Artificial Intelligence
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Chapter # 02

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Rational Agents (Chapter 2)

Act Rationally Approach

Today's Outline

- ❑ Agents and Environments
- ❑ Autonomy, Rationality & Omniscience
- ❑ PEAS (Performance measure, Environment, Actuators, Sensors)
- ❑ Environment types
- ❑ Agent types

Agent Definition (1)

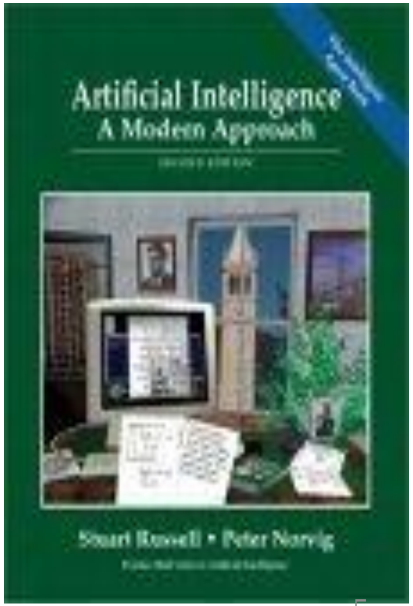
- An agent is an entity which is:
  1. ***Situated*** **in some** ***environment***.
  2. ***Autonomous***, in the sense that it can act without direct intervention from humans or other software processes, and controls over its own actions and internal state.
  3. ***Flexible*** which means:
     - ***Responsive (reactive)*****:** agents should perceive their environment and respond to changes that occur in it;
     - ***Proactive*****:** agents should not simply act in response to their environment, they should be able to **exhibit opportunistic, goal-directed behavior** and take the initiative when appropriate;
     - ***Social*****:** agents should be able to interact with humans or other artificial agents

"A Roadmap of agent research and development", N. Jennings, K. Sycara, M. Wooldridge (1998)

Agent Definition (2)

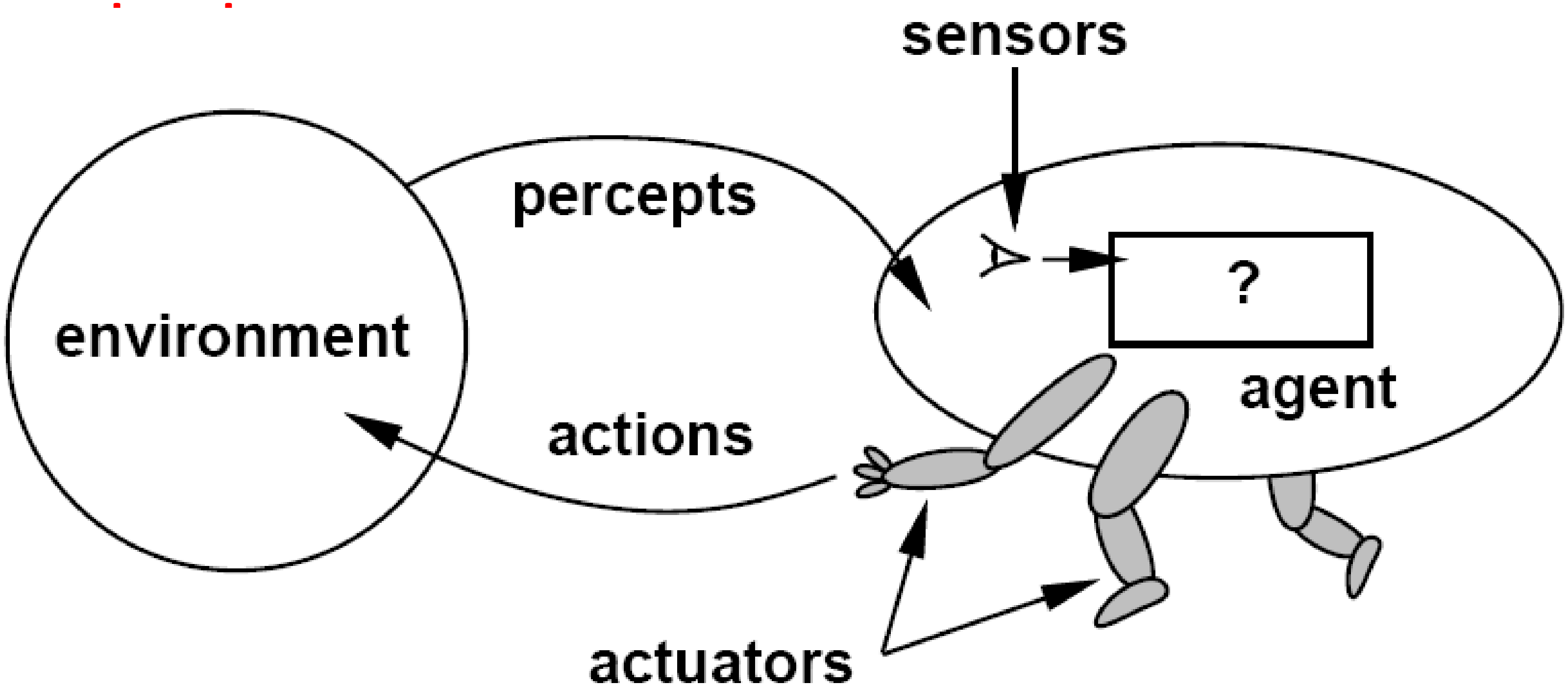
- *"An agent is anything that can be viewed as* ***perceiving*** *its* ***environment*** *through sensors and* ***acting*** *upon that* ***environment*** *through effectors/actuators.“*

