Predicting Learning Styles in a Conversational Intelligent Tutoring System

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Abstract. This paper presents Oscar, a conversational intelligent tutoring system (CITS) which dynamically predicts and adapts to a student's learning style throughout the tutoring conversation. Oscar aims to mimic a human tutor to improve the effectiveness of the learning experience by leading a natural language tutorial and modifying the tutoring style to suit an individual's learning style. Intelligent solution analysis and support have been incorporated to help students establish a deeper understanding of the topic and boost confidence. Oscar CITS with its natural dialogue interface and classroom tutorial style is more intuitive to learners than learning systems designed specifically to capture learning styles. An initial study is reported which produced encouraging results in predicting several learning styles and positive test score improvements in all students across the sample.

Keywords: Intelligent Tutoring System, Conversational Agent, Learning Style

Introduction

Intelligent Tutoring Systems (ITS) use intelligent technologies to improve the effectiveness of the student learning experience [1]. ITS can help students by providing personalised tutoring at a time and a pace to suit the individual, and offering the facility to explore in depth topics which have not been fully understood. Such benefits may not be offered in a face-to-face class full of students with varying needs and levels of expertise. Most ITS present personalised content according to student knowledge or characteristics [2], but few attempt to truly mimic a human tutor by leading the tutorial and engaging the learner in discussion [3]. A conversational intelligent tutoring system (CITS) employs a conversational agent interface to allow discourse in natural language. Human tutors pick up cues from students which indicate their learning preferences, and adapt their tutoring style accordingly. Learning styles model the way in which groups of students learn most effectively, for example by trial and error or observation [4]. Some ITS adapt tutoring to an individual's learning style, determined by using a formal questionnaire [5] or analysing learner behaviour [6]. However, there are no tutor-led CITS which can predict and adapt to learning style during the tutoring session like a human tutor.

The research presented in this paper aims to develop a CITS which can dynamically predict and adapt to a learner's learning style during the tutoring session. Rather than specifically designing a learning interface to capture the learning style of the user as in [6], the focus of the research has been on imitating a human tutor and determining if it is possible to predict learning style from the student's behaviour and interaction throughout the tutorial. Whilst this considerably increases the complexity of the task of predicting learning style, conversational interfaces are intuitive to use and an ability to discuss a problem can aid the deeper learning of a topic.

In this paper, section 2 introduces some background concepts of the Index of Learning Styles [7], intelligent tutoring systems and conversational agents. Section 3 describes the Oscar CITS and presents its architecture. Section 4 outlines the experimental methodology and a sample learner dialogue. Section 5 includes the results and discussion, and Section 6 describes the conclusions and future work.

Background

The Index of Learning Styles

In their Index of Learning Styles (ILS) model [7], Felder and Silverman described the learning styles in engineering education and suggested different teaching styles to address learners' needs. The ILS model defines four separate dimensions of preferred learning style, each relating to a step in the process of receiving and processing information as follows:

Perception – learners are *sensory* or *intuitive* depending on the type of information they prefer to perceive (e.g. external (sensory) or internal (intuitive)).

Input – learners are *visual* or *verbal* according to the way they prefer to receive external information (e.g. diagrams (visual) or explanations (verbal)).

Processing – learners are *active* or *reflective* according to the way information is converted into knowledge (e.g. discussion (active) or introspective consideration).

Understanding – learners are *sequential* or *global* depending on their progression towards understanding (e.g. continual steps (sequential) or large jumps (global)).

The ILS uses a self-assessment questionnaire with 11 questions per learning style dimension, resulting in a score for each dimension. Each learning style dimension may be thought of as an axis with the opposite learning styles at either end (e.g. Visual versus Verbal), and the ILS questionnaire score places each learner on the axis according to the strength of their preferred learning style. There are 16 (2^4) learning styles overall (an example being sensory/visual/active/sequential).

The ILS model was chosen for the Oscar CITS as it describes engineering students, who will make up the initial experimental groups. However, the Oscar CITS is not restricted to the ILS model and its modular structure allows Oscar to be adapted to incorporate other learning style models, such as Honey and Mumford [4].

ILS in Practice

Whilst the ILS defines a formal questionnaire for students to identify their learning style, in practice it is not common for lecturers to use a formal tool when planning to teach a course. A lecturer will typically use their knowledge and experience of different groups of learners to incorporate different types of material and activities. During tutorials, lecturers will intuitively pick up informal behavioural cues from students which indicate their level of understanding and their preferred learning style, and use these observations to adapt their teaching style accordingly.

Felder and Silverman described typical learner behaviours and associated teaching styles for each learning style in their model. This information is useful when informally grouping types of learners and also when building the ILS model into a CITS. A summary of the behaviour descriptions is given below:

Perception. Sensing learners prefer facts and experimentation, are patient with detail, comfortable with symbols (e.g. words) and careful but slow. Intuitive learners prefer principles and theories, are bored by detail, uncomfortable with symbols and quick but careless.

