## **Artificial Intelligence**

Dr. Qaiser Abbas

Department of Computer Science & IT,

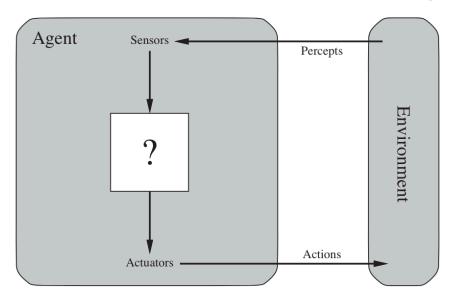
University of Sargodha

qaiser.abbas@uos.edu.pk

# 2. Intelligent Agents

#### 2.1 AGENTS AND ENVIRONMENTS

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



# 2. Intelligent Agents

#### 2.1 AGENTS AND ENVIRONMENTS

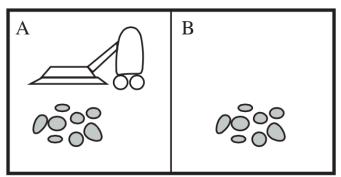
- The term percept refers to the agent's perceptual inputs at any given instant.
- An agent's percept sequence is the complete history of everything the agent has ever perceived.
- An agent's behavior is described by the agent function that maps any given percept sequence to an action.
- The agent program is a concrete implementation, running within some physical system.

## 2.1 AGENTS AND ENVIRONMENTS

#### Example of vacuum-cleaner world

- Has just two locations: squares A and B.
- Perceives which square it is in and whether there is dirt in the square.
- Choose to move left, right, suck up the dirt, or do nothing.
- Simple agent function: if the current square is dirty, then suck; otherwise, move to the other square.
- The pictorial representation is as follows:
  - Vacuum Cleaner World
  - A partial tabulation of this agent function
  - An agent program that implements it

## 2.1 AGENTS AND ENVIRONMENTS



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
<b>:</b>	:
[A, Clean], [A, Clean], [A, Clean]	Right
[A, Clean], [A, Clean], [A, Dirty]	Suck
<b>:</b>	:

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

# 2.2 GOOD BEHAVIOR: THE CONCEPT OF RATIONALITY

- A rational agent is one that does the right thing, but what does it mean to do the right thing?
  - When an agent is plunked down in an environment, it generates a sequence of actions according to the percepts it receives.
  - This sequence of actions causes the environment to go through a sequence of states. If the sequence is desirable, then the agent has performed well.
  - This notion of desirability is captured by a performance measure that evaluates any given sequence of environment states.

# 2.2 GOOD BEHAVIOR: THE CONCEPT OF RATIONALITY

- Example: vacuum-cleaner agent from the preceding section.
  - If performance measure: <u>the amount of dirt cleaned up in a single eight-hour shift</u>.
  - A rational agent can maximize this performance measure by cleaning up the dirt, then dumping it all on the floor, then cleaning it up again, and so on.
  - If performance measure: <u>one point could be awarded for each clean square at each time step (perhaps with a penalty for electricity consumed and noise generated).</u>
  - Which one would be better between these two mentioned?
- General rule: Better to design performance measures according to what one actually wants in the environment, rather than according to how one thinks the agent should behave.

## 2.2.1 Rationality

- What is rational depends on four things:
  - Performance measure: defines the criterion of success.
  - Prior knowledge of the environment.
  - Actions that the agent can perform.
  - Percept sequence to date.

#### Definition of a rational agent:

 For each possible <u>percept sequence</u>, a rational agent should select an <u>action</u> that is expected to maximize its <u>performance measure</u>, given the evidence provided by the percept sequence and whatever <u>built-in knowledge</u> the agent has.

# 2.2.1 Rationality

- Example: Does the vacuum-cleaner agent function on <u>Slide 5</u>, is a rational agent?
  - That depends on what the performance measure is, what is known about the environment, and what sensors and actuators the agent has. Let us assume the following:
    - If **performance measure** awards one point for each clean square at each time step, over a "lifetime" of 1000 time steps.
    - If the "geography" of the **environment is known** as *in* Figure of <u>Slide 5</u> but the dirt distribution and the initial location of the agent are not.
    - Clean squares stay clean and sucking cleans the current square. The Left and Right actions move the agent left and right except when this would take the agent outside the environment, in which case the agent remains where it is. Only available actions are Left, Right, and Suck.
    - The agent correctly perceives its location and whether that location contains dirt.

