Chapter 2

DESIGN, MODELING, AND ANALYSIS OF COLLABORATIVE LEARNING

Introduction to PART I

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Over the past 20 years, computer-based training software has become increasingly successful at addressing the learning needs of individuals. Yet, the problems we face in meeting the needs of learning groups continue to be a challenge, both on line and in the classroom. As Webb and Palincsar (1996) explain, studying group learning involves much more than studying a synthesis of individual behaviors:

"Consider the numerous intraindividual factors (e.g., prior knowledge, motivation, language) that influence the learning of one child in "individualistic" activity. Place this learner in a group context, and not only does one have to contend with all the issues that attend this interaction among the group members (from the very mundane resource issues to the more lofty issues of attaining intersubjectivity), but in addition, other intraindividual factors that may have receded into the background when considering individualistic activity now emerge as salient, indeed critical (e.g. the learner's gender and social status)." (p. 867)

Just as supporting individual learning requires an understanding of individual thought processes, supporting group learning requires an understanding of the processes of collaborative learning. These processes are shaped by the group members' individual behaviors, and the dynamics of their interaction. The chapters in Part I of this book bring together cognitive, social, and computational perspectives to evolve advanced methods for designing, modeling, analyzing, and evaluating online collaborative learning activities. To be consistent with the contributions that follow, we limit our discussion to collaborative learning activities that occur at a distance, over a computer network, although many of these ideas may be derived from, or may also pertain to face-to-face collaborative learning.

Guidelines for studying the collaborative learning process are by no means straightforward, however the pay off tends to be quite attractive. The collaborative learning experience has the potential to motivate students to seek new insights and perspectives, ask questions openly, and practice explaining difficult concepts, thereby gaining a better understanding of the domain (Doise, Mugny, & Perret-Clermont, 1975). The extent to which these benefits are realized depend largely on the effectiveness of the group interaction. The overall goal of the approaches described in this section is to help students interact effectively, so that they may maximize their potential learning gain. Many different factors may influence group dynamics, which in turn influence student learning. Some of these factors include group composition and cohesion, group size, task structure, student and teacher roles, discourse styles, nature of facilitation, rewards or incentives, training in communication skills, group processing, and the learning environment (Levine & Moreland, 1998; Webb & Palincsar, 1996). In the interest of positively influencing the process of collaborative learning through computational means, Part I of this book views these factors in terms of those that must be decided before the students begin collaborating (e.g., group composition, rewards), and those that may be altered as the collaboration progresses (e.g., roles, facilitation methods).

The chapters that follow cover two fundamental approaches to promoting effective group interaction. The first approach varies the assortment and intensity of *external* environmental factors such as the group's composition or the learning context. For example, a (human or computer) facilitator might construct a learning group for a specific task by selecting members with the most compatible knowledge, skills, and behaviors in anticipation that this will create the dynamics needed to produce effective learning. The second approach focuses on the modeling and diagnosis of *internal* group interaction factors by analyzing the group interaction after the students have begun an assigned task. In this case, the facilitator might study the progression of the group conversation or the development of the group's shared solution. By applying a combination of these approaches, the system may glean enough information from the analysis to dynamically facilitate the interaction, propose new problem sets that target specific skills, or alter the environment to adapt appropriately to the students' changing needs.

Part I begins with a chapter by Wessner and Pfister in which they discuss the effect of both external environmental factors, such as group formation, and internal group interaction factors, such as the structuring of the learners' communication and collaboration processes, on web-based cooperative learning. They introduce the notion of "points of cooperation" that describe opportunities to cooperate within specific learning contexts, and they extend this discussion to explain how activities may vary in the degree to which they are integrated in the web-based course design. For example, generic cooperation activities may be less integrated than spontaneous or intended cooperation activities. Special attention is given to the "intended points of cooperation", because these represent the optimal degree of logical (in relation to other parts of the course) and didactical (dependent on the type of instructional content or media) integration. Intended points of cooperation include cooperative learning methods such as pro/contra-disputes or brainstorming. These may be defined during course authoring and treated as course units.

