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ARTICLE

The Intertwined Histories of Artificial Intelligence and Education

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Abstract

In this paper, I argue that the fields of artificial intelligence (AI) and education have been deeply intertwined since the early days of AI. Specifically, I show that many of the early pioneers of AI were cognitive scientists who also made pioneering and impactful contributions to the field of education. These researchers saw AI as a tool for thinking about human learning and used their understanding of how people learn to further AI. Furthermore, I trace two distinct approaches to thinking about cognition and learning that pervade the early histories of AI and education. Despite their differences, researchers from both strands were united in their quest to simultaneously understand and improve human and machine cognition. Today, this perspective is neither prevalent in AI nor the learning sciences. I conclude with some thoughts on how the artificial intelligence in education and learning sciences communities might reinvigorate this lost perspective.

Keywords Artificial intelligence · Learning sciences · History · Cognitive science · Information-processing psychology · Constructivism

> Before we embark on the substance of this essay, it is worthwhile to clarify a potential source of confusion. For many, AI is identified as a narrowly focused field directed toward the goal of programming computers in such a fashion that they acquire the appearance of intelligence. Thus it may seem paradoxical that researchers in the field have anything to say about the structure of human language or related issues in education. However, the above description is misleading. It correctly delineates the major *methodology* of the science, that is, the use of computers to build precise models of cognitive theories. But it mistakenly identifies this as the only purpose of the field. Although there is much practical good that can come of more intelligent machines, the fundamental theoretical

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goal of the discipline is understanding intelligent processes *independent* of their particular physical realization. (Goldstein & Papert, 1977, pp. 84–85)

Over the past few decades, there have been numerous advances in applying artificial intelligence (AI) to educational problems. As such, when people think of the intersection of artificial intelligence and education, what likely comes to mind are the applications of AI to enhancing education (e.g., intelligent tutoring systems, automated essay scoring, and learning analytics). Indeed, this is the focus of the International Artificial Intelligence in Education Society: “It promotes rigorous research and development of interactive and adaptive learning environments for learners of all ages, across all domains” (International Artificial Intelligence in Education Society, n.d.). In this paper, I show that historically, artificial intelligence and education have been intertwined in more principled and mutually reinforcing ways than thinking of education as just another application area of artificial intelligence would suggest.

My goal is by no means to present a complete history of the field of artificial intelligence or the field of education research. I also do not intend to provide a detailed history of the field of artificial intelligence in education (AIED). Rather, my goal is to present a narrative of how the two fields of artificial intelligence and education had intertwined histories since the 1960s, and how important figures in the development of artificial intelligence also played a significant role in the history of education research.[1] I primarily focus on some of the leading researchers in the early history of AI (1950s-1970s) in the United States and (to a lesser extent) the United Kingdom.

The focus on early pioneers in the field is to show that the very development of the field was intertwined with education research. As such, this means that I do not focus on many important leaders of the field of AIED as they are not typically recognized as major figures in the early history of AI at large; however, the history I speak to does intersect with the development of AIED, as described below. It also means this history focuses primarily on White male researchers. This is largely an artifact of who the active researchers were in the field of AI (and academic research, more broadly) at the time. It is important to acknowledge that many of these researchers worked with women and non-White researchers who may not be as well-recognized today, and that the diversity of researchers working in these areas has naturally increased over the years. Moreover, most of the early work in “sanctioned” AI history[2] was happening in the US and the UK, although there were likely AI pioneers

[1] On the education side, much of my focus is specifically on educational psychology, and in particular, the learning sciences, broadly conceived. However, I often use the much broader labeling of “education research” or even “education,” because the history described here at times had far-reaching consequences on education research—and, at times, even educational practice—especially to the extent that learning theories influenced broader educational thought.

[2] The “sanctioned” history of AI is typically said to begin with the Dartmouth Workshop in 1956, discussed below. However, both prior to that time and after that time, other fields and activities have existed that were working on similar problems and/or ones that would later get adopted by mainstream AI. Cybernetics is one such field that predates AI. The interdisciplinary study of human and machine learning described here was also present in cybernetics. Although cyberneticians were also working in education, their work has not had as obvious of an impact on education as that of the AI researchers discussed here. A full treatment of the intertwined history of cybernetics and education is worthwhile, but beyond the scope of this paper.

elsewhere in the world. An exploration of whether researchers in other countries in the early days of AI were also exploring the mutual interplay between AI and education would be an interesting area of further research.

Although glimpses of this story are told in the histories of individual fields, to my knowledge, the intertwined histories of these two fields have never been fully documented previously. For example, in his insightful chapter, "A Short History of the Learning Sciences," Lee (2017) highlights that the early days of the learning sciences had roots in artificial intelligence and cognitive science:

> The so-called "cognitive revolution" led to interdisciplinary work among researchers to build new models of human knowledge. The models would enable advances in the development of artificial intelligence technologies, meaning that problem solving, text comprehension, and natural language processing figured prominently. The concern in the artificial intelligence community was on the workings of the human mind, not immediately on issues of training or education.

It is easy to read the above as suggesting that AI provided tools that were later applied by others to educational problems. While to some extent it is true that the "the concern in the artificial intelligence community was…not immediately on issues on issues of training or education," the narrative I present below suggests that many AI pioneers *were* committed to advancing education. In another chapter that is also called "A Short History of the Learning Sciences," Hoadley (2018)—who, as an undergraduate, worked with AI pioneer Seymour Papert—makes only brief mention of how the birth of computing, AI, and cognitive science were some of the many seeds for the learning sciences. Moreover, Pea (2016) in his "Prehistory of the Learning Sciences," focused on specific people and events that led to the formation of the learning sciences, but did not explicitly mention the role that artificial intelligence played at all, aside from passing mentions of the Artificial Intelligence in Education community. In her seminal history of education research, Lagemann (2002) dedicates a few pages to discussing the rise of cognitive science and as such, mentions some of the pioneers discussed in this paper (mainly Simon and Newell), but she does not explicitly connect these figures to education research.[3]

Histories of artificial intelligence fare no better. Nilsson's (2009) 700-page book on the history of AI only makes a couple of passing remarks about how education intersected with that history. Pamela McCorduck's humanistic account of the history of AI mostly only discusses education in the context of Papert's work with Logo in a chapter called "Applied Artificial Intelligence" (McCorduck, 2004). Interestingly enough, even Howard Gardner, a prominent education researcher, makes almost no mention of education in his book on the history of cognitive science (Gardner, 1987).

[3] Interestingly, Lagemann (2002) does acknowledge the influence of Herbert Simon's earlier work (prior to AI) on educational administration. I do not discuss that here, as it is outside the scope of this paper, but it is worth keeping in mind that Simon's work influenced other areas of education as well.

The learning sciences and artificial intelligence are both fairly new fields, having only emerged a few decades ago. Therefore, much of the history presented in this paper is still held in the individual and collective memories of individuals who either played a role in this history or who witnessed its unfolding. As such, it might seem odd that someone who was not alive for most of this history should be one to write it. Nonetheless, perhaps the story will be slightly less biased if it comes from someone who was not involved in it and who had to reconstruct this story from primary sources. Indeed, much of what is narrated here might be "obvious" to earlier generations of researchers in artificial intelligence or education, and as such, these researchers might face expert blind spots (Nathan et al., 2001) in constructing this narrative. If my own experience as a novice at the intersection of these two fields is telling, this rich history is *not* obvious to novices entering these fields. As time passes, if this history goes unwritten and untaught, I think what is obvious to current experts may be lost to the next generation of researchers in the fields of artificial intelligence, education, and AIED.

To construct this historical narrative, I used a combination of publications from the key figures involved, unpublished grey literature, historical sources, and archival material, especially from the Herbert Simon and Allen Newell Digital Collections. The paper alternates between sections focused on specific AI pioneers—describing their work in both AI and education—and sections focused on the formation of fields or subdivisions within fields that are relevant to this history. The sections on AI pioneers begin by describing their overall approach to AI research and end by discussing their direct and indirect contributions to education. The sections on fields discuss broader trends in the histories of AI and education that move beyond the specific pioneers. The majority of the paper spans work covering the 1950s-1990s. In the final section, I discuss where the relevant fields have headed since the 1990s, how the ethos present in earlier days of AI and the learning sciences has seemingly disappeared, and what we might do about that.

Overall, the historical narrative presented in this paper arrives at two overarching claims:

1. Early artificial intelligence pioneers were cognitive scientists who were united in the broad goal of understanding thinking and learning in machines *and* humans, and as such were also invested in research on education. The point is not just that they were cognitive scientists whose work had implications for education, but rather that these researchers were also at times *directly* involved in education research and had a significant impact on the course of education research. In this sense, such researchers differ from most AI researchers and most learning scientists today.
2. There were largely two different (and, at times, opposing) approaches, which manifested in various ways in both the history of AI and the history of education research.

The second claim was also made by me in another article (Doroudi, 2020), where I claimed that there is a "bias-variance tradeoff" (a concept drawn from machine learning) between different approaches in education research. That article drew on similar examples from the histories of AI and education to make this point. However, the present paper puts such claims in a broader historical context and more clearly describes how the "two camps" have evolved over time. Moreover, by juxtaposing the two aforementioned overarching claims, the overall picture that emerges is one in which early researchers who took different approaches in AI and education were at once united, *despite* their differences. The hope is that understanding and charting these historical trends can help make sense of and possibly repair ongoing fault lines in the learning sciences today, and perhaps reinvigorate this lost perspective of synergistically thinking about AI and education.

Simon and Newell: From Logic Theorist to LISP Tutor

In 1956, a workshop was held at Dartmouth College by the name of "Dartmouth Summer Research Project on Artificial Intelligence." This event, organized by John McCarthy, along with Marvin Minsky, Nathaniel Rochester, and Claude Shannon, is widely regarded as the origin of artificial intelligence and the event that gave the field its name. Gardner (1987) singles out four of the workshop attendees—Herbert Simon, Allen Newell, Minsky, and McCarthy—as the "Dartmouth Tetrad" for their subsequent work in defining the field of artificial intelligence. After the formation of the American Association of Artificial Intelligence in 1979, Newell, Minsky, and McCarthy would all serve as three of its first five presidents.

The story I present here will begin with the work of three of the Dartmouth Tetrad (Simon, Newell, and Minsky), along with their colleagues and students. In this section, I begin by briefly describing the early pioneering work of Simon and Newell in the fields of artificial intelligence and psychology, and then discuss their contributions to education and how it related to their work in AI.

An Information-Processing Approach to AI

While the Dartmouth Workshop was a seminal event in the formation of AI, the first AI programs were being developed prior to the workshop. In 1955, Simon and Newell, professors at Carnegie Institute of Technology (now Carnegie Mellon University), along with J. C. Shaw, created the Logic Theorist, a program capable of proving logical theorems from Russell and Whitehead's *Principia Mathematica* (a foundational text in mathematical logic) by manipulating "symbol structures" (Nilsson, 2009).[4] Simon and Newell presented this program at the Dartmouth Workshop. Shortly thereafter, in a paper titled "Elements of a Theory of Human Problem Solving," Newell et al. (1958) describe the Logic Theorist and its links to human problem solving:

[4] Although tangential to this history, it is interesting to note that both Russell and Whitehead, who were mathematicians and philosophers, also published texts on the philosophy of education, Russell's *On Education, Especially in Early Childhood* and Whitehead's *The Aims of Education and Other Essays.*

> The program of LT was not fashioned directly as a theory of human behavior; it was constructed in order to get a program that would prove theorems in logic. To be sure, in constructing it the authors were guided by a firm belief that a practicable program could be constructed only if it used many of the processes that humans use. (p. 154)

In this paper, the authors laid the foundations of *information-processing psychology*. In a follow-up paper, "Human Problem Solving: The State of the Theory in 1970," Simon and Newell (1971) describe the theory of information-processing psychology and their strategy for developing it over 15 years. The first three steps of their strategy culminate in the development of an artificial intelligence program like the Logic Theorist:

> 3. Discover and define a program, written in the language of information processes, that is capable of solving some class of problems that humans find difficult. Use whatever evidence is available to incorporate in the program processes that resemble those used by humans. (Do not admit processes, like very rapid arithmetic, that humans are known to be incapable of; p. 146)

But this was not the final destination; the next step in Newell and Simon's strategy was to actually collect human data:

> 4. If the first three steps are successful, obtain data, as detailed as possible, on human behavior in solving the same problems as those tackled by the program. Search for the similarities and differences between the behavior of program and human subject. Modify the program to achieve a better approximation to the human behavior. (p. 146)

The fourth step of their procedure was carried out with extensive "think--alouds" of experts solving a variety of problem solving tasks such as cryptarithmetic, logic, chess, and algebra word problems. They followed what Ericsson and Simon (1980) would later formalize as the think-aloud protocol, which has since become a popular method for eliciting insights into human behavior in the social sciences, including education research.

