Computers, Productive Agency, and the Effort toward Shared Meaning

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ABSTRACT

Computers provide fresh opportunities for enhancing and understanding collaborative learning. They permit new research methodologies such as simulations of cooperating agents, and they present new design challenges including computerized peers and supporting collaborations across cultural boundaries. This article has two goals. One goal is to offer recent examples and findings that may help design computer-supported collaboration. The other is to begin a theoretical discussion that focuses on the individuals who collaborate. This differs from much of the collaborative and cooperative learning literature that emphasizes the rules and structures for enforcing collaboration (e.g., group roles and joint accountability). We start with individuals because we believe that much of the learning that occurs during collaboration develops out of individuals' efforts to share meaning and understand one another. We consider prerequisites to people's effort to share meaning, and we particularly focus on the important role of the productive agency that leads people to contribute rather than just borrow knowledge. We consider the type of knowledge likely to develop during collaboration, and we suggest ways to prepare and help people learn from the language that permeates collaborations as well as formal classroom lectures and texts.

Keywords: Collaborative learning, small group research, agency, cultural exchange, distributed artificial intelligence

There is a long tradition of research on small group interaction and its effects on learning and performance (see, for example, Kelly & Thibaut, 1969). Computers are a new and invigorating addition to this tradition. They permit new research methodologies including simulations of cooperating computer programs, often called agents. And, they present new challenges like creating computerized peers (Cassell et al., 2000) and supporting collaborations across cultural boundaries (Lin & Schwartz, 2000). In our attempt to bring computers to the topic of collaboration, this article has two objectives. One is to present recent examples and findings relevant to the design of technology-assisted collaborative learning. The other is to offer a theoretical discussion that focuses on collaborating individuals rather than the various rules of cooperation that dominate the literature on collaborative learning (e.g., turn-taking scripts, jigsaw rules, reciprocal teaching procedures).

In the first section, we describe how computer science has led us to emphasize individuals, though our topic is collaborative groups. Weiss and Dillenbourg (1999), in their discussion of computer agents and robots, suggest it may be very difficult to pre-specify all the rules or social conventions needed to orchestrate successful collaborations among computerized agents. Collaborations are often too complex to plan for all the contingencies that may arise (Suchman, 1987). Consequently, if we want agents -- computerized or human -- to collaborate successfully, we must empower them to reorganize their collaborations and to self-improve when difficulties arise. To inform this effort, researchers cannot simply study the in-place social conventions that regulate collaboration. They must also focus on the properties of individuals that make collaborative behaviors emerge. We believe the way to focus this inquiry starts with an understanding of productive agency.

In the second section, we develop the notion of productive agency. We notice that among the many definitions of collaboration and cooperation there is no mention of agency. Without agency, collaboration appears to be constituted by people following social laws as though they were physical laws. Yet, people need to choose whether and when to collaborate and whether to go beyond the minimum necessary to satisfy the rules of collaboration (Barron, 2000). We propose that the engine of collaboration is agency and its expression in the effort to represent and share in other people's thoughts.

In the third section, we consider the motivations that lead people to collaborate. There are many well-documented, instrumental motivations (Slavin, 1983); for example, joining to beat a common enemy. But we would like to focus on motivations that involve learning per se. Many discussions view collaborative learning as the appropriation of ideas from others. We want to propose another view, one that emphasizes the importance of being a contributor rather than a borrower. People appropriate knowledge when they have opportunities to produce knowledge.

In section four, we explore the relationship between knowledge production and language during collaborative learning. It is tempting to think of learning as due to the direct communication of linguistic ideas from one collaborating agent to another. Computer models of collaboration, for example, often rely on the exchange of propositions between agents. But, one does not really learn a proposition, one learns from a proposition (Bransford & Nitsch, 1978). Linguistic representations only play a partial role in learning from a partner. We explore the nature of this partial role to help pinpoint what knowledge is most likely to be constructed in collaboration.

All told, we paint a psychological picture in which productive agency plays a central role in the characterization of collaboration. One way this agency is expressed is by the decision to collaborate and the effort to reach an understanding when social rules are insufficient for successful collaboration. Another way agency is expressed is by the motivation to produce and contribute. Finally, productive agency appears in the very way we learn -- we construct knowledge (e.g., Piaget, 1972).

COMPUTERS FOR UNDERSTANDING COLLABORATION

Computers offer new potentials for enabling and understanding collaboration (Robertson, Zachary, & Black, 1990). Technologies that permit previously impossible collaborations, for example between a person and a robot, will create new empirical phenomena that demand new theories -- theories that can guide education and inform the study of collaboration in general. In this section, however, we would like to emphasize the computer as a basic research tool. In the tradition of cognitive science, computers offer a way to model and elucidate the nature of cooperation among humans. As a research tool, the computer lets us emphasize the individuals within collaboration. The computer can model multiple interacting entities, as in the case of separate molecules in a flow simulation or individuals in a cooperative simulation. This is something we could not do prior to computers. Additionally, artificial intelligence techniques offer a form of modeling that is ideally suited to characterizing individuals within collaborations. Artificial intelligence allows us to model people's thoughts in the terms they experience; terms such as, "She likes me," and, "My goal is to win." This modeling ability may be very useful for studies of collaboration, because a critical component of collaboration involves the representations that individuals have of one another's thoughts.

Weiss and Dillenbourg (1999) state, "The 'deep secret' of collaborative learning seems to lie in the cognitive processes through which humans progressively build a shared understanding" (p. 75). If true, then it seems that the capability of computers to model thought, even if poorly, is particularly relevant for understanding collaboration. Computers can model the way we construe other people's thoughts. In fact, this is exactly what computer models of cognition are; they are models of other people's thoughts. In this light, computers give us a chance to explore how people's models of other people's thoughts might affect collaborative learning. To this distant end, this article explores some prerequisites behind individuals' attempt to understand one another.

Of course, learning in groups does not always require the representation of a partner's mental states. For example, in a foraging task, robot A can coordinate with robot B by noting simply where robot A is and has been (Joiner, Issroff, & Demiris, 1999). There are many situations, for example traffic lights, where people coordinate and learn behaviors by relying on social conventions. But, we do not believe these types of joint activities are what we should keep in mind when we think of collaboration in education.

