

Analyzing Learners' Relationship to Improve the Quality of Recommender System for Group Learning Support

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Abstract—Recommender systems are now a popular research area and have become powerful tools to present personalized offers to users in many domains (e.g. e-commerce, e-learning). In this paper, we introduced an approach of personalization which extracts learners' relationship based on learning processes and learning activities (e.g. note taking) to provide more authenticity, personalized recommendations for group learning support. Base on learners' learning activities some interaction factors are extracted by using natural language process technologies and data mining automatically. Then, extracted interaction factors are utilized to generate some relationship indicators for inferring the learners' directive relationship. These indicators are as symbols in order to describe a situation and relative degree which knowledge and understanding are socially distributed among group learners. Thirdly, we use a machine learning approach for acquiring a learner relationship identify module according to the relationship indicators. The experimental result shows that the proposed approach can give a more satisfying and qualified recommendation.

Index Terms— social interaction, Markov chain model, recommender system, group learning

I. INTRODUCTION

Computer support collaborative learning (CSCL) is an emerging research field that focuses on how collaborative learning, supported by technology, can enhance peer interaction and work in groups, and how collaboration and technology facilitate sharing and distributing knowledge and expertise among community members [1]. The main goal of CSCL is to maximize individual learning based on group work. Many researches work on CSCL have tried to discover the factors and design interface for promoting interaction in collaborative and computer-based condition [2]. And research on CSCL has been extensively done because it may generate useful tools to ease students' learning and knowledge building [14].

Recommender systems, which filter out useful information and generate recommendations, are becoming popular tools for reducing information overload and to provide personalization. In order to improve the "educational provision" [3] to implement the e-learning recommender system, we have proposed a new

recommendation approach - Learner's Role based Multi Dimensional Collaborative Recommendation (LRMDCR) - which has been proven to be more suitable to realize personalized recommendation based on not only learning histories but also learning processes [4] [5]. One interesting extension of LRMDCR is using the learners' type to support multidimensional collaborative filtering. The learners of group were automatically divided into advanced and beginner learners based on their learning processes, and they have the different weight in recommendation phase according to their types.

We ran a learner group study of LRMDCR and found that the accuracy of recommendation has been improved, but we also found some weaknesses. For example, recommendation approach rely upon implicitly or explicitly acquired behavioral data denoting learners' interest and the factors that characterized the learners themselves, but ignored concerned with factors such as learning activity. In addition, since we don't consider learners' reputation of learning materials, there is an apprehension of recommending the no meaningful learning materials to learners.

To address these weaknesses, in this paper, we focused our efforts on considering learners' learning activities, and automatically extract some interaction factors based on learners learning activities. Then, we use these interaction factors to generate some relationship indicators. These indicators are as symbols in order to describe a situation and relative degree which knowledge and understanding are socially distributed among group learners. Thirdly, we use machine learning approach for acquiring a learner relationship identify module according to the indicators. The results so obtained are the assigned to improve the accuracy of previous mentioned LRMDCR approach.

The remainder of this paper is structured as follow: Section 2 describes the related work, section 3 presents our proposed approach and shows how the proposed approach is generated in a case- Collabo-eNOTE system, section 4 presents experimental evaluation and demonstrates effect of proposed approach, and section 5 presents conclusion and future work.

II. RELATED WORK

A. Recommendation Method

Recommender system [6] is a typical example of personalization systems and typically suggests items (e.g., products, documents) that are of interest to users, according to user demographics, features of items, and/or user preferences and provides users with recommendations about products and services they may like. They are becoming popular tools for reducing information overload. A variety of techniques have been proposed as the basis for recommender systems. According to these techniques, we can classify the recommender systems in three categories [9]: Content-based filtering (CBF), Collaborative filtering (CF), and Hybrid approaches. Content-based recommendation systems use data about the requested items and the information regarding only the active user [7]. They try to suggest items similar to those considered interesting/useful for a given user in the past. These methods, also known as search-based or item-based methods, treat the recommendation problem as a search for related items. Collaborative filtering was proposed to automate the process of “word-of-mouth” [8] by leveraging like-minded users’ opinions. It is an information filtering technique that depends on human beings’ evaluations of items. It infers the interests/preferences of an individual based on the interests/preferences of others with similar tastes. Hybrid filtering combines collaborative and content-based approach. Content-based and collaborative methods can be combined into the hybrid approach in several different ways [9].

