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Evaluating Bayesian networks' precision for detecting students' learning styles

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Abstract

Students are characterized by different learning styles, focusing on different types of information and processing this information in different ways. One of the desirable characteristics of a Web-based education system is that all the students can learn despite their different learning styles. To achieve this goal we have to detect how students learn: reflecting or acting; steadily or in fits and starts; intuitively or sensitively. In this work, we evaluate Bayesian networks at detecting the learning style of a student in a Web-based education system. The Bayesian network models different aspects of a student behavior while he/she works with this system. Then, it infers his/her learning styles according to the modeled behaviors. The proposed Bayesian model was evaluated in the context of an Artificial Intelligence Web-based course. The results obtained are promising as regards the detection of students' learning styles. Different levels of precision were found for the different dimensions or aspects of a learning style.
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1. Introduction

The problem of detecting how students learn and acquire knowledge has gained great interest in the last decade. Students learn in many different ways (Felder & Silverman, 1988) by seeing and hearing; reflecting and acting; reasoning logically and intuitively; memorizing and visualizing; drawing analogies and building mathematical models; steadily and in fits and starts. Teaching methods also vary. Some teachers lecture, others discuss or demonstrate; some emphasize memory while others understanding. How much a given student learns depends on the student's ability and prior preparation, and also on the compatibility of his/her learning style and the teacher's teaching style. Studies have shown that greater learning may occur when the teaching style matches the students' learning styles than when they are mismatched (Allinson & Hayes, 1996; Felder & Brent, 2005).

The concept of learning and teaching styles appears also in computer-based and Web-based education approaches. In a Web-based education system the teaching styles are characterized by: the content of courses, that is texts, examples, exams and exercises proposed; how information is presented to students; the interaction mechanisms among students and between students and teachers, that is chat rooms, forums, frequently asked questions, email systems; and the order in which contents are organized and presented within a course. One of the most desired characteristics of a Web-based education system is that of being adaptive and personalized (Brusilovsky & Peylo, 2003; Weber, Kuhl, & Weibelzahl, 2001; Weber & Specht, 1997), since it has to be used by a wide variety of students with different skills and learning styles. To achieve this goal, and then reduce the gap between students' learning styles and the system's teaching styles, we should discover each student's learning style and adapt the courses or assist the student according it.

Some education 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 education system. Students' behavior while using the system, such as the type of reading material preferred, the amount of exercises done, and participation in chats and forums, can be used to discover each student's learning style automatically.

In this work, we evaluate Bayesian networks' (BN) precision for representing and detecting students' learning styles in a Web-based education system. We have chosen this technique because it enables us to model both quantitative and qualitative information about students' behavior. Besides, Bayesian inference mechanisms enable us to make inferences about the students' learning styles. In our model, the nodes in the BN represent the different student behaviors that determine a given learning style. The arcs represent the relationships between the learning style and the factors determining it. The information used to build the Bayesian model is obtained by analyzing students' log files. These log files contain records of the tasks carried out by the students in the system and the participation of students in activities such as chat rooms and forums.

The article is organized as follows. Section 2 describes some related works. Section 3 briefly describes the different learning styles we are considering. Section 4 explains how we use BN to model and detect students' learning styles from students' behavior. Section 5 presents some experimental results. Finally, Section 6 presents our conclusions and future work.

2. Related work

There are numerous articles addressing the problem of student modelling (for example, see (Brusilovsky & Peylo, 2003) for a review). These works can be categorized according to different factors, such as the content of the student model, the type of student being modeled, how the student model is updated, what the model is used for, among others. Our work can be placed among those modeling psychological characteristics of students, such as ARTHUR (Gilbert & Ham, 1999) which considers three learning styles (visual-interactive, reading-listener, textual), CS388 (Carver, Howard, & Lavelle, 1996) and MAS-PLANG (Peña, Marzo, de la Rosa, & Fabregat, 2002) that use Felder and Silverman styles; the INSPIRE system (Papanikolaou, Grigoriadou, Magoulas, & Kornilakis, 2002, Papanikolaou et al., 2003) that uses the styles proposed by Honey and Mumford (1992).

