Partner Modeling Is Mutual

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Abstract. It has been hypothesized that collaborative learning is related to the cognitive effort made by co-learners to build a shared understanding. The process of constructing this shared understanding requires that each team member builds some kind of representation of the behavior, beliefs, knowledge or intentions of other group members. In two empirical studies, we measured the accuracy of the mutual model, i.e. the difference between what A believes B knows, has done or intends to do and what B actually knows, has done or intends to do. In both studies, we found a significant correlation between the accuracy of A's model of B and the accuracy of B's model of A. This leads us to think that the process of modeling one's partners does not simply reflect individual attitudes or skills but emerges as a property of group interactions. We describe on-going studies that explore these preliminary results.

Introduction

It is now broadly admitted that learners do not benefit from collaboration simply because they are in a group but because collaboration triggers additional activities such as explanation, disagreement and mutual regulation (Dillenbourg, 1999). According to Roschelle and Teasley (1995), many CSCL scholars conceptualized collaborative learning as an activity in which shared knowledge is constructed by peers through their interactions with each other and also with their environment. The notion of shared knowledge is derived from psycholinguistic concept of “grounding” (Clark &Wilkes-Gibbs, 1986): during interactions, the “interactants” constantly try to ensure a good mutual understanding. Grounding is the collective process through which individuals engaged in a conversation try to ensure their mutual understanding. 'Shared understanding' or 'mutual understanding' is a very intuitive concept, both for analyzing interactions and for designing applications, which probably explains their impact on CSCL. However, the notion of shared understanding is questioned both within psycholinguistics (Sperber & Wilson, 1986) and within CSCL (Baker, Hansen, Joiner & Traum, 1999; Koschmann & LeBaron 2003). Our research questioned mutual understanding in a different way: we zoom in on the mechanics of grounding by analyzing how a shared solution emerges from the sum of a long sequence of contributions (Dillenbourg & Traum, 2006). We further attempt to understand the socio-cognitive benefits of co-constructing a shared understanding. We investigate a mechanism that is hypothesized to lie at the heart of grounding. For Clark and Brennan (1991), common grounds are a set of *mutual beliefs* defined as the amount of information shared (e.g. presuppositions, knowledge, assumptions, beliefs). Establishing this set of beliefs requires that the co-learners build some representation of their partners’ knowledge, beliefs and goals. We refer to the process of building assumptions about the beliefs and the knowledge of their partner(s) as **mutual modeling** (Dillenbourg, 1999). However, the abstract and unobservable aspect of this process raises methodological challenges regarding its comprehension by researchers. Therefore, this paper attempts to ask a general question about the socio-cognitive nature of mutual modeling by assessing whether the process of modeling one's partner is grounded at the individual or the group level.

The paper does not describe environments for collaborative learning but reports basic research on the socio-cognitive mechanisms related to mutual modeling. The first section explores the concept of mutual modeling and its relationship with CSCL features such as scripts and awareness tools. The second and third sections describe two empirical studies in which the accuracy of mutual models is measured. The concluding section describes how the hypotheses arising from these two studies are currently being investigated through two other studies, which focus on a CSCL setting with a stronger educational flavor.

Mutual modeling in collaborative tasks

The ability to perceive a partner's understanding and to adapt to his/her viewpoint has been investigated under the labels of intersubjectivity (Wertsch, 1985; Bromme, 2000) and audience design (Lockridge & Brennan, 2002). Suthers (2006) recently proposed “the technology affordances of intersubjective meaning-making” as an integrative agenda for CSCL research. For him, a common denominator of understanding learning in a collaborative setting is the peers' attempt to make sense of situations and of each other. Intersubjectivity is *played* in the field of the physical and historical context available to the participants to *jointly compose interpretations*, which could be considered as a new gist for collaborative learning, an alternative to the notion of producing mutual-beliefs about making unshared information shared. To sum up, taking into account the peer's perspective is a crux facet of intersubjectivity on which most of the social activities depend. As highlighted by Malle (2003), the ability to represent and reason about self and other's mental states (e.g. beliefs, desires, intentions, mere thoughts, experiences, emotions, attitudes) is a great achievement in the evolution of the human mind and is considered a prerequisite for many social and cognitive processes such as natural language acquisition, social interaction, reflexive thought, and moral development.

