STyLE-OLM: Interactive Open Learner Modelling

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Abstract. There is a strong argument in Artificial Intelligence in Education which advocates that computer-based learning systems need to adapt to the needs of learners if they are to provide for effective personalised instruction (Self, 1999a). Diagnosing a learner's cognitive capacity is a crucial issue in building adaptive systems. We have explored an interactive open learner modelling (IOLM) approach which conceives diagnosis as an interactive process involving both a computer system and a learner that discuss and together construct the learner model. This paper outlines the architecture of an interactive open learner modelling system and illustrates the method in a terminological domain. We discuss an evaluative study of an IOLM demonstrator – a system called STyLE-OLM. The results from the study demonstrate potential benefits of the method for improving the quality of the learner model and providing a means for fostering reflective thinking. We argue that IOLM is a fruitful approach which may be employed in intelligent learning environments both for obtaining a better model of a learner's cognitive state and engaging learners in reflective activities.

INTRODUCTION

Teachers have to address the needs of their learners in order to provide effective advice, assistance, explanation, guidance, instruction. Learners expect to be understood and may be willing to participate in a discussion about their problems rather than being given a quick, inappropriate, or incomprehensive response. Diagnostic interactions are an essential feature of the proficient teacher's practice. During such interactions, the teacher may ask questions to elicit what the learners need and to ensure that they understand the material. Frequently, the learners may be asked to approve what the teacher has elicited about them and this may trigger further discussions to uncover additional relevant aspects. The result of such diagnosis will be constructing a picture of the learner's needs with the active involvement both of the teacher and the learner. Not only is this diagnosis likely to be more accurate and to enable effective instruction but the learners themselves may understand better their needs and problems. Moreover, when interactive diagnosis does take place in an educational context, it can bring deeper insights both for the teachers in terms of reflections on their own practice and the learners in terms of promoting important meta-cognitive skills.

It is apparent that the effectiveness of interactive diagnosis depends on the *diagnosee's involvement* and the *diagnoser's ability to encourage this involvement*. In contrast, traditional computer diagnostic systems seek to infer reasons for the learners' behaviour and elicit models of the learners' cognitive state without direct help from the learners.

A trend that focuses on involving learners in diagnosis has emerged recently. The method was proposed by John Self (1990) as a feasible research direction that could accommodate the dynamics of student's behaviour and make student modelling more tractable. Self argued that the diagnosis should be made *interactive and collaborative*, which required that the learner model (LM) be made accessible to the learners who should be given a collaborative role while the system could become an assistant helping them clarify their beliefs. These issues were later elaborated by Cumming and Self (1991) who suggested a "switch from ITS-as-instructor to IES-as-collaborator" and argued that the learner modelling should be a *shared activity* with a learner model even being open to inspection and change by the learner. In the following ten years a number of overt diagnostic architectures that consider the diagnostic process open for inspection and direct influence from the learner have been developed (Paiva & Self, 1995; Kay, 1995; Bull et al., 1995; Bull & Smith, 1997; Bull & Brna, 1997; Greer et al., 1998; Bull & Brna 1999; McCalla et al., 2000). Several empirical studies have investigated different aspects of involving the learner in diagnosis (Bull et al., 1999; Kay, 1999; Morales et al., 2000; Zapata-Rivera & Greer, 2001).

The existing computational architectures are not sufficiently capable of accommodating interactive diagnosis where a computer diagnoser and a human diagnosee are involved in an *ongoing dialogue* and *together construct* a picture of the diagnosee's knowledge. Interactive open learner modelling (IOLM) is proposed here as one possible approach for simulating interactive diagnosis in computer tutors. Adding the issue of interaction to open learner modelling, which makes the learner model open to the learner both for inspection and discussion, brings a new sense of openness - such "an open learner model might entice a learner" to interact with it (Self, 1999b). Consequently, the approach may lead to improving the quality of diagnosis, as the learner would be more involved in constructing a model of their cognition. Moreover, the interaction can be expected to provide a means for reflective learning by engaging a learner in discussions about the domain and challenging the robustness of their domain competence.

Interactive open learner modelling conceives diagnosis as an interactive process involving a computer system and a learner that discuss and modify the content of the learner model. In such a process both agents can influence the content of the LM. Our main goal has been to formalise this process in order to support the development of various computer diagnosers capable of participating in interactive open learner modelling. A framework for IOLM has been presented elsewhere (Dimitrova et al., 1999; Dimitrova et al., 2000; Dimitrova 2001). It includes distinctive components: a discourse model manages diagnostic interactions providing both a diagnoser and diagnosee with a common communication method and symmetrical power in dialogue maintenance (Dimitrova et al. 1999) while a formally defined mechanism maintains a jointly constructed LM (Dimitrova et al., 2000). Based on this framework we have developed STyLE-OLM - an IOLM system in a terminology domain. An evaluative study with STyLE-OLM has been conducted to examine the behaviour of the system and to validate the framework. The study has also allowed us to examine some advantages of the approach in terms of improving the quality of the learner model and providing the means for reflective learning.

This paper will outline the interactive open learner modelling approach and will present a demonstrator – the STyLE-OLM system. Potential computational and educational advantages of the approach will be discussed on the basis of the evaluative study of STyLE-OLM. We argue that computer tutors would benefit from interactive open learner modelling since a better picture of the learners' cognition can be obtained and hence the opportunity for more effective personalised tutoring can be provided. In addition, the learners may benefit from interactive open learner modelling as they will be provided a means for reflective learning.

INTERACTIVE OPEN LEARNER MODELLING

Involving the learner in diagnosis

Diagnosis is regarded here as involving (at least) two agents - a diagnoser and a diagnosee - who share responsibilities in building an explanation of the latter's behaviour. Without a doubt, the diagnoser's diagnostic capabilities and knowledge are crucial for the diagnosis. However, in many situations the quality of the diagnosis will depend significantly on the diagnosee's participation, for example, in medical diagnosis the patients' ability to express their symptoms is essential. Likewise, student diagnosis depends on the learner's involvement and is intrinsically collaborative (Dillenbourg, 1996). The diagnosee (the student) is not (or should not be) a passive agent with no interest in the process of diagnosis as they have the most to gain from a successful diagnosis. The learner might be motivated to engage in the diagnostic process in order to improve the system's adaptability. On the other hand, a learning environment may face problems due to fallacies or gaps in student diagnosis and may benefit from the learner's help in maintaining the LM.

There are two ways of involving the learner in diagnosis: *implicitly* and *explicitly*. As Dillenbourg (1996) points out, the learner's interpretation of the system's actions reveals his/her understanding of the system's understanding of his/her cognition. A learner's comments on a system's misunderstanding of his/her behaviour could be used as a source for adjusting the system's diagnosis. We consider this as an *implicit* involvement of a learner in diagnosis.

Providing learners with some control over the diagnostic component by allowing them to inspect, change and discuss the content of the LM involves them *explicitly* in diagnosis. Figure 1 outlines this process. The diagnoser, which in this case is a computer diagnostic system that simulates the behaviour of a human diagnoser (a teacher or a peer), is expected to have some domain understanding that will yield diagnostic decisions. The computer diagnoser aims to elicit a learner model that comprises beliefs about the learner's domain knowledge. In the traditional diagnostic systems such a model is based only on the diagnoser's beliefs about the learner's domain beliefs. Explicit involvement of a learner in diagnosis implies that the learner's beliefs about their domain knowledge are taken into account and influence the construction of the learner model. The diagnosee shall be provided with a means to inspect the LM and encouraged to render statements about his/her domain beliefs that can alter the LM content. Hence, a learner and a system together construct a learner model that later becomes the system's diagnostic resource.

In this paper, we are concerned only with the explicit involvement of a learner in diagnosis. The arrow in Figure 1 highlights the importance of interaction in involving a learner in diagnosis - both the system and the learner should be provided with a communication medium to reflect on the learner's beliefs. Moreover, interaction is the means by which a learner provides information about the LM and assists the system in diagnosis. If well managed, the interaction could provide a means for encouraging the learner's participation in diagnosis, which may promote constructive, successful learning as well as improve the system's understanding of the learner's cognitive state. The issue of interaction, which is discussed next in this section, is crucial in the interactive open learner modelling approach we propose here.

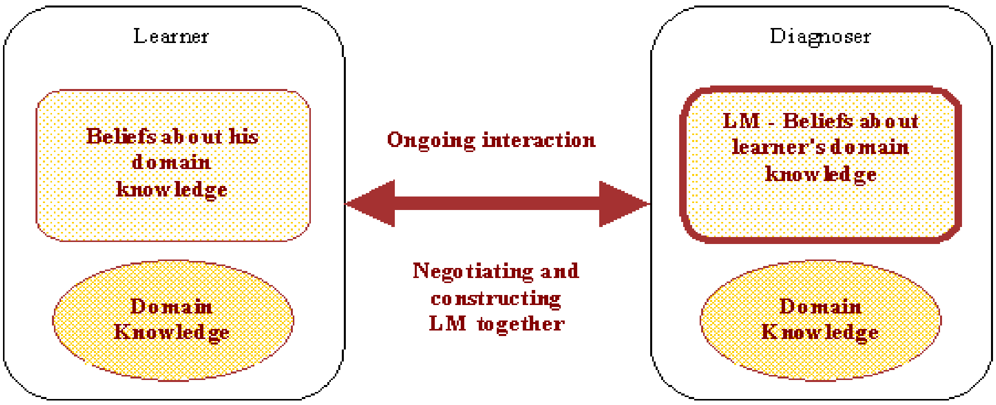

Figure 1. Explicit involvement of a learner in diagnosis.

The issue of interaction

Interaction is a stimulus for reflection and plays an essential role in environments that involve learners in the diagnostic process. When learners are engaged in a discussion about the learner models they are *reflecting upon their domain knowledge re-calling and re-considering ideas of which they are aware*. This reflective activity involves the perception of relationships and connections between the parts of the experience and provides opportunities for the learners to be engaged actively in what they are learning (Boud et al., 1996). According to Dewey, "reflection implies belief on evidence", i.e. "something is believed in (or disbelieved in), not in its own direct account but through something else which stands as witness, evidence, proof, voucher, warrant; that is, as *ground of belief*" (Dewey, 1960, p. 11, italics are from the original). When discussing their cognitive state with a tutor, learners are encouraged to *search for the grounds of and validate their beliefs*. Situations which support learners in *externalising their knowledge and experience* have the potential to provide for reflective learning (Draper, 1997).

Reflection entails that different possibilities for alternative courses of actions are revealed and examined (Dewey, 1960). This aims at discovering the grounds of a student's beliefs and refers to *argumentative actions* such as proposing, challenging, justifying, and withdrawing. Grundy stresses the importance of *interaction and collaboration* for researching and evaluating ideas, which results in new knowledge (Grundy, 1982). She also points out the *equal power in student-tutor (student-computer in our case) relationships and the freedom to choose* as an essential issue in planning a reflective interaction. Consequently, a learner should be provided with a means to challenge or disagree with a system's claims as well as power to influence the content of the LM. In addition, symmetry in the style of communication is needed, which allows both sides to use equally expressive tools and share the responsibility for interaction management.

All these issues raise the importance of the interaction for promoting reflection and argue in favour of collaborative and interactively constructed learner models.

Involving learners in diagnosis may bring other positive effects. The process of negotiating the learner model may foster the articulation of concepts and relationships in the domain. This may lead potentially to the development of *explicit domain knowledge*, which would improve learners' *domain awareness* (Bull et al., 1995). Kay argues that when learners are reflecting on the computer's models of their knowledge, they can develop skills to *judge when they know something* and to *know how to go about learning something* (Kay, 1999). Putting learners in situations where they need to formulate and externalise their ideas may help them *articulate* these ideas and make *tacit knowledge explicit* (Collins, 1996).

The importance of interaction is demonstrated in genuine diagnostic situations involving humans, for example some peer diagnostic systems where learners are building models of themselves as well as models of peers and then discuss these models with the peers. In these systems diagnostic interactions show a richness of communicative actions (e.g. Bull & Brna, 1997): learners make claims about their beliefs; challenge views of their peers; express agreement or disagreement; justify when the robustness of their models or the validity of the assessment they have given to their peers is challenged; ask questions which may open new discussion topics; respond to questions their peers ask; clarify uncovered issues; elaborate on a topic providing explanation and supporting their claims with new facts; give and receive feedback on their claims. The dialogue is symmetrical in terms of using a common means of communication and sharing the responsibility of maintaining the interaction. Although peer diagnosis systems provide rich diagnostic interactions, the learner models elicited from these interactions are very limited due to the complexity of natural language understanding.

The issue of interaction has not been explicitly addressed in the existing computational architectures of computer diagnosers that involve users in diagnosis. In TAGUS (Paiva & Self, 1995), um (Kay, 1995), and PACMOD (Morales, 2000) the system's claims are rendered in viewers that externalise the LM and the learners are provided with some command options to form their statements about the content of the LM. The learners can ask for explanations and justifications of the computer's opinions. Mr Collins (Bull, 1997) provides a more enhanced interaction means in a menu-based environment for negotiating the LM. The negotiation is initiated when conflicts between the system and learner's views about the LM arise.

The computational diagnosers discussed above do not employ discourse models and the diagnosee (the learner) is the only one who has any modelling of the interaction (following Grice (1975) when humans are involved in a dialogue they have "discourse culture" and commitment to contribute to the discussion). On the other hand, the learner's participation is strictly delimited by the restricted set of command options or menu choices that the diagnostic system provides.

