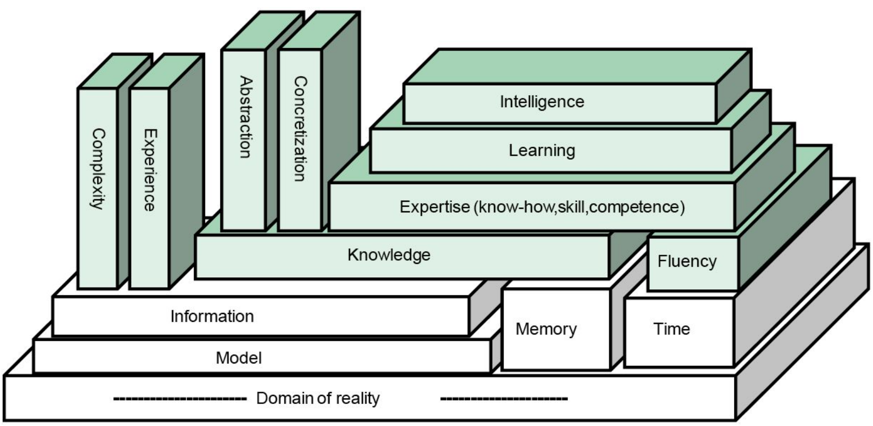
Jean-Daniel Dessimoz

Cognitics

Definitions and Metrics for Cognitive Sciences and Thinking Machines



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Preface

The world of cognition is entering an exciting new era. While cognitive activities had been mostly reserved for human beings in the past, current progresses in technologies and theories allow for transferring many of these human activities to artificial systems. The latter are becoming numerous, inexpensive and yet as fascinating as the other.

The cognitics initiative involves two complementary approaches, each diametrically opposite and yet as fascinating the one as the other:

- In one direction, the human being serves as a reference and defines the tasks to be realized and the purposes to be reached. Sometimes, the purpose is to replace the human, but it's generally to assist him or her instead.
- In the other direction, the metrics developed in the present, MCS theory, and the accuracy of analysis applied to artificial systems in order to design, repair, and improve them are useful for better revealing the cognitive properties of humans.

I wrote this book for a broad public, and I discuss essentials rather than more detailed or applied elements, which I leave for other media, such as specialized conferences or scientific journals. The main goal here is that each reader can understand and make use of the general results of present theory and comments in his or her everyday life. A second more focused goal relates to specialists, for whom it should help with the following:

- Opening new ways for improving design and development of robots, computers, and automated systems in general (cognitics).
- Improving knowledge of human nature (cognitive sciences)

J.-D. Dessimoz

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1. Introduction

Humans have evolved, inventing an ever-larger variety of tools and methods. This has allowed them to grow in numbers, live longer, and explore an ever more diversified part of the world.

Schematically speaking, over a time period, two kinds of progress have developed in rather independent ways:

- One involving the immaterial world of ideas
- The other involving the world of physical objects

Only humans seemed to be capable of establishing a link between those two worlds, especially via spoken language, written systems, and drawing. Marginally speaking, it happened moreover via sculpture and architecture.

During the twentieth century, the revolution of long-distance communication has occurred, which the formalization of a first path between physical world and immaterial universe (theory of information) has accompanied. It was essential to establish a precise correspondence between ideas to communicate and physical objects supporting them (messages). This correspondence has been established in the information theory.

Nowadays, a new stage opens up where machine-based systems cannot only pass, often very easily, from the physical world to the world of ideas and reciprocally. Moreover, it is even possible for such systems to:

- Process ideas on their own
- Induce precedents and draw conclusions
- Abstract, or, in contrast, elaborate concretizations (decide and create)

This is the domain of cognitics, the automated taking on, by machines, of cognitive activities traditionally exclusively reserved to humans.

In order to progress in cognitics, it is appropriate to rigorously define the essential concepts for the field as well as to set up a measuring system (specific metrics). The current theory, model for cognitive sciences (MCS), provides this. In the same way as it is easy to guess whether a human being can jump over the wall when he or she knows the height, it is very useful to have a metric, quantitative approach in the cognitive world as well. Publications of core concepts in this regard have already been made (R1–3) and especially a recent integrated work in French though (R4), mostly under the name of MCS theory. MCS includes an ontological approach in the fundamental meaning of the word. It is not just a computer-based structure with coherent internal definitions and relationships among concepts, but it aims to describe the very nature of things. In this theory, it also shows how limited any description may be and how to cope with these limitations. MCS is more than a glossary or a lexicon. Not only does it give definitions, but it also provides metric units and associated estimation formulas, ultimately reaching into the real world. I present MCS here in several sections. To reach easier understanding, I first give an overview of the chronological development stages of MCS. Then I sketch the main features of the model. Finally, in a progressive and well-structured way, I examine each of the main concepts with precision.

But before reaching the vast plains of cognitics, it is necessary to climb two classical passes, strangely much more difficult to cross than I initially thought. MCS theory is strongly based on the concept of information, originally defined by Claude Shannon (R5). It appears, however, that this classic basis (information) as well as older concepts yet (namely “model” and “memory”) require discussion from a cognition perspective. Subsequent cognitive entities, such as complexity, knowledge, expertise, or intelligence, inherit some underestimated yet crucial features of those classic concepts. Numerous discussions with many and varied masters of ceremony have convinced me that crossing these preliminary passes turns out a necessary condition for enjoying the new proposed landscape comfortably and without reserve. So I am about to accompany readers on grounds usually considered as very well-known, mostly the notions of information and model.

2. Familiar Grounds?

Experience shows that most people actually do not yet know the concepts of “information” and “model” well, which, in principle, have been well established for decades or even millennia and are usually wrongly taken as well understood. So it is useful to visit these notions again. In order to underline critical properties of classical notions, we give various elements of theory that correspond to insufficiently known principles, under the subtitles of “theorems.” These classical notions will provide a firm basis to define new concepts in cognitics.
Notice that we must intuitively approach some of the notions mentioned subsequently in the first phase. Then we can revisit them after we have seen the formal definitions introduced in the sequel.

2.1 Information

Definitions:

Information allows the cognitive system (CS) that receives it to build up and update the representation he/she/it maintains for oneself of a certain cognitive domain, that is, his/her/its ad hoc model (figure 1). Intuitively, it could be said, “Information shapes opinion.”

Messages convey information. Correspondence in a probability has defined the quantity of information that a message conveys. Essentially, it is related to the instantaneous expectation the CS has of incoming messages. When messages can be perfectly forecast, information quantity is nil. If messages are very much unexpected, a large quantity of information is received.

The fundamental function, which defines the quantity of information in a message (Q), dates back to the middle of twentieth century, and Claude Shannon provided it.

A low probability actually corresponds to a lot of information. The mathematical function that describes this phenomenon is the inverse of probability of occurrence of the message:

A low probability actually corresponds to a lot of information. The mathematical function that describes this phenomenon is first the inverse of probability of occurrence of the message[1]:

$$Q = f\,(1/p). \qquad \text{Equation 1}$$

Moreover, it looks adequate that, if several messages occur, their respective information quantities add up. Now if considerations remain at the level of probabilities, the appropriate operation is multiplication. For example, if two independent signals have individual probabilities of occurrence of one-third, one-ninth denotes the chance that both occur simultaneously. In order to keep using simple additions, logarithms[2] are required:

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[1] The fundamental definition is expressed, like here, for the case of discrete (discontinuous) messages. But in fact, this is not really a limit as pathways exist in order to extend it to other cases, such as, notably, continuous signals.

[2] The quantity of information conveyed by a message can be intuitively approached by counting how many significant zeroes are contained in the number expressing the occurrence probability of this message. See also Appendix C.

$$Q = \log_2\left(\frac{1}{p}\right) \text{ bit} . \qquad \text{Equation 2}$$

In equation 2, the unit is the "bit," a contraction of "BInary digiT," referring to the base-2 selected for logarithm evaluation.[3] We can observe that the formula gives a nil amount (0 bit) of information for the case of messages that can be totally forecast (probability equal to one).

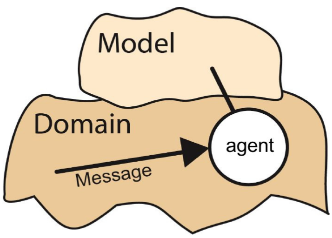

Fig.1 *Information*. Information is conveyed by messages, which allow cognitive agents to form and update their opinion (model) relating to some subset of reality (domain)

Comments:

The classic definition of information is well established and does not need modification. Nevertheless, we should understand two of its essential properties: perishable and subjective characters.

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[3] In theory, logarithms with bases 10 and "e" have also been used, thus leading to "dit" and "nit" units. But in practice, these variants are not widespread.

Theorem 1: Information Is Immediately Perishable

Proof:

Equation 2 defines the quantity of information that a message conveys based on its probability of occurrence, as estimated before reception (i.e. “a priori”), by receiver. The formula gives a nil amount (0 bit) of information for the case of messages that can be totally forecast (probability equal to one).

Now precisely, the purpose of all messages is to change this probability. Upon receiving what was previously just a probability for receiver transforms into certainty*. After reception (i.e. “a posteriori”)* the typical certainty of received message corresponds to a probability amounting to 1. Equation 2 gives 0 bit in these new circumstances. The message is now well-known, and it does not contain information any longer.

Discussion:

Let’s consider a cognitive domain corresponding to the single, random toss of a coin. Before receiving, two messages are possible: heads or tails. We expect a probability of one-half for each one. After the message arrives, however, respective probabilities change. The probability for one message (for example, heads) becomes 1 and 0 for the other message. For this unique toss, it is useless to repeat the message. Equation 2 indeed gives a quantity of information amounting to 1 bit for the initial message and then 0 bit for all possibly repeated messages.

It is important to understand this peculiarity of information. This contrasts with respect to experience gained with other metric units in the physical world. In principle, repeating the estimation of a weight, length, or time always gives the same result in kilograms, meters, or seconds. Repeating the same message in the same circumstances does not bring any information any longer; 0 bit are contained in repeated messages from the receiver's perspective. The following are some informal examples where the time-varying character of information plays a particularly obvious role:

- In practice, the same person does not read the same newspaper twice.
- It is usually poor judgment to tell the end of the movie to friends if they are about to go and watch it.
- It is hard to prepare collectively and deliver a surprise for a person at a given point in the future.
- Insiders are forbidden to perform stock exchanges operations.

Theorem 2: Information Is Essentially Subjective

Proof:
Equation 2 gives the quantity of information in a message. It can be seen there that it is grounded on occurrence probability as the receiver estimates. So information has an essentially subjective character.

Discussion:
The objective property of received messages is not guaranteed at all by basis of equation 2. Intuitively, people tend to believe in such an objective character, especially for the two following reasons:

- In simple technical domains, such as those for which the theory of information has first been developed, models are standardized and rigidly defined in conformity for emitters and receivers in the framework of coherent systems.

- In general, all members of a group have largely gained in life experiences similarly, so they tend to develop a certain uniformity of their respective models.

Yet the very same message may simultaneously have as many different probabilities as there are different receivers. For example, in the domain of tossing a coin, let's consider two very different receivers:

- One typically estimates the probability of heads state to be one-half.
- The second is a joker who has provided the coin, a special coin stamped heads on both side.

For the latter player, the probability of receiving the heads message is already a priori amounting to 1 (100 percent). In such a situation, the message (heads) conveys 1 bit of information to the first receiver and 0 bit to the second receiver.

It is useful to take the critical role of receiver well into account. Even if information often seems to have a very objective property in practice, for example, when referring to measuring units or very common objects, a whole spectrum of situations exists, which sometimes also reach far toward the other extreme, for example, to so-called modern art objects or even Rorschach inkblot tests.

2.2 The Notion of Model

Definitions:

A model is a simplified representation of reality, typically elaborated in order to reach a certain goal.

Discussion:

Sometimes, correspondence with reality is not a strong constraint. It is then a question, by extension, of the representation of other, virtual worlds. As subsequently defined in the MCS model, in as much as a model allows for reaching a certain goal, it can be qualified as good for this goal. The correspondence link between model and reality defines the notion of sense, or meaning, which is essential for semantics.

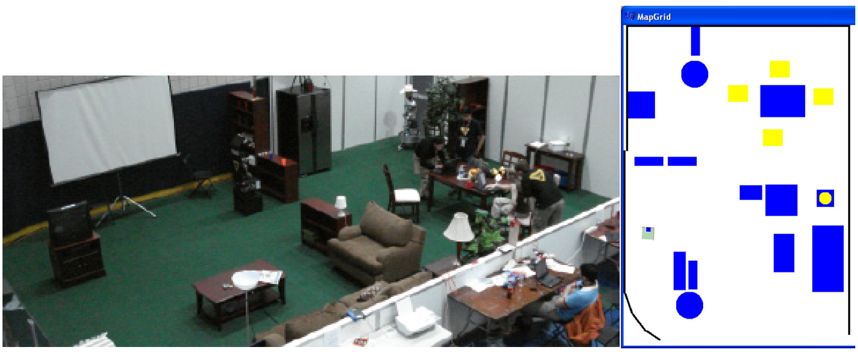

Fig. 2. *Model or reality?* There is always a huge difference between a real object and any model adopted to describe it. Nor the picture (*left*) nor the map (*right*) are close to exhaustively describing the home of Robocup Congress in Atlanta (2007).

Theorem 3: Information Requires the Notion of Model

Proof:

The very definition of information requires the notions of message and associated probability quantitatively estimated in a representation appropriate for the receiver (equation 2). This set of elements (messages, probabilities, and appropriate representation) de facto constitutes a model (figure 2).

Discussion:

Temptation is constant for human beings to establish a direct bridge between cognitive world and reality. But this is practically impossible. Some philosophers, like Socrates, Kant, or Hegel, especially represent efforts made to formalize this problem and propose solutions. Socrates is forced to notice that the reach of our perceptions typically limits them to shadows and reflections on cave walls. Kant postulates the existence of categories already established for the human mind in prerequisite to any perception. For Hegel, the importance of representations is such as these constitute the main part of our world, going as far as rejecting reality, of which we can, in the extreme case, even doubt any existence.

In our approach, similarly, it might be desirable to apply the metric technique defined for information estimation directly to reality, but this is impossible. We shall come back to this point in the discussion of theorem 4.

Theorem 4: Subject to a Goal Reached in Similar Ways, the Preferred Model Is the Most False

Proof:

The essential quality expected from a model is that it allows for reaching a certain goal. With the fulfillment of this condition, the model can be defined as good. Now, if we can reach the goal in a similar way with a simpler model, that is, with a model that can be described with less information, the latter model is generally considered as preferable. In order to get simpler, a model must ignore some aspects and become even less complete with respect to reality. And if a model is more incomplete, it must be globally considered as more false. So, subject to a goal being reached in a similar way, the preferred model is typically the most false.

Discussion:

It is a classic statement that theories should be simple (notably the “law of parsimony” or “Occam’s razor”). This is surely an attractive quality for a model. But in this formulation, the extent by which reality is abstracted, respectively ignored, remains hidden. Einstein with his word “Everything should be made as simple as possible, but not simpler” raises the veil a little on the risk of abstracting too much from reality. The difficulty grows if several goals are considered. A model adequately simple for one goal turns out too simple for another goal. Unfortunately in all cases, huge amounts of reality are filtered out, so, as George Box puts it, “Essentially, all models are wrong, but some are useful.” The present theorem and, more generally, the approach aiming at a quantitative estimation of cognitive entities push this statement yet further. In substance, there can be useful and good qualities in the process of doing simple, but we should also note that, in terms of correspondence to reality, models always remain extremely lacunary, or incomplete.

People sometimes state that experts know how to very selectively focus their attention on critical domain dimensions, thus knowing how to ignore all other aspects and making the situation confusing for beginners.

A common mistake is to think that:

- A model could have some qualities of truth, a capability to represent reality at the same time in compact and exhaustive ways
- It could simply retain the reality it represents without any loss of the quintessence.

When a quantitative estimation is attempted, force is to notice that all simultaneous compact and exhaustive representations are impossible.

No matter how constrained and restricted a domain of reality is delineated, an infinite amount of information remains necessary to exhaustively describe this domain. In practice, we can only perceive very limited aspects. This is for example true for RoboCup Homes. In figure 2, neither the displayed picture nor the map is close to exhaustively describing the home of RoboCup Congress 2007 in Atlanta.

Let's take another example, the famous painting of Magritte "Ceci n'est pas une pipe (This is not a pipe)." Even though the representation looks accurate, it is nevertheless just a painting and there is no way to fill it with tobacco and smoke. Similarly, even if the question is to describe a certain cubic millimeter of the fire region of the corresponding real pipe, the necessary quantity of information for this goal explodes ; for example :

- What are the properties of those wooden fibers?
- Are there preserving agents in the material?
- Where does the wood come from?
- Does insurance cover it?

* Were the workers who produced the pipe treated ethically?

In practice, to answer those questions and others, models are used. Depending on the current goal, it is one very particular aspect of reality that is retained or another as exclusively as possible. So the pipe will be described by:

* An order number for the accounting department
* Visibility information and possibly a normalized color code for pictorial rendering
* Information about possibly bad taste for the pipe smoker

Briefly expressed, the principle could read "The better model, the more false"!

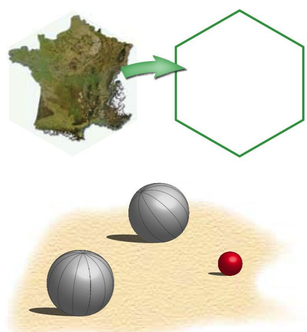

Fig. 3. *Good and false*. Models are false. For example, France is often called after its shape, hexagon (*top*). But they can be good for a goal. As a red jack attracts metal bowls in petanque game (*down*), a goal is a prerequisite for elaborating good models.

Jim Harrison for example, gives an artistic view of the same problem, referring to his memoirs in 2010:

> The truth? I could write every day the same chapter of my life, I would tell every time something different. Never ask a writer to tell you the truth when it is working to his memoirs, the writer must be sincere and not transparent. (R6)

For practical interest, we should insist once more on the necessity to be always very clear with respect to circumstances: target domain, adopted model, and selected goal. Jesuits have long been used to modestly limit themselves to *hic et nunc* (here and now). Recent management methods in software engineering (extreme programming) similarly require that specifications be met as strictly as possible, that is, without any bonus in terms of extra search for universal solutions, which are, by principle, considered as impossible to reach. For example, if it is a question of the person's weight, we might consider different domains and perform clarification. Is this while wearing clothes? In the morning at wake-up time? On Earth or Mars? Consider another example, the message delivering a phone number. Does it directly state the number (for example, +12 345 6789), or does it give the number indirectly (for example, "John's phone number")? In quantitative cognitics, it appears that some of these various domains may very strongly differ from other ones.

2.3 Memory

Definition:

A memory is a support, the essential property of which is the preservation of information through time.

Discussion:

Memory deserves a particular comment. As a physical support for long term, for example, standing stones, memory does not present a big interest from a cognitive point of view. Simply, what we expect in this regard is just a long-lasting stability of the physical support. By definition, what is expected is to be able to later get back exactly what has been written in a first phase. In this sense, predictability is total. The amount of generated information is nil.

From another point of view, observing a microelectronic memory device shows the important role of addressing circuits, as well as of the circuits responsible for writing and reading. Generally, in as much as the notion of memory would include those processes (addressing, writing, and reading), one or several rather complex CS would then be implied. For example, it would no longer be a question of a standing stone alone, but the human being who had shaped it up. For a library, it would be question not only of a collection of books on shelves, but also of the librarian capable to first adequately go and file information and then later demand to search and find it back.

In MCS theory, the property of (unlimited) permanence is essential for memory. This property, however, does not seem to deserve much developments here. Besides, we can actually consider the processes of addressing, writing, and reading separately, just as any other cognitive process.

3. Main Development Stages of MCS Theory

In order to make the MCS theory more easily understood, it is useful to retrace, first in a somewhat informal way, the chronological development of MCS theory. We will present three main stages, relating respectively to knowledge, expertise, and other developments.

3.1 Toward the Concept of Knowledge

Initially, the goal was to address intelligence and AI, which were attractive concepts, yet they lacked scientific and technical foundations in terms of definition and metrics. It was obvious from the beginning that information was closest to this domain. That was well established, scientifically and technically. Between information and intelligence, it progressively turned out that knowledge and expertise were the most appropriate intermediate notions to clarify. Furthermore, knowledge appeared as the first notion to be established on the basis of information.

In common English, we use the word “knowledge” in a relatively nonspecific way, conveying multiple notions without any difference, including information, expertise, or skills. Now it is worth attributing specific names for these respective notions, which the MCS theory contributes to achieve. In the classical tradition, the state of the art is fuzzy, and such differences may look slight in this context, but, in fact, they are generally important, and we will show subsequently that different, specific units are required in order to allow clear and quantitative estimations.

If the concept of knowledge would indeed only correspond to the one of information, it would not need be further considered here and in MCS. At the least, it is already interesting to note the close vicinity of knowledge to information, that is, to the notion on which the intention was to ground it.

What is the meaning of knowledge? Of knowing? The triggering brain wave could show that information was again the right road, not as an ontological answer (in which information is not knowledge in the MCS theory) this time, but as a way to figure out what this different concept denotes. An observer may judge a possible knowledge in a system on the basis of the information he or she gets from it. In particular, this is how teachers traditionally assess students in schools. The main idea here is that a system featuring knowledge (a CS) has the ability to generate, upon request, a certain piece of information.

Intuitively speaking, these notions conveniently allow for a distinction between different phenomena: a musician performing in playback mode (pre-stored information) and a musician performing live (knowledge, that is, the ability to generate information upon request). This latter, cognitive behavior is even more apparent in the case of improvisation or jazz. In order to highlight how the concept of information allows for defining the one of knowledge, let's consider what knowledge is useful for, that is, providing relevant information when it is wished.

For example, when you know a city, you can describe that city, determine if pictures show that city, or give accurate instructions to a taxi driver. In all cases, knowledge allows you to generate pertinent information upon request. In short, knowledge allows you to do things right.

3.2 Toward the Concept of Expertise

The previous stage, including not only a rigorous, well-structured definition of the notion of knowledge but also associated metrics (developed subsequently), could bring other new and interesting results. And other elements have, in turn, caused a surprise!

