Facilitate collaborative recommendation based on community knowledge awareness tool

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Abstract: - In large-scale e-learning environment, it is very difficult or even impossible for the tutors to give “one-to-one” instruction to the distributed learners. In this paper, we first presented a multi-agent framework to group e-learners into communities with similar learning status. Then through an integrated visualization platform, we enabled the tutors to gain insight to the characteristics of each individual community including knowledge structure, learning progress and existing problems. Based on this, the tutors can then assign further reading, group discussion to give personalized instructions to each community. Furthermore, the tutors can collaborate with the e-learners in the process of community construction to achieve better efficiency. Experimental results derived from real application have shown that this collaboration between the e-learners and tutors indeed improves the learners’ learning achievements.

Key-Words: - **Collaborative Recommendation, E-Learning, Computer Supported Collaborative Learning**

1 Introduction

Lack of interaction in e-learning always leads to unguided learning after class. As a reason, collaborative learning problem solving is becoming increasingly important. Two strands of research address problems relative to computer-supported collaborative learning (CSCL) [1].

There are approaches that support teacher to monitor learners’ dynamic learning status and give them personalized learning guiding. In a formal educational context, these traces of learning data and interaction have potential as an important source of information to teachers who want to guide learners to improve their skills in group work and to evaluate the value of various learning interventions [2]. The mining of such data is an important research direction as can be shown by the recent workshops on Educational Data Mining held at ITS, AIED and AAAI conferences [3-4]. However, guided learning becomes difficult when teachers face to large-scale learners like the situation in China or other Asia countries. Learners should be treated as different groups, in which group they have similar learning status and requirement. For teachers, they only need to analyze the learning structure of each group and give same learning guiding to the whole group, which require the accurate learning group exploiting algorithms to ensure the efficiency of this method.

This paper focuses on resource-based learning environment and primarily solves two problems in collaborative learning. One is on teachers’ side, this paper firstly proposes a novel distributed learning group exploiting algorithm, which can track the dynamic learning behavior and requirement of dispersed learners. Based on the features of each group, this paper develops a community knowledge and information awareness tool, which enable monitor the community formation process, visualize the knowledge structure of each group, recommend personalized learning resource according to different learning status of each group, specify relative tests to evaluate the efficiency of recommendation. The other is on learners’ side, each learner can access to a special collaborative learning website, in which they can read different learning resources recommended by the teacher. For each document, every learner can publish personal tags, mark interesting sentences, ask question and note experience. Every learner in the common group can read this information and help to solve problem in resource reading. All collaborative data is also available for teacher which can help them to provide further learning guide.

2 E-Learner Community Exploiting Algorithm

E-learning is quite a complex process that needs to be supported by many architectural components. Learners can exhibit many kinds of behaviors, such as accessing different kinds of online courseware, completing assignments, submitting questions, or search for additional learning resources. All these behaviors reflect the users' learning status and interest from one aspect or another. So the main purpose of constructing a user profile is to retrieve, clean and formulate useful information from the learning log data so that the learner community exploiting algorithm introduced later can use it effectively.

Learning behavior comprises the set of activities that an e-learner performs on learning resources. It can be roughly classified into three categories based on the way we can use a resource. The first category is stored as web logs, which mainly consist of courseware browsing and downloads. The second is the data accumulated in the database of different assistant learning systems. The last one includes the discussion threads and notes an e-learner made during the process of learning particular topics or working with individual resources.

Based on their learning behaviors related to underlying learning concept, we can evaluate the corresponding learning status and generate a profile of each e-learner. Let $C = \{c_1, ..., c_i, ..., c_n\}$ be the set of knowledge points corresponding to a specified learning domain. The learning feature vector of learner *a* can then be defined as $SV_a = \{(c_1, s_1), (c_i, s_i), (c_n, s_n)\}$, where $c_i \in C$ is a knowledge point and s_i is a learning status evaluation on c_i of learner *a*. The learning status evaluation can be obtained in two ways: explicit and implicit. The explicit evaluation data discussed here can be a learner's vote on a learning resource or her score in a test, while the implicit evaluation data can be quantitative data reflecting complex learning behavior, such as access frequency, learning duration, repetitive accesses to the same source or the like. As is well known, e-learning log data contain a wealth of detail compared to off-line learning data, which provides information essential to understanding the learning behavior of students, including what materials they look at and what materials they may be interested in. In our prototype solution we proved a component to analyze both explicit and implicit learning data, which results in a more accurate overall evaluation of learning status than the mere analysis of access records can do.

