Teacher Agents: The Current State, Future Trends, and Many Roles of Intelligent Agents in Education

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Abstract. Since their development in the 1980's, Intelligent Tutoring Systems (ITS) have experienced a widespread success in such varying areas of education as military training, personal tutoring, and vocational instruction[9], [12], [19], [36]. ITSs are not without limitations, however, and have often proven to be costly and inflexible. Combining these systems with Intelligent Agents (IA), first proposed in the 1990s, is intended to address some of the shortcomings of ITSs; notably the cost of building new learning objects. While IA provide a mechanism for generating dynamic content tailored to a specific learner, a lack of standardization in IA ontologies and a narrow focus on pedagogy provides rich veins for reseach. In this paper we broadly survey the development of IAs in education with an eye towards further exploration of their possibilities.

Keywords: Intelligent agents, education, chatbot, tutoring systems.

1 Introduction

Speaking at the 2010 commencement of Hampton University, U.S. President Barack Obama remarked

> *First and foremost, your education can fortify you against the uncertainties of a 21st century economy. In the 19th century, folks could get by with a few basic skills, whether they learned them in a school like Hampton or picked them up along the way. For much of the 20th century, a high school diploma was a ticket to a solid middle class life. That is no longer the case. Jobs today often require at least a bachelor's degree...[2]*

Mr. Obama's observations iluminate a movement that has been emerging since the century mark. U.S. Census data shows that college enrollments nationwide are up 17 percent since 2000, while college costs continue to climb rapidly [42] and government support for higher education continues to decline. Of particular concern in these diverging trends is the fact that many more of the students enrolling in college, and particularly community colleges, since 2000 require intervention services and remediation in the core subjects of mathematics, reading, and writing [31]. Rising

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enrollments, too few instructors, stagnant budgets, and students poorly prepared for the rigors of a college education produce a toxicity that must be diluted if the U.S. is to retain its competitiveness in the global economy of this century.

The traditional method of addressing student deficiences and individual needs has been the personal tutor, generally an individual who is both a subject domain expert, and takes the time to get to know his or her students personally, so that instruction can be matched to the student's particular learning style and goals. With increasing success, this role has been shifting (or at least supplementing) from human to human interaction to human to machine sessions; starting in the early 1960's [9].

Initially, these systems, typically known as Computer Aided Instruction (CAI), automated routine testing and drilling, with little differentiation between their operation and earlier wholly mechanical systems -- except they ran on computers. But advances in the fields of artificial intelligence and computer hardware, along with evolving perspectives in education and cognitive psychology, enabled ambitious researchers in the 1970s to model and develop 'intelligent' computer based instruction, commonly referred to as 'Intelligent Tutoring Systems' (ITS) [9].

2 Intelligent Tutoring Systems: Design, Characteristics, and Types

The term 'Intelligent Tutoring System' is expansive in scope, entailing any computer application that possesses intelligence and is used in instruction. Generally, an ITS should be comprised of one or more autonomous software agents (discussed in greater detail below) that interact with students, present content, and provide assessment, without the immediate oversight of human instructors [9] [11].

ITSs have been constructed from a variety of languages and tools, and run on different platforms; and vary in the degree of intelligence they exhibit [11]. All of them, however, share specific architectural characteristics: the domain or expert model, the student model, the tutor model, and the interface or environment model. [9], [17]. Each of these is a component of a larger system.

2.1 Design

Domain Model. The domain or expert model contains the knowledge, behaviors, and formalisms that make up the content being taught, both declarative (facts) and in some measure, procedural (processes for manipulating facts). It is a repository of the rules and inferences a subject-matter expert would follow would to solve a particular problem, such as doing addition in mathematics or diagnosing a breakdown of an automobile air conditioning system. Called an 'expert system' in artificial intelligence (AI), many researchers also refer to this component as the 'cognitive model', as there is an implicit relationship between the content and the 'knowledge state' of the expert working through the problem. The knowledge state, in turn, are those points transitioned to along the path in which the expert possesses increasing understanding of the task at hand.

Student Model. The student model tracks and saves the active knowledge states of the student user in constructs such as Bayesian networks, so that progress can be mapped. This component provides the student with a map of his or her learning, and dovetails into the tutor model. Student models have three tasks ([45] as cited in [41]):

1. By explicit (asking questions) or implicit (tracking the student's navigation) means, they must collelate data about the student and compare it to other student responses.
2. This data must be used to map the student's knowledge and learning. Taking the form of 'buggy' models (representation's of the student's knowledge as deriviations from established 'expertise'), the model will attempt to predict future student responses. These are compared to the actual responses, and a more precise map of the student's knowledge states can then be made.
3. The model must further diagnose the current state of the student's knowledge, so that optimal learning strategies can be chosen to present subsequent domain information for mastery.

