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in education

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# Invited Article: Will knowledge building remain uniquely human?

*Marlene Scardamalia\**, *Carl Bereiter\*\**

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## Abstract

If AI is to have a positive transforming effect on education, it will be through the community norms, collective practices, and solidarity that emerge around it. In Knowledge Building, this means fuller realization of such principles as collective responsibility for idea improvement, idea diversity, and knowledge building as a way of life. AI can aid the development of this kind of community by providing powerful tools students themselves can use to strengthen their knowledge-building efforts and eventually by making intelligent machines active collaborators in these efforts. This paper describes advances currently taking place in Knowledge Building technology. Although full collaboration between humans and machines in knowledge creation may be years away, education can start preparing students for their role in it by emphasizing those capabilities that arise from the multifarious personal and social lives they lead.

**Keywords:** Knowledge Building; Knowledge Creation; AI; Black Box, ANN (Artificial Neural Net); Epistemic Agency

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## Introduction

John Seely Brown (2017) has claimed that the triumph of Google's AlphaGo over the world's greatest Go player was a cultural turning point, changing everything – how we should conduct our lives, what knowledge means, and how we conceive of ourselves when we are no longer indisputably the smartest beings on the planet. AlphaGo demonstrated an ability to invent new strategies – new knowledge that human players can adopt and use to their advantage. *Collaboration* between skilled player and inventive machine has thereby produced a thus far unbeatable team. The possibility of similar knowledge-creating collaboration between student and machine is imminent. The 2015 PISA test included an experimental test of collaborative problem solving in which the individual examinee collaborated with a computer. The AI involved was primitive, little more than a branching script, but it is easy to foresee a process in which the computer brings to the collaboration the capabilities that enabled it to devise winning strategies in board games. Where would this leave the student? Where would this leave the pedagogical practice, esteemed since Socrates' day, of posing to students challenging and thought-provoking questions? Simple inquiry learning, in which children raise their own questions and then work to find answers is already needing to be rethought by the fact that almost any question students enter into a web search engine will retrieve a direct answer.

The only educational approaches in which collaborating with a machine in knowledge processes could enhance rather than defeat the approach are those in which knowledge creation by students – that is, the disciplined production and improvement of concepts, explanations, designs, inventions, theoretical models, knowledge-embodying physical artifacts, and the like – is a central concern. Although there are a number of educational approaches that have some of this, the only approach that has knowledge creation at its core is Knowledge Building (Chen & Hong, 2016; Scardamalia & Bereiter, 2014, in press). “Knowledge Building” is in fact synonymous with “knowledge creation”, amplified by a concern with educational benefit to the participants (Bereiter & Scardamalia, 2014). Accordingly, our discussion

of the role of AI in education takes Knowledge Building as the context in which transformative possibilities may be realized. This is not to discount the significance of AI contributions in such areas as testing, information access, educational games, and laboratory instrumentation; each of these deserves separate consideration and critical analysis. However, we see Knowledge Building as a harbinger of what education will become as it strives to achieve increasing relevance to the emerging knowledge society, and the kind of educational practice in which AI is most likely to have a revolutionary and not merely an incremental effect.

The possibilities for human-machine collaboration are endless, as are the problems associated with them. We can imagine an art museum audioguide that did not simply give little lectures but that interacted with the user to develop a personalized response to an artwork, with the user's tastes and prior experience brought into the process; but to what extent could and should the device attempt to educate the user's tastes versus merely being responsive to them? We can imagine a GPS guidance system that did not merely guide the driver along a route determined by the system's algorithms but that engaged in collaborative trip planning with the driver, also taking account of the person's interests, prior experience, and perhaps skill level; but what if the result was a more passive driver or a more annoyingly meddlesome guidance system? These examples are complex because of the extent to which the whole person is involved in the collaboration. In this paper we will not try to contend with this complexity and the broad range of social, emotional, aesthetic, and cognitive issues related to human-machine collaboration. We will focus instead on the admittedly over-simplified case where the collaboration is in generic knowledge processes of problem-solving, planning, invention, and idea improvement, and where the desired outcome is advances in community knowledge, a principal focus of Knowledge Building.

