AI Applications in Education

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Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

AI pioneer Marvin Minsky and his colleagues highlighted key aspects of vision for Artificial Intelligence in Education (AI in Ed):

> '…we could try to build a personalized teaching machine that would adapt itself to someone's particular circumstances, difficulties, and needs. The system would carry out a conversation with you, to help you understand a problem or achieve some goal. You could discuss with it such subjects as how to choose a house or car, how to learn to play a game or get better at some subject, how to decide whether to go to the doctor, and so forth. It would help you by telling you what to read, stepping you through solutions, and teaching you about the subject in other ways it found to be effective for you. Textbooks then could be replaced by systems that know how to explain ideas to you in particular, because they would know your background, your skills, and how you best learn." (Minsky et al., 2004, p. 122)

Similar visions can be found in Pressey's teaching machines (1924), the "Illustrated Primer" of Neal Stephenson's science fiction novel The Diamond Age (1995), and many other contemporary sources. Although, the vision of a conversational tutor which can help anyone to learn any topic more quickly or easily has not yet been achieved, researchers have made many advances on aspects of this vision.

For example, researchers have developed applications of AI in Ed that can:

- track the "mental steps" of the learner and underlying goal structure of problem solving tasks (Anderson et al., 1995)
- diagnose misconceptions and estimate the learner's understanding of the domain (VanLehn, 1988)
- provide timely guidance, feedback and explanations (Shute, 2008)
- promote productive learning behaviors, such as self-regulation, self-monitoring, and self-explanation (Azevedo & Hadwin, 2005)

- prescribe learning activities at the right level of difficulty and with the most appropriate content (VanLehn, 2006)

Indeed, over the course of different investigations, nearly every AI technique – natural language processing, uncertain reasoning, planning, cognitive modeling, case-based reasoning, machine learning and more – has been applied to challenges of learning (Woolf, 2009).

In particular, AI techniques can enable educational technologies to better track, adapt to, and support individual learners. For example, AI technologies can track learners by building a model of what a students knows based on their successes and errors in solving problems. AI technologies can adapt to students by changing the sequence of problems presented to students and by changing the interactions of the computer with the student on specific steps of a problem. AI technologies can give students help within well-defined and carefully limited domains in the style of a conversational agent, sometimes even with a virtual avatar.

Many AI in Ed systems have aimed to mimic the benefits of one-to-one tutoring shown in Bloom (1984); some of these systems now outperform untrained tutors in specific topics and can approach the effectiveness of expert tutors (VanLehn, 2011). Close analyses have found that much of the benefit of both human and AI tutors arises from intervening at the specific step where a student makes a mistake, rather than giving feedback only on the correctness of the entire problem solution (Corbett & Anderson, 2001; Shute, 2008). Implementing step-based feedback on a computer requires representing how problems are solved step-by-step; AI technologies are a good choice for specifying these step-by-step processes. In general, however, building an expert model that is suitable for use in education is a difficult and slow undertaking, requiring highly skilled labor and access to expertise. Therefore, a key difference between the Minsky's vision and practical accomplishments of AI in Ed is the careful selection of a constrained and well-specified domain of knowledge.

One particularly well-known and fruitful line of work began with development of John Anderson's ACT-R theory (Anderson, 1983, 1993). This theory models how people learn to solve problems in terms of if-then rules, called "productions." ACT-R implements the theory in a kind of programming language, which can be programmed to solve information processing tasks in the way people do. This line of work gave birth to a type of Intelligent Tutor System (ITS) called the Cognitive Tutor. The cognitive tutor can simulate how an expert would solve the same problem that a student is currently working on. This simulation is used to

trace differences between student and expert problem solving, and when the steps diverge, to provide feedback. This approach has led to commercial products from Carnegie Learning such as the Algebra Tutor, and these products have been used with hundreds of thousands of students. Some careful analyses of these products have found positive results, although results in other cases have been mixed (What Works Clearinghouse [WWC], 2010). A meta-analysis that compared outcomes of learners using an ITS to outcomes of learners using other instructional methods found that over a wide array of conditions, learning from ITS was associated with higher outcome scores (Ma et al, 2014).

AI in Ed today is not limited to simulating expert human tutors and teachers. For example, the use of physiological monitoring technologies (e.g., skin conductance, posture) is helping researchers understand the role of emotions in learning and develop new models of pedagogical intervention. Further, work on teachable agents leverages the idea of reciprocal teaching by having the (human) student take on the role of teacher. Here, AI techniques are used in a variety of ways, such as simulating human communication, learning, and emotions. A final example is the use of narrative learning environments and educational games that can be designed to provide customized experiential learning opportunities and better maintain learner motivation and engagement.

AI is poised to play a pivotal role in growing the field of learning analytics and personalized learning. There is also potential for the use of AI to create unique learning pathways in MOOCs and adaptive systems for use blended and online learning, however this vision is yet to be fully realized. In a recent special double issue of AI Magazine (Chaudhry, et al., 2013), these topics were addressed in some detail.

AI techniques can thus continue to provide deeper insights into human learning, inspire curiosity and interest in the world around us, and ultimately help keep educational technologies caught up with the rest of the world – if they can be made smart enough.

Issues

A series of AI Grand Challenges for Education were proposed (Woolf, et al., 2013):

1. **Virtual mentors for every learner**: omnipresent educational support; brings together knowledge representation, user modeling, social simulation, and many more.

2. **Addressing 21st Century skills**: our educational technologies must go beyond conveying knowledge and support learners with self-direction, self-assessment, teamwork, and more.
3. **Analysis of interaction data**: the vast amounts of data about learning, social contexts, learning contexts, personal interests, and more is a key source of information that must be leveraged in future educational technology research.
4. **Universal access to global classrooms**: ensuring that the classrooms of tomorrow are interconnected, accessible, and personalized requires a great deal of computational and automated reasoning power.
5. **Lifelong and lifewide technologies**: understanding, modeling, and guiding learning in the context of a learner's life outside of school is critical if we are to improve education. Persistent models, interoperable systems, intelligent search, and more all contribute to the vision of technology that stays with you and helps you learn throughout a lifetime.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Speech recognition:

- CAP: Building Partnerships for Education and Speech Research

Intelligent tutors and tools:

- EAGER: Exploiting Keystroke Logging and Eye-Tracking to Support the Learning of Writing
- EAGER: Collaborative Research: Virtual STEM Buddies for Personalized Learning Experiences in Free Choice Informal Learning Settings
- EXP: Helping Teachers Help Their Students: Teachers' Use of Intelligent Tutoring Software Analytics to Improve Student Learning.
- EAGER: Computational Models of Essay Rewritings
- EXP: Partners in Learning: Building Rapport with a Virtual Peer Tutor

More posts: intelligent-tutors

Resources

AAAI topics page on education (from the Association for the Advancement of Artificial Intelligence)

Ken Koedinger Podcast on Intelligent Tutoring

International Artificial Intelligence in Education Society, which organizes the biennial AIED Conference.

International Journal of Artificial Intelligence in Education

Full text of The Handbook of artificial intelligence, Volume 2

A Roadmap for Learning Technology (from the CCC, CRA, and NSF)

Readings

Key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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