IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 4 Issue 9, September 2017
ISSN (Online) 2348 – 7968 | Impact Factor (2016) – 5.264
www.ijiset.com

Towards a Personalized Learning Path based on Learning Style

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Abstract
In education, the ultimate goal of every teacher is to transmit to the learners in a controlled and directed way, a know-how to acquire a competence in correct conditions. The heterogeneity of learners is a handicap to this learning process. Therefore, an optimal pedagogical path for one is not necessarily the same for the other. In our proposal, it is a question of offering each learner a personalized course for the acquisition of the competence targeted on the basis of the collaborative filtering and adopting a system based on services focused on the learner's profile and his preferences. The evaluation of the performance of the proposed approach was tested. The results of the test show the accuracy of the proposed method.

Keywords: *Personalized Learning, Learning Path, Learning Style, Collaborative Filtering, Services-Oriented Architecture*

1. Introduction

Learning is defined as a process where knowledge is created through transformation of experience [1],[2]. The most common perceptions about learning include that it is a quantitative increase in knowledge or acquiring information of 'knowing a lot', memorizing or storing information that can be reproduced, acquiring facts that can be reproduced; acquiring; interpreting and understanding reality in a different way [3], [4].

E-Learning is a type of distance learning, and is characterized by "the use of new Internet 's technologies multimedia to improve learning quality by facilitating on the first hand the access to resources and services, and on the other hand exchanges and collaboration at a distance "[5]. This training mode has been the subject of several research studies to define standards, develop specifications, standardize and implement tools and platforms. Admittedly, Web technologies' use in education field offers new opportunities to implement new didactic intentions in new learning contexts. However, the quality of these pedagogical approaches in computing environments depends on their ability to provide learners with pedagogical paths adapted to their needs. In fact, learning process is a variable that depends on the prior knowledge, motivation and needs of individual learners, [6]. This understanding poses a problem that emphasizes the importance of developing an adaptive system, which considers the individual needs of learners towards an effective learning process and acquisition of knowledge.

The notion of adaptation is defined as the concept of making adjustments in the educational environment to accommodate diversity in the learner needs and abilities, in order to maintain the appropriate context for interaction. Adaptive sequencing is defined as the process for selecting of learning objects (LO) from a digital repository and sequencing them in an appropriate way which is appropriate for the targeted learning community or individuals [7].

In this perspective, many works have been done in this last decade about personalization and adaptation of learning using E-learning system [9], [10], [11]. In fact, several adaptive system were introduced, most are based on learner preferences [9], [10], [12].

The main of our work is to propose a personalized e-learning system based on collaborative filtering methods according to the cognitive style and learners learning preferences. Our proposal consists to adapt learning path to a learner's preferences by implementing an orchestrated web component in a service-oriented architecture. These components are responsible for extracting and collecting learners' traces, and adapting and regulating learning paths to learners preferences.

This paper is structured as follows: Section 2 presents learning profiles. In Section 3 we present the design of our proposed system. The conclusion is given in the last section.

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2. Learning Profiles

In e-learning, learner is confronted with himself, he must be able to gradually take ownership of his learning profile. He must become the teacher who analyzes and interprets his learning process to gradually discover all the implications. Thus, the system must collect and sort information related to the learning process and then make it available to the learner so that he can exploit them [13]. In particular, it is important that the environment allows the learner to become aware of his weaknesses in assessments [14] in terms of knowledge.

The personalization of the pedagogical path is based on the learner profile. A learner profile is a collection of information about an individual learner. Its aim is to provide a view of current development and future potential in terms of self-learning access [15].

The Learner Profile is constructed from learner learning style of which contains about the learner preferences and characteristics, and learner learning objectives, competencies and knowledge.

[16], studying the work of Kostadinov [17], Proposed a three-dimensional profile (Figure 1) :

- Preferences data for search preferences and user interests;
- Personal data,
- Data on the user's work environment (location Geographic, software and hardware configuration).