Various techniques have been used to represent student models, such as rules (Jeremic & Devedzic, 2004), fuzzy logic (Xu et al., 2002), Bayesian networks, and case-based reasoning (Peña et al., 2002). As regards BN, ANDES (Gertner & VanLehn, 2000) and SE-Coach (Conati, Gertner, & VanLehn, 2002) use this technique to model student knowledge in Physics. Desktop Associate (Murray, 1999) models students skills at using a word processor with BN. 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-learning system, and amount learned from observable student behavior recorded in a log file.' In Gamboa and Fred (2001), the authors use BN 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 is novel since it proposes the use of BN to model a student learning style, an aspect not considered in the previous Bayesian student models.

3. Learning styles

A learning-style model classifies students according to where they fit in a number of scales belonging to the ways in which they receive and process information. There have been proposed several models and frameworks for learning styles. In this work, we use the one proposed by Felder and Silverman for engineering students (Felder & Silverman, 1988).

Felder's model comprises 32 learning styles. Each learning style con be defined by the answers to the following five questions:

- What type of information does the student preferably perceive: sensory (external) sights, sounds, physical sensations, or intuitive (internal) possibilities, insights, hunches?

- Through which sensory channel is external information most effectively perceived: visual pictures, diagrams, graphs, or verbal words, sounds?
- With which organization of information is the student most comfortable: inductive or deductive?
- How does the student prefer to process information: actively through engagement in physical activity or discussion, or reflectively through introspection?
- How does the student progress towards understanding: sequentially in continual steps, or globally in large jumps, holistically?

Table 1 shows the dimensions of the learning styles obtained from the previous questions. For example, the sensory/verbal/deductive/active/sequential is a learning style.

Sensors like facts, data and experimentation; intuitors prefer principles and theories. Sensors are patient with detail but do not like complications; intuitors 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, and more of what they hear or read and say.

Induction is a reasoning progression that proceeds from particulars to generalities. Deduction proceeds in the opposite direction. Induction is the natural human learning style. Experiments have proved that most engineering students are inductive learners (Felder & Silverman, 1988). Thus, this dimension is not considered and 16 learning styles remain.

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; 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.

Table 1
Dimensions of Felder's learning styles

Perception	Sensitive Intuitive
Input	Visual Verbal
Organization	Inductive Deductive
Processing	Active Reflective
Understanding	Sequential Global

Although these learning styles have not been developed for e-learning environments, we can easily adapt them by discarding the dimensions that are not observable in these environments, and by making a parallel between the characteristics of each style and the behaviors we can observe in a Web context. Consequently, the data recorded from the observation of a student's behavior throughout various Web-based courses or throughout different units or topics within a course, is used to automatically detect the learning style in which a student best fits. In this work, we propose and evaluate the use of Bayesian networks to carry out this process.

4. Proposed approach: Bayesian networks

A BN is a compact, expressive representation of uncertain relationships among parameters in a domain. A BN is a directed acyclic graph where nodes represent random variables and arcs represent probabilistic correlation between variables (Jensen, 1996). The absence of edges in a BN denotes statements of independence. A BN encodes the following statement of independence about each random variable: a variable is independent of its non-descendants in the network given the state of its parents (Pearl, 1988). A BN also represents a particular probability distribution, the joint distribution over all the variables represented by nodes in the graph. This distribution is specified by a set of conditional probability tables (CPT). Each node has an associated CPT that specifies this quantitative probability information. Such a table specifies the probability of each possible state of the node given each possible combination of states of its parents. For nodes without parents, probabilities are not conditioned on other nodes; these are called the prior probabilities of these variables.

In our problem, random variables represent the different dimensions of Felder's learning styles and the factors that determine each of these dimensions. These factors are extracted from the interactions between the student and the Web-based education system. Thus, a BN models the relationships between the learning styles and the factors determining them. A simple BN is shown in Fig. 1. This network models the relationships between the participation of a student in chats and forums and the processing style of this student. Thus, the BN has three nodes: chat, forum, and processing. The "chat" node has three possible states: participates, listens, and no participation. The "forum" node has four possible states: replies messages, reads messages, posts messages and no participation. Finally, the "processing" node has two possible values, namely active and reflective. The model is completed with the simple probability tables for the independent nodes and the CPT for the dependent node. The values of the simple probabilities are obtained by analyzing a student's log file. The values of the CPT are set by combining expertise knowledge and experimental results, as explained later.