Much of the theory articulated in their paper was about how experts *solve* problems, but how does a human *learn* to solve problems? Simon and Newell (1971) postulated a theory for how people might come to develop a means of solving problems in terms of what they called production systems:

> In a production system, each routine has a bipartite form, consisting of a condition and an action. The condition defines some test or set of tests to be performed on the knowledge state...If the test is satisfied, the action is executed; if the test is not satisfied, no action is taken, and control is transferred to some other production. (p. 156)

Learning then becomes a matter of gradually accumulating the various production rules necessary to solve a problem. The development and analysis of production systems subsequently became an important part of information-processing psychology (Newell, 1973).

Overall, this 1971 paper describes a program of research that simultaneously defined information-processing psychology, a major branch of cognitive psychology, as well as the symbolic approach to artificial intelligence that dominated the early days of the field. But this work also played a role in the development of educational theory and educational technology to the present day. At the end of their paper, Simon and Newell (1971) have a section on "The Practice of Education." This short section of their paper is very insightful on the way that Simon and Newell conceived of their work's impact on education. They motivated their work's impact by calling on the need to develop a science of education:

> The professions always live in an uneasy relation with the basic sciences that should nourish and be nourished by them. It is really only within the present century that medicine can be said to rest solidly on the foundation of deep knowledge in the biological sciences, or the practice of engineering on modern physics and chemistry. Perhaps we should plead the recency of the dependence in those fields in mitigation of the scandal of psychology's meager contribution to education. (p. 158)

Simon and Newell (1971) then go on to explain how information-processing psychology could answer this call to improve educational practice:

> The theory of problem solving described here gives us a new basis for attacking the psychology of education and the learning process. It allows us to describe in detail the information and programs that the skilled performer possesses, and to show how they permit him to perform successfully. But the greatest opportunities for bringing the theory to bear upon the practice of education will come as we move from a theory that explains the structure of human problem-solving programs to a theory that explains how these programs develop in the face of task requirements—the kind of theory we have been discussing in the previous sections of this article [i.e., production systems]. (p. 158)

However, Simon and Newell did not just leave it to others to apply information-processing psychology to advance education; they tried to directly advance education themselves.

Forgotten Pioneers in Education

In 1967, Newell and his student, James Moore, had actually worked on developing an intelligent tutoring system, Merlin, fittingly to teach graduate artificial intelligence (Moore & Newell, 1974). However, for Moore and Newell (1974), this was actually a much bigger undertaking than simply creating a tutoring system; they were trying to create a system that could understand:

> The task was to make it easy to construct and play with simple, laboratory-sized instances of artificial intelligence programs. Because of our direct interest in artificial intelligence, the effort transmuted into one of building a program that would understand artificial intelligence—that would be able to explain and run

> programs, ask and answer questions about them, and so on, at some reasonable level. The intent was to tackle a real domain of knowledge as the area for constructing a system that understood. (pp. 201–202)

In 1970, in a workshop on education and computing, Newell gave an invited talk entitled "What are the Intellectual Operations required for a Meaningful Teaching Agent?" Referring to his work on Merlin, Newell (1970) outlined 12 aspects of intelligence that they found need to be embodied in a meaningful teaching agent. Newell mentioned that there were two routes to go about automating intelligent operations in a computer: (1) automating that which is currently easy "for immediate payoff, at the price of finding that the important operations have been left untouched," or (2) identifying "the essential intellectual operations involved" and automating those "at the price of unknown and indefinite delays in application." Newell had opted for the second approach.

According to Laird and Rosenbloom (1992), "Merlin contained many new ideas before they became popular in mainstream AI, such as attached procedures, general mapping, indefinite context dependence, and automatic compilation" (p. 31). However, after six or so years of work, Merlin was apparently never created as a tutoring system and the various parts were not coherently put together. According to Laird and Rosenbloom (1992),

> Even with all its innovations, by the end of the project, Newell regarded Merlin as a failure. It was a practical failure because it never worked well enough to be useful (possibly because of its ambitious goals), and it was a scientific failure because it had no impact on the rest of the field. Part of the scientific failure can be attributed to Newell's belief that it was not appropriate to publish articles on incomplete systems. Many of the ideas in Merlin could have been published in the late sixties, but Newell held on, waiting until these ideas could be embedded within a complete running system that did it all. (p. 31)

In the end, he had to pay the price of "indefinite delays in application." Merlin is virtually undocumented in the history of intelligent tutoring systems (see e.g., Nwana, 1990; Sleeman & Brown, 1982). The first intelligent tutoring system was created in 1970 by Jaime R. Carbonell. Had Newell gone with the "immediate payoff" route of automization, he might have been credited with creating the first intelligent tutoring system.

In 1966, slightly before Newell began working on Merlin, Simon (1967) coined the term "learning engineering" (Willcox et al., 2016) in an address titled "The Job of a College President":

> The learning engineers would have several responsibilities. The most important is that, working in collaboration with members of the faculty whose interest they can excite, they design and redesign learning experiences in particular disciplines. (p. 77)

Simon remained interested in systematic efforts in improving university education and worked on founding the Center for Innovation in Learning at CMU in 1994 (Reif & Simon, 1994; Simon, 1992a, 1995). The center was dedicated to cross-campus research in education, including supporting a PhD program in instructional science (Hayes, 1996). Although at least some of Simon's interest in this area was due to his passion for teaching as a university professor, his interest in the educational implications of cognitive science played a role as well. Indeed, the effort to form the Center for Innovation in Learning seemingly started in 1992 with Simon sending a memo to the vice provost for education with the subject "Proposal for an initiative on cognitive theory in instruction" (Simon, 1992b). The concept of learning engineering seemingly only gained widespread interest in the 2010s with the formation of campuswide learning engineering initiatives, including the Simon Initiative at CMU (named in honor of Herbert Simon), and the broader formation of the learning engineering research community, a group of researchers and practitioners with backgrounds in fields such as educational technology, instructional design, educational data mining, learning analytics, and the learning sciences interested in improving the design of learning environments in data--informed ways.

In 1975, Simon applied for and received a grant from the Alfred P. Sloan Foundation to conduct a large-scale study with other researchers at CMU on "Educational Implications of Information-Processing Psychology," effectively drawing out the ideas first suggested by Simon and Newell (1971). This grant had several thrusts including teaching problem solving in a course at CMU and developing "computer-generated problems for individually-paced courses." The longer term objective for the latter thrust was that it "should also be extendable into a tutoring system that can diagnose students' specific difficulties with problems and provide appropriate hints, as well as produce the answer," a vision that would later be largely implemented in the large body of tutoring systems coming out of Carnegie Mellon as described below. Newell had actually already embarked on some of this work. In 1971, Newell created a method for automatically generating questions in an artificial intelligence course. Ramani and Newell (1973) subsequently wrote a paper on the automated generation of computer programming problems. Although they submitted the paper to the recently formed journal *Instructional Science*, it was never published. The work conducted under the grant, while of relevance to education, was mostly conducted under the auspices of psychology (e.g., studying children's thinking).

Later, Zhu and Simon (1987) tested teaching several algebra and geometry tasks using only worked examples or problem-solving exercises and showed that both could be an effective way of learning these tasks when compared to traditional lecture-style instruction. They also showed, using think-aloud protocols, that students effectively learn several production rules for an algebra factoring task. Finally, they showed that an example-based curriculum for three years of algebra and geometry in Chinese middle schools was seemingly as effective as traditional instruction and led to learning the material in two years instead of three. Zhu and Simon (1987) constructed their examples and sequenced them by postulating the underlying production rules, and therefore their claim is that carefully constructed examples based on how experts solve problems can be an efficient form of instruction. This is one of the earliest studies comparing worked examples with problem solving tasks and lecture-based instruction, and probably the earliest large-scale field experiment of the benefit of worked examples (Sweller, 1994). The use of worked examples was one of six evidence-based recommendations given in the What Works Clearinghouse Practice Guide on "Organizing Instruction and Study to Improve Student Learning," which explicitly cited Zhu and Simon (1987) as one piece of evidence.

John R. Anderson joined Newell and Simon at Carnegie Mellon in 1978 and was interested in developing a cognitive architecture that could precisely and accurately simulate human cognition (American Psychological Association, 1995). He developed the ACT theory (standing for Adaptive Control of Thought) of human cognition, which has since evolved into ACT-R. After publishing his 1983 monograph "The Architecture of Cognition," Anderson needed to find a way to improve his ACT theory, which seemed to be complete, so he tried to break the theory by using it to create intelligent tutoring systems (American Psychological Association, 1995):

> The basic idea was to build into the computer a model of how ACT would solve a cognitive task like generating proofs in geometry. The tutor used ACT's theory of skill acquisition to get the student to emulate the model. As Anderson remembers the proposal in 1983, it seemed preposterous that ACT could be right about anything so complex. It seemed certain that the enterprise would come crashing down and from the ruins a better theory would arise. However, this effort to develop cognitive tutors has been remarkably successful. While the research program had some theoretically interesting difficulties, it is often cited as the most successful intelligent tutoring effort and is making a significant impact on mathematics achievement in a number of schools in the city of Pittsburgh. It is starting to develop a life of its own and is growing substantially independent of Anderson's involvement.

Indeed, this work led to the extensive work on intelligent tutoring systems at Carnegie Mellon and affected research on such systems worldwide. As a result of these endeavors, in 1998, Carnegie Mellon researchers, including Anderson and colleagues Kenneth Koedinger and Steve Ritter, founded Carnegie Learning Inc., which develops Cognitive Tutors for algebra and other fields that are still being used by over half a million students per year in classrooms across the United States (Bhattacharjee, 2009). While Newell's pioneering work on intelligent tutoring did not see the light of day, Anderson's became very influential.

From the above, it is clear that Simon, Newell, and Anderson made several contributions to the field of education, but their impact in the field goes far beyond these direct contributions. In the 1950s, the predominant learning theory in education was behaviorism; due to the work of Simon, Newell, and their colleagues, information-processing psychology or cognitivism offered an alternative paradigm, which became mainstream in education in the 1970s. In the 1990s, Anderson and Simon, along with Lynne Reder, wrote a sequence of articles in educational venues to dismiss new educational theories that were gaining popularity at the time, namely situated learning and constructivism, by bringing myriad evidence from information-processing psychology (Anderson et al., 1996, 1998, 1999). One of these articles, "Situated Learning and Education" (Anderson et al., 1996), was published in *Educational Researcher*, one of the most prominent journals in the field of educational research, and led to a seminal debate between Anderson, Reder, and Simon on the one hand and James Greeno on the other, who had moved from being a proponent of information-processing psychology to being an influential advocate for the situative perspective (Anderson et al., 1997, 2000; Greeno, 1997). Based on Google Scholar, Anderson et al. (1996) is currently the 25th most cited article in *Educational Researcher*. The ninth most cited article in the journal was one of many articles that tried to make sense of this debate: "On Two Metaphors for Learning and the Dangers of Choosing Just One" (Sfard, 1998). It is important to note that Anderson, Reder, and Simon were not proposing an alternative to trendy theories of learning (situativism and constructivism); rather they were *defending* the predominant paradigm in educational research on learning after the heyday of behaviorism.