PRODUCTIVE AGENCY AND THE EFFORT AFTER SHARED MEANING

Controlling collaboration: Roles versus choices

We propose that individual agency is a significant prerequisite to collaboration. Consider a recent proposal to build hundreds of "insect" robots that can swarm over foreign territory to collect information. A significant question is how to coordinate the robots' activities. Should the robot agents follow globally specified procedures, or is it better to let cooperative behaviors emerge from procedures local to each robot? In human terms, this is the issue of whether individuals or social conventions dominate collaborative interactions. Naturally, it is both, and the balance should change depending on the situation. Regardless, we think the essence of collaboration involves local control.

There are two types of local control. Local automata, like termites, have simple rules that, when coupled with other automata, can lead to complex structures. The global structure of behavior emerges from locally determined rules. This differs from situations involving agents with local autonomy who choose a particular behavior. It is this latter notion of autonomy that is particularly important for collaboration. If people are bound to a social role or predetermined local rules, then it is difficult to say they are collaborative; instead, they are behaving without agency, something like termites in a hive. To collaborate, individuals have to enter into relationships, they have to produce ideas, they have to choose whether to communicate, and they have to choose whether to compromise their goals.

Collaborative learning is not constituted by people complying with roles. Collaborative learning takes agency and productive effort precisely because people must develop shared meaning across the differences in their roles and knowledge. To develop the point, we introduce "the effort after shared meaning."

Identity versus shared meaning

To understand what is unique about research on collaboration, we can compare it to other social research. In socio-cultural research a common question is how individuals fit into their cultural milieu through structures like roles, rules, and social practices. In terms of psychology, a key construct here is the notion of identity. Individuals gain their identity by adopting a role offered by a cultural practice. Identity binds individuals to their society. It is the desire to gain an identity that drives individuals to appropriate and come into compliance with the practices of a culture.

While identity and compliance with cultural practices are central aspects of humanity, there are others. To borrow Bartlett's (1932) phrase, "the effort after meaning" is also important.

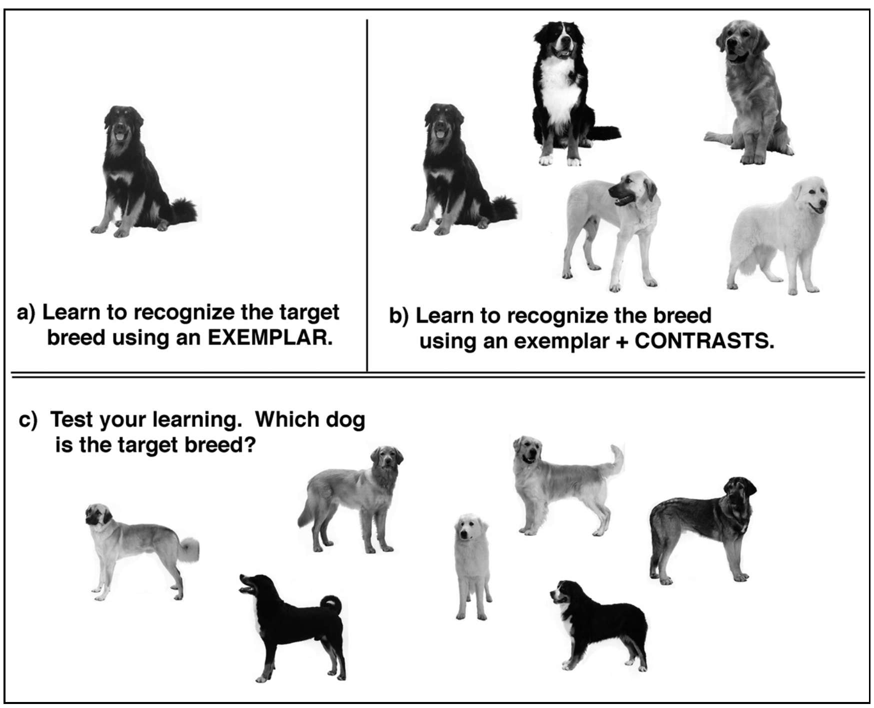
Piaget, as well as most of cognitive science, has investigated people's pursuit of meaning and its effect on learning. For example, when people understand the meaning of a text passage they remember more (Bransford & Johnson, 1972). People's effort after meaning also appears in social settings with "the effort after shared meaning." When we talk to our family, friends, or colleagues, we want them to understand us, and we want to understand them. The desire to understand and be understood -- to share meaning -- is a strong motivator of human behavior and deserves the status of a basic psychological construct. In terms of cognitive science, one might say that individuals want accurate representations of other people's thoughts, and individuals want other people to have accurate representations of their thoughts. Although we can never reach this idealized state, the effort after shared meaning helps explain one reason we learn when we collaborate. When working on a math problem, for example, if our collaboration is going well, our partners' explanations help us learn because we want to understand what they mean. We want to share their meaning.

Many of the questions for research on collaboration should be about how individuals construct local interactions to understand one another. Such questions are about how individuals interact with individuals, not how individuals interact with "culture." Of course, we should not ignore the culture that pervades interaction, or the social rules that make exchange possible. Nor should we disregard the importance of identity in a group (e.g., being the team captain). But, sometimes it is worth minimizing the emphasis on our cultural constitution and overemphasizing our efforts to achieve shared meaning. For example, people from remote cultures can meet electronically to create joint projects. Often, the individuals do not have a common culture to regulate their interactions. Yet conceivably, assuming they want to maintain a collaboration, their differences can serve as catalysts that propel them to learn. When people cannot rely on common ground, they will need to make the effort after shared meaning to sustain the collaboration, and this often entails learning and negotiating an understanding with one another.

Overcoming role boundaries to improve the effort after shared meaning

Collaborative learning often occurs when people cannot assume the common ground of similar thoughts, roles, and goals. For example, we asked a Hong Kong classroom to work on a mathematics activity developed in the U.S. (Lin, in press). Because the video-based Jasper Adventure that anchored the activity was quite novel in its demands (Cognition & Technology Group at Vanderbilt, 1997), the teachers and students eventually broke their traditional roles to become collaborators and make a special effort after shared meaning. Conversely, collaborative learning often fails when people are trapped in their roles. Teachers and pupils, for example, may fail to communicate because they cannot cross boundaries. For example, students are afraid to ask questions, because it can signal an ignorance that will affect their grade. It is important to explore ways that computers may help overcome classroom barriers. For example, the introduction of an on-line discussion tool in Japanese schools changed teacher-student collaboration styles (Oshima & Oshima, in press) and offered potentials for encouraging contributions from women compared with face-to-face exchanges (Lin & Hatano, in press).