The term "mutual modeling" does not imply that collaborators maintain a detailed representation of their partner's knowledge, nor an explicit one. Simply stated, if A is able to (dis-)agree with B, it means that A needs has representation of B's intentions; if A wants to repair B's misunderstanding, A needs some representation of what B has understood. Mutual modeling is as functional as the grounding process: the degree of accuracy depends on the task requirements; an extremely high level of accuracy is demanded if two pilots collaborate on landing a plane, as in Hutchins' (1995) observations, but the level of accuracy can be much lower if the pilots are discussing their last party. Moreover, mutual modeling does not occur in a vacuum but is based on multiple inference mechanisms. Common grounds are initialized by the assumptions people make about their partner from cues such as his/her community membership (age, culture, profession, ...) and from co-presence (e.g. common ground includes any event to which A and B attended together) (Clark & Marshall, 1981). Several scholars studied how this initial modeling impacts communication, namely because it can easily be manipulated. For instance, Slugoski, Lalljee, Lamb & Ginsburg (1993) pretended to their research subjects that their (fake) partner had or had not received the same information. They observed that the subjects adapted to their partner by focusing the explanation on the items that (s)he was supposed to ignore. Brennan (1991) showed that the subjects used different initial strategies in forming queries depending on who they were told their partner was. Other simpler inference mechanisms such as default reasoning rules (e.g. B agrees with me unless he disagrees) are developed according to the conversational context. Mutual modeling could not occur independently from culturally acquired interaction schemata that constrain the space of interpretation of the other's behavior. Actually, the CSCL notion of 'scripts' (Dillenbourg, 2002) can be conceptualized as providing co-learners with an explicit schema that narrows down the space of interpretations and therefore serves as prosthesis for mutual modeling. Another prosthesis for mutual modeling is the notion of awareness tools (Greenberg & Roseman, 1996); these are features of CSCW environments in which A is informed about the actions of B that A has not directly perceived.

Even when mutual modeling is not detailed and explicit, reasoning about what one's partner believes involves some cognitive load. For Clark & Wilkes-Gibbs (1986), what is important is not the individual effort made by the receiver of a communicative act, but the overall least collaborative effort. The cost of producing a perfect utterance may be higher than the cost of repairing the potential problems which may arise through misunderstandings. For instance, subjects are less careful about adapting utterances to their partner when they know they can provide feedback on his/her understanding (Schober, 1993). We introduce instead the notion of 'optimal collaborative effort' (Dillenbourg et al, 1996) to stress that misunderstanding should not be viewed as something to be avoided (even if this were possible), but as an opportunity to explain, to justify, and so forth. Here we enter the global argument regarding cognitive load in learning activities, namely in discovery learning environments: there is no learning without cognitive load, but overload may hinder learning (Paas, Renkl & Sweller, 2003). In the context of collaborative learning, we understand the cognitive load induced by mutual modeling as part of Schwartz's (1995) notion of effort towards a shared understanding. For instance, conflict-resolution scripts or JIGSAW scripts are purposely designed for augmenting (reasonably) the effort group members have to engage to reach a shared solution.

Mutual modeling has many dimensions, from which we dissociated 'dispositional' versus 'situational' aspects. The 'dispositional' aspects refer to A's representation of B's long term knowledge, skills or traits. It is thus closely related to the notion of transactive memory (Wegner, 1987; Moreland, 2000). 'Situational' aspects refer to A's representation of B's knowledge, behavior or intention specifically activated in the situation in which A and B are collaborating.

This leads us to the long term research question that underlies our work: does the mutual modeling process contribute to the learning outcomes of collaborative problem solving? This question is difficult to investigate because the degree of mutual modeling is both difficult to manipulate as an independent variable, and difficult to measure as a dependent variable. Measuring it is difficult because, as soon as one asks learners what their partner knows, is doing or intends to do, we trigger a modeling process beyond what it would 'naturally' be. Controlling the degree of mutual modeling is also difficult. As we mentioned earlier, scripts and awareness tools potentially influence the mutual modeling process, acting as a kind of prosthesis. Now, like any prosthesis involved in learning, we ignore whether scripts and awareness tools will augment the mutual modeling process (by scaffolding it) or inhibit it (by making it useless). Moreover, it is difficult to estimate the accuracy of a mutual model in absolute terms. Thus, this study focuses on a simple question: considering M(A,B) as being A's representation of B, **what is the relationship between M(A,B) and M(B,A)?**

An alternative hypothesis is that participants do not build a representation of their partners' mental states but instead build a representation of the interaction process at the group level: instead of modeling who knows what, who does what or who said what, the team members could maintain a representation of what the team knows, has done or has said. We refer to this as the group model. This alternative is directly inspired by distributed cognition theories (Pea, 1993; Salomon, 1993; Hutchins 1995) and the team mental model (Canon-Bowers, Salas, Converse, 1993). The two hypotheses are of course complementary since these two models feed each other.

