CS 4700:
Foundations of Artificial Intelligence

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Structure of intelligent agents and environments

R&N: Chapter 2

Outline

Characterization of agents and environments

- **Rationality**
- **PEAS (Performance measure, Environment, Actuators, Sensors)**

Environment types

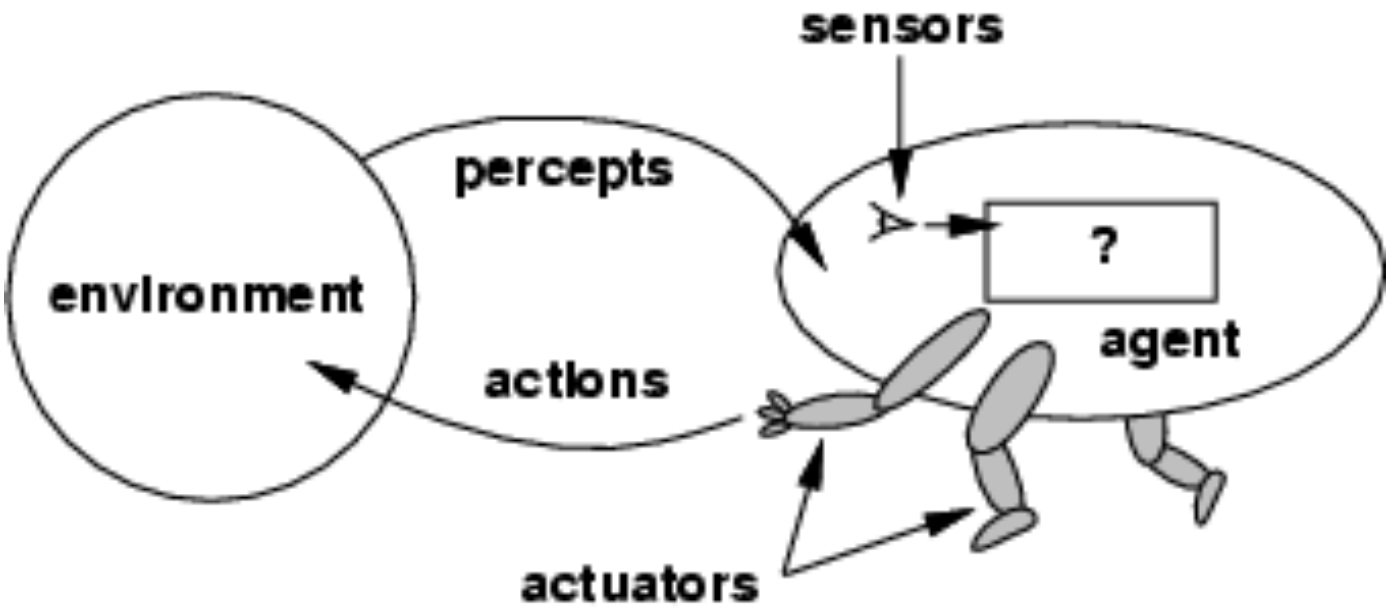
Agent types

Intelligent agent-view provides framework to integrate the many subareas of AI.

Warning: Chapter 2 is somewhat high-level and abstract. Much of the technical framework of how intelligent agents are actually built is introduced later.

Agents

Definition: An agent perceives its environment via sensors and acts upon that environment through its actuators



The agent view is really quite generic.

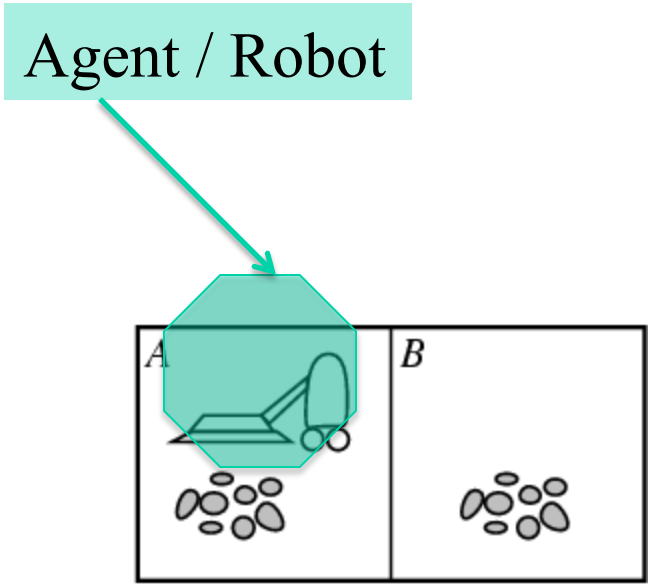
p. 36 R&N:

> **In a sense, all areas of engineering can be seen as designing artifacts that interact with the world. AI operates that end of the spectrum, where the artifacts use significant computational resources and the task and environment requires non-trivial decision making.**

But, the definition of "agents" does technically also include, e.g., calculators or cars, artifacts with very limited to no intelligence. (Self-driving cars come closer to what we view as intelligent agents.)

Next: definition of rational agents. Sufficiently complex rational agents can be viewed as "intelligent agents."

E.g., vacuum-cleaner world



Percepts: location and contents,
e.g., [A, Dirty]

Actions: *Left*, *Right*, *Suck*, *NoOp*

iRobot Roomba® 400
Vacuum Cleaning Robot

iRobot Corporation

Founder Rodney Brooks (MIT)

- Powerful suction and rotating brushes
- Automatically navigates for best cleaning coverage
- Cleans under and around furniture, into corners and along wall edges
- Self-adjusts from carpets to hard floors and back again
- Automatically avoids stairs, drop-offs and off-limit areas
- Simple to use— just press the Clean button and Roomba does the rest

Rational agents

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

Performance measure: An *objective criterion for success* of an agent's behavior.

