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Generalized metrics for the analysis of E-learning personalization strategies

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ABSTRACT

For personalizing E-learning, several different strategies and characteristics can be used and considered by teachers and course authors/designers. In order to make appropriate decisions on how to best implement personalized E-learning, this paper focuses on the question: How to foresee personalization strategies that are appropriate for particular courses? To answer this question, we present an approach for recommending personalization strategies based on the learning objects included in the course as well as on how well they support particular combinations of learners' characteristics. In particular, the paper presents generalized metrics which support teachers for analyzing and comparing personalization strategies, as well as deciding which one should be applied for personalizing each course. The approach was validated through experiments in order to test its feasibility and success when applied to a large number of learning objects and learners' characteristics.

1. Introduction

Advance personalized learning is one of the 14 most important challenges of the 21st Century (National Academy of Engineering, 2014). Personalization of E-learning considers the individual learners' differences for adapting courses and learning scenarios. Concerning the individual learners' differences, they are modeled in the form of learner profiles which include specific learners' characteristics such as *advanced* according to the personalization parameter *learner's level of knowledge*. Building the learner profile constitutes a fundamental step of the E-Learning personalization process. Several and different learner profiles/models are reported in the literature (Essalmi, Jemni Ben Ayed, Jemni, Kinshuk & Graf, 2010a). This difference constitutes a richness which should be exploited. An important question that needs to be studied before building the learner profile is: what are the personalization parameters (e.g., learner's level of knowledge, motivation level, etc.) to consider in the learner profile? The motivation of this question is: There are several personalization parameters reported in the literature and it is very difficult to use all these parameters to personalize each course. For example, if we have to consider 19 personalization parameters for personalizing a course and if we assume that each personalization parameters includes three different learners' characteristics (e.g. the personalization parameter *learner's level of knowledge* includes the learners' characteristics: beginner, intermediate and advanced). In this case, the professor responsible for the course has to prepare 57 (=19 $\times$ 3) different learning scenarios. Furthermore, learners have to be evaluated with regard to 19 personalization parameters. In this case, the evaluation process will be time consuming and could decrease the learners' motivation. As an answer to the question (what are the personalization parameters to consider in the learner profile), this paper presents generalized metrics analyzing combination of personalization parameters. These metrics allow selecting the combination of personalization parameters to use according to the specificities of courses.

There has been an important academic revolution in E-learning systems. This revolution considers the leaner's individual profiles in order to generate personalized courses. The whole aim of this revolution is the comfort of learners (learning the appropriate content in the appropriate way). There are many scientific papers which study this kind of personalization. For example, Brusilovsky and Millán (2007) presented different user profiling features. Furthermore, Brusilovsky and Millán (2007) present methods about how these features could be modeled in E-learning systems. In Table 1, we present 24 examples of E-learning personalization systems. For example, Despotović-Zrakić, Marković, Bogdanović, Barać, and

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Krčo (2012) used the Felder–Silverman Learning Styles Model (FSLSM) (Felder & Silverman, 1988) to provide adaptivity in courses in Moodle (2014). In particular, Despotović-Zrakić et al. (2012) used data mining techniques to classify students into clusters with regards to Felder–Silverman learning styles model. Chookaew, Panjaburee, Wanichsan, and Laosinchai (2014) presented an E-learning environment which allows personalizing computer programming courses according to the learner's level of knowledge and the Felder–Silverman learning style. As another example, we cite Lecomps5 (Limongelli, Sciarrone, Temperini, & Vaste, 2011), a web-based educational system which allows the production and adaptation of the course based on learner's level of knowledge and Felder–Silverman learning styles.

Another academic revolution has started in the new generation of E-learning personalization systems. The aim of this academic revolution is personalizing each course according to the appropriate personalization strategy (e.g., it is possible to personalize the course "Microsoft Word" by including personalization parameters different to the personalization parameters used to personalize the course "Programming Language Maple".). This second revolution is new and there are few works reporting approaches about the appropriateness of personalization strategies to courses. Essalmi et al. (2010a), Essalmi, Jemni Ben Ayed, Jemni, Kinshuk and Graf, (2010b) studied the architecture of personalization systems which allow personalizing courses with different personalization strategies. However, this previous work does not study generalized metrics analyzing personalization strategies. Furthermore, Kurilovas and Zilinskiene (2013) presented a method evaluating the suitability of learning scenarios to particular learning styles. However, this method does not evaluate or select the appropriate personalization strategy. It just evaluates the learning scenarios. Our approach is different since it proposes generalized metrics which support teachers to select the appropriate personalization strategy.

