Clustering of Learning Objects with Self-Organizing Maps

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Abstract - The increasing availability of digital educational resources in the Internet, called learning objects, has been followed by the definition of indexing standards. However, the lack of consensus about the definition of learning objects, as well the diversity of metadata approaches for its classification hinders the selection process of these elements. This scenario requires new investigations that allow the establishment of parameters for the creation of a specific model of artificial neural network for the clustering of learning objects. The implementation of this model is related to a theoretical-methodological approach, based on standard metadata criteria, which makes the formation of input samples possible for the construction of a Self-Organizing Map (SOM - Kohonen model) through algorithms and mathematical models. Consequently, the development of this proposal for the clustering of learning objects can support the educational work in face-to-face and online environments and collaborate with the reusability of learning objects. Another goal of this research was the determination of a weight mask, one of the Kohonen model's parameters, and how it would affect the final result. For that, a comparison was made between the training results with and without the mask, showing the relevance of this method for obtaining better clustering results.

Index Terms – learning objects, self-organizing maps, neural networks, clustering.

INTRODUCTION

The contemporary society, denominated as net society, is characterized by its processing capacity expansion, the establishment of differentiated combinations and by the flexibility with regard to the distribution of information [1]. This configuration also implies in a revision process of the educational practices, having in mind the availability of learning objects that improve the educational processes.

However, the exponential availability of information by Internet leads to an increase in the difficulty to find pertinent educational resources to the contexts, and to teachers' and institutions’ proposals. The current research tools, in their majority, allow the search through keywords, resulting in a huge quantity of information being selected manually; which increases the successive number of searches and, sometimes, makes the process non-effective.

Because of this, the present work proposes the establishment of input parameters for an Artificial Neural Network with the objective of clustering learning objects. This proposal intends to collaborate with the betterment of the organizational and structural capacity of these educational resources in order to improve their reusability.

The improvement in the search process, as well as the potential increase in the application of learning objects in an educational environment, such as a course, can be accomplished by Self-Organizing Maps (SOM) and the elaboration of evaluative parameters. From this approach, it becomes possible to cluster learning objects by similarity in the output layer of the Artificial Neural Network. This method can subsidize the educational work (face-to-face and online), once it enables teachers to perform the research by using characteristics and likeness of learning objects as parameters.

The present work is organized as follows. Learning Objects outlines the theoretical background related to concept, uses and to learning objects’ repositories. Evaluation of Learning Objects introduces the theoretical-methodological proposal for the evaluation of learning objects. Neural Networks and Self-Organizing Maps present definition terms relevant to research and other elements related to this technique. Methodology describes and details the phases and configurations related to the experiment. The Results section discusses the elements achieved. Finally, Conclusions and Further Works shows the conclusions and presents the possibilities for a continued research.

LEARNING OBJECTS

The IEEE Learning Technology Standards Committee [2] characterizes learning objects as digital elements that can be used, reused or even be referred to through a technologically mediated learning process. As a result, that definition includes the necessity to establish a delimitation that attributes accuracy. According to [3] texts, images, graphics, sound elements, videos and other educational resources in digital format, accompanied by observations about their uses, can be considered learning objects. In this sense, learning objects are independent educational resources that can be combined with others to constitute units, according to the context and goals defined. In doing so, they can be tutorials, simulations, demonstrations, models, case studies, serious games, exercises, tests, and so on.

From these different points of view, one can realize that learning objects can be characterized as an independent collection of reusable and granular educational elements. Those may enable a contextual meaning without necessarily configuring an element that can be only used in a single context [4]. The reuse of the learning objects involves use of metadata for their classification and storage.
In this sense, an analysis of the definitions of learning objects allows one to verify that the reusability concept is similar to that of guided programming for objects used in software development. Instead of rewriting a previously elaborated code, the programmer performs a search in code library (metadata), then selects and inserts it in his own pre-written program. In a similar manner, when teachers create a course, module, or any learning element, they may perform a search in a library (repository) and select the most adequate result for the educational proposition, goals, methodology, learning styles, difficulty degree, prerequisites, and so on.

The increasing availability of learning objects on the Web and their ease of access imply on a need to properly manage them. To this end, new proposals allow the optimization of the search and selection of educational materials, increasing their reusability and making the educational process more meaningful.

As a result, repositories of Learning Objects are witnessing an increase in number, where huge databases use metadata to catalog and evaluate them. Thus, these kinds of repositories constitute digital libraries that store learning objects or references along with their properties in a standardized manner, facilitating their utilization.

This phenomenon also implies in the creation of different qualification methods and diverse storage patterns like IEEE-LOM [2], DublinCore [8], IMS Learning Design, ARIADNE and so on. But the present paper will not focus on this specific problem because it considers that the evaluation of learning objects must take into account different approaches related to appraisers, users, developers, students, and teachers, among others [5]. In this work, the appraiser point of view is highlighted. It was selected because teachers and professors are the primary users of learning objects, and need information and tools to select appropriate learning objects to develop didactical strategies based on specific instructional design elements related to this context [9].