Russell & Norvig



Agent Visualization

- An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through

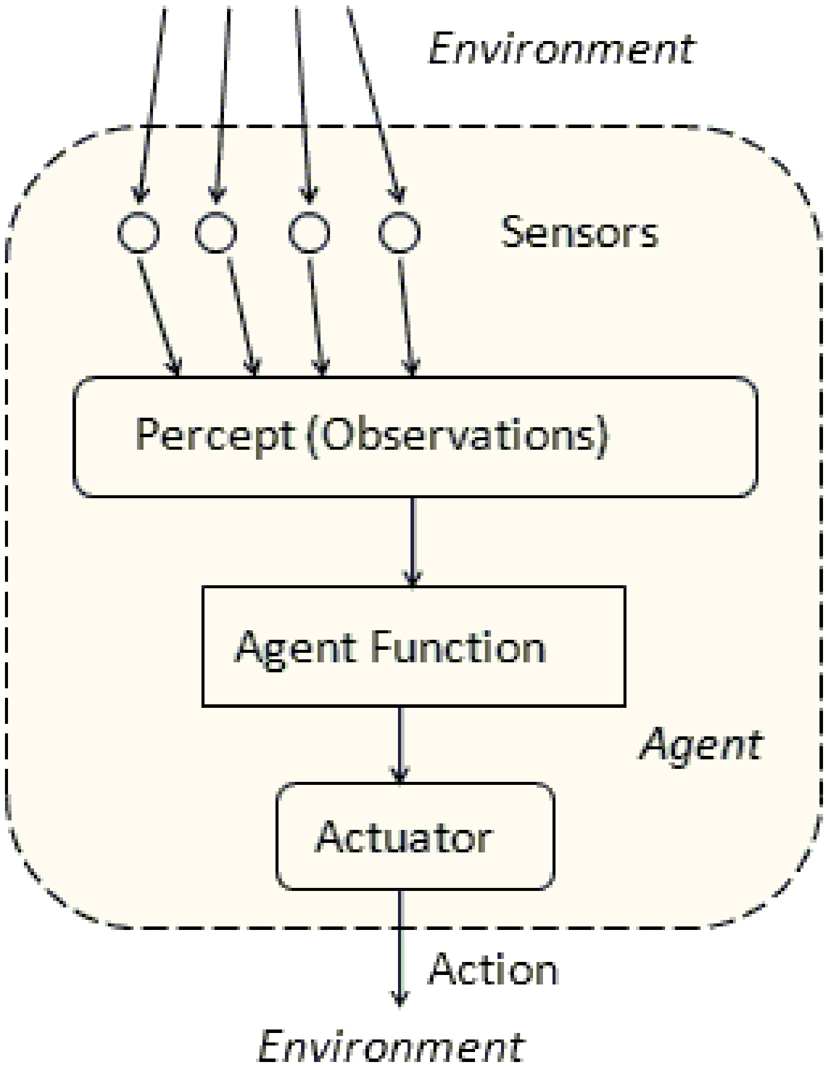


Agent Function & Program

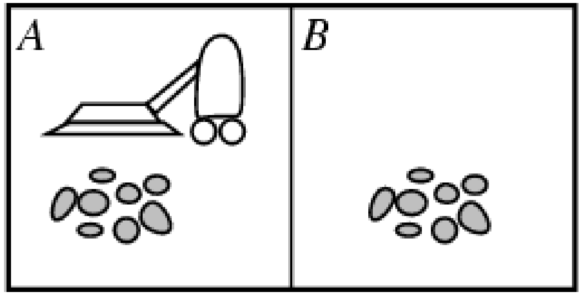
- The **agent function** maps from **percept histories** to actions:

  $[f: \mathcal{P}^{\star} \rightarrow \mathcal{A}]$

- The **agent program** is an implementation of f that runs on the physical **architecture** to produce f
- **agent = architecture + program**



Example: Vacuum-cleaner world



- **Percepts**: location and contents, e.g., [A,Dirty]
- **Actions**: *Left, Right, Suck, NoOp*
- ***Agent's function*** → *look-up table*
  - *For many agents this is a very large table*

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

Other Agent Examples…

- **Human agent**:
  - eyes, ears, and other organs for **sensors**;
  - hands, legs, mouth, and other body parts for **actuators**
- **Robotic agent**:
  - cameras and infrared range finders for **sensors**
  - various motors for **actuators**

Rational agents

- **Rationality:** What is rational at any given time depends on four things i.e.
  1. **Performance measure** that defines success
  2. Agents **prior knowledge** of **environment**
  3. **Actions** that agent can perform
  4. Agent’s **percept** sequence to date
- **Rational Agent:** 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.

