Humans and Machines: Nature of Learning and Learning of Nature

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Old and recent theories stress that any understanding of the processes by which humans can learn requires to fully appreciate the relationships between the "nature of learning" and the "learning of nature." From a constructivist viewpoint, acquiring knowledge is, like any human activity, dissociable neither from its underlying project nor from the knowing subject. We relate the lessons from philosophy, psychology, didactics and ethics to our work in computational scientific discovery that aims at empowering learning machines with the task of assisting human researchers (Dartnell, Martin, Hagège, & Sallantin, 2008). We conclude with didactical and ethical considerations.

INTRODUCTION

Reflecting on learning, knowledge and reality is consubstantial with occidental philosophy, from its very origin in ancient Greece, more than two thousand years ago. Since that time and right to the 20th century, philosophy and what we today call "science" – the *phusikè* of Aristotle (384 BC – 322 BC) – were viewed as one and the same activity. Descartes (1596 – 1650), considered as the initiator of modern philosophy, exposed in his *Discourse on the Method of Rightly Conducting the Reason, and Searching for Truth in the Sciences* (1637) a way of considering the relationship between on one hand an agent thinking on reality, and on the other hand the preconditions and actions from which true knowledge can emerge. He expressed the need to start from a *tabula rasa* by putting into question any previously constituted knowledge or belief. The only piece of certainty one can start with is one's own existence ("I think therefore I am"). Also one should "divide difficulties into small enough parts to be able to resolve them" and select true statements that appear "clear and sound in the mind" (Descartes, 1637). He so much imprinted our occidental vision of science and our relationship to reality that the inherited "Cartesiano-positivist institutional epistemologies" would constitute the base of "the social contract between science and society, and thus the status of teachable knowledge" (Le Moigne, 1995 p. 8). Paradoxically, such epistemologies are "at the same time individually disputed and institutionally accepted" (Le Moigne, 1995 p. 14). This could be partly explained by the "astonishing lack of epistemological culture of scientific researchers" (Le Moigne, 1995 p. 8) and by the contemporary institutional separation between science and philosophy. It is fair to say that in our work, we attempt to restore this lost unity.

The so-called "Cartesiano-positivist epistemologies", that we will explicit later on, have thus persisted under different forms until now, while interactions between science, technology and society have been shaping our world and our way of thinking. For instance, with the advent of the industrial revolution, the transformation of matter into energy has been as much of a reality in everyday life as in theoretical physics. More recently, the advent of the information era has also constituted a big revolution and various scientific disciplines have emerged to model the processes that underlie learning (artificial intelligence [AI] and neurosciences). Together with more traditional disciplines (psychology, philosophy and linguistics), they have been grouped under the generic term of cognitive sciences (Vignaux, 1991 p. 9). Different underlying paradigms provide a variety of approaches to learning and help study the relationships between intelligent machines and human beings.

The aim of this paper is to address the following questions. What scientific models do we use to understand human learning and to produce learning machines? Where do these models come from? What are their scopes and limits? How and why do we choose to use those models? What do they tell us is possible or is out of reach?

In the first section, we will overview i) the models that western societies have recently produced in order to explain the nature of learning and ii) the models that they have developed about the learning of nature, particularly through the prism of so-called "scientific discovery." In the second section, we will present the general evolution that occurred in the field of AI about assisting human discoveries with learning machines and then introduce the main aspects of our work in this domain. Finally, we will discuss the didactical and ethical dimensions inherent to discovering how learning of nature is performed, and to using assisting machines.

HUMAN LEARNING

Nature of Learning

After a few preliminary considerations, we review the conceptions on human learning as they evolved in western culture. We then focus on a particular model of the scientific activity, and highlight how the two conceptualisations of "general learning" and of "scientific learning" converge to constructivist paradigms.

Preliminary Considerations: Different Objects of Human Learning, One Fundamental Base

We would like to answer the question: "how do we learn?" But one might preferentially ask "how do we learn what?" It is of striking evidence that we do not learn mathematics the same way as we learn how to ride a bicycle or to be a respectful person. These examples correspond to different categories of knowledge (in the sense of the French word *savoirs*) that have been called in the French curricula *savoirs, savoir-faire* and *savoir-être* (and which could roughly be translated respectively as declarative knowledge, procedural knowledge and self knowledge or as intellectual skills, practical skills and self-management skills). Thus it seems that different processes could underlie different kinds of learning. Can we unravel a common denominator to all human learning activities?

Despite this remarkable heterogeneity, our ontological development consists, from a psychological point of view, in learning to be human and then to be a particular individual in the human community. In fact, soon after birth, the baby is fused to the totality of his environment, encompassing his mother, other living beings and also the surrounding non living things (Searles, 1960 p. 47). Normal development would therefore be firstly to differentiate from the nonliving environment, secondly to recognize oneself as part of mankind, and thirdly to assess oneself as an individual, notably distinct from the mother (Searles, 1960 p. 60). The adolescent has normally become fully aware of being human, has turned away from nonhuman objects, and focuses on humans (Searles, 1960 p. 98). As Piaget (1896 – 1980) remarked, teenagers feel destined to save the world; maybe they want to save other people from the nonhuman experience they just got rid of (Searles, 1960 p. 101).

To answer our preliminary question, we thus need to know what a human is. This is a vast question… Nowadays everyone seems to agree that we are animals with something more. From a biological point of view, this "something" seems to be more quantitative than qualitative (Marchand, & Chaline, 2002). We share similar structures with chimpanzees but some of them, such as the neurological structure, are more developed (for instance, we have a bigger brain). However, a recent study, which has yet to be confirmed, argues that humans may possess particular neurons that would make their frontal neocortex more efficient than the chimpanzees' (Molnar et al., 2008). From a philosophical point of view, this something is often claimed to be qualitative. According to Morin (1921 –), being human is a ternary concept that entwines the individual, the species and society, such that none of these terms can be reduced nor subordinated to any other (Morin, 1973). Along the same lines, Anselme conceives of humans in terms of a tension between a cosmic evolution (our biological dimension, what Morin designed under the term of *species*) and an ethical evolution, which prevents us to be solely "gladiators in the arena" (Anselme, 1989 p. 35). This ethical evolution would have emerged with consciousness, which gave rise to a collective will to refuse, denounce and fight natural injustices to overcome them. The first known writings in human history are indeed descriptions of behavioural norms, meant to keep us away from animality (Anselme, 1989 p. 21).

To summarise, our fundamental learning task would be to first become aware that we are a social being, with a duty by the community, and then to be a singular human in this community. These considerations can offer an interesting angle to analyse any particular object of learning and make up a privileged frame in the present article.