For an operational decision on the appropriate personalization strategy, teachers need to have an idea about personalization strategies which could be easily used. Analyzing personalization strategies allows discovering information useful to select the appropriate one for a course. This analysis collects and discovers relations between metadata of learning objects and the learner characteristics to be included in the personalization strategy.

1.1. Technical terms

This subsection explains technical terms and provides examples of them. The technical terms used in the paper are: personalization parameter, personalization strategy, combination operator, learning scenario and learning object.

A personalization parameter could be considered as a set of complementary learners' characteristics such as the *learning style model* or the *learners' level of knowledge*. A set of complementary learners' characteristics includes the opposite characteristics. For example, if the learners' characteristic "*active*" of the active/reflective dimension of the *Felder–Silverman learning style model* is included then the opposite characteristic "*reflective*" has to be included too. Personalization parameters could be combined to have a personalization strategy. For example, it is possible to personalize a course by considering the two personalization parameters *learner's level of knowledge* and active/reflective dimension of the *Felder–Silverman learning style model*. In this case, a combination operator such as "*and*" or "*or*" could be used. In particular, for the combination of the characteristics *active* of the active/reflective dimension of the Felder–Silverman learning style model "*and*" *advanced* of the parameter learner's level of knowledge, a personalized learning scenario must contain the learning objects which are appropriate for both the characteristic *active learning style* and the characteristic *advanced level of knowledge*. But, when combining the same characteristics with the operator "*or*", personalized learning scenarios could be represented by the learning objects which are appropriate to the characteristic *active learning style* together with other learning objects which are appropriate to the characteristic *advanced level of knowledge*. A learning scenario can be represented by a graph of learning objects. "A learning object is any entity -digital or non-digital- that may be used for learning, education or training" (IEEE, 2002, p. 5).

1.2. Paradigm of generalized metrics

The development of personalized learning scenarios requires more efforts and time than the development of a static course which uses a one-size-fits-all approach. These efforts and time depend on the number of divergent learning scenarios and on

Table 1
Examples of personalization systems classified according to personalization parameters.

Personalized E-learning system	Personalization parameters
Interbook (Brusilovsky et al., 1996)	Learner's level of knowledge
KOD (Sampson, Karagiannidis, & Cardinali, 2002)	Learner's level of knowledge, language preference, learning goals
SIMBAD (Bouzeghoub et al., 2003)	Learner's level of knowledge, learning goals, media preferences
MetaLinks (Murray, 2003)	Learner's level of knowledge, learning goals, media preferences
INSPIRE (Papanikolaou et al., 2003)	Learner's level of knowledge, learning goals, learning style of Honey and Mumford
MLTutor (Smith & Blandford, 2003)	Learning goals (based on user's browsing history)
COLER (Constantino-González, Suthers, & Santos, 2003)	Participation balance, progress on task, waiting for feedback
SQL-Tutor (Mitrovic, 2003)	Learner's level of knowledge
EPSILON (Soller, 2004)	Learner's level of knowledge
SIETTE (Conejo et al., 2004)	Learner's level of knowledge
PERSO (Chorfi & Jemni, 2004)	Learner's level of knowledge, media preference
ELENA (Dolog, Henze, Nejdl, & Sintek, 2005)	Learner's level of knowledge, language preference, learning goals
e-aula (Sancho et al., 2005)	Learner's level of knowledge, learning goal, dimensions of the Felder–Silverman learning style
AHA! (Stash, Cristea, & de Bra, 2006)	Dimensions of the Felder–Silverman learning style, media preference, navigation preference
Milosevic et al. (2006)	Kolb learning cycle, motivation level
Graf et al. (2010)	Dimensions of the Felder–Silverman learning style
PASER (Kontopoulos et al., 2008)	Learner's level of knowledge, learning goals
Isotani et al. (Isotani et al., 2009)	Learning goals
Protus (Aleksandra et al., 2011	Learner's level of knowledge, dimensions of the Felder–Silverman learning style
Lecomps5 (Limongelli et al., 2011)	Learner's level of knowledge, dimensions of the Felder–Silverman learning style
Despotović-Zrakić et al. (2012)	Dimensions of the Felder–Silverman learning style
Dwi and Basuki (2012)	Learner's level of knowledge
AMDPC (Yang et al., 2013)	Dimensions of the Felder–Silverman learning style, cognitive traits
Chookaew et al. (2014)	Learner's level of knowledge, dimensions of the Felder–Silverman learning style