean square per time step
  - possibly with penalty for consumed energy
    - minus one per move?
- General rule:
  - design performance measure based on desired environment state
  - not on desired agent behavior

Rational Agent

A **rational agent** *chooses whichever action maximizes the expected value of the performance measure given the percept sequence to date and prior environment knowledge.*

That is for each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.

- **Rational ≠ omniscient**
  - An omniscient agent knows the actual outcome of its actions.
- **Rational ≠ perfection**
  - Rationality maximizes expected performance
  - This may not be the optimal outcome
  - Example:
    - the expected monetary outcome of playing in the lottery/casino, etc. is negative (hence it is rational not to play)
    - but if you're lucky, you may win...

PEAS

What is rational at a given time depends on four things:

P: the performance measure that defines the success

E: the agent's prior knowledge of the environment

A: the actions that the agent can perform

S: the agent's percept sequence to date

- *Example:* Fully automated Taxi

PEAS

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S: the agent's percept sequence to date

- *Example:* Fully automated Taxi
  - Performance
    - Safety, destination, profits, legality, comfort
  - Environment
    - Streets/freeways, other traffic, pedestrians, weather, …
  - Actuators
    - Steering, accelerating, brake, horn, speaker/display,…
  - Sensors
    - Video, sonar, speedometer, engine sensors, keyboard, GPS, …

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- *Example:* Internet Shopping Agent

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S: the agent's percept sequence to date

- *Example:* Internet Shopping Agent
  - Performance
    - price, quality, appropriateness, efficiency
  - Environment
    - the Web: current and future WWW sites, vendors, shippers
  - Actuators
    - display to user, follow URL, fill in form
  - Sensors
    - parsing of HTML pages (text, graphics, scripts)…

PEAS

What is rational at a given time depends on four things:
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- **E**: the agent's prior knowledge of the environment
- **A**: the actions that the agent can perform
- **S**: the agent's percept sequence to date

- *Example:* Chess Program

PEAS

What is rational at a given time depends on four things:

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- *Example:* Chess Program
  - Performance
    - number of games won, ELO rating,...
  - Environment
    - the chess board
  - Actuators
    - moves that can be performed
  - Sensors
    - placement of pieces in current position, whose turn is it?, ...

PEAS

What is rational at a given time depends on four things:
- **P**: the performance measure that defines the success
- **E**: the agent's prior knowledge of the environment
- **A**: the actions that the agent can perform
- **S**: the agent's percept sequence to date

- *Example:* Medical Diagnosis System
  - Performance
    - Healthy patient, reduced costs ,...
  - Environment
    - Patient, hospital staff, …
  - Actuators
    - Display of questions, tests, diagnoses, treatments, referrals, ..
  - Sensors
    - Keyboard entry of symptoms, findings, patenient’s answersm ...

Environment Types

- *Fully observable*
  - the complete state of the environment can be sensed
  - at least the relevant parts
  - no need to keep track of internal states
- *Partially observable*
  - parts of the environment cannot be sensed

Task Environment	Observable
Sudoku	
Chess With a Clock	
Poker	
Backgammon	
Taxi driving	
Medical diagnosis	
Image Analysis	
Part-Picking Robot	
Refinery Controller	
Interactive Tutor	

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Sudoku	*Fully*
Chess With a Clock	*Fully*
Poker	*Partially*
Backgammon	*Fully*
Taxi driving	*Partially*
Medical diagnosis	*Partially*
Image Analysis	*Fully*
Part-Picking Robot	*Partially*
Refinery Controller	*Partially*
Interactive Tutor	*Partially*

Environment Types

- *Deterministic*
  - the next environment state is completely determined by the current state and the executed action
- *Strategic (which can also be stochastic)*
  - only the opponents' actions cannot be foreseen. That is, the environment is deterministic except for the actions of other agents
- *Stochastic*

Task Environment	Observable	Deterministic
Sudoku	*Fully*	
Chess With a Clock	*Fully*	
Poker	*Partially*	
Backgammon	*Fully*	
Taxi driving	*Partially*	
Medical diagnosis	*Partially*	
Image Analysis	*Fully*	
Part-Picking Robot	*Partially*	
Refinery Controller	*Partially*	
Interactive Tutor	*Partially*	

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Sudoku	*Fully*	*Deterministic*
Chess With a Clock	*Fully*	*Strategic*
Poker	*Partially*	*Strategic*
Backgammon	*Fully*	*Stochastic*
Taxi driving	*Partially*	*Stochastic*
Medical diagnosis	*Partially*	*Stochastic*
Image Analysis	*Fully*	*Deterministic*
Part-Picking Robot	*Partially*	*Stochastic*
Refinery Controller	*Partially*	*Stochastic*
Interactive Tutor	*Partially*	*Stochastic*

Environment Types

- *Episodic*
  - the agent's experience can be divided into atomic episodes
  - Per episode the agent perceives and then performs a single action
  - the choice of action depends only on the episode itself
- *Sequential*
  - the current decision could influence all future decision

Task Environment	Observable	Deterministic	Episodic
Sudoku	*Fully*	*Deterministic*	
Chess With a Clock	*Fully*	*Strategic*	
Poker	*Partially*	*Strategic*	
Backgammon	*Fully*	*Stochastic*	
Taxi driving	*Partially*	*Stochastic*	
Medical diagnosis	*Partially*	*Stochastic*	
Image Analysis	*Fully*	*Deterministic*	
Part-Picking Robot	*Partially*	*Stochastic*	
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Interactive Tutor	*Partially*	*Stochastic*	

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Task Environment	Observable	Deterministic	Episodic
Sudoku	*Fully*	*Deterministic*	*Sequential*
Chess With a Clock	*Fully*	*Strategic*	*Sequential*
Poker	*Partially*	*Strategic*	*Sequential*
Backgammon	*Fully*	*Stochastic*	*Sequential*
Taxi driving	*Partially*	*Stochastic*	*Sequential*
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*
Image Analysis	*Fully*	*Deterministic*	*Episodic*
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*
Refinery Controller	*Partially*	*Stochastic*	*Sequential*
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*

