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Machine learning at the learner's hand: a support to theory formation in collaborative discovery learning environments

G. M. da Nóbrega and **E. J. R. de Castro** and **E. Ferneda**[1] and **S. A. Cerri**[2] and **F. Lima**[1]

Abstract. In the last decade the design of collaborative discovery learning environments (CDLE's) has received increasing attention. In this paper, we are concerned with the design of CDLE's in which theory formation arises as a synergetic combination of both inductive and hypothetical-deductive approaches. The "moving engine" allowing a theory to evolve is the notion of $contradiction$: learning is supposed to occur as a side effect of contradiction detection and overcoming during theory formation by peers. By playing different roles, peers are assisted by an Artificial Agent capable of both inducing and deducing. The dynamics within the environment is illustrated through a scenario.

1 INTRODUCTION

In Educational literature, Discovery Learning appears as an approach in which the learner builds up his/her own knowledge by performing experiments within a domain and inferring/increasing rules as a result. Such an approach "[...] has appeared numerous times throughout history as a part of the educational philosophy of many great philosophers particularly Rousseau, Pestalozzi and Dewey, 'there is an intimate and necessary relation between the process of actual experience and education [7]'. It also enjoys the support of learning theorists/psychologists Piaget, Bruner, and Papert, 'Insofar as possible, a method of instruction should have the objective of leading the child to discover for himself' [2]" [1]. Such a constructivist approach has been largely exploited for the design of computational artifacts with learning purposes, the so-called Discovery Learning Environments (DLEs). One known feature of such environments is the autonomy degree required for students to succeed while handling a domain.

In his introduction [9] to the book "Collaborative learning: cognitive and computational approaches" P. Dillenbourg considers the notion of collaborative learning in a three-dimension space generated by the following three axis: (i) the scale of the collaborative situation in terms of the amount of people involved, (ii) what is actually concerned to learning, and (iii) how collaboration is provided (face-to-face or computer-mediated, synchronous or not, ...).

In the last years, several scholars have been investing efforts to bring together both collaborative learning and discovery learning, thus leading to the emergence of the collaborative discovery learning approach [15]. In order to show the effectiveness of the collaborative discovery learning approach, a number of systems have been designed, such as Belvedere (groupware for learning scientific argumentation) [14]. Such environment combines three approaches to learning, namely, collaborative learning (groupware), guided learning (Intelligent Tutoring Systems), and learning by doing (simulation).

Often, research pursued in Artificial Intelligence (AI) related to user modelling aims to provide system intelligence such as to improve user's assistance. When concerned with educational purposes, AI researchers follow the widespread community by investing in the design of smart systems that should respond to student's individual behaviour and needs. An overview on AI techniques related to education, as well as usefull pointers to the subject may be found in [8]. Particularly, the field of machine learning has received considerable attention at the system's side within the design of Intelligent Tutoring Systems for the construction of the so-called student models [13].

Current efforts on AI in CSCL address coletive behaviour modelling, both benefiting from lessons learned from individual user modelling and dealing with increased complexity.

In this paper, grounded on a collaborative discovery learning perspective, we propose to make available for students an induction engine in order to support their collaborative work of theory formation. In §2, we introduce several assumptions we made in order to support our proposal. Then, we develop a scenario in which machine learning is exploited by students during a process of theory co-construction. Finally, in §3, we draw-up our concluding remarks and discuss ongoing efforts.

2 THEORY FORMATION AND AUTOMATED INDUCTION FOR COLLABORATIVE LEARNING

The model Phi-calculus [6, 3] of computer-supported knowledge construction relies on a synergetical combination of two rationales from empirical sciences, namely, the inductivist approach and the hypothetical-deductive dynamics. Within Phi-calculus, theory formation is a negotiation process aiming at an agreement on observed phenomena/objects intended to be predicted/explained by theoretical elaboration in an acceptable and useful manner. In previous work, we show how Phi-calculus could be instantiated in the context of human-machine collaborative work with learning purposes, going up to submit the model (through a Web-based tool) to a real learning situation in Law [4].

