Using Bayesian Networks to Detect Students' Learning Styles in a Web-based education system

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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 goals 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. We propose the use of Bayesian Networks to detect the learning style of a student in a Web-based education system. The information obtained can be then used by an intelligent agent to provide personalized assistance to students, delivering teaching material that best fits students' learning styles.

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 [4] by seeing and hearing; reflecting and acting; reasoning logically and intuitively; memorizing and visualizing; and 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 [5, 8].

In the field of computer-based education, it is necessary to represent students' learning styles and students' models or profiles computationally. Artificial Intelligence has provided several valuable tools in this direction such as intelligent tutoring systems, intelligent learning environments, environments for multimedia education, and Web-based education systems [1, 20, 21].

One of the most desired characteristics of a web-based education system is being adaptive and personalized, since it has to be used by a wide variety of students with different skills and learning styles. One of the ways of achieving adaptation and personalization is through intelligent agents [12]. An intelligent agent can observe how the student interacts with the system in order to learn the student's learning style.

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Then, the agent can provide useful assistance to this student by suggesting further reading or more exercises, for example, according to his/her learning style.

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 [18]. The problem with these tests is the time students spend answering questions and the accuracy of the results obtained. If questionnaires are too long, students tend to choose answers arbitrarily instead of thinking about them.

In this work we propose the use of Bayesian networks (BNs) to represent and detect students' learning styles in a Web-based education system. The nodes in the BN represent the different variables that determine a given learning style. The arcs represent the relationships between the learning style and the factors determining it. There have been proposed several models and frameworks for learning styles. We use the one proposed by Felder and Silverman for engineering students [4].

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

2 Learning Styles

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 [4].

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 auditory – 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/auditory/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.

Learning Style	
Sensory Intuitive	Perception
Visual Auditory	Input
Inductive Deductive	Organization
Active Reflective	Processing
Sequential Global	Understanding

Table 1. Dimensions of Felder's learning styles

Visual learners remember best what they see: pictures, diagrams, time lines, films, demonstrations. Auditory learners remember much of what they hear and more of what they hear 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 [4].

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.

Although 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. In the following section we describe the dimensions we have selected and how we detect them.

3 Proposed approach: Bayesian Networks

A BN is a graphical representation of uncertain knowledge. A BN allows us to discover new knowledge by combining expert domain knowledge with statistical data. A BN is a directed, acyclic graph whose nodes are labeled by random variables [10]. In agent applications, random variables stand for features of a domain of interest. In our problem, random variables represent the different dimensions of Felder's learning styles and the factors that determine each of these aspects. These factors are extracted from the interactions between the student and the web-based education system.

A BN is also a compact, expressive representation of uncertain relationships among parameters in a domain. In particular, a BN can model the relationships between the learning styles and the factors determining them. Arcs connecting the nodes in the graph represent a probabilistic correlation between variables. 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 [16].

In addition to representing statements of independence, a BN also represents a particular probability distribution. This distribution is specified by a set of conditional probability tables (CPT). In order to complete the Bayesian model for a given user, we need to specify the conditional probability functions for each node in the network conditioned just on its parents. 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. Therefore, a complete specification of the probabilities for a set of random variables involves a BN for these variables along with CPT for each node in the network.

3.1 Representing learning styles with BNs

One way to build BNs is to use knowledge engineering. A knowledge engineer can interact with a domain expert to identify qualitative problem aspects, such as direct relationships between the problem variables. These relationships then become encoded in the network structure.

We adopt a knowledge engineering approach to build the BN that represents the learning style of a certain student. 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.

As shown in Figure 1, we model 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 [4].

The second step in constructing a BN is to build a directed acyclic graph that encodes assertions of conditional independence. We call this graph the Bayesian-network structure. Given a domain $V=\{V1,V2,...,Vn\}$ and an ordering on the variables ($V1,...,Vn$), we can write the joint probability distribution of V using the chain rule of probability as follows:

$$p(v1,...,vn/\varepsilon)=\prod_{i=1}^{n} p(vi/v1,...,vi-1,\varepsilon)$$

Now, for every Vi there will be some subset $\Pi_i \subseteq \{V_1,...,V_n\}$ such that V_i and $\{V_1,...,V_n\}$ are conditionally independent given Π_i. That is,

$$p(vi/v1,...,vi-1,\varepsilon)=p(vi/\prod i,\varepsilon)$$

These conditional independencies define the Bayesian-network structure. The nodes in the structure correspond to the set Π_i.

