

L⁴F: A P2P ITS FOR RECOMMENDING ADDITIONAL LEARNING CONTENTS BY MEANS OF FOLKSONOMIES

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Abstract: Intelligent Tutoring Systems (ITSs) aim at providing personalized and adaptive tutoring to students by the incorporation of a student modeling component. Besides, Web 2.0 technologies have achieved great acceptance, bringing new applications which empower multiuser collaboration, such as collaborative tagging systems. In this paper, we present L⁴F, a peer-to-peer system which provides students with new additional learning elements related to the course they are following. This is achieved through the collaboration of several ITSs and using folksonomies.

1 INTRODUCTION

In the last few years, Web 2.0 technologies have achieved great acceptance among the users. In the field of Web 2.0 applications, collaborative tagging is becoming a popular practice to annotate resources on the Web (which has even reached e-learning initiatives). In such a scenario, both the users and the contents have their own tag clouds. In the case of users, the tag cloud is composed of the tags the user has ever assigned, whereas for the contents, it is composed of the tags users have ever assigned to it. In both cases the weight of the tags, i.e., its importance, is proportional to the number of times they have been assigned (by the user or to the content, respectively). From annotations provided by users, a new structure, called folksonomy, arises. It shows the relationships between the different tags in the system. Applying folksonomies in the field of e-learning—and extending collaboration from users to systems—, some interesting scenarios will appear when multiple systems exchange information in order to learn from their experiences. This is particularly interesting in learning and tutoring systems, to offer specific contents to each student taking into account previous experiences.

Intelligent Tutoring Systems (ITSs) (Brusilovsky et al., 1997) were designed as intelligent tutors based on knowledge, to serve as a guide in the student learn-

ing process. They are programs that aim at improving the learning process through personalization of contents depending on the student's skills and knowledge about the topics that they are learning about. They try to emulate the way in which a human tutor guides his/her students throughout the learning process.

Concerning the use of folksonomies in ITSs, it makes that one resource is described based on the tagger's experiences and beliefs (John and Seligmann, 2006). The cited proposal uses user's tags and bookmarks to find an expert user on a particular topic when needed. In ours, the ITSs, based on the past experiences, are the ones which act as experts when they recommend additional learning content to users who are having trouble on the topic.

In order for ITSs to collaborate with each other, Peer-to-Peer (P2P) seems to be an appropriate technology, since it has been very popular and successful for managing distributed databases. Peer-to-peer (P2P) architectures scale and self-organize themselves in the presence of a highly variable population of nodes, with network and computer failures, without the need of a central server and the overhead of its administration. The inherent characteristics of such architectures are typically scalability, and increased access to resources (Theotokis and Spinellis, 2004).

This paper presents L⁴F (Light Long-Life Learning with Folksonomies), a P2P framework

model made of ITSs which collaborate with each other to provide users with additional learning material related to the course they are following. Those ITSs propose this additional material taking into account the users' interests and knowledge, as well as the previous success or failure of other similar users with the additional content. In order for the ITSs to recommend this new material, L⁴F provides a reasoning algorithm based on folksonomies which are created from the tags the users annotate the learning elements with.

In this paper, we describe the system (Sect. 2), according to its P2P structure, its content and user modeling and its decision capabilities. Finally, we present the conclusions and expose our future lines of research (Sect. 3).

2 SYSTEM DESCRIPTION

L⁴F is a framework model, where users can annotate the learning elements of the system using tags. In L⁴F, each user is associated with an ITS which stores his/her profile and provides the user with learning material.

If the ITS detects that the user is having trouble with a particular learning element (see Fig. 1), it looks for additional related content in its own database, and communicates with other ITSs using a P2P model (Sect. 2.1) to obtain related material from their databases. The recommendation of new learning elements is based on two different criteria. On the one hand, the system looks for contents which are similar to the one the user is following (by comparing contents' tag clouds, see Sect. 2.3). On the other hand, it searches for a learning element which has been successful for similar users. For this to be possible, contents have a new type of tag cloud: the target user tag cloud, which is obtained from the tag clouds of the users who have followed the learning element, taking into account their success or failure. In this manner, to compare users with target users, the method explained in Sect. 2.3 is used.

The last step in the process of finding new additional content is selecting the most appropriate one from those the consulted ITSs have proposed (Sect. 2.4).

2.1 Peer-to-Peer System Description

We consider our system, composed by multiple ITSs, as a P2P system. We organize the whole system in a similar way to Kazaa (Liang et al., 2004), i.e., the peers are hierarchically distributed in two levels.