To illustrate these ideas, Wessner and Pfister describe a learning environment developed for the project "L^3–Lifelong learning as a basic need." Different group formation criteria are considered depending on the learning mode (class vs. individual) and the cooperation mode (synchronous vs. asynchronous). Depending on the learning mode, the group formation may be accomplished either manually or automatically. Management tools assist the tutor in manually constructing the group by considering the constraints of the intended cooperative activity (e.g., number of participants required, knowledge preconditions for the task). When no tutor is available, the automatic group formation algorithm enables the learning system to automatically extract the information needed to select and group participants. The system supports collaboration during intended interactive activities by providing group members with the information and tools they need (e.g., the topic to be learned or discussed, number of participants, duration, additional information for discussants, cooperation scripts) to initiate and manage the cooperative learning process.

The second chapter in Part I, authored by Nakakoji, Ohira, Takashima and Yamamoto, focuses on a computational environment that supports "breakdowns" as opportunities for lifelong learning. Winograd and Flores explain that a breakdown is, "*not a negative situation to be avoided, but a situation of non-obviousness, in which the recognition that something is missing leads to unconcealing (generating through our declarations) some aspect of the network of tools that we are engaged in using* (Winograd & Flores, 1986, p. 165)." Nakakoji and colleagues propose two approaches to support lifelong learning; (1) experiencing a breakdown, and (2) asking for information relevant to the breakdown. Knowledge-based critiquing systems have been studied to support these processes by monitoring human performance, identifying potentially problematic situations, alerting the users about potential problems, and providing explanations for the criticism and information relevant to the problem. Although they have been found to be effective, such systems do not support synchronous collaborative learning among practitioners. Nakakoji and colleagues complement the knowledge-based critiquing approach with their presentation of EVIDII (Environment for Visualizing Individual Differences of Impressions), a system that helps group members visualize the differences between set associations (e.g., pictorial images and words). While interacting with EVIDII, users experience breakdowns when they encounter unexpected associations made by other group members and are encouraged to ask the other members about the association. These activities are intended to prompt further communication and knowledge construction among group members. Throughout the case studies, the authors observed that conversations often started with phrases such as "Really?" indicating that users did experience breakdowns while interacting with the system, and most such breakdowns occurred when participants discovered differences or seemingly conflicting associations.

Methods for dynamically analyzing peer interaction after the students have begun to collaborate form the basis for the approaches to promoting effective group interaction described in the next two chapters in Part I (Soller & Lesgold, and Constantino-Gonzalez & Suthers). These authors describe computational methods can be applied to model and analyze different aspects of group interaction.

In general, a student's understanding of a concept is reflected in his actions, and his explanations of these actions. In a one-on-one tutoring environment, this information is available, and in most cases, straightforward to analyze. The system would typically watch the student solve a problem, perhaps ask pointed questions to evaluate the student's understanding of key concepts, and once in a while, interrupt him if remediation is necessary. Evaluating the learning of a group of students solving the same problem, however, presents a few new challenges. If one student solves the problem successfully while explaining his actions, and his teammates acknowledge and agree with his actions, to what degree should we assume his teammates understand how to solve the problem themselves? If a student is continually telling her partner what to do, and her partner is simply following her instructions without questioning her, who should get credit for solving the problem? The only way to know for certain which group members understand which material is to have some knowledge about how the group conversation relates to the student actions.

Unfortunately, introducing natural language understanding technology means introducing its underlying issues of ambiguity in language, increasing the complexity of the problem substantially. There have been a few different approaches to dealing with this issue. The software may restrict the students' natural language to a formal language (e.g., Tedesco and Self, 2000), or it may structure the students' language by having them select opinion buttons (e.g., "OK", "I agree"), or begin their utterances with sentence openers (e.g., "I think", "Do you know"). A combination of these approaches may also be used. For example, Soller and Lesgold present an approach that assesses group interaction by analyzing students' communication patterns, in the form of speech act sequences (e.g., Request, Inform, Acknowledge) and performs a coarse-grained analysis of student workspace actions. The approach in Constantino-Gonzalez and Suthers' article combines an analysis of the students' participation trends, and student opinions about problem solving actions in private and shared workspaces, to guide the interaction.

