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Human Discovery and Machine Learning

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Submission to IJCINI

This paper studies machine learning paradigms from the point of view of human cognition. Indeed, conceptions in both mahine learning and human learning evolved from a passive to an active conception of learning. Our objective is to provide an interaction protocol suited to both humans and machines, to enable assisting human discoveries by learning machines. We identify the limitations of common machine learning paradigms in the context of scientific discovery, and we propose an extension inspired by game theory and multi-agent systems. We present individual cognitive aspects of this protocol as well as social considerations, and we relate encouraging results concerning a game implementing it.

Introduction

The processes involved in scientific discovery such as acquiring knowledge and organizing it within general representations, the discovery of new facts and theories through observation and experimentation, can be seen as those of problem solving (P. Langley & Zytkow, 1987). Since the inception of artificial intelligence, researchers have aimed at endowing machines with such abilities. Computational scientific discovery became an active field of research when machine learning techniques started showing conclusive results in the late 70s. These results motivated the simulation of historical discoveries (Lenat, 1983), (Langley, Bradshaw, & Simon, 1981), (P. Langley & 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). (Langley, 1998) or (Langley, 2000) provide examples of such discoveries assisted by machines. Our work follows this line of research, but we place the user at the heart of the system, to build interactively with an adaptive problem solver an adequate description model of the studied phenomena : 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 modeling for simulation and prediction. During this interaction, the user acts in turn as a learner or as a teacher. However, instead of focusing on isolated problem solvers and their capabilities, our contribution lies in the definition of an interaction protocol encompassing both human and machine learning, resulting in a formal foundation for discovery platforms. We emphasize the fact that in machine learning as well as human learning, the role of the learner have evolved from a passive role to an active one.

In common machine learning formalizations, a learner can query an *oracle* to gather data concerning the target function to be learned. This is often unrealistic as the oracle usually needs to be endowed with capabilities that go beyond the power of a universal Turing machine. In the particular context of scientific discovery, where studied problems are not yet solved, no model or theory might be available, and a software assistant has to cope in this context with uncertainty, pattern discovery, interactive ontology building (Nobrega, Cerri, & Sallantin, 2003), etc. Moreover, to interact with a researcher, it is necessary to produce statements comprehensible to a human and emit scientific judgments about them.

This challenging objective implies a pluri-disciplinary approach involving logical and epistemic considerations, as well as machine learning theory and multi-agents systems. This paper attempts to synthesize our work in these domains. (Sallantin, Dartnell, & Afshar, 2006) described the minimal logical prerequisite to endow a problem solver with a pragmatic logic of scientific discovery in order to interact efficiently with a scientist. We will informally summarize these requirements in the first section. (Dartnell & Sallantin, 2005) reflected on machine learning paradigms that we will further develop to situate our protocol. An experimentation of this protocol, in collaboration with researchers in epistemology and didactic, produced results were reported in (Hagège, Dartnell, & Sallantin, 2007) and will also be synthesized to validate the relevance of our platform to human learning. We will finally explore new directions in machine learning, ba-

sed on cognitive aspects of the learner, to introduce time as a complexity measure and provide general heuristics to help eliminate conjectures during experimentation.

Logical Prerequisite for an Adaptive Problem Solver

Common definitions of a problem solver take into account the type of solvable problem which characterizes it, as a differential equation problem solver, or a nonlinear equation system solver : common problem solvers are designed to perform the computation of a known problem which has already been solved and modeled. So for any presented instantiation of a specific problem, the solver is able to tackle it and produce solutions. An adaptive and autonomous problem solver should be able to acquire new capabilities by learning how to solve new problems, and then use this knowledge and experience to find solutions. To solve a problem, one has to observe the problematic situation, analyze it,and build a language describing the situation and highlighting the dimensions which are pertinent for reasoning. These dimensions determine the definition domain of the variables characterizing the problem and influencing the computation of a solution. This language is used to formulate assumptions and hypotheses that have to be validated by experiments, and compare their results to theoretical computations. Experiments can reveal contradictions between theory and reality and therefore lead to a revision of the description model and to the formulation of new hypotheses. By analogy with the process of scientific discovery, where neither the *ontology* nor the *theory* are known *a-priori*, we define below the functionalities that an adaptive autonomous problem solver should be empowered with to define the process of discovery. It should be able to :

