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E-Learning Recommendation Systems – A Survey

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Abstract:- Recommendation systems are the agents that help the learner to identify a subset of suitable learning resources from a variety of choices. Recommendation Systems is a widely explored field since the last decade. Much of the work is going on in recommendation systems that are based on the evaluation of resources and users' data. In this paper we concentrate on E-Learning Recommendation Systems. An E-learning recommendation system is a derivative field of recommendation systems in which the resources are specifically the available bulk of learning material either online or offline. The aim of E-learning software is to select the useful piece of material which the learner actually requires to study. Our aim in this paper is to study various recommendation techniques with their virtues and shortcomings. Further we will discuss E-learning recommendation systems with a brief review of some major milestones in the field of E-Learning.

Keywords:- Recommendation systems, E-learning,E-learning Recommendation Systems, Various techniques of recommendation systems, learner's performance

I. INTRODUCTION

History of Recommendation Systems goes back since 1990's with the concepts collaborative filtering [1].The software GroupLens was used for collaborative filtering in netnews.This helped people to search for the relevant news article that will interest them amongst huge number of articles residing on net. Ringo is a personalized recommendation system based on similarities between the interest profile of that user and those of other users [2]. Another such system is mentioned in [3], PloyLens.This system is made for recommending movies for a group of users. The availability of immensely vast choices for resources of interest (movies, music, study material and many other commodities of e-commerce) is accountable to the same extent to the users' convenience as it is for their bewilderment. It takes lots of time and knowledge for judging and selecting the best and the most suitable resource. But most of the time the user ends up in confusion and opt for the resource that does not qualify his/her requirements.

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II. RECOMMENDATION SYSTEMS

Recommendation systems proved to be the eminent solution of the above discussed problem. The research area has become a popular zone for researchers as it contains a lot of practical scope. The major problem that an internet user faces these days is availability of resources in bulk. The dilemma arises when the learner/user gets mystified what resources to be selected amongst the entire range available. Recommendation systems help the user/learner to select the most appropriate subset of resources that may interest the user and valuable for him/her. Another reason to forethought is that the field can be expanded to a much wider area of application. Successful efforts have already been made to apply recommendation systems in selecting movies for e.g. MovieLens [4], Music CDs [5] [6], news articles [1], learning material recommendations [7], [8] and adaptive learning systems [9] and many more.

The predictions in recommendation systems are based on the data available with the recommendation system. This data may include exclusive information of the user profile like demographic information [10], user's prior likes/dislike information [11], ranking given by user to various resources [1], [2], [4], information about the resource's features that are preferred by the user in past [12].Apart from the above mentioned the information may be a amalgam of one or more of these categories [13].

III. POPULAR APPROACHES FOR RECOMMENDATION SYSTEMS

According to the information chosen amongst the above mentioned categories following techniques have been successfully applied for prediction in recommendation systems:

A. Collaborative Filtering: This is the most widely used and implemented technique in recommendation systems. The ratings given to a particular resource by the user are aggregated and compared with the ratings given by other users. The similarity measure is calculated between the users. Users who emerge as similar i.e. with high similarity measure can predict the ratings for one another. If the user has not rated the resource yet means he has not used it in past. If the user similar to him liked the resource/item then it can be concluded that the resource may be of some value to the target user. Though this technique faces many problems when the number of available users or resource ratings is insufficient.

B. Content-based Filtering: If user has preferred some items in past having some distinct features that are liked by the user then item with similar features are recommended to the user. In contrast to the collaborative filtering where recommendation are made by finding similarity between users, here in content-based filtering it is done by finding similarities between items. This requires the number of features of resource to be larger to make a better prediction.

C. Hybrid Filtering: Apart from the above mentioned techniques there are several other techniques used for recommendation systems Knowledge – based techniques, Demographic information based etc. To further improve the performance of the RSs all these techniques can be combines used making it hybrid [13].