Tutor Model. Wenger stated that when 'learning is viewed as successive transitions between knowledge states, the purpose of teaching is accordingly to facilitate the student's traversal of the space of knowledge states' ([45] as cited in [41]). The tutor model, which Wenger called 'pedagogical expertise', monitors the progress captured in the student model, and intervenes in situations where there are discrepancies between the rules established in the domain model. Aptly named, it is the role of the tutor model to manage adaptive teaching strategies, such as learning path maps and recommendations; sending the student remedial instruction and positive reinforcement through the interface model as warranted. These goals are addressed through two modes of support states ([45] as cited in [41]):

1. Diagnosis, in which the ITS extrapolates state information from the student's observable behavior, knowledge level, and learning style
2. Didactics, in which an appropriate curriculum is dynamically created and adjusted to match the student's current level.

Interface Model. Not surprisingly, the interface model is the means through which an ITS user interacts with the system – both human student and human instructor. The complexity or 'richness' of the interface is dictated by the detail needed for the student to view and complete a problem, and for human monitor to administer the system, making refinements to the domain model as needed. Wenger suggested that the Interface must consist of two component ([45] as cited in [41]):

1. The discourse model, which detects abiguities in student answers and provides a corrective responses.
2. Knowledge presentation, which provides guidance to keep the student from missing key elements of the knowledge being conveyed.

2.2 Characteristics

Woolf et al., 2001 [46] describe six characteristics or abilities of ITSs. They must:

- generate 'appropriate instructional material'
  - This quality distinguishes intelligent tutors from computer aided instruction, which uses a finite set of problems and responses.

- model student performance
  - Assessments need to be formative and immediate, so that a catalog of student strengths and weaknesses can be created and used to update instructional material and provide feedback.
    - Formative assessments are used to determine if students are learning the material currently being presented. They are intended as a 'feedback loop' for the instructor. This type of assessment can be contrasted with summative assessements, which are generally used to measure a student's overall performance with the objective of assigning a grade or mark. [16]
- model expert performance
  - This is the location of the tutor's knowledge base, which gives the tutor domain intelligence.
- model pedagogical strategies
  - Provides the tutor with the adaptibility to accommodate students at various levels of learning.
    - To accomplish, the tutor must be 'aware' of a student's current knowledge state and learning style; and possess the ability to define learning strategies dynamically.
- model natural dialog
  - A tutor must at least give the appearance of natural communication. (This is being realized now through developments in natural language processing).
- self-monitor performance
  - A tutor should be capable of reflective activity that will improve its 'teaching' over time.

Interestingly enough, Woolf et.al., stated that every ITS should possess at least one of these qualities; however it seems more likely that every truly intelligent tutor should possess all of them. Domain knowledge and student tracking are features of CAIs, necessary but insufficient for genuine teaching.[1] Reflecting on the ongoing processes, developing strategies for aiding students; in effect 'getting to know' the learner are essential virtue for any teacher.

There is a clear and self-validating relationship between Woolf et.al.'s list of ITS features and the architecture of these tutors that has evolved over the last twenty years, as shown in figure 1.

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[1] Meeriam and Caffarella identify four distinctive theories of education ([22] as cited in [35]):

1. Behaviorist: Focused on skill development and training, views the learning process as tantamount to behaviorial change
2. Cognitive: emphasizes 'learning how to learn', sees learning as an internal mental structuring
3. Humanistic: defines the learning process as an act of self-fulfillment and stresses self-directed learning
4. Social/situational: proposes that learning is the relationship that evolves between student and environment, and that the role of teaching is to create or identify communities of practice.

In addition, an often referenced theory of learning in ITS literature is constructivism. Based on the work of Vygotsky and others, constructivist-based learning articulates a model similar to that of the social/situational theory: learning is a process of 'enculturation' into a knowledge community [35].

