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The Influence of Knowledge Modeling on the Communication Process

1. Timothy Koschmann stated in the introduction of the CSCL2002 conference proceedings that CSCL is "centrally concerned with meaning and the practices of meaning-making in the context of joint activity, and the ways in which these practices are mediated through designed artifacts." What does this mean for the technical development of computer-enriched learning scenarios?

My work on computer support for collaborative learning (CSCL) focuses on the design of representations, so I will reply from that perspective. When people engage in a conversation for learning or problem solving, they often use external representational aids. There is a large literature on representations in individual learning and problem solving which might be summarized with "representation matters" – there are clear influences on how easily individuals solve problems. In CSCL we are more concerned with group rather than individual cognition. The roles that representational aids can play in the meaning-making activities of two or more participants are very complex, but I will highlight a few important aspects.

The representations can be the topic or intended product of the conversation, for example when two people are co-constructing a schematic for the design of a physical or information artifact. In such cases the representations are clearly essential for the meaning-making activity. Recently I have been calling these kinds of conversations "artifact-centered discourse." Artifact centered discourse is very common in learning applications, so it is disturbing that many online learning environments, including some well-known commercial ones, don't provide much support for discussions about user-provided artifacts. My most recent line of work on artifact-centered discourse focuses on how to better integrate discourse representations with other representations such as disciplinary and knowledge representations (Suthers & Xu, 2002).

The representations can be secondary to the purpose of the conversation yet still play important roles in a joint meaning making activity. The creation or modification of shared representations can lead to new negotiations of meaning that may have not taken place without the representation. A participant may feel an obligation to discuss additions or modifications to a shared representation before they are executed. Additionally, new representations can also be put forth before agreement about their meanings or even clarity on the part of the representer exists. In either case questions implicitly arise: what will this representational device signify to us? What does the configuration we have created or propose to create imply for our understanding of the problem at hand? Then, once shared representations have been infused with meaning for the participants by the processes just described, the representations can then function as proxies for these meanings, which can be invoked by pointing at the appropriate portion of the representation. This ease of reference can enable richer (not just more efficient) conversations about the topic at hand.

All of this suggests that it is critical for technology designers to attend to how the representations they provide might influence individual cognition and mediate group cognition. The semantics of representations are not totally unconstrained. The visual properties of the representations, the rules or "epistemic games" (Collins and Ferguson, 1993) associated with their use, and their operational semantics in the computer environment (that is, how they behave or cause the computer to behave) all can affect how people appropriate the representations, and hence what kinds of meaning-making activities more naturally take place with a given computer tool. Also we need to look carefully at how learners will want to use *all* of the representations in a computer environment – not just those explicitly intended to support discourse – as resources for conversations.

Designers of computer environments for learning can also support "meaning-making in the context of joint activity" by attempting to empower the computer to itself be an agent in this activity. Here of course I refer to pedagogical agents in the artificial intelligence tradition. Some thinkers find it premature or even philosophically untenable to speak of the computer as a true party to meaning-making, but such a stance does not necessarily preclude the potential utility of automated checking and prompts as a device to raise the level of meaning-making of the human participants. This is what Angeles Constantino and I are trying to do with the COLER system (Constantino et al., 2002).

2. You imply that software has a big influence on the communication. It mediates communication and offers the means to structure the communication process and the content. This is not only the case for distributed cooperation but also for face-to-face situations where external representations are used. In your publications you have introduced the concept of a "representational bias". Which effects do shared representations have on the cognition?

In response to your previous question I indicated various roles that external representations can play in supporting meaning making during joint activities. One might ask: are all representations equal in how they might provide this support? The phrase "representational bias" implies that the answer is "no." The concept of representational bias comes from the machine learning literature (Utgoff, 1986). A machine learner may learn certain concepts more or less efficiently (or not at all) depending on the expressiveness and heuristic value of the internal representations it uses to express concepts. I appropriated this term for external representations where the human rather than the machine is the "interpreter" of the representation. Recently, I have been calling this concept "representational guidance" as educators do not appreciate the meaning of "bias" in the same way as the artificial intelligence researcher!