It should by now be clear that over the span of several decades, Simon, Newell, and Anderson simultaneously made direct contributions to education (largely as applications of their pioneering work in psychology) and helped shape the landscape of theories of learning and cognition in education for decades. But beyond that, they were committed to reminding the education community that information-processing psychology provided *the* science that education needed to succeed. In their paper critiquing radical constructivism, Anderson et al. (1999) made a call for bringing information-processing psychology to bear on education research, similar to the call that Simon and Newell (1971) had made earlier, but with seemingly greater concern about the "antiscience" state of education research:

> Education has failed to show steady progress because it has shifted back and forth among simplistic positions such as the associationist and rationalist philosophies. Modern cognitive psychology provides a basis for genuine progress by careful scientific analysis that identifies those aspects of theoretical positions that contribute to student learning and those that do not. Radical constructivism serves as the current exemplar of simplistic extremism, and certain of its devotees exhibit an antiscience bias that, should it prevail, would destroy any hope for progress in education. (p. 231)

But the proponents of these "antiscence" positions (radical constructivism and situativism) were no strangers to cognitive science and many of them were actually originally coming from the information-processing tradition and artificial intelligence itself. They turned away from it, because, to them, it lacked something. So what was the science of Simon and Newell lacking?

The Situative Perspective as a Reaction to AI

If 1956 saw the birth of cognitive science and artificial intelligence, we might say that 1987 saw the birth of situativism, which emerged to address what its proponents saw as limitations to the information-processing approach (which also became known as cognitivism). In the 1980s, several researchers from a variety of fields independently developed related ideas around how cognition and learning are necessarily context-dependent, and not taking the situation into account can lead to gross oversimplifications. Lauren Resnick, the president of the American Educational Research Association in 1987, gave her presidential address on the topic of "Learning in School and Out" (Resnick, 1987), which synthesized work emerging from a variety of disciplines pointing to how learning that happens in out-of-school contexts widely differs from in-school learning. In the same year, James Greeno and John Seely Brown founded the Institute for Research on Learning (IRL) in Palo Alto, California. This organization brought together many of the researchers that were thinking about the situated nature of cognition and learning, and was highly influential in the turn that such research took over the next few years. Situativism is not really one unified theory, but a conglomerate of a variety of particular theories developed in different fields. Given the different focus of each field, the terms "situated cognition," "situated action," or "situated learning" are often used. However, Greeno (1997) suggested that such terms are misleading, because "all learning and cognition is situated by assumption" (p. 16), advocating for the term "situative perspective" instead.

The situative perspective is also related to and influenced by much earlier sociocultural theories drawing on the work of Vygotsky and other Russian psychologists, which gained attention in the US in the 1980s through the work of Michael Cole and others. It is also related to a number of overlapping theories that all emerged around the same time in reaction to cognitivism, such as distributed cognition (Hutchins et al., 1990; Salomon, 1993), extended mind (Clark & Chalmers, 1998), and embodied cognition (Johnson, 1989; Varela et al., 1991).

To those who are familiar with situativism, it is perhaps abundantly clear that it arose in reaction to the limitations of cognitivism as a theory of how people learn. What I suspect is less clear is the extent to which it arose in reaction to the broader field of artificial intelligence, and the extent to which AI influenced the thinking of the pioneers of the situativism. Indeed, many of the early proponents of the situative perspective were coming from within the AI tradition itself but had seen limitations to the traditional AI approach. John Seely Brown and Allan Collins, who wrote one of the early papers advocating for situated learning (Brown et al., 1989)—the second most cited paper published in *Educational Researcher*—had worked on some of the earliest intelligent tutoring systems (Brown et al., 1975a, b; Carbonell & Collins, 1973). Brown et al. (1975a) explicitly proposed a tutoring system rooted in production rules. Moreover, Brown in particular conducted core AI research on various topics as well (Brown, 1973; De Kleer & Brown, 1984; Lenat & Brown, 1984). Etienne Wenger, who coined the concept of "communities of practice" with Jean Lave, initially wanted to write his dissertation "in the context of trying to understand the role that artificial intelligence could play in supporting learning in situ" but it " became clear fairly early on that the field of artificial intelligence as it was conceived of was too narrow for such an enterprise" since "the traditions of information-processing theories and cognitive psychology did address questions about learning but did so in a way that seemed too out of context to be useful" (Wenger, 1990, p. 3). Lave and Wenger (1991) wrote the second most cited book in the field of education, and Wenger's (1999) book on communities of practice is the third most cited book in education (Green, 2016).[5]

[5] Green (2016) conducted a citation analysis of the most cited books in the social sciences according to Google Scholar in 2016, though as far as I can tell, these rankings still hold.

Moreover, despite engaging in a debate with Anderson, Reder, and Simon, James Greeno acknowledged that he “had the valuable privileges of co-authoring papers with Anderson and with Simon and of serving as a co-chair of Reder’s dissertation committee” (Greeno, 1997, p. 5). Outside of education, another important pioneer of situated cognition, Terry Winograd, was a student of Seymour Papert and Marvin Minsky (whom we will discuss shortly) and made very important contributions to the early history of artificial intelligence. Two exceptions to this trend are Jean Lave and Lucy Suchman, who were anthropologists by training, but even they were operating in collaboration with AI researchers. For example, Suchman (1984) acknowledged John Seely Brown as having the greatest influence on her dissertation, which subsequently became an influential book in human-computer interaction and the learning sciences.

Thus, it is clear that situativism arose in reaction to the limitations of AI, but did AI have any further influence on the direction of situativist researchers? The majority of research in this tradition gravitated towards using methods of deep qualitative inquiry, such as ethnography to understand learning in situ, but some of the very pioneers of situativist theories still advocated for the use of computational methods to enhance our understanding of learning, a point I will return to in the final section of this paper. However, the use of these methods did not gain much traction as researchers turned more and more towards qualitative methods to understanding learning in context. Much of the work in the learning sciences today is rooted in situativist theories of learning, but the origins of such theories as reactions to artificial intelligence would not be apparent without taking a historical look at the field.

Different Approaches to AI: Symbolic vs. Non-symbolic and Neat vs. Scruffy

While situativism was reactionary to AI, it was not part of AI per se. Even AI researchers who adopted a situativist perspective gravitated towards other fields, such as anthropology and human-computer interaction to conduct their work. However, within the field of artificial intelligence, there were also competing approaches that challenged the one taken by Simon, Newell and their colleagues. I will now give a very high-level exposition of different approaches to AI research, in order to set the stage for how a competing approach resulted in a different line of inquiry in education as well.

The early days of AI, from the 1950s to the 1980s, was dominated by what is often called symbolic AI or good-old fashioned AI (GOFAI) (Haugeland, 1989), which is embodied in the work of Simon, Newell, and those influenced by their work. This approach is in stark contrast to a competing approach that has taken a number of forms throughout the history of artificial intelligence, but which may be broadly characterized as non-symbolic or subsymbolic AI. The current dominant paradigm in AI is a type of non-symbolic AI: machine learning. Within machine learning, an increasingly popular approach is deep learning, which is rooted in an early approach called connectionism. Connectionism—which involves simulating learning via artificial neural networks—actually first emerged in the 1940s (McCulloch & Pitts, 1943), and so it predates the birth of AI, but this approach was not taken seriously in the early days of AI by researchers who supported symbolic AI (Nilsson, 2009; Olazaran, 1996). However, neural networks made their way back into mainstream AI after advances in algorithms—such as the development of the back propagation algorithm in the 1980s—and currently dominate the field of AI.

If connectionism and machine learning are the antithesis to symbolic AI, then what was the analogous antithesis to information-processing approaches to education? This is where the story gets a little complicated. As we have already seen, the pushback to information-processing psychology came from situativism and radical constructivism. But these theories share no immediately obvious relationship with neural networks. Interestingly, some connections have been drawn between connectionism and situative and constructivist theories (Doroudi, 2020; Quartz, 1999; Shapiro & Spaulding, 2021; Winograd, 2006), but these connections have not had practical import on approaches in education. However, there was another competitor to symbolic AI, which I believe is often obscured by the distinction between symbolic and connectionist approaches. To understand this other approach, we need to examine a different dichotomy in the history of AI: neats vs. scruffies.

The distinction was first introduced by Roger Schank in the 1970s (Abelson, 1981; Nilsson, 2009; Schank, 1983). According to Abelson (1981), "The primary concern of the neat is that things should be orderly and predictable while the scruffy seeks the rough-and-tumble of life as it comes." Neats are researchers that take a more precise scientific approach that favors mathematically elegant solutions, whereas scruffies are researchers that take a more ad hoc and intuition-driven engineering approach. According to Kolodner (2002), who was Roger Schank's student,

> While neats focused on the way isolated components of cognition worked, scruffies hoped to uncover the interactions between those components. Neats believed that understanding each of the components would provide us with what we needed to see how they fit together into a working system of cognition. Scruffies believed that no component of our cognitive systems was isolated, but rather, because each depends so much on the workings of the others, their interactions were the key to understanding cognition. (p. 141)

Kolodner (2002) specifically refers to Simon, Newell, and Anderson as "quintessential neats," and Schank, Minsky, and Papert as "quintessential scruffies" in AI. Extending the definitions to education, situativist and constructivist education researchers fall largely on the scruffy side of the spectrum. Therefore, to better understand the parallels in AI and education that rejected the information-processing perspective we must now turn to the founders of AI on the scruffy side (Minsky and Papert, and in a later section, Schank).

Papert and Minsky: From Lattice Theory to Logo Turtles

As mentioned earlier, Marvin Minsky was one of the Dartmouth Tetrad. Seymour Papert was not present at the Dartmouth Conference, but joined the AI movement early on when he moved to the Massachusetts Institute of Technology (MIT) in

1964, and formed the AI Laboratory with Minsky. I believe it is common to regard Minsky as one of the founders of AI and Papert as a seminal figure in educational technology. However, this is an oversimplification; Minsky and Papert both played important roles in the field of AI and in the field of education. They coauthored *Perceptrons: An Introduction to Computational Geometry*, an important technical book in the history of AI. Minsky's book *The Society of Mind* was originally a collaboration with Papert (Minsky, 1988). Moreover, Papert acknowledges in one of his seminal books on education, *Mindstorms*, that "Marvin Minsky was the most important person in my intellectual life during the growth of the ideas in this book" (Papert, 1980). A recently published book edited by Cynthia Solomon, *Inventive Minds: Marvin Minsky on Education*, collects six essays that Minsky has written about education (Minsky, 2019). Furthermore, Minsky and Papert were both associate editors of the *Journal of the Learning Sciences* when it formed in 1991 (Journal of the Learning Sciences, 1991).

Minsky and Papert's 1969 book *Perceptrons* played an important role in devaluing research on connectionism in the 70 s. According to Olazaran (1996), the book did not completely end all connectionist research, but it led to the institutionalization and legitimization of symbolic AI as the mainstream. While this may very well be true, I think it obscures Minsky and Papert's actual positions in AI research by suggesting they were proponents of symbolic AI. Indeed, Olazaran (1996) claims they *were* symbolic AI researchers. Perhaps, their role in "shutting down" perceptrons research was seen as so large that other researchers were naturally inclined to situate them in the symbolic camp. Indeed, Newell (1969) wrote a very positive book review of *Perceptrons* reinforcing the idea that he was in the same camp as the authors. Moreover, Simon and Newell have, to my knowledge, never entered into any public disputes or debates with Papert and Minsky over their approaches to AI. Perhaps, they saw each other with respect as early proponents of a new field that exhibited mathematical rigor who shared some common "foes": connectionism and philosophical critiques against AI (Dreyfus, 1965; Papert, 1968). But in fact, their approaches were sharply different in both AI and education. This can be gauged by taking a closer look at the work of Papert and Minsky; we will begin with a look at their approach to AI research, followed by an exposition of Papert's contributions to education (which as outlined above were developed in collaboration with Minsky).

