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eTeacher: Providing personalized assistance to e-learning students

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ABSTRACT

In this paper we present eTeacher, an intelligent agent that provides personalized assistance to e-learning students. eTeacher observes a student's behavior while he/she is taking online courses and automatically builds the student's profile. This profile comprises the student's learning style and information about the student's performance, such as exercises done, topics studied, exam results. In our approach, a student's learning style is automatically detected from the student's actions in an e-learning system using Bayesian networks. Then, eTeacher uses the information contained in the student profile to proactively assist the student by suggesting him/her personalized courses of action that will help him/her during the learning process. eTeacher has been evaluated when assisting System Engineering students and the results obtained thus far are promising.

1. Introduction

One of the most desired characteristics of e-learning systems is that of being personalized, since they have to be used by a wide variety of students with different skills (Brusilovsky & Peylo, 2003; Weber, Kuhl, & Weibelzahl, 2001). Different students learn in different ways. Some of them process information reflectively while others actively. Some students prefer abstract material while others prefer concrete examples. Some study steadily while others in fits and starts. Thus, to be effective, e-learning systems should consider each student's learning preferences and skills.

A widely used alternative to provide personalization in different domains is intelligent agent technology (Godoy, Schiaffino, & Amandi, 2004; Lieberman, Fry, & Weitzman, 2001; Maes, 1994). Intelligent agents are computer programs that learn users' interests, preferences, and habits and give them proactive, personalized assistance with a computer application. In this work, we present eTeacher, an agent that provides personalized recommendations to students depending on their profile and on their performance with a certain Web-based course. To achieve its goal, eTeacher has to build first a student profile. In eTeacher, the student profile is given mainly by the student's learning style. A learning style model classifies students according to where they fit on a number of scales belonging to the ways in which they receive and process information. The use of learning styles for experimental research in Web-based educational systems has demonstrated that providing material according to students' learning styles can enhance students' learning (Peña, Marzo, de la Rosa, & Fabregat, 2002; Paredes & Rodriguez, 2004; Walters, Egert, & Cuddihy, 2000), and that these styles are linked to quantitative differences in both navigation behavior and learning performance (Chen, Magoulas, & Dimakopoulos, 2005; Dufresne & Turcotte, 1997; Ford & Chen, 2000).

There have been proposed several models and frameworks for learning styles (Felder & Silverman, 1988; Honey & Mumford, 1992; Kolb, 1984; Litzinger & Osif, 1993). In this work we use the one proposed by Felder and Silverman for engineering

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students (Felder & Silverman, 1988). This model categorizes students as intuitive/sensitive, global/sequential, visual/verbal, and active/reflective. We chose this model after analyzing several learning styles models and frameworks, first, because it was designed for engineering students and second, because we observed that for students of exact sciences (math students, computer science students) providing material and teaching according to students' perception dimension values helped them improve their understanding in regular classes. Thus, we decided to take this experience from classrooms to e-learning.

Some educational systems use tests to assess the students' learning styles, which consist of a number of questions and compute the sums and averages of all the questionnaire answers (Paredes & Rodriguez, 2002). The problem with these Web-based tests is that if they are too long or students are not aware of the consequences or future uses of the questionnaires, students tend to choose answers arbitrarily instead of thinking carefully about them. Thus, the results obtained can be inaccurate and may not reflect the actual learning styles. An alternative (or complimentary) approach is detecting the learning style by observing how students learn and interact with a Web-based educational system. The proposed agent, eTeacher, detects a student's learning style automatically. It uses a Bayesian model (Garcia, Amandi, Schiaffino, & Campo, 2007) to infer the learning style given the observation of certain student behaviors, such as the type of reading material preferred, the amount of exercises done, and participation in chats and forums. In addition, eTeacher considers certain parameters of the student's performance, such as the number of exercises done correctly, the results in exams submitted, the stage within the course, among others. Then, eTeacher uses this information to assist the student in a personalized way. eTeacher recommends courses of actions that will help the student improve his/her performance with the subject he/she is studying.

The proposed agent was evaluated with a set of system engineering students taking an artificial intelligence course. In this context, eTeacher provided recommendations with respect to the type of reading material, the exercises done, the exams, and reminders of future events and task deadlines. To evaluate the precision of eTeacher's assistance we analyzed students' feedback and we also asked students to answer a questionnaire evaluating the agent's performance. The results obtained thus far are quite promising and encouraging.

The rest of the article is organized as follows. First, Section 2 reviews some related works. Then, Section 3 presents a general overview of eTeacher's functionality. Section 4 describes how this agent builds a student profile. Section 5 shows how the agent assists students in a personalized way. Then, Section 6 describes the experiments we carried out and the results obtained. Finally, Section 7 presents our conclusions and future work.

