Design Perspectives of Intelligent Tutoring System

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Abstract. Intelligent Tutoring Systems (ITSs) have come a long way, since their inception decades ago. Its prospects have revolutionized e-Learning, curriculum instructions and workplace training. The field has witnessed significant developments towards many possible directions and as a result, numerous ITSs have been developed to date. Recent tutoring systems have moved from research labs to classrooms [1]. However, it is still a costly affair and lacks established standards. Human learning phenomena are very complex and itself is an ongoing research activity right through the history of mankind. This paper attempts to identify some key instructional/learning aspects that must be addressed while designing a successful tutoring system. In this regard, we have reviewed some of the well-known ITS design principles and report an analysis of their success in modelling the learning/instructional ingredients.

Keywords: Intelligent Tutoring System, Student Modelling, Domain Knowledge, Learning ingredients, Emotion, ICAI

1 Introduction

Given a rich intellectual history of decades, ITSs have already drawn the attention, funding, and research largely from disciplines such as computer science (AI), psychology (cognition) and education and training. Starting from the early days of Computer Aided Instruction (CAI), the field has come across a great success and the recent tutoring systems have claimed to achieve success in real world applications as well. However, their success is still limited mainly because it takes a lot of development time (generally 200 hours of development time for one hour of teaching/instructions) and thus many researchers even describe the ITS development as notoriously costly.

Any software having some degree of intelligent behaviour and used for the purpose of addressing individualized learning/instruction to a considerable extent is referred to as ITS or ICAI. However, human learning is a very complex phenomenon and is being investigated through the lenses of psychologists, psychiatrists, educationist, cognitive scientist and various others. Thus, the success of a tutoring system depends heavily on our ability to understand and model
these factors through the four basic ITS modules like domain, pedagogy, student and interface. An ITS may be very much domain rich but adopts a poor policy of providing feedback [26]; while another may be good at feedback but pays a little attention towards student's affective states as well as to well-deserved individualized instruction [17]. An ideal tutoring system needs to be developed keeping in mind possibly all the aspects and thus ITS research has to be highly envisioned/advocated interdisciplinary in nature. However, most of the existing tutoring systems lack one or more of these aspects. In the next section, we try to enlist the major requirements of a full-fledged ITS, as identified by various experts. We have studied some of the existing tutoring systems and reported which aspects of learning are being successfully addressed by each of them and the technology used.

2 Instruction

In a real classroom, an expert human teacher who is rich in domain knowledge explains the concepts to the students using various tools. Evaluations are conducted to test the mastery of the student over the subject (mostly through final exam). During these interactions, the teacher tries to assess and model individual student behaviour to accordingly decide upon the pedagogical strategy. A tutoring system should attempt to mimic the best of the collectively human teachers while putting major effort on individualized attention, because this is where teacher fails or falls short to deliver due to time and other constraints.

An ITS attempts to achieve this goal by the use of various Artificial Intelligence (AI) techniques and studying human learning psychology. An ITS generally has a domain module to store the information to be taught, student module to store various information regarding the student, pedagogical module to control the learning process and a communication module. In the following discussions, we describe some of the key research directions on the ITS development which can be the building blocks for future research on tutoring systems.

3 Knowledge Representation

Domain model contains a representation of the information to be taught, provides input into the expert module, and ultimately is used to produce detailed feedback, guide problem selection/generation, and as a basis for the student model [28]. The domain model may take many forms, depending on the knowledge representation used, the domain it represents, and the level of granularity. A major chunk of ITS development time is supposedly consumed in accomplishing such ingredients.

Over the years, many artificial Intelligence (AI) techniques have been used for knowledge representation in ITSs. Some of them are Semantic Web, Bayesian Networks (BN), Neural Networks (ANN), Case Based Reasoning (CBR), Symbolic Rules, Fuzzy Logic and some Hybrid approaches. A few important ones are described briefly as follows:
3.1 Ontology and the Semantic Web

Semantic Web opens a number of new doors and multiplies the prospects of Web-based education [8]. It is considered a suitable platform for implementing e-learning systems as they provide mechanisms for developing ontologies for learning, the semantic annotation of materials, their combination to define courses and its evaluation [9]. Ontologies have become a standard knowledge representation technology after the emergence of the Semantic Web together with Semantic Web Services and the Semantic Grid. In the structure of ITS, the use of ontology largely focuses on operationally defined learning objects (LO). Anderson [2] identifies the three fundamental requirements of educational semantic web as:

- The capacity for effective information storage and retrieval.
- Capacity for non-human autonomous agents to augment the learning and information retrieval of human beings.
- The capacity of the Internet to support, extend and expand communications capabilities of humans in multiple formats across the bounds of time and space.

