Recommender Systems for Smart Lifelong Learning

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Abstract

The majority of current web-based learning systems are closed learning environments where courses and learning materials are fixed and the only dynamic aspect is the organization of the material that can be adapted to allow a relatively individualized learning environment. In this paper, we propose an evolving web-based learning system which can adapt itself to its users. More specifically, the novelty with respect to the system lies in its ability to find relevant content on the web, and its ability to personalize and adapt this content based on the system's observation of its learners and the accumulated ratings given by the learners. Hence, although learners do not have direct interaction with the open Web, the system can retrieve relevant information related to them and their situated learning characteristics. Lifelong learning scenarios have particular differences in their need for personalized recommendations that make not possible reusing existing general approaches of recommender systems. The paper describes those challenges and presents a hybrid proposal that combines different recommendation techniques to navigate learner in learning process and make lifelong learning system personalized.

Keywords: lifelong learning, recommender systems, personalization

1 Introduction

Research on e-learning has gained more and more attention thanks to the recent explosive use of the Internet. The Lifelong Learning (LLL) paradigm supports the idea that learning should occur throughout a person's lifetime (Santos and Boticario, 2008). This paradigm promotes a user-centered approach that removes social, physical and cognitive barriers, where dynamic support may foster attitudes and skills to improve the effectiveness of the learning process. In mediating this process, technology is playing an important role. In this sense, a dynamic support that recommends learners what to do to achieve their learning goals is desirable. Traditionally, Intelligent Tutoring Systems (ITS) intend to provide direct customized instruction to students by finding the mismatches between the knowledge of the expert and the actions that reflect the assimilation of that knowledge by the student (Santos and Boticario, 2008). Their main limitations are: 1) ITS are specific of the domain for which they have been designed (since they have to be provided with the expert knowledge) and 2) it is unrealistic to think that it is possible to code in a system all the possible responses to cover the specific needs of each student at any situation of the course.

However, the majority of current web-based learning systems are closed learning environments, where courses and materials are fixed and the only dynamic aspect is the organization of the material that can be adapted to allow a relatively individualized learning environment. In this paper, we will propose an evolving web-based learning system which can adapt itself not only to its users, but also to the open Web in response to the usage of its learning materials. Our system is open in the sense that learning items related to the course could be added, adapted, or deleted. Our proposed e-learning system adapts both to learners and the open Web. In a traditional adaptive e-learning system, the delivery of learning material is personalized according to the learner model. However, the materials inside the system are a priori determined by the system designer/tutor. In open lifelong system, learning materials are automatically found on the web and integrated into the system based on users' interactions with the system. Therefore, although users do not have direct interaction with the open Web, new or different learning materials in the open Web can enrich their learning experiences through personalized paper recommendations(Tang and Mccalla, 2004). Other ability of our systems is working powerful in critical fields and high tolerance in unknown situation like new generation of science with related information shortage or new user with no specification of his interests. Another superiority of our systems is suitable architecture for social networks like facebook[1]. There is similarity between social networks and lifelong learning therefore we think we can use social networks in learning. We propose combination of different adapted recommendation algorithms to address lifelong systems requirements.

The organization of the paper is as follows: in section 2 we overview the related work done in recommender systems in lifelong learning (LLL), focusing more on recent systems. We introduce our solution including high level architecture and required details in section 3. The conclusion of the paper comes in section 4 along with some recommendations for future work.

2 Related work:

Work on LLL systems is in initial stage, but improve quickly. In (Santos and Boticario, 2008) introduce inclusive scenarios of recommender systems and LLL and propose recommending strategies for LLL. In (Derachesler and Hummel and koper, 2007) propose a combination of memory-based recommendation techniques that appear suitable to realize personalized recommendation on learning activities in context of e-learning. As described earlier, our proposed e-learning system makes individualized recommendations of materials for learners chosen from a dynamically evolving paper repository. There are several related works concerning tracking and recommending technical papers. Basu (Basu et al,2001) define the paper recommendation problem as: "*Given a representation of my interests, find me relevant papers*." They studied this issue in the context of assigning conference paper submissions to reviewing committee members. Reviewers do

