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Enhancing E-Learning Experiences through Collaborative Filtering and Ontology-Driven Recommendations

Dr. Kaitlyn R. Patel, Dr. Ethan M. Reyes

Dr. Kaitlyn R. Patel, Department of Computer Science, University of California, Berkeley; Dr. Ethan M. Reyes, Institute for Artificial Intelligence, University of Southern California

***Abstract*—**In recent years, e-learning recommender systems has attracted great attention as a solution towards addressing the problem of information overload in e-learning environments and providing relevant recommendations to online learners. E-learning recommenders continue to play an increasing educational role in aiding learners to find appropriate learning materials to support the achievement of their learning goals. Although general recommender systems have recorded significant success in solving the problem of information overload in e-commerce domains and providing accurate recommendations, e-learning recommender systems on the other hand still face some issues arising from differences in learner characteristics such as learning style, skill level and study level. Conventional recommendation techniques such as collaborative filtering and content-based deal with only two types of entities namely users and items with their ratings. These conventional recommender systems do not take into account the learner characteristics in their recommendation process. Therefore, conventional recommendation techniques cannot make accurate and personalized recommendations in e-learning environment. In this paper, we propose a recommendation technique combining collaborative filtering and ontology to recommend personalized learning materials to online learners. Ontology is used to incorporate the learner characteristics into the recommendation process alongside the ratings while collaborate filtering predicts ratings and generate recommendations. Furthermore, ontological knowledge is used by the recommender system at the initial stages in the absence of ratings to alleviate the cold-start problem. Evaluation results show that our proposed recommendation technique outperforms collaborative filtering on its own in terms of personalization and recommendation accuracy.

I. Introduction

IN the last few years, recommender systems have been widely used as a solution towards addressing the information overload problem. Similarly, e-learning recommender systems solve this problem by automatically recommending suitable learning materials to learners based on their personalized learner preference and profile. They play an
important educational role in supporting online learners in elearning environments by providing personalized recommendations of learning materials for better achievement of the learning goals [1]. Examples of applications using
recommender systems include Amazon for recommending books; Netflix for recommending movies; and Coursera for recommending courses [2]. Researchers have been working on recommender systems using several techniques but with the same goal of filtering out irrelevant information from relevant information [3]. Adomavicius and Tuzhilin [4] points out that conventional recommendation techniques such as collaborative filtering and content-based deal with only two types of entities namely users and items and do not consider other additional information about the user and items in making recommendations. In the e-learning scenario, learners have different characteristics such as learning style, study level and skill level which can influence the learner preferences. As a result, conventional recommendation techniques cannot guarantee accurate recommendations to the learner due to their lack of incorporation of additional learner characteristics. To achieve better personalization and accuracy in e-learning recommendations, learner characteristics should be incorporated into the recommendation process.

In this paper, we propose an e-learning recommendation technique for recommending learning materials to online learners by combining collaborative filtering and ontology. Our goal is to improve personalization and accuracy of recommendations. Ontology is used to incorporate learner characteristics such as learning style, study level and skill level into the recommendation process. Our contribution in this work is two-fold:

1) First, we use ontology to incorporate learner characteristics such as learning style, study level, and skill level into the recommendation process. Additionally, ontological knowledge is used to alleviate cold-start problem at the initial stages of recommendation in the absence of ratings.
2) Secondly, the proposed e-learning recommender aggregates both ratings and ontological knowledge in computing similarities and generating recommendations for the learner.

The rest of this paper is structured as follows: Section II presents a review of related work. In Section III, we present the recommendation approach. In Section IV, we present

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the experiments and evaluation including discussion of results. Finally, conclusion and future work is discussed in Section V.

