

Using Bayesian Networks in the Global Adaptive E-learning Process

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Abstract

In this paper, we show the use of *Bayesian Networks* in the modelling of global personalized learning process (adaptive e-learning). *Adaptive e-learning* is a teaching system which adapts the selection and the presentation of contents to the individual learner and his learning status, his needs, his learning style, his previous knowledge and preferences. A *Bayesian network* is a Direct Acyclic Graph (DAG) in which nodes typically represent “concepts” and edges indicate cause/effect dependencies between concepts. The DAG can be used to calculate the probabilities that the learner makes each activity. We believe that is possible the modelling based on Bayesian Networks to tune up the learning process within a bigger frame (Suricata Model).

Keywords: Adaptive e-learning, Metrics, Bayesian Networks.

1 Introduction

In this paper, we show the use of Bayesian Networks^[3], in the modelling of global personalized learning process (adaptive e-learning). We have developed a new socio-technical model of innovation within organizations (named Suricata Model)^[7]. Within the frame of “Suricata Model”, it has been designed and developed a LMS (Learning Management System named “Suricata Platform”) that allows optimize the learning, by customizing and personalizing the process adapted to the profile of each learner.

In Suricata model, context of formal learning process is usually divided into three stages (so-far adaptive e-learning): **First stage:** *Learning pre-process*. Here, predominant learning style of each learner is determined using the Honey-Alonso’s questionnaire^[6,1,5] LSQ (Learning Styles Questionnaire). “Learning style” term suggests method that learner uses for learn. According to Kolb^[1] there are four learning styles: active, reflexive, theoretical, and pragmatic and optimum learning is obtained when these phases are worked. We have designed a tool that it be able to suggest to teacher learner’s predominant “learning style” Previous knowledge is detected using a test when a course or module is initiated and according to results obtained, learning activities are designed for each learner. **Second stage:** *Learning process*. Here, objectives are confronted with personal learning activities of each learner and the activities are

selected and/or are designed, these activities allow achieve an efficient and effective learning. **Third stage:** *Learning post-process*. Here, the results of learning activities made in the second stage are assessed (evaluation by instructor and assessment by learner).

2 Metrics requirement

People are interested at how technology may improve or optimize learning methods, and at how could be measured those effects. We think that is possible the modelling based on Bayesian Networks to tune up the learning process within a bigger frame (Suricata Model). For we optimize a global personalized learning process, is necessary that we collect **learning metrics**. By 'Learning Metrics' we mean all kinds of formative and summative assessments, all kinds of information about learning activity and processes, and all ways of recording development of learning. It is impossible to improve and to optimize our individual learning processes, if we can not measure the activities that we do. Many learner and/or professionals, regularly do not measure their efforts that they do in their scholar and/or professional practices, therefore, they do not know their effectiveness, efficiency and their pleasure. Either they do not know the usability metrics of communication and information systems that they handle. The introduction of *learning metrics* in current both e-learning and e-teaching systems, can generate pedagogical and psychological research that could improve this system remarkably.

By the way, the extended learning and personalized learning opportunities that Information and Communications Technologies (ICT) brings enable learners to take much greater personal responsibility for learning. It is this, combined with the different mechanisms through which ICT adds value to teaching and learning, which is a major factor in producing the great improvements in learning, than are seen in schools and colleges that have fully embedded ICT use. To enable students to take greater personal responsibility for their learning - whether this is a matter of slightly increased concentration in class, or fully autonomous learning in and out of class - learning needs to become more explicit. Students need to be able to see their progress. Teachers need to be able to use information on students' approaches to learning and progress, to help them. Though ICT enables much more work to be done on computers, and at a distance, which makes it more difficult for teachers to see what their

students are doing, it can also capture information on the learning process in ways that have not been possible before. Data is becoming accessible in a wide variety of the systems, software and content used for learning. The problem is how this data can be captured and analysed effectively, so that teachers' and learners can use it. In this paper, we show two cases by means of Bayesian networks.

3 Determining learner's profile

Adaptive e-learning^[2] is a teaching system which adapts the selection and the presentation of contents to the individual learner and their learning status, their needs, their learning style, their previous knowledge and preferences. Many different **types of adaptivity** have been identified focusing on objects and objectives of adaptivity. **Objects** of adaptivity can be, i.e., the selection of learning objects, their presentation, or the choice of input methods and devices. **Objectives** of adaptivity can be, i.e., the learners' pre-knowledge, their curriculum and aimed knowledge state, special needs, learning styles, or cognitive styles. In this new model, the interaction of the individuals through technological means is possible, allowing the formation of social networks, leaving behind the unidirectional communication, characteristic of the traditional formation.