In this paper, our objective is to elaborate in the direction of human-human collaborative theory formation for learning as an extention of Phi-calculus to a social context. Indeed, the theory for-

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mation process should be assisted by a machine learning tool, to be available to the users/learners while searching for an agreement.

In such a context, we see two degrees of challenging questions concerning grounding, from a perspective of the users taking part in a computer-aided collaborative learning process:

1. To reach an agreement about a vocabulary. Under a symbolist (and indutivist) reasoning perspective, building concepts or domain theories requires firstly a vocabulary over which to represent $observations$ about objects/phenomena. Often, it happens that different individuals employ distinct terms to refer to a single observation. On the other hand, a shared vocabulary would minimize conflicts that would arise when trying to achieve shared concepts or domain theories within a group. In such a case, this shared vocabulary might be seen as providing a first level of "semantic interoperability" between the (human) agents intending to reach an agreement. We see then an agreement about a vocabulary as an initial step towards the achievement of concepts or domain theories shared by a group (and overall, thought-of as resulting from a co-construction process).
2. To reach an agreement about meaning of concepts (in a domain), which are to be built over a shared vocabulary. As stated above, a shared vocabulary should be obtained as a result of a co-construction process, representing a first level of agreement into a group. The second step is then to collaborate aiming at an agreement on concepts or a domain theory that the group intends to be competent on.

In the present paper, we focus on the above question 2. The reason for such is that we intend to highlight on machine learning and its (potencial) interest to collaborative learning from the users' perspective, and, by now, we see this as immediately related with the above question 2, considering the current state of our work.

In what follows, we exploite a scenario on a classical toy-domain in order to present our elaboration of Phi-calculus as a model of collaborative discovery learning environments, supported by machine learning. In order to develop the scenario, we shall position the underlying collaborative (potential) learning situation with respect to Dillenbourg's 3-D space evoked in §1. Concerning the scale axis, we adopt the small scale end of the continuum: we develop the scenario by considering collaboration between *two learners* guided by a teacher/facilitator. We think that such a choice does not exclude the possibility of exploiting the proposed collaborative discovery learning approach to a large scale situation. Instead, if one considers only the amount of people involved, the small scale situation might be thought-of as included in a large scale one, as long as it becomes feasable to apply techniques for creating sub-groups, by identifying complementarity in individuals skills or knowledge. An analysis of sub-groups formation is performed by Hoppe and Plöetzner in [10].

The second axis of Dillenbourg's 3-D space characterizing a collaborative learning situation would stand for what is understood by "learning" such as to provide it. In previous work [4, 3], we have addressed that question by avocating in favour of the model Phi-calculus to support the design of Learning Environments. However, within those work emphasis is given to human-computer collaborative work. In such a context, the theory formation process underlying the model is supposed to promote learning as a side-effect. Phi-calculus relies on a synergetic combination of both $inductivist$ and *hypothetical-deductive* rationales. The "moving engine" of the theory formation process is the notion of $contradiction$ [5]: a theory is supposed to evolve by contradiction detection and overcoming. Contradiction should arise during confrontation between current theory and incoming experiment (Examples/Counter-examples). It is supposed to reveal disagreement between individual's observations and the current available theory. In addition, a machine support to the theory construction process is provided, under the form of an *induction engine*, accounting for Learning from Examples approach [11].

Considering yet the above mentioned human-computer collaborative context, communication between a human agent and his/her Artificial Agent takes place by means of *constrained dialogues* [16]. In our work, constrained dialogues correspond to messages formalized under the form of the speech acts ask and $tell$ [12], representing, respectively, (i) agent A asks something to agent B (or vice-versa) and (ii) agent A informs something to B (or vice-versa). Also, messages in constrained dialogues rely on exchanging (asking and telling) what we have called "knowledge types" [3, 5] within Phi-calculus. Such types should account to the states that an evolving theory (or a concept being formed) should assume. In this paper we exploite only the Knowledge Types needed to develop the proposed scenario.

