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# Evaluation of Personalization Strategies Based on Fuzzy Logic

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***Abstract*—Teachers and course authors need to apply various instructional strategies in order to personalize their courses. It is not a trivial task and the time, the efforts and the learning objects needed for preparing personalized learning scenarios depend on the personalization strategy to be applied. This paper presents an approach for selecting appropriate personalization strategies according to the feasibility of generating personalized learning scenarios with minimal burden on the author. Two metrics are proposed for putting in order and selecting useful personalization strategies. The calculation of these metrics is automated based on the analyses of the Learning Object Metadata (LOM) standard according to the semantic relations between data elements and learners' characteristics.**

***Keywords- LOM standard, learners' characteristics, evaluation of personalization strategies, fuzzy logic, metrics.***

## I. INTRODUCTION

The personalization of learning scenarios requires adaptation of the presentation of learning objects to a set of learners' characteristics [1]. This adaptation has the promise to motivate learners and reduce the time needed to achieve their objectives [2, 3]. Bates and Wiest [2] claim that personalization increases motivation of learners. In addition, Cakir and Simsek [3] claim that personalized learning affects student achievement positively. Learners can learn and understand more easily when the learning scenarios are generated according to their characteristics such as their level of knowledge, learning styles, cognitive traits, preferences and so on. However, considering all learners' characteristics at once could be constrained by two limits. First, the course must contain a lot of different learning objects to suit any sets of learners' characteristics. Typically, in order to fulfill this constraint, a teacher would need to spend a lot of time and effort on extending his/her course with additional learning objects which represent the learning material in different ways, for learners with different characteristics. Second, learners would have to respond to many questionnaires for determining all characteristics which is a time consuming and fastidious task [4, 5]. According to [4], defining the user preference for systems is a fastidious task. Essalmi et al. [5] point out that responding to many questionnaires for determining many learners' characteristics (such as their level of knowledge, motivation, cognitive traits, learning styles, and so on) is a huge task. An operational solution consists of selecting a subset of complementary[1] learners' characteristics which are considered by the learning objects that are already included in the course. In this way, the first constraint is satisfied and the course will contain the necessary learning objects for personalizing it. In addition, the second constraint is lightened given that only a subset of the characteristics will be considered and learners will have to respond only to the questionnaires of this subset of characteristics.

In this paper, 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 learners' characteristics. This approach is automated based on the LOM standard [6] and an ontology specifying semantic relations between values of data elements (such as the value *image* of the *data element 4.1 Format*) and learners' characteristics included in personalization parameters (such as the *learner media preference* of *graphic*). The approach can additionally generate personalized learning scenarios.

This paper is structured as follows. Section II presents mathematical definition of the proposed approach. Then, section III concludes the paper with a summary of the work and futures perspectives.

## II. MATHEMATICAL DEFINITION OF THE PROPOSED APPROACH

This section presents mathematical definition of relations for selection of appropriate and not appropriate learning objects. In addition, this section presents

[1] A set of complementary learners' characteristics includes the opposite characteristics for already included characteristics. For example, by considering the learners characteristic "verbal" of the Felder-Silverman learning style model, the opposite characteristic "visual" has to be considered too.

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mathematical definition of metrics for the evaluation of personalization strategies. These relations and metrics are based on fuzzy logic. This logic is flexible because it considers the degree of certainty about the meaning coincidence of metadata elements and learners' characteristics. Mathematical notation is used for two reasons. First, mathematical notation enhances the rigor/precision of our approach. Second, the high abstract level of mathematical notation is used for defining the approach as a generic solution.

The approach presented in this section is based on metadata (which is commonly used for the reuse of learning objects), courses, and Semantic Relations between Values of Data elements and Learners' characteristics (SRVDL).

### A. *Metadata*

A metadata is a set of data elements useful for the description of learning objects [6]. A metadata element has a name which might not be unique. For that reason a data element has a unique identifier. For the description of a learning object, the data element has to be associated with a specific value which characterizes the learning object. For example, the data element *4.1 Format* [6] associated with the value *image* is useful for describing a learning object which presents an image. In this case, the identifier of the data element is *4.1*, its name is *Format*, and the value is *image*.

Formally, a metadata (useful to annotate learning objects) *is described as 5-tuple M=(DEI, DEN, DE, DEV, DDE) where:*

- DEI: is a set of Data Elements Identifiers.
- DEN: is a set of Data Element Names.
- DE (Data Elements): is a relation from DEI to DEN.
- DEV: is a set of Data Element Values[2].
- DDE (Descriptive Data Element): is a relation from DE to DEV. DDE defines the value associated to a metadata element for describing a learning object.

### A. *Course*

A course is a set of concepts represented by learning objects. We assume that a concept could be represented by more than one learning object. We assume also that each learning object is annotated with metadata.

Formally, a course is described as a 4-tuple $C = (Ct, \Omega, Rep, Đ)$ where:

- Ct : is a set of concepts to be studied by learners
- $\Omega$ is a finite set of learning objects, representing the concepts of the course
- Rep is a relation from Ct to $\Omega$. Rep determines the learning objects representing a concept
- Đ is a relation from $\Omega$ to $\mathcal{P}$ (DDE)[3]. Đ defines the set of metadata describing each learning object

[2] A data element value is a linguistic term.

[3] $\mathcal{P}$ denotes the set of partitions.