We embarked upon the challenge of building a computational architecture of a computer diagnoser that is capable of participating in interactive diagnostic interactions. Following Self

(1995), we employ the term *interactive diagnosis* to emphasise the view of diagnosis as an interactive process involving two agents, a diagnoser and diagnosee (a system and a student), who play symmetrical (to a certain extent) roles and are involved in an ongoing dialogue constructing together the diagnosee's model. A constructive interaction guided by the diagnoser is the means for involving the diagnosee in diagnosis where both agents reflect on the diagnosee's domain knowledge. We have investigated a specific kind of interactive diagnosis, called *interactive open learner modelling*, where learner model inspection is combined with domain discussion aimed at eliciting a learner's domain beliefs and, consequently, modifying the learner model that in turn can be inspected which can trigger further domain interactions.

There are four main issues that need to be addressed in computational architectures for IOLM:

- Defining knowledge querying algorithms that extract the necessary knowledge from the domain ontology.
- Designing a communication medium for inspecting and discussing the learner model.
- Defining a dialogue framework for managing diagnostic interactions.
- Defining a mechanism to maintain a jointly constructed learner model.

These issues have been examined in the framework for IOLM described in Dimitrova (2001). In this framework:

- knowledge querying algorithms that extract knowledge for the purposes of IOLM have been defined and exemplified with conceptual graphs (CGs) (Sowa, 1984).
- A communication medium for interactive open learner modelling that combines text and graphics, specifically graphical representation of conceptual graphs, in a flexibly structured way has been proposed.
- A dialogue framework for managing diagnostic interactions based on approaches known as dialogue games (Levin & Moore, 1977; Walton, 1984) has been defined.
- A theory that employs a belief modal operator (Davis, 1990) to formalise the maintenance of a jointly constructed learner model has been defined.

To assess the validity of the framework, we have developed a diagnostic system, called StyLE-OLM. STyLE-OLM is the Open Learner Modelling component in STyLE (Scientific Terminology Learning Environment) developed in the framework of the EU funded Larflast[1] project. STyLE-OLM is an environment for interactive diagnosis where learners can inspect and discuss aspects of their conceptual knowledge and influence the content of the LM.

In the remaining part of the paper we discuss the learning of technical terminology (the task where IOLM has been illustrated), outline the STyLE-OLM system, and discuss the results of an evaluative study of the system, concentrating on potential benefits from IOLM.

INTERACTIVE OPEN LEARNER MODELLING AND LEARNING TECHNICAL TERMINOLOGY

To exemplify our IOLM framework we have explored the task of learning technical terminology in a foreign language, for instance non English speakers studying Finance terminology in English. Despite the importance of such a task, underlined nowadays by the expansive business and technical contacts between different countries, it has not been principally investigated in intelligent computer assisted instruction.

[1] The project involved partners from UK (University of Leeds and UMIST), France (LIRMM, Montpellier), Bulgaria (Bulgarian academy of sciences and Virtech Ltd.), Romania (Romanian academy of sciences), and Ukraine (Simferopol State University). Details about the project can be found at http://www-it.fmi.uni-sofia.bg/larflast/.

Most of the existing computer-assisted learning systems concerned with terminology have tended to focus on the user's exploration of the subject area and function as terminological dictionaries and domain encyclopaedias (e.g. Sager, 1990; Smith, 1998; Stanford, 1999). Typically they provide little teaching assistance or guidance. Moreover, because of the system's lack of modelling of users' conceptual understanding, it may well be the case that the information provided by the system contains terms a user is not familiar with.

Several computer assisted language learning projects consider terminology as an instructional domain (e.g. Chanier, 1996; Berleant et al., 1997) and explore primarily multimedia technology to simulate realistic language situations. These systems, like the terminological resources mentioned above, suffer from the lack of adaptability. A major obstacle to having adaptable terminology tutors is that there is little attention paid to modelling the learners' cognition in this domain - a task that requires sophisticated learner models elicited by advanced diagnostic mechanisms. We have proposed applying IOLM for discussing the learner's conceptual knowledge and eliciting a model of the learner's domain cognition.

Applying IOLM to learning technical terminology in a foreign language

Terminology is a language for special purposes whose acquisition in a non-native domain commonly implies *fluency in the foreign language* as well as *conceptual understanding* (Vitanova, 1999). Foreign language special purposes courses, which usually follow traditional ones based on grammar and basic vocabulary, require that language teachers have some expertise in the subject area, which is often difficult to satisfy (Dicheva & Dimitrova, 1998). There is an instant need for effective learning environments that address both language learning and mastering of conceptual knowledge. IOLM appears a fruitful approach as it has the potential to foster reflective learning whilst building a computational model of a learner's domain understanding. We have explored IOLM to facilitate and diagnose a learner's conceptual understanding. This can be part of a learning environment for foreign language terminology learning which comprises various components to address both improving users' language capabilities and enhancing their domain competence.

Generally, learners who study terminology in a foreign language are *adults*. This is an important factor in applying IOLM, because, as discussed in Knowles (1995):

- Adult learners often know the reasons for their mistakes and what knowledge they lack but are afraid (ashamed) to ask a (human) teacher, which may inhibit learning. We believe that these learners may benefit from a domain discussion with a computer and might appreciate the opportunity to influence the model the computer builds of them.
- Adults are usually self-motivated and persistent in their learning. They can, therefore, be expected to engage in extensive interactions about their domain knowledge.
- Adults are often afraid of failure and need a friendly environment which fosters deep understanding and provides a means for self-assessment. As discussed above, IOLM facilitates self-diagnosis and is expected to foster reflective learning that can lead to an enhanced domain understanding.

Another important issue in learning foreign language terminology is the *diversity of learner groups* which vary from language professionals who are also domain experts (e.g. specialised translators) to people who are novices both in the language and the domain (e.g. university students whose subject area education goes in parallel with their foreign language learning). One group of learners may face problems that never occur in another group and the adopted teaching activities depend predominantly on the users' needs. Diagnosing the learners' domain competence is vital for developing effective personalised learning environments for foreign language terminology learning. This justifies the need for methods that can build relatively accurate learner models. IOLM, which is expected to improve the quality of a learner model and to enhance the system's diagnosis, can be considered as a fertile approach in this domain.

The conceptual understanding task

As mentioned above, we have utilised IOLM to address conceptual understanding in learning technical terminology in a foreign language. The importance of understanding term meanings for text comprehension and production in terminological domains is significant. This follows a more general argument about *the importance of word meaning in language learning*. Research in psycholinguistics has shown that language comprehension and production depends, amongst many other factors, upon people's knowledge about the meaning of the words (Singer, 1990). Most linguists believe that the meaning of the words is decomposed in to *concepts* and the meaning of the text depends in a complex way on word meanings (Whitney, 1998). Johnson-Laird (1983) has proposed a possible explanation of how word referents are represented in the human mind in terms of mental models, which are internal representations of situations in the world. He argues that building mental models, i.e. understanding word semantics, requires *placing concepts in the context of a large system of knowledge and relating them to other concepts*.

Various methods for building conceptual models have been explored, such as *generalisation* (e.g. inferring from examples), *explanation* (e.g. justifying certain properties), *deduction* (e.g. inferring more specific knowledge about category exemplars), and *analogy* (e.g. reasoning using similarities) (Thagard, 1992). Most of the research on concept learning refers to acquiring a domain conceptualisation by applying corresponding theories and methods. This is often not the case with learners who may *misapply* or *fail to apply* the correct classification rule. Therefore, in educational contexts, both finding possible explanations for learner's conceptual errors and facilitating learner's conceptual understanding play an essential role.

The approach we adopt in STyLE-OLM to facilitate conceptual modelling is related to two sets of research on conceptual modelling in an educational context. Firstly, Graesser et al. (1993) argue that adults can obtain conceptual knowledge by *active inquiry* in the form of question asking and answering. An important feature of such inquiries is their systematic relation to the content and organisation of knowledge structures underlying concepts. Secondly, the role of *reflective dialogue* in addressing domain misconceptions is discussed in Katz et al. (2000).

STyLE-OLM aims at fostering conceptual understanding by providing the following activities:

- Discussing domain knowledge with the learners where they need to form and understand propositions with domain terms.
- Articulating pieces of a learner's conceptual model (in a graphical manner).
- Challenging the robustness of a learner's conceptualisation.
- Allowing learners to ask questions about domain facts and generating corresponding answers.
- Exploring concept definitions as well as concept similarities and differences in the discussion with the learner.

THE STYLE-OLM ARCHITECTURE

STyLE-OLM has a modular architecture. Its four main modules, shown as grey square-edged components in Figure 2, are:

- a module which maintains the communication medium;
- a module which manages diagnostic dialogue with the learner;
- a module that extracts domain knowledge for dialogue planning and maintaining the LM;
- and a module which updates the learner model.

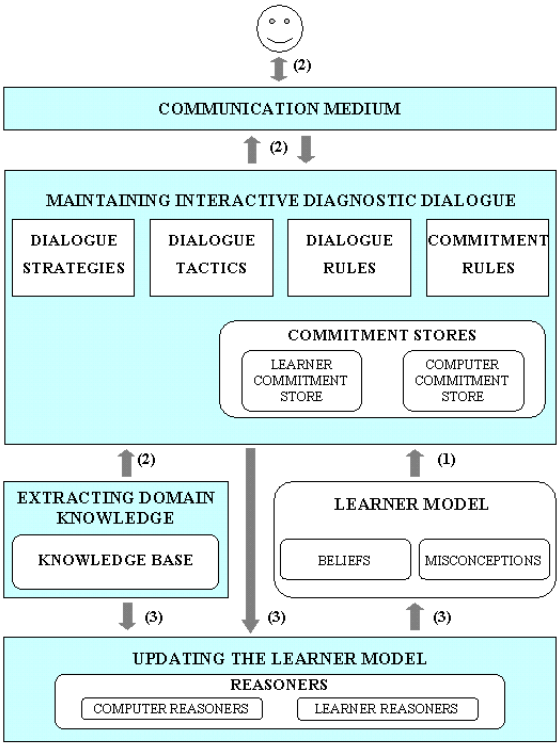

Figure 2. The STyLE-OLM architecture. There are three main phases [1] - Initialisation, [2] - Interaction and [3] - Learner model update.

Next in this section, we will discuss these modules in detail. As shown in Figure 2, the interaction in STyLE-OLM is organised in three main stages:

[1] *Initialisation* where an initial learner model, which can be imported from a learning environment that utilises IOLM, is converted into commitment stores. The later accumulate computer and learner's beliefs throughout the interaction and are used in the dialogue module.

[2] *Interaction* where the learner's conceptual understanding is targeted. The interaction is organised as a loop that involves the communication medium, where both the computer and the learner utter their communicative acts, and the dialogue module that analyses learner's utterances, updates the participants' commitment stores, and generates the system's next communicative act. For the latter, the dialogue module calls expert knowledge queries that extract the relevant knowledge needed for planning the dialogue and maintaining its focus.

[3] *Learner model update* where the temporarily stored commitment stores are used as a source for updating the learner model. The diagnostic module confirms with the expert knowledge in order to assign a measure of correctness to the beliefs in the LM.

The STyLE-OLM implementation incorporates two parts: a Prolog engine processes the three stages mentioned above while a Java interface, which communicates with the Prolog engine, implements the communication medium.

Domain ontology in STyLE-OLM

STyLE-OLM imports a domain ontology encoded with conceptual graphs. Conceptual graphs (Sowa, 1984) have been designed as a "system of logic that can express the propositional content of sentences in natural language in as simple and direct a manner as possible" (Sowa, 1991, p. 157). In various projects, conceptual graphs have served as an intermediate language that simplifies the mapping of computer-oriented formalisms to and from natural languages. Their graphical representation provides a human readable and understandable representation of formal meaning of sentences.

Conceptual graphs have been adopted in STyLE-OLM because they are:

- suitable for terminology where we will exemplify our interactive open learner modelling framework;
- rigorous, permitting reasoning for interaction planning and student diagnosis;
- relatively understandable having a comprehensible graphic form advantageous for learner model inspection and discussion.

Two instantiations of STyLE-OLM have been implemented - in a Computing and in a Finance domain. Initial tests of the system have been made with a domain ontology that encodes knowledge about Programming Languages (examples of this instantiation of the system are discussed in Dimitrova, 2001). The instantiation presented in this paper is in a Finance domain and covers the topic Financial Markets. The domain ontology used in this STyLE-OLM instantiation has been built as part of the Larflast project, see Angelova et al. (2000).

An inference engine in STyLE-OLM elicits the domain knowledge needed for interactive diagnosis. The engine incorporates:

- *basic conceptual graph operations*, i.e. copy, join, restrict, simplify (Sowa, 1984);
- *more advanced operations*, such as generalisation, specialisation, generalisation with substitutions, common generalisation (Sowa, 1984);
- *operations for eliciting knowledge from the type hierarchy*, e.g. examining parent-child relationships between concept types, finding all parents (or children) of a type, finding a common parent of two types.