As a first step towards extending Phi-calculus to a human-human collaborative leaning context, we borrow both the contradiction-driven theory formation process underlying Phi-calculus, and its constrained dialogues perspective to support communication. Different from largely known communication concepts relying on Internet (like chat, forum, and e-mail), constrained dialogues are considered here on the basis of its suitability to promote concentration in a certain task to be accomplished (in the present case, a domain theory or concept to be co-constructed). Following our previous implementations, the interface design should render the formalism behind interactions (Ask/Tell along with Knowledge Types) totally transparent to the users-learners.

A scenario. Let us now start our hypothetical scenario by supposing that a History class interested in the study of historical monuments intends to formalize the concept of "Arch". As stated above, we assume that the whole class is divided into peers groups. The scenario is developed within a single group.

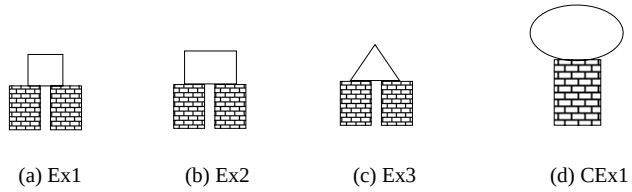
2.1 Context setting

The study begins with the announcement of the studying subject by the Human Agent responsible for guiding the study, to which we will refer as to the $Teacher$. Then the Teacher assigns a role to each one of the peers: *Mr(s). Example*, who is responsible to propose positive examples in order to build up the intended theory about the concept, and *Mr(s). Counter-example*, who is responsible to propose negative examples of the concept. Such roles are established to provoke contradictions to arise during the theory collaborative formation process. As stated above, contradiction facilitates a theory to evolve, being thus the rationale "moving engine".

2.2 Analyzing and prototyping

The result of this phase should be a prototype of the intended theory, which includes: (i) a Hierarchy of Terms representing the vocabulary supporting the study, and (ii) a Set of Constraints, which role is to constrain the usage of those Terms, as the constraints achieve formal relations among the Terms.

Let us suppose that, during a trip around the world, the Teacher has taken some pictures (Figure 1) found interesting to begin the study.



(a) Ex1 (b) Ex2 (c) Ex3 (d) CEx1

Figure 1. Hypothetical objets to begin the study of the concept "Arch".

2.2.1 *Hierarchically organizing a vocabulary to fit (positive/negative) examples*

Having previously classified the objects as positive and negative examples, the Teacher submits them to be analized by the peers, according to the roles they play. The speech acts

1. `Tell (T, MEx, [url])`
2. `Ask (T, MEx, vocabulary)`
3. `Ask (T, MEx, [Positive_Ex])`

represent, respectively (1) Teacher tells Mr(s). Example a list of URL's, each pointing to a page containing one positive example; (2) Teacher asks Mr(s). Example a vocabulary needed to represent the provided pictures; and (3) Teacher asks Mr(s). Example a list of Examples to represent the pictures, relying on the vocabulary.

Let us suppose that Mr(s). Example considers each received object ($Ex1$, $Ex2$, and $Ex3$) as being composed of a number of pieces, each one generally named, say, a $form$. Then he/she distinguishes the following forms: $rectangle$, $triangle$, $square$, as well as the $blocks$ supporting them, which are by their turn, distinguished as left-hand side block and write-hand side block. Such a reasoning would lead to the vocabulary shown in Figure 2, along with the exchanges needed to render it explicit.

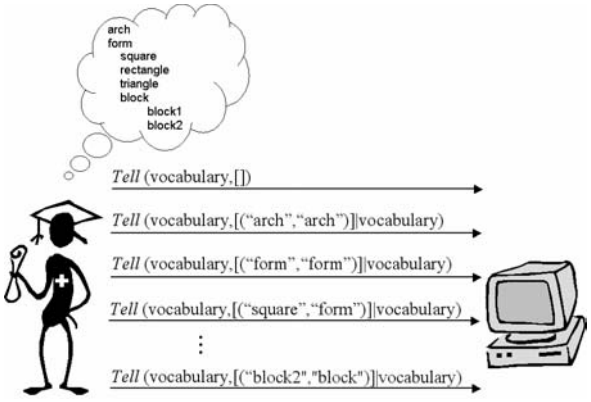


Figure 2. Mr(s). Example tells the Artificial Agent the vocabulary needed to represent his/her examples.