The mathematical model underlying BN is Bayes' theorem, which is shown in Eq. (1). Bayes' theorem relates conditional and marginal probabilities. It yields the conditional probability distribution of a random variable A, assuming we know: information about another variable B in terms of the conditional probability distribution of B given A, and the marginal probability distribution of A alone. Eq. (1) reads: the probability of A given B equals the probability of B given A times the probability of A, divided by the probability of B.

$$P(A/B) = \frac{P(B/A)P(A)}{P(B)}. \tag{1}$$

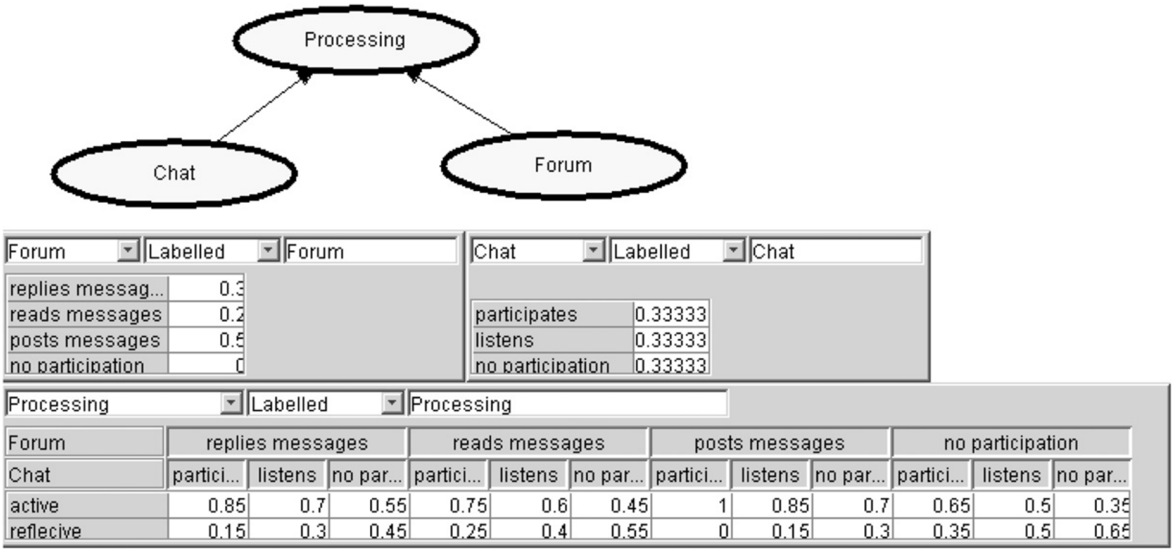

Fig. 1. A simple Bayesian network.

4.1. Modeling students' behavior with a BN

We adopt a knowledge engineering approach to build the BN that represents the learning style of a certain student. To build the BN we must, first, build a graph that contains the variables of interest and the relationships between these variables, and second, assign the probability distribution to each node in the graph in order to indicate the strength of the relationships previously modeled.

Thus, the first step towards the construction of a BN is determining the variables that are worth modeling and the states of these variables. In our application domain, variables represent: the different factors we analyze in students' behavior, the different dimensions of the learning styles we can observe in a Web environment, and the learning styles themselves.

The behaviors we can record and measure generally depend on the functionality of the underlying Web-based education system. In this work we consider only three dimensions of Felder's framework, namely perception, processing and understanding. We model each dimension with a variable in the BN. The values these variables can take are sensory/intuitive, active/reflective, and sequential/global, respectively. We discarded the input dimension because we are currently not considering videos or simulations as part of the Web courses. We also discarded the organization dimension because it has been demonstrated that most engineering students are inductive learners (Felder & Silverman, 1988).

