Intelligent Agents (RN Ch. 1 + Ch. 2)

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CMPS3140 – Introduction to Artificial Intelligence

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https://nmattei.github.io/cmps3140/

Many Thanks

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- Jihun Hamm (Tulane University)
- Lirong Xia (RPI)
- K. Brent Venable (IHMC)

All About Agents

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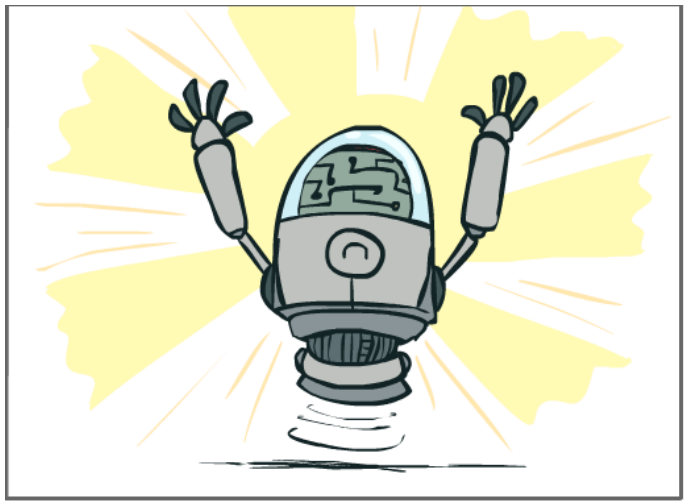
1. Example Agents
    1. Vacuum world
    2. Rationality

2. Task environments
    1. PEAS (Performance measure, Environment, Actuators, Sensors)
    2. Properties of task environments

3. Agent types / architecture



1/3. Agent

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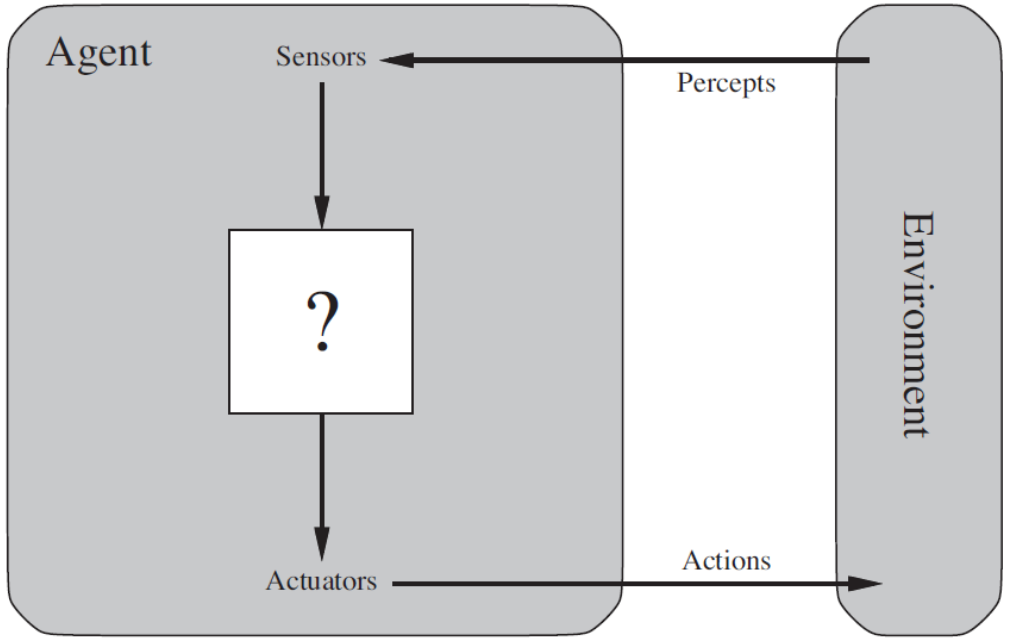
- Agent: Entity that *perceives* and *acts*.

- Formally: An **agent** is anything that can be viewed as **perceiving** its **environment** through **sensors** and **acting** upon that environment through **actuators.**

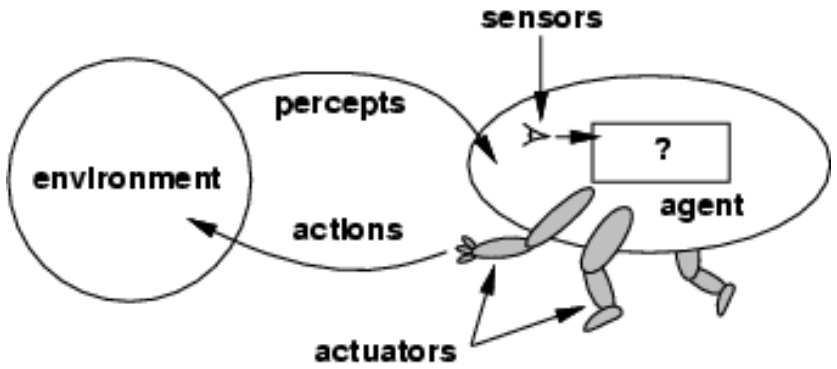
- What is a human agent?
  - Sensors: eyes, ears, touch..
  - Actuators: hands, legs, mouth…
- What is a robotic agent?
  - Sensors: cameras and infrared range finders
  - Actuators: motors, arms, legs..
- What is a software agent?
  - Sensors: image from screen, text search…
  - Actuators: screen, game moves..



1/3. Agent

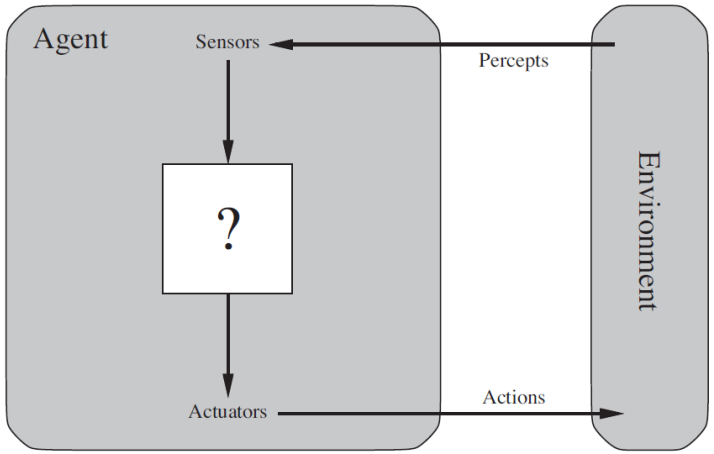
- Agent: Entity that *perceives* and *acts*.

- The **agent function** maps from histories or sequences of percept to actions:
  - *f: P* -> A*



- The **agent program** runs on the physical architecture to produce *f*.