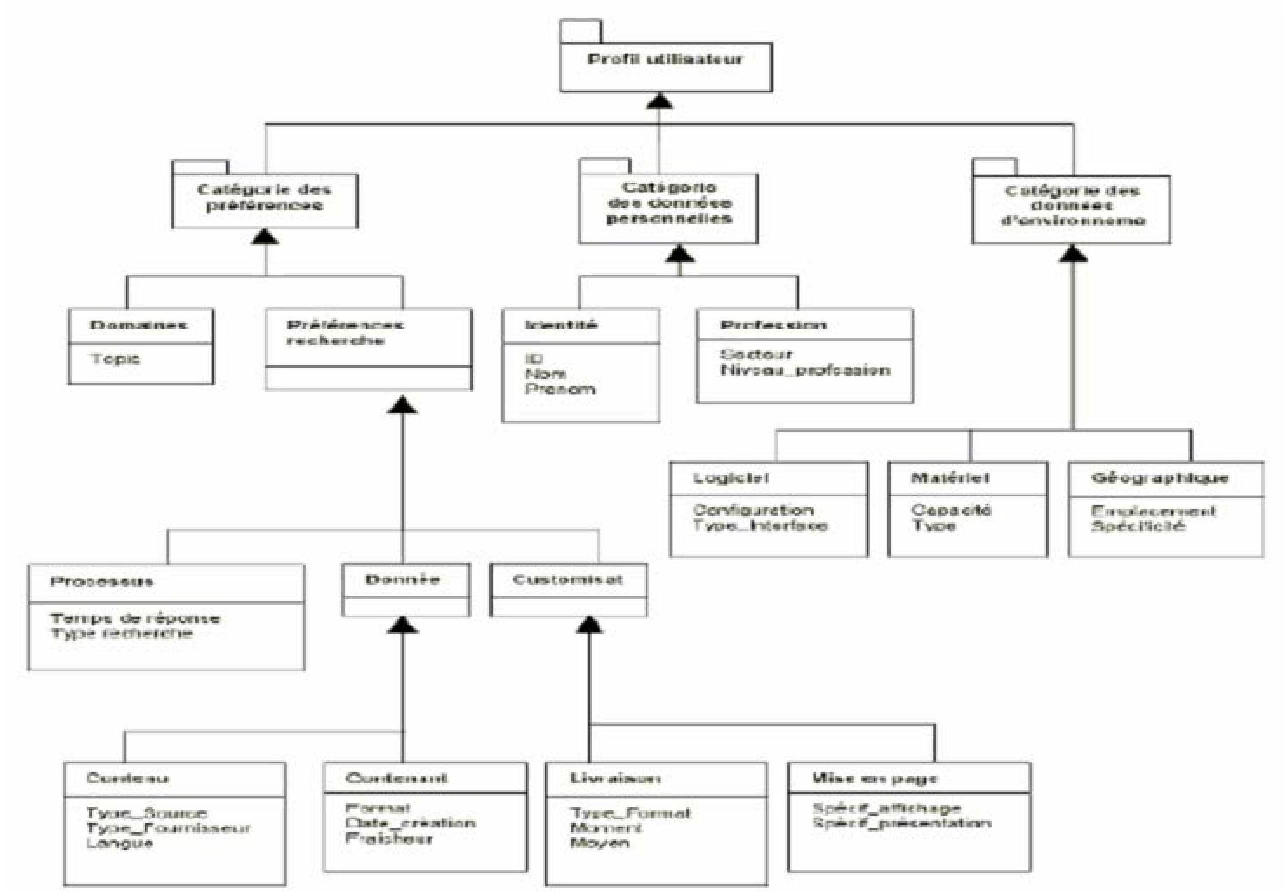

Fig. 1 : Multidimensional Representation of Learner Profile [16]

2.1 Preferences

A learner preference is a set of descriptions encompassing :

- The activities which his intends to accomplish in the system
- How to do it
- Type, order of results and how to display information.

We distinguish three types of preferences [18]:

- Activity Preferences: Concerns the activities that a user wants and can accomplish in the system.
- Result Preference: Concerning the content and preferred format of the functionality.
- Display Preferences: About how the user wants to display.

2.2 Learning Styles

Several researches in psychology and education science asserts the impact of the learning style on the learning process and encourages its integration into learning strategies in order to facilitate learners and improve their results.
In the literature, several definitions of learning styles have been proposed, that of Beshuizen et al. "A predisposition of some students to adopt a particular learning strategy independent of the specific requirements of the learning task" [19].
Several approaches exist for the implementation of Learning Styles: The Myers-Briggs Type Indicator, Kolb's Experiential Learning Model, The Felder-Silverman Model [20], Dunn and Dunn learning style model [28] Honey and Mumford model based on [29]. In our approach, we implement the method presented by Felder-Silverman [37]. The Felder and Silverman model classifies learners according to the means they use to collect information and process that information.

Our analysis of learning style models shows that the most widely used model nowadays is Felder-Silverman learning style model (FSLSM) [24] (Table 1).

