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A conversational intelligent tutoring system to automatically predict learning styles

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Abstract

This paper proposes a generic methodology and architecture for developing a novel conversational intelligent tutoring system (CITS) called Oscar that leads a tutoring conversation and dynamically predicts and adapts to a student's learning style. Oscar aims to mimic a human tutor by implicitly modelling the learning style during tutoring, and personalising the tutorial to boost confidence and improve the effectiveness of the learning experience. Learners can intuitively explore and discuss topics in natural language, helping to establish a deeper understanding of the topic. The Oscar CITS methodology and architecture are independent of the learning styles model and tutoring subject domain. Oscar CITS was implemented using the Index of Learning Styles (ILS) model (Felder & Silverman 1988) to deliver an SQL tutorial. Empirical studies involving real students have validated the prediction of learning styles in a real-world teaching/learning environment. The results showed that all learning styles in the ILS model were successfully predicted from a natural language tutoring conversation, with an accuracy of 61-100%. Participants also found Oscar's tutoring helpful and achieved an average learning gain of 13%.

Keywords:

Architectures for educational technology system
Human-computer interface
Intelligent tutoring systems
Interactive learning environments
Teaching/learning strategies

1. Introduction

The widespread use of computers and access to the Internet has created many opportunities for online education, such as improving distance-learning and classroom support. Intelligent Tutoring Systems (ITS) extend traditional content-delivery computerised learning systems by adding intelligence to improve the effectiveness of a learner's experience (Brusilovsky & Peylo 2003). This normally involves personalising tutoring using factors such as learner knowledge, emotion or learning style to alter the sequence and style of learning material. Most ITS are hyperlink menu based (Cha, Kim, Park, Yoon, Jung & Lee 2006; Klasnja-Milicevic, Vesin, Ivanovic & Budimac 2011; Popescu 2010; Wang, Wang & Huang 2008) and adapt the tutoring by reordering menu items (Garcia, Amandi, Schiaffino & Campo 2007), allowing learners to manage their own study at a time and place to suit them. This experience has more in common with computerised textbooks than classroom tutorials, where human tutors direct the learning. An extension of ITS is Conversational Intelligent Tutoring Systems (CITS), which integrate natural language interfaces rather than menus, allowing learners to explore topics through discussion and to construct knowledge as they would in the classroom. However, it is a complex and time consuming task to develop a CITS which can converse naturally. Consequently only a few CITS exist at present (D'Mello, Lehman, Sullins, Daigle, Combs, Vogt *et al* 2010; Arnott, Hastings & Allbritton 2008; Sarrafzadeh, Alexander, Dadgostar, Fan & Bigdeli 2008).

A CITS that can imitate a human tutor by leading an adaptive tutorial conversation uses a familiar format which can help improve learner confidence and motivation, leading to a better learning experience. Human tutors adapt their tutoring style and content based on cues they pick up from learners, such as their level of understanding and learning style. Learning styles model the way groups of people prefer to learn (Felder & Silverman 1988; Hsieh, Jang & Hwang 2011), for example by active experimentation or by observation. Some ITS adapt tutoring to an individual's learning style, either determined using a formal questionnaire (Papanikolaou, Grigoriadou, Kornilakis & Magoulas 2003) or by analysing learner behaviour (Kelly & Tangney 2006). However, there are no tutor-led CITS that can predict and adapt to learning style during the tutoring session like a human tutor.

This paper describes the architecture and methodology for creating a novel CITS called Oscar that dynamically predicts and adapts to an individual's preferred learning style during a tutorial conversation. The aim of the research was to imitate a human tutor by using knowledge of learning styles and learner behaviour to predict learning style rather than an interface specifically designed to capture learning styles, as in (Cha et al 2006). Whilst this considerably increases the complexity of predicting learning styles, conversational interfaces are intuitive to use and the discussion of problems can prompt a deeper understanding of topics. This paper also

describes a series of experiments that aim to determine if it is possible to predict learning style from a learner's behaviour during a tutorial conversation, and thus validate the proposed methodology and architecture.

In this paper, section 2 introduces some background and related work of intelligent tutoring systems, conversational agents and the Index of Learning Styles (Felder & Silverman 1988). Section 3 introduces the Oscar CITS, and Sections 4 and 5 describe a generic methodology and architecture for creating an Oscar CITS. Section 6 describes the implementation of Oscar CITS and the real-world experiments conducted to investigate the prediction of learning styles from a natural language tutoring dialogue. Section 7 presents the experimental results and discussion and Section 8 outlines the conclusions and future work.

2. Related work
2.1. Intelligent tutoring systems
Computerised learning systems were traditionally information-delivery systems developed by converting tutor or distance-learning material into a computerised format (Brooks, Greer, Melis & Ullrich 2006). The popularity of the Internet has enhanced the opportunities for e-learning, however most online systems are still teacher-centred and take little account of individual learner needs (Spallek 2003). Within the field of computerised learning systems, adaptive educational systems attempt to meet the needs of different students by offering individualised learning (Brusilovsky & Peylo 2003). Intelligent Tutoring Systems (ITS) are adaptive systems which use intelligent technologies to personalise learning according to individual student characteristics, such as knowledge of the subject, mood and emotion (D'Mello et al. 2010) and learning style (Yannibelli, Godoy & Amandi 2006).

There are three main approaches to intelligent tutoring (Brusilovsky & Peylo 2003):
Curriculum sequencing introduces adaptation by presenting students with learning material in a sequence and style best suited to their needs (Klasnja-Milicevic *et al* 2011).
Intelligent solution analysis adds intelligence to ITS by giving students detailed feedback on incomplete or erroneous solutions, helping them learn from their mistakes (Mitrovic 2003).
Problem solving support techniques offer learners intelligent assistance to reach a solution (Melis, Andres, Budenbender, Frishauf, Goguadse, Libbrecht *et al* 2001).

Curriculum sequencing is the most widely used technique (Brusilovsky and Peylo 2003). Traditionally ITS adapt to existing student knowledge but more recently learner affect factors have been incorporated, such as emotion (Ammar, Neji, Alimi & Gouarderes 2010), personality (Leontidis & Halatsis 2009) and learning style (Popescu 2010). Few ITS incorporate all three techniques as they are complex and time-consuming to develop, but the Oscar CITS presented in this paper will incorporate all three intelligent technologies by personalising learning material and discussing problems and solutions with students.

