Designing a Dynamic Bayesian Network for Modeling Students' Learning Styles

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Abstract

When using Learning Object Repositories, it is interesting to have mechanisms to select the more adequate objects for each student. For this kind of adaptation, it is important to have sound models to estimate the relevant features. In this paper we present a student model to account for Learning Styles, based on the model defined by Felder and Sylverman and implemented using Dynamic Bayesian Networks. The model is initialized according to the results obtained by the student in the Index of Learning Styles Questionnaire, and then fine-tuned during the course of the interaction using the bayesian model, The model is then used to classify objects in the repository as appropriate or not for a particular student.

1 Introduction

Some traditional Adaptive Educational Hypermedia Systems (AEHS) have implemented several learning style models for better adapting their educational resources to their users [1]. Among them, AES-CS [2] implements the Witkin's Field Dependent/Field Independent Model to adapt the amount of control (program vs. learner), instructional support, navigational tools and feedback to assessment questions in Multimedia Technology Systems. INSPIRE [3] applies the Honey and Mumford model to adapt the method and order of presentation of multiple types of educational resources within educational material pages. iWeaver [4] implements the Dunn and Dunn model to adapt navigation and content presentation. Finally, TANGOW/WOTAN [5], WHURLE [6], and CS383 [7] make use of the Felder and Silverman model to adapt content presentation to the student.

Besides traditional AEHS, a considerable number of on-line educational data designed as *Learning Objects Repositories* (LORs) has been created over the last years. Some popular LORs are MERLOT [8] and ARIADNE [9]. Using the object format is a way to increase the flexibility and manageability of rich stores of learning resources available on-line from academic institutions, publishers and organizations. In such a LOR, learning objects are shared across different learning environments and can be accessed on demand either by learners and instructors. On one hand, learners have access to a vast amount of different learning objects in order to fully acquire the knowledge or skills that match their requirements. On the other hand, instructors can borrow each other's materials for further use in their classrooms.

IEEE-LTSC [10] is a technical specification for the universal sharing of learning objects proposed by the IEEE Computer Society Standards Activity Board. IEEE-LTSC provides internationally accredited technical standards, recommended practices and guides for learning technology. Among them, the Learning Object Metadata (LOM) [11] is a standard to specify the syntax and semantics of learning objects using a set of attributes that fully/adequately describe a learning object. One of the key issues concerning the use of LORs is the retrieval and searching facilities of learning objects. To solve this problem, we propose to "*filter*" and "*sort*" the learning objects according to the current student's learning style and preferences, so he/she can make a better use of it. We determine the current preferences through a probabilistic decision model that represent the matches between learning styles and learning objects in order to determine how much a given object is interesting to a student. The decision model behaviour is quite similar to a content-based recommender system[1]. The information about the learning object (the item to recommend) and the student's learning style (the user's features) are presented to the classifier as input, having as output a

[1] A recommender system tries to present to the user the information items he/she is interested in. To do this the user's profile is compared to some reference characteristics. These characteristics may be from the information item (the content-based approach) or the user's social environment (the collaborative filtering approach).

probability that represents the appropriateness of the learning object for this student (or how interesting the item is for this user). For more details about the probabilistic decision model see [12][13].

This paper is focused on the design of a Dynamic Bayesian Network (DBN) for modeling students' learning styles. The next section briefly introduces the Felder-Sylverman Learning Style Model (FSLSM) and the rationale of our approach. Next, we explain the design of the DBN and present the results obtained with a simple test aimed at evaluating that the model behaviour corresponds to our requirements. We conclude with a summary and a description of ongoing and future work.

2 The Learning Style Model

Learning Style (LS) can be defined as the way a person collects, processes and organizes information. Among the different proposals for modeling LS, we choose the FSLSM [14] since it is one of the more successful models and has been implemented in many e-learning systems. FSLSM classifies students in four dimensions:

- *Active / Reflective* (Processing). Active people consider having understood a piece of information only if they have discussed it, applied it or tried to explain it to other people. Reflexive people, on the other hand, prefer reflecting about the issue before assuming any practical posture.
- *Sensing / Intuitive* (Perception). Sensing people are meant to learn from tasks related to problems and facts that could be solved by well-behaved methods, with no surprises or unexpected effects. Besides, this style usually refers to students that are fond of details and very good memorizers of facts and practical applications. Conversely, intuitive students are meant to discover alternate possibilities and relationships by themselves, working with abstractions and formula, which allows them to understand new concepts and to quickly and innovatively perform new tasks.
- *Visual / Verbal* (Input). Visual-driven people find no difficulties in interpreting, for an example, pictures, diagrams, timelines or movies. Distinctly, verbal students' personal learning processes are driven by written or spoken explanation.
- *Sequential / Global* (Understanding). Sequential people structure their learning process by logically, successively chained steps, each one of them related to the search for solutions. On the other hand, global students learning processes are distinguished by random jumps: they often are able to solve a complex problem, although they do not know how they arrived at the solution.

Felder and Soloman proposed a psychometric instrument, the Index of Learning Style Questionnaire (ILSQ) [15], that classifies the preferences for one or the other category as *mild*, *moderate* or *strong*. In the majority of traditional AEHS that make use of a learning style model for adaptive purposes, the assumptions about the student's learning style are usually acquired by a psychometric instrument like ILSQ, e.g. [3][5]. Nevertheless, the use of such a test has some drawbacks. First, students tend to choose answers arbitrarily. Second, it is really difficult to design tests capable of exactly measuring "how people learn". Therefore, the information gathered trough these instruments encloses some grade of uncertainty. Moreover, this information, as a rule, is no longer updated in the light of new evidences from the student's interactions with the system. An alternative approach that uses a Bayesian Network (BN) to model the student's LS, instead of acquiring it by a psychometric test, is proposed in [16][17]. Using a BN as a LS model allows that observations about the user's behaviour can be used to discover each user's LS automatically using the inference mechanisms. In these works the BN structure is designed by the experts and the parameters are specified from data obtained from both the expert and the log files.

In this paper we propose to design the LS model using a hybrid approach. For each student a DBN is initialized as his/her model and the scores obtained in the ILSQ are used as the initial beliefs of the four FSLSM's dimensions. We then observe the student's selections of different learning objects to set them as evidences in the DBN. Therefore, whenever new evidences about the preferences of the student arrive (student's selections and feedback) a new time slice of the DBN is instantiated, automatically triggering the propagation mechanism and getting up-to-date beliefs for the LS. This makes it possible to refine the initial values for the student's LS acquired by the ILSQ as the student interacts with the system, thus becoming more and more confident over time.

3 The Dynamic Bayesian Network

A Bayesian Network (BN) [18] is composed of two components: the *qualitative part* (its structure) and the *quantitative part* (the set of parameters that quantifies the network). The structure is a directed acyclic graph which nodes represent random variables, and the arcs represent dependencies between these variables. The parameters are conditional probabilities that represent the strength of the dependencies. DBNs [19] extend the BN model in order to deal with changing environments. Therefore, for modeling LS using a

DBN, we should first to determine the variables of interest and the relationships between these variables, that is, the structure of the BN. In our model we consider three kinds of variables:

- <u>Variables to represent the student's LS</u>: we model each dimension of the FSLSM with a variable. The list of variables and the set of possible values is given below:
  - *Input* = {visual,verbal}
  - *Processing* = {active, reflective}
  - *Perception* = {sensing, intuitive}
  - *Understanding* = {sequential, global}
- <u>Variables to represent the selected learning object:</u> whenever a student selects a new learning object, we must account for the values of the attributes selected. In our model we use one variable for each LOM attribute that we consider significant for modeling LS. Table 1 shows the selected LOM attributes for each LS. The list of variables of the BN along with their possible values is given below:
  - *SelectedFormat* = {text, image, audio, video, application }
  - *SelectedLearningResourceType* = {exercise, simulation, questionnaire, figure, index, table, narrative-text, exam, lecture}
  - *SelectedInteractivityLevel* = {very-low, low, medium, high, very-high }
  - *SelectedInteractivityType* = {active, expositive, mixed }
  - *SelectedSemanticDensity* = {very-low, low, medium, high, very-high }

Table 1 LS and LOM attributes relationships

Input	Technical.Format Educational.LearningResourceType
Processing	Educational.LearningResourceType Educational.InteractivityType Educational.InteractivityLevel
Perception	Educational.LearningResourceType
Understanding	Technical.Format Educational.LearningResourceType Educational.SemanticDesnsity

- <u>A variable representing the student rating for that learning object.</u> The student can rate the selected object from 1-star to 4-stars.
  - *SelectedRating* = {star1, star2, star3, star4}

Regarding the relationships between the variables, we consider that the student's learning style determines the student's learning objects selections. The selected learning object and the student's learning style determine the rating value for that object. In order to clarify the design of the structure we proceed to model each learning style dimension separately. Fig. 1 depicts the BN structure for the *Input* dimension (the remaining dimensions are modelled in a similar fashion).

