What is an intelligent system?

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Abstract

The concept of intelligent system has emerged in information technology as a type of system derived from successful applications of artificial intelligence. The goal of this paper is to give a general description of an intelligent system, which integrates previous approaches and takes into account recent advances in artificial intelligence. The paper describes an intelligent system in a generic way, identifying its main properties and functional components. The presented description follows a pragmatic approach to be used in an engineering context as a general framework to analyze and build intelligent systems. Its generality and its use is illustrated with real-world system examples and related with artificial intelligence methods.

1 Introduction

Mankind has made significant progress through the development of increasingly powerful and sophisticated tools. In the age of the industrial revolution, a large number of tools were built as machines that automated tasks requiring physical effort. In the digital age, computer-based tools are being created to automate tasks that require mental effort. The capabilities of these tools have been progressively increased to perform tasks that require more and more intelligence. This evolution has generated a type of tool that we call intelligent system.

Intelligent systems help us performing specialized tasks in professional domains such as medical diagnosis (e.g., recognize tumors on x-ray images) or airport management (e.g., generate a new assignment of airport gates in the presence of an incident). They can also perform for us tedious tasks (e.g., autonomous car driving or house cleaning) or dangerous tasks such as exploration of unknown areas (e.g., underwater exploration).

The development of such a type of systems is now an engineering discipline of information technology that requires effective methods and tools. The precise characterization of an intelligent system is non trivial because it is based on concepts related to cognition, an area that is not fully understood, whose terminology and level of abstraction may differ according to the area of study (neuroscience, computer science, robotics, philosophy, cognitive psychology, etc.). Some of the used terms can even change with the proposal of new computational models of intelligence and new scientific findings related to our understanding of the mind.

The main purpose of this paper is to present a characterization of an intelligent system that integrates and updates previous conceptions of such type of system. It follows a pragmatic approach to be useful in an engineering context as a general framework to analyze and build intelligent systems. The presented description first includes what can be understood as an intelligent system from the point of view of an external observer. In addition, the paper identifies the types of processes that are typically part of intelligent systems, according to the current state of the art.

The remainder of the paper is organized in the following way. Section 2 presents a first definition of an intelligent system based on it observable external behavior. Section 3 describes a characterization that follows a functional decomposition to identify the usual processes that are part of an intelligent system. Section 4 presents an overview of artificial intelligence methods used to develop the different components of intelligent systems. Finally, section 5 describes examples of intelligent systems using the presented characterization, covering both recent systems and systems with classical approaches.

2 Characterization based on external behavior

An intelligent system is understood in this paper as a machine designed to perform a task of some utility to humans such as car driving, medical diagnosis of infectious diseases, recommendation of economic investment or vacuum cleaning. But what does it mean to say that a machine is intelligent? In this paper, we give a first answer to this question based on the observation of the behavior of the machine. This view follows one of the common approaches in artificial intelligence that describes an intelligent machine as a system that operates as an agent and behaves rationally.

Operating as an agent means that the system is capable of acting and perceiving its environment. In addition, the system may interact with other agents (e.g., humans or other artificial systems). Rational behavior is considered in this paper separately in two possible ways. On the one hand, an observer may decide that the system acts rationally if the system performs actions that maximize the chances of success. On the other hand, the observer may conclude that the system thinks rationally if the system is able to provide justified reasons that explain its beliefs. The following definition summarizes this description:

Definition. An intelligent system is an artificial system that (1) operates as an agent, i.e., the system perceives its environment, acts in the environment and interacts with other agents, and (2) exhibits rational behavior, i.e., the system acts rationally (to maximize the success of its tasks) and shows rational thinking (justifies beliefs through reasoning).

This definition is not intended to be a rigid description to determine whether a system is intelligent or not. Instead, it aims to identify possible characteristics typically associated to intelligent behavior, some of which may not be present in certain intelligent systems.

Figure 1 synthesizes graphically the previous definition. The rest of this section extends this definition by describing first the characteristics related to agent operation, which is described in two separated sub-sections corresponding respectively to interacting with the environment and with other agents. Then, a third sub-section describes rational behavior with a distinction between acting rationally and thinking rationally. Finally, a last sub-section describes learning (a capability that intelligent systems may exhibit) in relation to the characterization presented in this section.

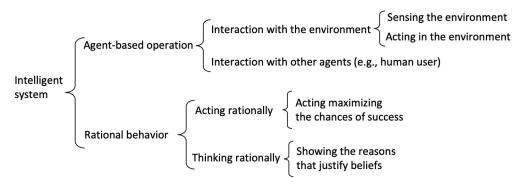


Figure 1: Characterization of an intelligent system based on its external behavior.

2.1 Interacting with the environment

In general, an intelligent system operates as an *agent* which means that it is able to act (e.g., with the help of actuators) using data about the state of the environment (e.g., measured through sensors)¹ (see Figure 2). The use of sensors and actuators, which may be real or virtual, separates the body of the intelligent system from the rest of the environment. This characteristic is called *embodiment*. We also say that an agent is *situated* in a environment because the agent operates in a close-coupled interaction with the environment in a continuous sequence of sense-act.

¹The essential meaning of the word *agent* can be expressed as "one who acts", based on its derivation from the Latin word *agens*. The notion of agent has been used by different authors to identify characteristics of intelligent systems (Wooldridge and Jennings 1995) (Franklin and Graesser 1996) (Russell and Norvig 2014).

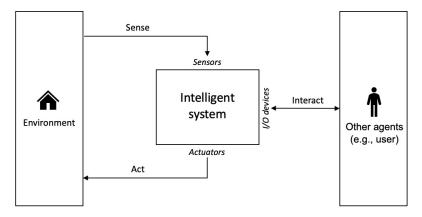


Figure 2: An intelligent system observes features of the environment, executes actions in the environment and interacts with others agents (e.g., with the human user).

Environment property	Description
Static (or dynamic)	The environment does not change (or changes) while an
	agent is making a decision.
Discrete (or continuous)	The observed state of the environment, time or actions are
	discrete (or continuous).
Fully-observable (or partially-observable)	Sensors detect (or do not detect) all aspects that are rele-
Taily-boser value (of partially-boser value)	vant to the choice of action.
Deterministic (or etechnotic)	The next state of the environment is (or it is not) com-
Deterministic (or stochastic)	pletely determined by the current state and the action.
Episodic (or sequential)	Actions do not have influence (or they have influence)
	future actions.
Known (or ambroaum)	The outcomes for all actions are known (or they are not
Known (or $unknown$)	known) by the agent in advance.