A Piagetian Approach to AI

To understand the difference in approach, a bit of background on Papert is needed. Papert obtained two PhDs in mathematics in the 1950s, both on the topic of lattices. In 1958, he then moved to Geneva where he spent the next several years working with the famous psychologist and genetic epistemologist, Jean Piaget, who is the founder of constructivism as a psychological theory. Piaget's influence on Papert affected his approach to AI research and education: "If Piaget had not intervened in my life I would now be a 'real mathematician' instead of being whatever it is that I have become" (Papert, 1980, p. 215). In 1964, Papert moved to the Massachusetts Institute of Technology (MIT) to work with Minsky on artificial intelligence. Papert (1980) notes the reason for moving from studying children with Piaget to studying AI at MIT:

> Two worlds could hardly be more different. But I made the transition because I believed that my new world of machines could provide a perspective that might lead to solutions to problems that had eluded us in the old world of children. Looking back I see that the cross-fertilization has brought benefits in both directions. For several years now Marvin Minsky and I have been working on a general theory of intelligence (called "The Society Theory of Mind") which has emerged from a strategy of thinking simultaneously about how children do and how computers might think. (p. 208)

Minsky and Papert's early approach to AI is well encapsulated in a 1972 progress report on their recently formed MIT AI Laboratory. After mentioning a number of projects that they were undertaking, Minsky and Papert (1972) describe their general approach:

> These subjects were all closely related. The natural language project was intertwined with the commonsense meaning and reasoning study, in turn essential to the other areas, including machine vision. Our main experimental subject worlds, namely the "blocks world" robotics environment and the children's story environment, are better suited to these studies than are the puzzle, game, and theorem-proving environments that became traditional in the early years of AI research. Our evolution of theories of Intelligence has become closely bound to the study of development of intelligence in children, so the educational methodology project is symbiotic with the other studies, both in refining older theories and in stimulating new ones; we hope this project will develop into a center like that of Piaget in Geneva.

Like Simon and Newell's approach, Minsky and Papert were interested in studying both machine and human cognition, but some of the key differences in their approaches are apparent in the aforementioned quote. Minsky and Papert were interested in a wider range of AI tasks, like common sense reasoning, natural language processing, robotics, and computer vision, all of which are prominent areas of AI today. Moreover, they were interested in children, not experts. Relatedly, they emphasized learning and development (hence the emphasis on children) over performance, which is markedly different from Newell and Simon's approach of emphasizing the study of performance. Indeed, according to Newell and Simon (1972),

> If performance is not well understood, it is somewhat premature to study learning. Nevertheless, we pay a price for the omission of learning, for we might otherwise draw inferences about the performance system from the fact that the system must be capable of modification through learning. It is our judgment that in the present state of the art, the study of performance must be give precedence, even if the strategy is not costless. (p. 8)

Minsky (1977) later provided justification for this choice to focus on development as follows:

> Minds are complex, intricate systems that evolve through elaborate developmental processes. To describe one, even at a single moment of that history, must be very difficult. On the surface, one might suppose it even harder to describe its whole developmental history. Shouldn't we content ourselves with trying to describe just the "final performance?" We think just the contrary. Only a good theory of the principles of the mind's development can yield a manageable theory of how it finally comes to work. (p. 1085)

Later in their report, Minsky and Papert (1972) explicitly state limitations of research on "Automatic Theorem Provers" (without making explicit mention of Newell and Simon) such as the lack of emphasis on "a highly organized structure of especially appropriate facts, models, analogies, planning mechanisms, self--discipline procedures, etc." as well as the lack of heuristics in solving proofs (e.g., mathematical insights used in solving the proof that are not part of the proof itself). They then use this to motivate the need for what they call "microworlds":

> We are dependent on having simple but highly developed models of many phenomena. Each model—or "microworld" as we shall call it—is very schematic…we talk about a fairyland in which things are so simplified that almost every statement about them would be literally false if asserted about the real world. Nevertheless, we feel they are so important that we plan to assign a large portion of our effort to developing a collection of these microworlds and finding how to embed their suggestive and predictive powers in larger systems without being misled by their incompatibility with literal truth. We see this problem—of using schematic heuristic knowledge—as a central problem in Artificial Intelligence.

Indeed, confining AI programs to tackling problems in microworlds or "toy problems"—another phrase attributed to Papert (Nilsson, 2009)—became an important approach at MIT and in AI in general to this day. But as indicated by the quote above, Papert and Minsky's goal was to see how to combine microworlds to develop intelligence that is meaningful in the real world. This is indicative of Papert and Minsky's general approach to AI. Namely, they were interested in building up models of intelligence in a bottom-up fashion. Rather than positing one grand "unified theory of cognition" (Newell, 1994), they realized that the mind must consist of a variety of many small interacting components, and that how minds organize many pieces of localized knowledge is more important than universal general problem-solving strategies. It is the interaction of all these pieces that makes up intelligence and gives rise to learning.

This naturally leads to the question: how does the mind represent knowledge? Knowledge representation is a fundamental concern of AI (and an important but understudied concern in education as well). Minsky (1974) wrote one of the seminal papers on knowledge representation describing a representation he called "frames":

> Here is the essence of the theory: When one encounters a new situation (or makes a substantial change in one's view of the present problem) one selects

> from memory a structure called a *Frame*. This is a remembered framework to be adapted to fit reality by changing details as necessary.
> A *frame* is a data-structure for representing a stereotyped situation, like being in a certain kind of living room, or going to a child's birthday party. Attached to each frame are several kinds of information. Some of this information is about how to use the frame. Some is about what one can expect to happen next. Some is about what to do if these expectations are not confirmed.

Frames allow for navigating unforeseen situations in terms of situations one has seen before. It means that early on, one might make mistakes by extrapolating based on a default version of a frame, but as a situation becomes clearer, one can customize the frame (by filling in certain "terminals" or "slots") to meet the needs of the situation. Importantly, frames were meant to be relevant to a variety of areas of artificial intelligence, including computer vision, language processing, and memory (Goldstein & Papert, 1977).

Frames became one component of Minsky and Papert's broader bottom-up approach to artificial intelligence, which is outlined in Minsky's famous book, *The Society of Mind*, which as mentioned earlier was jointly developed with Papert. As the name suggests, Minsky (1988) suggests the mind is a society of agents:

> I'll call Society of Mind this scheme in which each mind is made of many smaller processes. These we'll call agents. Each mental agent by itself can only do some simple thing that needs no mind or thought at all. Yet when we join these agents in societies—in certain very special ways—this leads to true intelligence. (p. 17)

Ironically, this approach shares some commonalities with connectionism. Both posit a bottom-up process that gives rise to learning. Like Minsky's agents, each individual neuron is not sophisticated, but it is the connections between many neurons that can result in learning to do complex tasks. Indeed, in a chapter that "grew out of many long hours of conversation with Seymour Papert" (p. 249), Turkle (1991) classified both connectionism and the society of mind theory as part of "Emergent AI," which arose as a "romantic" response to traditional information-processing AI. But there is a clear difference—each of the agents in Minsky's society is itself still *interesting* and there are several *distinct* kinds of agents that are designed to play conceptually different roles. In their prologue to the second edition of *Perceptrons*, Minsky and Papert (1988) claim that "the marvelous powers of the brain emerge not from any single, uniformly structured connectionist network but from the highly evolved arrangements of smaller, specialized networks which are interconnected in very specific ways" (p. xxiii). Minsky and Papert (1988) further admit when discussing the often dichotomized "poles of connectionist learning and symbolic reasoning", that "it never makes any sense to choose either of those two views as one's only model of the mind. Both are partial and manifestly useful views of a reality of which science is still far from a comprehensive understanding" (p. xxiii).

Papert: The Educational Thinker and Tinkerer

In tandem with developing this work in AI, Papert made critical advances in educational technology and educational theory. In 1966, Papert—along with Wallace Feurzeig, Cynthia Solomon, and Daniel Bobrow—conceived of the Logo programming language to introduce programming to kids (Solomon et al., 2020). (Bobrow was a student of Minsky's and a prominent AI researcher in his own right who became president of AAAI in 1989.) According to Papert (1980), his goal was to design a language that would "have the power of professional programming languages, but [he] also wanted it to have easy entry routes for nonmathematical beginners." Logo was originally a nongraphical programming language designed "for playing with words and sentences" (Solomon et al., 2020, p. 33), but early on Papert saw the power of adding a graphical component where children write programs to move a "turtle" (either a triangle on the screen or a physical robot connected to the computer) that traces geometric patterns (Papert, 1980).

In 1980, Papert wrote his seminal book, *Mindstorms: Children, Computers, and Powerful Ideas*, which described how he envisioned the ability for computers to enact educational change (through Logo-like programs). Papert took the idea of a "microworld" that he and Minsky had earlier used in AI and repurposed it to be a core part of his educational theory. In fact, I believe those familiar with the concept of microworld in Papert's educational thought would likely not realize the AI origins of this concept as he does not seem to explicitly link the two—to Papert, it was a natural extension. A microworld in Logo is "a little world, a little slice of reality. It's strictly limited, completely defined by the turtle and the ways it can be made to move and draw" (Papert, 1987b). The fact that these microworlds were not completely accurate renditions of reality was not a disadvantage, but rather a testament to the power of the approach:

> So, we design microworlds that exemplify not only the "correct" Newtonian ideas, but many others as well: the historically and psychologically important Aristotelian ones, the more complex Einsteinian ones, and even a "generalized law-of-motion world" that acts as a framework for an infinite variety of laws of motion that individuals can invent for themselves. Thus learners can progress from Aristotle to Newton and even to Einstein via as many intermediate worlds as they wish. (p. 125)

To Papert, this would not confuse students but rather help them understand central concepts like motion in more intuitive ways (Papert, 1980). The fact that many students (including MIT undergraduates that Papert's colleague, Andrea diSessa, studied) struggle with the concept of motion is precisely because of the way they learn the underlying mathematics and physics; they do not get the intuition they would otherwise get from experimenting with microworlds:

> And I'm going to suggest that in a very general way, not only in the computer context but probably in all important learning, an essential and central mechanism is to confine yourself to a little piece of reality that is simple enough to understand. It's by looking at little slices of reality at a time that

> you learn to understand the greater complexities of the whole world, the macroworld. (Papert, 1987b, p. 81)

Clearly this is a drastically different conception of learning than the one traditional information-processing psychology espouses. Here, learning is not an expert transmitting certain rules to a student, but rather the student picking up "little nuggets of knowledge" as they experiment and discover a world for themselves (Papert, 1987b). Moreover, not every child is expected to learn the same things; each child can learn something that interests them (Papert, 1987b): "No two people follow the same path of learnings, discoveries, and revelations. You learn in the deepest way when something happens that makes you fall in love with a particular piece of knowledge. (p. 82)".

As such, Logo became more than a tool for children to learn programming, but also a tool to help children learn about and experience various subjects including geometry, physics, and art. However, Logo did not teach these subjects as an intelligent tutoring system would; it allowed students to discover the powerful ideas in these domains (with guidance from a teacher and peers). As described by Abelson and diSessa (1986), two of Papert's colleagues, "The abundance of the phenomena students can investigate on their own with the aid of computer models shows that computers can foster a style of education where 'learning through discovery' becomes more than just a well-intentioned phrase." (p. xiii). Moreover, Abelson and diSessa (1986) explain, "turtle geometry" not only changes the way students interact with the content, but it also changes the *nature* of geometric knowledge that students engage with:

> Besides altering the form of a student's encounter with mathematics, we wish to emphasize the role of computation in changing the nature of the content that is taught under the rubric of mathematics....Most important in this endeavor is the expression of mathematical concepts in terms of constructive, process-oriented formulations, which can often be more assimilable and more in tune with intuitive modes of thought than the axiomatic-deductive formalisms in which these concepts are usually couched. As a consequence we are able to help students attain a working knowledge of concepts such as topological invariance and intrinsic curvature, which are usually reserved for much more advanced courses. (p. xiv)

This approach contrasts sharply with the proof-based geometry tutoring systems being developed by Anderson, Koedinger, and colleagues around the same time (Anderson et al., 1985; Koedinger & Anderson, 1990).