[1] www.facebook.com

not need to key in their research interests as they usually do; instead, a novel autonomous procedure is incorporated in order to collect reviewer interest information from the web. Bollacker (Bollacker et al, 1999)refine CiteSeer, through an automatic personalized paper tracking module which retrieves each user's interests from well-maintained heterogeneous user profiles. Woodruff (Woodruff et al, 2000) discuss an enhanced digital book with a spreading-activation mechanism to make customized recommendations for readers with different types of background and knowledge. McNee (McNee et al, 2002) investigate the adoption of collaborative filtering techniques to recommend papers for researchers. They do not address the issue of how to recommend a research paper; but rather, how to recommend *additional* references for a target research paper. In the context of an e-learning system, additional readings in an area cannot be recommended purely through an analysis of the citation matrix of the target paper, because the system should not only recommend papers according to learners' interests, but also pick up those not-so-interesting-yet pedagogically suitable papers for them (McNee et al, 2002). In some cases, pedagogically valuable papers might not normally be of interest to learners and papers with significant influence on the research community might not be pedagogically suitable for learners. Therefore, we cannot simply present all highly relevant papers to learners; instead, a significantly modified recommending mechanism is needed(Tang and Mccalla, 2004).

3 Proposed Approach

We describe our system in four phases(figure 1) : 1)Input 2)Process 3)Output 4)Feedback Processing. There are three type of inputs, Actors that described later include four type of role. Candidate items are contents that recommender systems select N number of them for recommendation. Other one is input information such as user models, friend weights, learning map and so on that explain perfectly in section 3.1. All inputs process in process phase to make recommendation. Recommended items present to user and collect his/her feedbacks in output phase. Finally, by processing feedbacks system can update itself to predict and recommend better. Feedback processing phase provide restoration by reform user modeling, friends weight and other related essential information to increase system accuracy. Our proposed approach summarized in Fig. 2 with more details.

In figure 2 the generic view of our proposed approach is illustrated. According to figure four main phases is recognizable. Each of these phases will explain completely at following subsections.

3.1 Input phase

In this phase four roles exist including: user, friends, group member and teacher. Friends are users that directly interact with targeted user. Interests and opinions of friends according to their similarity to targeted user have different weights. These weights are applied in producing recommendation. The other role is group member that indirectly interacts with targeted user and system uses them to give more accurate recommendations. If group member interests and opinions are similar to targeted user, system will recommend targeted user to add this member as his/her friend. By increasing number of friends and updating their weight a better clustering is made and consequently system gives a more accurate recommendation. Also this method works well when user has few friends. The other role is teachers who have enough knowledge about the discussed topics in learning group and they can be an intelligent agent. System can make a learning group without a teacher. This is a notable attribute of system especially when learning group topic is very update and advanced, so an adequate teacher can't be found. Most important teacher works in this system listed as follows:

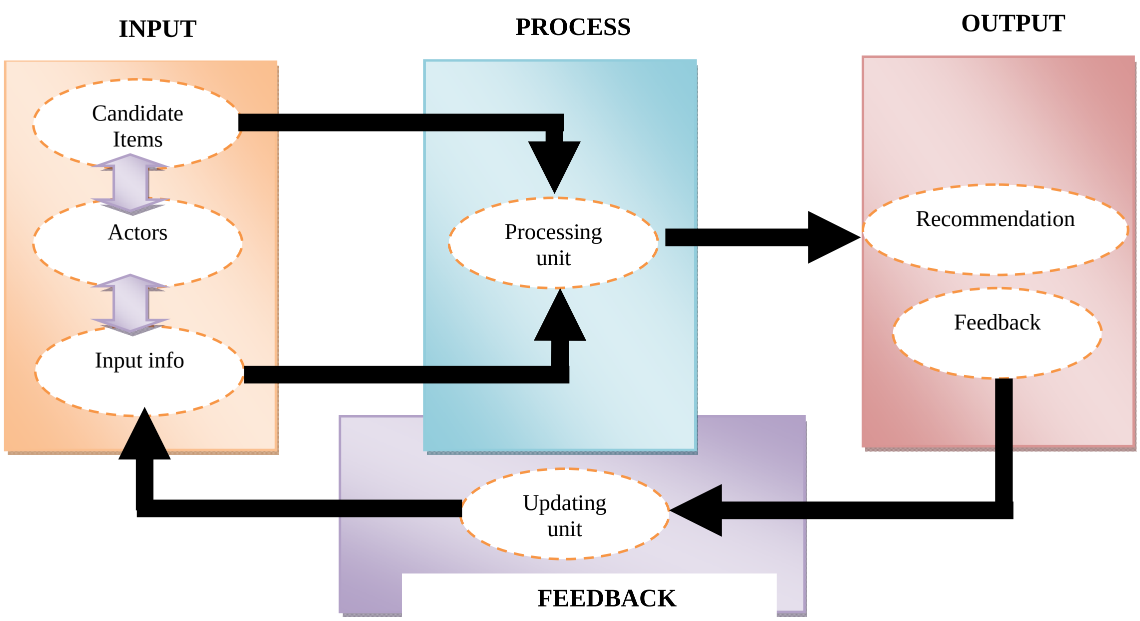

Fig. 1. Concept model of our Proposal

- Learning contents recommendations.
- Submission of recommendation when the system recommendation value is bellow 2 (Recommendation value is a parameter from 0 to 5 and calculates at the time of proposing it.).
- Submission of users' annotation or summarization after they study learning content.

One of the important elements in lifelong learning system is learner modeling. Because of accuracy and efficiency of two part user modeling approaches (Kardan and Einavypour, 2008) we use a modified version of it. Figure 3 shows an overall view of proposed learner modeling approach. At first system hasn't any idea about learner, so to accomplish this problem uses questionnaire and inviter learner model. For joining learning group each learner should at least have tow invitation from tow learning group members. Also he/she can alternatively answer the questionnaire includes questions about learner individual information such as: age, geographical location, religion, educations and more, as well as questions about the relation between learner and members who invite him/her such as: how much he/she knows inviters, how he/she be familiar with them and more. TLM_0 shows learner temporary model at first stage (Burke,2000). After learner interaction with system, system validates TLM0 considering learner feedbacks, how much is the learner model close to real learner? , then TLM_0 is updated to TLM_1. This process repeats *n* time, the value of n relates to system efficiency, then TLM_n convert to permanent learner model.

