Toward More General Criteria of Conformity Between Learner and Learning Objects

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Abstract— **The paper deals with IEEE 1484.12.1 – 2002 Standard for Learning Object Metadata (LOM) and IMS Learner Information Package (LIP) specification. The main goal is to develop Web-based Learning System which is characterized with high level of adaptability. The LOM is used for the description of learning objects, making possible the creation of well-structured descriptions of learning resources, while LIP describes learner's profile. Conformity criteria for best matching learning object and learner's profile are investigated. Previously introduced solutions are based on If-Then rules with low level of adaptability. The original contribution of this work is the adoption of similarity relation and more general logical operations in order to achieve greater adaptability. It is shown how the similarity relation, as well as general logical operations, could be incorporated in Web-based Learning System.**

I. Introduction

Nowadays, web-based learning systems (WLS) are widely accepted and used, covering a variety of scientific domains. WLSs are available in many different languages and intended to be used by users who differ in skill level, age, affiliation, competency, interests, etc. This variety requires an exempt adaptability by WLS in order to be useful for every individual user. Nowadays, it is possible to develop a WLS which, to a certain extent, overcomes time – space constraints and provides a suitable environment for users. In addition to the interactivity, there is also an adaptive component. WLS, that is capable of adaptation to the specific user needs, can create a user's profile, and track profile changes in order to adapt its actions. In general, the actions that the system takes are related to the presentation of educational content in many different ways. An adaptation process involves selection of content and the way it will be presented to the user.

In many studies [1, 2, 3] a significant positive correlation between the success of the student's achievements and self-regulation is confirmed. Self-Regulated Learning (SRL) is type of WLS, which allows user to determine the level and manner of content presentation. This one, and similar research works were primarily related to the academic level of education. SRL is understood as the ability to adapt characteristics of the content that has been delivered by WLS to the user. So, user's preferences (students in this case) are main input to SRL. It has been also observed that students with low ability of self-regulation while learning were less successful at university courses, compared to students with high ability of self-regulation while learning [4, 5, 6].

More contemporary study that was conducted by Chen [7] introduced two indicators reflecting the level of capabilities of self-regulation while learning:

- Self-Regulated Learning Competence Index.
- Self-Regulated Learning Performance Index.

The values of both indicators are calculated by the exact formula, based on:

- The time consumption by a student while learning.
- The accuracy of his/her answers to questions.

Chen has developed PELS system (Personalized E Learning System) which is the implementation of concepts that were introduced by Zimmerman in previous investigations in this domain. The user has an interactive interface that can be customized.

Based on Chen's results, different approach was developed by Biletskiy [8]. He defined two entities:

- Learning Objects (learning content) which conceptual model was defined by IEEE Standard 1.12.1484 (Learning Object Metadata - LOM, IEEE LOM, 2002).
- Student (learner) whose conceptual model is based on the IMS Learner Information Package specification (IMS LIP, 2010).

Therefore, LOM provides metadata for learning content while IMS LIP provides user's metadata. Various relations between LOM instances and IMS LIP instances can be defined.

In [9] is presented the system for automatic generation of IMS compliant courses based on explicitly expressed machine-readable instructional design templates. IEEE Learning Object Metadata (LOM) was used, while binding of data was done by XML. A new domain-specific language named ELIDL is proposed. The system is used for generating Web Programming course at the Faculty of Technical Sciences in Novi Sad, but generated course is static because it represents the sequence of predefined learning activities.

A tutoring system named Protus that is used for learning basic concepts of Java programming language is described in [10]. Protus uses ontologies, and Semantic Web concepts for performing personalization.

The main goal of this work is to investigate possible differences in WLS implementation when similarity relation is used. The proposed relation should estimate similarity between learner's profile and learning objects. This should result in WLSs with better adaptability.

This paper is organized as follows: Section II contains a brief description of IEEE LOM standard and IMS LIP specification. Section III deals with previously introduced conformity criteria, while Section IV deals with more general approach to conformity criteria. Section V describes a case study. Finally, Section VI gives some conclusions and guidelines to future work.