Table 1: Terminology used to describe properties of environments (Russell and Norvig 2014).

In addition, the system can interact with other agents (e.g., human users or artificial computer-based agents) to accept requests and to generate answers to questions using, for example, in-put/output devices for human-computer interaction (e.g., keyboard, monitor, mouse, microphone, etc.). In this paper, we distinguish other agents from the rest of the environment because the kind of interaction between the intelligent system and other agents presents significant differences (e.g., use of language) in comparison with the interaction between the intelligent system and the environment.

A thermostat is a simple example that illustrates this kind of operation. The task of the thermostat is to regulate the temperature in the environment (e.g., house rooms). The thermostat uses a thermometer to sense the temperature of the room, and actuates by starting or stopping a heater. The thermostat also communicates with a human user who can start and stop the thermostat and can establish the desired temperature.

Typically, the information about the environment that the intelligent system needs to perform its task is not completely known or its complexity exceeds the information processing capacity of the intelligent system. For example, sensors of autonomous robots usually obtain partial and noisy information from the environment. In the case of the chess game, it is not possible to evaluate all potential movements, because the amount of combinations is too high. Table 1 shows a commonly used terminology to describe the properties of an environment and classify its complexity with respect to the agent (Russell and Norvig 2014). For instance, the environment of a chess player is static, discrete, fully observable, deterministic, sequential and known. In the case of a self-driving car, the environment is continuous, partial observable, stochastic, sequential and known.

2.2 Interacting with other agents

The human user is a type of agent with whom an intelligent system typically interacts because these systems, like other machines, are built for the purpose of helping humans to perform certain tasks. To provide such help to users, the system can adopt two different roles depending on who is acting in the environment (the system or the user).

An intelligent system plays a *delegate* role when the user delegates to the system a task to be performed and the system acts autonomously in the environment to perform that task making its own decisions on how to do it without any intervention from the user. For example, an autonomous self-driving car decides the path to follow and controls the driving mechanisms to perform the task of transporting a passenger from a specific origin to a specific destination. A system that plays a delegate role can also reject requested tasks from the user according to certain reasons, based on the current situation of the environment or its own goals (e.g., safety goals or social norms). For this purpose, the system can verify the correctness and feasibility of a requested task before it is performed and explain to the user the reasons that justify why a requested task is rejected.

An intelligent system can also play an *advisor* role. In this case, the user makes the decisions about what actions should be performed in the environment and it is also the user who executes those actions. The role of the system is to give advice by providing useful information to facilitate such decisions to the user. A system that adopts an advisor role can perform tasks (such as planning, design, or resource allocation) that suggest to the user what actions to take. The system can also perform other kinds of tasks (e.g., detecting the presence of problems, diagnosing causes of problems, or predicting future states) in order to help the user understand the behavior of the environment.

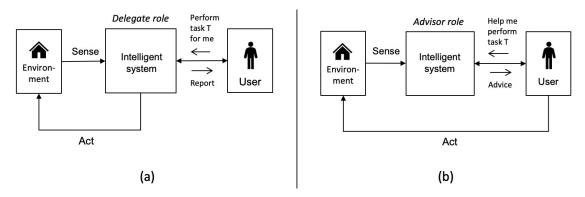


Figure 3: An intelligent system can play two different roles during its interaction with the user: (a) delegate (the system acts in the environment) and (b) advisor (the user acts in the environment).

During the interaction with a user, an intelligent system may be *proactive* instead of passive². This means that the system does not have to wait until a user requests a task, but it takes the initiative to perform a task based on its own goals and what it perceives from the environment.

In addition to the human user, the system can also interact with other agents that are part of a complex organization (e.g., other machines or other human users with different roles). This type of organization can be seen as a multi-agent system (Wooldridge 2009) in which individual agents interact using social coordination mechanisms to cooperate to achieve common goals or to compete for limited resources.

2.3 Rational behavior

It is said that an agent *acts rationally* if the decisions it makes about its actions seek to optimize a performance measure³. For example, a financial analyst makes decisions about investments to maximize the economic profit obtained. A self-driving car selects the path to follow according to a performance measure that minimizes the travel time (and other possible factors such as as fuel consumption or toll costs)).

Rational action can be analyzed from an outside perspective of an artificial system, without having to know the internal mechanisms that generate such behavior. The performance measure specifies the goal of the system and can be used to quantify a degree of success, i.e., to determine how well a system performs the task for which it has been designed. An external observer may conclude that a machine acts rationally if it consistently takes actions that successfully optimize the performance measure.

 $^{^{2}}$ Some authors use the term *reactive* as the opposite of proactive. However, in this paper we will use the term reactive as the opposite of deliberative as it is generally used in agent-based systems.

³The notion of rationality in decision making has been described in artificial intelligence with the principle of rationality (Newell 1982) and it is also used in other disciplines such as philosophy or economy (Edwards 1954).

Acting rationally is related to one of the meanings we typically associate to intelligence. Comparing how two agents perform a task using a performance measure is one way of assessing their degree of intelligence. For example, we say that a chess player (or an investment advisor) is smarter than another player (or another investment advisor) if the former wins more games (or makes more profit). This approach, which understands intelligence as an ability to achieve goals, is commonly accepted in artificial intelligence (McCarthy 2007) (Albus 1991) (Goertzel 2006) (Kurzweil 2000)⁴.

Besides rational action, we can say that an agent exhibits *rational thinking* if it is able to provide reasons for what it does or what it believes. External observers can verify whether a system thinks rationally if the system uses an understandable language to describe its own beliefs and justifications about how conclusions are reached.

A common form of rational thinking is logical reasoning. Machines can deduce conclusions from beliefs using efficient algorithms based on automated reasoning (e.g., automated theorem provers). Machines can also use other forms of reasoning such as approximate reasoning (e.g., using probabilistic representations) or analogical reasoning (e.g., case-based reasoning).

The capability of humans to examine and describe to others their own knowledge and reasoning through introspection is a significant feature related to intelligence. A machine can simulate that it is aware of its knowledge by showing and justifying what it knows by means of a representation language that is understandable to others.

This capability is especially useful in the context of what is called *explainable artificial intelligence* (Phillips et al. 2020). Explanations help human users to trust the system's decisions, which is especially important when they have to take responsibility for those decisions. They are also useful for identifying wrong behaviors (e.g., failures or behaviors that do not follow human values).

2.4 Learning

Learning is one of the characteristics commonly associated with intelligent behavior. Two forms of understanding learning are distinguished here: a performance-based approach and a knowledge acquisition approach.

