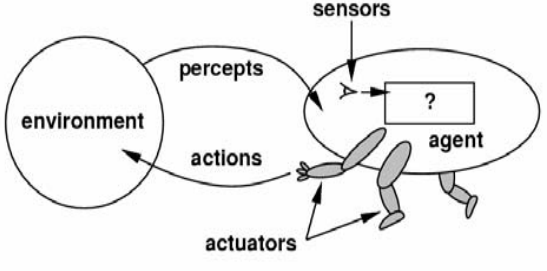
Agents and Environments

Berlin Chen 2003



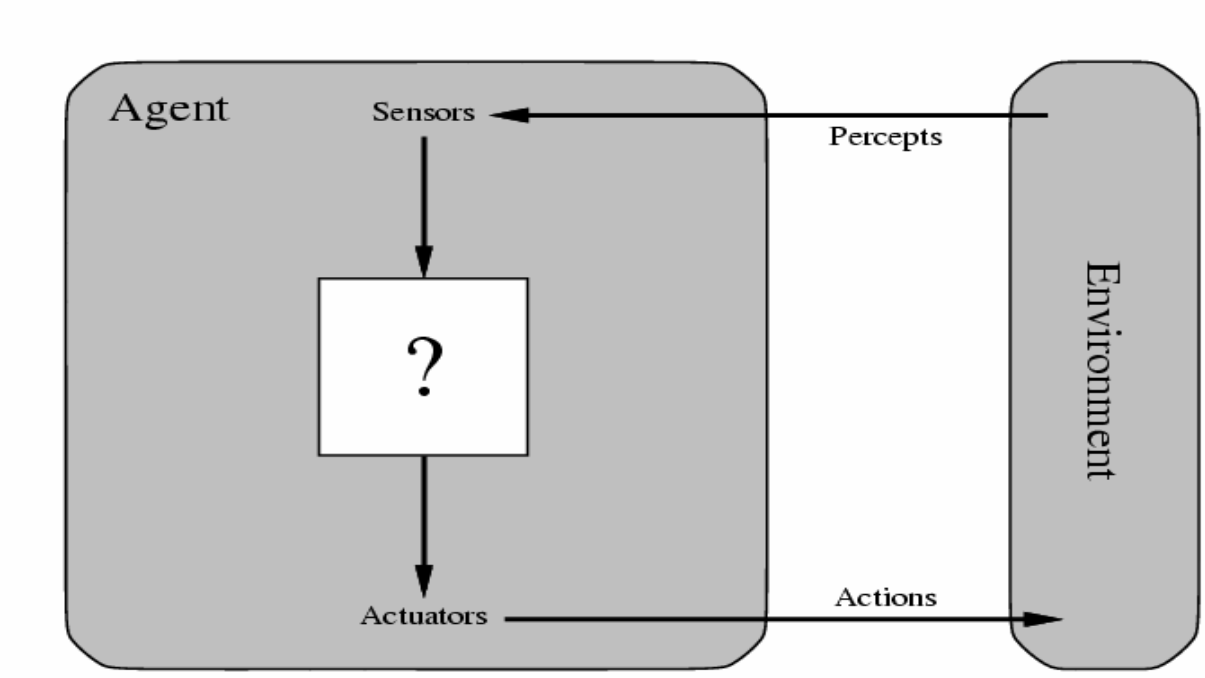
Reference:

1. S. Russell and P. Norvig. Artificial Intelligence: A Modern Approach, Chapter 2

What is an Agent

- An agent interacts with its environments
  - Perceive through sensors
    - Human agent: eyes, ears, nose etc.
    - Robotic agent: cameras, infrared range finder etc.
    - Soft agent: receiving keystrokes, network packages etc.
  - Act through actuators
    - Human agent: hands, legs, mouse etc.
    - Robotic agent: arms, wheels, motors etc.
    - Soft agent: display, sending network packages etc.
- A rational agent is
  - One that does the right thing
  - Or one that acts so as to achieve best expected outcome