2. Related work

When we talk about providing a personalized service in e-learning systems, there are two main research directions: adaptive educational systems and intelligent tutors (agents). Adaptive educational systems adapt the presentation of content and the navigation through these contents to a student's profile. This profile may comprise the student's learning style, knowledge, background, goals, among other features. Different adaptive methods are: adaptive ordering, link hiding, link removal, and adaptive link annotation. Examples of these systems are: MLTutor (Smith & Blandford, 2003), MAS–PLANG (Peña et al., 2002), KBS-Hyperbook (Henze & Nejdl, 2001) and ELM–ART (Brusilovsky, Schwarz, & Weber, 1996). On the other hand, intelligent tutors recommend educational activities and deliver individual feedback according to the student's profile, which generally includes the student's knowledge or activities within the course he/she is taking. Example of intelligent tutors in different domains are: SQL-Tutor (Mitrovic, 2003); German Tutor (Heift & Nicholson, 2001); ITSPOKE (Forbes-Riley, Litman, & Rotaru, 2008) in the domain of physics problems; CIRCSIM-Tutor (Evens et al., 2001), who helps students solve a class of problems in cardiovascular physiology dealing with the regulation of blood pressure, and KERMIT (Suraweera & Mitrovi, 2002), who teaches conceptual database design using the Entity-Relationship data model. Our agent can be considered as an intelligent tutor, which recommends educational tasks to students depending on their profile. Particularly, it has been used to assists students taking an artificial intelligence course.

As regards the problem of student modelling, many works in the two areas discussed above have addressed it (see (Brusilovsky & Peylo, 2003) for a review). These works can be categorized according to different characteristics, such as the content of the student model, the type of student being modelled, how the student model is updated, what the model is used for, among others. Our work can be placed among those modelling psychological features of students, such as ARTHUR (Gilbert & Han, 1999) which considers three learning styles (visual-interactive, reading-listener, textual), CS388 (Carver, Howard, & Lavelle, 1996) and MAS-PLANG (Peña et al., 2002) that use Felder and Silverman styles; and the INSPIRE system (Papanikolaou, Grigoriadou, Knornilakis, & Magoulas, 2003) that uses the styles proposed by Honey and Mumford (Honey & Mumford, 1992). Our work is more related to those using Felder's model. However, the way in which the learning style is detected is different. Most systems use the ILS questionnaire[1] to determine the learning style. Our work is innovative since it discovers the learning style automatically from the observation of the student's behavior.

Finally, different techniques have been used to represent student models such as rules (Jeremic & Deyedzic, 2004), Bayesian networks, and case-based reasoning (Peña et al., 2002). As regards Bayesian networks, ANDES (Gertner & VanLehn, 2000) and SE-Coach (Conati, Gertner, & VanLehn, 2002) use this technique to model students' knowledge in Physics. IDEAL (Shang, Shi, & Chen, 2001) uses this technique to categorize students into novice, beginner, intermediate, advanced, or expert. In Arroyo and Woolf (2005) the authors build a Bayesian model to detect a student's hidden attitudes, perception towards the e-

[1] http://www.engr.ncsu.edu/learningstyles/ilsweb.html.

learning system, and amount learned from observable student behavior recorded in a log file. In Gamboa and Fred (2001) the authors use Bayesian networks to assess students' state of knowledge and learning preferences, in an intelligent tutoring system. In Xenos (2004) BN are used to model the behavior of students in an open and distance education system, aiding student data processing and teachers decision making. Our work uses Bayesian networks to model a student's learning style, an aspect not considered in the previous Bayesian student models.

3. Agent overview

To provide personalized assistance to students, eTeacher must build a student profile. To achieve this goal, eTeacher unobtrusively observes the student's behavior while he/she is taking a course via an e-learning system. The agent records the student's actions and then it uses these data and the data logged by the system to build the student profile. As said before, the student profile comprises the student's learning style and the student's performance with a given course, such as the number and type of exercises done, the topics studied, and the results in exams. The student's learning style is determined by a Bayesian network. Bayesian networks (Jensen, 2001) enable eTeacher to model quantitative and qualitative information about a student's behavior with the e-learning system. The agent can infer the student's learning style using the Bayesian network given different student behaviors observed. For example, if a student participates in chat rooms and forums, eTeacher can infer that the student processes information actively and not reflectively.

Then, when eTeacher detects situations in which the student might need assistance or guidance, it provides him/her help according to the student's learning style, his/her stage in the course, and his/her performance. After eTeacher's recommendations, the student can provide feedback to the agent's assistance. This feedback can be explicit, through a user interface provided for this purpose, or implicit, if the agent observes the student's actions after assisting him/her. In turn, the feedback provided can be positive, when the student accepts the agent's suggestions, or negative, if the student rejects the agent's assistance. eTeacher uses this feedback to adjust the information it has about the user and act accordingly in the future. Fig. 1 shows an overview of the agent's functionality. In the following sections we describe in detail each of the functionalities represented in this figure.

4. Building a student profile

In this section we briefly describe how to automatically detect a student's learning style from the observation of a student's actions in an e-learning system and the analysis of the student's log files. A more detailed description of this process can be found in Garcia et al. (2007). The focus of this article is on how to use the knowledge about students' learning styles to provide them assistance in order to improve their learning process, as shown in Section 5.