The factors we analyze to determine the perception of a student are: whether the students revises the exams and how long this revision takes; how long it takes the student to finish an exam and deliver it; the amount of times the student changes his/her answers in an exam; the type of reading material the student prefers (concrete or abstract); the number of examples of a given topic the student reads; the number of exercises a student does on a given topic. This information is obtained by analyzing the data recorded in a student's log file. According to Felder, we can say that 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 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 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.

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 mentioned before are encoded in the network structure. The resultant network is shown in Fig. 2.

The following sentences describe in detail the different states the independent variables can take:

- Forum: posts messages; replies messages; reads messages; no participation.
- Chat: participates; listens; no participation.
- Mail: uses; does not use.
- 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%.

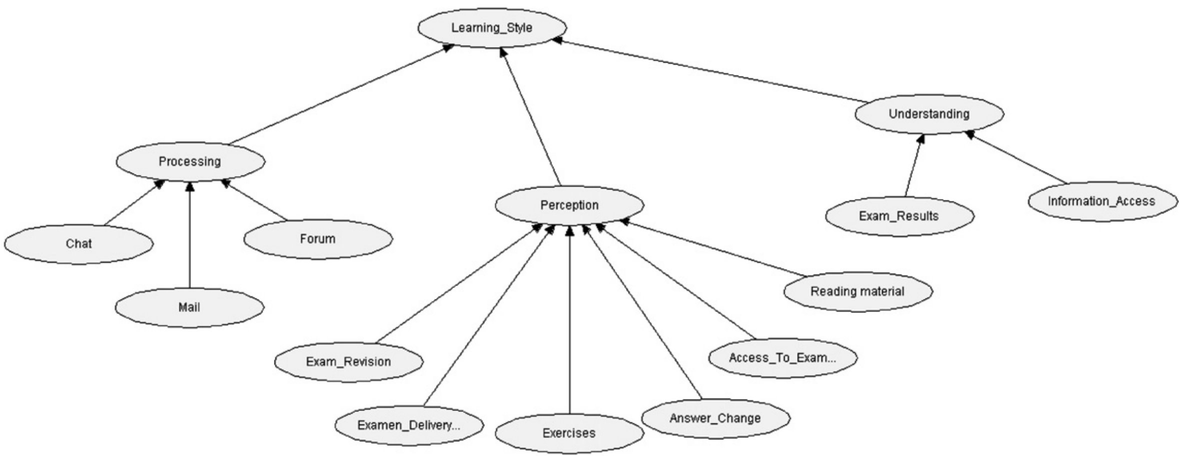

Fig. 2. Bayesian network modeling a student's learning style.

- 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).

The final step in constructing a BN is to assess the local distributions $p(v_i/\Pi_i)$. The model is completed by establishing the probability values associated with each node v_i of the graph; one distribution for every state of its parents, Π_i.

The probability functions associated with the independent nodes are gradually obtained by observing the student interaction with the system. As an example, Fig. 3 shows the probability values obtained for a certain student for the ‘‘Forum’’, ‘‘Exam revision’’ and ‘‘Exercises’’ nodes, respectively. The third cell of the second column in the ‘‘Forum’’ table indicates that 50% of the times the student used the application he/she posted messages to the forum.

Initially, probability values for independent nodes are assigned equal values. Then, the values are updated as the system gathers information about the student behavior. The probability functions 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 students' interaction with the system is obtained. Eventually, at a certain point in the interaction, the probabilities reach equilibrium. That is, as new information is entered the probability values show a very small variation (with respect to a predefined threshold). The values obtained at this point represent the student's behavior.

Fig. 4 shows the CPT for the ‘‘Understanding’’ node. For example, the second cell in the first (numbered) column indicates that if the student reads in fits and starts and he/she gets high marks in the exams, the probability that this student is a global learner is 100%.

Exam_Revision	Labelled	Exam_Revision
less than 10 %	0.2	
between 10 and...	0.6	
more than 20 %	0.2	

Forum	Labelled	Forum
replies messag...	0.3	
reads messages	0.2	
posts messages	0.5	
no participation	0	

Exercises	Labelled	Exercises
many	0.7	
few	0.3	
none	0	

Fig. 3. Probability tables for some of the independent nodes.