Agent and Environments



Assumption: every agent can perceive its own actions

Agent and Environments

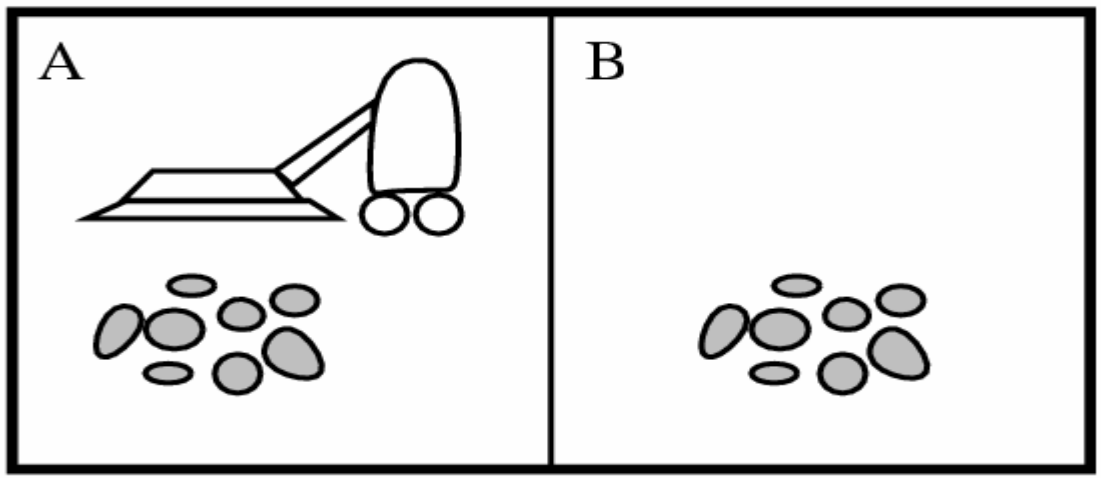
- Percept (*P*)
  - The agent's perceptual inputs at any given time
- Percept sequence (*P**)
  - The complete history of everything the agent has ever perceived
- Agent function
  - A mapping of any given percept sequence to an action

$$f : P^* \left(P_0, P_1, ..., P_n \right) \rightarrow A$$

  - Agent function is implemented by an agent program
- Agent program
  - Run on the physical agent architecture to produce f

Example: Vacuum-Cleaner World

- Percepts:
  - Square locations and Contents, e.g. [A, Dirty], [B. Clean]
- Actions:
  - Right, Left, Suck or NoOp