Notably, a large difference had sometimes appeared between the quantities of knowledge estimated by the theory and one's intuition. A certain task seemed to require an enormous quantity as computed from MCS equations, but that task seemed easily performed.[4]

In those cases, it appeared particularly relevant for us to also integrate the quantity of time necessary for the CS to elaborate on the delivered information or, similarly, fluency, the inverse of this property. This resulting new entity synthetically describes the ability of CS to do things both right and fast, that is, the concept of expertise (know-how, competence, and so forth). This property is surely the most important for a CS, and its merits do not limit themselves to the surprising cases evoked previously.

It may seem astonishing that time has any connection with cognition, yet it plays a very significant role here. And yet, watching chess tournaments or taking school exams makes it obvious that the duration of time plays a critical role in cognition as well.

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[4] Being a teacher, I sometimes ironically call this paradox the "paradox of professors."

3.3 Other Developments

The definition of the notions of knowledge (with its associated unit, the lin) and expertise are no doubt the most revolutionary elements of MCS theory. And with this momentum furthermore inheriting the classical notions of information and model, many entities of the cognitive world can be defined easily and clearly: abstraction, concretization, experience, learning, intelligence, simplicity, and more. A real ontology for cognitive sciences can take place. In some publications, which are not related here for reasons of thematic boundary, extensions have been made, reaching into various domains (economy, automation, and ethics), no doubt with useful contributions to more clarity.

The notion that deserves a special remark here is the one of complexity. In classical references, Chaitin-Kolmogorov (CK) theory looks the closest to MCS in this regard for defining complexity. But there is an important difference in the way complexity is defined in each context:

- In CK theory, the length of a minimal program is the essential property of the complexity of the chain it generates, and we cannot define these entities.
- In present MCS theory, we can easily estimate the complexity of a program and, in a similar and independent way, so can the complexity of a chain. Furthermore, MCS defines and quantifies the reductibility of a chain as the ratio of its own complexity over the complexity of the program that could generate it. Moreover, we define complexity here in a direct and natural extension of the concept

of information, to the point of inheriting the same measuring unit.

It may look very restrictive to only consider chains of characters and programs. However, for CK and even more so for MCS theories, chain and program are just two examples of a universal way to represent information and knowledge. So generalization is possible, and we can similarly expect benefits drawn from considering chains and programs with all kinds of other representations and contexts.

After this survey of the main development stages of MCS theory, it is now time to concretely address the main features of the proposed model.

4. Core Features of Defined Model

The MCS model has three core attributes. It is behavioral, scale invariant, and, conceptually, independent from the physical nature of implementation support.

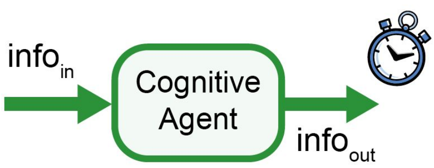

Fig. 4 – *Behavioral model*. A CS is mainly characterized, in MCS theory, by incoming information, (I_{in}), and, respectively, outgoing information, (I_{out}). In essence, a CS has the capability of generating the relevant information, (I_{out}). Time is sometimes also a significant dimension.

4.1 Behavioral Model

In MCS theory, the reference model is behavioral. Cognitive entities are essentially defined here on the basis of incoming message flows (I_{in}) and, respectively, outgoing ones (I_{out}). The CS itself is not explicitly specified in terms of internal structures. It can just be considered as a “black” box (figure 4). The set of possible input messages, with their corresponding output messages, constitutes a cognitive domain (D).

The essential property of a CS is the ability to generate pertinent output information (I_{out}), that is, information corresponding to a considered domain (D). In principle, it may happen that the quantity of input information of a CS be nil, even for useful applications. On the contrary, a CS that would not deliver any outcoming information would have no practical interest.

4.2 Applicability of MCS Model at All Levels of Detail (Granularity)

The CS typically proposed in MCS theory is recursive. In particular, it is possible to refine analysis and address structures internal to the black box introduced previously (substructures). And reciprocally, it is possible to zoom out in order to possibly handle, always in behavioral way, at a holistic level (from a global input-output point of view) much larger systems, such as groups consisting in sets of single cognitive agents.

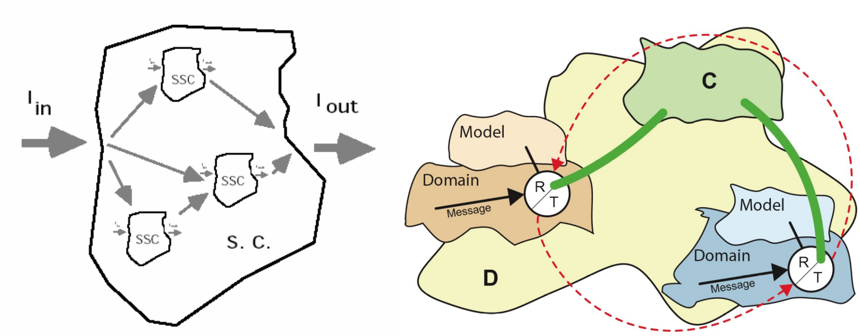

Fig. 5 – *Free granularity*. The schematical agent illustrated in the previous figure (figure 4) can be considered at various scales, for example, at more detailed levels, expliciting internal structures (left), or at more global levels, as for a group that integrates several individual agents. The latter communicates and shares a common culture (right).

4.3 Independence of MCS Models from Physical Nature of Implementation Media

The scope of applicability of MCS reference models is, in principle, not restricted to a specific nature of implementation support, such as to:

- Chemicophysical implementation for the case of humans
- Microelectronics for digital circuits and computers

By the way, the classical concept of information totally shares this same property of independence from the physical type of implementation layer.

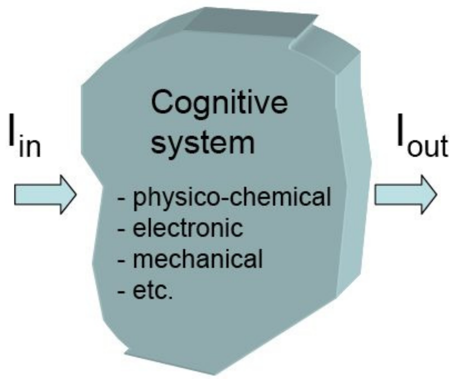

Fig. 6 – *Nonphysical nature of CS*. As for the case of information, a CS, in MCS theory, is defined independently from the nature of physical support required for implementation.

4.4 Examples of CS

Figure 7 displays several representative cases of CS. We can see systems at very different scales: microscopic and then macroscopic for the case of man and implementations of different natures, chemicophysical and microelectronic.

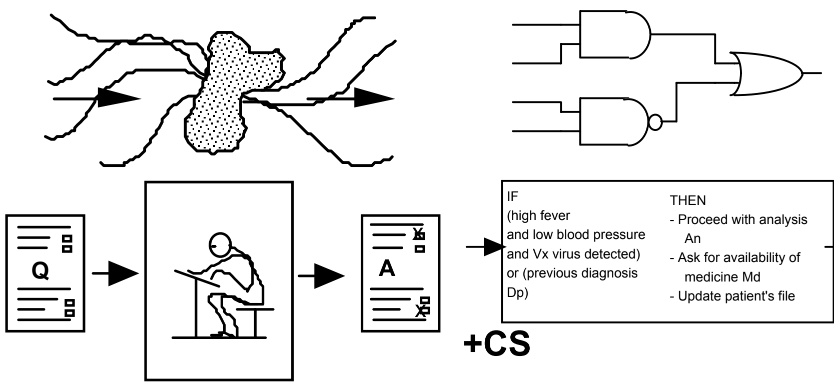

Fig. 7 – *Examples of CS*. Schematic representation of a neuron (upper left), of a combinational logic circuit (upper right), a person answering a multiple-choice quiz

(lower left), a computer running a production rule (lower right). All cases can be modelized in a similar way. We can estimate their cognitive properties: complexity, quantities of knowledge and expertise, index of abstraction, and so forth.

Today, we often communicate knowledge in the form of information, for example, as description of methods, list of instructions, or executable code. But knowledge effectively appears only when it is implemented on a cognitive agent, such as a human or as a computer, and indeed put into operation. In this regard, to be complete, the fourth example previously, which displays a computer instruction and a rule of production, should also refer to the computer and all resources necessary for realization of the CS.

4.5 Goal of MCS Theory

Finally, as shown previously,[5] a model can have some quality (can be somehow considered as good) only for a given goal. So it is appropriate to clearly state what is the goal addressed with the help of current MCS theory. The goal is to precisely define key cognitive entities and to be able to assess them quantitatively. This should no doubt be useful for the context of classical cognitive sciences and all intellectual properties and processes (for example, knowledge, expertise, or learning). Furthermore, this approach becomes absolutely

[5] See “Notion of a Model.”

necessary in the course of automating cognitive processes, therefore, for cognitics.[6]

[6] A first stage being now passed through, it appears that, beyond cognition itself, the study of pertinent goal(s) for cognition cannot be evaded. Logically, the next ground to explore is the one of ethics. Similarly, implementing the results of cognition requires other dimensions: energy, structures and mechanical elements, emotions, and so forth.

5. Essential Cognitive Concepts in MCS Theory

Because we understand the classical notions of model and information well, we are well equipped to approach the theory presented here for cognition domain, MCS. Time is also one of the basic dimensions relevant here. We will consider it later.

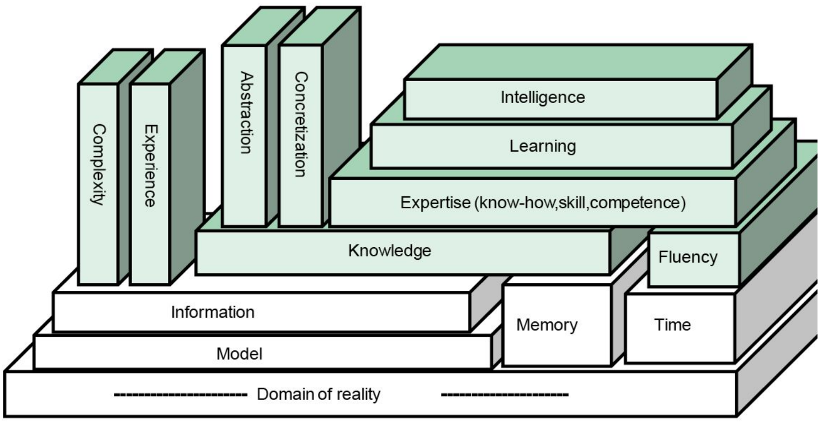

Fig. 8. *Main cognitive entities in MCS theory*. Important cognitive concepts, defined in MCS theory, are colored in green (left). They are based on a few classic entities, including time. Information, model and memory, though classic, need a discussion from a cognitive perspective, which follows.

It is naturally also necessary to accept right away that all cognitive concepts based on the notions of model and information inherit their apparently limiting features: nonstationnarity and perishable character, subjectivity, and incompleteness with respect to reality.

In the first section, we define the term “cognitics.” Then we successively introduce about twenty essential concepts. For all of them, the title is followed by a number that indicates the logic order by which definitions best interlock. For example a notion with number 4x requires understanding of some notions of level 3 and below. Figure 8 gives an overview of developed concepts.

5.1 Cognition and Cognitics (0)

This section reports on cognition and cognitics, automated cognition. Automation requires clear definitions and, beyond usual dictionaries, lexicons or glossaries, a proper metric system that is presented soon.

Mankind has invented an ever-increasing variety of tools and methods, thereby getting populations to grow in number, individuals to live longer, and an ever-larger part of our universe to be explored. Schematically, two kinds of progress have been made quite independently from each other, relating to:

- The intangible world of ideas
- The world of physical objects

Only the human beings seemed to have the ability to establish a link between these two worlds, in particular with speech, writing, and drawing and possibly sculpture and architecture.

During the twentieth century, the formal expression of a first connecting channel between physical world and intangible world (information) has accompanied the revolution of long-distance communications. It was essential to establish a well-defined correspondence between ideas to communicate and physical objects supporting messages, and this has been done.

Today, a new stage opens in front of us, where man-made systems can not only commute, often with much ease, between the physical world and the world of ideas. Moreover, it is even possible for such systems to process ideas on their own, draw conclusions, induce precedents, abstract, or, in contrast, concretize. Here is the field of cognitics (automated management of cognitive activities), which, traditionally speaking, were typically or even exclusively reserved for the human beings.

Definitions :

Cognition is essentially the faculty, ensured by specific internal structures and operation flows, to process information with high performance levels, for example, in terms of complexity, abstraction, learning, or expertise. Cognitics is the field of sciences and techniques relating to automated cognition, that is, of cognition implemented on machines.

Discussion

Classically, we consider cognition as the main faculty of human brain, ensured by specific structures of the mind and mental operation flows, which is essentially capable of high performances in terms of information processing. It also applies to animals, computers, or machines, that is, in general, systems capable of similar capabilities.

Cognitics bring an appropriate response to the challenge set by complexity, which does not stop growing.[7] In

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[7] Obviously, more and more information accumulates, and scientific exploration by humans keeps progressing. Under this

cognitics, powerful operators notably include those that allow a fast access to information, such as sorting lists by alphabetical, numerical, or chronological order. A very powerful paradigm for automatic learning is cache memories. In this latter case, a second access to the same data in cache can be faster than the initial one in main memory. This translates, according to MCS developed subsequently, into an increase of expertise (the ability to learn). Another example is the management of bookmarks and preferred Internet links.

The availability, thanks to MCS theory, of formal definitions and metrics for cognitive properties, such as complexity, knowledge, abstraction, or intelligence makes advances in cognitics easier. To clearly state the care taken in cognitics for the possibility to metrically assess cognitive entities, the expression "quantitative cognitics" is also sometimes used.

In the context of cognitics, it appears that systems that rate high in terms of expertise are also, in principle, the most valuable. Intelligent systems (systems capable of learning) are comparatively less interesting because, by definition, they start operating with lower expertise levels.

Cognition includes intelligence aspects, and the field of cognitics overlaps widely with artificial intelligence (AI) in the sense, we usually understood the latter. Cognitics, however, is more general, hosting many other concepts, notably those of knowledge, expertise, learning, abstraction, or concretization, for example.

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angle then, our representations get richer. And yet reality unveils itself only in infinitesimal ratio.

5.2 Model (1a) and Domain (1b)

Definitions :

As introduced earlier, a model is a simplified (incomplete by essence) representation of reality, that is found useful in order to reach some specific goal. In MCS theory, the basic reference model is behavioral. A domain of reality (D), is in principle represented as D_m, a set of N associations of behavioral type , A_i , including pairs of corresponding messages, « input messages – output messages»:

$$A_i : (I_{in}, I_{out})_i \qquad \text{Equation 3}$$

$$D_m : \{(I_{in}, I_{out})_1, (I_{in}, I_{out})_2, \ldots, (I_{in}, I_{out})_n\} \qquad \text{Equation 4}$$

Such a cognitive domain can be viewed as a kind of (virtual) table, which contains as many rows as possible incoming message types. For quantitative assessment, each row is characterized by the instant probability of occurrence for the corresponding input message and contains the corresponding output message as well.

Discussion

The goal of the MCS model is to allow the quantitative assessment of key cognitive properties, such as knowledge, expertise, or learning. We introduce the notion of domain to express the fact that, at a given moment, attention is, in principle, not addressing the whole reality and all virtual worlds, but only focuses on a very limited element, a certain domain. So there is always a first constraint that we need to keep in mind : Which domain are we talking about here and now? In practice, difficulties often arise from the peculiarities of the aspects of reality being addressed, which are ambiguous or insufficiently defined.

A second limit stems from the fact that a model, by nature and as already discussed, keeps few aspects of the domain it addresses. In principle then, for the same D domain of reality, we can consider multiples models ($D_{m\,i}$).[8] So it is also critical to adopt the one appropriate for each context.

Example

Consider, for example, the task to ensure that a coin be laid on the tail side. Two associations can represent this domain:

- 1 - the case of a coin initially laid on its tail side
- 2 - the case of a coin initially laid on its head side

In the first case, we don't need to do anything. In the second one, we need to reverse the coin. A possible representation for this cognitive domain is, for example, the following:

$$D_m : \{(tail, nothing-to-do)\ ,(heads, reverse-the-coin)\ \}$$

Equation 5

Theorem 5 – We Cannot Directly Apprehend Reality

Proof:

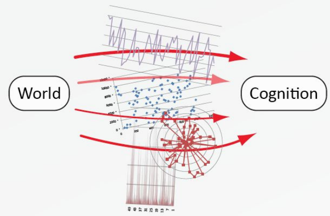
A domain of reality (D) is not directly manageable in MCS theory. A certain representation (D_m) is necessary, as defined by equation 4.

[8] A drastic alternative to using a model consists, as Parmenides proposed, to let observers directly facing domain (D) itself, “What is, is; what is not, isn't.” For humans, experience (what has been lived through) seems hard to be circumvented as a precondition for all modeling. Yet it would be worth the trouble to attempt precisely that—or at least to keep this stage minimal—in particular as a preparation toward total automation.

Discussion

Restrictions already defined by theorems 1 to 4, relative to the classical notions of information and model, are inherited here. In coherence with the constraint of continuity, which requires basing the new theory, in particular, on the firm foundation that the theory of information provides, we must recognize that our models trap us. Nevertheless, the latter have at least two merits: M1 (a certain finitude) and especially M2 (a certain ability to help the agent cognitive to reach his/her/its goals). In the previous example, we retain a single bit of information for the coin under consideration, its heads or tail state.

a



b

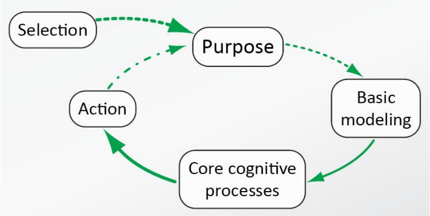


Fig. 9. Quantitative assessment shows that the complexity of the world is infinite, no matter how restricted the domain, and immediate cognition is consequently impossible (a). Nevertheless, when attention is focused on a specific purpose, it very often appears that crude, tractable, world representations (models) may be sufficient (b) and cognition may successfully proceed in this context.

In plain reality, this coin has an infinity of additional features, which will possibly turn out critical in some situations: nature of material it is made of, thickness, type of currency, surface defects, identity of owner, and so forth.

5.3 Information (2a)

We have presented the concept of information before as well as illustrating it in figure 1. Let's briefly discuss what the main elements relative to information are:

- Messages convey information
- A CS builds up or updates an internal, simplified representation (model) of reality
- Messages are expected with a certain probability

Definition

Information allows a CS to update his/her/its model, and the quantity of received information is a function of the probability of received messages.

Discussion

In the definition, we have considered the case of a system that receives information, but it may happen that a system transmits some information. In fact, we handle the situation similarly. If a certain probability characterizes the transmission of a message, the same equation 1 gives the corresponding quantity of information.

In MCS theory, we give special attention to the information entering a CS, as well as to the information going out of the system (generated by it). Equation 1 was giving the quantity of information conveyed by a message (Q) (essentials). In general, several messages are possible. And for each of them, equation 1 is, of course, applicable, particularly giving information quantity (Q_i) for the i^{ith} message. It is worth adding here that, in practice, the average quantity of information conveyed in a message (Q_m) often becomes interesting as a global indicator:

$$Q_m = \sum_{i=1}^{N} p_i Q_i = \sum_{i=1}^{N} p_i \log_2\left(\frac{1}{p_i}\right) \text{ bit} \qquad \text{Equation 6}$$

Thus, the latter equation will apply in order to estimate information quantities entering (n_{in} bit) and, respectively, stemming out from a CS (n_{out} bit).

5.4 Message (2b)

Definition

A message is a piece of information. Essentially, its probability of occurrence determines the quantity of information it conveys.

Discussion

As already debated, the significant probability of occurrence is the one the receiver of the message estimates, and this is all retained of messages in order to estimate the quantity of conveyed information.

Today, many people have some experience of computer systems, and they are often much influenced by the digital representations they meet. It is true that the way a message has been digitally encoded can a posteriori turn out to be a meaningful indicator of the quantity of information it contains. Nevertheless, equation 1 is still critical. In case of conflict, two situations can schematically occur:

- Either the used code seems to consist in more bits than necessary and thus contains, by definition, redundancy. This may be useful, for example, in case of communication in presence of disturbances
- On the contrary, the code may seem to consist in less bits of information than necessary for such a message, but one should be aware that this is not

possible in theory. We must surely do analysis again carefully in order to locate the errors.

In principle, simple and effective methods are available in order to minimally encode messages (implement them with just the amount of bit specified by equation 1, especially Huffman code). Equation 1 also sets the ultimate lower limit for all attempts to compress information without errors.

Notice that, by etymology, the word “message” refers to an emitter. This was appropriate for the early days of information theory when communication issues prevailed. In current context, cognitive sciences, the focus is moving more to the receiver side. From the latter perspective, we generally perceive information as news, sensations, and discoveries. A symmetric general word for an incoming item of information could be “receptage.”

5.5 Complexity (3a)

Definition

Complexity is the property to require a lot of information for an exhaustive description. Quantitatively, complexity is the amount of required information for this description. The measurement unit is therefore the same as for information (the bit)[9].

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[9] Other authors have proposed definitions for complexity. The definition closest to the present one, in MCS theory, is probably the one of Chaitin-Kolmogorov. This point is further discussed subsequently in Reductibility

Discussion

Very directly, this definition carries over the properties of information itself to complexity: nonstationarity and subjectivity (theorems 1 and 2).

An additional useful equation for quantifying information is the one that computes the average information quantity of messages for cases of equiprobability. This allows for a fast estimation of information quantities and gives an upper boundary in all cases. Here is the equation, in the case of N possible different messages, all being equiprobable:

$$Q_m = \sum_{i=1}^{N} p_i \log_2\left(\frac{1}{p_i}\right) = \sum_{i=1}^{N} \frac{1}{N} \log_2\left(\frac{1}{\left(\frac{1}{N}\right)}\right) = \log_2(N) \text{ bit} \qquad \text{Equation 7}$$

The surest mean to limit complexity consists in restricting oneself in as much as possible to small contexts (a minimal number of different messages). Classical methods for implementing this ideal strategy include hierarchical[10] representations and sorting mechanisms. Efforts are then carried from the direct management of a complex context over to the optimization of addressing and navigation techniques from one context to another.

