Using Ontologies to Support Theory-aware Collaborative Learning Applications

Seiji Isotani and Riichiro Mizoguchi (advisor)
Osaka University, Japan

1. Problem and Motivation

Two of the most important research subjects during the development of **intelligent educational systems (IES)** are the modeling of knowledge and the extraction of knowledge flows from theory to practice [4; 7; 14]. It bridges the gap between theoretical understanding about learning and the practical foundations of design and how to analyze the knowledge of intelligent systems that support the learning process.

To support knowledge flows of IES, it is essential to exploit a well-designed and shareable knowledge that enables the extraction of domain independent flows. Usual approaches represent the knowledge of the system using a set of heuristics coded in procedures. As a result, these systems cannot share knowledge, nor provide knowledge flows systematically or scientifically [14]. In this context, our research intends to innovate how knowledge flows are provided by a comprehensive methodology in which knowledge is created, represented, discovered, shared and efficiently applied, especially within the context of collaborative learning.

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

The use of ontological engineering and ontologies for knowledge systematization have shown significant results in bridging the deep conceptual gap between how to represent the knowledge of educational environments (considering educational theories) and how to use it adequately [2]. In practical terms, ontological engineering helps achieve [4]: (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.

The main problem now being addressed is how to propose an *effective* group formation using CL theories to facilitate the design and analysis of groups' activities and later, the re-formation of groups based on previous information concerning successful/unsuccessful group formations and learners' interactions (accumulation of knowledge). By *effective*, we mean maximization of achieved educational benefits by selecting an appropriate set of learning theories to allow group formation that offers (a) fundamental settings to design group activities that assign roles and strategies to each learner and (b) essential conditions that analyze learners' interactions facilitating the prediction of educational benefits. The design of a CL session in a principled way is a requisite for maximizing educational benefits and minimizing the load of interaction analysis.

Our approach relies on the achievements of the Learning Science community (especially CL theories) and previous achievements using ontologies to support collaborative learning that at first establishes a common understanding of what a CL theory is in terms of explicit and formalized concepts and vocabulary. In other words, we aim at making theories understandable for both computers and humans; we then propose techniques for reasoning on these theories, which contribute to solving the problem of selecting an appropriate set of CL theories to form a group and to facilitate the development of systems to support dynamic guidance, instructional planning, and interaction analysis. Thus, we enable fluent knowledge flow from theoreticians and authoring practitioners.

2. Background and Related Work

Collaborative learning has a long history in Education [5]. In spite of this, proposing an effective group formation and capturing what really happens in each session are still very complex issues due to a lack of comprehensible models for representing what is occurring [7]. Conventional research focuses on automating group formation without careful representation of CL theories. Some studies have focused on developing heuristics for multi-agent systems that allow the automation of some steps of group formation [11; 12]. The main problem with such an approach is that there is no guarantee that the suggested group formation will help learners achieve educational benefits. Others propose programs that automate the utilization of common practices used in classrooms to form groups [6; 16]. However, these systems do not have the necessary knowledge to support the identification of adequate roles and goals for learners and match them with feasible interactions that can lead learners to achieve their desired goals. A few studies have considered the use of CL theories during the design rationale of their systems [3]. Nevertheless, they did not have an explicit representation of CL theories, thus it remains complicated the use of different CL theories to make the CL processes more effective. Our initial intention is not to automate but to provide theoretical frameworks and models to form a group on which we can validate and justify the effectiveness of our recommendations. Our main goal is to formalize CL theories that have already been extensively evaluated by the Learning Science community and use this formalization to improve group formation, the design of CL activities and the analysis of learner's interactions.

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

Therefore, to provide systems with theoretical knowledge for collaborative learning we must a) establish a common conceptual infrastructure on which we can build a model that describes what a CL theory and collaborative learning are; b) clarify how CL theories can help the design of group activities and enhance learning outcomes; and c) support theory-driven group formations that facilitate the design of CL activities and the analysis of interactions.

Usually, the design of CL activities and the analysis of interactions are treated separately. There is a clear boundary between them. To improve the design, most researchers focus on developing a set of instructions specifying how learners in a group should interact and collaborate in CL sessions (also known as CSCL scripts) [13]. Conversely, to understand the effect of interactions in the learning process, many researchers have been analyzing how learners construct their knowledge through social interactions [17]. Because of this division, there are only a few studies addressing how the design of CL activities can guide the analysis of interactions. Furthermore, there is a lack of research addressing the influence of group formation in the design of CL activities and its impact on the CL process.