A Vacuum-Cleaner Agent

- Tabulation of agent functions

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 simple 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
```

Definition of A 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 to date and whatever built-in knowledge the agent has

  – Performance measure
  – Percept sequence
  – Prior knowledge about the environment
  – Actions

Performance Measure for Rationality

- Performance measure
  - Embody the criterion for success of an agent's behavior
- Subjective or objective approaches
  - Objective measure is preferred
  - E.g., in the vacuum-cleaner world:
    amount of dirt cleaned up
    or the electricity consumed per time step
    or average cleanliness over time
    (which is better?)
- How and when to evaluate?
- Rationality vs. perfection (or omniscience)
  - Rationality => exploration, learning and autonomy

A rational agent should be autonomous!

Task Environments

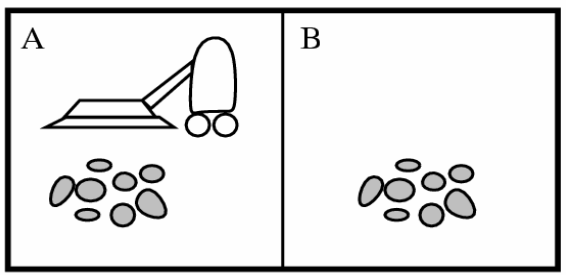
- When thinking about building a rational agent, we must specify the task environments
- The **PEAS** description
  - Performance
  - Environment
  - Actuators
  - Sensors

Agent Type	Performance Measure	Environment	Actuators	Sensors
Taxi driver	Safe, fast, legal, comfortable trip, maximize profits correct destination	Roads, other traffic, pedestrians, customers places, countries	Steering, accelerator, brake, signal, horn, display talking with passengers	Cameras, sonar, speedometer, GPS, odometer, accelerometer, engine sensors, keyboard

Figure 2.4 PEAS description of the task environment for an automated taxi.

Task Environments

- Informally identified in some dimensions
  - Fully observable vs. partially observable
  - Deterministic vs. stochastic
  - Episodic vs. sequential
  - Static vs. dynamic
  - Discrete vs. continuous
  - Single agent vs. multiagent



Task Environments

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Crossword puzzle	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 English tutor	Partially	Stochastic	Sequential	Dynamic	Discrete	Multi

Figure 2.6 Examples of task environments and their characteristics.

The Structure of Agents

- How do **the insides** of agents work
  - In addition their behaviors

- A general agent structure

  Agent = *Architecture* + *Program*

- Agent program
  - Implement the agent function to map percepts (inputs) from the sensors to actions (outputs) of the actuators
  - Run on a specific architecture

- Agent architecture
  - The computing device with physical sensors and actuators
  - E.g., an ordinary PC or a specialized computing device with sensors (camera, microphone, etc.) and actuators (display, speaker, wheels, legs etc.)

The Structure of Agents

- Example: the table-driven-agent program