A Little Allegory of the Scientific Model of Human Learning

Chapter 1: In the Light of the Cartesiano-Positivist Epistemologies

We start the story with the neuropsychological studies in the first part of the 20th century. The works of the Russian psychologist Pavlov (1849 – 1936) have been translated in English for the first time in 1927. His experiments with dogs and how they can learn to associate a sound signal with the presentation of food lead to the concept of classical conditioning (a type of associative learning). The dog learns to salivate after repeated association of both signals. Following sufficient training, the dog salivates even when the food is not presented, providing evidence that it has been conditioned to salivate when it hears the sound signal. This form of learning (external stimulus → response) is better described as training and cannot be easily applied to wild animals or young humans who learn a lot through self-initiated exploration (Astolfi et al., 1978 pp. 123-124). Kornoski discovered operant learning in 1928: the stimulus is self-initiated after a self-initiated action (Astolfi et al., 1978 p. 124). These studies, together with philosophical logical positivism, inspired Skinner[1] (1904 – 1990).

In the late 20's in Europe, the philosophical and normative movement dedicated to unifying the various sciences has been constituted. It represents an emblematic "Cartesiano-positivist epistemology" (Le Moigne, 1995, p. 15). The so-called Vienna Circle focused on defining a universal method, primarily following an empirical approach, which could ascertain the constitution of true knowledge. Given this line of ideas, a central point of behaviourism is that the mind, or any related concept, depends on metaphysical considerations and cannot constitute an object of scientific research. The only empirical object worthy of scientific investigation about learning would thus be behaviour – the only empirically observable output of learning. Behaviour is considered as the result of a linear causal process that originates from a stimulus. This stimulus can be either external (Pavlov's dog) or internal (operant conditioning, the second type of associative learning). Skinner is well known for his work on the latter, where the stimulus has an endogen origin (for example when a button activated by accident triggers feeding). He also studied classical conditioning and invented famous experimental devices, notably to study associative learning in rodents. The matter was to evaluate how rodents learn to avoid or implement a particular behaviour (depending on the experimental setup) after a particular stimulus. The expected behaviour is rewarded (positive reinforcement) or the behaviour to avoid is penalized (negative reinforcement). For example, in the "shuttle-box" the rodent has to learn to move from one part of the box to the other soon after a light flash has occurred in order to avoid an electric shock from the bottom of the part of the box where it is. Skinner extended his theory to human learning, arguing that positive reinforcement was a key mechanism in education. He also developed a theory about programmed teaching where children learn school contents by themselves, without any teacher intervention, with the help of a protocol support (Astolfi et al., 1978 p. 125).

Nowadays Skinner's radical behaviourism tends to be associated with negative values, emblematic of times when society was an authoritarian patriarchy. However, we should note that reinforcement in human education might not be sufficient, but still seems undisputedly effective.

The field of neuropsychology led to a further categorisation of learning, notably by studying brain areas and neuron connections involved in particular processes and requiring different kinds of memories (from human or animal models). Procedural memory (that deals with the ability to implement particular tasks, for instance, riding a bicycle) has the particularity of being "overconceptual", i.e. people are unable to explain how they did learn or how they performed the task (Vignaux, 1991 p. 205). "Simple learning" (non-associative) can give rise to sensitization or habituation, depending on whether the response increases or decreases with the repetition of a similar stimulus. "Observational learning", or imitation, is considered to be a predominant and ancestral way of human learning. The astonishing recent discovery of mirror neurons, which are activated when one performs a given task or looks at someone who is performing it, suggests that these biological structures play an important role in imitation. However, this is controversial (Dinstein, Thomas, Behrmann, & Heeger, 2008).

Beside these biological approaches, which also fall under the Cartesiano-positivist framework, the Swiss biologist and psychologist Piaget brought a conceptual revolution in the way he modelled learning. Contrary to the behaviourists, he tried to model what happens in the "black-box" and, moreover, he proposed a radically different paradigm to conceptualise learning, as we will explain in the next chapter. To be able to understand this epistemological shift, let us first briefly outline the now common Cartesiano-positivist epistemologies. According to Le Moigne (1931 –), they are based on two related hypotheses that concern the nature of knowledge: i) an ontological hypothesis, which postulates the existence of a reality per se, external to the subject and pre-existing to his learning activity (Le Moigne, 1995 p. 21) and ii) a determinist hypothesis, in relation to this external reality (Le Moigne, 1995 p. 24). The assertion that some domains of reality are not amenable to any deterministic description is also considered a form of determinism – and even chaos is now determinist (Le Moigne, 1995 p. 24). Popper (1902 – 1994) tried to go beyond this notion in *The Open Universe: An Argument for Indeterminism* (1982), but still resorts to an ontological reality (Le Moigne, 1995 p. 26). The knowable reality would have a proper rationale and this rationale would not necessarily depend on observational determinations.

Chapter 2: In the Light of the Constructivist Epistemologies

Piaget defined *epistemology* broadly « in first approximation, as the study of valid knowledge constitution", thus grouping common and scientific knowledge. Let us describe the counterparts to the hypotheses of the Cartesiano-positivist epistemologies. i) The phenomenological hypothesis posits, as Piaget wrote, "the inseparability between the act to know an 'object' and the act to know the 'self'" (Le Moigne, 1995 p. 75). Thus the knowable reality is phenomenological, and it is what the subject experiments. This means that knowledge is at the same time a building process and the result of this process. The learning process is no longer understood as a duality between the knowing subject and the environment, but as a co-construction of both poles of the interaction. ii) The teleological hypothesis underlines the project, the intentionality that underlies any act of knowing (Le Moigne, p.79).

Piaget opposed the methodological postulate of the behaviourists and advocated that non-observable phenomena have to be modelled. He was not interested in individual subjects, but in an epistemic subject "modelled as all the mechanisms common to all subjects of a same level" (Astolfi et al., 1978 p. 133). He made numerous observations on his own children. Thanks to repeated contacts with the environment, a child develops elementary units of intellectual activity, which Piaget called « schemes ». Schemes exhibit a circular causality between an action in the environment and its perception. They can evolve through assimilation (of a novel object to a pre-existing scheme) and accommodation (of a modified pre-existing scheme to a novel object). Conflicts provoked by distortion between representation and perception play a motor role in learning. This theory falls in the realm of structuralism because learning is defined as the reorganisation of pre-existing knowledge (Foulin & Mouchon, 1998 p. 13). To Piaget, this "genetic epistemology" rests on logic (Astolfi et al., 1978 p. 135). In his work *Traité de Logique* (1949), he represents the main conceptual thought processes in the form of symbolic operations, formalised as an algebraic calculation, from the simplest tasks of comparison and ranking to elaborated abstract constructions (Astolfi et al., 1978 p. 136).

