Intelligent Agents

An agent is just something that acts. Of course, all computer programs do something, but computer agents are expected to do more: operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, and create and pursue goals. A rational agent is one that acts so as to achieved the best outcome or, when there is uncertainty, the best expected outcome.

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

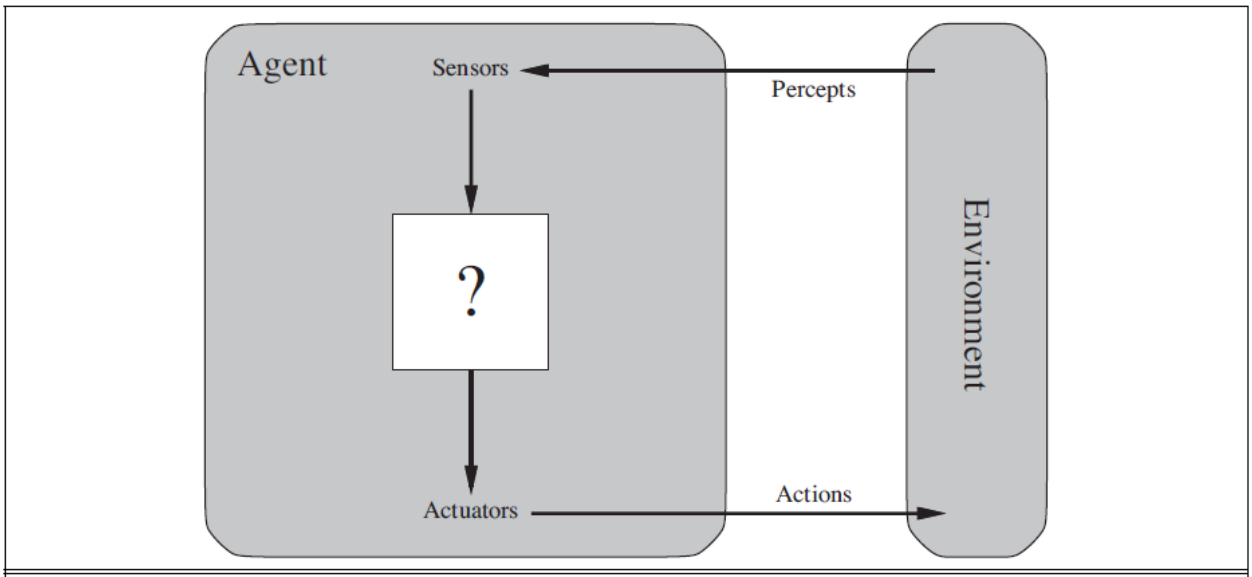


Figure 2.1 Agents interact with environments through sensors and actuators.

A human agent has eyes, ears, and other organs for sensors and hands, legs, vocal tract, and so on for actuators. A robotic agent might have cameras and infrared range finders for sensors and various motors for actuators. A software agent receives keystrokes, file contents, and network packets as sensory inputs and acts on the environment by displaying on the screen, writing files, and sending network packets.

We use the term **percept** to refer to the agents' perceptual inputs at any given instant. An agent's **percept sequence** is the complete history of everything the agent has ever

perceived. In general, an agent's choice of action at any given instant can depend on the entire percept sequence observed to date, but not anything it hasn't perceived. Mathematically speaking, we say that an agent's behavior is described by the **agent function** that maps any given percept sequence to an action. **Internally**, the agent function for an artificial agent will be implemented by an **agent program**. It is important to keep these two ideas distinct. The **agent function** is an abstract mathematical description; the agent program is a concrete implementation, running within some physical system.

Good Behavior: The concept of Rationality

A **rational agent** is one that does the right thing. Obviously, doing the right thing is better than doing the wrong thing,

but what does it mean to do the right thing?

Let considering the consequences of the agent's behavior. When an agent working in its environment, it generates a sequence of actions according 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. Obviously, there is not one fixed performance measure for all tasks and agents, typically, a designer will devise one appropriate to the circumstances.

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 that agent has.

Omniscience, learning, and autonomy?