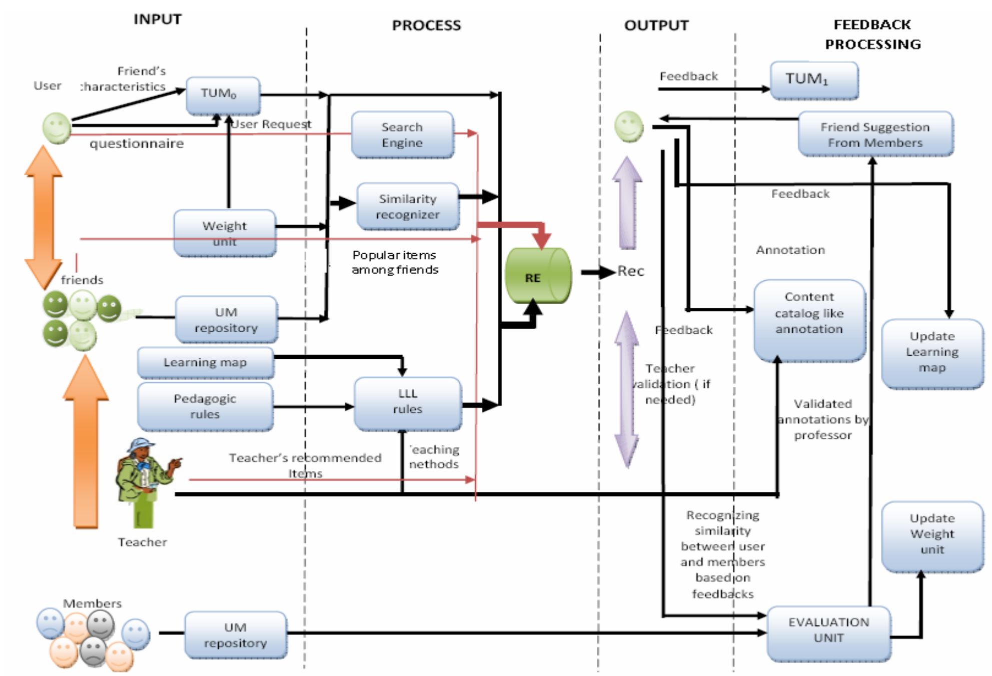

Fig. 2. Proposal for combining recommending techniques in

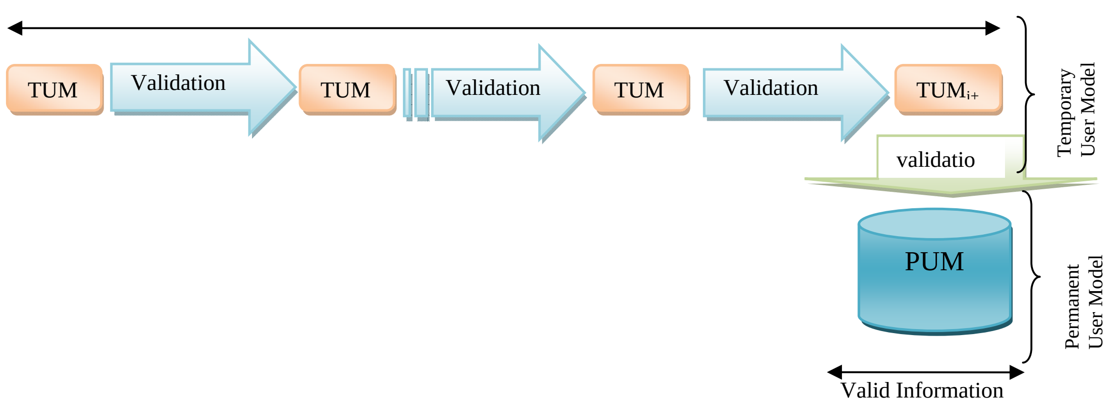

Figure 3: learner modeling

The other input phase features are friends and group members learner model repository that is saved distinctively r. The amount of similarity between a learner and his/her friends is saved in weight unit. Last two features of this phase are learning map and pedagogic rules. Pedagogic rules define what and when a learning content should use. For example a difficult technical paper isn't appropriate for a beginner. We propose ranking and tagging paper based on paper publication time, paper level according to learner (beginner, average, and expert) and teaching ways of teacher. Learning map has meaning relation with pedagogical rules. This map is saved for every learner and helps them to see their learning process. System using this map finds which content has been learned.

3.2 Process phase

All processes and recommendation is done at this phase. We propose a mixture approach for making recommendation in lifelong learning systems. In contrast to common approaches that work with limited amount of content, our proposed approach let learner contact universal web and search needed content through web at time of learning process. As mentioned before CF isn't proper approach for lifelong learning system because the lifelong learning system nature is working with varied and very detailed information. So using CF for lifelong learning system much information with no learner comment or enough comment will be made. To accomplish this weakness we mix it by an efficient approach that doesn't need learner feedback very. Like (Joachims and Freitag and Mitchell, 1997) reinforcement learning is used for filtering presented documents and information to learner. In this system the WAIR (Web Argent for Information Retrieval) is used.