The theory of self-organizing systems, which draws from several scientific disciplines (logic, cybernetic, biology, anthropology…), shares common points with Piaget's theory. Both consider the learning system as an open system able to modify the laws that keep it operational and its responses, through interactions with its environment (Astolfi et al., 1978 p. 132). Those theories focus on the scale of the subject (or the learning system), modelled only in his cognitive dimension, and neglecting the roles of symbol manipulation and of social influences (Foulin & Mouchon, 1998 p. 18).

The socio-constructivism of the Russian Vygotsky (1896-1934) was exposed in his major work *Thought and Language* (1934). Whereas Piaget considered mostly intra-individual processes through 2 poles "learning subject"-"object", to Vygotsky, learning is fundamentally a movement from inter-individual to intra-individual processes (3 poles: alter-subject-object, Foulin & Mouchon, 1998 p. 35). Learning thus consists in the intra-individual reconstruction of tools that have been deposited by others in the underlying culture, with language as the most important of all. Vygotsky insists on the fact that people mostly do not learn alone, but need educators.

Education science has promoted a synthesis of these aspects (Doise & Mugny, 1997). The notions of socio-cognitive conflict, of problem based learning and of peer regulation are supposed to guide the implementation of a socio-constructivist way of teaching (Prince, 2004).

Let us go now a little bit further. To Grize (1984), "natural logics" correspond to circular cognitive processes known as "means-ends analysis" (Le Moigne, 1995 p. 89): means give rise to intermediate finalities, which suggest novel means, which evoke other possible ends. The modalities of dialogical reasoning guide the consultation of anterior experiences that constitute a pool of plausible heuristics, selected with the help of a "feasibility" criterion (Le Moigne, 1995 p. 89). Those heuristics do sometimes have a lot in common with what

Aristotle called “abduction” (but they are not constrained by a demand of formal truth, as advocated by Pierce, Le Moigne, 1995 p. 89). They can also resort on techniques that play with shape and meaning such as word plays, metaphors and schematisation (Perelman, & Olbrechts-Tyteca, 1970). So the natural logics that underlie the human construction of knowledge and learning are always associated with imagination, poetry, emotions… and proceed through somehow obscure ways. But in cognitive sciences, the computational metaphor has had a strong (and practical) influence on the way human learning is conceptualized. Piaget himself, as we have seen, cast his theory in a formal language. Le Moigne (1995) suggests a slight paradigm shift that we think is of prime significance (p. 80). This shift is prompted by the consideration of the teleological hypothesis, which according to Le Moigne, raises difficulties (Le Moigne, 1995 p. 80). “The meditation of the object by the subject always the takes form of a project”, writes Bachelard (1934). Albeit issued from cybernetics, the concept of teleology does not seem to be amenable to a full formal reduction. Is there a cognitive model that captures the notions of will, of motivation, of drive to achieve a goal?

All theories that we have presented until now have in common that they focus on the “cognitive”[2] dimension, which learning and intelligence have long been subordinated to. Piaget explicitly and intentionally excluded the affective dimension; his epistemic subject is ideally motivated. This model does not explain learning failure or difficulty. One learns with one’s “intelligence” (pre-existing schemes) and with one’s emotions. Even in the context of traditional learning, such as a scientific course at school, there is no doubt that “emotional features” – referred to as *affects* in psychology – play an important role. To dare learn something it is essential to feel secure and not be afraid of failure, error or “mistake” (a term which often has a moral connotation), it is essential to be self-confident (Favre, 2007). But more is needed: learning stems from an impulse, an envy, an aim, what in psychology is called a *motivation*. Affects and motivation are psychological concepts that would help give support to the teleological hypothesis proposed by Le Moigne. They can be considered as motors or brakes, depending on the situation. They depend on our personal history: our ontological development relying on past interactions (not only with other human beings). They correspond to our internal physiological state and reactions (hormonal, cardiac…) when we face a particular situation, and to the associated feelings (pleasure, pain…). In the central nervous system, neural circuits involved in processing this “affective information” are also those that process the “cognitive information”; both dimensions are biologically integrated in learning (Favre, 2006). Affects and motivational factors are difficult to express with words, they are not easily conceptualized, nor formalised with logico-mathematical operations. They seem diffuse and sometimes are overwhelming as we do not have full control over them. In western culture, they are traditionally neither analyzed nor harnessed, contrary to the teachings of oriental culture (through meditation for instance). Research in science education has shown that language can contribute to regulating emotions (Favre, 2007). Transforming emotions into an object of learning is an introspection process that can be called metacognition (Bell, 1991) and that can give rise to valuable skills. These ideas prompted the distinction between several forms of intelligence, such as the intrapersonal and the interpersonal forms of Gardner (1984) and as the emotional form of Goleman (1997), which correspond to being skilful at managing emotions.

Conclusion

The last point is to us a key aspect of an education system that recognizes the complexity of human nature. Emotion management is a tool that, if no better than « traditional knowledge », seems necessary at least "not to be only a gladiator in the arena". The factors that are typically human (as opposed to machines), motivation and affects, have until now been marginalised in our occidental approach and scientific decoding to learning, and are outside the realm of machine learning. The pleasure to learn is an important motivation, but unfortunately school enforces the view that learning is a very serious activity, seldom a game. The last two remarks allow us to make a point that we will later seriously address. Knowledge is a status acknowledged with values (this is the axiological dimension of knowledge). Notably, in western society, scientific, conceptual, academic *etc*. knowledge has a privileged status, that is denied to other forms of knowledge (Fourez, 2002 pp. 115-117); it is considered a better reference and more valid generally. It is widely recognised as "useful", "good" and "beautiful", and associated conception qualifications to these values are "objective", "realistic", "universal" and "issued from reason" (Hagège, 2007). This legitimation of the scientific knowledge originates from the Cartesiano-positivism ambient epistemologies and often gives rise to scientism and technocratism (Le Moigne, 1995 p. 23).

Every sort of human activity would be subsumed by some kind of project, which relies on values. A major point of constructivism is indeed that one cannot separate any knowledge, conception, object… from the human project whose construction has been shaped, individually or socio-historically, by them (Fourez, 2002 p. 37). The "object" of learning[3], once assimilated, is part of the learner and thus contributes to constitute his self. Thus, during learning, the identity of the learner is at stake. In fact, if one follows the phenomenological reasoning right to its end and assumes that no form of reality precedes learning and has an existence per se, then the same position should be adopted for the learning subject who is co-constructed through the learning process. Thus we are sent back to our preliminary considerations, and claim that what is fundamentally at stake, while learning, is learning to be one human self. We have come full circle.