- agent = architecture + program



Vacuum Cleaner World

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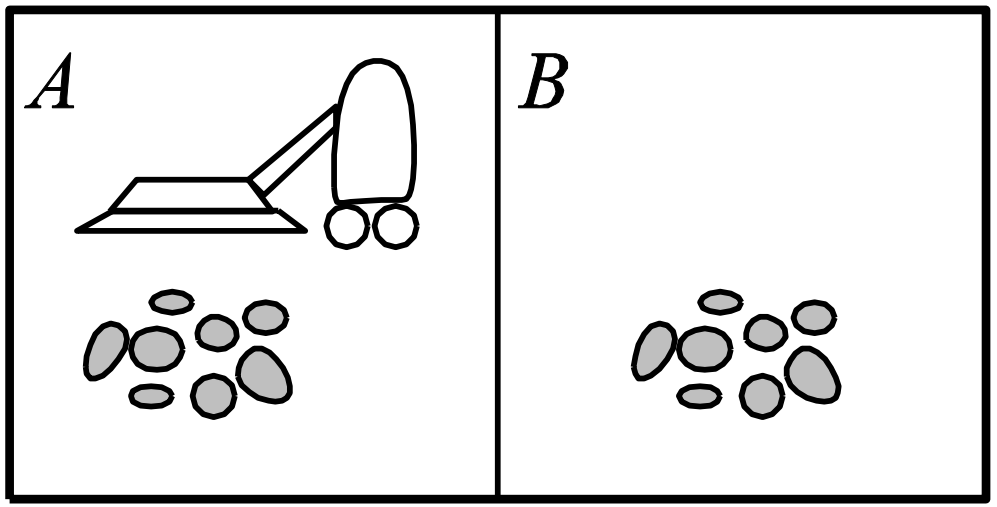
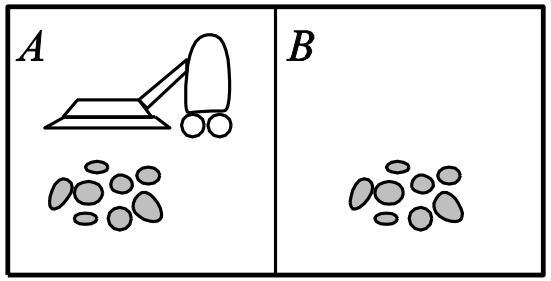
- Two locations (A & B)
- Vacuum agent perceives the location and the presence of dirt at the location
- Vacuum agent can move *left*, *right*, or *suck* dirt



Agent function



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

- An agent is fully characterized by the agent function: *percept sequence* → *action*
- This is an example of a Table Lookup Agent

Agent Functions and Programs

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- An agent is completely specified by the agent function mapping percept sequences to actions
- Aim of AI: design programs that implement the agent functions concisely
  - **Agent = architecture + program**
- Architecture:
  - feeds the percepts from the sensors to the program
  - runs the program
  - feeds the actions to the actuators

```
function TABLE-LOOKUP_AGENT(percept)
returns an action
persistent: percepts, a sequence, initially empty
            table, a table of actions, indexed by percept
                   sequences, initially fully specified
append percept to the end of percepts
action ← LOOKUP(percepts,table)
return action
```

- Drawbacks:
  - Invoked for each new percept
  - Huge table (chess 10^{150} entries)
  - Takes a long time to build the table
  - No autonomy
  - Even with learning, need a long time to learn the table entries
  - Who knows how to build it?!

Evaluating the basic agent

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- An agent should strive to "***do the right thing***", based on what it can perceive and the actions it can perform.
- The right action is the one that will cause the agent to be most successful

- Need a performance measure to evaluate agent's behavior…
  - Maximize amount of dirt picked up?
  - Maximize ratio of dirt to energy expended?
  - Maximize ration of dirt to combination of energy and time?

- Wrong performance measures lead to rational but unwanted outcome
  - Vacuum: Maximize amount of dirt sucked → ?
  - The Matrix/Skynet: End pain and bring peace to the world → ?
    (By the way, Elon Musk donated $10M to keep AI beneficial to humanity, Jan 15, 2015)

Rationality

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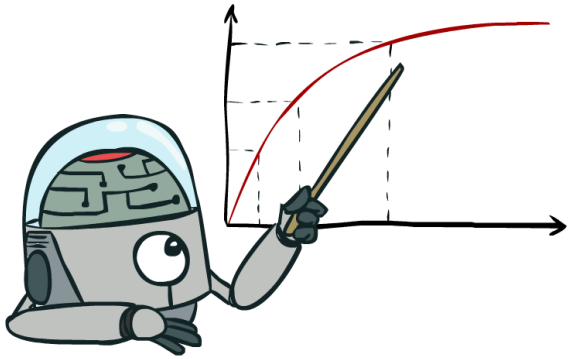
- *Rational Agent: For each possible percept sequence, a rational agent should select an action that is expected to maximize its (expected) performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.*
  - i.e., maximize it's expected utility given everything it knows!



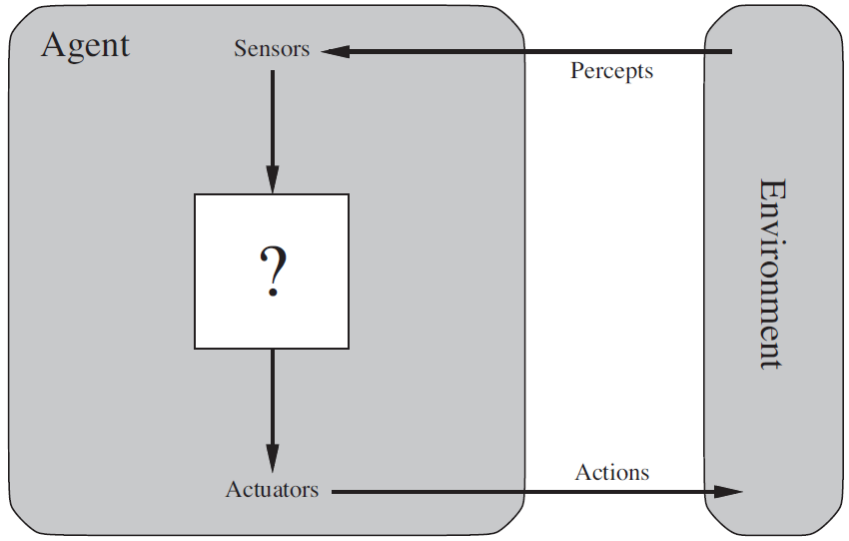
- Rational ≠ omniscient nor clairvoyant
  - Percepts may not supply all relevant information
  - Action outcomes may not be as expected
  - Hence, rational ≠ successful (e.g., lottery)

- The definition of rationality implies that a rational agent should be able to:
  - explore the world to gather more information – use precepts to do new things (**information gathering, exploration**)
  - Ideally: equip an agent with some prior knowledge and the ability to learn
  - autonomous rather than follow what it's designed to do (i.e., that it should learn and adapt with it's experience).