In this context, our research aims at using ontologies to enable a theory-driven group formation that links the design of CL activities with the analysis of interaction processes. This approach allows for the identification of intended goals, roles, and strategies for a group and its members during the design process. Thus, it is possible to suggest interaction patterns (knowledge flows) that can lead learners to achieve desired goals. We can then more easily analyze individuals' and groups' interactions to identify if the proposed interactions are successfully carried out or not and if learners attained the expected benefits (goals) or not.

Past achievements have successfully applied ontologies for solving some problems accrued while using CL theories [7; 8]. Nevertheless, there remain some limitations: (a) there is no explicit relation among interaction patterns and learner's growth (knowledge acquisition and skill development); (b) it is not easy to determine which CL theory is appropriate for explaining the learner's development through a set of events; and (c) it is difficult to propose activities in compliance with the theories to enhance interactions among learners and lead them to achieve the desired goals.

The contribution of our research is to overcome these limitations by re-analyzing several CL theories and clarifying their characteristics and relationships. Then, we propose ontologies and a model to describe them. Finally, we summarize our achievements by providing sophisticated methods and systems to support effective group formation and to extract knowledge flows for the design of CL activities and the analysis of learners' interactions, based on well-grounded theoretical knowledge.

3. Approach and Uniqueness

To understand and clarify the characteristics of CL theories, we call upon techniques of ontological engineering to re-analyze seven different CL theories frequently used to support CSCL activities: Cognitive Apprenticeship, Anchored Instruction, Peer Tutoring, Cognitive Flexibility, LPP, Socio-cultural Theory and Distributed Cognition (For more information, see reference [9]). Furthermore, to build our ontology to represent CL theories, we rely on previous works of Inaba et al. [7], which propose interaction patterns for CL theories, offer vocabulary and expected interaction flows to describe interaction processes, and clarify the use of theories in CL scenarios.

To comprehend each interaction in an interaction pattern and its potential benefits for learners, we divided the interaction process into two events: **instructional** and **learning**. Every *instructional event* has a reciprocity relationship with the *learning events*. In other words, during the teaching-learning process, when a person speaks, another person listens, when someone asks a question, another answers, and so on. Each event has a corresponding action (or actions) and possible educational benefit for the initiator of the action. These actions and educational benefits are directly related to the context (CL theory and learning strategy) in which the events are executed. We call this intrinsic relationship between instructional events and learning events an influential I_L event (Figure 1b). Influential I_L events are essential for describing CL theories and clarifying the benefits of interactions in the learning process.

The representation of the ontological structure of a CL theory consists of two main parts (Figure 1a): the **learning strategy** and the **teaching-learning process**. The *learning strategy* specifies how (Y<= I-goal) the learner (I-role) should interact with another person (You-role) to achieve his or her objectives (I-goal). For instance, in a Cognitive Apprenticeship, a learner interacts with other learners to guide them through the resolution of a problem. In this case, the learning strategy (Y<= I-goal) used by this learner is "*learning by guiding*"; his or her role (I-role) is known as the "*master role*"; the role of the learner who receives the guidance (You-role) is known as the "*apprentice role*". The goals of the learner who guides (I-goal) are to acquire cognitive skills (and meta-cognitive skills) at an autonomous level. It is also possible to identify roles, strategies and objectives from the perspective of the learners who receive the guidance. Thus, all learners can harmoniously interact by playing different roles and strategies in order to achieve their goals. Previous works of our group [8; 9] show the strategies (Y<= I-goal), learner's roles (I-role and You-role) and individual goals (I-goal) of different CL theories.

The teaching-learning process specifies interaction patterns of a CL theory represented by the necessary and desired interaction activities (processes) among two people (for instance, master and apprentice). As mentioned before, we can describe interactions using the influential I_L event for explicitly representing the interaction and its benefits from the points of view of both the actors and recipients.