According to a *performance-based* approach to learning, a system learns if it is able to improve its performance in carrying out tasks. For example, chess players improve the ability to beat their opponents with the experience of multiple games. Note that we can understand this view of learning as a consequence of rational action, where the agent seeks to optimize a performance measure (in this case, using the experience of multiple interactions with the environment). This approach has been used in the context of machine learning by Tom Mitchell, who formulated the following definition:

Learning: A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E (Mitchell 1997).

Complementary to the previous approach, we can understand learning from another perspective. According to a *knowledge acquisition* approach to learning, an agent learns by acquiring new beliefs. An external observer can verify that the agent acquires new beliefs if the agent is able to describe its own knowledge with a language understandable to the observer (as explained above in the description of rational behavior).

An intelligent system can acquire new beliefs by different methods. For example, the system can learn in this way by observing new features of the environment. It can also acquire new beliefs by reasoning (e.g., deductive or inductive reasoning) from other beliefs.

Another form of acquiring new beliefs is by knowledge transfer between agents through the use of language. With this scheme, an agent A can learn new beliefs from another agent B if agent B is able to describe its own knowledge with a language whose meaning agent A can understand. For example, consider the belief expressed as "zebras are horse-shaped and have striped skin". An agent

⁴In general, the degree of intelligence of an agent is not only determined by how well the agent performs a task but also by the diversity of tasks that the agent is able to do. For example, a system designed to play chess may be able to perform this task with great success but it is not able to do other types of tasks. In contrast, human intelligence is able to cope with a wide range of different situations and perform different types of tasks. This aspect has been emphasized by Legg and Hutter who propose a theoretical definition of intelligence with a formal expression based on the idea that intelligence measures an agent's ability to achieve goals in a wide range of environments (Legg and Hutter 2007).

that has never seen a zebra might be able to recognize this animal using the symbolic description provided by another agent⁵.

Learning facilitates adaptation to changes in the environment. An agent that learns from its experience in interacting with the environment can adapt its behavior to changes in that environment. In addition to this individual form of adaptation, agents that acquire new beliefs from other agents through the use of language can save the effort of interacting with the environment in order to learn these beliefs, which is an effective mechanism of social adaptation for groups of agents.

3 Characterization by functional decomposition

The previous section characterizes an intelligent system by considering the overall behavior that the system exhibits to an external observer. However, it is also useful to identify the type of processes that may generate this behavior in order to facilitate the analysis and design of intelligent machines. In this context, an intelligent machine is understood as a *system*, i.e. as the integration of a set of components that are organized according to a specific purpose⁶. This section follows a functional decomposition method that breaks down the overall behavior of an intelligent system into smaller parts in order to identify the main processes that intelligent systems usually include.

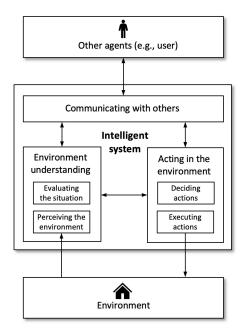


Figure 4: Block diagram showing the main functions of an intelligent system at a high level of abstraction.

Figure 4 shows a block diagram that identifies the main functions of an intelligent system at a high level of abstraction. For example, the figure shows a function called *environment understanding* that includes the perception of the environment (e.g., by sensors) and the evaluation the situation (e.g., by diagnosing causes of problems or by predicting future states). Another main function is *acting on the environment* which may be divided into deciding the actions to be done (e.g., by planning or configuration), and executing the actions by monitoring their performance (e.g., to detect unexpected events during execution). Finally, another main function is the *communication with others*, which usually involves both interpretation and language generation.

The functional characterization presented in this section is intended to provide a common view that generalizes the typical processes observed in existing intelligent systems. Therefore, the functions identified here may or may not be present in a particular system. For example, a rule-based expert system for medical diagnosis like Mycin (Buchanan and Shortliffe 1984) could

⁵This form of learning has been called *zero shot learning* (Xian et al. 2018), which consists of learning to recognize new objects without any examples, only having their symbolic description.

⁶This integrated view is in line with the common approach that defines intelligence as a complex ability resulting from the combination of separate cognitive functions (Gottfredson 1997) (Hayes-Roth 1995) (Anastasi 1992).

be an example of intelligent system, which includes the functions of environment understanding (evaluating the situation through diagnosis) and communication with the user. However, it does not include other described functions (e.g., perceiving the environment or executing actions). In contrast to this, a collaborative autonomous industrial robot is an example of intelligent system that may have the majority of the functions identified here.

The following sub-sections elaborate this characterization with more details breaking down the main functions into smaller functions in order to identify more specific information processes that may be part of an intelligent system.

3.1 Environment understanding

One of the important functions of an intelligent agent is its ability to understand the environment. There are two main reasons why an agent may need this function. On the one hand, it may be a prerequisite to be able to make decisions about what to do. On the other hand, it may be necessary to help another agent (e.g., a user) understand properties of the environment that are not directly observable⁷.

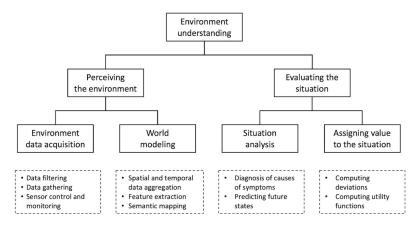


Figure 5: Specific functions into which the overall function of environment understanding may be divided. The lower part of the figure shows examples of some specific functions for illustrative purposes.

An intelligent agent can use multiple sources of information to understand the environment. This includes sensor measurements about the state of the external environment (e.g., the temperature of the room) or about the state of the body of the system (e.g., the battery charge). An agent can also receive information from other agents about the state of the environment. For example, a human user may inform the system about events that cannot be measured by sensors.

Figure 5 shows examples of more specific functions into which the global function of environment understanding may be divided. This decomposition includes on the one hand perceiving the environment whose goal is to interpret data from the environment in order to form a representation of the current situation. On the other hand, environment understanding may also include evaluating the current situation by considering a broader context (e.g., reasoning about the past or the future) and by assigning a value that expresses how good or bad is the situation. The following sections give more details about the set of specific functions presented in this figure.

3.1.1 Environment data acquisition

The objective of the environment data acquisition is to obtain the required measurements about the state of the environment (e.g., using sensors) that allow the intelligent system perform the task for which it has been designed.

Typically, a sensor measures a certain physical magnitude of the environment at a certain time and place. An intelligent system may include multiple sensors to measure different aspects of the external environment (images, temperatures, pressures, accelerations, etc.) or about the state of the own body (e.g., battery charge).