Under these circumstances the agent is indeed rational;

# 2.2.2 Omniscience, learning, and autonomy (Read it yourself)

- **Omniscience** is knowing everything, which is not possible.
- Rationality <u>maximizes expected performance</u>.
  - For example: looking both sides (percept sequence) before crossing the road. Or doing actions in order to modify future percepts sometimes called information gathering or exploration is an important part of rationality e.g. traffic blocking information and route modification.
- A rational agent is expected not only to gather information but also to **learn** as much as possible from what it perceives.
  - Prior knowledge of the environment as the <u>agent gains experience</u> may be <u>modified and augmented</u>.
  - In extreme cases, the environment is completely known a <u>priori</u>. Then
    the <u>agent does not need to perceive or learn</u>; it simply acts correctly
    e.g. lowly dung beetle or <u>female sphex wasp</u>.

# 2.2.2 Omniscience, learning, and autonomy (Read it yourself)

- If the agent relies on the prior knowledge of its designer rather than on its own percepts, then the agent lacks **autonomy**.
- A rational agent should be autonomous—it should learn what it can, to compensate for partial or incorrect prior knowledge.
  - For example, a vacuum-cleaning agent that learns to foresee where and when additional dirt will appear will do better than one that does not.

#### • 2.3.1 Specifying the task environment

- It consists of PEAS (Performance, Environment, Actuators, Sensors). All in one group.
- In designing an agent, the first step must always be to specify the task environment as fully as possible.
- Example: let us consider a more complex problem: an automated taxi driver.

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

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

In Figure 2.5, we have sketched the basic PEAS elements for a number of additional agent types.

Agent Type	Performance Measure	Environment	Actuators	Sensors
Medical diagnosis system	Healthy patient, reduced costs	Patient, hospital, staff	Display of questions, tests, diagnoses, treatments, referrals	Keyboard entry of symptoms, findings, patient's answers
Satellite image analysis system	Correct image categorization	Downlink from orbiting satellite	Display of scene categorization	Color pixel arrays
Part-picking robot	Percentage of parts in correct bins	Conveyor belt with parts; bins	Jointed arm and hand	Camera, joint angle sensors
Refinery controller	Purity, yield, safety	Refinery, operators	Valves, pumps, heaters, displays	Temperature, pressure, chemical sensors
Interactive English tutor	Student's score on test	Set of students, testing agency	Display of exercises, suggestions, corrections	Keyboard entry
Figure 2.5 Examples of agent types and their PEAS descriptions.				

#### Internet shopping agent:

- Performance measure?? Price, quality, appropriateness, efficiency
- Environment?? Current and future WWW sites, vendors, shippers
- Actuators?? Display to user, follow URL, fill in form
- Sensors?? HTML pages (text, graphics, scripts)

#### Question-answering system

- Performance measure?? User satisfaction? Known questions?
- Environment?? Wikipedia, Wolfram alpha, ontologies, encyclopedia, . . .
- Actuators?? Spoken/written language
- Sensors?? Written/spoken input

2.3.2 Properties of task environments

Task environments can be categorized into following.:

- Fully observable vs. partially observable:
  - If an agent's sensors give access to the <u>complete state of the</u> <u>environment</u> at each point in time, then we say that the task environment is **fully observable**.
  - An environment might be partially observable because of noisy and inaccurate sensors or because parts of the state are simply missing from the sensor data—for example, a vacuum agent with only a local dirt sensor cannot tell whether there is dirt in other squares.
  - If the agent has no sensors at all then the environment is unobservable.

#### — Single agent vs. multiagent:

- An <u>agent solving a crossword puzzle</u> by itself is clearly in a <u>single-agent environment</u>, whereas <u>an agent playing chess</u> is in a <u>two-agent environment</u>.
- In chess, the opponent entity B is trying to maximize its performance measure, which, by the rules of chess, minimizes agent A's performance measure. Thus, chess is a competitive multiagent environment.
- In the <u>taxi-driving environment</u>, avoiding collisions maximizes the performance measure of all agents, so it is a partially **cooperative** multiagent environment.