II. Related Work

A. Recommendation Techniques

Recommender systems are classified according to the technique used in recommendation. The main classifications are collaborative filtering, content-based, knowledge-based and hybrid filtering [5]-[7]. *Collaborative filtering (CF)* recommends to the target user items similar to those other users with similar preferences liked in the past [8], [9]. The underlying assumption is that if users had similar tastes in the past they will have similar tastes in the future [10]. CF is the most popular and commonly used recommendation approach. CF uses ratings of items in computing similarities of users or items and making recommendations. On the other hand, in *content-based (CB)* approach, the recommender recommends items that are similar in content features to the ones the target user liked in the past [11]. The similarity of items is calculated based on the features associated with the compared items [6]. In this approach, items are compared with items previously liked by the users and the best matched items are then recommended [12]. In *knowledge-based (KB)* technique, domain knowledge is used to make inference about the user needs and preferences [13]. In the context of e-learning, knowledge based technique aggregates the knowledge about the learner and learning materials to apply them in the recommendation process. *Ontology-based* recommenders are KB recommender systems that use ontology for knowledge representation. Like KB recommender systems, ontologybased recommenders do not experience most of the problems associated with conventional recommender systems such as cold-start and sparsity problem [14]. In contrast, *hybrid* recommender system combines two or more recommender systems for purposes of improving performance [6]. By combining different recommendation techniques in hybrid filtering, drawbacks of individual recommendation approaches can be alleviated.

B. Previous Related Studies

In the last few years, researchers of recommender systems have explored hybridization of recommendation techniques as an approach for developing effective recommender systems. Hybrid filtering entails combining two or more recommendation techniques to improve performance. Recent studies have shown that hybridizing recommendation techniques results in effectiveness of the recommender systems. For instance, Wei et al. [12] propose a recommendation technique that combines CF and deep learning to alleviate cold start problem for new items. Their recommendation approach showed significant improvement in alleviating cold-start problem. Da Silva et al. [15] propose an evolutionary approach for combining results of recommendation techniques based on CF while using genetic algorithm as a search algorithm. Their findings revealed improvement of performance. Takano and Li [16] on the other hand propose a recommender system for e-learning by utilizing a hybrid feedback method that extracts a user's preference and Web-browsing behavior while [17] propose a hybrid recommender system based on semantic web technologies, context-awareness and ontology for recommending movies. Their hybrid recommender systems showed improved performance. Similarly, Ting et al. [18] propose a personalized recommender system based on web log mining and weighted bipartite graph. Their experimental results indicate that combining web log mining and weighted bipartite graph is feasible and improves the recommendation results. Yu [19] used ontology to enhance CF recommendation based on community. Their results show that CF based on community achieves better performance than traditional method. Salehi et al. [20] propose a hybrid recommender system for learning materials based on genetic algorithm and multidimensional information model and equally achieved better performance as well as alleviation of cold-start and sparsity problem. Chen et al. [21] presented a hybrid recommendation algorithm for learning items by combining CF and sequential pattern mining. Experimental results of their hybrid recommender showed good performance. Zheng et al. [22] similarly propose a hybrid trust-based recommender system for online communities of practice. Their hybrid algorithm provided more accurate recommendations than other related CB algorithms. Moreover, several studies on recommender studies dedicated to e-learning have been carried out in the recent years. For instance, Salehi [23] propose a learning resource recommendation approach based on CF and BIDE. Their results show that the method outperforms previous algorithms on precision and recall measures. Drachsler et al. [24] carried out a comprehensive survey and analysis of recommender systems in Technology Enhanced Learning (TEL) for the period from 2000 – 2014. They investigated 82 e-learning recommender systems and clustered the recommenders according to their characteristics and contribution to the evolution of TEL recommender systems research field. Wan and Niu [25] propose a learner oriented recommendation approach based on mixed concept mapping and immune algorithm. Their approach shows high adaptability and efficiency in recommending e-learning materials. Capuano et al. [26] developed a system for recommending learning goals for learners using an adaptive learning system. Evaluation of their system provided good results. Dascalu et al. [27] propose an ontology-based educational recommender system for application in lifelong learning. Their educational recommender system proved that recommender systems can successfully support new learning paradigms. Rodríguez et al. [28] propose a hybrid recommender system for learning materials by combining CB, CF and KB recommendation techniques, and the tests of their system on a database with real data provided promising results. Wang et al. [29] propose a CF algorithm based on user clustering and slope one scheme. Their hybrid recommendation algorithm provided more accurate recommendations than previous algorithms. Cobos et al. [30] present a system that allows lecturers to define their best teaching strategies for use in the context of a specific class.

Their system namely "Recommendation System of Pedagogical Patterns" (RSPP) is a hybrid system which combines both CB and CF for recommendation and uses ontology for representation of pedagogical patterns. Dos Santos et al. [31] propose a method of clustering learning objects to improve their recommendations using CF algorithm. Their results show that clustering learning objects before using CF techniques improves recommendation performance.