IV. E-LEARNING RECOMMENDATION SYSTEMS : A SURVEY

In reference to E-Learning, Recommendation system act as prominent tool to recommend the best suited and useful piece of learning material for the learner. Every so often learner faces the problem of spending so much of time in searching the desired material but most often end up in irrelevant or not so important learning material. High redundancy of the learning material, lack of detail and many other problems are faced by the learner[14].Though a significant number of RSs are successfully used in today's scenario for recommending items in a variety of domains but the application for RSs in E-Learning requires special thoughtfulness. There are several particularities to be considered regarding what kind of learning is desired, e.g. learning a new concept or reinforce existing knowledge may require different type of learning resources.[15]. Taking into account the necessity of these recommendation systems we are discussing some important work done in the field. In [15], Nikos Manouselis with his colleagues mentioned two settings of learning:

A. Formal setting for learning – It offers from educational institutions(e.g. universities, schools) within a curriculum or syllabus framework , and is characterised and highly structured, leading to a specific accreditation and involving domain experts to guarantee quality .

B. An informal setting – a learning phase of so called lifelong learners according to their own preferences and choices.

One of the recommendation criteria can be on the basis of the above mentioned settings or the context of the learner. This paper also deals with the related work in TEL(Technology Enhanced Learning) like – *AEH: Adaptive Educational Hypermedia* (web based systems that adapt to the behaviour of user including goals, tasks, interests and other characteristics) and Learning *Networks* : A category of systems that runs on the contribution of the users. The research material is extracted to enhance the knowledge. These systems are highly flexible. Each user is allowed to add, edit, delete or evaluate learning resources at any time.

In [16], Katrien Verbert and colleagues discussed the importance of the contextual information in the recommendation process. The contextual information refers to the information regarding the learner's learning environment. It can be the location of the user like cafeteria where the noise level is high, finding of peer learners who are working on the similar learning activities as the use so that the learning process can be collaborated and the last one is the kind of device that the user is using so that the study material in the appropriate form can be provided to the user. The other important dimensions for contextual information are: Computing environment, location, time, physical conditions, activity, resources, social relations and the user himself. Second, is an in-depth analysis of context-aware recommendation systems that have been deployed for educational purposes. Third are the future challenges for the development and validation of context-aware recommendation systems for learning. Results of the survey indicate that there has been much advancement in the development of context-aware TEL recommenders in recent years.

In [17], Nuanwan Soonthornphisaj and colleagues introduce the concept of global e-learning using web service. The idea is to extend the e-learning system from local learners to global learners. Each e-learning website administrator must register to be the member of the recommender system web service (a database of materials in order to do the collaboration filtering process. The benefit includes availability of wide variety of material for the learner across the local boundaries.

In [18] Jie Lu proposed a framework of a personalized learning recommender system (PLRS), which aims to help students find learning materials they would actually require to study. The significance of lies in the fact that student's individual needs are fulfilled aiming to improve not only the career but personal life as well. The proposed framework by Jie Lu can easily be applied to online teaching and learning sites. The information required for PLRS is learning material database and student's personal information. The students' learning requirement can be obtained and matched with the existing learning material by using the computational analysis model. The proposed PLRS consists of four components: Getting students information, Student requirement identification, Learning material matching analysis and learning recommendation generation. The PLRS has several advantages including like handling sparsity problem, preventing false positive errors and providing more accuracy in recommending the appropriate learning material.

Khairil Imran Gauth and Nor Aniza Abdulla in [19] illuminate a vital aspect of measuring the performance on e-learning recommendation systems. Most of the research work on E-learning recommendation systems focussed on the applying different concept to make smart e-learning system however not much research has been done to measure the learning outcomes of the learners when they use e-learning with a recommender system. This study provides empirical evidence which clearly demonstrate the value of user rating as a collaboration tool in helping other learners by suggesting suitable items. The system promotes collaboration of learners to help each other during the learning process. The "good learner rating" feature is used in which the learners who studied the learning material and obtained more than 80% in the post-test can give the rating to that learning material. Learning outcomes of several groups of students who used different e-learning recommendation systems is compared. The outcome revealed that inclusion of good learners' ratings in the content-based RS significantly improves the performance of the students. Here we can get a good estimate of the knowledge gained by the student.

V. CONCLUSION AND FUTURE WORK

This study provides an introduction to recommendation systems and the specialized field of E-learning Recommendation System. Emphasis was given on the prominent approaches applied in this area till now. A significant work has been done on E-Learning recommendation systems but still it a naïve field in which a lot has to be contributed in future. Despite the progress made in the area there lies a lot of scope for improvement. Development of E-learning Recommendation System using trust and other aspect can be one of the researches for future. The emphasis will be on the improved performance of the learners.