Environment Types

- *Dynamic*
  - the environment may change while the agent deliberates
- *Static*
  - the environment does not change while the agent deliberates
- *Semidynamic*
  - the environment does not change, but the agents' performance score may

Task Environment	Observable	Deterministic	Episodic	Static
Sudoku	*Fully*	*Deterministic*	*Sequential*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	
Poker	*Partially*	*Strategic*	*Sequential*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	
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Task Environment	Observable	Deterministic	Episodic	Static
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*
Poker	*Partially*	*Strategic*	*Sequential*	*Static*
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*

Environment Types

- *Discrete*
  - finite number of actions / environment states / percepts
- *Continuous*
  - actions, states, percepts are on a continuous scale
- this disctinction applies separately to actions, states, and percepts
  - can be mixed in individual tasks

Task Environment	Observable	Deterministic	Episodic	Static	Discrete
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*	
Poker	*Partially*	*Strategic*	*Sequential*	*Static*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	
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Poker	*Partially*	*Strategic*	*Sequential*	*Static*	*Discrete*
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	*Discrete*
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	*Continuous*
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	*Continuous*
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Discrete*

Environment Types

- *Single-Agent*
  - No other agents (other agents may be part of the environment)
- *Multi-Agent*
  - Does the environment contain other agents whose performance measure depends on my *actions?*
  - other agents may be *co-operative* or *competitive*

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*	*Discrete*	
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*	*Discrete*	
Poker	*Partially*	*Strategic*	*Sequential*	*Static*	*Discrete*	
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	*Discrete*	
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	*Continuous*	
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	*Continuous*	
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Discrete*	

Environment Types

- *Single-Agent*
  - No other agents (other agents may be part of the environment)
- *Multi-Agent*
  - Does the environment contain other agents whose performance measure depends on my *actions?*
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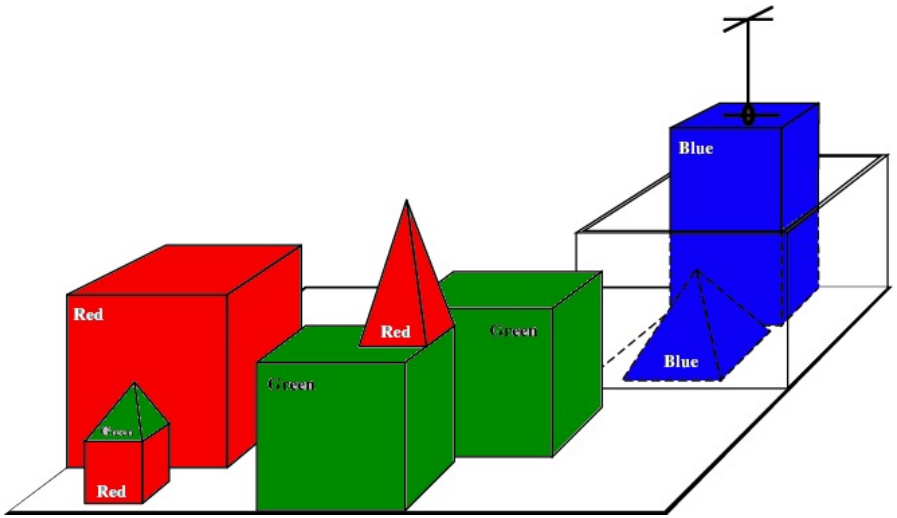
Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Sudoku	*Fully*	*Deterministic*	*Sequential*	*Static*	*Discrete*	*Single*
Chess With a Clock	*Fully*	*Strategic*	*Sequential*	*Semi*	*Discrete*	*Multi*
Poker	*Partially*	*Strategic*	*Sequential*	*Static*	*Discrete*	*Multi*
Backgammon	*Fully*	*Stochastic*	*Sequential*	*Static*	*Discrete*	*Multi*
Taxi driving	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	*Multi*
Medical diagnosis	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	*Single*
Image Analysis	*Fully*	*Deterministic*	*Episodic*	*Semi*	*Continuous*	*Single*
Part-Picking Robot	*Partially*	*Stochastic*	*Episodic*	*Dynamic*	*Continuous*	*Single*
Refinery Controller	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Continuous*	*Single*
Interactive Tutor	*Partially*	*Stochastic*	*Sequential*	*Dynamic*	*Discrete*	*Multi*

Environment Types

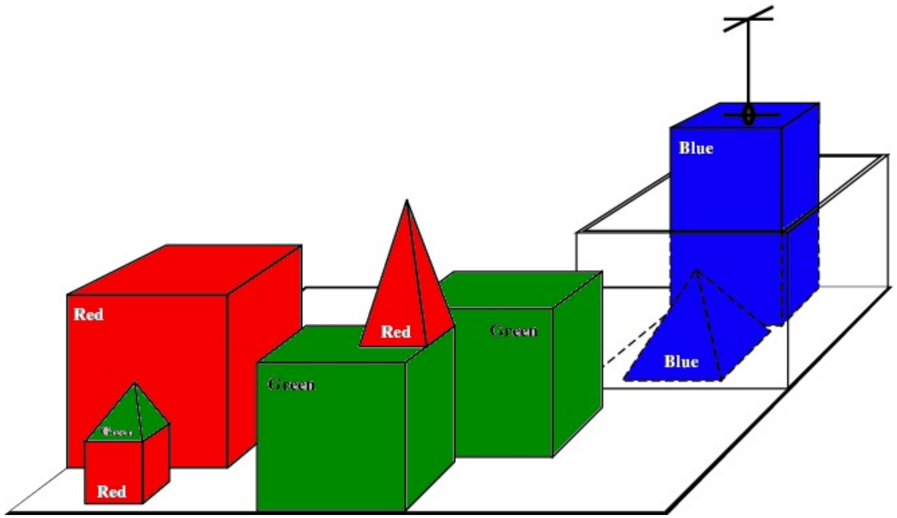
- The simplest environment is
  - fully observable
  - deterministic
  - episodic
  - static
  - discrete
  - single-agent