```
function TABLE-DRIVEN-AGENT(percept) returns an action
  static: 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
```

  - Take the current percept as the input
  - The “table” explicitly represent the agent functions that the agent program embodies
  - Agent functions depend on the entire percept sequence

The Structure of Agents

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

The Structure of Agents

- Steps done under the agent architecture

    1. Sensor's data → Program inputs (Percepts)
    2. Program execution
    3. Program output → Actuator's actions

- Kinds of agent program
  - *Table-driven agents -> doesn't work well!*
  - Simple reflex agents
  - Model-based reflex agents
  - Goal-based agents
  - Utility-based agents

Table-Driven Agents

- Agents select actions based on the entire percept sequence
- Table lookup size: $\sum_{t=1}^{T} |P|^t$
  - P: possible percepts
  - T: life time

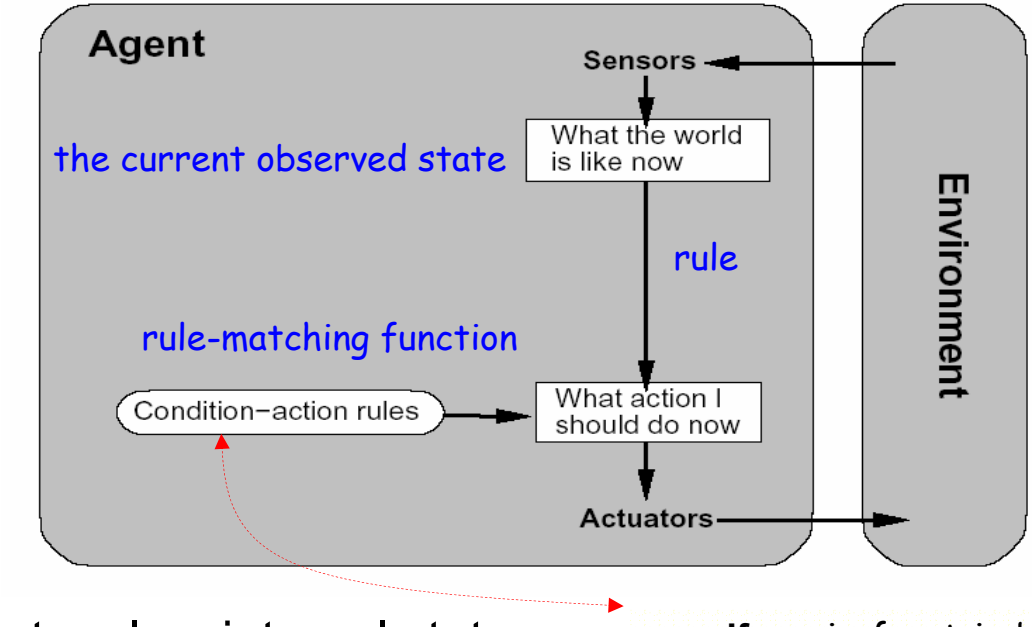
- Problems with table-driven agents
  - Memory/space requirement
  - Hard to learn from the experience
  - Time for constructing the table

How to write an excellent program to produce rational behavior from a small amount of code rather than from a large number of table entries

- Doomed to failure

Simple Reflex Agents

- Agents select actions based on the current percept, ignoring the rest percept history
  - Memoryless
  - Respond directly to percepts



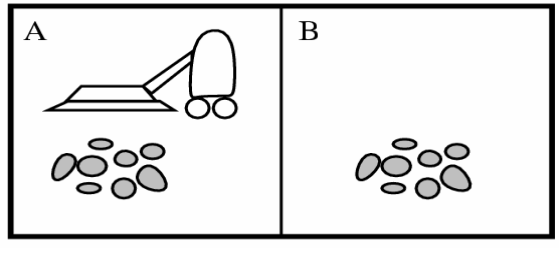
  - Rectangles: internal states