This is not to imply that role assignments are arbitrary and easily crossed. People’s roles, like those of teacher and pupil, often reflect real differences in knowledge. These differences are hard to bridge, in part because they make it difficult for pupils to help in the effort after shared meaning. For example, in a recent study, we looked at 32 student-teacher pairs (Schwartz & Morse, 2000). Each teacher (a dog expert) tried to help a student learn to identify dog breeds. In the Exemplar condition, teacher-student pairs had an image of an exemplar dog to anchor their discussion (e.g., Fig. 1a). In the Contrast condition, the pairs had the exemplar dog plus dogs from slightly different breeds. As measured by the students' subsequent abilities to identify new instances of the target breed, the contrasts helped the pairs communicate better. One reason is that the contrasts increased the pupil's abilities to contribute to the instructional effort. The contrasts helped students articulate questions and observations; for example, "You said, 'The Shepard has narrow hips,' does this dog have narrow hips too?" Remarkably, the students more than doubled their collaborative production in the Contrast condition, as measured by their gestures to the dogs (compared to a 15% increase by the teachers). Evidently, the contrasts increased the students' ability to contribute to the effort after shared meaning despite differences in knowledge and role, because they could better express their partial understanding.



<u>Figure 1.</u> Pupils helped an expert teach them how to recognize dog breeds when they could use the contrasts to express their incipient understandings.

What counts as collaboration?

By exclusively emphasizing the conventions and roles that structure collaboration, we can slip into the study of local automata without autonomy. In such theories of collaboration, we do not factor in the agency involved in collaboration. For example, think of the slaves who built the great pyramids. One would say they complied with their masters' rules and the prevailing social conventions (on pain of death), but one would not say they collaborated. Of course, the slaves may have collaborated with one another, for example, by helping to carry a load when they did not have to. But, simply following a social role does not make behavior collaborative, it simply makes it compliant.

We can further this point by considering the following definition: Collaboration is "a coordinated, synchronous activity that is the result of a continued attempt to construct and maintain a shared conception of a problem" (p. 70, Roschelle & Teasley, 1995). Though valuable, this description does not distill collaboration as it appears to the individuals involved. It provides little acknowledgment of the agency with which people choose to collaborate or not, or choose to make the effort to understand one another. It does not capture the sense of compromise and choice that is the hallmark of any collaboration. By this definition, for example, we might have to say that the slaves were collaborating with their bosses as they built the pyramid. After all, they did maintain some shared understanding of the problem -- to build a pyramid.

This definition also identifies collaboration primarily by its outcome, "coordinated and synchronous activity." It is not clear to us what constitutes coordinated activity. People have their reasons for collaboration and their definitions of coordination, and these reasons and definitions change during the course of an interaction. Unless a researcher is willing to impose particular norms of successful collaboration, it seems that a general definition of collaboration should be defined with an eye towards the view of those people involved.

If we view collaboration as something that involves individuals representing one another's thoughts, then perhaps the most relevant definition of collaboration would be from the eye of the beholder, or "representor" as it were. So, how do we decide if we are interacting with a collaborator? We propose the following Test: A partner is collaborative if you believe it is possible that the partner could be non-collaborative. In other words, you believe the partner has enough knowledge of your mental states and enough personal agency that the partner could intentionally thwart you or choose to disengage.

Though circular and surely insufficient, the Test does tell us something. Collaborative behaviors probably depend a great deal on the extent to which people trust one another or estimate their collaborative intents. Will you collaborate with another scholar before you have had a chance to assess their views on intellectual property rights and ownership of joint products? If collaboration depends on representing another person's mental state, then surely one of the mental states we appraise is a person's goals and likelihood of collaborating at any moment.

The Test provides some useful analytic distinctions among frequently conflated ideas. First, it points out that communication and collaboration are distinct. Imagine that you are in perfect communication with your word processing machine. The computer records every keystroke perfectly. Does that mean the computer is collaborating? Not really, unless you believe it could intentionally put the wrong letter on the screen every now and then. Or, take the reverse, imagine that we speak Hindu and you speak Japanese. Even though we would have miserable communications, this does not mean we are not collaborating. We know, for example, that if you get frustrated enough, you might choose to quit. Although communication and the effectiveness of collaboration are empirically correlated, they are still different things.

The Test also clarifies that outcomes are insufficient criteria for identifying collaboration. If team A continually loses to team B, this does not necessarily mean that team A is less collaborative. In fact, one might suspect that team A needs to be much more attentive to collaborative issues because there is a high risk of people becoming uncooperative in a failing group. Finally, the Test helps eliminate some of the slippery slope that occurs when we consider embedded systems like individuals in a group, termites in a hive, and neurons in a brain. We see no sense in saying that the termites or neurons in the brain are collaborating. They have no choice in what they do.

MOTIVATIONS TO PRODUCTIVE AGENCY

The ability to express agency plays an important role in people’s motivation and benefit from collaborative learning. First, people should have the intent to learn while interacting (Bereiter & Scardamalia, 1989). Although people learn incidentally, in many cases it is not enough to simply join forces. There are many examples in which people have scripted cooperation among children, and the children replicate the script rather than generate the knowledge they were supposed to learn through cooperation (Vye et al., 1998). More profoundly, people are motivated to collaborate and share meaning when they can exert their agency through productive behavior. Next, we discuss the intent to learn, and then production and motivation.

Appropriation is not necessarily learning

A wonderful example of the importance of the intent to learn comes from a story involving Eskimos and Athabascan Indians in Alaska. In the Middle Yukon region, a thin mountain range separates the Indians and Eskimos. In times past, the Indians purportedly crossed this range and stole into Eskimo villages to kidnap women (McClellan, 1971). They did not take the Eskimo women because there were insufficient Indian women. Rather, they took the women because the Eskimos had developed excellent technologies. The Indians appropriated the women to gain access to their know-how. Interestingly, when a woman died, the Indians would kidnap another. This is because they never bothered to learn what the women knew; they simply appropriated the technology not the understanding.