Our definition of rationality does not require omniscience, then, because the rational choice depends only on the percept sequence to date. We must also ensure that we haven't inadvertently allowed the agent to engage in decidedly underintelligent activities. For example, if an agent does not look both ways before crossing a busy road, then its percept sequence will not tell it that there is a large truck approaching at high speed. Does our definition of rationality say that it's now OK to cross the road? Fat from it! First, it would not be rational to cross the road given this uninformative percept sequence: the risk of accident from crossing without looking is too great. Second, a rational agent should choose the "looking" action before stepping into the street, because looking helps maximize the expected performance. Doing actions in order to modify future percepts; sometimes called, **information gathering**. Is an important part of rationality. A second example of information gathering is provided by the **exploration** that must be undertaken by a vacuum-cleaning agent in an initially unknown environment.

Our definition requires a rational agent not only to gather information but also to learn as much as possible from what it perceives. The agent's initial configuration could reflect some prior knowledge of the environment, but as the agent gains experience this may be modified and augmented. There are extreme cases in which the environment is completely known a priori.

To the extent that an agent relies on the prior knowledge of its designer rather than on its own percepts, we say that the agent lacks **autonomy.** A rational agent should be autonomous, it should learn what it can to compensate for partial or incorrect prior knowledge. It would be reasonable to provide an artificial intelligent agent with some initial

knowledge as well as an ability to learn. After sufficient experience of its environment, the behavior of a rational agent can become effectively ***independent*** of its prior knowledge. Hence, the incorporation of learning allows one to design a single rational agent that will succeed in a vast variety of environments.

The Nature of Environments?

Building rational agent first required to think about **task environments**, which are essentially the "problems" to which rational agent are the "solutions". Hereafter, we show how to specify a task environment.

Specifying the task environment: in our discussion of the rationality of an agent, we had to specify the performance measure, the environment, and the agent's actuators and sensors. We group all these under the heading of the **task environment**. For acronymically minded, we call this the **PEAS** (**P**erformance, **E**nvironment, **A**ctuators, **S**ensors) description. In designing an agent, the first step must always be to specify the task environment as fully as possible.

Figure below summarizes the PEAS description for the taxi's task environment.

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

First, the **performance measure** to which we would like our automated driver to aspire? Desirable qualities include getting to the correct destination, minimizing fuel consumption and wear and tear, minimizing the trip or cost. Minimizing violations of traffic laws and

disturbances to other drivers, maximizing safety and passenger comfort, maximizing profits, obviously, some of the ese gals conflict, so tradeoffs will be required.

Next, what is the driving **environment** the taxi will face? Any taxi driver must deal with a variety of rads, ranging from rural lanes and urban alleys to freeways. The roads contain other traffic, pedestrians, stray animals, road works, police cars, puddles and potholes. The taxi must also interact with potential and actual passengers.

The **actuators** for an automated taxi include those available to human driver: control over the engine through the accelerator and control over steering and braking. In addition, it will need output to a display screen or voice synthesizer to talk back to the passenger's, and perhaps some way to communicate with other vehicles.

The basic **sensors** for the taxi will include one or more controllable video cameras so that it can see the road, it might augment these with infrared or sonar sensors to detect distances to other cars and obstacles. To avoid speeding tickets, the taxi should have a speedometer, and to control the vehicle properly, especially on curves, it should have an accelerometer. To determine the mechanical state of the vehicle, it will need the usual array of engine, fuel, and electrical system sensor. Like many human drivers, it might want a global positioning system (GPS) so that is doesn't get lost. Finally, it will need a keyboard or microphone for the passenger to request a destination.

Properties of task environments: The range of task environments that might arise in AI is obviously vast. We can, however, identify a fairly small number of dimensions along which task environments can be categorized.

1. **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. A task environment is effectively fully observable if the sensors detect all aspects that are relevant to the choice of action. An environment might be partially observable because of noisy and inaccurate

sensors or because parts of the state are simply missing for the sensor data. For example, an automated taxi cannot see what other drivers are thinking.

2. **Single agent vs. multiagent:** the distinction between single-agent and multiagent environments may seem simple enough. For an example, 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.
3. **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 fully observable, deterministic environment. If the environment is partially observable, however, then it could appear to be stochastic.
4. **Episodic vs. sequential:** in an episodic task environment, the agent's experience is divided into atomic episodes. 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. 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.
5. **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. Dynamic environments, on the other hand, are continuously asking the agent what it wants to do. Taxi driving is clearly dynamic: the other cars and the taxi itself keep moving while the driving algorithm dithers about what to do next. Crossword puzzles are static.