Input. Visual learners remember what they see, like pictures and diagrams and prefer visual demonstration. Verbal learners remember what they hear, like discussion and prefer verbal explanation.

Processing. Active learners like to do something with information (discuss or test), they are experimentalists and process information by testing an idea. Reflective learners like to examine and manipulate information internally, are theoreticians and process information by postulating explanations and drawing analogies.

Understanding. Sequential learners like to follow a linear reasoning process, can work with partially understood material and prefer information presented in a steady progression of complexity. Global learners make intuitive leaps, have difficulty working with material they have not understood and prefer to jump directly to complex material.

The Oscar CITS was designed to imitate a human tutor-led tutorial rather than being developed specifically to predict learning styles. Therefore Oscar requires knowledge of the theory of learning styles and their associated behaviours rather than the diagnostic questionnaire in order to imitate the practice of a human tutor.

Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) are computer-based educational systems which employ intelligent technologies to provide individualised instruction. There are three main approaches to intelligent tutoring: curriculum sequencing, intelligent solution analysis and problem solving support [1]. Curriculum sequencing systems present students with learning material in a sequence and style best suited to their needs [2]. Intelligent solution analysis gives detailed feedback to the student on incomplete or erroneous solutions [8], and problem solving support techniques present intelligent assistance to reach a solution [9]. Curriculum sequencing alone is little better than selecting chapters from a book, but by including intelligent solution analysis and problem solving support an ITS can get close to offering support available from a human tutor. Although combining these three technologies adds benefits such as a more effective learning experience and improved student confidence and motivation, few ITS incorporate all three approaches as they are complex and time-consuming to develop. The Oscar CITS presented in this paper will include all three intelligent technologies by personalising learning material and conversing with the student, helping them to construct knowledge and learn from their mistakes.

Personalisation in ITS was traditionally based on student knowledge but has now been extended to include user affect, such as emotion [10], personality [11] and learning style [12]. Some ITS capture learning styles using a formal questionnaire [5], [13] whilst others analyse a student's behaviour within the ITS [6], [14]. Completing questionnaires is onerous for students, who do not always lend enough attention to complete them accurately. Predicting learning style using a history of student behaviour means adaptation is delayed until several modules have been completed, and also a student's learning style may change over time or for different topics. EDUCE [15] and WELSA [16] both estimate learning style dynamically for curriculum sequencing, but do not include a conversational interface or incorporate other intelligent tutoring technologies. The Oscar CITS will dynamically predict learning style throughout the tutoring conversation and adapt its intelligent tutoring style to suit the learning style.

Conversational Agents

Conversational agents (CAs) allow people to interact with computer systems using natural language dialogues. CA interfaces are intuitive to use and have been engaged effectively in many applications, such as web-based guidance [17], database interfaces [18] and intelligent tutoring systems [19]. Most ITS do not have a natural language interface as CAs are complex and time-consuming to develop, however to adequately mimic a human tutor an ITS should support the construction of knowledge through discussion [20]. The complexity of developing conversational tutors means that CAs are often included in ITS to help with the learning management system (e.g. how to use the system) [21] rather than conduct the tutoring. Two ITS with CA tutors are AutoTutor [3], which helps students construct knowledge about computer literacy and physics, and CIRCSIM-tutor [22], which engages students in discussion to solve physiology problems. Unlike the Oscar CITS, neither AutoTutor or CIRCSIM-tutor consider learning styles during tutoring.

There are three main approaches to developing CAs: using natural language processing [23], pattern matching [24] or artificial intelligence [25] methods. The Oscar CITS adopts a pattern matching CA, which is most reliable in coping with student utterances including grammatically incorrect or incomplete language (as commonly found in student communications such as chat programs and SMS text messaging). Pattern matching CA systems use an algorithm to match key words and phrases within a user utterance to a set of pattern-based rules. A rule normally consists of an identification, a set of stimulus patterns, the rule's current status and a response pattern. The algorithm decides the best fitting rule to fire, thus producing the CA response. There are usually numerous patterns in a given context, leading to many hundreds of rules in the CA's knowledge base, which demonstrates the complexity and time required to script rules for a CA (and the reason CAs are rare in ITS).

