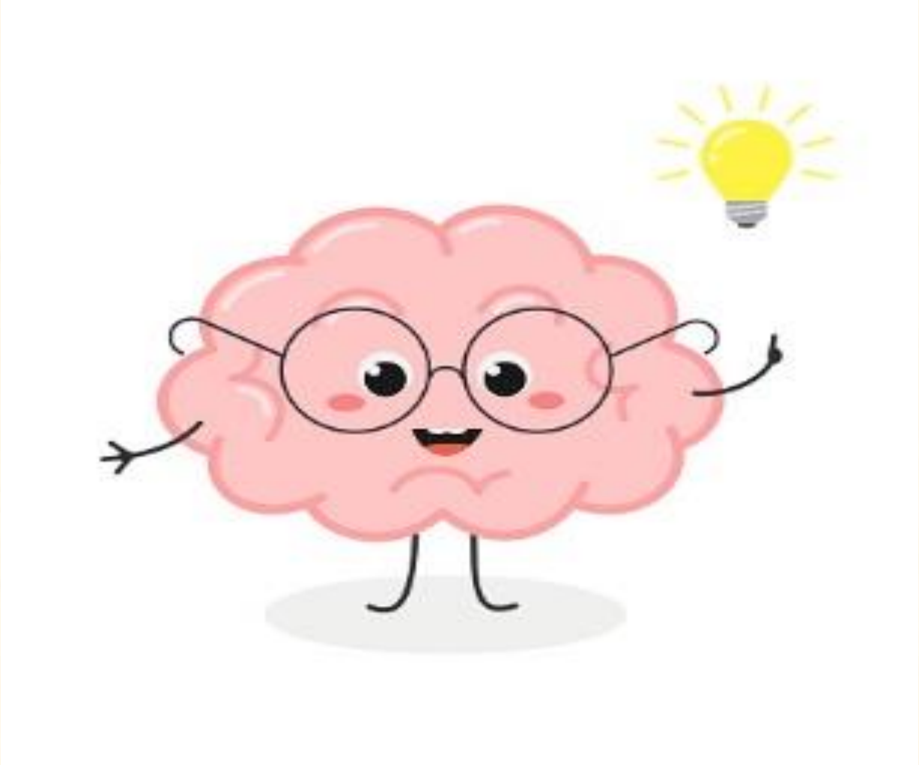
Chapter 2
Intelligent Agents



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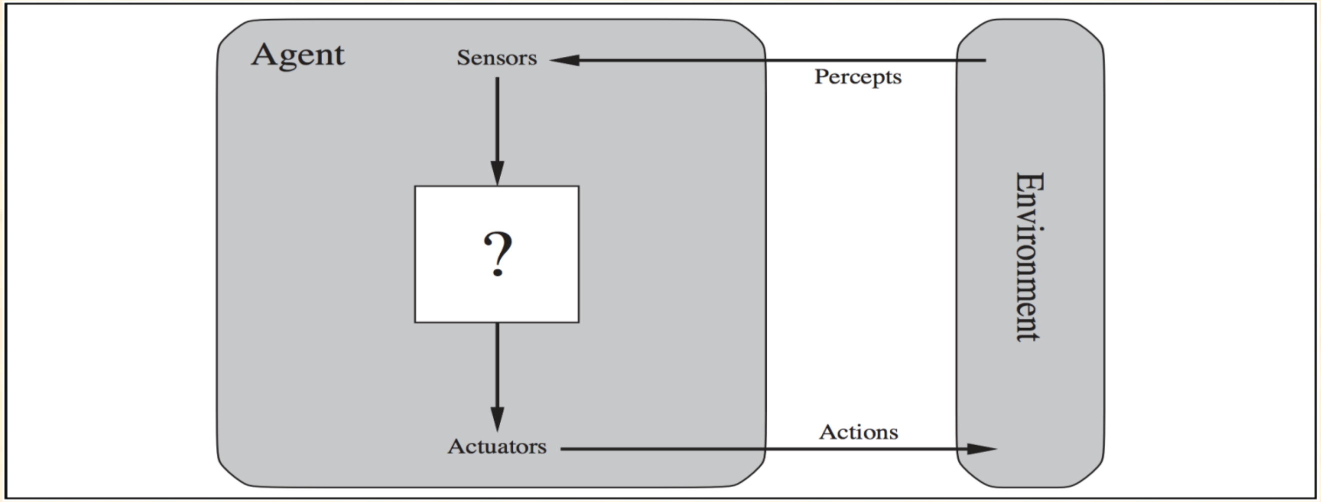
Outline

- Agents and environments
- Rationality
- PEAS (Performance measure, Environment, Actuators, Sensors)
- Environment types
- Agent types

Agents

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



Human agent: sensors - eyes, ears, and other sensory organs; **actuators -** hands, legs, mouth etc

Robotic agent: sensors - cameras and infrared range finders ; **actuators -** various motors for actuators

Software agent: sensors - Key strokes, file contents, network packets
actuators - Displaying on screen, writing files, sending network packets