TABLE I.
FELDER AND SILVERMAN LEARNING STYLE MODEL

LEARNING STYLE	characteristic
Active/Reflective	**Active :** retain and understand information best by discussing it, applying it or explaining it to others; prefer group work; **Reflective:** retain and understand information best by thinking about it first ; prefer working alone ; needs thinking time during lectures.
Sensing/Intuitive	**Sensing :** like to learn facts; tend to be more practical and careful; do not like courses that have no apparent connection to the real world **Intuitive**: prefer discovering possibilities and relationships ; like innovation and dislike repetition; tend to work faster and are more innovative but may be careless
Visual/Verbal	**Visual** : remember best what they see, (e.g. pictures, diagrams, demonstrations); **Verbal**: gets more out of words, either written or spoken explanations.
Sequential/Global	**Sequential:** gain understanding in small sequential, logical steps; tend to follow logical stepwise paths while problem solving; may not understand material fully but are still able to solve problems and pass tests. **Global:** seem to learn in large jumps, absorbing material almost randomly without seeing connections, then suddenly "getting it"; may be able to solve complex problems quickly, or put things together in a novel way once they have grasped the big picture; may have difficulty in explaining their knowledge;

In this work, we adopted the FSLSM's model [26], for three major reasons. Firstly, for its simplicity it is easy to implement. Secondly, it is the most widely used in the design of adaptive systems. Thirdly, FSLSM is based on tendencies, saying that learners with a high preference for certain behavior can also act sometimes differently [27].

In our approach we use the Index of Learning styles Questionnaire (ILSQ) proposed by Felder-Silverman model ,with 44 questions for assessing preferences [30]. For each question, the learner must choose one answer out of two alternatives a and b. The 44 questions fall into four sets of 11 questions each. Each set of questions defines one dimension of learner's cognitive model, which is thus made up of four dimensions according to Felder (Table 2). The questions are provide four values, between +11 and -11, representing the learner's learning style preferences of each dimension.

TABLE 2: LEARNING STYLE DIMENSIONS.

Dimension	Learning style		ILS sets of Questions
processing	Active	Reflective	Q1,Q5,Q9,Q13,Q17,Q21,Q25,Q29,Q33,Q37,Q41
perception	sensing	intuitive	Q2,Q6, Q10, Q14,Q18, Q22,Q26, Q30,Q34, Q38, Q42
reception	Visual	Verbal	Q3,Q7, Q11, Q15,Q19, Q23,Q27, Q31,Q35, Q39, Q43
understanding	Sequential	Global	Q4,Q8, Q12, Q16,Q20, Q24,Q28, Q32,Q36, Q40, Q44

4. Proposed System

Our approach allows for choosing an effective learning path with regard to parameters such as learner learning style, and understanding degree, as well as the difficulty of course topics, and course learning materials. For this, we opted for a model based on a service oriented architecture (SOA). The goal is to decompose the functionality of our web services model. We propose three orchestrated components in a SOA. These services are responsible for collection, analysis, adaptation, prediction and regulation of leaning objects (LO) to personalize learning path. Figure 2 shows the various stages of the proposed approach.

In our approach, The Teacher or the engineer pedagogue is responsible for the teacher's functionalities. He organize the course into chapters, each chapter is composed into learning objects (LO) , i.e., knowledge objects to acquire, each LO is associate with learning materiel (educational hypermedia). This information represent the domain model and is stored in the Global database.