**EVALUATION OF LEARNING OBJECT**

According to [10], a methodology for the definition of these elements lists itself in two groups: Intrinsic Characteristics of Learning Objects (related to inherent qualities and showing their potential) and Learning Object Educational Value (which measures the educational potential of the resource).

It is relevant to point out that the intrinsic evaluation is complemented by the learning object’s educational value, which is also structured from the weights attributed to the criteria. In the same way, there are criteria with weight 3. Such is the case of user orientation, which concerns the availability of information in order to use the resource. The criteria with weight 2 relates to matters such as interface usability [11]. Finally, the criteria with weight 1 consider the interactivity levels [12] (determined by a second level of criteria that considers the chain of actions related to objects or buttons, contextual help systems, problem handling, complex systems, and hypertextual navigation).

The proposal of combining intrinsic and extrinsic elements constitutes a simplified architecture that keeps the most important elements in the IEEE-LOM and, due to this flexibility, presents some complementary items that can contribute to the selection of learning objects in educational situations; even if they are online, face-to-face hybrid situations.

LOM (Learning Object Metadata) is a conceptual metadata outline for learning objects defined by the IEEE Learning Technology Standard Committee (IEEE-LTSC). This standard holds a hierarchical model that describes the relevant characteristics of the object to the context in which it is applied, constituting a tree structure of 67 elements grouped in nine categories [2]. LOM also aims to facilitate the sharing and changing of learning objects, allowing the learning units to develop (through linkage and/or combination of learning objects), catalogs and inventories.

As a result, this work proposes that the evaluation of learning objects should start from a verification list that will ponder key elements through weights and notes. The notes would then be attributed to each item, allowing intelligent tools to work with this information, collaborating with the reusability of the learning objects.

**NEURAL NETWORKS AND SELF-ORGANIZING MAPS**

Neural Networks constitutes one of the fields of Artificial Intelligence that has as its motivation the acknowledgment that the human brain processes information in a way that is entirely different from the conventional digital computer [12]. This implies in the utilization of a parallel processing system that is both distributed and non-algorithmic, and, in some level, resembles the structure of the human brain.

This system has as its primary function the storage of experimental knowledge availability for usage. In a complementary way, it resembles the brain in two aspects [13]: the knowledge is acquired through a learning process, and the synaptic weights are used to store the acquired knowledge.

In a similar way, artificial neural networks are composed by nodes or neurons. These are initially formed by mathematical models that are behaviorally similar to their biological counterparts.

The Kohonen networks method, also known as Self-Organizing Maps (SOM) was developed by Teuvo Kohonen [7] in the decade of 80. The Self-Organizing Map is based on evidence that the brain is organized by regions that answer to the different stimuli such as speech, vision, motor control, sensitivity to the touch, and so on [7]. The neurons, when spatially observed, are ordered inside these areas, and thus, neurons in the topological vicinity tend to answer to similar stimuli.

Using these biological characteristics, and in order to make artificial neural networks similar to natural neural networks, the Self-Organizing Maps are conceived by two layers (input and output layers). The connection between these layers is made through a vector of synaptic weights. These are also known as a characteristics map [14].

Observing the biological similarities, one can realize that the output neurons become specialized during the training in order to react to input vectors of determined groups, and to represent typical shared characteristics of
those; then constituting areas in the reticulate in a way similar to that of the brain [15]-[14]. This kind of technique can be applied to problems of different areas such as the organization of document collections [16], knowledge extraction [17] and so on.

Kohonen's network presents basically the following function structure: when an input vector is presented, the networks search the neuron most similar to the vector. During the training, the network increases the likeness of the chosen neuron and its vicinity to the input vector. Thus, the network builds a topologic map where similar neurons that are nearby answer in a similar manner to that of the standard input, sharing an affinity of characteristics [15].

From this approach, the software MatLab version 7 with SOM Toolbox [18, 19] was adopted for clustering the learning objects with Kohonen networks. The methodology related to the experiment is described in next section.

**METHODOLOGY**

Initially, elements that could constitute evaluation parameters were searched, in order to establish the sample variables of the input network. In this phase, 20 variables were structured. The study was developed with 80 learning objects previously evaluated as network input data.

Countless tests were performed for the determination of network parameters. The results were always analyzed by two metrics as pointed by [7]: Quantization Error (QE) and Topological Error (TE). To reduce the values of these metrics, a methodology was used for defining the size of the reticulate. This was made by starting with tests of various sizes, without any concern for performance in what refers to the slowness of the training process. A weight mask that demonstrated to the network which were the priority elements in the clustering process was also defined. After the definition of this mask, QE increased and it became necessary to change the lot-training algorithm in order to enable the sequential adjustment of other parameters.

In this phase several tests were performed with a number of different types of training and with the 16 possible combinations of training functions, setting a function for the ordination phase and a function for the training convergence phase that presented both metrics mentioned previously with values near or equal to zero.