- build and maintain an *Ontology* of the domain. By *Ontology*, we mean a logical language relevant to observations describing the variables involved in the resolution of the problem. An Ontology emerges from the learning process.
- analyze and correlate gathered information and learn ontological statements to constrain the relations between the values of the problem's dimensions, *i.e.*, infer logical rules.
- discover, name, and symbolically use regularities of the analyzed data, and revise the ontology by introducing new dimensions to the problem's formulation. This ability to transform a property observed into a symbolic object and re-use it is called the *Nominalization* principle.
- formulate and express a *theory* to explain the problem and predict further results. By *theory*, we mean the computation rules of a problem's solutions.
- design experiments to test and (in)validate the formulated theories. This ability is called the *Reducibility* principle.

The principles of nominalization and reducibility are key to a problem solver's adaptability. Nominalization allows one to build an abstraction of the studied phenomena (we propose a logical formalization of the introduction of new concepts in (Dartnell & Martin, 2008)), and reducibility allows to instanciate these symbolic concepts in a concrete way, to design experiments and validate their relevance (Figure 2). 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.

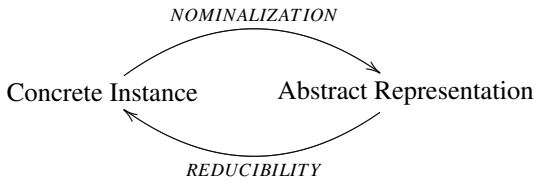

FIG. 2. Complementarity of Nominalization and Reducibility

The use of contradictions as a dialectic engine implies three requisites concerning the interactive problem solving process :

- a *Paraconsistence* allows one to reason in presence of contradictions and to maintain obligations.
- a *Deontic modalities* such as *Obligation*, *Forbiddance* and *Permission* allow one to organize past knowledge into norms.
- a *Defeasability* allows one to revise the model when new contradictory facts occur.

(Nakamatsu, Kato, & Suzuki, 2003) give an elegant example of paraconsistency based on a defeasible deontic logic : Deontic logic is used to localize contradictions and provoke a revision in the set of defeasible theories. Paraconsistency allows the solver to adapt the ontology to new facts and new observations and therefore to use incremental learning.

Machine learning with graphs and Galois lattice theory (Liquière, 1998), (Nobrega et al., 2003), for instance, can be used to find relevant logical implication and equivalence rules between the descriptors introduced by the user to describe the facts being observed (see Figure 1). These rules can be easily understood by the researcher since they are formulated in his own language.

Moreover, modalities can be used to type the products of this learning activity. (Sallantin et al., 2006) defines the set of modalities useful for the researcher and his assistant to exchange logical judgments all along the discovery process. This set, which is closed by negation since the negation of one of those modalities does not involve a new modality, is visually represented as a geometrical figure based on Aristotle's square of opposition. Moreover, the underlying logic is shown to be equivalent to the logic S_5.

In the following section, we discuss from the point of view of machine learning the interaction protocol needed to enable the dialectical management of contradictions.