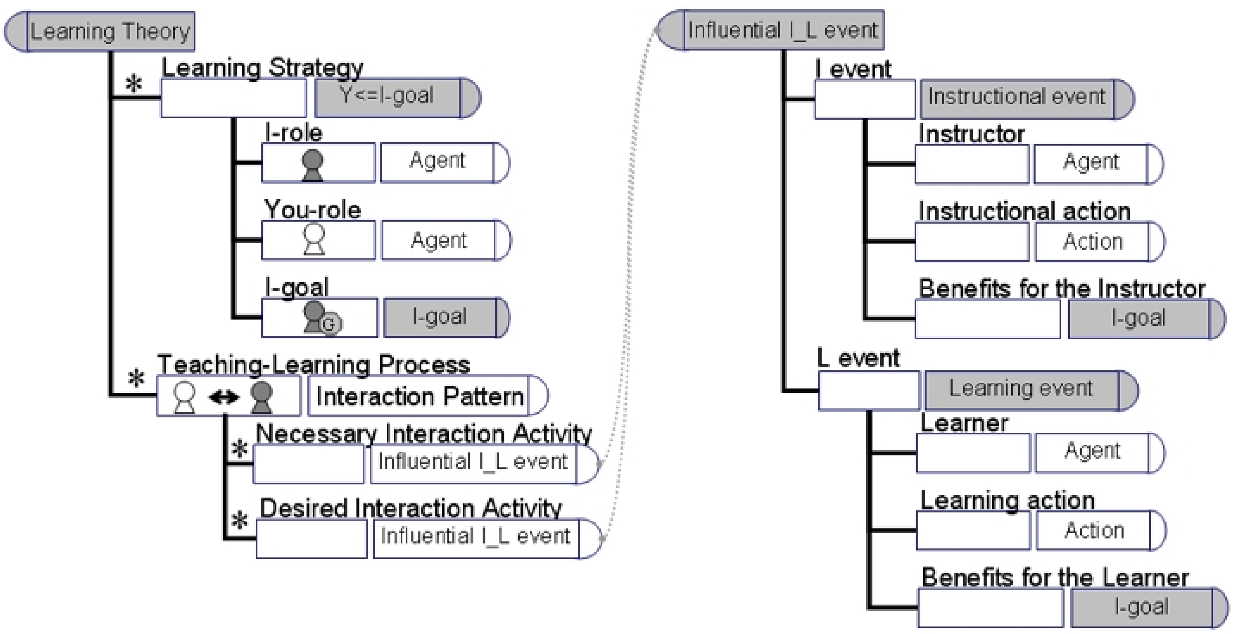

Figure 1. Ontological structure representing a CL theory

3.1 Graphical Representation of CL Theories

Using the representation of interaction patterns through I_L events and our structure of a CL theory, we can identify the interaction activities and their benefits for an instructor and learner in the context of a CL theory. At present, we have identified more than 13 influential I_L events and their respective benefits used by the seven CL theories presented in the beginning of section 3. Thus, to facilitate users to visualize CL theories and computers to reason on these theories, we propose the **Growth Model Improved by Interaction Patterns (GMIP)** [9]. It has been built upon the two previous successful works of Inaba et al. [7; 8]. With the GMIP, we clarify how learning strategies prescribed by CL theories can help learners acquire desired goals and explicitly identify the relationships among interactions, learning strategies and learning goals.

The GMIP is a graph model based on our ontological structure describing an excerpt of CL theory. It represents, in a simplified way, the learner's knowledge acquisition process in compliance with the work of Rumelhart and Norman [15] and the skill development process in compliance with the work of Anderson [1]. For such representation, we must explain more about two processes: knowledge acquisition and the development of skills.

The process of acquiring specific knowledge includes three qualitatively different kinds of learning: **accretion**, **tuning**, and **restructuring** [15]. *Accretion* is adding and interpreting new information in terms of pre-existent knowledge. *Tuning* is understanding knowledge through the application of this knowledge in a specific situation. *Restructuring* is considering the relationships in acquired knowledge and thus rebuilding 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 initially presented 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 2) which represent the levels of the learner's development at a certain moment of learning. Each node is composed of 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 showing possible transitions in compliance with [1] and [15]. ***s(x,y)*** is the simplified form of representing 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*; *s(0,1)* represents the stage of skill development that is *nothing* and the stage of knowledge acquisition that is *accretion*.