Environment Types

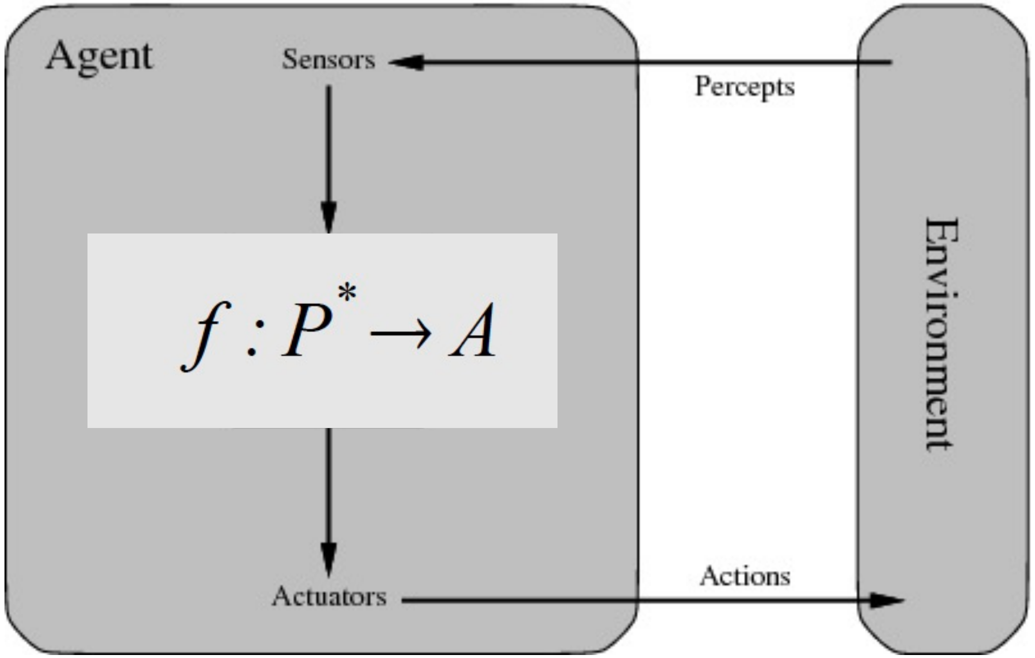
- The simplest environment is
  - fully observable
  - deterministic
  - episodic
  - static
  - discrete
  - single-agent

- Most real situations are
  - partially observable
  - stochastic
  - sequential
  - dynamic
  - continuous
  - multi-agent



Agent Function

- The agent function maps percept histories to actions



- The agent function will internally be represented by the agent program.
- The agent program runs on the physical architecture to produce f.

Agent = Architecture + Program

A Simple Vacuum Cleaner Agent

- Table of mappings from Percept sequences to actions:

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

A Simple General Agent

```
function TABLE-DRIVEN-AGENT(percept) returns an action
    static: percepts, a sequence initially empty
            table, a table of actions, indexed by percept sequence

    append percept to the end of percepts
    action ← LOOKUP(percepts, table)
    return action
```

- has a table of all possible percept histories
- looks up the right response in the table
- Clearly infeasible:
  - if there are $|P|$ percepts and a life-time of T time steps, we need a look-up table of size $\sum_{t=1}^{T} |P^t|$
- For example: chess:
  - about 36 moves per position, average game-length 40 moves
    $\longrightarrow 1054260070290587008980707796982228065224506571886212325909 65$

A Simple Vacuum Cleaner Agent

- Strategy

> "If current room is dirty then suck, otherwise move to the other room."

- As an agent program

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*

- Obvious Questions:
  - Is this the right agent?
  - Is this a good agent?
  - Is there a right agent?

Agent Programs

The key challenge for AI is to write programs that produce rational behavior from a small amount of code rather than a large number of table entries

- Writing down the agent functions is not practical for real applications
- But feasibility is also important
  - you can write a perfect chess playing agent with a few lines of code
  - it will run forever, though...