This example highlights that there is a difference between a culture of appropriation and a culture of learning. It complements an observation by Baker, Hansen, Joiner, and Traum (1999) that learning seems more likely to occur to the extent that agents expend more cognitive effort towards mutual understanding than that which would be minimally required for communication. Evidently, the Indians were happy to communicate with their Eskimo women and did not put in the intentional effort needed to learn.

Karl Marx and the reciprocity of production and appropriation

What causes people to give that extra cognitive effort towards mutual understanding? There are many things ranging from potential rewards to supports for communication. In terms of basic motivations we would like to highlight the importance of production and original contribution. This seems neglected lately, perhaps because of our overemphasis on the appropriation of cultural practices. Appropriation is important, but it is only half the story. Marx (1939/1973) spoke of two great forces that constitute a person. One was appropriation -- we become ourselves by appropriating the ideas and artifacts of those around us. Alienation occurs when we cannot appropriate the contributions of others. But, Marx did not view appropriation as the essence of humanity. Instead, he felt people are builders. We want to produce and create ourselves in the world through our ideas and our material products. This way we put our element in the social matrix, and other people may appropriate our ideas. At the same time, we may re-appropriate our creations as they have been realized in the world, culture, and others. This serves as feedback about our learning, our environment, and ourselves. Without production, there is no feedback and no self.

For Marx, the key to a complete person was not simply access to the material and intellectual wealth of a society, but also access to the means of production. Marx did not advocate a welfare state. He advocated a productive state where people could contribute and impress themselves upon the world. Individuals are builders of their society, not simply recipients. For Marx, the key issue was always who had the means of production.

The emphasis on production is a contribution of Marx that has faded somewhat. In Vygotsky (1978), we read about the movement from external to internal but less often read of the movement from internal to external. This suggests a model of intellectual welfare, and individual productivity fades. An emphasis on appropriation without production strikes us as problematic when we consider collaborative learning.

What makes you most content in a conversation? Is it when you have been told something and understand it -- when you have appropriated someone else's idea? Or, is it when you have contributed substantially to the conversation -- when you have produced ideas that move other people and that help contribute to the interaction? Perhaps the most irritatingly uncooperative agent is the one who denies you agency within the group. In contrast, when you are a substantial contributor, you are willing to go beyond the minimum necessary to communicate and function collaboratively.

It is important to understand that Marx did not argue that people should only be producers, any more than he argued they should only be appropriators. In isolation, each activity leads to alienation from other people and society. Recast in terms of collaborative learning, the goal is the effort after <u>shared</u> meaning -- not an effort after your meaning only (self-centered production) or an effort after our meaning only (selfless appropriation). Production and appropriation are synthetic, so that one makes the other more complete. For example, if you adopt some other people's language, then they will be better able to understand your intellectual productions when you express them.

<u>An example of the beneficial effects of production on subsequent appropriation</u>

The dialectic between production and appropriation suggests that the opportunity to produce should increase people's readiness to appropriate. Consider a recent study on teacher professional development in which we asked a teacher in Hong Kong, Selina, and a teacher in the U.S., Sandy, to teach a group of students a biology lesson. The teachers never met each other or their students face-to-face. Instead, they worked in a web-based, virtual learning space (VLS). Figure 2 offers an overview. To enhance the teachers' productive agency, they had complete control of the lesson and their collaboration. Moreover, they had the joint responsibility of teaching real children in real time (as opposed to exchanging personal teaching stories as is frequent in professional development). Our hope was that Selina and Sandy, collaborating across cultures and time zones, would learn about teaching from one another. For example, Sandy stated she benefited from Selina's scientific expertise, and Selina appreciated Sandy's social management.