It is obvious today that content-based addressing and hyperlinks, methods that current information and network

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[10] In a report, for example, we have in particular: a title as a very abstract way to transfer without excessive information content of the report in the broader context of a library or a bibliography; in the context of the summary, a presentation of the entire report in an abstract form; or, within the report, particular contexts allow to specifically describe respective details.

technologies support, allow humans to validly consider a very large number of different contexts and keep each of them at a manageable level of complexity. Globally, the complexity of our worlds on computer is nowadays counted in terabytes[11] at the scale of an individual workstation and probably 10^{10} more at the scale of the Internet.

In particular, it appears that the present definition of complexity solves a classical paradox in AI, the paradox of experts. The more one knows, the easier one can learn some more.[12] Experts can largely anticipate messages. By definition, the latter convey less information for the experts. They are then, also by definition, less complex. What follows is no longer a paradox. It is logical that one can more easily learn what is less complex.

Example

The definition of complexity in MCS theory is held in about two lines. This corresponds to roughly twenty words, that is, about 200 bit.[13] Consequently, the quantity of complexity of this definition is 200 bit.

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[11] One byte equals eight bit.

[12] This is contrary of the phenomena that are usual in the physical world. For example, there is increasing the pressure in a tire. The more one pumps, the more it becomes difficult to pump further.

[13] Assuming one thousand common words in English, all with equal probability, the probability of a word is 1/1000. With Shannon's equation for the quantitative estimation of information (equation 2), this yields about 10 bit of information per word.

5.6 Abstraction (3b)

Definition

Abstraction is the property of a system that generates, as output messages, less information than it receives. Quantitatively, in MCS theory, the abstraction index (i_{Abs}) is defined as the ratio of incoming information quantity (n_{in} bit) over outgoing information quantity (n_{out} bit) :

$$i_{Abs} = \frac{n_{in}}{n_{out}}$$ (without unit) (Equation 8)

Discussion

While we measure input and output quantities of information in bit, the abstraction index itself is without unit. Typically, the abstraction index is larger than or equal to one. If on the contrary, the quantity of information is larger on the output side than on input side, there is no real abstraction, but rather some concretization.

Abstraction is typical for perceptive processes and pattern recognition and, in general, characterizes understanding and scientific research. Obviously, this also qualifies modeling.

5.7 Concretization (3c)

Definition

Concretization is the property of a system that generates, as output messages, less information than it receives. Quantitatively, in MCS theory, we define the abstraction index (i_{Concr}) as the ratio of outgoing information quantity (n_{out} bit) over incoming information quantity (n_{in} bit):

$$i_{Concr} = \frac{n_{out}}{n_{in}}$$ (without unit) Equation 9

Discussion

While we measure input and output quantities of information in bit, the concretization index itself is without unit. Typically, the concretization index is larger than or equal to one. If on the contrary, the quantity of output information is smaller than in input, there is no real concretization, but rather some abstraction. Concretization processes are typical for synthesis, for realization. They are creative and evidently generate information. To generate information and, more particularly, perform concretization are synonyms for art (as found in particular in the words artisan and artist).

5.8 Knowledge (4a)

Definition

Knowledge makes systems capable to generate the relevant information. The generated information is relevant (pertinent or correct) if it corresponds to the considered cognitive domain. Quantitatively, in MCS theory, a function of average incoming (n_{in}) and outgoing information quantities (n_{out}) assesses knowledge. We define the quantity of knowledge (K) as follows:

$$K = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right)$$ lin Equation 10

The logarithm is taken in basis 2; the unit is the lin (logarithm of information). The relevant information may be stored internally as such, but, in general, it is dynamically elaborated. Systems with knowledge are called CS. So knowledge is the essential property of CS.

CS generate information either actually proactively or in reaction to some incoming information.

Discussion

Knowledge allows CS to do right. Knowledge is the notion the most evidently related to CS and even cognition in general, as the old roots of these words indicate. Let’s consider in a first phase the type of information traditionally generated by humans in the past. In those days, the user in search of a piece of information either had to refer to another human or restore the past result of cognitive processes of human nature from some kind of memory.

Here are two examples: the table of multiplication for pupils, acquired by rote learning (one times one until twelve times twelve) or, as a more complex example, the table of logarithms and trigonometric functions.

The revolution, made possible by artificial cognitive systems (ACS), is that the information sought by humans can suddenly be elaborated on demand, without having been stored at all, without prior tabulation. The name of cognitive agent, sometimes also used to describe a CS, makes this point well.

Let’s return to our two examples. The first pocket calculators date to the 1970s. Since then, they have been, for example, capable to quickly show the result of a computation such as thirteen times thirteen or log(5) without using any memory containing pre-elaborated, explicit answers.

A CS largely thus spares the need of prior development of very large amounts of information. This comes, however, at a certain price. On the contrary of stored information, which is static and virtually immediately available, cognition involves by nature processes (action) and therefore necessarily requires a certain amount of time. What is essential, as said, is:

- The exemption from the need to prepare the information that might be perhaps required later
- The emerging need to implement a process

This interchangeability of roles between information pre-established and processes capable of generating it on demand inspires in MCS theory how to assess the quantities of knowledge.

The basic idea is to assess the amount of knowledge of a CS as a function of the amount of predetermined information that can be replaced. At the heart of equation 9, we introduce the term M for this purpose:

$$M = n_{out} \cdot 2^{n_{in}} \qquad \text{Equation 11}$$

The product term reflects the fact that we can conveniently see a knowledge domain as the set of all corresponding possible input-output associations. One can imagine a memory, a table whose width would be n_{out} bit wide. The number of lines corresponds to all possible input messages ($2^{n_{in}}$ lines, assuming an optimal code). (The latter would yield a minimum size.)[14]

The presence of the amount of incoming information as an exponent of the basis 2 should alert us. The growth of such a function is very fast. With 10 as an exponent, the

[14] There is no essential difference between the size of the virtual table (M), the complexity of the cognitive domain where a cognitive system operates (D_m), and the quantity of information necessary to describe all possible associations, A_1, A_2, ... A_N, in this context.

number 2 yields about one thousand. With 30, it yields one billion.

Indeed, it appears that, in general, cognitive processes for human perception, the amount n_{in} lies in the thousands range or even much more. So the size of this virtual table (M) is so huge that it would be quite impossible to physically implement it. To lighten the notation somewhat, a logarithmic[15] function has been added to the estimate[16] of equation 11, essentially yielding equation 10.

It must also be remembered that the goal here is to simply develop a standard, a conceptual reference to quantify the knowledge of CS and not directly to make it operational, using a table of predetermined answers. (Even if this method may be possible for very simple systems, it cannot be the solution in the vast majority of cases.)

The presentation is restricted here to situations where CS make no error. We consider extensions in the next section for the case of errors.

In CS, knowledge lies in the structure and organization of components. It emerges when multiple elements are interrelated and may gain momentum when many dynamically interact/communicate. Thus knowledge is

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[15] A similar scheme has been done in the domain of acoustic power, for example, which has led to the Bell (and dB) unit(s).

[16] In a theoretical case, somewhat nonsensical, where no information would be virtually stored (n_{out}= 0 bit), it would be reasonable that the equation gives 0 lin of knowledge as well, rather than -$\propto$. For this reason, the +1 term is added in equation 9, but, in general, this quantity does not significantly affect the result and can be neglected.

tightly bound to the very essence of systems. Notice that, in the same manner as various kinds of physical signals convey information, knowledge may be embedded in mechanical systems (old office calculators, Babbage's engine, and so forth) in electrical, physio-chemical ones, or structures of another nature yet.

Example

In the case of coin tossing mentioned earlier (D_m), we had two equally probable incoming messages, heads or tail, and therefore one bit of information.

$$D_m : \{(tail, nothing - to - do)\ ,(heads, reverse - the - coin)\ \}$$

Equation 12

For the corresponding messages in output, *nothing-to-do* and *reverse-the-coin*, we also have two equally likely messages and therefore 1 bit of information as well. Consequently, the amount of knowledge (K) of a CS capable of assuming this task is as follows:

$$K = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) = \log_2(3) \cong 1.6 \text{ [lin]}$$ Equation 13

In principle, we have said everything. Here we have 1.6 lin of knowledge. Let's nevertheless consider the case in detail in order to intuitively feel a little the analogy cited previously with a virtual table that would contain the complete set of associations. To tabulate the domain, we would need $2^{n_{in}} = 2^1 = 2$ rows. The first one could be the case for heads and the second one for tails. We have already seen that the corresponding actions (output messages *nothing-to-do* and *reverse-the-coin*) also convey 1 bit of information. These two messages could be respectively encoded as 0 and 1, and it clearly appears that, in this case, the table size would be the following: $M = n_{out} \cdot 2^{n_{in}} = 2$ (bit), the value we already had in equation 11.

Theorem 6 – The Quantity of Knowledge of a CS is Much More Related to the Quantity of Information It Can Perceive Than to the Quantity of Information It Can Generate.

Proof

Consider the core element of equation 10, which allows the estimation of knowledge (K). This is also the term M of equation 11. The average amount of generated information (n_{out}) appears as a factor, whereas the amount of perceived, incoming information (n_{in}) participates as an exponent.

With equal values, n_{in}=n_{out}=n, n_{out} typically brings a contribution to K that is negligible with respect to n_{in}. If n is nil, the situation is less obvious as the constant term equal to 1 then dominates. But a CS that does not deliver output information does not make much sense. And for all values of n equal to or larger than 1, $2^n > n$ or even $2^n >> n$.

Discussion

The basic equation for measuring information, equation 1, includes a logarithm for mapping probabilities into amounts of information.[17] So the inverse function (the function to map information quantities into probabilities) includes an exponential. This mainly affects the contribution of n_{in}. In a different way, the same logarithmic function implies that, if one considers several

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[17] Equation 6 makes even more evident the logarithmic law that binds quantity of information and number of possible messages.

generated messages simultaneously, their corresponding amounts of information simply add up. This affects mainly the contribution of n_{out}.

The analogy of the virtual table, as developed in the previous example, allows us to see the asymmetry of effects of input and output quantities. Here are two additional examples, of more intuitive nature:

An ordinary CD player quite simply maps the ordinal number of songs ($n_{in} \cong 4$ bit) into generated musical sounds (ten minutes of music or about $n_{out} \cong$10 * 60 * 44,000 * 20 = 528Mbit), whereas a system capable of recognizing such pieces of music ($n_{in} \cong$528 Mbps; $n_{out} \cong 4$ bit) is hardly conceivable.[18]

It is much easier today to make a speech synthesizer (transformation in the direction from text to speech) than voice recognition (transformation in the direction from voice to text). And it turns out that the amount of information corresponding to a message in voice form is much greater than the same message in usual text form.

Theorem 7 – We Cannot Make Common CS as Simple Readers of Pre-Computed Answers

Proof

It is commonplace today to add three numbers in quadruple precision, both by computer or directly by manual operation. Now this means we know how to add three numbers, consisting of thirty-four digits each. A table containing all the possibilities of this task should

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[18] Notice this is very different from the type of recognition of songs that starts to happen on the Internet, in karaoke style. A quick quantitative evaluation proves it. Even for much simplified domains, symmetry remains far away.

contain 10^{3*34} rows, each containing a number of thirty-five digits. But such a number of rows is more than a billion of billion times the number of particles (electrons, protons, and neutrons) in the known universe (10^{80}). This means it is totally excluded today to remember a priori all the possible answers in this domain.

Discussion

In previous example, the quantity of knowledge (K) amounts to about 350 lin. Yet this is a rather small amount of knowledge in the world of CS. For example, it is common today that automated systems attempt to recognize spoken words, or images.

A second of speech in CD quality amounts to about 44,000 × 8 bit of information. It would be necessary here to rely on a table with $10^{100,000}$ rows to tabulate all possible one-second-long sounds. The corresponding quantity of knowledge equals approximately 350,000 lin.

Imagine, as was reported in news media, that we consider an automated, visual control for identifying humans at the border. An image of television quality traditionally consists in about 600 rows and the equivalent of about 800 columns. Even if we neglect the color and retain only the saturated black and white levels for each picture element, this already amounts to about 500,000 bits of information. A table with $10^{145,000}$ rows would be required to a priori store the appropriate response to each possible image. In such contexts and if the issue is to quantify the amount of knowledge, output information quantities can generally be neglected (theorem 6). If a single bit of information is stored by row (for example, accepted or rejected) and then possibly outputted, the amount of knowledge (K) is 500,000 lin. If, as the opposite extreme case, an amount of information similar to a whole dictionary is stored on each row (1 Mb per line). This could, for example, be a very detailed curriculum of the person recognized or possibly, in the other example, a copy of the picture with many comments. K' would reach a mere 20 additional lin, K' = 500,020 lin.

In the world of cognition, numbers can definitely be very large. These two examples seem banal and yet mobilize the gogol with exponent 1,000 and more.

Theorem 8 – The Amount of Knowledge of a Truly Random Generator Is Infinite

Proof

At a minimum, a generator of truly random information has no entry; n_{in}= 0 bit. On the contrary, output information is virtually unlimited. Consider elementary output messages, comprising a single bit, for example, 0 or 1. In practice, it is not sufficient to get a single response. Such a generator, truly random, is expected to provide numerous output messages, numerous successive 0 and 1, without any regularity at infinity. Therefore, $n_{out} = \infty$ bit.

The amount of knowledge of such a CS is as follows:

$$K = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) = \log_2\left(\infty \cdot 2^0 + 1\right) \cong \log_2(\infty) = \infty \text{ lin}$$

Equation 14

Discussion

This is a surprise. The traditional intuition is that only a small amount of knowledge is necessary to generate random information. But equation 14 shows that a very large amount is required. This result is correct and can be understood as follows : the virtual memory containing the information of the domain must be at least as large as the one of all output messages. If the expected sequence, apparently random, that is unpredictable by the user, is globally not of limited length, the memory must also be infinite in size.

In practice, it is common in electronics and computers that number generators are provided, not only somehow random, but mostly pseudo-random. Typically, the sequences generated are cyclical. The corresponding amount of knowledge is of the order of tens of lin. This is obviously very far from a truly random generator, and it is not on this basis that the law authorizes lottery games and raffles.

A common alternative approach for a CS is to transfer as output some information acquired from an external source that itself is considered as random, for example, the instantaneous hundredth of a second, according to the dashboard clock. For example, if we want a computer to say randomly and with equal probability "hello" or "good morning" when it is turned on, we could ask it to read the current time at power on. (This time, it could be 9h 10min 12s and 20/100, for example.) So the hundredth is even. (Here, with 20, it is the case.) Then we should hear "hello." In principle, the method works and is even probably satisfactory for this simple application. But without doubt, the precise analysis of individual cases is difficult, and this does not constitute in itself a guarantee of quality for the randomness of the result. The problem fully remains at the level of the external source. (Here, the process that turns the computer on, and especially its time specifics.)

5.9 Experience(4b)

Definition

Experience (R) is the property of a CS that has been exposed to a cognitive domain. Quantitatively, we traditionally evaluate the experiment in terms of duration (T), that is, in terms of time. The unit is then the second (s).

$$R_t = T \quad \text{(s)} \qquad \text{Equation 15}$$

Another view, more fundamental in MCS theory, is to measure experience (R) based on the amount of information conveyed in input-output message associations (A_i), to which the CS has been exposed:

$$R_i = \sum_{i=1}^{N} \left(n_{in\,i} + n_{out\,i}\right) \quad \text{bit} \qquad \text{Equation 16}$$

$n_{in\,i}$ and $n_{out\,i}$ correspond to the quantities of information of the input message and the message of the ith output of the i[th] association.

Discussion

Although we have traditionally measured experience with time units, the nature of the environment is clearly not without significance. The two definitions converge if one describes a given environment by the average flow of relevant associations that can be met there.

Example

A CS was able to attend the tossing of hundreds of coins, followed by a possible reversing on the tail side, that is, a hundred executions of the task described previously, each yielding one A_i association that belongs to the same cognitive domain (D_m). Therefore, for this system, we have the amount of experience as follows:

$$R_i = \sum_{i=1}^{N} \left(n_{in\,i} + n_{out\,i}\right) = \sum_{i=1}^{100} \left(1+1\right) = 200 \quad \text{bit} \qquad \text{Equation 17}$$

We could also measure this as the experience of a day, adopting the traditional definition. Then it should be noted that, in this context, one can observe an average of one hundred associations (A_i) in the domain (D_m) per day.

5.10 Fluency (4c)

Definition

Fluency (f) is the property of a CS that delivers information quickly. Quantitatively, in MCS theory, fluency is estimated as the inverse of the time duration (Δt) needed to prepare output messages. The unit is then the inverse of the second:

$$f = 1/\Delta t \quad \text{(1/s)} \qquad \text{Equation 18}$$

Discussion

We can see fluency as the processing speed of CS. It also qualifies the ability of CS to respond to information (input messages).

Examples:

A CS can give its response 0.5 seconds after receiving each message entry. Its fluency in this area is then 2 (1/s).

A random number generator, as defined previously, delivers its messages (1 bit each) every 0.1 seconds. Its fluidity is then 10.

5.11 Simplicity (4d)

Definition

In MCS theory, we define simplicity as the property of an object to require little information to be exhaustively described. Quantitatively, we can estimate the amount of simplicity as the inverse of the information quantity necessary of this description. So the unit of measurement for simplicity is the inverse of the one for information, (1/bit).

Discussion

Simplicity is the opposite of complexity. We can estimate these two quantities very directly, based on the amounts of associated information. Remember, however, that the notion of information, as conventionally defined, has sometimes disturbing peculiarities, as evidenced in theorems 1 and 2, fluctuations over time and subjectivity. These peculiarities are inherited here. Fluctuations over time and subjectivity are consequently also essential features of simplicity.

Example

The definition of simplicity in MCS theory holds in two and half lines, representing approximately 20 words or 200 bit. On this basis, the simplicity of the definition amounts therefore to about 1/200 = 0.005 (1/bit).

5.12 Expertise (5a)

Definition

In MCS theory, expertise is the property of a CS to quickly deliver relevant information. Quantitatively, we define the expertise (E) as the product of knowledge (K) and fluency (f):

$$E = K \cdot f \quad \text{(lin/s)} \qquad \text{Equation 19}$$

The unit of measurement for expertise is the ratio of lin per second, (lin / s).

Discussion

Expertise enables CS to do right and fast. Expertise is a feature of CS that describes not simply their knowledge level, but also considers their fluency. Equation 15 states, in particular, that two CS may reach a similar level of expertise even if one features more knowledge (is more knowledgeable) than the other. For this to be true, the latter must operate quicker.

Expertise is the most fascinating property of CS. In general language, expertise has many synonyms: know-how, skill, competence, ability, excellence, and so forth. If a system is decomposed into subsystems or, vice versa, multiple systems are integrated to form a more comprehensive system, most of the corresponding cognitive characteristics, including expertise, cannot be combined directly in a standard way. The analysis of each case must be made in detail, showing the following for each subsystem:

- Input information and corresponding outputs
- and fluency.

The amounts of information respectively entering and leaving the system, at the largest scale, certainly remain constant for a given cognitive domain. But depending on the adopted structure of (de-)composition, it may appear, within the overall system, a large number of variants and, therefore, different interfaces between subsystems. Of course, the respective sizes of the various cognitive subsystems also reflect this.

Example 1

Again consider the coin example seen previously, relating to domain (D_m). If a CS can correctly decide whether to flip the coin or not, in the 0.5 second following the random toss, the amount of expertise is as follows:

$$E = K \cdot f = 1.6 \cdot 2 = 3.2 \quad \text{(lin/s)} \qquad \text{Equation 20}$$

Example 2

A mobile robot, such as RH3-Y in Suzhou during the RoboCup World Championship in July 2008, can follow a person without contact in an open context. That is, it moves in the context of a group of people, including the public, at a speed of about 1 meter per second with very gentle movements. How much does it demonstrate expertise in this domain? We can, of course, give the answer in a comprehensive manner (at a global level). We will do it at the point E2.4 of the example. But in fact, for reasons of optimization at implementation stage, it is worthwhile to decompose the overall CS into three sequentially organized subsystems: perception, decision, and locomotion. And in order to answer the previous question, the analysis will first be made for each of these subsystems. Finally, the point E2.5 puts the various intermediary results into perspective.