4.1. Learning styles

As we have said before, a learning style model classifies students according to where they fit on a number of scales belonging to the ways in which they receive and process information. In this work we use the one proposed by Felder and Silverman for engineering students (Felder & Silverman, 1988). This model comprises 16 learning styles. Table 1 shows the dimensions of the learning styles in this model, namely perception, input, processing, and understanding. The perception

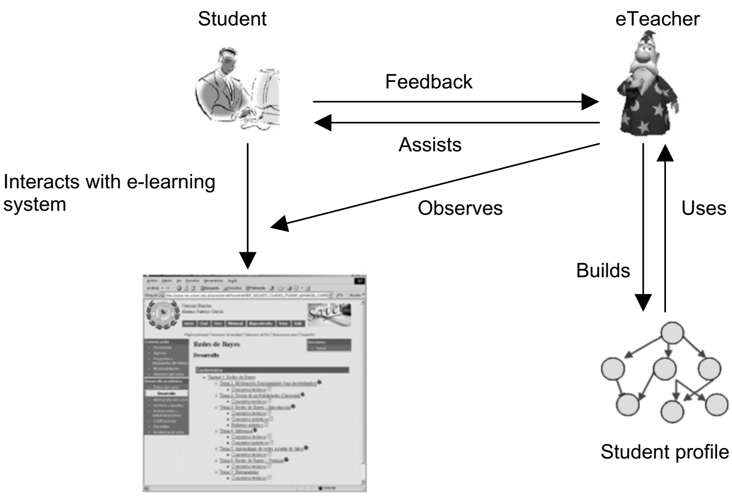

Fig. 1. eTeacher overview.

Table 1
Felder's learning styles

Dimension	Values
Perception	Intuitive – Sensitive
Input	Visual – Verbal
Processing	Active – Reflective
Understanding	Global – Sequential

dimension indicates the type of information the student prefers to receive: sensory (external) such as sights, sounds, physical sensations; or intuitive (internal) such as possibilities, insights, hunches. The input dimension models the sensory channel through which external information is most effectively perceived by the student: visual pictures, diagrams, graphs, demonstrations, or auditory words, and sounds. The processing dimension indicates how the student prefers to process information: actively through engagement in physical activity or discussion, or reflectively through introspection. Finally, the understanding dimension shows how the student progresses towards understanding: sequentially in continual steps, or in fits and starts.

According to this model, sensitive students like facts, data and experimentation; while intuitive students prefer principles and theories. Sensitive students are patient with detail but do not like complications; intuitive students are bored by detail and welcome complications.

Visual learners remember best what they see: pictures, diagrams, time lines, films, demonstrations. Verbal learners remember much of what they hear or read.

Active learners do not learn much in situations that require them to be passive, and reflective learners do not learn much in situations that provide no opportunity to think about the information being presented. Active learners work well in groups; reflective learners work better by themselves or with at most one other person.

Sequential learners follow linear reasoning processes when solving problems; while global learners make intuitive leaps and may be unable to explain how they came up with solutions. Sequential learners can work with material when they understand it partially or superficially, while global learners may have great difficulty doing so.

In this work we consider only three dimensions of Felder's framework, namely perception, processing and understanding, given the type of material provided to students in the Web-based courses considered.

4.2. Modeling students' behavior with Bayesian networks

Bayesian networks (BN) enable eTeacher to model both qualitative and quantitative information about students' learning styles. A BN is a compact, expressive representation of uncertain relationships among variables of interest in a domain. A BN is a directed acyclic graph that represents a probability distribution, where nodes represent variables and arcs represent probabilistic correlation or dependency between variables (Jensen, 2001). The strengths of the dependencies are given by probability values. For each node, a probability table specifies the probability of each possible state of the node given each possible combination of states of its parents. These tables are known as conditional probability tables (CPT). Tables for root nodes (or independent nodes) just contain unconditional probabilities.

In our agent, random variables represent the different dimensions of Felder's learning styles and the behaviors that determine each of these dimensions. These behaviors are extracted from the interactions between the student and the e-learning system. Table 2 shows the behaviors that help the agent determine each of the dimensions. This information is obtained by analyzing the data recorded in a student's log file. With respect to the Perception dimension we can say that, according to Felder, a student who does not revise his/her exercises or exams is likely to be intuitive. On the other hand, a student who carefully checks the exams or exercises is generally sensory. A student who reads or accesses various examples of a given topic is more sensory than one who reads just one or two. As regards the type of reading material the student prefers, a

Table 2
Behaviors observed

Dimension	Behaviors observed
Perception	Time dedicated to exam revision
	Time it takes the student to finish and submit the exam
	Number of changes in exam answers
	Type of reading material preferred (abstract, concrete)
	Number of exercises done
	Number of examples read
Processing	Participation in forums
	Use of chat and mail systems
	Participation in collaborative/group tasks
Understanding	Pattern of access to information
	Exam results

sensory learner prefers concrete (application oriented) material, while an intuitive learner usually likes abstract or theoretical texts.

To detect whether the student prefers to work things out alone (reflectively) or in groups (actively), we analyze his/her participation in forums, chats, and mail systems. As regards forums, we analyze whether the student begins a discussion, replies to a message, or just reads the messages posted by other students. The frequency of this participation is also important. The participation in chat and mails can give us some information, but it is not as relevant as the one we can obtain with a forum access log. To enable students to work collaboratively, most Web-based educational systems provide a collaborative facility. Given a certain problem solving activity, students use this tool to propose solutions to the problem, to make a counterproposal to a proposed solution and to read the solutions available thus far. They can also send messages to other members of the group or read messages posted by others. In addition, the system logs the participation of each student in the group activity.