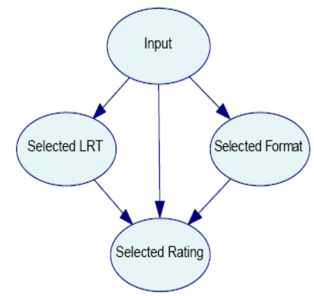


Fig. 1 BN for modeling the *Input* dimension

As stated, this BN should be dynamic. This means that each time a student selects a learning object (and eventually rates it) a new time slice is created and the selected values are used as evidences to update the beliefs for the learning style dimension. After that, the selections nodes are cleared of evidence, thus becoming available for future use. This process is commonly called roll-up.

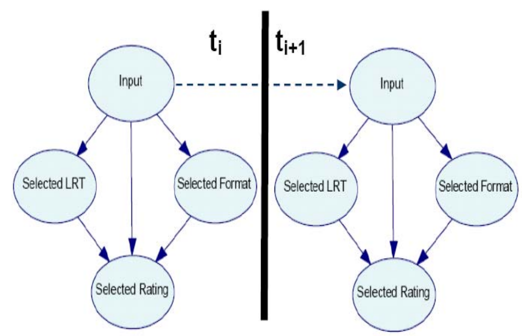
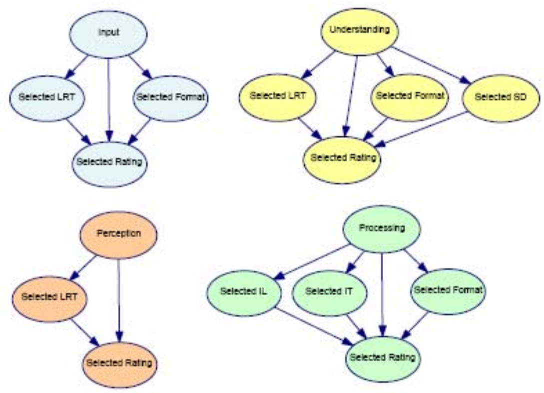


Fig. 2 DBN for modeling the *Input* dimension

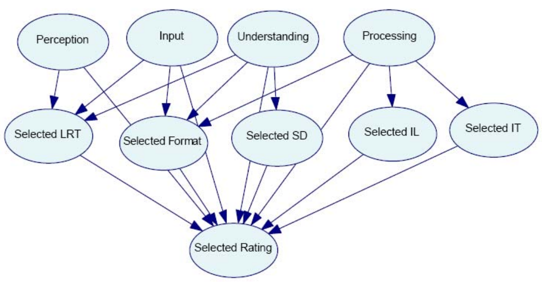
Fig. 2 shows the DBN for the *Input* dimension. As shown in Fig. 3, we have explored two possibilities for modeling the remaining LS dimensions:

- *Option 1*: we consider each dimension separately (four networks). In this case, the number of parameters needed for the higher CPT is 1350.
- *Option 2:* we join the four dimensions in a single network. In this case, the number of parameters needed for the higher CPT is 162000.

Obviously, we have chosen option 1, due to the excessive computational complexity of option 2.



Option 1



Option 2

Fig. 3 Alternatives for modeling the four dimensions of the learning style

To define the DBN's parameters we set the a priori distribution of the nodes representing the LS according to the score obtained by the student in the ILSQ if the student took the test, or distributed uniformly otherwise. Regarding the conditional probability tables (CPTs) that represent the relationships between the dimensions of the LS and the LOM attributes, we estimated these CPTs taking into account the matching tables defined by the expert.

3.1 Sample Assessment [2]

We now give an example of how the DBN refines the student's LS as he/she interacts with the system. For simplicity, we here show only the results using the DBN for the *Input* dimension. Suppose a student that takes the ILSQ and obtains the following scores for the *Input* dimension: *visual*= 3, *verbal* = 8. This student is classified by FSLSM as *verbal-.moderate*. The initial state for the DBN is shown in Fig. 4.