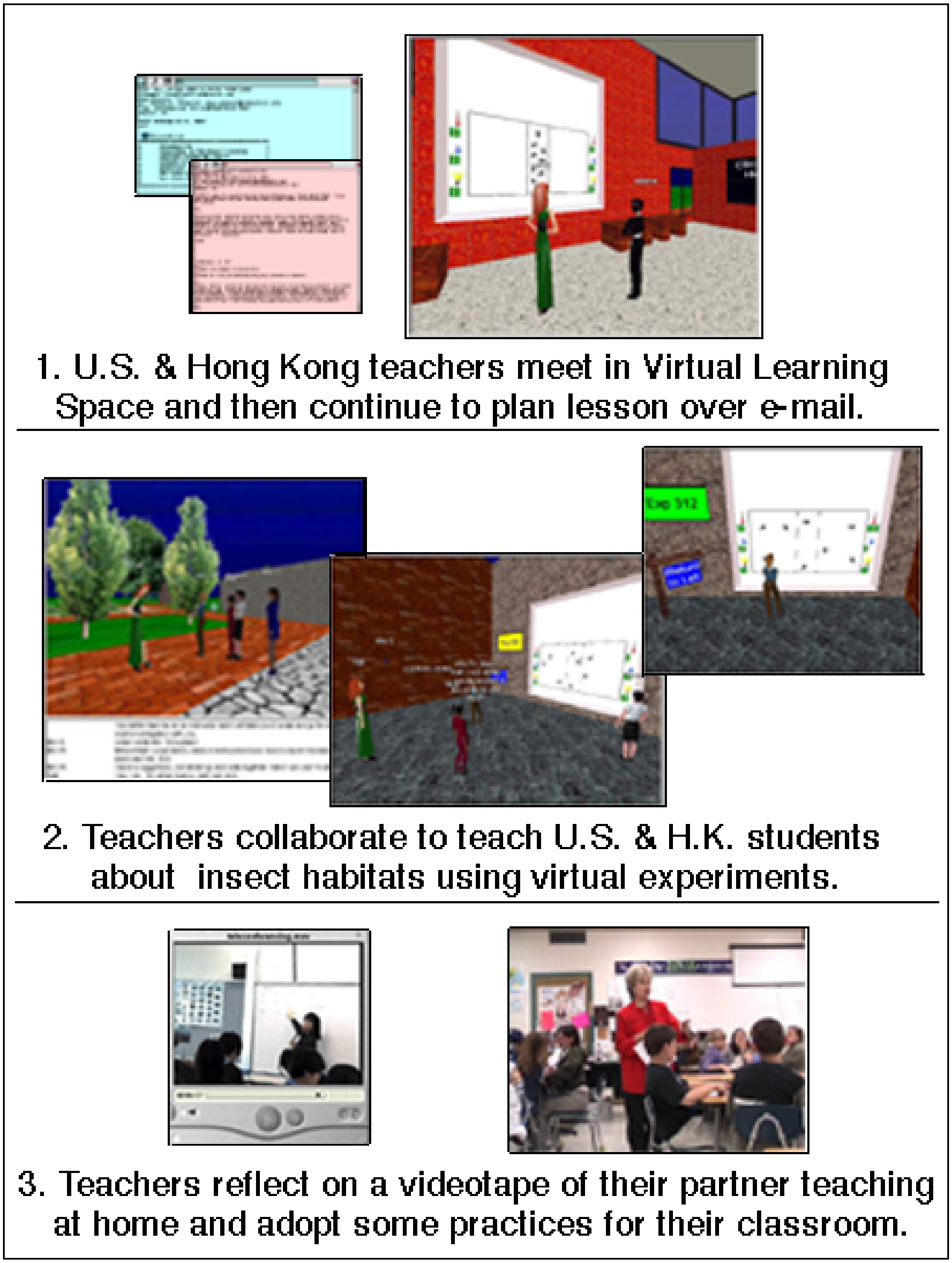


Figure 2. As an exploration into new possibilities for professional development, we asked teachers from different cultures to meet and collaboratively teach students in a virtual learning space.

Of particular relevance is whether the opportunities for productive agency affected the teachers' willingness to appropriate from one another. As an initial exploration, we collected videotapes of Sandy and Selina working in their regular classroom. We asked uninvolved teachers to observe the videotapes and notice any valuable lessons for themselves, just as they might do in a professional development setting. These control teachers made little effort after shared meaning, and they tended to dismiss any novel practices they noticed. For example, the control teachers from the U.S. claimed that the high structure and intellectual discipline of the Hong Kong teacher's classroom required a Chinese culture and could not happen in America.

We also asked Sandy and Selina to observe one another (once they got over the inevitable surprise of seeing what they each looked like). Sandy, like the other U.S. teachers also noticed the high structure of Selina's classroom. But Sandy tried to understand why Selina used so much structure, and she used this as a catalyst to reflect on her own classroom expectations and whether she had let them become too low. We believe formal studies on the benefits of production on subsequent appropriation and the effort after shared meaning would make a profound contribution to the collaborative learning literature.

THE LEARNING PRODUCED IN COLLABORATION

One of the reasons that production is important to collaborative learning is that learning is productive. People construct their knowledge. They do not simply assimilate someone else's knowledge or practices; they actively produce their understanding. The constructive nature of learning has implications for how people learn, how they come to understand one another, and what they are likely to learn in groups. In particular, there are implications surrounding language especially relevant to collaborative learning, because language typically plays a large role in the attempt to establish understanding among partners.

Implications of constructivism for shared meaning

To begin our analysis, it is important to recognize that when someone says something, we do not simply assimilate or copy that expression into a mental database. Words only serve as a starting point for constructing knowledge. Even if we come from the same culture, there is a distinct possibility that we will construct something very different from what a speaker thinks his or her words mean. Consider these newspaper headlines:

- Drunk Gets Nine Months in Violin Case
- Survivor of Siamese Twins Joins Parents
- Iraqi Head Seeks Arms
- New Study of Obesity Looks for Larger Test Group
- Kids Make Nutritious Snacks
- Miners Refuse to Work after Death

We doubt the newspaper editors had the amusing alternatives in mind. The sentences show that people do not simply assimilate meaning from the language of others. People actively generate meanings, meanings that may be quite different from what the speaker had in mind.

Although language is notorious in this regard, it is important to remember that “perceptual things” suffer the same fate. They are not simply assimilated like photographs into the head. People generate understanding using the input of the physical world just like they do from the verbal world. If we look at the same thing, there is no guarantee that we will see the same thing. Mere physical co-presence does not ensure a common ground between two people.

Consider the squiggles in Figure 3. Imagine that the artist who drew the squiggles is at your side. The artist would probably see something different than you do. Fortunately, breakdowns in shared meaning are not irreparable. In the current case, the artist could probably help you “see” with a bit of supportive language. For example, “Turn the figure clockwise 90^{o} and match each of the following labels to its squiggle: James Dean, Babyface, St. Nick, Baseball Bob.” Let us reiterate this point telegraphically: We never see the same thing.

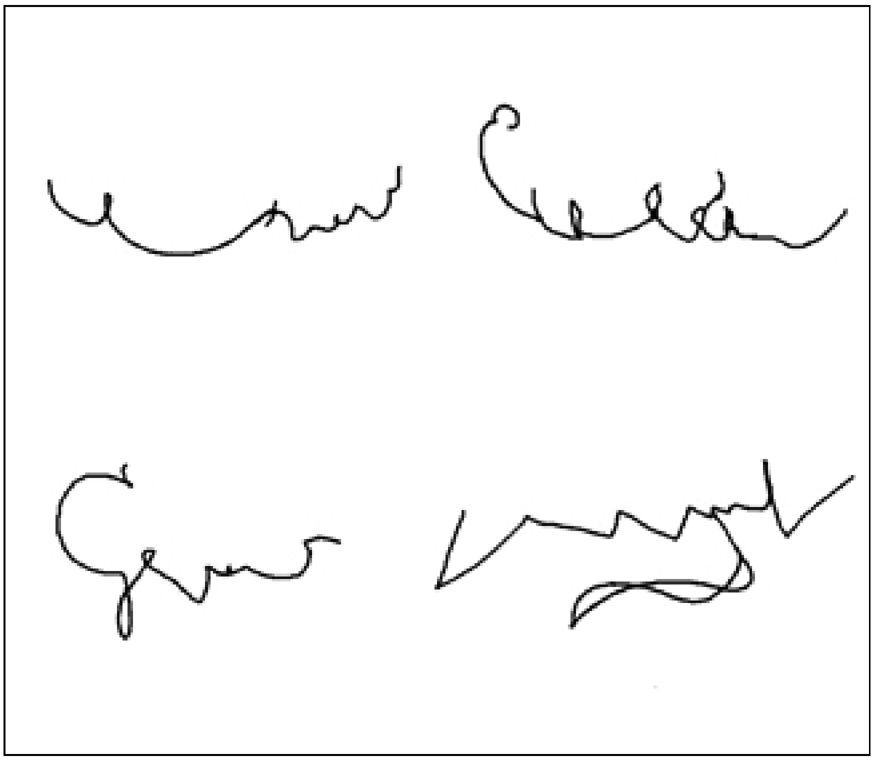


Figure 3. Do you see the same thing as the original artist? (From Schwartz, 1999; adapted from Gibson, 1969.)