E2.1 Decision:

As input information for the decision subsystem, the system considers the position, relative to the robot, of the human it follows. Considering an accuracy on the order of 1 percent for the spatial coordinates of the human being followed is sufficient (two coordinates, for example, of distance and angular direction), we have about 15 bit of input information for this subsystem:

$$n_{in} = 2 \cdot \log_2(100) \cong 15 \quad \text{bit} \qquad \text{Equation 21}$$

Based on internal considerations, including acceleration, deceleration, and control protocol and internal state variables, this subsystem finally transmits the following instructions to the subsequent system (locomotion): instantaneous target values for tangential (forward/backward) and turning (right/left) speeds. An accuracy of 1 percent is more than enough:

$$n_{out} = 2 \cdot \log_2(100) \cong 15 \quad \text{bit} \qquad \text{Equation 22}$$

The optimal fluency in this subsystem is 1/(25 ms), that is, 40 (1/s). Consequently, this is the amount of expertise of the subsystem for decision-making:

$$E_{Decision} = K \cdot f = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \cdot f = \log_2\left(15 \cdot 2^{15} + 1\right) \cdot 40 \cong 800 \ \text{lin/s}$$

Equation 23

E2.2 Perception

But how to know the position of the tracked human (guide)? The solution adopted for RH3-Y is based on the estimation by a planar laser scanning ranger of about 700 radial distances, each acquired with a precision of the order of 1 percent as well:

$$n_{in} = 700 \cdot \log_2(100) \cong 4650 \quad \text{bit} \qquad \text{Equation 24}$$

We can consider the amount of information coming out of the sub-collection system as identical to that entering the next decision subsystem (equation 17). Therefore, $n_{out} \cong 15$ bit. A fluency of 1/(0.1 s), or 10 (1/s), is largely sufficient. The amount of expertise for perception is the following:

$$E_{Perception} = K \cdot f = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \cdot f = \log_2\left(15 \cdot 2^{4650} + 1\right) \cdot 10 \cong 46500 \ \text{lin/s}$$

Equation 25

R2.3 Locomotion:

Not only does the locomotion subsystem consider the instantaneous target values for speed, received from the decision subsystem, but some possible disturbances on the wheels as well, mostly due to local ground peculiarities. Considering an accuracy of about 1 percent on speed target values and angular coordinates of the two-wheel drive, we have about 30 bit of input information for this subsystem:

$$n_{in} = 4 \cdot \log_2(100) \cong 30 \quad \text{bit} \qquad \text{Equation 26}$$

On output side, the system commands an appropriate current in each of the two active wheels. An accuracy of 1 percent is quite sufficient:

$$n_{out} = 2 \cdot \log_2(100) \cong 15 \quad \text{bit} \qquad \text{Equation 27}$$

Fluency should be 1/(1 ms), or 1,000 (1/s), for motor control, according to dynamic constraints not discussed here. So the amount of expertise in the system is:

$$E_{Locomotion} = K \cdot f = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \cdot f = \log_2\left(15 \cdot 2^{30} + 1\right) \cdot 1000 \cong 34000 \quad \text{lin/s} \qquad \text{Equation 28}$$

E2.4 Overall Evaluation

To complete the example, it is also possible to assess the amount of expertise of the robot from a global point of view. Overall, input information consists in the 700 radial distances and 2 positions of the wheels (702 values known with a precision of the order of 1 percent):

$$n_{in} = 702 \cdot \log_2(100) = 4664 \quad \text{bit} \qquad \text{Equation 29}$$

Globally as well, the system generates as output the target values of electric current in the two-wheel motors. Consider an accuracy on the order of one percent:

$$n_{out} = 2 \cdot \log_2(100) \cong 15 \quad \text{bit} \qquad \text{Equation 30}$$

Furthermore, it is necessary to manage with good fluency the currents in the motors, f = 1000 (1/s). So the amount of expertise of the system as a whole is the following:

$$E_{Global} = K \cdot f = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \cdot f = \log_2\left(15 \cdot 2^{4664} + 1\right) \cdot 1000 \cong 4668000 \quad \text{lin/s} \qquad \text{Equation 31}$$

E2.5 General Comment

The detailed example shows several interesting points that are very representative. The amount of expertise required at the global level is very high. We can see it as an upper limit, required a priori by the task. We need resources, labor, and ingenuity to find a solution. Structuring the overall task in order to judiciously allocate the three subsystems, respectively of perception, decision, and action, is an important contribution, which reduces the integral quantity of expertise ultimately required.

Rather large amounts of expertise are notable for the tasks of perception and action. In the first case (the perception task), the large values for expertise reflect the relatively large quantity of input information to process. In the second case (the action subsystem), the fast fluency is the major factor for expertise size. The amount of expertise required for the task of decision is comparatively small.

5.13 Reductibility (5b)

Definition:

Reductibility is the property of an object for which it is simpler to describe how to describe it rather than to describe it directly. In MCS theory, we quantitatively evaluate reductibility as the ratio of the complexity of the object on the complexity of its indirect description.

$$\mathrm{Re}\,ductibility = \frac{Complexity(Object)}{Complexity(Description(Object))}$$ Equation 32

Reductibility is a ratio, so it is without unit.

Discussion

In MCS theory, directly describing the object determines the object’s complexity. To describe the object indirectly is different. This means that some instructions are given. Those instructions are necessary to elaborate the direct description of the object elsewhere. To describe the object indirectly means to specify how to describe the object.

The classic definition of Chaitin-Kolmogorov (CK) for complexity focuses on something called the indirect description here. In essence, according to CK, the complexity of a string[19] is the length of the program to generate the string.

We must understand the word “object” here in very general terms. Like in “object-programming,” for example, this word, in the definition of complexity, may as well denote a process or a virtual idea as a physical entity.

In MCS theory, we consider it useful to be able to distinguish between objects intrinsically simple and objects that can be reduced. It is similarly useful to distinguish between direct and indirect description. In the latter case, complexity may look smaller, but we definitely need time and resources to finally obtain, if all goes well, the object description.

We can also see reductibility as the property of a system that subsystems of integral complexity smaller than the complexity of the system itself can implement.

Examples

Three examples about reductibility follow. Here, a reductibility indicator, showing how some simpler kinds of descriptions may sometimes apply, complements the complexity of objects estimated in the MCS sense.

[19] Any object can be reduced to this type of representation.

Example 1

Consider the following, fifty-character-long string, “Zzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzzz zzzzzzzzz.” We can also describe this character string in about twenty-five characters, as follows, “Repeat the character *z* 50 times.” Let’s call this indirect description a method or a program. In this example, the object is reducible. Quantitatively, the reductibility is worth about 2:

- The complexity of the string of characters is of 50 × 8 = 400 bit, considering that one-byte-long ASCII code represents each “z.”
- The complexity of the previous program is approximately 31 characters of 31 × 8 = 248 bit, with the same ASCII code. (Notice that, to actually get the target character string, we still need to find a well-prepared computer or a human volunteer in order to read the program and do the job of writing zs.)

- $$\mathrm{Re}\,ductibility = \frac{Complexity(Object)}{Complexity(Description(Object))} = \frac{400}{248} = 1{,}6$$

Equation 33

Example 2

Consider the number π in three different descriptions.

E2.1 Explicit Description

The number π requires an infinite number of characters to be described directly, explicitly. This is not possible in practice. Complexity = ∞ bit.

E2.2 Indirect Descriptions

The number π has a reductible complexity in the sense that it can be indirectly described by simple means, mathematical laws, or programs, for example, as follows:

- The number π is the ratio between circumference and diameter for any circle
- $\pi \cong 4 \cdot \left(1 - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} etc.\right)$

In the latter, this sequence converges to the exact value. The complexity of these two indirect descriptions is on the order of the hundreds of bit each, which leads to infinite reductibility of π complexity in both cases.

E2.3 Conclusion

It is also possible to approximately describe the number π as follows: $\pi \cong 3.1416$. The complexity of this description is then about 20 bit. On this basis, the reductibility of number π is infinite again, but, considering its approximate nature, the case is questionable. Can we expect anything in practice better than an approximation for an object whose complexity is infinite?

This second example leads to two main conclusions:

- Points E2.1 and E2.2 imply the reductibility of the number π is infinite (∞/100 = ∞)
- Although the conclusion gives us a fairly rough estimate of number π, we generally prefer this term, direct or immediate, rather than formulation E2.2, which itself is simple and precise, but needs to be interpreted in order to concretely and ultimately obtain anyway just an approximation of number π.

Example 3

Consider the addition of two integers with *n* digits. When n is greater than 1, the domain is reducible.

E3.1

The complexity (C) of the domain corresponding to the addition of two integers with *n* digits each is as follows:

$$C \cong (n+1) \cdot 3.3 \cdot 10^{2 \cdot n} \quad \text{bit,} \qquad \text{Equation 34}$$

Considering each digit conveys 3.3 bit of information, the (virtual) table contains $10^{2 \cdot n}$ rows of solutions, and each line contains a result with n+1 digits.[20]

E3.2

The addition rule can be described as follows, “The resulting number is obtained by adding the rightmost digit of the first operand to the similar digit of the second operand, and then the process repeats in the left direction, digit by digit, until exhaustion. If the result for a position is greater than 9, 10 is subtracted and 1 (carry) is added to the next position.” The complexity (C) of this rule is about 350 characters worth (about 2,900 bit), assuming the average information quantity of a character amounts to 8 bit.

In conclusion of this third example, one might intuitively feel that, for large numbers, the complexity of the domain is overvalued as assessed by the formula specified in E3.1, that is, according to the definition proposed in the MCS theory for complexity. Nevertheless, we must note that, in fact, the simple description by E3.2, indirect, does not give any concrete results. The computation work remains to be done with ad hoc resources and time to be identified and found,

[20] In the case of addition, the resulting numbers are not equiprobable, strictly speaking. But it is not necessary to look for more accuracy here because this would not fundamentally change the example.

which becomes even practically impossible for n taking arbitrarily large values. The possible complexity of an object cannot be ignored. Its possible reductibility does not equal simplicity. Therefore, the definitions declared in MCS theory are useful.

5.14 Learning (6)

Definition

Learning is the ability of a CS to raise its level of expertise over time (t), or more generally speaking, with experience (r). According to MCS theory, we can estimate a quantity of learning (L) as the change in expertise levels occurred during the learning phase. The unit of measure is the same as for expertise (lin per second or lin/s):

$$L = E(t_1) - E(t_0) \quad \text{lin/s} \qquad \text{Equation 35}$$

$$L = E(r_1) - E(r_0) \quad \text{lin/s} \qquad \text{Equation 36}$$

Discussion

A CS that learns can increase its level of expertise, that is, to get progressively more accurate (more knowledge) or faster (more fluency). It may also happen that a system unlearns in the sense that the amount of expertise decreases in some cases over time and experience.

Examples

A robot explores a maze at first. Subsequently, it can cross it and reaches out faster because it has memorized where the dead ends are located and does not travel through them any longer. The amount of knowledge remains the same (in the sense that, like before, the robot can reach out), but the fluency improves.

In Atlanta, for RoboCup 2007 in the league At-Home, the RH2-Y robot learned movements to be performed simply by observing movements performed by humans as an example (so-called CopyCat test). Before observation, there is no knowledge. After observation, in the simplest case shown, the amount learned is about the following:

$$L = K \cdot f = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \cdot f = \log_2\left(2 \cdot 2^{320*240*24} + 1\right) \cdot \frac{1}{240} \cong 7680 \text{ lin/s}$$

Equation 37

5.15 Intelligence (7)

Definition

Intelligence is the property of a CS capable of learning.[21] In MCS theory, we can estimate intelligence quantitatively as an index, as the ratio between amounts learned (L) and experience (R). In coherence with the dual definitions of experience as defined previously (one more conventional and intuitive as a function of time and the other more rigorous as a function of observed information), we introduce two different equations for measuring intelligence:

$$i_{I_t} = \frac{L}{R_T} \quad [\frac{lin}{s^2}]$$

Equation 38

[21] MCS theory aims at clarity and essentials, in general as well as in the particular case of this definition. It must be admitted that, in common parlance, the word “intelligence” is more ambiguous, sometimes conveying a variety of other meanings, such as information, knowledge, enquiry, or understanding.

$$\dot{i}_{I_i} = \frac{L}{R_i}\ [\frac{lin}{s \cdot bit}]$$ Equation 39

Discussion

In differential terms, we can thus see intelligence as the derivative of expertise with respect to experience. If possible, it seems preferable for a CS to immediately operate with the highest possible level of expertise (without having to learn). Even if, consequently, the intelligence index would give 0 in this case, this might seem paradoxical.

The definition of intelligence, as declared here in the MCS theory, is believed to be the most appropriate, and it is equally applicable to humans and nonhuman systems. However, given the importance of this concept, we briefly present and discuss some of the major other definitions:

- D1. The expression “AI” for artificial intelligence was coined more than fifty years ago, yet AI research has gone through several winters, as its results repeatedly failed to be sufficiently convincing for investors and supporters
- D2. The most common definition for AI is the one of Alan Turing. A machine is proven to be intelligent if it can apparently chat like a human. But the critique of this definition is well founded. It is too much anthropocentric and culturally biased. What would be the outcome of computers reciprocally rating humans? Could we fool the computers?
- D3. A factual approach can describe what happens in laboratories and offices labeled as being related to intelligence (for example, ability to play chess,

translate texts, emulate neural networks, and so forth)

- D4. Many people, not only in the public but even among specialists, categorically reject the notion of AI, implicitly if not explicitly. For them, intelligence is a cognitive property unique to humans. In practice, for them, as long as calculators did not exist, arithmetic was absolutely in the domain of intelligence, likewise for playing chess, translations, machine vision, robot locomotion, and so forth. However, similarly, the very day machines could do the trick, they were actually demonstrating that this was not AI. The public makes this assumption intuitively. Some specialists state, “AI is for processes where there are no known solutions!”
- D5. Some researchers have been advocating, with a certain level of success in selected niche fields, a radical paradigm by which a certain kind of intelligence could be approached without the hurdles of modeling and theoretical developments, simply by embedding agents in reality, “The model is the world” (R7). In such a scheme however, drastic limits restrict time (present only), space (here only), and many more dimensions. The past, future, remote, and all virtual worlds are out of reach (also out of cognitive reach)
- D6. As regards to the common language, we refer the reader to classical dictionaries. We can observe that, depending on the context under focus, the meaning of the word “intelligence” can vary substantially. In particular, although the definition according to the MCS theory corresponds broadly to the general sense of the word, it is also true that

people sometimes use the word “intelligence” as a loose synonym for other specific concepts precisely defined in MCS theory, knowledge, expertise, and so forth.

6. Extended and Associated Concepts

Previous sections have introduced preparatory items. Then we defined the core concepts for MCS theory and cognition in general. Now additions follow for some other concepts related to cognition, yet less central. In this section:

- We update the law for quantitative estimation of knowledge for cases where CS sometimes make errors.
- We give special attention to time aspects and dynamics as they play a role just as important in the immaterial world of cognition as in physical domain.
- We deal with control, an important application area for CS as well as an essential ingredient of cognitics (automated cognition).
- We discuss the role of intelligence, possibly artificial, along with implementation media, such as thinking machines, computers, and robots.
- Finally, a large subsection formally presents numerous notions of interest both for robots and humans, including truth, ethics, culture, life, and emotions.

6.1 Knowledge Estimation in Presence of Errors

In the previous section, we have presented the main concepts of MCS theory. In particular, we have defined the concept of knowledge for the basic case, namely for the case of systems that deliver correct information, possibly limited to a small domain, but nevertheless always correct. (equation 10). Let us remind the reader of the MCS equation for assessing knowledge (K):

$$K = \log_2\left(n_{out} \cdot 2^{n_{in}} + 1\right) \text{[lin]} \qquad \text{Copy of (E10)}$$

n_i is the quantity of information entering the system; n_o is the quantity of information that the system delivers.

An extension is very useful for assessing cognitive properties in the case where a CS delivers information flows that are not totally error-free.[22] In such a case, the system does not perfectly know a given domain (D_e). A particular output message ($d_{os\,j}$) does not necessarily correspond to the correct corresponding one ($d_{o\,j}$). Equation 10 is still applicable, but the part of outflowing information that does not correspond to D_m (“noise” or “error”) should not be included in the equation yielding K quantity. The quantity of correct information that the system (n_{osc}) delivered must then be estimated in each case and injected into equation 10:

$$K = \log_2\left(n_{osc} \cdot 2^{n_{in}} + 1\right) \text{ bit} \qquad \text{Equation 40}$$

We define the quantity n_{osc} in the following way:

$$n_{osc} = \sum_{j=1}^{n} p\left(d_{os\,j}\right) \cdot p\left(d_{os\,j} = d_{o\,j}\right) \cdot \log_2((p\left(d_{os\,j}\right))^{-1}) \text{ bit} \qquad \text{Equation 41}$$

[22] An early version of this extension can be traced to (R34), even though other symbols were used there.

$p\left(d_{os\,j}\right)$ is the probability of occurrence of message $d_{os\,j}$ flowing out of the system; $d_{o\,j}$ is the corresponding correct result (the result that belongs to the knowledge domain under consideration when a specific message, $d_{i\,j}$, enters the system). The term $p\left(d_{os\,j} = d_{o\,j}\right)$ is the probability of the jth output message of the system to be correct. The basic idea here is that the information quantity that each output message delivers should be weighted by its probability of being correct. If the system answers actually are all correct, the second term on the right side of equation 41 has a null effect (factor equal to 1). Consequently, the two quantities n_{osc} and n_{out} will be the same, as well as the quantity that the system delivers (n_o). On the other extreme, if output messages are unrelated to the knowledge domain or, to put it briefly, answers are wrong, n_{osc} will be zero, leading to 0 lin of knowledge, even if n_{os} is much larger than n_{osc} is.

6.2 Time Aspects and Dynamics

Many notions are common or similarly relevant both in cognition and many other domains. Some of the main ones include time and closely associated concepts, change, and dynamics.

This section starts by defining time and presents considerations about change. Then we define dynamics, along with close concepts such as power, energy, motion, or forces. Combining with previous definitions for cognitive domain, this extends to the cross concept of cognition dynamics. We present classical analogies in the context of human psyche, including motivation and emotional forces, which may be pertinent in inspiring yet new concepts in cognition dynamics and quantitative cognitics. Finally, we define agility.

6.2.1 Time and Change

Definition

Time is the usual measure of change; its unit is the second (s).

Discussion

We usually consider time as a specific dimension of reality and it is given its own unit (second in the SI international unit system). But other views may be useful. For example, the ancient Greek Parmenides invites us to consider reality as a permanent whole without any dimensions at all (what is, is). In astronomy, it is particularly evident that yet another model of reality where time and space are dependent of each other may also have some merit. In astronomy, distances are counted in years. Reciprocally, far objects are old ones.

Here, we discuss time more generally in its interrelations with change. Intuitively, it appears that time can be defined in reference to change. For example, the basic cycle of natural light change typically somehow defines a daylong time duration.

More rigorously and quantitatively, a change is not sufficient intrinsically to define time duration. We need to consider other factors. There are numerous common laws (equations) in physics or cognition where time appears, which provides as many ways to define time. An amount of time may, for example, be precisely related to:

- A change in space by a speed factor
- A change in energy by a power factor

- A change in momentum by a force factor
- A change in knowledge by an expertise factor

In the context of automatic control, the time constant, a time-related feature of systems that qualifies their reaction time, is very significant. We usually understand the time constant of a system as the time it takes for the system to essentially reach its asymptotic response state, measured from the moment when a starting excitation is applied.

6.2.2 Dynamics, in Physical World and in Human Psyche.

Definition

Dynamics describes second-order changes, typically including related causes, consequences and power aspects.

Discussion

We generally accept that dynamics refers to time evolution of physical processes. It may also refer to forces and motions of objects. The original Greek form of the word "dynamics" means "power."

Time has been shown related by a power factor to energy. Now we define energy, in general, as the product of a driving cause by the corresponding effect. For example, we may estimate an amount of energy in physics as the product of:

- A force by a distance
- A voltage by some electric charges
- A pressure by a volume

Similarly, since energy is the product of power by time, we can consider power as a general cause for change. Time then becomes simply the corresponding effect!

Experience confirms that, in the cognitive world as in the physical one, we subjectively estimate time as a function of changes. The factors linking changes to time are not always evaluated correctly. This principle sometimes leads to large errors in time estimation, especially when driving causes for changes are intense.

For describing dynamics in human psyche, people have traditionally used analogies with the physical world: energetic person, powerful argument, and so forth. We give special places to mechanics, forces, and motion. Emotions and motivations are two words sharing the same Latin root (“movere” or “to move”), which is also found in the physically related concept motion.

6.2.3 Agility

CS have a real importance in as much as actions follow their deliberations. This is particularly relevant for control systems. A useful concept in this context is the one of agility. Agility combines the notion of time with the one of action. Both words, “agility” and “action,” share the same Latin root, “agere.” In current English, this is to act, to do, or to make. In common English, agility has a connotation of referring to animal or human motions in space. This character may, however, be generalized by an analogy to other forms of action. Quantitatively, let us define agility of a system as the inverse of its time constant, which implies 1/s as a unit.

6.3 Control and Automation

Automation and control may concern a large spectrum of processes and applications. In simpler cases, automation and control develop their effects without continuous reference to what happens in the controlled systems. For example, typically, a switch simply turns off the light. Typically, a mass-produced printer draws a picture without much care about what the actual resulting colors are. But, for more complex cases, typically when external disturbances could significantly impact results, some feedback, some perception of what is happening, must be handled. The key word here is "closed-loop control." In such cases, while control and automation can often help, it is also true that instability becomes a threat that we cannot ignore. We shall see what properties are critical for success in this regard and then mention what will be made about further improvements that may result from granting some autonomy to subsystems.

6.3.1 Stability of Automated Processes

In automation, the necessary approach for controlling systems that unpredictable perturbations affect includes an estimate of system state based on measurements or perceptive data, the so-called feedback. We commonly describe this type of control as closed-loop. Closed-loop control includes a broad range of situations and can risk instability or may not be feasible at all in some circumstances. It is shown subsequently that time properties play a crucial role in this regard.

Schematically, we may encounter three classes of situations. The first two bring stable solutions; the third brings instability.

1. It may sometimes be very easy to realize the control system, and the latter proves very effective.
2. Sometimes, tuning is more difficult. Performances, without being as good (fast, accurate, or simple), as in the previous example, nevertheless remain at an acceptable level.
3. The third typical class of situations includes those cases where failure cannot be avoided: either the target system is hardly set into motion, or it moves in oscillatory or erratic ways.

Now an extremely interesting indicator for possible system (in-)stability consists in the ratio (Ar) of two agilities, the one of controller (including perception, decision, action, and communication phases) versus the one of controlled system. With Ar larger than 20, a system typically belongs to class 1. Otherwise, the system belongs to class 2 unless Ar is smaller than 2. In which case, it falls into the third, unstable, case.[23]

In summary, some time properties (here, respective agilities) turn out to be critical parameters or at least provide a critical indicator for successful system behavior in automation and cognitics domain.

6.3.2 Closed-loop Control, Consequences on Time Properties, and Autonomy

In fact and ultimately, the own (natural) time properties of a particular system may not always prove to be the relevant criteria for success. This is especially true in the context of perturbations and control and even more so in

[23] This can be straightforwardly deducted from previous publications, where the inverse of this ratio is used (the ratio of time constants) (R3).

common practical cases where nonstationarities and nonlinearities prevail.

Powerful systems are complex and usually organized as a multiplicity of interconnected subsystems (for example, hierarchies, cascades, parallel or distributed structures, and so forth). In this context, it is regularly verified that an elementary system may behave with much improved time properties with the help of a dedicated, autonomous associated control system.

By this approach, far from representing absolute constraints, we may just view the natural time properties of an element as contingent features, which appropriate design and engineering may drastically improve at system level. The paradigm of granting local autonomy is also very effective in improving the potential agility of control system in the closed loop.

6.4 Role of Cognition, Computers, Thinking Machines, and Robots

This section extends the attention beyond core cognition domain, in the direction of concrete goals and appropriate means. After analyzing the role of cognition, either natural in humans or machine-based (including AI), we review the main implementation media types: computer systems, thinking machines, and robots. We consider performance rating and differences between robots and humans.