REFERENCES

[1]. Resnick, P., N. Iakovou, M. Sushak, P. Bergstrom, and J. Riedl. GroupLens: An openarchitecture for collaborative filtering of netnews. In Proceedings of the 1994 ComputerCooperative Work Conference, 1994.

[2]. Shardanand, U. and P. Maes. Social information filtering: Algorithms for automating ‘word of mouth’. In Proc. of the Conf. on Human Factors in Computing Systems, 1995.

[3]. Mark O’Connor, Dan Cosley, Joseph A. Konstan, and John Riedl : PolyLens: A Recommender System for Groups of Users, ECSCW 2001,Proceedings of the Seventh European Conference on Computer Supported Cooperative Work 16–20 September 2001, Bonn, Germany 2002, pp 199-218.

[4]. Miller, B. N., I. Albert, S. K. Lam, J. A. Konstan, and J. Riedl. MovieLens Unplugged:Experiences with an Occasionally Connected Recommender System. In Proceedings of the International Conference on Intelligent User Interfaces, Miami, Florida, 2003.

[5]. Takanobu Nakahara ,Hiroyuki Morita, Recommender System for Music CDs Using a Graph Partitioning Method, In Proceeding KES '09 Proceedings of the 13th International Conference on Knowledge-Based and Intelligent Information and Engineering Systems: Part II Pages 259 – 269.

[6]. Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to item , collaborative filtering. Internet Computing IEEE, 7(1), 76–80.

[7]. Ghauth, K. I. & Abdullah, N. A. (2010). Learning materials recommendation using good learners’ ratings and content-based filtering. Educational Technology Research and Development.DOI: 10.1007/s11423-010-9155-4

[8]. Ghauth, K. I. & Abdullah, N. A. (2009). Building an e-learning recommender system using vector space model and good learners average rating. Ninth IEEE International Conference on Advanced Learning Technologies (ICALT 2009), Latvia, 194-196.

[9]. Hokyin Lai, Minhong Wang,Huaiqing Wang, Intelligent Agent-Based e-Learning System for Adaptive Learning.

[10]. Krulwich, B. (1997). Lifestyle Finder: Intelligent user profiling using large-scale demographic data. Artificial Intelligence Magazine, 18(2), 37–45.

[11]. Deepa Anand , Kamal K. Bharadwaj, Utilizing various sparsity measures for enhancing accuracy of collaborative recommender systems based on local and global similarities, Expert Systems with Applications 38 (2011) 5101–5109.

[12]. Lang, K. (1995). NewsWeeder: Learning to filter netnews. In Proceedings of the 12th international conference on machine learning, Tahoe City, CA.

[13]. Robin Burke, Hybrid Recommendation Systems : Survey and Experiments, In User Modeling and User-Adapted Interaction Kluwer Academic Publishers Hingham, MA, USA, Pages 331 – 37

[14]. Saman Shishehchi, Seyed Yashar Banihashem, Nor Azan Mat Zin, Shahrul Azman Mohd. Noah, “Review of personalized recommendation techniques for learners in e-learning systems publication”, 2011 International Conference on Semantic Technology and Information Retrieval, 28-29 June 2011, Putrajaya, Malaysia

[15]. Nikos Manouselis, Hendrik Drachsler, Riina Vuorikari, Hans Hummel,Rob Koper, “Recommender Systems in Technology EnhancedLearning”,Springer Recommender Systems Handbook 2011, pp 387-415

[16]. Katrien Verbert, Nikos Manouselis, Xavier Ochoa, Martin Wolpers, Hendrik Drachsler, Ivana Bosnic, Erik Duval , Context-aware Recommender Systems for Learning: a Survey and Future Challenges, IEEE Journal Of Latex Class Files, Vol. 6, No. 1, January 2007.

[17]. Nuanwan Soonthornphisaj, Ekkawut Rojsattarat, and Sukanya Yim-ngam, Smart E-Learning Using Recommender System, D.-S. Huang, K. Li, and G.W. Irwin (Eds.): ICIC 2006, LNAI 4114, pp. 518 – 523, 2006.© Springer-Verlag Berlin Heidelberg 2006.

[18]. J. Lu, "Personalized e-learning material recommender system," In Proceedings Of International Conferene On International Conference Information Technology for Application, 2004,pp. 374-379.

[19]. Kalil Imran Gauth and Nor Aniza Abdulla, Measuring learner’s performance in e-learning recommendation systems in Australasian Journal of Educational Technology, 2010, 26(6), 764-774.