Though a number of related studies have been carried out previously, our work differs from other studies in the sense that we combine both CF and ontology to improve personalization and accuracy. Furthermore, in our study, we use ontology to incorporate learner characteristics into the recommendation process as well as alleviate the cold-start problem. Other related studies used ontology to achieve different goals.

III. Our Recommendation Approach

The following model (Fig. 1) summarizes our recommendation approach. The main components of the model are the learner ontology, the learning object ontology, data preprocessing component, the recommendation engine and the personalized learner recommendations component. In this section, we explain in detail how the recommendation model works.

1) The Learner Profile: The learner profile component contains the information and preferences of the learner. Information in the learner profile is acquired both explicitly and implicitly. Information such as personal demographic data (name, gender, age, username, and password) as well as learner characteristics such as study level, skill level and learning style among others is stored in the learner ontology. The learner ontology personalizes the learner profile according to learner preferences and characteristics. The CF recommendation engine will make use of this learner ontology information alongside the learning object ontology information in computing predictions of ratings as well as generating recommendations for the active learner.
2) Learning Object Model: The learning resource ontology contains information about the learning materials. This component stores information about the learning materials such as formats which may be text, image, audio or video.
3) Data Preprocessing: The data from both the learner and learning object ontology is prepared and preprocessed into the right format for the recommendation engine at the data preprocessing component.
4) Recommendation engine: Once the data has been prepared and preprocessed, the recommendation engine computes the similarities and predictions of ratings of the target learner based on the learner and learning object ontology. Finally, the recommendation engine generates personalized recommendations for the target learner.

In computing the similarities of learning objects, we use the Adjusted Cosine Similarity (1). This is a commonly used measurement of similarity.

$$sim(i,j) = \frac{\sum (r_{l,i} - \bar{r}_l)(r_{l,j} - \bar{r}_l)}{\sqrt{\sum (r_{l,i} - \bar{r}_l)^2}\sqrt{\sum (r_{l,j} - \bar{r}_l)^2}} \quad (1)$$

where $r_{l,i}$ is the rating given to learning object *i* by learner *l*,

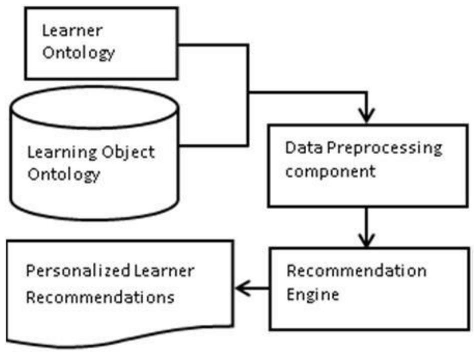

Fig. 1 The ontology-based recommendation model

The higher the value of similarity in the similarity matrix, the more similar (nearest neighbors) the learning objects are. Prediction of ratings is computed using the *k* most similar learning objects (*k* nearest neighbors) who have

[1] $_l$ is the mean rating of all the ratings provided by *l* based on ontology knowledge.

rated the learning object *i*. To compute the predictions of ratings, we use the following formula.

$$P_{l,i} = \frac{\sum_{t \in N} (Sim(i,t) \times r_{l,t})}{\sum_{t \in N} (|Sim(i,t)|)} \quad (2)$$

where N represents the learning object *i*'s similar learning object set, and $r_{l,t}$ is the rating given to learning object *t* by learner *l*.

A. Recommendation Algorithm

To generate the recommendations (top N) for the target learner based on the ontology and the predicted ratings (2), we use the following algorithm (Algorithm 1).

Algorithm 1: Recommendations ($I, l, o, r_{i,l}$)

Input

Set of learning objects

$LO = \{i_2, i_2, i_3, \ldots, i_n\}$

Ontology

O = {*learner, learning objects*}

Output

Predicted ratings & top *N* recommendations

Method

1: **for each** $i \in LO$, $o \in O$, **do**

2: Compute ontological similarity Sim(i_q, o, i) using (1)

end for each

3: Compute predicted ratings $P_{l,i}$ using (2) 4: Generate top *N* recommendation for target learner l_t.

IV. Experiments and Evaluation

Experiments were carried out to evaluate the accuracy and performance of the proposed ontology-based recommender system for recommending learning materials. In our study, ontology is used for personalization as well as representing knowledge about the learner and learning resources.