#### Deterministic vs. stochastic.

- If the <u>next state of the environment is completely determined by the current state and the action executed by the agent</u>, then we say the environment is **deterministic**; otherwise, it is **stochastic**.
- If the environment is partially observable, then it could appear to be stochastic but next state may not be predicted precisely.

- **Example:** Taxi driving is clearly stochastic in this sense, because one can never predict the behavior of traffic exactly; moreover, one's tires blow out and one's engine seizes up without warning.
- An environment is **uncertain** if it is not fully observable or not deterministic.
- "Stochastic" generally implies that uncertainty about outcomes is quantified in terms of probabilities;
- A **nondeterministic** environment is one in which actions are characterized by their possible outcomes, but no probabilities are attached to them.

#### – Episodic vs. sequential:

- In an episodic task environment, the agent's experience is divided into episodes. In each episode the agent receives a percept and then performs a single action. Crucially (critically or decisively), the next episode does not depend on the actions taken in previous episodes.
- For example, an agent that has to spot defective parts on an assembly line bases each decision on the current part, regardless of previous decisions; moreover, the current decision doesn't affect whether the next part is defective.
- In sequential environments, on the other hand, the current decision could affect all future decisions. Chess and taxi driving are sequential: in both cases, short-term actions can have long-term consequences.

#### – Static vs. dynamic:

• If the environment can change while an agent is deliberating (engage in long and careful consideration), then we say the environment is dynamic for that agent; otherwise, it is static. (Read it Yourself)

#### Discrete vs. continuous: (Read it yourself)

- The discrete/continuous distinction applies to the *state* of the environment, to the way *time* is handled, and to the *percepts* and *actions* of the agent.
- A discrete environment has fixed locations or time intervals. A continuous environment could be measured quantitatively to any level of precision.

#### Known vs. unknown: (Read it yourself)

- This distinction refers not to the environment itself but to the agent's state of knowledge.
- In a known environment, the outcomes (or outcome probabilities if the environment is stochastic) for all actions are given.
- If the environment is unknown, the agent will have to learn how it works in order to make good decisions.

**Environment class:** to evaluate a taxi driver in simulated traffic, we would want to run many simulations with different traffic, lighting, and weather conditions called environment class.

Task Environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle Chess with a clock	Fully Fully	Single Multi	Deterministic Deterministic		Static Semi	Discrete Discrete
Poker Backgammon	Partially Fully	Multi Multi	Stochastic Stochastic	Sequential Sequential	Static Static	Discrete Discrete
Taxi driving Medical diagnosis	Partially Partially	Multi Single	Stochastic Stochastic	•	•	Continuous Continuous
Image analysis Part-picking robot	Fully Partially	Single Single	Deterministic Stochastic	Episodic Episodic	Semi Dynamic	Continuous Continuous
Refinery controller Interactive English tutor	Partially Partially	Single Multi	Stochastic Stochastic	Sequential Sequential	•	Continuous Discrete
Figure 2.6 Examples of task environments and their characteristics.						

#### agent = architecture + program

 Program runs on some sort of computing device with physical sensors and actuators we call this the architecture

 The job of AI is to design an agent program that implements the agent function— the mapping from percepts to actions.

#### 2.4.1 Agent programs

- To build a rational agent, we as designers must construct a table that contains the appropriate action for every possible percept sequence.
- Figure 2.7 shows a rather trivial (little importance) agent program that keeps track of the percept sequence and then uses it to index into a table of actions to decide what to do.

**function** TABLE-DRIVEN-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  $action \leftarrow Lookup(percepts, table)$  **return** action

**Figure 2.7** The TABLE-DRIVEN-AGENT program is invoked for each new percept and returns an action each time. It retains the complete percept sequence in memory.