  - Ovals: background information

e.g., **If** car-in-front-is-braking **then** initiate-braking

Simple Reflex Agents

- Example: the vacuum agent introduced previously
  - It's decision is based only on the current location and on whether that contains dirt
  - Only 4 percept possibilities/states (instead of 4^T)

[*A, Clean*]
[*A, Dirty*]
[*B, Clean*]
[*B, Dirty*]




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

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

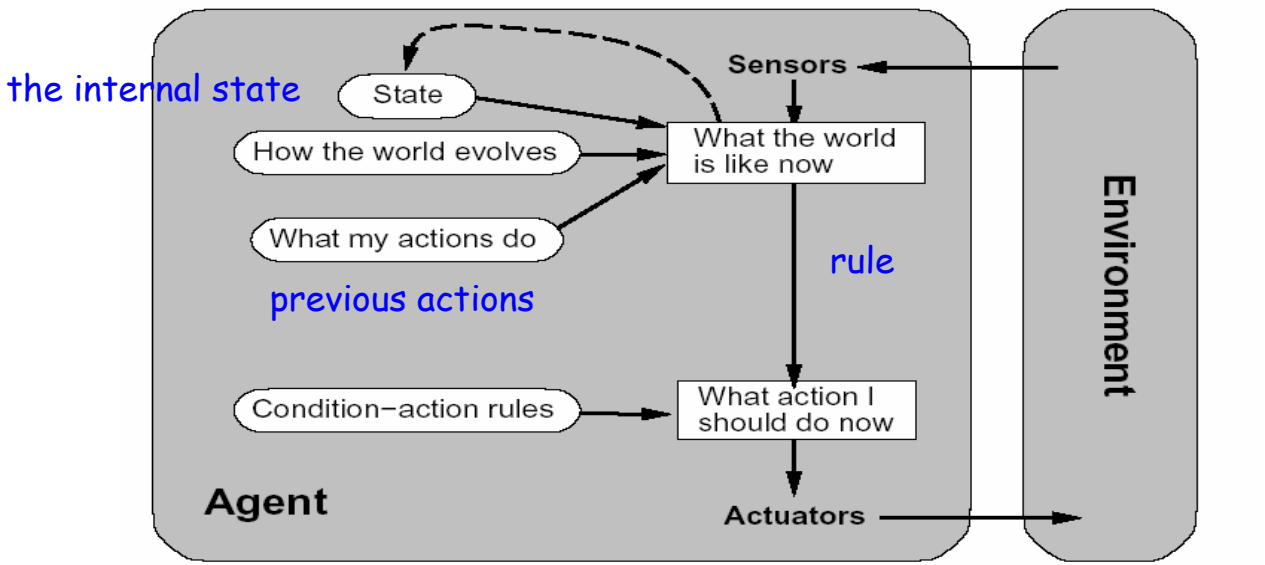
Simple Reflex Agents

- Problems with simple reflex agents
  - Work properly if the environment is fully observable
  - Couldn’t work properly in partially observable environments
  - Limited range of applications

- Randomized vs. deterministic simple reflex agent

Model-based Reflex Agents

- Agents maintain internal state to track aspects of the world that are not evident in the current state
  - Parts of the percept history kept to reflect some of the unobserved aspects of the current state
  - Updating internal state information require knowledge about
    - Which perceptual information is significant
    - How the world evolves independently
    - How the agent's action affect the world



Model-based Reflex Agents

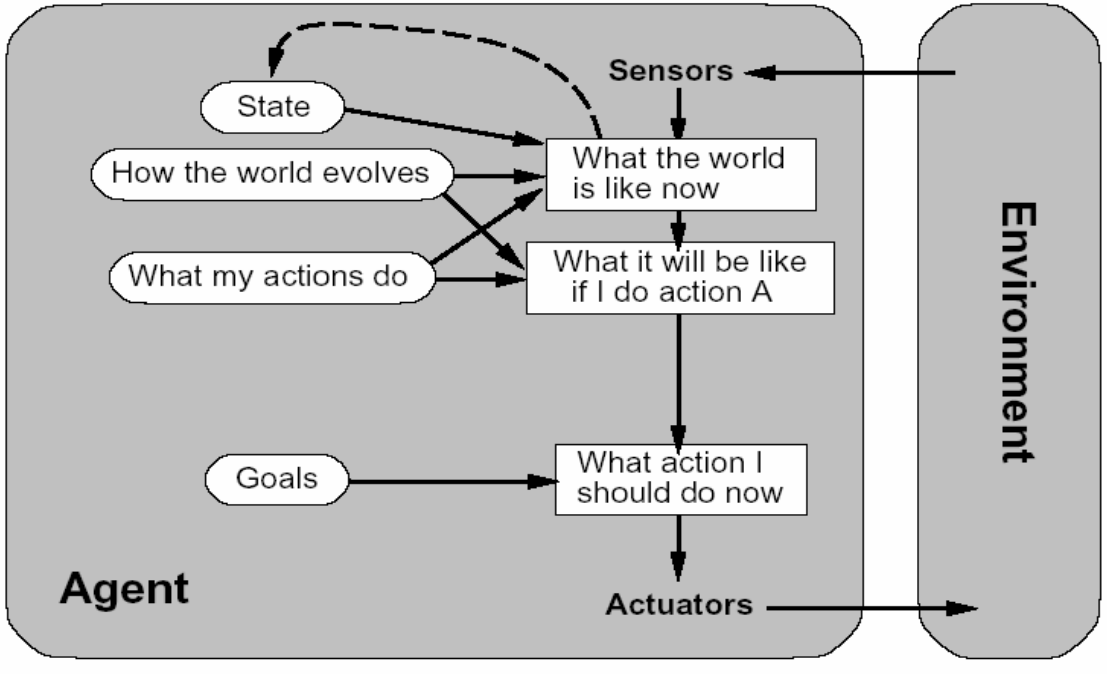
```
function REFLEX-AGENT-WITH-STATE(percept) returns an action
  static: state, a description of the current world state
          rules, a set of condition–action rules
          action, the most recent action, initially none