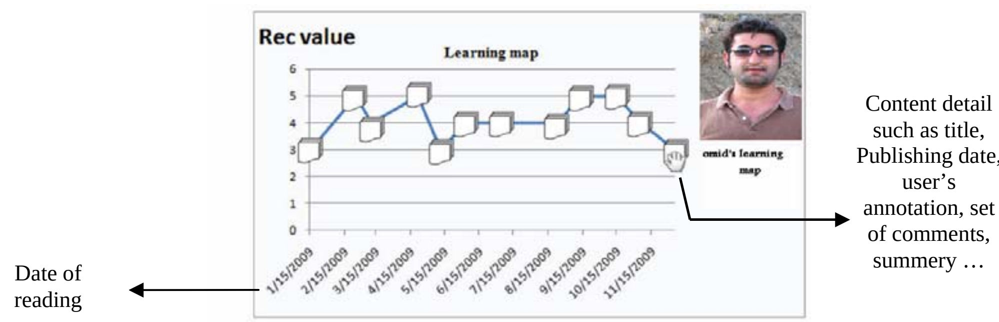

Figure 4: learning map indicate records about user's activities

This architecture includes user interface agent, information filtering agent and information retrieval agent and with using search engines and learner profiles receives documents for learners. The main point of this system is constructing and updating learner profile. The profile at first is made of some key words learner inputs system and general learner characteristic likes language, educations, intelligence and other things is gotten by him/herself or by his/her friend. These key words during learner and system interaction and by receiving learner feedbacks are updated. Updating includes add new words to profile, omit some key words and change learner profile key words weight. Formally learner profile is a vector of weight like the fowling vector:

$$w_p = < w_{p,1}, w_{p,2}, ..., w_{p,n} > \qquad (1)$$

is equal to weight of word k and $\|w_p\| = 1$

According to the profile WAIR sends a query to search engines that every word existence probability is related to its weight in profile after receiving documents. Rank of each document likes i for profile p calculates according to two vector cosine. For system learning implicit and explicit feedbacks is received. Implicit feedback $R_E(i)$ that is received at beginning of system work is the points learners give to documents. Explicit feedbacks $R_I(i)$ includes learner study time, and links is followed by learner. Reward for each document is made of the combination all this rewards:

$$r_i = \delta R_E(i) + (1-\delta) R_I(i) \qquad (2)$$

Based on this reward learner profile updates as follow:

$$w_{p,k}^{(i+1)} = w_{p,k}^{(i)} + \beta r_i I(x_{i,k}) \qquad (3)$$

In above formula $I(X_{i,k})$ is a threshold function that its output is 0, 1 and -1. After results are gained, contents are revised from the point of LLL rules. If any content contravenes LLL rules, they will be omitted. LLL rules made of learning rules and teaching ways is proposed by teacher according to learning map. Some sample of LLL rules come as follows.

LLL rule validation (user profile, content profile){

If (level of content i=A) & (intelligence of user = 40) then reject content.

If (language of content i="English") & (language of user = "Farsi") then reject content

If(mastery level of user=A) & (Date of publishing content = 1990) then reject content.

…}

In addition to recommendations are gained from learner search, by investigating friend uses and finding similarity between learner and their friends so recommendations produced based on CF. An important point in CF is used in our approach is the way of weighting to friends recommend. As mentioned before learner weights are kept in one place and at time of using CF these weights are used for assigning similarity. Like previous way the results of this approach are checked by LLL rules. Another list belongs to teacher recommendations. The teacher according to his content and learner recognition recommend to learner. These recommendations are checked by LLL rules to minimize human errors. Relations with them recommendations are checked are as follows:

***S**earch **I**tems*$=\{I_i, I_j, \ldots, I_m\}$ ***P**rofessor **P**roposal*$= \{I_i, I_j, \ldots\}$ ***f**reinds **P**opular **I**tems*$=\{I_a, I_r, I_o, I_j, I_c, \ldots, I_s\}$	Input
$U_{filtering}=SI$ *filtering results = LLL rule validation{ Filtering(*$U_{filtering}$*,User Profile)}* *CF results= LLL rule validation {Collaborative filtering(friends Popular Items, friends Weight) = CF(FPI, FW)}* *Professor Proposal result = LLL rule validation{ Professor Proposal}*	Process
Rec results = (filtering results U CF results U Professor Proposal results}=$\{I_N, I_{N-1}, I_{N-2}, \ldots, I_0\}$	Output

3.3 Output phase

In this phase if the value of recommendation is bellow 2 the teacher should assign that a learning content is proper or not. But if the value of recommendation is more than 2 validation isn't necessary. The value 2 is an empirical quantity and has been assigned for system efficiency.