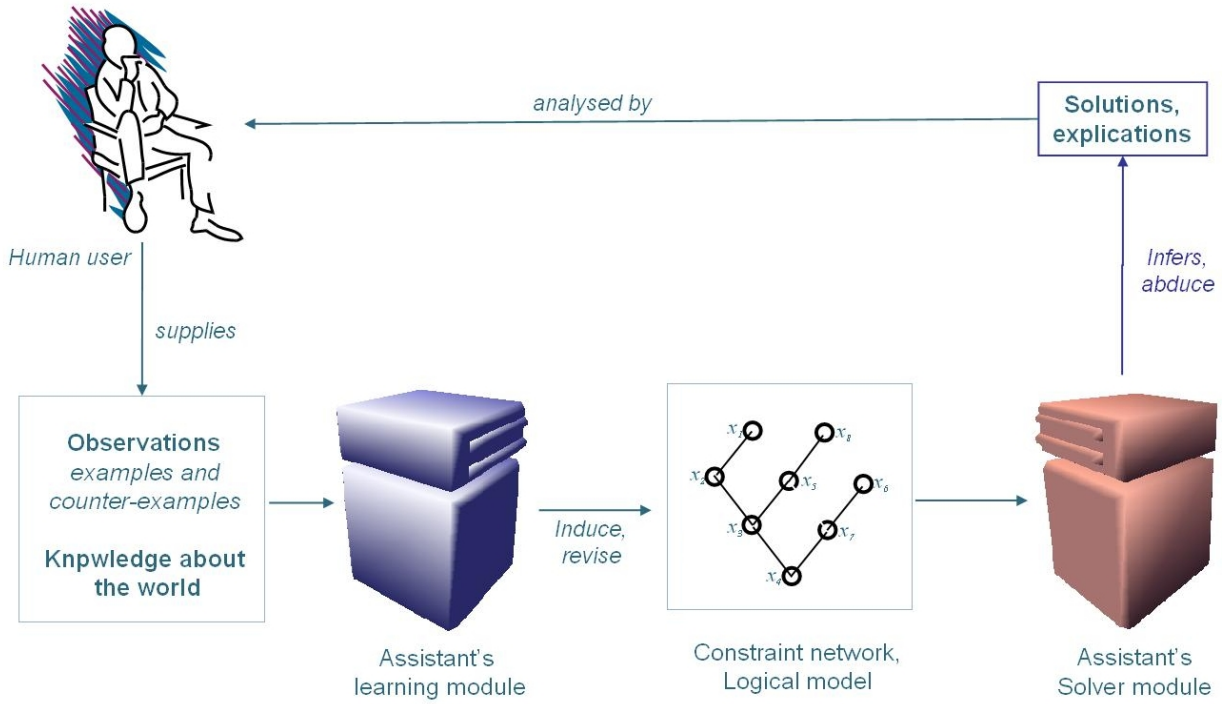

FIG. *1*. Human-Machine interaction cycle

A Social Learning Protocol

The formalization needed to fully present this topic is currently under publication (Dartnell & Martin, 2008). We summarize it informally in this section. Since the inception of machine learning almost 50 years ago, several learning paradigms have been proposed to provide study frameworks and analysis tools to qualify and quantify this process. Among those, we can cite identification in the limit (Gold, 1967), query learning (Angluin, 1988), and *PAC*-learning (Valiant, 1984) for their impact on the machine learning community. Each of them proposes a different form of reality, a different form of interaction between the learner and his 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. A comparable change of role can be found in common conceptions of human learning. 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 forms 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 learner, has a vocabulary $\mathcal{V}$ allowing him to describe exactly any card at any position, for example $\mathcal{V} = \{ace, two, \ldots, jack, queen, king\} \cup \{hearts, diamonds, clubs, spades\}$, 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, "$queen(\overline{0})$, $hearts(\overline{0})$, $ace(\overline{1})$, $spades(\overline{1})$, $queen(\overline{2})$, $hearts(\overline{2})$, $ace(\overline{3})$, $spades(\overline{3})$". After discovering each card, the learner expresses a conjecture, under the form of a logical program which exactly describes a unique infinite sequence of cards. For instance the following program is a conjecture consistent with the preceding sequence.

$$\begin{aligned} &queen(\overline{0}), hearts(\overline{0}), \\ &\forall x, queen(x) \wedge hearts(x) \rightarrow ace(x+\overline{1}) \wedge spades(x+\overline{1}), \\ &\forall x, ace(x) \wedge spades(x) \rightarrow queen(x+\overline{1}) \wedge hearts(x+\overline{1}), \end{aligned} \tag{1}$$

The identification is considered successful if after no more than a finite number of steps, the learner converges toward a correct conjecture, *i.e.*, if he changes his mind a finite number of times. An acceptable strategy for this game would then

be to arbitrarily order the set hypotheses and select, every time when a new hypothesis is needed, the next one which is consistent with the current knowledge concerning the sequence. Note that this kind of learning belongs to the paradigm of function learning as presenting positive data is equivalent to presenting both positive and negative data since the latter can be retrieved from the former.

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

Active Learning

We illustrated passive learning with a game in which a learner 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 learner has to exactly identify an *equivocal* program, that is, 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 learner's hypothesis set.