Finally, to determine how students understand, we analyze access patterns to information, which are recorded in students' log files. If the student jumps through the course contents we can say that he/she does not learn sequentially but in fits and starts. The results the student gets in the exams while he/she is jumping over the contents give us an indication of his/her understanding style. If the student gets a high mark in a topic despite having not read a previous topic, we can conclude that the student does not learn sequentially.

The dependencies between learning styles and behaviors are encoded in the Bayesian model through the arcs that go from the nodes representing student behaviors to the nodes representing learning style dimensions. Fig. 2 shows the Bayesian model used by our agent. The values the different variables can take are summarized below:

- Forum: posts messages; replies messages; reads messages; no participation.
- Chat: participates; listens; no participation.
- Mail: uses; does not use.
- Tasks: makes proposal for group task; makes counterproposal; reads proposal.
- Messages: sends message; reads message (within group task).
- Participation: participates; no participation.
- Information access: in fits and starts; continuous.
- Reading material: concrete; abstract.
- Exam Revision (considered in relation to the time assigned to the exam): less than 10%; between 10% and 20%; more than 20%.
- Exam Delivery Time (considered in relation to the time assigned to the exam): less than 50%; between 50% and 75%; more than 75%.
- Exercises (in relation to the amount of exercises proposed): many (more than 75%); few (between 25% and 75%); none.
- Answer changes (in relation to the number of questions or items in the exam): many (more than 50%); few (between 20 and 50%); none.
- Access to Examples (in relation to the number of examples proposed): many (more than 75%); few (between 25% and 75%); none.
- Exam Results: high (more than 7 in a 1–10 scale); medium (between 4 and 7); low (below 4).

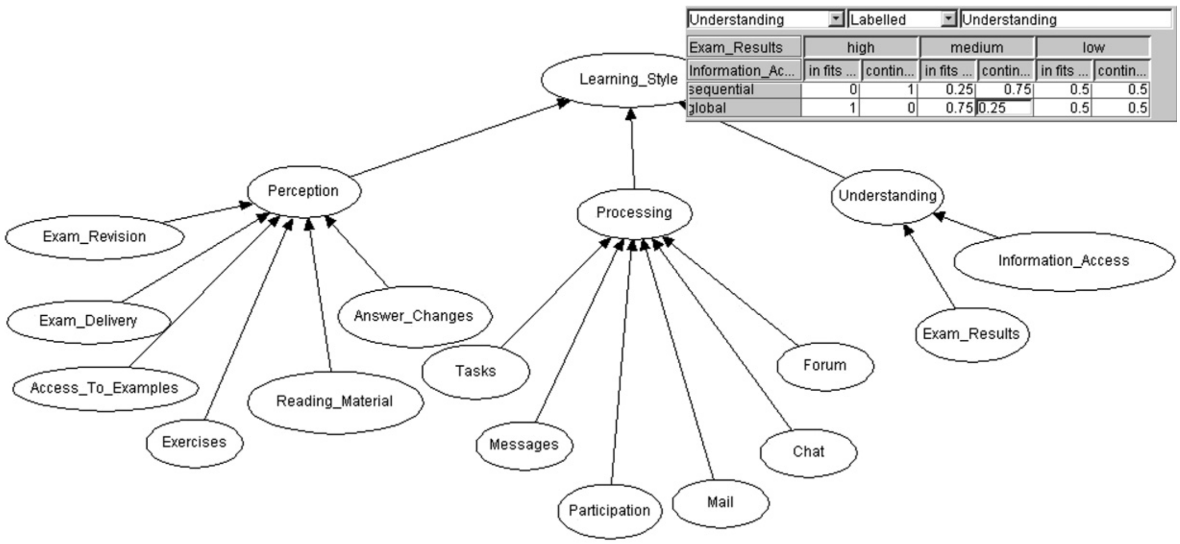

Fig. 2. Bayesian network used to detect learning styles.

Table 3
Examples of recommendations

Dimension	Value	Assistance
Understanding	Sequential	I recommend you to study topic X before studying topic Y
	Global	I recommend you to read the introduction and summary of this topic first
Perception	Sensitive	I recommend you to do more exercises about topic X
		I recommend you to study more examples of topic X
		I recommend you to carefully revise the exam before submitting it
	Intuitive	I recommend you to read theoretical explanations of topic X
		I recommend you to read the suggested bibliography of topic X
Processing	Active	I recommend you to participate in the debate about topic X in the forum
		I recommend you to participate in the debate about topic X in the chat room
	Reflective	I recommend you to take some minutes to think about topic X
		I recommend you to take some minutes to think about group task X before talking to other group members

Fig. 2 also shows an example of CPT for the understanding node. In this table, we can see the probability of each possible state of the understanding node, given all the combinations of states of the behaviors that determine it. For example, the second value in the first column indicates that if a student studies in fits and starts and gets high marks in his/her exams, then it is 100% probable that this student is a global learner.