In this work, 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 its 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. 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 sensitive. A student who reads or accesses to various examples of a given topic is more sensitive than one who reads just one or two. As regards the type of reading material the student prefers, a sensitive learner prefers concrete (application oriented) material while the intuitive learner usually likes abstract or theoretical texts.

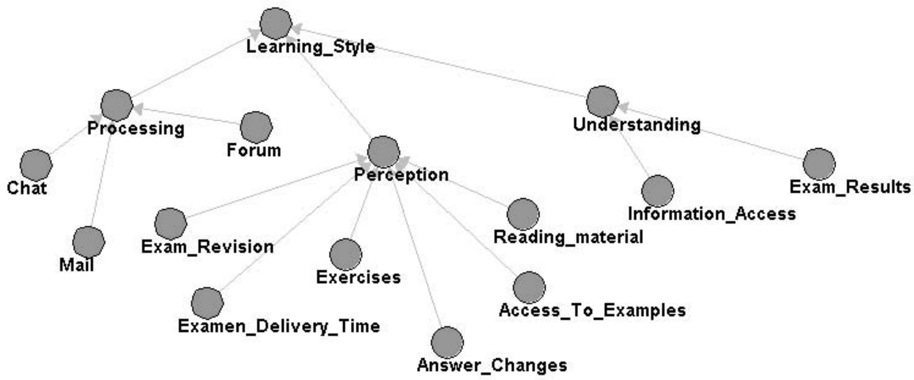

Fig. 1. Bayesian Network modeling students' learning styles

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. 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 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; sequential.
- 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).

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

Forum	Probability
Posts message	0.50
Replies message	0.30
Reads message	0.20
No participation	0.00

Table 2. Forum probaility function

The probability functions associated with the independent nodes are gradually obtained by observing the student interaction with the system. As an example, Table 2 represents the probability distribution of node “Forum” for a certain student. The first cell of the second column indicates that the 50 percent of the times the student used the application he/she posted messages to the forum. Initially, probability values are assigned equal values. The values are updated as the agent gathers information about the student behavior.

Table 3 shows the CPT for the “Understanding” node. For example, the third cell in the second coulmn 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%. In this table, IA stands for information access and ER stands for exam results.

The probability values in the different CPT were obtained via a combination of expert knowledge and experimental results. To determine the values experimentally we interviewed a set of 30 Computer Science Engineering students using the ILS

(Index of Learning Styles) questionnaire[1]. Then, we let them used the education system and recorded their interactions with the system. This information was used to determine the parameters of the BN.

Understanding	IA = In fits & Starts ER = High	IA = In fits & Starts ER = Medium	IA = In fits & Starts ER = Low	IA = Continuous ER = High	IA = Continuous ER = Medium	IA = Continuous ER = Low
Sequential	0	0.25	0.5	1	0.75	0.5
Global	1	0.75	0.5	0	0.25	0.5

Table 3. Understanding conditional probaility table

The Bayesian model is continuously updated as new information about the student's interaction with the system is obtained. The probability functions attached to the independent nodes are adjusted to represent the new observations or experiences [14]. At a certain point in the interaction, the probabilities reach an 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.

3.2 How to infer the learning style using a BN

An important characteristic of BNs is that Bayesian inference mechanisms can be easily applied to them. The general setting for probabilistic inference is that we have a set, V, of propositional variables $V_1,V_2,....V_k$, and we are given, as evidence, that the variables in a subset E of V have certain definite values, $E=\mathbf{e}$ (of true or false). We desire to calculate the conditional probability, $p(Vi=vi/E=\mathbf{e})$, that some variable Vi has value vi given the evidence. We call this process probabilistic inference.

Since V_i has the value true or false, there are two conditional probabilities in which we might be interested, namely $p(Vi=true/E=\mathbf{e})$ and $p(Vi=false/E=\mathbf{e})$. Using the definition for conditional probability, we have:

$$p(Vi = true / \varepsilon = e) = \frac{p(Vi = true, \varepsilon = e)}{p(\varepsilon = e)}$$

$p(Vi=true/E=\mathbf{e})$ is obtained by using the rule for calculating joint probabilities:

$$p(Vi = true, \varepsilon = e) = \sum_{Vi=true,\varepsilon=e} p(V1,...,Vk)$$

where the V_i, $i=1,...,k$ constitute the collection of propositional variables. That is, we sum over all values of the joint probability for which $Vi=true$ and for which the evidence variables have their given values. The calculation of $p(E=e)$ can be done in a similar manner.