### B. *Semantic Relations between Values of Data elements and Learners' characteristics(SRVDL)*

SRVDL defines semantic relations between descriptive data elements and learners' characteristics. A learners' characteristic is a linguistic term with respect to a personalization parameter for describing learners. For example, the data element *4.1 Format* associated with the value *image* is related to the term *visual* in *Felder-Silverman learning style*. In addition, SRVDL defines the coincidence degree between descriptive data elements and learners' characteristics. For example, the coincidence degree between the data element *difficulty difficult* and the learners' characteristic *advanced level of knowledge* could be defined as 0.8 (The values *difficult* and *very difficult* of the data element *difficulty* could be associated respectively with the degrees 0.8 and 1. In fact *difficult* describes a level of complexity less that *very difficult*.).

Formally, SRVDL is described as 5-tuple *R=( LT, PP, LC, MLC, CDMLC)* where:

- LT (Linguistic Terms): is a set of terms in natural language describing possible learners' characteristics in relation to personalization parameters.
- PP (Personalization Parameters): is a set of learner dimensions which can be used for personalization of courses. Each personalization parameter is related to a set of linguistic terms that describe possible learners' characteristics with respect to the personalization parameter.
- LC (Learners' characteristics): is a relation from LT to PP. LC defines the linguistic terms that are related to a particular personalization parameter.
- MLC (Metadata element associated with Learners' Characteristics) is a relation from $\mathcal{P}$ (DDE) to LC, where $\mathcal{P}$ denotes the set of partition.
- CDMLC (Coincidence Degree of Metadata elements with Learners' Characteristics) is a relation from MLC to [0..1]. CDMLC specifies the coincidence degree of metadata elements and learners' characteristics.

Let *M=(DEI, DEN, DE, DEV, DDE)* be a metadata, $C = (Ct, \Omega, Rep, Đ)$ be a course and R*=( LT, PP, LC, MLC, CDMLC)* a SRVDL. The subsections D and E present the mappings for determining learning objects appropriate to learners' characteristics, and then determining metrics for prevision of appropriate personalization strategies.

### C. *Appropriateness degree of learning object to learners' characteristics*

In this subsection, we present a relation for determining the degree of learning objects appropriateness to a learners' characteristic. In addition, we define a relation for determining the degree of non appropriateness to a learners' characteristic. These relations are defined as follows:

- AppDegree (Appropriateness Degree)
  AppDegree: $LC \times \Omega \rightarrow [0..1]$

AppDegree($x_1$, $x_2$) = Max{*CDMLC* (y, $x_1$) / y: $\mathcal{P}$ *(DDE)* and ($x_2$, y) ∈ Ð}.
AppDegree determines the appropriateness degree of a learning object to a given learners' characteristic.

- NotAppDegree (Not Appropriateness Degree)
NotAppDegree: LC × Ω → [0..1]
NotAppDegree($x_1$, $x_2$) = 1-AppDegree($x_1$, $x_2$).
NotAppDegree determines the non-appropriateness degree of a learning object to a given learners' characteristic.

The relations AppDegree and NotAppDegree are defined based on general definitions of Metadata, courses and SRVDL (Semantic Relations between Values of Data elements and Learners' characteristics). These relations are not limited for a specific personalization parameter. But, they could be used for determining learning objects appropriate or not appropriate to any learner characteristic.

Appropriate and non appropriate learning objects could be used for personalizing E-learning courses. For example, in an adaptive navigational support, appropriate learning objects could be marked with green icons and non appropriate learning objects could be marked with red icons. If there is no available information for the adaptation decision for some learning objects, the adaptation is considered as neutral for these learning objects.

### D. *Metrics defined based on fuzzy logic*

Two metrics are defined in this subsection in the form of the relations CRCHDegree (Concept Representation for a learners' CHaracteristic with a Degree) and CRPDegree (Concept Representation for a personalization Parameter with a Degree). Each of these two metrics is based on the relation AppDegree which determines appropriateness degrees of learning objects to learners' characteristics. Mathematical definition of the declared relations is presented in the following bullet list.

- CRCHDegree (Concept Representation for a learners' CHaracteristic with a Degree)
CRCHDegree: LC × Ct → [0..1]
CRCHDegree($x_1$, $x_2$) = Max{AppDegree($x_1$, y) / y: Ω and ($x_2$, y) ∈ Rep}.
CRCHDegree determines the representation degree (degree of representation) of concepts by learning objects with respect to a given learners' characteristic.
- CRPDegree (Concept Representation for a personalization Parameter with a Degree)
CRPDegree: $\mathcal{P}$ (LC) × Ct → [0..1]
CRPDegree($x_1$, $x_2$) = Min{CRCHDegree(y, $x_2$) / y: LC and y ∈ $x_1$}.
CRPDegree determines the representation degree of concepts by learning objects which are complimentarily appropriate to the learners' characteristics included in a personalization parameter.

The relations CRCHDegree and CRPDegree are defined based on general definitions of Metadata, courses, SRVDL and AppDegree. These relations are not limited for a specific personalization parameter. But, they could be used for evaluating the feasibility of personalizing any course according to any personalization parameter.

## III. CONCLUSION

In this paper, we presented a rigor and generic approach for the automatic prevision of personalization strategies as well as their application for generating personalized learning scenarios.

Concerning the prevision of appropriate personalization strategies, the proposed approach defines 2 metrics based on fuzzy logic, which are CRCHDegree and CRPDegree.

Concerning the generation of personalized learning scenarios, the proposed approach exploits learning objects annotated with LOM standard and semantic relations between data elements and learners' characteristics to determine learning objects appropriate to learners' characteristics.

Future directions of this research will deal with extending the proposed metrics for comparing combinations of personalization strategies.

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