Learning of Nature

At first sight, scientific knowledge seems to be a particularly efficient way to learn about nature. In this part, we will briefly review some prominent theories that aim at explaining scientific discoveries, and also discuss, as we have begun already, the link between learning through scientific discovery and general learning.

A Little Allegory of the Scientific Understanding of Scientific Processes

As has been recalled, Piaget proposed an extensive definition of epistemology, but this term is also used in a narrower sense; it designates the study of science at work. Thus we will here distinguish between “common knowledge” and “scientific knowledge”, since science is usually considered to be the (only) enterprise devoted to building valid knowledge. We already evoked positivism and its normative approach to science inherited from the Cartesian occidental philosophy. “Normative” means that the theory is focused on “how science should be.” This movement advocated an empirical method based on a principle of verification. Popper was among the first to advocate a descriptive approach to science (Lecourt, 2001 p. 73). I.e., he was mainly interested in “how science really is.” He based his reflection on the study of history of physical sciences. If an experiment validates a hypothesis, it just indicates that the latter offers a satisfying model for interpreting reality, relatively to the context of the experiment. Such a model is not the only possible one and cannot be tested in all possible contexts. Thus it may one day happen that some aspects of the model will be refuted in another context (Chalmers, 1976 p. 74). This refutation is the only genuine proof that one can hope for. The decision of whether or not a hypothesis or a theory should be adopted or promoted is regulated by the scientific community. This falsifiability theory has been a big revolution in epistemology and will provide a foundation to our implementation of machine learning paradigms. First the current body of scientific knowledge is no longer viewed as a repository of definite truths, but as a set of tools to solve problems. Second, objectivity in science is no longer a property that emanates from nature or natural objects, which scientists just have to discover (literally “to remove the cover that was hiding them”) but it has become an intersubjective construct. Scientific objects do not pre-exist in nature; so one cannot separate which part of the construction comes from humans, and which part comes from nature or reality (Fourez, 2002 pp. 175-177, 254).

Popper’s student Lakatos (1922 – 1974) proposed a more refined theory after applying Poppers’ theory to the history of mathematics (1976). One can consider that he refuted his master’s theory. He proposed to reconstruct scientific history *a posteriori*, by only considering how scientific ideas evolve, a method related to the internalist approach in history of sciences – this point will oppose him to Kuhn's approach. To him, hypotheses or theories are not independent from each other, which implies that the refutation process is not so simple: some theories are more important than others; they constitute the hard core of a research program on which all the rest is based[4] (Chalmers, 1976 p. 135). Thus they will not be easily refuted. A so called "protective belt" of auxiliary hypotheses preserves them. If those hypotheses are changed, the program can still progress. So if a counterexample arises, *ad hoc* hypotheses will be created and put in the protective belt to protect the core hypotheses. Scientific theories are seen as embedded into structures and research programs are either progressive (enriching the hard core) or degenerative (only creating *ad hoc* hypotheses). This conception changed the previous linear conception (progress through conjectures and refutation) into a vision where both parameters – theories and relations between theories – are taken into account to explain rational advancement in science.

Kuhn (1922 – 1994) studied history of physics and added another dimension to the model of scientific progress: the social dimension (1962). To him, rational considerations only are not sufficient to understand scientific evolution. There are also non-rational factors like confidence or faith in a theory that explain why people trust a theory more than another one. Moreover, "normal science" is hosted in a paradigm (Chalmers, 1976 p. 151). A paradigm is a disciplinary matrix that comprises theories, legitimated questions and panels of admissible responses but also cultural traditions of what is considered a valid method to conduct a proof, that changes over time. For example in molecular biology, in the 70's, one had to do *in vitro* experiments to demonstrate a molecular mechanism – *i.e.*, to purify, isolate components and make them react in a tube. Today this sort of proof is considered accessory, and one needs an *in vivo* argument to convince one's peers (Hagège, 2004). Kuhn emphasized that extraordinary events sometimes happen: a crisis, followed by a paradigmatic revolution, as occurred for the transition between Newtonian and Einsteinian physics. He pointed out that both paradigms, which correspond to non-reconcilable visions of the world, are incommensurable; to judge the validity, the quality or the efficiency of a paradigm, one needs tools that are part of the paradigm. Thus, there is no external tool thanks to which one could rationally (or "absolutely") compare which paradigm would be best.

The study of science has then been enriched with other dimensions, including anthropological and psychological dimensions. For the last thirty years, science has witnessed a major overhaul, becoming a techno-sciences system, encompassing studies about its very nature. The so called "science studies" bring various pictures of scientific dynamics (Pestre, 2006 p. 5). The object called "science" appears to be a protean process and all general assertions about science that we have evoked now seem insufficient, sometimes meaningless. Meaning can only be found in a particular context, at a particular epoch, concerning some singular actors and could be constructed over and over again, depending on our cultural reading (Pestre, 2006 p.7). Those science studies conclude that there is no tangible criterion that demarcates science from other human activities, no proper method that would be intrinsic to the scientific activity. If one wants to characterise the scientific activity, one should study what has been called "science" at a given time, in a given context. Science does not have any substance, any essence, does not exist per se; its meaning is constructed by its actors and by those who relate to it, making it to their own image, given their projects and the way they construct themselves. We can here recognise an important feature of constructivist epistemologies, which naturally embrace the ethical considerations that we will evoke later on. Let us first note that the fact that science lacks essence puts the Cartesiano-positivist institutional epistemologies into question, as the privileged status of science in the western countries is precisely grounded in the tacit acceptance of a universal proof administration mode, of a proper and undoubted optimal method.

Conclusion 1: Nature of Learning and Learning of Nature

The foundations of constructivism that Le Moigne (1995) proposes can be apprehended intellectually but do not seem easy to instantiate in our everyday acts and thinking, particularly the phenomenological hypothesis. Indeed, those with a western background tend to think on the basis of a duality principle (that opposes the self -- a thinking self (*cogito ergo sum*)-- to the rest of the world) which are kept well distinct[6]). But is it possible to know without separating[7]? Arguably, this is possible in cultures (see e.g. Scheurmann, 1920 pp. 115-124) that seek a unifying knowledge, not dependent on language and concepts, a form of omniscience as Buddhists attribute to the historical Shakyamuni Buddha (David-Néel, 1977 pp. 240-242).