Oscar Conversational Intelligent Tutoring System

The Oscar CITS is a conversational intelligent tutoring system designed to dynamically predict a student's learning style during a tutoring conversation, and to adapt the tutoring style to suit the individual learner. Oscar's pedagogical aim is to provide the learner with the most appropriate learning material for their learning style leading to a more effective learning experience and a deeper understanding of the topic. Rather than being designed with the purpose of picking up learning styles (such as [6]), the Oscar CITS attempts to mimic a human tutor by leading a two-way discussion and using cues from the student dialogue and behaviour to predict and adapt to their learning style. Oscar's natural dialogue interface and classroom tutorial style are intuitive to learners, enabling them to draw on experience to feel more comfortable and confident in using the CITS. Oscar CITS is a personal tutor which can answer questions, provide hints and assistance using natural dialogue, and which favours learning material to suit each individual's learning style. The Oscar CITS offers 24-hour personalised learning support at a fixed cost. Oscar's intelligent approach includes presenting learning material in the sequence and style most suited to the individual's learning style (curriculum sequencing), analysing and giving feedback on incomplete and erroneous solutions (intelligent solution analysis) and giving intelligent hints and discussing questions (problem solving support). By combining all three intelligent technologies with a conversational interface, Oscar's intelligent support aims to build the confidence of the learner and improve motivation and deep understanding of the subject.

Oscar CITS Architecture

Fig. 1 shows the modular structure of the Oscar CITS, which has been designed with component reuse in mind. This structure allows alternative knowledge bases and conversational agent scripts to be simply 'plugged in' to the system to adapt the tutoring to new subjects.

The central *controller* manages communication between all components and the user interaction. The *graphical user interface* (GUI) displays a webpage which provides instructions, displays questionnaires, tests, images, documents, interactive movies and the chat area used to send communication to and from the user. The *CA* receives natural language text and information about the topic and learning style and generates a natural language response using a database of scripts. The *student model* holds information about the student, such as their identifier and password, level of knowledge, topics visited, test scores and learning style. The *knowledge base* component manages course information, such as syllabus, related tests and categorised teaching material, which is accessed from a tutor material database. Teaching material is categorised according to teaching style, which is related to learning style. Finally, the *learning styles* component receives information from the CA, GUI, knowledge base and student model, and accesses the learning styles database to predict a student's learning style. Further details of the development of the Oscar CITS can be found in [26].

Fig. . Oscar CITS structure

Experimental Methodology

An initial study was conducted to investigate the Oscar CITS prediction of learning style. For the study, the Oscar CITS was scripted to deliver a revision tutorial for an undergraduate Sequential Query Language (SQL) course. There were 17 hypotheses to be tested, covering the learner's behaviour and use of language during the tutorial.

The results covering three hypotheses for the perception (Sensor/Intuitor) and input (Visual/Verbal) ILS dimensions are reported in [26]. These experiments considered the student learning path (accuracy of 70% for Sensor/Intuitor, 50% for Visual/Verbal), the number of interactions (accuracy of 70% for Visual/Verbal) and reading time (accuracy of 70% for Visual/Verbal).

This paper will focus on two hypotheses (H) which relate to the processing (Active/Reflective) and understanding (Sequential/Global) ILS learning dimensions:

H1: a student's learning path through the tutorial is indicative of learning style.

H2: choosing to be guided through a process (or not) is indicative of learning style.

Twenty people were chosen whose first language was English and who had previous experience of an undergraduate SQL course and various levels of SQL expertise. Each person registered anonymously for the Oscar CITS and was then asked to complete the formal ILS questionnaire followed by a multiple choice test to assess existing SQL knowledge. Next, each person engaged in a personalised tutoring conversation led by Oscar. During the tutoring, each learner answered questions and completed various tasks in SQL. Depending on their level of knowledge, students were exposed to various resources and given hints and help as required. At the end of the tutorial, each person was asked to complete the same multiple choice test to measure their learning over the session. Various log files recorded the dialogue, timings, knowledge and other factors throughout the tutorial.

Table . Aspects of ILS behaviour built into the Oscar CITS

Active	**Reflective**
Do something with information: discuss/ explain/ test.	Examine and manipulate information introspectively.
Experimentalists.	Theoreticians.
Process information by setting up an experiment to test an idea, or try out on a colleague.	Process information by postulating explanations/ interpretations, drawing analogies, formulating models.
Sequential	**Global**
Follow linear reasoning processes.	Make intuitive leaps.
Can work with material they have only partially or superficially understood.	Difficulty working with material not understood.
Learn best when information is presented in a steady progression of complexity and difficulty.	Sometimes better to jump directly to more complex and difficult material.

The tutorial log files were analysed and compared to the results of the ILS questionnaire to establish whether the information was indicative of learning style. For H1, aspects of the student's behaviour had been mapped to the ILS model (see Table 1) and learning style scores were incremented depending on the student's interaction during the tutorial. The final scores for each end of the ILS dimension were compared to give the overall learning style tendency for that dimension, e.g. for the processing dimension if the score for Active was higher than the score for Reflective, the learner was considered to be Active. For H2, the learner's approach to writing queries was considered. Two questions involved writing complex SQL queries to solve a problem, and learners who attempted the query straight away were classed as Global learners whilst students who asked for guidance were classed as Sequential learners. Section 5 presents and discusses the results of the experiments.