Agents

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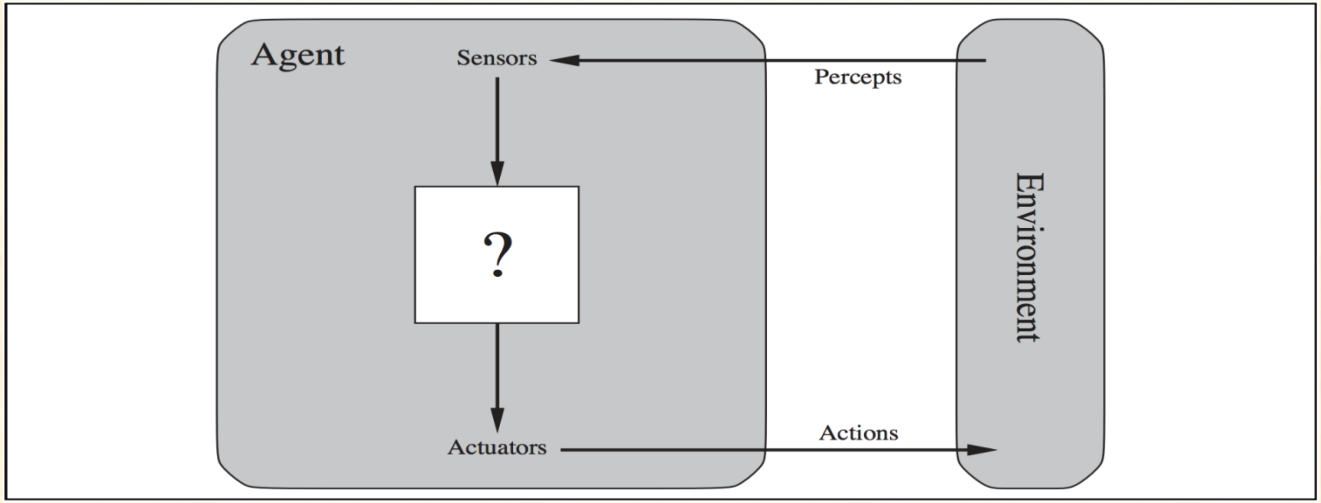


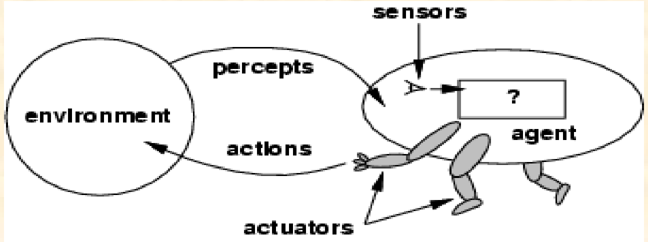
Percepts: agents perceptual inputs at any given instance
Percept sequence: complete history of agents perceived inputs
Agent functions: describes the agent's behavior

The agent function maps from percept histories to actions:

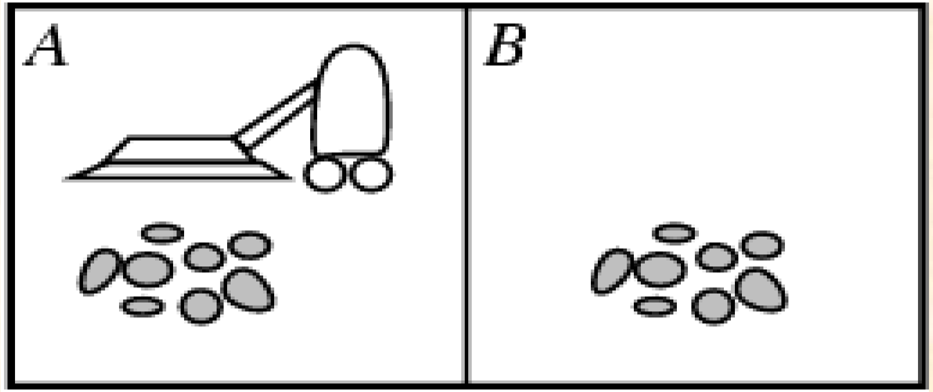
$$[f: \mathcal{P}^* \rightarrow \mathcal{A}]$$