To Le Moigne (1995), Popper and Kuhn fall under the Cartesiano-positivist epistemologies because of their subscription to the ontological and determinist hypothesis (p. 15). Fundamentally, he blames them for not applying to their own discourse what they apply to others' (p. 14). We notice, in their defence, that such a circular demand rapidly makes head spin, because of the duality principle from which one cannot really escape – except maybe Buddha. Our natural cultural propensity is to place ourselves outside of discourse or of the "observed reality". and to look at reality and apprehend it "from the outside". Yet other authors qualified Kuhn as a constructivist (Strike, & Posner, 1992) and Popper, because of his clear move from logical positivism, could also be considered as one. Kuhn's and Piaget's conceptions of knowledge construction are indeed comparable – at two different scales, either the scientific community or the individual – with respect to both following features. First, knowledge does not increase through a linear accumulation of "units of information", but consists in a qualitative reorganization of the initial knowledge structure (Lonka, Joram, & Brysin, 1996; Strike, & Posner, 1992). Second, every knowledge depends on a knowing subject (Fourez et al., 1997), so it is subjective by nature. Thus, opinions, points of views and beliefs all belong to science and learning (Bachelard, 1971; Kuhn, 1962). Knowledge then appears to be no dissociable from its sociological, historical and psychological dimensions and therefore its status can only be approximate and provisional. We can add a third common feature to the various facets of socio-constructivism (cf. Vygotsky and Kuhn), namely, the fundamental regulatory role that the community places on learning.

Conclusion 2: Implications for Learning of Nature in the Classroom

Scientific knowledge is often presented as having an intrinsic value, independent of human history and of any context. In fact, science teachers and students do not spontaneously make theirs the conceptions of constructivist science (Boulton-Lewis, Smith, McCrindle, Burnett, & Campbell, 2001; Lemberger, Hewson, & Park, 1999; Waeytens, Lens, & Vandenberghe, 2002). For instance, to future biology teachers, knowledge is an “external truth that can be discovered through observation, discussion, sense-making” and also “a collection of additive facts” (Lemberger et al., 1999). In that sense, experiment can play the role of a supreme referee to verify theories. This naive, positivist labelled epistemology also comes with a realist view, according to which the world is intimately knowledgeable, so that scientific knowledge is all about truth: the world as it is. Experiments are thus presented as proving something absolute and sciences as composed of accumulated knowledge (or facts) that have a stable and universal interpretation. Moreover, teachers often hope that students will be able to rediscover these truths by themselves and will be convinced of their truthfulness by the strength of evidence they contain. In addition, students should acquire a universal scientific method, even though epistemologists agree that no such method exists.

To solve these issues, science education studies suggested that science should be taught in a way that would allow students to gain knowledge they would master a tool that can be usefully applied to one of their own projects (Fourez, 2002 pp. 84-85). That is why Problem Based Learning (PBL) appeared as more efficient than traditional magisterial teaching (Vernon, & Blake, 1993). PBL is mostly practiced in small groups and the teacher only plays the role of an accompanist, and not of a “Nature representative who knows how the world is made” as in traditional courses. These assumptions have several important implications, which we will not discuss here, particularly concerning the attitude of a constructivist teacher and the coherent modalities of evaluation he or she should implement.

Altogether, this presentation implies that it is of utmost importance to form people, notably teachers, to epistemology. For the sake of coherence and efficiency, this can be done neither in a magisterial nor in a dogmatic way. In the next section, we emphasise that the evolution we mentioned has also started to affect machine learning paradigms, and we will present an attempt to bring this evolution one step further. The implementation we propose can serve as a basis for a game that can be taken seriously and fulfils our expectations.

HUMAN AND MACHINE ASSOCIATED LEARNING OF NATURE

Since the inception of artificial intelligence, researchers have aimed at endowing machines with learning and problem solving abilities. “Computational scientific discovery” became an active field of research when machine learning techniques started showing conclusive results in the late 70’s. These results motivated the simulation of historical discoveries (Lenat, 1983; Langley, Bradshaw, & Simon, 1981; Langley, Simon, & Zytkow, 1987), and since the beginning of the 21st century, research in this domain has been oriented toward the discovery of unknown rules (Simon, Valdés-Pérez, & Sleeman, 1997). Our main contribution is to define an interaction protocol encompassing both human and machine learning, resulting in a formal foundation for discovery platforms: the machine learns at the same time as the user, and this co-learning leads to a pertinent understanding of the problem and a pertinent modelling of the processes of simulation and prediction. A complete presentation of this work can be found elsewhere (Dartnell, Martin, & Sallantin, 2008; Dartnell, 2008), and we will succinctly synthesise its key aspects in relation to the philosophical, psychological, and didactical considerations discussed in the first part of the present paper.

Since machine learning and problem solving are often associated in literature, for the sake of clarity we will use the term *solver* to refer to an *artificial learner*. Many machine learning methods have been developed, such as neural networks (Haykin, 1998), genetic algorithms, Bayesian networks (Heckerman, Geiger, & Chickering, 1995) or symbolic learning with Galois lattices (Liquière, & Sallantin, 1998) and our point is not so much to discuss their relevance or efficiency than to show the limits of the paradigms to which they correspond in the light of the previous discussion.

The principles of nominalization and reducibility are essential to give a problem solver the ability to adapt. Nominalization is the ability to build an abstraction of an observed phenomenon and reducibility is the ability to instantiate these abstract and symbolic concepts in a concrete way, by the means of action or experimentation.

Therefore, interaction between the solver and its environment are *sine qua non* conditions of its evolution: by comparing the results of theoretical computations and the results of its interactions with the environment, the solver is able to detect contradictions between "reality" and the formulated theories.

The use of contradictions as a dialectic engine and the revision of a theory imply logical pre-requisites that we will not discuss here. However, these questions correspond to the modelling of logic programs as proposed by Lakatos: how does a logical system deal with contradictions and how could a protective belt be formalized and implemented? (Dartnell, Martin, Hagège et al., 2008) proposed to explore the paths of paraconsistent, deontic, and defeasible logics.

We now focus on the main existing machine learning paradigms and outline their evolution, which can be put into correspondence with the evolution of the conceptions on with human learning, as will be highlighted.

A Little Allegory of Learning from Each Other

Several learning paradigms have been proposed to provide frameworks of study and tools of analysis that can qualify and quantify the learning process. Among those, we can cite "identification in the limit" (Gold, 1967), "query learning" (Angluin, 1988), and "PAC-learning" ("Probably Approximately Correct-learning", Valiant, 1984) as having a strong impact on the machine learning community. Each of them proposes a different form of reality, a different form of interaction between the learner and the environment, and different criteria of successful learning. One of the main evolutions concerns the role played by the learner during the learning process, which has evolved from a passive role to a more active one.