If we take seriously the idea of human-machine *collaboration* in knowledge creation, we must recognize that we are talking about a two-way process. It is not simply a matter of the machine having certain capabilities we can use. It is a matter of machine and human bringing different capabilities to a collaborative process, and so there

is a need to consider what distinctive assets human partners have to contribute. The latter is an important question for education because, if human-machine collaboration comes to play an important role in productive work, education will be expected to improve those human assets. Traditional appeals to creativity, critical thinking, imagination, and social skills as uniquely human attributes no longer suffice. It is not that intelligent machines render these human attributes irrelevant, it is that they are defined in such a broad way that they are not useful for identifying human assets that accrue naturally to humans by virtue of the multifarious lives they lead. It would be difficult to imbue a machine with these assets except by having the machine lead a human-like life. Paramount among these are *commonsense knowledge* and *social intelligence* of the breadth and situatedness humans acquire. Then there is *depth of understanding* (not to be confused with “deep learning” in the sense of multi-level AI models), which does not come about spontaneously the way commonsense knowledge does but is driven by the distinctly human need to understand. Such a need, or its functional equivalent, may someday be built into machines, but the human drive, which increasingly takes the form of a community effort, provides something that is likely to be of long-term value. Finally, there is something commonly described as “seeing the forest through the trees”, or “taking the large view”, and more technically as *understanding the problem situation*. What makes this a distinctively human asset is that it builds on the first three. In the following sections we discuss these four assets with particular attention to the role of Knowledge Building in developing and utilizing them.

## Commonsense Knowledge

Commonsense knowledge is the vast body of everyday knowledge of the natural, social, and built environment that we typically acquire incidentally, unconsciously, and without thought. Although for these reasons Knowledge Building and formal instruction do not have much direct role in acquiring it, commonsense knowledge plays a vital role in the building of other knowledge.



Here is a commonplace example of commonsense knowledge. Suppose you are at home and you hear a knock at your front door. First of all, you know with a high degree of confidence that the knock was caused by a human being who is on the other side of the door. This is not trivial. An intelligent machine might not know this or know enough to be able to figure it out. It is also not trivial that you know the knock is at your front door, which means the person is outside your home, not inside. From its sound, you know if the knock was made by knuckles, a fist, a wood object, a metal object, or something unlikely (such as a guitar). From the intensity and rate of knocking you may recognize it as a request for you to open the door or a demand, an emergency, or no hurry. You may even identify the person by their characteristic way of knocking. None of this requires deductive thought; it is just stuff you and most other people simply know but that a machine highly likely will not know. This happens to be knowledge acquired through social interaction. Other similarly ordinary kinds of knowledge are acquired through preparing and consuming food, shopping for clothing, traveling by bus, skiing or skating, gardening. Not all commonsense knowledge is accurate. Misconceptions may be found in practically every area. But right or wrong, commonsense knowledge provides an intuitive substrate that is essential for building more systematic formal knowledge (deKleer & Brown, 1985).

Knowledge Building frequently starts with students' commonsense knowledge, but their efforts to integrate it with newly acquired knowledge often lack an organizational framework to bring pieces of knowledge together, as illustrated in the following snatch of grade 1 conversation about water:

Jessica: ... all the theories do come together, like in water.

Avril: Why is water clear?

Rebecca: Because it is a liquid.

Tobias: So why is water a liquid?

Mark: Well, water can be a solid.

Noah: Then it goes down back into the ground.

Daniel: It is like a cycle, it goes, and it evaporates.

Sheila: Why does water evaporate?

These young students are exhibiting something not found in machines or in nonhuman organisms: An actual *need* to understand, to explain the how and why of what they observe. That need, which may take the form of curiosity, uncertainty, or dissatisfaction with their state of knowledge, is something important students can bring to their collaboration with machines in advancing community knowledge. However, moving beyond simple explanations to ones that, as Jessica says, “come together” requires a larger view of a knowledge or problem domain – “seeing the forest through the trees”, as discussed in a later section.

## Social Intelligence

Machine intelligence is making impressive advances in the kinds of social and emotional intelligence that earlier generations liked to think were uniquely human. Machines are getting skillful at reading people’s emotions from facial expressions, tone of voice, and word usage. Poker-playing automata not only surpass human players in probabilistic reasoning but can equal them in reading clues from other players, detecting bluffing, and even using bluffing as a strategy (Brown & Sandholm, 2019).