6.4.1 Role of Cognition

Cognition allows for high-performance information processing. The types of goals pursued may vary including for humans, entertainment, education, or meditation, for example. In the majority of cases, however, cognition has the role of delivering the critical information for doing well, of controlling with success.

In the context of control and, more generally, automation, cognition may help in several regards. Cognition supports modeling and, in particular, suppresses the need for many measurements, not only along the time axis in the future, but also virtually in all dimensions considered.

A sufficient amount of application-dependant knowledge can support open-loop control (actions decided without any information perceived for the environment). For example, humans often walk up and down stairs without watching every individual steps. In the case of cognitive errors, attempt is typically made to walk one step more or less than the exact stair count, which may cause falling.

Cognition can virtually help travel in space, time, and other dimensions yet, which tremendously increases control possibilities.

Time

A good knowledge of the controlled system allows for forecasting its behavior. By this token, a cognitic controller may, in principle, compensate for some or all control loop delays. This paradigm commonly allows for improvements in effective agility and, consequently, commonly brings significant improvements in performance.

Space

A robot sensor is located at any given time in a single place. If, at the same time, similar estimates by the sensor would be useful at other locations for control purposes, then modeling and, more generally, a cognitic approach can help to provide a flexible alternative.

Other dimensions.

The power of cognitics is not bound to extrapolation in time and space. Cognition can extend estimation possibilities in domains out of physical reach. It is, in principle, quite universal and may often prove similarly useful in almost all other physical dimensions and more. For example, ABB robots accept a weight parameter in their “grasp” instruction, allowing for updates in the dynamic model of the arm and ultimately improving their performance. Cognitics improves the possibilities of classical regulation and often leads to drastic improvements in system dynamics and stability, including:

- Identifying relevant factors and processes
- Determining critical values
- Sparing measurements
- Reducing or sometimes even eliminating critical delays
- Anticipating impacts and compensating for disturbances.

6.4.2 Thinking

Human cognition is implemented in the brain. It involves, as defined previously, high-performance information processing. Common language often refers to brain operation as “thinking” or “thought.” Nonhuman, artificial thinking might indeed be viewed as the essential operation of all CS (information processing).

In the MCS model, however, and strictly speaking, thinking is neither relevant nor accessible actually. We represent CS here as behavioral systems, so only their output information is both visible and meaningful. If we assume the existence of machines that just think and do not generate output information, such would be useless and not differ from a passive wall or an empty socket. Considering this issue more broadly, however, we might integrate the previous view and additionally define thinking as implicit, necessary internal processes accompanying the generation of (relevant output) information. Interestingly, if we split a system into subsystems, thinking might then gain in visibility and appear as the communication processes among subsystems with exactly the same pattern presented at a higher integration scale at the group level.

6.4.3 Computer Systems

Currently, computer systems provide the preferred implementation media for artificial CS. From the MCS perspective, via benchmarks and experimental tests, computer systems have been proven to be implementation media capable of high-cognitive performance levels in many domains, for example, learning with the cache-memory paradigm. In theoretical terms, however, we do not consider the physical nature of the implementation medium.

More generally speaking, it may also be worth noting that people often unduly underestimate the role and need of computer systems and, more broadly, cognitive engines. Consider, for example:

- A program in the context of Chaitin-Kolmogorov algorithmic complexity, or equivalently
- Knowledge in the MCS framework, or as another instance

- A statement in a computer program (for example, PI=C/2R)

In all of these three cases, the final information cannot be elaborated and made available without time and the support of a physical system, the cognitive engine, typically nowadays a computer. In contrast to information, which, in principle, is immediately available (for example, pi = 3.1416), the cognitive processes implied in these three examples require an engine and time to actually elaborate their outcomes.

6.4.4 Machines

The concept of machine presents mainly two aspects here:

- A machine is not a human, but an artifact.
- By etymology, machines have power. They act and make changes happen.

From the MCS perspective, the first aspect is, in principle, irrelevant. We do not make any difference between humans and machines within the MCS framework. The second aspect has two contrasting components:

- It is totally compatible with the MCS approach in placing the priority on results.
- While in the MCS framework, CS generate relevant output information, and machines do more. They also provide the necessary physical contributions, notably in terms of energy, power, and mechanical structures, to change the world.

6.4.5 Robots, as Human Clones?

Karel Capek coined the word “robot” in a theater play where the main character, Mr. Rossum, created some kind of mechanical slaves (R8). From the very beginning, there has been ambiguity in the definition of robots. Some observers have understood Rossum’s creatures primarily as machines capable of providing flexible services to humans while others have been concerned with the idea of artificially replicating humans, ultimately producing some kind of clones or Frankensteins.

Clearly, the approach of the first definition is easier to adopt, that is, to develop robots according to requirements that are rather task-oriented and functional. Engineers typically favor this approach. It also offers additional benefits in terms of robustness and economy. Depending on applications, the requirement of exact similarity between robots and humans is debatable. In the same way as a plane does not need moving wings like a bird in order to usefully transport people and goods, the practical solution chosen for a robot to fulfill specifications may often be validly different from human solutions. For example, a robot might move on wheels rather than feet. Yet as the number of specific duties transferred from humans to robots increases, there may be more advantages to approaches where robots are more akin to humans: humanoids (limbs more or less similar to humans) or androids (very similar look). Here, some partial solutions are already welcome. Here also, if robots do their jobs better than humans, this is perceived as an advantage.

The second definition puts humans in the center of the scene. Not only should robots be capable of performing duties similar to those of humans, that is, in order to free the latter from work and unwanted tasks, they should ideally proceed in the same way. Ultimately, robots should be human in all respects. Obviously, this task is impossible to fulfill via nonbiological means. Also in biological terms, if required, the most promising road might theoretically be to improve cloning techniques and then to concentrate on a very focused education. But such a road is ethically, of course, completely unacceptable. It also practically leads to an impasse.

To advocate the first approach again, it is worth noting that humans are already not only the result of a well-defined, linear genetic legacy. In biology, lateral transfer occurs for some genes; external influences often randomly change some other genes. Moreover, when living, humans are increasingly complemented with artificial accessories like spectacles, auditory aids, pacemakers, wooden legs, artificial forearms and hands, infrared goggles or telescopes, cars, cellular phones, tools, pharmaceuticals and drugs, and so on. Bionics, cyborgs, and avatars are examples of engineered extensions of the human body. So to develop and provide robotic artifacts and accessories for the service of humans is surely a worthwhile and reasonable endeavor. Now to develop robotic machines specifically as exact replicas of humans may have some value in understanding better humans, but let us state here that this is typically not our goal. Even if it were the case, we would have to face the fact that we are very far from reaching such a goal. No robot is in sight yet, so akin to humans that a risk of schizophrenia would threaten it, letting it wonder whether it has become a human or still is a machine.

6.4.6 Computers, Machines and Robots, to Help Humans

It is suggested that machines are useful for mankind. In this sense, their development is an attractive goal. Aiming toward humanlike performance offers the potential to create the equivalent of many additional workers and helpers for humans, conveniently and widely made available as, for example, in the case of automatic teller machines (ATMs).

For this purpose, however, more than just computers are required. Namely, we need sensors to get information from the real world, structures, and actuators, as in machines, to physically change the world. Quantitative cognitics shows that AI-grade concretization processes (for example, path generation and grasping objects) and, even more so, AI-grade perception processes (for example, speech recognition, image understanding, and so forth) call for very large amounts of knowledge and expertise, usually much more than decision-making.

It is therefore no surprise that we commonly take robots as targets and/or testbeds for progress in AI. Robots include sensors, decision-making resources, and actuators. They are often mobile and can communicate.

Moreover, we know how necessary communication and a common culture are for human societies to develop. So it is natural to consider the problem of mixed human-robot groups, that is, to develop cooperating robots.

Such robots are complex, dynamical systems. On the engineering side, they appear to require, in addition to cognition, many other elements for successful implementation in real world and real time (R9).

In the MCS framework, the behavioral approach and the target-oriented modeling call for the careful definition of selected goals. In fact, this should be considered to be just as much necessary for human cognition in general as for the purpose of designing expert artifacts. For example, the true path of the planet Earth around the Sun is not an ellipse. In this regard, notably, the RoboCup Initiative and, in particular, the league at home (R10) provide an excellent context for improving the state of the art in AI, for designing novel thinking machines and novel robots, with the goal of serving humans.

6.4.7 Human-like/ Human Performance Rating

We often make informal comparisons between artificial systems and virtual humans that are not representative. The average human does not translate from one language to another, play chess, and so forth. Many humans do not read or write. If the criterion for AI is the lowest level of human performance, the level is low indeed. Moreover, even in the best of cases, humans require a lot of training to acquire their capabilities.

Humans are often perceived as ideal learning systems (ideally intelligent agents) while they do actually suffer from severe limitations. The latter are obvious in the physical domain, for example:

- Very limited vision and audio bandwidths.
- No perception capability at all for magnetic fields
- Inability to fly

Many philosophers have observed severe limitations in the cognitive domain as well, for example, Kant and his necessary preexistence of categories for making perception possible (priority of knowledge on reality).

6.4.8 Boundary between Robots and Humans in Cognitive Domain

Considering the definitions of the MCS theory, we strictly confine our attention to cognitive abilities. In this context, the MCS model applies without distinctions to humans and machines, such cognitive agents being all represented as purely behavioral systems. Clearly, robots already have the possibility to do better than humans can in quantitative terms: more bits of information perceived, more knowledge, more expertise, learning, intelligence, generated information, and so on.

Differences remain in various domains that relate specifically to those domains: physical perception (for example, infrared is only perceived by some robots and not by humans) and action channels (for example, ten-fingered hands with skin are currently only the features of humans), language, exposure to news, repeatability, and so on.

6.4.9 Cognition versus Computer Speed, for Progress

Computers are crucial for implementing nonhuman cognition processes. So it often seems that the basic processing speed of computers dictates cognitive progress. Typically however, this is not the case as cognition can bring much larger benefits. In support of these brief considerations, let’s revisit the striking case of the accurate estimation of pi. Computer technology here is a necessity. Yet reciprocally, a quantitative approach quickly demonstrates that cognitive processes can be a very powerful complement to mere computer technology. Pi can simply be defined as an infinite series as follows: Pi = 4*(1-1/3+1/5-1/7 …).

Standard technology naturally gives a very limited accuracy. A standard, double-precision number system yields, say, forty significant digits. For sake of simplicity, it is nevertheless sufficient for this example to very optimistically assume that we can compute numbers with arbitrarily large numbers of digits. An elementary operation (denominator update, inverse, and subtraction) takes one nanosecond on a computer. The accuracy of the estimate is here on the order of the number of operations, the nth element being worth about 1/n. By this token, after one second of operation, $n = 10^9$, we have an accuracy of about 10^{-9}. This yields about 9 significant digits for pi. The problem is that improvements are very slow, logarithmically slow. After one year of computation (10^7 additional seconds), we would have seven more significant digits (sixteen of them in total). If the computer could already have been computing since the big bang 10^{10} years ago, we would now have a mere ten additional significant digits, thus a total of twenty-six digits. The same applies for technology. Assume that computers could get a billion times faster. We would only get ten more digits from this series. Meanwhile, cognition, or we can loosely say, ingenuity, is unbelievably powerful. Twenty years ago, four thousand digits had been discovered. By 2001, 100 million digits were identified. By 2005, 200 million digits (R5) were accurately identified!

6.5 Extended MCS Definitions for Robots and Humans

In addition to the core concepts of MCS theory defined previously, especially in section 5, it is useful to present many other commonly used notions in coherent way. They apply both to humans and robots, either because:

- They share common grounds
- Notions classically elaborated for humans can efficiently be reused for artificial agents
- They may cooperate and therefore need to communicate with common references
- As recently introduced, some robots may even ensure the mediation between humans and machines.

This section first extends cognition in the direction of represented reality and selected goals, yielding notions such as truth and wisdom. Then we develop the case for concretization, leading to creativity and ingenuity. The third subsection defines concepts ranging from simple deliberation to control and hierarchical structuring. Subsection 4 defines groups and associated features. Then definitions relating to operational, possibly reflective, behaviors follow (conscience, life, and so forth). Finally, this section discusses emotion-related topics.

6.5.1 Truth, Ethics, Wisdom and Sapience (beyond cognition)

Some additional cognitive elements are presented here (right, wrong, and sapience). Some provide the basis for other ones that reach beyond the purely logical world of models, out in direction of reality (true and false) and ethics (good, bad, and wisdom).

A. Right (8a)

Definition

« Right » is the quality of a piece of information that complies with a considered law. Typically, it consists in a Boolean value.

Discussion

In MCS theory, « right » is the contrary of « wrong ».

Example

For example if the considered statement (assertion, law) is the following: « Elements A and B belong to set C», then it is right that « A belongs to C ».

B. Wrong (8b)

Definition:

"Wrong" is the quality of a piece of information that is contrary to a certain law. Typically, it consists in a Boolean value.

Discussion:

In MCS theory, "wrong" is the opposite of "right".

Example

If the considered assertions are e.g. « A and B belong to group C » and « element D belongs to group E », it is wrong that « A belongs to E ».□

C. True (9a)

The correspondence link between model and reality defines the notion of sense or meaning, which is essential for semantics.

Definition

"True" can be defined on the basis of "right". True is equal to "right" when the considered law is as follows: « correspondence to reality ». Typically, it consists in a Boolean value.

Discussion

In MCS theory, "true" is the opposite of "false".

For example it is true that braking reduces speed.

D. False (9b)

Definition

False can be defined on the basis of " wrong ". " False " is equal to "wrong", when the law is considered as follows: "correspondence to reality”. Typically, it consists in a Boolean value.

Discussion

In MCS theory, "false" is the antonym of "true".

Example

For example, it can be considered "false" that "braking increases speed”.

E. Good (9c)

Definition

Good is defined on the basis of “right”: “Good” is “right” when the law to comply with is “to progress towards a defined goal”. Typically, it consists in a Boolean value.

Discussion

In MCS theory, « good» is the antonym of « Bad».

Example

For example, we can consider as "good" to switch on the power circuits if the goal is for a robot to move.

F. Bad (9d)

Definition

"Bad" can be defined on the basis of "wrong". " Bad " is equal to "wrong", when the considered law is as follows: "Progress towards a defined goal." Typically, it consists in a Boolean value.

Discussion

In MCS theory, "bad" is the antonym of "good."

Example

For example, “to switch off the power circuits” can be considered "bad", if the goal is for a robot to move.

G. Wisdom (10)

Definition

Wisdom is a specific property of cognitive agents, referring to their ability to take good decisions (to be expert in delivering the messages that make agents reach a given goal). In MCS theory and quantitative terms, wisdom is estimated in Boolean terms, true or false, depending on whether the goal is reached or not

Discussion

To make it simple and easy, the quantity of wisdom for an agent, on a given domain, is estimated here in Boolean terms. Without being essential, a usual feature of wisdom is to relate to complex situations and major or meta goals: to survive, win the game, or gain a place in the Hall of Fame.

H. Sapience (11)

Definition

Sapience is the essential property of cognitive agents (active structures capable of cognition). It appears under a number of signs, such as knowledge, expertise, or intelligence (already defined and made measurable in MCS theory). Quantitatively, sapience may be characterized by an index ($i_{sapience}$) in reference to humans (homo sapiens). Sapience (index) is thus a ratio and remains without specific unit.

Discussion

We should estimate the performance levels of humans on the same basis as for artificial systems, even if only to quantify the wisdom. Initial assessments suggest the capacity of humans typically tends to be overestimated when this rating is done intuitively. A particular practical difficulty is that the characteristics of humans are stochastic variables.

6.5.2 Creativity, Ingenuity, and Chance

Cognition is necessary but probably insufficient for strong innovation. Cognition is necessary for managing complexity and providing knowledge, expertise, abstraction, concretization, and many other information-based entities and processes. Today, a huge number of (artificial) CS routinely run successful operations and deliver information that is physically impossible to be stored a priori, in particular, impossible to be integrally collected from experiments or precompiled even with human help.[24]

But how can we create new models and novel CS? How can we make quantum leaps in improvements? It is

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[24] In quantitative terms, a rough and conservative upper bound on the knowledge (K), for which a direct memory-based implementation may technically be possible, can be estimated at 1,000 lin.

tempting to think of ingenuity, yet another cognitive property. But any attempt to quantify this property meets serious problems.

We must conclude that, so far, the basis on which to quantitatively estimate this cognitive property is still lacking. Or we could view ingenuity essentially as just a regular cognitive process, here immediately embedded in a specific domain of reality, which would call for infinite amounts of knowledge and expertise.

In fact, there is chance, a powerful possible source for strong innovation. In the MSC model, the theory shows that random processes, as they are capable of generating an infinite amount of unpredictable information, actually prove to feature an infinite amount of knowledge in their domain.

Thus, counterintuitively, we could consider ingenuity not as a specific cognitive property, but rather as a regular cognitive process that evaluates and keeps selecting the best of several (often many) models or CS that are randomly generated by external, random sources (chance). This strangely brings us back to trial and error, one of the most fundamental paradigms in AI.

Chance is a possible source for innovation, but it may take a lot time for success. Here, cognition (experts) may bring advantages by keeping focus on minimal-sized domains to explore, keeping track of improvements, and possibly tuning up contingent solutions.

We will formally define creativity, ingenuity, and chance subsequently. A more general conclusion is drawn about numerous cognitive properties that can be defined on the basis of the small number of core cognitive properties defined in section 5.

A. Creativity (12a)

Definition

Creativity is a particular kind of knowledge (measuring unit: lin) that features a concretization index higher than 1.

Discussion

We have already formally defined knowledge and concretization in the MSC ontology. The specificity of a creative system is simply to ensure that there be actually some concretization. (More pertinent, domain-relevant information is generated by the system than the system itself receives.) Creativity is a very common feature of CS. Here are two examples: building a family house for an architect or generating a navigation path from the living room to the fridge for a domestic service robot.

B. Ingenuity (12b)

Definition

Ingenuity is a particular kind of knowledge (measuring unit: lin), that is, knowledge in a specific domain that contains reality as the input space and information about novel, improved CS (for example, better knowledge, better expertise, better intelligence, better abstraction, and so forth) as the output space.

Discussion

In fundamental terms, ingenuity is knowledge and, as such, already defined in the MSC ontology. The specificity of the domain is of a contingent nature in the same way as knowing a language contains the instances of knowing French or English. Ingenuity is a particular kind of knowledge, involving here a fourth specific cognitive domain. In particular, ingenuity may be considered as the most desirable and prestigious element in the following list of mostly existing MSC concepts related to the generation of information:

- Expression (just generating any sort of information)
- Knowledge (expressing correct information)
- Expertise (doing it correctly and quickly)
- Intelligence (increasing expertise)
- Creativity (knowledge with a concretization index higher than 1)
- Ingenuity, (a kind of meta-intelligence by which the CS itself is reengineered to yield a quantum improvement in its expertise).

C. Chance (12c)

Definition

Chance is a particular kind of knowledge (measuring unit: lin), that is, knowledge in a specific domain. The domain contains no input space, but an output space consisting of totally unpredictable information

Discussion

In fundamental terms, chance is knowledge and, as such, already defined in the MSC ontology. The specificity of the domain is that it consists of a totally stochastic output space. In quantitative terms, in as much as the information delivered is purely stochastic of potentially unlimited size, the quantity of knowledge here is infinite! As a consequence, in practice, to engineer chance (to design a perfectly stochastic source) is impossible. Pragmatic solutions, which are satisfactory for some applications, include approaching chance with finite resources (for example, pseudo-random generators) and, very often, redirecting information that an external, natural source of random information (chance) generates.

D. About Secondary Concepts in MSC

In the summary of this subsection, it appears that the core elements of MSC model, defined in small number, offer a strong basis for cognitive theories and are quite universal. In the same way as all electronic circuits are made from a very few basic blocks (resistor, diodes, and so forth), all logic circuits could be made of NAND gates, or one could argue that virtually all texts could be made out of twenty-six letters, one hundred and twenty-eight ASCII characters, or two to four Morse-encoding moments. A wealth of other concepts is debated in the world of cognition and cognitics. We cannot ignore them, so we should also formally define them. But they should remain derivatives and sometimes simply special cases of existing, well-defined core concepts (domain, model, information, knowledge, expertise, and so forth). In mathematical terms, we could conclude that the number of concepts commonly discussed far exceeds the actual dimensionality of the space.

6.5.3 Deliberation, Control and Hierarchical Structures

A particular role of cognition is to guide systems toward a given goal. This implies operations that may range from simple cases to very complex ones, depending on considered applications. In the same order, we present the concepts of deliberation and control, possibly reactive and/or hierarchical, from MCS theory perspective. The section finishes with the cases of hierarchies (for example, analysis, design, or implementation) where processes schematically develop in top-down or bottom-up fashion.

A. Deliberation (12d)

Definition

Deliberation is a particular kind of cognition, that is, cognition that involves a specific domain, typically decision-making.

Discussion

The root of the word "deliberation" refers to Roman scales by which weights were measured. The basic test, "which side of the scale is lower," maps directly to the central instruction of computers, the IF statement, as well as to Boolean, On/Off, reactive control systems. Here again, from the MSC perspective, we can consider deliberation as the regular operation of CS, and input-output information flows (behavior) and time fully describe it. Thus, all derived cognitive entities (knowledge, expertise, complexity, and so forth) are equally applicable, and no new concept and units are required for them. We may also loosely consider "decision-making" or "data processing," other words or expressions that are commonly used, as synonyms for deliberation. In fundamental terms, deliberation is cognition in a specific domain and, as such, already defined in the MSC ontology. The specificity of the domain is of a contingent nature, in the same way as knowing a language contains the instances of knowing French or English. Deliberation is a particular kind of cognition, involving here a fourth specific cognitive domain.

B. Control (12e)

Definition

In the MSC theory, control is a particular kind of cognition, that is, cognition that involves a specific domain, where input information typically represents target and status data and output information represents commands.

Discussion

In the MSC model, a control unit or agent is just a regular CS, which, like any other one, is fully described by its input-output information flows (behavior) and time. All derived cognitive entities (knowledge, expertise, complexity, and so forth) are equally applicable here. Generally speaking, control is a process that delivers commands to a system in order to reach some specific goal. While in general, the words “control” and “commands” imply power, forces, and/or other physical entities, we only consider the informational aspects here.

