A Personalized E-Learning Recommender System Using the Concept of Fuzzy Tree Matching

G. Poorni
PG Student
SNS College of Engineering
Coimbatore

K. Balaji
Assistant Professor
SNS College of Engineering
Coimbatore

C. DeepthiNivetha
PG Student
SNS College of Engineering
Coimbatore

Abstract— **The rapid development of e-learning systems provides learners with large opportunities to access learning activities through online. This greatly supports and enhances learning practices of users. However the issues related to e-learning systems reduces the success of its application. This is because of many learning activities such as various learning materials, subjects, and learning resources that are emerging in this online world which makes an e-learning system difficult. The individual learners find it difficult to select optimized activities for their particular situations/requirements/query, because there is no personalized service belonging to that particular user. Recommender systems that aim in providing personalized environment for studying materials can be used to solve those issues in e-learning system. However, e-learning systems need to be able to handle certain special requirements or issues. They are 1) learning activities and learners' profiles that are often presented in tree structures; 2) learning activities contain more uncertain categories which additionally contain unclear and uncertain data 3) there are pedagogical issues, such as the precedence order for a particular user cannot be given separately for each user. To deal with these three requirements, this survey proposes two techniques called a *fuzzy tree-structured learning activity model* and a *learner profile model.* These two methods comprehensively explain the difficult learning activities and learner profiles. In these two models, fuzzy category trees and related preference orders are presented to know the semantic relations between learning activities or learner requirements of each individual learner.**

Index Terms—**E-learning, fuzzy sets, knowledge-based recommendation, recommender systems, tree matching.**

I. INTRODUCTION

Due to the advancement of web-based information and communication technologies E - Learning systems are becoming increasingly popular in educational departments. The rapidgrowth of e-learning systems has changed current learning behavior and presents a new framework to students. This greatly supports and enhances learning practices in online.

Both the learning activities and learner profiles have difficult explanation and parts. A learning activity contains several features of information, such as the content description, lecture information, prerequisite information and so on. Also a learner profile contains the learner's background information, learning goals, priorknowledge, learner characteristics, and so on. Each features of information can be described in detail with several sub-features. Thus, the data in the e-learning environment presents a hierarchical (tree) structure.

In a real life situation learning activities and learner profiles always contain uncertain data and uncertain value. One learning activity may be under several parts with different types of degrees. For example, the subject Appleis mainly explains the fruit details but also it describes the Apple computer, company or phone. Each learner's requirements are usually represented in linguistic terms such as "heavily required item" or "very important item". Fuzzy set techniques are adapted to deal with these undecided category data [13-15] and linguistic terms [16, 17].The fuzzy trees should be represented by the tree-structured learning activities and learner profiles.

The pedagogical issues also be considered in the learning activity recommendation system. Some learning activities require courses. For example, studying the subject called *Data Mining* requires the pre-knowledge in database and algorithms. The database concept included with the

ISSN: 2278 – 1323

subject called database management system and algorithm should include with the subject called Data Structure. Additionally, learners always want to learn something new or with higher rating details or advanced details or recently uploaded details. So these types of precedence relations among learning activities must be considered in E-Learning. It is not easy to make difference between two learning activities just from their IDs or names, because learning activities provided from different professors may have different names, such as one subject having the preference in word documentand another subject may have the preference in *PPT*, but the same or similar content.

To deal with the above special requirements in e-learning systems, this study proposes a fuzzy tree matching-based hybrid recommendation system. Based on our previous research on the fuzzy preference tree-based recommender system [18], a fuzzy tree-structured data model is proposed to describe individual learner profiles and learning activities. To handle these uncertain issues a fuzzy set techniques are applied. As the preference measure is the core technique in this recommendation approach and the relevant fuzzy tree similarity measures are developed. The recommendation approach should take advantage in both the knowledge-based and collaborative filtering-based recommendation approaches, and considers both the semantic and collaborative filtering similarities between learners. The learning activity precedence relations are also handled through analyzing the learning sequences, learner's behaviorand modeling the prerequisite learning activities.