But what does Papert's educational philosophy have to do with AI? In *Mindstorms*, Papert (1980) has a chapter titled "Logo's Roots: Piaget and AI." For Papert, Piaget provided the learning theory and epistemology that underpinned his endeavor, but AI allowed Papert to interpret Piaget in a richer way using computational metaphors: "The aim of AI is to give concrete form to ideas about thinking that previously might have seemed abstract, even metaphysical" (Papert, 1980, pp. 157158). In a sense, his use of AI is similar to that of Newell and Simon:

better understanding human intelligence by creating artificial intelligence. However, as we have already seen, his approach was quite different:

> In artificial intelligence, researchers use computational models to gain insight into human psychology as well as reflect on human psychology as a source of ideas about how to make mechanisms emulate human intelligence. This enterprise strikes many as illogical: Even when the performance looks identical, is there any reason to think that underlying processes are the same? Others find it illicit: The line between man and machine is seen as immutable by both theology and mythology. There is a fear that we will dehumanize what is essentially human by inappropriate analogies between our "judgments" and those computer "calculations." I take these objections very seriously, *but feel that they are based on a view of artificial intelligence that is more reductionist [than] anything I myself am interested in.* (Papert, 1980, p. 164, emphasis added)

Papert (1980) then gives a particular example of how AI has influenced his and Minsky's thinking about how people learn: how a society of agents can give rise to Piagetian conservation. Piagetian conservation refers to the concept that before the age of seven, children generally do not grasp the concept of how quantity is conserved even when it comes in different forms (e.g., the quantity of a liquid is conserved regardless of the size of the container holding it). Papert and Minsky argue that this theory could begin to be explained by a set of four simple-minded agents and their interactions (Minsky, 1988; Papert, 1980). Unlike Simon and Newell, Papert and Minsky did not actually believe they had found the exact cognitive mechanisms that explain this phenomena, but rather, they found insights into a process that could resemble it:

> This model is absurdly oversimplified in suggesting that even so simple a piece of a child's thinking (such as this conservation) can be understood in terms of interactions of four agents. Dozens or hundreds are needed to account for the complexity of the real process. But, despite its simplicity, the model accurately conveys some of the principles of the theory: in particular, that the components of the system are more like people than they are like propositions and their interactions are more like social interactions than like the operations of mathematical logic. (Papert, 1980, pp. 168-169)

This insight in turn presumably led Papert to realize the kinds of educational experiences that students need in order to develop their "society of mind," and thus the kind of educational experiences that Logo-like microworlds would need to support. Moreover, according to Papert (1980):

> While psychologists use ideas from AI to build formal, scientific theories about mental processes, children use the same ideas in a more informal and personal way to think about themselves. And obviously I believe this to be a good thing in that the ability to articulate the processes of thinking enables us to improve them. (p. 158).

Therefore, Logo provides an environment for children to articulate and think about their own thinking (just as the programming language Lisp allowed AI researchers to concretize their theories and models). Logo did not use AI directly, but its use was designed to embody a theory of learning that was influenced by Papert and Minsky's kind of AI.

Minsky and Papert's approach to simultaneously studying AI and education was exemplified in a press release describing a 1970 symposium hosted by the AI Labroratory called "Teaching Children Thinking" (Minsky & Papert, 1970).[6] Having held this symposium prior to publishing their first AI progress report, the press release pronounced:

> The meeting is the first public sign of a shift in emphasis of the program of research in the Artificial Intelligence Laboratory. In the past the principle goals have been connected with machines. These goals will not be dropped, but work on human intelligence and on education will be expanded to have equal attention....plans are being developed to create a program in graduate study in which students will be given a comprehensive exposure to all aspects of the study of thinking. This includes studying developmental psychology in the tradition of Piaget, machine intelligence, educational methods, philosophy, linguistics, and topics of mathematics that are considered to be relevant to a firm understanding of these subjects. (Minsky & Papert, 1970)

The press release then goes on to state how "current lines of educational innovation go in exactly the wrong direction" (Minsky & Papert, 1970). They claimed that "The mere mention of the 'new math' throws them into a rage. So do most trends in the psychology of learning and in programmed instruction" (Minsky & Papert, 1970). Perhaps ironically, the symposium had a panel discussion led by Marvin Minsky, with Allen Newell and Patrick Suppes as two of the three panelists. Newell was working on Merlin at the time, and Suppes was pioneering efforts in computer-assisted instruction, much of which consisted of teaching elementary school students elementary logic and new math. One wonders how much rage was present in the panel discussion!

In the twenty-first century, Logo has not fundamentally changed education in K-12 schools. However, Papert (1980) did not see Logo as *the* solution, but rather as a model "that will contribute to the essentially social process of constructing the education of the future" (Papert, 1980, p. 182). In a sense, Logo and Papert's legacy have had success in this regard. Many children's programming languages that have gained popularity in recent years were either directly or indirectly inspired by Logo. Scratch, the popular block-based programming language for kids, was developed by Papert's student Mitchel Resnick. Lego's popular robotics kit, Lego Mindstorms, was inspired by Papert and named after his book. However, Logo was about more than just computer science education; to reiterate, it could help students learn about topics such as geometry, physics, art, and perhaps most importantly, their own thinking.

Moreover, Papert has had an immense impact on educational theory. His theory of *constructionism* took Piaget's constructivism and augmented it with the idea that

[6] I thank Cynthia Solomon for sharing a draft of the "Teaching Children Thinking" symposium press release and schedule from Marvin Minsky's personal collection, courtesy of the Minsky Family.

a student's constructions are best supported by having objects (whether real or digital) to build and tinker with. This has been a source of inspiration for the modern-day maker movement (Stager, 2013). Many of Papert's students and colleagues who worked on Logo were or are leading figures in the learning sciences and educational technology.[7] In addition, one of Papert's student, Terry Winograd, made important contributions to AI before becoming one of the foremost advocates for situated cognition, as mentioned earlier. In fact, it appears that seeds of situated learning and embodied cognition existed in Papert's writings before the movement took off in the late 80 s (Papert, 1976, 1980). For example, Papert (1980) describes the power of objects like gears (his childhood obsession) and the Logo turtle in learning, by connecting the body and the mind:

> The gear can be used to illustrate many powerful "advanced" mathematical ideas, such as groups or relative motion. But it does more than this. As well as connecting with the formal knowledge of mathematics, it also connects with the "body knowledge," the sensorimotor schemata of a child. You can be the gear, you can understand how it turns by projecting yourself into its place and turning with it. It is this double relationship—both abstract and sensory—that gives the gear the power to carry powerful mathematics into the mind. (p. viii)

Beyond this legacy in educational technology and the learning sciences, Papert—who was an anti-apartheid activist in his youthful days in South Africa—should also be recognized as an education revolutionary, visionary, and critic who sought to fundamentally change the nature of schools. This puts him alongside the ranks of Paulo Freire, Ivan Illich, and Neil Postman. Indeed, discussions with Freire influenced Papert's thinking in *The Children's Machine: Rethinking School in the Age of the Computer*, which Freire in turn referred to as "a thoughtful book that is important for educators and parents and essential to the future of their children" (Papert, 1993, back cover).[8] However, unlike many technologists and entrepreneurs who want to "disrupt" education, Papert did not take a technocentric approach; in fact, he himself coined the term "technocentric" to critique it, as he recognized that technology was only secondary to "the most important components of educational situations—people and cultures" (Papert, 1987a, p. 23).

The Intertwined History of AI and Education in the UK

The narrative described so far is predominantly centered on the history of artificial intelligence and education in the United States. While the Dartmouth Tetrad are renowned for their pioneering contributions to AI, there was also early research in

[7] This list includes Cynthia Solomon, Andrea diSessa, David Perkins, Barbara White, Robert Lawler, Idit Harel, Yasmin Kafai, Ricki Goldman, Mitchel Resnick, Uri Wilensky, Gary Stager, Alan Shaw, Paula Hooper, David Williamson Shaffer, Marina Umaschi Bers, and Claudia Urrea.

[8] Paulo Freire's *Pedagogy of the Oppressed*, published in Portuguese in 1968, is the most cited book in education (Green, 2016).

AI happening in the United Kingdom. In this section, I briefly show that a lot of the aspects of the intertwined history of AI and education in the US were also paralleled by AI pioneers based in the UK.

Donald Michie, who had worked with Alan Turing and others as a Bletchley Park codebreaker in World War II, was one of the earliest AI researchers in the UK (Nilsson, 2009). In 1960, he created the Matchbox Educable Noughts and Crosses Engine (MENACE), an arrangement of 304 matchboxes and some glass beads that (when operated by a human properly) could learn to play the game of noughts and crosses (or tic-tac-toe; Nilsson, 2009). In 1965, Michie established the UK's first AI laboratory, the Experimental Programming Unit, which became the Department of Machine Intelligence and Perception a year later, at the University of Edinburgh. In 1970, the UK's Social Science Research Council awarded a $10,000 grant to Michie "for a study of computer assisted instruction with young children" (Annett, 1976). In 1972, SSRC awarded Jim Howe, one of Michie's colleagues and a founding member of the Department of Machine Intelligence, a $15,000 grant to investigate "An Intelligent Teaching System" (Annett, 1976). Howe would receive several other grants from SSRC over the next few years in the area of educational computing, including one on "Learning through LOGO" (Annett, 1976). Learning mathematics through Logo programming became a large project in Howe's group and several influential researchers in what would become the AIED community were part of that project, including Timothy O'Shea, Benedict du Boulay (who completed his PhD under Howe's supervision), and Sylvia Weir (who joined Papert's lab in 1978). This work included a focus on using Logo to help students with various disabilities (e.g., physical disabilities, dyslexia, and autism) to learn basic communication skills (Howe, 1978). From 1977 to 1996, Jim Howe was the head of the Department of Artificial Intelligence, which evolved out of the Department of Machine Intelligence and Perception.

Michie and Howe continued to pursue educational technology research throughout their careers. For example, in 1989, Michie and Bain (1989) wrote a paper advocating for the necessity of advancing machine learning for creating machines that can teach:

> It is our view that the inability of computers to learn has been a principal cause of their inability to teach. It is becoming apparent from the emerging science of Machine Learning that the development of a theoretical basis for learning must be rooted in formalisms sufficiently powerful for the expression of human-type concepts. (p. 20)

That same year, Michie et al. (1989) also published a paper called "Learning by Teaching," which advanced a relatively unexplored idea of using AI to support learning by having the student teach the computer using examples, rather than vice versa. In 1994, Michie, along with his wife and fellow AI researcher, Jean Hayes Michie, founded the Human-Computer Learning Foundation, a charity dedicated to enhancing education by designing software where "human and computer agents incrementally learn from each other through mutual interaction" (Human-Computer Learning Foundation, n.d.).