Learner model in STyLE-OLM

The LM in STyLE-OLM is yielded by a *perturbation method* which resembles an enumerative bug model (Holt et al., 1993). The LM incorporates *beliefs* that present the student's correct and incomplete knowledge as an overlay upon the domain while the student's beliefs that are not supported by the expert are added as erroneous parts. The LM comprises also some possible explanations of causes for the student's erroneous beliefs, which are defined as *misconceptions*. As shown in Figure 3, a misconception in STyLE-OLM is considered as potential reasoning that has lead to an erroneous belief, for instance, the student assigns a wrong attribute to FINANCIAL MARKET (i.e. knows wrongly that FINANCIAL MARKETS convert SECURITIES into CASH) applying wrongly a generalisation rule (i.e. because a subtype of FINANCIAL MARKET - MONEY MARKET - possesses this attribute, namely converts SECURITIES into CASH).

There are three types of beliefs included in the LM:

- *correct beliefs* (represented with `know` predicates) are student beliefs supported by the domain ontology;
- *erroneous beliefs* (represented with `know_wrongly` predicates) are student beliefs that are not supported by the domain ontology;
- *incomplete beliefs* represent facts from the domain ontology that the student does not believe - these beliefs can be either elicited by the system (represented with `not_know` predicates) or stated by the student with an "I don't know" answer to a system's question (represented with `self_not_know` predicates).

```
self_not_know(user1,capital_market,[[a_def,2035,_]],u_1_d_3,1,none,1).
know(user1,money_market,[[a_def,2050,_]],u_1_d_3,1,none,2).
know(user1,money_market,[[a_def,601,_]],olm,2,none,3).
know_wrongly(user1,financial_market,[[a_def,602,_]],olm,1,none,4).
not_know(user1,capital_market,[[b_def,2027,_]],olm,2,none,5).

misconception(misattribution(financial_market,602),misattribution1,[2050,601]).
% Error: The learner believes wrongly that
%        'Financial markets convert securities into cash'
%          (represented in graph 602)
% Explanation: Because the learner believes that
%        'Money markets are financial markets'
%          (represented with graph 601)
%        and
%        'On the money markets securities are converted into cash'
%          (represented with graph 2050).
```

Figure 3. Sample beliefs and a misconception from the learner model in STyLE-OLM presented in a Prolog form.

The arguments in the belief predicates shown in Figure 3 are as follows: (1) user ID, (2) domain concept, (3) list of conceptual graphs representing domain facts (`b_def` means basic definition, `a_def` stands for additional definition which is usually a situation that illustrates the term usage, the numbers are IDs of conceptual graphs), (4) the source of this belief (e.g. `u_1_d_3` stands for unit 1 drill 3 from the learning environment where STyLE-OLM is integrated, while `olm` means added after open learner modelling interaction), (5) the sequential number in the LM of the belief regarding the term presented, (6) comment, (7) the sequential number of the belief regarding all beliefs in the LM.

When the learner's beliefs differ from the expert's the learner's problems need some kind of explanation for a learning environment to decide what to do. We consider that the LM should contain explanations for the learner's errors at a conceptual level and define these explanations as *misconceptions*. This definition of misconceptions is similar to that of Sison and Shimura who describe misconceptions as "incorrect or inconsistent facts, procedures, concepts, principles, schemata or strategies that result in behavioral errors" (Sison & Shimura, 1998, p. 132).

Misconceptions in STyLE-OLM are derived from concept learning theories (e.g. Stevenson, 1993) and formalised with rules based on conceptual graphs. Two main classes of errors are considered:

- *misclassification* - an individual *I* is wrongly considered to be a member of a class *C*;
- *misattribution* - an attribute *A* is wrongly attached to a concept *c* (*c* can be a class *C* or an individual *I*).

Misconceptions are utilised in STyLE-OLM to provide possible explanations for misclassification and misattribution. These include:

- *Explanations for misclassification* - (1) an individual *I* may be wrongly considered as a member of a class *C* because *I* has features that are part of the definitional features for *C* (this explanation follows the classical concept learning theory (Stevenson, 1993)); (2) an individual *I* may be wrongly considered as a member of a class *C* by similarity with another individual that is believed to be a member of *C* (this explanation follows the family resemblance theory (Stevenson, 1993)).
- *Explanations for class misattribution* - (1) an attribute *A* has been wrongly attached to a concept class *C* because a subclass of *C* possesses the attribute *A* (this explanation suggests wrong class generalisation); (2) an attribute *A* has been wrongly attached to a concept class *C* because *C* has an individual concept (or a group of individual concepts)

that possesses the attribute A (this explanation suggests wrong generalisation from individuals to the whole class).

- *Explanations for individual misattribution* - (1) an attribute A has been wrongly attached to an individual I because the attribute A is possessed by an individual J from the same class as I (this explanation corresponds to class misattribution); (2) an attribute A has been wrongly attached to an individual I because the individual has been wrongly considered as a member of a class for which A is a defining feature (this explanation corresponds to misclassification).

In STyLE-OLM, schemata based on conceptual graphs define conditions which need to be checked in order to confirm the misconceptions.

The misconceptions are registered in the LM with predicates whose arguments are as follows: (1) error type, (2) type of misconception that may explain this error, (3) list of conceptual graphs that justify the existence of the particular misconception (these graphs are used for designing what shall be discussed next in maintaining the interactions with the user).

The belief part of the LM is open for inspection and negotiation with the learner while misconceptions are used for planning diagnostic dialogue.

Communicating and externalising learner beliefs in STyLE-OLM

The discussion and externalisation of learner's domain beliefs is accomplished in STyLE-OLM through a communication medium that employs a graphical representation of conceptual graphs. STyLE-OLM provides a multimodal communication environment that combines graphics, text, and some interface widgets such as menus and buttons. In this environment, learners can inspect and discuss their domain knowledge with the system. There are two modes:

- **DISCUSS** where learners can discuss aspects of their domain knowledge and influence the content of the learner model (Figure 4);
- **BROWSE** where learners can inspect the current state of their learner model (Figure 5).

A picture at the top right of the main STyLE-OLM window presents the current system mode (see both Figure 4 and Figure 5). The learner switches between the modes by pressing the button associated with this picture.

In DISCUSS mode, the system and the learner discuss the learner's domain knowledge. Both participants contribute to the discussion in the same way - by composing a *propositional content* represented with a conceptual graph and specifying *illocutionary force* rendered as a dialogue move. Figure 4 illustrates STyLE-OLM in DISCUSS mode. The top screen presents a system's communicative act. Its proposition appears in the drawing area as a conceptual graph and the illocutionary force is shown in the bottom of the drawing window.

The second screen in Figure 4 shows how students construct their utterances in STyLE-OLM. Graphical tools (at the top of the window) provide basic operations for manipulating graphical objects (create, select, drag, change, delete), and facilitate the students in composing conceptual graphs that will represent the propositions of their communicative acts. Learners add illocutionary force by selecting a dialogue move from the right area of the screen. Labels with sentence openers appear once a dialogue move is chosen (for some moves there is more than one option, e.g. *I think* and *I don't know* are different *Inform* options).

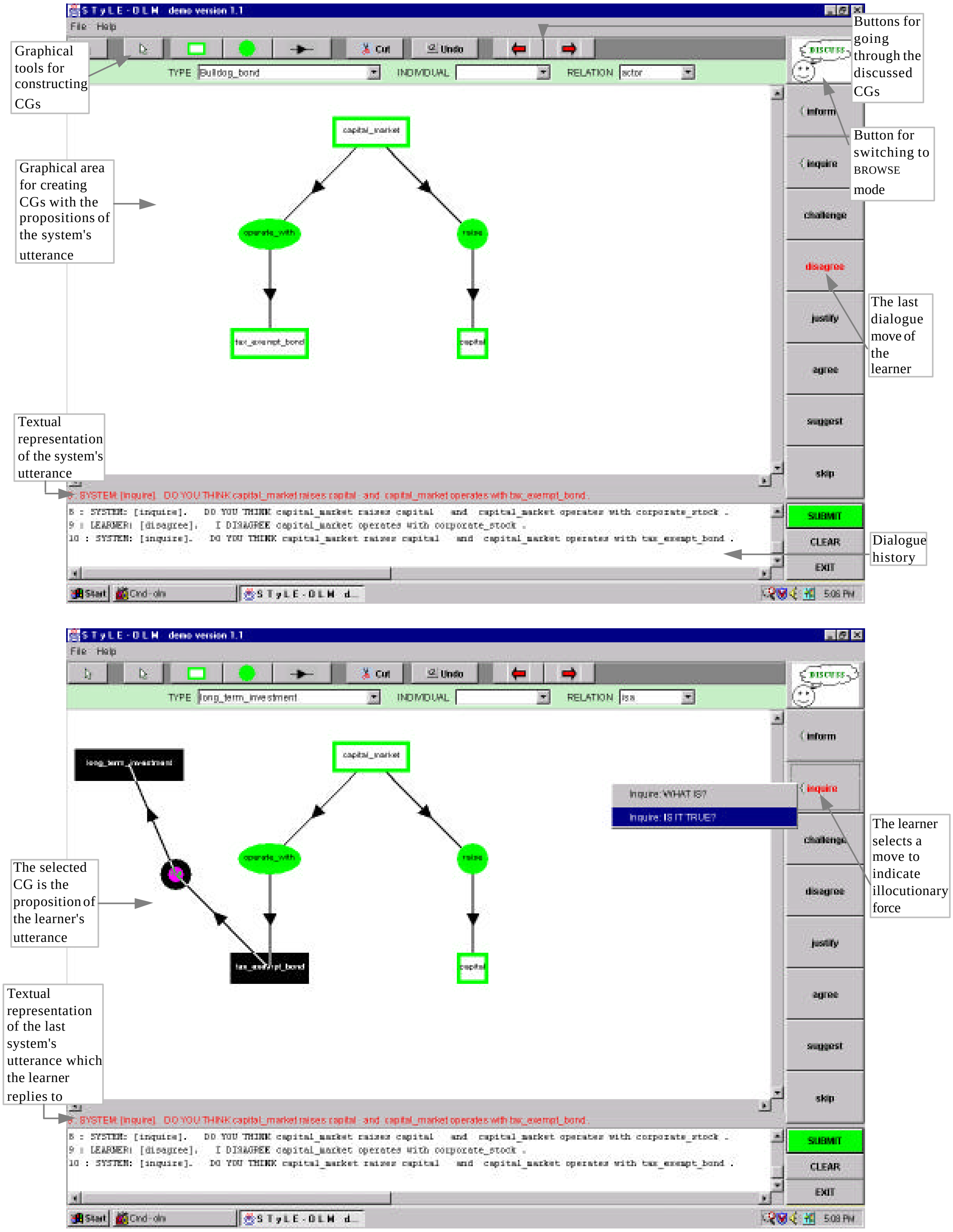

Figure 4. STyLE-OLM in DISCUSS mode - the system and the learner discuss the learner's domain beliefs. The top screen shows the system asking a question. In order to answer to the system's question, the learner needs to clarify a domain aspect and composes an inquiry, which is presented in the bottom screen. The screens present moves [1.10] and [1.11] from the first example dialogue given below.

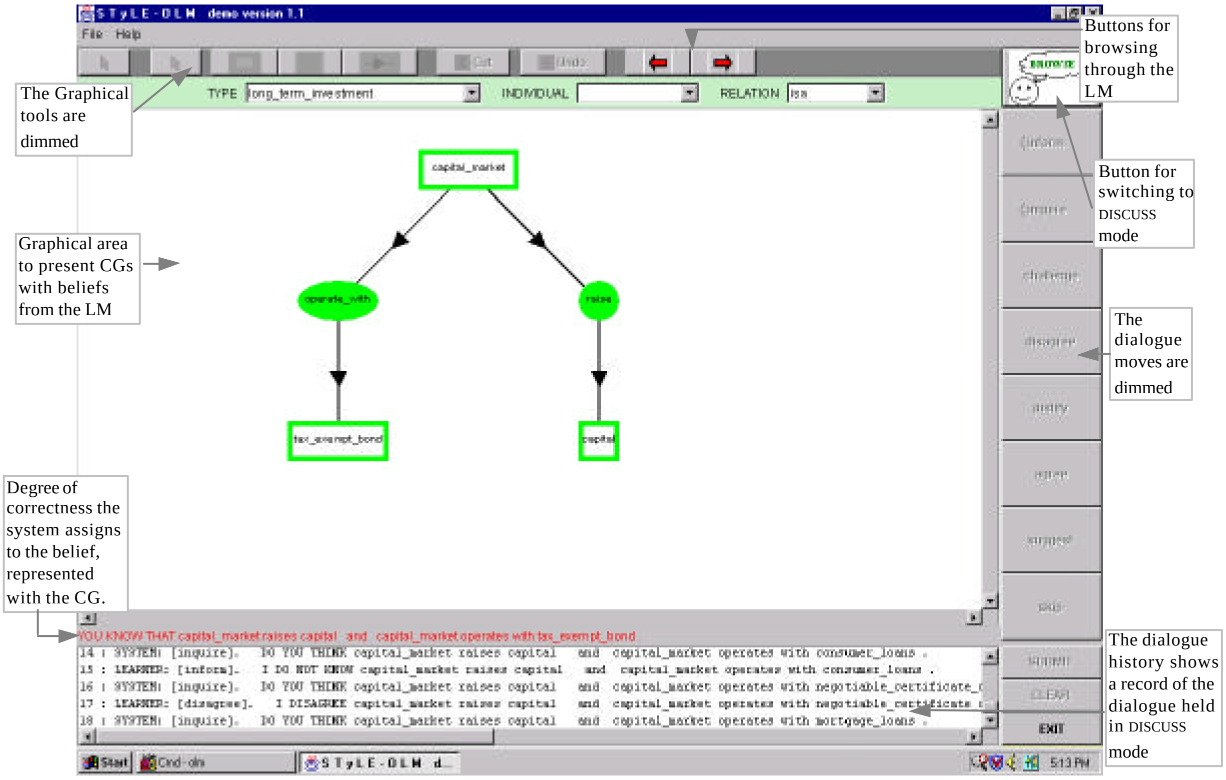

Figure 5. STyLE-OLM in BROWSE mode - the learner is enabled to browse through the beliefs in the learner model, extracted from the interaction in DISCUSS mode.