At each step, the learner 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 $X \in \mathcal{W}$, and the answer is true if $X \in \mathcal{W}_{target}$, or false if X is a counter example.
- *Equivalence* : the input is a set $\mathcal{W}_{\mathcal{H}} \subseteq \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_{\mathcal{H}} \equiv \mathcal{W}_{target}$, or a counter example X such that $X \subseteq \mathcal{W}_H \Delta \mathcal{W}_{target}$.
- *Subset* : the input is a set $\mathcal{W}_{\mathcal{H}} \subseteq \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_{\mathcal{H}} \subseteq \mathcal{W}_{target}$ or a counter example $X \in \mathcal{W}_{\mathcal{H}} - \mathcal{W}_{target}$.
- *Superset* : the input is a set $\mathcal{W}_{\mathcal{H}} \in \mathcal{W}$ of possible games, and the answer is true if $\mathcal{W}_{\mathcal{H}} \supseteq \mathcal{W}_{target}$, or a counter example $X \subseteq \mathcal{W}_{target} - \mathcal{W}_{\mathcal{H}}$.

The classification is said to be successful if after a finite number of queries and experiments, the learner converges toward a program $\mathcal{P}_{\mathcal{H}} \in \mathcal{H}$ such that $\mathcal{P}_{\mathcal{H}} \equiv \mathcal{P}_{target}$. This evolution of machine learning paradigms is in correspondence with the change of paradigms that occurred in human learning paradigms which evolved from a behaviorist point of view to a more constructivist one.

However, by our definition of a possible world, all these queries are co-semi-decidable. Supposing the existence of an oracle able to answer them would then require that it be more powerful than a Turing machine. Membership queries in particular are clearly not relevant, since we cannot decide whether an equivocal program is actually univocal, namely, describes a unique possible game. Moreover, in the context of scientific discovery, Nature can be viewed as a "silent" oracle which cannot answer a learner's queries.

Next section presents a multi-learner extension of this paradigm in which several learners learn from each other.

Interactive Learning and Collective cognition

A scientist does not work alone. According to (Popper, 1963), science is practiced within a community of researchers who exchange data and theories by publishing their conjectures and refuting them. A publication represents a state of the art, a current theory, a solution to a problem, which is accepted by the community until it becomes insufficient to explain Nature. We include this important aspect of scientific discovery in our protocol : science is a limiting process involving a community of agents. Inspired by multi-agent systems and game theory (Chavalarias, 1997), we propose to distribute the resolution of Equivalent queries on a community of learners confronted to the judgment of other learners to cope with the lack of oracle. Each learner can then publish his conjectures and refute existing ones according to a popperian conception of science. This point will be discussed further in the last section.

We symbolize the product of this 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 queries to score points and experimentation to confirm or refute a theory. The introduction of this social level can lead to experiment different gain functions to determine in which conditions the community formed by the learners converges faster to an acceptable solution, and we will describe one of them in the following. This point attribution leaves place for risk management and exploration strategies, but this will not be discussed here. When we use infinite objects, queries are co-semi-decidable, *i.e.*, the process of verification of a query will never end if the query is correct. However, if a counter example exists, it will be found at a finite stage of the process. This use of infinite objects is necessary in the context of scientific discovery to reflect the fact that each studied object can have a potentially infinite description (according to (Lakatos, 1976), there is always a level of precision at which a statement as simple as 1+1=2 can become arguable from a formal point of view). The gain function motivates the learners to try to search for such counter examples and ensure that publications will either remain as consensual references and gain credits, or be refuted in the limit.

This distributed learning protocol was implemented 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* [1] (Dartnell & Sallantin, 2005). Each learner is an agent, *Learner*, and belongs to a scientific community