These UK-based leaders in AI were not merely engaged in cutting-edge applications of educational technology, but like Simon, Newell, Papert, and Minsky, their interest in education was an extension of their mutual investigation of cognition and learning in humans and machines. According to Annett (1976),

> the real significance of the Edinburgh work lies in its AI orientation. When the results of this project are available we may be able to reach some preliminary conclusions on the future viability of knowledge-based teaching systems, but complex problems are involved which will not be solved on the basis of these projects alone. If they are solved in technical and educational terms the question of cost still remains and even a sanguine estimate suggests it will be considerable. Nevertheless the investigation of technical and educational fesibility seems a reasonable aim not just in case implementation may be possible in the long term, but because of the light which could be thrown on some of the basic issues of the nature of "knowledge and "understanding". This [work]…is breaking new ground in ways of conceiving the nature of the teaching/learning process. (p. 11)

As Howe (1978) described it,

> the learner is viewed as a builder of mental models, erecting for each new domain a knowledge structure that can be brought to bear to solve problems in that domain. Recent research in artificial intelligence suggests that building computer programs is a powerful means of characterising and testing our understanding of cognitive tasks (see, for example, Newell & Simon, 1972; Lindsay and Norman, 1972; Howe, 1975; Longuet-Higgins, 1976). An implication of the AI approach is that teaching children to build and use computer programs to explicate and test their thinking about problems should be a valuable educational activity.

Similarly, according to a report written by a working party, which included Christopher Longuet-Higgins, who was one of the founders of the Department of Machine Intelligence and Perception at Edinburgh and who coined the name "cognitive science" (Longuet-Higgins, 1973) for the emerging field:

> advances of our understanding of our own thought processes are also critical for improvements in education and training….Computer aided instruction is already useful, but the realization of its full potential must depend on further advances in our understanding of human cognition and on our ability to write programs that make computers function in an intelligent way. (cited in Annett, 1976, p. 4)

Other researchers also had the same attitude towards studying AI and education in an intertwined fashion. For example, Gordon Pask was a leading cybernetician who was designing analog computer machines that could adaptively teach students as early as the 1950s; he was also doing what would aptly be called AI research at this time (but as it was under the field of cybernetics, his work is typically disregarded in the "sanctioned" history of AI). Pask (1972) tried to clarify the distinction between AI (or "computation science") as a conceptual tool for reasoning about how people think and learn, and "computer techniques" as the infrastructure that enables computer-assisted instruction (CAI):

> Computation science deals with relational networks and processes that may represent concepts; with the structure of knowledge and the activity of real and artificial minds. Computation science lies in (even *is*) the kernel of CAI; it lends stature to the subject and bridges the interdisciplinary gap, between philosophy,

> education, psychology and the mathematical theory of organisations. Computer techniques, in contrast, bear the same relation to CAI as instrument making to physics or reagent manufacture to chemistry. (p. 236)

The idea of supporting such interdisciplinary research that bridged between AI and education was also supported in a 1973 SSRC Educational Research Board report, where "It was proposed that 'learning science', a field involving education, cognitive psychology and artificial intelligence, should be supported…and probably in the form of a long term interdisciplinary research unit" (Annett, 1976, p. 4). The term "learning science," preempted a field that would emerge in the US nearly 20 years later. Learning Science did not take off as a new field in the UK in the 1970s, but a decade later, the seeds of another new field were being sowed in the UK, and that is where we turn our attention next.

Artificial Intelligence in Education: The Field

Now that we have seen how some of the key pioneers in AI were also making contributions to education, it is worth discussing how the intersection of AI and education crystallized into a field. The first and second International Conference on Artificial Intelligence and Education were held in Exeter, UK in 1983 and 1985. The name Artificial Intelligence *and* Education signifies that in the 1980s, researchers saw these two fields as overlapping rather than thinking of education as yet another field where AI could be applied. Indeed, according to Yazdani and Lawler (1986):

> When, in September 1985, the second international conference on Artificial Intelligence and Education was held in Exeter, it was clear that a new interest group had emerged; one which was committed neither primarily to AI nor to education matters, but to matters which fall into the overlap between them. Both subjects show an interest in knowledge acquisition (be it people or machines) and they need a theoretical framework in which to study learning and teaching processes. They can also help each other in many ways. (p. 198)

This sentiment was also shared by others, including John Self, an early AIED researcher and founding editor of the Journal of Artificial Intelligence in Education. As Self (2016) recalls:

> For a brief period in the 1980s (within which AIED 83, no doubt not coincidentally, fell), AI was at the peak of a 'hype cycle'. It became a bandwagon, with generous research funding, that it was worth trying to hitch a ride on. That, of course, was not AIED's motivation: we were enthused by what we considered the profound association between education and AI, with its concerns for knowledge representation, reasoning and learning. (p. 5)

The first conference had a lot of emphasis on Logo (from Papert and his colleagues) and other programming languages that could be used in education (Yazdani, 1984). The second conference seemingly had two threads of research, one focusing on intelligent tutoring systems and another focused on computer-based learning environments like Logo (Yazdani & Lawler, 1986). The conference led to a publication of a book that focused on these two themes in the conference and how to integrate them. In the preface to this book, Lawler and Yazdani (1987) remarked that:

> The 1985 conference ended with the exciting prospect of the 'coming together' of the two traditional streams of 'tutoring systems' and 'learning environments' to address common problems in the design of instructional systems from an Artificial Intelligence perspective. This volume marks the beginning of a synergy between the agendas of the various researchers which promises an interesting and productive future. (p. vii)

However, over the next few years the AIED conference seemed to lean towards the intelligent tutoring systems (Liffick, 1987; Sandberg, 1987). A comparison of paper titles in the 1985 proceedings with the 1989 proceedings shows this change of focus. Titles in the 1985 proceedings featured the word "microworld", the word "Logo", and "intelligent tutoring system" (or a variant) each three times. On the other hand, titles in the 1989 proceedings featured "microworld" and "Logo" only once each, but "intelligent tutoring system" (or a variant) 21 times.

But suddenly something changed. On August 4th, 1991—the day I was born—the first International Conference of the Learning Sciences (ICLS) commenced. It was meant to be a rebranding of the AIED conference. In fact, it was initially called the Fifth International Conference of the Learning Sciences. That rebranding did not last long; I discuss why in the next section. ICLS continued biannually since 1996, but AIED also returned in 1993 and has continued biannually (and annually since 2018), but with one critical change that most would probably overlook—it has since then been called the International Conference on Artificial Intelligence *in* Education.[9] This change in name was likely to match the Journal of Artificial Intelligence in Education, which was founded in 1989. However, I think this change of a seemingly unimportant word reflects the change from AIED as the intersection of two interrelated research areas—AI and education—to a field concerned with applications of AI to education, which is where the status of the field is today.[10] This change is symbolic of the fact that I believe the history I am narrating here is now "forgotten" by many researchers and practitioners interested in applying artificial intelligence to education. As John Self (2016) recalls, in the 1990s:

> the fact is that very few AIED researchers were able, or wished, to publish their work in the major AI journals and conferences. Not only did we not contribute much to AI, but we didn't really borrow much from it either, in my opinion. If

[9] It was actually called the World Conference on Artificial Intelligence in Education until 1997 and International Conference on Artificial Intelligence in Education since 1999.

[10] This is not to suggest that the new name was necessarily explicitly chosen for this reason. However, it is worth noting that Tim O'Shea and John Self had co-authored a book in 1983 called "Learning and Teaching with Computers: Artificial Intelligence in Education" (Self, 2016). Even though Self recognized the interdisciplinary interplay between AI and education (as quoted above), perhaps he (and others) had an affinity towards the phrasing "artificial intelligence *in* education." This affinity likely reflected the growing interest in using AI-based technologies (like intelligent tutoring systems) to enhance education. Regardless of why the new name was chosen, the name made sense for the evolving interests of the field.

> you looked at the AI conference proceedings of the time you'd find that almost all of it was apparently irrelevant to AIED. (p. 9)

In some ways this change reflects changes in the broader field of AI from broader questions of the nature of (human and machine) intelligence towards more technical questions that might have been less directly applicable to improving how people learn.

Recall that the change from "Artificial Intelligence and Education" to "Artificial Intelligence in Education" occurred right after there was an attempt to switch from AIED to ICLS in 1991. Why did the conference change and then quickly change back? To answer that, we need to turn our attention to another figure in early AI history: Roger Schank.

Schank: From Language Technologies to Learning Technologies

I already introduced Roger Schank as the source of the neat vs. scruffy distinction. Schank was an early pioneer in AI who joined the field as a student in the mid-1960s and made important contributions with his students at Yale (Schank, 2016). In 1977, he co-founded the journal *Cognitive Science* (which in its first two issues had contributions from Papert, Simon, and Anderson), and in 1979, he co-founded the Cognitive Science Society. Schank also made early advances in the field of natural language processing. Like the other AI pioneers we have examined, he was interested in building systems that resembled how humans think and learn. He realized it was important to model the many "scruffy" aspects of human thinking, which neat approaches tended to ignore.

A Scruffy Approach to AI

Schank's first main contribution to AI was the development of conceptual dependency theory, which emphasized natural language understanding (Schank, 1969, 1972). While Noam Chomsky and others had developed models of language based on syntax, Schank recognized that understanding language was about understanding the semantics—the concepts that underlie the actual words. In conceptual dependency theory, two sentences would share the same conceptual representation if they shared the same meaning, regardless of the language and syntax of each sentence.

Schank then made a series of other contributions to AI that built on one another, including scripts (Schank & Abelson, 1975), a theory of dynamic memory (Schank, 1982; Schank & Kolodner, 1979), and case-based reasoning (Riesbeck & Schank, 1989). Case-based reasoning provided an alternative to the "neat" rule-based reasoning, which was popular in AI. Rule-based systems (such as production systems and expert systems) use a collection of rules to deduce new information and take actions. However, Schank and his students noticed that people often do not actually reason using rules. Rather, they reason using prior experiences (i.e., cases) stored in their memory:

> Certainly, experts are happy to tell knowledge engineers the rules that they use, but whether the experts actually use such rules when they reason is another question entirely. There is, after all, a difference between textbook knowledge and actual experience.…In fact, in very difficult cases, where the situation is not so clear cut, experts frequently cite previous cases that they have worked on that the current case reminds them of. (Riesbeck & Schank, 1989, p. 10)

For example, when faced with a new patient, a doctor might consider prior patients with similar symptoms and family histories, a chef might create a new dish by considering similar recipes but using new ingredients, and a lawyer might argue for precedence based on similar prior legal cases. In short, "a case-based reasoner solves new problems by adapting solutions that were used to solve old problems" (Riesbeck & Schank, 1989, p. 25). Moreover, while rules are useful for finding the "right answer," case-based reasoning can be helpful when there is no clear right answer (e.g., when deciding which students to admit to a university) (Riesbeck & Schank, 1989). A powerful way of storing cases is as rich stories that can be applied to a variety of different situations.

Although not obvious at the surface, at a high level, Schank's scruffy approach was similar to that of Minsky and Papert. According to Schank, "Marvin Minsky is the smartest person I've ever known…Marvin should have been my thesis advisor. I wouldn't say that I'm his student, but I appreciate everything he does. His point of view is my point of view." (quoted in Brockman, 1996, p. 164). Indeed, Schank's scripts were a knowledge representation that built on Minsky's frames. Minsky similarly endorsed Schank's approach (Brockman, 1996), and some of Schank's ideas played a role in Minsky's society of mind theory.

As with the respect that Minsky and Papert had for Simon and Newell and vice versa, Schank was also respectful of Simon and Newell's work despite their differences in approach. In a review of Newell's (1994) book, Schank and Jona (1994) state:

> Newell has had a strong influence on our views of both psychology and AI. As AI researchers, we share many of the same opinions about the field of psychology. Our views on AI, however, while initially quite similar, have diverged. (p. 375)

Schank's criticisms of Newell's approach centered on issues such as the use of unrealistic tasks (e.g., cryptarithemtic and theorem proving) to develop AI and the lack of a sophisticated way of modeling the relationship between concepts in memory.