In order to show up the exchanges allowing Mr(s). Example to describe an object to the Artificial Agent as an Example, let us consider the object named *Ex1* from Figure 1(a). These exchanges are shown in Figure 3: $Ex1$ is described by stating that a square is $present$, a first block is $present$, a second block is $present$, and an arch is $present$. The description of an object corresponds in the model Phi-calculus to the Knowledge Type "Theorem", standing for a theorem to be proved out of Axioms that would compose the theory. Once a Theorem is built, it may become an Example, such an operation modelling the fact that the Artificial Agent should memorize the object for later use. By a sequence of messages as the ones shown in Figure 3, Mr. Example describes to the Artificial Agent the pictures received from the Teacher.

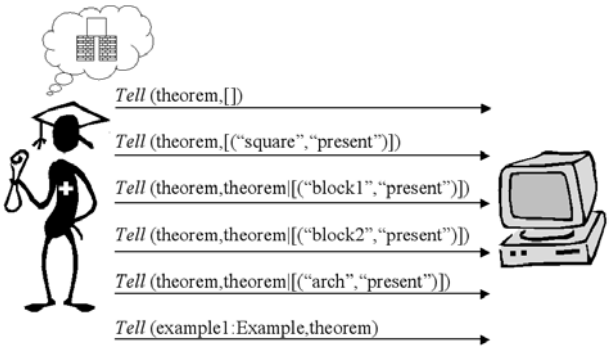


Figure 3. Mr(s). Examples proposes an object to the Artificial Agent.

Considering Mr(s). Counter-Example's turn, the speech acts

4. `Tell (T, MCEx, [url])`
5. `Ask (T, MCEx, vocabulary)`
6. `Ask (T, MCEx, [Negative_Ex])`

represent, respectively (4) Teacher tells Mr(s). Counter-Example a list of URL's, each pointing to a page containing one negative example; (5) Teacher asks Mr(s). Counter-Example a vocabulary needed to represent the provided pictures; and (6) Teacher asks Mr(s). Counter-Example a list of Negative Examples to represent the provided pictures, relying on the vocabulary.

Mr(s). Counter-Example should propose a vocabulary starting from the current vocabulary proposed by Mr(s). Example (it would be reformulated only if necessary). Let us suppose that, in order to represent the received single picture ($CEx1$), Mr(s). Counter-Example would find convinient to distinguish $stable$ forms from $unstable$. He/she proposes, then the reformulated vocabulary:

```
.arch
.form
.   stable
.      square
.      rectangle
.      triangle
.      block
.         block1
.         block2
.   unstable
.      oval
```

Once the vocabulary is proposed, Mr. Counter-Example describes the received picture (CEx1) to the Artificial Agent by stating that an arch is $absent$, an oval is $present$, and block1 is $present$. This is modeled by similar exchanges to the ones shown in Figure 3.

2.2.2 *Constraining a vocabulary*

The model Phi-calculus suggests that, in a given moment, a theory is represented by an Axiomatics. Considering the dynamical character of a theory, Axioms may join or leave an Axiomatics, according to experiments carried out. The model allows for Axioms to join an existing Axiomatics either in a $direct$ or an $indirect$ manner. The former case accounts for the situation in which users are able to identify a certain relation between the objects being studied, and then build up the corresponding constraints to stress the relations. The latter case accounts for the situation in which the user recalls the Artificial Agent's learning skill in order to look for promising relations. Hereafter, we show the exchanges modelling the indirect case, throughout three underlying sub-phases.