We illustrate these differences on several variations of the card game that was used in the experimentations related thereafter. We advocate that the last version is suitable for both human and machine learning and opens a gate to a human-machine collaborative learning/discovery platform.

We first present identification in the limit, which defines an infinite and passive process. Then we present how the use of queries transforms a passive learner into an active one. We do not present *PAC*-learning here since it deals with finite notions whereas we are interested in infinite processes and infinite representations of reality.

Passive learning

To illustrate the problem of identification in the limit, let us use a simple card game between two players. One of them, the game master, chooses an infinite sequence of cards such that any card can be referred to by its position in the sequence. Suppose the second player, the solver, has a vocabulary $\mathcal{V}$ allowing him to describe exactly any card at any position, for example $\mathcal{V}$ = *{ace, two, . . . , jack, queen, king}* $\cup$ *{hearts,* *diamonds, clubs, spades}*, with the usual ordering on the natural numbers. At each step, the game master reveals the next card in the sequence so that the learner discovers them one by one. For instance, "*queen(0), hearts(0), ace(1), spades(1), queen(2), hearts(2), ace(3), spades(3), ...*". After discovering each card, the solver expresses a conjecture, under the form of a logical program that *exactly* describes a *unique infinite* sequence of cards. The identification process is considered successful if after no more than a finite number of steps, the solver converges toward a correct conjecture, *i.e.*, if it changes its mind a finite number of times or none at all.

Every conjecture is then refutable in the limit, as each new card might invalidate the solver's current conjecture. On the other hand, at no step in the game can the solver have a proof that its current conjecture is correct. Moreover, the refutation might occur after a very long time and the solver has no option but passively observe the cards as they are presented to it. We now present how the use of queries can open the gate to active learning and the definition of search strategies.

Active learning

We illustrated passive learning with a game in which a solver has to exactly identify a univocal program, that is, a logic program describing a unique infinite sequence, which is revealed to him one card after the other. We shall now illustrate active learning with a classification game, in which the solver has to exactly identify an equivocal program: a logic program describing a possibly infinite set of infinite sequences, that is, a set of infinite sequences sharing certain properties, by querying an oracle to test his hypothesis.

Let $\mathcal{W}$ be the set of all infinite sequences, let P_{target} be an equivocal logic program describing a set $\mathcal{W}_{target} \subseteq \mathcal{W}$, and let $\mathcal{H}$ be a possibly infinite set of equivocal programs representing the solver's hypothesis set.

At each step, the solver is allowed to query an oracle using one of the types of queries introduced and studied in (Angluin, 1988, 2004):

– Membership: the input is a possible game $\mathcal{X} \in \mathcal{W}$, and the answer is true if $\mathcal{X} \in \mathcal{W}_{target}$, or false if $\mathcal{X}$ is a counterexample.

– Equivalence: the input is a set $\mathcal{W}_H \subseteq \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_H \equiv \mathcal{W}_{target}$, or a counterexample $\mathcal{X}$ such that $\mathcal{X} \in \mathcal{W}_H \, \Delta \, \mathcal{W}_{target}$ otherwise.

– Subset: the input is a set $\mathcal{W}_H \subseteq \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_H \subseteq \mathcal{W}_{target}$ or a counterexample $\mathcal{X} \in \mathcal{W}_H - \mathcal{W}_{target}$ otherwise.

– Superset: the input is a set $\mathcal{W}_H \in \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_H \supseteq \mathcal{W}_{target}$, or a counterexample $\mathcal{X} \in \mathcal{W}_{target} - \mathcal{W}_H$ otherwise.

The classification is said to be successful if after a finite number of queries and experiments, the solver converges toward a program $\mathcal{P}_H \in \mathcal{H}$ such that $\mathcal{P}_H \equiv \mathcal{P}_{target}$. This evolution of machine learning paradigms can be put in parallel with the notions of classical conditioning, in which the learner does not have any initiative (passive), and operant conditioning in which it initiates the stimulus (active).

Beside this, we could consider that the oracle plays the role of nature in a “Cartesiano-positivist world” in which nature is a perfect referee. The existence of an omniscient oracle, able to answer the solver’s queries, could therefore be seen as “reality’s resistance to experiment” and the learner as a purely rational observer.

The following variation, which we developed for our experiments, illustrates how to partly get rid of this limit by introducing pairs as imperfect oracles.

Social learning

As we mentioned earlier, an important trend in epistemology is to consider that learning proceeds through social interactions and we include this important aspect in our game. Inspired by multi-agent systems and game theory (Chavalarias, 1997), we propose to distribute the resolution of equivalence queries on a community of solvers confronted to the judgment of other solvers. Each of them can then publish his or her conjectures and refute existing ones according to a Popperian conception of science. We now drop the term “solver” and switch back to using the term “learner” to emphasise that this transposition of science to machine learning paradigms is, albeit simple, suited to both human and machine learning. It implies individual exploration and learning, social evaluation and institutional accreditation.

We symbolize the product of the social interaction by a gain function. By attributing or deducing points for each query, depending on the answer (refuted or not), we can create competitive or collaborative environment between multiple learners. This prompts for publications to score points and experimentations to corroborate or refute a published theory. The gain function motivates the learners to try and search for counterexamples and ensure that publications will either remain as consensual references and gain credit, or be refuted in the limit.

Implementation of the last variation

This distributed learning protocol was developed using the multi-agent system *Madkit* (Gutknecht, & Ferber, 1997), which implements the formalism *AGR* (Ferber, & Gutknecht, 1998). The resulting platform takes the form of a card game: *Eleusis+Nobel*[5] (Dartnell, & Sallantin, 2005). Each learner is an agent, *Learner*, and belongs to a scientific community sharing a set of problems. These problems are implemented as equivocal programs describing sets of infinite card sequences such as “alternation of black and red cards” for instance. An agent “Problem” is created to simulate each problem and can be accessed to validate finite card sequences. Membership queries are co-semi-decidable since they are defined on infinite sequences, but these restrictions to finite sequences are decidable and simulate experimentations. Dedicated messages corresponding to experimentation, publication and refutation have been defined as speech acts. “Experimentation” messages are synchronized (the sender waits for the answer) and sent directly to the agent in charge of simulating experimentations for the chosen problem. The sender receives the answer “yes” or “no” and the result is displayed as shown on Figure 3. The sequences are built by adding new cards to the existing sequence. Correct cards are displayed at the requested position, circled in green, whereas wrong cards are displayed under the main sequence, and circled in red. This part of the protocol is private, which ensures that each learner has his or her own private experimentation background.