6. **Discrete vs. continuous**: 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. For example, the chess environment has a finite number of distinct states. Chess also has a discrete set of percepts and actions. Taxi driving is continuous-state and continuous-time problem. The speed and location of the taxi and of the other vehicles sweep through a range of continuous values and do so smoothly over time.

Task Environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle	Fully	Single	Deterministic	Sequential	Static	Discrete
Chess with a clock	Fully	Multi	Deterministic	Sequential	Semi	Discrete
Poker	Partially	Multi	Stochastic	Sequential	Static	Discrete
Backgammon	Fully	Multi	Stochastic	Sequential	Static	Discrete
Taxi driving	Partially	Multi	Stochastic	Sequential	Dynamic	Continuous
Medical diagnosis	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Image analysis	Fully	Single	Deterministic	Episodic	Semi	Continuous
Part-picking robot	Partially	Single	Stochastic	Episodic	Dynamic	Continuous
Refinery controller	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Interactive English tutor	Partially	Multi	Stochastic	Sequential	Dynamic	Discrete

Figure 2.6 Examples of task environments and their characteristics.

The Structure of Agents?

The job of AI is to design an **agent program** that implements the agent function, the mapping from percepts to actions. We assume this program will run on some sort of computing device with physical sensors and actuators. We call this the **architecture**:

agent = architecture + program

Agent program: the agent programs take the current percept as input from the sensors and return an action to the actuators. There are **four basic kinds of agent programs** that embody the principles underlying almost all intelligent systems:

1. **Simple reflex agents:** the simplest kind of agent is the **simple reflex agent**. These agents select actions on the basis of the current percept, ignoring the rest of the percept history. A simple reflex behavior occurs in many environments. Imagine the automated taxi, if the car in front brakes and its brake lights come on, then the automated taxi program should notice this and initiate braking. In other words, some processing is done on the visual input to establish the condition we call, "the car in front is braking". Then, this triggers some established connection in the agent program to the action "initiate braking". We call such a connection a condition-action rule. Written as:

   If car-in-front-is-braking **then** initiate-breaking

   Figure below, gives the structure of this general program in schematic form, showing how the condition-action rules allow the agent to make the connection from percept to action.

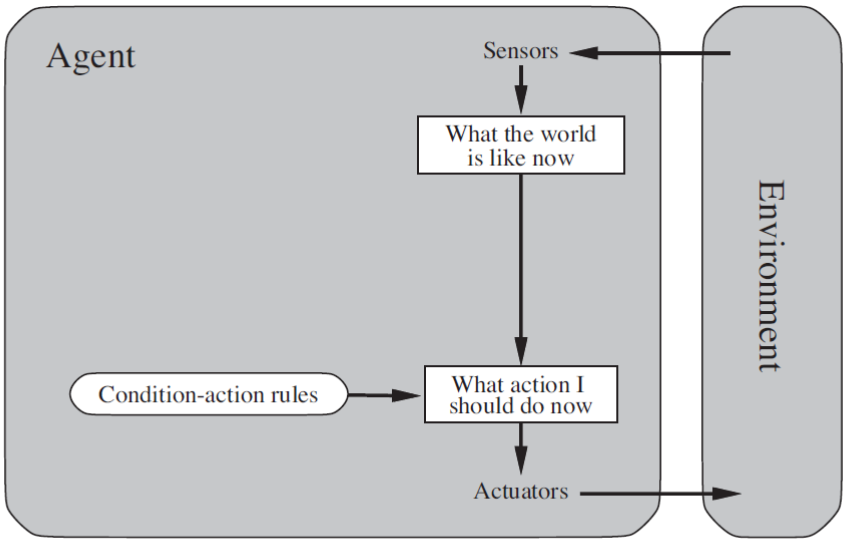


Figure 2.9 Schematic diagram of a simple reflex agent.

2. **Model-based reflex agents:** the most effective way to handle partial observability is for the agent to keep track of the part of the world it can't see now. That is, 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. For example, 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. Updating this internal state information as time goes by requires two kinds of knowledge to be encoded in the agent program. First, we need some information about how the world evolves independently of the agent. Second, we need some information about how the agent's own actions affect the world. This knowledge about "how the world works" is called a model of the world. An agent that uses such a model is called a model-based agent.