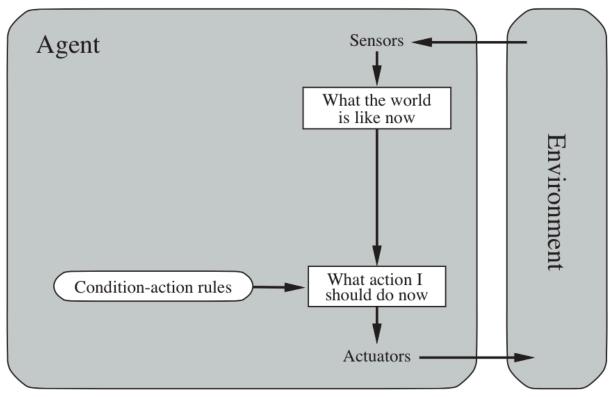
#### Drawbacks of table-driven approach:

- Table-driven approach to agent construction is doomed (unfortunate) to failure.
- Let P be the set of possible percepts and let T be the lifetime of the agent (the total number of percepts it will receive). The lookup table will contain  $\sum_{i=1}^{T} |P|^{i}$  entries.
- Daunting (difficult to deal) size of these tables.
- No physical agent in this universe will have the space to store the table.
- The designer would not have time to create the table,
- No agent could ever learn all the right table entries from its experience means no autonomy.
- Even with learning, need a long time to learn the table entries.

- The key challenge for AI is to find out how to write programs that, to the extent possible, produce rational behavior from a smallish program rather than from a vast table.
- Four basic kinds of agent programs are as follows:
  - Simple reflex agents;
  - Model-based reflex agents;
  - Goal-based agents; and
  - Utility-based agents.

#### 2.4.2 Simple reflex agents

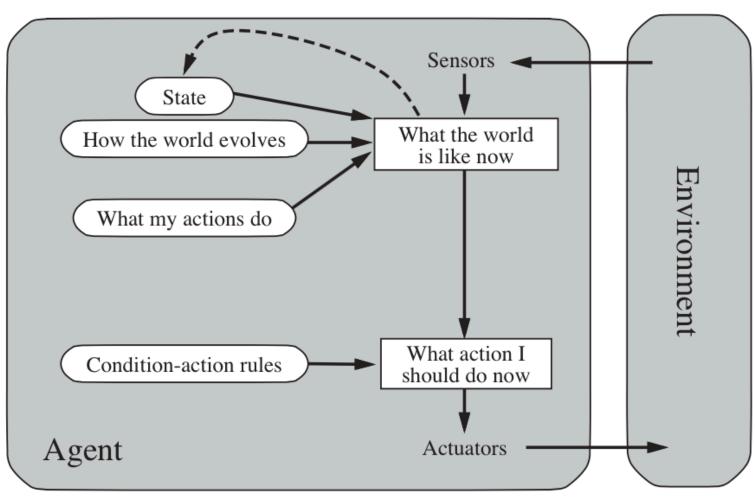
These agents select actions on the basis of the current percept, ignoring the rest of the percept history. For example, the vacuum agent whose agent function is tabulated in Figure on slide 5 is a simple reflex agent, because its decision is based only on the current location and on whether that location contains dirt. An agent program for this agent is shown in Figure on slide 5.



#### 2.4.3 Model-based reflex agents

- In this, the agent should maintain some sort of internal state that depends on the percept history and thereby reflects at least some of the unobserved aspects of the current state.
  - State: For the braking problem, the internal state is not too extensive— just the previous frame from the camera, allowing the agent to detect when two red lights at the edge of the vehicle go on or off simultaneously.
  - How the world evolves?: For example, an overtaking car generally will be closer behind than it was a moment ago.
  - What my actions do?: After driving for five minutes towards
     Makkah on the Highway, one is usually about five miles towards
     Makkah of where one was five minutes ago.