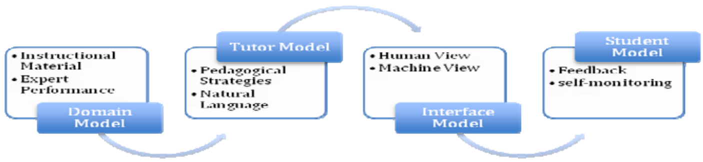

Fig. 1. Relationship between Woolf et.al.'s list of ITS features

Intelligent Agents. In a typical ITS, these abilities are manifested by a collection of autonomous but tightly coupled intelligent agents. A working definition of 'intelligent agent' can be elusive, because they are the subject of extensive research and reporting. Generally, though, they can be described as autonomous enities that observe and impinge upon their environment, which is a combination of application, data storage, knowledge source, and network. They are rational, goal directed agents [32], and usually software constructs [3].

2.3 ITS Types

ITSs can further be classified by the cognitive models they employ: Cognitive or Constraint Based [37]. Constraint Based, often referred to as the Behavioral approach, has its roots in the work of B.F. Skinner and other behavioral psychologists and identifies learning in terms of 'cause and effect' chains [8] or constraints [25]. An example of such a constraint would be: if <relevance condition> is true, then <satisfaction condition> must be true, otherwise something is wrong. This learning model is focused on an immediate, declarative problem and has no contextual awareness beyond the chain. Consequently, it is easier to implement as a rules based tutor, but is limited in its ability to provide feedback and reinforcement to the learner [37].

The Cognitive model is based on the theories of John Dewey, a philosopher of education, and the research of educational pyschologists Lev Vygotskey, Jean Piaget, and others [8]. It is holistic in approach and views learning as both declarative (facts) and procedural knowledge construction in a social context. Within the framework of an ITS, rules built on this model could take the following path [37]:

```
if the goal is to classify a shape
and
the shape has three sides
then
classify the shape as a triangle
because triangles have three sides
```

Facts are easy to code, procedure is more challenging. However, the cognitive model has the clear advantage in its inherent feedback loop.

3 An Additional Classification

We observe that there is a further classification of ITSs, and specifically those that constructed on the cognitive model. This additional subdivide is predicated on the source and substrate of their knowledge domain. While hardly trivial, there are domains in which declarative knowledge is well established and the procedures for deriving and manipulating facts are well known. Disciplines such as mathematics and the sciences are in this area. Their rules and knowledge construction can be described by human experts and crafted into ontologies[2] that can be used to built a knowledge base for an ITS. It's no coincidence that the most successful and widely known tutors in existence today provide training in mathematics and the sciences. Projects discussed in the literature include the PUMP Algbra Tutor Project, a partnership between Carnegie Mellon University and the Pittsburgh School System; SHERLOCK, a U.S. Air Force initiative to train jet plane mechanics; AutoTutor, a Physics instruction system at the University of Memphis; and CIRCSIM-Tutor, a natural language ITS project at the Illinois Institute of Technology, which teaches 1st year Medical students about circulatory system pressure. These systems are 'successful' because they encompass clearly defined rules and facts [9] [11].

In other domain areas in which content and knowledge is more unstructured, constructing an ontology is more difficult [28]. This is both the opportunity and challenge of the World Wide Web. An almost unlimited amount of data can be found there, but its minimal organization makes it hard to locate and use information efficiently. This is the issue that the 'Semantic Web'[3] is intended to redress [13], though the degree of uncertainty associated with web content makes this an arduous undertaking [18]. Still, the web is an unequalled source of material, and can be mined as a knowledge base for an ITS. We propose, then, to prototype an ITS that helps teach adult learners to read by using content from the web as source material.

Reading is a complex activity that typically takes years to master, but is a foundational skill in education and in the workplace. Without this skill, young adults can never hope to obtain the educational levels that President Obama stated are

[2] Ontologies are formal representations of knowledge within a domain. They define a vocabulary and semantics to describe the concepts within a domain and the interrelationships between those concepts [13]. More concretely for this discussion, an ontology is a text-based construct of reference/knowledge that is built with an ontology representation language by a domain expert; and can be consulted by intelligent agents as part of their knowledge base [10]. They are conceptually similar in purpose to XML. A simple example, decribed in the OIL (Ontology Inference Layer) ontology representation language, would be [10]:

```
class-def defined herbivore
subclass-of animal, NOT carnivore
slot-contraint eats
value-type plant
OR (slot-constraint is-part-of has-value plant)
```

A number of ontology representation languages have been created, with perhaps the most 'successful' being OWL (Web Ontology Language), which became a W3C recommendation in February 2004 [20]. Typically, domain experts will use ontology authoring tools such as Protege-2000 (http://protege.stanford.edu/) to create and modify ontologies, as their syntatic complexity makes hand coding error prone and tedious. Developing ontologies is time consuming and very expensive [23], and so a significant amount of research is ongoing to find ways to automate the process [37].

