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Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis

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ABSTRACT

A huge number of studies attest that learning is facilitated if teaching strategies are in accordance with students learning styles, making the learning process more effective and improving students performances. In this context, this paper presents an automatic, dynamic and probabilistic approach for modeling students learning styles based on reinforcement learning. Three different strategies for updating the student model are proposed and tested through experiments. The results obtained are analyzed, indicating the most effective strategy. Experiments have shown that our approach is able to automatically detect and precisely adjust students' learning styles, based on the non-deterministic and non-stationary aspects of learning styles. Because of the probabilistic and dynamic aspects enclosed in automatic detection of learning styles, our approach gradually and constantly adjusts the student model, taking into account students' performances, obtaining a fine-tuned student model.

1. Introduction

A large number of studies attest that learning is facilitated if the teaching strategies are in accordance with the students learning styles (LS), making the learning process more effective and considerably improving students performances, as pointed out by Haider, Sinha, and Chaudhary (2010), Graf, Liu, and Kinshuk (2008), Kinshuk, Liu, and Graf (2009), Graf and Liu (2008), Bajraktarevic, Hall, and Fullick (2003).

But, traditional approaches for detection of LS are inefficient (Graf & Lin, 2007, Price, 2004). Price (2004) analyzes the uncertainty aspect of the index of learning styles questionnaire (ILS) by identifying inconsistencies between its results and students' behavior. Roberts and Erdos (1993), as well as Price, analyzes this kind of instrument and the problems related to it. Castillo et al. asserts that the information about the students' LS acquired by psychometric instruments encloses some degree of uncertainty (Castillo, Gama, & Breda, 2005).

Therefore, automatic approaches tend to be more accurate and less susceptible to errors, since they analyze data derived from an interval of time, instead of data collected at a particular point in time (Graf, Kinshuk, & Liu, 2009a). According to (Giraffa, 1999), a realistic student model (SM) requires a dynamic updating while the system continuously evaluates the student's performance.

One problem with automatic approaches is related to obtaining sufficiently reliable information, in order to build robust and reliable SM (Graf & Lin, 2007). So, building this type of approach based on a probabilistic model is an important research problem (Danine, Lefebvre, & Mayers, 2006).

In this context, this paper presents an automatic, dynamic and probabilistic approach based on reinforcement learning (RL) (Sutton & Barto, 1998) for modeling students LS. The focus of this paper is the evaluation and comparison of three different strategies for updating the SM during the learning process.

The LS theory that supports this approach is the LS model proposed by Felder (1988), the Felder–Silverman's learning styles model (FSLSM). The FSLSM stands out from other theories by combining the main LS models, as pointed out by Kinshuk et al. (2009). Moreover, the FSLSM is the most often used in the construction of adaptive and intelligent educational systems (AIES) (Graf & Kinshuk, 2009).

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The following sections of this paper are described below. Section 2 analyzes the related work. Section 3 presents in detail the proposed approach. Section 4 presents and analyzes the results obtained through experiments. Finally, Section 5 presents conclusions and discusses future work.

2. Related work

Some recent studies have presented proposals for automatic detection of LS (Cha et al., 2006; Graf & Kinshuk, 2010; Graf & Liu, 2008; Graf et al., 2009a; Graf & Viola, 2009; Limongelli, Sciarrone, Temperini, & Vaste, 2009). These approaches use deterministic inference systems based on predefined behavioral patterns to infer students LS. One of the problems with these approaches is the uncertainty, difficulty and complexity of developing and implementing rules which are able to infer LS effectively from students' actions, and to treat students' behavior as evidences and not as possibilities.

Furthermore, these proposals ignore important considerations raised by Graf and Liu (2008), Marzano and Kendall (2007), Messick (1976), Graf and Lin (2007), Felder and Spurlin (2005), Roberts and Erdos (1993), which are related to the non-deterministic aspect of students behavior and to the dynamic aspect of LS. In this context, the approach presented in this paper brings advances in considering students LS as probabilities and not as certainties.

More complex approaches can be seen in Kelly and Tangney (2005), García, Amandi, Schiaffino, and Campo (2007), Carmona and Castillo (2008), Cabada, Estrada, and Garcia (2009), Zatarain-Cabada et al. (2009), Zatarain, Barrón-Estrada, Reyes-García, and Reyes-Galaviz (2010), Carmona, Castillo, and Millán (2007). These approaches use learning machine techniques, such as Bayesian and Neural Networks. Some of the problems with these approaches are both high complexity and computational cost, which are thought to be serious concerns when considering a high number of students using the system simultaneously. Besides, in general, these approaches are highly coupled, either to the system or to the whole teaching process, making them harder to be re-used in other systems. In some of these approaches, once acquired, the students' LS remain the same throughout the entire learning process (Castillo et al., 2005).