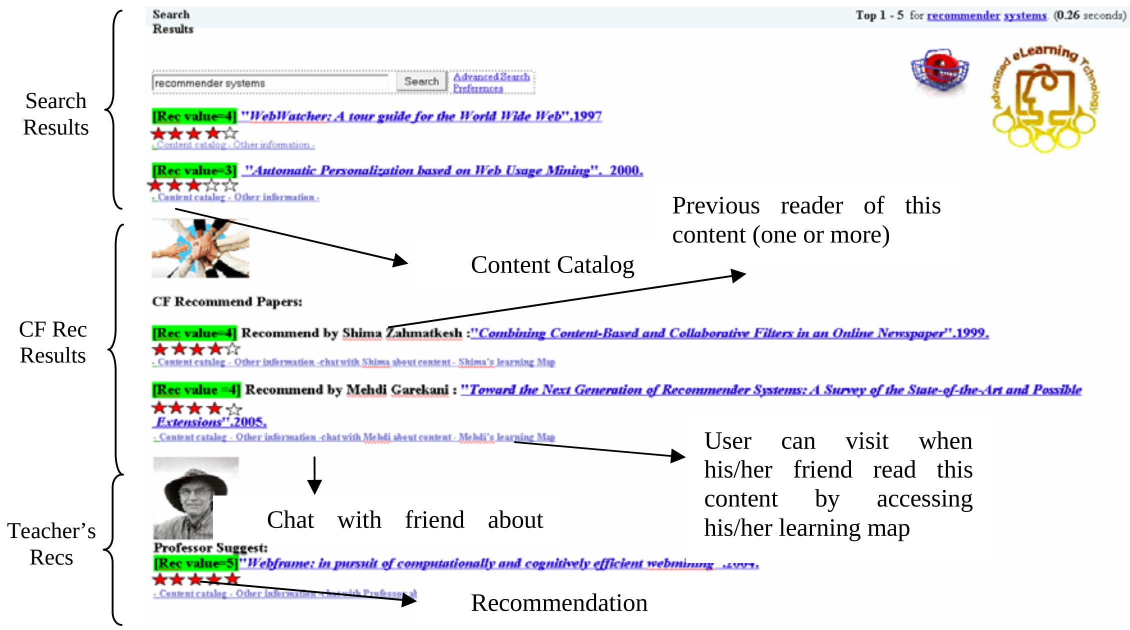

Figure 5: recommendation results

3.4 Feedback Processing phase

This phase happens when a learner has studied learning content. System can update itself, improve its recommendations by gathering learner feedback and analyzing it, updating learner model if it is necessary and design new learning map for learner. Feedbacks include information such as: paper level (from A to Z), edition type (weak 0, excellent 100), recommendation precise (from 0 to 100), usefulness percentage (from 0 to 100) and other things are mentioned by learner. Also learner can annotate or summarize the content has been studied. Every annotation saved with its author name and is useful for other learner wants to study those papers. Learner feedbacks make it possible to update weight of his/her friends. As friends have an important role in quality of system recommendation and modeling, by comparing learner model and other members system recommend most similar members to learner as a friend.

4 Conclusion and Future work

Current LLL systems have been focusing on the interrelations between users and the system. Hence, the system, if deemed intelligent, must be capable of detecting users' needs, following their footsteps, and finally adapting to their needs. We argue that this is not enough. We have been ignoring the dynamics of the open Web. As such, we believe that two kinds of collaborations should be considered here: one is the collaboration between the system and its users; another is the collaboration between the system and the open Web in response to the changing needs of the users. A system, which can fulfill especially the second type of collaboration, would indeed help its users to keep up-to date to the dynamics of information on the Web. Currently, we focused on developing

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