Understanding	Labelled	Understanding			
Exam_Results	high		medium		low	
Information_Ac...	in fits ...	contin...	in fits ...	contin...	in fits ...	contin...
sequential	0	1	0.25	0.75	0.5	0.5
global	1	0	0.75	0.25	0.5	0.5

Fig. 4. CPT for the understanding node.

The probability values contained in the different CPT were obtained via a combination of expert knowledge and experimental results. The expert knowledge was obtained from Felder's definition of learning styles. We took into account the influence of the different factors analyzed on the dimensions of the learning styles. To determine the values experimentally we gave a set of 50 Computer Science Engineering students the ILS (Index of Learning Styles) questionnaire.[1] This questionnaire produces as a result a set of numbers indicating a student's learning style according to Felder's scale. Then, we let these students use the education system and recorded their interactions with the system. Information about their recorded behavior was used to determine the conditional parameters of the BN, in combination with the expert knowledge.

4.2. How to infer a learning style with a BN

An important characteristic of BN is that Bayesian inference mechanisms can be easily applied to them. The goal of inference is typically to find the conditional distribution of a subset of the variables, conditional on known values for some other subset (the *evidence*). Thus a BN can be considered a mechanism for automatically constructing extensions of Bayes' theorem to more complex problems. The general setting for probabilistic inference is that we have a set V of propositional variables $V_1, \ldots, V_k$ and we are given, as evidence, that the variables in a subset E of V have certain definite values, $E = \varepsilon$ (of true or false). We desire to calculate the conditional probability, $p(V_i = v_i/E = \varepsilon)$, that some variable V_i has value v_i given the evidence.

In this work, we want to infer 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 marginal probability values of the learning style node given the values of independent nodes. The learning style of the student is the one having the greatest probability value. In the formulas described above, instead of true or false values, we have to compute the posterior probability that a certain dimension has a given value.

For example, suppose that we want to determine whether the student learns sequentially or globally, we have to compute the probability p(Understanding = Sequential), that is p(Understanding = Sequential/Information Access, Exam Results), and p(Understanding = Global), that is, p(Understanding = Global/Information Access, Exam Results).

Then, as shown in Fig. 5, the value of the dimension is the one with the highest posterior probability: sequential. Once we have obtained that the student belongs to a given category or dimension we have to map this probability value to the scale proposed by Felder. Felder's model ranks students in different levels within one dimension. The different levels are: 1, 3, 5, 7, 9, and 11. For example a student categorized as "sequential 1" has almost a neutral behavior in the understanding dimension. On the other hand, a student categorized as "sequential 9" shows a clear sequential behavior as regards understanding. Thus, we must match the probability value to this scale. For example, if the posterior probability corresponding to the sequential in state the understanding dimension is 75%, we can say that the student is a sequential learner with degree 7 in Felder's scale.