Effects of language on knowledge construction and collaborative learning

Understanding is generated and constructed. Physical reference suffers the same fate as words; neither guarantees common meaning and learning across individuals. Nevertheless, there are real differences between words and objects. Language helps construct a particular kind of knowledge. Language and other symbolic representations (e.g., mathematics) are good at helping people build and evaluate an articulate structure. To demonstrate the power of language with regards to structure, consider Figure 4a. What do you see? People see different things including a plane flying sideways or two olives on a toothpick. But let us assume that it is two men riding a tandem bicycle wearing large, round hats. You are looking down at them. Next, consider Figure 4b. What do you see? If you are like most people, you see four men on two bicycles. Now, notice how language re-structures your thought. It is not really men on bicycles; it is a bear cub clinging to the back side of a tree. The circles are its paws. Suddenly, new structures in the referent become important, like the distance between the two lines that portray the tree.

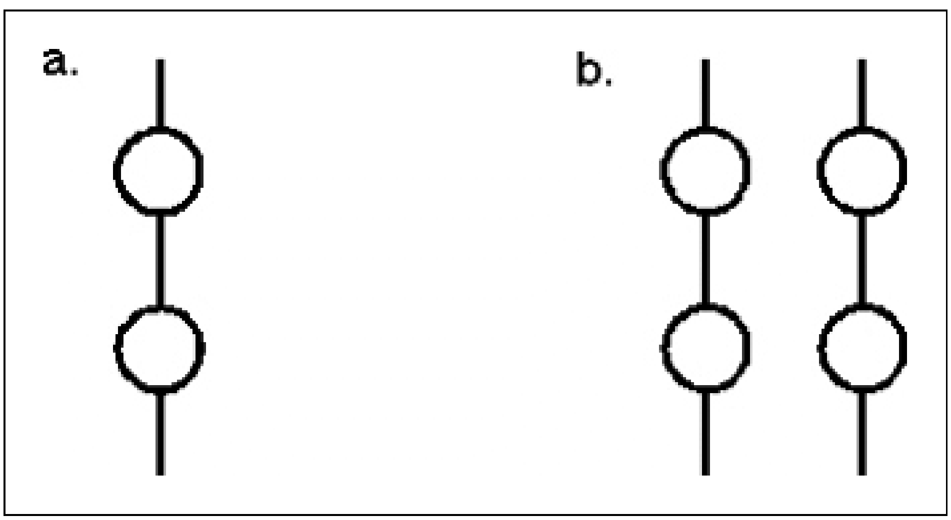


Figure 4. What do you see in the two figures? (From Schwartz, 1999)

Collaboration typically involves heavy doses of language. This language should lead cooperative groups towards structural descriptions in their learning. Moreover, groups may move towards abstractions as the members try to find a safe place to communicate where their idiosyncratic differences of interpretation will not interfere. The pull towards abstraction and structure in verbal communication is the sort of place to find a special effect of collaboration on cognitive outcomes.

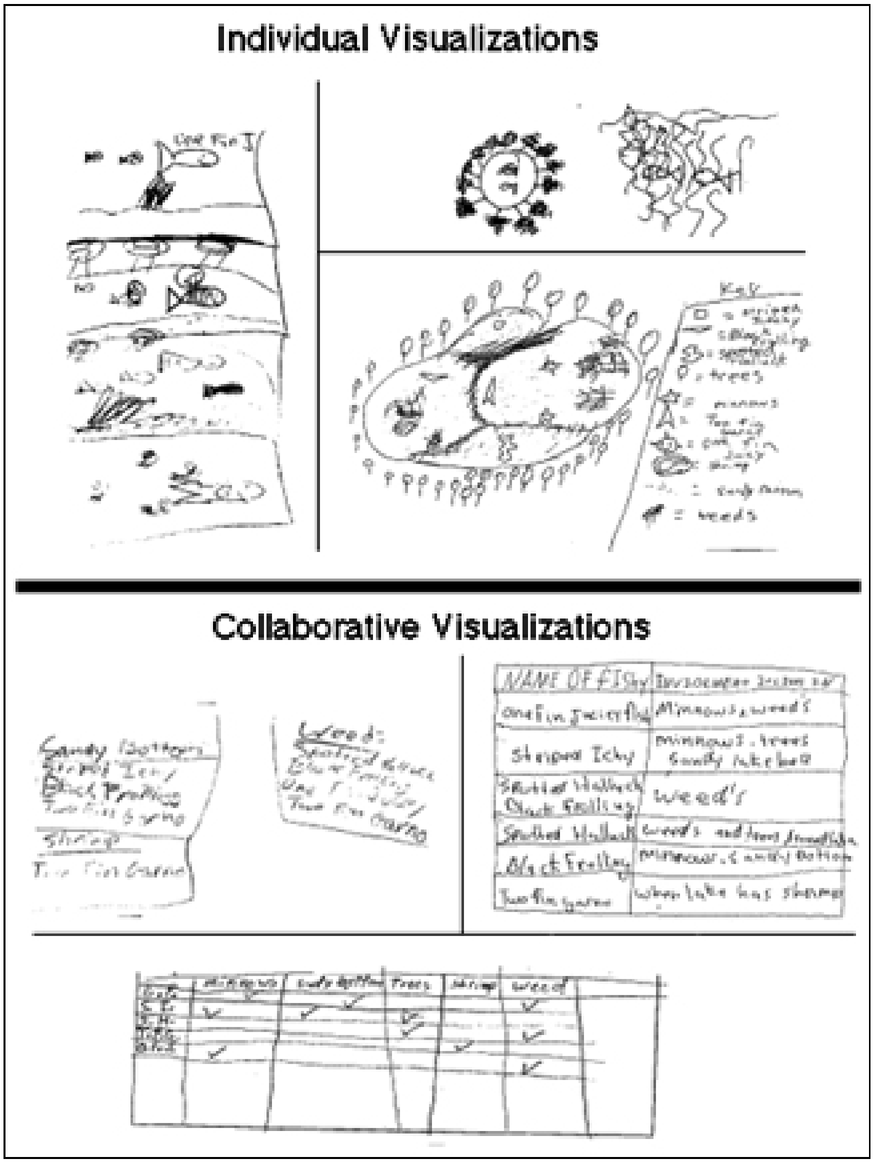


Figure 5. Pairs are more likely to generate abstract representations than individuals, as shown in these representative visualizations. (Adapted from Schwartz, 1995, by permission of Erlbaum)

