Deployment of Ontologies for an Effective Design of Collaborative Learning Scenarios

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Abstract. Two of the most important research subjects during the development of intelligent authoring systems (IAS) for education are the modeling of knowledge and the extraction of knowledge flows from theory to practice. It bridges the gap between theoretical understanding about learning and the practical foundations of design the knowledge of intelligent systems that support the learning process. Developing an IAS for collaborative learning is especially challenging in view of knowledge representation because it is based on various learning theories and given the context of group learning where the synergy among the learner's interactions affect the learning processes and hence, the learning outcome. The main objective of this work is to introduce an ontological infrastructure on which we can build a model that describes learning theories and to show how we can use it to develop programs that provide intelligent guidance to support group activities based on well-grounded theoretical knowledge.

Keywords: Collaborative learning design, ontological engineering, knowledge representation, intelligent authoring system, learning theory.

1 Introduction

In recent years, with the increasing use of technology, Artificial Intelligence has been gradually and successfully introduced into Education. However, major challenges still remain. Among these, we are interested in how to represent the knowledge of **intelligent authoring systems (IAS)** and then how to use this knowledge efficiently, especially within the context of collaborative learning.

Usual approaches to such issues provide their systems with a kind of expertise using a set of heuristics and domain theories built in the procedures (programming languages). This means that the programmers, not the systems, have an understanding of the knowledge being used. As a result, these systems cannot share or build new knowledge, they ignore the existence of theories on which the knowledge is based, and finally cannot justify their recommendations systematically and scientifically [2; 15].

To develop IAS to support **collaborative learning (CL)** is especially challenging in view of knowledge representation. Current knowledge concerning CL is based on various learning theories, which are always expressed in natural language and are particularly complex given the context of group learning where the synergy among learner's interactions affect the learning processes and hence learning outcome. It is in fact currently difficult for both humans and computers to clearly understand and differentiate between the various learning theories; however without their explicit representation, it is difficult to support the design of group activities based on well-grounded theoretical knowledge.

Our approach calls upon techniques of ontological engineering to, at first, establish a common understanding of what a learning theory is by representing it in terms of its explicitness, formalism, concepts and vocabulary. This makes theories understandable both by computers and humans. We then propose techniques of reasoning on these theories which contribute to dynamic guiding and instructional planning. And finally, we present the **CHOCOLATO** - a ***C**oncrete **H**elpful **O**ntology-aware **CO**llaborative **L**earning **A**uthoring **TO**ol* focusing on a sub-system that represents theories graphically to facilitate the design of effective CL activities with theoretical justifications.

2 Collaborative Learning and Learning Theories

Collaborative learning has become a popular method used by teachers in classrooms and in e-learning environments. In spite of that, designing effective CL sessions or analyzing the interaction processes among learners to capture what really happens in each session have been a very complex job due to a lack of comprehensible models for representing what is going on [10]. According to Dillenbourg [7], the key to understanding collaborative learning is to gain an understanding of the interactions among the individuals.

Many learning theories contribute to in-depth understanding and the support of collaborative learning (for instance, peer tutoring, anchored instructions, etc). However, it is not common to find models that allow explicit representation of these theories. One of the reasons is the difficulty to understand the theories due to its complexity and ambiguity. According to [9] different theories can describe the same situation using different terminologies. Moreover, each theory has its own point of view, learning focus, structure, besides many other aspects that need to be considered.

Therefore, to provide systems with theoretical knowledge for collaborative learning we must: a) to establish a common conceptual infrastructure on which we can build a model that describes what a learning theory is and what a collaborative learning is; b) to clarify how learning theories can help the design of group activities and enhance learning outcomes; and c) to propose models and structures that enable the sharing of findings and the use of computers to support the analysis and design of effective CL sessions in compliance with theories.

To deal with the problems presented above we provide a model based on an ontological structure to describe learning theories for collaborative learning and techniques to use it rationally. With that we aim to establish the initial foundations for the development of ontology-aware authoring systems for CL.

3 Graphical Representation of Learning Theories

The use of ontological engineering and ontologies for knowledge systematization have shown significant results to bridge the deep conceptual gap between how to represent the knowledge of authoring systems, considering educational theories, and how to use it adequately [6; 9; 15]. In practical terms ontological engineering helps to achieve the following [5; 16]: (a) a common vocabulary and highly structured definition of concepts; (b) semantic interoperability and high expressiveness; (c) coherence and systematization of knowledge; and (d) meta-models and foundations for solving different problems in a variety of contexts.

In CSCL (Computer Supported Collaborative Learning) research, ontologies have been successfully applied to solve problems such as: group formation [20], CL representation [12], interaction analysis and patterns [10] and modeling of learner's development [11]. With these achievements it is possible to some extent to successfully identify which kind of collaboration occurs in a CL session, to partially understand the essence of the group's interactions, and to estimate the expected educational benefits for each learner. Nevertheless, there are some limitations: (a) there is no explicit relation among interaction patterns and learner's development model; (b) it is not easy to determine what learning theory is appropriate for explaining the learner's development through a set of events; and (c) it is difficult to propose activities in compliant with the theories to enhance interactions among learners and lead them to achieve desired goals.