The knocking at the door example illustrates the kind of social intelligence, multiplied many times over in countless other situations, that machines will not be able to match until they begin to live lives that have the complexity of ordinary people’s daily round of interacting with one another. Although there is evident transfer of social intelligence from one situation to another, there is also situation-specific knowledge and skill. Despite the claims of one vendor of wall-climbing installations, the teamwork skills developed in wall climbing do not necessarily make one a skillful collaborator on a product design or marketing team. Collaborative projects in schools can be expected to develop some generalizable social skills but Knowledge Building has the special advantage that it engages students in collaborative, creative work closer to the social situations found in real-life knowledge work. Knowledge Building, in addition

to building systematic knowledge can develop social sensitivity and skills specifically attuned to collaborative knowledge creation. This is an educational outcome valuable in its own right. It is another kind of value humans can bring to human-machine collaboration in knowledge work.

## **Depth of Understanding**

Everyone is in favor of depth. A distinction can be made, however, between externally demonstrable depth and depth as an internal, subjective state. Externally, we can define depth as understanding deep things about a subject (Bereiter, 2006). For instance, natural selection is a deeper concept than adaptation and self-organization is a deeper concept than natural selection (Kauffman, 1993), so it can reasonably be claimed that understanding the deeper concept indicates greater depth of understanding.

There is, however, a personal view of depth that has to do not with the level of concepts you understand but with your feeling of understanding, what you are able to do with a concept, and the role it plays in your life. Machines may be able to provide evidence of depth in the sense of externally demonstrable depth, but understanding in the personal sense seems, for now at least, to be a uniquely human property (Entwistle & Nisbet, 2013). Knowledge Building has depth of understanding as one of its major goals. This includes both understanding deeper things and progressing from a level of understanding that enables students to pass tests to a level at which understanding an important idea changes the way one perceives the world. Marjorie Grene (1974) has said that when we understand something deeply enough, “We become what we know”. That is, the understanding changes us in fundamental and far-reaching ways. According to Landauer’s Latent Semantic Analysis Theory of verbal meaning (1987), that kind of massive reorganization of meanings is going on continually in humans, automatically and unconsciously. It is a behind-the-scenes process that enables the conscious meaning-making that we call “thinking” or “reasoning”. Machine intelligence can simulate the automatic pro-

cess; that is in fact what Latent Semantic Analysis does; but there is a long way to go before some new insight will be able to restructure the machine's intelligence.

## **Seeing the Forest Through the Trees**

In one primary grade Knowledge Building class a child asked where the lungs of a plant are. Instead of immediately informing the child that plants do not have lungs, the teacher said something on the order of "That's interesting! I never thought of plants having lungs just like we do. So, can we explain how could plants breathe if they do not have lungs like we do?" An intelligent machine would be unlikely to formulate the kind of response this Knowledge Building teacher did because it lacked the teacher's sense of the whole situation – a situation that involved actual children, their developmental status and trajectories, a scientific problem domain of considerable complexity, and knowledge about the teachability of particular concepts and commitment to the centrality of students' ideas. In combination these represent knowledge of a whole situation or "problem space" (Newell, 1980). To operate effectively in a complex problem space it is not enough to know its parts and how they are related; it is necessary also to have a sense of the whole – to see the forest through the trees.

This is something formal education commonly fails to deal with. Problems, whether posed by the teacher or arising from students' interest and puzzlement, may be related (all may involve triangles, for instance, or be about reducing greenhouse gases) but they are usually treated one-by-one. Questions pertaining to the larger problem situation tend to receive no attention: What is the context in which this problem arises? What makes it a problem? What are the surrounding problems and what do they have in common? Is there a central problem that is key to solving the other problems? Are there problems we can solve right now and that will give us information we need to solve the more difficult problems? What is crucial knowledge we need in order to make progress in this problem situation?

