2008 International Conference on Computer Science and Software Engineering

E-Learning Recommendation System

Huiyi Tan[1] , Junfei Guo[3]
International School of Software,
Wuhan University, Wuhan, China
tan6043@gmail.com

Yong Li[2]
Information School,
Estar University, Qingdao, China
liyong1982617@126.com

Abstract—**E-learning recommendation system helps learners to make choices without sufficient personal experience of the alternatives, and it is considerably requisite in this information explosion age. In our study, the user-based collaborative filtering method is chosen as the primary recommendation algorithm, combined with online education. We analyze the requirement of a web-based e-learning recommendation system, and divide the system workflow into five sections: data collection, data ETL, model generation, strategy configuration, and service supply. Moreover, an architecture is proposed, based on which further development can be accomplished. In this architecture, there are seven modules, and four of them are core modules: recommendation models database, recommendation system database, recommendation management, data/model management.**

Keywords-E-Learning, Recommandation System, Collaborative Filtering

I. INTRODUCTION

E-Learning is an umbrella term that describes learning done at a computer, usually connected to a network, giving us the opportunity to learn almost anytime, anywhere. It is widely accepted that e-Learning can be as rich and as valuable as the classroom experience or even more so. With its unique features e-Learning is an experience that leads to comprehension and mastery of new skills and knowledge, just like its traditional counterpart.

Instructional design for e-Learning has been perfected and refined over many years using established teaching principles, with many benefits to students. As a result colleges, universities, businesses, and organizations worldwide now offer their students fully accredited online degree, vocational, and continuing education programs in abundance. MIT open course ware supplies near 1800 courses. Learndirect.com offers around 500 different courses Over 600+ online education courses can be learned in Online-Education.net. In some web sites, countless informal courses are available, covering a range of subjects, including management, IT, Skills for Life and languages, at all levels.

However, in expanding to this new level of customization, businesses increase the amount of information that customers must process before they are able to select which items meet their needs. One solution to this information overload problem is the use of recommendation systems [1].

Recommendation systems are used by E-commerce sites to suggest products to their customers. The products can be recommended based on the top overall sellers on a site, based on the demographics of the customer, or based on an analysis of the past buying behavior of the customer as a prediction for future buying behavior. For instance, a recommendation system on Amazon.com suggests books to customers based on other books the customers have told Amazon they like. Another recommendation system on CDnow.com helps customers choose CDs to purchase as gifts, based on other CDs the recipient has liked in the past.

To produce the accurate and effective recommendations and ensure the real-time requirement of the system, researchers proposed several different algorithms, some of which derives from the achievements of data mining. The e-commerce recommending algorithms contains user-based collaborative filtering [2], Item-based collaborative filtering [3], Cluster-based collaborative filtering [4], Dimension reduction based collaborative filtering [5] , Horting Graph-theoretic collaborative filtering [6], Bayesian network based recommendation [7], association rules based recommendation [8].

In the related researches, recommendation technology is seldom applied in education field, but, considering the significance and seriousness of education, the help of recommendation system can improve efficiency and increase veracity of learners in the actual situation. In this paper, we analyze the requirements and functions of the recommendation system in an e-learning site, and combine the collaborative filtering algorithm with online education.

978-0-7695-3336-0/08 $25.00 © 2008 IEEE
DOI 10.1109/CSSE.2008.305

We divide the construction of a recommendation system into five steps: data collection, ETL, model generation, configuration, and service supply. And we discuss the system flow, and we proposed architecture based on which further development can be accomplished.

This paper is organized into five sections. We introduce the user-based collaborative filtering algorithm and non-personal recommendation means in Section 2. In Section 3, we give out the system workflow and the architecture of the system. Finally, we conclude the paper in Section 4.

II. ALGORITHMS

Learner-to-Learner correlation recommender systems recommend courses to a learner based on the correlation between that learner and other learners who have studied courses from the E-Learning site. This technology is known as “collaborative filtering”, because it originated as an information filtering technique that used group opinions to recommend information items to individuals.

In e-learning systems this is done in two ways. One, by having learners explicitly rate courses, in which case the system is moved part of the way towards Manual; the other, the learning is implicit from the studying patterns or click-stream behavior of the learners, in which case the system is pure Automatic. The proportion of actual studying hours to the total hours of the course is recorded as the implicit rating scores, and transformed to corresponding explicit rating scores, from 1 to 5. The learners’ rating scores can be donated in a m*n matrix, as table 1, where m is the number of users, n is the number of courses, and $R_{j,k}$ donates the rating of Course_k given by learner_j.