[1] http ://www.lirmm.fr/kayou/netoffice/eleusis/

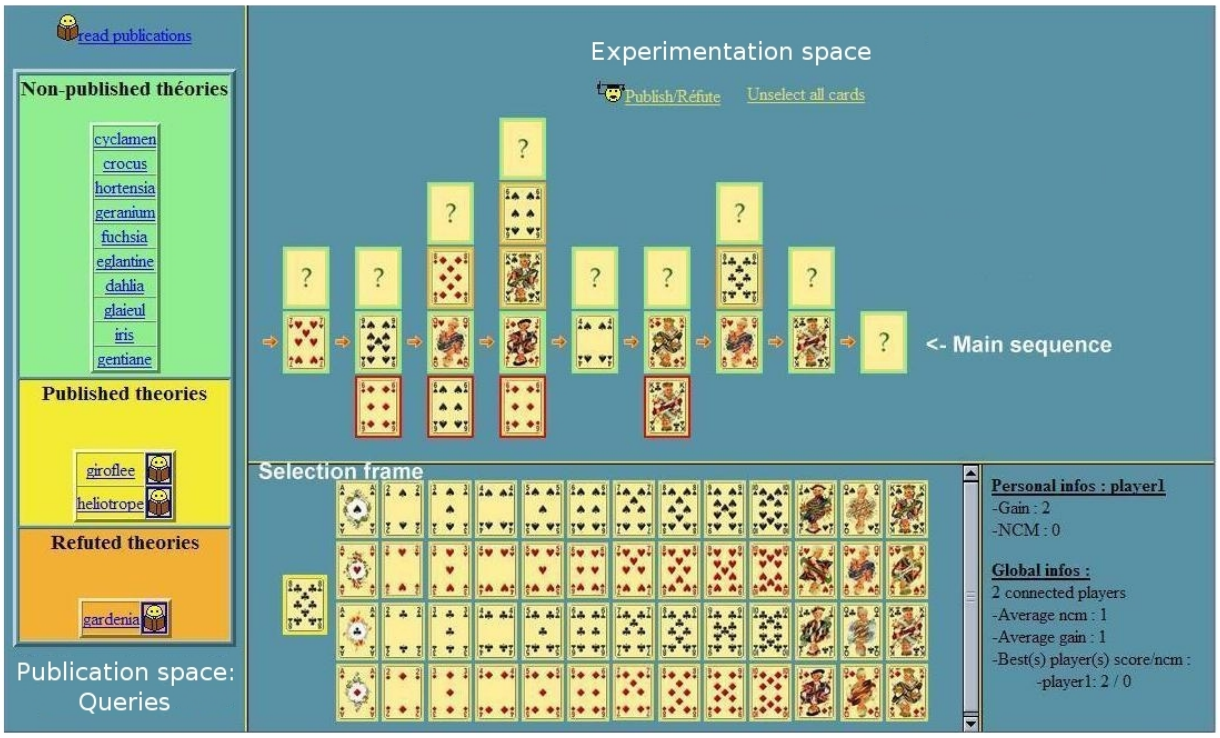

FIG. *3*. Eleusis + Nobel's web display

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. Each problem is given an arbitrary name and for each of them, an agent *Problem*, "knowing" the corresponding program is created 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 simulates experimentation. 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 own private experimentation background.

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 counter example selected in his 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.

The implementation is such that experimentations can easily be adapted to a different context. Each experimentation is described as a temporal sequence of objects (or events) identified as unique instances. *Learners* and *Problems* are then free to derive any representation according to their own model and theory.

Since the compatibility of our protocol with human learning is also one of our main concerns, we studied the impact of *Eleusis+Nobel* on future biology teachers in order to validate epistemological and didactic aspects of this protocol. We now present this experimentation, published in (Hagège, Dartnell, & Sallantin, 2007).

Experimentation and Validation

The first experimentations were made 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 fol-

lows : 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.

Impact of Distributing Queries

We compared the performance of isolated players to the one of a community. The first experiment showed that a human playing alone takes between 5 and 15 minutes to publish a theory concerning a problem implying only sequences of two cards. He usually considers his theory correct, and does not try to refute it. Moreover, the average number of published theories is between 10 and 20 (players stop before trying to solve the entire set of rules), and few of them are equivalent to the corresponding hidden rule. In contrast to these results, we made further experimentations involving multiple players, coming from different scholar backgrounds. The average time of a publication was the same, and we observed a period of roughly half an hour during which players published. Then they began to refute each other, and theories were revised and republished. We observed that a community of ten to thirteen players take between 1 hour and a half and 2 hours to reach a stable equilibrium of published theories (as opposed to the theoretical length of 5 hours and a half for one-player games). The amount of correct theories is also much superior. This practically confirmed the need to use queries together with experimentation (Angluin & Krikis, 2003), and the use of a community to confront experiences and points of views on a given problematic. An interesting alternative was to organize duels, between two players working on the same rule, until one of them admitted, without being sure, that the adverse theory was true : a consensus was made on a common description model. Although being very simple, this gain function allows one to observe three different behaviors when humans play : altruists publish often, regardless of refutation risks, opportunists never publish and only try to refute others conjectures when they are published, and the careful players seem to define a reasonable experimentation length before deciding whether a conjecture (theirs or not) is true. Clearly the latter is the richest behavior in terms of strategy and risk management, but the formers ensure a constant flow between published and refuted theories. This minimal interaction is then sufficient to create a process of classification in the limit.