ITS are normally menu or hyperlink based, with choices re-ordered or ranked to recommend a particular sequence to learners (Klasnja-Milicevic et al 2011; Garcia et al 2007). Whilst this design simplifies the capture of learner behaviour and choices, learners are really being assisted in self-learning rather than tutored, which is little different from recommending chapters of a book. CITS address this issue by employing natural language interfaces whose intuitive, dialogue-based tutoring is more comparable to classroom tutorials (Chi, Siler, Jeong, Yamauchi & Hausmann 2001; D'Mello et al 2010; Sarrafzadeh et al 2008). However, despite their more instinctive, teacher-led learning experience (which supports the construction of knowledge adopted by human tutors), it is difficult to automate natural conversations and so CITS are uncommon (D'Mello et al 2010; Woo Woo, Evens, Freedman, Glass, Seop Shim, Zhang et al 2006; Sarrafzadeh et al 2008).

ITS that adapt to learning styles capture them using a formal questionnaire (Papanikolaou et al 2003) or by analysing learner behaviour (Cha et al 2006; Garcia et al 2007). Whilst questionnaires are the simplest measure of learning styles, learners find them onerous and may not lend enough time or attention to complete them accurately (Yannibelli, Godoy & Amandi 2006). Implicitly modelling learning styles by analysing learner behaviour history (Garcia et al 2007) removes the requirement for a questionnaire, but delays adaptation until several modules have been completed. Also, this method does not incorporate changes in learning style which may occur over time or for different topics. EDUCE (Kelly & Tangney 2006) and WELSA (Popescu 2010) both estimate learning style dynamically for curriculum sequencing, but do not include a conversational interface or 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 predicted.

2.2. Conversational agents
Conversational agents (CAs) are computer programs which allow people to communicate with computer systems using natural language (O'Shea, Bandar & Crockett 2011). CA interfaces are intuitive to use, and have been used effectively in many applications, such as web-based guidance (Latham, Crockett & Bandar 2010), database interfaces (Pudner, Crockett & Bandar 2007) and tutoring (D'Mello et al 2010). CAs can add natural

dialogue to ITS, but are used infrequently as they are complex and time-consuming to develop, requiring expertise in the scripting of dialogues (O'Shea, Bandar & Crockett 2011). ITS which aim to mimic a human tutor (such as Oscar CITS) need CA interfaces to support the construction of knowledge through discussion (Chi et al 2001).

Textual CAs usually adopt a pattern matching (Michie 2001) or semantic based (Li, Bandar, McLean & O'Shea 2004; Khoury, Karray & Kamel 2008) approach. Semantic-based CAs seek to understand the meaning of the natural language whereas pattern-matching CAs use an algorithm to match key words and phrases from the input to a set of pattern-based rules (Pudner, Crockett & Bandar 2007). As pattern matching CAs match key words within an utterance, they do not require grammatically correct or complete input. However, there are usually numerous patterns in a given context (Sammut 2001), leading to many hundreds of rules in the CA's knowledge base, which demonstrates the complexity and time required to script rules for a pattern-matching CA. A pattern matching CA was adopted for Oscar CITS as it must cope with grammatically incomplete or incorrect utterances that are commonly found in text-based chat by students.

2.3. Index of learning styles
The Index of Learning Styles (ILS) model (Felder & Silverman 1988) describes the teaching and learning styles in engineering education. The ILS model represents an individual's learning style as points along four dimensions that indicate both the strength and the nature of their learning style preference. Each learning style dimension relates to a step in the process of receiving and processing of information, as illustrated in Fig. 1. The ILS is assessed using a 44-question forced-choice questionnaire (11 questions per learning style dimension), that assigns a style and score for each dimension.

Fig. 1. ILS dimensions.
In addition to the formal assessment questionnaire, the ILS model describes typical learner behaviours that can be used to informally group types of learners. The ILS model was adopted when implementing the Oscar CITS as engineering students make up the initial experimental groups. However, the Oscar CITS is generic and its flexible modular structure does not restrict the choice of learning styles model to the ILS.

3. Oscar CITS
The Oscar CITS is a novel conversational intelligent tutoring system which dynamically predicts a student's learning style during a tutoring conversation, and adapts its tutoring style appropriately. Oscar's pedagogical aim is to provide the learner with the most appropriate learning material for their learning style to promote 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 Cha et al 2006) the Oscar CITS aims to imitate a human tutor by leading a two-way discussion and using cues from the student's dialogue and behaviour to predict and adapt to their learning style. Oscar CITS incorporates intelligent technologies to sequence the curriculum according to learner knowledge and learning style, intelligently analyse solutions and give hints to assist learners in constructing knowledge. Oscar's natural language interface and classroom tutorial style are modelled on classroom tutorials (Crown copyright 2004), enabling learners to draw on their experience of face-to-face tutoring to feel more comfortable and confident in using the CITS. Oscar CITS is an online 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.

General descriptions of Oscar CITS, including its implementation, example learner dialogue and the results of initial studies in predicting learning styles, have been reported in Latham, Crockett, McLean, Edmonds & O'Shea (2010) and Latham, Crockett, McLean & Edmonds (2010). The Oscar CITS adaptation strategies were described in Latham, Crockett, McLean & Edmonds (2011), which reported empirical results showing that students whose learning material matched their learning styles performed 12% better than those with unmatched material.

The rest of this paper will describe an original methodology and architecture for creating an Oscar CITS and the experiments conducted to investigate its success in predicting learning styles in a real teaching/learning environment.

4. Predicting learning styles through natural language dialogue
CITS are complex and time-consuming to develop, requiring expertise in knowledge engineering (the capture and formatting of expert knowledge (O'Shea, Bandar & Crockett 2011), such as tutoring, learning styles and domain knowledge) and CA scripting. Formalising the development of a CITS which can be applied to different learning styles models and tutoring domains will help to speed up the development. This section presents a methodology for creating an Oscar CITS which can predict learning styles from a natural language dialogue.
4.1. Methodology for creating Oscar CITS

The methodology for creating an Oscar CITS consists of three phases as shown in Table 1. The first phase of the methodology relates to the creation of the learning styles module and the second phase to the tutorial subject domain. The third phase incorporates the learning styles predictor and tutorial conversation into a CITS architecture. Each phase will now be described.

Table 1.

3-Phase methodology for creating Oscar CITS.