To overcome these limitations in previous work we clarify the relationships among interactions and learners development to understand how learning strategies provided by learning theories can help learners to acquire desired goals [13]. To allow such understanding we analyze each interaction inspired by learning theories proposed in [10] and using a structure called influential I_L event we divided the interaction process in two events: instructional event and learning event. Every instructional event has a reciprocity relationship with the learning events. In other words, during the teaching-learning process, when a person speaks, the other listens; when someone asks a question, the other answers; and so on. Each event has a related action (or actions) and its correspondent educational benefits (*I-goal*) to the initiator of the action. These actions and educational benefits are directly associated with the context (learning theory), the strategies (*Y<= I-goal*) and the roles that learners use to collaborate with other learners (Figure 1).

Based on such understanding of interactions and considering the previous achievements we propose an ontological structure to describe an excerpt of learning theories as shown in Figure 2. This structure consists of two main parts: the Learning Strategy and the Teaching-Learning Process. The Learning Strategy, composed by the members of a group and the goals of one leaner (I-role), specifies how (*Y<= I-goal*) the learner (*I-role*) should interact with other member of the group (*You-role*) to achieve his objectives (*I-goal*). For instance, in Cognitive Apprenticeship a learner interacts with other learners to guide them during the resolution of a problem. In this case the learning strategy (*Y<= I-goal*) used by this learner is "*learn by guiding*", his role (*I-role*) is known as a "*master role*", the role of the learner who receives the guidance (*You-role*) is known as an "*apprentice role*", and the goals of the learner who guide (*I-goal*) are to acquire cognitive skills (and meta-cognitive skills) at an autonomous level. Previous works of Inaba et al. [12] show the strategies (*Y<= I-goal*), learner's roles (*I-role* and *You-role*) and individual goals (*I-goal*) of several learning theories.

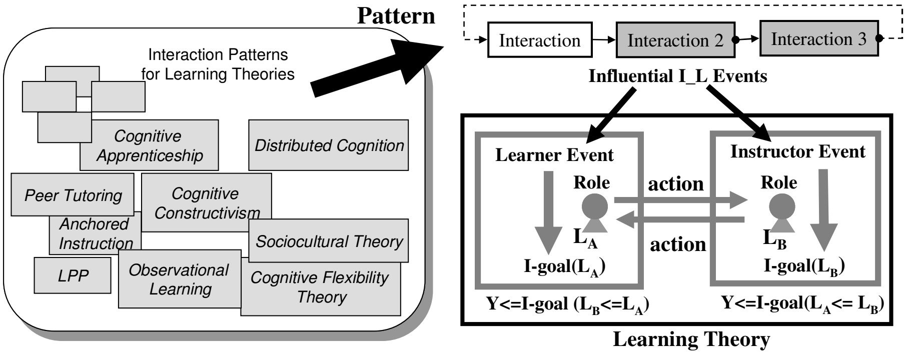

Figure 1. Analysis of interaction patterns – relationship among interaction, strategies and roles

The Teaching-Learning Process specifies the interaction pattern of a learning theory represented by the necessary and desired interaction activities (processes) among two member of a group (for instance, master and apprentice). As mentioned before, we can describe interactions using influential I_L event for explicitly representing the interaction and its benefits from both points of view: for those who do the action and for those who receive the action. Each Influential I_L event (instructional or learning event) is composed by an actor of an action, the action, and the benefits of the player of this action.

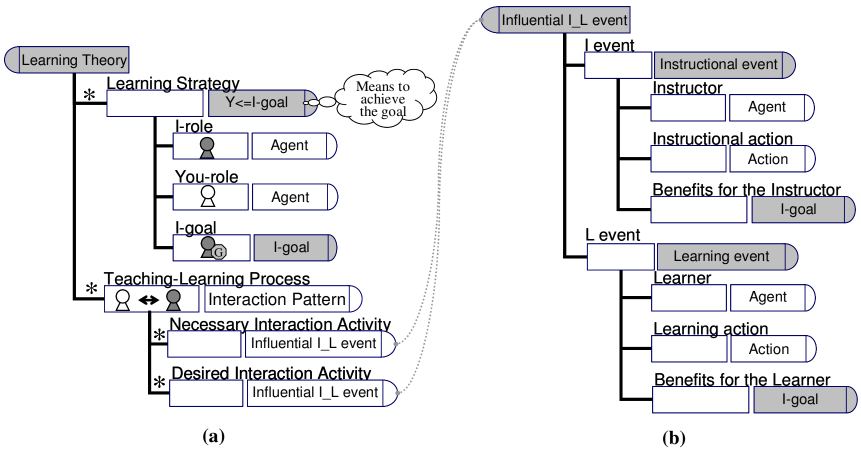

Figure 2. Ontological Structure to describe an excerpt of Learning Theories

Then, we re-analyzed seven different learning theories frequently used to support CSCL activities: Cognitive Apprenticeship [3], Anchored Instruction [4], Peer Tutoring [8], Cognitive Flexibility [19], LPP [14], Socio-Cultural Theory [21] and

Distributed Cognition [18]. And Finally, we proposed the **Growth Model Improved by Interaction Patterns (GMIP)** [13] to unify and to improve the benefits of two successful previous models that offer (a) an explicit representation of typical interactions based on learning theories [10]; and (b) a simplified way to represent the learner's growth (knowledge acquisition and skill development) [11]. With the GMIP we clarified how learning strategies prescribed by learning theories can help learners to acquire desired goals and explicitly identify the relationships among interactions, learning strategies and learning goals.