2/3. Task environments

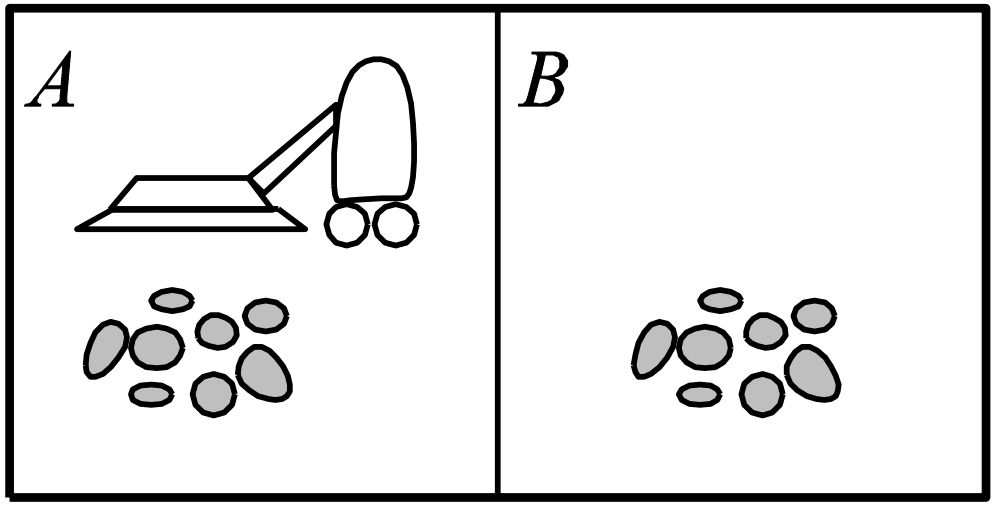
- "Task environment", or simply "task"
  - is the problem we would like to solve
  - involves both the agent and the environment
  - What we design agents as solutions for!

- Task environments are best described by PEAS description
  - P: Performance measure
  - E: Environment
  - A: Actuators (= effectors)
  - S: Sensors



PEAS for vacuum world

- Performance measure
  - Maximize ratio of dirt to energy/time usage
- Environment
  - Two squares A&B, with/without dirt
- Actuators
  - Wheels, vacuum
- Sensors
  - Location, dirt sensor



PEAS for Automated Taxi

- Performance measure
  - Safe, fast, legal, economical, and comfortable trip
- Environment
  - Road, traffic, pedestrian, passenger
- Actuators
  - Steering, accelerator, brake, signal, horn, display
- Sensors
  - Cameras, rangefinder, speedometer, GPS, odometer, accelerometer, etc.

PEAS: Medical Diagnosis System

- Performance measure
  - Healthy patient, minimize costs, lawsuits
- Environment
  - Patient, hospital, staff
- Actuators
  - Screen display for questions, tests, diagnoses, treatments, referrals
- Sensors
  - Keyboard (entry of symptoms, findings, patient's answers)

Take out a Piece of Paper

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- Get a partner or two around you…
  - Put everyone's name on the paper!

- Determine PEAS for the following "known" intelligent agents
  - Airplane autopilot
  - Recommender System (e.g. Amazon's)
  - Siri
  - Watson (Jeopardy)
  - Deepblue (Chess)

Properties of task environments

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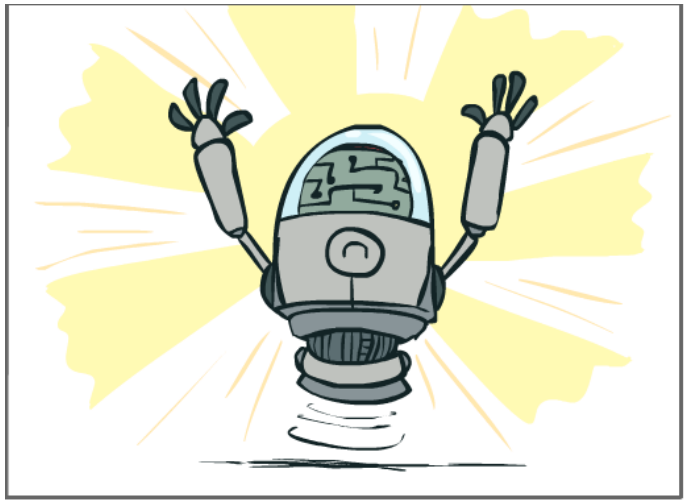
- PEAS describes the basics components of a task environment

- To design the agent, the properties of the task environment should be further analyzed:

  - Fully, partially, or not observable
  - Deterministic or stochastic
  - Single or multi-agent
  - Episodic or sequential
  - Static or dynamic
  - Discrete or continuous
  - Known or unknown



Properties of task environments

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- Observability - Can the agent get all **relevant** information from the environment using its sensors? (Not all information)

- If an agent's sensors give it access to the complete state of the environment at each point in time.
  - No need for an internal state of the world

- Fully observable
  - Chess: Positions of all the playing pieces
  - AI enemy in first-person shooter video game
- Partially observable
  - Poker: Only the cards in your hand
  - "You" in first-person shooter game
- Unobservable
  - No sensor at all

Properties of task environments

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- Deterministic vs Stochastic: Is the next state of the world **determined completely** by the current state of the world and the **action** executed by the agent?

- **Deterministic:** only determined by current state and action of the agent.
- **Stochastic:** There is uncertainty on the next state and it is expressed with probabilities.

- Vacuum world
  - Deterministic: suction and motor wheels always work
  - Stochastic: unreliable suction and/or motor wheels
- Chess: deterministic, except for the actions of other agents
- Automated taxi: stochastic

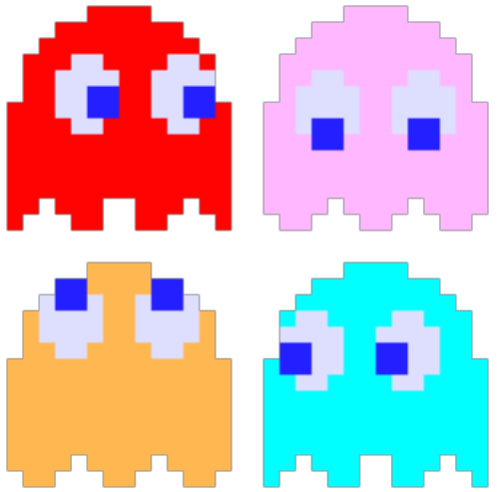
- **Non-Deterministic:** there is uncertainty but no probabilities (e.g., all possible goals).
- **Uncertain:** not fully observable and non-deterministic.

Properties of task environments

- Single vs Multi-agent: Is the agent operating by itself in an environment or are there others?

- Competitive: two agents are competing against each other.
- Cooperative: two agents are working together for a common goal.
- Mixed: ??