C. Reactive Control and Other Control Types (13)

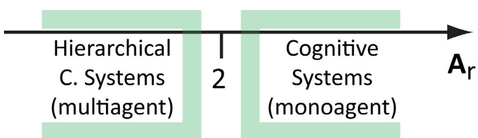
Definition

We have just defined control. The variations considered here, reactive and other ones (closed-loop and proactive), relate to specific domains in MSC theory.

Discussion

Reactive control is a particular type of control in which some particular kind of input information is relevant. Closed-loop control is a still more specific type of control, a subset of reactive control. Some input information entering the control system directly results from the commands (output information flowing out of the same control unit) issued to the system being controlled. (This specific input information is called “feedback.”) The opposite of reactive control would be proactive control. The control unit autonomously generates information. This information is transmitted as feed-forward, open-loop information toward the system being controlled. When integrated in complex systems, control units may simultaneously feature multiple control types, depending on the subsystems, information paths, and functions considered.

Many control systems are effective and work exclusively on the basis of what is known a priori of the systems to be controlled. Yet when unknown elements, in particular, disturbances, have a significant impact on systems, it becomes necessary to adopt another scheme. Specifically, it is then useful to incorporate a feedback scheme from the systems being controlled.



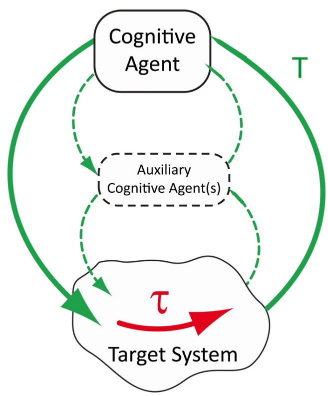


Fig. 10. An agent may successfully control a system in closed-loop mode only if its relative agility is better than 2. If the latter is smaller, we must consider a hierarchy of agents (figure from [R11]).

In such circumstances (that is, considering reactive systems), the primary concern is the relative agility, including input and output communication delays of the controlling agents, compared to that of the target element to be controlled. As defined previously, we estimate the agility as the inverse of the global effective reaction time.

The critical lower bound on the relative controller agility typically has a value of 2. Below the critical value, control becomes unstable or impossible. In these cases, changes are required. We classically explore three types of solutions: to increase controller agility, to decrease controlled element agility, or to split the overall system into a hierarchy of subsystems that individually satisfy to the relative agility constraint (figure 10).

For more than fifty years, control based on feedback measurements (closed-loop control) has gained a whole body of contributions, which today allow, for example, for the fast and accurate positioning of minute magnetic heads on dense hard disks as well as for the successful travel of space rockets toward precise targets at astronomical distances.

As mentioned, control processes sometimes need to rely on some feedback components, and the effective management of delays is critical for the effective operation of such closed-loop control systems. For years, it has been successfully verified that it is often possible to compensate for some delays, typically in practice by a prediction strategy based on signal derivatives. Now, many new possibilities arise when we use cognition in control systems as a mean to improve predictions, thereby improving effectiveness and even, in many cases, automating novel applications, such as robots cooperating with humans in cognitively demanding applications.

D. Top-down Approach

Definition

A top-down approach implicitly refers to a representation where multiple elements cooperate in a global system in a hierarchical pyramid. In the MSC model, considering multiple elements (agents and subsystems), there is no such exact notion of higher or lower levels (top-bottom). The MSC model is equally applicable at all granularity scales (that is, for the overall, integrated system as well as for each element, the top element, and any lower level subsystem). The top-down orientation implies an attention first given to higher, more general levels then shifting to lower, more specific components.

Discussion

In the MSC theory, there is no such exact notion of higher or lower levels (top-bottom). Nevertheless, in MSC, three notions primarily relate to interaction between agents and may partly overlap with the concept of top-down approach: input-output information flows, abstraction-concretization processes, and integral systems versus more elementary subsystems.

In the first case, the distinction and complementary aspects of input-output flows are obvious and apply symmetrically for each of the two communicating elements. Yet if the information does flow in a single direction, then one element is necessarily a pure transmitter, and the other one is a pure receiver. Schematically, top-level elements transmit information, and bottom elements receive it. Examples in the internal control hierarchy of a cooperating robot could be A, the control of stepper motors, or B, the synthesis of speech.

Abstraction is the property of cognitive agents that generate less information than they receive. Conversely, concretization generates more information. In quantitative terms, we estimate abstraction as the ratio of input information quantity with respect to output information quantity and concretization as the inverse of the latter ratio. In general, top-down organization calls for concretization. The previous examples also apply here.

The higher-level coordination level for motion control receives less information from previously (global target values and parameters for motion law) than it generates (interpolated low-level intermediate targets at higher rates).

The speech synthesis unit receives less information (text encoding) than it finally generates (CD-quality sound waves). Experience shows, however, that the correlation between the top-down approach and concretization is not absolute. High-performance cognitive approaches often rely, in some steps, on opposite strategies, for example, temporarily trading degrees of abstraction for improvements in fluency. For example, expertly sorting algorithms include the use of hash tables. Or in a subsumption architecture, lower-level reactions may cancel top-down command components.

The MSC model is equally applicable at all granularity scales. This means that, if we analyze a system as a set of subunits, for each subunit, the same scheme is applicable. Similarly, if we consider several CS in an integrated, synthetic way, the resulting meta-system can also be represented with the same scheme. The notion of hierarchy is therefore orthogonal or independent of it. By analogy, notice that, in a human group, social hierarchies are generally not apparent in the infrastructure, for example, human individuals, communication, and transportation networks. For another example, we similarly define the usual objects in a program no matter where they lie in a hierarchy. Another challenge is the mesh aspect of interconnections instead of a simple, unidirectional level axis (implicit in a top-down structure). What is useful in such contexts is the consideration of multiple dimensions with parallelism and nested loops. The MSC model supports these views.

E. Bottom-up Approaches

The discussion in the previous paragraph is applicable here by symmetry. In particular, while the previously discussed top-down organization was calling for concretization, here the bottom-up organization generally calls for abstraction. Examples of such bottom-up, high abstraction cognitive processes for a cooperating robot include vision- and laser-based localization and speech recognition.

6.5.4 Group, Global View, Atomic Members, Communication and Culture

As complexity grows, agents tend to team up, thus yielding groups. In this case, new notions appear, involving a communication channel between members and a common culture (figure 11). In MCS theory, a group can globally be considered just like any other CS.

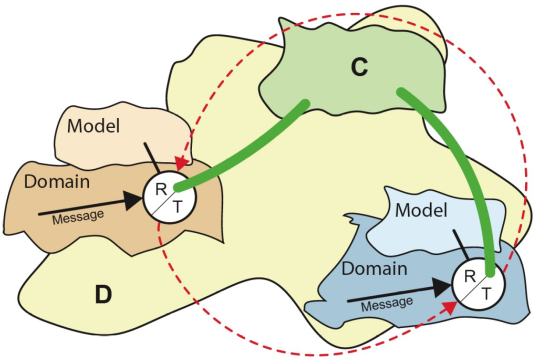


Fig.11 *Group*. Individual cognitive agents (blue, brown) may coordinate each other, and thus may collectivety form a group . For this purpose, a common culture (C, green), in reference to some common domain of interest (D, yellow) and some communication media are required among agents (R: receive; T: transmit). At a metalevel, the individual members may be considered as merging, to yield a new individual (the group) with its own collective model (C).

Yet a group is, in principle, more than an individual. Additional concepts are useful to handle this more complex form of organization. After a general definition, three views follow where we then adjust the focus on the holistic aspects, the individual properties, and, finally, the way the structure can be coordinated.

A. Group (12g)

Definition

A group is a particular kind of CS that consists in a number of individual cognitive agents.

Discussion

Definitions and metric equations in the MCS theory apply equally to individuals and groups. The behavioral model adopted in MCS can be applied at any granularity level in subsystems, for example:

- At the global level of an entity
- At a higher level of integration (group)

Essential properties of a group organization typically include:

- The holistic behavior of the group as a whole with collective properties
- The individual properties of group members

- The way the structure and means can support coordination.

B*.* Holistic Group Aspects (12g.2)

Definition

In the context of MCS core theory, the behavior at global level, as an integrated CS, characterizes a group. Quantitatively, all the metrics defined for the properties of CS apply

Discussion

With the behavioral approach, there is, in principle, no necessity to explicitly describe how groups are internally organized. Nevertheless, in the same way as cognition may address subsystems for analytical or design purpose, groups may be considered at the level of individual group members as well

C*.* Members (12g.3)

Definition

In the context of MCS theory, group members appear themselves as ordinary, elementary CS with their respective cognitive domains mostly defining their specificity.

Discussion

Surprisingly, even though a group is essentially made of individual members, the observation of those members alone may not say much of overall group behavior

D*.* Culture, Communication, Spirit (12c)

Definition

The socialization process operationally binds members together (coordinates them) in order to yield overall group properties. Prerequisites include the availability of a communication channel as well as some common culture and spirit. The communication channel is typically a physical medium that supports the transmission of information. We can view spirit and culture as a set of intangible underlying factors that ensure the coordination of individuals in order to achieve a specific collective identity and behavior. “Spirit” and “culture” consist in a system of common, shared references, values, and objectives, in reference to some common domain of interest, which may dynamically evolve and yet do not exist actually (that is, out of the members).

Discussion

Consider an orchestra playing without conductor. The group is the orchestra, members are musicians, and the spirit is the name retained for what makes it possible for the musicians to play together in a coherent way, even when there is no additional conductor nor outside regulating factor. For humans, numerous kinds of other collective structures have been explored and defined in addition to the notion of group (sociology). Nevertheless for MCS theory, they can just be considered as domain-specific synonyms.

6.5.5 Consciousness, Conscience, Life.

The quest for robots in domains traditionally reserved to humans goes on. As extended contributions, we soon discuss the notions of consciousness, conscience, and life, first in broader and somewhat informal terms and then with more focus and full compatibility with previously listed MCS theory items.

Even though the direct requirement here for notions such as consciousness, conscience, or life remains debatable, the following arguments do have some value for the good functioning of machines and robots:

- The potential for better human-robot communication
- The legacy of millennia of cultural developments in the human context
- A better understanding of human nature

A. Consciousness (12h)

Definition

In the MCS theory, consciousness is the ability of a system to perform its ordinary cognitive operations. Its value is essentially Boolean, corresponding to the presence or absence of consciousness. If required, we may address various degrees of consciousness in the MCS theory as different, specific domains for which the same definition of consciousness is applicable. (See the next discussion.) In quantitative terms, this simple view can be complemented by a finer attribute, a consciousness index, defined as the ratio of the current level of operation to the ordinary level of operation. Here in practice, we must make an exclusive choice, which is application-dependent. Either the Boolean view is sufficient, or the finer estimation approach is required instead.

Discussion

Consciousness, a property of CS, can be defined to different degrees. The etymology of the word contains a root referring to cognition (the ability of knowing) and a prefix referring to the subjective nature of this knowing. The very least degree of consciousness is simply awareness (the ability to know) and thus to cognitively accompany what is going on in the world around the cognitive agent. The ability to react may be a sufficient indicator of consciousness according to this minimal definition. A more demanding degree of consciousness calls for an additional, explicit, and regularly updated representation of what is going on around the agent. We attain a still higher degree of consciousness when some aspects of the agent itself are explicitly present in the agent's representations. Self-contemplation is performed. The scope of self-contemplation may vary, from some elementary self-aspects to more extensive ones, and even to the inclusion of external components, representing the environment in which the agent develops its activities.

B. Conscience (12h.2)

Definition

In the MCS theory, conscience is the property of a cognitive agent whereby it includes in its cognitive domain some aspects of itself, its own behavior, as well as the environment and related customs. It finally adapts its own actions as a consequence. The value we can give to conscience is essentially Boolean, corresponding to the presence or absence of conscience. For finer quantization, all the core MCS notions essentially also apply here (for example, information, complexity, knowledge, and expertise). The possible specific differences in quantities relate to the respective, specific cognitive domains considered.

Discussion

We can use conscience as a synonym of consciousness, especially in the most demanding, self-oriented interpretation given previously. In English, it includes a capability to judge the right or wrong character. In ethical terms, it includes an agent's decided actions. Not only does conscience implicitly require that cognitive agents include representations of themselves and their own behavior in their cognitive domain, agents must also include representations of their environment with its associated operational modes. Only at this point can the possibility emerge for cognitive agents to compare their own behavior to the customary norms of the environment and, consequently, to estimate the right or wrong character of their operations. Note that this description remains closely connected to the etymological meanings of the words ethics-environment and moral-customs.

For the case of our current robots, for laymen, ethics may not look relevant. It may seem hard to imagine that robots would ever attempt to break ethical laws. However, to make a right decision, we must first address the ethical question. Moreover, even in an environment of very moderate complexity, we must make choices in the face of conflicting ethical values, depending on the level of attention. For example, a lower-priority law is broken for the sake of a more general one. Of course, environments may be of various complexities and may include, for example, groups of agents to which the agent with a conscience may relate in diverse ways. Notice that, in the MCS models as well as in reality, what is immediately apparent of agents is their behaviors. Consciousness and its derived benefits can still improve if agents express themselves and share some of their internal representations. Communication develops, flowers bloom, and animals develop a common culture. An interesting example of the change of perspective of robots with consciousness and self-reflection is the sequence shown in (R12), where robots gradually learn how range sensor data is best sequenced with an egocentric perspective. An assumption of stability and continuity of its environment, subsequently taking a next step, leads to the persistence and stability of the environment and, in this context, to the explicit representation of the self as a mobile and situated agent.

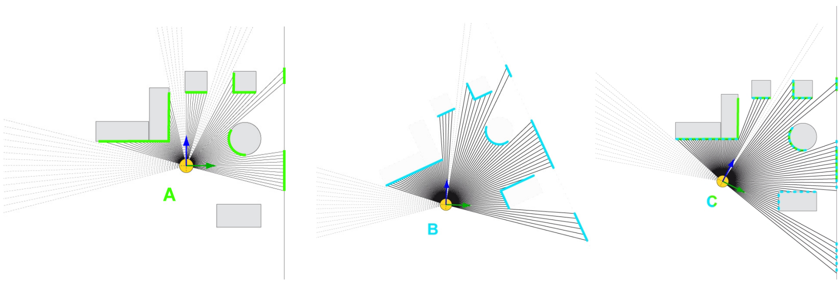


Fig. 12. An evident case of consciousness in our robots is illustrated here, where the application might relate to SLAM (simultaneous localization and modeling), pattern recognition, or positional calibration. In A, real egocentric distances are perceived with a scanning laser range finder. World elements are represented as green elements and are learned as a persistent model of the world. Later, in B, the robot is in another location with unknown orientation, along with the corresponding range data. A correlative process then matches data in B with elements of A. Consequently, the robot knows its own location in the world, C.

C. Life (12i)

Definition

In MCS theory, life is the property of agents to be able to perform their ordinary operations. Its value is essentially Boolean, corresponding to life or death. In quantitative terms, this simple view can be complemented by two finer attributes, a life intensity index (ratio of current level of operation with respect to ordinary level of operation) and a lifetime (a duration measured in time units).

Discussion:

Life is the property of agents to be able to perform their ordinary operations. We can define life in different grades of increasing requirements, which we can also view as related to the time duration of ordinary operation (functional activity) without discontinuity. Thus, the time unit seems to be a key unit here. In its most basic form, life refers to the operational continuity of agents themselves.

A more demanding definition for life requires the ability of agents to actively sustain their own operations and possibly recover from failures, thus possibly extending the duration of functional activity.

A still more demanding requirement refers to the ability to persist across generations. Life allows agents to replicate themselves, having children capable of taking over ordinary operations for longer periods.

Time span of functionality can still increase if we consider life as beyond the scale of a species over evolutionary phases and even, ultimately, at the scale of development of a whole life tree such as ours on planet Earth from its very beginning billions of years ago to a yet undefined future.

From a practical perspective, the first basic definition given previously for life is adequate, with variations in the possible requirements being equivalent to variant definitions for the cognitive agents under discussion (such as individuals, generations, and species). A quantization may be useful in terms of life intensity, finer than just a Boolean value, namely life or death. A ratio (life intensity index) of current level of operation with respect to the ordinary level of operations might do it. This may be closely connected to several other notions in psychology, for example, sleep, wakefulness, consciousness, and arousal. These connections, however, are not really dealt with here, even though the notion of domain in MCS context would allow to do it rigorously. More generally, the concept of life has led to many activities (for example, [R13], including an associated full page just for the purpose of disambiguation of meaning); yet we could not find reference however for specific questions addressing living versus nonliving artifacts.

6.5.6 Emotions

Cognition generates appropriate information. This usually has some effect on status appraisal and emotions. The latter are possibly communicated at group level, and collective actions and changes often follow. It is worth extending MCS theory in the direction of emotions, establishing well-defined basis as well for human understanding as for robotic operations.

This section first presents the main concepts in human emotions and the corresponding facial expressions. Then we consider images and icons. Other means of expression, follow. Finally, we review the role for emotions in cooperating robots.

A Main Concepts in Emotions

The world keeps changing, and so do robots, humans, and robots cooperating with humans. Now what makes humans change and drive their actions? Emotions. Do we need similar driving forces for robots? Should those be similar to human emotions? Furthermore, do we somehow need to express emotions and recognize them in others, that is, to communicate emotions?

Change is general and often very abstract. We could view it as somehow analog to time. Physical analogies are often used in natural language in order to describe more abstract concepts. In that way, we often describe changes in reference to locations and space dimensions: motion, speed, acceleration, forces, stability, and so forth.

Emotions, by their etymology, clearly relate to motion. Resulting from changes in environment, perception, and possibly projected consequences related to convergence or deviation between status and goals, we can consider emotions as psychological forces that trigger subject activities toward strategic goals. We commonly refer to ten to twenty different types of emotions, including happy, surprised, and tired, for example.

Definition

In MCS theory, emotion is a particular kind of cognition, that is, cognition that involves a specific domain, typically involving the main, subjective, strategic attitudes

Discussion:

Experts suggest representing emotions as vectors in a two- or a three-dimensional mathematical space with the following primitives/dimensional axes:

- *Arousal* denotes an activity level. Associated aspects include the ones of energy; quantity of perceived information, urgency, and intensity of desired changes; and planned actions. Arousal is always positive (or zero).

- *Valence* denotes a happiness degree. It can be either positive or negative. We might interpret it as the current balance, as subjectively perceived, of overall benefits and costs.
- Taken with less priority into account, *stance* is an attitude that may vary between open (open to dialogue or empathy) and closed (barring exchanges and cooperation).

B Images and Icons

In general, the communication of emotions among humans relies primarily on facial expressions. Although naturally expressed in full (three-dimensional) space, we can perceive most of emotional content on the basis of simple images.

It turns out that yet much simpler representations, such as caricatures or icons, cannot only retain essential emotion-related messages, but also may even be more expressive. Looking at some images of real people, along with a few RH3-Y samples of iconic facial expressions, can easily qualitatively validate this.

People sometimes attempt to express machine emotions by a real, three-dimensional, dedicated physical structure. Even though approaches of this type have some advantages, such as consisting itself as a display medium, the efficiency in terms of communication of emotions is, to say the least, not obvious. Extending the idea of icons, it is possible to parameterize expressions so as to get continuous changes, in particular, for smiles or eye opening (figure 13).

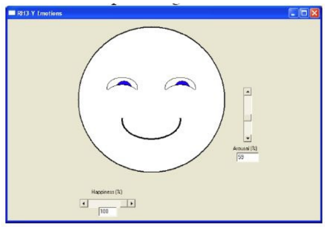


Fig. 13. The expression of emotions can be parameterized and continuously adjusted, for example, in terms of mouth shape and eye lid location (R14).

C Other Ways to Express Emotions

Specific facial patterns primarily express emotions, that is, internal (psychological) forces for behavioral changes. Classically however, robots such as ours can also show their status, processes, and intentions, that is, more or less explicitly rendering their emotions on various control screens, devices, and panels.

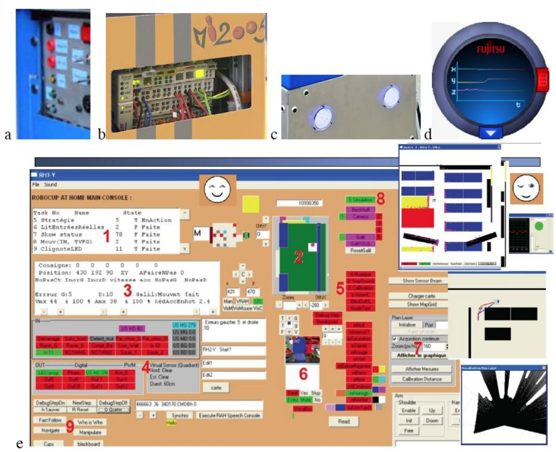


Fig. 14. The expression of status and intentions are classically described by panels, displays, and screens (a: Hornuss, b: Dude, c: programmable “eyes” or modulated headlights, RH3-Y; d: three-dimensional

acceleration components on supervising computer; and e: set of RH3-Y interactive control screens)

Now these classical data could be more systematically linked with iconic parameterizations (figure 15), leading to new head and facial expressions.

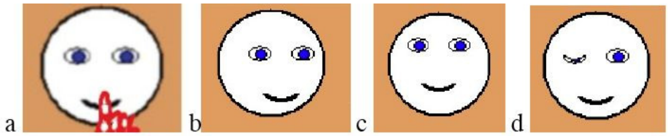


Fig. 15. The expression of robot status could evolve towards special adaptations of icons (a: mute behavior; b: leftwards intentionality; c: idem upwards; d: acknowledgement of common understanding.

Fig. 16. General view of RH4-Y robot.

RH-Y (figure 16) can express its emotions in many other ways yet: blinking (since 1998, considering previous developments in Eurobot context), speaking, delivering predefined sound waves (RH2-Y in Atlanta), or moving its body and arm in a way quite similar to dancing. And most naturally, those who know RH3-Y recognize some of its emotive states, such as when its motors enter some control modes or how its right wheel tends to lag behind when batteries run tired.

D. What Role for Emotions in Cooperating Robots

Emotions help explaining, in psychology, how humans make their short-term strategic choices. Emotions set a person in motion into a certain direction, toward a certain goal. Now does referring to emotions make sense for robots? For some purposes, it is useful. For others, it is not.