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

agent = architecture + program

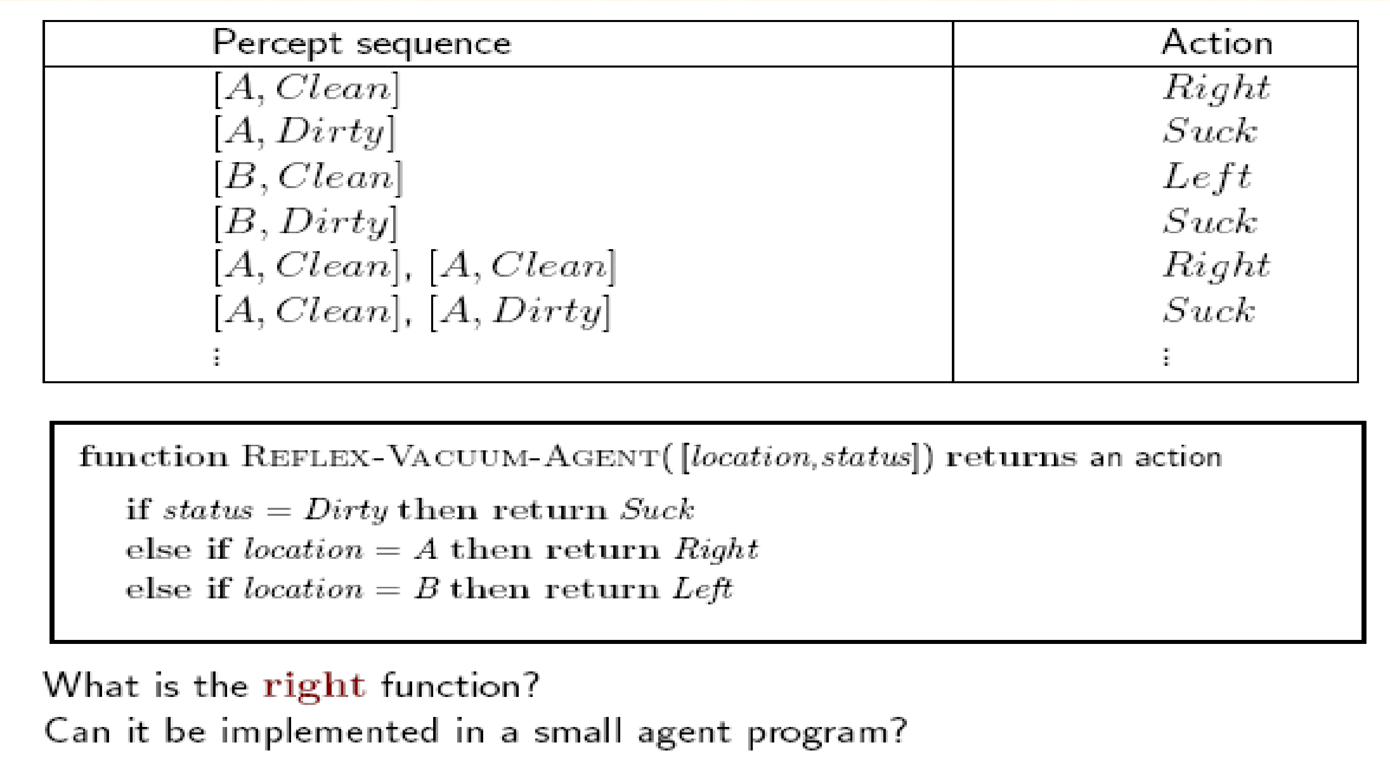


Vacuum-cleaner world



- Percepts: location and contents, e.g., [A, Dirty]
- Actions: *Left*, *Right*, *Suck*, *NoOp*

A vacuum-cleaner agent



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

```
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 $Left$
```

What is the right function?
Can it be implemented in a small agent program?

Good behavior: Concept of Rationality

Rational agent

- An agent should strive to "do the right thing", based on what it can perceive and the actions it can perform.
- All entry in the table for the agent function are filled correctly.
- The right action is the one that will cause the agent to be most successful

How to measure success????

- Performance measure: A criterion for success of an agent's behavior
- E.g., performance measure of vacuum cleaner
  - amount of dirt cleaned up,
  - amount of time taken,
  - amount of electricity consumed,
  - amount of noise generated, etc.

Selection of performance measure:

- Average performance Vs energetic performance with long breaks
- Reckless life or safe but simple existence
- Economy with moderate poverty for all or some are super rich + some are very poor

Good behavior: Concept of Rationality

What is rational??

- The Performance measure that defines the criterion of success
- The agent’s prior knowledge of environment
- The actions that the agent performs
- The agent’s percept sequence to data

Def: ***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.***

How to check if Vacuum cleaner is a rational agent?

- Performance measure: award one point for each clean square
- Environment: Geography of environment is known apriori – two squares A & B
- Actions: Left, Right, Such and NoOp
- Sensors: Agent perceives its location and checks if contains dirt or not

Under these circumstances Vacuum cleaner agent is rational.

Rational agents

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

- An agent should learn from what it perceives

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

Nature of Environment

- **Building rational agents**
  - Task environments : “problems”
  - Rational agent : “solutions”

- **Specifying task environment**
  - PEAS: (Performance measure, Environment, Actuators, Sensors)
  - e.g., the task of designing an automated taxi driver:
    - **Performance measure**: Safe, fast, legal, comfortable trip, maximize profits
    - **Environment**: Roads, other traffic, pedestrians, customers
    - **Actuators**: Steering wheel, accelerator, brake, signal, horn
    - **Sensors**: Cameras, sonar, speedometer, GPS, odometer, engine sensors, keyboard