In their Knowledge Building, naïve students will sometimes come up with deep and far-reaching questions and with ideas that have wide implications, but typically they will not see this. The teacher, like the leader of a creative design group, may take the wider view and help students see it. In the case of the young student asking about plants' lungs, the Knowledge Building teacher's response lifted the child's question from one that would have a simple and limited answer to one that opened up a whole problem space about plant respiration. If looking for the bigger question is made a regular part of Knowledge Building meta-discourse, students should become increasingly able to do this widening of the problem space themselves. In this way they can become leaders rather than followers in human-machine collaborative knowledge creation.

## **Taking Control of the Black Box**

A long-standing principle in Knowledge Building has been “epistemic agency” (Scardamalia & Bereiter, 1991; Scardamalia, 2002) – the principle that students should be in charge of their intellectual lives at the highest possible levels, and technology should support that principle. This has meant designing the technology now known as “Knowledge Forum” – to provide a congenial and supportive environment for representing, building on, and refining ideas, rather than informing, teaching, prescribing, and controlling. The entry of AI of any kind into educational processes raises concerns about its effect on student agency, but one kind that has special relevance to Knowledge Building is the “inherently opaque” or “black box” character of AI based on artificial neural nets.

Children are growing up surrounded by “black boxes” whose inner workings are unknown to them: Telephones (whether smart or dumb), television, electronic door locks, elevators, microwave ovens, traffic signals. Children become comfortable with these once they have learned to interpret or use them for their own purposes, and this can be true of AI tools as well. Of course, children are born with no understanding of even the simplest technologies – tableware, for in-

stance, and doorknobs. Exploratory play is one way they become familiar with and establish agency over these and the black boxes that surround them. Play works for spoons and doorknobs and just a little later it works for cell phones and tablet computers.

The potential of play as a way of establishing agency needs to be investigated and developed as AI gains a place in classroom infrastructure. More than 20 years ago we did a small pilot experiment using ECHO (Thagard, 1989), a neural net-based application for evaluating the coherence of theoretical explanations. ECHO is a typical black box in that there is no discoverable sequence of rational steps leading to the score it assigns to an explanation. We introduced ECHO to a group of grade 5 and 6 students, who had been studying the extinction of the dinosaurs. We had them enter relevant facts, hypotheses, positive or negative links between these, and then run the program to evaluate the asteroid theory versus the volcanic eruption theory. To everyone's surprise the volcanic eruption theory emerged victorious. We then asked whether there were any pertinent facts they had not entered. They identified as a neglected fact the iridium layer found around the world. When they entered this fact and marked it as consistent with the asteroid theory but not with the volcano theory, ECHO now scored the asteroid theory as stronger. Then an interesting thing happened. The students, having obtained a result consistent with what they had been taught, began playing with the software, varying the facts or connections to see what happened. They were delighted when they finally succeeded in convincing ECHO that the dinosaurs were not extinct after all. (Facts have a privileged status in ECHO, but they are not immune to elimination if they are inconsistent with a hypothesis that is highly coherent with other facts and hypotheses). When we asked them what they had learned from this experience, one of them volunteered, "Computers are stupid". Obviously, this was not true. ECHO had in fact mirrored the actual course of scientific thought, in which the iridium layer was crucial evidence that tipped the balance in favor of the asteroid theory. What we think the child was expressing rather was a shift in attitude, from seeing the computer in this context as awesome and commanding to seeing it as something they could make do what they wanted – including making it do stupid things.

## **Knowledge Building Technology and AI**

While maintaining the Knowledge Building principle of student epistemic agency in its basic design, Knowledge Forum has begun to incorporate feedback tools that work in non-transparent ways. Two of these, KBDex (Oshima, Oshima, & Matsuzawa, 2012) and LightSIDE (<http://ankara.lti.cs.cmu.edu/side/>) employ neural net kinds of AI. In KBDex, colored circles representing ideas in Knowledge Forum notes or note authors swim about on the computer screen and settle into arrangements that cluster these in meaningful ways, but not according to any stepwise reasoning. LightSIDE is a machine learning application that has been trained to analyze Knowledge Forum notes (Zhang & Chen, 2019). Both applications are being engineered so as to be usable by students for feedback on their collaborative knowledge building. Because these and other computational black boxes can be used in a variety of ways, care must be taken to ensure that they are used in ways that maintain student epistemic agency and that support larger knowledge building purposes. For instance, there is an important difference between configuring an AI-based tool to give advice, as in Summary Street (Kintsch, Caccamise, Franzke, Johnson, & Dooley, 2007), and configuring it to provide descriptive information, even though the underlying analytic process is the same and the tool only acts on request from the student. The role of advisor is inherently “one up” on the role of advisee, so that giving the machine an advisory role inherently challenges student agency. Giving the machine an informational role, however, leaves it up to the students to decide what use they will make of the information. For instance, a student in grade 5 may ask, “How does the scienticness of my Knowledge Forum notes compare with the scientificness of students in grade 4, or 6 or 9?” or, more pointedly, “What are words that appear in the notes of grade 9 students (or in Ministry of Education guidelines) that do not appear in my notes?” We have found that students are very interested in this kind of information and use it constructively.