Describing Examples to the Artificial Agent. As already considered in §2.2.1 this phase would only be re-taken in case that the peers find necessary to re-create Examples according to the resulting vocabulary from the last phase. Within the scenario, such a re-creation is not necessary since the Terms used by the peers to represent the received pictures were kept into the reformulated vocabulary. Let us thus assume that the Artificial Agent knows the Examples representing the objects of Figure 1, and thus it is ready to learn general rules (Constraints) about them. The model Phi–calculus assigns each learnt rule to a Knowledge Type "Lemma". The speech act

7. `Ask (T, MEx, Conjecture)`

stands for the Teacher asking Mr(s). Example to propose a theory. The theory should be constructed with the support of the Artificial Agent's learning skill, and considering as input both Examples provided by Mr(s). Example and Counter-Examples provided by Mr(s). Counter-Example.

The Artificial Agent proposes a number of Constraints. The exchanges between the agents are shown in Figure 4, over two illustrating Constraints that could have been learnt from the provided descriptions of the objects in Figure 1.

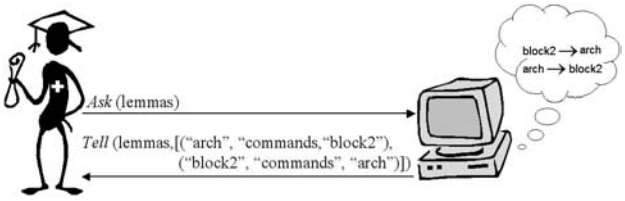


Figure 4. The Artificial Agent tells Lemmas to Mr(s). Example.

The Human Agent filters the Learnt Knowledge. Once informed about learnt Lemmas, Mr(s). Example may analyze them in order to compose what is formalized by the Knowledge Type "Conjecture". A Conjecture should retain only those Lemmas estimated by the Human Agent as pertinent. Once the analysis is over, the resuting Conjecture is memorized by the Artificial Agent as an Axiomatics ready to be exploited. In Figure 5 we show the exchanges supporting the composition of a Conjecture and then its status changing to become an Axiomatics. In our scenario, we suppose that Mr(s). Example accepts as a Conjecture (then as an Axiomatics) both two Constraints proposed by the Artificial Agent.

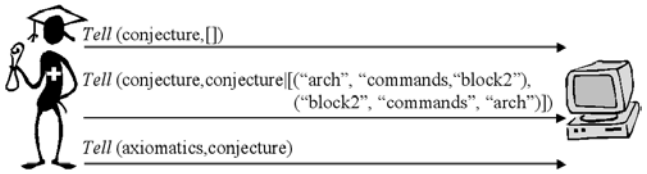


Figure 5. Mr(s). Examples tells the Artificial Agent a Conjecture.

2.3 Testing and revising

Up to this point we have shown Phi-calculus through some of the exchanges required to build a theory. As stated before, the model assumes that a theory is something constantly evolving as a consequence of experiments carried out (by peers). Once the Artificial Agent knows an Axiomatics, the peers may then test its validity, by proposing a number of objects unknown by the Artificial Agent and then inquiry this agent about the object's $Adequacy$ with respect to the current Axiomatics. We suppose now that Mr. Counter-Example proposes an unknown counter-example to the Artificial Agent. The testing object, proposed through the Knowledge Type "Theorem", is the one shown on the left-hand side of Figure 6. The figure shows as well the exchanges allowing the Human Agent to know the object's adequacy (with respect to the Artificial Agent's current Axiomatics).

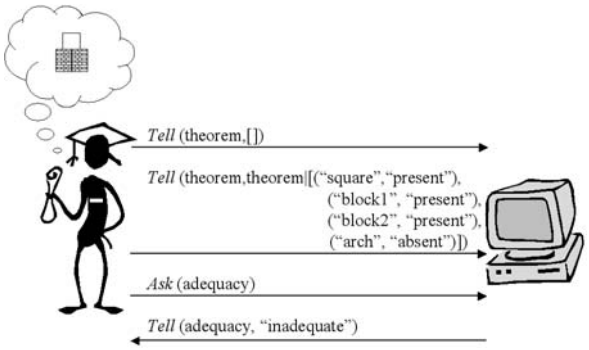


Figure 6. Mr(s). Counter-Example proposes an unknown object to the Artificial Agent, who judges the object as Inadequate.