PEAS

- Medical Diagnosis
- Part-picking robot

PEAS

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

- Agent: Part-picking robot
- Performance measure: Percentage of parts in correct bins
- Environment: Conveyor belt with parts, bins
- Actuators: Jointed arm and hand
- Sensors: Camera, joint angle sensors

Environment types

- Fully observable vs. partially observable:
  - Fully observable - An agent's sensors give it access to the complete state of the environment at each point in time.
  - Sensors detect all aspects relevant to choice of action (performance measure)
  - Agent need not maintain any internal state to keep track of the world
  - Partially observable - due to noise or inaccurate sensors or parts of state are missing
  - E.g. taxi cannot what other drivers are thinking

- Deterministic vs. stochastic:
  - Deterministic - The next state of the environment is completely determined by the current state and the action executed by the agent.
  - E.g. taxi driver is stochastic, vacuum cleaner example is deterministic
  - (If the environment is deterministic except for the actions of other agents, then the environment is strategic)

- Episodic vs. 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 environment, the current decision could affect all future decision
  - E.g chess playing , taxi driver – sequential
  - Fault detecting robot in assembly line - episodic

Environment types

- Static vs. dynamic:
  - The environment is changed while an agent is deliberating – dynamic else static.
  - Static – easy to deal, no importance to time
  - (The environment is semi dynamic if the environment itself does not change with the passage of time but the agent's performance score does)
  - E.g. taxi – dynamic, crossword puzzle – static, chess with clock - semidynamic
- Discrete vs. continuous:
  - Applied to state of environment, way time is handled, percepts/actions of agents
  - Discrete - A limited number of distinct, clearly defined percepts and actions.
  - E.g taxi – continuous ,
  - chess, crossword - discrete
- Single agent vs. multi agent:
  - Single - An agent operating by itself in an environment
  - E.g. crossword - single
  - Competitive multiagent – chess with opponent
  - Cooperative multiagent – taxi driving

Environment types

	Taxi driving	Chess playing with clock	Chess playing without clock
Observable	Partially	Fully	Fully
Deterministic	Stochastic	Strategic	Strategic
Episodic	Sequential	Sequential	Sequential
Static	Dynamic	Semi-dynamic	Dynamic
Discrete	Continuous	Discrete	Discrete
Agents	Multi	Single	Single

The real world is partially observable, stochastic, sequential, dynamic, continuous, multi-agent

Agent functions and programs

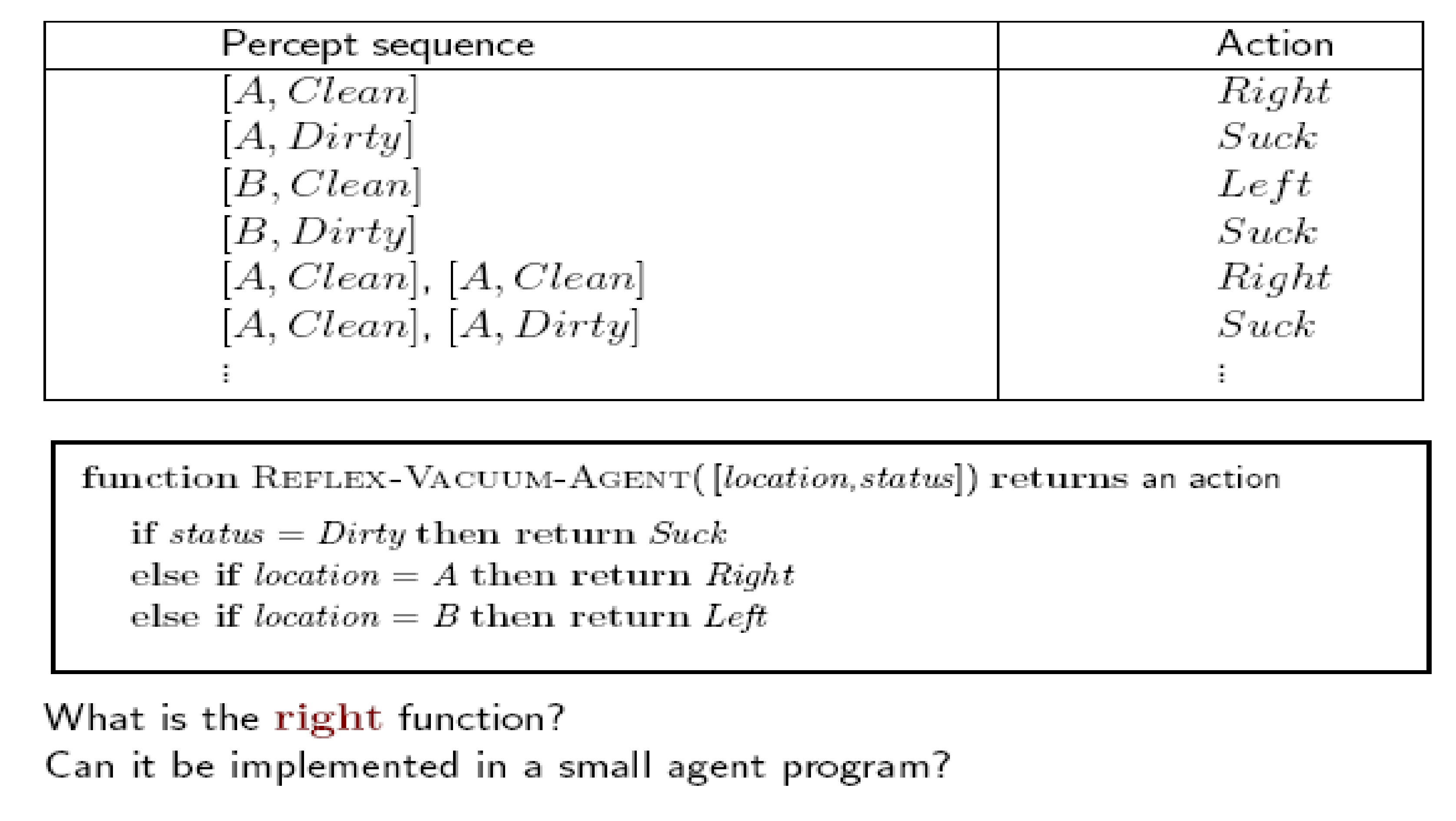
- An agent is completely specified by the agent function mapping percept sequences to actions
- One agent function (or a small equivalence class) is rational
- Aim: find a way to implement the rational agent function concisely