Phase 1: Create the Learning Styles Predictor Module

    1.1. Select a Learning Styles Model
          a.   Reduce the learning styles model if necessary
          b.   Extract the behaviour characteristics
    1.2. Map learning style behaviour to the conversational tutoring style
    1.3. Analyse the learning styles model for language traits
    1.4. Adapt the generic logic rules to predict learning styles

Phase 2: Design a Tutorial Conversation

    2.1. Capture the tutorial scenario and questions (including movies, voice, images, examples, etc.) from human tutors in a specific domain
    2.2. Determine the conversational structure/style
    2.3. Map tutorial questions onto the generic question styles and templates
    2.4. Script CA natural language dialogue for each tutorial question using the 3-level model
    2.5. Link tutorial dialogue to logic rules through CA variables

Phase 3: Construct the CITS Architecture

4.2. Methodology phase 1: create the learning styles predictor module

4.2.1. Step 1.1: select a learning styles model

The first step in creating the learning styles predictor module requires a learning styles model (Felder & Silverman 1988, Honey & Mumford 1992) to be selected. To illustrate and validate Phase 1 of the methodology, the ILS model (Felder & Silverman 1988) was selected as the initial experimental group will be university engineering students. The ILS questionnaire contains 44 questions, which is too many to incorporate into a single tutoring session without being onerous for students. To reduce the ILS model, a study was undertaken to investigate which were the best predictor questions (Latham, Crockett, McLean & Edmonds 2009). The study of 103 completed ILS questionnaires found that 17 questions predicted the overall learning style result in at least 75% of cases, with the top three questions predicting the result in 84% of cases. The resulting subset of the best ILS predictor questions formed the basis of further analysis in developing the Oscar CITS strategy for the prediction of learning styles.

The ILS model describes typical behaviour characteristics for each learning style. For clarity and ease of analysis, the behaviour characteristics were extracted from the ILS model and summarised in a table of common learner behaviour (Table 2).

Table 2.
Typical learner behaviour characteristics extracted from the ILS model.

Sensor	Intuitor
Prefer facts, data, experimentation	Prefer principles and theories
Prefer solving problems using standard methods	Prefer innovation
Dislike surprises	Dislike repetition
Patient with detail	Bored by detail
Do not like complications	Welcome complications
Good at memorising facts	Good at grasping new concepts
Careful but slow	Quick but careless
Comfortable with symbols (eg. words)	Uncomfortable with symbols

Visual	Verbal
Remember what they see	Remember what they hear, or what they hear then say
Like pictures, diagrams, flow charts, time lines, films	Like discussion
Prefer visual demonstration	Prefer verbal explanation
	Learn by explaining to others

Active	Reflective
Do something with information – discuss/explain/test	Examine and manipulate information introspectively
Active experimentation	Reflective observation
Do not learn much in passive situations (lectures)	Do not learn much if no chance to think (lectures)
Work well in groups	Work better alone
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
Strong in convergent thinking and analysis	Divergent thinking and synthesis
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

4.2.2. Step 1.2: map learning style behaviour to the conversational tutoring style

To map learning style behaviour to the conversational tutoring style, each behaviour characteristic extracted in step 1.1b (in Table 2) is assessed using the following criteria:

1. Is it possible to map the behaviour trait onto a two-way online conversational tutorial?
2. How could the behaviour trait be used to implicitly predict learning styles?

All behaviour traits that can be mapped onto a tutorial conversation and used to predict learning styles should be included in a summary table along with a description of how they could be used to predict learning styles (Table 3).

Table 3.
Aspects of learner behaviour for predicting learning styles from a natural language tutorial dialogue.

Behaviour by Learning Style	Implication for Learning Style Prediction
Sensor	
Prefer facts, data, experimentation	Perform better in questions with facts, examples and results
Dislike surprises	Prefer introductions, overviews and working in a sequential predictable order
Careful but slow	Consider timing interactions and number of errors
Comfortable with symbols (e.g. words)	Consider amount of discussion with the tutor
Intuitor	
Prefer principles and theories	Perform better in theory questions
Dislike repetition	Present information usually only once
Bored by detail	Perform better where information is summarised
Quick but careless	Consider timing interactions and number of errors
Uncomfortable with symbols	Consider amount of discussion with the tutor
Visual	
Remember what they see	Perform better in questions with diagrams, pictures, movies
Like pictures, diagrams, flow charts, time lines, films	Perform better in questions with pictures, diagrams, flow charts, time lines, films
Prefer visual demonstration	Perform better in questions with visual walkthroughs rather than textual explanation
Verbal	
Remember what they hear, or what they hear then say	Perform better in questions with movies and sound clips
Like discussion	Consider amount of discussion with the tutor
Prefer verbal explanation	Perform better in questions with movies, sound clips and tutor explanations
Learn by explaining to others	Consider amount of discussion with the tutor
Active	
Do something with information – discuss/explain/test	Consider amount of discussion with the tutor; perform better in questions with practical exercises
Experimentalists	Perform better in practical questions
Process information by setting up an experiment to test an idea, or try out on a colleague	Consider amount of discussion with the tutor; perform better in questions with practical exercises
Reflective	Consider amount of discussion with the tutor
Examine and manipulate information introspectively	Perform better in theoretical questions
Theoreticians	
Sequential	Perform better when information presented in a steady progression of complexity and difficulty
Follow linear reasoning processes	Perform better when information presented in a steady progression of complexity and difficulty
Learn best when information is presented in a steady progression of complexity and difficulty	
Global	Perform better where information is summarised and when they can attempt problems in one go
Sometimes better to jump directly to more complex and difficult material	

Next, it is necessary to decide which aspects of behaviour need to be captured during a tutoring conversation. Each behaviour trait in Table 3 was studied in turn and the list was reorganised according to behaviour, with similar behaviours grouped together. For example, as both Verbal and Active learners like discussion, they were grouped together under the 'like discussion' behaviour category. Next, this list of behaviours was reduced further by considering the behaviour that would need to be captured from a natural language conversation. For example, the 'like discussion' category now became the 'discussion' category and included also the Sensor (like discussion), Intuitor (do not like discussion) and Reflective (do not like discussion) learning styles. The result of this analysis is a list of behaviour cues to be captured during the conversational tutorial that can be used to predict learning style. Table 4 lists the behaviour to be captured during a tutorial conversation in order to predict ILS learning styles, and relates each behaviour variable to the learning styles it may be used to predict.

Table 4.
Learner behaviour cues to be captured during tutoring.