The study presented in this paper is first introduces a fuzzy tree-structured data model to model learning activities and learner profiles. It extends the contributions to both theoretical and practical issues in the fields of e-learning and recommender systems. At the theoretical level, fuzzy tree-structured data models and related fuzzy tree similarity measures are developed. At the practical level, a fuzzy tree matching-based hybrid recommendation approach for e-learning systems is developed.

II. EXISTING SYSTEM

Due to the emergence of various kinds of learning activities in the e-learning environment, learners find it difficult to select the learning activities based on the preference order is difficult. In the big data area the information overload problem is increasingly arise. It is very important for an e-learning system to automatically generate personalized recommendations based on their preference to guide a learner's activities for each individual user [2], and as demonstrated by Lu [3]. Personalized recommendations are necessary in making a e-learning recommender system. The motivation of this study is to develop a recommendation approach that support learners in the selection of the most appropriate learning materials based in their preference in an e-learning environment.

E-learning systems can be divided into two types based on their application environments they are a formal setting and an informal setting [4]. A formal setting e-learning system includes learning materials from educational institutions (e.g. universities, schools) within a curriculum or syllabus framework. An informal setting is described in the literature is considered a recommendation framework who having their own learning pace and path. The learning process should depend to a large extent also on individual preferences or choices, and is often self-directed [6]. Different from the formal setting, the informal setting may provide numerous learning activities to different providers, where learners are also from different backgrounds and having different preferences. There is not usually a curriculum or syllabus framework. Therefore, it is very difficult for students to choose proper learning activities in the informal setting. This can cause high materials drop-out rates and low completion rates [7, 8]. This study focuses on supporting learners in the informal setting system through the development of a new personalized recommendation approach.

Most recommendation systems are designed either based on content-based filtering (CB) or collaborative filtering (CF).CB filtering techniques suggest items similar to the ones that each user liked in the past, taking into evaluate the object content analysis that the user has evaluated in the past [7].A collaborative filtering system recommends items that are liked by other users with similar interests i.e. materials with high rating order. Both types of systems have inherent strengths and weaknesses.

A. Content-Based Filtering

This strategy uses the features of items for recommendation. Case-based reasoning (CBR) or data mining techniques support those features may be used by for recommendation. CBR assumes that if a user likes a certain item or certain preference in particular category means she/he will probably also like similar items or similar preference in another category. This approach recommends new but similar items. However, data mining techniques recommend items based on the matching of their attributes to the user profile. CBR mechanisms have to evaluate all the cases in the case materials and retrieve those most similar case(s), which makes their efficiency strongly. [8].

The performances of CBR mechanisms are closely related to the preference representation and preference indexing approach, so their performances are unstable and cannot be

ISSN: 2278 – 1323

guaranteed and change over time at the time of searching. Semantic and multi criteria recommender systems also consider attributes of items. Instead of using syntactic matching technique Semantic recommender systems use inference techniques borrowed from the Semantic Web. This approach uses preferences about the semantics of items and user preferences to discover complex associations between them [9]. Rating systems can model a user’s utility for a given item with the user’s ratings for each individual criterion [10]. Since more people will wait in a searching area and usually they don’t want not spend more time in a searching area. The rate based on each individual criterion in multi criteria recommenders system is introduced. Khribi et al. [11] used learners’ recent navigation histories, similarities, and dissimilarities among the contents of the learning resources for online automatic recommendations.

B. Collaborative Filtering

One of the important and useful strategies in recommender system is a Collaborative filtering [12]. CF approaches used in e-learning environments focus on the preference among users having similar interests and can be divided into three categories. They are Neighbor based, model based and collaborative based. The first approach called the Neighbor-based CF finds similar items or users based on rating information and predict ratings using the weighted average of similar users or items. The second approach called Model-based techniques predicts the ratings of a user by learning from complex patterns based on the training data (rating matrix). The third approach called the demographics approach, users with similar attributes are matched; and then, this method recommends items that are preferred by similar users. The collaborative e-learning field is strongly growing [13], [14], converting this area into an important provider of learning materials.