Table-lookup agent

action 🡐 LOOKUP(percepts, table)

- Drawbacks:
  - Huge table
  - Take a long time to build the table
  - No autonomy
  - Even with learning, need a long time to learn the table entries

Agent program for a vacuum-cleaner agent



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$\vdots$	$\vdots$

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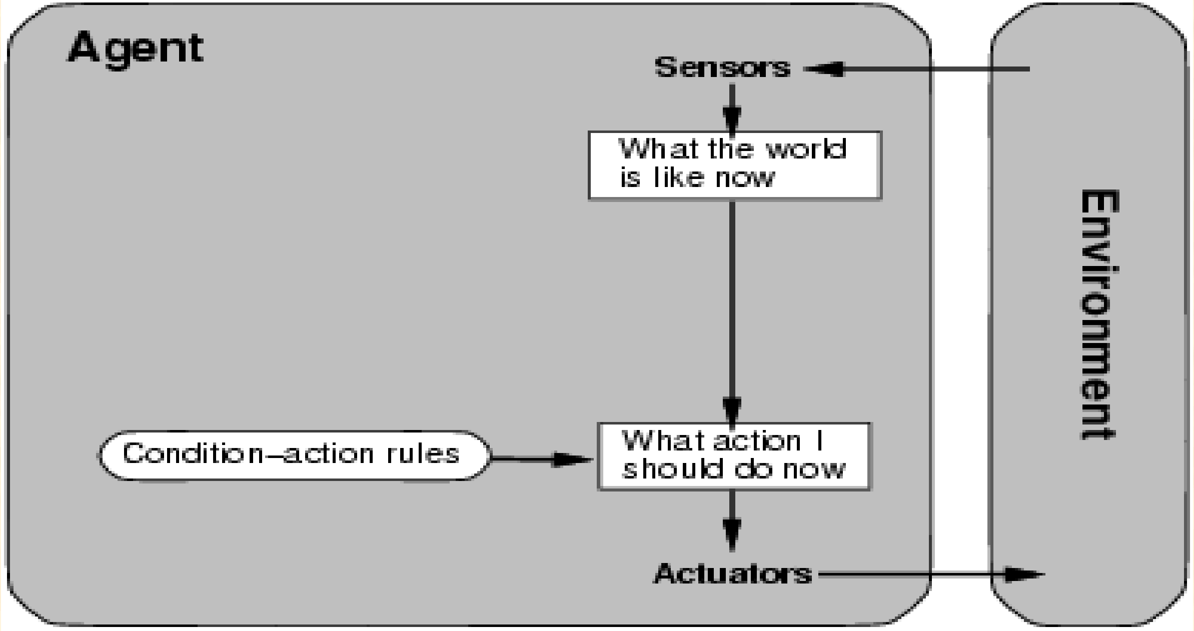
Agent types

Four basic types in order of increasing generality:

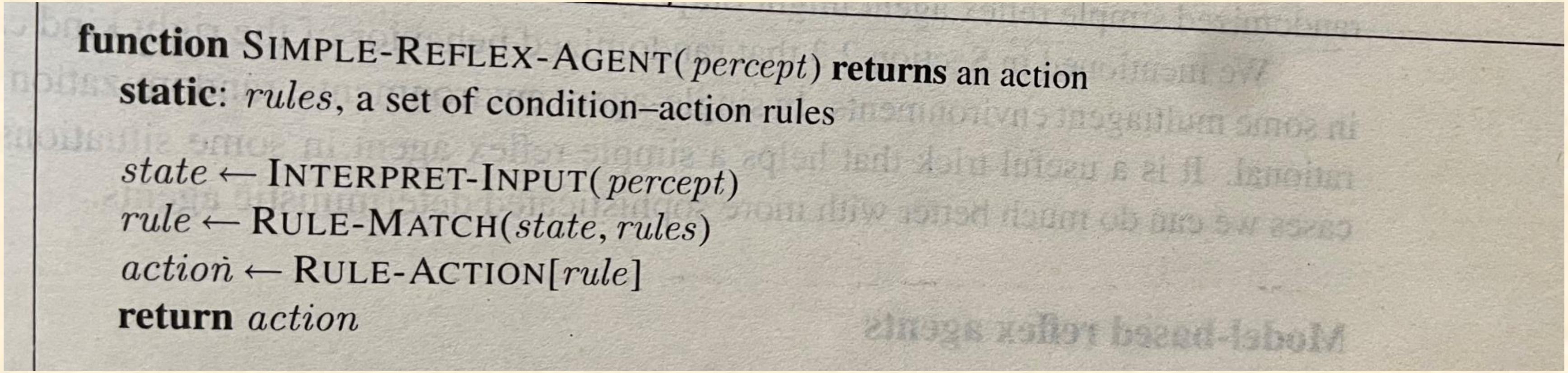
- Simple reflex agents
- Model-based reflex agents
- Goal-based agents
- Utility-based agents
- Learning agents

Simple reflex agents



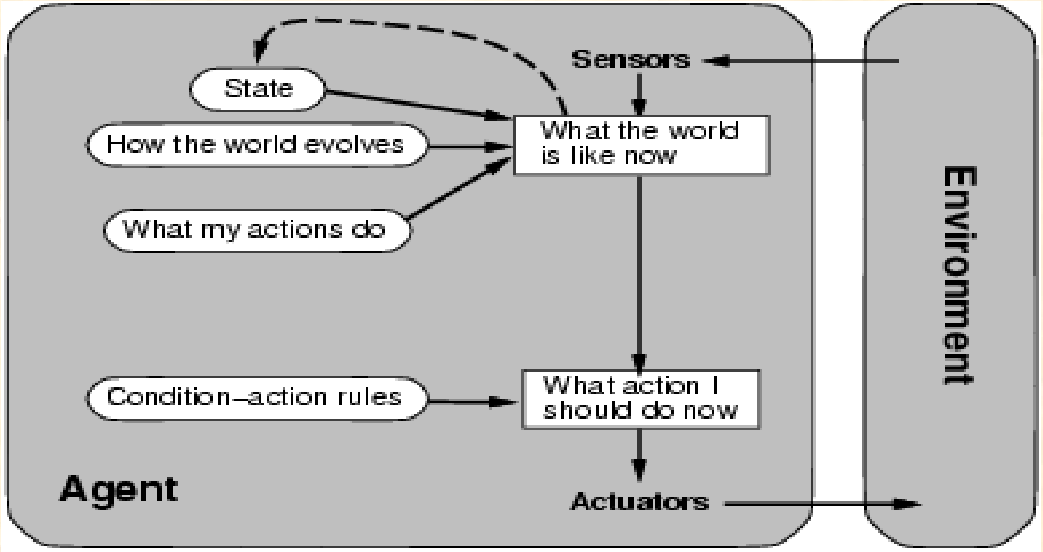
- Select action on current percept
- Ignore percept history
- Actions based on condition-action rule
- Problems?? – works only in fully observable environment