Behaviour variable to be captured	Learning style
Number of discourse interactions	Sensor, Intuitor, Verbal, Active, Reflective
Number of questions asked	Sensor, Intuitor, Verbal, Active, Reflective
Tutorial duration	Sensor, Intuitor,
Reading time	Sensor, Intuitor, Visual, Verbal
Number of errors due to not reading the question	Sensor, Intuitor
Right answer after seeing an image	Visual
Right answer after seeing a movie/walkthrough	Visual, Verbal, Active
Right answer after an explanation of theory	Intuitor
Right answer after seeing an example	Sensor
Choose to be guided through the steps of solving a problem	Sensor, Sequential
Choose to solve a problem straight away	Intuitor, Global
Score for practical questions	Active, Sensor
Score for theoretical questions	Reflective, Intuitor

4.2.3. Step 1.3: analyse the learning styles model for language traits

Mairesse, Walker, Mehl & Moore (2007) showed that it was possible to automatically recognise an individual's personality type using language cues (such as the type of vocabulary used) from conversation and text (essays). As learning style is linked to personality (Coffield, Moseley, Hall & Ecclestone 2004), it may be possible that the type of vocabulary used can indicate an individual's learning style. Özpolat and Akar (2009) mapped a short list of key words to ILS learning styles, and analysed student Internet search terms to successfully predict learning styles for three of the four ILS dimensions. Step 1.3 of the methodology involves analysing the learning styles model to extract any language traits that could be indicative of learning style. The key words list in Ozpolat & Akar (2009) was extended by analysing the descriptions of behaviour traits in the ILS model. Indicative words and phrases used to describe behaviour traits were extracted and mapped to learning styles. This key words list was then expanded using a thesaurus to produce an initial set of key words and phrases that were indicative of learning style. For example, the key word *show* (e.g. "Can you show me an example") indicates a Visual learning style, whereas the keyword *tell* (e.g. "Can you tell me what to do") indicates a Verbal learning style. The process of discovering associations between key words and particular learning styles requires experimentation and analysis of tutoring dialogues, so the content of the list should be tested and expanded by analysing actual tutoring discourse once the Oscar CITS has been developed for a particular domain.

4.2.4. Step 1.4: adapt the generic logic rules to predict learning styles

The final step in phase 1 is to convert the knowledge of the learning styles model (the captured behaviour factors and key words gathered from steps 1.2 and 1.3) into a set of logic rules. The aim of such rules is to continually increment student learning style values as the tutoring conversation takes place. A generic set of 33 logic rules was created using the learner behaviour captured from the ILS (Table 4). As the generic logic rules relate to learner behaviour, the set should be adapted and expanded for different learning styles models that may define other behaviours. Table 5 shows two examples of logic rules developed using the behaviour cues in Table 4 and mapped to the ILS. The first example, rule 1, is generated from the behaviour cue 'Right answer after seeing an image' and is linked to the Visual learning style. If a student does not know the answer, is shown an image and then gets the answer right, this visual presentation has helped their understanding so the Visual learning style value is incremented. Rule 2 is generated from the 'Number of errors due to not reading the question' behaviour, linked to the Intuitor and Visual learning styles. If the answer to a question is given in the explanation text and a student gets the answer wrong, this behaviour indicates they are careless and not comfortable with reading text, so the Intuitor and Visual learning style values are incremented.

Table 5.

Example logic rules to adjust student learning style values based on tutoring conversation.

1. Example rule to test whether presenting information visually helps the student's information perception:
   IF   student shown image/diagram
   AND   student gives correct answer
   THEN   increase VISUAL;

2. Example rule to test how comfortable the student is with words and with detail:
   IF   answer is given in the explanation text
   AND   student does not know the answer
   THEN   increase INTUITOR
   AND   increase VISUAL;

The set of logic rules resulting from this step are to be applied during a tutoring conversation to dynamically predict learning styles.

This section has described the steps in phase 1 of the generic Oscar CITS methodology to create a Learning Styles Predictor module using the ILS model as an example.

4.3. Methodology phase 2: design a tutorial conversation

Phase 2 of the methodology involves capturing the tutorial from human tutors and iteratively developing a tutorial conversation with input from the human tutors. This part of the methodology will be illustrated using an example tutoring domain of the database Sequential Query Language (SQL).

4.3.1. Step 2.1: capture the tutorial scenario and questions (including movies, voice, images, examples, etc.) from human tutors in a specific domain

The first step in designing a tutorial conversation is to capture a tutorial scenario from human tutors. The domain of SQL was selected as the target audience for the pilot study is undergraduate computing students, for whom a Databases course including SQL is compulsory. First, interviews were conducted with undergraduate level database course tutors to identify important SQL concepts for the tutorial syllabus. Ten tutorial questions and a multiple choice question (MCQ) test were devised to cover the learning outcomes of the tutorial. To capture the tutorial scenario, a document was produced in consultation with lecturers that contained a conversation script for each question, including possible learner answers and tutor's responses to these. For each learner response, a further tutor response was written, and so on, until each question in the tutorial had a number of different paths depending on individual learner knowledge and responses. The design of the tutorial

conversation was a time consuming and iterative process. However, by planning and detailing the dialogue at this point, the development of the conversational agent was more efficient. Resources such as examples, movies, images etc. were embedded into the tutorial conversation as appropriate.

4.3.2. Step 2.2: determine the conversational structure/style

A CITS that attempts to mimic a human tutor must be able to manage a tutoring conversation on a number of levels, each with a different goal. Step 2.2 of the methodology determines the structure of the CA tutorial conversation. Drawing on experience of classroom tutorials (Crown copyright 2004), three parts of a tutorial conversation with separate goals were distinguished and a three-level model of a tutorial conversation was designed (Fig. 2). At the highest level (the 'social level'), Oscar CITS needs the ability to maintain a natural language tutorial conversation, and like a human tutor must pick up cues if the learner is not engaging in the tutorial (e.g. use of bad language) and choose to end the session. At the main 'tutoring level', Oscar CITS directs the tutorial, explains topics and asks questions, guiding the learner towards an understanding of the topic. This may involve Oscar CITS giving feedback on erroneous or incomplete solutions (intelligent solution analysis), explaining the topic using different methods if required, such as practical examples (curriculum sequencing) and giving hints to help the learner construct a solution (problem solving support). During a tutorial, learners may discuss a related topic to help their understanding, requiring a deeper 'discussion level' with the ability to discuss and explain a predefined set of Frequently Asked Questions related to the domain.

Fig. 2. 3-Level model of a tutorial conversation.

As part of this step, a list of FAQs and answers should be captured from the human tutors, scripted in natural language and added to the tutorial conversation document.

4.3.3. Step 2.3: map tutorial questions onto the generic question styles and templates

The third step in phase 2 of the methodology links the captured tutorial questions to the behaviour characteristics identified in phase 1 step 1.2. This is done by mapping tutorial questions to the set of generic question styles and templates. During the development of the Learning Styles Predictor module (Phase 1 steps 1.1 and 1.2), questions and behaviour from the ILS model were mapped to a conversational tutoring style. Applying this knowledge, a set of four generic question styles (e.g. practical and theoretical style questions) and two generic question templates were developed. The set of question styles and templates should be expanded when different learning styles models and domains are implemented.