Useful Aspects

The useful aspects of dealing with emotions include experience, legibility, and communication.

Humans inherit thousands of years of experience relating to emotions. Attempting to transfer even just part of it to machines could be worth the effort. Describing machine attitudes and behaviors in terms of emotions may get them familiar and immediately understood by humans for design as well as for developmental, operational, and debugging purposes. Improved communication may be the strongest advantage that emotional messages provide. Thus in addition or as an alternative to other means, the exchange of information between robots and humans can be conveyed through a channel (emotional expressions) very natural for humans.

Limits

On the other hand, emotion-based approaches also have strong limits due to the nature of robots, media, and the domain of emotions itself.

Robots are not humans. Their differences are far more numerous than potential similarities. So it is now generally considered preferable to let users clearly recognize that they do not deal with humans so as to limit impossible expectations. Furthermore, the same argument of legibility plays the opposite role for those observers who are more familiar with concrete machine peculiarities rather than human affect psychology.

Robots feature different media, such as color screens or blinking lights, that allow for novel communication paths.

And in fact, even for humans, the domain of emotions is not so well-known today so transposing classical knowledge of this field to machines also means transferring current uncertainties.

Synthesis

Let's attempt a balanced conclusion, drawing from general considerations as well as from specific RoboCup at Home (RAH) and RH3-Y contexts. Here, communication is also a key function to consider.

It is universally true that reality is minimally upon reach. So it is critical here to also set the priority on a goal-oriented strategy.

Our goal relates to robotic help at home. And the latter has been further specified in RAH tests and rulebook. Cooperation between humans and robots is very important in this context. Communication helps in synchronization, for example, asking for or providing mutual help, coordinating intentionality, interest, attention, vergence (pointing with two eyes), or possibly threatening. For communication purpose and more generally successful interaction, expression seems mandatory. Very often, however, the latter simply result from functionality. For example, an emotion may induce a backward robot gesture. For the observer, just perceiving that gesture may be sufficient to be aware of inducing emotion.

We have given numerous examples for communicating emotions, in the study case of RH3-Y. Another interesting one (the latest one implemented and experimented with RH-Y) is the acknowledgement of user commands in switching active or resting modes for the FastFollow test. Within a fraction of a second, the robot can react with a green or red panel color and diodes to control gestures of human users. This provides a significant improvement with respect to previous situations where we based dialogue on the perception of potential changes in robot motions (about ten times faster reactions).

A final point relates to the nature of machines, which being different from humans, gains in being granted beyond classic human emotions, a wealth of variety in terms of internal affect forces and strategic attitudes.

7. Applications and Examples

What benefits do we gain by adopting the described quantitative approach in cognitive domain, and how do we proceed? We can find an idea in these respects in three application areas described subsequently: soccer or domestic chores in RoboCup context, the economical evaluation of knowledge, and, finally, handling of objects in manufacturing operations.

7.1 Robotics and AI: Soccer and Domestic Help

A major initiative for cognitics for the development of machine-based cognition has been the launch of RoboCup (R15). In its basic formulation, RoboCup has brought together three major components: AI, robotics, and soccer. In later phases, pioneers have added a socially more important application area to the initial plan, domestic help relying on smart cooperating robots.

In parallel to the World Cup of Soccer for humans (FIFA World Cup), RoboCup, another world competition for soccer, this one employing robots, is regularly organized. In 2010, FIFA Soccer competition was held in South Africa, and RoboCup was held in Singapore. The latter event has gathered three thousand active participants, traveling from forty countries. The main goal, defined since 1996, is to integrate AI and robotics for developing robots able of defeating the best human team at the World Cup 2050. In fact, the RoboCup initiative grows in several threads. In addition to leagues focusing exclusively on soccer (football), there is a particular application domain generally perceived of higher priority for society, helping humans in domestic environment (league RoboCup @ Home[25] or RaH).

This year (2010), two new elements have appeared particularly significant.

In the first case, with RH-Y team (R16), the mediation of a humanoid robot demonstrated just how dialogue between humans and other machines could conveniently happen. “Daniel,” sitting on a living room couch, responded positively to a proposal by the humanoid “Nono,” who, perched on the omnidirectional platform OP-Y, has alerted his partner RH-Y, who brings drinks and snacks to Daniel (figure 17–18).

Fig.17 Nono, a humanoid of Nao type (lower right) mediates between humans and other machines. OP-Y is the platform on which Nono is installed; RH-Y is the robot who brought drinks and snacks. http://rahe.populus.ch .

[25] Switzerland is represented in RoboCup @ Home since the creation of the latter in 2006 by a team of HESSO.HEIG-VD.

Fig.18 Detailed view of the mediating robot. On this picture, Nono wears an external microphone in order to broadcast his speech on the public facilities.

In the second case, collectively for our league, part of the competition took place in a public facility, a self-service store located in the heart of a shopping mall. In particular, our robot RH-Y, guided by the natural movements of a human, moved up to displays in order to learn where to search, later on independently, some items that the jury specified (figure 19).

Forecasting the progress expected in the coming years, until year 2050, robots capable of helping at home and those capable of playing soccer will certainly overlap in the major part of their abilities.

Fig. 19 Robot HR-Y follows a team member, learning, in a first phase, how to get to the shelves where some objects that the referees defined are displayed. In the next phase, the robot is expected to again find the shelf on his own, moving to pick only one object as specified by referees and finally bringing it to the exit.

7.2 Economical Evaluation of Knowledge

The following example is interesting in illustrating the benefit of a quantitative cognitive estimation for economic assessment. The text has been published (R17–18) and is replicated here with minor differences (suppression of MCS declaration in order to avoid useless repetition).

In the world, very large amounts of information are now routinely exchanged and processed. The current section presents various ways by which the proposed metrics for cognition can lead, in particular, to the economical estimation of information and knowledge values, as well as to the economical appraisal of associated CS.

Information has been defined scientifically a long time ago. In particular, its quantitative assessment is usually not a challenge. In the section, a brief presentation is made of basic equations along with a minimal context for its definition, including the concepts of model, messages, and domain. What is more uncertain is the economic assessment of information. Main difficulties are related to two factors: immateriality of information and the fact that a piece of information is, by nature, bound to a given context, singular domain and receiver's model. In practice, such contexts are extremely numerous and diverse, preventing information, in many cases, from behaving as a commodity. Information elements most often appear as specific, heterogeneous objects rather than as standard occurrences of large, uniform classes.

Information is now pervasive, yet something more powerful is emerging, knowledge, and associated ACS. The core property of CS lies in their ability (knowledge) to generate information, either spontaneously or reacting to external data and events. So far, the lack of accurate and quantitative definitions has forced experts to limit their economical evaluation of knowledge to individual, subjective, qualitative utility feelings, preventing them from estimating quantitative, collectively verified (market-compatible exchange values). But the new definitions allow a drastic change of the situation.

Technology in microelectronics today boosts supply of CS in various domains, causing a third revolution in the information world, in information domains. Where ACS can work, information requirements in terms of storage, replication, and transport costs are drastically reduced. Consequently, the economic value of information in those fields tends to sharply decrease. In addition to it, current CS have the interesting property of being able, in numerous cases, to react to their environment with high knowledge and/or expertise levels for a very low cost. This possibility is new for man-made artifacts. Consequently, humans in those areas lose their economic value. As another, more positive consequence, the decreasing cost of CS make it possible to envision many applications that were not economically rational in the past or which are yet unforeseen.

7.2.1 Some Background

For ages, mankind has been primarily busy with food management. In the last two centuries, industry (material processing) has become of utmost importance. Now the trend is clearly toward ubiquitous information-related activities.

Our industrialized societies routinely exchange and process very large amounts of information, creating a very strong impact on world economy. Now people start to realize that something more powerful yet is emerging, knowledge.

On the theoretic field, there is an increasing interest in developing relationships between information and economy (for example, [R19–21] or, in a more applied way, [R22–25]). See also (R26–27). Particular attention is given to this problem in the context of libraries and public information repositories (for example, [R28–29]).

Similarly, various authors have studied and reported their thoughts about links between knowledge and economics. For example, at the beginning of the 20th century, C.S. Peirce laid some foundations to the domain (R30). Closer to our time, other investigators have also contributed to formalize it (R31–33). But so far, the economics of knowledge have been mostly understood as the efficient allocation of resources for scientific inquiry. “Concern for answering our questions in the most straight-forward, most cost-effective way is a crucial aspect of cognitive rationality in its economic dimension” (R31, p.14). Moreover, the lack of accurate and quantitative definitions has forced experts themselves to limit their evaluation to individual, subjective, qualitative utility feelings, preventing them from estimating quantitative, collectively verified market-compatible exchange values.

Now knowledge has been defined scientifically, essentially by building on two well-grounded concepts, information and time. Appropriate metrics have been introduced (R34–36 and more directly, see previous pages). The goal of this section is to present various ways by which such metrics can lead in particular to the assessment in economical terms of information, knowledge, and ACS.

The section mainly includes two parts. In part 7.2.2, we set the framework in order to quantitatively estimate cognitive properties and assess economical values. Then part 7.2.3 addresses the problem of turning quantitative physical and/or cognitive values into economic terms (considering jointly quantitative assessment and economical estimation).

7.2.2 Theoretical framework

In order to assess information and knowledge values in economical terms, one must stand at the crossing point of two main streams. One is of cognitive nature, so we first present essentials of a new metric system for quantitative appraisal of cognitive properties. The other one relates to the economical world, and we present the corresponding ground definitions in the next section (Basis for Estimation of Value).

A Assessing Information, Knowledge and Other Cognitive Properties, in Quantitative Terms

CS essentially process information. A certain quantity of knowledge and expertise can characterize such systems. But other properties are often of interest as well. We have defined these cognitive concepts previously in the book, so we do not duplicate the corresponding part of the original article here.

B Basis for Estimation of Value

Measuring an asset in physical or cognitive units is an important step toward its economic evaluation. But it is insufficient. Here we review the essence of what basically makes the value of an object. We assign a broad meaning to the word “object,” covering physical products as well as intangible ones, such as information, knowledge, or services. We discuss the impact on economical value both of objective and subjective criteria.

B.1. Classic Definition of Economical Value

In our market-driven economies, global supply/demand patterns essentially dictate economical values (elementary courses in economy). And there is an obvious link between individually perceived usefulness values and the collective building up of demand.

Classically, we sort economical values in two groups: utility/usefulness values and exchange values. In the former case, qualitative, individual, and subjective aspects dominate. Quantitative and collective aspects mainly characterize the second group, and it corresponds directly to the market price.

Utility value . Utility value is the primary reason for a consumer to buy a good. It is very subjective, depending, for instance, on individual situation and experience, elements of proof at hand (logical reasoning), or reference to other people's opinions that are themselves (subjectively) perceived as credible.

By nature, utility value is rather qualitative. People like/need a good or do not. (Ultimately, they buy, or they do not). If they don't like the good, that's the easy case. But if they do, another problem usually arises. One must select among a number of competing possible buys, which one cannot simultaneously acquire all due to limits in buyer's assets.

Therefore, very naturally, a ranking appears by decreasing order of utility versus cost ratio, and this leads to the concept discussed next, exchange value.

Exchange value . Intuitively (historically), value is (has been) perceived as tightly linked with rarity, but the current, well-accepted view is different. The critical point here is the relative weight in the market of demand versus supply.

Utility and exchange values depend on each other. If many consumers perceive an object as very useful, its demand will grow. At least initially, its exchange value also will. Reciprocally, if a product becomes more valuable in exchange terms (that is, price increases), its perceived usefulness decreases. We also notice an additional regulatory effect. A higher exchange value (market price) tends to attract production resources, which will then increase supply and thereby reduce price.

B.2. Exchange value assessment

As already theorized a century ago, exchange value assessment is inherently quantitative (metric). Price for a good appears to be valid for a certain quantity, be it per square foot, per pound, per hour, per unit, per share, and so forth. Of course, this unit alone is insufficient, and we must consider the specifics of market and good in appropriate detail (domain of validity).

For example, the value of a share depends on the:

- Corresponding company (for example, VRDE Ltd).
- Stock exchange particulars (for example, Toronto).
- Date (for example, opening on March 1, 2010).

As a second example, consider the weight unit. The value of one pound is meaningless if other features such as material (for example, prime rib steak) and exchange place (for example, supermarket A&P) are not specified.

Reciprocally, that is, if no proper metrics exist or considered, exchange value assessment becomes highly subjective. Imagine how difficult and unpredictable it would be for brokers to exchange shares without counting them or for people to trade meat without weighting scales! Yet this is what prevails today in the fields of knowledge and expertise.

Value assessment is easily done for existing goods and markets. Direct reading of market situation and statistical tools provide a simple answer. For prospective markets, other approaches are required, such as expert consultation (Delphi studies), potential consumer inquiries, or econometric models.

Econometric models may seem to be the ultimate tool, but, as is well-known in weather forecasting or more generally in the theory of chaos, there is always somewhere a fundamental limit on predictability. For example, in the case of value assessment, notice that important market variations often result from a small set of mundane triggering events or even from a single one of them. In no way would it be practically possible to track the individual states of all such factors and to accurately model all of their possible interactions.

The latter limitation applies as well to common goods than to yet somewhat exotic, cognitive products. But the latter have some other limiting peculiarities, which are worth examining.

B.3. Limits to Our Discussion

We restrict our analysis here to key aspects for the case of a free-market economy. It may be useful, however, to remind the reader about some known problems with this approach.

Free-market negative aspects. Purely market-driven economies suffer from many shortcomings, including such things as:

- Risk of oligopoly
- Exclusion of social welfare and other ethical aspects
- Time-horizon distortions
- Difficulty of responsibility tracing
- Possible conflicts between individual and collective interests
- Health and life-threatening actions
- Irrational consumer behavior

These restrictions not only hold for physical goods, but they also do for immaterial ones such as services and knowledge.

7.2.3 Translating Quantitative Values into Economical Terms (Particulars of Information and CS)

CS deal with information. Let us see first how we handle information from an economic perspective, and then we do the same for CS.

A Information

While we presented the concept of information from a technical angle, we subsequently review its most salient properties from an economical perspective. In conclusion, we show that uncertainties in economical appraisal of information are bound in practice by cost and/or gain opportunities.

A.1 Bit and Related Units

The well-accepted, theoretically sound unit for measuring information quantities is the bit. But all sorts of derived units are equally acceptable. In a manner analog to the meter, which is often replaced without loss of substance by millimeter, micron, light-year, mile, foot or inch, and the like, many alternate units for information exist in practice. To name a few, there are byte, nibble, dit (decimal digit), character, word, page, picture, CD, movie, and so forth.

On the market, prices usually refer to units that not only measure involved information quantities, but encapsulate also some trade particulars. For example, page primarily designates a unit quantity of information, but, moreover, it implicitly refers to written material.

A.2 Short lifetime

By essence, information brings up surprise and unpredicted messages. As one result, the lifetime of information items is very short. In principle, a second copy of a given message to the same receiver brings him or her no information at all. So information is a very perishable good.

A.3 Subjectivity

Theory shows that a given message may carry more or less information depending on what the receiving subject knows already and can predict (current state of receiver's model).

But this is by no means singular in economy. Nearly all (in particular material) goods can also have highly variable subjective values. In fact, if subjective values were not variable, no transactions would ever be made.

A.4 Heterogeneity of information

For a market to exist, there must be a certain quantity of standard good to exchange. Unique objects have a very high volatility because the law of large numbers does not smooth out the subjective utility assessment of transacting agents. By definition, we cannot expect the regulatory effect of production resource adjustments here.

It turns out that information is not actually homogeneous. On the contrary, it is highly domain dependant. One megabit of television broadcast is not the same as one megabit of music. And as surveys regularly indicate, one megabit of television broadcast may have very different utility values depending on domain particulars: channel, time, actors, producer, and so forth.

Nevertheless, some domains are large enough so that markets develop, as proven by numerous everyday transactions where pure information is bought and sold.

A.5 Immateriality

In practice, information usually needs a physical support. As such, it is embedded in particular states of the real world, either as:

- Primary phenomena (semantic contents relating directly to reality[26])
- Representative phenomena (symbols, conventional descriptions of reality or nonexistent worlds ; the latter is commonly the case in novels, science fiction, modal logic,[27] and so forth.)

But information is essentially immaterial, intangible. This view is consistent with the very definition and equation replicated previously. It is also obvious when one considers the virtually unlimited representational power of language or other expression media such as art and animated graphics.

In summary, even though information is imbedded in material supports (for example, newspapers, Statue of Liberty, electromagnetic signals, CDs, and so forth), the latter usually have a minor economic cost. The

[26] See, for example, the “model is the world” approach, which is popular in part of the AI research community.

[27] Modal logic does not restrict itself to a single, objective view of facts. It deals simultaneously with multiple, mostly virtual realities. For example, past, future, and hypothetic alternative worlds (if-worlds) may be considered in a common conceptual framework.

immateriality of information has important economic consequences, particularly the following ones:

- No-cost copying/diffusion. In that regard, the printing industry has brought the first revolution in the information world,
- No-time transportation. Electronic communications have induced a second revolution.

Among other consequences, control of ownership and protection against theft are difficult to achieve.

A.6 "Direct" information , versus Information about Knowledge

Schematically, we can classify information in two groups:

- In a first, main group, information consists simply of data, which are immediately useful for the receiving agent. We could refer to it as direct information.
- In the second one, information is more subtle. It describes knowledge. That is, it represents cognitive structures and procedures, which, when implemented and run, will ultimately generate the pieces of information useful for the receiver.

The limit between either type is not very sharp. Depending on the point of view, we can often classify the message in either way. What is direct information for a user can be knowledge representation for another one.

A.7 Economic Value of Information.

As seen previously, the concept of information is well understood, and it has some properties very different from those of physical goods. But nevertheless, assessing the economic value for a piece of information is a task that is not fundamentally easier or more difficult than for physical goods. On all markets where information is exchanged (for example, databanks, libraries, books, weather forecasts, or movies), the practice is similar to the one for physical goods. For example, in the same way as one ounce of gold or one ton of coffee may fluctuate in value, so can information do (for example, one kilobit of weather forecast on central Europe, stock exchange data at a given point in time, one Spielberg's movie on videocassette, ten pages of photocopies at the library, and so forth).

We often use two particular ways to assess economic value for goods. These are fully applicable for information and knowledge as well are indirect. They consist in estimating the economic value in terms of:

- Effectively incurred costs to acquire goods (information, knowledge, or something else).
- Actual or expected gains, possibly as an alternative to other potential approaches

B Cognitive systems

On the economic scene, CS have been nearly exclusively human until recently. For a few decades, ACS have started to appear, but it is only since the 1990's with the progress in microelectronics technology that social impact has started to be significant. Impact has been strong in information economics, but also directly in cognitive activities where workers are displaced and new applications considered. Before attacking the case of ACS, let us briefly review the one of man.

B.1 Economics of CS 1 - The Case of Man.

For very long, humans have performed as an important source of mechanical energy as well as a CS. Nowadays, except for limited areas (for example, sports), their professional roles are mainly related to cognition. Good performance levels in terms of knowledge or expertise are domain-dependant and can be attained by various modes of learning.

An economic view of the situation makes it clear that supply/demand equilibrium has impacted the value of individuals. To reduce the cost of experts, appropriate actions have been taken in education and the dissemination of know-how (for example, public broadcasting services or patents). On the contrary, some professional corporations have artificially retained or increased the value of its members by provoking a higher demand (for example, advertising or problem-making) or forcing a restricted supply through rules and other actions (for example, license systems, lobbying, and retaining know-how through secrecy).

B.2 Advent of ACS

Until recently, only humans and, to some very limited extent, living animals had been capable of cognitive performance. But now, in addition to them, progress in electronics and information processing (that is, by previously listed definitions, knowledge-related, or, in short, cognitive) engineering has brought about numerous and extremely powerful artifacts.

ACS consist in electronic hardware (for example, analog/digital circuits such as modulators and logic gates) or programmable devices (computers, notebooks, microcontrollers for industrial control or videotape recording, and so forth).

Performance levels in terms of expertise routinely could approximately reach in the year 2000, for ACS, tens of millions (lin/s), at a cost lower than one hundred dollars. By comparison, the cognitive performance levels of humans in domains related to perception may be roughly similar. But by contrast, conscious cognitive activities, such as language processing or logical reasoning, fall far behind, as evidenced by psychological investigations with on the order of a few hundred (lin/s) only.

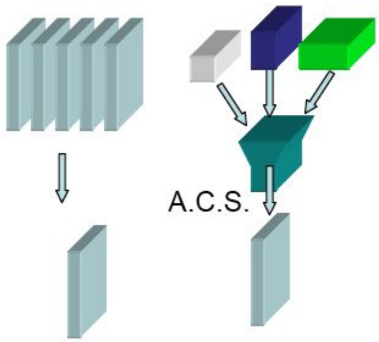
What is missing in most cases today is the knowledge required to map ACS natural cognitive domain onto the ones that potential buyers find most useful. In other words, like in most cases for humans, the cognitive power is there, but many methodological developments (for example, education, training, or inquiry) remain to be done.

B.3 Effect on Information Economics

We stated previously that information replication was somewhat free of charge (no cost) and its transportation was immediate (no time). This is not quite true. In relative terms, cost (information value versus support charges) and delays (information transportation time versus human time scale) can be really very low. But they are not strictly zero. And in our developed world, information replication and transfers reach such large amounts (in bit and bit per second) that even those tiny values accumulate and globally reach considerable and sometimes quasi prohibitive levels. Knowledge helps here.

Knowledge and, physically speaking, CS have the power of reducing by orders of magnitude the amounts of information to store, replicate, and transport for a given task. It follows from their definition that such systems can generate relevant information as many times as they exist and immediately where they are. By the tremendous impact that this has on information world economics, CS[28] are responsible there for a third revolution.

Fig. 20. Schematic view of a cognitive library. Traditional delivery of stored information (left) and user-requested information generated with knowledge (right).