Example Learner Dialogue

Table 2 shows part of a student's tutoring dialogue logged during this experiment. In utterance 33, Oscar continues a question about datatypes. The student gives the wrong datatype in utterance 34, and next Oscar indicates that the answer is wrong and gives the student a second chance to answer in case of spelling errors, repeating the question. In utterance 36 the student tries again, still with the wrong answer. Oscar gives feedback that the answer is wrong (utterance 37), and helps by showing an image of the most common datatypes to see if the student is able to pick out the required answer. In this action, Oscar is helping the student learn by reminding them of the common datatypes and asking them to think about the correct datatype rather than simply telling them the answer. In utterance 38 the student enters the correct datatype, extended to include the decimal places, and Oscar then confirms that they have the right answer and repeats the solution to reinforce the knowledge.

Table . Example tutoring dialogue snippet logged during the experiment.

Utterance	Dialogue
33. Oscar>	Now, in our books table suppose we want to store the price of the book where the maximum price of a book is 99.99. What would be the datatype?
34. Student>	VARCHAR2
35. Oscar>	I'm sorry, that's wrong. Check your spelling and try again - type in the datatype for book price (with a maximum of 99.99).
36. Student>	VARCHAR2 MAX 99.99
37. Oscar>	That's still wrong. Take a look at the table of common datatypes - can you now type in the datatype for book-price where the maximum price is 99.99?
38. Student>	NUMBER(2,2)
39. Oscar>	That's correct - we need a datatype of NUMBER(2,2) in order to show the decimal point in book-price, with a maximum of 99.99.

Results and Discussion

Table 3 shows the results of the experiments. The ILS questionnaire results showed that the split of learning styles for each dimension across the sample was nearly equal, with 9 Active and 11 Reflective learners and 10 Sequential and 10 Global learners.

Table . Experimental results

Hypothesis	Learning Style	Prediction Accuracy
H1 – learning path	Active	100%
	Reflective	0%
	Sequential	80%
	Global	40%
H2 – approach to queries	Sequential	80%
	Global	75%

For H1, the prediction of learning style by Oscar CITS depended on the learner's path through the tutorial. When compared to the ILS questionnaire results, Oscar accurately predicted an Active learning style in 100% of cases, however it was not possible to predict a Reflective learning style. The characteristics of reflective learners described in the ILS model suggest that they spend time after learning to reflect on what they know and put it together as knowledge. As this activity happens after learning, it may not be possible to predict a reflective learning style during a tutorial. However, these results are not intended to be taken in isolation, and the development of an algorithm to combine different analyses may improve accuracy. Sequential learners were predicted with an accuracy of 80%, however Oscar was not able to predict Global learners using this method, with an accuracy of only 40%.

H2 relates to the Sequential/Global learning style dimension, as it considers a student's approach to writing complex queries. The results of this measure were better than H1, with Oscar's prediction of Global learners the same at 80% accuracy, but of Sequential learners much improved at 75% accuracy. Overall, user feedback after completing the tutorial indicated that Oscar was well received, understandable and helpful. Of the 18 students who did not achieve full marks in the pre-test, all of them improved their test scores, with an average improvement of 25%.

Conclusions and Further Work

This paper has presented Oscar, a novel CITS which implicitly predicts and adapts to a student's learning style during a tutoring conversation. Oscar CITS imitates a human tutor by leading a tutorial in natural language, intelligently analysing solutions and offering problem solving support rather than simply presenting the answers. In providing the learner with the most appropriate learning material for their learning style, Oscar CITS aims to improve the effectiveness of the learning experience and provoke a deeper understanding of the topic, and thus improve confidence. An effective, personalised online tutor such as Oscar CITS could support class-based courses and help to widen access through distance learning.

The results of the initial study are promising, with an accuracy of predicting learning style on the Sequential/Global dimension of 75-80%. The Oscar CITS performance on the Active/Reflective dimension was interesting, with a 100% accuracy in predicting Active learners, but no ability to predict Reflective learners at all. When considering the ILS description of reflective learners this is perhaps not surprising – reflective learners prefer to examine and manipulate information introspectively, behaviour that would be most difficult to capture during a tutorial over a short period of time. It may therefore be concluded from this experiment that it is not possible to predict reflective learners in the Oscar CITS, however a further study with a larger sample size is required before drawing any firm conclusions. Further experiments with a larger group are currently being undertaken, and an algorithm is being developed to combine several of the 17 aspects of behaviour to improve the accuracy of learning style prediction. Overall, the results have shown that the Oscar CITS tutoring seemed to help learning as all students who did not initially achieve full marks improved their test scores by an average of 25%.

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