The 8th International Scientific Conference
eLearning and software for Education
Bucharest, April 26-27, 2012
10.5682/2066-026X-12-093

RECENT SOFT COMPUTING APPROACHES IN DIGITAL LEARNING OBJECT EVALUATION

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***Abstract**: Digital learning objects are powerful units for building learning, education or training materials based on ICT recent developments. Not only text and photos, but also audio, video, and simulation units are used to build high quality e-lessons (available online), or blended learning resources. There are a large plethora of types of digital resources used in e-Learning content development, and for every category a particular set of criteria are used by experts (mainly e-education experts) to recommend some optimum configuration. Content quality (including presentation design), standards compliance (mainly for portability reason), learning goal alignment (accreditation goals), accessibility and interaction usability, and reusability are common criteria for every type of digital learning object. Specific aspects concerning text (font size/colour), images (resolution, multilevel approaches, animation), audio (resolution), video (resolution), and the general presentation including the quality of characters' voice are necessary to be taken into consideration in order to select the best quality digital learning objects in order to obtain an attractive, motivational, and efficient (not only for the teacher, but most important for the student) meeting with valuable pieces of knowledge for life. This paper describes the usage of some soft computing techniques for the evaluation of DLOs, including intuitionistic fuzzy multi-criteria approaches. Firstly, the multi-criteria decision-making methods are briefly reviewed combining the general decision-making process. There are many approaches in soft computing decision-making: neural networks, evolutionary optimisation, fuzzy computing, etc. The multi-criteria approaches under consideration are based on fuzzy and intuitionistic fuzzy numbers (triangular, trapezoidal, etc), distance evaluation, and multi-criteria decision strategies. Final considerations on applying such methodologies for digital learning objects' evaluation are presented.*

***Keywords:** digital learning objects, multi-criteria decision-making, intuitionistic fuzzy approaches*

I. INTRODUCTION

The important role of digital objects in modern education was proved by various researches. According to Janson & Janson (2009), "DLOs enable students, both individually and collaboratively, to work hands-on with complex content and ideas. Students can, for instance, manipulate and experiment with variables, carry out simulations, prepare exhibitions with authentic artefacts, and explore new concepts in game formats. DLOs challenge students to question, investigate, analyze, synthesize, problem solve, make decisions, and reflect on their learning." An historical overview and classification of traditional and DLOs is presented by Zuckerman which defined three categories of LOs and DLOs: Construction & Design (associated with Froebel), Conceptual Manipulation (associated with Montessori), and Reality Role Play (associated with Dewey).

In the context of distance learning based on e-learning many universities already developed a large collection of multimedia learning objects. These are available on-line and can be used interactively. As Nash (2005) remarks: “In the mid-1990s, relatively simple learning objects were made available informally, as instructors shared syllabi, lesson plans, and learning activities”. Recently, more complex and/or topic specific repositories are provided by museums, journals and magazines, educational television, and other organizations which place content on the web.

The teaching team or the instructor and his/her assistants will select the most suitable learning object in order to create a course from COTS (components off-the-shelf). If such an object is not available it should be created and stored for future use. During creation the team should apply the strategy of quality improving by design. As selection criteria, firstly, the team can use the following set: 1) attractiveness; 2) interface design; 3) content quality; 4) usability; 5) adequacy to self-learning. After that, a second set of criteria can be applied. These criteria take into consideration the following aspects: 1) objectives fulfilment; 2) content validity; 3) feedback; 4) cognition development, and 5) Compliance to standards. The first set is student-oriented, while the second set is teacher-oriented. Such a practice creates the need for digital object learning evaluation based on multi-criteria subjective information. However, different criteria should be selected when the LO/DLO should be classified in order to be selected for a repository, as Currier et al (2004) established experimentally.

This paper continues some previous investigation on multi-criteria evaluation of learning objects, like those described in [1]. The approach was tested for the evaluation of learning objects mentioned in [1], and for the learning objects developed in [2].

II. RANKING DIGITAL LEARNING OBJECTS

According to [1], a learning object is “a set of resources, viewed as independent and reusable entities, useful to create various educational pieces suitable to some pedagogical hierarchy”. By IEEE LTSC WG12, Los are defined as “any entity, digital or non-digital, which can be used, reused or referenced during technology supported learning [computer-based training systems, interactive learning environments, intelligent computer-aided instruction systems, distance learning systems, and collaborative learning environments]”. IEEE LTSC WG12 identifies the following Los: multimedia content, instructional content, learning objectives, instructional software and software tools, and persons, organizations, or events referenced during technology supported learning.