3.2 Hybrid Rule Based Technique

Prentzas et, al. applied a hybrid approach called Neurule [16]. Neurules are a type of hybrid rules integrating symbolic rules with neurocomputing. The system models the students’ knowledge state and skills; based on this information, constructs lesson plans; and selects the appropriate course units for teaching each individual user [26]. Neurules improve the performance of symbolic rules and require fewer computations in order to derive the inferences. This makes them suitable for web-based ITSs because the Web imposes additional time constraints [26]. Neurules are functionally independent units. So it is easy to add/remove neurules without making any changes in the knowledge base. But, one of their major drawbacks is the difficulty in acquiring rules through the interaction with experts. Methods based on decision trees construct rules from training examples and deal with this problem. Another drawback is the inability to draw conclusions when the value of one or more conditions is unknown.

3.3 Artificial Neural Network (ANN)

During the last few years, artificial neural networks have been used quite often in the development of expert systems. Some of their advantages are the ability to obtain knowledge from training examples (with better generalization than the rules produced from decision trees), the high level of efficiency, the ability to reach conclusions based on partially known inputs and the ability to represent complex and imprecise knowledge[26]. However, their primary disadvantage is the fact that they lack the naturalness and modularity of symbolic rules. The knowledge encompassed in neural networks is in most cases incomprehensible.
The limitations of the above mentioned techniques indicates that none of them can fully address all the issues related to knowledge representation. We need to have a standard generic template based domain module which can simply be filled each time by a subject expert and get a quickly developed ITS ready to use. In Cognitive tutors, the domain model consists of low-level production rules that completely describe the expected student behaviour down to atomic thought components while Constraint-based systems describe the possible valid states that an answer may occupy.

4 Student modelling

Student module plays a very important role in ITSs and stores information about each individual student such as his current state of the domain knowledge, history, and other pedagogical aspects. Numerous modelling approaches have been devised over the years, such as overlay modelling, enumerative bug modelling, generative/reconstructive modelling, constraint-based modelling, as well as some other successful hybrid approaches. Each of them intended to achieve a particular goal in student modelling and thus the content of student models varies widely [36]. We should be clear about what aspects of the student to model while working on a specific tutoring system. Two prominent approaches are being described and analyzed as follows:

4.1 Cognitive vs. Constraint Based Tutoring

Two of the most popular techniques are cognitive tutoring (also called model tracing (MT)) and constraint based modelling (CBM). The learning theories that underlie these two approaches are: ACT-R (MT) and “learning from performance errors” (CBM) [21]. MT tutors represent domain knowledge as production rules while CBM tutors represent domain knowledge in a declarative form.

Cognitive tutors [17] have been developed for a number of domains including algebra, geometry and LISP. They employ immediate feedback, i.e. react to each step the student makes while solving a problem. An error is detected either when a student step does not match any rule, or it does match one of the buggy rules, which represent typical mistakes.

Constraint-Based Modelling (CBM) arises from Ohlsson’s theory of learning from performance errors [24]. “The process of learning from errors consists of two phases: error recognition and error correction”. A student needs declarative knowledge to detect an error. If the student does not possess such declarative knowledge, the ITS plays the role of a mentor and inform him about the mistake. A carefully designed sequence of feedback messages that reflects the action of a human teacher helps the student to overcome problems in his/her knowledge. Examples of tutors developed through CBM are SQL-Tutor [21], CAPIT [18], KERMIT [32], and NORMIT [20].

Model tracing tutors force students to follow a fixed set of desirable approaches to problem solving [34]. But CBM neither imposes nor supports any
particular strategy, since it evaluates the current state in problem solving. Cognitive Tutors typically offer immediate feedback, while constraint-based tutors provide feedback on demand [22].

Another important issue is the completeness of the knowledge base. In model tracing, an incomplete knowledge base may mean that there are some correct or buggy rules missing. Cognitive Tutor developers work hard to avoid it, but it is possible that a correct rule is missing in such a case, and that the student’s step is actually correct. Creating constraint-based modelling systems tend to require less time and effort, but the result tends to be less comprehensive in terms of specific advice-giving capabilities [22]. Creating model-tracing tutors tends to require more time and effort, but results in more specific advice-giving capabilities [22].

To conclude with, both approaches have their strengths and weaknesses. Model tracing is an excellent choice for domains where appropriate problem solving strategies are well-defined, and where comprehensive feedback is desirable. On the other hand, CBM offers a workable alternative when such strategies are not available or appropriate, or there is too little time or resources to build a model-tracing knowledge base. However, CBM and model-tracing are viable, complementary approaches to building real-world tutors.