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

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

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 have 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)* Given the probability values obtained from observation (evidence) for the *Information Access* and *Exam Results* shown in Tables 4 and 5, the CPTs associated to the *Understanding* node, and applying causal reasoning [10] we can obtain these values.

Information Access	Probability
Sequential	0.8
Global	0.2

Table 4. Probability function obtained from observation for Information Access

Exam Results	Probability
High	0.7
Medium	0.3
Low	0.0

Table 5. Probability function obtained from observation for Exam Results

*p(U=seq/IA, ER) = p(U=seq/IA=f&s,ER=h) * p(IA=f&s) * p(ER=h) + p(U=seq/IA=f&s,ER=m) * p(IA=f&s) * p(ER=m) + p(U=seq/IA=f&s,ER=l) * p(IA=f&s) * p(ER=l) + p(U=seq/IA=c,ER=h) * p(IA=c) * p(ER=h) + p(U=seq/IA=c,ER=m) * p(IA=c) * p(ER=m) + p(U=seq/IA=c,ER=l) * p(IA=c) * p(ER=l) =1*0.2*0.7 + 0.5*0.2*0.3 + 0.75*0.2*0 +0.25*0.8*0.7 +1*0.8*0.3 + 0.5*0.8*0 = 0.55*

*p(U=glo/IA, ER) = p(U= glo /IA=f&s,ER=h) * p(IA=f&s) * p(ER=h) + p(U= glo /IA=f&s,ER=m) * p(IA=f&s) * p(ER=m) + p(U= glo /IA=f&s,ER=l) * p(IA=f&s) * p(ER=l) + p(U= glo /IA=c,ER=h) * p(IA=c) * p(ER=h) + p(U= glo /IA=c,ER=m) * p(IA=c) * p(ER=m) + p(U= glo /IA=c,ER=l) * p(IA=c) * p(ER=l) =0*0.2*0.7 + 0.5*0.2*0.3 + 0.25*0.2*0 +0.75*0.8*0.7 + 0*0.8*0.3 + 0.5*0.8*0 = 0.45*

Then, the value of the dimension is the one with the highest posterior probability, that is 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. For example, if the posterior probability corresponding to the state sequential in the understanding dimension is 55% (45% global), we can say that the student is a sequential learner with degree 1 in Felder’s scale (equivalent to neutral in this dimension).

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 [10].

4 Experimental Results

We have evaluated our proposed approach with 10 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. Figure 2 shows two snapshots corresponding to the education system used in our experiment, named SAVER (acronym for "*Software de Asistencia Virtual para Educación Remota*"). Figure 3 shows the characteristics of the students that participated in the experiment according to the dimensions we have studied.