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

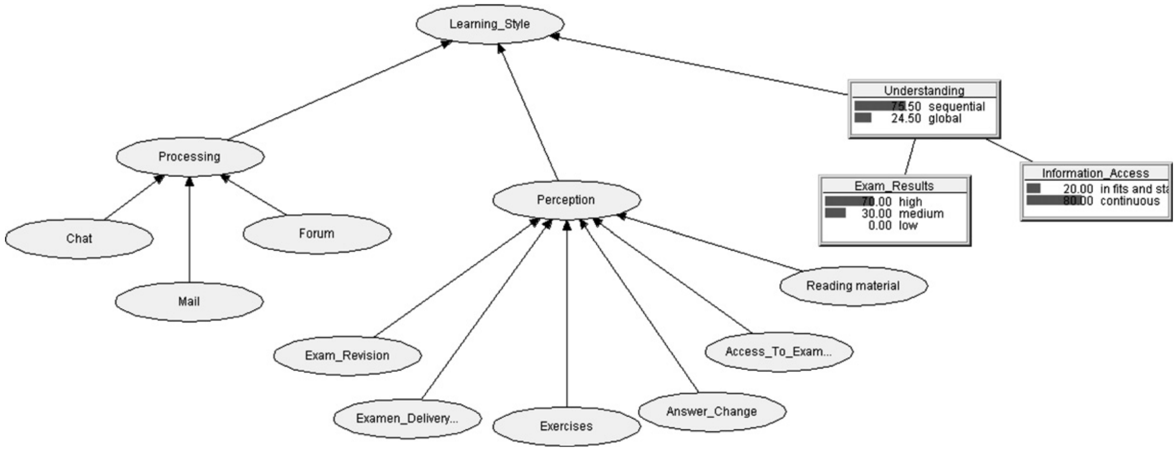

Fig. 5. Inference of understanding posterior probabilities.

Despite the calculus looks simple for the understanding dimension, it becomes complicated for the perception dimension. Bayesian inference mechanisms already implemented help us in these calculations (Jensen, 1996).

5. Experimental results and discussion

We have evaluated our proposed approach with 27 users. The application field was an Artificial Intelligence course taken by Computer Science Engineering students. These students had no previous knowledge on the topics taught in the Web-based course. We considered a course unit or topic as the minimum observation unit. The results obtained in our experiment were computed by averaging the students' behavior in different units. Each unit is, in turn, divided into a set of topics. For each topic students have 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.

Fig. 6 shows the characteristics of the population of students that participated in the experiment according to the dimensions we have studied. Fig. 7 shows the expertise of the students at using Web-based courses.

To evaluate the precision of our approach we compared the learning style detected by the BN model against the learning style obtained with the ILS questionnaire proposed by Felder. The data used for evaluating the BN (testing data) is obviously different from the data used for determining the parameters of the network (training data).

Table 2 shows the results we obtained. The table describes for the different users the dimensions of the learning styles assigned by our proposed approach and by the ILS questionnaire. To make

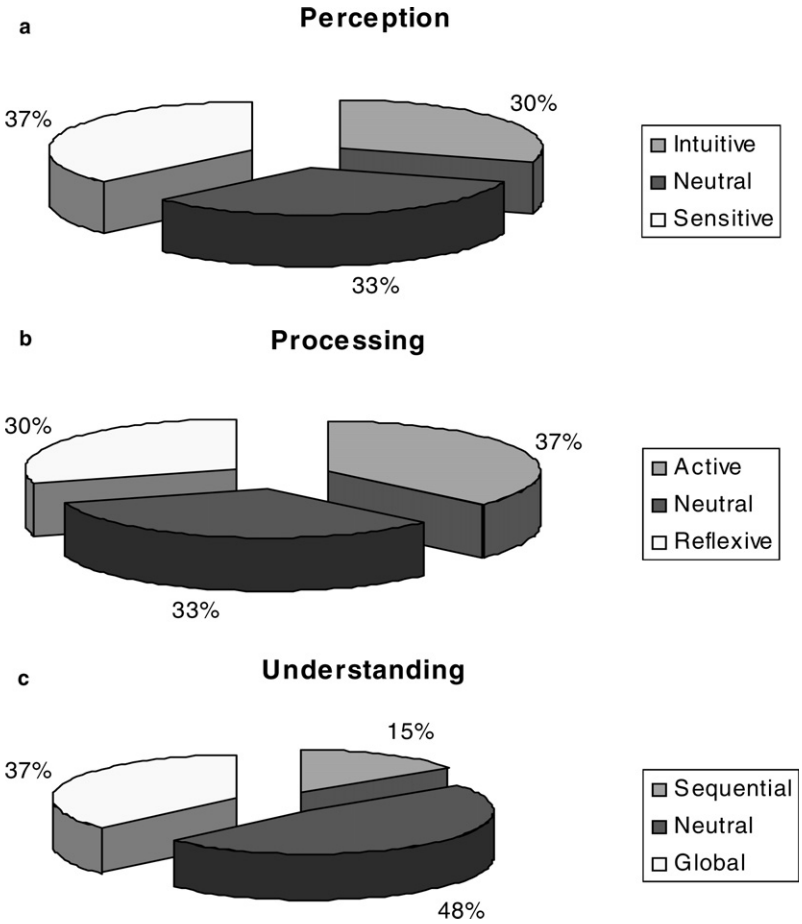

Fig. 6. Population of students: learning styles.