4.2 Neuro-Fuzzy Inference

A fuzzy neural network or neuro-fuzzy system is a learning machine that finds the parameters of a fuzzy system by exploiting approximation techniques from neural networks [6]. This neuro-fuzzy synergism is a hybrid approach for student modelling and has got a lot of researchers’ attentions. Here, Fuzzy logic techniques are used to provide human-like approximate diagnosis of student’s knowledge and cognitive abilities. Neural networks are trained to imitate human teacher’s decisions regarding student’s characteristics and fixed weight neural networks are used to evaluate and aggregate membership functions [30].

ITS interaction data are measured and then transformed into linguistic terms. This is a four step process: a fuzzifier, a fuzzy relational system, a fuzzy aggregation network and a defuzzifier (Figure 1). The student model is implemented as a set of connectionist networks, each one processing the fuzzy information regarding student’s behaviour.

![Diagram](Fig. 1. The four stages of the Neuro-Fuzzy model [28])
i. The connectionist network fuzzifies inputs that contribute to the evaluation of a specific characteristic of the student.

ii. Neural networks are trained to realize fuzzy relations operated with the max-min composition. These relations represent the estimation of human tutors to the degree of association between an observed response and a student characteristic.

iii. A fuzzy aggregation network is applied for the generation of the final fuzzy set.

iv. A back propagation neural network is trained to decide regarding the different characteristics like knowledge level, misconceptions, etc. of a student by classifying him to different levels (categories).

5 Evaluation and Feedback

Evaluation and Feedback Simply solving problems through ITS without any feedback may not improve skills or deeper understanding of the subject. Learning occurs best when the learner receives feedback from the system as it improves the learning process on the basis of a continuous assessment of results, the analysis of their quality and performance and feedback for necessary corrections. Generally feedback encourages desired learning behavior and discourages undesired one, allows understanding how successfully the learner acts, whether he/she applies relevant knowledge and provides opportunities to remove misconceptions. Cognitive tutors try to check if the student’s current solution is on track and, if not, assess what has gone wrong while constraint-based systems evaluate the student solutions against the constraints to determine what concepts have been misunderstood. A few prominent aspects are described as follows:

5.1 Hint vs. Detailed Feedback

It might be useful to provide a detailed feedback after a session is complete or when a module is finished in order to provide an effective learning experience [3]. Learner would get confidence on the ITS through this as it would lead to a more humanly touch in the learning process. On the other hand, ITS can simply provide hints when error is being made during problem solving. However, the insufficient amount of information in a hint can cause frustration and desire to request the subsequent hints without attempts to solve a problem by the learner.

5.2 Immediate vs. Delayed Feedback

An ITS called E-tutor [27] was evaluated to check the benefit of ‘scaffolding’, ‘hint-on-demand’ and ‘delayed feedback’. E-tutor with dialog led to better learning and represents a more interactive tutor than the “hints on demand” control condition. Also, it was observed that honours students do the best in the delayed feedback condition and regular students do best in the scaffolding + hints
condition. Students who come in with less knowledge benefit more from the scaffolding + hints than students who come in with more knowledge. Students who come in with more knowledge benefit from the delayed feedback relatively more than the other groups.

With the LISP tutor, Corbett and Anderson [6] showed that immediate feedback leads to three times reductions in the learning time compared to delayed feedback condition. In addition to cognitive benefits, there are also motivational benefits of timely feedback. Students know right away that they are making progress and having success at a challenging task. Further, because the system does not make a big deal out of errors, students do not feel the social stigma associated with making an error in class or on homework.

6 Affective factors

Curiosity is considered as an indicator of motivation level [14, 31] and learners with more intrinsic interest display greater levels of pleasure, active involvement [15, 33], task persistence [19] and lower levels of boredom [19], anxiety and anger [25]. The role of affective states in learning was investigated from the perspective of a constructivist learning framework through an ITS called AutoTutor [10–12], which teaches introductory computer literacy using natural language based tutorial dialogue. It tracked the learners' emotions during interactions and these emotions were then correlated with learning outcome measures as shown in table 1. Six different affect states observed include frustration, boredom, flow, confusion, eureka and neutral [7], are described in a tabular form as shown below:

<table>
<thead>
<tr>
<th>Affective States</th>
<th>Learning outcome/Measuring criteria (example)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frustration</td>
<td>Student is angry or agitated</td>
</tr>
<tr>
<td>Boredom</td>
<td>Uninterested in the activity or respond slowly to the system</td>
</tr>
<tr>
<td>Flow</td>
<td>Shows interest, pays attention and responds quickly</td>
</tr>
<tr>
<td>Confusion</td>
<td>Puzzled, not sure how to continue or struggling to understand the material</td>
</tr>
<tr>
<td>Eureka</td>
<td>Shows transition from a state of confusion to a state of intense interest, like typing in answers very quickly after a period of inactivity</td>
</tr>
<tr>
<td>Neutral</td>
<td>Void of emotion and no facial features or emotions could be determined</td>
</tr>
</tbody>
</table>