Shared representations can differ in their effects on cognition because of their constraints and their salience. Constraints are an aspect of expressiveness. If a representation constrains you to use certain concepts and to express certain kinds of relationships, then users of the representation may be more likely to focus on those concepts and relationships. Salience is to be understood as a relation between the human (or other agent's) perceptual system and the features of the representation. There are two aspects to salience: Once you represent some information, what aspects of that information are easiest to recover? The other aspect of salience is prompting: what does the representation tell you is **missing** and should be sought? Cognitive Science has a research tradition on this topic going back to at least Larkin and Simon (1987).

The connection to group cognition is found largely in my reply to your previous question, where I discussed ways in which external representations can mediate (initiate and enhance) meaning-making negotiations. If a representation prompts for certain kinds of information, constrains its users to express certain kinds of concepts or relationships, or makes some information structures more salient than others, then these differences (as compared to other representations) will influence what potential modifications to the representation are discussed and made, and what ideas are easy to refer to by pointing. In short, the biases that affect individual cognition are magnified to the extent that they affect the focus of group discourse. There may be additional ways in which representational bias functions uniquely in group situations. For example, Micki Chi has suggested (personal communication) that a group participant may be less likely to ignore discrepancies between his or her ideas and the shared representation because he or she is aware that the other group members may also notice such discrepancies. Externalized representations in a nonvolatile medium provide a reified common ground that cannot be ignored as easily as utterances in a volatile medium such as speech.

3. Have you been able to demonstrate these effects empirically?

Our empirical work so far has used behavioral measures – we have not yet ventured into making inferences about cognitive state in our analyses – so I would not presume to have demonstrated features of shared cognition. Rather, I can tell you what we see in the dialogue of participants using different representations. We designed three representations for recording relationships between data and hypotheses: a node-link graph representation akin to concept maps but using consistency and inconsistency relations between empirical and theoretical statements; a matrix representation that also relates empirical and theoretical statements with consistency and inconsistency relations placed in the cells of the matrix; and a simple text editor provided as a control condition. Our predictions focused on how much participants would address issues of evidence or evidential relationships. We predicted – and observed – significantly more discussion of evidential relations by users of the matrix tool, simply because the users are prompted by the empty cells of the matrix (without any special instructions from us) to consider all possible evidential relations. However, we have evidence that this prompting is excessive, and the graph users may be more focused on the essential relations. We also observed differences in elaboration – how and when participants revisit a previously represented idea – and in the extent to which the work with the representations influenced the contents of essays subsequently written by participants. Our predictions were straightforward, but this was the first time anyone had shown this kind of influence of representation on discourse, so it's the beginning of a potentially very interesting research area. A paper on this work will appear in the Journal of Learning Sciences (Suthers and Hundhausen, to appear). This was a laboratory study: my colleagues and I will also be reporting a study of classroom artifacts showing differences in properties of argumentation (Toth et al, to appear).

4. During the last years you have developed the Belvedere system. Its main intention is to teach students scientific argumentation. Can you summarize some experiences with that tool and some main design backgrounds?

There's a fairly comprehensive summary of Belvedere in the book "Smart Machines in Education," edited by Forbus and Feltovich (Suthers, et al., 2001). Alan Lesgold and his colleagues at the University of Pittsburgh started the project a little before Alan hired me. The hands-on movement in science education had students doing observations and experiments, but we wanted them to understand the larger context of science: the discourse that takes place in a given scientific community and drives the empirical work. Initially the approach was two-pronged: to use visual representations to help students grapple with the full complexity of scientific argumentation, and to build an automated coach that would interact with individual students in natural language to help them build and critique arguments.

The focus of the project shifted when we did some informal studies with two or more students in front of the computer, as might be expected in a classroom. We found that much of the most interesting argumentation took place verbally between the students and was often not represented in the software. Yet the tool was not irrelevant: the argumentation was initiated by discussion of what to do with the diagram, and sometimes was influenced by the choices the tool presented or by information that the diagram made salient. This shifted my perspective from seeing Belvedere as an argumentation-modeling tool to seeing it as a stimulus to and possibly a guide of the argumentation that would take place between students. I began to simplify the representations to focus on the distinctions that were most important for students to attend to. This is what led to the representational bias work.

The work on the automated coach was also influenced by the realization that the computer would not have access to all of the students' argumentation. Instead of attempting to make it a participant in the argumentation process, we tried to design it to be stimulus and guide, like the representational tools. The focus was on identifying and suggesting constructive work that the students could undertake. We also followed an incremental research strategy of building the simplest advisor we could imagine, then testing it to determine its value and the need for further functionality. I wanted to be able to identify what knowledge engineering effort yielded what functionality, so others could choose their own cost/benefit tradeoff.