In order to monitor the dynamic behavior of e-learners and try to find similar e-learners in the distributed e-learning environment, we propose two-layer multi-agent structure which consists of both the learner agents and group agents. Based on JADE platform, each group agent can communicate with both the local learner agents and other group agents, which enable it to locate learners with similar interests and managing the association of learners to sub-communities in a distributed and open e-learning environment.

Each LA *a* will first choose a GA *g* randomly and report its initial learning feature vector SV_a. Now GA *g* constructs its member sets A_g and the group learning feature matrix SM_g based on the learning feature vector SV_a of each community member. During the learning process, LA *a* will send a message (a, c_i^a, s_i^a, SV_a) to *g* if the monitored learner has learned a concept, where *a* is the identification of LA, (c_i^a, s_i^a) is the 'concept-status' tuple and SV_a is the updated learning feature vector. Once GA *g* receives this enquire, it will send this message to its members and randomly forward to several other GAs *g'*, the match width is a number defined as *topSearch*. Each LA *l* that received this message will check if it has learned this concept and if the status difference between *l* and *a* is lower than a threshold α, defined as $S_i^l \neq NIL \; and \; |S_i^a - S_i^l| < \alpha$, it will calculate the similarity between SV_a and SV_l based on the Pearson Correlation Coefficient defined in equation 1:

$$sim_{a,l} = \frac{\sum_i (s_i^a - \overline{s^a})(s_i^l - \overline{s^l})}{\sqrt{\sum_i (s_i^a - \overline{s^a})^2 \sum_j (s_i^l - \overline{s^l})^2}} \quad (1)$$

If the similarity value is higher than a threshold β, that means LA *a* and *l* has similar learning status, then LA *l* will feedback $(l, Sim_{a,l})$ to *g*. Also if the message *l* received is forwarded by GA *g'*, *l* will feedback to *g'* and *g'* will return this message to *g*.

After a waiting time *T*, *g* will ascendingly sort the feedback results on the similarity value and choose the matched learner *l* with the highest value. Then *g* will check if learner agent *a* and *l* are managed by the same group agent. If the answer is false, the GAs *g* and *g'* will calculate the inter-similarity of each learner agent using a method similar to Equation 1 and move the learner agent from the community with smaller inter-similarity to another community. Based on this strategy, e-learners that have similar learning status will be re-grouped into the same community gradually. The detailed description and efficiency analysis of the algorithm can be found in [5].

3 Key functions of collaborative recommendation system

The collaborative recommendation system has six key functions as “Group formation monitor,” “Group knowledge structure spy,” “Group resources recommendation,” “Group tests customization,” “Personalized Resource Adding,” “Personalized tests adding.” First is to track the learner communities’ formation process as shown in Figure 1. Each small circle in Figure 1 represents a learner agent with different color denoting various learning status of the learner. The group agent is represented by a bigger circle with the same color of the group members. For each circle on behalf of a learner, the proportion of the color fill in the circle represents the membership degree of the group. Once the color fill is less than a predefined threshold, it may be move to another group fit for its current learning status. In the group tree as shown in the left panel of Figure 1, each group is represented as a letter from a set as {A, A-, B+, B, B-, C+, C, C-}, where A describes the learning status of this group is the best one of the whole learners while C- means the worst one. By expanding the group tree, the teacher could monitor the general group feature and decide which group should be chosen to monitor its knowledge structure and provide additional recommendation and learning guidance.

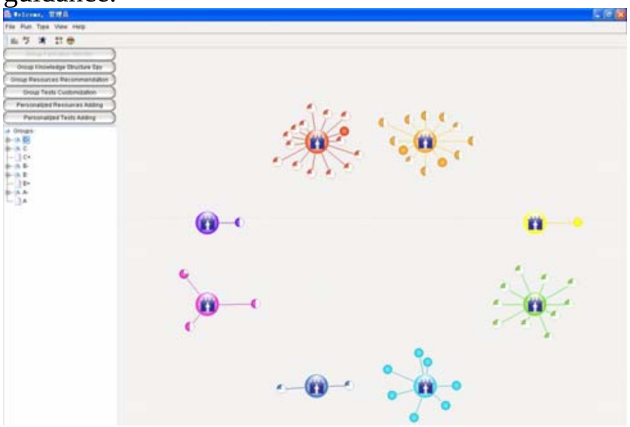

Figure 1. Group Formation Monitor

By choosing a special group and clicking the “Group knowledge Structure Spy” button, a teacher could choose a group which needs extra learning guidance and monitor its group knowledge structure as shown in Figure 2.