⁷The idea of environment understanding presented in this paper is similar to the notion of *situation awareness* used in various disciplines (e.g., psychology or military) (Endsley 1995).

The data acquisition process can use data requests (provided by the user or by another system process) that focus attention on the part of the environment to be observed at each moment. This information can be used to filter data in order to eliminate non-useful measurements or to implement active data gathering mechanisms (e.g., using planned strategies for data acquisition). Data requests can also be used to control the behavior of sensors that accept different modes of operation.

In addition, environment data acquisition can include monitoring processes to detect measurement errors and sensor malfunctions. For example, sensor measurements may be subject to a validation phase before they are considered acceptable, checking that they are in a range of possible values.

3.1.2 World modeling

The creation and dynamic adaptation of representations of the world from sensor data has received the name of world modeling (Burgard, Hebert, and Bennewitz 2016) (Albus and Meystel 1996). For example, a self-driving car with multiple sensors (lidar, camera, GPS, acoustic sensors, etc.) generates a world model in the form of a map with mobile objects by integrating features extracted from sensors such as vehicle location, vehicle acceleration, traffic signals, mobile obstacles (e.g., pedestrians and other vehicles), etc.

World modeling requires efficient algorithms to keep the model updated with the dynamic state of the environment using information that is periodically received from sensors, sometimes with a high frequency and in large volumes (e.g., camera images). This process has to cope with difficulties such as the fact that sensors typically measure incomplete information, the presence of noise in sensor measurements, and the need to fusion data from multiple sensor types.

The world model is often formulated using task specific representations in order to facilitate tasks to be done. For example, mobile robots may use geometric map representations in order to facilitate path planning. However, instead of using only one particular representation for the world model, intelligent systems often combine multiple forms.

A practical way to structure a complex world model is to use a hierarchical organization with multiple layers for different levels of abstraction (Pronobis and Jensfelt 2012) (Hughes, Chang, and Carlone 2022). In such models, the bottom layers represent information close to sensor measurements (e.g., point clouds, camera images, metric-based representations) and the top layers represent information close to the user's language (e.g., names of places on a map, room categories in a building, classes of recognized objects, etc.). Efficient algorithms use these representations for example to aggregate information (bottom-up in the hierarchy) or top-down to restrict possible interpretations of values.

3.1.3 Situation analysis

Environment understanding may include a step to analyze the situation in a broader context. This type of analysis allows inferring unobserved facts such as beliefs about the past, generated by diagnosing the causes that justify the current situation, or beliefs about predictions of future states that are possible consequences of the recent state of the environment.

For instance, an intelligent system in a medical domain can determine by means of abductive reasoning that the cause of a certain symptom of a patient is a specific viral infection. Similarly, a system in urban transportation can predict the bus passenger demand in the short-term future in a particular city, considering the current hour and date.

For this purpose, the intelligent system can use background knowledge about the behavior of the environment and its properties (e.g., knowledge about causes and their effects, behavior patterns, etc.). In the previous examples, the system for medical diagnosis can use knowledge that relates observable symptoms to infectious diseases and the system in urban transport can use knowledge about patterns of bus demand according to hours and types of date (weekdays, seasons, etc.).

3.1.4 Assigning value to the situation

Understanding the environment may also require assessing to what extent a situation fits the user's desires or the system's objectives. This assessment can be done by assigning a value to the situation that measures how good or bad it is.

A simple mechanism that can be used to assign value to a situation is to compute the deviation of observed measurements with respect to desired measurements. An example of this value in an aerial robot is the deviation between the current battery charge and the minimum desired charge. When this deviation is small, the robot may decide to return to the charging point. However, if the deviation is large, the robot will have to make a more drastic decision, such as landing immediately to avoid possible damage. Note that this deviation can be understood as a representation of a feeling of the agent similar to affective or emotional states observed in living beings (e.g., hunger, tiredness, happiness or fear)⁸.

Other ways to assign a value to the situation may use more complex evaluation functions based user's desires or the system's goals. For example, the value that a system playing chess assigns to a given situation can be determined by the pieces and the chessboard positions controlled by the system. Similarly, a urban public transport system can evaluate the severity of a situation with delayed buses by computing the average delay time per passenger based on the estimated demand of public transport.

3.2 Acting in the environment

As introduced above, one of the main functions of an intelligent agent is acting in the environment. This includes, first, deciding what actions should be performed in the current situation and, second, executing these actions in the environment.

Some systems can both decide and execute actions (e.g., an autonomous aerial robot landing at the end of a mission), while other systems decide actions that are executed externally. For example, an intelligent system for design assistance can suggest to a mechanical engineer a possible configuration of an elevator based on specifications provided by a customer.

Figure 6 shows examples of more specific functions into which acting in the environment may be divided. The following sections explain more details about the set of specific functions presented in this figure.

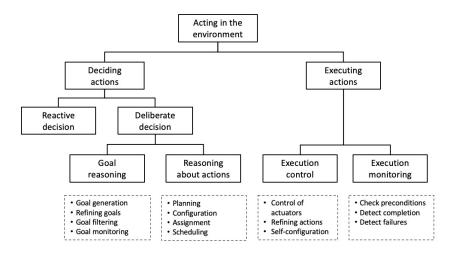


Figure 6: Specific functions into which acting in the environment may be divided. The lower part of the figure shows examples of some specific functions for illustrative purposes.

3.2.1 Reactive decision

In some cases, an intelligent system should decide the actions to be taken in a reactive way, i.e., as an immediate response to what is observed in the present time. For example, if a self-driving car perceives that there is an obstacle in the road in front of the vehicle, it should stop immediately. Similarly, if an aerial robot perceives that the charge of its battery is too low, it should land to avoid potential damage.

⁸This evaluation process has been analyzed extensively in psychology in the context the appraisal theory (Scherer, Schorr, and Johnstone 2001). In artificial intelligence, emotions have been analyzed using the OCC model (Ortony, Clore, and Collins 1988).

The reactive selection of actions is an efficient way to respond to changes in the environment. This behavior is observed for example in animal reflexes that generate immediate responses to stimuli detected by the body's senses. This mechanism does not require a complex representation about the world because decisions are mainly influenced by the present state of the world perceived through sensors. The used representation may include deviations of observed measurements with respect to desired measurements similar to the affective states described in the previous section (e.g., the deviation of the current battery charge of an aerial robot from the minimum acceptable charge).

