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Design of a Reading Recommendation Method Based on User Preference for Online Learning

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Abstract*— A design of reading recommendation method based on user preference for online learning namely, RM-UP is proposed. The aim of this study is to design an online learning recommendation system to support automatic information extract, dynamic user preference analysis and conduct an accurate recommendation of reading materials to relevant users.

Keywords—Recommendation method, Knowledge base, User preference, Online learning.

I. Introduction

Today, majority of people acquire information from internet. Online learning has become a favourite learning mode (Chen, 2013). However, with the increase of website information, information overload becomes a critical problem. It is difficult for user to find out the information of their interest from website. They have to spend a lot of time to find out the reading materials. (Chen et al., 2014; Bian et al., 2014). At the same time, the accuracy and precision in locating information will decrease drastically when the amount of information content increases (Salehi et al., 2012). This would affect users' learning interest. It is necessary to design a reading recommendation method that can efficiently achieve the information estimating automatically and recommend the reading material to the users. Existing recommendation algorithms such as Collaborative Filtering algorithm, Content-Based algorithm and Knowledge-Based algorithm are successful in practice of this field, but it is not enough in the accuracy and efficiency in recommendation task. First, dynamic user preference is not sufficiently considered. Moreover, the feedback comments of information materials are not be effectively used in these algorithms (Bian et al., 2014; Qiu et al., 2014). To address these problems and improve the efficiency and effectiveness existing recommendation systems, RM-UP for online learning is proposed. This method automatically extract user's information and reading materials, dynamically analyzes user preference and grade feedback comments of reading materials, then recommends suitable materials to relevant users based on the result of analysis by knowledge base.

II. Related Work

RM-UP is to recommend different learning materials to relevant user based on the result of user preference analysis (Lian, 2013). In previous study work of this field, Collaborative Filtering algorithm is the first method in the recommendation system (Resnick et al., 1997). It recommends the information based on the score of the history given by users (Herlocker et al., 2004; Salehi et al., 2012; Loepp et al., 2014). But it does not combine the information of the users and the information of the documents. It would fail to be applied on new users and new documents because there are no historical behaviors on them which causes the cold-start problem (Amatriain et al., 2009; Bian et al., 2014).

Content-Based algorithm (Elkahky, 2015; Perkio et al., 2005) and Knowledge-Based algorithm (Kaminskas et al., 2012; Rego et al., 2013) are also applied on the recommendation system. Content-Based recommendation does not need user to evaluate recommendation object (Fan et al., 2012; Tintarev et al., 2011). Instead, it extracts feature of document, analyzes user preference according to user's history and recommend the higher matching document content to the user. This method effectively addresses the cold-start problem of new document but the cold-start problem still exists for new user. Moreover, this method cannot deal with media files (Chen et al., 2014; Salehi et al., 2012). Knowledge-based recommendation has solved the cold-start problem, but its recommendation is static (Chen et al., 2014). The content of user interest always changes with the time. Thus, it is necessary to apply a dynamic recommendation. More researchers combine two kinds of algorithms mentioned above to avoid the weakness of single algorithm. This improved method is called Hybrid algorithm. Hybrid Recommendation successfully combined the advantages of each algorithm (Braunhofer, 2014; Dooms, 2013; Liu et al., 2014; Sun et al., 2012), but it increases the computational complexity. In other words, it takes long time to generate recommendation result. It consumes more computer processing power (Chen et al., 2014).

Although these algorithms were successful on the personalized recommendation, every method has its shortcoming and limitations. Most of the methods mentioned above depends on CTR (Click-through Rate) of feedback (Hofmann et al., 2014). However, it is not easy to obtain a reliable CTR. Sometimes, user clicking the content is not

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because they are interested in the content or it would be a mistake action by user. Such an unreliable estimation of CTR would result in incorrect recommendation (Amatriain et al., 2009). Knowledge base is a technology to store, analyze and manage data. It is a cluster which is easy to operate, use and fully organized (Yang et al., 2014; Suchanek et al., 2014). So far, the application of knowledge base is still new and immature in the field for RM-UP. In next section, the design detail of this method will be described.

III. RM-UP Design

In this section, a RM-UP design for online learning is proposed. It is an early attempt to use knowledge base to improve the efficiency and effectiveness of recommendation system. The design detail of this method as follows.

Web user's online learning flow

The design of web user online learning operation flow consists of four steps (Fig. 1): (1) Learner's registration and login Website, (2) Learner's query for learning materials, (3) Learners browse learning materials, (4) Learners give feedback comment for learning materials. The web user's online learning flow is explained in detail as follows:

1. The learners have to register when they first access the website. Some particular information of themselves has to be provided to the website, such as: user name, user profession, user hobbies, educational background etc. After that, they need to login when they access the website.
2. The learners make query on learning material of their interest from the website. Learning materials are calculated, ordered and recommended to the relevant learners.
3. The learners select and browse the recommended reading materials.
4. The learners give feedback comments on every learning material after finish browsing.