II. IEEE LOM AND IMS LIP

The IEEE 1484.12.1 – 2002 Standard for Learning Object Metadata (LOM) is an internationally recognized open standard. The LOM is used for the description of "learning objects", making possible the creation of well structured descriptions of learning resources. As in [11] LOM enables:

- Sharing descriptions of learning resources between resource discovery systems.
- Tailoring learning resource.
- Labeling learning resources by LOM along with other specifications.

Therefore, LOM provides the description of learning resources which results in cost reduction, customization, optimization, as well as easy accessibility and interoperability of learning resources. The LOM comprises a hierarchy of elements. The basic elements are given in Table I. Each basic element comprises sub-elements.

The IMS Global Learning Consortium created Learner Information Package (LIP) as a specification for a standard means of recording information about learners. All data created according to LIP can be transferred between different software applications. As in [12] LIP can be used for:

- Moving learner information between institutions when students transfer courses.
- Producing a lifelong record of a learner's achievement.
- Providing information about learner's achievement to employers.
- Personal development planning process.
- Storing information about learner preferences to support widening participation for learners with disabilities.

Rather than plain text, LIP uses XML to record information about learners. For purely illustrative purposes, a small portion of XML is taken from [12]:

```
<language>
    <typename>
        <tysource sourcetype="imsdefault"/>
<tyvalue>German</tyvalue>
    </typename>
    <contentype>
        <referential>
<indexid>language_01</indexid>
        </referential>
    </contentype>
    <proficiency profmode="OralSpeak">Excellent</proficiency>
    <proficiency profmode="OralComp">Excellent</proficiency>
    <proficiency profmode="Read">Good</proficiency>
    <proficiency profmode="Write">Poor</proficiency>
</language>
```

TABLE I. IEE LOM AND IMS LIP ELEMENTS

IEEE LOM Elements	IMS LIP Elements
General: e.g. title, language, and keywords	*Identification*: e.g. name, address, demographic, and agent
Life Cycle: e. g. version, and status	*Accessibility*: e.g. language, disability, preferences, and eligibility
Meta-metadata: e.g. identifier, and contribution	*Goal*: learning, career and other objectives and aspirations
Technical: e.g. format, size, and location	*Qcl*: qualifications, certifications, and licenses
Educational: e.g. interactivity level, and semantic density	*Activity*: e.g. educational program
Rights: e.g. cost, and copyright	*Competency*: acquired learning competencies e.g. awards
Relations: e.g. kind, and resource	*Transcript*: summary records of academic performance
Annotation: e.g. entity, date, and description	*Interest*: hobbies and recreational activities
Classification: e.g. purpose, and taxon path	*Affiliation*: membership of learned, professional, civic and recreational organizations
	Security key: e.g. passwords, and public key
	Relationship: the relationship to be established between the other core data structures
	Extension: the extension facility for top-level ''learner information"

Table I. contains LIP elements that were used in previous research works. IMS contributed to the drafting of the IEEE LOM. It is obvious that IMS LIP must be compatible with the IEEE LOM. Therefore, data binding should be used, and obvious choice was XML.

III. CONFORMITY CRITERIA

As in [8] it is good to focus on those LOM and LIP elements that are useful as criteria of conformity of learning object to learner profile. Table I contains selected elements which are considered to be the best match for conformity criteria. The goal is to find best matching learning object for specific learner. This task can be done by ranking process with pre-defined parameters, but in such case the adaptability is minimized or ignored. The generalized criterion K_j of estimation of conformity of learning objects to the specific learner is introduced by (1).

$$K_j = \sum_{i=1}^{n} \alpha_i k_{ij} \qquad (1)$$

where $\alpha_i \in [0,1]$, $j=1,2,\ldots,P$, $k_{ij} \in \{0, 0.5, 1\}$

As there are multiple learning objects that potentially can be delivered to the learner, a proper selection of learning object is challenging task. If there are P learning objects (LOM instances), then conformity of j-th learning object is calculated by (1), where α_i is the coefficient of importance of i-th criterion of learner's profile, and n is a total number of criteria. Most important parameter is k_{ij}, the measure of conformity of the i-th criterion of the learner to the i-th criterion of j-th LOM instance. In the end, learning object with maximal value of K_j, is delivered to the learner.