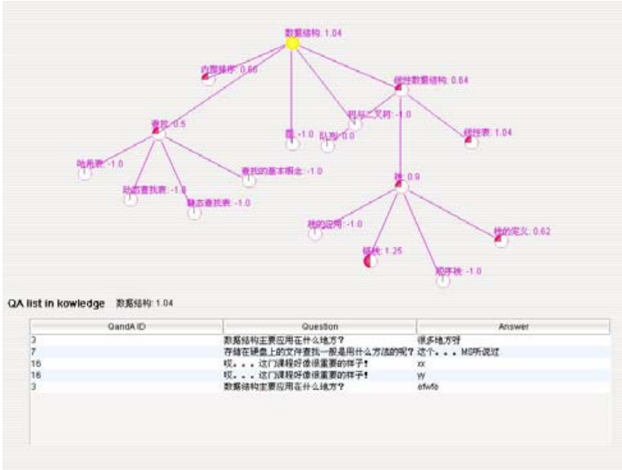

Figure 2.Group Knowledge Structure Spy

Concept maps are a type of knowledge visualization for representing the knowledge of a learner by means of nodes displaying concepts and labeled links between the nodes representing the relations between the concepts. While traditional concept maps were created by using paper and pencil, computer-based concept mapping tools allow for the creation of digital concept maps. By contrast, advanced digital concept mapping tools allow the representation of content knowledge as well as hyper-linking a concept with additional information regarding the concept.

In this system, we develop a community knowledge and information awareness tool which has three advanced features compared with traditional concept map. Firstly, it could show the group learning grasp degree of each knowledge concept which could be analyzed by the group learning feature matrix. As shown in Figure 2, the portion of each knowledge concept represents the learning grasp degree of this group. Less proportion shows more requirements for extra learning guidance. Secondly, the knowledge awareness tool also represents the general learning data including group’s performance and submitted question related to each knowledge concept as shown in the bottom panel of Figure 2.

Based on the knowledge structure of the group, the teacher could analyze the learning weakness and requirement of each group after the class. Furthermore, the teacher could select suitable supplement learning materials corresponding to different knowledge concept.

In order to evaluate the efficiency of recommendation and check if it is useful to enhance the learning effect, the system also provides the tests customize tool for teachers to specify personalized tests according to different learning status of different group. These tests could not only help learners to strengthen their knowledge but also help teachers to evaluate the effect of learning guidance.

4 Collaborative learning among group members

After the class, each learner could log into the learning website and access recommended resources. As discussed above, each recommended resource is marked with personal tags, which enable the recommendation lists is different and personalized for each learner.

For a resource-based e-learning environment, what kind of collaborative learning approach could help learners to enhance their learning effect? Based on the investigation of e-learners, we found that the possible effective way is to make every learner of the group become responsible. For instance, a learner could give a note on important keywords or sentences, ask question of a special problem where it appeared in the resource. Also a learner also could publish his positive or negative review on different notes, answer questions, and solve problems required by other group members.

As shown in Figure 5, you could see a simple case study for collaborative learning based on recommended resources. Suppose learner "Zheng Zhong" logged into the learning website and found that there were several recommended resources by his teacher. He then chose the resource "data structure of Tree" and browsed the .pdf document by Internet Explorer. He could read the content of the recommended resource, and many tags made by other learners of the same group as shown in Figure 3.