7 Analysis

During the ITS evolution, many approaches have been followed by researchers from various disciplines. In the foregoing descriptions and discussions, we have
tried to cover some of the possible methodologies for Intelligent Tutoring System. Domain knowledge module, student modeling, role of feedback and some affective factors are briefly addressed. An extensive study of all the possible directions in ITS development is beyond the scope of this paper. Following are some of the very important factors that need to be incorporated while working towards a well designed tutoring system [23, 29, 5, 4]:

Table 2. Popular ITS Design Criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Target to achieve</th>
</tr>
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<tbody>
<tr>
<td>Feedback</td>
<td>Should be individualized based on student motivation level</td>
</tr>
<tr>
<td>Difficulty of learning material</td>
<td>Based on learner’s performance on the easier questions.</td>
</tr>
<tr>
<td>Development costs</td>
<td>Should be lower. (Researchers are often forced to design architecture from scratch. Pattern language [13, 35] looks promising and may reduce the development time)</td>
</tr>
<tr>
<td>Complexity to develop AI algorithms</td>
<td>Lower. (Complexity related to AI techniques makes the task difficult).</td>
</tr>
<tr>
<td>Integration of AI techniques</td>
<td>To be chosen carefully. (The development and maintenance of hybrid AI systems is hard)</td>
</tr>
<tr>
<td>Interactive tools</td>
<td>Higher (student’s Interaction with the ITS as well as with the peer increases learning).</td>
</tr>
<tr>
<td>Scalability</td>
<td>Higher (ready to be implemented on the web, i.e., to a larger audience).</td>
</tr>
<tr>
<td>Sharing materials with other ITSs</td>
<td>Should be compatible</td>
</tr>
<tr>
<td>Consistence of metadata</td>
<td>Yes (Domain ontologies have to be constructed and maintained)</td>
</tr>
<tr>
<td>Extensibility</td>
<td>Yes (extensibility to add new functionalities and extensibility of standards to use more expressive languages)</td>
</tr>
<tr>
<td>Interoperability</td>
<td>Yes (should have the the interoperability of data and services)</td>
</tr>
<tr>
<td>Maintenance costs</td>
<td>Should be lower</td>
</tr>
</tbody>
</table>

Majority of the research work on ITS design concentrates merely on the creation of a domain knowledge base, teach the domain knowledge and implement a simple feedback policy. They do not put much effort on indentifying the instructional ingredients and their role in successful teaching/learning. But it is high time that the goal for ITS research should be to understand successful instruction procedure. We need to know how an ITS should react in situations like: if a student gets bored during learning; how to gain his interest back in learning; how to treat a learner who likes to be challenged always; how to deal with learners who dislike theory and learn through problem solving, etc. Similarly, a look through a finer granularity level would be to consider, for example, what font size and color to use while designing a user interface form as this may affect the learner’s mood. Existing systems do not emphasize much on these and thus there is not much difference between e-Learning and ITSs. This may
be the reason why most of the ITSs have stayed in the realm of research labs. The success of ITSs depends on our effort to identify instructional ingredients and taking a broad interdisciplinary coverage in tutoring system research. The following points give an idea about the current research trends of ITS/ICAI and the reason for their limited success in practical settings:

A. Current review of the field shows that mostly people from the field of AI are the active workers. However, as mentioned earlier, to model a human teacher in the classroom, we should try to learn various micro-level factors/instructional ingredients. This demands the active shareholding participation from educationists, computer scientists, psychologists and various others. But, at present only people from various fields of computer science are trying to find the application of their works in ITS developments without trying to understand the human learning/instruction process.

B. The semantic web is showing a promising direction that can be used to leverage our effort towards domain modelling particularly in today’s web-based situation.

C. Although there are lots of work being done on ITSs, very few studies work on the effective aspects of student during instruction and how to address them.

8 Conclusions

An attempt has been made to describe the important design specifications for a generic intelligent tutoring system through the review of some of the prominent works on ITS developments and their results. Various learning/instructional ingredients have been identified and their effectiveness is explained. For example, the benefit of immediate vs. delayed feedback, small hints vs. detailed help etc. are compared. ITS development is a costly affair in terms of cost and complexity. The need to develop standardized reusable components which can be used to develop any domain specific tutor in a short span of time and in a cost effective manner is emphasized. Thus, we believe that this paper serves in-depth specifications for a novice ITS designer. In future works, we plan to model a general purpose tutoring architecture emphasizing the role of various factors during a learner’s interaction with the ITS.

References