Performance measures of a vacuum-cleaner agent: amount of dirt cleaned up, amount of time taken, amount of electricity consumed, level of noise generated, etc.

Performance measures self-driving car: time to reach destination (minimize), safety, predictability of behavior for other agents, reliability, etc.

Performance measure of game-playing agent: win/loss percentage (maximize), robustness, unpredictability (to “confuse” opponent), etc.

Definition of Rational Agent:

For each possible percept sequence, a rational agent should select an action that maximizes its performance measure (in expectation) given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.

Why "in expectation"?

Captures actions with stochastic / uncertain effects or actions performed in stochastic environments.
We can then look at the expected value of an action.

In high-risk settings, we may also want to limit the worst-case behavior.

Rational agents

Notes:

Rationality is distinct from omniscience ("all knowing"). We can behave rationally even when faced with incomplete information.

Agents can perform actions in order to modify future percepts so as to obtain useful information: information gathering, exploration.

An agent is autonomous if its behavior is determined by its own experience (with ability to learn and adapt).

Characterizing a Task Environment

Must first specify the setting for intelligent agent design.

PEAS: Performance measure, Environment, Actuators, Sensors

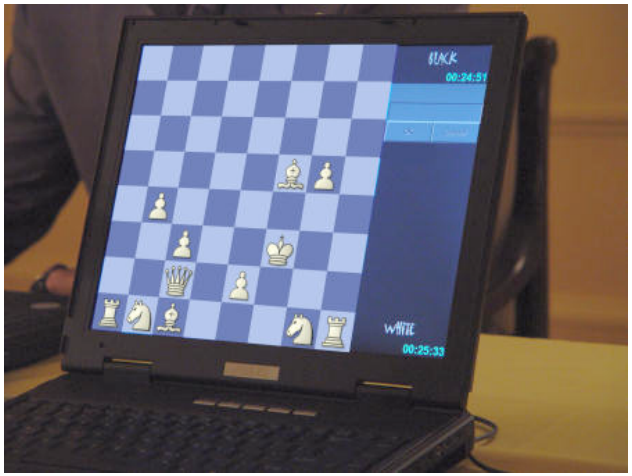
Example: the task of designing a self-driving car

- **Performance measure** Safe, fast, legal, comfortable trip
- **Environment** Roads, other traffic, pedestrians
- **Actuators** Steering wheel, accelerator, brake, signal, horn
- **Sensors** Cameras, LIDAR (light/radar), speedometer, GPS, odometer engine sensors, keyboard

Task Environments

1) Fully observable / Partially observable

- **If an agent's sensors give it access to the complete state of the environment needed to choose an action, the environment is fully observable.**
  (e.g. chess – what about Kriegspiel?)



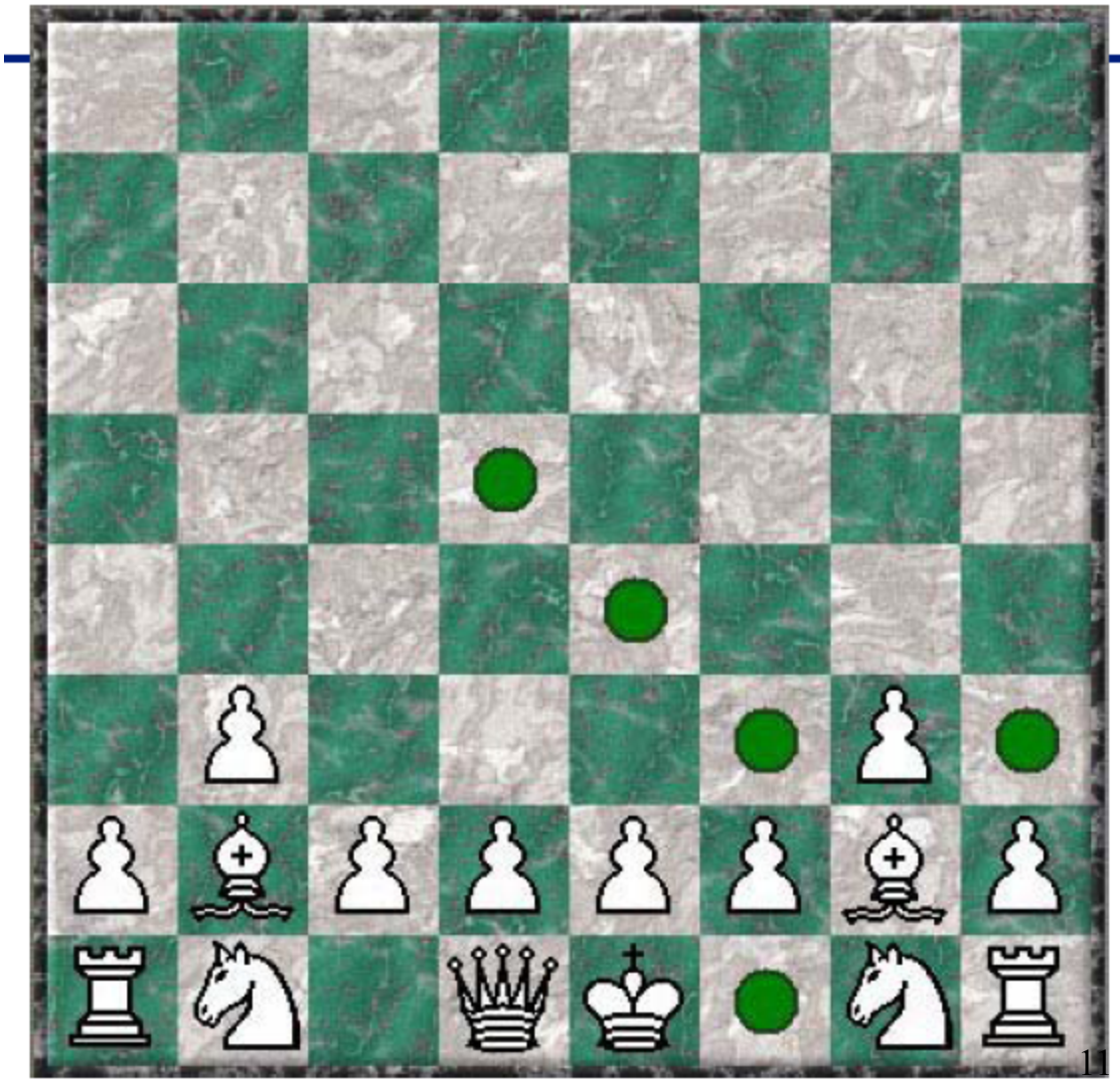
Incomplete / uncertain information inherent in the game.