In current approaches on tutoring systems for e-learning, a student is commonly modelled in terms of learner's "knowledge". The system keeps trace of lessons a given learner exploits, and stores in the "student model" the fact that pupil has acquired the related "knowledge". The "student model" is then evaluated in order to find knowledge weaknesses and derive the list of learning objects a given learner must exploit in order to reach a given goal.

The LMS aforementioned have incorporated several objects adaptivity (i.e. wiki, chat, forum, help, manuals, workshop, presentation, devices, etc). We could model learners by means of "learning attitudes". A "learning attitude" defines the approach students choose to achieve certain knowledge. Students, in fact, can tend to work alone or in group, exploit tutors' suggestions more or less frequently, etc. Based on "learning attitudes", we have designing a tool that it be able to suggest to learners who exploit self-study learning objects to try collaborative learning objects in order to develop their workgroup abilities. This tool also will include validation. Teachers could observe the effectiveness of learning objects, software applications, and whole learning system. Teachers could also observe the learning behaviours of their students and further augment the effectiveness of the automatic tutoring system.

Considering it before exposed, student's profile will be determined for his learning style, previous knowledge and conduct form. Conduct form will determined for information about the ability of learners to exploit correctly learning modalities and applications that LMS provides them. Metadata generated for LMS will be incorporated and processed in order to generate learner's profile. Process is

illustrated in the figure 1. Determination learner's profile process will be based in Bayesian networks.

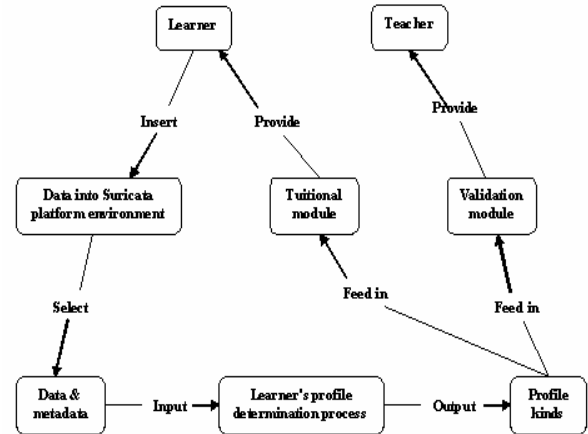


Figure 1 Process for determine student's profile.

4 Bayesian Networks introduction

A Bayesian network is a graphical description of a probability distribution that permits efficient probability propagation combined with a rigorous formalism. Is a Direct Acyclic Graph (DAG) in which nodes typically represent "concepts" and edges indicate cause/effect dependencies between concepts. Final nodes can be thought of as "facts" (values gathered from the environment) while highest-level nodes can be thought of as "causes". In particular, a set of random variables defines the nodes in the network and a set of edges connects pairs of nodes. Each node has a **conditional probability** table that quantifies the effects the parents have on the node (i.e. the probabilistic dependencies between parents and the node). If a node has no parent the table just reports the probability values of the related random variable.

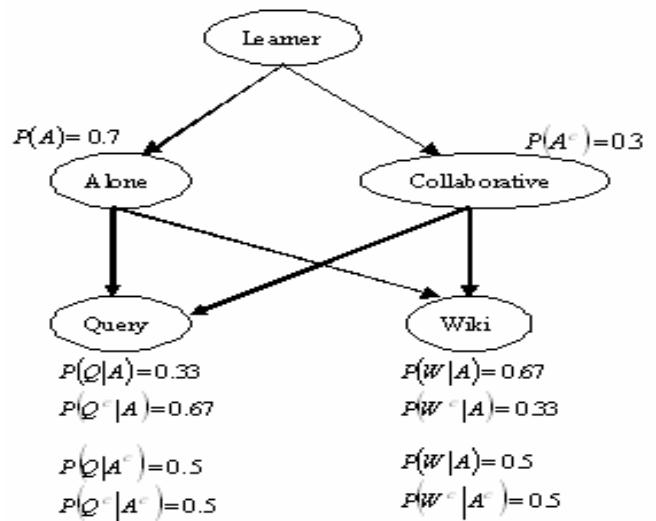


Figure 2 DAG with conditional distributions for two nodes.

The DAG can be used to calculate the probabilities that the learner makes each activity. Figure 2 shows a DAG with conditional distributions for two nodes (Query and Wiki).

A Bayesian network^[4] for a given domain represents the joint probability distribution, $p(x)$, over the set of random variables, X , of the domain, as a set of local distributions combined with a set of conditional independence assertions. This joint probability is computed from expression,

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i | \Pi_i) \quad (1)$$

where, for each variable x_i , $\Pi_i \subseteq \{x_1, x_2, \dots, x_{n-1}\}$ is a set of variables of which x_i is conditionally dependent.