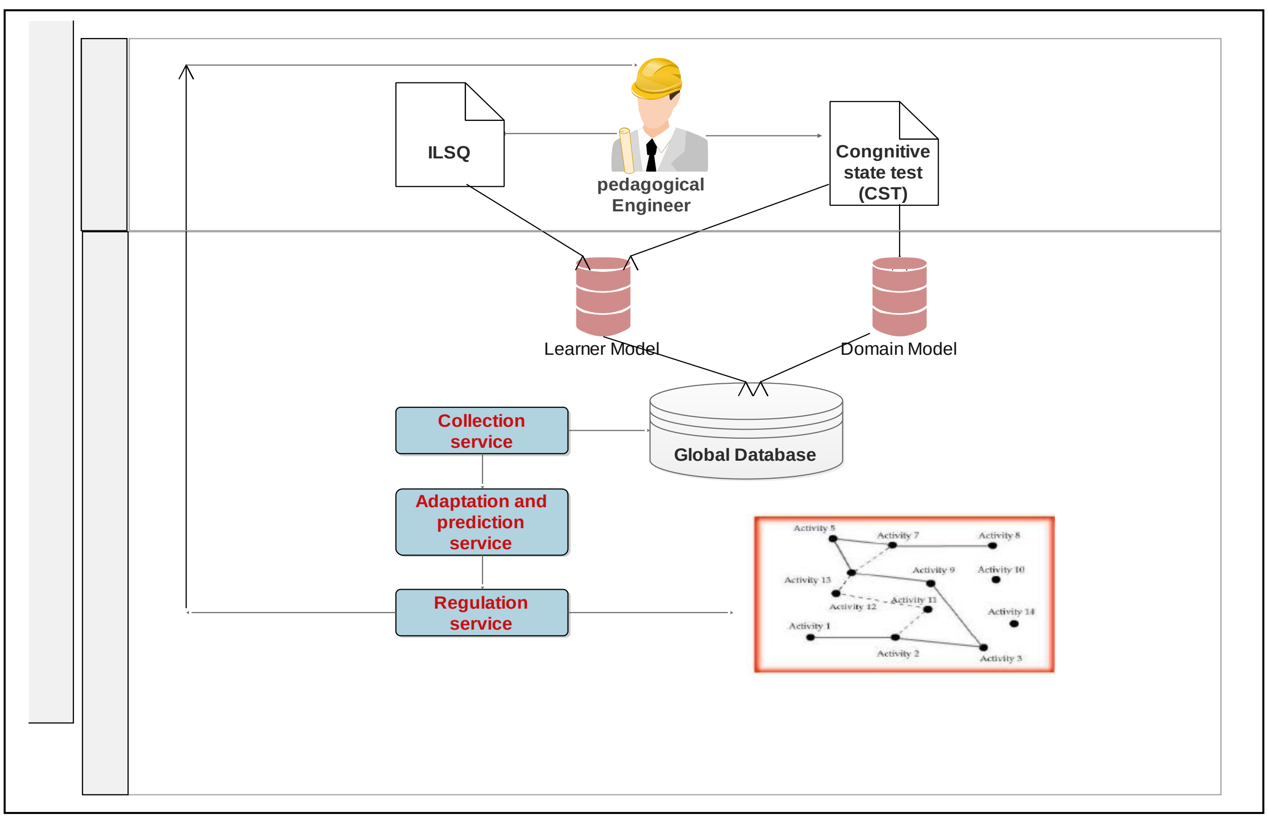

Fig2 : The proposed System Architecture

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The teacher is also responsible to define tests related to each LO for an eventual evaluation, and to create the initial Cognitive State Test (CST) for evaluating the starting knowledge of the learner, that is the knowledge already possessed by the learner with respect to the topic to be learned. the learner fills in both the CST and ILSQ developed by Felder and Silverman (FS), that extracts the learner's learning preferences according to the four dimensions of the FS Model. This information initialize the learner model LM and stored in the global database. The learner model contains in addition to these dynamic data that represent the learner's learning style (LS), other static information about learner such as name, age,.. etc

The teacher specifies also her didactic strategies and defines for each topic her own instructional goal.

Before going into details about the components of the system, we introduce some definitions about the elements we are going to work with.

DEFINITION 1: Threshold value

A threshold value σ_{LO} is a real number associated to LO defined as:

$$\sigma_{LO} = S_T / S_{max} \qquad 0 < \sigma_{LO} \leq 1 \qquad (1)$$

being S_T the lowest score of an assessment test of LO, as fixed by the teacher, in order to consider the LO acquired; S_{max} is the highest possible score for that test

DEFINITION 2 : Test

A Test is a set of k questions with $k \in N$. To each question is associated a weight $Q_j \in R$. Each question has m answers, with $m \in N$ and to each answer is associated a weight $p_i \in R$.
S_{LO} is the score associated to a test; it assesses the learner knowledge of a LO

$$S_{LO} = \sum_{j=1}^{k} (Q_j \ . \ \sum_{i=1}^{m} p\, i) \qquad (2)$$

where $p_i = 0$ for the answers the learner does not select.

4.1 Collection service

This service is responsible to collect acquired data from the global database using SQL instructions.

4.2 Adaptation and prediction service

The adaptation and prediction service use the K-NN algorithm, which is the most popular method used for classification, estimate, and prediction [32, 33]. This service classify learners and give predictions for learning objects. The idea is to find other learners whose past ratings for learning objects are similar for the active learner and use their ratings to predict current learner's preference for a learning object he/she has not rated.
The measurement for the weight for similarity between two learners *u, v* is the Pearson correlation coefficient [34, 35, 36].

$$w(u,v) = \frac{\sum_j^m (r_{u,j}-\bar{r}_u)(r_{v,j}-\bar{r}_v)}{\sqrt{\sum_j^m (r_{u,j}-\bar{r}_u)^2}\ \sqrt{\sum_j^m (r_{v,j}-\bar{r}_v)^2}}$$

where :

- $\bar{r}_u$ et $\bar{r}_v$ are the averages of learner u's and v's ratings respectively
- $r_{u,j}$ and $r_{v,j}$ are learner u's ratings and learner v's ratings for the learning object *j*.

If the learner *u* and *v* have a similar rating for a LO, $w(u,v) > 0$. $|w(u,v)|$ indicates how much learner *u* tends to agree with learner *v* on the LO that both learners have already rated. If they have opposite ratings for a LO $w(u,v) < 0$. $|w(u;v)|$ Indicates how much they tend to disagree on the learning object that both again have already rated. Hence, if they don't correlate each other, *w(u,v)* can be between -1 and 1.

6. Conclusions

Give the learner an adapted learning path to his needs is one of the most important objectives in e-learning. Several studies have focused on pedagogical personalization according to several angles. Our proposal is different, it is based on web services' independence and reusability to implement three components that are responsible for collection, prediction and regulation of leaning objects.

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