It is possible control the whole behavior of certain type of intelligent systems by using only a combination of reactive decisions. In this case, a complex global behavior of the intelligent system can emerge from the combined operation of multiple reactive decisions. This approach was followed by a line of work in artificial intelligence, called Nouvelle AI, that was applied successfully to develop certain kinds of autonomous robots⁹.

3.2.2 Goal reasoning

In contrast to a reactive approach, decisions can be made through a reasoning process that analyzes alternative hypotheses of actions based on certain goals. This form of decision making is *deliberate*, i.e., it is motivated by the intentions expressed by the goals of the intelligent system¹⁰. In this deliberative approach to deciding actions, we can distinguish the decision of *what to do* from the decision of *how to do it*, which correspond respectively to goal reasoning and reasoning about actions shown in Figure 6.

The objective of goal reasoning is to determine the goals that the system should achieve according to the state of the environment. This ability is present in the case of autonomous systems (e.g., a vacuum cleaner domestic robot) but may be not included in systems whose goals are established by the user.

Part of goal reasoning includes a selection process that may consist of two different phases. First, goals are generated directly from what is perceived from the environment (e.g., if a mobile robot has a low battery charge, the robot could generate as a goal to return to the home base to recharge). Then, the intelligent system has to commit to one or several specific goals taken from the set of candidate goals considering, for example, a priority scheme that expresses how to prefer some goals over others when they are in conflict.

Goal reasoning can also include a goal monitoring process that helps to determine for example when goals have been satisfied or when they have to be dropped because they cannot be achieved after some attempts.

3.2.3 Reasoning about actions

According to the deliberative approach, the decision about how to reach a goal is done through a reasoning process that analyzes alternative hypotheses of actions. Table 2 shows examples of this type of reasoning in different kind of systems. As this table illustrates, reasoning about actions may correspond to planning (finding a sequence of actions to reach a certain goal), configuration (assembling components in order to create an complex artifact that satisfy certain specifications), assignment (assign needs to resources), etc. In contrast to reactive decisions, this process considers different actions taking into account potential states of the environment that may not be perceived at the present moment.

Reasoning about actions may include evaluation mechanisms to select the best options. These mechanisms are based on the rational behavior described in section 2 in which the system selects actions that optimize a performance measure (e.g., using an objective function that is optimized by a search procedure). For example, a mobile robot considers multiple valid paths to follow and selects the one that minimizes travel time. However, it is important to note that this selection is usually made with uncertainty, since the system cannot anticipate with complete certainty the value of the performance measure of future actions.

⁹The idea of generating global intelligent behavior through a combination of simple reactive behaviors was proposed by the behavior-based paradigm in robotics (Brooks 1991) (Arkin 1998).

¹⁰Deliberation is usually understood in artificial intelligence as opposite of reactive behavior (Wooldridge 2009) (Murphy 2019). Ingrand and Ghallab describe a comprehensive view of deliberation functions in robotics (Ingrand and Ghallab 2017).

System	Example of reasoning about actions
Chess player	A chess player analyzes possible moves and their consequences
	before deciding on the most appropriate one.
Mobile robot	A mobile robot considers potential paths to follow (using a
	map of the environment) and chooses the best path according
	to a performance measure (e.g., minimum travel time).
Medical system	To prescribe a treatment to a sick patient, an intelligent medical
	system may analyze the impact of future treatments.
Mechanical design	To design the machinery of an elevator, an intelligent system
	may consider valid configurations of its components (cabin,
aid system	cables, door, engine, etc.) taking into account the specifications
	provided by a customer.
	An intelligent system generates an assignment of airport gates
Airport terminal	to flights (e.g., in the presence of an unexpected event) by ana-
management system	lyzing whether the possible assignments satisfy the operational
	constraints of the airport.

Table 2: Examples of forms of reasoning about actions in different kind of systems.

In general, intelligent systems usually integrate methods for deciding actions that follow the two approaches described above: certain actions are selected in a reactive way and others are decided in a deliberative way¹¹. In the development of intelligent systems, the combination of both approaches is a non trivial problem that requires specific design decisions (e.g., when to favor deliberation over reaction). In certain situations, for example, deliberation should inhibit reactive decisions when immediate responses need to be postponed to achieve better long-term goals.

3.2.4 Execution control

Some intelligent systems such as autonomous robots are capable of executing actions in the environment with the help of actuators. Typically, executing actions requires specialized processes because actions (as generated by planning) cannot be executed directly in the environment. They have to be refined into detailed commands for actuators, taking into account dynamic details of the current situation in the environment. For example, in the case of a self-driving vehicle, the execution of the overtaking action of a slow vehicle (e.g., a truck) is performed by translating such action into specific commands for the driving devices (e.g., steering, brake and accelerator) taking into account the dynamic changes in location and speed of the vehicles.

Action execution shares with planning that both processes refine a global task into more specific operations. However, planning usually corresponds to a process that is done in advance, generating a complete plan before it is executed. In contrast, action execution refines actions in continuous interaction with the environment, waiting certain amount of time to complete each step and considering that, during the execution, unexpected events may happen that require alternative execution methods.

One form of executing an action is by setting the reference value of a controller. For example, in a self-driving vehicle, a speed controller generates commands to the throttle to increase the speed or to the brake to decrease the speed. This controller operates in a continuous loop using as input the observed state (e.g., the current speed of the vehicle) and the reference value (e.g., the desired speed of a vehicle). The action of stopping the vehicle can be executed by setting the desired speed to a zero value. In general, the mechanism used by this type of controllers is formally described in the field control theory.

A more complex form of action execution may generate references for multiple controllers. The whole execution process consists of several controllers operating in sequence or concurrently, and each controller is in charge of a specific control aspect. For example, the overtaking action mentioned above may generate a sequence of references of controllers specialized in certain behaviors such as approaching the vehicle ahead, following the vehicle, changing to the next lane, passing the vehicle and returning to the lane.

¹¹The distinction between the deliberative and reactive approaches has been described in psychology by dual process theories (e.g., (Evans 1984) (Kahneman 2011)). For example, Kahneman describes this duality using the names of System 1 and System 2. System 1 (or intuitive thinking) is similar to the reactive approach presented in this paper in which decisions are based on feelings rather than on facts or evidence. System 1 is fast, automatic, unconscious and non-linguistic (difficult to verbalize). On the contrary, System 2 (or deliberative reasoning) is slow, logical, effortful, conscious, linguistic (can be described verbally) and makes complex decisions.