The GMIP is a graph model based on an ontological structure to describe an excerpt of learning theory [13]. It represents, in a simplified way, the learner's knowledge acquisition process in compliance with Rumelhart and Norman's work [17], and skill development process in compliance with Anderson's work [1]. It explains more precisely the relationships between learning strategies, educational benefits and interactions used to achieve these benefits. To introduce the GMIP, we have to explain more about two processes: knowledge acquisition and development of skill.

The process of acquiring specific knowledge includes three qualitatively different kinds of learning: **accretion**, **tuning** and **restructuring** [17]. *Accretion* is to add and to interpret new information in terms of pre-existent knowledge. *Tuning* is to understand knowledge through application of this knowledge in a specific situation. *Restructuring* is to consider the relationships in acquired knowledge and thus to rebuild the existent knowledge structure.

Considering the development of skills, there are also three phases of learning: the **cognitive stage** (rough and explanatory), the **associative stage** and the **autonomous stage** [1]. The cognitive stage involves an initial encoding of a target skill that allows the learner to present the desired behavior or, at least, some crude approximation. The associative stage is the improvement of the desired skill through practice. In this stage, mistakes presented initially are gradually detected and eliminated. The autonomous stage is one of gradual continued improvement in the performance of the skill.

Using these concepts, the GMIP graph has twenty nodes (Figure 3), which represent the levels of the learner's development at a certain moment of learning. Each node is composed by two triangles. The upper-right triangle represents the stage of knowledge acquisition, while the lower-left triangle represents the stage of skill development. The nodes are linked with arrows that show possible transitions between nodes in compliance with [1] and [17]. $s(x,y)$ is the simplified form of representing these nodes in our model: x represents the current stage of skill development and y represents the current stage of knowledge acquisition. For instance, $s(0,0)$ represents the node where the stage of skill development and knowledge acquisition is *nothing*; and $s(0,1)$ represents that the stage of skill development is *nothing* and the stage of knowledge acquisition is *accretion*.

Using the GMIP graph, we show the benefits of learning strategies by highlighting its path on the graph and associating each arrow with the interactions. In Figure 1 we show an example of the GMIP graph for the learning strategy "***learning by apprenticeship***" used by the learning theory "***Cognitive Apprenticeship***". Bold arrows represent the transition from one stage to the other, which is facilitated through this learning strategy using the labeled interactions. There are two kinds of interactions: the necessary interactions, represented by a black circle, and the complementary interactions, represented by a white circle. The interactions are linked by ellipses. The dashed ellipse represents a directed link between two interactions and the full ellipse represents a cyclical link between two interactions.

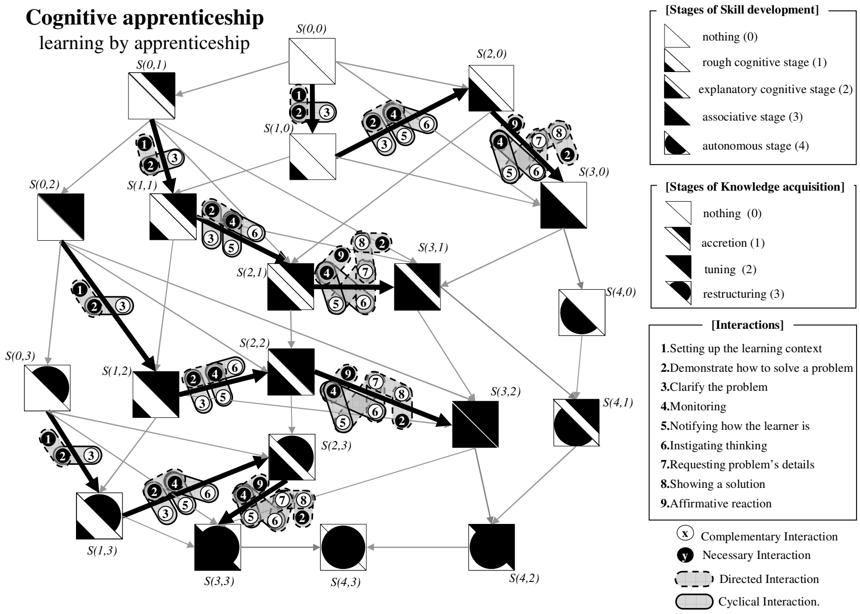

Figure 3. Example of GMIP for learning by apprenticeship used by Cognitive Apprenticeship

The GMIP clarifies, more precisely, how interactions can affect learner's development, facilitating the learning design based on events. Thus, it becomes a powerful tool helping designers to select events (interactions) and roles for each learner considering interaction patterns and learning strategies appropriate for desired learning goals and sub-goals (and vice versa). Furthermore, we believe this model is the first step to explain what a learning theory is, making tacit characteristics explicit: for instance, clarifying expected benefits, use restrictions, guidelines for leading/performing activities, in addition to other important aspects of the teaching-learning process.