Initially, probability values for independent nodes are assigned equal values. Then, the values are updated as the system gathers information about the student's behavior. The probabilities attached to the independent nodes are adjusted to represent the new observations or experiences (Olesen, Lauritzen, & Jensen, 1992). Consequently, the Bayesian model is continuously updated as new information about the student's interaction with the system is obtained. On the other hand, the probability values contained in the different CPT were obtained via a combination of expert knowledge and experimental results.

Once we have the Bayesian model, the goal of eTeacher is inferring the values of the nodes corresponding to the dimensions of a learning style given evidences of the student's behavior with the system. Thus, we obtain the probability values of the learning style node given the values of the related independent nodes. The learning style of the student is the one having the greatest probability value.

5. Providing assistance to students

eTeacher assists students who are taking courses through an e-learning system named SAVER.[2] The agent considers a course unit or topic as the minimum observation unit. In this system each unit is, in turn, divided into a set of topics. Each topic has reading material available that is categorized either as abstract or concrete.

Students are presented with a number of examples for a certain topic, and they can optionally access to more examples if they need them. Similarly each unit has a set of exercises students can optionally do to test themselves. The system automatically marks these exercises. In most cases, there are no prerequisites within a course. That is, no units are mandatory within a course and no previous units are required to read a given topic. At the end of the course, students must submit a final exam. All the material is provided to students through the e-learning system.

eTeacher uses the information contained in the student profile and the stage of the student in the course to suggest courses of actions. In this work, the assistance provided by eTeacher tends to favor the student's learning style. That is, the actions suggested coincide with the actions a student having the style of the student under observation would carry out. Table 3 shows some examples of the recommendations made by eTeacher for different learning styles.

For example, consider a sensitive student who is studying a certain topic. The student is reading theoretical material. Thus, eTeacher recommends him/her to revise practical examples about this topic, as shown in Fig. 3. eTeacher suggests this course of action because sensitive students capture concrete information more easily than abstract information. On the other hand, suppose that eTeacher detects that a student is not performing well when solving problems of a given topic. If the student is intuitive, the agent recommends him/her to read theoretical texts on this topic in order to improve the student's performance.

Now, consider for example that eTeacher detects that a sequential student is studying a given topic without studying another topic that is before the first one in the curricula. Then, the agent recommends the student to read the topic he/she has not read yet, because it is probable that he/she will need its content for the current unit. However, if eTeacher detects that a global student started to study a topic without reading the topic summary or the introduction, the agent recommends him/her to read these texts before proceeding with the topic. Global students tend to understand first the general idea of a subject and then they capture the details of the different parts of the subject. This assistance is shown in Fig. 4.

As another example, consider that eTeacher detects that an active student is reading a certain topic and that there is a debate about this topic in the forum or chat room. Then, it suggests the student's participation in this debate because it will help him/her understand the topic.

[2] http://www.e-unicen.edu.ar.

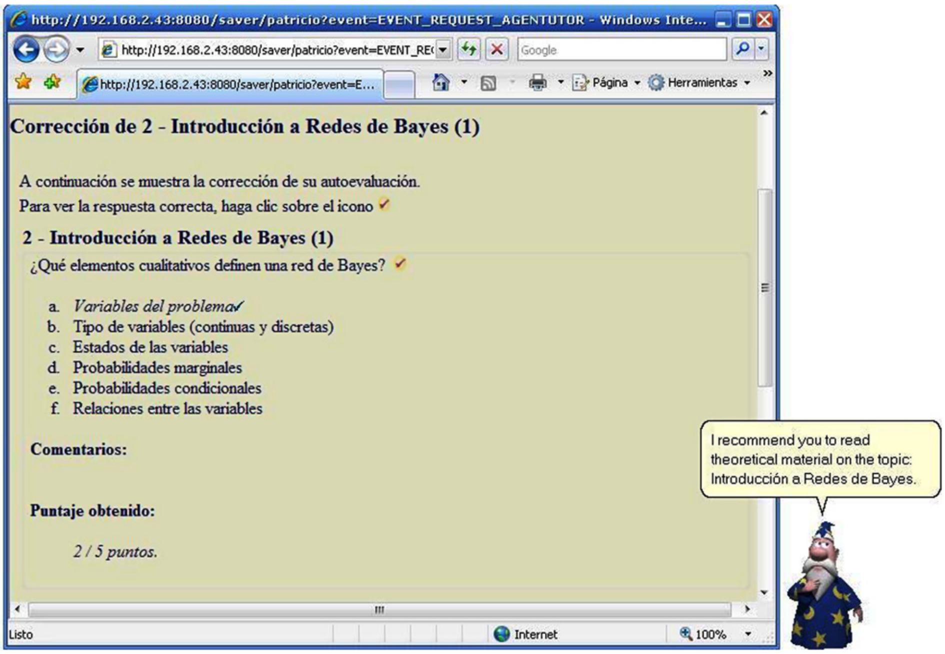

Fig. 3. Example of recommendation for sensitive learners.

Fig. 4. Example of recommendation for global learners.