2.4.3 Model-based reflex agents

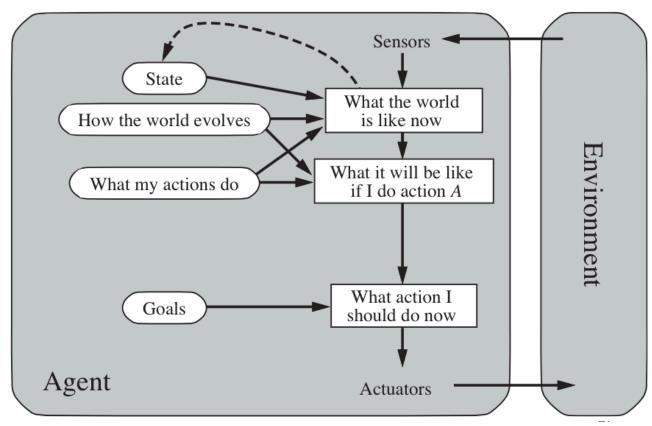


#### 2.4.4 Goal-based agents

The agent needs some sort of goal information that describes situations that are desirable—For example, at a road junction, the taxi can turn left, turn right, or go straight on. The correct decision depends on where the taxi is trying to get to.

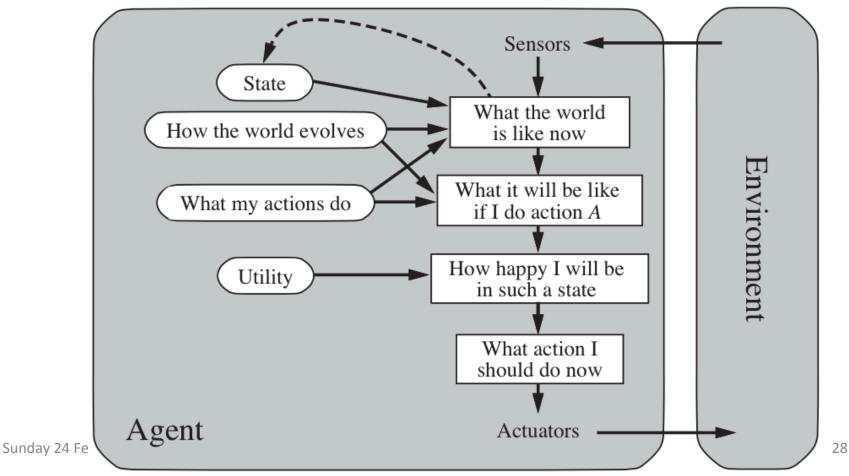
The agent program can combine this with the model- based reflex agent to choose actions that

achieve the goal.



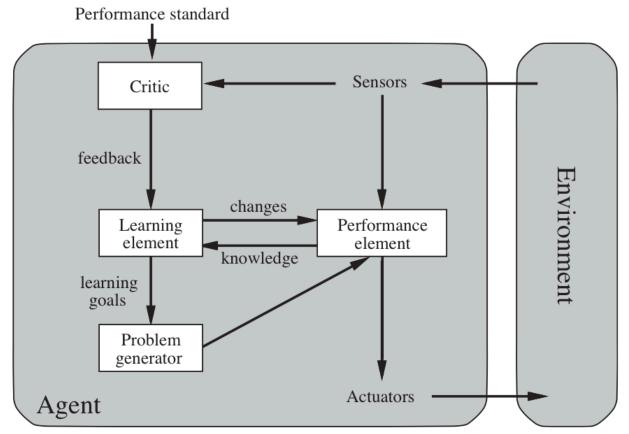
#### 2.4.5 Utility-based agents

 Utility-based agents addresses the partial observability and stochasticity and decision making under uncertainty.



#### 2.4.6 Learning agents

- Learning allows the agent to operate in initially unknown environments.
- Performance element is responsible for selecting external actions.
- Learning element is responsible for making improvements. It takes feedback from the critic on how the
  agent is doing and determines changes for the performance element to do better in the future.
- Critic tells the learning element how well the agent is doing with respect to a fixed performance standard.
- If the agent is willing to explore a little and do some suboptimal actions in the short run, to help much better actions for the long run. The problem generator's job is to suggest these exploratory actions.



## **Assignment No.2**

Understand the Vacuum Cleaner World given at the following link:

http://web.ntnu.edu.tw/~tcchiang/ai/Vacuum%20Cleaner%20World.htm

- 2. Download the source code, configure it and execute it. After having a hands on experience, submit the report with complete discussion of steps you made to make this source code executable along with the explanation of handmade output screenshots.
- 3. Be ready for your presentation at any time.