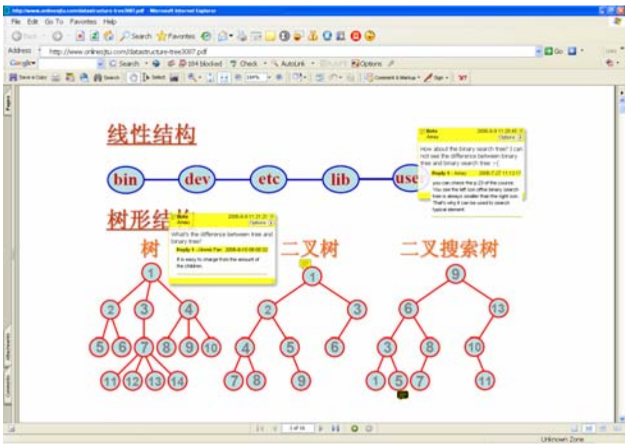

Figure 3. Screenshot of collaborative learning

Based on the commenting tools of Adobe, Zheng Zhong could highlight text or add new notes. Furthermore, in order to enable learners share learning experience and answer questions collaboratively, we developed a special plug-in tool which could enable learners to save the personal tags made for the resource, send and receive comments to our web server which could enable each learner to read the updated tags synchronously. As shown in Figure 4, Zheng Zhong noticed that Bo Xie asked a question "How about the binary search tree? I could not see the difference between binary tree and binary search tree." He thought this is a simple question and wanted to help Bo Xie. Using the "reply" function of the "commenting" tool, Zheng Zhong gave his own answer as "you could check the p.23 of the course. You see the left son of the binary search tree is always smaller than the right son. That's why it could be used to search typical element." After that, he could click the function button as "send and receive comments." Then the system will inform Zheng Zhong that "You are about to upload your comments to the server, where they will be posted for other reviewers to see. This action couldn't be undone." By clicking the "send" button, the new tag will be uploaded to our server, and every group member could see this change.

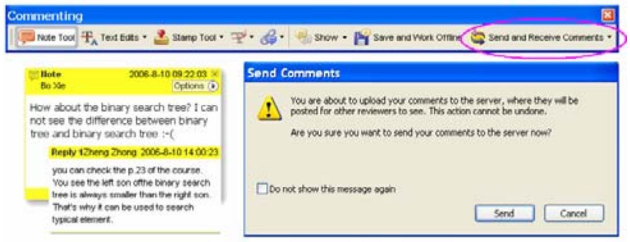

Figure 4. Collaborative tagging tools pluged in Adobe

6 Experimental results

This experiment investigated whether a tool for supporting recommendation regarding the awareness of group knowledge and information of learning leads to more efficient personalized learning. Also this experiment evaluated a tool for enabling collaborative learning (in the sense of coordination and communication) of a group could provide more efficient problem solving compared to a condition with groups that did not use our tools.

Participants were 100 students (54 female, 36 male). All students are major in computer science and average age was 22.3. The students were randomly assigned to the control condition group or to the normal condition group. Both the amount of these two groups is 50. In the control conditions, the participants were provided with our collaborative learning tools. Each participant could see the recommended resources, add individual learning tags, and answer questions submitted by other group members. In the normal condition, the learners could not use our tools.

The participants of the control condition group were required to learn in a spatially distributed, synchronous fashion with agent-based, group-recommendation and collaborative-learning tools. Their learning behaviors were monitored by the learner agent and could be dynamically divided into learning groups according to his learning status. The teacher could see the group formation process and check the group knowledge structure after the class.

The experimental course used in this study is “data structure”, which consisted of 13 basic concepts and 82 background resources (in parts divisible in sub-elements).

The experimental analysis was based on a comparison of the control condition group and the normal condition group. Some questionnaire items were analyzed that consisted of three-point rating scales with the number one for “no satisfaction”, the number two for “partial satisfaction” and the number three for “complete satisfaction”. The evaluation criteria was based on three parameters: the satisfaction of receiving learning resources recommendation ((CS_{res}), the satisfaction of receiving tests recommendation (CS_{test}), and the satisfaction of the collaborative learning functions (CS_{cl}). As represented in Table 1, the control condition group agreed with high percentage on that it was helpful to use the primary functions of our collaborative learning tools. (CS_{res} = 0.71; CS_{test} = 0.67; CS_{cl} = 0.84).

Table 1. Satisfaction of using collaborative learning tools

Evaluation	CS_{res}	CS_{test}	CS_{cl}
Complete satisfaction	0.71	0.67	0.84
Partial satisfaction	0.22	0.23	0.10
No satisfaction	0.07	0.10	0.06

7 Conclusion

The main purpose of our work is to help e-learners to collaboratively recommend useful and interesting materials with other similar e-learners based on their different backgrounds, preferences, learning purposes and other meaningful attributes. In this article we presented a collaborative learning system based on recommendations among the members of e-learner communities, in which the learners have similar learning interests and experiences. Especially, the system can help the learners of the common group to share learning experience, publish personal learning tags, solve problem collaboratively.

In order to further improve the system, we plan to roll out this system with more classes in different subjects. In addition, we will examine how the system can be used to facilitate collaboration among large numbers of learners.

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