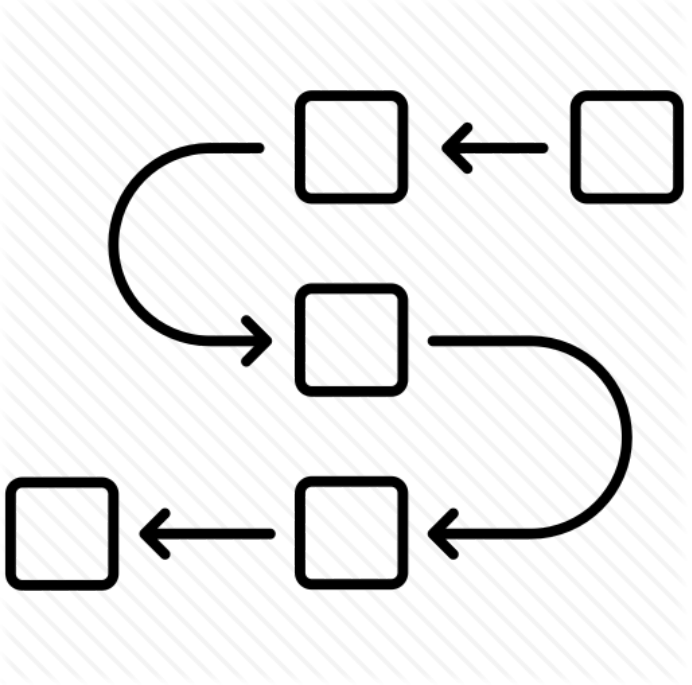
- We sometimes call an environment **strategic** if everything about the environment is **deterministic except for the actions of other agents.**
  - Example??



Properties of task environments

- Episodic V. Sequential

- The agent's experience is divided into **atomic "episodes"** (each episode consists of the agent **perceiving** and then performing a single **action**), and the choice of action in each episode depends only on the episode itself.
- In sequential environments a current decision may affect future decisions



- Episodic: current action affects only the current episode.
  - E.g., a single recommendation.

- Sequential: future episodes as well
  - e.g., chess, or taxi driving, or pacman

Properties of Task Environments

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- Static vs. Dynamic

- What happens to the environment during deliberating?

- **Static:** time halts while agent makes a decision – no need to keep looking at the world or worry about time.
  - Turn-based games (e.g., Monopoly)

- **Dynamic:** world changes on while agent decides
  - Pac-man
- Semi-dynamic: world stands still, but decision time has an effect on performance score
  - Tournament-level chess

Properties of Task Environments

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- Discrete vs. Continuous: How is time handled in the environment?
- Discrete: A **finite number** of distinct, clearly defined states, percepts and actions.
- Continuous: Sweep through a range of values smoothly over time.
  - Is time handled in chunks or continuously?
  - Is a state … ?
  - Is an action … ?
  - Examples: chess vs automated taxi

Properties of task environments

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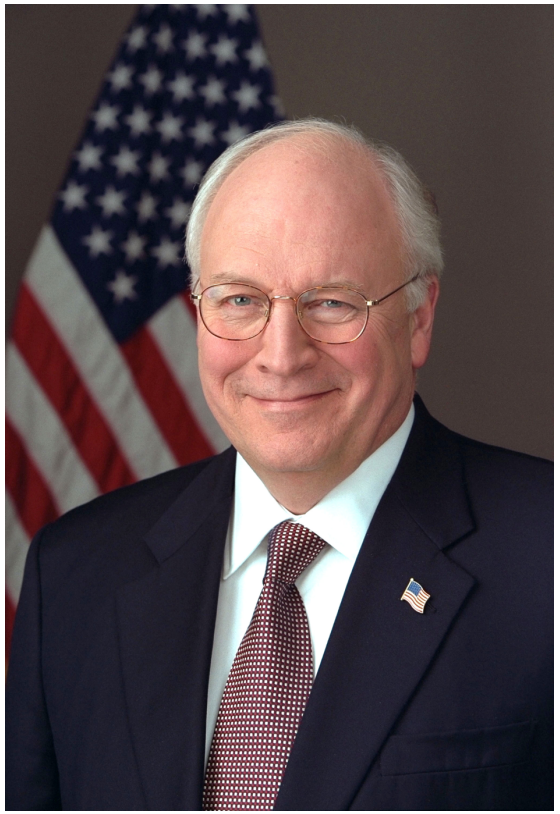
- Known vs. Unknown.
  - What is the knowledge of the agent or the designer of the agent with respect to the rules governing the environment.



- Known: agent knows how its action affects the state of the world (e.g., chess)
  - Deterministic: known outcome
  - Stochastic: probability distribution

- Unknown: environment is unknown to agent (more in Part 3, reinforcement learning)
  - We show it a game but don't tell it the rules.

- An environment can also be
  - known and partially observable (for example, a card game)
  - unknown and fully observable (a videogame)

Examples of task environments

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Robot soccer						
Internet book-shopping						
Autonomous Mars rover						

Examples

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Robot soccer	Partially	Stochastic	Sequential	Dynamic	Continuous	Multi
Internet book-shopping						
Autonomous Mars rover						

- Internet book-shopping: buying a used AI textbook online
  - P: quality/price
  - E: used book sales websites (Ebay, Amazon, Craigslist, etc)
  - A: clicking links or buttons
  - S: web-browser

Examples

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Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Robot soccer	Partially	Stochastic	Sequential	Dynamic	Continuous	Multi
Internet book-shopping	Partially	Deterministic*	Sequential	Static*	Discrete	Single
Autonomous Mars rover						

- Internet book-shopping
  - Sequential? Episodic?
  - Static? Dynamic?
  - Single-agent? Multi-agent?
- No absolutely correct answer; depends on how to formulate the task

Examples

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Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Robot soccer	Partially	Stochastic	Sequential	Dynamic	Continuous	Multi
Internet book-shopping	Partially	Deterministic*	Sequential	Static*	Discrete	Single
Autonomous Mars rover	Partially	Stochastic	Sequential	Dynamic	Continuous	Single

Examples

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Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Robot soccer	Partially	Stochastic	Sequential	Dynamic	Continuous	Multi
Internet book-shopping	Partially	Deterministic*	Sequential	Static*	Discrete	Single
Autonomous Mars rover	Partially	Stochastic	Sequential	Dynamic	Continuous	Single

- Real world problems:
  - partially observable, stochastic, sequential, dynamic, continuous, multi-agent
- Properties of the task environment largely determines the agent design

3/3. Agent architecture

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- Five different designs of agents
  - Reflex agent
  - Model-based reflex agent
  - Goal-based agent
  - Utility-based agent
  - Learning agent