Another important aspect of action execution is the possibility that an agent can dynamically select and combine its own physical or logical resources to execute a given action. This self-configuration ability is important when resources are limited and the agent can optimize their use based on certain performance measures (e.g., minimizing electricity consumption). Self-configuration has been described as a form of adaptation to changes (Hayes-Roth 1995) (Oreizy et al. 1999) (Molina and Santamaria 2021), which facilitates operating in dynamic and partially known environments.

3.2.5 Execution monitoring

Executing actions usually requires a monitoring process to supervise the correct execution. This supervision is carried out through several operations performed at different moments of the execution process.

For example, before an action is executed, execution monitoring verifies that the current situation presents the conditions for which the action can be executed (e.g., the action landing may be executed only if the aerial robot is flying). During the execution of an action, execution monitoring verifies that the situation progresses as expected (e.g., it is expected that the altitude of an aerial robot decreases during landing) and it does not takes more time than it is expected (using a timeout value). Finally, execution monitoring detects when the execution of an action has been completed and informs about the result of the execution in terms of success and failure.

Then, the result of this monitoring task is used by other processes to continue with the execution of the next actions of the mission plan (when intermediate actions are successfully completed) or to reconsider the execution of the plan when one of the actions has failed.

3.3 Communicating with others

An intelligent system may be able to communicate with other agents by sending and receiving messages through speech, written messages, graphical representations or other means. The passenger in a self-driving car, for example, can communicate the desired destination to the vehicle by writing the address (e.g., street name and number in a city). The vehicle shows the path to follow in a screen using a graphical representation of the environment (in the form of a map) that helps the passenger to monitor the correct execution of the trip.

In general, communication facilitates multiple agents to operate in complex social organizations in order to perform tasks in a distributed way. Messages between agents allow, for example, sharing information about the environment or requesting tasks to be performed by other agents. During such interaction, each agent can update its beliefs about the environment and, in addition, update beliefs about other agents (using a model about the others), which dynamically conditions the interaction process.

Agent communication is an area of study covering multiple aspects that may be analyzed with the help of the speech act theory (Austin 1962) (Searle 1969) and languages for multiagent systems (Finin et al. 1993) besides other approaches from the general field of human-computer interaction. The communication process can make use of specific functions such as speech recognition, natural language interpretation, dialog management, natural language generation, etc.

A significant aspect of communication between agents is the use of language. Language is composed of symbols in the form of words or other representations (e.g., mathematical symbols, musical notation, etc.). Such symbols are public in the sense the agent agrees their meaning in advance with other agents. In the previous example of self-driving car, the written address of the destination is a symbolic representation whose meaning is shared by both agents, vehicle and passenger.

An intelligent system may recognize the meaning of a new symbol by using other symbols or through mechanisms based on perception (linking sensory information to the symbol) or on action (linking goals or specific actions to the symbol). This is related to the symbol grounding problem (Harnad 1990), i.e., how to ground the meaning of a symbol in anything different than other symbols. In general, symbol grounding is a non trivial problem, especially for intelligent systems that operate in dynamic environments¹².

¹²The symbol grounding problem has been addressed with partial solutions in robotics, for example, with the idea of perceptual anchoring (Coradeschi and Saffiotti 2002) under which a symbol and sensor data (e.g., an image observed through a camera) are related with the help of data structures called anchors that are handled with specialized procedures.

General functions	Examples of computational methods
Perceiving the world	Statistical data aggregation, feature extraction with neural networks (e.g., convolutional neural networks), extended Kalman filters.
Evaluating the situation	Rule-based systems, automated logic deduction, bayesian networks, semantic networks, constraint satisfaction algo- rithms.
Deciding actions	Classical AI planning using domain languages (e.g., PDDL), HTN planning, temporal-action logics, constraint satisfac- tion algorithms, rule-based systems.
Executing actions	Control theory (e.g., PDI controllers), finite-state machines, behavior trees, rule-based systems, deep reinforcement learning.
Communicating with others	Language models using neural networks, languages and interaction protocols for multiagent systems (e.g., FIPA standards, etc.).

Table 3: Examples of computational methods used for building intelligent systems.

4 Building intelligent systems

The development of an intelligent system usually requires combining several artificial intelligence methods. Table 3 shows a sample of common methods used for building intelligent systems according to different functions.

These methods can be divided according to two main distinguished approaches. On the one hand, a *connectionist* approach, corresponds to methods based on neural computation (e.g., convolutional neural networks or deep reinforcement learning). On the other hand, a *symbolic* approach corresponds to methods following formal semantics based on logic (e.g., automated logic deduction, rule-based systems and constraint satisfactions algorithms), based on probability (e.g., bayesian networks) or hybrid approaches (e.g., fuzzy logic)¹³.

Symbolic and connectionist approaches have complementary strengths and weaknesses (Franklin 1995). At present, there is a lack of understanding of how information processing performed by symbolic approaches can be mapped onto computations performed by connectionist methods. The term *computational explanatory gap* (Reggia 2014) has been used to express that it is unclear how the two approaches are related.

Symbolic methods are typically used to implement cognitive abilities that are consciously accessible (such as processes related to reasoning). These methods represent beliefs using expressions that contain symbols whose meaning is shared with humans¹⁴.

On the other hand, connectionist methods are used to implement abilities of intelligent systems such as sensorimotor skills, which are usually carried out in humans in an unconscious way. These methods are also used for building language models to facilitate communication (e.g., speech recognition). Connectionist methods do not require the developer to know in advance the model that supports these abilities. Instead, the model can be learned automatically from examples as it described in the next section.

4.1 Automatic methods for building intelligent systems

It is possible to apply automatic methods to help in the development of certain components of intelligent systems. This approach has gained popularity in the last decades due to the higher computational power and the increasing availability of large amounts of data with different formats such as images (photographs or videos), structured data (e.g., data bases with alphanumeric data or temporal series) or non-structured text written in natural language.

Thus, we can use machine learning algorithms to automatically build models that correspond to one or more functional components of an intelligent system (e.g., for perception, control of actuators, reasoning, communication, etc.). For instance, a neural network can be trained using

¹³The symbolic approach for building intelligent systems was formulated by Allen Newell and Herbert Simon as the "physical symbol hypothesis", i.e., a physical symbol system has the necessary and sufficient means of general intelligent action (Newell and Simon 1976). This approach was the dominant paradigm in artificial intelligence until the 1990s

¹⁴This idea is present in what is called the "knowledge representation hypothesis" (Smith 1985) which assumes that a knowledge representation should be understandable by us, as external observers of the system.

thousands of x-ray images of tumors labelled as positive and negative examples. The trained neural network can be used as part of an intelligent system that helps physicians recognize the presence of tumors. Similarly, in order to build a rule-based expert system for medical diagnosis, a rule induction method could be applied to a data base with examples of diagnoses relating diseases and symptoms to generate candidate rules for the knowledge base.