In Soller and Lesgold's approach, a machine learning algorithm is used to train a computer to generate a model of knowledge sharing between peers. Soller and Lesgold identify knowledge sharing as a critical aspect of collaborative learning, since it initiates the questioning, explaining, and critical discussion that often follows the exchanging of new concepts and ideas. Their system learns by iteratively constructing a probabilistic state-based model that generalizes classified examples of knowledge sharing interaction. Sequences of knowledge sharing interaction are coded by the system using conversational acts (such as "Request", "Acknowledge", or "Motivate") that represent the sentence openers the students may choose to begin their utterances. Soller and Lesgold use this system to (1) identify the student playing the role of knowledge "sharer" during knowledge sharing conversation, and (2) determine the effectiveness of the interaction.

Distributing the knowledge needed to solve a problem among the group participants enabled Soller and Lesgold to capture and study the social process of information sharing. Specialized knowledge distribution, however, may have the effect of distributing task roles, creating a local expert effect in which each student independently applies his or her knowledge to the problem (Stasser, 1999). When this happens, it may inhibit the group's ability to collaboratively construct new knowledge. One way of dealing with this problem is to create a private workspace that students can use to individually solve the problem, or try out solutions before proposing them to the group. Constantino-Gonzalez and Suthers describe COLER, a system that builds on this idea to help students learn Entity-Relationship modeling, a formalism for conceptual database design.

COLER's private individual workspaces help students independently develop their ideas, while its shared group workspace enables students to jointly construct a shared representation. Decision trees drive the system's back end by analyzing both task-based and conversational interaction, and dynamically generating recommendations for improving group problem solving. Students are required to express their agreement or disagreement (by clicking on "Agree", "Disagree", or "Not Sure" buttons) each time an item is added or changed on the group's shared workspace. This information, along with student participation statistics, and differences between students' private and group workspaces, is used by COLER's personal coaches to dynamically facilitate the group. For example, Jim's COLER coach might observe his teammate adding a node to the group's shared diagram, and might notice that this node is missing in Jim's private diagram. If Jim disagreed with his teammate's new addition, his coach might then recommend that the two students discuss a few alternatives so that they may learn from each other, and perhaps come to consensus.

Modeling and analyzing collaborative learning means accounting for the spectrum of activities that groups engage in while learning. Separating a student's participation from the quality of his contributions, or studying discourse and action separately, may produce an inadequate understanding of the group activity. The articles in this section should be viewed as corresponding to pieces of a pie that represents a comprehensive model of group interaction and learning. For example, Wessner and Pfister focus on group composition within the context of specific learning opportunities, Nakakoji and colleagues focus on addressing learning breakdowns, and Soller and Lesgold focus on knowledge sharing dialog. Finally, Constantino-Gonzalez and Suthers specifically study the interaction between student participation, opinions, and differences in structured representations. These articles should not be viewed independently, but rather as a toolbox of methods and strategies for understanding and supporting various aspects of online collaborative learning behavior. This toolbox reflects the perspectives of both the software designer and the educational practitioner, enabling the marriage of theory and implementation. Modeling collaborative learning activities means modeling both verbal and nonverbal interactions, and both task and social aspects of group learning. Studying these aspects separately allows researchers to deal with difficult issues (such as natural language understanding), while controlling for the variability inherent in collaborative learning. Future research along these lines should help to develop a more complete toolbox of methods for computationally analyzing collaborative learning activities. With a more complete toolbox at hand, researchers may be better suited to adopt holistic views of supporting collaborative learning communities.

Knowledge about how students interact is useful to a system only if it can apply this knowledge to recognize specific situations that call for intervention.

Classroom teachers learn to analyze and assess student interaction through close observance of group interaction, trial and error, and experience. Developing a system to analyze group conversation, however, poses its own challenges. Focused research in computational modeling of peer interaction will help in making the transition from understanding how to mediate learning groups to understanding how to train a system to mediate learning groups.