To illustrate the actions undertaken by a student to compose a communicative act, let us consider the example in Figure 4 (it shows the STyLE-OLM interface for moves [1.10] and [1.11] from the first interaction transcript given below). The system has asked whether CAPITAL MARKET operates with TAX EXEMPT BONDS. In order to answer, the student wants to first check whether TAX EXEMPT BONDS are LONG TERM INVESTMENTS (knowing, perhaps, that CAPITAL MARKET operates with LONG TERM INVESTMENTS). The composition of this question is shown in the bottom window in Figure 4. The learner selects LONG TERM INVESTMENT from the *concept type* combo box in the area below the graphical tools, then selects the rectangle (for drawing concepts) from the graphical tools, and then clicks in the drawing area. A new concept representing LONG TERM INVESTMENT appears. In a similar manner, the learner creates an ISA relation: he selects the relation from the *relation* combo box in the area below the graphical tools, then selects the circle (for drawing relations) from the graphical tools, and then clicks in the drawing area. A new relation named ISA appears. To finish the composition of the CG for his question, the learner selects the *link* from the graphical tools and clicks sequentially on the graphical objects that represent TAX EXEMPT BOND, ISA, and LONG TERM INVESTMENT. The objects are linked. The learner now selects the graph that represents the proposition of his communicative act by clicking on the corresponding nodes. If the graphical area comprises only the graph that is the student's proposition, such selection is redundant, which is not the case in this example and the student has to identify which part of the graphical composition represents his proposition. To add illocutionary force, the student clicks on the *Inquire* button and a menu with two sentence openers pops up - "*What is*" is used for inquiries about a concept and "*Is it true*" is used for finding the validity of domain propositions. The learner selects the second option. He has now completed the composition of his communicative act and clicks on the *Submit* button at the bottom right of the screen.

When the *Submit* button is pressed the learner's communicative act is passed to the system. It then shows a window with a textual form of the submitted communicative act and asks the learner for confirmation. If the learner does not accept a communicative act, he/she returns to the graphical window to make the necessary changes. A submitted communicative act is passed to the dialogue module for analysis and generation of a system's response.

A text window at the bottom area of the window shows a transcript of the dialogue. The learner can browse through the dialogue history either in its textual form at the bottom of the screen or by using the arrows in the graphical tools at the top.

In BROWSE mode, a user is allowed to inspect the jointly constructed learner model elicited from the discussion. Similarly to (Kay, 1999), (Morales et al., 2000), and (Zapata-Rivera & Greer, 2001), STyLE-OLM externalises a learner's knowledge in a graphical manner. As Figure 5 shows, the layout in this mode is akin to the DISCUSS mode but the graphical widgets are disallowed (to indicate this, the widgets are dimmed). The bottom line of the graphical area shows the level of correctness that the system has assigned to the beliefs in the learner model. The arrows on the top allow browsing backwards and forwards through these beliefs.

The screen in Figure 5 shows an instance of inspecting a belief from the learner model, which has been undertaken by the learner during the interaction in Example 1 presented later in the paper (see moves [1.18] - [1.19]). The learner can see that his belief represented with the CG in the graphical area has been confirmed by the system: it shows the message "YOU KNOW THAT CAPITAL MARKET raises CAPITAL and operates with TAX EXEMPT BONDS" in the area under the graphical region. When the learner's belief has not been confirmed by the system, a CG with this belief is again shown in the drawing area but the system's message starts with "YOU KNOW WRONGLY THAT…". Similarly, when a belief from the system's domain expertise has not been acquired by the learner, the domain fact is rendered graphically and the system's message starts with "YOU DO NOT KNOW THAT…".

Managing the interaction with the learner in STyLE-OLM

The interaction with the learner in STyLE-OLM is maintained through a *dialogue game* based model that combines both a linguistic approach for modelling human dialogues (Levin & Moore, 1977) and a philosophical approach for maintaining argumentative interactions (Walton, 1984). The rationale of combining both approaches is based on the argument in Pilkington et al. (1992) who suggest that an interactive model based on logical dialogue games should employ *strategies* to fulfil certain goals, *focusing heuristics* to amend its moves according to the user's moves, and a corpus of *relevant knowledge* from which to argue. These requirements introduce the need for dialogue planning approaches, such as the linguistic dialogue games. Recently, several computational architectures have followed this design line (Burton et al., 2000; Ravenscroft & Pilkington, 2000; Grasso et al., 2000), which has been adopted also in our dialogue framework for managing diagnostic dialogue as described below.

Dialogue moves are used to indicate the illocutionary force of the agents' communicative acts (see Figure 4). Dialogue moves in StyLE-OLM have been adapted from the DISCOUNT scheme (Pilkington, 1999) for analysing educational dialogues and include:

- *Inform* (the speaker believes a proposition and informs the hearer about that);
- *Inquire* (the speaker asks about a proposition);
- *Challenge* (the speaker doubts a proposition);
- *Disagree* (the speaker disagrees with a proposition);
- *Justify* (the speaker explains why a proposition is correct);
- *Agree* (the speaker agrees with a proposition);
- *Suggest* (the speaker suggests a new topic for a discussion);
- *Skip* (the speaker skips their turn and passes the initiative to the hearer).

Dialogue rules define when the moves are permitted. Example dialogue rules in STyLE-OLM are shown in Figure 6. These rules help the computer both to guide a coherent interaction and understand the learner's contributions. When the system's next dialogue move has to be defined, the dialogue module extracts a list with moves that can follow the current learner move. A move confirmed with the dialogue strategy (described below) is selected. While learners are not restricted to follow the dialogue rules, the system considers these rules when analysing learners' utterances and may initiate a new discussion episode if a learner's move is not confirmed by the rules.

```
% preceding moves for INQUIRE(p)
preceding([inquire,q],[inquire,p]).
preceding([inform,q],[inquire,p]).
preceding([agree,q],[inquire,p]).
preceding([suggest,q],[inquire,p]).
preceding([skip,_],[inquire,p]).

% preceding moves for JUSTIFY(p)
preceding([challenge,q],[justify,p]).
preceding([disagree,q],[justify,p]).
```

Figure 6. Dialogue rules in STyLE-OLM. Note that p and q indicate different propositions, which are represented with conceptual graphs.

Commitment stores accumulate the beliefs that the agents have committed to in the dialogue (Walton, 1984). The commitment stores in STyLE-OLM represent 'working copies' of the system and learner's beliefs about the learner's domain knowledge and are collected throughout the interactions in DISCUSS mode. When the interaction is interrupted by switching to BROWSE mode, the commitment stores are combined to obtain a resultant learner model (see the section "Maintaining a jointly constructed learner model") that is open for inspection by the learner. Conventional learner modelling architectures consider only a computer's commitment store, i.e. what the computer believes about the beliefs of the learner, which forms the learner model in these architectures. IOLM requires taking into account the learner's views about their knowledge. The domain beliefs expressed by the learner throughout the dialogue are accumulated in a learner's commitment store. The commitment stores are represented in STyLE-OLM with *believe* predicates, such as the ones given in Figure 7. The learner and the system's views about the learner's knowledge may differ. The views of the two agents may consider different aspects of the learner's domain expertise, e.g. in Figure 7, the system does not believe that the learner believes the fact represented with graph 2033, while the learner's store does not include information about this belief because the learner has not expressed explicitly his/her view about the proposition presented in graph 2033. The learner and system's views may contradict at times, e.g. such views regarding the belief represented with graph 2027 are shown in Figure 7.

```
from the system commitment store
believe(system,believe(learner,2050).
believe(system,notbelieve(learner,2027).
notbelieve(system,believe(learner,2033).
believe(system,believe(learner,2050)-
>believe(learner,602)).

from the learner commitment store
believe(learner,2050).
believe(learner,2027).
notbelieve(learner,2035).
believe(learner,601->602).
```

Figure 7. Example beliefs from the commitment stores in STyLE-OLM. The numbers present IDs of conceptual graphs that may be from the domain ontology, dynamically generated by the system throughout the dialogue, or constructed by the learner.

Commitment rules define the effects of moves upon the participants' commitment stores and assign their beliefs. The mechanism for assigning beliefs from communicative acts and maintaining the belief stores, which is presented in Dimitrova et al. (2000), utilises a simple belief revision method similar to the one proposed in Paiva and Self (1995). Each commitment rule includes four parameters - speaker, hearer, dialogue move, and proposition (represented as CG). When certain conditions about these parameters have been identified corresponding beliefs are added in the system and the learner's commitment stores. For instance, Figure 8 shows a Prolog example of a commitment rule that will be applied after a learner's justification. The last two lines define the beliefs that will be added to the learner's commitment store provided that the previous move of the learner has been inform (i.e. it is assumed that the learner provides a justification for a previous claim they have made). Note that the system's commitment store will not be changed. However, after applying the mechanism for extracting the jointly constructed LM (see below) the two beliefs added to the learner's commitment store may be included in the resultant LM if they do not contradict the beliefs in the system's commitment store.

```
commitment_rule([learner,system,justify,Graph]):-
        history([learner,system,inform,PrevGraph]),
        add_belief(believe(learner,Graph)),
        add_belief(believe(learner,->(PrevGraph,Graph))).
```

Figure 8. Example commitment rule used in STyLE-OLM. It assigns semantics to *justify*: the learner justifies with `Graph` after the system has challenged or disagreed with his/her previously stated proposition `PrevGraph` that is extracted from the dialogue history.

The dialogue in STyLE-OLM is organised as a sequence of interaction episodes, which correspond to certain diagnostic goals. An episode's goal triggers some regularity related to the function of the dialogue. Following Levin and Moore (1977), we have defined these regularities as *dialogue games*. There are three major types of dialogue games in STyLE-OLM:

- An *exploratory game* addresses domain aspects related to a topic and aims at collecting more information about the learner's domain knowledge. Both agents may initiate such games, e.g. the student may suggest a new discussion topic or the computer may search for more information about the learner's domain beliefs in order to decide how to react to the learner's errors.
- An *explanatory game* aims at discovering a possible reason for a learner's erroneous knowledge. Such games can be initiated when the diagnoser recognises the pattern of the learner's error and has a schema that identifies a possibility for a learner’s misconception and suggests relevant domain aspects that should be addressed in following interactions.
- A *negotiative game* aims at clarifying agents' positions when a discrepancy in their views is discovered. These games have been examined in (Bull, 1997). In STyLE-OLM negotiative games may be initiated by both parties when asking the other side for justifications, e.g. the student may challenge the validity of the computer's beliefs about the student's knowledge, while the computer may ask for clarification after it discovers an inconsistency in the student's beliefs or finds out that suggested changes in the LM do not correspond to its views.

Following Levin and Moore (1977), we consider a game consisting of: *parameters* that present values specific for the game, *specifications* that declare conditions necessary to hold in order for the game to take place, *components* that determine a sequence of utterances the game generates.

At each moment of the conversation, the participants are involved in one dialogue game which represents the conversational regularities followed at the current dialogue point. This game is called an *active dialogue game*. The dialogue games for previous episodes that have not yet been completed are considered as *open dialogue games*. The open dialogue games can become active in future interactions if the participants shift back to uncompleted issues. A *dialogue game stack*[2] has on its top the active game and contains all games that are open at the current point.

An active game can be terminated and deleted from the stack or suspended and left in the stack while its top place is taken by another active game, which can be either a newly initiated game or an open game re-activated. The last case may require changing the sequence of communicative acts in the game tactic.

Generally, there might be several possible operations over the *dialogue game stack*. StyLE-OLM uses heuristics, called here *dialogue strategies*, to guide the dialogue management decision taking. *Dialogue strategies* define a meta-level of dialogue and decide which particular game STyLE-OLM should 'play' at each time of dialogue. The strategies are encoded as rules that search for particular conditions and assign some changes to be made in the dialogue games stack. The following conditions are monitored:

- There is a conflict in the commitment stores – this could be either internally in a participant's commitment store or between the views of the computer and the learner. In these cases, the initiation of a new negotiation game is suggested.
- The learner has submitted a proposition that is not confirmed by the expert knowledge base. In this case, the strategies suggest the initiation of new dialogue games (or re-activation of existing ones) that will examine misconception conditions.
- The last proposition does not conform to the focus of the current game (the global focus of the game is considered). In this case, the strategies can suggest either the initiation of a new exploring dialogue game or re-activation of a game with a corresponding focus.
- The last proposition does not conform to the local focus (the proposition of the preceding communicative act). In this case, the strategies can either trigger some changes in the dialogue tactics selecting a relevant proposition or initiate a new exploring dialogue game.

STyLE-OLM maintains a simple mechanism which selects the first applicable rule. Consequently, the order of applying the strategy rules may sometimes be essential for assigning an active game.