A. Experimental Setup

The experiment was carried out in a university where e-learning is used to support teaching and learning. A group of 300 students using e-learning to support their learning participated in the experiment. The teachers uploaded 450 learning materials to the e-learning portal for access by the students for their learning. The LMS allows the students to access the learning materials as well as rate them on a scale of 1 – 5 (1 – very irrelevant, 2 – fairly irrelevant, 3 – irrelevant, 4 – relevant, 5 – very relevant). The recommender system can then recommend the learning materials to students according to their personalized learner profile acquired through ratings simialrity and ontological knowledge.

B. Description of the Dataset

Our dataset is a real world dataset obtained from 300 students using e-learning in a university. The dataset was collected within a period of 3 months. The following table (Table I) illustrates the detailed description of the dataset and learning materials.

TABLE I
Description of Dataset

No. of students	No. of learning materials	No. of ratings
300	450	28,152

For the purpose of evaluating our proposed ontology-based algorithm, the dataset was split into two sub-datasets for training and testing set.

C. Experimental Results

Two experiments were carried out using the same dataset in order to evaluate the performance of our proposed algorithm. The first experiment was a combination of collaborative filtering and ontology (*Ontology-CF*). The second experiment was carried out using *CF* on its own. The results from the two experiments were then compared.

1. Accuracy Experiments

The accuracy of our proposed algorithm was evaluated using the mean absolute error (MAE) evaluation metric (3). MAE is used to evaluate the capability of the system to predict users' ratings accurately [32]. MAE computes the deviation between predicted ratings and actual ratings. The MAE for our proposed algorithm was computed for different sizes of neighborhoods.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |p_i - r_i| \quad (3)$$

Fig. 2 shows the results of prediction accuracy of our proposed algorithm (*Ontology-CF*) in comparison to the conventional *CF* algorithm. From Fig. 2, it is evident that *Ontology-CF* achieves more accurate predictions than the conventional *CF* algorithm. The two algorithms give the most accurate predictions when the number of neighbors is 30. Generally, at any number of neighborhoods, *Ontology-CF* outperforms the conventional *CF* algorithm.

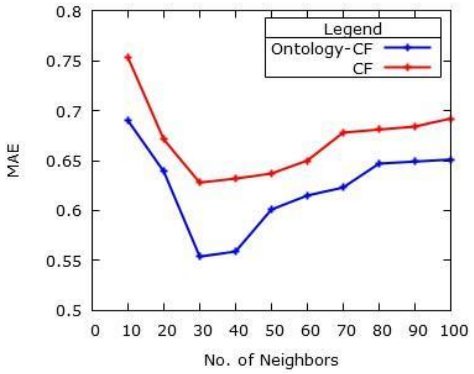

Fig. 2 Comparison of accuracy using MAE

2. Performance Measure

To evaluate the performance of our proposed ontologybased algorithm (*Ontology-CF*) in comparison to the conventional *CF* algorithm, we use F1 measure metric (4). F1 measure combines both precision and recall into a single value for ease of comparison and at the same time, giving equal weight to precision and recall [32].

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \quad (4)$$

Fig. 3 shows the comparison in performance in terms of F1 measure between *Ontology-CF* and the conventional *CF* algorithm using the F1 measure metric. It is evident from Fig. 3 that the performance of *Ontology-CF* which combines ontology and CF performs better the conventional CF algorithm on its own.

