The Effective and Efficient of an Online Intelligent Tutoring System Using Machine Learning Algorithm

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Abstract

This paper is aimed at developing an Intelligent Tutoring System that provides immediate and customized instruction or feedback to learners, usually without intervention from a human being (teacher). The research was motivated by the need to enhance effective and efficient learning, thereby increasing learning capacities'. The objective of this paper is to generate videos and provide materials needed to tutor an individual on particular areas, provide questions and answers section after every lesson, as well as provide an instant feedback system to express satisfaction or lay complaints. It also aids an individual to learn from any location at his/her convenience as the system runs online. The machine learning algorithm is adapted to developing this system as it aids effective analysis of the above problem using a series of well defined steps that builds upon each other. The development is done using technology such as html, css and JavaScript for its frontend; PHP for its backend and the MySQL database for data collection. The expected result will be an Intelligent Tutoring System that will improve learning without the need for human intervention.

Keywords: *Online intelligent, Tutoring system, Machine learning algorithm*

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Background to the Study

Technologies to support learning and education, such as Intelligent Tutoring Systems (ITS), have a long history in artificial intelligence. AI methods have advanced considerably since those early days, and so have intelligent tutoring systems. Today, Intelligent Tutoring Systems are in widespread use in colleges and higher institution, as such enhancing the student learning experience (Graesser *et al.,* 2005). As a specific example, Cognitive Tutor mathematics courses are in regular use, about two-days a week, by 600,000 students a year in 2600 middle or high schools, and full-year evaluation studies of Cognitive Tutor Algebra have demonstrated better student learning compared to traditional algebra courses (Ritter et al. 2007).

Computers have been employed to achieve a variety of educational goals since the early 1960s. Some of these goals include automated testing and routine drill and practice tasks that had been mechanized with earlier technologies, as far back as the thirties. Other computer assisted instructional programs engage the students in challenging and entertaining reasoning tasks and capitalize on multimedia capabilities to present information (Ford, 2008). Computer- based instruction has successfully penetrated all education and training markets: home, schools, universities, business, and government, but remains far from the modal educational experience. In the early 1970s a few researchers defined a new and ambitious goal for computer-based instruction. They adopted the human tutor as their educational model and sought to apply artificial intelligence techniques to realize this model in "intelligent" computer- based instruction. Personal human tutors provide a highly efficient learning environment (Ford, 2008) and have been estimated to increase mean achievement outcomes by as much as two standard deviations.

The goal of intelligent tutoring systems (ITSs) would be to engage the students in sustained reasoning activity and to interact with the student based on a deep understanding of the student's behavior. If such systems realize even half the impact of human tutors, the payoff for society promised to be substantial. An Intelligent Tutoring System (ITS) is a computer system that aims to provide immediate and customized instruction or feedback to learners (Nkambou et al, 2010), usually without intervention from a human teacher. ITSs have the common goal of enabling learning in a meaningful and effective manner by using a variety of computing technologies. There are many examples of ITSs being used in both formal education and professional settings in which they have demonstrated their capabilities and limitations. There is a close relationship between intelligent tutoring, cognitive learning theories and design; and there is ongoing research to improve the effectiveness of ITS. An ITS aims to solve the problem of over-dependency of students over teachers for quality education. It aims to provide access to high quality education to each and every student, thus reforming the entire education system. While there has been a sustained research effort in the application of artificial intelligence to education over the past twenty-five years with some notable success stories, intelligent tutoring has had relatively little impact on education and training in the world. There are several reasons for this lack of penetration. Intelligent tutoring systems are expensive to develop and until relatively recently, the necessary computing power was expensive to deploy. However, we believe that an even more important reason can be traced to the ontogeny of the field and the consequences for soft ware evaluation. The creative vision of intelligent computer tutors has largely arisen among artificial intelligence researchers rather than education specialists. Researchers recognized that intelligent tutoring systems are a rich and important natural environment in which to deploy and improve Al algorithms. We have outlined elsewhere a variety of consequences that de rive from this history in Al, (Ritter et al, 2007) but the bottom line is that intelligent tutoring systems are generally evaluated according to artificial intelligence criteria; the coverage of the systems in interpreting and responding to student behaviors rather than with respect to a cost/benefit analysis educational effectiveness.

Objectives of the Study

The general objective of the paper is to develop an efficient Intelligent Tutoring System that will enhance learning without the need for human intervention.

The specific objectives include;

i. Create a database to store the details of all registered individuals.
ii. Generate videos and available materials that can tutor an individual on particular fields.
iii. Provide question and answers section after every lesson to test the capability of a student.
iv. Provide an instant feedback system to make suggestions and lay complaints.

Significance of the Study

This paper will help to drastically improve learning and as such, reduce the over-dependence of students on teachers for quality education. People can learn at their own convenience and without being constrained to geographical location.