Once eTeacher has made a recommendation, the student can provide explicit feedback to the agent. As shown in Fig. 5, the student can accept the recommendation (that is, give a positive feedback) or reject the recommendation (give a negative feedback). If the student rejects a certain recommendation, then eTeacher takes this rejection into account when the same situation arises in the future. Through the interface shown in the Figure students can also ask the agent for help explicitly

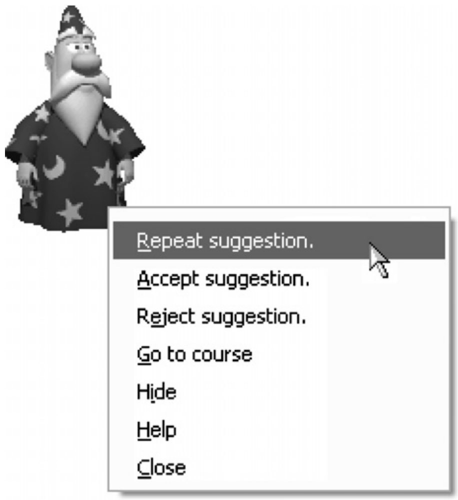

Fig. 5. User feedback.

when they need assistance, they can ask the agent to repeat a suggestion made previously, and they can access the part of the course mentioned in the agent's recommendation.

6. Experimental results

The precision of our Bayesian model at detecting students' learning styles was evaluated in previous experiments. The results can be found in Garcia et al. (2007). In this work, the goal is evaluating the performance of eTeacher when assisting e-learning students. We evaluated the behavior of our agent with a set of 42 System Engineering students. These students took an Artificial Intelligence course using an e-learning system. As a requirement of the course they had to submit an individual exam and carry out a group activity. eTeacher provided them personalized assistance throughout the whole course as described in Section 5.

As regards the population of students participating in the experiment, 14% of them were female and 86% were male. With respect to students' learning style dimensions, 84% of students were sensitive while 16% of them were intuitive; 81% were reflective while 19% were active; 70% were global learners while 30% were sequential learners. Regarding previous interactions with interface agent, 18 out of 42 had never interacted with an agent, while 24 had some experience at interacting with agents such as Microsoft Clippit. Only one of the students had previous experience at using a distance learning system. Most of the students did not have knowledge about the subject being taught (67%), two of them knew the subject (5%), and only a few had some idea about it (29%).

To evaluate the performance of our agent we obtained data from two different sources. First, we analyzed students' feedback to the agent's recommendations and students' actions with the system. Second, we asked students to complete a questionnaire evaluating different aspects of their interaction with eTeacher and with the e-learning system.

6.1. Results based on the students' interaction with the agent

Analyzing students' log files, we observed that eTeacher provided a total of 854 assistance actions to students. Fig. 6 shows the percentages of the different types of interactions with students: 38% of the interactions corresponded to greetings and warnings or notifications; 9% of the interactions were recommendations about reading material; 31% of the assistance actions were reminders about future events and task deadlines; and 22% were recommendations about exercises and exams.

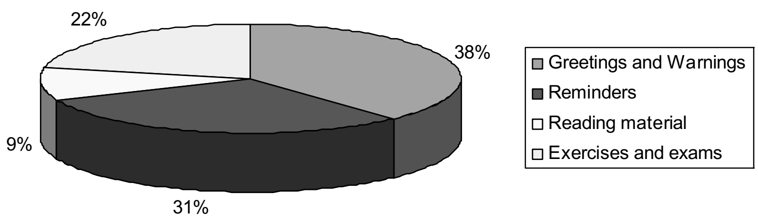

Fig. 6. Type of recommendations provided by eTeacher.

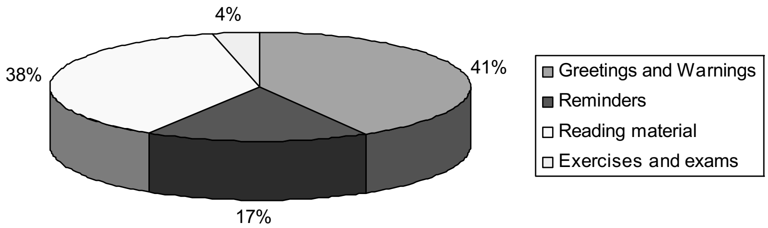

Fig. 7. Positive feedback.

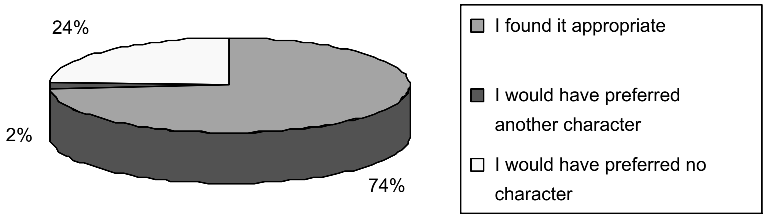

Fig. 8. Evaluation of the agent's interface.