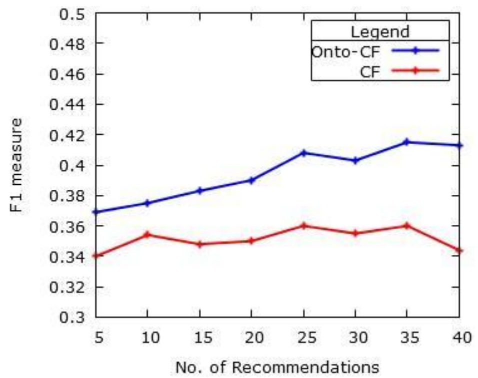

Fig. 3 Comparison of performance using F1 measure

D. Discussion

In order to evaluate the accuracy and performance of our proposed ontology-based approach that combined CF and ontology, similar experimental evaluations was also conducted for CF algorithm on its own using the same dataset and the results compared. The experimental results have revealed that combining CF and ontology improves performance and prediction accuracy of a recommender system. In both the two experiments, measuring accuracy of predictions using MAE (Fig. 2) and measuring performance of the algorithm using F1 metrics (Fig. 3), *Ontology-CF* outperformed the conventional *CF* algorithm on its own. The benefit of the proposed ontology-based approach is the incorporation of additional learner characteristics such as learning style, study level as well as skills level into the recommendation process using the ontology domain knowledge. Furthermore, ontology helps alleviate cold-start problem during the early stages of recommendation in the absence of sufficient and overlapping ratings.

V. CONCLUSION AND FUTURE WORK

E-learning recommender systems play an important role in alleviating information overload problem arising from explosion of online learning resources on the internet. Furthermore, it assists the learners to find useful learning materials from a large space of possible options. However, conventional recommendation techniques such as CF and CB face unique challenges in dealing with learners with different characteristics such as learning style, study level and skills level. In this paper, we propose a recommendation technique combining CF and ontology for recommending personalized learning materials to online learners taking into account the learner characteristics. In our approach, ontology is used to incorporate learner characteristics into the recommendation process. Experimental results show that our proposed ontology-based recommendation approach outperforms CF algorithm on its own. Furthermore, our recommendation technique alleviates cold-start problem at the initial stages of recommendation by using ontological knowledge in the absence of sufficient ratings.

REFERENCES

[1] H. Drachsler, H. G. K. Hummel, and R. Koper, "Identifying the goal, user model and conditions of recommender systems for formal and informal learning," *J. Digit. Inf.*, vol. 10, no. 2, pp. 1–17, 2009.

[2] J. A. Konstan, J. D. Walker, D. C. Brooks, K. Brown, and M. D. Ekstrand, "Teaching Recommender Systems at Large Scale: Evaluation and Lessons Learned from a Hybrid MOOC," *ACM Trans. Comput. Interact.*, vol. 22, no. 2, pp. 10–23, 2015.

[3] S. T. Cheng, C. L. Chou, and G. J. Horng, "The adaptive ontology-based personalized recommender system", *Wireless Personal Communications*, vol. 72, no. 4, pp. 1801–1826, 2013.

[4] G. Adomavicius and A. Tuzhilin,"Context-Aware recommender Systems", In F. Ricci, et al. (Ed.), *Recommender Systems Handbook,* pp. 217–253, 2011.

[5] N. Manouselis, H. Drachsler, R. Vuorikari, H. Hummel, and R. Koper, "Recommender Systems in Technology Enhanced

Learning," in *Recommender Systems Handbook*, Springer US, 2011, pp. 387–415.

[6] R. Burke, "Hybrid web recommender systems," in *The adaptive web*, 2007, pp. 377–408.

[7] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, 2005.

[8] J. A. Rodrigues Nt, L. F. C. Tomaz, J. M. de Souza, and G. Xexéo, "Bringing knowledge into recommender systems," *J. Syst. Softw.*, vol. 86, no. 7, pp. 1751–1758, 2013.

[9] C. He, D. Parra, and K. Verbert, "Interactive recommender systems : A survey of the state of the art and future research challenges and opportunities," *Expert Syst. Appl.*, vol. 56, pp. 9–27, 2016.

[10] D. Jannach, M. Zanker, A. Felferning, G. Friedrich, Recommender Systems: An Introduction, Cambridge University Press, 2010.

[11] M. J. Pazzani and D. Billsus, "Content-based recommendation systems," *Adapt. web*, pp. 325–341, 2007.

[12] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, "Collaborative filtering and deep learning based recommendation system for cold start items," *Expert Syst. Appl.*, vol. 69, pp. 29–39, 2017.

[13] S. Bouraga, I. Jureta, S. Faulkner, and C. Herssens, "Knowledge-Based Recommendation Systems:," *Int. J. Intell. Inf. Technol.*, vol. 10, no. 2, pp. 1–19, 2014.

[14] T. Ruotsalo, "Methods and Applications for Ontology-Based Recommender Systems,", Ph.D. thesis, 2010.

[15] E. Q. Da Silva, C. G. Camilo-Junior, L. M. L. Pascoal, and T. C. Rosa, "An evolutionary approach for combining results of recommender systems techniques based on collaborative filtering," *Expert Syst. Appl.*, vol. 53, pp. 204–218, 2016.