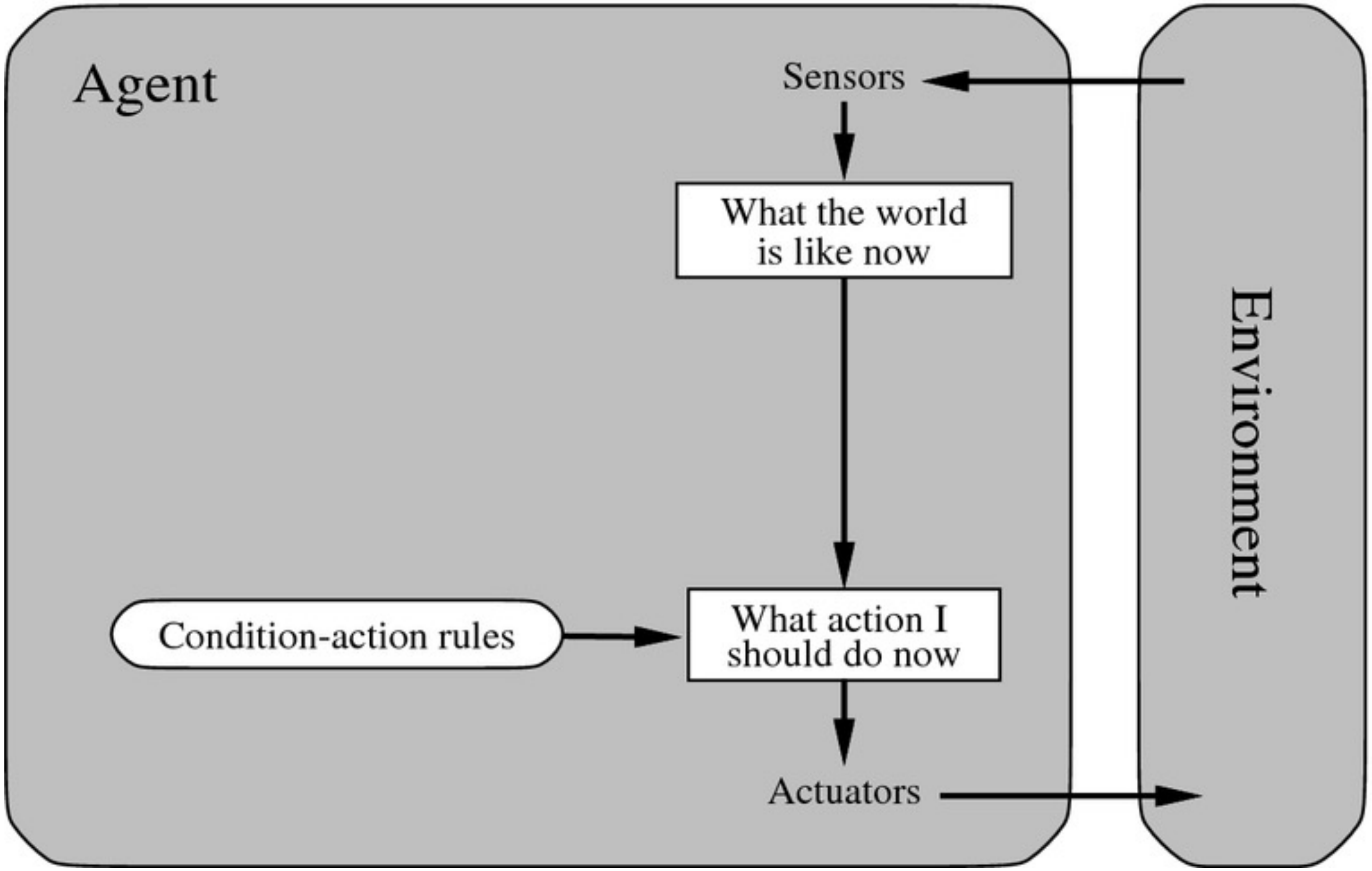
Agent = architecture + program

Agent Types

- Four basic kinds of agent programs will be discussed:
  - Simple reflex agents
  - Model-based reflex agents
  - Goal-based agents
  - Utility-based agents
- All these can be turned into learning agents.

Simple Reflex Agent

- Select action on the basis of only the current percept
  - ignores the percept history



Simple Reflex Agent

- Select action on the basis of only the current percept
  - ignores the percept history
- Implemented through condition-action rules
- Large reduction in possible percept/action situations
  - from $\sum_{t=1}^{T} |P^t|$ to $|P|$
- But will make a very bad chess player
  - does not look at the board, only at the opponent's last move (assuming that the sensory input is only the last move, no visual)

Example:

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*

General Simple Reflex Agent

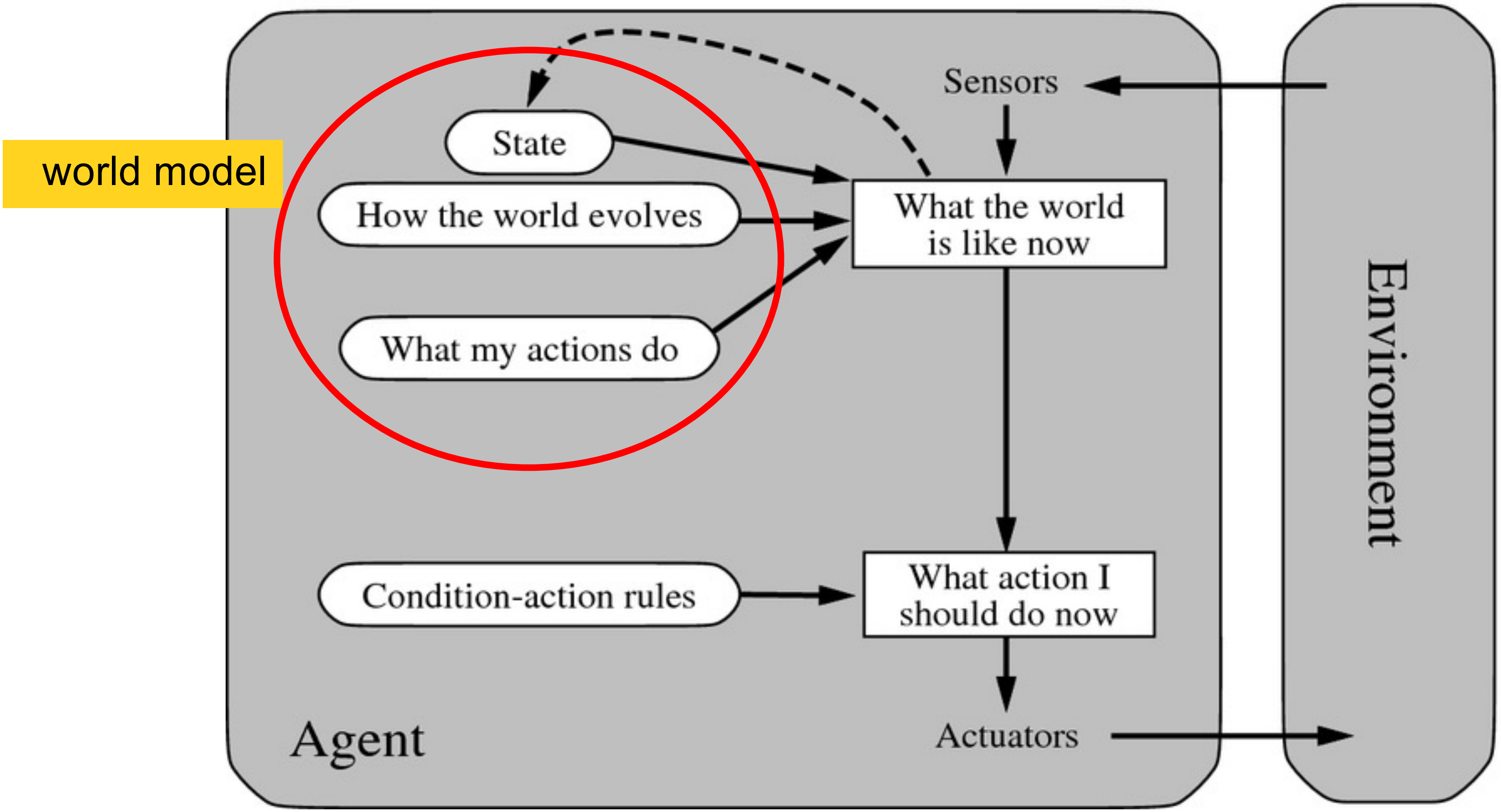
function SIMPLE-REFLEX-AGENT(*percept*) **returns** an action
  static: *rules*, a set of condition-action rules

  state ← INTERPRET-INPUT(*percept*)
  rule ← RULE-MATCH(*state*, *rule*)
  action ← RULE-ACTION[*rule*]
  return *action*