Autonomy in Agents

The **autonomy** of an agent is the extent to which its behaviour is determined by **its own experience**, rather than knowledge of the designer.

- Extremes
  - No autonomy – ignores environment/data
  - Complete autonomy – must act randomly/no program
- Example: baby learning to crawl
- Ideal: design agents to have some autonomy
  - Possibly become more autonomous with experience

Rationality vs Omniscience

- Rational is different from **omniscience**
  - Percepts may not supply all relevant information
  - E.g., in card game, don't know cards of others.
- Rational is different from being perfect
  - Rationality maximizes **expected outcome,** while perfection maximizes **actual outcome**.
- To **design** a rational agent you need to specify it's task environment.

Specifying the Task Environments

- **Task Environment** are essentially the **problems** to which **rational agents** are the **solutions**.
- In designing an agent the first step must always be to specify the **task environment** as fully as possible a.k.a PEAS (Performance measure, Environment, Actuators, Sensors)
- **Example (Automated Taxi):** Consider, e.g., the task of designing an automated taxi driver agent:

1. **Performance measure:** Safe, fast, legal, comfortable trip, maximize profits
2. **Environment:** Roads, other traffic, pedestrians, customers
3. **Actuators:** Steering wheel, accelerator, brake, signal, horn
4. **Sensors:** Cameras, sonar, speedometer, GPS, odometer, engine sensors, keyboard

PEAS - Example # 02

Agent: Part-Picking Robot

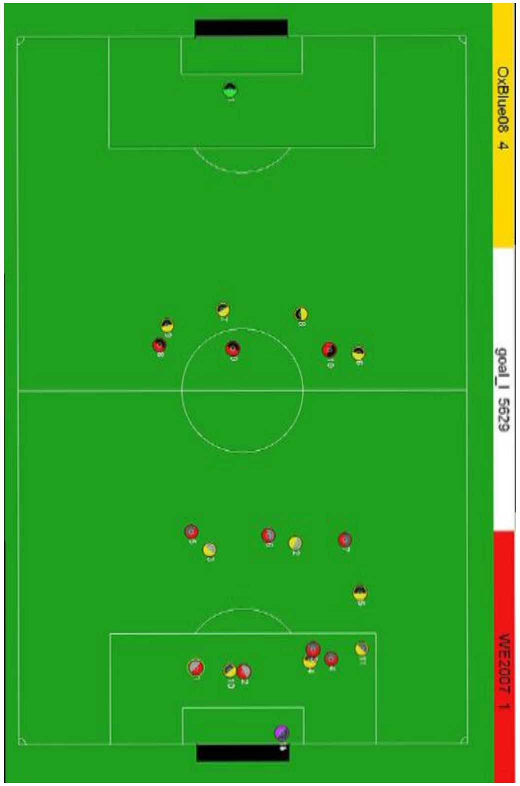
1. **Performance measure:** Percentage of parts in correct bins
2. **Environment:** Conveyor belt with parts, bins
3. **Actuators:** Jointed arm and hand
4. **Sensors:** Camera, joint angle sensors

Environment types

- Fully observable vs. partially observable
- Deterministic vs. stochastic
- Episodic vs. sequential
- Static vs. dynamic
- Discrete vs. continuous
- Single agent vs. multi-agent
- Known vs. unknown

Fully observable vs. partially observable

- Do the agent's sensors give it access to the complete state of the environment?
  - For any given world state, are the values of all the variables known to the agent?



vs.

Source: L. Zettlemoyer

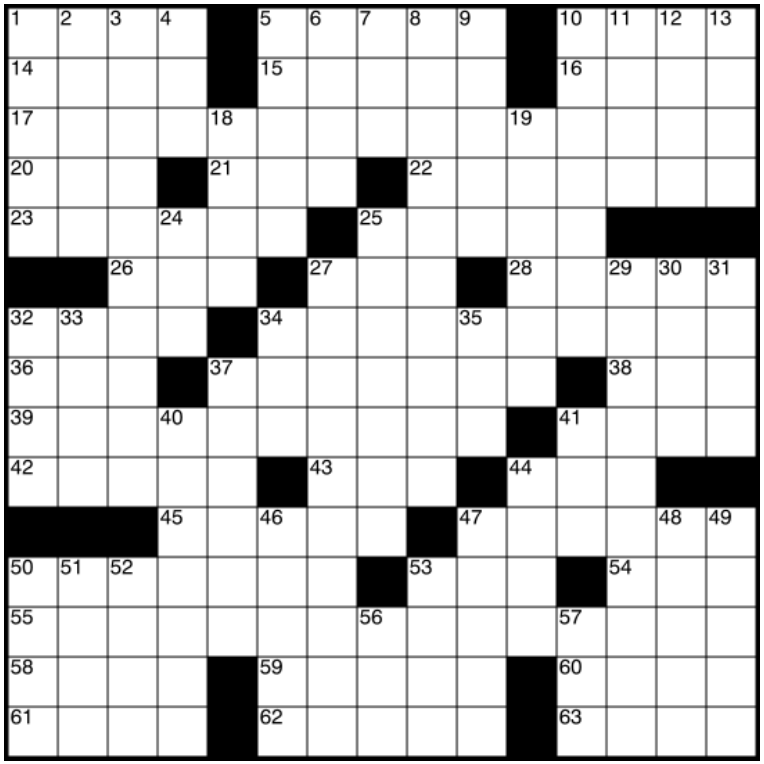
Examples

Poker Game (Partially)

Backgammon (Fully)

A task environment is effectively fully observable if the **sensors detect all aspects that are *relevant* to the choice of action**; relevance, in turn, depends on the performance measure.