Recommender systems are becoming an important way to support knowledge acquisition. They assist learner to find the best alternatives that satisfy their necessities using recommendations, leading them to interesting items, or hiding those useless and unattractive ones. Various recommender systems for e-learning have been developed [10]-[13].

B. LRMDCR

LRMDCR is a learner’s role based multi dimensional collaborative recommendation system proposed by [4] [5]. The recommendation is designed based on a hybrid approach and includes mainly two mechanisms: the learners’ learning processes and the analysis of social interaction. In the approach, firstly we use a machine learning approach for acquiring a Learner’s Type Divide Model. We are interested in automating the acquisition of group learners’ relationship and social interaction. Group learners are divided into advanced learners and beginner learners based on Markov Chain Model by using learning processes. Secondly we use the multidimensional collaborative filtering based on learners’ explicit influence and implicit influence to decide the recommendation learning objects to every learner of the group. And advanced and beginner learners have the different weight in recommendation phase. However, there is an apprehension of inferring the incorrect advanced learners only based on learning processes.

In this research, we propose a new approach to address the weaknesses of LRMDCR. The proposed approach can infer the learners’ relationship. The results so obtained are the assigned to improve the accuracy of LRMDCR approach and it can derive validity weight much more efficiently.

III. PROPOSED APPROACH

A. Collabo-eNOTE

We have developed an e-NOTEBOOK system, called Collabo-eNOTE which provides inquiry based collaborative learning environment. This system is designed to provide a scaffold for group learners as they learn to conduct collaborative, open-ended investigations. It is as a forum for expressing their ideas, recording their actions and communicating with others. In our system, learners are assigned to groups and provided with an ill-defined and ill-structured problem. Group learners must organize themselves, define objectives, assign responsibilities, conduct research, analyze results, and preset conclusions. The problems are purposely “ill-defined” and “ill-structure”, causing group members to work collaboratively to define specific issues, problems, and objectives. By trying to explain their ideas to other students and interacting with their peers around academic content, students sharpen their thinking and gain new knowledge in Collabo-eNOTE system. Our system has the functions such as note taking, comment taking etc.(fig.1) Learners can perform group learning by using several ways such as (1) Learning by teaching; (2) Learning by diagnosing; (3) Learning by open discussion in our system.

When a group of learners work together to solve the problem, the learners are necessary to search and study a variety of special subjects on the web. Since the information on the Internet is neither well-organized nor quality controlled, and web pages are not simply constructed with learning in mind, they are necessary to process, reconstruct and represent. In Collabo-eNOTE (fig.2), after the learner read the useful learning materials about the subjects which were sought on the web, they can record the contents (links) of the web pages, write the abstracts of the web pages and express their remarks as notes. In addition, the system has a unique implementation of threaded comments, called comment space. The comment space allows learners to post some comments to notes and respond to comments already posted, whereby participants create comments and explicitly reply to each other using a “reply to” button. As such, comments are hierarchical, and tree structure with a clear flow of messages from the initial parent post to subsequent ideas and thoughts.