At this point we reach the heart of Phi-calculus as a contradiction-ddriven approach to (collaborative) theory formation. The Inadequacy of an object declared by the Artificial Agent lies on the basis of a $contradiction$ revealed while the agent confronts the object description with the current Axiomatics. A revision process should then take place in order to reach a coherent behavior for the Artificial Agent. Such a revision process would require, however, the peers to know how to reestablish the coherent status of the theory. As this is not always evident, before such a revision process could take place, the peers may need to find out why a contradiction arises. The exchanges are shown in Figure 7, in which Mr. Example asks the Artificial Agent the reasons of its judgment.

By means of the Knowledge Type "Object", the Artificial Agent shows how it sees the proposed object: the description is a result of both the description from Mr. Counter-Example and the propagation of the Constraints (Axioms) from the current Axiomatics. In our scenario, the Term $Arch$ is evaluated both as $present$ (as a consequence of propagating the constraint **Block2** $\rightarrow$ **Arch**) and $absent$,

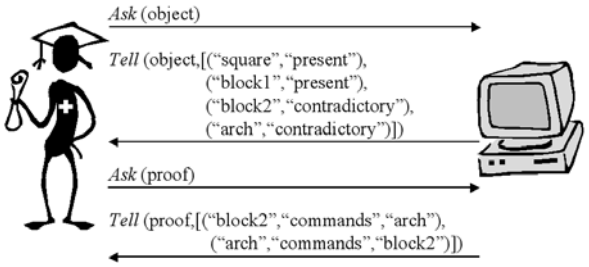


Figure 7. Mr(s). Example asks "why"? The Agent answers.

(from the Human Agent's description), thus, $contradictory$. Moreover, by means of the Knowledge Type "Proof", the Artificial Agent shows to the peers the Axioms causing its judgment (i.e., the violated Constraints). The Teacher may then ask Mr. Example to propose a revised theory.

Having assumed the theory as over-constrained, the revision process may consist for Mr(s). Example to tell the Artificial Agent to forget unsuitable Axioms. This may be a relatively simple way of revision. A more complex revision process is the one requiring to go back farest in the theory formation process, for instance, the need to reformulate the vocabulary and then to reformulate the Examples' descriptions, and yet to ask the Agent to re-learn over the (positive/negative) Examples, and so on. In fact, this whole reformulation would be the case if we would go on with our scenario, since, provided that Mr. Example would relax the Axioms responsible for Inadequacy, the Artificial Agent would not be able anymore to decide about the property of being an Arch neither for $Ex1$ nor for $CEx2$. Excepting the evaluation of the Term $Arch$ itself, the description of these two objects are quite similar, so that the learnt rules could not capture their distinctions.

3 CONCLUSION

In this paper, we start from previous elaboration (both in conceptual level and in pragmatics) in order to identify a potential interest of the use of machine learning by learners involved in a collaborative discovery learning process.

In such a context, we think that a relevant question to be answered is "under what conditions students are $capable$ and $motivated$ to hold the challenge of handling an induction engine while collaborating, considering the state-of-the-art of the disciplines concerned (machine learning, representing languages, human-computer interaction, human-human interaction, among others). Another question to be addressed is related to pedagogical foundations underlying the model: should we define a students category to which the approach would be better adapted (considering the required autonomy degree to drive theory formation)? In our early experiments, Teacher has even invited the (DEA) students to search by themselves Examples on the Web.

As an attempt to respond to such questions, ongoing work include deeper theoretical investigations aiming to increase conceptual foundations. In addition, feedback from experimental work is also to be provided, as the model becomes enough solid to be instantiated as a computer system to be handled by real users. In such a direction, an architecture is being designed to account for asynchronous collaborative model construction (in the present case, theory formation). Students may both work individually and contribute to the group theory. An added value of such an approach with respect to largely known communication concepts relying on Internet is the possibility for the group to draw up a collective conclusion, a kind of negotiated consensus.

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