Balance exploitation (best move given current knowledge) and exploration (moves to explore where opponent's pieces might be).

Use probabilistic reasoning techniques.

Making things a bit more challenging…

Kriegspiel --- you can't see your opponent!



2) Deterministic / Stochastic

- An environment is deterministic if the next state of the environment is completely determined by the current state of the environment and the action of the agent;
- In a stochastic environment, there are multiple, unpredictable outcomes. (If the environment is deterministic except for the actions of other agents, then the environment is strategic).

In a fully observable, deterministic environment, the agent need not deal with uncertainty.

Note: Uncertainty can also arise because of computational limitations. E.g., we may be playing an omniscient ("all knowing") opponent but we may not be able to compute his/her moves.

3) Episodic / Sequential

- In an episodic environment, the agent's experience is divided into atomic episodes. Each episode consists of the agent perceiving and then performing a single action.

- Subsequent episodes do not depend on what actions occurred in previous episodes. Choice of action in each episode depends only on the episode itself. (E.g., classifying images.)

- In a sequential environment, the agent engages in a series of connected episodes. Current decision can affect future decisions. (E.g., chess and driving)

4) Static / Dynamic

- A static environment does not change while the agent is thinking.

- The passage of time as an agent deliberates is irrelevant.

- The environment is semidynamic if the environment itself does not change with the passage of time but the agent's performance score does.

5) Discrete / Continuous

- If the number of distinct percepts and actions is limited, the environment is discrete, otherwise it is continuous.

6) Single agent / Multi-agent

- If the environment contains other intelligent agents, the agent needs to be concerned about strategic, game-theoretic aspects of the environment (for either cooperative *or* competitive agents).
- Most engineering environments don't have multi-agent properties, whereas most social and economic systems get their complexity from the interactions of (more or less) rational agents.

Example Tasks and Environment Types

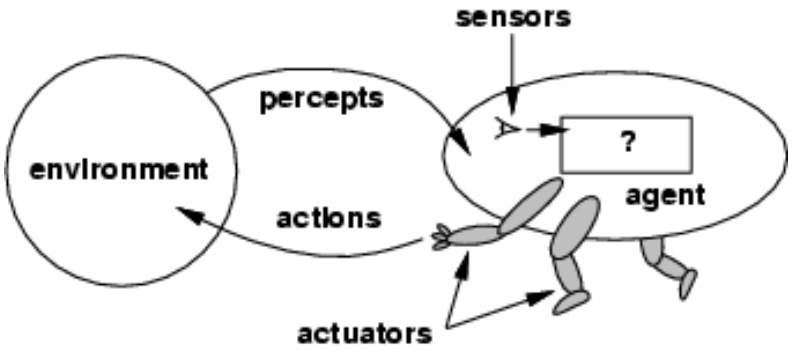
	Chess with a clock	Chess without a clock	Taxi driving
Fully observable	Yes	Yes	No
Deterministic	Strategic	Strategic	No
Episodic	No	No	No
Static	Semi	Yes	No
Discrete	Yes	Yes	No
Single agent	No	No	No

The environment type largely determines the agent design

The real world is (of course) partially observable, stochastic, sequential, dynamic, continuous, multi-agent

How to make the right decisions? **Decision theory**

Agents and environments



The agent function maps from percept histories to actions

$$f: \mathcal{P}^* \rightarrow \mathcal{A}$$

The agent program runs (internally) on the physical architecture to produce f

agent = architecture + program

our focus

Design an agent program assuming an archictecture that will make the percepts from the sensors available to the program.

Types of Agents

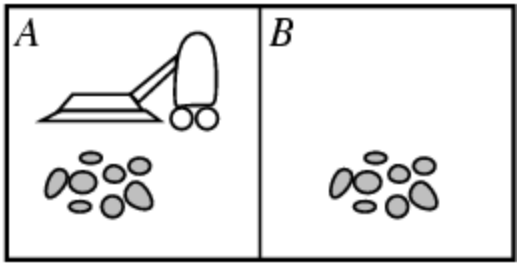
I) --- Table-lookup driven agents

Uses a percept sequence / action table in memory to find the next action. Implemented as a (large) lookup table.