- Note that rules are just used as a concept
  - actual implementation could, e.g., be logical circuitry
- Will only work if the environment is *fully observable*
  - everything important needs to be determinable from the current sensory input
  - otherwise infinite loops may occur
    - e.g. in the vacuum world without a sensor for the room, the agent does not know whether to move right or left
    - possible solution: randomization

Model-Based Reflex Agent

- Keep track of the state of the world
  - better way to fight partial observability



General Model-Based Reflex Agent

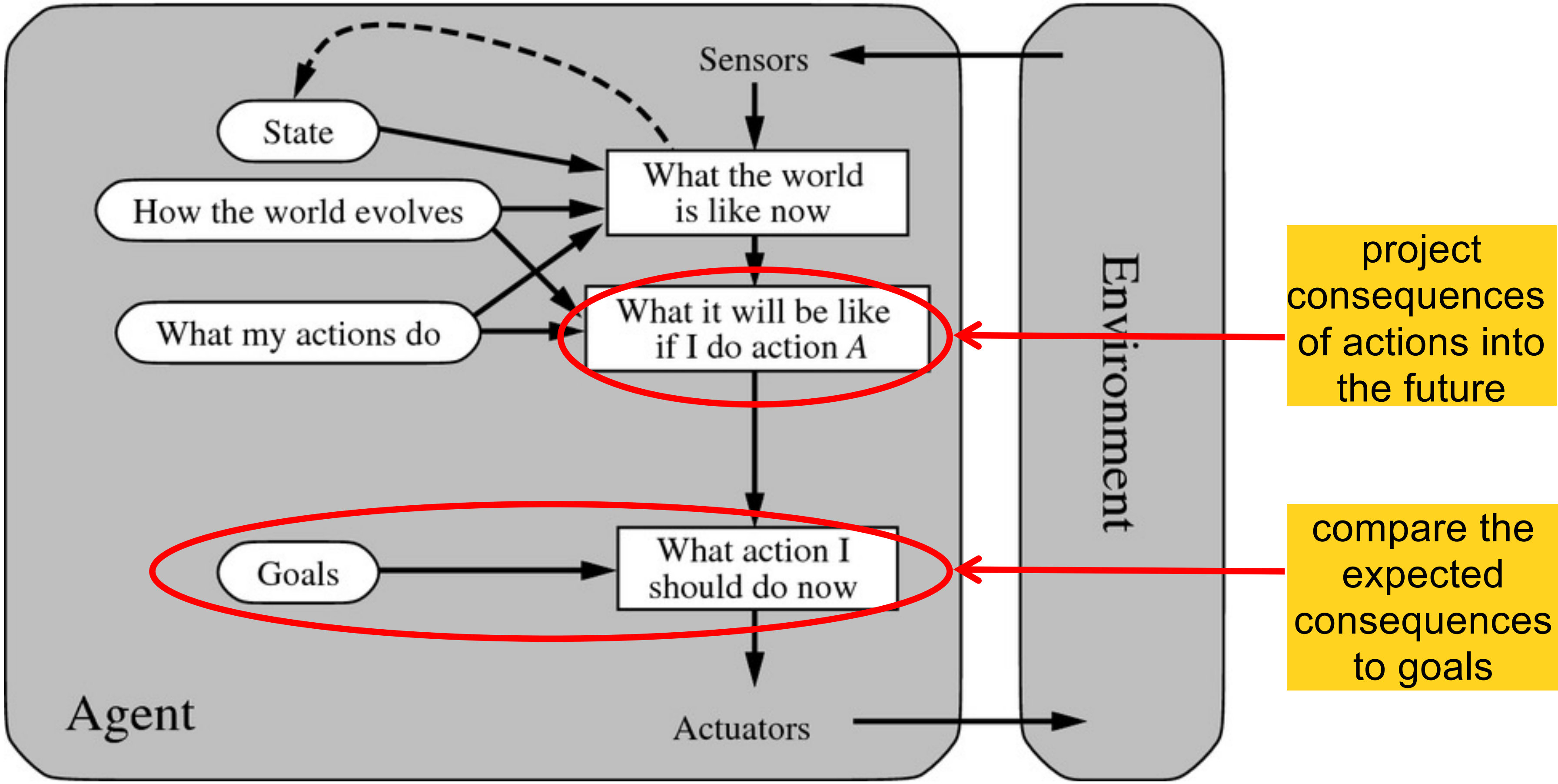
function REFLEX-AGENT-WITH-STATE(*percept*) **returns** an action
  static: *state*, a description of the current world state
    rules, a set of condition-action rules
    action, the most recent action, initially none

  state ← UPDATE-STATE(*state*, *action*, *percept*)
  rule ← RULE-MATCH(*state*, *rule*)
  action ← RULE-ACTION[*rule*]
  return *action*

- Input is not only interpreted, but mapped into an internal state description (a world model)
  - a chess agent could keep track of the current board situation when its percepts are only the moves
- Internal state is also used for interpreting subsequent percepts
- The world model may include effects of own actions!