Digital learning objects are powerful units for building learning, education or training materials based on ICT recent developments. Not only text and photos, but also audio, video, and simulation units are used to build high quality e-lessons (available online), or blended learning resources. There are a large plethora of types of digital resources used in e-Learning content development, and for every category a particular set of criteria are used by experts (mainly e-education experts) to recommend some optimum configuration. Content quality (including presentation design), standards compliance (mainly for portability reason), learning goal alignment (accreditation goals), accessibility and interaction usability, and reusability are common criteria for every type of digital learning object. Specific aspects concerning text (font size/color), images (resolution, multilevel approaches, animation), audio (resolution), video (resolution), and the general presentation including the quality of characters' voice are necessary to be taken into consideration in order to select the best quality digital learning objects in order to obtain an attractive, motivational, and efficient (not only for the teacher, but most important for the student) meeting with valuable pieces of knowledge for life.

According to Ochoa (2008), LOs can be ranked by peer evaluation (human review) where subjective data have to be used. Other ranking approaches considers: text similarity (assign a relevance value to all the objects returned in a search), user profile (a better adaptation to changes in the needs), web page ranking (based on Web Graph), journal impact factor (the relevance of a scientific journal in a given field), etc.

A ranking of Digital Learning Objects has the following types of relevance: *algorithmic* (query-object matching), *topical* (real world – object approximation), *pertinence, cognitive or personal* (information object – information need/perceived), and *situational* (object-generator relation).

The following ranking metrics were proposed are used in literature.

- BT – *Basic Topical Relevance Metric* which is an adaptation of the Impact Factor metric:

$$BT(o,q) = \sum_{i=1}^{NQ} d(q,q_i)s(o,q_i),$$

where NQ is the total number of similar queries of which the system keeps record, o represents the learning object to be ranked, q is the query performed by the user. q_i is the representation of the ith previous query. The distance d between q and q_i can be seen as the similarity between two queries, and s(o,q) = 1 if and only if the object o was clicked (selected) in the query q, otherwise the value is zero.

- CST - *Course-Similarity Topical Relevance Ranking*. Two courses are considered similar if they have a predefined percentage of learning objects in common.

$$CST(o,c) = \sum_{i=1}^{NC} SR(c,c_i)\, p(o,c_i),$$

where NC is the total number of courses, NO is the total number of objects, o represents the learning object to be ranked, c is the course where it will be inserted or used. c_i is ith course present in the system,

$$SR(c_1,c_2) = \sum_{i=1}^{NO} p(o_i,c_1)\, p(o_i,c_2),$$

and $p(o, c) = 1$ if and only if o appear in c.

- IT - *Internal Topical Relevance Ranking*. If o represents the learning object to be ranked, c_i represent the ith course where o has been used, and N is the total number of courses using o, then

$$IT(o) = \sum_{i=1}^{N} inc(c_i, o),$$

where $inc(c_i, o)$ give the degree of linkage between the object o and the course c_i.

- BP - *Basic Personal Relevance Ranking*. Let N be the total number of objects under ranking, o represents the learning object to be ranked, f represents a field in the metadata standard and v is a value that the f field could take, $val(o, f)$ represents the value of the field f in the object o. Let f_i be the ith field considered for the calculation of the metric and NF the total number of fields. The frequencies for each metadata field are calculated counting the number times that a given value is present in the given field in the metadata:

$$freq(u, f, v) = \frac{1}{N} \sum_{i=1;\, o_i \text{used by } u}^{N} count(o_i, f, v),$$

where $count(o, f, v) = 1$ if and only if $val(o, f) = v$, otherwise is equal to zero.
The BP metric is given by:

$$BP(o,u) = \sum_{i=1;\, f_i \text{ appears in } o}^{NF} \mathrm{freq}(\mathrm{u}, \mathrm{f}_\mathrm{i}, val(o, f_i)).$$

- USP - *User-Similarity Personal Relevance Ranking*. Let o represents the learning object to be ranked; u - the user that performed the query, u_i - the representation of the ith user, NU - the total number of users. The metric is computed as follows:

$$USP(u,o) = \sum_{i=1}^{NU} SR(u,u_i)K(o,u_i),$$

where $SR(u,v)$ measures the similarity between users u and v, and $K(o, u)$ measures the reusability index of o by u ($K(o,u) = 1$ if and only if u uses o, otherwise is equal to zero).