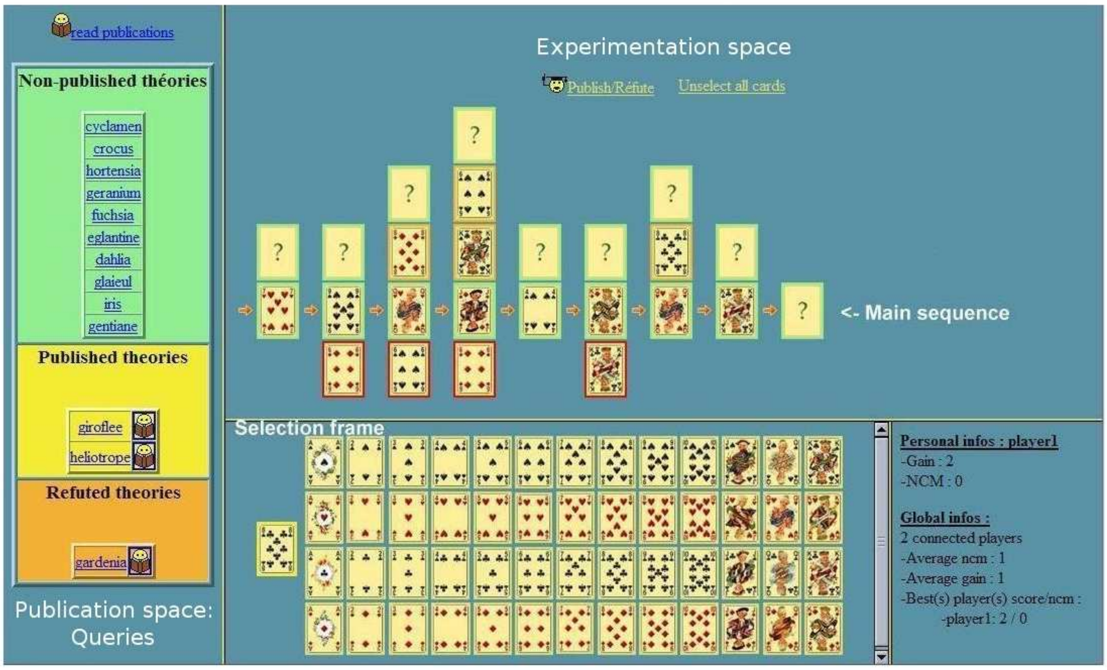

Figure 1 Eleusis + Nobel's Web Display

After considering the risk associated with the publication of their conjectures, learners can send a “Publication” message to the community. Since this kind of query is co-semi-decidable, publication messages are unsynchronized. Each learner receives this public query and can send a refutation message containing a counterexample selected in his or her own experimentation panel. The agents in charge of simulating experimentations simply react to these queries by switching role to *Published* or *Refuted* so that the state of the art is always visible.

Learning Impact of the Game

The first experimentations were designed to quantify the impact of distributing queries among players. The second one, more meticulous, aimed at qualifying the epistemological impact of Eleusis+Nobel. Both of them shared the same set of 33 hidden rules, and the gain function was defined as follows: publishing was rewarded with $P = 1$ point, and refuting (respectively, being refuted) was rewarded (sanctioned) by a gain (a loss) of $R = 2$ points. Subset and superset queries were not implemented in this version of the game.

We wanted to study the impact of the game on students who aspire to become science teachers. Success, to us, would mean that they acquire a vision of science which can be qualified as constructivist. As we already mentioned, several psychosociological studies already showed that pre-service teachers spontaneously make them a positivist and realistic vision of science (Boulton-Lewis et al., 2001; Lemberger et al., 1999; Waeytens et al., 2002). As reported elsewhere (Hagège, Dartnell, & Sallantin, 2007), we used psychometric tools (answer sheets) to evaluate how science conceptions evolve by querying third year university biology students who aim at becoming teachers. We used “negative controls”, in the form of a set of students from the same group who did not play to the game, but who also fulfilled the pre-test and the post-test. In contrast, the “players” played Eleusis+Nobel during two hours between the pre-test and the post-test.

We evaluated several aspects related to constructivism. The aspect that has been recurrently and significantly changed concerns the role of subjectivity in the scientific process. As all observed changes of answers did not focus on themes that were explicitly dealt with in the game, but were just practiced, we inferred that this constructivist conception had been subconsciously assimilated, in the Piagetian sense.

Moreover, open questions in the post-test addressed feelings during play. Answers vastly differed: either players liked it much, or they got “very frustrated because of cheats”. This highlights what we also observed during the game: they really got involved into it. Previous experiments with 13 or 20-year-old pupils lead to the same conclusion. When time was over, a majority was disappointed and wanted to continue (that rarely happens with a traditional course!). Altogether, this indicates that Eleusis+Nobel game can constitute a very interesting complementary tool to teach epistemology.

Extensions on Machine Learning

As we mentioned in the previous section, both the traditionalist and the constructivist teaching and learning conceptions can be opposed (Chan, & Elliott, 2004). In the first conception, teaching is considered as a non problematic transfer of untransformed knowledge from an expert to a novice. Learning thus corresponds to absorbing such knowledge. At the other end, learning is the creation and acquisition of knowledge through reasoning and justification. Teaching facilitates learning, and does not consist in knowledge transmission.

The formal learning models presented earlier can be described as the transmission from a teacher to a learner of a program that represents the target concept, either directly or indirectly through examples or queries. Extensions in machine learning, based on the previous cognitive considerations, explore the case where this transmission is impossible. Human learning involves complex agents, who are all different and unique, have limited modelling abilities and have an incomplete knowledge of themselves. Such constraints, which evoke the introduction of *limited rationality* by Simon in economics theory, lead to a change of paradigm since simulation becomes out of reach for agents ignoring the way they operate.

These constraints are clearly illustrated by Angluin (2003) with the example of juggling, for which anyone knowing how to juggle can play the role of a valid teacher (or model) for the learner. However, this learner can learn by imitation, without knowing the involved process, resorting to procedural memory (see "Nature of learning"). In contrast to formal learning models that give the learner the capacity to simulate, Angluin and Krikis (2003) propose to take into account and formalize the fundamental differences between agents and how difficult it is to each of them to achieve a given task.