The learners construct their own knowledge by explaining ideas and approaches based on their prior knowledge and experiences, applying these to a new situation, and integrating the new knowledge gained. Learners engage in socially self-enhancing behaviors, such as making mutually supportive coordinated contributions (e.g. taking notes). On the other hand, learners also compensate for other group learners’

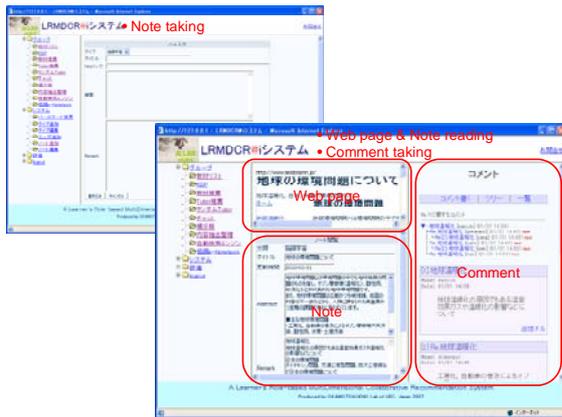


Figure 1. GUI of note-taking and comment-taking

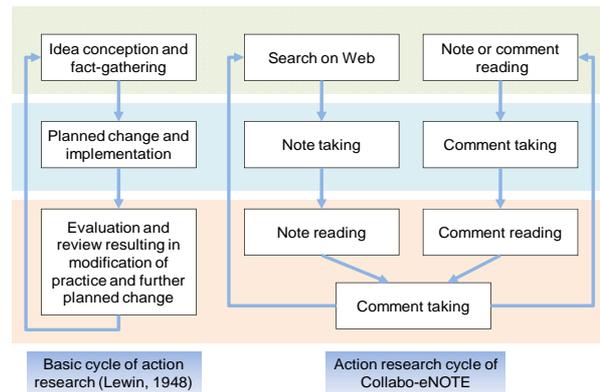


Figure 3. Action research cycle

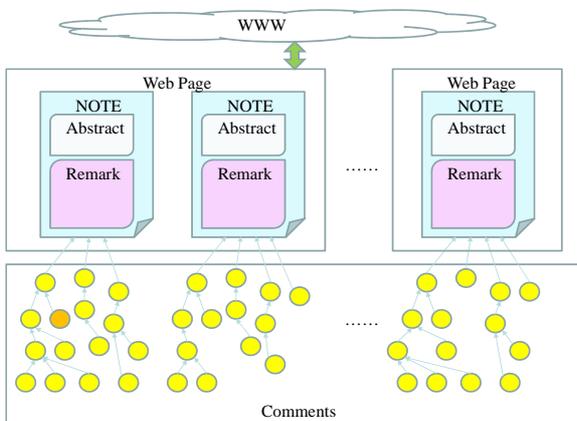


Figure 2. The structure of note-taking and comment-taking

shortcomings by helping out or doing extra work through writing comments. There are five basic learning activities in the system: (1) searching on web and found a useful web page thus note taking; (2) note reading; (3) after note reading, to write a comment; (4) after comment reading, to write a comment; (5) comment reading. [31] define action research as below: “Action research is a form of self-reflective enquiry undertaken by the participants (teachers, students or principals, for example) in social (including educational) situations in order to improve the rationality and justice of (a) their own social or educational practices, (b) their understanding of these practices, and (c) the situations (and institutions) in which these practices are carried out”. Lewin proposed a basic cycle of action research consists of (1) idea conception and fact-gathering (2) planned change and implementation (3) evaluation and review resulting in modification of practice and further planned change [32]. Fig. 3 shows how this was generated in Collabo-eNOTE system. The inquiry based collaborative learning process and the learners constructing knowledge are based on this cycle.

In summary, the Collabo-eNOTE system is characterized by (1) Notes and comments are as products and contributions utilized to present learners’ knowledge, at the same time, they are as learning materials providing opportunities for constructing new and rich understanding; (2) Each learner acts as both a knowledge provider and a knowledge receiver; (3) Participating in our system allows to develop two aspects of collaboration: peer interaction that enables negotiation and co-construction of artifacts, and expert to novice interaction which is because of learners act as experts and novices at the same time on different topics.

B. Interaction factors extractor

From the CSCL viewpoint, the learners build their own learning processes and generate knowledge. [17] claimed that people’s creativity is the result of interaction and collaboration with other individuals in a society. Since the relationship between interaction and learning is a central concern of the learning sciences, analysis of interaction has emerged as a major theme within the current literature on CSCL. [18] classified interactions to three types in distance education. His three-part interaction scheme included: (1) learner-instructor, (2) learner-learner, and (3) learner-content interaction. Since Collabo-eNOTE system is learner-centered, the main focus here is on the interactions that include: (1) learner-learner; (2) learner-content.