[16] K. Takano, K.F. Li, An adaptive e-learning recommender based on user's web-browsing behavior, in: Proc. - Int. Conf. P2P, Parallel, Grid, Cloud Internet Comput. 3PGCIC 2010, 2010: pp. 123–131.

[17] L. O. Colombo-Mendoza, R. Valencia-García, A. Rodríguez-González, G. Alor-Hernández, and J. J. Samper-Zapater, "RecomMetz: A contextaware knowledge-based mobile recommender system for movie showtimes," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1202–1222, 2015.

[18] Y. Ting, C. Yan, and M. Xiang-wei, "Personalized Recommendation System Based on Web Log Mining and Weighted Bipartite Graph," *2013 Int. Conf. Comput. Inf. Sci.*, pp. 587–590, 2013.

[19] L. Yu, "Using ontology to enhance collaborative recommendation based on community," *Proc. - 9th Int. Conf. Web-Age Inf. Manag. WAIM 2008*, pp. 45–49, 2008.

[20] M. Salehi, "Hybrid attribute-based recommender system for learning material using genetic algorithm and a multidimensional information model," *Egypt. Informatics J.*, vol. 14, no. 1, pp. 67–78, 2013.

[21] W. Chen, Z. Niu, X. Zhao, and Y. Li, "A hybrid recommendation algorithm adapted in e-learning environments," *World Wide Web*, vol. 17, no. 2, pp. 271–284, 2014.

[22] X. L. Zheng, C. C. Chen, J. L. Hung, W. He, F. X. Hong, and Z. Lin, "A Hybrid Trust-Based Recommender System for Online Communities of Practice," *IEEE Trans. Learn. Technol.*, vol. 8, no. 4, pp. 345–356, 2015.

[23] M. Salehi, "Application of implicit and explicit attribute based collaborative filtering and BIDE for learning resource recommendation," *Data Knowl. Eng.*, vol. 87, pp. 130–145, 2013.

[24] H. Drachsler, K. Verbert, O. C. Santos, and N. Manouselis, "Panorama of Recommender Systems to Support Learning," in *Recommender Systems Handbook*, F. Ricci, L. Rokach, and B. Shapira, Eds. Boston, MA: Springer US, 2015, pp. 1–37.

[25] S. Wan and Z. Niu, "A learner oriented learning recommendation approach based on mixed concept mapping and immune algorithm," *Knowledge-Based Syst.*, vol. 103, pp. 28–40, 2015.

[26] N. Capuano, M. Gaeta, P. Ritrovato, and S. Salerno, "Elicitation of latent learning needs through learning goals recommendation," *Comput. Human Behav.*, vol. 30, pp. 663–673, 2014.

[27] M.-I. Dascalu, C.-N. Bodea, M. N. Mihailescu, E. A. Tanase, and P. O. de Pablos, "Educational recommender systems and their application in lifelong learning," *Behav. Inf. Technol.*, vol. 35, no. 4, pp. 290–297, 2016.

[28] P. Rodríguez, S. Heras, J. Palanca, N. Duque, and V. Julián, "Argumentation-based hybrid recommender system for recommending learning objects," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2016, vol. 9571, pp. 234–248.

[29] J. Wang, K. Lin, and J. Li, "A collaborative filtering recommendation algorithm based on user clustering and Slope One scheme," in *Proceedings of the 8th International Conference on Computer Science and Education, ICCSE 2013*, 2013, pp. 1473–1476.

[30] C. Cobos, O. Rodriguez, J. Rivera, J. Betancourt, M. Mendoza, E. León, E. Herrera-Viedma, A hybrid system of pedagogical pattern recommendations based on singular value decomposition and variable data attributes, Inf. Process. Manag. 49 (2013) 607–625.

[31] H. L. dos Santos, C. Cechinel, R. M. Araujo, and M. Á. Sicilia, "Clustering learning objects for improving their recommendation via collaborative filtering algorithms," in *Communications in Computer and Information Science*, vol. 544, 2015, pp. 183–194.

[32] G. Shani and A. Gunawardana, "Evaluating recommendation systems," *Recomm. Syst. Handb.*, pp. 257–298, 2011.