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

Goal-based Agents

- The action-decision process involves some sort of goal information describing situations that are desirable
  - Combine the goal information with the possible actions proposed by the internal state to choose actions to achieve the goal
  - **Search** and **planning** in AI are devoted to finding the right action sequences to achieve the goals

What will happen if I do so? Consideration of the future

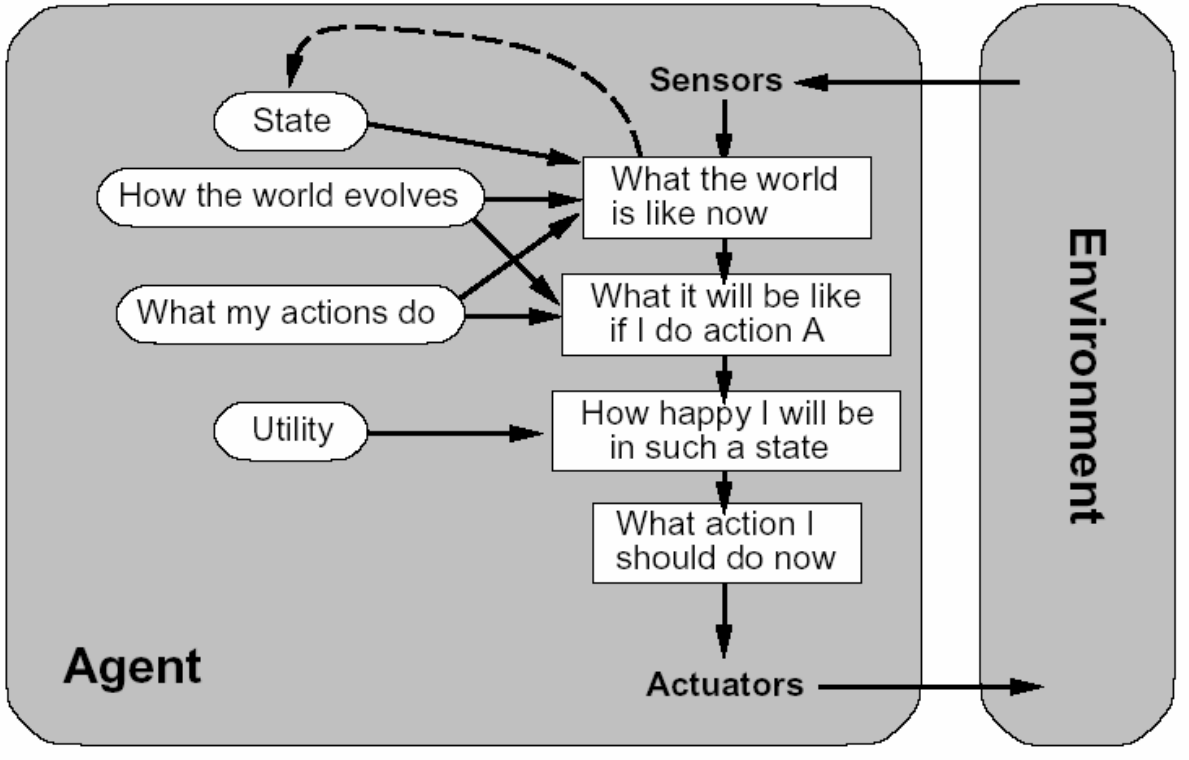


Utility-based Agents

- Goal provides a crude binary distinction between “happy” and “unhappy” sates
- Utility: maximize the agents expected happiness
  - E.g., quicker, safer, more reliable for the taxis-driver agent
- Utility function
  - Map a state (or a sequence of states) onto a real number to describe to degree of happiness
  - Explicit utility function provides the appropriate tradeoff or uncertainties to be reached of several goals
    - Conflict goals (speed/safety)
    - Likelihood of success