Another intriguing feature of GMIP that deserve some attention is the possibility of blending learning strategies. Because each strategy is intrinsically represented as paths on the GMIP graph, we can find common points (stages) between strategies, and thus, provide guidelines to blend learning theories by "*linking*" two or more strategies from different theories to achieve a desired goal. Considering such possibility during the design process a user could choose one strategy to lead learners to obtain some benefits and after change to another strategy to obtain other benefits that the first strategy could not offer. Note that we are not trying to say that it is possible to blend any strategy and any theory, what we want to point out is: *if we deeply understand the theories providing formal methods to represent them explicitly, it is possible to identify common points among theories and then propose techniques* *to blend them rationally.* To blend learning theories for CL is a challenging task and will be addressed more carefully and deeply in future research.

In summary, the main contributions of GMIP for CL design are (a) to allow the graphical visualization of theories and their characteristics. Thus, users can quickly interpret the theories, their benefits and propose sequence of activities in compliance with them; and (b) to provide a formal structure based on ontologies which allows systems to reasoning about the theories and the features (actions, roles, strategies, etc.) prescribed by them. Thus, it is possible to offer new alternatives for intelligent guidance (as shown in section 4) providing **suggestions of CL activities** for users during the design process.

4 Towards a Complete Ontology-Aware Authoring Tool for CL

As we mentioned before to propose a group formation there are many learning theories such as Anchored Instruction, Peer Tutoring, Cognitive Apprenticeship, etc. Then, to assign roles and strategies for members of a group we can select appropriate set of learning theories considering the necessary pre-conditions of learners and the educational benefits we expect to be improved for each learner in the end of a CL session. This flexibility of choosing different learning theories can therefore provide us with many ways to design and conduct learning processes. However, it also suggests the difficulty of selecting the appropriate set of learning theories during the instructional design to ensure learners' benefits and the consistency of learning processes. Therefore, to help users (instructors, teachers, designers, etc) to design effective group activities we need an elaborated authoring system that considers different learning theories to support the design in compliance with them.

According to [15] there is a deep conceptual gap between knowledge of authoring systems. Because of that these systems cannot share or accumulate new knowledge, usually are based on only one theory that is built in the procedures (programming code) to support the design of learning activities, and do not justify their recommendations systematically and scientifically.

Through a survey and an analysis of existing educational authoring systems (especially for intelligent tutoring) Bourdeau and Mizoguchi [2] verified that: "*few environments combine authoring tools and knowledge representation of instructional theories and principles, and that none of them possesses desired functionalities of an intelligent authoring system such as Retrieve appropriate theories for selecting instructional methods or Provide principles for structuring a learning environment*"

To solve these problems we have been developing a theory-aware authoring system for CL, called *CHOCOLATO – a Concrete and Helpful Ontology-aware Collaborative Learning Authoring Tool*. It is based on our model GMIP and the ontological structure to describe learning theories, besides previous achievements presented in section 3. Through the use of ontologies, the theories and their features are declaratively and formally represented which (a) prevent unexpected interpretations of the theories; (b) provide a common vocabulary to describe them; (c) enable us to share and accumulate the knowledge; and (d) provide enough information for computational semantics to provide assistance for users based on theories. Furthermore, through the use of GMIP the system offers graphical and textual support for users providing "intelligent" guidance with theoretical justifications during the authoring process.

The architecture of CHOCOLATO is shown in Figure 4. The system is sub-divided in different sub-systems that aim to support different levels of guidance during (a) group formation that maximize the educational benefit considering the individual and group goals; (b) designing of CL activities; (c) recommendation of learning materials; (d) analysis of individual and group outcomes minimizing the difficulties during this process; and (e) proposing group re-formation and a new CL session based on learner's pre-conditions, desires and requirements. All sub-systems of CHOCOLATO are able to use three different ontologies (Learning Theory Ontology, Learning Process Ontology and CL Ontology) to support their reasoning. The connection among the sub-systems and the ontologies is made using the HOZO API (*http://www.hozo.jp*). The CL design manager controls the use of each sub-system during the design process through the authoring interface.

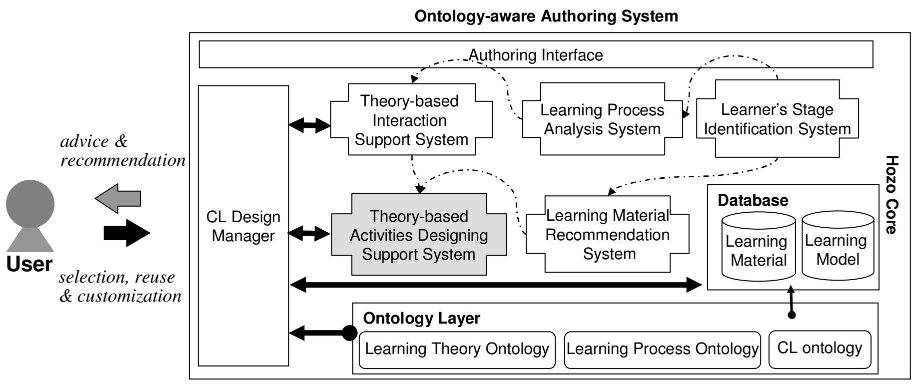

Figure 4. Architecture of CHOCOLATO: Concrete Helpful Collaborative Learning Authoring Tool.

This system assists both novice and expert users. For example, during the design process, for novice users, the design manager of CHOCOLATO provides a structured guidance considering different learning theories. Through an authoring interface using the GMIP it allows users to set initial conditions and goals for a learner or the group and the system automatically recommends theories, strategies, roles and activities to be performed by learners to achieve the desired goals. Furthermore, users can customize the recommendations in order to satisfy requirements depending on particular situations. For expert users, it offers a common language and guidelines to formally express CL activities, the interactions' flows learner's roles, strategies and benefits for learners. Thus, it is possible to describe new strategies and roles for learners, reuse and share them, and finally combine sequence of interactions to fit in different scenarios.