This paper does not directly examine these general research questions but reports results collected in two empirical studies on mutual modeling, one occurring in a virtual environment and the second in real space. These results are discussed in light of social and cognitive theories. The discussion also mentions on-going studies on the mutual modeling process within more traditional collaborative learning settings.

Study 1

We attempted to measure mutual modeling by using awareness tools in a collaborative video game called Spaceminers. The research question was to study the impact of an awareness tool on group performance and mutual modeling. The availability of an awareness tool was our independent variable. The main results have been published in (Nova, Wehrle, Goslin, Bourquin, Dillenbourg, 2006). We focus here on the question addressed in the introduction, that is, the relation between the modeling performed by each user or the relation between M (A,B) and M (B,A). Our main dependent variable is the mutual modeling accuracy, henceforth referred to as MM-accuracy

Experiment design

SpaceMiners is a 3D computer game that involves two players in space missions in which they have to collect minerals located in asteroids and bring them to a space station. To do so, they shoot drones through the space after choosing their initial direction and speed. Once launched, the trajectory of drones is only influenced by the gravity of planets and by specific tools that players collaboratively position between planets.

During the experiment, the teams were confronted with three increasingly complex situations. The experiment was 2 hours long, with a 30 minutes tutorial and 3 levels of 30 minutes. Thirty-six persons participated in this study, all native French speakers. We constituted 18 pairs of participants (N = 18) who were not familiar with each other. The pairs were assigned randomly to either the control condition (without the awareness tool) or the awareness condition (with the awareness tool). In the awareness condition, team members could view what their partner was looking at and were therefore expected to more accurately infer his/her teammate's intentions. Each player sat in front of a distinct computer located in different rooms. They interacted with the game using a regular Logitech joystick and communicated with each other through an audio channel.

Measures

Task performance was measured by the score reached by the subjects after three situations. In order to evaluate the mutual modeling accuracy during the task, we used two questionnaires as shown on Figure 1. Both of them were displayed during each of the three phases of the game, as a transparent layer appearing on the game level. The first questionnaire concerned the player's intended actions. It asked each player about what they were intending to do at the moment (guide his partner, try to understand his strategy, try to establish a common strategy, adjusting a shot, etc.). The second questionnaire asked each player about what he thought the partner was intending to do. Some answers were identical in both questionnaires (like "adjusting a shot") while others were reversed. For instance, the answer "guide him" was reversed as "guide me" and vice-versa. Each questionnaire then had 10 questions that covered the basic actions that could be performed.

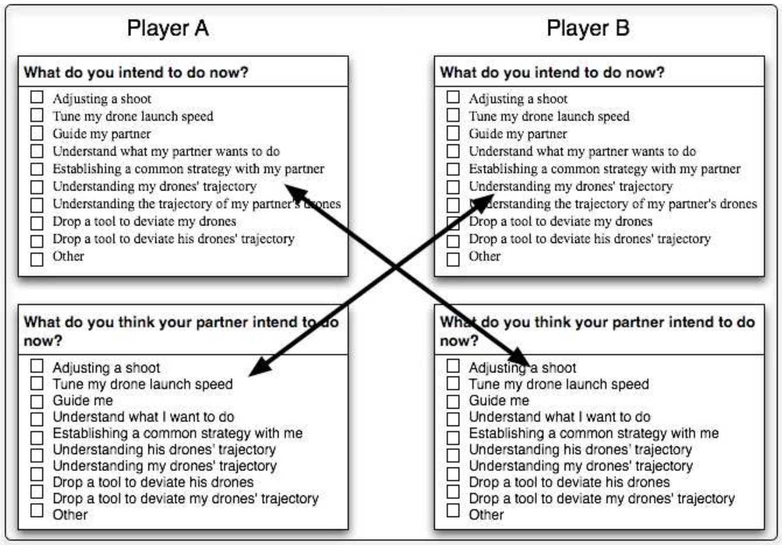

Figure 1: Crossed questions for measuring mutual modeling accuracy.

These questionnaires gave us the possibility of comparing player A's prediction about B's intentions with B's self-declared intentions. Of course, this method presents the same limitations of any questionnaire in which somebody has to self-declare his or her intentions. We compared the first answer of a player (about what A is intending to do) to the answer of his partner to the second question (about what B believes A is doing). Our estimation of MM -accuracy has been computed as the number of common answers given by the two players to those two questionnaires: does A's prediction of B's answer matches B's actual answer? Since there were 3 evaluations (one per level), we computed the MM-accuracy per individual for each level of the game. The global MM-accuracy is the sum of these 3.