The many factors that influence collaboration often interact with each other in unpredictable ways, making it very difficult to measure learning effects (Dillenbourg, Baker, Blaye, and O'Malley, 1995). This may be one reason why the focus of collaborative learning research shifted in the nineties from studying group characteristics and group products to studying group process. With an interest in having an impact on the group process, the focus has recently shifted again – this time from studying group processes to identifying computational strategies that positively influence group learning (Soller, 2001). Furthermore, since the choice of mediation strategy must be based on an analysis of the group's needs, there is a need for the integration of evaluation in the modeling and analysis cycle. Ideally, the system would model and analyze the group process, and then select and apply one or more mediation strategies. The next logical step would be to evaluate the effect of the mediation with respect to the group process and product. This evaluation would then, in turn, be used to modify the group process model, which would then be used to analyze the group process, and so on (Jermann, Soller, and Muehlenbrock, 2001). Few systems have achieved this, although some of the systems described in this section have taken steps in this direction.

For example, COLER was evaluated based on the appropriateness of the computer coach's advice (as judged by a domain expert) and the students' reactions to the advice. Future research should build upon these notions to not only develop computational methods for identifying and analyzing group interaction needs, but also link these needs to suggested facilitation strategies (which are grounded in psychological literature), and evaluate the utility of this process for supporting on line collaborative learning.

Although computer-based approaches to individualized instruction have met with great success, many unresolved issues still exist in the realm of computer-supported group learning. The processes underlying peer interaction are complex, and not yet fully understood by practitioners in the educational and social sciences (Dillenbourg, 1999; Levine & Moreland, 1998) – a challenge that presents opportunities for new technologies to help in understanding and supporting this rich source of learning, but one that introduces uncertainty in the theoretical foundations of the technology. Because of this uncertainty, computational methods for analyzing peer interaction tend to focus on key aspects of the process that are thought to influence learning outcomes. The four articles in this section cover factors such as group composition, participation, individual and group problem-solving actions, socio-cognitive conflict, and knowledge sharing. Many of these issues are new to computer-based instruction, and because of this, the authors have been careful to ground their computational approaches in existing research on collaborative learning and group dynamics wherever possible.

This section aims to further our understanding of a few group specific issues, so that we may better support the process of on line collaborative learning in the future. We hope that you will find the ideas and methods presented in the following four articles informative and helpful in furthering your own research program.

REFERENCES

Dillenbourg, P. (1999). *Collaborative learning: Cognitive and computational approaches*. Elsevier Science.

Dillenbourg, P., Baker, M., Blaye, A., & O'Malley, C. (1995). The evolution of research on collaborative learning. In H. Spada and P. Reinmann (Eds.), *Learning in Humans and Machines*, Elsevier Science.

Doise, W., Mugny, G., & Perret-Clermont, A. (1975). Social interaction and the development of cognitive operations. *European Journal of Social Psychology*, 5(3), 367-383.

Jermann, P., Soller, A., & Muehlenbrock, M. (2001). From mirroring to guiding: A review of state of the art technology for supporting collaborative learning. *Proceedings of the First European Conference on Computer-Supported Collaborative Learning*, Maastricht, The Netherlands, 324-331.

Levine, J. M. & Moreland, R. L. (1998). Small groups. In D. Gilbert, S. Fiske, & G. Lindzey (Eds.), *The Handbook of Social Psychology* (4th ed.) Boston, MA: McGraw-Hill, 415-469.

Soller, A. L. (2001). Supporting social interaction in an intelligent collaborative learning system. *International Journal of Artificial Intelligence in Education*, 12(1), 40-62.

Stasser, G. (1999). The uncertain role of unshared information in collective choice. In L. Thompson, J. Levine, and D. Messick (Eds.), *Shared Knowledge in Organizations* (pp. 49-69). Hillsdale, NJ: Erlbaum.

Tedesco, P. & Self, J. A. (2000). Using meta-cognitive conflicts in a collaborative problem solving environment. *Proceedings of the 5th International Conference on Intelligent Tutoring Systems*, Montreal, Canada, 232-241.

Webb, N. & Palincsar, A. S. (1996). Group Processes in the Classroom. In D. Berlmer & R. Calfee (Eds.), *Handbook of Educational Psychology* (pp. 841-873). New York: Simon & Schuster Macmillan.

Winograd, T. & Flores, F. (1986). Understanding Computers and Cognition: A New Foundation for Design, Ablex Publishing Corporation, Norwood, NJ.