Considering the interaction analysis, it is difficult to know when learners acquire the desired benefit because we need to capture what roles the learners played and what kind of interactions occurred in the session. To help such process, the analysis system of CHOCOLATO identify when a CL session proceeds conform the initial scenario designed by the user. Thus, we can predict whether the learners interacted as expected and whether the CL session was successful or not. It is worth to point out that if the initial scenario of a CL session is not established previously it is much more difficult to expect concrete benefits and to analyze (quantitatively and qualitatively) how much benefits were attained by learners.

In this work we are focusing on design process in order to produce effective CL sessions. Thus, we would like to present a sub-system of CHOCOLATO (shaded block in figure 4) used to support the design of CL activities. This sub-system is called **MARI** – ***M****ain* ***A****daptive* ***R****epresentation* ***I****nterface*. It is an ontology-aware system that uses ontologies developed in Hozo ontology editor to provide its theoretical knowledge and represent them on the screen using the GMIP. Through the use of ontologies MARI allows high expressiveness and interoperability among theories and their features. Nowadays MARI has 6 theories and 12 strategies, besides other information in its database.

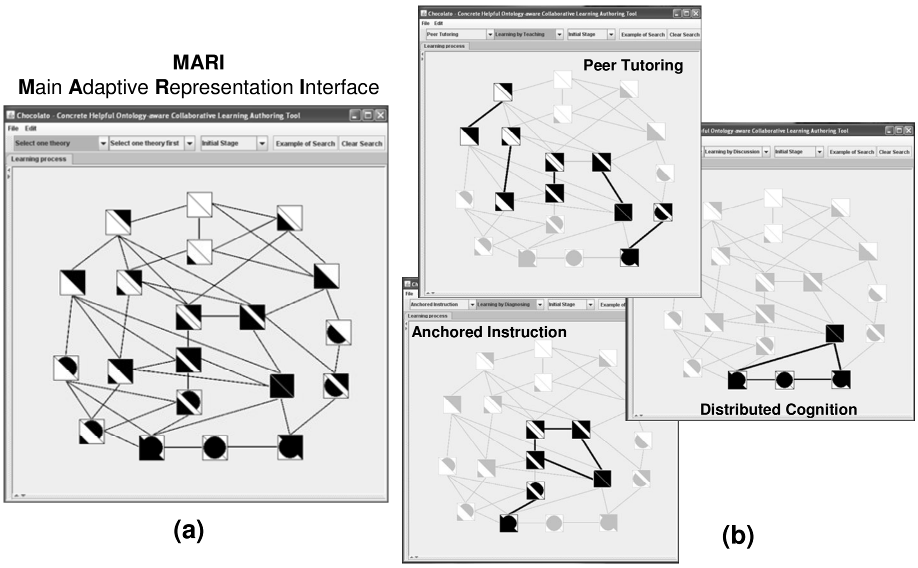

Figure 5. Graphical visualization of different learning theories using different strategies

MARI starts with a neutral network (Figure 5a) that can represent any theory we analyzed by selecting theories/strategies through MARI's interface. MARI reasons on the ontologies to provide a graphical visualization of them using the GMIP. For example, in Figure 5b we show the theories: Peer Tutoring (using the strategy learning by teaching), Distributed Cognition (using the strategy learning by discussion) and Anchored Instruction (using the strategy learning by diagnosing). As you can observe, each of these theories has different pre-conditions to be performed and also different goals to be achieved. In the case of Peer Tutoring, a learner who follows the strategy learning by teaching (and plays the role of tutor) needs, as a pre-condition, the knowledge about a specific content in accretion stage, but does not necessary need skills about how to use it. In such situation, the main goal of the tutor is to acquire knowledge in tuning stage.

Each theory has strong and weak points, in our example, because the main focus of the theory Peer Tutoring is to help the tutor to obtain his benefits, it gives less attention to benefits for the learner who plays the role of tutee. On the other hand, in the case of Anchored Instructor using the strategy learning by diagnosing the learner who plays the role of instructor must have knowledge about the specific content and skills to use it to help other learners who have problems. Thus the learner-instructor can diagnose the problems of other students and solve them. The Anchored Instruction theory is interested in solving learner's problems (called anchors), thus the learner-instructor receive less attention in such situation.