Findings and Discussion

The awareness tool permitted higher group performance, but it did not improve the accuracy of the mutual model. However, within the experimental group, the pairs who intensively used the awareness tools obtained a significantly higher MM accuracy (for more details, see Nova et al., 2006). In order to compare M (A,B) and M (B,A), we computed intraclass correlation as described by Kenny et al. (1998) from the answers to the cross-questionnaires. We found a positive and significant correlation ($r = .38$, $p < .05$) between M (A,B) and M (B.A). This sounds like a minor result for this particular study but actually conveys an important outcome: mutual modeling appears to be a group variable rather than a personal activity. We expected MM-accuracy to be a personal parameter, i.e. that some participants spontaneously pay more attention or engage more effort in monitoring their peer. This could be due to some social attitude or to specific cognitive skills required to build a mutual model. This strong correlation between M (A,B) and M (B.A) supports a different hypothesis in which mutual modeling emerges as a property of the quality of interactions among peers: some pairs seems to collaborate in such a way that their verbal and non-verbal interactions produce more cues available to both partners so that they can build a mutual model. This does not remove individual variability (correlation was not 1). Interestingly, we found that the relation between M(A,B) and M(B,A) was not very different in the two conditions: the average absolute difference between MM-Accuracy (A,B) and MM-accuracy (B,A) is not significantly different with or without the awareness tool ($F[1,13]= 0.1445$, p-value = 0.7097)

Study 2

In this second study, instead of evaluating mutual modeling during the task, we chose to measure it after task completion. This experiment was based on a pervasive game called Catchbob. As in the previous experiment, this game was used to evaluate the influence of awareness tools on group performance and MM-accuracy, but we will focus here on the results concerning the relationship between M(A,B) and M (B,A).

Experimental design

Catchbob is an experimental platform implemented as a mobile game in which groups of 3 players have to solve a joint task. The game was played on the school campus and participants had to find a virtual object ('Bob') and catch it by forming a triangle around it. Players used a Tablet PC that displays a map of the campus and an indication of their personal distance from Bob. Their annotations on the map were shared with the two other players, but fadeout after a few minutes. The awareness tool displayed the location of the two other players on the map. Henceforth, we will refer to this information as mutual location awareness (MLA). It constituted our independent variable.

In this study, we selected groups of students from the same class and who therefore knew each other. Ninety students participated in this experiment. We assigned 10 groups of 3 persons to each of our three experimental conditions: the control condition (without MLA) and two experimental conditions: synchronous MLA (display current position of each player) and asynchronous MLA (display current position of each player and their spatial trace). We controlled group gender so that each condition was made up of 25% of female and 75% of male.

Measures

As a dependent variable, we measured MM-accuracy by asking players to draw their own path and the one of each of their partners after the game. This enabled us to calculate the number of errors players made while drawing the path of their partners. We compared the path player A attributed to B with B's real paths recorded by the system and the same for A&C or B&C as depicted on Figure 2.

Figure 2. (Left) Drawing A made of B's path; (Right) Real path followed by B as extracted from the logfile.

We computed the number of errors between M(A, B) and M(system, B). What we counted as an error was either drawing a place where the partner had not been or not drawing a place where he/she had gone. Three criteria were defined to describe these errors: distance (if the line was longer than the maximum size of our campus corridor), presence of an obstacle (door/wall/glass), and walking back (not perceived as an error). An individual MM-accuracy is the sum of errors made by a player about his/her two partners' paths. We calculated MM-accuracy for each individual (M (A,B), M (B,A), M (A, C), M (B,C),…) and for each group (the sum of the individual measures). It is important to stress that subjects made very few mistakes when drawing their own path on the campus (85% made 0 errors). This enables us to consider mistakes in their partners' path as being due to a lack of mutual modeling accuracy instead of being due to spatial skills (e.g. a difficulty in reporting trajectories on a map).