Conclusion

Machine learning paradigms have evolved from passive learning to active learning. We selected identification in the limit and learning with queries as the most suited ones in the context of scientific discovery, and we used them to formalize the problem of scientific discovery. In this context, conceptions of reality are infinite and as an oracle has to be part of the equation, answering queries is unrealistic, as the oracle needs to be endowed with capabilities that go beyond the power of a universal Turing machine. We proposed to distribute the resolution of queries in a social game of publication and refutation, and we evaluated *Eleusis+Nobel*, an implementation of our protocol, on a human community. This experiment highlighted two important features:

– the protocol is suitable for human learning, since the community was able to find a consensus concerning a set of thirty-three more or less difficult rules in a reasonable time (two hours).

– the protocol is appropriate to teach constructivist conceptions to students, which means that the epistemic notions on which it is founded are acceptable and significant of how science is practiced "in reality." Moreover, conceptual changes occurred in a procedural manner, with potentially longer effects than the kind of learning that requires declarative memory.

Moreover, our natural conception choices of multi-agent systems led us to define an *AGR* model of interactive learning, and the abstraction level of the implementation allows one to adapt the current platform to other contexts than cards. These three points tend to indicate that this protocol is a good candidate to design interactive platforms for assisted science discovery, pedagogic tools, or other "science" games. Inspired by more cognitive considerations and related new work in machine learning, we proposed several extensions to this protocol, among which:

– the introduction of a complexity measure such as time, to introduce a heuristic and restrain co-semi-decidable membership queries to decidable complexity queries;
– the implementation of subset and superset queries to favour the interaction between learners and to favour an increased competition among theories, in a more Popperian conception of science.

GENERAL CONCLUSION

In this paper, we reviewed some models of human and machine learning. We also presented our own conception and our work on machine assisted science discovery for human researchers.

What Can We Expect, or Not, From Machine Assisted Human Learning?

Our conception of human learning is that of a complex process, which cannot be fully understood. The scientific procedures which aim at dissecting "reality" consist in a reductionist approach that makes us separate entities that are essentially linked together (for instance subject/environment or self/reality as it is, knowledge/affects, human/machine…). Thus, the product of our analytic mind, as learning machines, would never be as complex as their designers. What takes the role of "reality" for the machine is determined and digitalized by the initial input, with separate objects and an associated language to describe them. "The machine simulates the bias of the programmer".

Nevertheless, we can stress some advantages of assistant machines over human tutors. An important advantage concerns the affective dimension of learning. The machine, devoid of value judgment, constitutes an impartial interface, so that shy or aggressive people for instance probably would have fewer barriers to interact with a machine. Moreover, the superior computing abilities of a machine could be used as a tool to select and provide relevant information to the user. A protocol such as Eleusis+Nobel could automate the exploration, and help in sorting out and understanding the data via a unified interaction protocol between humans and machines. Machine learning is necessary to have access to the interests and the needs of a user in such a way that the latter does not need to program his assistant. One can imagine that if internet sites implement « Problem » agents corresponding to the information they intend to communicate, then the acquisition of this knowledge could be done via a learning game and no longer through lectures (a magisterial procedure).

What Do We Expect From Machine Assisted Human Learning?

The advent of intelligent machines in western societies changed our way of thinking, learning and communicating. We face a relationship to our human condition. We already suggested that what is fundamentally at stake in learning is to learn to be human. Integrating the constructivist principles, we update at every moment our definition of humankind and the definition of our individual and collective identities, through every one of our actions. We would claim that humanity does not have a proper existence or essence, but that we give a meaning to the notion of humanity every time we act. It is permanently reconstructed in the underlying co-constructed framework. Thus the question that would ideally guide each one of our actions – and *a fortiori* those of our actions that have important consequences – is: in which world do we want to live? What humanity do we want to defend? What do we want to do? How? And what for? This ethical and pragmatic questions call for an axiological one. What values are important to us? Do we want machines to reinforce competitiveness and individualism? Or do we want them to value equity and solidarity? Listening to Anselme (1989), in order to reinforce our ethical evolution (vs. our cosmologic evolution), we should choose actions that favor cooperation, and are open to others, and promote respect and responsibility. But the ethical process implies that it is up to everyone to choose his actions, in full consciousness, after having thought about the consequences in a discursive way (Simon, 1993 p. 172).

ENDNOTES

1. Note that Wiener, the father of cybernetics, was together with Skinner a member of the North American Institute for the unity of science. This highlights the links between the initial proposals to model animal and machine learning in terms of circulation of information, even if a theoretical rupture has taken place between Wiener's approach to teleological behaviour and Skinner's radical behaviourism, which keeps *intention* out of the model (Ségal, 2003 p. 183). We will consider later a reduction that is pragmatically

operated, even if not necessarily theoretically, by identifying "cognition" with a set of logico-mathematic operations, thus precisely denying the specificity of human learning as opposed to machine learning.

2. There are several acceptations of the term "cognitive". Here we take its meaning from psychology, where it is restrained to logico-mathematic operations, to reasoning on linguistic representations or to procedural acquisition… all "traditional 'objects'" of learning which lack any affective dimension. As we will emphasise later, though the "cognitive sciences" are supposed to consider all aspects of learning, their object is actually pragmatically reduced to the same unique dimension as in psychology (Vignaux, 1991 p. 13). The term "cognitive" designates the "form of 'representations' and of 'data processing'" (Vignaux, 1991 p. 198).
3. In accordance with a constructivist point of view, we consider that there is no "object" of learning that would exist per se, before a learning act, and that would be the same for several individuals. This notion of object is just a practical denotation that facilitates communication.
4. Note that others argue that some hypotheses or laws, such as the first principle of thermodynamics (energy of the universe is constant), are not falsifiable; one cannot go through it with the fine-tooth comb of experiment (Fourez, 2002 p. 71).
5. http://www.lirmm.fr/kayou/netoffice/eleusis/
6. To argue that this is a paramount problem – that only Buddhas could overcome? – it suffices to underline that i) believing that our vision of the world corresponds to the world as it is and ii) adjusting our acts on the basis of this belief is the cause of every war. This belief, this representation is associated with such a strong feeling about reality - from which it is so hard (or impossible?) to distant oneself – that some people are prompt to kill to defend it.
7. The idea that we want to advance here is that the primary duality consists in considering the self separated from the rest of the world. Moreover, we mostly act as if this separated self were permanent: as if we were, to ourselves, the most important person on earth. Then, by a mirror effect, as one sees the world as one's own image, one could know by dissecting reality, by "artificially" isolating objects and considering them i) permanent and ii) separated from each other. Yet "objects", such as "the self", are fundamentally impermanent and linked to "the rest of the world"; they do not have a proper existence.

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