Using the GMIP graph, we show the benefits of CL theories/strategies by highlighting their path on the graph and associating each arrow with the interactions. In Figure 2 we show an example of the GMIP graph for the learning strategy "**learning by apprenticeship**" used by the CL 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.

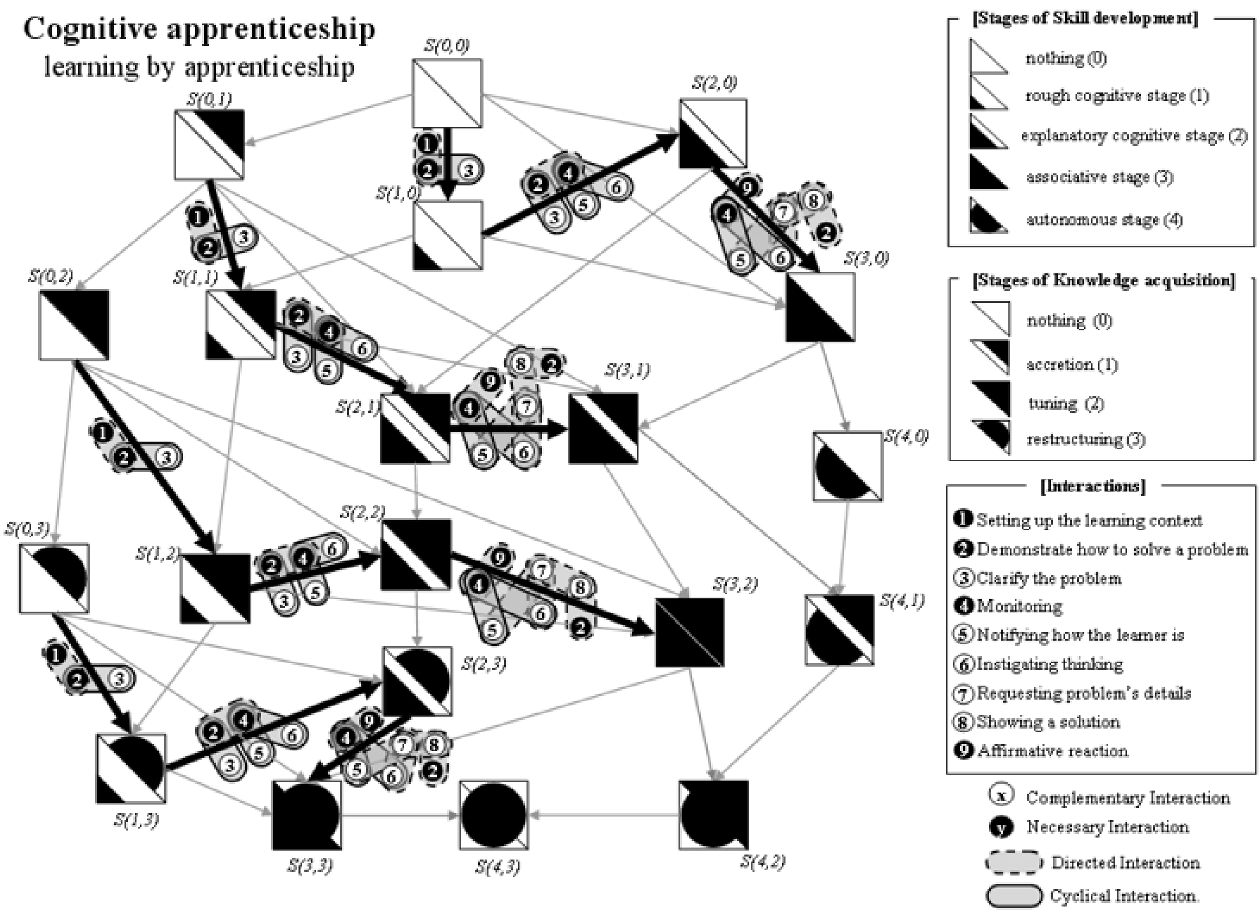

Figure 2. Example of GMIP for *learning by apprenticeship* used by *Cognitive Apprenticeship*

The GMIP more precisely clarifies how interactions proposed by theories can affect learners' development and facilitate theory-driven group formation and learning design/analysis based on learners' goals and events. Thus, our model plays a central role in the decision-making process concerning how, when, and why we should use theories to form a group that considers personal and social (group) goals.