Interestingly, in his review, Schank also discusses the implications of the book for education. He comments on how Newell had little to directly state about education, and as a result seems to suggest that Newell did not have an (explicit) interest in education. As we have already shown, Newell did have an interest in education and was conducting pioneering educationally-relevant research in the 1960s-1970s, but perhaps by the 1990s, his interest in the area had died down. (Simon on the other hand was still actively committed to enhancing education and engaging in debates in the field.) Schank ended his review with a powerful call-to-action:

> Newell argues that it is time for psychologists to come out of their experimental laboratories and put their heads together to build more unified theories of cognition. That is a step in the right direction, but it does not go far enough. More importantly, it is time for all cognitive scientists to realize that, by virtue of their work on learning, memory, and cognition, they have a voice in the debate on education. Good theories of cognition have a practical and important role to play in restructuring the process of education. The separation of the fields of education and cognitive science is both artificial and harmful. A unified theory of cognition must, now more than ever, be put into practical use as the cornerstone of the educational system. (p. 387)

In 1994, it was likely the case that many cognitive scientists were not actively engaged in pursuing the connections of the research on cognition to education; but as we have shown, historically researchers at the forefront of cognitive science were actually committed to education as well. As a pioneer in cognitive science and AI, Schank had joined an earlier generation of AI researchers in acknowledging the importance of their work to education, and he was practically demanding that the rest of his colleagues in cognitive science do the same. But what drove Schank to education in the first place?

Founder of the Learning Sciences

In the early 1980s, Schank gave a keynote speech at the National Reading Conference, and the support he got from the audience about the "awful stuff that [he] was complaining about in schools" led him to change his research focus from then on—his focused shifted to improving education (Schank, 2016, p. 22). His early thinking on education can be seen in a virtually uncited defense of Papert and his work on Logo, against some critics. Schank (1986) ended his article by saying:

> Right now, with the exception of LOGO and one or two other kinds of software that are also openended, nobody is doing anything very interesting with children and computers. We must learn to encourage and finance other LOGO-like attempts, not criticize the only ones we have. (p. 239)

It was not long before other such attempts would be financed. In 1989, Schank and 24 of his colleagues and students left Yale with $30 million from Anderson Consulting to start the Institute for the Learning Sciences (ILS) at Northwestern University. In 1991, Roger Schank helped form the *Journal of the Learning Sciences*—which was edited by his former student Janet Kolodner until 2009—and chaired the first International Conference of the Learning Sciences. With these moves, Schank played a pivotal role in the formation of a new field, the learning sciences—another term that Schank coined. But while these moves were intended to be field-building, they were also seen by many as field-fracturing.

Unbeknownst to members of the burgeoning AIED community until it was "too late," Schank unilaterally renamed the conference and selected his colleagues and "friends" (many of whom were situativist and constructivist researchers who were not previously part of the AIED community) to make up the program committee (Self, 2016; see also, Kolodner, 2004).[11] As Self (2016) recounts, "In short, AIED 91 had been turned into an advertisement for ILS, to the exclusion of the majority of the newly-developing international AIED community" (p. 6). This event (and the feeling of betrayal that many AIED researchers felt) was likely a major force in distancing researchers who identified more with the AIED community and those who identified with the ICLS community. However, it is important to acknowledge that aside from Schank's role, there were many factors that led up to the formation of the learning sciences, including a growing interest in situativist accounts, in contrast to traditional information-processing approaches; a desire to design microworld-based systems, which were losing popularity in the AIED community; and a growing group of education researchers interested in the interdisciplinary study of learning who were not using AI methods (Kolodner, 2004). As such, it appears likely that some kind of learning sciences community would have formed had Schank not initiated it (but perhaps leaving less of a sour taste).

The International Conference of the Learning Sciences has continued to have a conference every other year since 1996. The learning sciences community as embodied in ICLS, largely attracted researchers coming from situativist and constructivist traditions. While some information-processing-oriented researchers also participated in the first few ICLS conferences and published papers in the *Journal of the Learning Sciences*, many of these researchers found the AIED community to be more closely aligned to their work (both methodologically and theoretically).

Using case-based reasoning as a theoretical underpinning, Schank and his students developed the idea of case-based teaching, which is premised on the ideas that (1) "experts are repositories of cases" (Schank & Jona, 1991, p. 16) and that (2) "good teaching is good story telling" (Schank, 1990, p. 231). This work led to designing a variety of interactive software where students are put into authentic problem-solving situations that are meant to be of inherent interest. When students need support, they can seek help, at which point the receive a story which they can hopefully apply when reasoning about similar situations in the future. However, Schank and Jona (1991) did not believe that all good teaching should be confined to using cases and stories; they also developed five other teaching architectures, including "simulation-based learning by doing" and "cascaded problem sets." This work later led to the development of goal-based scenarios, which suggested that good teaching should involve a grounded goal that the student is trying to accomplish, such as creating a TV news program (Schank et al., 1994), identifying if a Rembrandt-style painting is authentic (Bain, 2004; Riesbeck, 1998), and figuring out why bats are dying in a zoo (Riesbeck, 1998). As Schank et al. (1994) explicitly admit, the idea that learning "takes place within some authentic activity" (p. 307) was supported by the newly burgeoning theories of situated cognition and cognitive apprenticeship (Brown et al., 1989). Indeed, Allan Collins, one

[11] I thank three anonymous reviewers who corroborated this account (including the feeling of AIED researchers at the time) and provided additional details based on their own witnessing of the events.

of the pioneers of situated learning and cognitive apprenticeship, was a close colleague of Schank; together they cofounded the *Cognitive Science* journal and the Cognitive Science Society, and Schank hired him as a faculty member of the Institute for the Learning Sciences. Despite all the sophisticated AI methods that motivated the case-based teaching architecture and goal-based systems, according to Schank et al. (1994), "perhaps the simplest way to express the fundamental principle underlying our ideas about education" is "an interest is a terrible thing to waste" (p. 305).

In the 1990s, Roger Schank and the Institute for the Learning Sciences, were impressively productive in churning out a variety of interactive learning software based on the principles outlined above. However, the particular technologies they developed are virtually unknown today, and phrases such as "case-based teaching architecture" and "goal-based scenarios" are rarely used today. "Case-based learning" is still in use, but often in the context of using cases in medicine, law, and business schools, a form of instruction that predated Schank's use of the term. However, as per Google Books Ngram Viewer (Michel et al., 2011), the term became popular in the late 1980s, so it seems likely that Schank and his colleagues played a role in popularizing the broader concept. Regardless, Schank's legacy in education far outweighs these specific contributions; he helped spearhead the learning sciences, a movement that originally brought together a group of like-minded people who took similarly "scruffy" approaches to AI and education (in contrast to the approach of Newell, Simon, and their colleagues)—a movement that continues to grow to this day.

To the Present and Beyond

The narrative I have told begins with the birth of artificial intelligence and cognitive science in 1956 and traces how pioneers of the field from its conception (i.e., Simon, Newell, Minsky, and Michie) and pioneers who joined the field a few years later (e.g., Papert and Schank) played a key role in altering the course of research on learning and education to the present day. In some cases, their work left a theoretical legacy that influenced future generations of researchers (e.g., through the development of cognitivism as the dominant learning theory for decades in the case of Simon and Newell, and through the development of constructionism in the case of Papert). In other cases, these pioneers created educational technologies and conducted educationally relevant research themselves. In yet other cases, they helped established new fields within education (e.g., the learning sciences and, in some sense, learning engineering).

Moreover, these researchers largely led two strands of work in AI and education that developed in parallel: one strand pioneered by Simon, Newell, Anderson, and their colleagues, and another strand pioneered by Papert, Minsky, Schank, and their colleagues. Figure 1 depicts some of the key events in the histories of these two strands. In 1985, there was some hope of convergence; that the work from the information-processing/tutoring system strand and the work from the constructivist/learning environment strand would "come together," as Lawler and Yazdani (1987) stated in the aforementioned quote. After all, Simon, Newell, Papert, and Minsky

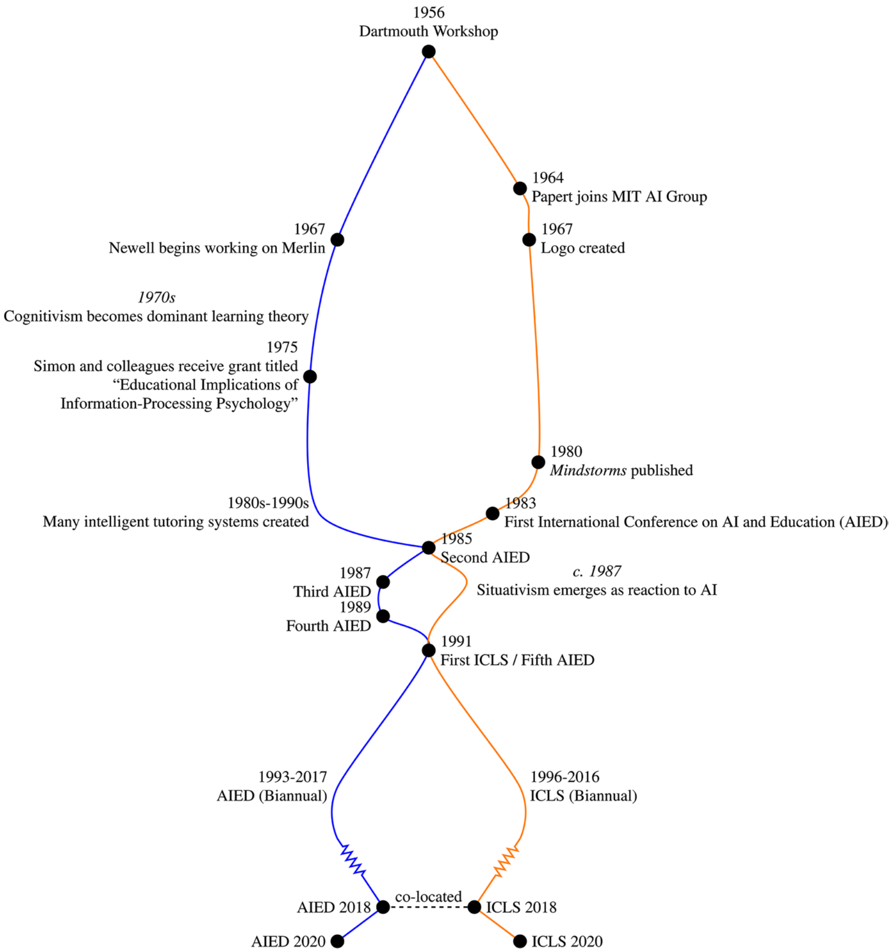

Fig. 1 Parallel timelines for two strands within the intertwined history of AI and education. The timeline on the left shows events aligned with the information-processing strand and AIED, while the timeline on the right shows events aligned with the constructivist strand, situativism, and ICLS. The vertical axis follows a linear timescale, except for the period from 1991 to 2018, where twelve years are skipped as indicated by the zigzag patterns. The horizontal axis very loosely represents the "distance" between the two strands from each other over time; points of intersection indicates points at which the two strands were intellectually or physically in contact with one another (e.g., the 1985 Artificial Intelligence and Education conference or the 1991 ICLS/AIED conference)

seemed to get along just fine in the world of artificial intelligence. The 1985 conference seemed to bring together people who were interested in how children and machines think, and who were interested in foundational questions at the intersection of learning, knowledge representation, and technology. This is evident by scanning the proceedings' table of contents, with papers titled "Knowledge Acquisition as a Social Phenomenon," "The Schema Mechanism – Translating Piaget to LISP," "The Epistemics of Computer Based Microworlds," "The Role of Cognitive Theory in Educational Reform," and "Observational Learning by Computer."