The calculation of k_{ij} is done by multiple If-Then rules. In [8] there are 13 rules proposed. Some of proposed rules are:

```
If (typical_age_range.min ≤ (date-birth_date) ≤ age_range.max) Then kij=1 Else kij=0
```

```
If current_activity='active' ∨ activity_type=context Then kij=1 Else kij=0
```

Meaning of the rule 1 is: if learning object is appropriate to learner's age, then k_{ij} is 1, but if this is not the case then k_{ij} is 0.

Meaning of the rule 2 is: if user's current activity is "active" or activity type is same as context, then k_{ij} is 1, else k_{ij} is 0. Context and activity type are kind of enrollment, e.g. "school", "training", "research", etc.

Formally, it is possible that the value for k_{ij} is in the range [0, 1], but that raises the question of foundation of such a decision. Only possible way to change rules is to recalculate values of the coefficients of importance. This research deals with different definition of the If-Then rules and their application to LOM-LIP ranking process.

IV. TOWARD MORE GENERAL CONFORMITY CRITERIA

By insight to IEEE LOM standard it is evident that most of elements are textual and descriptive. The "Educational" element consists of 11 sub-elements, most importantly: Interactivity Level, Difficulty, Semantic Density and Typical Learning Time. These four sub-elements are chosen to be criteria while calculating the measure of conformity. It is possible that values of these four criteria are numerical, e.g. percent or some value from [0, 1] range. Now it is possible to define learner's profile as a 4-tuple $\langle a, b, c, d \rangle$ where a corresponds to Interactivity Level, b corresponds to Difficulty, c corresponds to Semantic Density and d corresponds to Typical Learning Time. Learning objects are defined as a 4-tuple, analogously to the definition of learner's profile. There are many ways to define more general measure of conformity, some of them are:

- It is possible to use some similarity relation instead of binary relations such as =, ≥, ≤.
- It is possible to use more general logical operators that deals with values from [0, 1] instead of logical AND, OR and NOT operators that deals with values from {0, 1}.
- It is possible to use multiple sets of pre-defined rules instead of one set of 13 pre-defined rules, as proposed in [8].
- It is possible do use logical implication on [0, 1] instead of Boolean logical implication on {0, 1}.

In this research we adopted the usage of similarity relation while logical operations are defined on [0, 1].

A. Similarity Relation

If similarity relation between two objects is defined as a negation of distance between them [13, 14], then we can use many types of distance measures such as: Euclidean, Squred Euclidean, Chebyshev, Mahalanobis, Manhattan, Minkowski, City-Block, etc. According to [14] the distance between two values a_1 and a_2 can be calculated by (2):

$$dist(a_1, a_2) = \frac{|a_1 - a_2|}{max_{val} - min_{val}} \qquad (2)$$

where $\max_{val}$ is maximal possible value and $\min_{val}$ is minimal possible value. As values a_1 and a_2 are from [0,1], we have $\max_{val} = 1$ and $\min_{val} = 0$. Now, (2) is transformed to simple form:

$$dist(a_1, a_2) = |a_1 - a_2| \qquad (3)$$

If similarity of two objects is defined as negation of their distance, and negation of value $x \in [0, 1]$ is defined as $1-x$, then similarity of two objects a_1 and a_2 is defined as:

$$sim(a_1, a_2) = \alpha(1 - dist(a_1, a_2)) \qquad (4)$$

where α is the coefficient of importance.

B. Implication on [0,1] and Rules

There are many definitions of the logical implication A→B (A implies B), when A and B are taking values from [0, 1]. Some of them are compatible with Boolean implication, but some are not. As in [15, 16] the simplest possible way to define implication A→B is to use *min* function (Mamdani implication):

$$A \rightarrow B \Leftrightarrow \min(A, B) \qquad (5)$$

Antecedent A of the implication defined by (5) is formed as an aggregation of similarities between learner's profile criteria and corresponding learning objects criteria, while consequent B is a constant that is related to conformity criterion k. The aggregation of similarities is done by application of AND logical operator that is implemented as t-norm [15, 16]. Most common t-norms are: *min* function and *prod* (algebraic product). Logical OR operator is commonly implemented as *max* function.

If the measure of similarity of learner's profile and learning object is μ then the form of the rule is: If μ Then k. Finally, there is no need for multiple rules. Now, only one rule of the form: If μ Then k is needed. Multiple sets of rules can be emulated by varying the value of k: if k=1 the rule is strict, but for k<1 we have relaxed rules.