Drawbacks:

- **Huge table (often simply too large)**
- **Takes a long time to build/learn the table**

Toy example: Vacuum world.



Percepts: robot senses it's location and "cleanliness."

So, location and contents, e.g., [A, Dirty], [B, Clean].

With 2 locations, we get **4 different possible sensor inputs.**

Actions: *Left*, *Right*, *Suck*, *NoOp*

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*
⋮	⋮
[*A*, *Clean*], [*A*, *Clean*], [*A*, *Clean*]	*Right*
[*A*, *Clean*], [*A*, *Clean*], [*A*, *Dirty*]	*Suck*
⋮	⋮

Figure 2.3 Partial tabulation of a simple agent function for the vacuum-cleaner world shown in Figure 2.2.

Table lookup

Action sequence of length K, gives 4^K different possible sequences. At least many entries are needed in the table. So, even in this very toy world, with K = 20, you need a table with over 4^20 > 10^12 entries.

In more real-world scenarios, one would have many more different percepts (eg many more locations), e.g., >=100. There will therefore be 100^K different possible sequences of length K. For K = 20, this would require a table with over 100^20 = 10^40 entries. Infeasible to even store.

So, table lookup formulation is mainly of theoretical interest. For practical agent systems, we need to find much more compact representations. For example, logic-based representations, Bayesian net representations, or neural net style representations, or use a different agent architecture, e.g., "ignore the past" --- Reflex agents.

II) --- Simple reflex agents

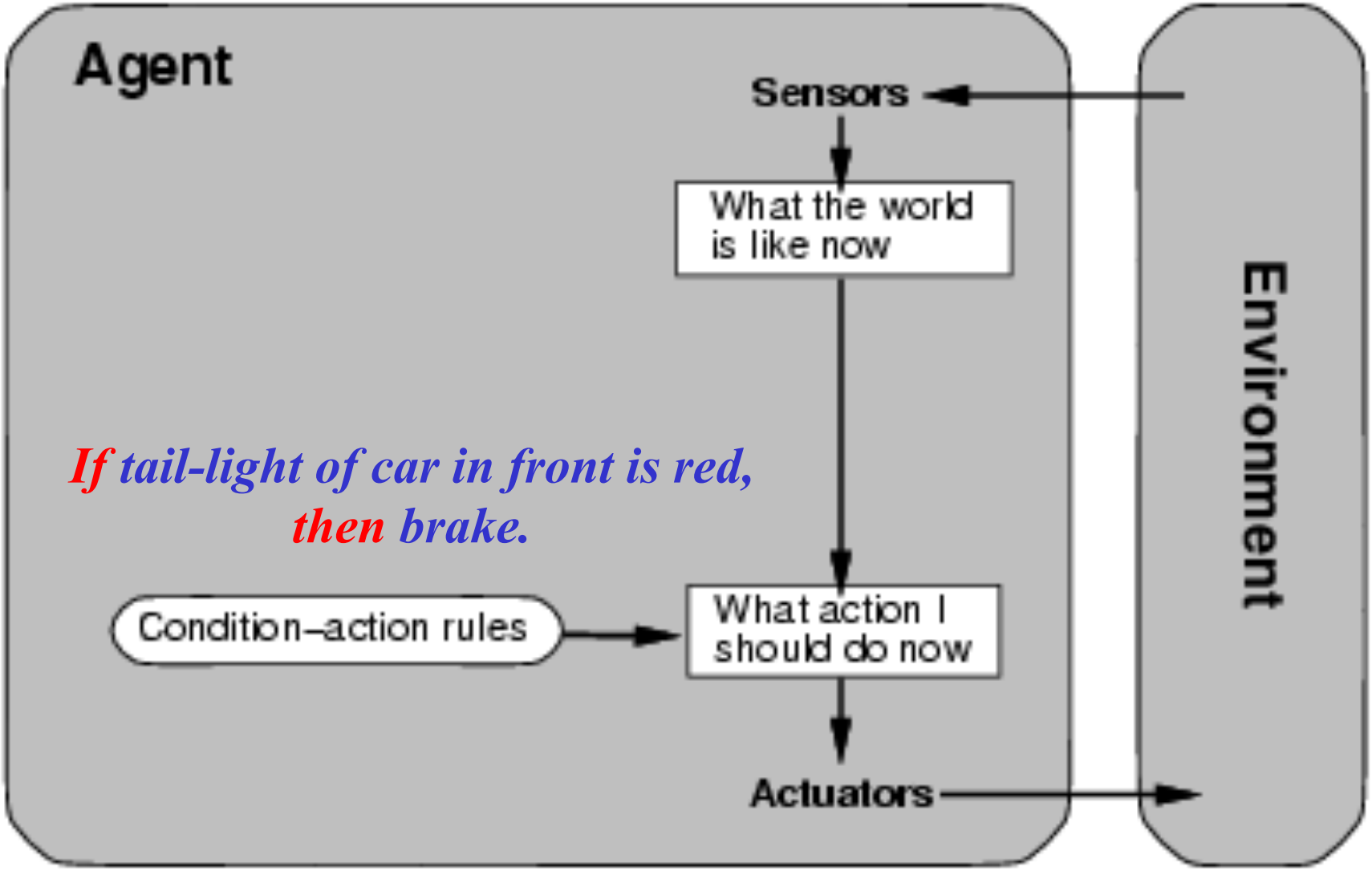
Agents **do not have memory** of past world states or percepts.

So, actions depend solely on **current percept**.