- CSS - *Context Similarity Situational Relevance Ranking*. Similarly to the calculation of the BP metric, the N objects contained in the course are “averaged” to create a set of relative frequencies for different fields of the learning object metadata record.
- Other Metrics can be proposed by adapting the existing metrics and considering subjective data and/or probabilistic (subjective probabilities) values.

III. SOFT COMPUTING MULTI-CRITERIA DECISION

Solving practical situations under different levels of imprecision is a great challenge. Recent treatments on imprecision cover aspects related to vagueness (“vague; indistinct; not perfectly apprehended”) and chance dependency (“dependent on chance or unpredictable factors; doubtful; of unforeseeable outcome or effect”). The approximate reasoning is used to manage those situations when experts use vague concepts for the evaluation, observation and decision on a system evolution based on different models likes: arithmetic intervals, fuzzy numbers, intuitionistic fuzzy numbers, fuzzy logic, and fuzzy devices. In order to deal with uncertainty, probabilities are attached with objects under manipulation (probabilistic trees, probabilistic networks, probabilistic generative mechanisms, probabilistic thinking). In large, probabilistic reasoning, and fuzzy logic were identified as possible approaches. If subjective probabilities, fuzzy sets/logic, neural networks, evolutionary computing and hybrid approach, such a framework is called soft computing based.

Assume that for a subject to be covered during teaching/training/learning there are available, from different sources, a nonempty set of DLOs $\{o_1, o_2, \ldots, o_m\}$ with similar difficulty level, similar psycho-pedagogical and curricular objectives. Two types of analysis can be realized. In the first case, the instructor has to select the most appropriate learning object to be used during training/teaching activities. The second case addresses the existence of p users/experts $\{e_1, e_2, \ldots, e_p\}$ evaluating every learning object used during self-learning.

The selection is based on a nonempty set of criteria/attributes $\{c_1, c_2, \ldots, c_n\}$ taking into consideration weights indicating the importance (priority) of every criterion. Both trainer/teacher and users/experts use linguistic variables like: very low, low, medium, high, very high (or very poor, poor, average, good, very good), to describe the performance of every learning object related to every criterion.

For every linguistic variable there are defined a membership and a non-membership function. In general, if Ω is the universe of discourse, an intuitionistic fuzzy set A in Ω is given by $A = \{(\omega, \mu_A(\omega), \nu_A(\omega)), \omega \in \Omega\}$, where $\mu_A(.): \Omega \to [0, 1]$ gives the degree of membership, and $\nu_A(.): \Omega \to [0, 1]$ gives the degree of non-membership of ω to A. The expression $1 - \mu_A(\omega) - \nu_A(\omega)$, denoted by $\tau_A(\omega)$, is called the hesitancy degree [1].

Let us consider, in the following, as universe of discussion the set of learning objects $O = \{o_1, o_2, \ldots, o_m\}$. The matrix of linguistic performance is obtained and should be used to choose the “awarded” learning object. In this manner a three dimensional array of linguistic values is obtained: $OCE = \{(\mu_{ijk}, \nu_{ijk}); i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; k = 1, 2, \ldots, p\}$ describing both the degree of acceptance and the degree on non-acceptance (rejection) by the user/expert k, of the learning object i, related to the criterion j. Every user/expert e_k associate a weight (a positive real number) for every criterion c_j according his/her belief for the importance of the criterion: a matrix $W = (w_{ik}; i = 1, 2, \ldots, p; k = 1, 2, \ldots, n)$ is built.

When p = 1 it is obtained the single expert model (useful when a teacher/trainer has to select one learning object from a set of ‘similar’ learning objects), and if p > 1 the multi-expert model is obtained (useful to assess the degree of acceptance of the used learning object by the students, or by the members of the quality assessment team).