Fig. 3 shows an example generic question template that could be applied to both practical and theoretical question styles. The template is for a question where different kinds of hints are given to learners and information is captured about the type of help that is most effective. In Fig. 3, the question is asked in box 1 and if the learner responds with the correct answer at any point, they are given feedback and taken to the next question (response 2). If the learner does not know the answer or their answer is wrong, Oscar explains the concept and repeats the question (response 3). If the learner still does not know the answer or their answer is wrong, Oscar shows different resources and repeats the question (responses 4, 5 and 6). Finally, if the learner still does not know the correct answer, Oscar tells them the answer, suggesting that they revise the topic (showing additional resource links), then asks if they wish to continue with the tutorial (response 7). If the learner wishes to continue, they are taken to the next question; if not the tutorial is ended.

Fig. 3. Example generic question template with hints.

In this step, tutorial questions are mapped onto the generic styles and templates, with extra resources included as required, and the dialogue updated in the tutorial conversation document.

4.3.4 Step 2.4: script CA natural language dialogue for each tutorial question using the 3-level model

Step 2.4 of the methodology involves creating CA scripts to conduct the tutoring dialogue defined in steps 2.1, 2.2 and 2.3 (and recorded in the tutorial conversation document). This involves first adopting a CA that can capture and receive information using variables, then scripting the conversation using an appropriate scripting language. Convagent Ltd (2005) InfoChat CA was selected as it is a pattern matching CA that allows information to be captured using variables. CA scripts, organised into contexts, were developed for the tutorial based on the tutorial conversation document and applying the 3-level tutorial conversation model. Overall, there were 38 contexts containing around 400 rules written using the InfoChat PatternScript language (Michie & Sammut 2001). An example FAQ rule from one of the tutorial scripts is shown in Table 5. In the rule, a is the activation level used for conflict resolution (Michie 2001); p is the pattern strength followed by the pattern that is matched against the user utterance. r is the CA response. Also seen in the example is the wildcard (*) and

macros (<explain-0>) containing a number of standard patterns that are each matched separately. When the rule fires, the variable *FAQ* is set to 'true' by the *<set> command.

Table 6.
Example CA script: FAQ rule.

```
<Rule-01>
a:0.01
p:50    *<explain-0> *select*
p:50    *select* <explain-0>*
p:50    *<remind-0> *select*
p:50    *select* <remind-0>*
p:50    *<confused-0> *select*
p:50    *select* <confused-0>*
r:      The SQL SELECT command is used to retrieve data from
        one or more database tables. *<set FAQ true>
```

4.3.5. Step 2.5: link tutorial dialogue to logic rules through CA variables
The final step in phase 2 of the methodology links the behaviour captured by the tutorial conversation to the set of logic rules (produced in phase 1) that predict learning styles. Moving through the tutorial conversation document, for each learner behaviour found, annotate the document with the learning style defined in the associated logic rule. The logic rules from Phase 1 (step 1.4) specify which learning styles are to be incremented when particular events occur (such as incrementing the Sensory learning style value after an example is shown). Next, the CA scripts must be updated to capture the behaviour by setting variable values when particular rules fire. Now that the tutorial conversation has been fully scripted for a CA it must be tested and verified by expert human tutors.

This section has described the steps of the generic methodology to design a tutoring conversation illustrated by the development of a tutorial for SQL using the InfoChat CA.
4.4. Methodology phase 3: construct the CITS architecture
Once the learning styles predictor module and the tutorial conversation have been designed, it is necessary to incorporate them into a CITS architecture. The CITS will require a CA that allows information to be passed in and out, a Graphical User Interface (GUI) and a Student Model. The next section will propose a standard Oscar CITS architecture that is generic and incorporates the required components.
5. Oscar CITS architecture
The proposed Oscar CITS architecture is shown in Fig. 4. The Oscar CITS is independent of the learning styles model adopted and the subject domain being taught. As such, the proposed Oscar CITS architecture is modular, allowing individual components to be reused or replaced as necessary. The proposed generic architecture allows alternative tutorial knowledge bases and CA scripts developed following phase 2 of the methodology to be simply 'plugged in' to adapt the tutoring to new subjects. Similarly, different learning styles models may be applied by replacing the Learning Styles Predictor component (created following the methodology phase 1).

Fig. 4. Oscar CITS system architecture
Each component in the proposed architecture will now be briefly described.

- The *Controller* is the central manager of the system, responsible for instantiating objects and system variables, communicating with all components and managing the learner interaction.

- The *Learning Styles Predictor* component receives information from the CA, GUI and student model to predict a student's learning style, using information about learning styles held in a knowledge base. This module is developed following phase 1 of the Oscar CITS methodology.

- The *Student Model* component receives and sends information from and to the controller about the student, such as their level of knowledge, topics visited, test scores and learning style.

- The *Graphical User Interface (GUI)* component is responsible for display, managing events (such as clicking of buttons) and sending communication to and from the user. The display consists of a webpage that provides instructions, displays questionnaires, tests, images, documents, interactive movies and the chat area used to communicate with the user.

- The *Tutorial Knowledge Base* is responsible for managing course information, such as topics and their breakdowns, related tests and teaching material. The tutorial knowledge base receives information and instructions from the GUI, learning styles predictor and CA components via the controller, and sends information to the GUI and CA via the controller.

- The *Conversational Agent* component is responsible for accepting natural language text and information about topic and learning style from the GUI, tutorial knowledge base and learning styles components via the controller, and generating a natural language response. The CA accesses a database of tutorial conversation scripts (related to but not linked to the tutorial knowledge base) in order to match the input to rules that generate a response. The CA records the dialogue in log files that can be accessed by the controller.

A modular, generic architecture and an original, generic methodology have been proposed for creating an Oscar CITS. The Oscar CITS architecture has been designed with component reuse in mind, and can be adapted for different learning styles models by following phase 1 of the Oscar CITS Methodology to develop another learning styles predictor module. Similarly, different subject domains can be applied by following phase 2 of the Oscar CITS Methodology to develop the tutorial conversation. The next section will describe the experiments carried out to validate the proposed Oscar CITS methodology and architecture.

6. Experiments

The Oscar CITS was implemented and tested by real university students in a real teaching/learning environment in order to:

validate the Oscar CITS prediction of learning styles from a natural language tutoring dialogue;

analyse the effectiveness of Oscar CITS as a learning tool;

study the impact of the Oscar CITS natural language tutoring on students.