Findings and Discussion

We did not find any significant difference regarding the task performance between the three experimental conditions. However, our surprise was that the absence of the awareness tool led player to higher MM-accuracy: players better remembered their partners' path if they did not see their position permanently. We will not enter into the details of these results but simply stress that teams without MLA made more annotations on the map. It seems that permanent MLA has an underwhelming effect (Nova et al., 2005). Let us now focus on the relationship between

M (A,B) and M (B,A). We checked the intra-group dependence of the results through the computation of intra-class correlation: the correlation is again positive ($r = .41$) and significant ($p = .01$). The number of errors made by the subjects is correlated with the number of errors made by the other partners. This result confirms the correlation found in the first study. This second result is even more surprising for us than the former: despite the high heterogeneity of spatial representation skills among adults (see for instance Liben et al, 1981), this high correlation indicates again that MM-accuracy reflects more group processes than personal features. Since team members did not interact massively during the task, the intra-group correlation may not be explained by the quality of verbal interactions but by other aspects of their collaboration, probably the quality of the task strategy that emerged in the group. However, the relation between strategy and MM-accuracy is complex: if we do a post-hoc split, groups with a high level of MM-accuracy do not perform better than pairs with low MM-accuracy ($F[1,17] = 1.4456$, $p = 0.2452$).

Discussion and further studies

The results of these two studies revealed a correlation between the model peers built about each others' behaviors and intentions. Simply stated, if team member A builds an accurate model of nember B, then B also tends to build an accurate model of A. The conclusion we draw at this point is that the activity of modeling the partner is not reciprocal but mutual. A reciprocal relationship means that modeling is an individual activity where A infers M (A,B) from B's actions and utterances. A mutual relationship implies that M(A,B) and M(B,A) are jointly constructed through interactions. The term 'mutual' may mean not only that A builds M(A,B), but he also builds M(A, M (B,A)). We will not enter in the long debate on an infinite regress of nested models (discussed in Smith, 1982 or in Clark, 1996). Another interpretation is that team members actually build a model of the group-in-interaction, something like M (A, AB). We are not able to choose among different hypotheses at this stage.

These findings are not very robust because they emerged as side-effects of other research questions, but, nonetheless convincing since the same correlation has been observed in two different contexts: virtual space in study 1 versus real space in study 2; groups of 2 in study 1 versus groups of 3 in study 2. Moreover, these results have been found using different methods: on-task in study 1 versus off-task in study 2, subjective validation (comparing A's model to B's answer) in study 1 versus objective validation in study 2 (comparing A's model with B's behavior). This diversity somewhat consolidates our results but these results are still preliminary: the selected tasks were not proper learning tasks and, overall, we still face serious methodological difficulties. On the one hand, asking learners 'on task' what their partner knows, is doing or intends to do triggers a modeling process which could alter the natural modeling process. On the other hand, providing learners with an 'after-task' survey implies mnemonic and rationalization biases. In other words, the nature of mutual modeling implies methodological challenges that call for indirect measures and assessment methods. Furthermore, mutual modeling in everyday life involves a large variety of mental states to be represented such as knowledge, behaviors, beliefs, desires, intentions, emotions, traits, attitudes, etc. Three of these mental states are particularly relevant in collaborative learning situations, namely inferences about partners' knowledge, behavior, goals (intentions). Study 1 focused essentially on inferences about peers' intentions while study 2 investigated inferences about peers' behavior. Our on-going study focuses on the inferences about peers' knowledge that is expected to be important in collaborative learning.

Our current empirical studies investigate the mutual modeling process in conceptual learning. The goal of these experiments is twofold. Our theoretical question is whether or not the mutual modeling effort enhances collaborative learning gains. Our methodological question is to capture the mutual modeling mechanisms. In order to avoid the 'anticipation' and 'rationalization' biases, we use interaction analyses and parallel gaze analysis. We are therefore using two eye-tracking machines and we perform an automatic comparison of the eye paths of both learners as in (Richardson & Dale, 2005). These experiments use the two mutual modeling prostheses described in the introduction, awareness tools and scripts. In both cases, subjects start by reading a text individually (Phase 1) and then have to build a concept map together (Phase 2). In the first experiment, the independent variable is an awareness tool available during Phase 2: A is informed of B's knowledge on three different chapters of the learning material; this knowledge has been previously measured through a pre-test at the end of Phase 1. In the second experiment, different scripts are implemented by providing subjects with complementary partial texts (jigsaw script) or conflictual texts (argumentation scripts) in phase 1. Both of these experiments manipulate the mutual modeling process in complex collaborative learning situations. Awareness tools about peer's knowledge (and behavior in general) may trigger mutual modeling facilities whereas the 'collaborative scripts' may strain effort of mutual understanding and by extension, enhance mutual modeling and perspective taking and making efforts. In a circular (if not spiral) manner, this increased mutual modeling effort may elicit interaction processes such as audience design, mutual regulation, elaborated explanation asking and providing, which are known to be beneficial for learning.

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Acknowledgments

We gratefully acknowledge the contribution of Fabien Girardin, Khaled Bachour and Kamni Gill. These researches are funded by the Swiss National Science Foundation (grant #102511-106940).