Examples



Cross Word (Fully)

Part Picking Robot (Partially)

Deterministic vs. stochastic

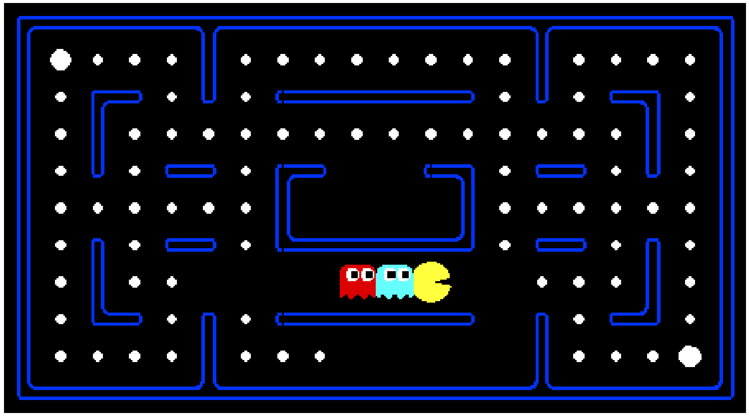
- Is the next state of the environment completely determined by the current state and the agent's action?
  - Is the transition model deterministic (unique successor state given current state and action) or stochastic (distribution over successor states given current state and action)?
  - **Strategic:** the environment is deterministic except for the actions of other agents

vs.

Episodic vs. sequential

- Is the agent's experience divided into unconnected episodes, or is it a coherent sequence of observations and actions?
  - Does each problem instance involve just one action or a series of actions that change the world state according to the transition model?

vs.

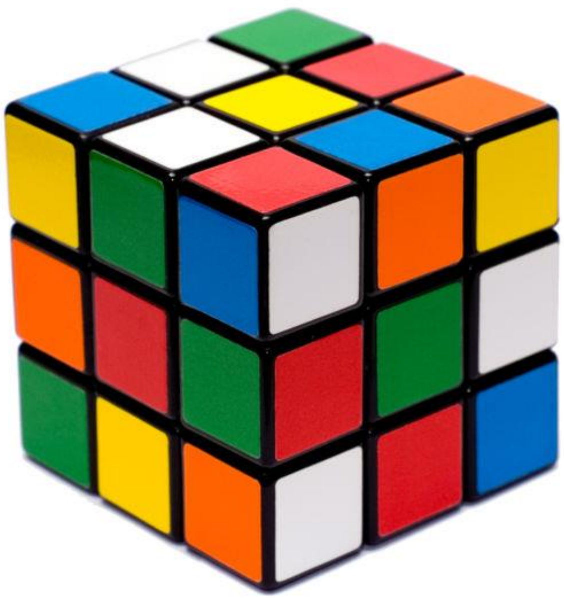


Episodic (vs. sequential):

- Is the choice of current action
  - Dependent on previous actions?
  - If not, then the environment is episodic
- In non-episodic environments:
  - Agent has to plan ahead:
    - Current choice will affect future actions

Static vs. dynamic

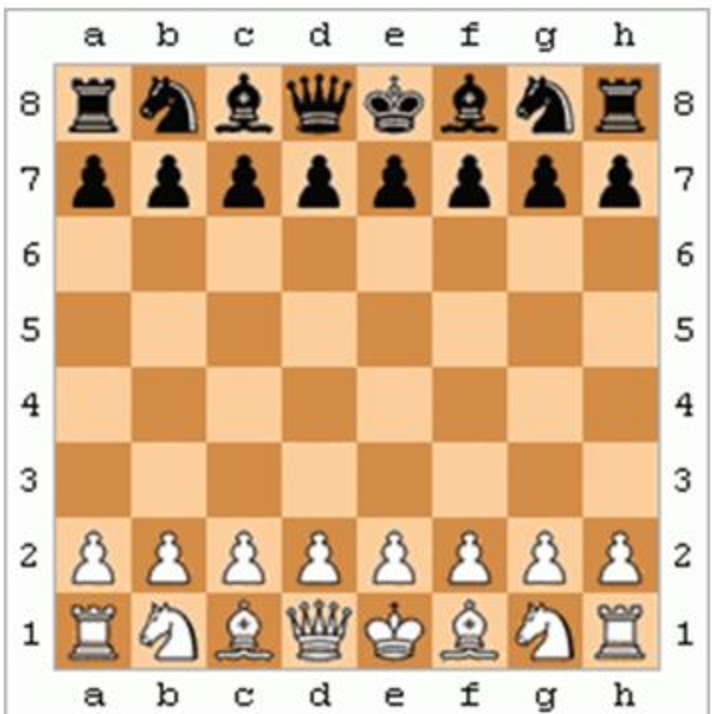
- Is the world changing, while the agent is thinking?
  - **Semidynamic:** the environment does not change with the passage of time, but the agent's performance score does



vs.