Simple reflex agents



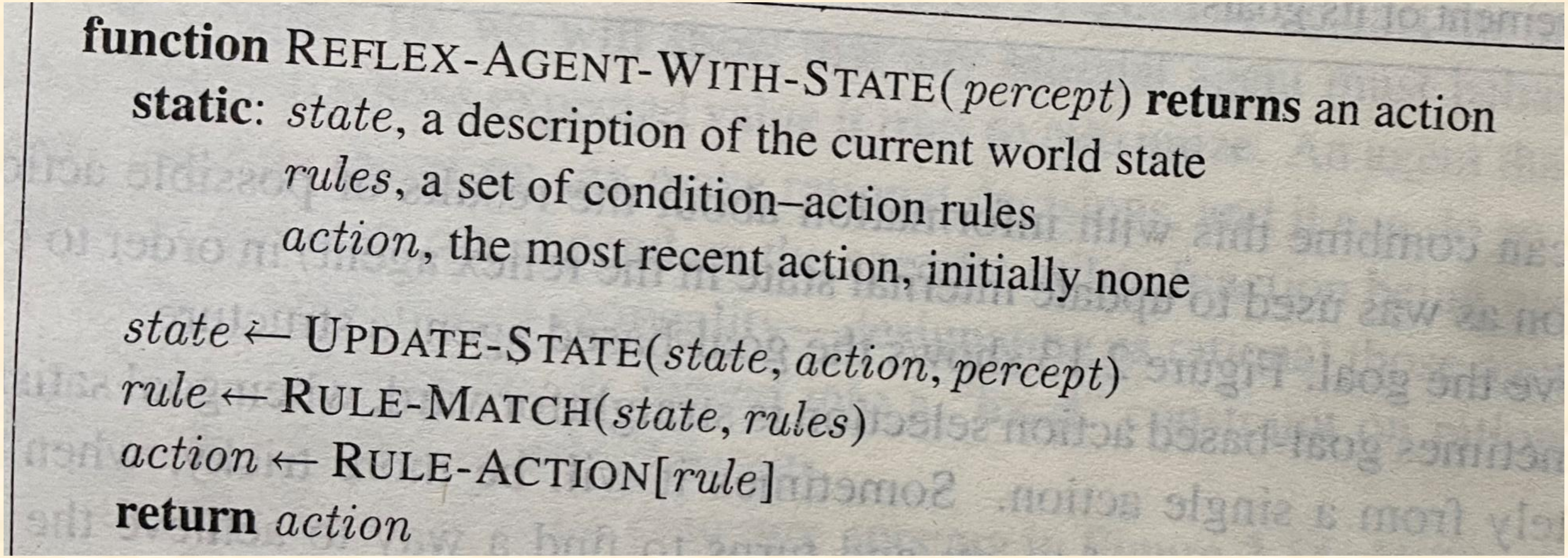
```
function SIMPLE-REFLEX-AGENT(percept) returns an action
    static: rules, a set of condition–action rules

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

Model-based reflex agents



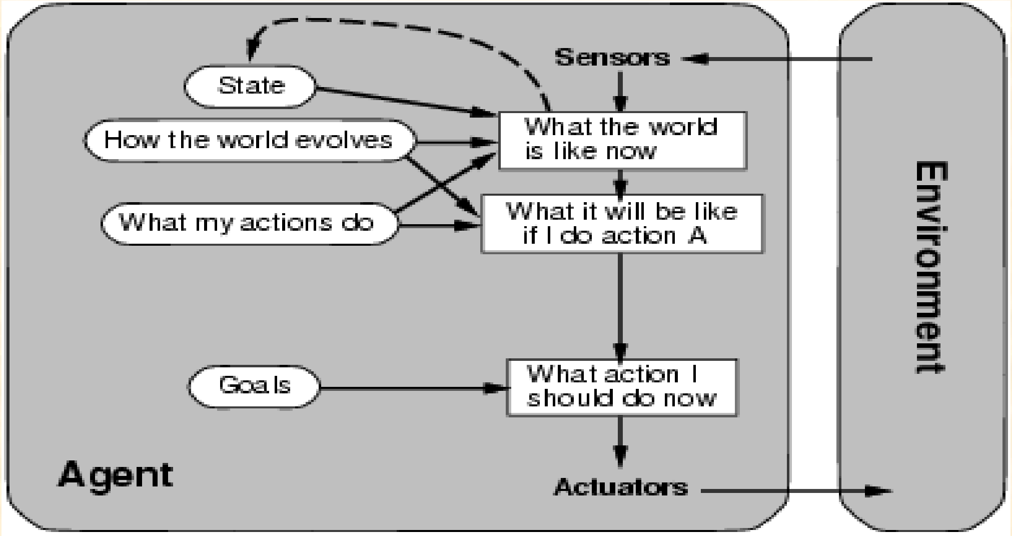
- Keep track of current state of the world agent can't see
- Maintain an internal state that depends on percept history n reflect unobserved aspects
- updating internal model requires knowledge about how the world evolves independent of the agent and how agent actions affect the world
- Model of the world → knowledge about how the world , hence the name

Model-based reflex agents



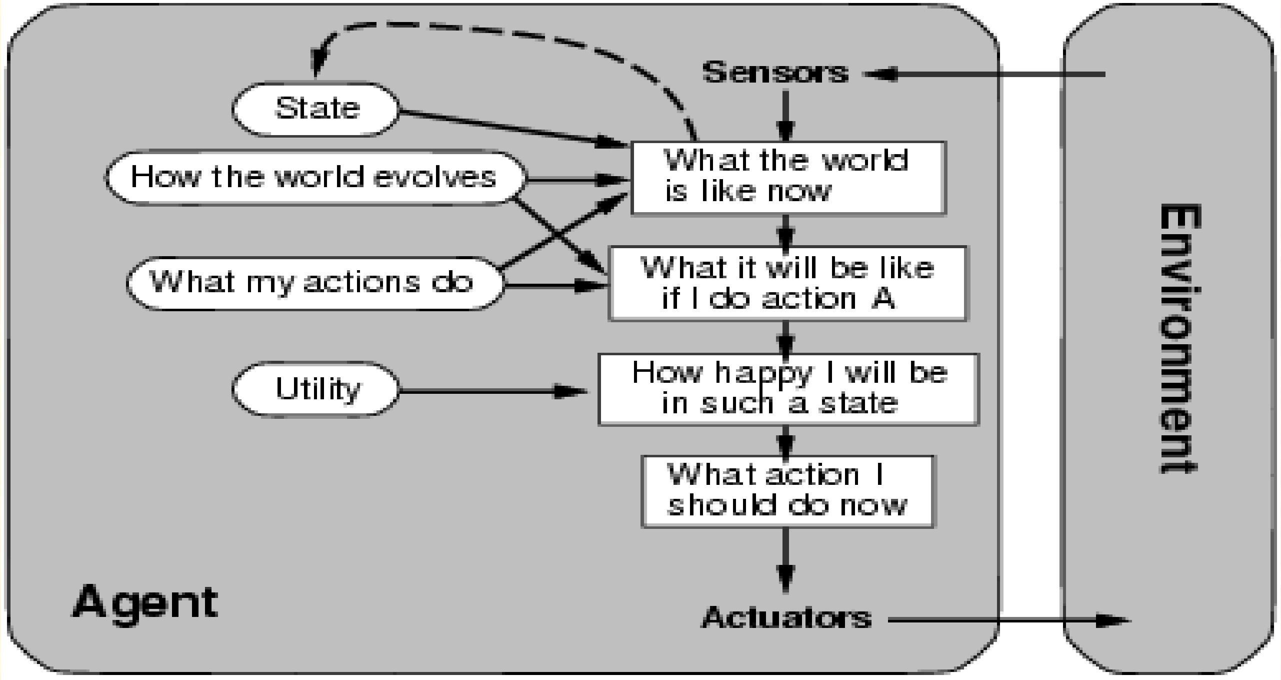
```
function REFLEX-AGENT-WITH-STATE(percept) returns an action
    static: state, a description of the current world state
            rules, a set of condition–action rules
            action, the most recent action, initially none