Action becomes a “reflex.”

Uses **condition-action rules**.

Agent selects actions on the basis of *current* percept only.



Simple reflex agents

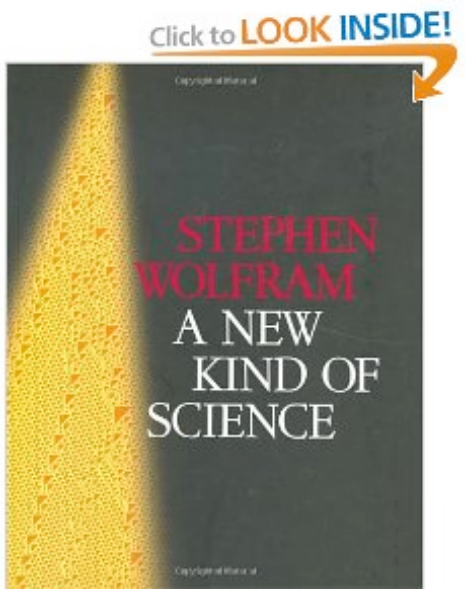
Closely related to "behaviorism" (psychology; quite effective in explaining lower-level animal behaviors, such as the behavior of ants and mice).

The Roomba robot largely behaves like this. Behaviors are robust and can be quite effective and surprisingly complex.

But, how does complex behavior arise from simple reflex behavior?
E.g. ants colonies and bee hives are quite complex.

~~A. Simple rules in a diverse environment can~~ give rise to surprising complexity.

See A-life work (artificial life) community, and Wolfram's cellular automata.



III) --- Model-based reflex agents

Key difference (wrt simple reflex agents):

- Agents have **internal state**, which is used to keep track of past states of the world.

- Agents have the ability **to represent change in the World**.

Example: Rodney Brooks' Subsumption Architecture

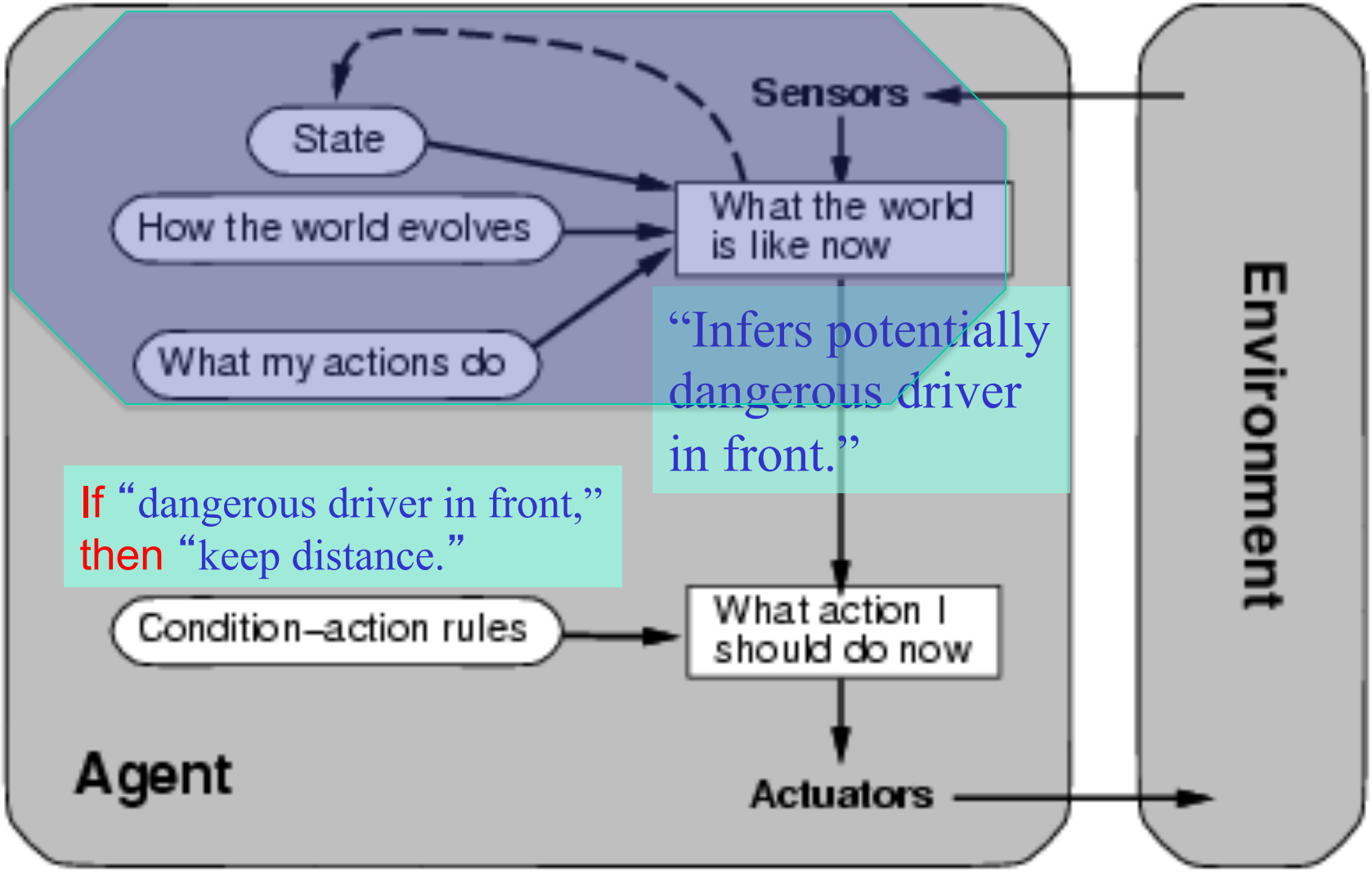
--- behavior based robots.