Goal-Based Agent

- the agent knows what states are desirable
  - it will try to choose an action that leads to a desirable state

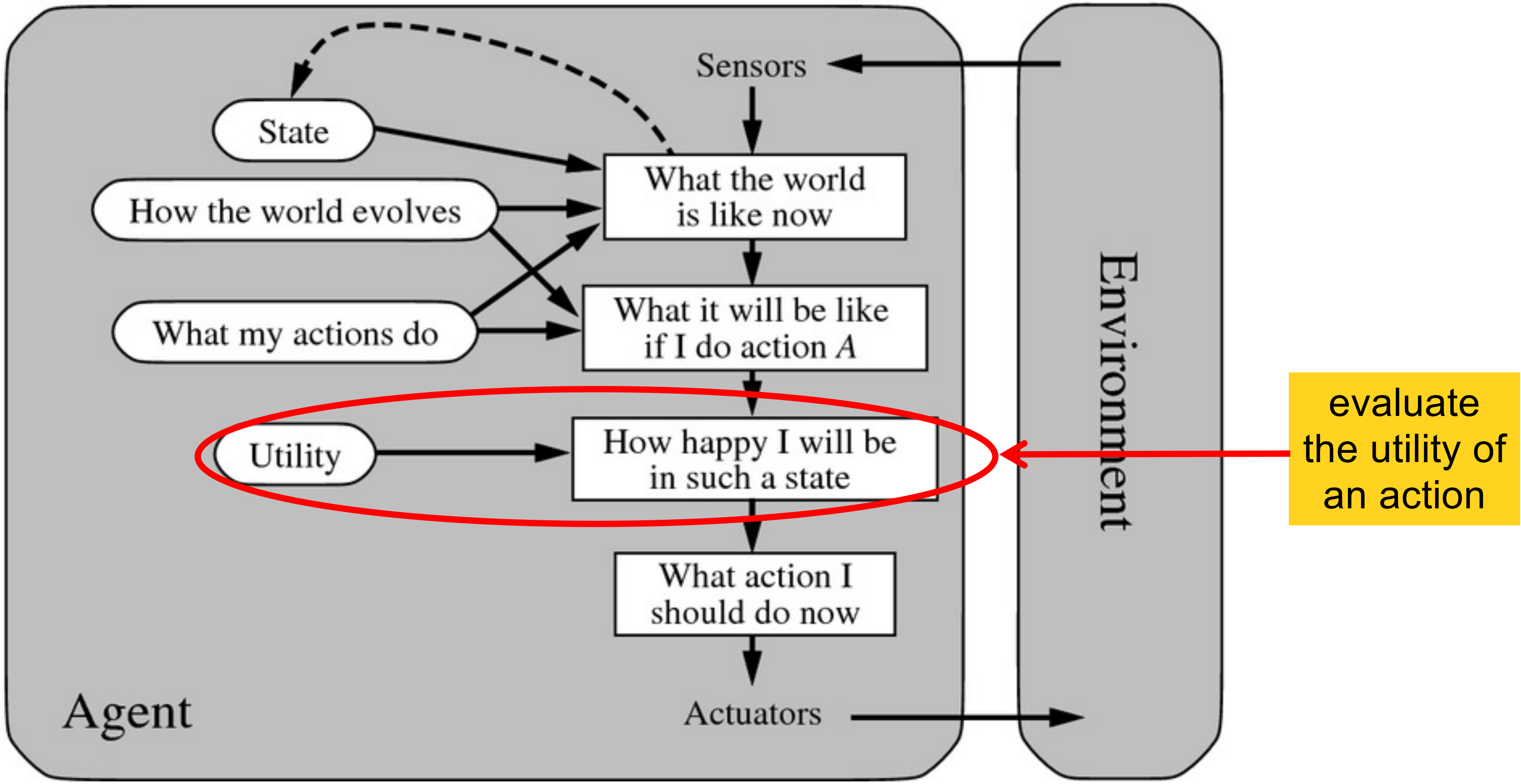


Goal-Based Agent

- the agent knows what states are desirable
  - it will try to choose an action that leads to a desirable state
- things become difficult when long sequences of actions are required to find the goal
  - typically investigated in search and planning research
- main difference to previous approaches
  - decision-making takes future into account
    - “What will happen if I do such-and-such?”
    - “Will this make me happy?”
- is more flexible since knowledge is represented explicitly and can be manipulated
  - changing the goal does not imply changing the entire set of condition-action rules

Utility-Based Agent

- Goals provide just a binary happy/unhappy disctinction
  - utility functions provide a continuous scale