Oscar CITS was implemented to deliver an SQL revision tutorial by applying the methodology and architecture proposed in sections 4 and 5. First, the ILS model was adopted and analysed following Phase 1 of the Methodology described in section 4 to develop the Learning Styles Predictor module. In the next phase of the Methodology (phase 2) a ten question SQL revision tutorial was captured from university lecturers and the generic tutorial question templates and styles were applied. A 12 question MCQ test was devised to assess the tutorial learning outcomes. The InfoChat pattern-matching CA (Convagent Ltd 2005) was adopted, and the tutorial conversation was scripted using its PatternScript language (Michie & Sammut 2001). The logic rules developed for the Learning Styles Predictor module were then mapped to the CA scripts to ensure that relevant behaviour was captured using variables. In Phase 3 of the methodology, the proposed Oscar CITS architecture was implemented using the .net framework and mySQL, and the Oscar CITS was installed onto a web server. The Oscar CITS is at present available via the Internet to Manchester Metropolitan University (MMU) students. Oscar CITS conducts its tutoring conversations in real time and is currently being used to support a number of undergraduate and postgraduate computing modules within MMU. The Oscar CITS GUI is shown in Fig. 5.

Fig. 5. Oscar CITS

The experiments described in this paper have been selected from a larger study to demonstrate how different types of behaviour may be used to predict learning styles.

6.1. Experimental design

As the aim of the experiments is threefold, the Oscar CITS will be evaluated on three levels:

1. Can Oscar CITS predict learning styles dynamically from a two-way tutoring discourse? How successful is the prediction of learning styles? The Oscar CITS prediction of learning styles will be measured against the results of the ILS questionnaire. The main hypothesis 'it is possible to predict learning style from a two-way tutoring conversation' was broken down into five hypotheses (H) as follows:

    H1: the success of a learner after experiencing a particular style of tutoring is indicative of learning style.

    H2: a lack of attention to detail in answering questions is indicative of learning style.

    H3: choosing to be guided through a process (or not) is indicative of learning style.

    H4: the success of a learner in a particular style of tutoring question (theoretical or practical) is indicative of learning style.

    H5: a learner's reading time is indicative of learning style.

2. Does Oscar CITS successfully tutor learners, i.e. do they learn anything? Learning gain will be evaluated by comparing the MCQ pre-test score (completed before the tutoring conversation begins) to the MCQ post-test score (completed after the tutoring conversation ends) to see whether test scores have improved, as follows:

    Learning_gain = post-test_score – pre-test_score

3. How comfortable and confident do learners feel in using the tutoring system, and would they use Oscar CITS in practice? Satisfaction from the learners' perspective will be determined via a questionnaire

using a set of subjective metrics. The design of the evaluation questionnaire was based on a user satisfaction questionnaire for rating dialogues with text-based CAs (O'Shea, Crockett & Bandar 2011). The questionnaire requires participants to rate aspects of the Oscar CITS tutorial using a six-point Likert scale (which forces participants to express a positive or negative opinion). Additionally, open questions were included to capture positive and negative comments.

Participants
This paper presents results collated from two studies and evaluated on all three levels. The studies had different participants who had no previous experience using Oscar CITS.

Study 1 – An initial pilot study was undertaken to explore whether the implementation of Oscar CITS was successful in tutoring and whether sufficient information was captured to predict learning styles. Ten participants were chosen whose first language was English and who had previous experience of an undergraduate ORACLE SQL course (but with various levels of expertise).

Study 2 – There were 104 participants who had previous experience of an undergraduate SQL course and various levels of SQL expertise. Participants were second and final year undergraduate students on a computer science degree at MMU. The Oscar CITS SQL revision tutorial was integrated into the first teaching week and during the timetabled classes, participants were asked to complete the revision tutorial. In order to promote full completions of the tutorial, participants who completed the Oscar CITS revision tutorial were awarded marks in recognition of their engagement.

6.2. Experimental methodology
Study 1 was a controlled study that took place in an office setting where participants could be unobtrusively observed during their Oscar CITS tutorial. Participants completed the tutorial individually in a single session. Study 2 was undertaken in several computer laboratories. Participants started the Oscar CITS revision tutorial in the laboratories, and those who did not complete the tutorial in a single session were able to continue the revision via the Internet at another time.

Each participant registered with the Oscar CITS anonymously, which involved being assigned a user ID and creating a password, that were recorded in the student model. Next, participants completed the formal ILS questionnaire, also recorded in the student model. Before starting the conversational tutorial, participants completed a pre-tutorial 12 question MCQ test, known as the pre-test, to assess their existing SQL knowledge. The pre-test results were stored in the student model. Next, Oscar CITS directed a two-way conversational SQL revision tutorial that took on average approximately 43 minutes, with each participant following an individual learning path depending on their existing knowledge and the dialogue. During the tutorial, the participant dialogue was recorded in log files along with captured aspects of participant behaviour. There were ten main SQL tutorial questions. At the end of the tutorial, participants completed the same MCQ test (known as the post-test) to assess their learning gain, with the results being stored in the student model. Next, Oscar CITS presented participants with a comparison of their test results (indicating their learning gain) and some feedback on their tutorial performance. Finally, participants were asked to complete a user evaluation questionnaire. For the purpose of the experiments, the participant behaviour data recorded during tutorial interactions was analysed to generate a learning styles prediction after all tutorials were complete (rather than during the tutorial conversation like the full working system). The next section will describe the analysis of participant behaviour for the five reported experiments.

6.2.1. Analysis of participant behaviour
Experiment 1: logic rules
This experiment relates to a participant's individual learning path during the tutorial. During the tutorial, logic rules increment associated learning style scores when particular behaviour occurs. For each ILS dimension the two related learning style scores were compared to give a prediction of learning style for that dimension. For example, for the processing dimension if the score for Active is higher than the score for Reflective, the participant is predicted to be Active. Where scores were equal, the learning style dimension remained unclassified and was excluded from the analysis. To calculate the prediction accuracy, the predicted learning style for each dimension was compared to the ILS questionnaire results. The number of correct predictions for each learning style was counted to produce an accuracy value that is the percentage of correct predictions for each learning style. This experiment tests the hypotheses H1, H2 and H3 and generated prediction accuracies for all learning style dimensions.