There are some ITSs whose agents behave as peer leaders (a peer leader is dynamically selected taking into account the number of times its learning elements have been followed) who have a set of children (normal peers) linked to them. The peer leader has a summary of the tag clouds of the learning elements available in the repositories of its children, determining its profile.

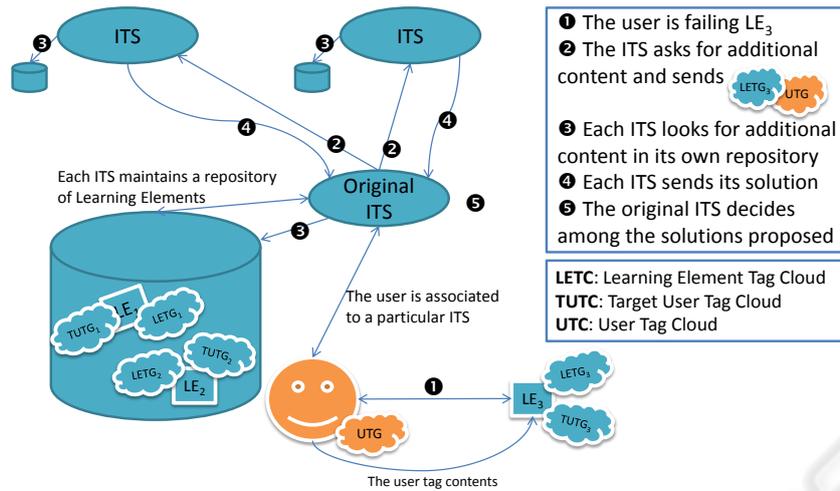
Now we will describe the behavior of the system considering a new peer ITS (ITS_{new}) joining the P2P system, to publish information, to search for a committee of peers, and finally to fetch the appropriate learning elements to solve its problems:

- **Join:** A new ITS (ITS_{new}) is set up and wants to join the ITS P2P network. ITS_{new} selects the peer leader ITS_{PL} closer to its contents' tag clouds and connects with it as a normal peer (child).
- **Publish:** ITS_{new} sends to ITS_{PL} a summary of contents' tag clouds for indexing purposes.
- **Search:** When ITS_{new} has problems to find an additional learning element for a particular user, it connects with its leader ITS_{PL} asking for a solution to its problem. Then, ITS_{PL} checks its own repository and contacts with its children returning to ITS_{new} a committee of peers with similar learning elements. If none of its children has any similar solution, then ITS_{PL} sends the request to the other leaders. The result is always that ITS_{new} receives a committee of peers CP or the empty set.
- **Fetch:** ITS_{new} sends the request to the peers in the committee CP and receives a set of solutions (i.e. learning elements which can be valid as additional contents for the course the user is following). Then, ITS_{new} needs to decide which is the most appropriate solution (see Sect. 2.4). Once the user has studied the selected additional learning element, ITS_{new} propagates the results to the rest of peers in CP to provide feedback.

2.2 User and Content Modeling

The tags assigned by users to the contents are used to build the contents' tag cloud. The weights of the tags are proportional to the number of users that have used a particular tag to describe the content. We describe how this works in the following paragraphs.

The tags the users choose to describe the learning elements they follow constitute their tag cloud, i.e., their profiles. Tag clouds for users are slightly different, since the weight of the tags is not only proportional to the number of times the user has assigned this tag, but also to the degree of interest (DOI) and knowledge (DOK) shown for the content tagged. In



The P2P scheme has been ignored in this figure to facilitate comprehension.

Figure 1: Structure of the system.

fact, the tags in the user's tag cloud have two different weights, one for the degree of interest and the other one for the degree of knowledge of the user in this tag.

A folksonomy is created from the contents' tag clouds. It can be represented as an undirected graph where nodes are the tags of the systems and transitions, the relationship between tags they link (Fig. 2) (Michlmayr et al., 2007). The relationships are calculated from the number of times the tags appear together in a tag cloud, the weights of the tags in this tag cloud, as well as the index of popularity (IOP) of those contents described by both tags at the same time (for more detailed information, see (Rey-López et al., 2010)).

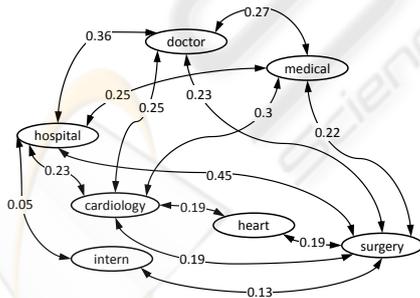


Figure 2: Example of folksonomy.