The weighted average of the linguistic performance value is calculated for each DLO *i* as follows: $\lambda_{ik} = \sum_{j=1}^{n} \mu_{ijk}\theta_{kj}$, $\eta_{ik} = \sum_{j=1}^{n} \nu_{ijk}\theta_{kj}$, $\varepsilon_{ik} = 1 - \lambda_{ik} - \eta_{ik}$, standing for a weighted average membership, non-membership, and hesitation to be considered by the user/expert k, where $\theta_{kj} = \dfrac{w_{kj}}{\sum_{j=1}^{n} w_{kj}}$.

Single user/expert model will select the learning object having the largest weighted average membership degree (optimistic scenarios), the smallest weighted average non-membership degree (pessimistic scenarios), or the smallest weighted average hesitation degree (prudent scenarios). When there are many users/experts then if there is an object o_{i_0} having the weighted average performance acceptable (with the largest/ smallest/ smallest membership/ non-membership/ hesitation degree) by all users/ experts then o_{i_0} will be selected as the winner. Otherwise, a consensual ranking is required. As a natural fact, users/experts are resistant to option changing, and the model should consider both membership and non-membership degrees:

$$f_k(x, y; \lambda_{ik}, \eta_{ik}) = 1 - \frac{1}{e^{(x-\lambda_{ik})^2 + (y-\mu_{ik})^2}},$$

where (x, y) describes the weighted average linguistic performance when consider all users/experts and learning objects. The target is to identify those cases with small resistance to option changing.

Distance–based similarity study is another approach. Different distances have been defined in literature based on geometrical representation of intuitionistic fuzzy sets (2D, 3D, spherical). For the case study discussed in the next section, the normalized Euclidian distance was used, namely, if A and B are intuitionistic fuzzy sets in O, the normalized Euclidean distance d(A, B) is given by:

$$d(A,B) = \sqrt{\frac{1}{2m}\sum_{i=1}^{m}\left[\alpha^2 \;\; \mu_A(o_i) - \mu_B(o_i) \;\;^2 + \beta^2 \;\; \nu_A(o_i) - \nu_B(o_i) \;\;^2 + \gamma^2 \;\; \tau_A(o_i) - \tau_B(o_i) \;\;^2\right]},$$

where α, β, and γ give the importance of the membership, non-membership, and hesitation function during analysis process. The case $\alpha = \beta = \gamma = 1$ was considered, but variations can be used for simulation reason.

IV. APPLICABILITY

When apply the aggregation method described above, a table having the structure given below is obtained:

	u_1	u_2	…	u_k	…	u_p
o_1	(λ_{11}, μ_{11})	(λ_{12}, μ_{12})	…	(λ_{1k}, μ_{1k})	…	(λ_{1p}, μ_{1p})
o_2	(λ_{21}, μ_{21})	(λ_{22}, μ_{22})	…	(λ_{2k}, μ_{2k})	…	(λ_{2p}, μ_{2p})
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
o_i	(λ_{i1}, μ_{i1})	(λ_{i2}, μ_{i2})	…	(λ_{ik}, μ_{ik})	…	(λ_{ip}, μ_{ip})
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
o_m	(λ_{m1}, μ_{m1})	(λ_{m2}, μ_{m2})	…	(λ_{mk}, μ_{mk})	…	(λ_{mp}, μ_{mp})

The following matrix of distances between objects considering preferences of all users/experts is obtained and used for similarity analysis: $D_O = (d_{ij})_{1 \le i,j \le m}$, where

$$d_{ij} = \sqrt{\frac{1}{2p}\sum_{k=1}^{p}\left[\;\lambda_{ik} - \lambda_{jk} \;\;^2 + \;\; \mu_{ik} - \mu_{jk} \;\;^2 + \;\; \varepsilon_{ik} - \varepsilon_{jk} \;\;^2\right]}.$$

Similarly, a matrix D_U containing the distance computed between users when considering objects as their attributes can be generated and analyzed for a better decision.

V. CONCLUSIONS

In this paper the usage of intuitionistic fuzzy sets were used to evaluate the quality of learning objects based on the multi-criteria approach under subjective information.

Acknowledgements

During this research, the first author was supported by the Research Centre of the Faculty of Mathematics and Informatics according to the programs: “Applied informatics for software engineering” 107/2010, and “Research in theoretical informatics and computing methodologies” 106/2010. The second author acknowledges the support of the “UNESCO” Department of the University of Oradea.

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