Methodology

Machine Learning and Data-Driven ITS Development

Historically, most intelligent tutoring systems (ITS) have been built through extensive knowledge engineering, and ideally cognitive task analysis, to develop models of student and expert skill and performance. These models are then used to generate hints and feedback (inner loop of Figure 1.1). In particular, two classes of effective tutors, cognitive tutors and constraint-based tutors, rely on knowledge representations, "production rules" or "constraints" that require extensive programming, expertise and often empirical research to develop (Cen *et al.,* 2013). In contrast, data-driven methods can enable more rapid development of new intelligent tutoring systems. We now present different data-driven symbolic and/or statistical machine learning approaches for automated or semi-automated development of the key components and functionalities of intelligent tutoring systems as illustrated in Figures 1.1.

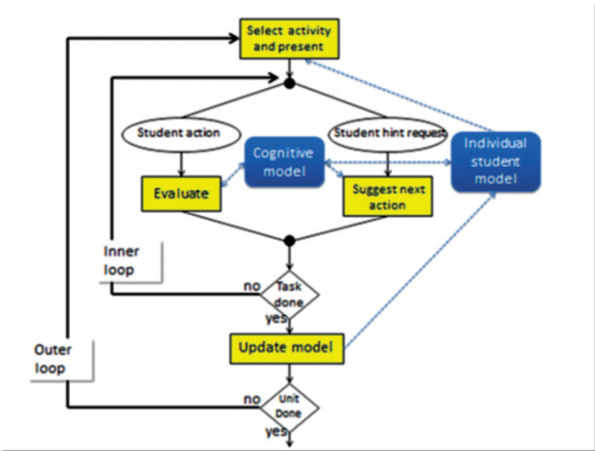

Figure 1: Functions of Intelligent Tutoring Systems
Source: Cen *et al.,* 2013

The figure 1.1 above describes the key components of Intelligent Tutoring Systems. Intelligent Tutoring Systems both guide students through a curriculum of instructional activities in an outer loop, and monitor step-by-step progress on an activity within an inner loop (Li *et al.,* 2012). As shown in Figure 1.1, the outer loop starts with selecting and presenting an activity to the student. Such activities are often multi-step problems to solve, but may also include interactions in a simulation, game, or a dialogue. Once an activity is selected, the inner loop takes over and, as shown in Figure 1.1, persists until the student has completed the activity. Within the inner loop, a tutor must decipher and evaluate each student action given the context of prior actions and a cognitive model of student reasoning and performance. The tutor uses the cognitive model to evaluate this action (in the context of a plan) and determines it is incorrect. In addition to evaluating student actions (the left branch of the inner loop in Figure 1.1), an intelligent tutor can also suggest a next action when a student is stuck (the right branch). This suggestion may come in the form of a series of as-needed hints that get increasingly specific. To perform the evaluate and suggest functions, the tutor uses a cognitive model, that represents possible solutions to the activity, infers how a student's input may relate to common misunderstandings, and predicts what feedback or hints will best help the student complete the activity.

SimStudent is a theory of student learning instantiated in a software tool that facilitates the development of cognitive models (Li *et al.,* 2012). A primary use is to allow non-AI-programmers to “program by tutoring” to create the central cognitive model component of an ITS. In this approach, authors first use Cognitive Tutor Authoring Tools (Aleven *et al.,* 2009) to create a graphical user interface which students will use to solve tasks (e.g., a table of rows for steps in an algebra equation solution). The author iteratively enters tasks into the interface (e.g., an equation to solve) and then evokes SimStudent to solve each task. Initially, SimStudent has no relevant productions, so asks the author to demonstrate a step. The demonstration is used to induce a candidate production rule for accomplishing the step. On future steps, previously induced production rules (which may be overly general) are used to generate candidate next steps and the author gives yes-no feedback on the correctness of the step. When the author states the step is incorrect, SimStudent relearns the production rule given the past history of demonstrations and feedback it has received and tries again until it either gets positive feedback or runs out of options. In the latter case, it asks the author for a demonstration of that step and induces a new production rule.

Li *et al.* (2012) explained that SimStudent employs multiple AI and machine learning techniques to learn a rule-based production system. Example problem and solution steps are used by probabilistic context-free grammar learning to generalize a hierarchical state representation that production rules manipulate. If part of each production rule is acquired using a version space search for generalizing information retrieval paths and inductive logic programming for learning preconditions, which refine correctness and search control? If part of production rules is acquired by an inductive search of function compositions that are consistent with prior action records. The acquired production system serves as the cognitive model component of an ITS that is used for all of its functions: evaluate, suggest, update, and select. SimStudent has been applied to learn cognitive models in many domains including algebra equation solving, multi-column addition and subtraction, and fraction addition.

Finding
A database and a query is embedded in a procedure were to develop the Intelligent Tutoring System that aims to provide immediate and customized instruction or feedback to learners, usually without intervention from a human teacher.

Conclusion
ITS is not a new term, but the problem is still actual. In addition to the continuing work on ITS, one important research issue is to use methodologies of AI as a theoretical base of the ITS, as well as learning theory, instructional design, instructional strategies, pedagogy, and teaching methods. This connection can open new perspectives in e-learning research area. Seeing no really usable practical results, ITS is still perceived by many as a technology of the future, but the rapid growth of learning software and artificial intelligence is making it a viable option.

Recommendations
This paper should be implemented in all departments in higher as sole dependence on teachers for a better education would be curtailed.

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