The proposed system collects user preference information from learning resources and then propagates them into the form of word-of-mouth recommendations about the qualities of the resources. Lemire et al. [16] proposed a rule-applying collaborative filtering (RACOFI) composer system. This system combines two recommendation approaches by combining a collaborative filtering engine with an inference rule engine. The collaborative filtering engine works with ratings that users provide for learning resources and the inference rule engine is mining association rules between the learning resources and using them for recommendation. The query sharing and interactive assignments (QSIA) for learning resources sharing, assessing, preferences and recommendation were developed by Rafaeli et al. [17].

C. Learning styles

Many researchers have long days tried to relate personality profile information of learners’ to teaching and learning style. Cooper and Miller [1], report the level of learning style/teaching style is related to academic performance and to student evaluations of the course and instructor. Furthermore, Jungian based psychologists add the people’s personal preferences in the learning, as well as take responsibility for the self-direction [2] and discipline [3]. So it is need identify a student's individual learning style and then adapt instruction toward that person's strengths and preferences. In fact, adjusting instruction to accommodate the learning styles of different types of students can increase both the students’ achievement and their enjoyment of learning.

III. PROPOSED SYSTEM

A recommender system [9] is one of the most popular applications of personalization recommendation techniques. It is proposed and applied in the e-commerce area for product purchase. Recommender systems can be considered as software programs that attempt to recommend items to users. This could be done by predicting a user’s preference in a given item based on various types of information, including particulars about items, users and the interactions between users and items. The basic idea of recommender systems is that similar users like similar items. Therefore, the preference measure for users or items is good in the application of recommender systems, since it is impossible to have same trees for all users in practice. For this purpose a fuzzy tree matching method is carefully discussed. A fuzzy tree matching-based hybrid learning activity recommendation approach is then developed. This approach create hybrid approach by taking advantage of both the knowledge-based and collaborative filtering-based recommendation approaches, and considers both the semantic and collaborative filtering similarities between learners. Finally, an e-learning recommender system prototype is well designed and developed based on the recommendation approach. The proposed recommendation approach provides good accuracy performance of the proposed approach. A complete study about learning activity recommendation further demonstrates the effectiveness of the fuzzy tree matching-based personalized e-learning recommender system in practice.

IV. ADVANTAGES OF PROPOSED SYSTEM

- Recommender systems have been widely used in various web-based applications in e-commerce [10], e-business [11], e-tourism [4], and e-government [12].

ISSN: 2278 – 1323

- The main reason is that e-learning activities have special features and demands that are different to commercial products [1] in e-commerce and e-business.
- Preference measures improve the quality of learning material recommendations.
- The proposed e-learning recommender system will be further compared with existing recommender systems which don't use fuzzy tree-structure data models.
- The features and characteristics of groups of learners will be considered and the methods to identify learner groups and make group recommendations will be exploited to improve the recommendation performance.