Utility-Based Agent

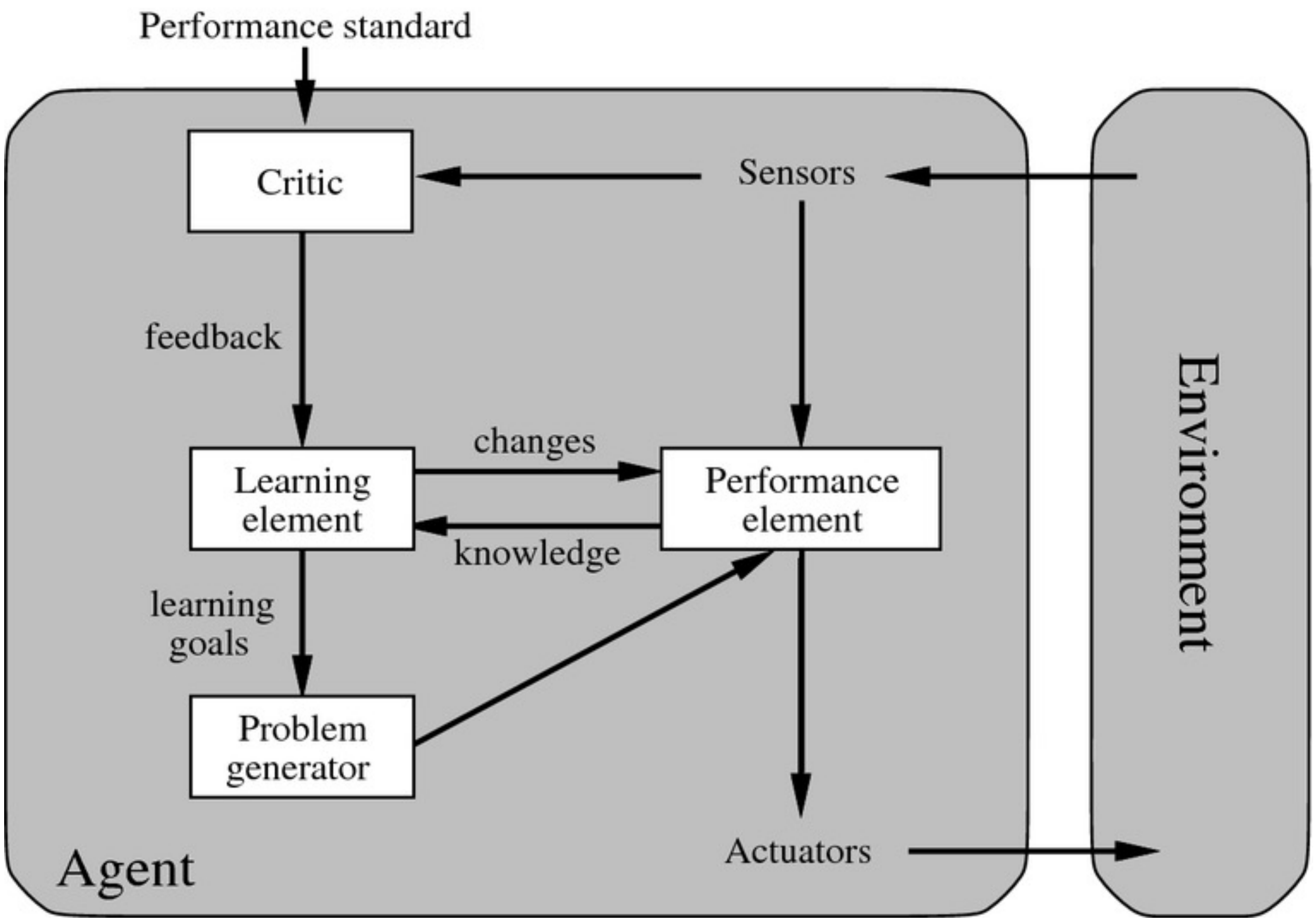
- Goals provide just a binary happy/unhappy disctinction
  - utility functions provide a continuous scale
- Certain goals can be reached in different ways.
  - “Alle Wege führen nach Rom”
  - Some ways are quicker, safer, more reliable, cheaper, ...
    - → have a higher utility
- Utility function
  - maps a state (or a sequence of states) onto a real number
- Improves on goals:
  - selection between conflicting goals (e.g., speed and safety)
  - selection between goals based on trade-off between likelihood of success and importance of goal

Learning

- All previous agent-programs describe methods for selecting actions
  - yet they do not explain the origin of these programs.
- Learning mechanisms can be used for acquiring programs
  - teach them instead of instructing them
  - but you still have to program the learning mechanism!
- Advantage
  - robustness of the program toward initially unknown environments.
- Every part of the previous agents can be improved with learning, but proving things about the learned program might hard(er)

Learning in intelligent agents can be summarized as a process of modification of each component of the agent to bring the components into closer agreement with the available feedback information, thereby improving the overall performance of the agent.

Learning Agent



Learning Agent

- Performance element
  - makes the action selection (as usual)
- Critic
  - decides how well the learner is doing with respect to a fixed *performance standard*
  - necessary because the percepts do not provide any indication of the agent's success
    - e.g., it needs to know that checkmate is bad
- Learning element
  - improves the performance element
  - its design depends very much on the performance element
- Problem generator
  - responsible for *exploration* of new knowledge
    - sometimes try new, possibly suboptimal actions to acquire knowledge about their consequences
  - otherwise only *exploitation* of (insufficient) current knowledges

Big Picture

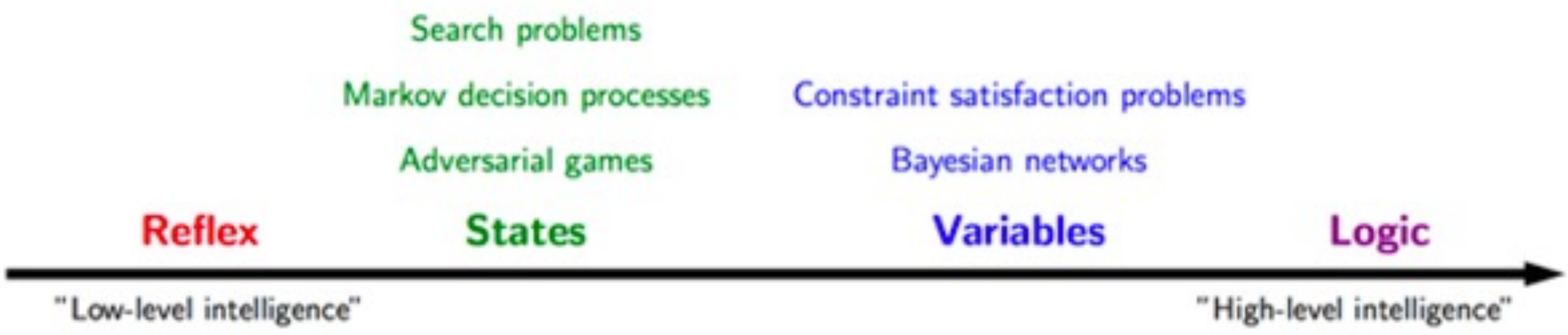


Image due to Percy Liang

As the agents get complex, so does their internal structure. The way in which they store the internal state changes. By its nature, a simple reflex agent does not need to store a state, but other types do.