Discrete vs. continuous

- Does the environment provide a fixed number of distinct percepts, actions, and environment states?
  - Are the values of the state variables discrete or continuous?
  - Percepts and actions of the agent are discrete or continuous?
  - Time can also evolve in a discrete or continuous fashion

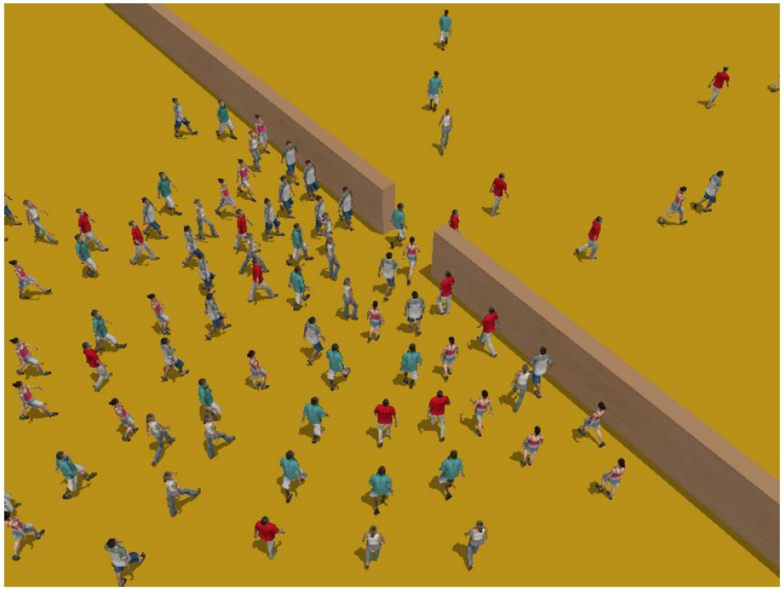


vs.

Single-agent vs. multiagent

- Is an agent operating by itself in the environment?

vs.



Known vs. unknown

- Are the rules of the environment (laws of physics, transition model and rewards associated with states etc.) known to the agent?
  - Strictly speaking, not a property of the environment, but of the agent's state of knowledge

Monopoly game

vs.

A new video game

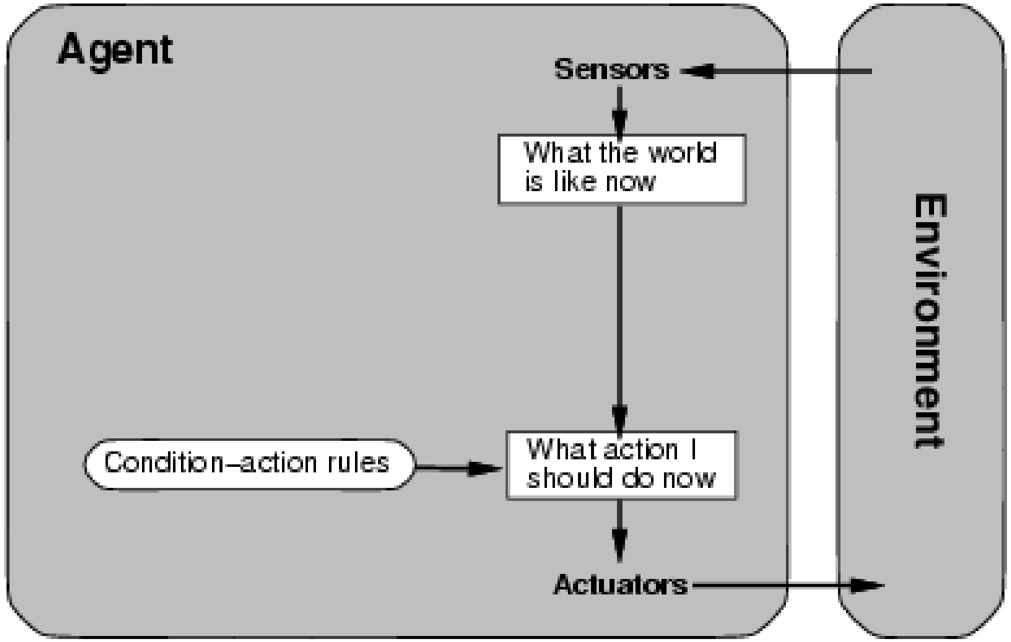
Summary

	Observable	Deterministic	Episodic	Static	Discrete	Agents
Cross Word	Fully	Deterministic	Sequential	Static	Discrete	Single
Poker	Partially	Stochastic	Sequential	Static	Discrete	Multi
Backgammon	Fully	Stochastic	Sequential	Static	Discrete	Multi
Taxi driver	Partially	Stochastic	Sequential	Dynamic	Conti	Multi
Part picking robot	Partially	Stochastic	Episodic	Dynamic	Conti	Single
Image analysis	Fully	Deterministic	Episodic	Semi	Conti	Single