Each communicative act submitted by the student is analysed by comparing this communicative act with the current dialogue state. The consistency of a learner's contribution with the focus of the *active dialogue game* is examined by using domain inference techniques that relate the proposition of the communicative act to the *focus space* of the *active game*. In a similar manner, the learner's current contribution is assessed as to whether it is consistent with the *local focus* of the last communicative act. An examination of the correctness of a learner's statement requires appropriate domain reasoning to check whether the student's proposition has been confirmed by the computer's domain expertise. Investigations about whether the learners' errors are likely to be due to misconceptions also require domain inference. In this case, STyLE-OLM tries to recognise the errors, searching for possible schemata that may define relevant propositions to be checked in order to confirm the misconceptions. Should the analyser manage to identify schemata (more than one possibility for misconceptions that explain the same error may occur), the potential misconceptions may be discussed in further conversation.

[2] The name *stack* might be misleading here as the *dialogue game stack* is actually a more complex structure which contains dialogue games that are themselves compound structures. The notion of the stack is used to give some association with the main operations with dialogue games, which in most of the cases resemble the management of a stack structure. However, we also allow reshuffling the games within the dialogue game stack and moving upwards a game whose focus is the closest to the student's contribution.

Maintaining a jointly constructed learner model

Allowing for the system and the learner to have symmetrical diagnostic roles entails maintaining different views about the LM. The assumption that the LM will be used by other components of a learning environment implies the need for obtaining a jointly constructed and mutually accepted learner model, which absorbs agreements between the computer and student's views. Conflicts in different views should be accumulated for further negotiation. The mechanism for maintaining a jointly constructed learner model used in StyLE-OLM is based on a theoretical framework (Dimitrova et al., 2000) that accommodates a belief modal operator (Davis, 1990). Part of the diagnostic mechanism is concerned with managing the commitment stores, which in STyLE-OLM is incorporated in the dialogue module. The commitment rules assign changes to the system and learner's commitment stores. The new beliefs are not added directly, instead the commitment stores maintainer checks for potential inconsistencies in the commitment stores (see Figure 9), removes conflicting beliefs and then adds the new beliefs. The dialogue strategies will be informed for registering a conflict in the commitment stores and this may trigger a new negotiative game.

Inconsistencies in the system's commitment store

```
In the store
   believe(system,believe(learner,2050).
To be added
   notbelieve(system,believe(learner,2050).

In the store
   believe(system,believe(learner,2048).
   notbelieve(system,believe(learner,603).
To be added
   believe(system,believe(learner,2048)->believe(learner,603)).
```

Inconsistencies in the learner's commitment store

```
In the store
   believe(learner,2055).
To be added
   notbelieve(learner,2055).

In the store
   believe(learner,2022).
   believe(learner,2022->604).
To be added
   notbelieve(learner,604).
```

Figure 9. Example inconsistencies in the commitment stores in STyLE-OLM. The numbers represent IDs of conceptual graphs.

When STyLE-OLM needs to elicit what has been agreed about the learner's knowledge (for example, the learner switches to BROWSE mode), it employs a mechanism that takes the beliefs in the commitment stores as *initial sets of beliefs* and expands them, eliciting the beliefs of the computer about the learner and the beliefs of the learner about themselves by applying commonsense *reasoners* (correspondingly, reasoners of the computer about the learner's beliefs and reasoners of the learner about his/her beliefs) upon the beliefs in the initial belief stores. This follows Mackenzie's notion of *de facto commitments* (Mackenzie, 1979) to emphasise the distinction between publicly proclaimed beliefs and private beliefs that agents hold applying some reasoning rules. The agents' beliefs are then combined and agreements between both agents about the learner's knowledge are elicited. For example,

```
agreement(notbelieve(learner,2014),believe(system,notbelieve(learner,2014)),
          notbelieve,2014).
```

registers an *implicit agreement* between the system and the learner that the learner does not believe the proposition encoded in the graph with an ID number 2014. The first two arguments in the predicate show the belief in the student's commitment store and the belief in the computer's commitment store respectively. On the basis of these two beliefs the system elicits the agreement about the belief of the student represented in the last two parameters. While implicit agreements consider beliefs elicited by applying reasoning over the agents' beliefs, *explicit agreements* register consent between the agents using only what has been proclaimed in the dialogue. The predicate

```
agreement(none,believe(system,believe(learner,2015)),believe,2015).
```

registers an *assumed agreement* between the system and the learner that the learner believes the proposition encoded in the graph with an ID number 2015. The presence of 'none' as a parameter shows that the corresponding commitment store (student's in this case) does not support the belief (but does not contradict with it either) and the agreement is elicited on the basis of a belief in one of the commitment stores (computer's in this case).

STyLE-OLM also registers conflicts between the student and the system's commitment stores. For example,

```
conflict(believe(learner,675),
         believe(system,notbelieve(learner,675)),675).
```

registers an *implicit conflict* between the computer and the learner about the proposition represented in the graph with ID 675.

Before being added to the learner model in STyLE, the agreements about the learner domain beliefs are assigned a level of correctness. The diagnostic mechanism calls the module for extracting domain knowledge that contains a procedure which confirms the graphs represented in the agreements with the expert knowledge base. Then, the propositions in the agreements are assigned a level of correctness - *correct*/*wrong*/*missing*. The LM is updated by adding the agreed beliefs about the learner and registering possible misconceptions.

THE EVALUATIVE STUDY

An evaluative study was conducted aimed primarily at formative evaluation, which examined the behaviour of STyLE-OLM, specifically the use of the communication medium, the dialogue management, and the learner model maintenance. The results from the formative evaluation, presented in detail in Dimitrova (2001), validated the framework for IOLM used as a basis for implementing STyLE-OLM. The study also allowed us to examine some issues of the computational and educational benefits of IOLM which are discussed below. We focussed on:

- *The quality of the obtained learner model* - what was the difference (if any) between the initial LM STyLE-OLM was run with and the LM obtained at the end of the session, was the quality of the obtained LM better and in what respect?
- *The validation of the student model* - was the obtained LM valid, i.e. did it satisfy the diagnosee, the student who had been diagnosed, and a human diagnoser, a teacher who could perform the diagnosis instead of the computer?
- *The presence of reflection* - was there any evidence for engaging learners in reflective activities while interacting with STyLE-OLM?

Participants

The study involved seven postgraduate students at the Computer Based Learning Unit, Leeds University. All participants had good knowledge of English both in reading and writing and for five of them English was not a mother tongue. Most of them were novice in Finance, only one participant appearing to have a substantial understanding of the domain from his past experience. All participants participated on a voluntary basis.

In addition, an expert - a foreign language teacher in a Finance domain - helped with the evaluation of the dialogue maintenance and the validation of the learner model.

Task

Each learner attended an individual session. About a week before the session, each learner was given an introductory text to familiarise with target Finance terms from the topic Financial markets, presented in the domain ontology. Prior to their sessions, the learners were asked to answer several drill questions about the terms they studied. This took about twenty minutes. The learners' performance was assessed and initial LMs obtained (by hand). The interactions with STyLE-OLM were initiated using these LMs. Training with the communication medium was provided which was generally half an hour and allowed the students to interact with the Computer Science instantiation of STyLE-OLM.

In a session with STyLE-OLM running in a Finance domain, the learners were asked to help the computer system to obtain a better model of their domain conceptualisations. It was explained to the participants that this would facilitate the system's adaptability in future pedagogical situations like generating explanations, providing feedback, selecting instructional materials. The learners were encouraged to inspect the LM, discuss their domain knowledge, and influence the content of the learner model. Generally, each session lasted about half an hour and was terminated by the learner.

Method

Every learner session was observed and monitored by the experimenter. Log files were recorded for a thorough examination of the system's behaviour. At the end of each session, a learner was given a questionnaire, with the dialogue transcripts and the resultant learner model enclosed, to elicit their subjective view about the system's performance. Some learners were briefly interviewed to explore interesting issues arising in the interactions. A questionnaire with enclosed dialogue transcripts, initial and obtained LMs from learner sessions were given to a teacher who was experienced in teaching Financial English to non-English students.

Examples

To illustrate the learner activities in STyLE-OLM we show below two transcripts of sessions with STyLE-OLM recorded during the evaluative study. The results of the study are presented and discussed in the following section.

According to their performance at the initial drills (which influenced the initial learner models), the participants were classified into two groups - *more knowledgeable* students whose initial LMs presented mostly `known` facts and *less knowledgeable* students whose initial LMs presented mainly `missing` and `erroneous` knowledge.

Example 1: A more knowledgeable learner discusses his domain knowledge in STyLE-OLM

Here, we will present an extract from a dialogue with a learner whose initial LM showed a reasonably strong knowledge in Financial markets. It will be demonstrated how the robustness of the learner's domain beliefs is challenged and he articulates aspects of his conceptualisation.

In the above sections, we showed examples of the graphical communication medium. Here we will omit screen shots but will include some of the experimenter's observations and learner's commentaries, which can provide a flavour of the interactive process.

The initial situation in this example is that the learner confuses the terms CAPITAL MARKET and MONEY MARKET. The initial learner model contains the following information about the learner's domain beliefs (we have extracted only the aspects about the two confused terms):

```
[L1] know - Money market operates with short term investments.
[L2] not_know - On the money market, securities are converted into cash.
```

[L3] know - Capital market operates with long term investments and raises capital.
[L4] know - Capital market supports building new homes, factories, schools, highways and shops.

STyLE-OLM initiates the dialogue.

[1.0] STyLE-OLM$_{[inform]}$ YOU THINK that CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS.

[1.1] Learner$_{[agree]}$ I AGREE that CAPITAL MARKET raises CAPITAL and CAPITAL MARKET operates with LONG TERM INVESTMENTS.

[1.2] STyLE-OLM$_{[inform]}$ YOU THINK that MONEY MARKET operates with SHORT TERM INVESTMENTS.

Learner's comments:

"Oh, No. This is not true…"

[1.3] Learner$_{[disagree]}$ I DISAGREE that MONEY MARKET operates with SHORT TERM INVESTMENTS.

[1.4] STyLE-OLM$_{[inform]}$ YOU THINK that CAPITAL MARKET supports building new HOMES, FACTORIES, SCHOOLS, HIGHWAYS and SHOPS.

Learner's comments:

"I see, this is a compound sentence, a conjunction of several statements. Need to check every single statement… "

He looks at the graph very carefully. Decides that every sub-statement in it is correct and makes a claim.

[1.5] Learner$_{[inform]}$ I THINK that CAPITAL MARKET supports building new HOMES, FACTORIES, SCHOOLS, HIGHWAYS and SHOPS.

[1.6] STyLE-OLM$_{[inquire]}$ DO YOU THINK CAPITAL MARKET is a FINANCIAL MARKET?

[1.7] Learner$_{[inform]}$ I AGREE that CAPITAL MARKET is a FINANCIAL MARKET .

[1.8] STyLE-OLM$_{[inquire]}$ DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with CORPORATE STOCKS?

[1.9] Learner$_{[disagree]}$ I DISAGREE that CAPITAL MARKET operates with CORPORATE STOCKS.

[1.10] STyLE-OLM$_{[inquire]}$ DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with TAX EXEMPT BONDS.

Learner's comments:

"I see, it's asking me about tax exempt bond now… It might be true if tax exempt bond is a kind of long term investment. I can ask the system this, can I…"

[1.11] Learner$_{[inquire]}$ IS IT TRUE that TAX EXEMPT BOND is a LONG TERM INVESTMENT .

[1.12] STyLE-OLM$_{[inform]}$ I KNOW that TAX EXEMPT BOND is a LONG TERM INVESTMENT .

Learner's comments:

"I see. Then I can answer the question it asked me earlier… "

The learner goes back in the dialogue history, stops at move [1.10] and makes a statement:

[1.13] Learner$_{[inform]}$ I THINK that CAPITAL MARKET raises CAPITAL and operates with TAX EXEMPT BONDS.

[1.14] STyLE-OLM$_{[inquire]}$ DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with CONSUMER LOANS.

Learner's comments:

"We haven't discussed about consumer loans, have we? I don't know the answer, perhaps I shall say this…"

[1.15] Learner[inform] I DO NOT KNOW that CAPITAL MARKET operates with CONSUMER LOANS.

[1.16] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with NEGOTIABLE CERTIFICATES OF DEPOSIT.

Learner's comments:

"Can't we change the topic…"

[1.17] Learner[disagree] I DISAGREE that CAPITAL MARKET operates with NEGOTIABLE CERTIFICATES OF DEPOSIT.

[1.18] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with MORTGAGE LOANS.

Learner's comments:

"I shall think of which market operates with mortgage loans"

The learner goes through the Finance terms. He does not seem to find the term he is looking for and decides to see his model. He goes to BROWSE mode, looks mainly at the graphs, but seems happy with the information in the learner model.

The learner goes back to DISCUSS mode and continues the dialogue.

[1.19] Learner[inform] I THINK that NEGOTIATED MARKET operates with MORTGAGE LOANS.

[1.20] STyLE-OLM[inquire] DO YOU THINK MORTGAGE LOAN is a LONG TERM INVESTMENT?

The interaction continues with a short elaboration on MORTGAGE LOAN and is soon terminated by the student, quiting STyLE-OLM. After the interaction finishes, STyLE-OLM updates the LM. As shown below, the resultant LM presents a more elaborated picture about the learner's domain knowledge, particularly about the terms discussed:

[UL1] **know** - Capital market raises capital and operates with long term investments.

[UL2] **know** - Capital market supports building new homes, factories, schools, highways and shops.

[UL3] **know** - Capital market is a financial market.

[UL4] **know** - Capital market rises capital and operates with tax exempt bonds.