V. ARCHITECTURE DIAGRAM

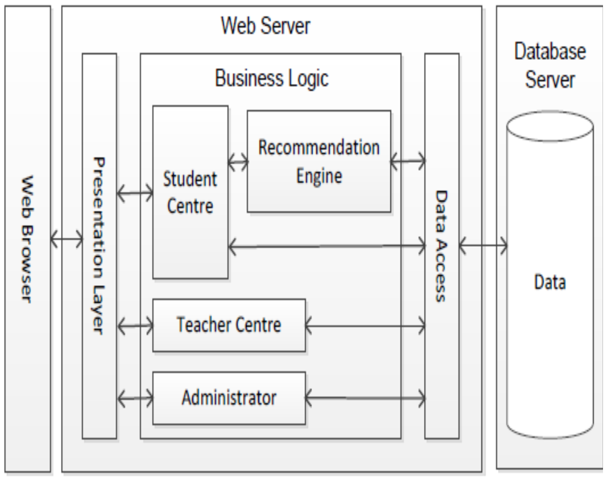

Figure 1:-Architecture Diagram of Recommender Approach

The three types of users should be used in the e-learning recommender system administrators, teachers and students. The roles of the users are described as follows. The role of the system administrator is to maintain the framework of the learning activity category and the career list of learners, which are used to support the whole operation of the system. The teachers are responsible for maintaining the learning activities. They input is the learning activities with detailed descriptions into the system. When a learning activity is input, its categories and the related membership degrees are specified by the teacher. During the operation of the system the architecture of the e-learning activity recommender system is depicted in Figure 1. The e-learning recommender system has a standard multi-tier architecture, which includes web browser, web server, and a database server. The main components of the system are described as follows. The database stores all the data about the system which includes the data of user profiles, learning activities, learning activity categories, user ratings, and so on. The application in the web server contains three layers: the presentation layer, business logic layer and data access layer. The first layer called the presentation layer is responsible for creating the requested web pages and handling the user interface logic and events for the three kinds of users. The business logic layer realizes the business services and the core recommendation algorithm. It contains four main parts: the student centre, the teacher centre, the administrator centre, and the recommendation engine. The student centre collects the user's profile and requirements, tracks the user's learning behavior, and provides the search and recommendations of learning activities. The recommendation engine implements the proposed recommendation approach and generates recommendations for student users. Teachers input and manage the learning activities in the teacher centre. The administrator centre is used by administrators to manage the users and common data. The data access layer deals with the data operations of the database.

VI. CONCLUSION

This paper has outlined the development of a fuzzy tree matching-based hybrid recommendation approach for an e-learning system. This approach develops both a fuzzy tree-structured learning activity model and a fuzzy tree-structured learner profile model. A fuzzy tree similarity measure is presented to evaluate the similarity between learning activities or learners. In the fuzzy tree-structured learning activity model, a fuzzy category tree is defined to specify the categories that each learning activity roughly belongs to, and the fuzzy category similarity measure is developed to evaluate the semantic similarity between learning activities. The precedence relations between learning activities are also handled through analyzing the learning sequences and modeling the prerequisite learning activities. In the fuzzy tree-structured learner profile model, a fuzzy required category tree is defined for learners to express their requirements. The recommendation approach takes advantage of both the CF and KB recommendation approach.

VII. REFERENCES

[1] MojtabaSalehi, Isa NakhaiKamalabadi, and Mohammed B. GhaznaviGhoushchi, "An effective Recommendation Framework for Personal Learning Environments using a Learner Preference Tree and a GA," IEEE Transactions on learning technologies, vol. 6, No. 4,2013

[2] M. Salehi, M. Pourzaferani, and S.A. Razavi, "Hybrid Attribute-Based Recommender System for Learning Material Using Genetic Algorithm and a