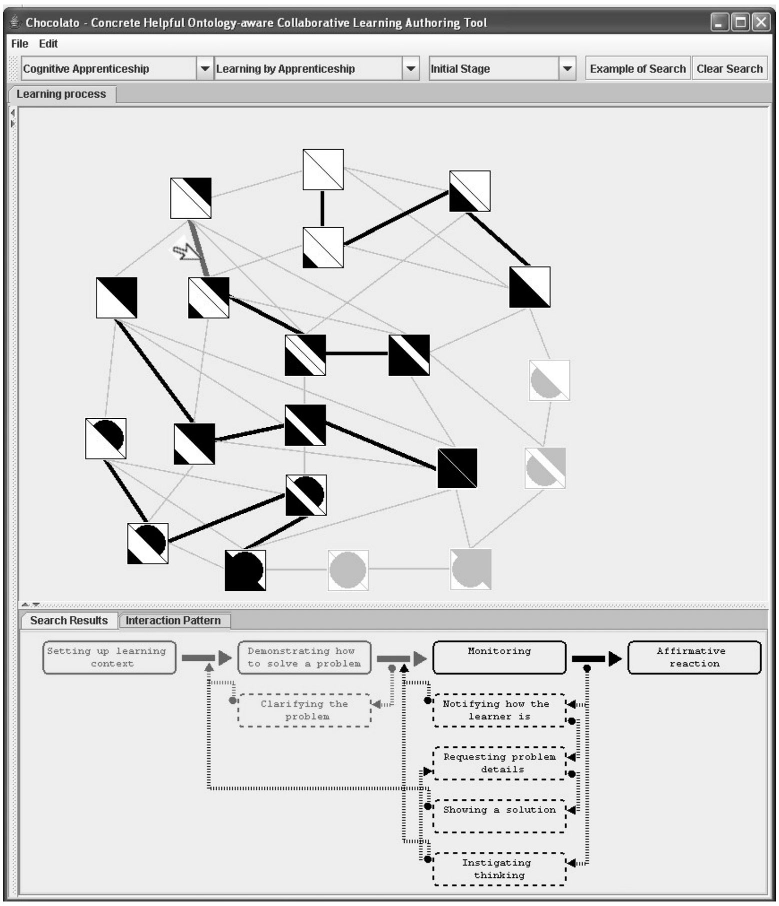

Figure 6. MARI interface: visualization of the *Cognitive Apprenticeship* Theory. In the top it shows the learning path of the strategy *learning by apprenticeship* and in the bottom its related interactions pattern.

MARI has all these information in its database and can give recommendations for users offering an easy and quick interpretation of necessary pre-conditions and educational benefits for learners. Furthermore, by clicking in the bold arrows the system can suggest CL activities (interactions) prescribed by the selected theory which help learners in one stage to achieve the next stage. For example, using the theory Cognitive Apprenticeship and the strategy learning by apprenticeship presented in Figure 3, MARI shows in Figure 6 the necessary and complementary interactions as full boxes and dashed boxes, respectively (bottom of Figure 6). Finally when the user click in one bold arrow in the GMIP path (top of Figure 6), it shows which interactions are associates with this arrow (transition of stages).

Another useful function in MARI is to search theories by given a stage of learner's development. We can select an initial stage of a learner in the GMIP and the system will reason on the ontologies to search for any theory/strategy that has the selected stage in the beginning of the path. As same as before we can select a final stage and the system will search for any theory/strategy that has the selected stage in the end of the path. And finally, the system can search for any theory/strategy that has a path through the selected stage (it means any stage in the path). All these ways of search can be combined, thus, users can select, for example, an initial stage (pre-conditions) and a final stage (expected benefits) of a learner and the system will find the theories/strategies that help this learner to achieve the desired benefits. If more than one theory/strategy is found, users can select one of them and the system suggests activities in compliance with it.

In case we do not find any theory/strategy that helps a learner (or a group of learners) considering his initial conditions (initial stage) and desired goals (final stage), the idea of blended learning theories in the end of section 2.2, could be considered. In such a case a possible solution to help a learner is to use the GMIP to work with theories at the macro-level (strategies, learner's stages, etc) to select a strategy ***S1***, which help learners in an stage ***G1*** (initial stage) to achieve a following stage ***G2*** (sub-goal), and then, to select another strategy ***S2***, which help learners in an stage ***G2*** to achieve a following stage ***G3*** (final stage) that cannot be achieved by ***S1***. After that, working with theories at the micro-level (activities, learner's roles, etc) the system is able to identify the sets of interactions of the strategies ***S1*** and ***S2***, combining them rationally, to finally, propose a sequence of CL activities that maintain the consistence of the learning process. These steps enable us to connect the strategies ***S1*** and ***S2*** and to create suitable set of interactions to help a learner in the initial condition, ***G1***, to achieve his desired goals, ***G3***.

To give an example of how to use the GMIP to blend strategies lets propose a problem: "*In a group, the desired goal of learner **L**, who does not have any content specific knowledge or skills, **s(0,0)**, is to attain skills in associative level and content specific knowledge in accretion level, **s(3,1)**. Considering that how can we design a collaborative learning session, supported by the theories, to help him?*"

To solve such problem, first, it is necessary to choose a theory and a strategy that lead the learner from *s(0,0)* to *s(3,1)* and after propose activities in agreement with it. To choose the theory/strategy, on Table 1 we show six learning theories, their strategies, roles for learners, and their respective paths in the GMIP graph. By using only a single theories in Table 1 it is impossible to help the learner ***L*** to achieve the desired goal *s(3,1)*.

Table 1. Relationships among learning theories, roles, strategies and expected benefits.