[UL5] **know_wrongly** - Negotiated market operates with mortgage loans.

[UL6] **not_know** - Money market operates with short term investments.

[UL7] **not_know** - Capital market operates with corporate stocks.

[UL8] **not_know** - Capital market operates with consumer loans.

[UL9] **not_know** - Capital market operates with negotiable certificates of deposit.

[UL10] **not_know** - On the money market, securities are converted into cash.

[UL11] **not_know** - Capital market raises capital and operates with mortgage loans.

We will discuss the validity and the quality of the updated learner model in the next section.

This authentic fragment of an interaction with STyLE-OLM reveals some issues regarding planning the interaction with the learner. It shows a broader picture of the tactics for elaborating domain knowledge: in moves [1.0] and [1.2] the system elaborates on term definitions; move [1.4] refers to a graph representing a situation with a domain term; in move [1.6] the system extracts a fact from the type hierarchy; moves [1.8], [1.10] and [1.14] illustrate graphs generated by the system as specialisations of an expert graph. In addition, this example demonstrates changing the focus of the dialogue which is initiated by the student (in move [1.19]). As move [1.20] depicts, the dialogue strategies give priority to such changes and suspend the current dialogue game, initiating a game that explores domain aspects with the new focus. In this case, the system puts the terms NEGOTIATED MARKET and MORTGAGE LOAN in a global focus for the new dialogue game. The conversation continues with MORTGAGE LOAN because it is more relevant to the preceding discourse.

Example 2: A less knowledgeable learner reflects upon his domain knowledge inspecting the LM

This case shows a less knowledgeable participant who, being aware of his gaps, tries immensely to find means to benefit from a session with STyLE-OLM. The extract below reveals how an extensive inspection of the learner model, when aspects of the learner's conceptualisation have been challenged by the system in an interaction mode, may lead to a sequence of reflective activities.

The initial situation is that the learner confuses the terms CAPITAL MARKET and MONEY MARKET. STyLE-OLM initiates the dialogue.

[2.0] STyLE-OLM$_{[inquire]}$ CAPITAL MARKET raises CAPITAL and operates with WHAT?

The learner does not know how to answer. He decides to look at the learner model. He says that he is not familiar with the domain and prefers to see in the LM what his problems are. The learner goes to BROWSE mode.

He starts looking at the information presented in the LM very carefully, tries to understand everything there. He is looking mostly for what is marked as known and seems to agree with it.

Browsing through the model, the learner confirms aspects of his domain knowledge presented in the LM. At a certain point, he sees in the LM that he does not know the domain fact 'MONEY MARKET operates with SHORT TERM INVESTMENTS'. The learner does not agree with this information about his domain beliefs and decides to challenge the content of the learner model. He goes to DISCUSS mode.

[2.1] Learner$_{[inform]}$ I THINK that MONEY MARKET operates with SHORT TERM INVESTMENTS.

[2.2] STyLE-OLM$_{[inquire]}$ WHAT does CAPITAL MARKET support?

The learner's domain knowledge is challenged. He realises that he has problems in this domain and decides to browse the learner model again. The learner goes to BROWSE mode. He says that he does not understand the domain and needs to study more.

Learner's comments:

"I can initiate a discussion about something which I don't know, perhaps I can learn about the domain then. Let me see what might be interesting."

He browses through the LM and looks for domain aspects which he does not know. He finds that he does not know 'CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS'[3] (which information has been added after the learner has failed to answer the question in move [2.0]).

Learner's comments:

"That's the information I was looking for before. I found it now! Yes, I agree, I don't know this. But…in fact, I know it now... I'll change the model then... Hmm, but if this is not correct, do I know it...

Well, I'll tell the system that I know it, since I have seen it anyway. Then I will have a look at the model to see if this is marked as 'known wrongly' which will mean that this information is not correct... "

The learner goes to DISCUSS mode.

[3] In a browse mode, STyLE-OLM shows a graph representing the proposition supported with the texts 'You don't know that CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS'.

[2.3] Learner[inform] I THINK that CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS.

[2.4] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET is a FINANCIAL MARKET?

Learner's comments:

"Aha, that's something I know. It finally understood that I want to talk about capital market. Perhaps I can carry on with this... "

[2.5] Learner[inform] I THINK that CAPITAL MARKET is a FINANCIAL MARKET.

[2.6] STyLE-OLM[challenge] WHY DO YOU THINK that CAPITAL MARKET is a FINANCIAL MARKET.

Learner's comments:

"OK, I see the system does not believe that I know capital market. I am not aware too... "

The learner scans through the dialogue. He seems to look for something but cannot find it.

Learner's comments:

"This time I am going to say something that should convince the computer... I need to find the justification the computer is asking me for..."

The learner goes through the concepts, looks for a concept that relates to FINANCIAL MARKET and CAPITAL MARKET. He stops at CASH and says that this term will help him to justify.

[2.7] Learner[justify] IT IS TRUE BECAUSE CAPITAL MARKET contains CASH.

[2.8] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with CORPORATE STOCKS.

Learner's comments:

"I see... It's checking my knowledge about capital market. Perhaps the computer is still not convinced about the statement I made... What was this statement..."

The learner goes backwards in the dialogue history and stops at move [2.3] where the proposition is 'CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS'.

Learner's comments:

"I see... It's making almost the same statement. Well, I think it should be true..."

The learner goes forwards in the dialogue history and stops at the last move (move [2.8]). Then, he makes a statement.

[2.9] Learner[inform] I THINK that CAPITAL MARKET raises CAPITAL and operates with CORPORATE STOCKS.

[2.10] STyLE-OLM[inquire] DO YOU THINK that CAPITAL MARKET raises CAPITAL and operates with TAX EXEMPT BONDS.

Learner's comments:

"I see... It will keep asking me about this statement. It's tax exempt bond now... Might be true if tax exempt bond is a kind of long term investment but I have no idea whether this is true... This time I shall say I don't know"

[2.11] Learner[inform] I DO NOT KNOW that CAPITAL MARKET raises CAPITAL and operates with TAX EXEMPT BONDS.

[2.12] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with CONSUMER LOANS.

Learner's comments:

"Should be true..."

[2.13] Learner[inform] I THINK that CAPITAL MARKET raises CAPITAL and operates with CONSUMER LOANS.

[2.14] STyLE-OLM[inquire] DO YOU THINK CAPITAL MARKET raises CAPITAL and operates with NEGOTIABLE CERTIFICATES OF DEPOSIT.

Learner's comments:

"I don't know... Perhaps, looking at my model could help"

After a couple of moves, the interaction is ended by the user.

It has been shown in this example how a *less knowledgeable* learner has been often provoked by the system to examine the validation of his domain beliefs. Since following a discussion about the domain appears hard for him, the student often switches to BROWSE mode to inspect his domain model and to see the level of correctness the system assigns to the beliefs in the LM. Such situations were frequently monitored in sessions with less knowledgeable participants.

STyLE-OLM perceived by users

On the whole, STyLE-OLM provided an environment adequate for discussing and inspecting the LM. The students did not experience major problems with the communication medium - they could relatively easily construct and understand communicative acts as well as examine the beliefs in the LM. In the beginning of each session, the learners mainly read the text shown in the bottom of the graphical window. After getting more familiar with the graphics, the participants tend to examine both the conceptual graphs and their text equivalents generated by the system. They found the graphical form helpful for articulating the main concepts and relations between them. Many learners acknowledged as useful to have both text and graphics to render propositions, however, the text was confusing at times lacking coherence due to the simple template-based mechanism used in STyLE-OLM. The evaluation of the communication medium is discussed in detail in Dimitrova et al. (2002). The learners were asked about their preferences of text or graphics - some preferred text, others wanted to communicate with graphics. The study was too limited to examine thoroughly the usefulness of text and graphics, further investigation is needed which could follow the argument in Cox (1999) and examine the use of the external representations depending on the task, properties of representations and the users' cognitive styles.

The majority of participants viewed the interaction they experienced in sessions with STyLE-OLM as a discussion about their domain knowledge and believed that they could influence the system's diagnosis. This allows us to conclude that the dialogue in STyLE-OLM fulfils the requirements of IOLM. An important feature of the interaction with STyLE-OLM was that learners were allowed to take the initiative in maintaining the dialogue by changing the focus of conversation or initiating new dialogue games. The participants found the dialogue moves natural and the sentence openers very useful. The focus maintenance (based on CG inference) was relatively robust and allowed discussing connected terms and elaborating more aspects of a learner's domain knowledge. This was regarded as positive by all participants. A major deficiency of the dialogue in STyLE-OLM was the lack of semantic structure in rendering the system's communicative acts. As a result, some learners found that the system jumped from sentence to sentence without any obvious reason and they hardly followed what was going on. The teacher and two learners pointed out that the language used by the system to formulate its communicative acts was rather frustrating at times which was result of the lack of explanation of the purpose of the system's communicative acts. Further improvement of the STYyLE-OLM interface is needed to navigate the learner through the dialogue by indicating, for instance, what the current tactic is, why the system is changing the tactic, and when the system goes back to a previously initiated dialogue game.

We will now discuss the results from the study focusing on the potential impact of IOLM in terms of possible improvement of the LM quality and providing opportunities to engage learners in reflective activities.

ON THE QUALITY OF THE UPDATED LEARNER MODEL

The quality of the resultant LM will be analysed with respect to the initial LM. We define that a learner model L_{new} is of a *better quality* than a learner model L if:

[1] L_{new} removes the inconsistencies in L if such exist;

[2] L_{new} presents a larger scope of learner's beliefs;

[3] L_{new} provides more explanations of the learner's errors;

[4] L_{new} includes a higher proportion of valid assertions about the learner's knowledge;

[5] L_{new} minimises the number of invalid assertions about the learner's knowledge.

The **first criterion** refers to problems with LM consistency often experienced by observational diagnosis, e.g. a fact that contradicts the beliefs in the LM needs to be added. Some of the initial LMs in the study contained inconsistent predicates such as a learner *knows* a fact *G* together with he/she *does not know G*. The diagnostic mechanism in STyLE-OLM removed the beliefs that were inconsistent with the one stated last and the interaction clarified and elaborated relevant domain aspects. As a result, the inconsistent information was removed and more facts related to this uncertain aspect of a student's knowledge were added.

However, at times the resultant LMs contained conceptually conflicting domain facts somehow hidden and not captured by the conceptual graph inference engine, e.g. when two graphs represented facts that were paraphrases of one another. The following extract from a teacher's comment illustrates such contradictions.

> I do not understand how the learner does not know 212 and 213, and yet knows 211 which is a paraphrase of 212 and 213. Actually, 211 combines the statements made in 212 and 213. Please look at that in the initial learner model.
> (Author's note - numbers here indicate IDs of conceptual graphs as follows: 211 - 'Primary market operates with (trades with) new issues of security and supports new investments', 212- 'Primary market is the process by which a corporate stock is issued for the first time', 213- 'Primary market supports new investment through the selling newly issued stocks'.)

The validity of these facts may be addressed in further interactions with STyLE-OLM. The learner could also identify such problems inspecting the LM and initiate a discussion which would clarify inconsistent aspects. Nevertheless, extended domain reasoning would be needed to capture the problems pointed out by the teacher and to ensure the omission of the inconsistencies she identified.

The **second criterion** concerns articulating learner's beliefs and expanding the LM. As Table 1 shows, this was observed in each experimental session.

Table 1. Changes upon the beliefs in the LMs after sessions with STyLE-OLM.

Learner ID	Total number beliefs in the initial LM	Beliefs from the initial LM deleted in the obtained LM	Beliefs from the initial LM included in the obtained LM	New beliefs added in the obtained LM	Total number beliefs in the obtained LM	Length of the interaction (number moves)
L_1	11	1	10	15	25	25
L_2	11	1	10	10	20	17
L_3	13	0	13	7	20	26
L_4	13	2	11	6	17	34
L_5	13	2	11	5	16	15
L_6	11	0	11	5	16	19
L_7	11	0	11	3	14	18

The expansion of the learner model did not depend crucially on the length of the interaction. L_4 who had the longest interaction with the system had not actually added many new beliefs since he was mainly confirming existing ones. Similarly, the interactions of L_6 and L_7 were mainly approving aspects of their learner models. On the other hand, L_1, L_2, and L_3 explored more aspects of the domain (which resulted in LM expansions). While L_1 and L_3 spent more time engaged in a conversation and did very little inspection of their models (example 1 from the previous section presents an excerpt from the L_1's session), L_2 was predominantly inspecting his learner model (an excerpt from this session is given in example 2 in the previous section). L_5 followed a similar style of mainly scrutinising the LM but he did not manage to explore many new aspects. The few deletions that were made were either due to the learner's withdrawal of a system's claim about his beliefs or his challenge of facts in the inspected LM.

The **third criterion** refers to finding possible learner's misconceptions, which are defined in STyLE-OLM as explanations for the learner's errors at conceptual level (see above). We found that several explanatory dialogue games aimed at discovering possible learners' misconceptions were initiated throughout the study when the users rendered erroneous facts and the system could invoke misconception schemata to generate dialogue tactics for the particular situations. However, only a few misconceptions were actually registered in the LMs during sessions in the Finance domain. The analysis of the interactions revealed that the learners frequently discovered their errors and made claims changing the LM. As a result, registered potential misconceptions were not confirmed, i.e. not included in the resultant LM. We also discovered that some learner misconceptions were not confirmed because learners changed the flow of the dialogue by initiating new conversational topics.