Experiment 2: tutorial question style
This experiment considered the style of tutorial questions where participants gave the correct answer by counting the number of correct theoretical and the number of correct practical questions. The number of correct answers of each style was compared, taking into consideration the possible number of correct answers for theoretical and practical questions, using the formula below:

$$\frac{\text{Correct practical questions}}{\text{Total practical questions}} \quad \text{compared to} \quad \frac{\text{Correct theoretical questions}}{\text{Total theoretical questions}}$$

Participants who performed equally well in both styles of question were unclassified and excluded from the analysis. Where participants performed better in practical questions, the Oscar CITS predicted their learning style to be Active and Sensory. Participants who performed better in theoretical questions were predicted to be Reflective and Intuitive. The Oscar CITS prediction was compared to the ILS questionnaire results and the number of correct predictions counted for each learning style, to produce a prediction accuracy percentage. This experiment tests the hypothesis H4 and generated prediction accuracies for the perception (Sensory/Intuitive) and processing (Active/Reflective) ILS dimensions.

Experiment 3: approach to queries
In Experiment 3, the learner's approach to writing queries was considered. Two questions in the tutorial applied a generic question template (methodology step 2.3) with a choice of approach to writing SQL queries to solve a problem. For each question, participants who attempted the query straight away were predicted to be Global learners whilst participants who asked for guidance were predicted to be Sequential learners. Each participant had two predictions, one for each question. The predicted learning style was compared to the ILS questionnaire results, and the number of correct predictions counted for each learning style to produce a prediction accuracy percentage. This experiment tests the hypothesis H3 and generated prediction accuracies for the perception (Sensory/Intuitive) and understanding (Sequential/Global) ILS dimensions.

Experiment 4: attention to detail
One tutorial question applied a generic 'trick question' style (methodology step 2.3), that includes the answer in the explanatory text to test the participant's attention to detail and reading skills. Participants who did not answer the question correctly were predicted to be Visual and Intuitive learners, whereas those who answered correctly were predicted to be Verbal and Sensory learners. The predicted learning style was compared to the ILS questionnaire results, and the correct predictions counted for each learning style to produce a prediction accuracy percentage. This experiment tests the hypothesis H2 and generated prediction accuracies for the perception (Sensory/Intuitive) and the input (Visual/Verbal) ILS dimensions.

Experiment 5: reading time
Experiment 5 considers a participant's aptitude with words by investigating their reading speed. As each learner follows an individual learning path, calculating reading time from the total number of words read over the duration of the tutorial would not produce a fair comparison. The only text common to all participant interactions is the introductory text for the first tutorial question, so reading time was defined as the time taken to read this text. Each participant's reading time was then compared to the average (both mean and median) reading time across the sample. Where a participant had an above average reading time, Oscar CITS predicted they were Sensory and Visual learners, and where they had a below average reading time, they were predicted to be Intuitive and Verbal learners. The predicted learning style was compared to the ILS questionnaire results, and the correct predictions counted for each learning style to produce a prediction accuracy percentage. This experiment tests the hypothesis H5 and generated prediction accuracies for the perception (Sensory/Intuitive) and the input (Visual/Verbal) ILS dimensions.

7. Results and discussion
There were 114 participants over both studies, with 75 participants completing the full revision tutorial. The distribution of learning styles across the 75 participants was approximately equal for all but the Visual/Verbal dimension, which contained many more Visual than Verbal learners. This finding is consistent with the ILS model, which states that "most people of college age and older are visual" (Felder & Silverman 1988). This has implications for the analysis of results for predicting the Visual/Verbal learning styles, as the dataset is so biased towards the Visual learning style. The distribution of the 75 participants is shown in the first row of Table 7 (prior probability). The experimental results will now be discussed.

7.1. Experimental results
Table 7 shows the prediction accuracy results, representing the ability of Oscar CITS to predict a participant's learning style for that experimental measure. Experiments 3, 4 and 5 did not require the completion of the entire tutorial and so the number of participants analysed is higher. The *prior probability* is the accuracy of predicting a learning style based on the distribution of learning styles across the sample. This is included as a fairer comparison than simply using 50% because the spread of learning styles across the sample is not exactly equal. This is particularly true for the Visual/Verbal dimension where 87% of participants are Visual. Each experiment's results will now be discussed.

Table 7.
Experimental results: accuracy of prediction of learning styles.

	n	Sensory	Intuitive	Visual	Verbal	Active	Reflective	Sequential	Global
Prior probability	75	60%	40%	87%	13%	57%	43%	60%	40%
Experiment 1 – logic rules	75	4%	80%	68%	10%	100%	0%	82%	33%
Experiment 2 – tutorial question style	70	36%	50%	-	-	53%	73%	-	-
Experiment 3a – approach to queries (Q5)	89	65%	38%	-	-	-	-	74%	48%
Experiment 3b – approach to queries (Q9)	76	70%	56%	-	-	-	-	70%	61%
Experiment 4 – attention to detail	94	59%	28%	94%	17%	-	-	-	-
Experiment 5 – reading time	95	51%	78%	47%	71%	-	-	-	-

Experiment 1: logic rules

Using this measure, Oscar CITS was able to predict three learning styles with higher accuracy than the prior probability – Intuitive (80%), Active (100%) and Sequential (82%). For the Visual learning style, even though Oscar CITS accurately predicts Visual participants in 68% of cases, the unequal spread of participants for this dimension means that this is not significant when compared to the prior probability of 87%. This measure was not able to predict the Reflective learning style, probably because Reflective learners spend time after the learning experience reflecting on what they know and put it together as knowledge. The results support hypotheses H1, H2 and H3 and show that logic rules are the most successful factor in predicting the Intuitive, Active and Sequential learning styles.

Experiment 2: tutorial question style

70 participants showed a preference for practical or theoretical tutorial questions; those participants whose success was the same for both question styles remained unclassified. Oscar CITS was able to predict the Intuitive (50%) and Reflective (73%) learning styles better than the prior probability. The results support hypothesis H4 and show that tutorial question style was the most successful factor in predicting the Reflective learning style, with the accuracy of 73% being far better than the prior probability of 43%.

Experiment 3: approach to queries

This experiment predicted learning styles depending on a participant's approach to writing queries. Table 7 reports results for two relevant tutorial questions as Experiments 3a and 3b. 89 participants completed question 5 (Experiment 3a) and 76 participants completed question 9 (Experiment 3b). Apart from the Sequential learning style, results for the second question were higher – probably because having experienced the style of question before, participants has a better idea of their preferred approach. All learning styles (except the Intuitive in experiment 3a) were predicted with higher accuracy than the prior probability. Experiment 3b was the most successful factor in predicting the Sensory (70%) and Global (61%) learning styles, and the results support hypothesis H3.