Knowledge extraction using natural language processing methods can also be used to aid in the construction of intelligent systems. These methods are able to extract knowledge from text documents written in natural language. For example, a large corpus of text documents corresponding to a professional domain can be analyzed using natural language processing techniques to generate instances of classes and and relations to be used by a question/answer system.

Note that that machine learning and natural language processing can play two different roles in relation to intelligent systems. On the one hand, they can be used offline as it is described in this section, playing the role of tools used by developers to automatically create system components. On the other hand, they can be used online if the final intelligent system includes such methods to have the ability to communicate in natural language (using natural language processing methods) or the ability to learn continuously during their operation (using machine learning methods).

4.2 Issues in the evaluation of intelligent systems

The evaluation of intelligent systems presents certain issues related to the use of machine learning algorithms. One of the existing difficulties is that the model generated after a training process using connectionist machine learning methods (neural networks) is not directly understandable by developers. However, sometimes it is important for developers to be able to understand what the system has learned, for example, when it is necessary to trace how the system has reasoned in order to find the causes of wrong decisions made by the system.

The evaluation process should also ensure that the system operates in accordance with ethical values such as ensuring fairness (avoiding group biases) or limiting harmful use¹⁵. For instance, an intelligent system trained using biased data may be not able to ensure a fair operation. This situation happened with Tay, an experimental conversational chatbot developed by Microsoft in 2016. This chatbot was trained with uncontrolled public data based on the interaction with people which generated a racist bias in the system.

In order to facilitate an adequate evaluation of the intelligent system in these situations, symbolic methods can be used as an alternative or complement to connectionist methods using, for example, hybrid neurosymbolic approaches. Within the field of explainable artificial intelligence (Phillips et al. 2020), statistical methods that analyze the behavior of connectionist models have also been proposed to verify critical aspects (e.g., the presence of decision biases).

5 Examples of intelligent systems

This section describes examples of intelligent systems that illustrate the functional characterization presented in this paper. Figure 7 shows diverse types of intelligent systems organized in a hierarchy of categories (this hierarchy is not intended to be accurate and exhaustive but illustrative of the kind of existing systems). The following sections describe in more detail some of these categories.

5.1 Autonomous robots

An autonomous robot is a representative case of intelligent system that usually includes the majority of the functions considered in this paper. In this category, there are systems with different degrees of complexity such as industrial collaborative robots (e.g., Baxter), autonomous vehicles (e.g., self driving cars, planet explorer Curiosity), assistive robots, domestic robots (e.g., house cleaning robot Roomba), entertaining robots (e.g., Sony Aibo, Furby), etc.

One example of this type of system is an aerial robot for airplane inspection developed as a demonstrative prototype in 2019 for the company Airbus (Bavle 2019). The goal of this robot is to help maintenance engineers inspect the surface of an airplane in order to locate possible defects. The robot is able to fly near the surface of the aircraft and process images obtained with the help

¹⁵The ethical behavior of autonomous vehicles has been analyzed by Bonnefon et al. (Bonnefon, Shariff, and Rahwan 2016) considering extreme situations in which the vehicles have to choose between running over pedestrians or sacrificing their passenger to save the pedestrians.

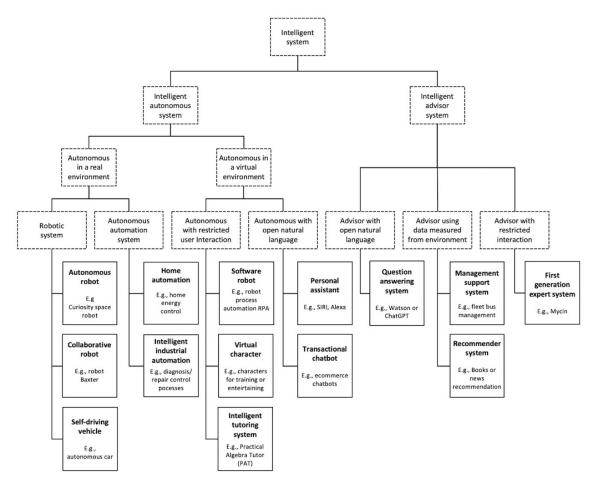


Figure 7: Examples of intelligent systems.

of on-board cameras. Figure 8 shows the functional organization corresponding to this system, according to the approach presented in this paper, which includes the following specific functions:

- Environment data acquisition. The aerial robot is equipped with multiple sensors such as (1) inertial measurement unit (IMU) to provide information about orientation, angular velocities, and linear accelerations, (2) cameras to calculate velocity using visual odometry, (3) a lidar sensor that generates a 3D point cloud, and (4) a high resolution frontal camera.
- World modeling. The system represents the world using a 3D space and localizes its position through data fusion from multiple sensors using EKF (Extended Kalman Filter).
- Situation analysis. The high resolution camera is used to recognize anomalies on the surface
 of the airplane using computer vision, which are spatially located according to the position of
 the aerial robot.
- Reactive decisions. The system includes a reactive mechanism that stops the vehicle to avoid unexpected obstacles detected with the help of the lidar sensor. The aerial platform also includes a safety mechanism to land immediately when the battery charge is too low.
- Reasoning about actions. The system generates an inspection plan (by path planning) to cover the surface of the airplane.
- Execution control. The system uses motion control mechanisms to execute the navigation plan. It uses a motion controller with a path tracking algorithm and PID control.
- Execution monitoring. Motion control is monitored in order to detect when partial goals are completed. The system also includes certain mechanisms to detect the correct execution of actions (although this part is not fully developed because the robot is a demonstrative prototype).

• Communicating with others. The operator provides the geometry of the airplane with relevant locations to inspect. The operator can stop the mission execution if an emergency happens.

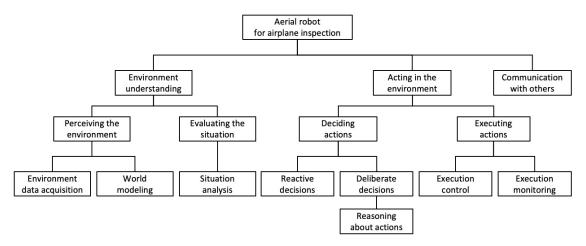


Figure 8: Functional decomposition corresponding to the autonomous aerial robot for airplane inspection.