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

Goal-based agents


Sensors
State
How the world evolves
What my actions do
What the world is like now
What it will be like if I do action A
Goals
What action I should do now
Agent
Actuators
Environment

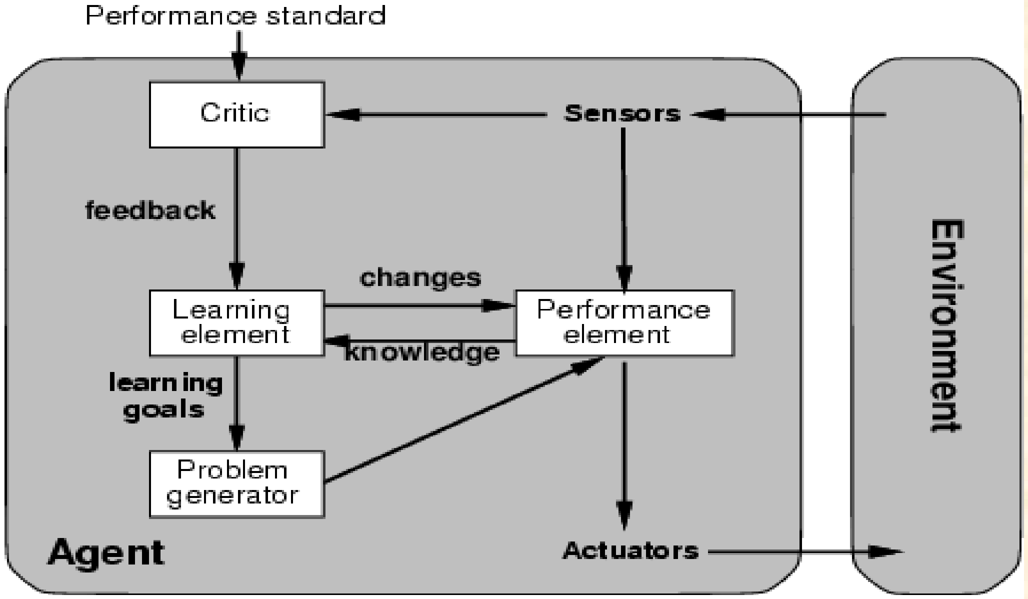
- Keep track of current state of the world and set of its goals
- Search and planning are required to achieve goals
- Decision making involves consideration of future – what will happen and will I be happy
- It is less efficient but more flexible s knowledge is explicit and can be modified
- Agents behaviour can be changed to a different location

Utility-based agents


Sensors
State
How the world evolves
What my actions do
Utility
What the world is like now
What it will be like if I do action A
How happy I will be in such a state
What action I should do now
Agent
Actuators
Environment

- Goals alone are insufficient to generate high quality behaviour
- Goals provide crude distinction between happy and unhappy state – need how happy
- Instead higher Utility of agent is preferred
- utility function maps a state to real number – degree of happiness
- Allows rational decision where goal is inadequate : in conflicting goals and in selecting goals that can be achieved

Learning agents



- Learning allows agent to operate in initially unknown environment
- Learning element : making improvements
- Performance element : selecting external actions
- Critic : provides feedback on how the agent is doing and determines how the performance element should be modified
- Problem generator: suggesting actions

Conclusion

- Agents can have variety of components
- Each component can be presented in a variety of ways
- A variety of learning methods but one unifying theme
- Learning in intelligent agent is a process of modification of each component to bring them into a closer agreement with available feedback information thereby improving overall agent performance