Consider the following study (Schwartz, 1995). Seventh grader's received descriptions of fictitious fish and their habitat requirements. For example, "the Spotted Frolling lives in lakes with weeds," "the One-Finned Halluck needs weeds and a sandy bottom." Their task was to construct a visualization of the relationships. Students worked alone or in pairs. The students who worked alone drew lakes with fish (Fig. 5). Only 6% created visualizations that were abstract in the sense that they did not actually look like fish and lakes. In contrast, 67% of the pairs constructed abstract representations like a matrix or chart. This percentage is well-above the probability that a pair would have included at least one member who would have constructed an abstract representation working alone. Collaboration led students to generate something new that was not found in otherwise similar individuals.

How lectures can become an effort after shared meaning

By considering the types of understanding that people generate with the aid of language, it should be possible to prescribe particularly appropriate times to share linguistic representations during knowledge growth. For example, we have examined whether there is a "time for telling" (Schwartz & Bransford, 1998). In a study on helping psychology students learn about memory, we separated the students into three instructional treatments. In the double-telling treatment students wrote a three-page summary of a brief chapter on memory. Five days later, they heard a lecture on the concepts and experiments in the chapter. In the double-discovery treatment, students tried to discover patterns in data sets from relevant memory experiments (see Table 1) and repeated the activity five days later. In the discovery-plus-telling condition, the students also worked with the data sets, but five days later they heard the same lecture as the double-telling students. A week later, we tested learning by asking everyone to predict the outcomes of a new study on memory.

<u>Table 1. An example of the guided-discovery tasks used to prepare students learn from a lecture on memory (adapted from Schwartz & Bransford, 1998, by permission of Erlbaum).</u>

Draw graphs of the interesting results from the following study:

Eight subjects read 12 passages about different topics. The paragraph of experimental interest was the one describing John's visit to the doctor.

<u>The Doctor Visit</u>

> *John checked in with the doctor's receptionist. While he waited he read magazines. The nurse called his name. John undressed. John talked to the nurse. The doctor came in to the examination room. The doctor was very friendly. The doctor prescribed some pills for John. John left the doctor's office.*

Twenty minutes after reading the paragraphs, the subjects received a recognition test. They rated sentences from a low of 1 to a high of 7 as to how sure they were that they had actually read the sentence. Here are the sentences they rated, afterwards are their ratings:

A) John checked in with the doctor's receptionist.
B) John sat down.
C) While he waited he read magazines.
D) John followed the nurse.
E) John undressed.
F) John talked to the nurse.
G) The nurse tested John in the examination room.
H) The doctor greeted John.
I) The doctor examined John.
J) The doctor prescribed some pills for John.
K) John made another appointment.
L) John left the doctor's office.

	A	B	C	D	E	F	G	H	I	J	K	L
S1	7	7	6	3	4	3	6	1	7	4	2	7
S2	7	5	6	1	5	4	7	3	5	3	1	7
S3	6	7	7	4	3	5	5	4	3	5	3	6
S4	7	6	7	3	6	4	4	3	7	2	4	7
S5	7	6	5	3	4	3	7	2	5	6	4	6
S6	7	4	7	2	5	5	6	3	6	3	2	7
S7	7	7	7	2	3	3	5	5	7	5	1	7
S8	5	5	7	4	5	5	4	2	4	4	3	7

The results were definitive. Students in the discovery-plus-telling condition made over twice as many correct predictions and fewer incorrect predictions than students in the other two conditions. One interpretation of this result is that the discovery activity helped students discern important empirical properties of memory, and the subsequent lecture provided the structure that enabled these students to construct an understanding of why these properties are significant. For example, the lecture explained how schema theory predicts when people will falsely remember things they never saw even better than things they actually did see.

The results of the study show that individuals needed both forms of knowledge. Without the "discovery," the "telling" simply provided a set of inert facts to be memorized. And, without the "telling," the results of discovery were simply piecemeal observations. This result provides an important lesson for those who believe that direct teaching (e.g., a lecture) is contrary to constructivist ideals. As argued above, people construct their knowledge regardless of whether the input comes from the physical or linguistic world. The current study points out that there is a place for texts and lectures in a classroom; namely, when students have had opportunities to discern sufficient features of the domain (which instructors often take for granted) so the students can use expository materials in a constructive manner.

Further evidence on the effects of production on receptivity

Importantly, well-structured activities that allow students to produce (generate, discover) knowledge not only prepare students to understand formal ideas presented in a lecture, they also prepare students to make the effort after shared meaning with their peers. In beginning statistics instruction, for example, we ask students to invent formulas to help them differentiate the variability of pairs of distributions. For example, students might invent something like a range formula to differentiate the sets: {2, 4, 6} v. {5, 6, 7}. By using different pairs of contrasting sets, we can get students to notice different features of distributions such as set size ({2, 2, 4, 4, 5, 5} v. {2, 4, 5}) or skew ({1, 2, 3, 4} v. {1, 1, 1, 4}). These activities attune students to the features of distributions that a good variance formula should take into account (set size, dispersion, range, etc.). Although students rarely produce conventional solutions, the invention activity (like the discovery activity above) prepares students to see the purpose and elegance of expert solutions and explanations (e.g., standard deviation; Moore & Schwartz, 1998). Of additional importance, the opportunity to produce mathematical inventions enhances students' readiness to appropriate from their peers. We asked several classes of students who had completed the invention activity to evaluate the quality of novel procedures for finding variance (Moore & Schwartz, 2000). We told them the procedures came from students elsewhere. Over 75% of the students from the invention classes noted good qualities of these procedures, often qualities they had not included in their procedures (e.g., handles negative numbers). In contrast, we also asked students who had completed introductory statistics courses. Over two-thirds simply stated that the procedures were "wrong." They did not notice any merit nor even how the procedures improved upon what they had been taught. These latter students were complying with rules, whereas the productive students made the effort after shared meaning and appropriated new knowledge from their anonymous peers. As fits our general story, opportunities to produce increase the readiness to appropriate.