Epistemological Impact of the Game

Problematic. In science education and epistemology, a constructivist vision of building knowledge has been developed (Fourez, Englebert-Lecomte, & Mathy, 1997), (Kuhn, 1962), (Strike & Posner, 1992), to which a majority of researchers in these domains seem to adhere (Lederman, Abd-El-Khadick, Bell, & Schwartz, 2002). According to constructivism, all knowledge is linked to a subject who knows (Fourez et al., 1997), so its profound nature is subjective. Thus conviction, points of views and beliefs are part of science and learning (Bachelard, 1971), (Kuhn, 1962). On the other hand, all knowledge is issued from a construction process. This process consists in qualitative reorganization of initial knowledge structure (Lonka, Joram, & Brysin, 1996), and can be assimilated to change of conceptions (Strike & Posner, 1992). Conceptions play an organizational role in thinking and learning (Strike & Posner, 1992), but affects and values also do (Hagège, 2007). Here, we refer to personal epistemology as a system of interacting attitudes related to knowledge construction objects (such as conjecture, error, science, ...). Attitudes are composed of a cognitive and an affective component (*i.e.*, conception of an object, and affective relation to this object (Hagège, Reynaud, & Favre, 2007)). They interact together and norms and associated values emerge from this epistemic attitudes system (Hagège, 2007). Norms are rules telling how the subject should behave in a particular situation and values consist in general principles which justify the corresponding norms.

Most studies on epistemology learning and teaching concern conceptions, *i.e.* what we call the cognitive component of attitudes. Science teachers and students do not own spontaneous constructivist science conceptions (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 constitute a supreme referee to verify theories. This naive, positivist labeled epistemology also contains a realist view, given which the world is intimately knowledgeable (in opposition to an idealist conception), so that scientific knowledge tells us about truth : the world as it is. This positivist and realist vision is coherent with naive (Schommer, 1994) and traditionalist (Chan & Elliott, 2004) epistemologies evaluated by other authors, in the sense that knowledge would be composed of information units which are progressively added, thus allowing knowledge progress. In fact, a majority of secondary teachers define teaching as a "maximum information transfer" and learning as "every information absorption" (Boulton-Lewis et al., 2001), (Waeytens et al., 2002).

In the following, we evaluate the impact of playing *Eleusis+Nobel* on science conceptions, values, and to a less extent, affects. We used the standard pre-test/post-test procedure. The test was mostly composed of a Likert-type scale and of Osgoods semantic differentiators (OSD). Values are considered to be implicit in all adjectives, but some of those explicitly refer to values, such as good and beautiful. Affects correspond to pleasure and pain domain. Conceptions are here considered as ranging from a positivist and realist end to an idealist and constructivist one. One has to notice that we refer to philosophical corresponding notions, to be able to characterize students undifferentiated epistemology. These students initially had no deep thought about scientific process. *Eleusis+Nobel* implements the popperian intersubjective construction of objectivity concept, which is a central point of what became constructivism. That is why we expected *Eleusis+Nobel* to favor the development of a constructivist epistemology.

Procedure and subjects. The study has been realized in south France, in the University Montpellier II. In January 2007, 43 third year general biology students filled up the initial test (*initial experiment*). All these students aimed at becoming secondary biology teachers (or primary school teachers) and were enrolled to follow the same science education and epistemology courses. One and half month later, 14 of them (*Pl* for Players) played *Eleusis+Nobel* then filled up the final test (6 days later), whereas 14 others (*NC* for Negative Controls) filled up the final test without having played. The final test corresponds to the initial test plus some additive questions. For both *Pl* and *NC* groups, the initial experiment is called the *pre-test* and the final one the *post-test*. Players have been told that this game mimics scientific discovery as it occurs - in community. During the game, *Pl* was mixed together with 24 other students and the whole sample was split into 16 teams of 2 or 3 players. All 16 computers were in the same room. The game lasted 2 hours and the winner team won a 1kg candy box (the Nobel Price).