ISSN: 2278 – 1323

Multidimensional Information Model," Egyptian Informatics J., vol. 14, no. 1, pp. 67-78, 2013.
[3] Yi Li,JianWang,LinMei,"A Personalized Recommendation System in E-Learning Environment based on Semantic Analysis", Information Science and Service Science and Data Mining (ISSDM), 6th International Conference on New Trends 2012.
[4] J. kay, "Lifelong Learner Modeling for Lifelong Personalized Pervasive Learning," IEEE Trans. Learning Technology, vol. 1, no. 4, pp. 215-228, Oct. 2008.
[5] V. Kumar, J. Nesbit, and K. Han, "Rating Learning Object Quality with Distributed Bayesian Belief Networks: The Why and the How," Proc. Fifth IEEE Int'l Conf. Advanced Learning Technologies (ICALT '05), pp. 685-687, 2005.
[6] N. Manouselis, H. Drachsler, R. Vuorikari, H. Hummel, and R. Koper, "Recommender Systems in Technology Enhanced Learning," Recommender Systems Handbook, P.B. Kantor, F. Ricci, L. Rokach, and B. Shapira, eds., pp. 387-415, Springer, 2011.
[7] P. Lops, M. de Gemmis, and G. Semeraro, "Content-Based Recommender Systems: State of the Art and Trends," Recommender Systems Handbook, pp. 73-105, Springer, 2011.
[8] P.-C. Chang and C.-Y. Lai, "A Hybrid System Knowledge-Based Systems, Combining Self-Organizing Maps with Case-Based Reasoning in Wholesaler's New-Release Book Forecasting," Expert Systems with Applications, vol. 29, no. 1, pp. 183-192, 2005.
[9] Y. Blanco-Fernandez et al., "A Flexible Semantic Inference Methodology to Reason about User Preferences in Knowledge- Based Recommender Systems," Knowledge-Based Systems, vol. 21, no. 4, pp. 305-320, 2008.
[10] G. Adomavicius, N. Manouselis, and Y. Kwon, "Multi-Criteria Recommender Systems," Recommender Systems Handbook, pp. 769- 803, Springer, 2011.
[11] M.K. Khribi, M. Jemni, and O. Nasraoui, "Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval," Educational Technology and Soc., vol. 12, no. 4, pp. 30-42, 2009.
[12] J. Bobadilla, F. Serradilla, and J. Bernal, "A New Collaborative Filtering Metric That Improves the Behavior of Recommender Systems," Knowledge Based System, vol. 23, no. 6, pp. 520-528, 2010.
[13] E. Garcı´a, C. Romero, S. Ventura, and C. Castro, "An Architecture for Making Recommendations to Courseware Authors Using Association Rule Mining and Collaborative Filtering," User Modeling and User-Adapted Interaction, vol. 19, no. 1, pp. 99-132, 2009.
[14] E. Garcı´a, C. Romero, S. Ventura, and C.D. Castroa, "A Collaborative Educational Association Rule Mining Tool," Internet and Higher Education, vol. 14, no. 2, pp. 77-88, 2011.
[15] A. Walker, M. Recker, K. Lawless, and D. Wiley, "Collaborative Information Filtering: A Review and an Educational Application," Int'l J. Artificial Intelligence and Education, vol. 14, pp. 1-26, 2004.
[16] D. Lemire, H. Boley, S. McGrath, and M. Ball, "Collaborative Filtering and Inference Rules for Context-Aware Learning Object Recommendation," Int'l J. Interactive Technology and Smart Education, vol. 2, no. 3, pp. 179-188, 2005.
[17] S. Rafaeli, Y. Dan-Gur, and M. Barak, "Social Recommender Systems: Recommendations in Support of E-Learning," Int'l J. Distance Education Technologies, vol. 3, no. 2, pp. 29-45, 2005.
[18] N. Manouselis, R. Vuorikari, and F. Van Assche, "Simulated Analysis of MAUT Collaborative Filtering for Learning Object Recommendation," Proc. First Workshop Social Information Retrieval for Technology Enhanced Learning, pp. 27-35, 2007.
[19] W. Chen, Z. Niu, X. Zhao, and Y. Li, "A Hybrid Recommendation Algorithm Adapted in E-Learning Environments," World Wide Web, Sept. 2012, doi:10.1007/s11280-012-0187-z.
[20] L. Yu, Q. Li, H. Xie, and Y. Cai, "Exploring Folksonomy and Cooking Procedures to Boost Cooking Recipe Recommendation," Proc. 13th Asia-Pacific Web Conf. Web Technologies and Applications (APWeb '11), pp. 119-130, 2011.
[21] C. Romero, S. Ventura, A. Zafra, and P. de Bra, "Applying Web Usage Mining for Personalizing Hyperlinks in Web-Based Adaptive Educational Systems," Computers and Education, vol. 53, no. 3, pp. 828-840, 2009.

ISSN: 2278 – 1323