[Here]

Module:
Logical Agents
Representation and Reasoning:
Part III/IV R&N

Model-based reflex agents

How detailed?



An example: Brooks' Subsumption Architecture

Main idea: build complex, intelligent robots by decomposing behaviors into a hierarchy of skills, each defining a percept-action cycle for one very specific task.

Examples: collision avoidance, wandering, exploring, recognizing doorways, etc.

Each behavior is modeled by a finite-state machine with a few states (though each state may correspond to a complex function or module; provides internal state to the agent).

Behaviors are loosely coupled via asynchronous interactions.

Note: minimal internal state representation.

p. 1003 R&N

Subsumption Architecture, cont.

In subsumption architecture, increasingly complex behaviors arise from the combination of simple behaviors.

The most basic simple behaviors are on the level of reflexes: • avoid an object; • go toward food if hungry, • move randomly.

A more complex behavior that sits on top of simple behaviors may be "go across the room."

The more complex behaviors subsume the less complex ones to accomplish their goal.

How much of an internal model of the world?

Planning in and reasoning about our surroundings appears to require some kind of internal representation of our world. We can "try" things out in this representation. Much like an running a "simulation" of the effect of actions or a sequence of actions in our head.

General assumption for many years:

The more detailed internal model, the better.

Brooks (mid 80s and 90s) challenged this view:

The philosophy behind Subsumption Architecture is that *the world should be used as its own model.* According to Brooks, storing models of the world is dangerous in dynamic, unpredictable environments because representations might be incorrect or outdated. What is needed is the ability to react quickly to the present. So, use minimal internal state representation, complement at each time step with sensor input.

Debate continues to this day: How much of our world do we (should we) represent explicitly? Subsumption architecture worked well in robotics.

IV) --- Goal-based agents

Key difference wrt Model-Based Agents:

In addition to state information, have **goal information** that **describes desirable situations to be achieved**.

Agents of this kind take future events into consideration.

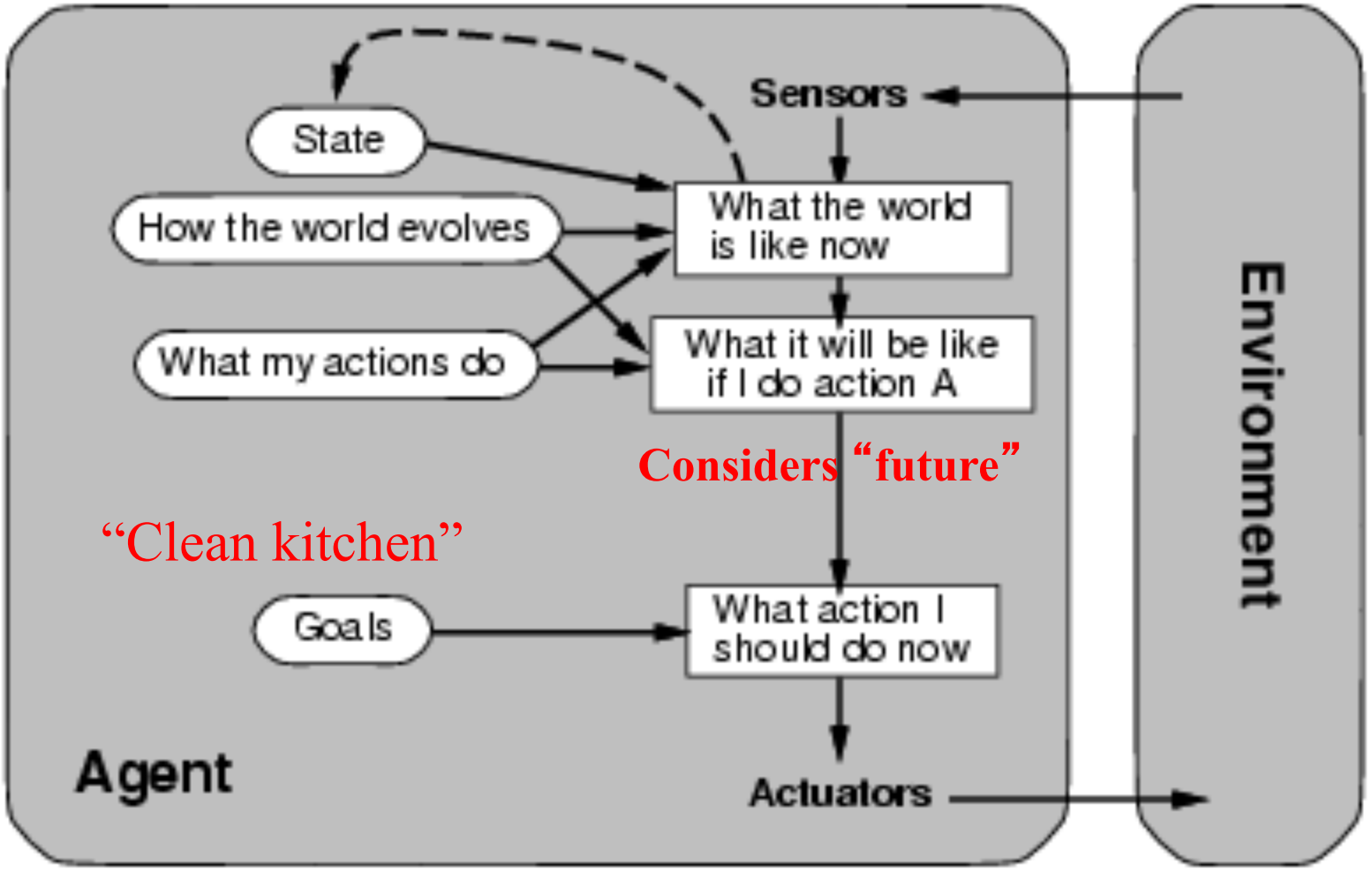
What *sequence* of actions can I take to achieve certain goals?

