Learning Object Recommendation System Evaluation

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***Abstract*— New technologies have been supporting teachers and facilitating students' learning. An example is the learning object, which is defined as any content that aims to teach something. Learning objects are stored in repositories that also provide methods to retrieve and index them. The recommender algorithm was applied on the repository mentioned and analyzed afterwards. Thus, this paper aimed to verify how recommender systems help users to find objects in a repository of the Federal Institute of Rio Grande do Sul.**

Keywords- Recommender systems, learning objetcs, learning objects repositories.

I. Introduction

Learning object (LO) can be defined as a digital or physical resource used for teaching purposes [1, 2, 3, 4], such as text, pictures, movies. Computationally, a LO has a metadata file [5] that answers the its usage, for whom and any requirement regulated by entities such as [6, 7, 8]. Repositories are systems, for example MERLOT [9] and OBAA [10], that use metadata to catalogue a set of LOs.

However, finding LOs in a repository is not an easy task. Users must seek keywords that match the object's title or description. The best option is to use Artificial Intelligence to improve the repository, e.g., recommender systems.

Recommender systems offer a way to find information easily and quickly [14]. Several approaches are used to make suggestions that match the user's interests and also ensure that information is made available effectively [15]. LorSys [11], E-LORS [12] and DICA [13] are some examples.

This paper aims to investigate how a recommender system allows users to find appropriate LO in a repository. The analyzed repository was developed at a Brazilian institution that uses OBAA learning object metadata.

II. Recommendation Algorithm

A content-based recommendation algorithm was developed. It uses the Model of Vector Space (MVS) for similarity calculation of title, keywords, description and educational description; and Case Based Reasoning (CBR) for educational resource and level. Eq. 1 shows the equation used, where *textFieldsSimilarity* is the MVS fields and *rbcFieldsSimilarity* is the fields where CRB was used. The weights applied were 0.7 and 0.3, respectively.

$$Similarity(Q,D) = 0.7 \cdot textFieldsSimilarity + 0.3 \cdot rbcFieldsSimilarity \quad (1)$$

A. TextFieldsSimilarity

The formula for obtaining the *idf* is done using equation of Eq. 2. Here, *n* is the number of objects (documents) in the collection and *dfj* the number of documents in which the *j* term appears.

$$idf = log_2(\frac{n}{df_j}) \quad (2)$$

After the term frequency of calculation and inverse document frequency is calculated by the weight *wij* of each term. This, for *j* term in a document *i* is calculated by multiplying the *tfj* by *idfj*, as shown in Eq. 3. Each field has a different weight, with title weighing 0.4; keyword, 0.3; description, 0.2 and educational description, 0.1.

$$w_{ij} = tf_{ij} \cdot idf_{ij} \quad (3)$$

The fields are calculated separately using the similarity equation (Eq. 4), where given the fields *Q* and *D* for two objects, the sum of the product is made between weights (*wqfk* * *wdfk*), obtained in both objects, all terms (*fk*) in field *f*. This value is divided by the square root of the product of the sums of the weights of each high term squared (*wqfk2*).

$$FieldSim(Q_f, D_f) = \frac{\sum_{k=1}^{ft} w_{qfk} \cdot w_{dfk}}{\sqrt{\sum_{k=1}^{ft}(w_{qfk})^2 \cdot \sum_{k=1}^{ft}(w_{dfk})^2}} \quad (4)$$

The similarity of each field is multiplied by its respective weight and summed to represent similarity between the LOs.

B. RbcFieldsSimilarity

For level and learning resource fields type CBR is used to calculate similarity (Eq. 5). Similarity to the level field (*lvlSimilarity*) has weight 0.2, whereas the type of educational resource (*lrtSimilarity*) weighs 0.8. This is because it is believed that the type of educational resource is an attribute that has the highest importance level.

$$RBCFieldsSimilarity = lvlSimilarity \cdot 0.2 + lrtSimilarity \cdot 0.8 \quad (5)$$

The first step for calculating similarity of the field level is to measure the distance between values of two objects (*pit - ValB*), then calculate the module of this value so that the distance is always positive. After diminishes maxDistance this value, which represents the greatest possible distance value to the field, this is equal to the number of possible cases 1, for the case of the maxDistance level field value is equal to 12. Finally, the value obtained is divided by

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maxDistance in order to normalize the result. The value obtained through the Eq. 6 is between 0 and 1, where 0 is the lowest similarity possible and 1 the highest similarity.

$$rbcSimilarity(val_a, val_b) = \frac{maxDistance - |val_a - val_b|}{maxDistance} \quad (6)$$

The calculation of the distance between two objects is made by using Eq. 7 equation.

$$lrtSimilarity(Q, D) = \frac{\sum_{i=1}^{lrt} maxSimQ_iD}{lrt} \quad (7)$$

The recommendation process occurs when a user accesses a detail page of a LO. We showed the 20 more similar items in each recommendation lists.

III. Research Design and development

This study used the exploratory research approach and the case study technique. The participants were undergraduate students and teachers of Math, Physical, Systems Development programs.

Initially, participants accessed the Task System to answer questions about their experience using computers and LO. Second, they saw a LO and a list with descriptions of recommendations generated by the algorithm. We asked them to compare the LO data with each description on the list, and to link them. 510 out of 790 recommendations were considered relevant or satisfactory for the repository users.

On the following test, three different groups with 3 LOs each were selected in the repository. Two search tasks were designated to participants that should be performed separately in a repository with and without recommendations (Repositories 1 and 2). Both were selected randomly to reduce the repetition as the participants performed the search. After that, participants filled out a form describing the difficulties experienced and how the recommendations from Repository 2 helped them to complete the task.

We observed that, even in the repository that contained recommendations, the number of LOs was significantly low. Table 1 shows the percentage of LOs from each group. About the task difficulty, most participants classified it as moderately difficult and difficult in Repository 1 and 2. On the other hand, the majority of participants classified the recommendations as being among moderately useful or even extremely useful.

Table 1. Comparison of results of the tasks in the repositories

Task	Found		Not found	
	Repository 1	Repository 2	Repository 1	Repository 2
1	30.30%	39.34%	69.70%	60.66%
2	12.82%	7.14%	87.18%	92.86%
3	64.39%	56.35%	35.61%	43.65%

IV. Conclusion

This study aimed to verify how a recommendation algorithm helps finding learning objects in a repository. The elements used were: keywords; description; title; coverage; format, educational and resource type. From these metadata, when a user selects an LO repository, recommended are similar objects from a list generated by the algorithm that was developed in this study.

Finnaly, we noticed that users got information faster, since they knew the LO subject. After all, without the recommendations, they sailed through the menus, or used the search and had to visit each LO, until the desired. Already in the repository with recommendations, it would be in the recommended list, reducing the number of LOs users should access to check if it was what they would find, that is, the search was facilitated in a way.

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