2.3 Measuring Similarity

To be able to find the appropriate additional learning elements, a reasoning mechanism is needed in order to measure the similarity between contents' tag clouds, as well as users' tag clouds and target user's tag clouds.

The simplest way to measure this value would be to consider the number of coincident tags in both tag clouds, i.e., the higher the number of coincident tags and its weight, the higher the degree of relationship between the two tag clouds.

But our algorithm does not only consider the number of coincident tags and their weights (*direct relationship*, $R_0(D_k, D_l)$ (Eq. (1))), but also the degree of relationship between the tags of both tag clouds (*one-hop relationship*, $R_1(D_k, D_l)$ (Eq. (2))).

$$R_0(D_k, D_l) = \sum_{\forall i/t_i \in T_k \cap T_l} (-1)^n \sqrt{|w(t_i, D_k)| |w(t_i, D_l)|} \quad (1)$$

$$R_1(D_k, D_l) = \sum_{\substack{\forall i/t_i \in T_k \\ \forall j/t_j \in T_l}} (-1)^n \sqrt{|w(t_i, D_k)| |w(t_j, D_l)|} \cdot r_{ij} \quad (2)$$

where D_k is the set of tags in the tag cloud of item i , D_l is the set of tags in the tag cloud of user u , $w(t, D)$ is the weight of tag t in the tag cloud D , and r_{ij} is the relationship in the folksonomy between the tags t_i and t_j . In equations above, $n = 1$ if $w(t_i, D_k) \cdot w(t_j, D_l) < 0$ and $n = 2$ otherwise

In this manner, the total relationship takes into account both Eq. (1) and (2), and it is calculated

$$R(D_k, D_l) = \alpha R_0(D_k, D_l) + (1 - \alpha) R_1(D_k, D_l) \quad (3)$$

being α the parameter used to indicate the importance of each type of relationship ($\alpha \in [0, 1]$).

These equations can be used to measure three different degrees of relationships: i) R_C is the one between the original content and the additional one; ii)

R_{DOI} is the relationship between the user and the target user profile, concerning his/her interest; and iii) R_{DOK} is the relationship between the user and the target user profile, concerning his/her knowledge.

2.4 Final Decision

Each ITS of the committee of peers needs to determine which is the best learning element to fulfill the learning needs of the user studying the original content. For this to be possible, it follows this algorithm:

1. First, it filters the contents according to R_C , sorting them according to this value and discarding those ones which differ more than a magnitude order with respect to the previous one.
2. Next, it measures R_{DOI} and R_{DOK} for the remaining candidates and calculates R_U (the relationship regarding the user) as follows:

$$R_U = |U_k| \cdot (\beta R_{DOI} + (1 - \beta) R_{DOK}) \quad (4)$$

being β a constant provided by the original ITS which reflects the degree of importance the user gives to his/her interests and knowledge, and $|U_k|$ the number of users who have followed the learning element c_k .

3. It selects that content with the highest R_U and sends R_C and R_U to the original ITS.
4. Finally, the original ITS selects the most appropriate element from those received following steps 1–3, asks for it to the correspondent ITS and offers it to the student.

3 CONCLUSIONS AND FUTURE WORK

In this paper, we have presented L⁴F, a P2P system composed of multiple ITSs which collaborate with each other in order to provide users with additional material for the courses they are following. While we centered our description on the ITS domain, we consider that the model described here can be extended and useful, for recommending learning contents, to the whole spectrum of learning systems.

For the recommendation of the aforementioned material, the ITSs do not only measure the similarity of the additional content with the original one, but also the appropriateness of the material for the user. This is accomplished by maintaining for each piece of content a target user profile, created from the information of success or failure of all the users which have studied this element.

For the user and content model, we have selected a solution which is being very successful in the field of Web 2.0: collaborative tagging and folksonomies. Based on this solution, this paper presents as well a reasoning algorithm which aims to help ITSs determine which is the most appropriate additional learning element for a given user and original learning material. The main advantage of this solution is its flexibility and adaptability, since it changes in time reflecting the opinion of current users.

In the field of reasoning, future work will address the improvement of the system finding a solution for those users who are passive and do not collaborate in tagging contents. This fact prevents the system to obtain a user profile for these users. A possible solution would be obtaining the user profile from the tag clouds of the contents he/she has followed.

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