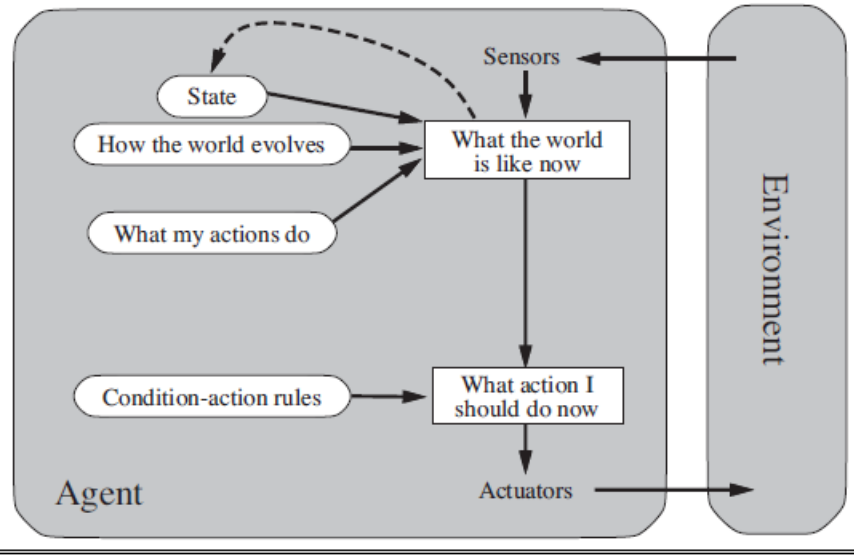
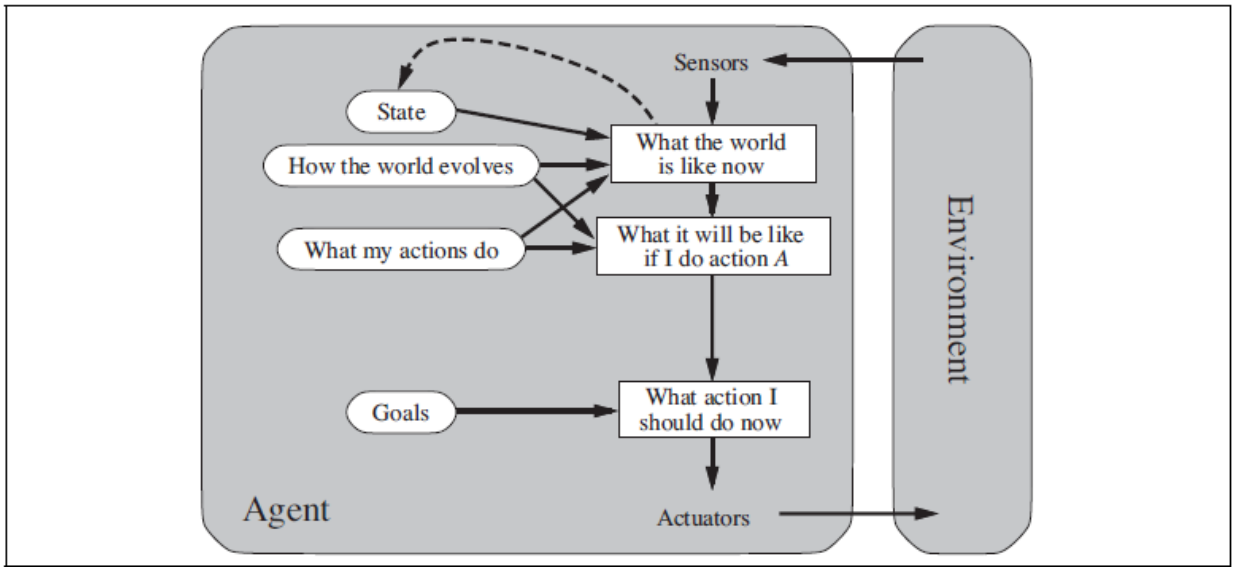
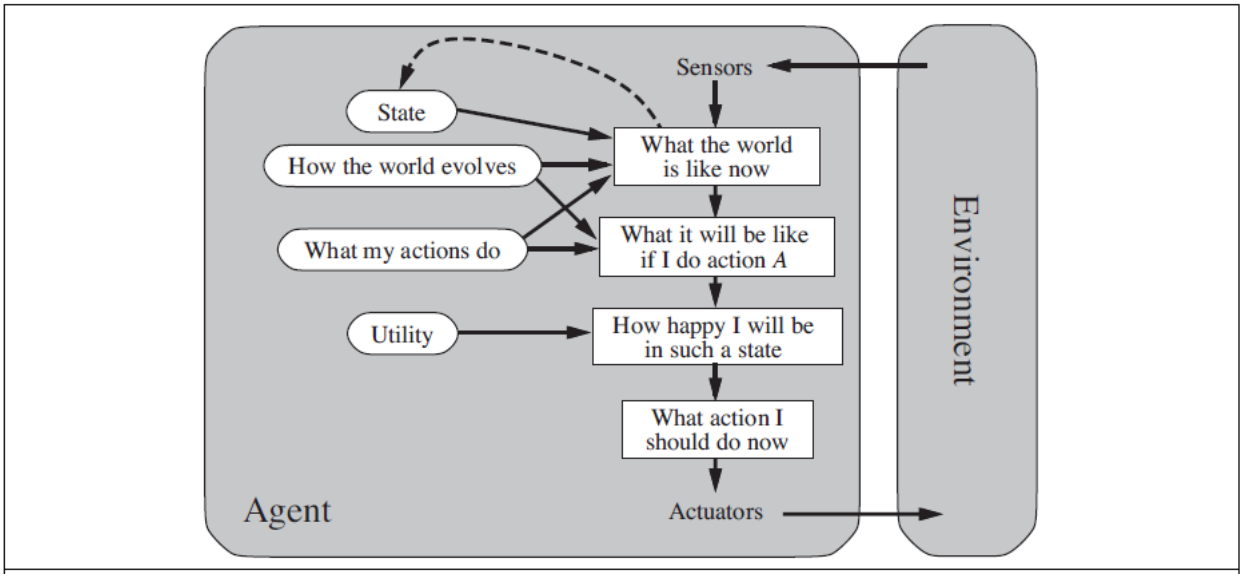