Make rational decisions

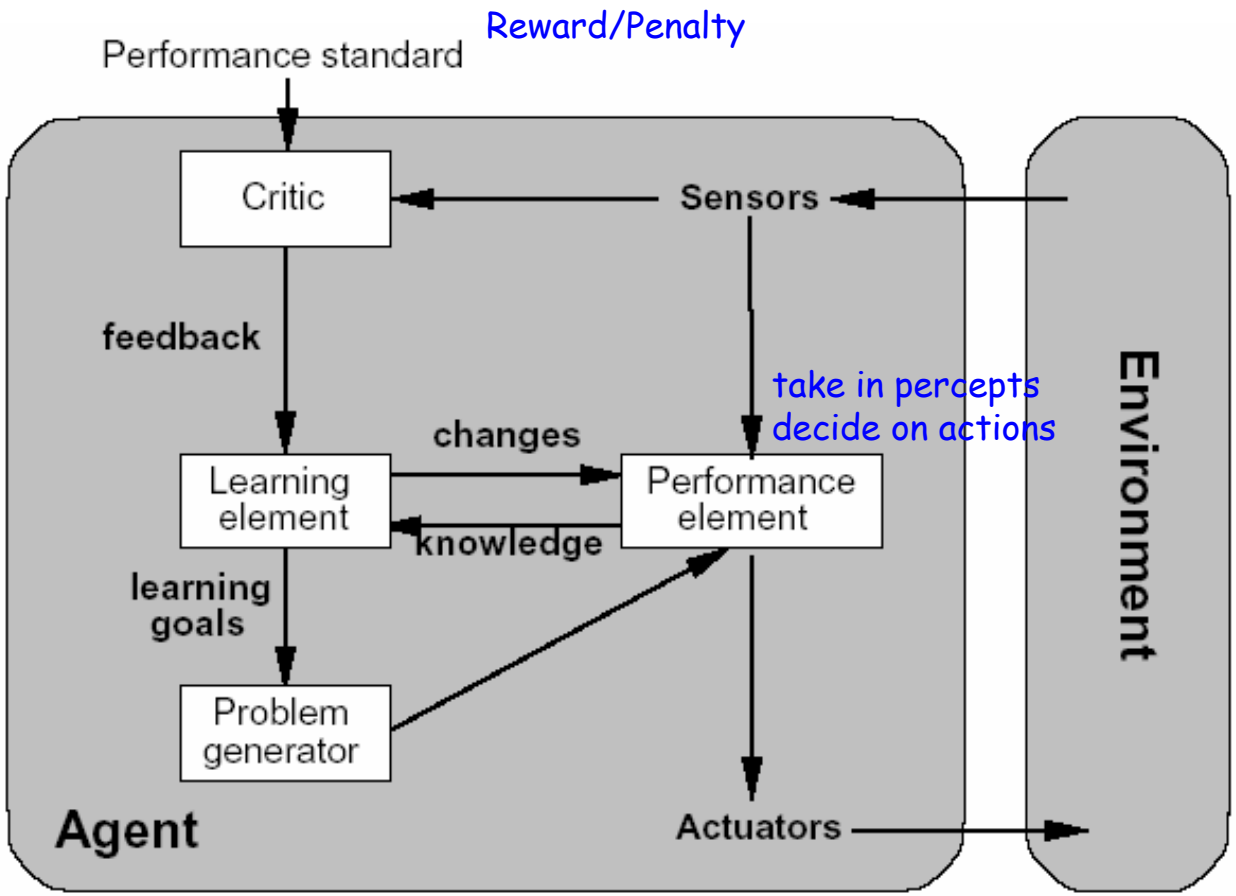
Utility-based Agents



Learning Agents

- Learning allows the agent to operate in initially unknown environments and to become more competent than its initial knowledge might allow
  - Learning algorithms
  - Create state-of-the-art agent!
- A learning agent composes of
  - **Learning element**: making improvements
  - **Performance element**: selecting external action
  - **Critic**: determining how the performance element should be modified according to the learning standard
  - **Problem generator**: suggesting actions that lead to new and informative experiences if the agent is willing to explore a little

Learning Agents



Learning Agents

- For example, the taxis-driver agent makes a quick left turn across three lines if traffic
  - The critic observes the shocking language from other drivers
  - And the learning element is able to formulate a rule saying this was a bad action
  - Then the performance element is modified by install the new rule
- Besides, the problem generator might identify certain areas if behavior in need of improvement and suggest experiments,
  - Such as trying out the brakes on different road surface under different conditions