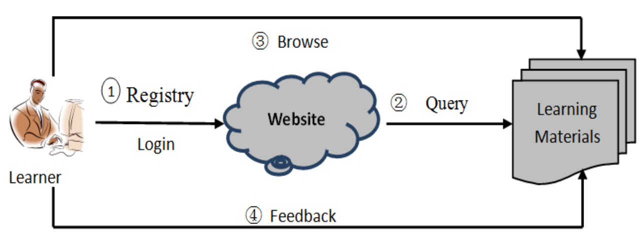

Fig. 1: Web user's online learning flow

Recommendation model design

The model of the RM-UP is shown in Fig. 2. The model is composed of three modules: website, database and knowledge base.

- The website module includes user registration, login, browsing learning materials and giving the feedback comments.
- The database module saves the information of users and learning materials.
- The knowledge base module extracts users' information and learning materials' information from database, automatically analyzes user preference and divides the users having the same or similar preference into one group. Moreover, it calculates the grade of learning materials based on the feedback comments given by users and learning materials' information. Finally, it recommends the suitable materials to the relevant users based on the result of analysis.

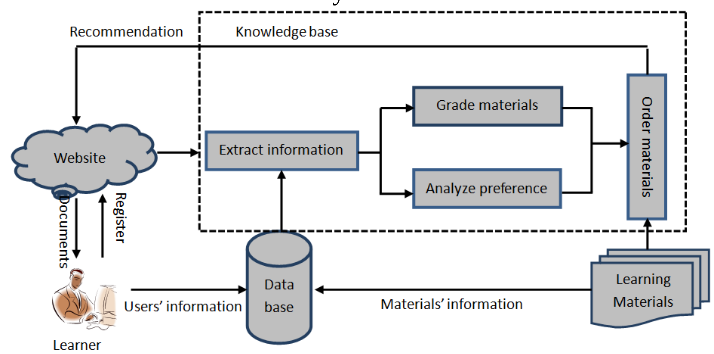

Fig. 2: Design model of RM-UP

Data extraction

The data of this study is extracted from the database of online learning. It consists of two aspects data: user and learning material.

- The information of user includes user id, name, gender, age, profession, hobbies, educational background and the record of the user's browsing history.
- The information of learning material includes document id, title, category, person of upload, time of upload and the history of browsed document.

User preference analysis

The record of user accessing document is shown in Table 1. This study analyzes user preference by combining user's background information, the history behaviour and feedback comments given by the user. If the information of users is similar as well as their browsed contents and the feedback comments shows high similarity, the learning model perceives that they are having the same preference. Thus, these users are categorized into one group. The similarity is calculated by the following equation.

$$Sim(a,b) = \sum_{i=1}^{n} s_i^{ab} * w_i$$

where the similarity index of effect factors is denoted in such a way that s_i^{ab}, w_i represents the weight for s_i^{ab}. For new user, the weight of user's background information is assigned as 1 and the weight of user's history behaviour and feedback comments given by the user is assigned as 0. With the increase of the amount document viewed, the weight of user's background information will be decreased and the weight of

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user's history behaviour and feedback comments given by the user will be increased.

Table 1: Record of user access document

	document1	document2	...	documentm
user1	good	excellent	...	Very bad
user2	bad	No browse	...	bad
...	...	...	...	...
usern	good	excellent	...	bad

RM-UP Recommendation strategy

There are five grades for each feedback comment which are *bad*, *fair*, *good*, *excellent* and *perfect*. Firstly, the paragraph of the feedback comment will be divided into many single sentence based on punctuations. Then all the keywords will be extracted from the sentence one by one, such as '*good*', '*bad*', '*no*', '*not*', '*very*', '*but*'. The total score of feedback comment is assigned as 10. The recommendation rules are represented by fuzzy sets as showed in Fig. 3.

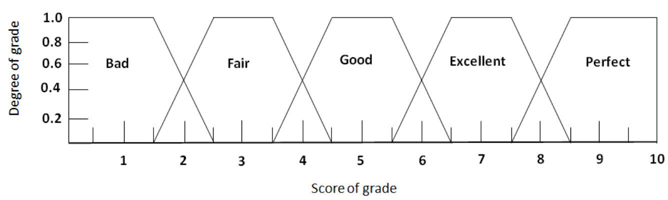

Fig. 3: Fuzzy sets of grade

Users with similar preference will be categorized into one group. RM-UP ranks the documents by the content information and user feedback comments. Similar to user preference analysis, there are two weights about the information and feedback comment of materials. The weights will be tuned according to the time of upload and the amount of the feedback comment. If the document is new, there will be no feedback comment. The weight of the information is assigned as 1. Then the weight of information will reduce while the weight of feedback comment will be increased. The feedback comments grade of one document will be compared with other documents from perfect grade. If the perfect grade score of document1 is higher than document2's perfect grade score, RM-UP will define that document1 is more preferred than document2. If these two scores are identical, the next grade will be compared until the good grade score. The document will not be recommended if the comment of fair and bad grade score is over 60%.

IV. Conclusion

RM-UP is proposed for online learning in this study. It adopts knowledge base to extract information of users and learning materials, analyze user preference and recommend suitable material to relevant user based on the result of analysis. This method is expected to save time in locating information of online learning, consume less computer processing power and improve the efficiency and effectiveness of recommendation system. It provides a new theoretical perspective optimizing recommendation system that can improve user online learning experience.

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