For users, the GMIP allows a graphical visualization of theories and their characteristics. Thus, users can quickly interpret the theories and propose group formation and sequences of activities in compliance with them. Finally, it also gives parameters that help measure the quality of the interaction among learners. For computers, GMIP provides a formal structure based on ontologies, which allows systems to reason theories and features (actions, roles, strategies, etc.) prescribed by them. Thus, it becomes a powerful tool, helping designers form a group and select events (interactions) and roles for learners and consider interaction patterns and learning strategies appropriate for the desired learning goals (and vice versa).

4. Results and Contributions

Our main results rely on the necessity of having a formal and shareable understanding about many CL theories and their features. However, it is very difficult for users (teachers, instructors, designers) to have such common understandings. Our approach uses ontologies to clarify fundamental characteristics of CL theories and essential conditions to use and share these theories and to propose intelligent systems that support sophisticated group formations.

Thus, the main contributions of our work in CL research are (a) to make tacit characteristics of CL theories explicit; (b) to identify the relationships among interactions, strategies, and goals (Table 1 shows a small example of these relationships for Cognitive Apprenticeship); (c) to propose a model (GMIP - Figure 2) and ontological structures (Figure 1) that formally represent CL theories and work as a skeleton where we can describe any theory we analyze; and finally, (d) to create tools and techniques that support effective group formation, the design of CL activities and the analysis of interactions.

In the context of IES, our approach offers a declarative and explicit representation of CL theories that allows computational semantics to be in compliance with well-grounded theoretical knowledge and, because it can be explicitly demonstrated, is much more convincing and flexible than usual approaches [9]. This is another step forward in the improvement of theory-aware educational systems that offer intelligent guidance for design CL activities supported by theoretical knowledge that solves, at least partially, the problems of representing and sharing the knowledge of IES [14], which lead to fluent knowledge flow from theory to practice.

Table 1. Example of relationships among theories, strategies, roles, events/interactions and expected benefits

CL Theory	Learner's Role	Learning Strategy	I_L Event (Instructor/Learning Event)	Expected Benefits Initial stage to Goal stage
Cognitive Apprenticeship	Master Role	Learning by Guiding	Monitoring (checking)	s(3, 2) to s(4, 2)
			Clarifying the Problem (identifying learner's problem)	s(3, 2) to s(4, 2)
	Apprentice Role	Learning by Apprenticeship	Clarifying the Problem (externalization of a problem)	s(0, x) to s(1, x); s(1, x) to s(2, x), x=0,1,2
			Monitoring (being checked)	s(1, x) to s(2, x); s(2, x) to s(3, x), x=0,1,2

The prototype of IES, using our model and ontologies, has shown good results [10]. With principled group formation, our system creates favorable conditions for learners to perform CL activities and help instructors more easily estimate how many benefits the learners may attain at the end of a session. Through an authoring interface using the GMIP, users can set initial conditions and goals for learners, while the system will automatically recommend group formation, theories, strategies, roles and activities/interactions 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, learners' roles, and strategies and benefits for learners. Thus, it is possible to describe new strategies and roles for learners, reuse and share them, and finally combine a sequence of interactions to fit different scenarios. Nowadays, the system (called MARI) has six theories, twelve strategies and ten learner's roles, besides other information, in its database.

We would also like to emphasize the intriguing possibility of blending strategies from theories using our model and our system as a feasible and novel solution to deal with the problem of unreachable goals (stages in GMIP that none of the analyzed theories has a path through by itself). Because each strategy is intrinsically represented as a path on the GMIP graph, we can find common points (stages) between strategies, and thus provide guidelines to blend CL theories by "linking" two or more strategies from different theories to achieve a desired goal. In such a case, during the CL design, the system can dynamically suggest a set of activities supported by blended theories that would allow users to find a suitable way to lead learners to achieve a desired benefit/goal.

Our ultimate objective is to complete the development of the foundations of an intelligent authoring tool for CL that supports group interactions, facilitates the design of learning environments and evaluates the quality of learning processes. We also plan to use our achievements to allow for a meaningful interaction analysis that could propose group formation and re-formation of groups based on an accumulation of knowledge.

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