The various interactions imply different learner roles. The interaction type definition naturally varies according to its usage. The factors of interaction frequently observed in our system are (1) Comprehension of Web page; (2) Adequacy of remark; (3) Agreement of comment.

Moreover, [19] proposed an Interaction Analysis Model (IAM) which divides knowledge construction from discussion into five aspects to conveniently analyze the depth of social knowledge construction. This coding scheme has been used in many past studies; this improves research validity in a quantitative content analysis [20]. We also used this coding scheme in our study to analyze the knowledge construction type and depth in learners.

[19][21] reported that knowledge construction in a group of online learning, the amount of posting apparently constituted the first two phase of IAM. In this research, we mainly consider the first two phases: (1) Sharing and comparing; and (2) Discovering and exploring.

Analysis of the information collected in the Collaborative NOTE requires a number of advanced data processing steps including extraction of dominant, recurring themes and ultimately characterization of the degree of innovation represented by the various notes (abstracts and remarks) and comments created in our system.

Describes of 3 interaction factors are in the following.

1) Comprehension of Web page (CoW)

Our system propose a mechanism for participates to write abstract after they learned the web pages. Comprehension of web page is the similarity of current web pages read by learners and current abstracts wrote by learners. The interaction factor – comprehension of web page belongs to learner-content interaction. The calculation of comprehension of web page is as follows:

Step1: Content filter. A learning material may be published on the Web in several formats: HTML, PDF, DOC, TEXT, and etc., but in all cases, the information it contains is to be enriched with particular character sequences, not intended for the user but for the computer visualization driver, such as the browser in the case of HTML Web pages. In order to keep the explanation as simple as possible, we shall henceforth deal only with HTML. In this phase, only the text would remain. It consists in removing all HTML instructions (i.e., tags) from an HTML page.

Step2: Keyword vectors generation. Not all terms of a text are necessarily relevant. The content of the web page which finished content filter phase and the content of the abstract are analyzed by a Japanese morphological analysis system automatically- Chasen [16], respectively. Keywords are noun and unfamiliar words which are extracted from the content. The length of the keywords is more than 2 letters. Keywords lists include keywords and the word appearance frequency. Note: the web page keyword vector consists of the words whose appearance frequency rankings are higher than 50% of the all.

Step3: Jaccard similarity. In this phase, the comprehension of web page is obtained.

Based on such keyword vector, we calculate a similarity to measure the overlap between the two keyword vectors, keyword vector of learning material (web page) and keyword vector of abstract, which in the end leads to mappings between them, i.e., the higher comprehension degree, the higher similarity and the higher probability they should be mapped.

The similarity between two keyword vectors is measured based on the overlap of their sets. There are many successful similarity measures: COSINE, Pearson, Jaccard similarity and etc. We finally retained the Jaccard similarity because it performed slightly better overall and it is good at computing the similarity between the sets (1).

$$CoW_{ij} = S_{Jaccard}(K_{Learner}, K_{Webp}) = \frac{|K_{Learner} \cap K_{Webp}|}{|K_{Webp}|} \quad (1)$$

There are two parameters which need to be taken into comprehension of web page: 1. the minimum similarity; 2. the minimal number of elements (keywords) shared by two keyword vectors. These two parameters in practice are set in an empirical way. After calculating comprehension, the web pages whose comprehension degree is smaller than certain thresholds θ are filtered out from the learners' learning processes.

2) Adequacy of remark (AoR)

After user read the note (Abstract and Remark) wrote by other users, they can purchase the note or express their opinions and ideas through writing comments. We have provided the mechanism, called comment space for users to write their comments. Adequacy of remark is the positive ratio of comments which point to remark directly (Assumption: each comment focuses on a single remark and contains opinion from a single opinion holder).