Reflex agent

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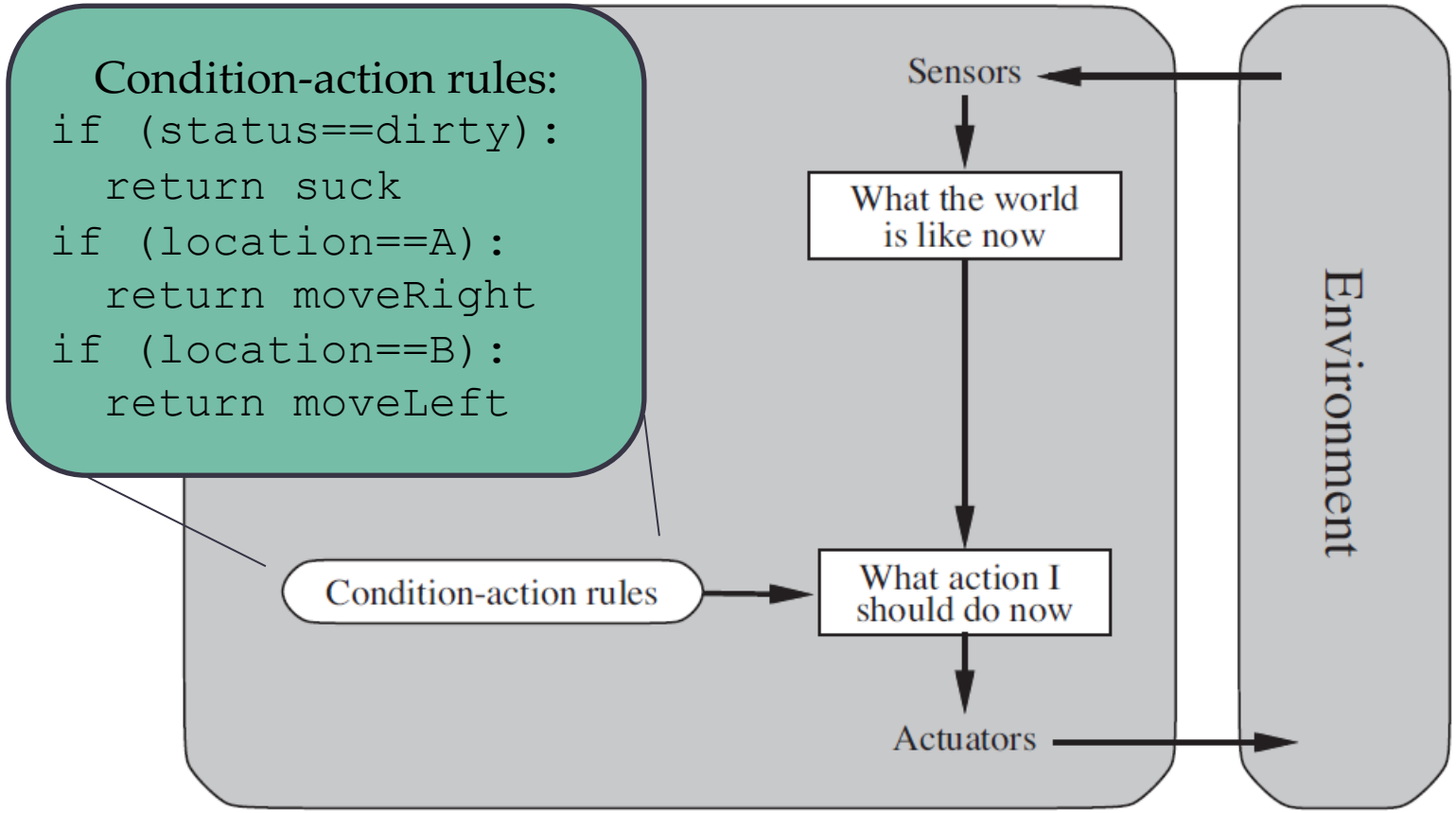
- Simplest kind of agents
- Choose action based on the current percept, ignoring the percept history
- Useful as a sub-agent of a bigger agent
  - Biological examples:
  - Closing eyes when something approaches eyes
  - Move the hand away when it touches something hot

- They work if the choice of the action **depends only on the current percept**
- That is, if the environment is fully observable
- Example: What happens to the vacuum deprived of the location sensor?

Reflex agent



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

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

Model-based reflex agent

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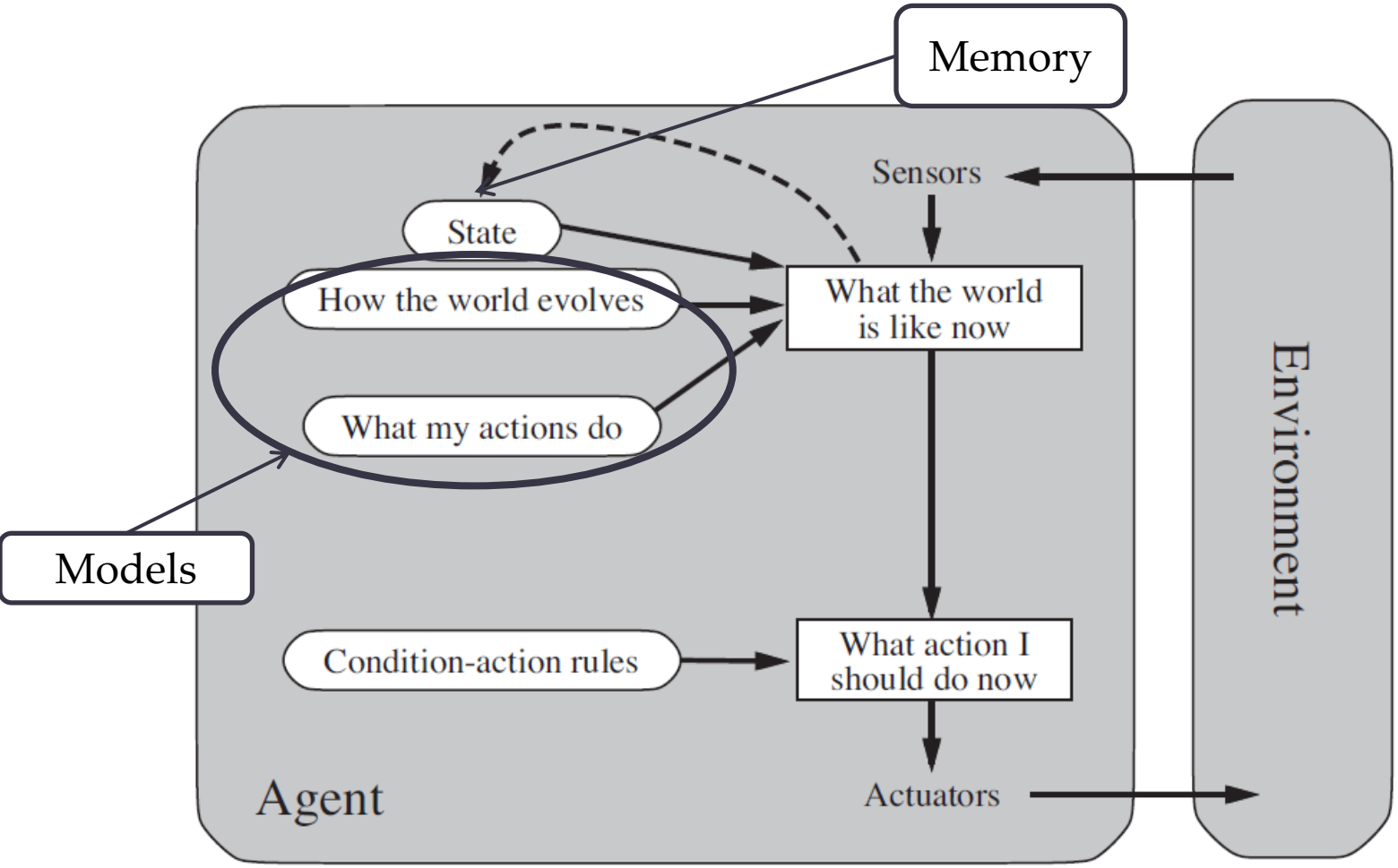
- In partially observable task environments
  - Need to keep track of unseen portions of the world
- Memory
  - Internal state: depends on the sequence of percepts
  - guess of unobserved portions
- Models
  - How the world evolves
  - What my actions do
- Examples
  - Navigating through a maze
  - Passing a car in a single-lane road
- Current state of a partially observable environment is usually not exact
- May be described succinctly

