ARTIFICIAL INTELLIGENCE

Lecture 02

1

Thinking Humanly	Thinking Rationally
"The exciting new effort to make computers think ... *machines with minds*, in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning ..." (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole *et al.*, 1998) "AI ...is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Figure 1.1 Some definitions of artificial intelligence, organized into four categories.

Focus of this course

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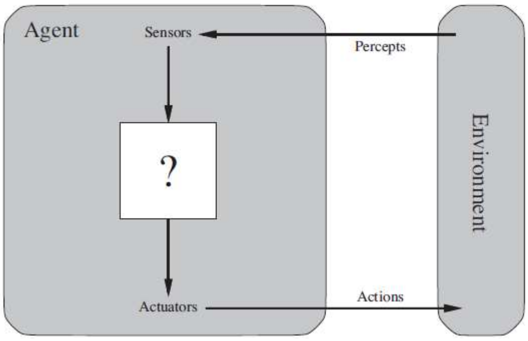
AGENTS AND ENVIRONMENT

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



Agent	Sensor	Actuator
Human	Eyes	Arms/Legs
Robot	Camera	Motors
Software	Keystokes File Receiving Receive Packets	Screen Display File Writing Sending Packets

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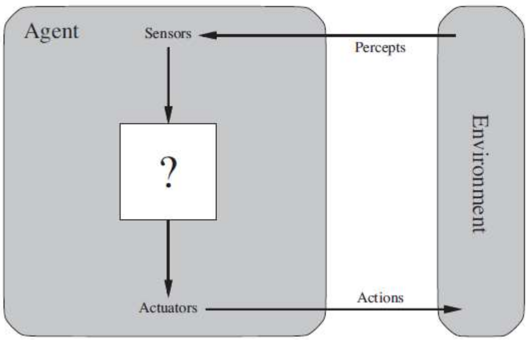
AGENTS AND ENVIRONMENT

We use the term **percept** to refer to the agent's perceptual inputs at any given instant.

Agent's **percept sequence** is the complete history of everything the agent has ever perceived.



percept → Agent Function → **Action**

Percepts/ Percept Sequence → Agent Function → **Actions/ Action Sequence**

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RATIONAL AGENT

A **rational agent** is one that does 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 of states 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.

Notice that we said *environment* states, not *agent* states.

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ENVIRONMENT VS AGENT STATE

We might propose to measure performance by the amount of dirt cleaned up in a single eight-hour shift.

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.

A more suitable performance measure would reward the agent for having a clean floor. For example, one point could be awarded for each clean square at each time step.

As a general rule, it is 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.

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RATIONALITY

What is rational at any given time depends on four things:
- The performance measure that defines the criterion of success.
- The agent's prior knowledge of the environment.
- The actions that the agent can perform.
- The agent's percept sequence to date

This leads to a **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 and whatever built-in knowledge the agent has.*

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PEAS (PERFORMANCE, ENVIRONMENT, ACTUATORS, SENSORS)

Agent: 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.

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PEAS (PERFORMANCE, ENVIRONMENT, ACTUATORS, SENSORS)

Agent: Medical Diagnostic System

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

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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.

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TYPES OF TASK ENVIRONMENT

Fully observable vs. **partially observable**

Single agent vs. **multiagent**

Deterministic vs. **stochastic**

Episodic vs. **sequential**

Static vs. **dynamic**

Discrete vs. **continuous**

Known vs. **unknown**

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Fully observable vs. **partially observable**
Single agent vs. **multiagent**
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Static vs. **dynamic**
Discrete vs. **continuous**
Known vs. **unknown**

FULLY OBSERVABLE VS. PARTIALLY OBSERVABLE

If an agent's sensors give it access to the complete state of the environment at each point in time, then we say that the task environment is fully observable.

Fully observable environments are convenient because the agent need not maintain any internal state to keep track of the world.

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, and an automated taxi cannot see what other drivers are thinking.

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

SINGLE VS MULTI AGENT

An agent solving a crossword puzzle by itself is clearly in a single-agent environment, whereas an agent playing chess is in a two agent environment.

For example, 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 taxi-driving environment, on the other hand, avoiding collisions maximizes the performance measure of all agents, so it is a partially **cooperative** multiagent environment.