Learning Theory	Learner's Role	Learning Strategy	Expected Benefits (I-goal) Initial stage → Following stage
Anchored Instruction	Anchor holder	Learning by being taught	s(x,0)→s(x,1)→s(x,2); x={0..4}
	Anchored instructor	Learning by diagnosing	s(2,1)→s(3,1)→s(3,2); s(2,1)→s(2,2)→s(3,2); s(2,3)→s(3,3);
Cognitive Apprenticeship	Apprenticeship	Learning by apprenticeship	s(0,y)→s(1,y)→s(2,y)→s(3,y); y={0..3}
	Master	Learning by guiding	s(3,y)→s(4,y); y={0..3}
Cognitive Flexibility	Audience	Learning by reflection	s(x,2)→s(x,3); x={0..4}
	Panelist	Learning by self-expression	s(2,y)→s(3,y); y={1..3}
Distributed Cognition	Full participant	Learning by discussion	s(3,y)→s(4,y) and s(x,2)→s(x,3); x={3,4}, y={2,3}
LPP	Peripheral participant	Learning by practice	s(0,y)→s(1,y)→s(3,y); y={0..3}
	Full participant	Learning by discussion	s(3,y)→s(4,y) and s(x,2)→s(x,3); x={3,4}, y={2,3}
Peer Tutoring	Peer Tutee	Learning by being taught	s(x,0)→s(x,1); x={0..4}
	Peer Tutor	Learning by teaching	s(x,1)→s(x,2); x={0..4}

Using the GMIP and the idea of blending strategies, to achieve *s(3,1)* from *s(0,0)* we can combine learning strategies to develop skills and acquire some knowledge. As showed on Table 1, there are four learning strategies that initiate from *s(0,0)*: *learning by being taught* (used by Anchored Instruction and by Peer Tutoring)*, learning by apprenticeship* (used by Cognitive Apprenticeship) and *learning by practice* (used by LPP). Nevertheless, none of them have a direct path to the desired goal *s(3,1)*. In such a situation, one strategy can be initially chosen and then be combined with another strategy to cover its lack. In Figure 7 we show one possible solution using the theory Anchored Instruction and the strategy learning by being taught. Thus, for this example we blended at the macro-level the strategies *learning by apprenticeship* (full arrows in Figure 7) and *learning by being taught* (dashed arrows in Figure 7) to find a path from *s(0,0)* to *s(3,1)*. This solution provides four possible paths, labeled as A, B, C and D, to achieve the goal (bottom of Figure 7).

As a result of blending these two strategies, in compliance with the GMIP (Figure 7), on the bottom of Figure 8 we show at the micro-level the suggested sequence of interactions that intends to help the learner ***L*** to achieve *s(3,1)* from *s(0,0)* supported by *Cognitive Apprenticeship* and *Anchored Instruction.* The bold-dotted arrows labeled ***A***, ***B***, ***C*** and ***D*** in Figure 8, have their correspondent in Figure 7, and show where the set of interactions inside of the gray box ***AI*** (top of Figure 8) should be placed in the sequence of interactions of *Cognitive Apprenticeship* (bottom of Figure 8) to solve the problem. The gray box labeled ***AI*** is the set of interactions provided by

Anchored Instruction which eventually helps the learner who plays the role of *anchored holder* to acquire some content specific knowledge in accretion stage, *s(x,1)*, using the strategy *learning by being taught*. This set of interactions supports the interactions provided by *Cognitive Apprenticeship*, which helps the learner who plays the role of *apprenticeship* to develop some skills in associative stage, *s(3,y)*, using the strategy *learning by apprenticeship*.

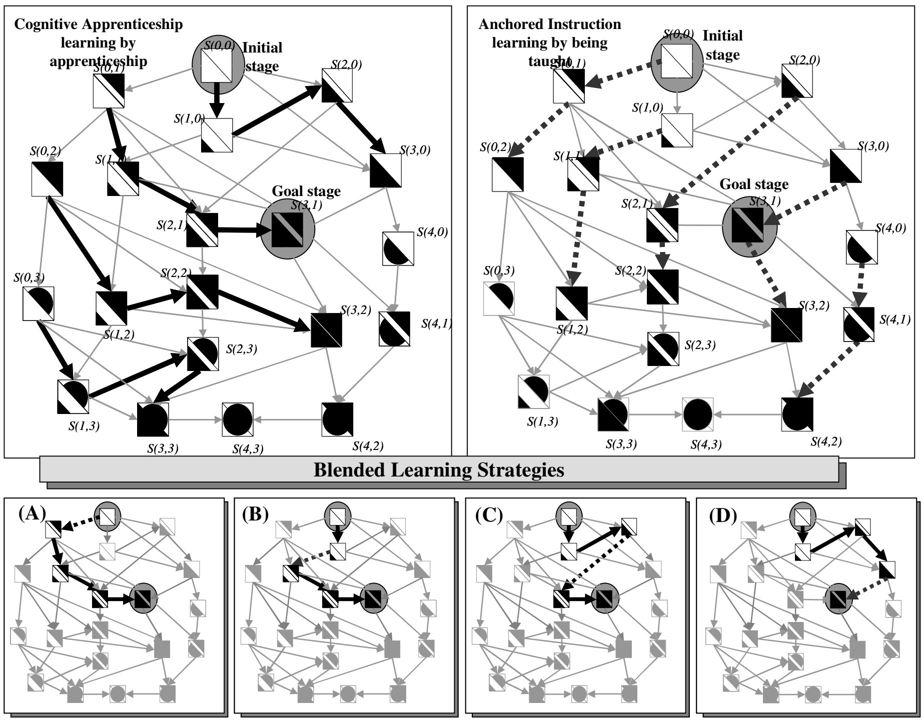

Figure 7: In the top, two different strategies: *Learning by apprenticeship* (full arrows) and *Learning by being taught* (dashed arrows) at the macro-level to achieve the goal *s(3,1)*. In the bottom, it shows four different paths to achieve *s(3,1)* from *s(0,0)* done by blending the learning strategies.