That is to say, the comments of first layer of the comment tree are valid (Fig.2). The interaction factor – adequacy of remark belongs to learner-learner interaction. We adopt the first two phases of Interaction Analysis Model (IAM) here. Therefore the important task here is to extract the opinion of each comment and to classify comments as positive and negative opinion.

The adequacy of remark is computed as follows.

Step1: Classify the comment as positive or negative.

Many researches of automated opinion detection have been proposed. Turney present a simple unsupervised learning algorithm for classifying a review as recommended or not recommended [22]. They use Pointwise Mutual Information (PMI) and Information Retrieval (IR) to measure the similarity of pairs of words of phrase. The semantic orientation of a given phrase is calculated by comparing its similarity to a positive reference word (such as “excellent”) with its similarity to a negative reference word (such as “poor”) [22]. More specifically, a phrase is assigned a numerical rating by taking the mutual information between the given phrase and the word “excellent” and subtracting the mutual information between the given phrase and the word “poor”. In addition to determining the direction of the phrase’s semantic orientation (positive or negative, based on the sign of the rating), this numerical rating also indicates the strength of the semantic orientation based on the magnitude of the number [22]. Since when using machine learning methods many training data is necessary, here we adopt the unsupervised learning algorithm proposed by [22] to classify the comment as positive or negative. Note: we assume that each comment focuses on a single remark and contains opinion from a single opinion holder.

In our system, the first step is to use a chasen- a Japanese morphological analysis system – to identify phrases in the comment that contain adjectives or adverbs or adjectival noun. The second step is to estimate the semantic orientation of each extracted phrase. The third step is to adding the given comment to a class, positive or negative. Where, in our system,

“excellent”= “いい (good) | よい (good) | 良い (good) | 良かった (good) | 良く (well) | 好き (like) | 大

好き(favorite) | 楽しい(happy) | 嬉しい(happy) | 面白い(interesting) | 素敵(lovely) | 素晴らしい(wonderful) | 満足(satisfaction) | 魅力(charm) | 欲しい(want)".

“poor”= “あまり(not good) | あんまり(not good) | 悪い(bad) | 悪く(bad) | まずい(bad) | 不良(bad) | 嫌い(dislike) | 嫌(dislike) | 辛い(painful) | 怖い(fearful) | 最悪(worst) | 苦手(hard) | だめ(useless) | 不安(worry) | 悲しい(sad) | 危険(risk) | 不満(dissatisfaction) | 不快(dissatisfaction)”.

Step2: Calculate the adequacy of remark using formula (2).

$$AoR = \frac{\#Comment(positive)}{\#Comment} \times 100\% \quad (2)$$

Where # denotes the number of.

3) Agreement of comment (AoC)

Since explicit structure has the advantages that they encourage participants to clarify their thinking [15], our comment space is a tree structure with a clear flow of messages from the initial parent post to subsequent ideas and thoughts. In terms of defining and evaluating the depth of knowledge interactions in a note, the extent of knowledge construction in comment space (i.e. posted comments and replies) is a key indicator for us to understand the depth of learners' interactions.

Agreement of comment consists of two parts: (1) identification of (response to parent comment) positive or negative; (2) calculation of value of each comment based on exceptional utterances method and recursive algorithm. Assumption: each comment focuses on its parent comment and contains opinion from a single opinion holder. The interaction factor – agreement of comment belongs to learner-learner interaction.

The agreement and value of comment can be computed as follows.

Step1: Classifying the comment as positive or negative.

We adopt the first two phases of Interaction Analysis Model (IAM) here as well. The first task here is to extract the opinion of each comment and to classify comments as positive and negative opinion. We also adopt the algorithm proposed by [22] to classify the comment as positive or negative.

Step2: Identifying exceptional utterances.

[23] have proposed a method for analyzing the utterances and mining potential of ignored utterances through a process of interactions between humans. And they also emphasize that the exceptional utterances are always have high values. In our system, the decision of the comment's role is based on the method proposed by [23].

Step3: Calculating the value of each comment.