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DETERMINISTIC VS. STOCHASTIC

If the next state of the environment is completely determined by the current state and the action executed by the agent, then we say the environment is deterministic; otherwise, it is stochastic.

In principle, an agent need not worry about uncertainty in a fully observable, deterministic environment. If the environment is partially observable, however, then it could *appear* to be stochastic.

Taxi driving is clearly stochastic in this sense, because one can never predict the behavior of traffic exactly; The vacuum world is deterministic.

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EPISODIC VS SEQUENTIAL

In each episode the agent receives a percept and then performs a single action. Crucially, the next episode does not depend on the actions taken in previous episodes. E.g. spotting faults in an assembly line.

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.

Episodic environments are much simpler than sequential environments because the agent does not need to think ahead

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STATIC VS DYNAMIC

If the environment can change while an agent is deliberating, then we say the environment is dynamic for that agent; otherwise, it is static.

Static environments are easy to deal with because the agent need not keep looking at the world while it is deciding on an action, nor need it worry about the passage of time.

If the environment itself does not change with the passage of time but the agent's performance score does, then we say the environment is **semidynamic**.

Taxi driving is clearly dynamic: the other cars and the taxi itself keep moving while the driving algorithm dicides what to do next. Chess, when played with a clock, is semidynamic. Crossword puzzles are static.

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CONTINUOUS VS DISCRETE

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

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.

Chess -> Discrete states, percepts and actions

Taxi Driving -> Continuous state-time problem including actions like steering angles, although location, speed of taxi and camera input can be "discretized".

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KNOWN VS UNKNOWN

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

Strictly speaking, this distinction refers not to the environment itself but to the agent's (or designer's) state of knowledge about the "laws of physics" of the environment.

In a known environment, the outcomes (or outcome probabilities if the environment is stochastic) for all actions are given.

The distinction between known and unknown environments is not the same as the one between fully and partially observable environments.

It is quite possible for a *known* environment to be *partially* observable—for example, in solitaire card games, I know the rules but am still unable to see the cards that have not yet been turned over.

Conversely, an *unknown* environment can be *fully* observable—in a new video game, the screen may show the entire game state but I still don't know what the buttons do until I try them.

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ENVIRONMENT ASSESSMENT: UNKNOWN

Known: If map of Romania wasn't available, then it would be Unknown

In Unknown environment, we don't know the outcome/resulting state of current action.

E.g. in case of absence of map, out of three actions from Arad, Go Sibiu, Go Timisoara or Go Zerind?

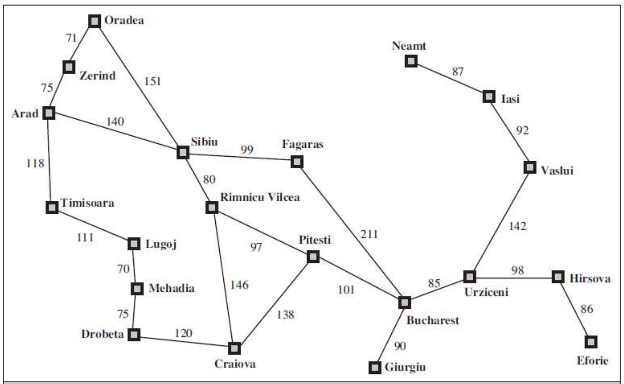

Figure 3.2 A simplified road map of part of Romania.

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ENVIRONMENT ASSESSMENT: OBSERVABLE

Observable: Agent known which city its currently in.

Assuming: Each city/town has signboards with city name.

In observable environment, agent knows which state its currently in.

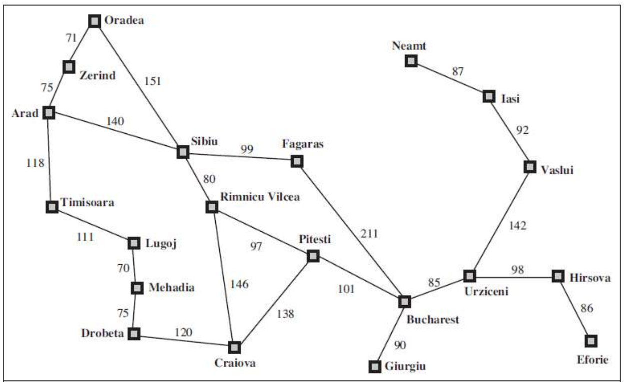

Figure 3.2 A simplified road map of part of Romania.