The Bayesian Network structure encodes the assertions of conditional independence as a directed acyclic graph such that: (a) each node corresponds to a variable; (b) the parents of the node corresponding to x_i are the nodes associated to the variables in Π_i . The pair formed by the structure (graph) and the collection of local distributions, $P(x_i | \Pi_i)$, for each node in the domain, constitutes the Bayesian Network for that domain.

In the figure 2, $P(A)$ is the probability that a specified learner works alone, $P(A^c)$ is the probability that this learner works in collaborative form, $P(Q|A)$ is the probability that this learner chooses Query option when he studies alone, and $P(Q|A^c)$ is the probability that this learner selects option Query when he works in collaborative form., From (1),

$$P(Q, W, A) = P(Q|A) \cdot P(W|A) \cdot P(A)$$

Therefore,

$$P(Q, W, A) = (0,33) \cdot (0,67) \cdot (0,7) = 0,1548$$

This is, the probability that learner mentioned works alone, chooses Query and Wiki options is 0.1548.

4.1 Probabilities determination Process

Process to determine a posterior probability in a Bayesian network is named *propagation*. These probabilities are calculated through the **probability propagation algorithms**. For complex Networks, calculus is done by means of *approximate propagation algorithms* and, for a specific number of nodes, previously select, *objective oriented algorithms* are used. Main function of these algorithms is, once a variable has been updated, to send information to a certain type of nodes to communicate that its probability has changed, this nodes at the same time, update their probabilities and transmit these change to the nodes related directly with them.

5 Using Bayesian network

Tuitional and Validation modules of figure 1 respectively will provides information and graphics learner and teacher, this modules will be based on "learning attitudes". In order to infer such attributes, we will implement a Bayesian network. Nodes in the network would represent discrete random variables that can assume one of three values: "low", "medium" or "high". This network will covers all aspects introduced for learner's profile. Initial node will represent attitude of a given learner to actively participate in Suricata platform. Interior nodes will represent data collected by platform Suricata. This data are filtered and randomized by learner's profile determination process in order to extract relevant data for a given learner. Figure 3 shows a network subset to determine "learning attitudes" by means of Suricata platform.

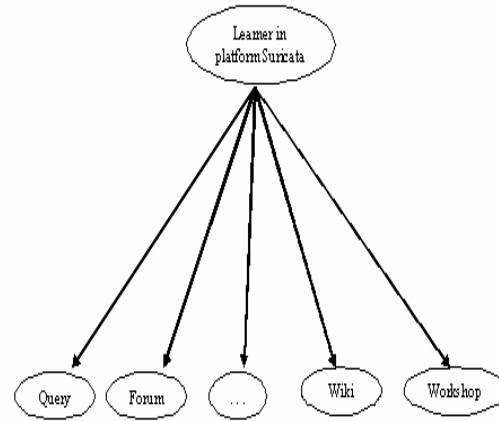


Figure 3 Subset of Bayesian network

Network states that "facts" expressed by interior nodes depend on whether the learner is active ("cause"). Probability tables associated to interior nodes state that highly active learners will report high values with high probability. Inference algorithm, starting from interior nodes, calculates the probability that a given learner has low, medium or high attitudes to actively participate with Suricata platform's learning objects.

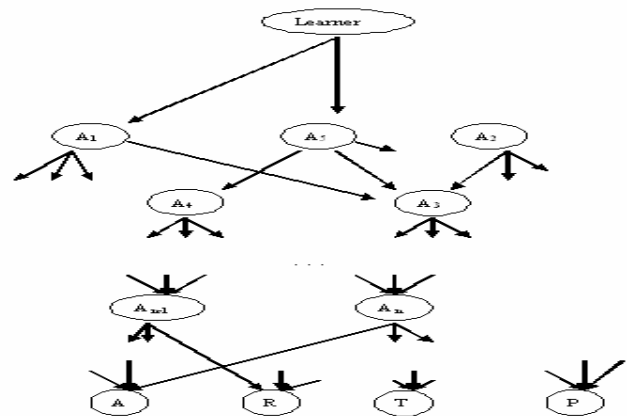


Figure 4 Activities' Bayesian networks

In addition, several activities have been designed and these are showed to learner in four different forms, one for each style, i.e. a same activity is done four times. Learner chooses activities that better are adapted to his learning approach. Figure 4 shows activities and one given pupil's possible choice. Nodes in the network represent probabilities for each one of learning styles and final nodes represent each one of four styles. This can help to determine in which ones styles the learner requires to be supported for optimize his learning.

6 Conclusions

Bayesian Networks can be used to determine learner's profile according to activities that they are selected and realized.

Learner's profile can be created and, the learner can visualize their progress in a certain subject.

Teachers can have access to learner's profiles and, they can design individual activities for each learner or create groups with similar or related characteristics.

Bayesian Networks could help to improve the current systems and, current self-learning models.

7 References

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