Figure 2.11 A model-based reflex agent.

3. **Goal-based agents:** knowing something about the current state of the environment is not always enough to decided what to do. 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. In other words, as well as a current state description, the agent needs some sort of goal information that describes situations that are desirable. For example, the passenger destination. The agent program can combine this with the model to choose action that achieve the goal. Figure below shows the goal-based agents structure.



4. **Utility-based agents:** goals alone are not enough to generate high-quality behavior in environments. For example, many action sequences will get the taxi to its destination (thereby achieving the goal) but some are quicker, safer, more reliable, or cheaper than others. We have discussed that a performance measure assigns a score to any given sequence of environment states. So, it can easily distinguish between more and less desirable ways of getting to the taxi's destination. An agent's **utility function** is essentially an internalization of the performance measure.



Summary?

- An agent is something that perceives and acts in an environment. The agent function for an agent specifies the action taken by the agent in response to any percept sequence.
- The performance measure evaluates the behavior of the agent in an environment. A rational agent acts so as to maximize the expected value of the performance measure, given the percept sequence it has been so far.
- A task environment specification includes the performance measure, the external environment, the actuators and the sensors. In designing an agent, the first step must always be to specify the task environment as fully as possible.
- Task environments vary along several significant dimensions. They can be fully or partially observable, single-agent or multiagent, deterministic or stochastics, episodic or sequential, static or dynamic, discrete or continuous, and known or unknown.
- The agent program implements the agent function. There exists a variety of basic agent-program designs reflecting the kind of information made explicit and used in the decision process. The designs vary in efficiency. Compactness, and flexibility. The appropriate design of the agent program depends on the nature of the environment.
- Simple reflex agents respond directly to percepts, whereas model-based reflex agents maintain internal state to track aspects of the

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world that are not evident in the current percept. Goal-based agents act to achieve their goals, and utility-based agents try to maximize their own expected “happiness (utility)”.

- All agents can improve their performance through learning.