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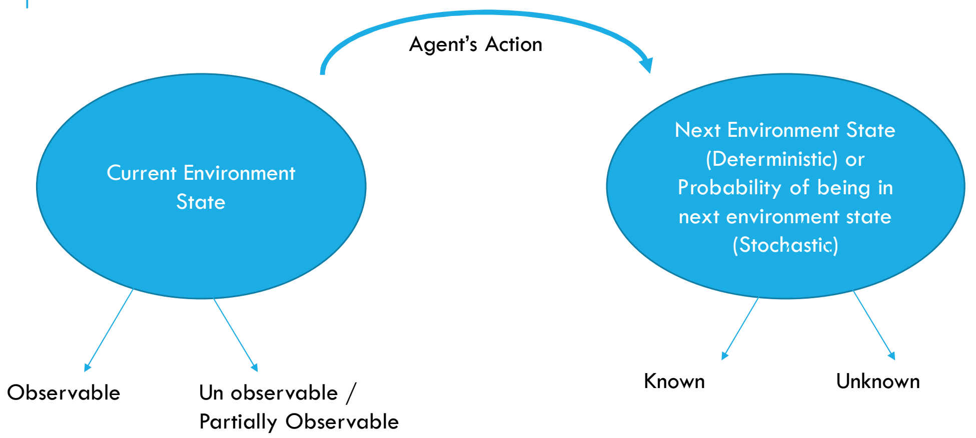
UNKNOWN VS UNOBSERVABLE VS STOCHASTIC



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ENVIRONMENT ASSESSMENT: DISCRETE

We also assume the environment is **discrete,** so at any given state there are only finitely many actions to choose from.

At most 4 roads leave from one city/state (Bucharest).

So possible actions from Bucharest {Go Guirgin, Go Urziceni, Go Pitesti , Go Fagaras}

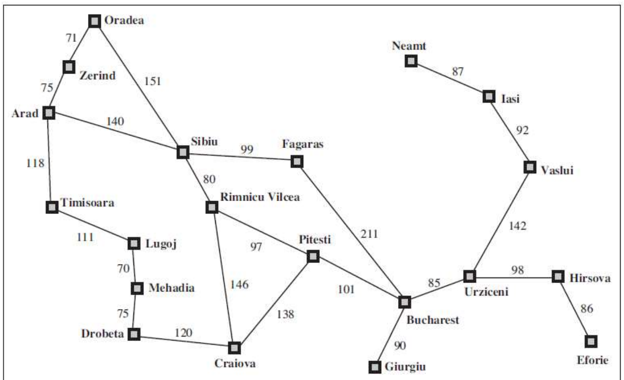

Figure 3.2 A simplified road map of part of Romania.

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ENVIRONMENT ASSESSMENT: DETERMINISTIC

we assume that the environment is **deterministic,** so each action has exactly one outcome.

If an agent chooses to drive from Arad to Sibiu, it does end up in Sibiu.

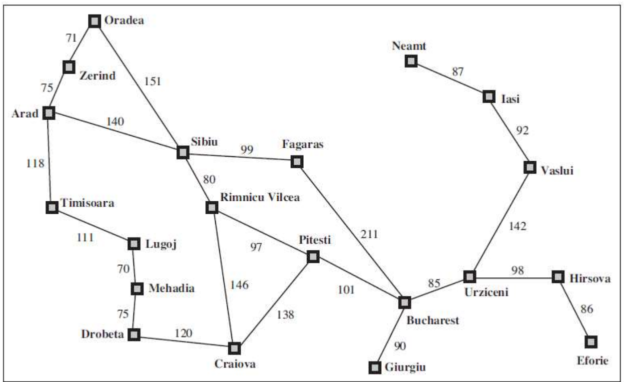

Figure 3.2 A simplified road map of part of Romania.

Known

Deterministic

Stochastic (If an agent chooses to drive from Arad to Sibiu, the probability of arriving in Sibiu is 0.8 (not the case here))

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