In contrast, there were considerably more misconceptions registered in the resultant LMs during the training interactions in the Computer Science domain (where, in fact, most of the initial testing of STyLE-OLM was done). Although, the domain expertise in this domain was fairly limited, it included aspects which we expected could lead to discovering possible learners' misconceptions whilst the Finance ontology was developed by knowledge engineers who did not explicitly address pedagogical needs. This stresses the importance of considering pedagogical aspects when encoding the domain expertise in intelligent learning environments. It also justifies the need to enhance the current IOLM architecture in order to accommodate limited or shallow domain expertise.

The **last two criteria** refer to validating the changes in the LM. As mentioned earlier, we consider that a LM obtained from a computer diagnoser is *valid* if it satisfies the diagnosee, the student who has been diagnosed, and a human diagnoser, a teacher who can perform the diagnosis instead of the computer. To validate the LM obtained, we asked the learners and the teacher to comment on the content of the resultant LMs. Table 2 summarises the students' opinions.

Table 2. Learners' views about the validity of the information in their LMs.

Learner ID	Does the LM **CORRESPOND** to your view about your domain knowledge 1-Exactly correspond 7-Does not correspond at all	Is there anything that should have **NOT BEEN ADDED** to LM (1-yes, 0-no)	Is there anything That should have **BEEN ADDED** To LM (1-yes, 0-no)	Are you **SURPRISED** By something in LM (1-yes, 0-no)
L_1	2	1	0	0
L_2	2	0	0	0
L_3	4	0	0	0
L_4	2	1	1	1
L_5	2	0	0	1
L_6	6			1
L_7	3	0	0	1

Five learners considered that the resultant LMs corresponded to their domain knowledge and one was neutral. L_6 thought that the obtained LM did not correspond to his domain knowledge. This learner disagreed with the LM containing 'known' facts he did not actually know. The facts concerned domain aspects not addressed in the discussion with STyLE-OLM but present in the initial LM of this user. Similarly, a fact not discussed with the system surprised L_4 as he thought he knew it but it was marked as unknown in the LM (following the initial LM). While such cases fortify the benefits of interactive open learner modelling, they also show potential pitfalls for missing necessary discussion topics (and leaving invalid pieces in the LM) because either dialogue tactics may not capture them or a learner could terminate the interaction and leave the session.

Differently from the learners, the teacher was rather neutral validating (on the basis of the observed interactions) the LMs she inspected. She questioned principally the approach of assigning correctness to someone's knowledge when, in her opinion, the system's expertise was not sufficiently refined. The teacher also challenged some dialogue strategies that might have hindered articulation of students' knowledge. For instance, there were cases when a learner stated a wrong fact and the system did not initiate a new game to explore the erroneous knowledge, which the teacher believed should have been also the priority in such interactions. This highlights the importance of collecting successful diagnostic tactics and strategies, which relates to the general issue of utilising human teaching tactics and strategies in educational environments (du Boulay, 2000).

Having a fairly generic dialogue model, STyLE-OLM provides a test bed for examining the applicability of different diagnostic strategies. The study discussed here regarded some strategies as *plausible*, e.g. the initiating of exploratory games when the learners' statements did not conform to the current global focus. The benefit of others was found more *controversial*, e.g. the initiating of a clarification dialogue game every time a conflict in the commitment stores was discovered was useful for managing the belief stores but often re-directed the dialogue and hindered possible misconception disclosures. The participants in our study *discarded* a strategy which led to not exploring a learner’s error (when a learner stated a wrong domain fact) but continuing the current dialogue game.

To sum up, the study demonstrated that interactive open learner modelling leads to improved quality of the learner model. We observed fewer inconsistencies in the resultant LMs, a larger scope of learners’ beliefs, and some explanations of the learners’ errors. The obtained LMs included a higher proportion of valid assertions about the learners’ knowledge and minimised the number of invalid assertions about the learners’ knowledge.

ON THE PRESENCE OF REFLECTION

We discussed earlier that involving a learner in diagnosis, if well maintained, increases the likelihood of educational gains in terms of reflective learning. We also argued that interactive open learner modelling is capable of fostering reflective learning as it incorporates the essential features: observation, interaction, and symmetry in student-computer relationships. The system we have developed has allowed us to monitor several *reflective activities* in interactive open learner modelling. In this section, we will discuss the presence of reflection on the basis of evidence found in the interaction transcripts of the experimental sessions.

The interaction transcripts, which combine the dialogue history and the experimenter's observations (in particular when the learner switches between DISCUSS and BROWSE modes or goes backwards in the dialogue history), have been analysed for the presence of reflective activities. We regard an *activity* as a fragment of the interaction that can be considered to have led to the fulfilment of a particular goal. We define the following *reflective activities*:

- **Activity 1 -** The students *render statements about their domain beliefs*, thus they externalise their knowledge and experience (Draper, 1997) as well as recall and reconsider domain aspects (Boud et al., 1996). Typical examples of such activities involve dialogue episodes containing *inform*, *agree*, *challenge*, or *disagree* moves from the learners. Not all claims made by the students demonstrate reflective activities, e.g. "I don’t know" statements.
- **Activity 2 -** The students *go back to claims about their beliefs and (possibly) change these claims*, thus they recall and reconsider domain aspects (Boud et al., 1996) and validate their domain beliefs (Dewey, 1960). These activities may include dialogue episodes (e.g. the system challenges a learner's claim and he makes a statement to alter the challenged claim), the learner makes a statement to change his/her previous claim

after going through the dialogue history, or being provoked by a system's move (e.g. *inquire* or *challenge*) the learner switches to BROWSE mode to inspect his/her model.

- **Activity 3 -** The students *investigate arguments to support their beliefs*, thus they search for grounds of their beliefs (Dewey, 1960). In this group of reflective activities we consider the learners' justifications of their claims (including *justify* or *inform* moves) in response to system's *challenges*. Another evidence for the students' searching for grounds of their beliefs are episodes when a system's *challenge* is followed by a student's *inquiry* to clarify domain aspects and then a student's claim that supports/withdraws his/her beliefs.

Table 3 summarises the reflective activities identified in the study with STyLE-OLM. Figure 10 condenses the results in Table 3 and presents the distribution of the reflective activities among the two learner groups – *more knowledgeable* and *less knowledgeable* learners - based on the mean percentage of each activity in regard to all activities the learners were engaged in.

The *more knowledgeable* participants were relatively well-engaged in discussions about their models. They experienced on average a total of 12.5 (S.D.=4) reflective activities in a session. While the interactions with the *less knowledgeable* students were shorter and had frequent focus changes, these students browsed their models more often when provoked by the system's inquiries or challenges. As a result, the average total number of reflective activities that the *less knowledgeable* students were involved in was only slightly lower: 11.3 (S.D.=1).

Table 3. Reflective activities identified in the study with STyLE-OLM.

Learner ID	Percentage of **ACTIVITY ONE** Render statement	Percentage of **ACTIVITY TWO** Go back to claim	Percentage of **ACTIVITY THREE** Investigate argument	**TOTAL NUMBER** Reflective activities	**TYPE OF LEARNER**
L_5	45%	36%	18%	11	Lees knowledgeable
L_2	58%	25%	17%	12	Less knowledgeable
L_6	55%	18%	27%	11	Less knowledgeable
L_1	85%	8%	8%	13	More knowledgeable
L_3	80%	0%	20%	10	More knowledgeable
L_4	61%	28%	11%	18	More knowledgeable
L_7	89%	0%	11%	9	More knowledgeable

Predominantly, we observed the first reflective activity - learners rendered statements about their domain beliefs. The results in Table 3 show that *more knowledgeable* students tend to make more claims about their beliefs. A one-tailed Mann-Whitney *U*-test for very small samples (Siegel, 1956) over the data in the first column in Table 3 with H_0='Both learner groups equally involved in the first reflective activity' and H_1='*More knowledgeable* learners made more claims about their domain beliefs, i.e. they were more often involved in the first reflective activity', $U = 0$, $n_1=3$, $n_2=4$ showed that the probability of occurrence under H_0 is $p=0.028$. Therefore, the study provides considerable evidence that *more knowledgeable* learners make more claims about their beliefs. This result correlates with the observations of researchers who examined the self-explanation effect and found that the more able students were capable of generating self-explanations (Barnard & Sandberg, 1996; Chi et al., 1989). Our study did not provide evidence for any difference in the distribution of the other two activities, nor for the total number of reflective activities experienced.

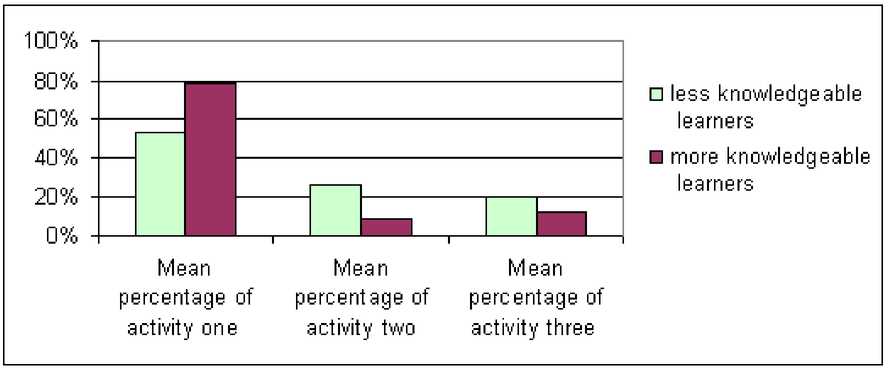

Figure 10. Distribution of the three reflective activities monitored in the sessions with STyLE-OLM. For every learner the percentage of each type of reflective activity in respect to all reflective activities that this learner has experienced, is calculated (see Table 3). Then, the mean percentage for the three reflective activities for both groups - less knowledgeable and more knowledgeable learners – are obtained.

The interactions with *more knowledgeable* learners contained relatively varied types of exchanges where participants made claims about their beliefs. Some of these exchanges were initiated by the system, e.g.

the system informs and the learner agrees

STyLE-OLM$_{[inform]}$. YOU THINK that CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS.

Learner$_{[agree]}$. I AGREE that CAPITAL MARKET raises CAPITAL and CAPITAL MARKET operates with LONG TERM INVESTMENTS.

the system informs and the learner disagrees or doubts

STyLE-OLM$_{[inform]}$. YOU THINK that CAPITAL MARKET supports building new HOMES, FACTORIES, SCHOOLS, HIGHWAYS and SHOPS.

Learner$_{[challenge]}$. I DOUBT that CAPITAL MARKET provides HOME BUILDING.

the system inquires and the learner informs or agrees

STyLE-OLM$_{[inquire]}$. CAPITAL MARKET raises CAPITAL and operates with WHAT?
Learner$_{[inform]}$. I THINK that CAPITAL MARKET raises CAPITAL and operates with LONG TERM INVESTMENTS.

Sometimes the learner initiated inquiries to clarify domain facts after which he made statement about domain facts, e.g.

Learner$_{[inquire]}$. IS IT TRUE that CAPITAL MARKET operates with NEGOTIABLE CERTIFICATES OF DEPOSIT.

STyLE-OLM$_{[inform]}$. I KNOW that CAPITAL MARKET operates with NEGOTIABLE CERTIFICATES OF DEPOSIT.

Learner$_{[inform]}$. I THINK that NEGOTIABLE CERTIFICATE OF DEPOSIT has a supertype that is LONG TERM INVESTMENT.

(They have discussed earlier that CAPITAL MARKET operates with LONG TERM INVESTMENTS.)

Typical reflective activities where *less knowledgeable* participants made claims about their beliefs were sequences of a system's inquiry followed by a learner's browsing through the LM and ended with a learner's statement to change the information in the LM (the last move could well change the discussion topic), e.g.

STyLE-OLM$_{[inquire]}$. CAPITAL MARKET raises CAPITAL and operates with WHAT?

The learner browses through the LM, decides to challenge a fact there.

Learner$_{[inform]}$. I THINK that MONEY MARKET operates with SHORT TERM INVESTMENTS.

These participants also made claims about their beliefs answering system's questions, e.g.

STyLE-OLM[inquire]. DO YOU THINK that CAPITAL MARKET raises CAPITAL and operates with CORPORATION STOCKS.

Learner[agree]. I AGREE that CAPITAL MARKET raises CAPITAL and operates with CORPORATION STOCKS.

Reflective activities of the second type were usually observed in situations where learners looked back at their claims both in the dialogue history and the obtained LM after they were challenged by STyLE-OLM. The system challenged either because there was not enough information to accept that the learner believed a domain fact or because the fact a learner stated had not been confirmed by the system's domain knowledge. *Less knowledgeable* learners experienced such situations more often (see Figure 10) since their claims were more frequently challenged by the system. These participants tend to browse their LMs in order to check the correctness of the claims they had made. Some *more knowledgeable learners* did not go back to claims they had made.

Finally, the system led the learners to search for and render grounds that support their beliefs promoting learners' justifications by challenging their domain claims, e.g.

Learner[inform]. I THINK that CERTIFICATE OF DEPOSIT raises CASH.

STyLE-OLM[challenge]. WHY DO YOU THINK that CERTIFICATE OF DEPOSIT raises CASH.

Learner[justify]. IT IS TRUE BECAUSE BANK is an instrument of CERTIFICATE OF DEPOSIT.

(In this case the system challenged the learner's statement since it was not confirmed by the domain knowledge base, the justification was not confirmed either, though the learner insisted these two facts were correct.)