Model-based reflex agent



function MODEL-BASED-REFLEX-AGENT (*percept*)
returns an action

persistent: *state*, the agent's current conception of the world state
model, a description of how the next state depends on current state and action
rules, set of condition-action pairs
action, the most recent action, initially none

state ← UPDATE-STATE(*state, action, percept, model*)
rule ← RULE-MATCH(*state,rules*)
action ← rule.ACTION
return *action*

Goal-based agent

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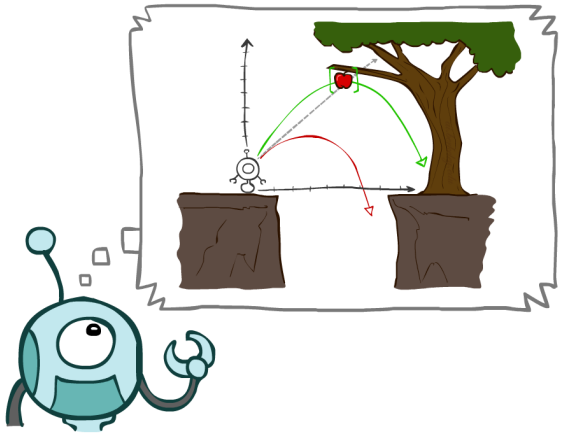
- Sometimes knowing the state of the environment isn't enough.
  - Information on goal is necessary.

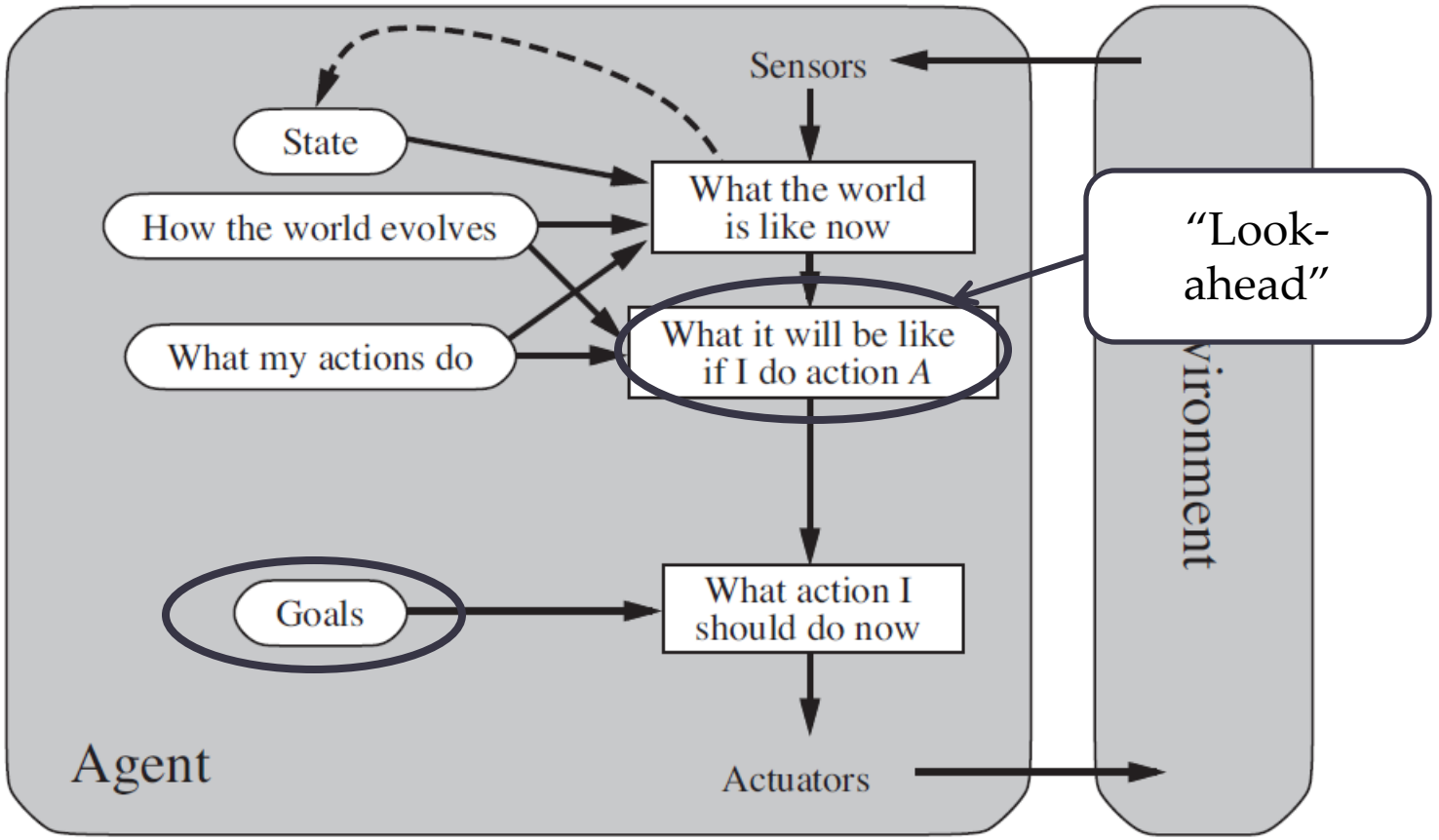


- Best current action is chosen by higher-level goals, not just the current percept
  - Goal: "arriving at destination x" for automated taxi
- Find a sequence of actions to achieve the goal
  - Actions: "left turn, drive 0.5 mile, right turn, drive 1.2 miles,…"

- Main design for Part 1 of the course – search and planning: find an action sequence that achieves a goal.