2 The models and test described in this paper were created using the GeNIe modeling environment developed by the Decision Systems Laboratory of the University of Pittsburgh (http://dsl.sis.pitt.edu).

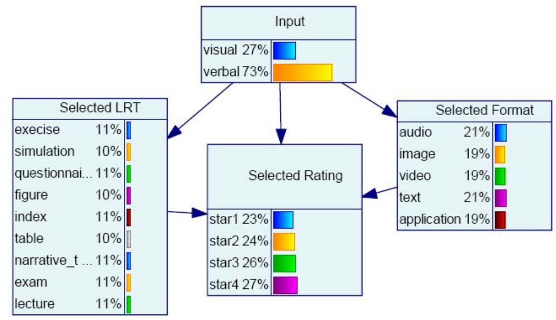


Fig. 4 Initial DBN (t_0)

Next, this students selects a learning object with values *LRT* = *figure* and *Format* = *image*. The student rates this object with two stars. The data provided by the expert relates the values *figure* and *image* with the *visual* category of the *Input* dimension, and establish that the rate *star2* means that the student likes the learning object in a 30%. We can interpret this selection as: among all the learning objects shown to the student, he/she selected a visual one, so at the beginning he/she showed some preference for this category. But at the end the student rated the learning object with 2 stars, so he/she did not like it very much. As depicted in Fig. 5, when the selected learning object and rate value are set as evidences, the values inferred for the *Input* dimension reflects a light decrease of the *visual* category.

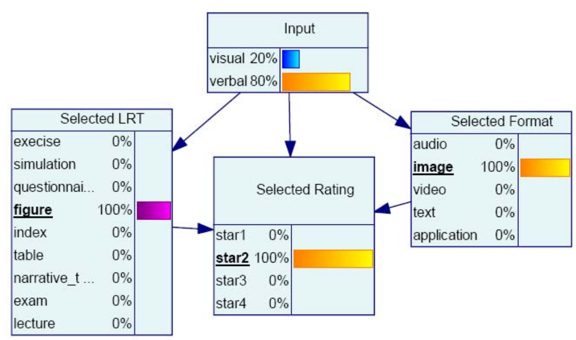


Fig. 5 DBN after a student's selection (t_1)

Now, suppose this student selects a learning object with the values *LRT = figure* and *Format = image,* but he/she does not rate it. In this case, the only information available is that the student selects that learning object among all the learning objects, so he/she must have some preference for the *visual* category. But since there is no feedback, we cannot know how much he/she really likes it. As shown in Fig. 6, now for the next time slice of our network, when this selection is set as evidences, the inferred values for the *Input* dimension reflects an increase of the visual category.

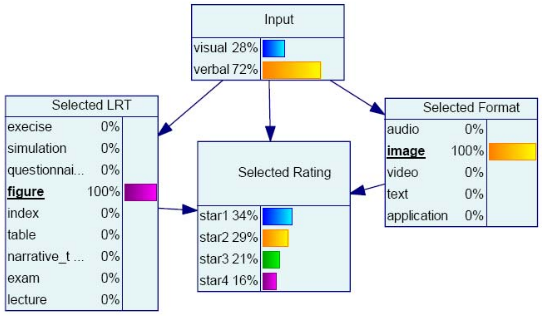


Fig. 6 DBN after a student's selection (t_2)

This simple example shows that every time a student makes a selection, his/her learning style changes accordingly, i.e. this network is able to refine the initial learning style. But if the student changes his/her preferences, that is, he/she begins to select objects that do not match with our current estimation of his/her learning style, this network is able to interpret and account for this information and update the model accordingly.

4 Conclusions and Future Work

This paper presents the design of a DBN for modeling student learning styles in a LOR. This design is based on how the learning styles can be updated given some evidences that are the student's selections of learning objects. We have provided a simple sample assessment to show how the learning style values are updated according to the student's selections of learning objects. Future work will involve a more exhaustive evaluation, both with simulated and real students. These evaluations must account also for changes in students' preferences. Once the model has been validated, it will be used in a decision model aimed at determining the more appropriate learning objects for each student.

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