Atomic representation

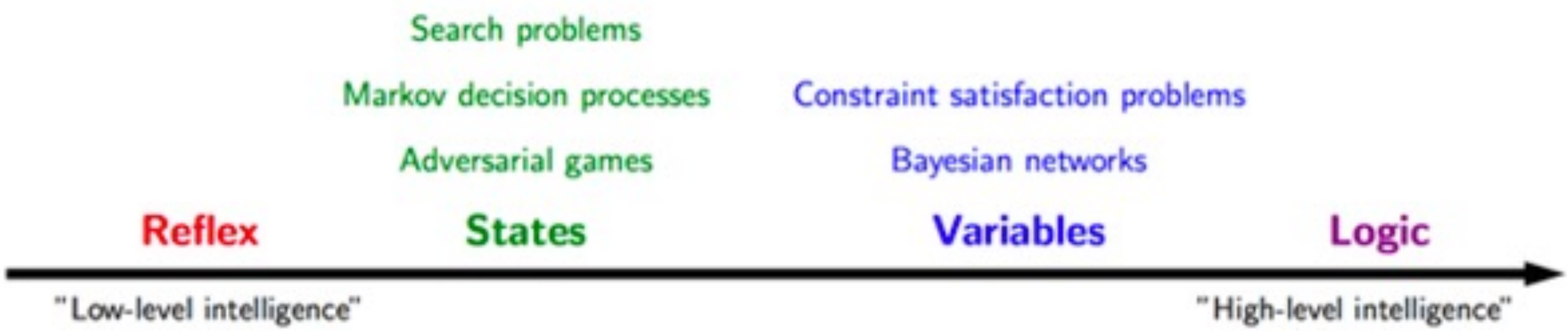


Image due to Percy Liang

State is stored as black box, i.e. without any internal structure.

For example, for Roomba (a robotic vaccum cleaner), the internal state is a patch already vaccumed, you don't have to know anything else. As depicted in the image, such representation works for model and goal based agents and ***used in various AI algorithms such as search problems and adversarial games.***

Factored representation

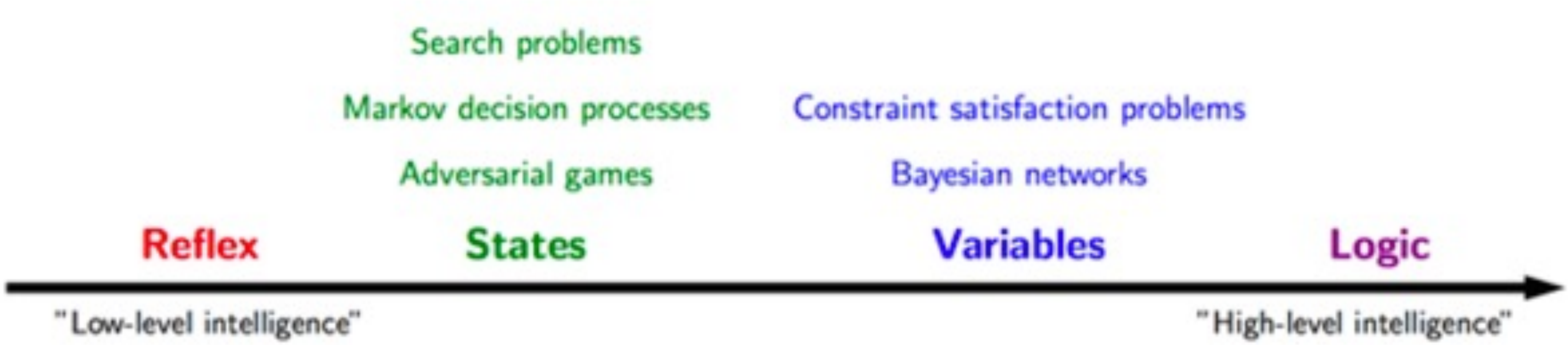


Image due to Percy Liang

State is no longer a black box. *It now has attribute-value pairs, also known as variables that can contain a value*.

For example, while finding a route, you have a GPS location and amount of gas in the tank. This adds a constraint to the problem. Factored representation works for goal based agents and are ***used in various AI algorithms such as constraint satisfaction and bayesian networks, even in deep networks***

Structured representation

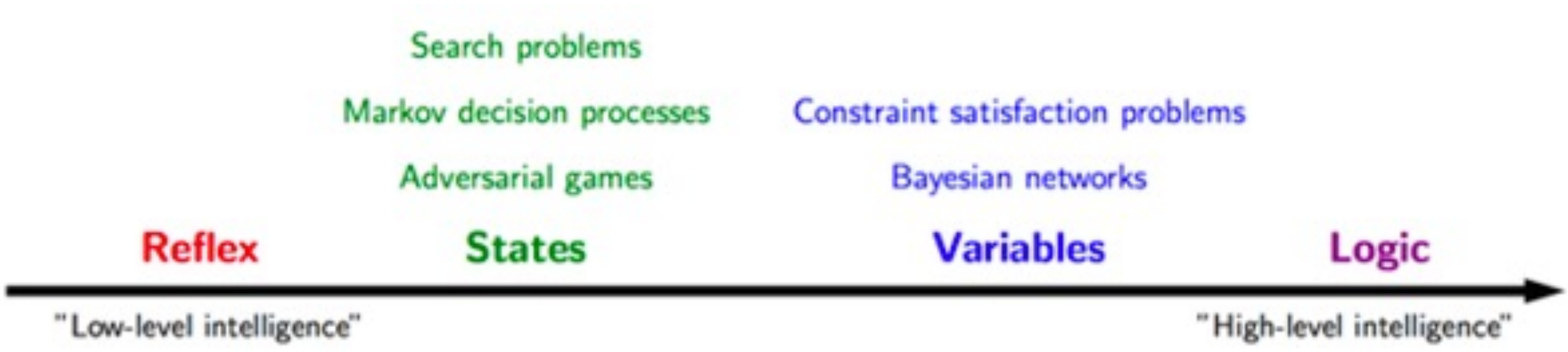


Image due to Percy Liang

Now, *we have relationships between the variables/ factored states. This induces logic in the AI algorithms.*

For example, in natural language processing, the states are whether the statement contains a reference to a person and whether the adjective in that statement represents that person. The relation in these states will decide, whether the statement was a sarcastic one. ***This is high level Artificial Intelligence, used in algorithms like first order logic, knowledge-based learning and natural language understanding. But also in deep networks***