TABLE I. LEARNER’S RATING MATRIX

	Course_1	**⋯**	**Course_k**	**⋯**	**Course_n**
Learner_1	$R_{1,1}$	⋯	$R_{1,k}$	⋯	$R_{1,n}$
⋯	⋯	⋯	⋯	⋯	⋯
Learner_j	$R_{j,1}$	⋯	$R_{j,k}$	⋯	$R_{j,n}$
⋯	⋯	⋯	⋯	⋯	⋯
Learner_m	$R_{m,1}$	⋯	$R_{m,k}$	⋯	$R_{m,n}$

The most important step in CF-based recommender systems is that of computing the similarity between learners as it is used to form a proximity-based neighborhood between a target customer and a number of like-minded customers. The neighborhood formation process is in fact the model-building or learning process for a recommender system algorithm. The main goal of neighborhood formation is to find, for each customer u, an ordered list of l customers N= {N1,N2,⋯,Nl} such that u $\notin$ N and sim(u, N1) is maximum, sim(u, N2) is the next maximum and so on. We now present two different aspects of neighborhood formation, the proximity measure and neighborhood formation algorithm. The proximity between two customers is usually measured using either the correlation or the cosine measure. In our e-learning recommendation system, the former one is adopted. In this case proximity between two learners a and b is measured by computing the Pearson correlation corr_{ab}, which is given by

$$coor_{ab} = \frac{\sum_i (r_{ai} - \bar{r}_a)(r_{bi} - \bar{r}_b)}{\sqrt{\sum_i (r_{ai} - \bar{r}_a)^2 \sum_i (r_{bi} - \bar{r}_b)^2}} \quad (1)$$

The final step of a CF-based recommender system is to derive the top-N recommendations from the neighborhood of customers. We use the association rule-based recommendation for performing the task. This technique is based on the association rule-based top-N recommendation technique. However, instead of using the entire population of learners to generate rules, this technique only considers the l neighbors while generating the rules. Note that considering only a few neighbors may not generate strong enough association rules in practice, which as a consequence, may result in insufficient courses to recommend. This can be augmented by using a scheme where the rest of the courses, if necessary, are computed by using the most frequent item algorithm.

Non-personalized recommender systems is applied in e-learning system as well, which recommends courses to learners based on what other learners have said about the products on average. The recommendations are independent of the learner, so each customer gets the same recommendations. Non-personalized recommender systems are automatic, because they require little learner effort to generate the recommendation, and are ephemeral, because the system does not recognize the learner from one session to the next since the recommendations are not based on the learner.

III. SYSTEM DESIGN

Accompanied with the increasingly more courses are offered on the internet, the traditional approach that users search for the interesting and useful courses is no more proper. Learners hope the site supplies personalized services, and automatically recommends interesting courses to them according to each one’ own needs and interests. For one thing, this recommender establishes a long-term stable relationship between users and the site, thus retains users effectively and reduce customer churn rate. For another, it can shorten the searching time, provides better services, and let learners study more useful and suitable courses.

We design the recommendation system independently from the e-learning system, to reduce the extra burden of the e-learning site. However, the corporation between the recommender and e-learning system is transparent for users. When a user sends a requirement to the service, he/she will receive corresponding recommendation pages, without knowing the implementation technologies. The union of e-learning services, and recommender system services supplies the personalized recommending services together, and the relationship between services and users is shown in fig. 1.

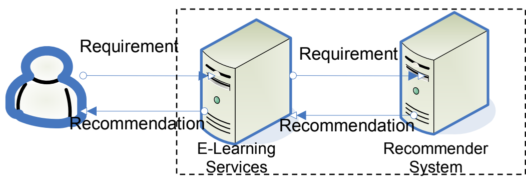

Figure 1. The process users acquire recommendations

As shown in Fig. 1, the central part of the services is the recommender system. The main workflow is the following five steps.

Data Collection: From mining the historical data, users' interests and frequent required pages are discovered. The web access logs, course information, and course rating scores are the primary data sources.

ETL: Useful data from the data resources is extracted, transformed, loaded to data warehouse. The extraction of data is determined by the recommender, different data are processed for various requirements.

Model Generation: According to the requirements of recommendation, models are generated using corresponding recommendation algorithms, and are stored in models database.

Configuration: Different models and algorithms are deployed in various recommendation strategies to supply different kinds of services.

Service Supply: Recommender system analyze the user's requirements, run the corresponding algorithms, and generate the results back to the e-learning system.

The process above is a constant circuit, when the data in transaction database updates to a certain degree, the datasets and models in data warehouse have to be updated, in order to track the change of the users' behaviors. The updating frequency differs to the system requirements, usually at fixed period.