But the two strands seemed to grow further apart over the next few years. In 1991, when Schank established the learning sciences and coopted the existing International Conference of Artificial Intelligence and Education to bootstrap the formation of the emerging field, there might have been hope for a convergence of the two fields again. However, at that point the two fields seemingly found that they had different interests, and Schank's attempt to change the conference did not help. Moreover, with the emergence of situativism around 1987, many researchers became disgruntled with the inability of AI to model the kinds of learning that take place in the real world (e.g., learning that is context-dependent and inherently social). The burgeoning field of the learning sciences was more attuned to these concerns than the field of AIED (i.e., AI *in* Education).[12] As such, the learning sciences had to open its doors to new approaches taken by researchers coming from more situativist and sociocultural perspectives, including qualitative methods like ethnography, and over time the learning sciences started steering further away from its AI roots.

In 2018, for the first time since 1991, the two conferences of ICLS and AIED were co-located in what was called the "Festival of Learning" in London. The two conferences chose themes that would reflect the intersection of the two fields. The ICLS 2018 theme was "Rethinking learning in the digital age: Making the Learning Sciences count" and the AIED 2018 theme was "Bridging the Behavioral and the Computational: Deep Learning in Humans and Machine." The AIED theme in particular shows a return to the original draw towards research on artificial intelligence *and* education: "learning in humans and machine," but now focusing on the AI of the times—deep learning. However, a quick scan of the conference proceedings of these two conferences shows that (a) the two fields had grown further apart over the past three decades, and (b) neither conference seemed to be focusing on the intertwined and mutually reinforcing questions that fueled AI and education research in earlier decades. Despite the conference theme, most of the work presented at AIED 2018 was not trying to bridge between human and machine learning. Rather there were many papers on using machine learning, computer vision, and natural language processing in service of improving educational technologies or gaining insights on learning in particular educational settings, as well as empirical studies that evaluate the efficacy of AIED technologies. In short, by this point the community was

[12] This is not to say that situativism was seen as mutually incompatible with AIED by all. For example, John Seely Brown, one of the pioneers of the situated learning and an early ITS researcher, wrote a thought-provoking chapter called "Toward a new epistemology for learning" for how work on intelligent tutoring systems could (and should) embrace the situative perspective (Brown, 1990). Indeed, echoing one of the themes of this historical review, Brown went so far as to say:

"it is this community that is most closely coupled to—or situated in—the full blooded complexity of human learning activity. Thus if we meet this challenge correctly, it may well be that, instead of ITS being merely one subset of the overall schema of AI, we will, instead, find that it is AI that becomes one subset of the overall schema of ITS." (p. 281).

While some researchers may have been intrigued by this call to action, it appears the ITS/AIED community did not "meet this challenge correctly.".

fully invested in applying state-of-the-art AI (mostly machine learning) in service of education.

One rare exception to this trend was Tuomi's (2018) paper that was provocatively titled, "Vygotsky Meets Backpropagation: Artificial Neural Models and the Development of Higher Forms of Thought." This paper actually addressed the conference theme of comparing learning in humans and neural networks, showing that a particular state-of-the-art neural network could not accurately learn concepts in the way that humans do, as outlined in the work of Russian developmental psychologists like Lev Vygotsky. This work suggests that perhaps deeper connections between AI and education may still be pursued in the age of deep learning, but such work is an outlier. It appears that this paper has been largely ignored and probably thought of more as an intellectual thought experiment rather than an interesting line of inquiry to continue pursuing within AIED.

Furthermore, from 2019 to 2021, IJAIED papers have also seemingly focused on the kinds of studies mentioned above: "applying state-of-the-art AI (mostly machine learning) in service of education." At least from the titles, I could identify almost no papers that tackle the kind of interdisciplinary approach to human and machine learning that has been the focus of this historical review. One possible exception is a paper on using Apprentice Learner models for interactively creating tutoring systems using feedback and demonstrations (MacLellan & Koedinger, 2022). While this paper still has an applied focus—more efficient ITS authoring—work on Apprentice Learner models in general (MacLellan, et al., 2016), and earlier work on SimStudent (Li et al., 2015; Matsuda et al., 2013), draw on the cognitive science tradition of using computational models of learning to develop insights on how people learn and to make practical changes in educational technology. Moreover, such work could also contribute back to the AI literature (Li et al., 2015).

Having attended the "Festival of Learning," I can also anecdotally claim that the overall sentiment seemed to be that the two conferences were quite different from one another with little overlap in the questions studied and methods used. AIED researchers found ICLS to be too focused on qualitative case studies that lacked the rigor, precision, and generalizability of AIED studies. ICLS researchers likely found AIED to be too focused on technologies that target limited forms of teaching and learning. In 2020, the ICLS theme was "Interdisciplinarity in the Learning Sciences." Yet the call for papers did not list any technical fields (such as computer science or artificial intelligence) in the list of fields that the conference was hoping to elicit contributions from.

Nonetheless, there is reason to believe that these fields could still unite. In 2016, the International Alliance to Advance Learning in the Digital Era (IAALDE) formed as an umbrella organization that encompasses ten different research societies committed to the study of learning in a technologically advanced world; ISLS and AIED are both part of this organization. IAALDE could strike meaningful dialogue across these societies, but these conversations might be more productive if points of common ground are clearly laid out. One path forward is to acknowledge the intertwined nature of early AI and education research that fueled both the early learning sciences and AIED communities.

In a talk that Papert gave in 2002, he remarked on how he "misses the good old days of 'big ideas' about the nature of knowledge and human learning" (as cited in Wright, 2002). As Papert put it,

> We started with a big 'cosmic question': Can we make a machine to rival human intelligence? Can we make a machine so we can understand intelligence in general? But AI was a victim of its own worldly success. People discovered you could make computer programs so robots could assemble cars. Robots could do accounting! (as cited in Wright, 2002)

Surely, Papert would agree that the learning sciences had also strayed from its roots in thinking about the "cosmic question" of understanding intelligence and learning in humans and machines. Is there still room today for a learning science that draws insights from artificial intelligence and simultaneously makes contributions to the study of thinking and learning in machines? Could the learning sciences return to their AI roots? Could the AIED community return to thinking about more central questions at the intersection of artificial intelligence and education? To answer these questions it may help to gain a better understanding of the ethos that pervaded the 1985 and 1991 AIED conferences or to take a closer look at the interdisciplinary work of the pioneers described above. That is beyond the scope of this paper. But if the AIED community is to return to its AI roots, it may depend on one of two things: either (a) the community puts a greater focus on early AI techniques, such as symbolic AI and the scruffier work of Papert, Minsky, and Schank; and/or (b) the community investigates the connections between machine learning techniques and human learning. As an example of (a), Porayska-Pomsta (2016) investigates how the use of knowledge representation and knowledge elicitation techniques from AI could inform teacher's metacognitive reflection on their own practice. Resonant with the key idea I am presenting here, Porayska-Pomsta (2016) suggests that this work.

> allows us to see AI not solely, albeit importantly, as the driver of back-end functionality of AIEd technologies (e.g. Bundy 1986), but equally as a front-end *technology-of-the-mind* through which educators can represent, experiment with and compare their practices at a fine-grained level of detail and engage in predictive analyses of the potential impact of their actions on individual learners. (p. 681)

One example of (b) is Tuomi's (2018) work on comparing neural networks with Vygotksy's theory of cognitive development. An emerging research community focused on "machine teaching" is also interested in investigating how to optimally teach machine learning algorithms and the implications that this might have on teaching human learners (Zhu, 2015). Whether such efforts will lead to powerful contributions to the fields of AI and education remains to be seen.

For the ISLS community to return to its AI roots, it seems like another question needs to be addressed: can researchers develop connections between AI and sociocultural theories of learning? There seems to be very little investigation in this direction in recent years, perhaps in part because most ISLS researchers are no longer typically trained in AI techniques. However, a look at the pioneers of situativism and other sociocultural theories of learning shows that this question may not be so far-fetched. Greeno, one of the foremost advocates of the situative perspective, advocated for continuing efforts on computational modeling in developing situative accounts of learning, but ones that could account for multiagent interactions (Greeno & Moore, 1993). Edwin Hutchins, one of the founders of distributed cognition, conducted a series of early studies on agent-based models (where each agent was described using connectionist models) that could describe learning as a cultural process (Hutchins & Hazlehurst, 1991, 1995). diSessa (1993) proposed a connectionist model to describe how conceptual change can occur in terms of his popular knowledge-in-pieces framework. Social scientist Kathleen Carley's (1986) paper "Knowledge Acquisition as a Social Phenomenon" presented a sophisticated theory and model that juxtaposed an AI-based knowledge representation (akin to frames or scripts) with a social network seeded with ethnographic data; a version of this paper was presented at the 1985 AIED conference. Despite these lines of inquiry being proposed by leaders in the field, seemingly none of them have been influential directions in the learning sciences. Perhaps following up on such lines of inquiry would be one way to bridge between the ICLS and AIED communities, by drawing on *theories* from the learning sciences and *methods* from artificial intelligence.

None of this is to suggest that existing work in AIED or the learning sciences is less important than investigating questions at the interface of AI and education. These different styles of work need not be seen as being in conflict with one another. In fact, even if the day-to-day work of most researchers in AIED and the learning sciences does not change, periodically revisiting big "cosmic questions" around how to improve our understanding of the nature of learning and how that can improve education can help ensure more incremental work is moving in the "right" direction.[13]

By advancing AI models to bring in insights from how people learn in a variety of educational environments, this work can potentially advance foundational work in AI as well. This could perhaps even push AI to re-consider the relevance of older theories that have been displaced in an era of deep learning. Moreover, the focus of AI (and the history presented in this paper) has primarily been on cognition and the cognitive aspects of learning; however, as AIED researchers have emphasized in recent years, education goes beyond the cognitive, with phenomena like metacognition, affect, and motivation playing important roles in learning (see e.g., Arroyo et al., 2014; Poryaska-Pomsta, 2016; Rebolledo-Mendez et al., 2022; Winne, 2021). Motivated by human learning, recent work in machine learning has begun to design learning algorithms that include metacognition (Savitha et al., 2014; Zhang & Er, 2016) or intrinsic motivation (Baldassarre et al., 2013; Barto & Simsek, 2005; Shuvaev et al., 2021). However, such work is primarily motivated by psychology and neuroscience, and does not consider what education might have to say about these phenomena. The AIED community could be in a unique position to consider educationally-relevant aspects of extra-cognitive factors in the design of AI models and in the use of those models to understand and improve how people learn.

[13] I thank an anonymous reviewer for bringing this idea to my attention.

I have given pointers for what it might take for the AIED, ICLS, and AI communities to return to an interdisciplinary investigation of learning in humans and machines. But it may still be hard to imagine what a future where such work is commonplace would look like. The past has given us many examples of this work, but we cannot expect to completely return to an older ethos, given the changes in the research communities involved, advances in technology, and changes in how we think about learning and teaching. Instead, it might be worthwhile to speculate about the kind of work we might see in the future. To that end, I offer several titles of completely hypothetical research papers that reflect the kind of interdisciplinary thinking that has been at the core of this paper:

- Embedding Socio-Cultural Constraints into Knowledge Spaces
- Machine Teaching vs. Active Learning: Comparing the Efficacy of Learning Algorithms in a Tutorial Environment vs. a Microworld
- A Montessori-Inspired Approach to Regularizing Neural Networks
- A Computational Model of Distributed Cognition for a Museum Learning Environment
- Can You Fool the Computer? Designing an Adversarial Teachable Agent Based on Generative Adversarial Networks
- Thinking About Thinking: Using AI Models to Foster Metacognitive Reflection in an Inner-City School

Of course, the previous paragraphs presuppose that it is worthwhile to reinvigorate the role that AI once had in education research. Some might suggest that whether or not this could be done, it is not a worthwhile endeavor. Regardless, it seems reasonable to think that to give a thoughtful answer to either the question of whether these communities *can* return to their AI roots or the question of whether they *should*, we must have a more accurate picture of the history of education research, including the ways in which artificial intelligence has interacted with this history. My hope is that this paper can help researchers have a more nuanced understanding of the history of research on learning in humans and machines, in order to make more informed decisions about the directions these fields should take going forward.

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