Agent Types

- Five basic types in order of increasing generality:
  1. **Simple reflex agents**
  2. **Reflex agents with state/model**
  3. **Goal-based agents**
  4. **Utility-based agents**
  5. **Learning based Agents**

Simple Reflex Agents



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*

Simple Reflex Agents

- Simple but very limited intelligence.
- **Action does not depend on percept history, only on current percept.**
- Therefore no memory requirements.
- **PROBLEM: Infinite loops if environment partially observable**
  - Suppose vacuum cleaner does not observe location. What do you do given location = clean? Left of A or right of B -> infinite loop.
  - Agent will behave like fly buzzing around window or light.
  - **Possible Solution**: Randomize action (flip a coin to decide action).
- For complex problems e.g., Chess
  - Lookup table (not a good idea in general)
    - 35^{100} entries required for the entire game

States: Beyond Reflexes

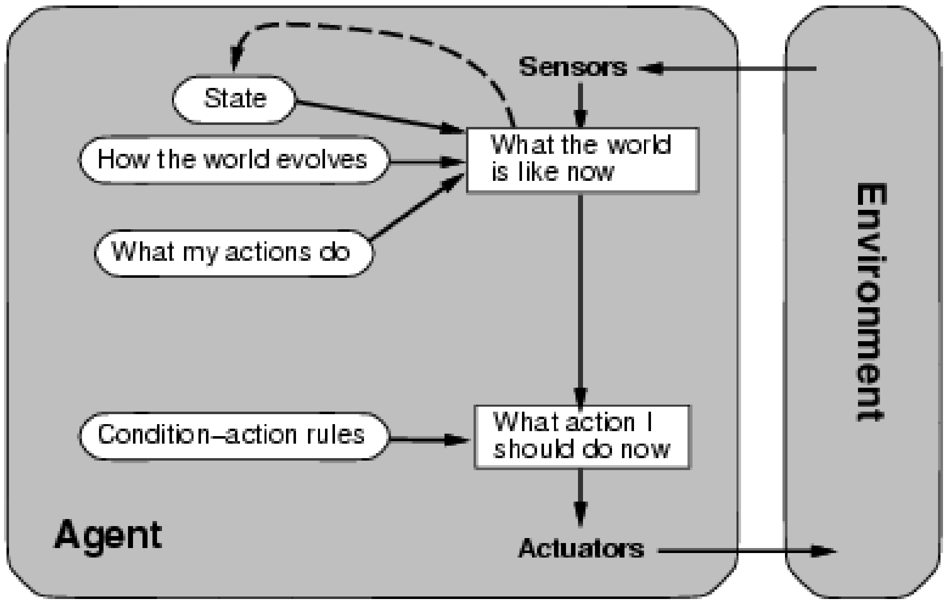
- Recall the agent function that maps from **percept histories** to actions:

$$[f\colon \mathcal{P}^{\star} \rightarrow \mathcal{A}]$$

- An agent program can implement an agent function by maintaining an **internal state**.
- The internal state can contain information about the state of the external environment.
- The state depends on the history of percepts and on the history of actions taken:

$[f\colon \mathcal{P}^{\star}, \mathcal{A}^{\star} \rightarrow \mathcal{S} \rightarrow \mathcal{A}]$ where $\mathcal{S}$ is the set of states.

Model-based reflex agents



1. Know how world evolves
   - Overtaking car gets closer from behind
2. How agents actions affect the world
   - Wheel turned clockwise takes you right