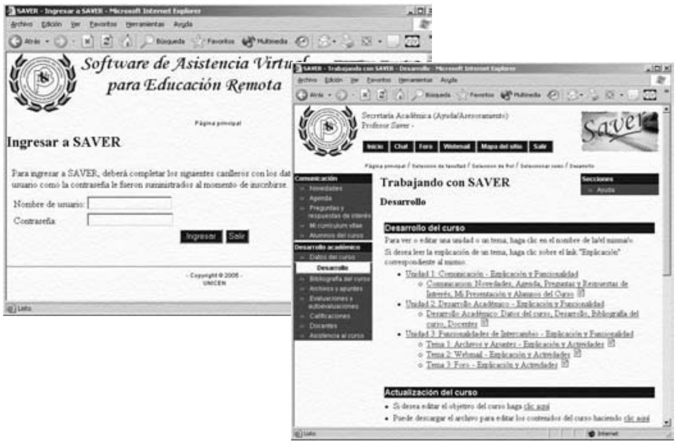

Fig. 2. Snapshots of SAVER

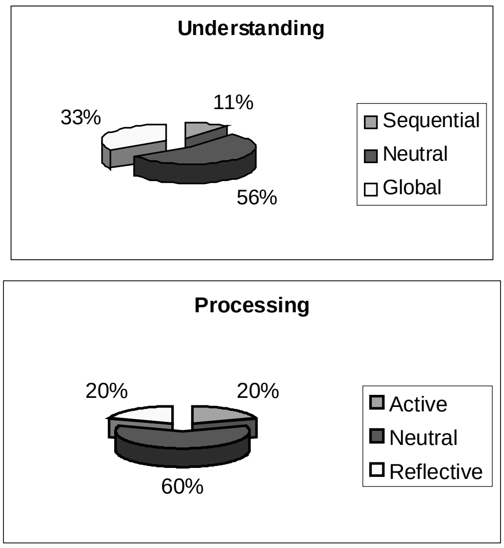

Fig. 3. Population of students

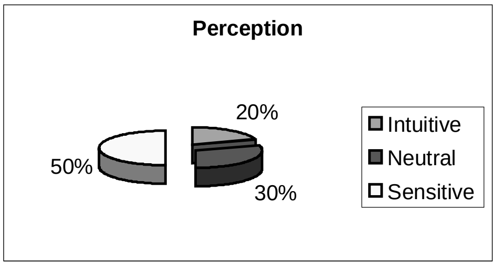

Fig. 3. Population of students (cont.)

To evaluate the precision of our approach we compared the learning style detected by our approach against the learning style obtained with the ILS questionnaire proposed by Felder. Table 6 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 the results comparable we considered for each dimension three values. For example, for the understanding dimension we considered the values sequential, neutral and global.

We can observe that the percentage of coincidences is of 100% for the understanding dimension, 80% for the perception dimension, and 80% for the processing dimension. In those cases where we found differences, we did not get opposite styles but a neutral value against a extreme value in the dimension. We can conclude that, in general terms, the Bayesian network allows us to determine the learning style of students with high degrees of precision.

User	**Understanding**		**Perception**		**Processing**	
	BN	**ILS**	**BN**	**ILS**	**BN**	**ILS**
1	(70% G) GLO	GLO	*(61% I) NEU*	*INT*	(70% R) REF	REF
2	(50% G) NEU	NEU	(70% S) SEN	SEN	(60% R) NEU	NEU
3	(64% G) GLO	GLO	(65% I) INT	INT	*(79% R) REF*	*NEU*
4	(51% S) NEU	NEU	(70% S) SEN	SEN	(55% R) NEU	NEU
5	(54% S) NEU	NEU	(68% S) SEN	SEN	(58% A) NEU	NEU
6	(70% S) GLO	GLO	(58% S) NEU	NEU	(60% A) NEU	NEU
7	(70% G) GLO	GLO	(71% S) SEN	SEN	(70% A) ACT	ACT
8	(70% S) SEQ	SEQ	(83% S) SEN	SEN	(70% A) ACT	ACT
9	(52% G) NEU	NEU	(60% S) NEU	NEU	(81% R) REF	REF
10	(50% G) NEU	NEU	*(70% S) SEN*	*NEU*	*(75% R) REF*	*NEU*

Table 6. Experimental results

5 Related Work

Related works on student modeling 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, among others. Our work can be placed among those modeling psychological characteristics of students, such as ARTHUR [7] which considers three learning styles (visual-interactive, lecto-auditivo, textual), CS388 [2] and MAS-PLANG [17] that use Felder and Silverman styles; the INSPIRE system [15] that uses the styles proposed by Honey and Mumford [9].

Various techniques have been used to represent student models, such as rules [11], fuzzy logic [22], Bayesian networks [3], and case-based reasoning [17]. For example, ANDES [6] and SE-Coach [Conati02] use Bayesian networks to model a student knowledge in Physics. Desktop Associate [13] models students' skills at using a word processor with Bayesian networks. IDEAL [19] uses this technique to categorize students into novice, beginner, intermediate, advanced, or expert. Our work is novel since it proposes the use of Bayesian networks to model a student learning style, an aspect not considered in the previous Bayesian student models.

6 Conclusions

We have described an approach to detect and model students learning styles with BNs. We have successfully evaluated the proposed Bayesian model by comparing it with the results obtained with the ILS questionnaire.

The proposed approach is currently being used by agents assisting students in a Web-based education system named SAVER. The information recorded during this interaction will be used to evaluate the usefulness of our approach as a supporting tool of a personalized web-based education system. The proposed model will be enhanced to support the other dimensions of the learning styles as new types of teaching material will be added to our courses.

As a future work, we are planning to compare the proposed Bayesian model with other models based on different Artificial Intelligence techniques, such as genetic algorithms, association rules and neural networks.

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