- Goal driven agents are flexible as they don't require rewriting with the condition rules or goal or space change.

Goal-based agent



Utility-based agent

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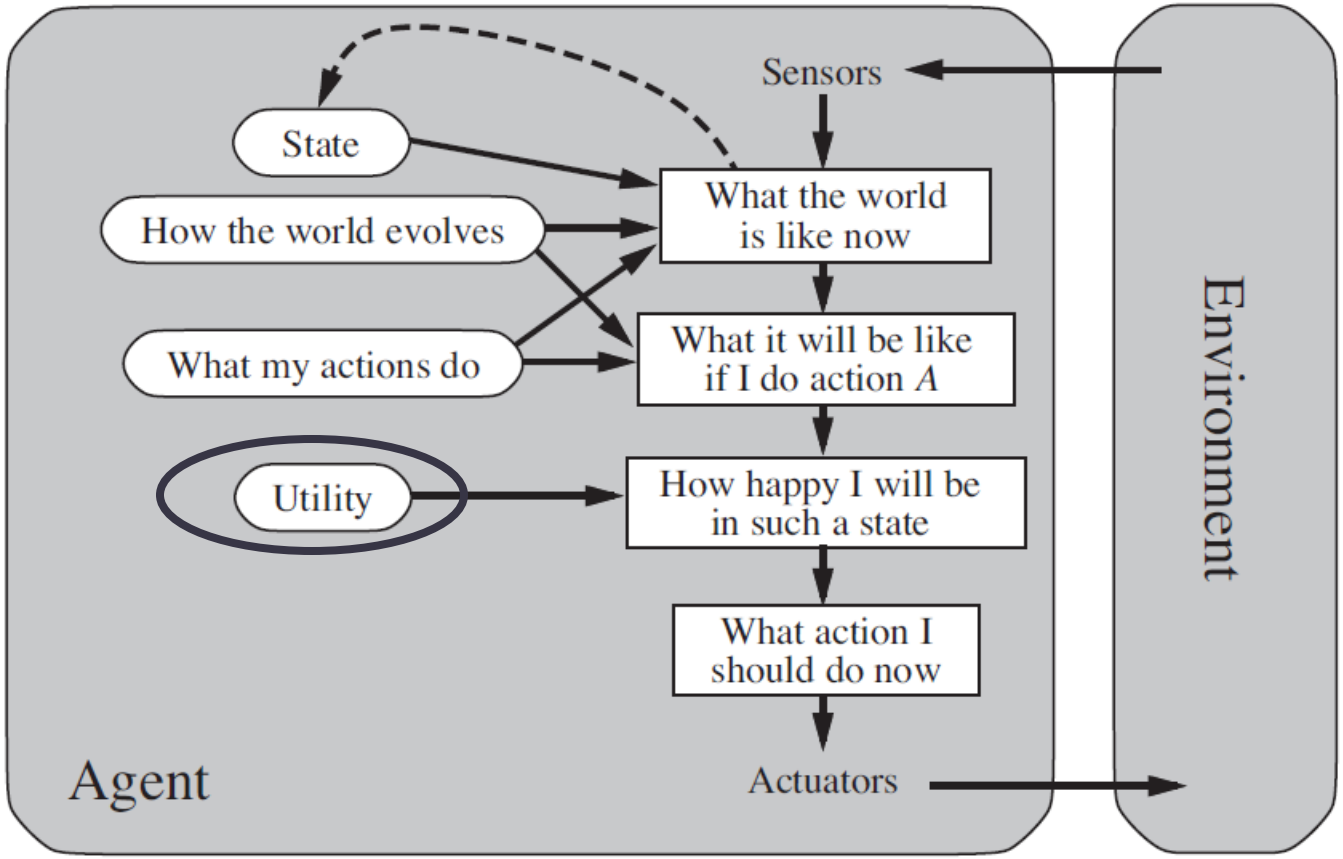
- Goal-based agent: successful or not
  - But not all ways to achieve goals are equally good!
  - How satisfied? --> utility function: represents an performance measure of the level

- Multiple goals: taxi
  - Goal 1: arrive at destination
  - Goal 2: minimize time/fuel consumption
  - Goal 3: passenger safety/comfort
- Utility can resolve multiple conflicting goals
  - Maximize the utility as the weight sum of multiple goals
- Furthermore, if the environment task is stochastic, maximize the *expected* utility

- More in depth in Part 3 Utility theory

Utility-based agent

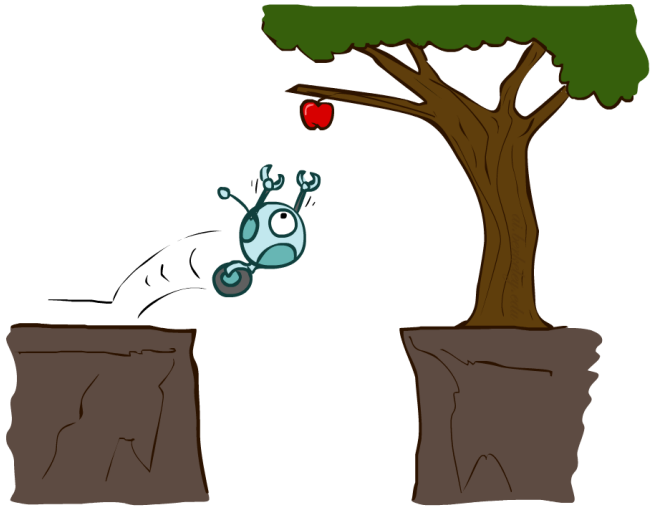


Learning agent

- From the early stages of AI, it became clear that programming agents able to learn and to teach them might often be a better option that programming intelligence directly