Choose actions so as to (eventually) achieve a (given or computed) goal.

→ ***problem solving and search! (R&N --- Part II, chapters 3 to 6)***

Module: Problem Solving

Goal-based agents



Agent keeps track of the world state as well as set of goals it's trying to achieve: chooses actions that will (eventually) lead to the goal(s).

More flexible than reflex agents → may involve search and planning

V) --- Utility-based agents

When there are multiple possible alternatives, how to decide which one is best?

Goals are qualitative: A goal specifies a crude distinction between a happy and unhappy state, but often need a more general performance measure that describes "degree of happiness."

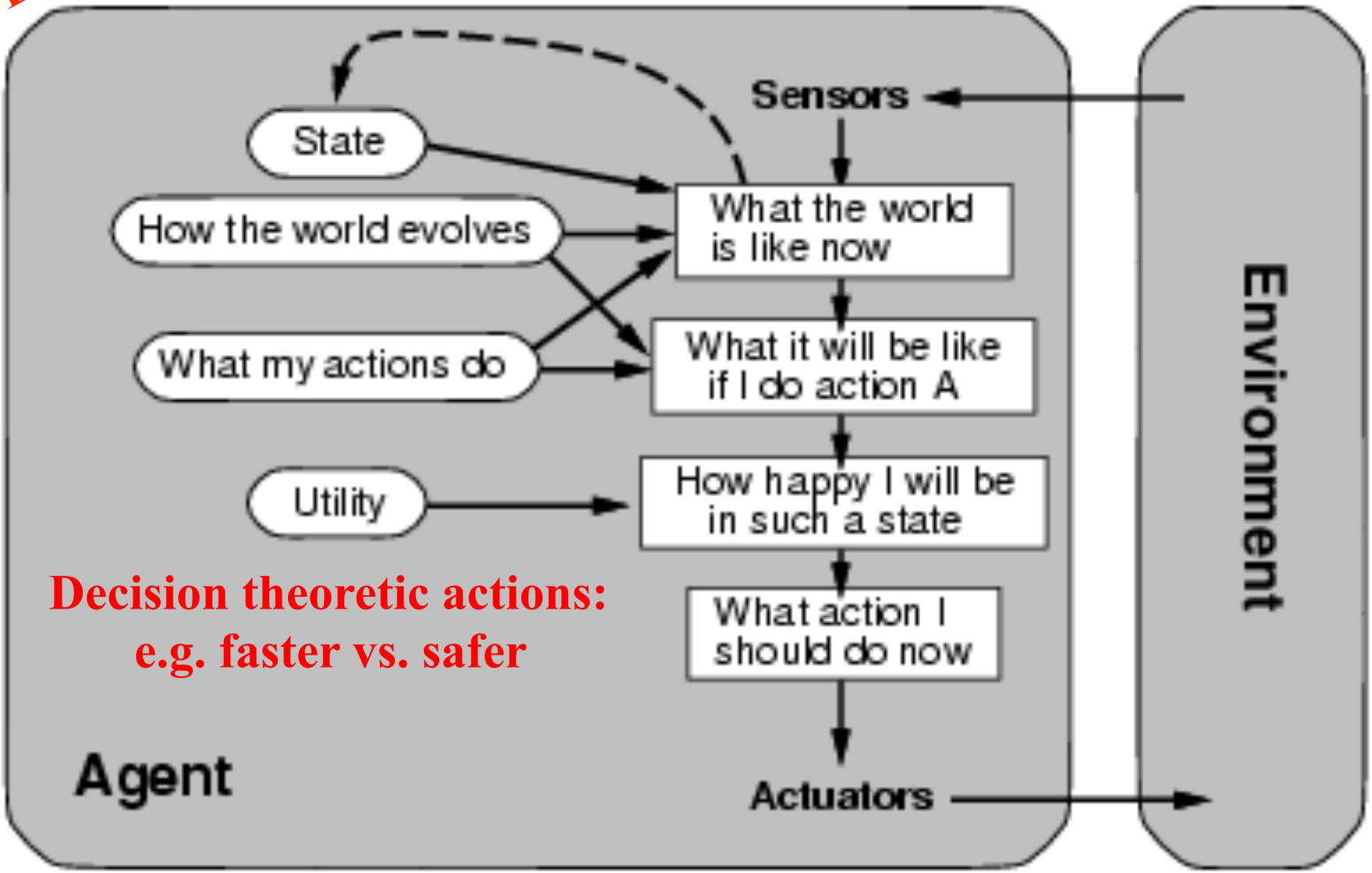
Utility function U: State → R indicating a measure of success or happiness when at a given state.

Important for making tradeoffs: Allows decisions comparing choice between conflicting goals, and choice between likelihood of success and importance of goal (if achievement is uncertain).

Use decision theoretic models: e.g., faster vs. safer.