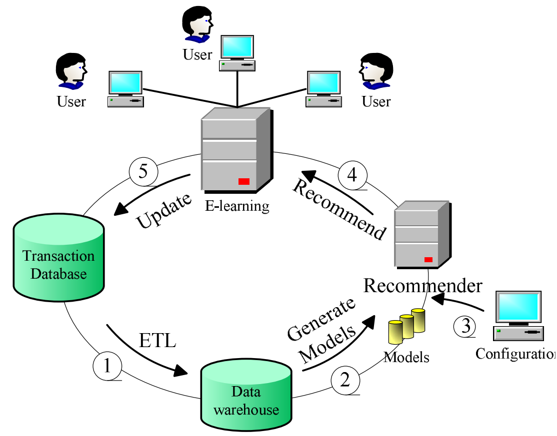

Figure 2. E-Learning System Flow

This recommendation system consists of online and offline parts, the online part receives the requirements, run the corresponding algorithm, and generates recommendation results; the offline part collects data, preprocess data and generates recommendation models. The Fig. 3 gives out the architecture of the recommendation system.

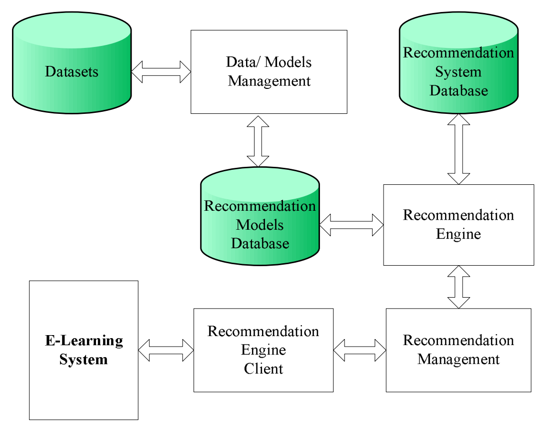

Figure 3. Architecture of E-Learning System

Some core modules in Fig. 3 are introduced as following:

Recommendation Models Database: The recommendation models are stored in this database which supplies different recommendation services. This database is administrated by "Data/Models Management" module, and it builds multiple recommendation models to generate different kinds of recommendation.

Recommendation System Database: It stores recommendation strategies. It establishes a one to one corresponding relationship with recommendation engine, and it is managed by recommendation management module. Recommendation engine load different strategies configuration in the recommendation system database, and generate recommendations.

Recommendation Management: This module administrates the strategies for recommendation engine, including recommendation algorithms and models, at the same time, controls the security of operating users and the operation of transaction engine, such as starting or stopping engines and recommendation strategies.

Data/model Management: This module administrates the models and dataset in the data warehouse including generating, deleting and modifying recommendations, loading, deleting, and updating the dataset.

IV. CONCLUSIONS

In this knowledge explosion age, increasingly more courses are offered on the internet, learners find it difficult to choose appropriate courses, so they hope the e-learning site supplies personalized services, and automatically recommend interesting and useful courses to them. To generate the efficient and precise recommendations, we design an e-learning recommendation system.

Among multiple recommendation algorithms, we choose the user-based collaborative filtering to generate recommendations, since it works well in other similar recommendation systems, like recommending CDs or movies. We use Person correlation to calculate the proximity between learners, and se the association rule-based recommendation for deriving the top-N recommendations from the neighborhood of customers.

In our study, the system workflow are divided into five sections: data collection, data ETL, model generation, strategy configuration, and service supply, all of which are essential for any education recommendation systems.

Furthermore, an architecture is proposed, based on which further development can be accomplished. In this architecture, there are seven modules: datasets, recommendation engine, engine client, recommendation models database, recommendation system database, recommendation management, data/model management, and four of them are hardcore.

In this web 2.0 ages, online education is more interactive and many kinds of items are tagged. In the future, we will pay more attention to recommend according to tags of each course.

V. ACKNOWLEDGMENT

The authors wish to acknowledge Person Li for many useful discussions and suggestion during this study.

REFERENCES

[1] A. Pongpech, M. E. Orlowska and S. W. Sadiq, "Personalized Courses Recommendation Functionality for Flex-eL", International Conference on Advanced Learning Technologies, 2007.

[2] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Analysis of Recommendation Algorithms for E-Commerce", ACM Conference on Electronic Commerce, 2000.

[3] J. B. Schafer, J. A. Konstan, and J. Riedl. "E-Commerce Recommendation Applications", Data Mining and Knowledge Discovery, 2001.

[4] W. S. Lee, "Online Clustering for Collaborative Filtering", National University of Singapore, School of Computing Technical Report TRA8/00, 2000.

[5] B. M. Sarwar, G. Karypis, J. A. Konstan, and J Riedl, "Application of Dimensionality Reduction in Recommender System -- A Case Study ", ACM WebKDD 2000 Web Mining for E-Commerce Workshop, 2000.

[6] C. C. Aggarwal, J. L. Wolf, K. L. Wu, and P. S. Yu, "Horting Hatches an Egg: A New Graph-Theoretic Approach to Collaborative Filtering", Proceedings of ACM SIGMOD International Conference on Knowledge Discovery & Data Mining, 1999.

[7] J. Herlocker, "Understanding and Improving Automated Collaborative Filtering Systems". Ph.D. Thesis, Computer Science Dept., University of Minnesota, 2000.