Most of our work was with an "evidence pattern advisor." This was the lowest cost advisor that I could imagine, because it would not require any new knowledge engineering for new application domains. Guided by principles of scientific argument, we identified configurations of students' evidence models that would suggest a possible critique. We then wrote rules with the evidence pattern as the antecedent and the suggested corrective action as the consequent. For example, the "confirmation bias" advice pattern looked for hypotheses that had many supporting empirical items, and asked whether disconfirming evidence had also been sought.

The advice patterns abstracted away from the subject matter, so were very general, but also limited in what they could suggest. In order to enable the advisor to suggest consideration of specific information, we implemented an "expert path advisor." This required some extra knowledge engineering: an expert or teacher would have to build an "expert model" using the same Belvedere interface as the students. When students added links to their graphs, the expert graph was searched to find paths between the corresponding nodes. Other information found along these paths was presented to students to either challenge or elaborate on their thinking.

The next step may have been to add other domain knowledge such as causal and structural knowledge, and see how that improved the range of advice. Unfortunately we did not evaluate and refine these coaches as much as I would have liked. However, I think we learned a lot about the potential value of simple techniques for generating prompts that help guide students' activity. Belvedere also formed the foundation for an excellent doctoral dissertation by Angeles Constantino (Constantino et al., 2002). Her focus is on coaching students to collaborate, particularly to address conflicts between their solutions, by comparing individual and group problem solutions and tracking their participation in the group workspace.

5. Very often knowledge communication is a process of knowledge co-construction. Co-construction needs tools to model the content, domains, or artifacts that are the topic of negotiation. The content objects could be imagined as very complex "intelligent" and interactive objects. But often communication tools are limited to dialogue-oriented support such as chats. What do you think about putting the emphasis on more constructive and semantically enriched communication tools?

I take "semantically enriched" to mean providing a tool with precise computational behaviors based on semantics intended by the designer. I think that this is a very promising area of research, but has its dangers.

The approach is promising because behavioral properties of the representations used in communication can enhance their utility as resources for building and sharing common ground between participants. Most fundamentally, if representations can be distinguished by their computational behavior, then participants would have the option of negotiating semantic differences based on these behavioral differences. Also, effects of representational guidance (or bias) may be based on behavioral properties as well as visual ones: certain behaviors may "naturally" imply certain semantics. Of course, computational media can also automate tedious tasks such as searching for relevant information.

The approach has its dangers because we have to be careful that when we impose semantics on computer-based representations we do it first for the sake of the human participants rather than to compensate for the limitations of a not-so-intelligent computer participant – a worry I have about constrained dialogue systems. Also, we cannot assume that users' semantics for the representations will be the same as those the designer intended, and we should allow for flexibility in users' appropriations of the representations. If the representations already have specific consensual semantics in a given community of practice to which learners aspire, then we can expect that the learners will seek to use the representations in a manner consistent with these semantics. Otherwise, the right approach is to provide modeling tools in which the representations have certain behaviors known to be useful for joint meaning making, but ultimately leave the use of these representations up to the users. The work of Ulrich Hoppe and colleagues (e.g., Pinkwart et al., 2001) is one of the best examples of this approach.

6. Which challenges in the field of knowledge modeling and knowledge communication do you think should be paid special attention to in the near future?

We've only just begun to study how the properties of representational systems (whether these properties are visual or behavioral) influence and support collaborative knowledge construction. The number of laboratories working on this problem should be an order of magnitude greater than at present, and covering range of methodologies in both laboratory and field settings. I think that the most critical need is for detailed analysis of how users of representational tools appropriate them in joint meaning making activities. What semantic roles do the representations fill as a function of their visual and behavioral properties? This is very time intensive work. Also we need to look closely at how multiple representational tools – for example, for data display and analysis, domain modeling, and argumentation and discourse – are used together. Clearly these different kinds of representations should be designed to be linkable to each other in appropriate ways to support their coordinated use. Yet we should not try to over-design the communication process itself. Some recent work in my lab shows that the distinction between "discourse" tools such as chat and "modeling" tools such as Belvedere is blurred online, with the actual discourse between participants being accomplished by actions in *all* of the available representations. Thus we need to study the coordinated use of multiple representations in practice, so that we may design to support that practice.

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