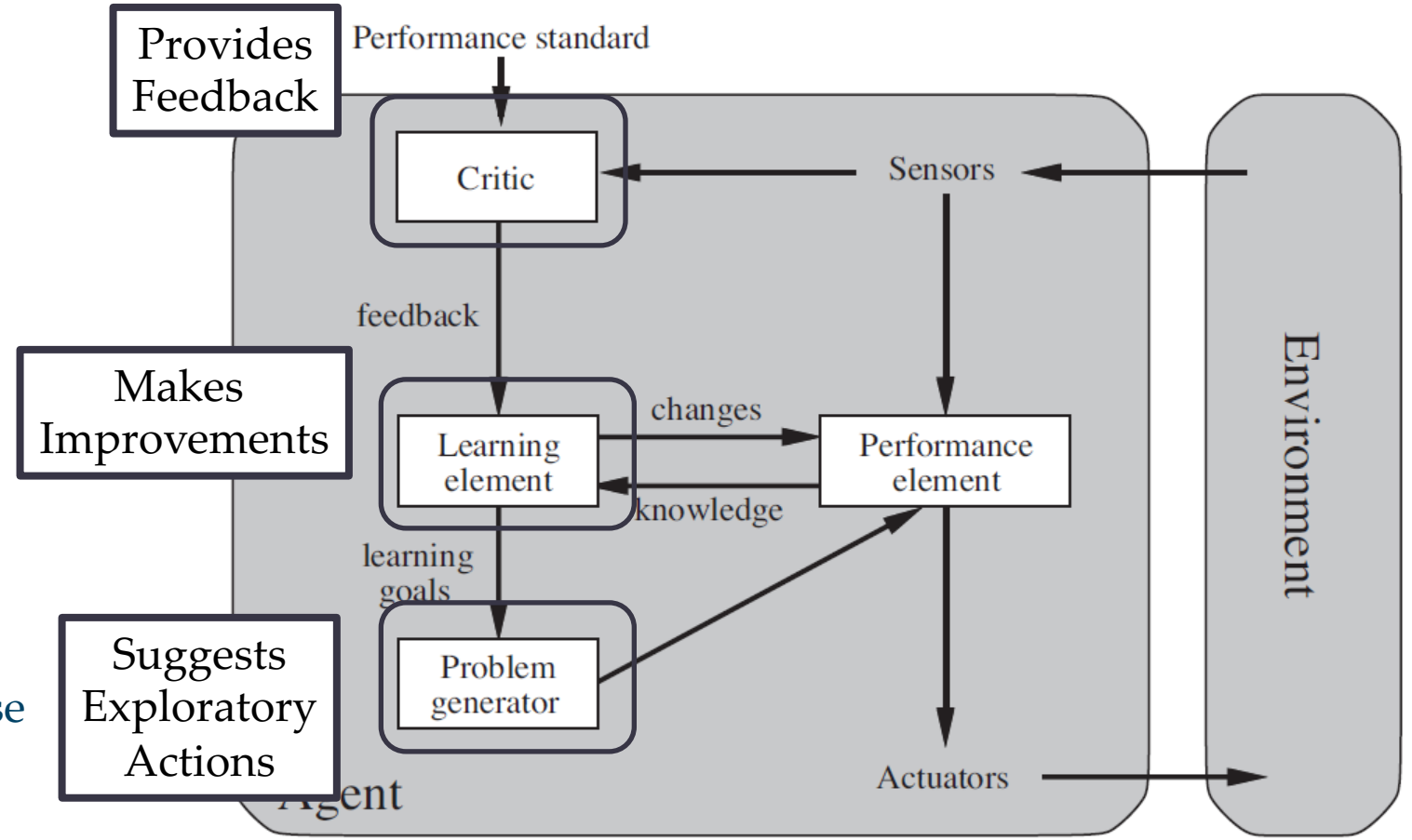
- If we have intermediate feedbacks (in addition to final performance measure) on the agent's performance, use it to refine the agent function
- Components of a learning agent
  - Performance element (=non-learning part)
  - Critic
  - Learning element: adjust behavior
  - Problem generator: exploration

- More in depth in Part 3 on RL!



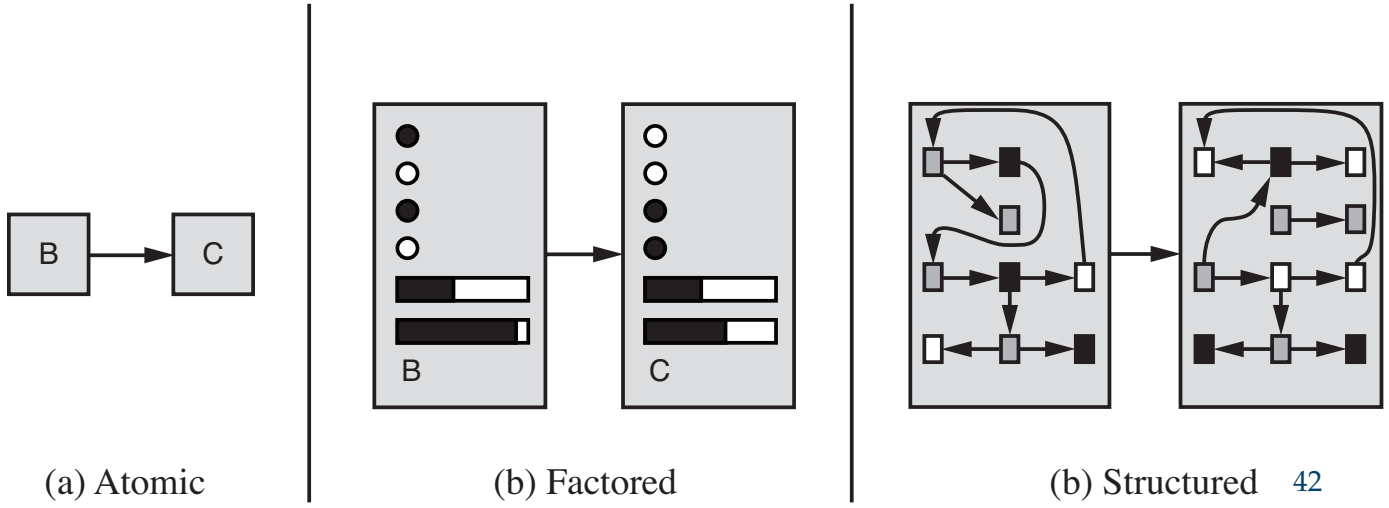
Learning agent

- Components of a learning agent
  - **Learning element**: responsible for making improvements
    - can change any component of the agent
  - **Performance element**: the actual agent
  - **Critic**: assesses how well the agent is performing w.r.t. a fixed performance standard (e.g. checkmate is good)
    - May be adapted to take utility into account and to enable the learning of utility information
  - **Problem generator**: generates actions that yield an information gain (otherwise the ones that are best given the current knowledge would always be chosen)
    - May suggest suboptimal actions which lead to find better actions in the long run



A Note About Problem Representations

- **Atomic representation:** each state of the world is indivisible and has no internal structure (possibly only from the agent view).
  - E.g., directions only by the name of a location.
  - mainly used by search agents and can be powerful (also MPSs and HMMs).
- **Factored representation:** each state has a fixed set of variables or attributes each with a value.
  - E.g., same GPS location but gas/no gas.
  - Used for many things classification, CSPs, propositional logic, planning.
- **Structured representation:** each state is has variables and attributes and we know relations between these objects.
  - E.g., cow in road in front of truck
  - mainly used by planning agents but also first order logic and relationships!
- Tradeoff: expressivity v. space!



(a) Atomic (b) Factored (b) Structured