the results comparable we considered for each dimension three values. For example, for the understanding dimension we considered the values sequential, neutral and global. For each dimension the table shows the number of experiences used to determine the value in the dimension. The figures in bold show the mismatches in the categories (opposite values) obtained with

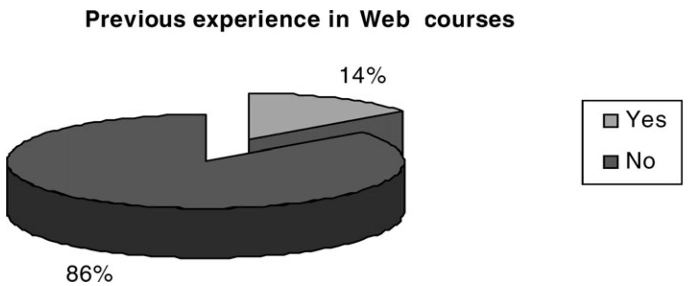

Fig. 7. Population of students: previous experience with Web-based courses.

Table 2
Experimental results

User	Perception			Understanding			Processing		
	ILS	BN	#Exp	ILS	BN	#Exp	ILS	BN	#Exp
1	NEU	NEU	24	**GLO**	**SEQ**	17	**ACT**	**REF**	3
2	**INT**	**SEN**	33	**GLO**	**SEQ**	26	**ACT**	**REF**	7
3	SEN	SEN	30	NEU	NEU	23	NEU	–	0
4	INT	INT	22	**GLO**	**SEQ**	15	*NEU*	*REF*	2
5	SEN	SEN	34	NEU	NEU	27	ACT	–	0
6	NEU	NEU	24	NEU	NEU	17	REF	REF	3
7	SEN	SEN	3	NEU	NEU	1	NEU	NEU	1
8	NEU	NEU	23	NEU	NEU	16	ACT	–	0
9	SEN	SEN	57	*NEU*	*SEQ*	50	*NEU*	*REF*	3
10	SEN	SEN	22	NEU	NEU	15	REF	–	0
11	NEU	NEU	40	*SEQ*	*NEU*	33	NEU	–	0
12	SEN	SEN	47	*NEU*	*SEQ*	40	*NEU*	*REF*	5
13	SEN	SEN	29	**GLO**	**SEQ**	22	REF	REF	4
14	*NEU*	*SEN*	38	**GLO**	**SEQ**	31	ACT	–	0
15	NEU	NEU	25	NEU	NEU	18	REF	–	0
16	NEU	NEU	34	NEU	NEU	27	*NEU*	*REF*	3
17	**SEN**	**INT**	5	SEQ	SEQ	3	ACT	–	0
18	**INT**	**SEN**	35	NEU	NEU	28	REF	REF	1
19	INT	INT	3	**GLO**	**SEQ**	1	*NEU*	*REF*	1
20	SEN	SEN	39	SEQ	SEQ	32	ACT	–	0
21	SEN	SEN	27	*GLO*	*NEU*	20	ACT	–	0
22	NEU	NEU	16	*SEQ*	*NEU*	9	NEU	–	0
23	**INT**	**SEN**	28	NEU	NEU	21	REF	REF	6
24	**INT**	**SEN**	25	*GLO*	*NEU*	18	REF	REF	3
25	*INT*	*NEU*	23	*GLO*	*NEU*	16	NEU	–	0
26	INT	INT	17	*GLO*	*NEU*	10	REF	–	0
27	NEU	NEU	19	NEU	NEU	12	**ACT**	**REF**	3

the ILS and with the BN. The figures in italic show a small mismatch between the values (neutral versus a extreme value).