Results. Both subpopulations were significantly the same in terms of age and were composed of the same number of males and females. Concerning background' socio-professional category, little is known since the majority of subjects answered "other" to that question, although our sampling did not seem biased by professions linked to scientific research or scientific education. We proposed a pre-test and a post-test to students who played *Eleusis+Nobel* for two hours and compared answer changes with the changes in the answers of the negative control (non-players). Before the game, the initial epistemology of *Pl* and *NC* where similar, except from esthetical values, which were higher for *Pl*. This heterogeneity effect points to a limit in our study : the smallness of our samples. Future experiment will be done with larger samples. Otherwise, positive values were expected from students who aim at becoming science teachers. We tried to evaluate several aspects linked to constructivism. Among these, the aspect which is recurrently and significantly changed specifically to *Pl* concerns the role of subjectivity in scientific process. These results are reinforced by those obtained with additional specific post-test questions who indicated putative conception changes focus on the role of community in scientific process. Thus, to us, the game allowed *Pl* to become aware of these central aspects of constructivism, so that they specifically assimilated them in the cognitive components of their epistemic attitudes. The only one result which was not predicted is the following one : *Pl* are in fact less likely to believe that several interpretations are possible in the face of a given result. Maybe they assimilated the term "possible", in the sense of what a research worker can rightly propose, with "right", in the sense of what is acceptable given a theory. Because it was difficult to find volunteers, we organized this experiment with our students, who were supposed to follow epistemology courses. This could explain why the scores of *NC* also changed between the pre-test and the post-test. However, statistics gave us a clear limit and the significance levels that we used were absolutely standard. So no statistically significant score change has been observed in the subpopulation *NC*.

As all observed changes of answers did not focus on themes that were explicitly dealt with in the game, but just practiced, we infer that this constructivist conception had been subconsciously assimilated, in the Piagetian sense. We cannot exclude that this effect occurred synergistically with traditional epistemology courses. Even so, observed changes are very encouraging, because they would have been caused by only two hours of playing. An important factor with such a teaching tool is the pleasure that players experience. Open questions in the post-test treated addressed feelings during playing. We noticed that 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 leaded to the same conclusion. When time was out, a majority was disappointed and wanted to continue (that rarely happens with a traditional course !).

Altogether, it indicates that *Eleusis+Nobel* game can constitute a very interesting complementary tool to teach epistemology which cannot, by essence, be taught in a dogmatic way.

Evolutions and Perspectives

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

Extensions on Machine Learning

The formal learning models presented earlier can be described as transmission from a teacher to a learner of a program representing the target concept, either directly or indirectly through examples or queries. Extensions in machine learning, based on the previous cognitive considerations, explore the case in which this transmission is impossible. Human learning involve complex agents which are all different and unique, which have limited modeling abilities and 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 their operate.

These constraints are clearly illustrated with the example of juggling, for which anyone knowing how to juggle can constitute a valid teacher (or model) for the learner. However, this learner only has a limited knowledge of the physical laws influencing the movements of the balls and his body, and even less knowledge concerning the neural connections determining the proprioreceptive abilities of his brain or of his teacher's. Moreover, synchronization is crucial as the learner does not have time for such an introspection. However,

without using physics and without cloning the teacher's cerebral areas involved during juggling to simulate their functioning, learning how to juggle is still possible by imitating the teacher and his movements.

In contrast to formal learning models supposing the learner's capacity to simulate, (Angluin & Krikis, 2003) propose to take into account and formalize the fundamental differences between agents and how difficult is it to each of them to achieve a given task. We now simplify this model for the sake of clarity.

Formally speaking, both the teacher and the learner are modeled as machines with an oracle access to a function box representing their personal abilities. This oracle access expresses the fact that agents only have access to inputs and outputs for these functions which must then be seen as blackboxes. The teacher is supposed to have a particular function, and the learner has to learn how to compose his own functions to imitate it. Since the learner and the teacher have different function boxes, simulation or outright coding is impossible. The teacher cannot give the index of the target function in his function box to the learner, or a set of indexes corresponding to the order in which he composes his own functions to achieve the target function, since the learner's functions might be different, or simply ordered differently.