Module:
Decision Making

Utility-based agents

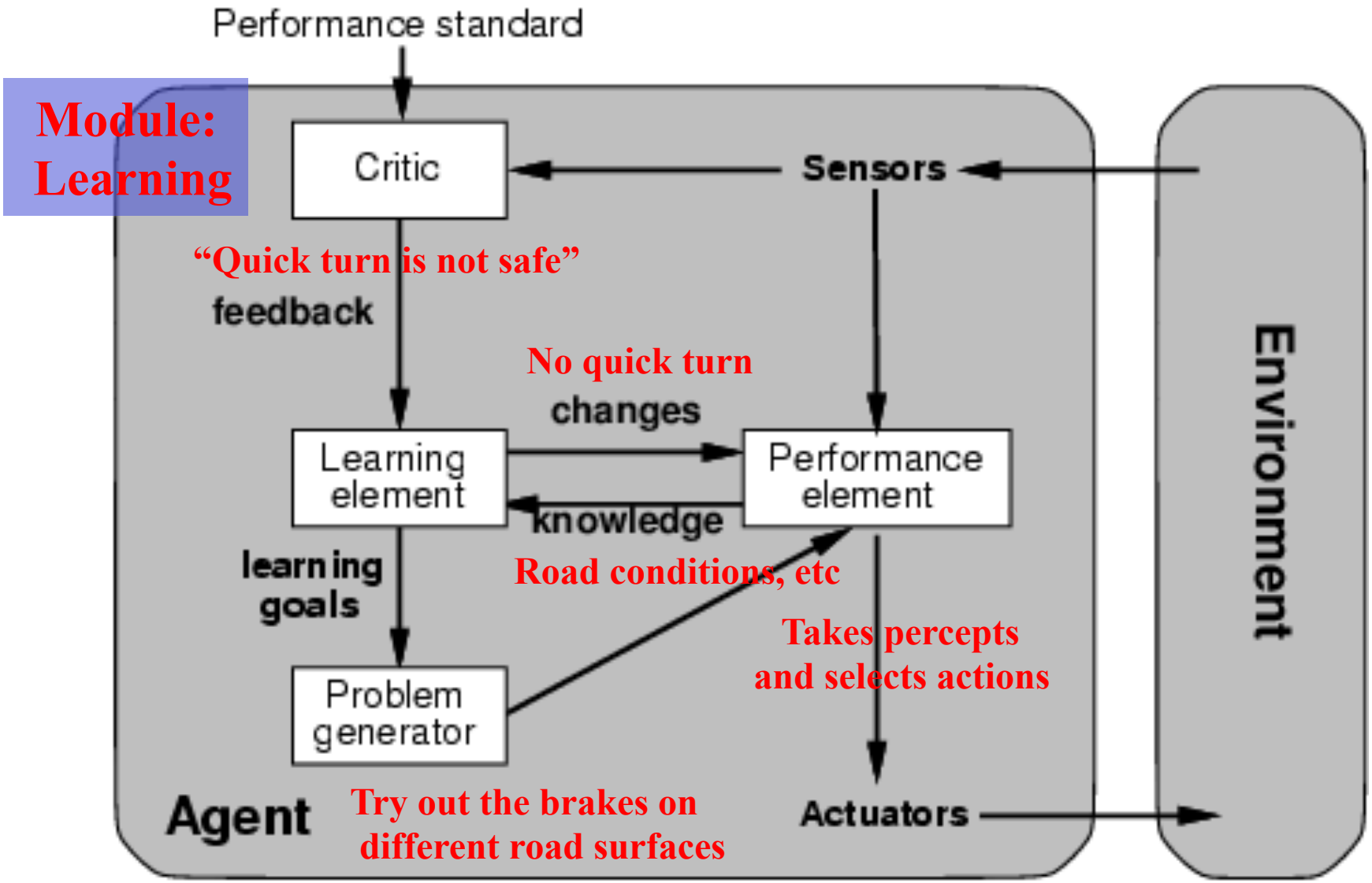


Decision theoretic actions:
e.g. faster vs. safer

VI) --- Learning agents

Adapt and improve over time

More complicated when agent needs to learn utility information: Reinforcement learning (based on action payoff)



Summary: agent types

(1) Table-driven agents

- use a percept sequence/action table in memory to find the next action. They are implemented by a (large) lookup table.

(2) Simple reflex agents

- are based on condition-action rules, implemented with an appropriate production system. They are stateless devices which do not have memory of past world states.

(3) Agents with memory - Model-based reflex agents

- have internal state, which is used to keep track of past states of the world.

(4) Agents with goals – Goal-based agents

- are agents that, in addition to state information, have goal information that describes desirable situations. Agents of this kind take future events into consideration.

(5) Utility-based agents

- base their decisions on classic axiomatic utility theory in order to act rationally.

(6) Learning agents

- they have the ability to improve performance through learning.

Summary

An agent perceives and acts in an environment, has an architecture, and is implemented by an agent program.

A rational agent always chooses the action which maximizes its expected performance, given its percept sequence so far.

An autonomous agent uses its own experience rather than built-in knowledge of the environment by the designer.

An agent program maps from percept to action and updates its internal state.

- Reflex agents (simple / model-based) respond immediately to percepts.
- Goal-based agents act in order to achieve their goal(s), possible sequence of steps.
- Utility-based agents maximize their own utility function.
- Learning agents improve their performance through learning.

Representing knowledge is important for successful agent design.

The most challenging environments are partially observable, stochastic, sequential, dynamic, and continuous, and contain multiple intelligent agents.

Reading: Chapter 2 R&N