[3] The term 'Semantic Web' was coined by Tim Berners-Lee and describes the technologies and mechanics that will allow machines, and specifically intelligent agents, to understand the meaning, the 'semantics', of information on the web [4]. This is an area of much active research.

essential in his commencement speech. Nevertheless, this remains an ongoing problem in post secondary education. A 2004 U.S. Department of Education study reported that 42% of 1st year students in public two-year institutions needed remediation [38]. At Northern Virginia Community College, the second largest school of its kind in the nation, and situation in one of the country's best educationed regions; over 60% of traditionally aged college students require remediation in reading [24]. There are numerous reasons why so many students come out of high school reading poorly. Social promotions and lack of adequate diagnosis in K12 impact student performance [27]; as do school district retention efforts (school systems 'dumb down' their programs to reduce student dropout). Additionally, a reluctance to inflict a sense of 'low self-esteem' on students [5]; and the simple fact that more students are enrolling in colleges today than in previous generations [43] all contribute to a situation that now needs to be addressed on an ongoing basis.

The use of a machine based tutor can help in aleviating this educational and social problem, by providing reading level appropriate material and assessments for students to practice. There are currently a number of machine based tutoring systems with ITS characteristics, but none appear to use the web as source of reading material. The use of 'canned' material can be problematic, as the content may be of no interest to the student and subsequently discourage additional practice. [29], [30].

4 Towards an Intelligent Reading Tutor

We envision a Cognitive model ITS in which remedial students select topics of personal interest, such as Sports news, or that have some utility, like want ads. A repository in the ITS would then be checked for matching material and, if found, presented to the student. Otherwise, the system would dispatch an agent to retrieve candidate documents from the web and place them into a database. This process would be ongoing. In the database the documents would be checked for reading level difficulty and semantically annotated with the ITS's 'priming' ontology – a basic set of patterns and responses that will provide a substrate for subsequent assessments. Because we are not attempting to map complex domain knowledge about the document contents, we believe that machine annotation will be possible. The material will then be annotated with Artificial Intelligence Markup Language (AIML), an XML compliant language that is used to create life-like dialog for an A.L.I.C.E chatbot [1]. We expect that this will enable the ITS to use a chatbot[4] for assessment, which will be informal and conversational. A possible use scenario would be:

1. Student selects reading material, which is fetched from database
2. The reading material is preannotated with agent generated AIML statements that ask the most fundamental of questions, such as 'Is this article about X' and 'When do the events talked about happen?'

[4] Chatbots, chatterbots, and conversational agents are 'talking' computers with antecendents in the research of Alan Turing. They are software constructs that, through various mechanisms used to acquire the appearance of natural language understanding, provide an interactive conversation with human users. The first actual implementation was 'ELIZA', developed at MIT in 1966 by Joseph Weizenbaum; with subsequent agents created to interact in commerce, education, and entertainment, including Second Life. [44]

3. Using a simple web interface, the student will read the selected material and answer the chatbot's questions. We will explore the feasibility of using a Baysian network to analyze the probability that the student's responses are correct.
4. The student's 'correct' responses will be used to formulate additional AIML statements. Answers marked as 'incorrect' will be flagged for review by a human expert. The student will be aware that he or she is 'training' the chatbot to understand the article being read, and is thereby contributing to a community of readers, in support of a constructivist or social/situational learning process.

Obviously, the chatbot cannot truly ascertain whether or not the student actually comprehends the material read, but we will look for emerging patterns in the student responses indicative of student learning – one of which will be the 'success' of subsequent readers in responding to the chatbot's questions. Scoring will then be dispatched to the agent that will maintain student profiling (and a human instructor for any arbitration), so that future reading selections are more finely tuned to the student's reading level and interest. We will also study the chatbot dialog to determine whether this type of unstructured communication might be useful in creating more complex ontologies.

The ITS we are proposing is not intended to replace human to human interaction and instruction. Learning is a highly social activity, especially in one as fundamental as reading comprehension. We wish to examine the interesting ramifications such an ITS might have on human-computer teaching and learning support, but ultimately, we hope to provide a tool that adults can use to improve their reading.

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