Experiment 4: attention to detail

94 participants had completed the 'trick question'. For the Sensory/Intuitive learning style dimension, the prediction accuracies of 59% and 28% are worse than the prior probability for the sample of 62% and 38% respectively. However, predictions for the Visual/Verbal learning style dimension were better than the prior probability at 94% and 17% respectively, with this measure producing the most accurate prediction overall for the Visual learning style. Therefore the results support hypothesis H6, a lack of attention to detail in answering questions is indicative of learning style.

Experiment 5: reading time

Reading time was calculated for 95 participants who had completed Question 1. The results were mixed, with poor predictions of Intuitive and Visual participants (those with a below average reading time) but good predictions of Sensory and Verbal participants (those with above average reading times). The prediction accuracies for the Intuitive (78%) and Verbal (71%) learning styles are much higher than the prior probabilities of 40% and 13% respectively. The results show that this measure is the best predictor of Verbal learning style, thus supporting the hypothesis H5. However, it must be borne in mind that the uneven spread of participants for the Visual/Verbal dimension prevents firm conclusions from being drawn.

7.2. Learning gain

Table 8 shows the participant learning gain results, with a total average test score improvement of 13%. Average learning gain was higher for study 1 (20%), which probably reflects the higher motivation of participants in completing the tutorial as this was a controlled setting. Study 2 involved real students completing the tutorial in a real educational environment, and so a lower learning gain was expected due to factors such as distractions.

The results suggest that Oscar CITS did help learning as participants increased their learning of SQL and improved their test results.

Table 8.

Learning gain results.

Study	n	Learning gain Mean (/12)	Standard deviation	Mean %
Study 1	10	2.4	2.01	20%
Study 2	63	1.44	2.07	12%
Total	73	1.58	2.07	13%

7.3. Participant evaluation

In general, the participant feedback showed that Oscar CITS was well received, understandable and helpful. 46 participants completed the evaluation questionnaire. 87% of participants rated the tutoring highly, with 51% awarding the tutoring the highest rating. 94% of participants found the tutoring helpful, with 72% giving the highest rating. An astounding 35% of participants stated that they would use Oscar CITS tutorial *instead* of attending a face-to-face tutorial. Slightly more than half of the sample (52%) would use Oscar CITS instead of reading a book, and 85% of participants would use Oscar CITS to support classroom tutoring. Overall, 89% of participants would use a resource like Oscar CITS if it were available. When openly asked for comments about Oscar CITS, half of the participants remarked that Oscar was easy to use and 43% noted that Oscar CITS was helpful. One participant commented "*is like having your own friendly tutor*", and another "*it gives instant feedback unlike a traditional test*". From these results it can be concluded that most people found the Oscar CITS tutoring easy to use, helpful, and would use Oscar CITS to support their studies.

7.4. Results summary

The experiments were conducted using real university students in a real teaching/learning environment. The results support the hypotheses and show that by adopting the Oscar CITS methodology and architecture, it is possible to successfully predict learning styles from a two-way natural language tutoring conversation. Oscar CITS helped participants to increase their knowledge and participants valued the Oscar CITS learning experience and would use Oscar CITS to support learning. Table 9 summarises the best prediction accuracies resulting from the five experiments described. In a full Oscar CITS learning style values are adjusted dynamically throughout the tutorial conversation based on learner behaviour, apart from the Reflective learning style, where the preferred question style is tested periodically at the end of each tutorial.

Table 9.

Oscar CITS best prediction accuracy.

	n	Sensory	Intuitive	Visual	Verbal	Active	Reflective	Sequential	Global
Oscar CITS	75-95	70%	80%	94%	71%	100%	73%	82%	61%

The methodology and architecture for Oscar CITS are independent of the learning styles model and subject domain chosen. Although the results show the successful prediction of ILS learning styles, before conclusions may be drawn about non-computing subject domains it is necessary to implement Oscar CITS and empirically test its prediction of learning styles with different models.

A comparison of results with other CITS is not possible as no other CITS can predict learning styles. On a superficial level, the results compare favourably with menu-based ITS that predict ILS learning styles (Ozpolat & Akar 2009; Cha *et al* 2006; Garcia *et al* 2007). However it is inappropriate to compare prediction accuracies with these ITS because, despite adopting the ILS, they classify learning styles differently, introducing a third 'Neutral' class for each dimension which describes learners with low strength learning styles (i.e. those at the centre of the dimension). Also, the method of calculating prediction accuracy for these ITS uses different scoring, by awarding a 0.5 score if the learning style prediction is mismatched with a Neutral classification, rather than a zero score for all mismatches used by Oscar CITS.

8. Conclusions

This paper has presented the Oscar Conversational Intelligent Tutoring System, a novel CITS which implicitly predicts and adapts to learning styles whilst directing a tutorial conversation. Oscar CITS imitates a human tutor by incorporating the intelligent tutoring techniques of curriculum sequencing, intelligent solution analysis and problem solving support. A tutorial is directed by Oscar CITS, which detects behaviour cues from learners to present learning material suited to their knowledge and learning style. Learners can participate in a personalised tutorial via the Internet, learning at their own pace at a time and place to suit them. Oscar's conversational style is intuitive to use, helping to improve motivation and build confidence, with one user remarking "*it encouraged me to think rather than simply giving me the answer*".

An original methodology and architecture for creating the Oscar CITS were described, which are independent of the learning styles model and subject domain being taught. The 3-phase methodology describes the development of the Learning Styles Predictor, Tutorial Knowledge Base and CA components and includes a number of generic tools to aid development (behaviour variables, key words, logic rules, 3-level conversation model,

question styles and templates). The generic architecture is modular, allowing different learning style models and subject domains to be applied whilst supporting the reuse of components.

Oscar CITS was implemented to deliver an SQL revision tutorial and evaluated empirically by real students in a real educational setting. The experimental results show that it is possible to predict learning styles from a two-way natural language tutoring conversation. Oscar CITS successfully predicted all learning styles in the Index of Learning Styles model, with accuracies ranging from 61-100%. Oscar CITS was well received by participants, who found it helpful, easy to use and successful in improving their knowledge.

Further work has been done in analysing different sorts of behaviour for predicting learning styles from natural language, including a preference for practical or theoretical questions, the number of words used, the amount of discussion, duration and vocabulary. An algorithm is now being developed to improve the accuracy predicting learning styles using a fuzzy set representation that combines different aspects of learner behaviour captured from a natural language tutorial. An Oscar CITS adaptation algorithm has been designed that selects the best fitting adaptation for each tutorial question by combining student learning styles with available teaching styles (Latham, Crockett, McLean & Edmonds, 2011). In future, a speech module could be incorporated into the Oscar CITS architecture to facilitate spoken tutorial conversations.

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