TEACHING AS A FORM OF COLLABORATION

Ploetzner et al., (1999) state, "Even if an agent models the other sufficiently to continue the dialogue, this might still be merely at a shallow level of understanding, not enough to actually learn" (p. 120). In the course of our discussion, we have tried to offer novel examples of ways to deepen collaborative dialogues and ways that computers can introduce new opportunities. We would like to end with an unusual example that helps to highlight our major theoretical commitments. The example comes from teaching, but in this case, students are teaching a computer. In a recent fortune cookie, we read the message, “He who teaches learns,” and we are trying to capitalize on this wisdom.

Teaching is a case study in productive agency. Even with thirty students, teaching is a collaborative effort. Teaching affords tremendous productive agency dedicated to sharing ideas, and when successful, it is immensely satisfying and educative. (Reciprocally, when disinterested students, oppressive social rules, or dictatorial curricula thwart productive agency, teaching is demoralizing.) There are many reasons teaching may enhance learning. For example, we have found students learn more when they prepare to teach than when they prepare for a test (Biswas et al., in press). We surmise this happens in part because students recognize that the class can choose not to cooperate and so they must prepare well. Also, when teaching, the feedback that reveals student (mis)understanding probably helps teachers reflect on their own knowledge and produce new structures of explanation for themselves and their students. To capitalize on these and other potential benefits of teaching, we have created computer agents whom students teach (Biswas et al., in press). Students are not merely recipients of computerized knowledge, they are producers. Figure 6 provides an example of a web-based agent named Betty’s Brain (apologies to the neuroscientists).

Students teach Betty by drawing a network of qualitative relationships. Betty can use her network (with simple AI techniques) to answer questions from students and teachers. Figure 6 shows the graphical and text-based response Betty gave to a specific question based on her larger network of knowledge. Based on Betty’s responses, students can improve her knowledge base. Students can also enter Betty into a contest in which a teacher poses a common question to several Bettys taught by different students. This way the students can assess differences in the answers to help them rethink their knowledge and Betty's.

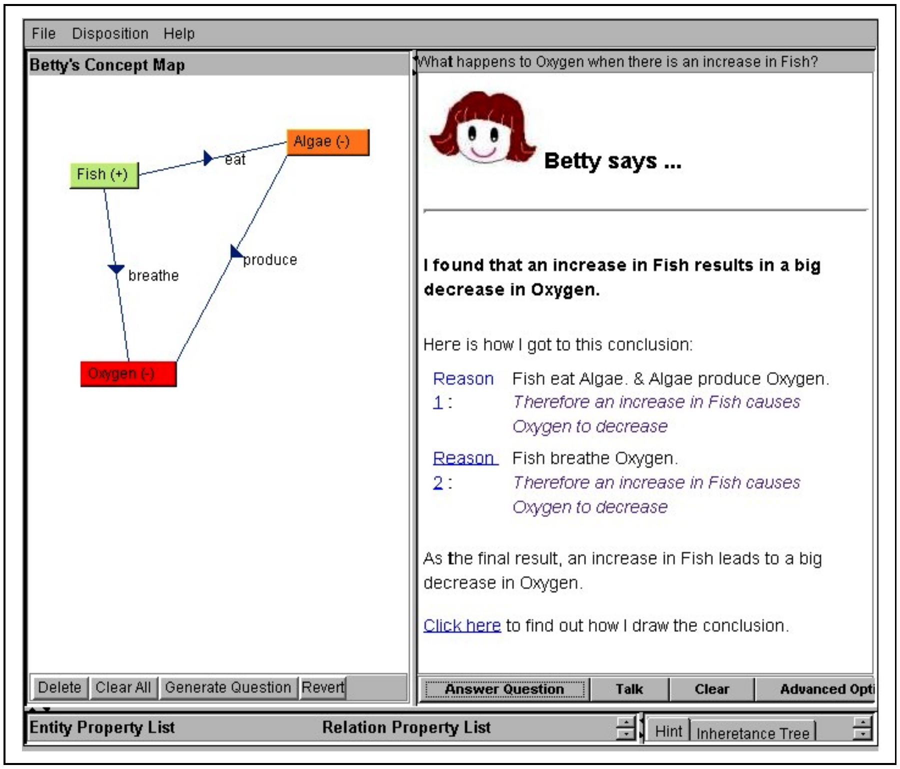


Figure 6. Students teach Betty's Brain by giving her a network of knowledge that she can use to draw inferences and answer questions. The small sample on the left side of the figure indicates which subset of a larger network Betty used to answer the question, "What happens to the oxygen when the fish increase?" The right side shows her reasoning in verbal form.

In addition to making an agent who reasons and learns, we have given Betty other human qualities. For example, Betty1 can collaborate with Betty2 and students can enter "Betty teams" into contests. Betty also has dispositions that students can adjust. For example, if Betty is too lazy she may only search one path in her network, and if she is too wordy, she may describe every single step of every path she tried. Betty can also refuse to cooperate and learn. These dispositions also extend to collaborations among Betty's. For example, a self-centered Betty may consult her network 90% of the time and her partner's network only 10%. These qualities give Betty the apparent agency that enjoins students into a collaborative relationship.

Betty embodies several of our theoretical observations, and allows us to recapitulate our claims about collaboration:

- Collaborative learning often grows from the attempt to represent another person's thoughts. (With Betty, students explicitly attempt to model her/their thoughts.)
- Collaboration organizes around agents who can choose whether and how to make an honest effort after shared meaning. (With Betty, dispositions affect her willingness to collaborate and student's sense of collaborative engagement.)
- Exerting productive agency by successfully bringing one's ideas to a collaborator facilitates knowledge appropriation. (With Betty, students produce her knowledge and this prepares them to re-appropriate the effects of their production as well as learn from formal treatments and peers.)
- Collaborative learning often generates abstract knowledge. (With Betty, students use the formal abstractions of network diagrams and qualitative reasoning.)

We have yet to explore the effects of Betty nor have we finished designing her interface, but it will be interesting to see what "collaborative" learning emerges in this novel setting made uniquely possible by computers. We will need a theory that explains what ultimately emerges. Ideally what we want is a theory that explains how collaboration and collaborative learning emerge, not simply how they look once they appear. We believe the best way to understand this emergence will be an analysis at the level of individuals choosing to produce the effort after shared meaning in collaboration.

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