Using the formula in Eq. (2), we obtained a precision of 77% in the perception dimension, 63% in the understanding dimension, and 58% in the processing dimension. This last percentage is computed only considering the styles that could be obtained by the BN (52% of the students). In this equation Sim is 1 if the values obtained with the BN and ILS are equal, 0 if they are opposite, and 0.5 if one is neutral and the other an extreme value; and n is the number of students studied.

$$\text{Precision} = \frac{\sum_{i=1}^{n} \text{Sim}(LS_{\text{BN}}, LS_{\text{ILS}})}{n}. \tag{2}$$

According to the BN the most popular processing style is reflective. We further analyzed the lack of information and the mismatches in this dimension by surveying the students who participated in the experiment. We found that most students made little use (or no use) of the chat, mail and forum facilities, as shown in Fig. 8. Thus, the number of experiences recorded in most cases was

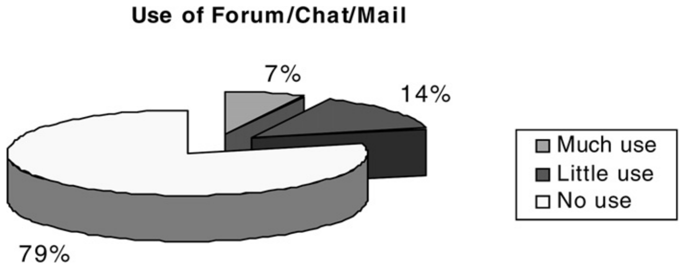

Fig. 8. Use of forum, chat and mail during the experiment.

small and the behavior of the BN was biased. If we have few experiences these experiences have a great impact in the calculus of probabilities, and hence, the probability values learned are not representative.

To study the causes of the situation described above, we asked the students to answer a questionnaire telling us why they had not use the forum, chat and email facilities. We found that 17 out of 27 students considered that the course did not promote the use of chat and forum facilities. The rest of the students said that they do not normally use these technologies for studying. Thus, to enable the BN discover to which category a student better fits in, we should encourage students to use tools such as mail, forum and chat by, for example, proposing collaborative tasks and exercises.

By analyzing students' logs, we found that most students have read the whole course, that is, they read most of the theoretical material, they did most of the exercises proposed and they read most of the examples. In turn, most of them did not skip units and read the material sequentially, independently of their learning styles. This phenomenon can be observed in the results obtained for the understanding dimension, where no global learners were discovered. It also explains why some intuitive learners behaved as sensitive learners while working with the Web-based course.

Through the questionnaires answered by students we found that one of the causes of this phenomenon is the inexperience of our students at working with Web-based courses, as shown in Fig. 7. In addition, the survey asked students whether they behaved differently when using the Web-based education system and when they study normally. Six of the students recognized that they behaved differently as they normally do. Two of them argued that they only searched for the items of interest. On the contrary, two students said that they wanted to read everything. And the remaining two considered that the characteristics of Web browsing lead them to study differently.

To summarize the results of the surveys, we can conclude that the BN can detect the processing and understanding style of students provided that they have some experience at working with Web-based courses and the size, organization and content of the courses enable and encourage them to behave as they would do in a "normal" learning environment.

Finally, we obtained good results for the perception dimension. The BN could estimate with high precision the category to which students belong in this dimension. As we have said before, the mismatches we found were due to the inexperience of students that made some of the intuitive learners behave like sensitive learners.

6. Conclusions

We have evaluated the capability of BN to model and detect students' learning styles. We have compared the BN approach with the results obtained with the ILS questionnaire. The results obtained are promising. They show that the BN enable us to determine the perception style of a student with high precision. As regards the understanding and processing dimensions, some mismatches were found.

We discovered that we should encourage students to make use of facilities such as forums and chat rooms in order to discover the active learners. We also found that the inexperience of students at working with Web-based courses made them study differently from the way they usually do. Finally, we learned that to detect correctly the sequential/global dimension we have to observe students' behavior while working with big courses, where the size is measured in terms of numbers of units, examples and exercises.

Although the number of students that participated in the experiment is quite restricted, the results obtained gave us valuable information about students' behaviors with Web-based courses. This information will be used in the future to enhance our proposed BN model. For example, some new variables may be considered to detect the processing style of students by further analyzing log files of collaborative tasks. In turn, further experiments will be carried out in order to validate the results obtained thus far.

In summary, provided that we take into account the situations mentioned before in the development of the Web-based course, the proposed BN model will enable us to discover students' learning styles with high precision.

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