Moreover, we highlight the high difficulty and high degree of subjectivity in the task of relating LS to students behavioral patterns in AIES, as pointed out by García et al. (2007). Consequently, obtaining training pairs is a complex and doubtful task, generating uncertain, data which may contain inconsistencies, resulting in misleading training of the network, and severely compromising the adaptivity process.

In this context, we strongly believe that an approach which learns in an unsupervised manner eliminates many difficulties and problems encountered in traditional approaches for automatic diagnosis of LS. Furthermore, the approach proposed in this paper is based on RL, which has as fundamental characteristics the incremental learning and the avoidance of using specific knowledge of the application domain, making the method more general and more easily reusable.

3. Proposed approach

In this approach, students LS are stored as probability distributions in the SM, indicating the probability of preference for each LS within each of the four dimensions of the FSLSM, here called probabilistic LS (LS_p). Thus, we propose a probabilistic SM in which LS are processed by the system as probabilities, and not as certainties. Table 1 shows an example of LS_p, representing a student who probably is reflective, intuitive, verbal and sequential.

If a self-assessment questionnaire is used for initialization of LS_p, as ILS (Felder & Spurlin, 2005), the SM can be booted from the data obtained by the questionnaire, considering the proportion of responses scored for each LS inside a dimension. If any self-assessment questionnaire is used, LS_p is initialized with 0.50 (undefined preference).

Therefore, we consider students' preferences as probabilities in the four-dimensional FSLSM model. Due to the probabilistic nature of LS in the FSLSM model, our approach is based on probabilistic LS combinations (Franzoni & Assar, 2009). A LS combination (LSC) is a 4-tuple composed by one preference from each FSLSM dimension, as stated by Definition 3.1.

Definition 3.1. Learning styles combination (LSC)

$LSC = (a, b, c, d | a \in D1, b \in D2, c \in D3, d \in D4)$

considering:

$D1 = \{Active(A), Reflective(R)\};$
$D2 = \{Sensitive(S), Intuitive(I)\};$
$D3 = \{Visual(Vi), Verbal(Ve)\};$
$D4 = \{Sequential(Seq), Global(G)\}.$

Therefore, there are 16 possible LSCs (LSCs = {(A,S,Vi,Seq), (A,S,Vi,G), (R,S,Vi,Seq), (R,S,Vi,G), (A,S,Ve,Seq), (A,S,Ve,G), (R,S,Ve,Seq), (R,S,Ve,G), (A,I,Vi,Seq), (A,I,Vi,G), (R,I,Vi,Seq), (R,I,Vi,G), (A,I,Ve,Seq), (A,I,Ve,G), (R,I,Ve,Seq), (R,I,Ve,G)}). Specifically, we propose that in each learning session, students must interact with learning objects (LO) (IEEE, 2010) that satisfy a specific LSC, relating LS characteristics to LO characteristics. The LSC to be considered during a learning session is selected according to students' LS_p. The probability of a specific LSC be selected is given by (1). Therefore, in our approach, a LSC is a specific combination of four random variables (Papoulis, Pillai, & Unnikrishna, 2002). Then, in our approach, LS_p describes the probability of four random variables: a; b; c; d; considering Definition 3.1.

$$P(a, b, c, d) = Pr_a \times Pr_b \times Pr_c \times Pr_d \tag{1}$$

Thus, the probability of selecting the LSC (*A,S,Vi,Seq*) is given by $P(A,S,Vi,Seq) = 0.28 \times 0.09 \times 0.45 \times 0.82$. The LSC defines the pedagogical strategy to be adopted for the presentation of course content during a learning session. In this context, the components related to the use of RL for LS modeling in AIES, in our approach, are:

- *States* (S): Possible settings of SM;
- *Actions* (A): Pedagogical actions that the system can execute with the intention of teaching content, maximizing the quality

Table 1
Probabilistic LS.

LS_p							
Processing		Perception		Input		Understanding	
Active	Reflective	Sensitive	Intuitive	Visual	Verbal	Sequential	Global
0.28	0.72	0.09	0.91	0.45	0.55	0.82	0.18