V. A CASE STUDY

For four criteria: Interactivity Level, Difficulty, Semantic Density and Typical Learning Time we have learner's profile defined in Table II, and four Learning objects defined in Table III.

TABLE II. LEARNER'S CRITERIA (LIP)

Interactivity Level (LIL)	Difficulty (LD)	Semantic Density (LSD)	Typical Learning Time (LTLT)
0.7	*0.5*	*0.8*	*0.4*

TABLE III. LEARNING OBJECTS CRITERIA (LOM)

No.	Interactivity Level (OIL)	Difficulty (OD)	Semantic Density (OSD)	Typical Learning Time (OTLT)
1.	*0*	*0.9*	*1*	*0.9*
2.	*1*	*0.6*	*0.8*	*0.9*
3.	*0.3*	*0.3*	*0.5*	*0.7*
4.	*0.8*	*0.2*	*0.1*	*0.5*

Strict rule is defined by:

```
If LIL is similar to OIL AND LD is similar to OD AND LSD is similar to OSD AND LTLT is similar to OTLT Then k=1.
```

For the coefficient of importance α=1, and for the first learning object, we can calculate similarities by (4):

LIL is similar to OIL: 1 – |0.7–0| = 1–0.7 = 0.3

LD is similar to OD: 1 – |0.5–0.9| = 1–0.4 = 0.6

LSD is similar to OSD: 1 – |0.8–1| = 1–0.2 = 0.8

LTLT is similar to OTLT: 1 – |0.4–0.9| = 1–0.5 = 0.5

After application of the logical AND operator implemented by *min* function, we have: *min*(0.3, 0.6, 0.8, 0.5)=0.3. Measure of similarity between learner's profile and first learning object is μ=0.3. Analogous calculus is done for all remaining learning objects (see Table IV). If AND logical operator is implemented as *prod*, different measures of similarities are achieved (see Table IV, column three).

TABLE IV. MEASURES OF SIMILARITY

No.	Measure of similarity μ *min*	Measure of similarity μ *prod*
1.	*0.3*	*0.072*
2.	*0.5*	*0.315*
3.	*0.6*	*0.2352*
4.	*0.3*	*0.1701*

Now, we calculate the final result by logical implication implemented as *min* function for previously calculated μ and k=1: min(0.3, 1)=0.3, min(0.5, 1)=0.5, min(0.6, 1)=0.6, min(0.3, 1)=0.3. It is obvious that best matching learning object for specific learner is learning object No. 3. Analogously, if logical AND operator is implemented as *prod*, best matching learning object for specific learner is learning object 2.

If rule is relaxed, so that k=0.5, we have: min(0.3, 0.5)=0.3, min(0.5, 0.5)=0.5, min(0.6, 0.5)=0.5, min(0.3, 0.5)=0.3. Now, if logical AND operator is implemented as *min*, then best matching learning objects for specific learner are objects 2 and 3, while if logical AND operator is implemented as *prod*, then there is no change.

VI. CONCLUSION

IEEE 1484.12.1 – 2002 Standard for Learning Object Metadata (LOM) and IMS Learner Information Package (LIP) specification, combined together via XML data binding enable elimination of the problems such as: moving learner information between institutions, producing a lifelong record of a learner's achievement, providing personal development planning process and storing information about learner preferences. While the execution of the data binding process, it is of great importance to find learning object which is the best match to learner's profile. In the past, this was done by simple Boolean If-Then rules. In this paper is proposed the introduction of similarity measure, as well as general logic operations. This led to the more general criteria of conformity between learner and learning objects. Generalization of logical operation is done by the introduction of t-norms, while the logical implication is implemented as Mamdani logical implication via *min* function. A case study shows that the adaptability of the Web-based Learning System is possible.

In [17] is underlined that there are problems regarding: National educational environments, Differences between beneficiary institutions, Flexibility, Teaching materials development and Delivery of the curriculum. By usage of IEEE LOM and IMS LIP joint data binding it is believed that those and similar problems would be minimized.

Future work will investigate the impact of different logical implication implementations such as: Kleene-Dienes implication, Lukasiewicz implication, etc. to the measure of the criteria of conformity of learner's profile and learning objects.

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