In this context, and provided a complexity measure for these functions has been given, the learner has access to *complexity queries* to estimate the complexity of the solution and find how to effectively imitate it with his own function box. Let f be a partial recursive function, $G = \{g_0, g_1, \ldots, g_n\}$ be the teacher's function box, and $G' = \{g'_0, g'_1, \ldots, g'_m\}$ be the learner's one. If the teacher's solution to effectively compute f is $f_T = g_i \circ g_k$, then an adapted complexity measure for f_T is the sum $F_T = G_i + G_k$ of steps needed by two Turing machines to compute g_i and g_k. A complexity query is then defined as a couple (x, s) such that x is an input for f, and s a natural integer representing a complexity bound. To answer this query, the teacher runs $f_T(x)$ for at most s steps. If the process halts in less than s computation steps, then the value $y = f_T(x)$ is returned to the learner. If not, an error value is returned and the learner who is now able to adapt the attended complexity of the solution and eliminate conjectures which are too complex.

Intuitively, answering a membership query consists in verifying an (infinite) instance, answering an equivalence query consists in achieving this verification on every instance in a given (infinite) set, and answering a complexity query consists bounding the *time* necessary to verify an instance. Complexity queries extend membership queries and enable their use in the context of scientific discovery. Results presented in (Angluin & Krikis, 2003) rely on the fact that all Turing machines are equivalent and that their performance can be bound by a function. This allows the teacher to take into account his own performance to estimate a complexity measure adapted to the learner's one. Given an estimation of the difference between the performance of the teacher's and the learner's function boxes, the complexity measure for the latter can be bound by a function $b(F_T)$. For instance, if the learner is twice as slow as the teacher and the latter needs n steps to compute $f(x)$, then the learner can bound the complexity of his conjectures to $2n$ for this given task.

Extensions of Eleusis+Nobel

As we observed, the experimented gain function is sufficient to create a dynamic for interaction. However, the use of equivalence queries only implies that each conjecture has to be refuted before publishing a new one. Different types of publications corresponding to subset and superset conjectures could be defined in accordance with the queries presented in the section related to active learning. This would allow one to publish incomplete theories, or more general observations. Several conjectures, potentially complementary or contradictory, could then cohabit without being refuted and gain credit. The gain function could then be adapted to take into account the fact that the longer a conjecture remains unrefuted, the more credit it has, and to report this credit to an eventual refutation. For instance, one can publish a subset query such as $\forall x, red(x) \rightarrow black(x + \overline{1})$, which is not possible in the current protocol since any sequence starting with a black card can refute it (incomplete theory). This would improve the interaction between learners, as well as the quantity of shared information. The discovery process would therefore be accelerated.

Another extension of this platform would be to introduce complexity queries. This would be relevant from the point of view of machine learning, as a restriction of membership queries or as the introduction of a heuristic such as time. It would also be relevant from the point of view of scientific discovery : when a scientist tries to recreate in vitro an experiment observed in vivo, he sometimes comes to the conclusion that the experiment, taking too long compared to the observation in vivo, is not concluding and aborts it. A complexity measure for equivocal programs could be the number of cards involved in the validation of a card sequence. For instance, a hidden rule might need five cards to decide the validity of the sixth, or it could also need five cards among which only three will really impact the validity of the sixth. We provide examples for such rules :

$$\exists x(queen(x) \wedge hearts(x)) \rightarrow black(x + \overline{5}) \tag{2}$$

$$\begin{aligned} &\exists x(queen(x) \wedge hearts(x)), \\ &\qquad \exists y(x < y < x + 5 \wedge king(y)) \rightarrow black(x + \overline{5}) \\ &\qquad \forall y(x < y < x + 5 \wedge \neg king(y)) \rightarrow red(x + \overline{5}) \end{aligned} \tag{3}$$

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 supposing the existance of an oracle answering queries is unrealistic as the oracle would then need 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 experimentation highlighted two important facts :

- 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 suitable to teach constructivist conceptions to students, which means that the epistemic notions on which it is funded are acceptable and significant of how science is practiced in reality.

Moreover, our natural conception choices of multi-agent systems led us to define an *AGR* model of interactive learning, and the genericity of the implementation allows one to adapt the current platform to other contexts than cards.

These three points tend to show that this protocol is a good candidate to conceive 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 evolutions for this protocol, among which are :

- 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 favorize the interaction between learners and to favour an increased competition among theories, in a more popperian conception of science.

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