Thus, the learner ***L*** can eventually acquire the desired benefits *s(3,1)* during a CL session by adopting the suggested sequence of interactions as shown in the bottom of Figure 8.

It is worth to point out that to completely realize blended learning for CL it is necessary to consider the relationships among many assumptions described by theories (for instance, context, delivery methods, learning preferences, etc), besides the synergy among learners in a group. It is our intention for future research to include a more deep study demonstrating some examples and possibilities to blend learning strategies semi-automatically.

Using ontologies and the GMIP it is feasible for our system to reason on the theories at the macro and micro levels and to create a link between them. This link allows us to select appropriate learning theories and strategies at the macro-level and to suggest consistent sequence of activities for learners in a group at the micro-level.

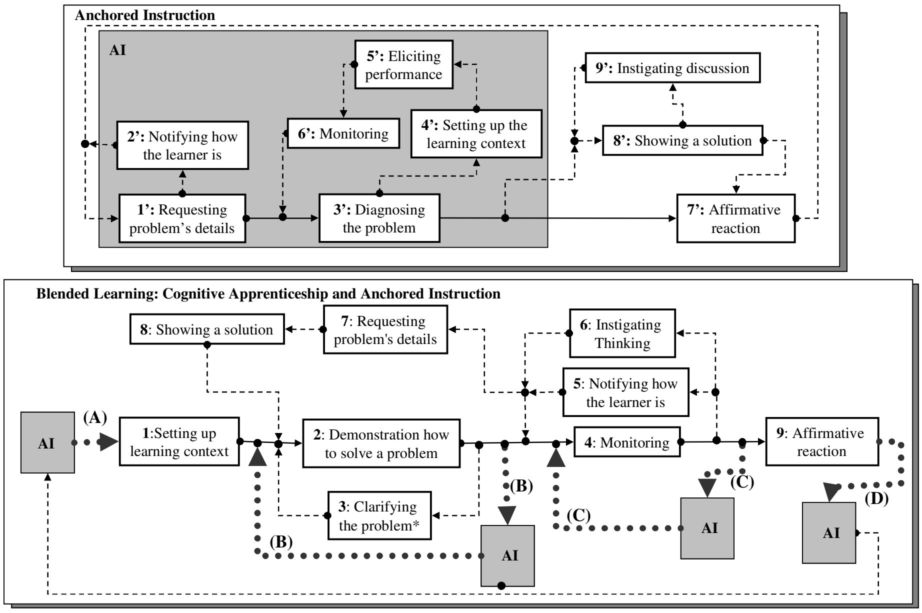

Figure 8: On the top, the interactions pattern of Anchored instruction. On the bottom the sequence of suggested interactions based on blended learning strategies at the micro-level.

The suggestions given by our system are only guidelines for users to propose CL activities based on theories which (a) preserves the consistency of the learning process; and (b) guarantees a suitable path for learners to achieve desired benefits. However, expert designers do not need to follow the suggestions. They can propose their own path on the graph and their own sequence of activities. In such case the system also can assist these users providing different kind of information about theories, activities, strategies, learner's roles and other related information that can be useful in various situations.

4 Conclusions

The main contribution of this research is to introduce our model GMIP based on an ontological structure to describe learning theories for CL and create techniques to use it rationally. This is another step forward in the improvement of ontology-aware authoring systems that offer intelligent guidance to design CL activities supported by theoretical knowledge that solves, at least partially, the problems of knowledge representation presented in [15]. The proposed system MARI supported by our model GMIP and theories described as ontologies allow us to work with theories at the macro and micro levels and to create a link between them. This link clarifies, more precisely, how interactions can affect learner's development which helps designers to select interactions and roles for each learner with justifications based on the theories. It also allows us to reasoning on these theories semi-automatically to suggest consistent sequence of activities for learners in a group.

We also showed roughly the intriguing possibility of blending learning strategies using our model and our system as a feasible solution to deal with the problem of unreachable stages (stages that none of the analyzed theories has a path through it by itself). In such a case, during the CL design the system can suggest for users a set of activities supported by blended theories to find a suitable way to lead learners to achieve desired benefits. Our future work will deal with many open questions about blended learning theories for CL to improve our model and our system.

One delicate point we would like to emphasize is the necessity of sophisticated group formation to set strategies, roles and activities for each learner before a CL session starts. We believe that the design of CL sessions is a requisite to maximize educational benefits and to minimize the load of interaction analysis. Such approach creates favorable conditions for learners to perform CL activities and help users to estimate more easily how much benefits learners attain in the end of a session. Our approach uses theory-driven group formation with suggestions of role assignment and sequence of interactions to offer fundamental settings for an effective CL session and essential conditions to predict the impact of interactions in the learning process.

The possibility of clarifying what a CL session is and to amplify its educational benefits has been a great challenge. In this context our approach offers a declarative representation of learning theories allowing computational semantics to support the design of CL sessions in compliance with well-grounded theoretical knowledge and, because it can be explicitly demonstrated, is much more convincing and flexible than usual approaches.

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