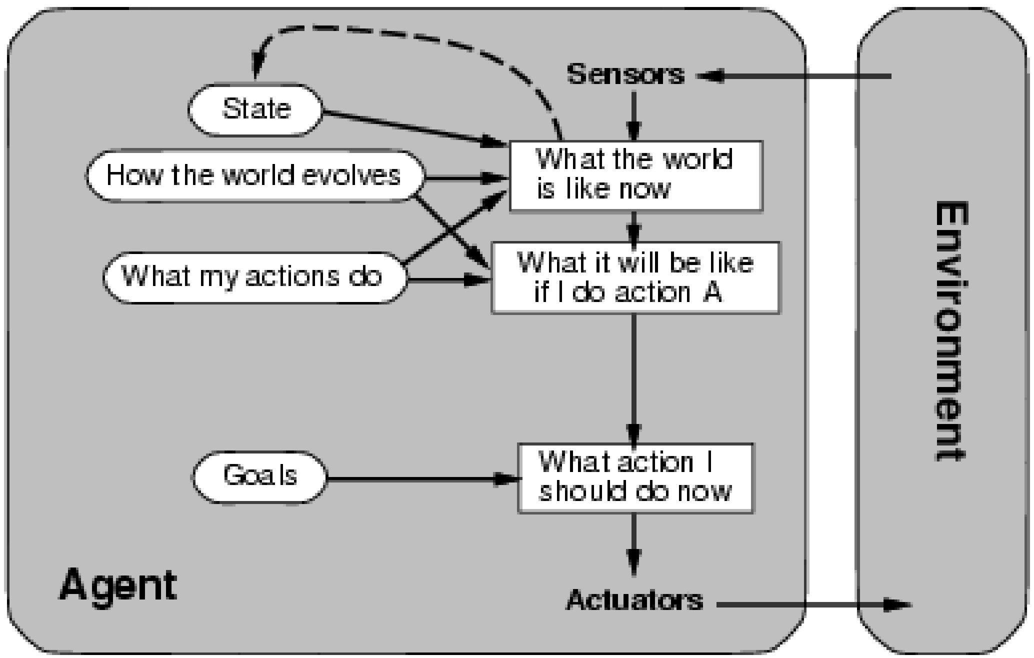
```
function REFLEX-AGENT-WITH-STATE(percept) returns action
   static: state, a description of the current world state
           rules, a set of condition-action rules

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

Goal-based agents

- Knowing state and environment? Enough?
  - Taxi can go left, right, straight
- Have a goal
  - A destination to get to
- Uses knowledge about a goal to guide its actions
  - E.g., Search, planning
- Modified brake behaviour in case of rain

Goal-based agents

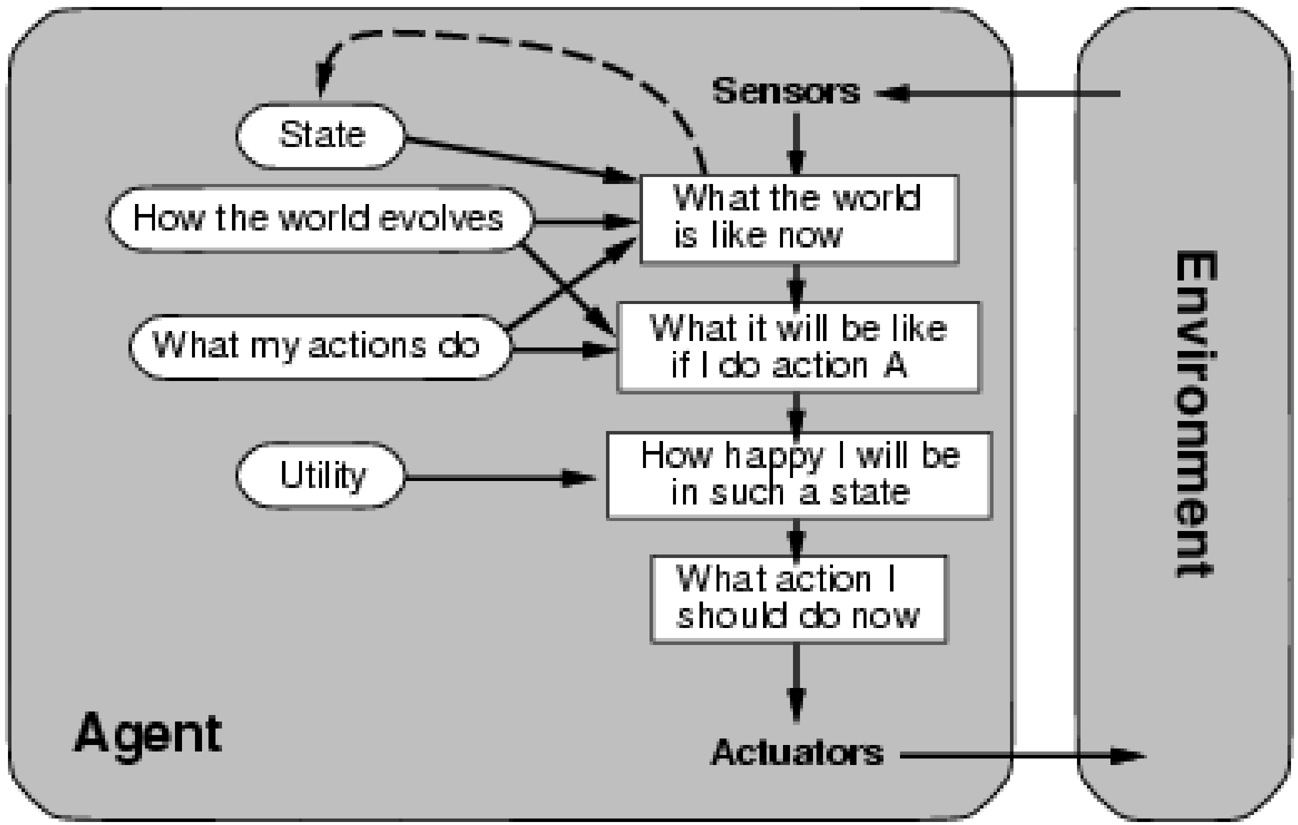


- Reflex agent breaks when it sees brake lights. Goal based agent reasons
  - Brake light -> car in front is stopping -> I should stop -> I should use brake

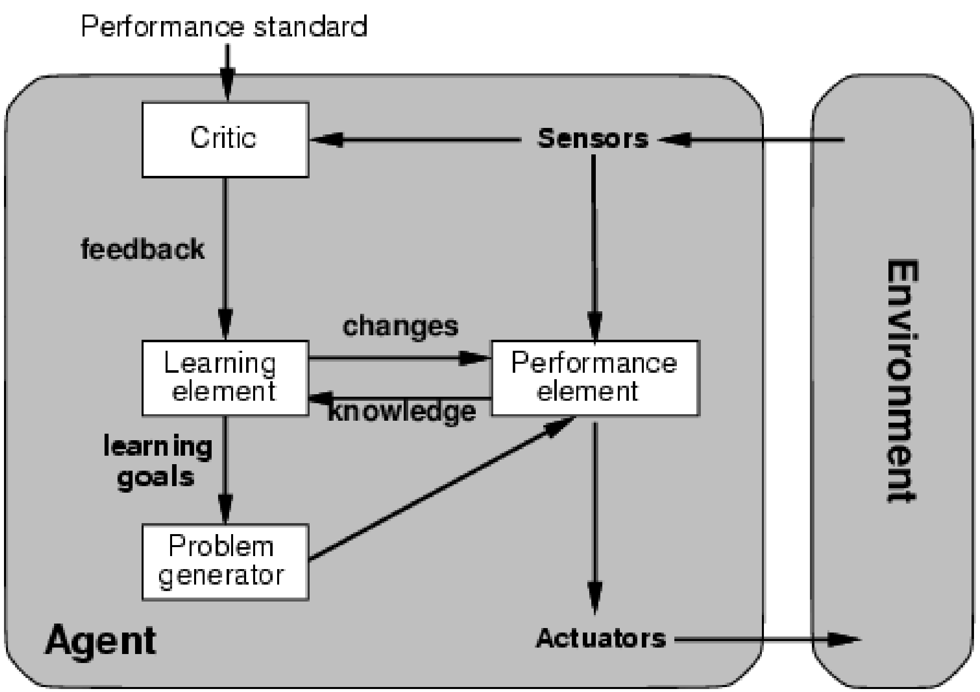
Utility-based agents

- Goals are not always enough
  - Many action sequences get taxi to destination
  - Consider other things. How fast, how safe.....
- A Utility function maps a state onto a real number which describes the associated degree of “happiness”, “goodness”, “success”.
- Where does the utility measure come from?