Thus, the next parameters for Kohonen's network were defined for this research:

<table>
<thead>
<tr>
<th>Element</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Input</td>
<td>80 samples</td>
</tr>
<tr>
<td>Reticulate Size</td>
<td>26 x 26</td>
</tr>
<tr>
<td>Training Mask</td>
<td>[10;10;10;10;10;10;10;10;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;5]</td>
</tr>
<tr>
<td>SOM Initialization</td>
<td>Linear</td>
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</tbody>
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<thead>
<tr>
<th>Ordination Training Phase</th>
<th>Algorithm</th>
<th>Neighborhood function</th>
<th>Ray of initial neighborhood</th>
<th>Ray of final neighborhood</th>
<th>Learning function</th>
<th>Rate of initial learning</th>
<th>Number of times</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Sequential</td>
<td>Cutgauss</td>
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<tr>
<th>Converge Training Phase</th>
<th>Algorithm</th>
<th>Neighborhood function</th>
<th>Ray of initial neighborhood</th>
<th>Ray of final neighborhood</th>
<th>Learning function</th>
<th>Rate of initial learning</th>
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<td></td>
<td>Sequential</td>
<td>Bubble</td>
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After setting these configurations, it would be necessary to define the number of times the training would be executed in order to present a satisfactory result for the network. For that, tests were performed several times, starting with 338 and going up to 3,500 times. Observing the graphic matrix of Unified Distances for the different numbers, it was verified that there was no significant change in the groups created. That way, the number chosen was 1,400, for having a QE next to zero and a TE equal to zero. This value (1,400 training executions) corresponded to 112,000 examples (1,400 times x 80 data samples) and is greater than the number usually used by [7].

From this setting the following results were obtained.

**RESULTS**

The studies demonstrated that the artificial neural networks with no supervised training using Kohonen's Algorithm can be used to cluster learning objects in a proper way.

It is relevant to point out that the results involve the use of a training mask with weights. This approach, after training, shows the grouping of learning objects by contextual proximity. The numbers used in the mask are related to the weights defined in the learning object evaluation section. The elements that have a weight 3 in the evaluation proposal are converted to 10 in the mask, those with weight 2 are converted to 5 and those with weight 1 are kept the same.

After the training, the U-Matrix (Figure 1) was generated, showing some clusters that were shaped in a better way by contextualization variables.
FIGURE 1
The 26x26 reticulate with weight mask and the resulting U-Matrix and Self-Organizing Map with learning objects after 1400 times. Red numbers identify the learning objects and the numbers in parenthesis show the quantity of learning objects that are positioned in the same neuron.

In the lower left corner of the Self-Organizing Map it is possible to identify a group formed by the learning objects 11, 21, 28, 32, 34, 35, 36, 37, 38, 39, 40, 44, 45, 48, 54 and 74. This is in accordance to the evaluation proposal of determining the data input on the neural network, because these objects have the same scores in the contextualization variables, only differing in other parameters.

Another cluster example, that has the same score in the contextualization variables, is formed by learning objects 5, 30, 52, 53, and 60. The learning object 13 is next to this group on the illustration; however it has a larger distance, which is topographically denoted by its color definition. This difference is verified in one of the contextualization variables pertaining to the rest of the group.

In this manner, this network is grouping learning objects by their contextual proximity, like the information samples that were used as input for the network training.

Another test was performed using the same network training parameters described above, but this time the training mask was changed from [10;10;10;10;10;10;10;10;10;10;1;1;1;1;1;1;1;1;1;1;5] to [1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;5;1;1;1;1;1;1;1;1;1;1] - in other words, it is not using weight to determine the most significant variables for the data space variables. This training resulted an QE equal to 0.16805 and TE equal to 0, which are better values than those generated by the training with the weight mask. However, by observing figure 2 it can be verified that the intended grouping was not found.

FIGURE 2
The 26x26 reticulate without the weight mask and resulting U-Matrix and Self-Organizing Map with learning objects after 1400 times. Red numbers identify the learning objects and the numbers in parenthesis show the quantity of learning objects that are positioned in the same neuron.

As demonstrated above, the use of adequate weights is fundamental for the qualification of variables depending on the input data model used.

CONCLUSIONS AND FURTHER WORKS

With the configuration established during the research it was possible to obtain learning objects through a research process by topological proximity, because learning objects with similar characteristics are properly placed near each other. This presents similar behavior to the brain function, which organizes the neurons in a way that similar information occupies adjacent positions.
It is important to bring attention to the fact that the test performed using the weight mask with the value 1 (one) for all the variables presented a \( QE \) next to zero and a \( TE \) equal to zero. However, the creation of few groups was observed in contrast to the network with different weights, and learning objects that should be nearby, belonging to the same group, were located within a large topological distance.

Actual repositories have a larger diversity of learning objects than presented in this work. Because of this, the practical results will be related to reusability and ease of search. For the future of this application, besides the consideration of a friendly interface for the user, it would be possibly interesting to build an ontology of contextualization variables to collaborate with the research and gathering process of learning objects. Another proposal would be to use the methodology developed in this work with some adaptations in order to extrapolate it for the clustering of other elements, such as: videos, documents, software modules, customer information, information management, information exchange and so on.

REFERENCES