5.2 First generation expert systems

The development of expert systems contributed to the success of AI in the 1980s with many commercial systems in multiple domains. The first generation of expert systems used mainly heuristic reasoning with symbolic knowledge representations such as rules. For example, Mycin was one of the first expert systems and was used as a model for building other systems in different domains. Mycin was developed at Stanford University in the early 1970s to diagnose infectious diseases (Buchanan and Shortliffe 1984). This system presents some of the functional components described in this paper:

- Communicating with others. The information about patients is obtained through the communication with the user. The dialogue with the user is developed in a question-answer process with prefixed sets of potential answers. Mycin asks questions about the patient and cultures. The user may answer with uncertainty and ask for explanations. Mycin presents the result of the diagnostic process and a recommended therapy.
- Situation analysis. Mycin diagnoses the causes of the symptoms finding the possible infectious organisms. Mycin uses a heuristic classification method with a knowledge base with about 450 rules and backward chaining. Mycin includes an original method for approximate reasoning (using certainty factors as values in the interval [-1,+1]). One of the interesting abilities of Mycin is that it is one of the first systems that was able to generate explanations. The content of the rules used by the system during reasoning were presented to justify how conclusions were reached.
- Reasoning about actions. Mycin recommends therapies for the identified infectious organism using an approach based on a generate and test procedure.

One of the limitations of this type of system is that its development usually includes a knowledge acquisition phase to manually create the content of the knowledge base (in the form of rules or another representation method). Since this manual process requires a significant effort, it is is restricted for the development of knowledge bases that are not too large. This limitation has received the name of knowledge acquisition $bottleneck^{16}$.

Another limitation is related to the way these systems acquires data about the environment. For example, Mycin gets information about the patient using prefixed sets of answers to questions. This

¹⁶The field of ontology engineering in artificial intelligence has proposed methods for common representations, understood as ontologies, that facilitate sharing and reusing contents of knowledge bases across different intelligent systems, which is a form to address the problem of the knowledge acquisition bottleneck.

communication mechanism may be too narrow and rigid in comparison with other forms of data acquisition (e.g., from unstructured texts or from sensors) and makes more difficult to integrate the expert system into day-to-day operations.

5.3 Management support systems

Modern sensor networks for monitoring the behavior of complex dynamic environments have been developed in strategic areas such as smart cities (transportation, climate, pollution monitoring) or Industry 4.0 (with sensorized industrial installations). In this context, expert systems have been built to assist operators in making decisions for the management of such environments. For instance, there are expert systems to help operators in public transportation management (Molina 2005), scheduling and coordination at an airport (Jo et al. 2000), emergency decision support in floods (Molina and Blasco 2003) or electric power operation (Filho et al. 2012).

The first example in the previous paragraph corresponds to an expert system that detects incidents and recommends how to respond in a urban bus transportation network. This system was included in 2002 as part of the fleet management system of the bus control center of the city of Vitoria in Spain.

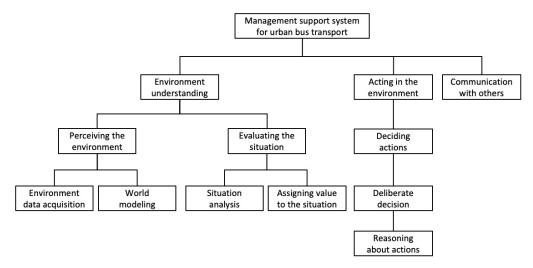


Figure 9: Functional decomposition corresponding to the decision support system for urban bus transport.

Figure 9 shows the functional organization corresponding to this system, according to the approach presented in this paper, which includes the following specific functions:

- Environment data acquisition. The system collects data about the spatial location of the fleets of buses using GPS sensors.
- World modeling. The system uses a map that represents the characteristics of the transport lines (including stops, distances, transfer points, etc.) and relates each bus to its position in the corresponding line. The model also includes reserve buses (located in parking lots) and maintenance vehicles.
- Situation analysis. The system detects the presence of incidents (e.g., detection of delays based on current positions and planned positions). The system predicts the bus passenger demand in the short-term future considering the current hour and date and using patterns derived from historic passenger demand.
- Assigning value to the situation. The system evaluates the severity of detected delays in every line by using the predicted bus passenger demand.
- Reasoning about actions. The system determines actions to be done to manage incidents (an automated planner based on hierarchical task network (HTN) planning is used to generate action plans).

• Communicating with others. The system presents to the operator detected incidents (e.g., bus delays). The operator can notify other events to the system that cannot be detected automatically with sensors (e. g., a broken bus, a blocked street, etc.). The system recommends actions (e.g., using additional buses, sending a repairing truck, etc.). The system justifies the recommended actions showing, for example, that some lines are prioritized based on the expected demand.

In general, a management support system such as the one described above uses a network of sensors to perceive the behavior of the environment and includes mechanisms to evaluate the situation and recommend actions to be taken. However, the operator is the one in charge of making the final management decisions and implementing the actions in the environment. Therefore, it is important that these systems be able to communicate their recommendations with sufficient justification, so that the operator can take responsibility for the decisions.

6 Conclusions

This paper has presented a characterization of an intelligent system by providing a generic description that identifies its main properties and functional components.

The presented characterization initially describes what may be understood as an intelligent system from the point of view of an external observer. This characterization follows the usual agent-based approach which considers the system as an agent that exhibits rational behavior. We distinguish here acting rationally (i.e., taking actions that maximize the chances of success) from exhibiting rational thinking (i.e., describing reasons that justify conclusions). The latter is important for intelligent machines to be able to explain to humans what they know and how they make decisions.

Besides the external view that an intelligent system exhibits to an observer, in this paper we also describe the typical processes that may generate intelligent behavior. This description is presented following a functional decomposition that identifies the main categories of processes classified according to three main functions: environment understanding (i.e., perceiving the world and evaluating the situation), acting in the environment (i.e., deciding actions and executing actions), and communicating with others.

The characterization presented in this paper attempts to provide, on the one hand, a unified view of what is meant by an intelligent system that that covers classical systems (e.g., rule-based systems), behavior-based systems, or more recent conceptions for autonomous systems. On the other hand, this characterization is intended to be not too abstract to help developers identify and classify the usual processes that are part of intelligent systems and relate them to common AI methods (both connectionist and symbolic approaches). The paper also demonstrates how the presented characterization is applicable to describe the functions of various real systems (e.g., expert systems and autonomous robots).

As future work, we hope to adapt and extend this general characterization to take into account results derived from new research on new computational models of intelligence.

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