  - Economics: money.
  - Biology: number of offspring.
  - Your life?

Utility-based agents

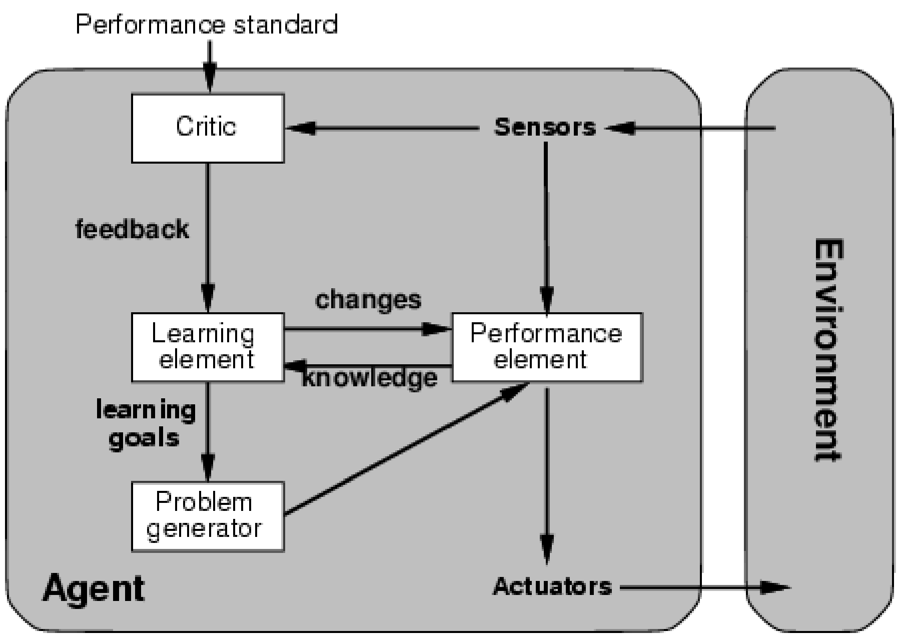


Learning agents



- Performance element is what was previously the whole agent
  - Input sensor
  - Output action
- Learning element
  - Modifies performance element.

Learning agents



- Critic: how the agent is doing
  - Input: checkmate?
  - Fixed
- Problem generator
  - Tries to solve the problem differently instead of optimizing.
  - Suggests **exploring** new actions -> new problems.

Learning agents(Taxi driver)

- Performance element
  - How it currently drives
- Taxi driver Makes quick left turn across 3 lanes
  - **Critics observe shocking language by passenger** and other drivers and informs bad action
  - Learning element tries to **modify performance elements** for future
  - Problem generator **suggests** experiment out something called Brakes on different Road conditions
- Exploration vs. Exploitation
  - Learning experience can be costly in the short run
  - shocking language from other drivers
  - Less tip
  - Fewer passengers

End of Lecture