In the third type of reflective activity we also included some inquiries: students grounded their domain beliefs by asking questions to clarify aspects of the domain relying on the system's domain expertise. While *more knowledgeable* learners constructed questions exploring aspects not discussed yet but following the preceding discourse (as in the extract below), a common pattern with the *less knowledgeable* students was to 'answer' a system's question by posing it back to the system (the reflectiveness of such inquiries is dubious).

STyLE-OLM[inquire] WHY DO YOU THINK MONEY MARKET operates with CORPORATE BONDS?

Learner[inquire] IS IT TRUE that CORPORATE BOND is a SHORT TERM INVESTMENT?

STyLE-OLM[inform] I DO NOT KNOW that CORPORATE BOND is a SHORT TERM INVESTMENT.

Learner[challenge] I DOUBT that MONEY MARKET operates with CORPORATE BONDS.

(The first two moves exemplify a learner searching for the grounds of his beliefs while the whole episode demonstrates a learner going back and changing his previous claims).

The occurrence of the above situations in interactions with STyLE-OLM has allowed us to make claims about the *presence of reflection*. To address the *effectiveness* of the reflective activities we consider two factors:

- Is the scope of articulated domain beliefs extending in a coherent manner so that not only have the learners recalled aspects of the domain but been able to build a consistent picture connecting related domain facts?
- Have the students been provided various alternatives to explore the domain, so that they can study the domain in-depth and see different aspects to expand their beliefs?

We argue that if learners are jumping from a domain fact to another exploring concepts distantly related to one another, they are less likely to build associations between the knowledge pieces they have reflected upon, than if they are constructively led to recall related facts and build a coherent picture of some domain aspects. Following this argument, for each session with STyLE-OLM we elicited the concepts included in the propositions of the communicative acts and grouped related concepts in sets. We consider that a set comprises *related concepts* if each two concepts are either directly linked in the type hierarchy or there is a conceptual graph in the expert knowledge base the two concepts belong to.

In general, each interaction explored at least one set which contained at least six related concepts. The longer the discussion episodes were (the learner stayed in a DISCUSS mode), the larger the articulated sets of related terms were. The learner with the longest dialogue had discussed four sets with nine, eight, four and two related concepts. Even the learners who switched frequently to a BROWSE mode had looked for terms related to the ones mentioned in the discussion with the system. Both the limited domain knowledge base and the short experimental interactions indicate that the reliability of these results has to be questioned. However, since the dialogue is guided by the system which employs a mechanism for extracting relevant domain facts from the expert knowledge base, we could expect future runs to show results similar to the study with the current prototype.

The second factor concerns exploring various alternatives related to one piece of knowledge. This was observed in most of the sessions and was utilised by dialogue tactics for conceptual understanding. The learners were referred to term definitions, situations with domain terms, hierarchical relations, and exemplars of generic terms. However, in some cases the interactions were slightly boring because the system generated specialisations of the same graph exploring predominantly exemplars of generic terms or hierarchical relationships due to the limited number of conceptual graphs in the knowledge base. Investigations with an improved knowledge base are required, in order to assess the tactics for exploring various domain alternatives.

These factors are by no means comprehensive in respect to analysing the effectiveness of reflection, as the learning effect has not been evaluated (which implies a larger scope of genuine participants engaged in authentic learning situations). It is fair to say that the effectiveness of the reflection is still a controversial issue. The discussion here can only be regarded as an interesting initial exploration. As Kolb (1984) stresses, the effect of reflection can only be seen after the learner returns to the experience where the new knowledge will be associated with that which is already possessed and conclusions will be drawn about the material which has been processed.

To summarise, we have monitored reflective activities in interactions with STyLE-OLM. The study showed that IOLM would be beneficial both for *more knowledgeable* and *less knowledgeable* learners. While the former would be engaged in reflective interactions about the domain, the later would be provoked to inspect their models and challenge the robustness of these models.

STYLE-OLM INTEGRATED INTO STYLE: THE ROLE OF IOLM IN LEARNING ENVIRONMENTS

The potential benefits of IOLM discussed above allow us to argue that it can play a *twofold role* in intelligent learning environments. On the one hand, IOLM may improve the quality of the LM and can be utilised as a diagnostic component that targets problems with traditional, observational, diagnosis. On the other hand, IOLM provides ways for engaging a user in reflective activities and can be considered as a learning activity in educational environments.

These issues have been addressed in the integration of STyLE-OLM in STyLE. STyLE[4] (Boytcheva et al., 2000) is an adaptive knowledge based web learning environment aimed at assisting learners from Bulgaria, Romania and Ukraine in acquiring Finance terminology in English. The STyLE users are university students who attend a Financial English course. STyLE addresses foreign language problems, such as understanding term morphological structure, mastering foreign language syntax and semantics, acquiring typical noun-verb collocations; domain problems, such as term context usage, metaphor understanding, awareness with what is encapsulated in the concepts behind the terms, understanding the meaning of concepts and the relations between them; some co-relations between language and domain understanding, e.g. syntactic/semantic errors that may lead to conceptual misunderstanding.

There are two types of learning activities in STyLE. Learners can *brush up their terminological knowledge* by freely exploring dictionaries and dynamically generated web pages with immersive contexts. They can also *verify their terminological knowledge* by going

[4] http://larflast.bas.bg/site/

through drills that test vocabulary, domain knowledge and situational use of terms. At each drill, learners are provided with adaptive feedback about their language and conceptual errors. For this purpose a LM is maintained. The model is also used by the instructional planning component in STyLE that offers appropriate drills or directs learners to relevant resources to improve their domain knowledge.

The instructional planner calls STyLE-OLM in situations where either the learner or the system need further dialogue, providing elaboration of learner's conceptual knowledge (Boytcheva et al., 2000). The following situations are catered for:

- *Contradiction in the learner model* – there are contradictory beliefs registered in the learner model. In this case, more elaboration on the learner's knowledge about these beliefs is needed. STyLE-OLM initiates a dialogue with the learner to solve the LM inconsistencies.
- *Confusion of close semantic concepts* – the drill analyser registers that the learner confuses semantically related terms (e.g. MONEY MARKET and CAPITAL MARKET). In this case, a STyLE-OLM session aims at elaborating similarities and differences between the terms.
- *Confusion of close language concepts* – the drill analyser registers that the learner confuses terms that may be related because of certain language similarities (e.g. CORPORATE BOND and AGENCY BOND). In this case, STyLE-OLM registers a potential conceptual problem caused by a linguistic error and, similarly to close semantic terms, elaborates on similarities and differences between the terms.

In STyLE-OLM, the learners are involved in an in-depth interaction about their domain understanding. Such interaction is expected to augment the system's picture of a learner's conceptualisation and to provide for reflective learning. STyLE-OLM is used in STyLE as:

- one of the learner modelling components and complements the modules that analyse the learner's performance;
- one of the STyLE modules that provide pedagogical activities.

CONCLUSIONS

There is a strong argument in Artificial Intelligence in Education which advocates that computer-based learning systems need to adapt to the needs of learners if they are to provide for effective personalised instruction (Self, 1999a). Computationally tractable methods for eliciting models of the learners' cognitive states are required. Approaches that bypass complexity problems of system-centred diagnosis by involving a teacher (e.g. Lund & Baker, 1999), a peer (e.g. Bull et al., 1999), or the learner (Morales et al., 1999) in the diagnostic process can be considered as fertile. The latter has been also suggested as a feasible approach in user modelling (Kobsa, 1990) and in building adaptive systems (Brusilovsky, 1996).

Interactive open learner modelling proposes a way of involving a learner in diagnosis. This approach goes beyond the idea of open learner models (Kay, 1995; Paiva & Self, 1995), where the learners' involvement is conceived mainly as scrutinising the externalised part of their models. It may well happen in open learner modelling that a learner browses the learner model passively not being able to focus on the relevant aspects, e.g. such situations occurred in experimental studies reported in Kay (1999) and Barnard and Sandberg (1996). In contrast, integrating the notion of openness with the idea of interaction allows challenging the robustness of the learners' domain expertise and not only provokes the learners' engagement in diagnosis but can also direct them to scrutinise the models in a more systematic way. Moreover, interactive open learner modelling provides more opportunities for fostering reflective thinking.

IOLM expands the idea of student model negotiation (Bull, 1997). While in the framework proposed by Bull the interaction is triggered chiefly by conflicts between the computer and the student's views about the student, IOLM manifests a constructive dialogue guided by the computer that flexibly switches between different diagnostic tactics. The diagnostic method presented in this paper is unique for it incorporates a discourse model for managing diagnostic interactions and provides both a diagnosee and a diagnoser with a common communication means and a symmetrical power in maintaining the dialogue. Another distinctive feature of this work is a more rigorous mechanism for maintaining different views about the learner's beliefs accumulated throughout the interaction. This mechanism maintains a jointly constructed learner model.

This paper has outlined the architecture of an interactive open learner modelling system and illustrated the method in a terminological domain. We have discussed an evaluative study with STyLE-OLM - the IOLM demonstrator we have built. The results from the study have been discussed in relation to the potential impact of the method, namely the quality of the obtained learner model and the pedagogical gains in terms of providing a means for fostering reflective thinking. Conclusions about the potential benefits from the method have been drawn. We have argued that IOLM is a fruitful approach which may be employed in intelligent learning environments both for obtaining a better model of a learner's cognitive state and engaging learners in reflective activities.

While the evaluation has demonstrated that STyLE-OLM provides a fruitful approach for fostering reflective thinking, the study performed was quite small to go beyond monitoring the presence of reflection and did not address the learning impact of IOLM and the effectiveness of learner reflection. These issues remain open and shall be examined in future studies with STyLE-OLM. We also have to acknowledge that the evaluation involved a rather specialised group of learners who were able to easily use the STyLE-OLM interface. Further investigation is needed to assess the potential of different environments (including textual and graphical representations) taking into account the uniqueness of the task of externalising and negotiating a learner's cognition. As a future work, the author intends to apply usability techniques to systematically evaluate existing media for externalising and negotiating learner models.

Although IOLM has been illustrated here in a terminological domain using conceptual graphs, the knowledge querying algorithms have been defined in STyLE-OLM in a domain independent manner and a feasible adaptation is expected in similar domains concerned with declarative knowledge. In this line, causal models can also be considered as a possible application. The proposed communication medium exploits a flexibly structured interface that allows dialogue participants to utter communicative acts combining graphics and text. Research justifies that such a communication manner has the potential to foster effective communication as it may reduce communication problems, elicit participants' beliefs, and facilitate reflection (Baker and Lund, 1997). Although we have experimented with a specific form of diagram, namely graphically rendered conceptual graphs, one can envisage a possible modification of the proposed communication means to employ another form of representation for externalising and discussing a learner model. Semantic networks and concept maps, being syntactically similar to conceptual graphs, are favourable candidates. In addition, some visual programming languages may be adopted due to their well-defined syntax and semantics. We have adapted commonly used computational methods for building interactive systems to simulate diagnostic dialogues. The dialogue model used in STyLE-OLM is fairly general and may be applied in student modelling interactions in different domains. Following the discussion in (Core et al., 2000), we have separated the domain operations from dialogue control operations, which enables the set of diagnostic tactics and strategies to be extended without changing the current communication architecture. The dialogue management mechanism in STyLE-OLM can be used as a basis for maintaining interactive diagnostic communications. We ought to mention, though, that a significant extension of the STyLE-OLM dialogue management is need in the more general case of interactive student modelling. The learner model inspection in IOLM has enabled some failures of the dialogue management to be overcome, since the learner is able to open the learner model at any time, monitor the changes resulting from the dialogue and initiate a discussion on incorrect attributions.

STyLE-OLM can be used as a testbed for further examinations of interactive open learner modelling. The system provides an opportunity to perform tests with different diagnostic tactics and strategies as the interaction is handled by a fairly general dialogue framework. Various tactics, such as comparison (Milosavljevic, 1997), explanation (McCoy,1989; Bontcheva & Wilks, 1999), inquiry dialogue (Kor, 2001; Wong et al., 1998), and error repair (VanLehn et al., 1998), can be incorporated into the current architecture by defining domain schemata for collecting the relevant knowledge to be addressed in the discussion. Studies with the system would allow the effectiveness of these tactics to be examined as well as different strategy rules adjusted to achieve more effective interaction.

It would be sensible to look at a possible use of the system in peer diagnostic contexts. The communication medium in STyLE-OLM adopts a flexibly structured interface used in collaborative human-human discussions (Baker & Lund, 1997; Robertson et al., 1998; Soller, 2001). This allows us to expect a feasible alteration of STyLE-OLM into peer diagnostic situations. We have shown in Dimitrova (2001) that the mechanism for maintaining a jointly constructed learner model can be applied in peer diagnosis to provide a computer system with an engine to build models of the peers and to mediate the interaction between them. STyLE-OLM can be used with students who discuss the domain in the communication manner provided (possible roles - a diagnoser and a diagnosee - may need to be assigned). The interactions of such a trial may be analysed and useful diagnostic tactics and strategies extracted - research has shown that tactics and strategies of inexperienced tutors may be beneficial for the design of computer tutors (Graesser et al., 2000).

We have begun this paper with the view that interactive diagnosis is an important feature of effective teaching. Interactive open learner modelling examines one possible method for interactive diagnosis by adding interactivity to open learner modelling. We believe that the architecture and the potential of interaction presented here justify the need for further exploration of interactive diagnostic approaches.

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