This is not to rule out advice giving via AI. After all, the spelling and grammar checker in our word processor gives advice. We do not find this diminishes our agency as writers, and we would be pleased if

AI could improve the quality of its grammar recommendations. But it is important that what emanates from the black box be treated only as information – especially if delivered in the form of advice – information that students are encouraged to evaluate critically, take into account along with other knowledge, or ignore as appropriate. Output of AI black boxes can play a similar positive role in Knowledge Building, but to ensure that it does, the information obtained should itself be treated as an object of collaborative inquiry and idea improvement. Knowledge Forum itself can provide a reflective layer on AI results that are manually or automatically brought into it. And, to echo an earlier point, those results should include the results of playing with the black box, finding out how to influence its output, getting it to give silly information or advice. Students should come to see the tool as something they can work with to serve their purposes.

As to human-machine collaboration in Knowledge Building, it is not too early to start enhancing knowledge-building technology so that it helps students make fuller use of the distinctly human strengths we have been discussing in this paper. This could include

- Encouraging fuller elaboration of commonsense knowledge as it applies to a knowledge-building effort, evaluating what this knowledge does and does not do, how it is similar to and different from the codified knowledge found in authoritative sources, and how it can be improved.
- Using social intelligence in collaborative Knowledge Building. Progress in Knowledge Building/knowledge creation/innovation often depends on forming a well-functioning team. Although machines may play a useful role (in match-making, for instance), humans must do the basic work of turning a collection of people into a functioning team; that is something students can learn to do in school, and knowledge-building technology could provide support.
- Pursuing deeper understanding. Currently, Knowledge Forum encourages depth through such epistemic markers as “a better theory” and “this theory does not explain”. Scaffolds can be developed and refined to encourage “going deeper”. Although the concept of “deep” may be only vaguely defined, it can acquire meaning in the process of trying to apply it.



- Supporting metalevel discussion of problem situations. If, for instance, electricity is a mandated topic, the metalevel discussion would deal not only with what we already know about electricity but also what it would mean to understand electricity, what we would be able to do that we are not able to do now, what is puzzling about the electrical things we encounter in our own lives. Knowledge Building teachers often conduct such metalevel discussion in face-to-face talk (“KB talk”) supported by visualizations of results from tools embedded in Knowledge Forum. A new multi-level architecture for Knowledge Forum is envisioned to provide supports for metalevel discussions for a broad range of discourse features and moves, so users can select visualizations appropriate to their particular context (e.g., language learning, math learning) and desired knowledge practices (e.g., explanatory coherence, rotating leadership). The discourse of the community represents a powerful source of input regarding these and many different facets of knowledge work, and the new multi-level architecture aims to bring these different facets to life through the many and varied metalevel discussions in can support.

## **Conclusion**

If AI is to have a positive transforming effect on education, it will be through the community norms, collective practices, and solidarity that emerge around it. In Knowledge Building, this means fuller realization of such principles as collective responsibility for idea improvement, idea diversity, and knowledge building as a way of life. Transforming a collection of people into a productive community is a thoroughly human process. It is essentially a self-organizing process; the community is an emergent result of a diversity of social interactions. Leadership can help community formation but cannot fully control it or make it happen. AI can aid the development of a Knowledge Building/knowledge-creating community by providing powerful tools students themselves can use to strengthen their knowledge-building efforts and eventually by making intelligent machines active collaborators in these efforts.

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