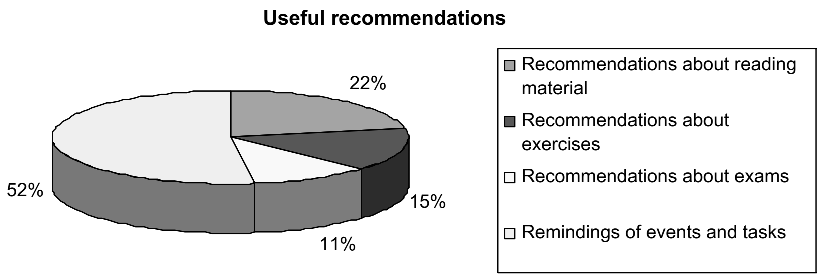

Fig. 9. Useful recommendations.

Then, we analyzed students' feedback to each type of assistance action. From the total number of assistance actions, 205 received explicit student feedback, 83% of them received positive feedback while 17% received negative feedback. We can consider this as a measure of the agent's precision at assisting students. Given this result, the performance of eTeacher is quite good. Fig. 7 shows the distribution of positive feedback for the different types of assistance actions.

6.2. Results based on questionnaires

From students' answers to the questionnaire, we obtained information about students' opinion of eTeacher interface. As shown in Fig. 8, 74% of students considered it appropriate, 2% of them would have liked another character (instead of a magician), and 24% of students would have preferred the same functionality but without a character.

With respect to the usefulness of recommendations, 70% of students said that eTeacher's recommendations were useful, and 30% found them useless. The precision of the agent according to questionnaires is lower than the precision of eTeacher obtained by analyzing students' log files. This difference is probably due to the fact that not all students provided explicit feedback, and this is what we measured with log files. We also found that different students preferred different types of recommendations. As shown in Fig. 9, 22% of students found recommendations about reading material useful, 15% preferred recommendations about exercises, 11% found suggestions about exams useful, and 52% appreciated reminders about events and tasks.

6.3. Discussion

By combining the information obtained from log files and from questionnaires we can conclude that the precision of eTeacher at assisting students is quite good (83% according to one source and 70% according to the other). However, we will carry out more experiments with more students to validate these initial findings. Although 42 students participated in the experiment and the agent interacting with them 854 times, only 205 of these interactions received student feedback.

With respect to the characteristic of Web courses, they have to be long and complete enough (measured in number of units, exercises, examples and exams) to guarantee eTeacher's learning. eTeacher learns about a student by observing his/her interaction with the system, so, when more observations are registered, the more can learn the agent about the student.

Finally, eTeacher needs some time to detect a student's learning style, that is, to let the Bayesian network make correct inferences. The agent might not provide any assistance when the student begins his/her interaction with the e-learning system. It might take some time to eTeacher to provide useful help, unless the agent knows the student's learning style from previous courses.

7. Conclusions

We have described eTeacher, an intelligent agent that assists e-learning students depending on their learning styles and on their performance with a Web-based course. eTeacher uses Bayesian networks to build the student profile. The agent has been successfully evaluated with real students and the results obtained are promising. In the future, we will further study students' log files to obtain more information about eTeacher's performance.

As a future work, we are planning to incorporate the input dimension in the student's model. Currently, eTeacher cannot distinguish between visual and verbal learners, and hence, it cannot provide them assistance accordingly. New suggestions and messages can be added to enhance eTeacher's functionality.

In addition, thus far, eTeacher recommends courses of actions according to the student's learning style, favoring the advantages of each style. We are working now towards a different research direction, that is, the agent can suggest actions that tend to complement the learning styles. For example, if a student is intuitive we know that he/she does not like to revise his/her exam and might make mistakes, that the agent recommends him/her to revise the exam before handing it out. Then, we will be able to compare the two approaches: assisting students favoring their learning styles vs. complementing their learning styles.

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References

Arroyo, I., & Woolf, B. (2005). Inferring learning and attitudes from a Bayesian network of log file data. In *Proceedings AIED 05, 12th international conference on artificial intelligence in education*.

Brusilovsky, P., Schwarz, E., & Weber, G. (1996). ELM–ART: An intelligent tutoring system on World Wide Web. In *Proceedings 3rd international conference on intelligent tutoring systems*, ITS 96, pp. 261–269.

Brusilovsky, P., & Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education, 13*(2–4), 159–172.

Carver, C., Howard, R., & Lavelle, E. (1996). Enhancing student learning by incorporating learning styles into adaptive hypermedia. In *Proceedings 1996 ED-MEDIA world conference on educational multimedia and hypermedia* (pp. 118–123). Boston.

Chen, S., Magoulas, G., & Dimakopoulos, D. (2005). A flexible interface design for web directories to accommodate different cognitive styles. *Journal of the American Society for Information Science and Technology, 56*(1), 70–83.

Conati, C., Gertner, A., & VanLehn, K. (2002). Using Bayesian networks to manage uncertainty in student modeling. *Journal of User Modeling and User Adapted Interaction, 12*(4), 371–417.

Dufresne, A. & Turcotte, S. (1997). Cognitive styles and its implications for navigation strategies. In *Proceedings of the world conference on artificial intelligence and education* AI-ED'97.