For example, pocket calculators have replaced logarithms and trigonometric tables. In the 1990's, the French Minitel system (mostly a set of ACS) had replaced tons and tons of dial books (raw information). Because of ACS (implicit knowledge), information exchanges on networks may also not explode as fast as expected by many observers today. Already very often today, sms, e-mails, or fax services replace traditional conversations over the line, sparing large amounts of transferred information. Actually the most significant change today in communication may be less the routing of information through the network lines (copper lines, radio waves, optical fibers, and so forth) than all the ACS

[28] Here we are talking of ACS. The contribution of man as a CS is also very important, but it is not new, so his contribution is already integrated and taken for granted here.

connected to it (answering devices, electronic mailboxes, rerouting relays, and so forth).

As an extreme case, in order to illustrate the power of knowledge and its potential impact on information management, one may imagine a cognitive library, a library capable of generating most of the desired pieces of information for the user. Consider two examples.

Based on a single version of a book in store, it would automatically generate, on demand, numerous variations:

- Translations in German, Russian, and Japanese.
- Short and extended abstracts.
- Lists of keywords
- Reference maps

Or the cognitive library would have music charts and profiles of music instruments, halls, and well-known artists. On this basis, it would, upon request, generate a particular mix, for example, Michael Jackson singing “La Marseillaise” at the Scala of Milan!

Such examples are extreme, but something of the same nature has already started, for example, automatic setup of reference lists on the basis of multiple user-defined criteria and automatic retrieval of selected information. In fact totally conceptual in the first published version of this text, the first example is today mundanely operational, to a large extent, for example with Google resources.

The formidable impact of ACS is not restricted to the information world. Their effect is important throughout society.

B.4 Economics of CS 2 - The case of ACS

ACS have many aspects that make them economically preferable to man in numerous domains. We discuss three of their most salient advantages: ease of replication, scarcity of requirements in physical and environmental costs, and virtual ACS transport.

Ease of replication. Since the 1990's, microelectronics technology allows tens of thousands (and more) of complex integrated circuits to produce in one batch. Those ACS are extremely inexpensive. Moreover, they can be designed in order to be later tailored for various knowledge domains, in a way, for that point, similar to humans. Specialization occurs through programming. Here again, replication is virtually free.

Scarcity of Requirements in Physical and Environmental Terms. Very small power requirements characterize current ACS. They are extremely small in volumes. The main material to process is silicium, which exists on Earth in practically limited quantity and immediate access.

Transporting Information instead of Physical Cognitive Systems. Current ACS tends to be general purpose. They can exchange, at considerable distance, knowledge about particular domains. So information transfers (for example, programs) can replace transport of physical CS. This has also been the case for humans through the mechanism of local representatives. But ACS performances in terms of accuracy, domain size, speed, and cost differ by orders of magnitude.

7.2.4 Synthesis

We have discussed essentials of the concept of information and some of its economic aspects. Even though information items differ by various properties (in particular immateriality) from physical goods, the process of assessing their economical value remains similar.

In addition to the ones of information, we have also addressed the most substantial properties of CS. Among other consequences, this allows a clear quantitative assessment of their performances. Today, technology in microelectronics allows boosting of supply of CS in various domains. And the discussion shows they have important effects in terms of information economics as well as in terms of reactive behavior.

After the invention of printing (Gutenberg) and long after the widespread use of electronic telecommunications, the current advent of CS brings about a third revolution in the world of information, where ACS can work. Information requirements in terms of storage, replication, and transport costs are drastically reduced. This revolution impacts the value of information, which, in such cases, tends to decrease sharply (for example, the value of tables of logarithms and printed encyclopedias). In this respect, ultimately, the value of a CS should be the value of the information it delivers.

But in addition to their impact on the information economy, current CS has the interesting property of being able to react to their environment with high expertise levels for a very low cost. This possibility of complex reactive behavior is qualitatively new for man-made artifacts. Consequently, humans in those areas lose their economic value. On another, more positive consequence, the decreasing cost of CS make it possible to envision many applications that were not economically rational in the past, for example, the twenty-four-hour per day opening time of cash delivery booths in thousands of locations. It also opens up other fields that are yet unforeseen. Considering the potential of ACS as reactive systems, we must also appraise their values in this regard (not in reference to informational aspects). When competing on common grounds with humans, their value has an ultimate upper bound, the cost of humans they might displace.

Humans lost a large part of their economic utility with the harnessing of modern sources of energy. Economically more attractive man-made artifacts are now increasingly challenging their role in cognitive activities. If market forces were let alone to work, they probably would, in the next phase, assign individual economic values to humans, that is, ultimately distribute wealth according to a primarily emotional rationale.[29] Appropriate regulation policies could, however, keep this evolution under control.

7.3 Film Cans and Manufacturing

The following example is interesting in illustrating the benefit of a quantitative cognitive estimation of task requirements. It relates to a case representative of many manufacturing operations, the handling of film cans. The text has been published (R37–38), and we replicate here with minor differences (color images, competition results, and, in the last part of conclusion, reference to the

[29] This has clearly started long ago for some stars in various entertainment businesses (for example, movies and sports) and maybe now starting to spread in other social activities (political leaders, religion communicators, and so forth).

general impossibility of keeping without loss the essence in a simple abstract).[30]

Assembly tasks may very much vary in complexity, depending on application specifics. Here the task is found moderately complex, as it implies about 10^{60} possible states on the perception side, each involving about thirty thousand bits of action data. The section presents two systems conceived in our lab to perform the task. In one case, we achieve perception in a classic sense, by video camera and original vision software. A robot induces action. In the second case, we reduce input space from 10^{60} possible states to one by purely mechanical, a priori designed, task-oriented devices. We compare both approaches in a discussion where we refer to coercive, adaptive, and cognitive paradigms.

7.3.1 Context

At PerAc '94 conference (From Perception to Action), a contest has been organized where competing systems should stack film cans in a limited amount of time. As starting state, ten cans are given, standing randomly, at least ten centimeters apart in a one-meter-diameter circle. The current paper reports on two systems liable to do the job and introduces first a common framework in which they can be compared.

Current work relates somehow to research activities in various areas. Mostly, it relates to the general field of AI (for example, [R39–40]), robotics, and more specific domains, such as motion control (for example, [R41]), vision, or sensors (for example, [R42]).

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[30] Fundamentally, the content of this publication is still absolutely valid today.

The work is well in line with previous research interests of some of us, namely the complementary, task-dependent requirements for robotic and nonrobotic systems in industrial automation (in particular [R43]) and basic issues in cognitive sciences (R36).

7.3.2 Theoretical Background

When facing a particular automation task, various types of approaches are possible. Here three of them, differing very much from one another, are discussed: coercive, adaptive, and cognitive paradigms. We will further illustrate the first two in the sequel of this article.

A Coercive Methods

A priori imposed, appropriate constraints may greatly reduce task complexity. For example, in practice, constraints are numerous in industrial automation (standardization, quality control, and so forth). In Per'Ac '94 assembly contest, task complexity is a priori reduced by constraints as per contest specifications (type of cans, size and shape of playground, and so forth) and can be further reduced in real time by a priori designed, blind mechanical constraints (7.3.4 Dedicated System - Case B).

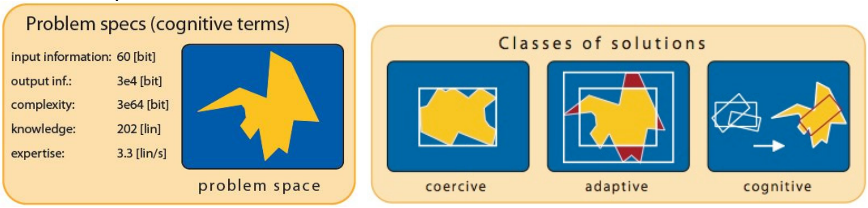

Figure 21. The assembly task of PerAc '94 contest is represented here as a particular polygon. Left: Schematic view of task domain. Coercive: Domain reduction by constraints. Adaptive: Task partially constrained. Some room is left where adaptive behavior

is required. Cognitive: Cognition implies mapping appropriate structures on task domain.

B Adaptive Methods

Modern automation resources allow machines to cope with tasks of relatively large complexity. The classical automation loop includes measurement, control, and output driving components. But now, measurement capabilities often increase, getting richer and more abstract and reaching toward perception. Similarly, control evolves toward decision and output function toward the general concept of action.

Adaptation is possible today with reasonable time and resources, if task complexity remains within relatively narrow boundaries. For PerAc '94, task complexity is mostly related to positional variations of film cans. Cans can be visually detected, and their positions can be estimated (perception). A robot can perform corresponding changes in mechanical motions (action) (7.3.3 Flexible, Robotic System - Case A).

C Cognitivistic Approach

Assembly task is a concept of infinite complexity, in the sense of common English as well as according to rigorous C-Model definitions (R36). In general and including the case for PerAc contest, appropriate specifications reduce concept complexity to a manageable amount. For PerAc, humans (organizing committee) have done the job. And teams attempting to solve the problem perform a similar cognitive work in reducing the scope of automation system concept and mapping it appropriately onto specified task domain.

Such a job of reducing infinite cognitive domains to some simple particulars, yet not losing essentials, is not obvious. One may even question whether this is possible at all. It is not easily achieved by humans and is totally out of reach of current man-made systems.

Examples of simple CS (mobile robots) featuring some learning capabilities on relatively small domains are shown in (R36).

7.3.3 Flexible, Robotic System (Case A)

Some of us (in particular, S. Ernst and L. Venries) have worked on solving PerAc contest with an adaptive, industrial-grade robotic system. A mass-produced camera (Panasonic NVS-7) captures the scene from above the playground and delivers a monochromatic image to digitizing board. Even though the digitizer is capable of a good resolution (512 rows by 512 columns) and the camera has a better resolution yet, in our solution, a coarse image is found to be preferable. This alleviates computational load. During processing, acquired images are implicitly resampled at twenty-five times lower resolution, and the camera is blurred accordingly, for anti-aliasing purpose.

On the software side, a dedicated program, running on an IBM-compatible personal computer (AT-286), achieves perception. The language is Borland Pascal. The PC is equipped with a simple Matrox image digitizer (PIP-1024). Images are scanned. When a bright pixel is detected, analysis is refined locally, using a centroid estimation algorithm. Centroid coordinates (coarse perceived can positions) are transmitted to robot controller via an RS-232 serial link.

A finer positional accuracy of film cans is retrieved later by passive mechanical constraints, gripper jaw-centering forces.

Cans are picked at their estimated random location and stacked at a given place with a well-known six-degree-of-freedom articulated robot, Unimation/Stäubli Puma 560. If they stand out of direct reach (inside the small circle of figure 22 or outside the larger one), they are pulled toward playground center by the robot holding a wiper. Then visual analysis is performed again.

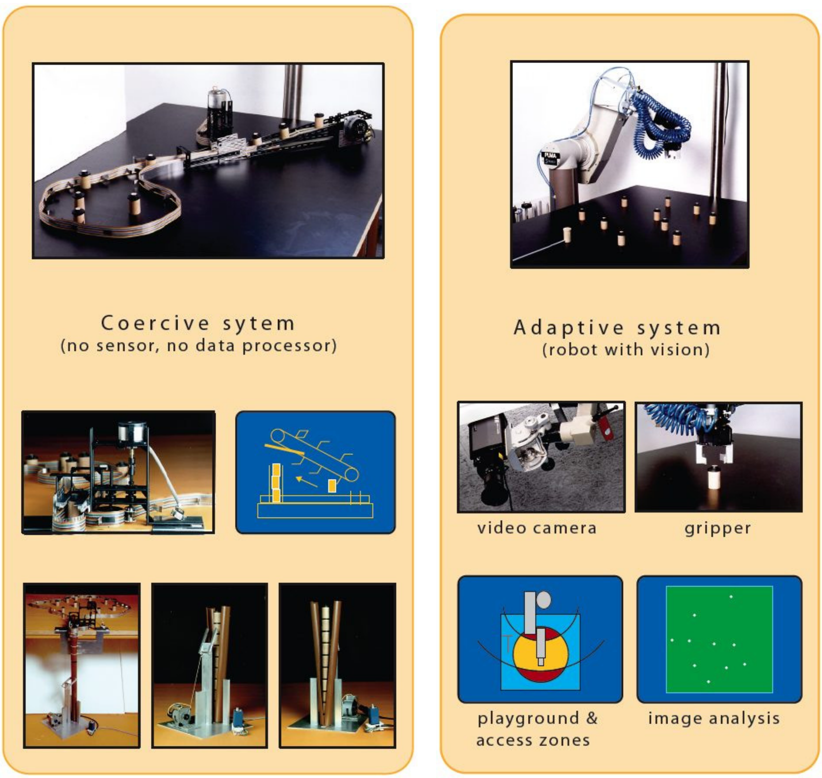

Figure 22. Experimental implementations. Left: coercive system (no sensor). Right: adaptive system (robot with vision).

In principle, the solution is simple, mostly because components are powerful: camera, two-dimensional real-time digitizer, vision primitives, computer, and robot. Puma robot controller is programmed in VAL, a language that supports Cartesian coordinates and full transformation matrix computation (that is, in practice, simple definition of relative coordinate frames).

But in order to get the system working, additional ingredients have been found useful or necessary. Particularly worth mentioning are the following ones:

- Interrupt-based (on PC-side) serial communication.
- Appropriate gripper design, allowing for low-accuracy visual estimation of target position and high tolerances in height specifications
- Careful calibration process for camera frame and robot-base frame relative registration
- Wiper similar to the one used on casino tables in order to pull remote cans into the restricted Puma working surface. See the T-shaped tool in figure 22. The robot might have had direct, full access to the one-meter-wide playground if hung from the ceiling).
- Nominal height (z) correction is a function of can position (x, y, or rather r, θ) on playground

7.3.4 Dedicated System (Case B)

Some of us (in particular, A. Beran and O. Olmo) have worked on a dedicated solution for the same PerAc problem. Here the challenge was set to perform the task without any sensor. This approach is actually quite typical in industrial automation (coercive method).

Humans do cognitive work at design time to make the system blindly remove all uncertainties at execution time by applying data-independent mechanical constraints (brute force approach).

A belt is manually laid around the playground during preparation phase. When execution phase starts, a DC motor winds up one side of the belt, which then sweeps the whole playground and gathers all cans in the outlet path (see figure 22, left). Temporarily trapped there in a queue, a fork successively takes cans, and these are carried up along an elevator (permanently moving belt) over a tube in which they are compelled to drop by a gauge (see figure 22, left). In the last phase of a run, the guiding tube opens up in order to satisfy the rule of free-standing pile.

Even though they are not implemented here with digital or electronic means, the mechanical system nevertheless features at least three regulatory effects:

- Limited friction on the belt, which stops moving cans when they stand in the queue.
- Synchronization of can progress along outlet with passing forks, through proper use of a mechanical lever
- Position-dependent can stacking. A baffle (gauge) forces cans to drop out of elevator when they hang over the pile.

7.3.5 Synthesis

At first glance, cases A and B appear to be fully antinomical. The former system looks extremely flexible and adaptive, and the one of case B looks purely brute force and limited. In fact, they are not that different and share at least the following elements. In both cases, mechanical constraints make a critical job of variation/uncertainty removal. Time and human resources required for systems to get operational have been similar. Obviously, inherent task complexity is the same for both. (PerAc contest rules dictate this.) What may be less expected is that they reach, on this singular domain, a similar level of knowledge (about 202 lin) and expertise (about 2 lin/s). In both cases, the amount of system cognitive properties (knowledge, expertise, and so forth) does not ultimately limit cycle time, but rather dynamic and power considerations related to mechanical motions along trajectories in space.

Our experiments indicate that one of the most significant features of any task, in cognitive terms, is its inherent complexity. When the latter is small, many approaches may be successful, no matter what their specific nature is. If large, not a single solution is feasible. Another critical feature is the time allotted to do the task, which cannot be arbitrarily reduced. In C-model, complexity and time appear as significant factors in equations yielding knowledge and expertise, among other concepts.

Here, the amount of complexity (C) can be estimated to be $C = I_{traj} * (N_{posx} * N_{posy})^{N_{cans}} = 30'000 * (1000 * 1000)^{10}$, that is, about $3*10^{64}$ bit. The number of positions in x and y is 1,000 for each coordinate because playground diameter is one meter long and a one millimeter resolution is sufficient to do the job. And the information required to stack one can is related to the definition of the trajectory, varying in x, y, and z coordinates, starting from initial location on playground and leading to final place in stack. This is a relatively small amount of complexity in the context of our modern resources, but it is far from negligible.

Both approaches have been successful, demonstrating the capability of gathering ten randomly laid film cans into a ten can high stack within one minute. The system of case A (flexible robotic solution) has been further documented in a VHS movie shown at the conference. And the one of case B (sensorless coercive setup) has taken part to the contest and has won first place.

Moreover, the definition of film cans for PerAc competition provides an interesting illustration of the loss that is practically always incurred when reality is represented by models.

Film cans were available in large variability on the market, as partly shown in the side figure 23 (top picture). To prepare concretely for a solution, the participants enquired about the specifications of the cans that would be used for the official competition.

Example of cognitive approach

What is a film can ?

Fig.23 The typical film can chosen for the robot competition was well defined, made available, but could not hold film rolls!,

A few weeks before the competition, the organizing committee therefore produced and delivered a standard can to the participants, as shown in the side figure 23 (lower picture). In wood, with centering hole in lower part and slanted peg on top with some particular black regions, the can was surely adequate for the competition, but, ironically, could not contain a film roll.

8. Conclusion

Having gradually replaced or assisted humans in their physical activities, such as power generation or mechanical work, automated systems have now begun to invade the cognitive domain.

The cognitive sciences have, in one form or another, begun millennia ago, and the concepts of model and information are mainly used here as foundations for the definition of major cognitive, central elements of the MCS theory.

Classical philosophers have rightly said, and the quantitative estimation that information theory allows confirms that the reality is perceptible only in infinitesimal part. If the goal of modeling were merely the representation of reality, failure would be almost total. But the goal is elsewhere. A good model has the great merit to allow CS, human or artificial, to reach the purposes for which they were defined.

In a first part of the book, the MCS theory rigorously defines key cognitive variables, including complexity, knowledge, abstraction and implementation, expertise, concepts of learning, and intelligence. It brings over a metric system for these concepts. We also consider possible random errors.

The MCS theory and quantitative techniques bring great clarity to the field, essentially rational, of cognition. They also reveal important limits. We must go beyond cognition and note that, in humans, other functions exist, especially intuition, ethics, and emotions. For every phase of the modeling, this intuition bridges the gap with reality. Ethics are fundamental for guiding the choice of goals to achieve. Emotions ensure a possible transfer from the domain of cognition to the domain of action, as a process of physical implementation, which changes the world.

In a second part, we have extended the MCS theory, and have formally defined associated concepts, in relation notably to time, control, thinking machines, robots, and humans.

Finally, we report three sample applications where we can illustrate the use and benefits of MCS theory and cognitics. They relate to cooperative robotics at home, the economics of cognitive entities, and a process representative of automated manufacturing operations.

Appendices

Appendix A. Summary Table of the Presented Concepts (Logical Order)

The logical order adopted subsequently ensures that the definitions can fit, that is to say that, when each is declared, it can refer to predefined terms.

Logical order of definitions	**Concepts**	**Table of content**

Core Cognitive Entities

0	Cognition, Cognitics	5.1
1.1	Model	2.2, 5.2
1.2	Domain	5.2
1.2	Time	6.2.1
1.3	Memory	2.3
1.3	Dynamics	6.2.2
1.4	Agility	6.2.3
2.1	Information	2.1, 5.3
2.2	Message	5.4
3.1	Complexity	3.3, 5.5
3.2	Abstraction	5.6
3.3	Concretization	5.7
4.1	Knowledge	3.1, 5.8
4.2	Experience	5.9
4.3	Fluency	5.1
4.4	Simplicity	5.11
5.1	Expertise	3.2, 5.12
5.2	Reductibility	3.3, 5.13
6	Learning	5.15

7	Intelligence	5.15

Extended and Associated Concepts

8	Right	5.16
8.1	Wrong	5.17
9	True	5.18
9.1	False	5.19
9.2	Good	5.2
9.3	Bad	5.21
10	Wisdom	5.22
11	Sapience	5.23
12.1	Creativity	6.5.2
12.2	Ingenuity	6.5.2
12.3	Chance	6.5.2
12.4	Deliberation	6.5.3
12.5	Control	6.5.3
12.52	Reactive Control and Other Control Types	6.5.3
12.6	Top-down Approaches	6.5.3
12.62	Bottom-up Approaches	6.5.3
12.7	Group	6.5.4
12.72	Holistic Group Aspects	6.5.4
12.73	Group Members	6.5.4
12.74	Culture, Communication, Spirit	6.5.4
12.8	Consciousness	6.5.5
12.82	Conscience	6.5.5
12.9	Life	6.5.5
13.1	Thinking and Thought	6.4.2
14	Robot	6.4.5
12.10	Emotion	6.5.6

Appendix B. Summary Table of the Presented Concepts (Aphabetical Order)

Concepts	**Contents**
Abstraction	5.6
Agility	6.2.3
Bad	5.21
Bottom-up Approaches	6.5.3
Chance	6.5.2
Cognition and Cognitics	5.1
Complexity	3.3, 5.5
Concretization	5.7
Conscience	6.5.5
Consciousness	6.5.5
Control	6.5.3
Creativity	6.5.2
Culture, Communication, and Spirit	6.5.4
Deliberation	6.5.3
Domain	5.2
Dynamics	6.2.2
Emotion	6.5.6
Experience	5.9
Expertise	3.2, 5.12
False	5.19
Fluency	5.1
Good	5.2
Group	6.5.4
Group Members	6.5.4
Holistic group aspects	6.5.4
Information	2.1, 5.3
Ingenuity	6.5.2
Intelligence	5.15
Knowledge	3.1, 5.8
Learning	5.15
Life	6.5.5
Memory	2.3
Message	5.4

Appendix C: Table of Probability Values, Logarithms and Information Quantities

Table displaying some representative values of probabilities, logarithms, and corresponding quantities of information:

Probability, p	*Probability, p*	*1/p*	*Log_{10} : dit*	*Log_2 : bit*
1	1	1	0	0
1/2	0.5	2	0.3	1
1/3	0.33	3	0.5	1.6
1/4	0.25	4	0.6	2
1/8	0.125	8	0.9	3
1/10	0.1	10	1	3.3
1/100	0.01	100	2	6.6
1/1000	0.001	1000	3	10.0
1/1000000	0.000001	1000000	6	19.9

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