Evens, M., Brandle, S., Chang, R., Freedman, R., Glass, M., Lee, Y., et al. (2001). CIRCSIM-Tutor: An intelligent tutoring system using natural language dialogue. In *Proceedings of the 12th midwest AI and cognitive science conference (MAICS 2001)*, pp. 16–23.

Felder, R., & Silverman, L. (1988). Learning and teaching styles. *Journal of Engineering Education, 78*(7), 674–681.

Forbes-Riley, K., Litman, D., Rotaru, M., 2008. Responding to student uncertainty during computer tutoring: A preliminary evaluation. In *Proceedings 9th international conference on intelligent tutoring systems (ITS)*, Montreal, Canada.

Ford, N., & Chen, S. (2000). Individual differences, hypermedia navigation, and learning: An empirical study. Chen. *Journal of Educational Multimedia and Hypermedia, 9*.

Gamboa, H.,& Fred, A. (2001). Designing intelligent tutoring systems: A bayesian approach. In *Proceedings ICEIS 01, 3rd international conference on enterprise information systems*.

Garcia, P., Amandi, A., Schiaffino, S., & Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers and Education, 49*, 794–808.

Gertner, A., & VanLehn, K. (2000). Andes: A coached problem solving environment for physics. In *Proceedings ITS 2000, intelligent tutoring systems*, pp. 131–142.

Gilbert, J., & Han, C. (1999). Adapting instruction in search of a significant difference. *Journal of Network and Computer Applications*, 22.

Godoy, D., Schiaffino, S., & Amandi, A. (2004). Interface agents personalizing web-based tasks – special issue on intelligent agents and data mining for cognitive systems. *Cognitive Systems Research Journal, 5*, 207–222. Elsevier (2004).

Heift, T., & Nicholson, D. (2001). Web delivery of adaptive and interactive language tutoring. *International Journal of Artificial Intelligence in Education, 12*(4), 310–324.

Henze, N., & Nejdl, W. (2001). Adaptation in open corpus hypermedia. *International Journal of Artificial Intelligence in Education, 12*(4), 325–350.

Honey, P., & Mumford, A. (1992). *The manual of learning styles* (3rd ed.). Maidenhead.

Jensen, F. (2001). *Bayesian networks and decision graphs*. Springer Verlag.

Jeremic, Z., & Deyedzic, V. (2004). Design patters ITS: Student model implementation. In *IEEE international conference on advanced learning technologies*.

Kolb, D. (1984). *Experiential learning: experience as the source of learning and development*. New York: Prentice Hall.

Lieberman, H., Fry, C., & Weitzman, L. (2001). Exploring the Web with reconnaissance agents. *Communications of the ACM, 44*, 869–875.

Litzinger, M., & Osif, B. (1993). Accommodating diverse learning styles: Designing instruction for electronic information sources. In *What is good instruction nows? Library instruction for the 90s*. Pierian Press.
Maes, P. (1994). Agents that reduce work and information overload. *Communications of the ACM, 37*(7), 31–40.
Mitrovic, A. (2003). An intelligent SQL tutor on the web. *International Journal of Artificial Intelligence in Education, 13*(2–4), 171–195.
Olesen, K., Lauritzen, S., & Jensen, F. (1992). aHugin: A system creating adaptive causal probability networks. In *Proceedings of the 8th uncertainty in artificial intelligence*.
Papanikolaou, K., Grigoriadou, M., Knornilakis, H., & Magoulas, G. (2003). Personalizing the interaction in a web-based educational hypermedia system: The case of INSPIRE. *User Modeling and User-Adapted Interaction, 13*, 213267.
Paredes, P., & Rodriguez, P. (2002). Considering learning styles in adaptive web-based education. In *6th world multiconference on systemics*, Cybernetics and Informatics. pp. 481–485.
Paredes, P., & Rodriguez, P. (2004). A mixed approach to modelling learning styles in adaptive educational hypermedia. In *Proceedings 3rd IASTED conference on web-based education* (WBE2004).
Peña, C., Marzo, J., de la Rosa, J., & Fabregat, R. (2002). Un sistema de tutoría inteligente adaptativo considerando estilos de aprendizaje. In IE 2002.
Smith, A. S. G., & Blandford, A. (2003). MLTutor: An application of machine learning algorithms for an adaptive web-based information system. *International Journal of Artificial Intelligence in Education, 13*(2–4), 233–260.
Shang, Y., Shi, H., Chen, S. 2001. An intelligent distributed environment for active learning. In WWW 01.
Suraweera, P., & Mitrovi, C.A. (2002). Kermit: A constraint-based tutor for database modeling. In *Proceedings 6th international conference on intelligent tutoring systems* ITS.
Walters, D., Egert, C., & Cuddihy, E. (2000). Learning styles and Web-based education: a quantitative approach. In *Proceedings 9th annual FACT conference on instructional technology*, pp. 115–177.
Weber, G., Kuhl, H., & Weibelzahl, S. (2001). Developing adaptive internet based courses with the authoring system NetCoach. *Lecture Notes in Computer Science, 2266*, 226–238.
Xenos, M. (2004). Prediction and assessment of student behaviour in open and distance education in computers using Bayesian networks. *Computers and Education, 43*(4), 345–359.