[24] discussed the Innovation Jam that IBM carried out in 2006, with the objective of identifying innovative and promising “Big Ideas” through a moderated on-line discussion between IBM worldwide employees and external contributors. [25] gave a micro analysis of how to identify the important utterances. Thread information

is shown to be an important resource for analysis of interaction among participants of a group. Our comment-taking method provides a tree structure for participants to submit comment. By using this tree structure of comments, the value of each comment itself can be calculated. The final value of each comment is calculated as follows:

Firstly, extracting the expression of each comment, and identifying the relationship such as positive or negative between parent comment and child comment (in our system, only positive (agreement) and negative (disagreement) two situations are be considered) based on Step1. Secondly, the value of comment itself is calculated based on Step2. Thirdly, calculate the final value of each comment by using a recursive algorithm. If the comment is agreed by many users, it is important and on the contrary it is not important. The importance is calculated using recursive algorithm (3).

$$C_i = S_i + \alpha \times \sum_j C_j \times R_{ij} \quad (3)$$

Where C_i is the final value of the comment. S_i is the value of comment itself. α is the propagate value. In our case, the adequacy of remark is defined as α . R_{ij} is the relation of comments. For example, $R_{ij}=1$ (agree) and $R_{ij}=-1$ (disagree).

C. Relationship indicator generator

[26] considers learning as a collective process that is linked to a specific context of action by focusing on how people participate and how they change their participation. Knowledge emerges by discursive assignment of meaning and social identification. This view is based on the idea that learner's ability to master and appropriate new or negotiated experience and also implies an understanding that learners have a relationship with themselves and others. In our system, group learners worked both individually and collaboratively with inquiry based collaborative learning. Based on extracted interaction factors, we defined some indicators such as indicator of CoW, indicator of AoR and indicator of AoC. These indicators are as symbols in order to describe a situation and relative degree which knowledge and understanding are socially distributed among group learners. The relationship of learners is defined as a group of collaborating and/ or competing entities that are related to each other. Each learner's learning process is different. In the group, all of the learners learn the same learning materials, but some learners master the knowledge deeply than other learners because of different learning abilities and comprehensive modeling experiences. Vygotsky's (1978) concept of the zone of proximal development, which is based on social learning theory, posits that by interacting with an experienced person, be that an instructor or peer, a learner can complete more advanced tasks, and learn and develop more than that might have done by himself [27]. The social interdependence theory of cooperative learning suggests that interaction processes are determined by how social relationships

among members of the group are designed into the learning environment.

The characteristics of relative learners are defined as supporting discussion, and supporting the learning process. In our study, the learners have joint ownerships such as effective learner, effective creator or effective collaborator: (1) Effective learners are the learners whose wrote abstracts are better than the others' wrote abstracts after searching, gathering and aggregating on the web. (2) Effective creators are the learners whose wrote remarks are better than the others' wrote remarks. (3) Effective collaborators are the learners whose comments are better than the others' comments.

Indicators between a pair of learners represent the amount of relationship between them. By using extracted interaction factors, we consider three types of indicators to infer the learner directive relationship.

1) The indicator of CoW (Comprehension of web page)

$$p_{1ia} = \frac{\sum_{k \in WP_{ai}} CoW_{ka}}{\sum_{k \in WP_{ai}} CoW_{ki}} \quad (4)$$

Then, we use $p_{1ia} = p_{1ia} / \sum_{i \in U} p_{1ia}$ to normalize p_{1ia} .

Where, p_{1ia} is the indicator of learner u_a being more effective learner than learner u_i based on the interaction factor comprehension of web page. WP_{ai} is the web pages that were learned by both learner u_a and learner u_i .

2) The indicator of AoR (Adequacy of remark)

$$p_{2ia} = \frac{\sum_{k \in WP_{ai}} AoR_{ka}}{\sum_{k \in WP_{ai}} AoR_{ki}} \quad (5)$$

Then, we use $p_{2ia} = p_{2ia} / \sum_{i \in U} p_{2ia}$ to normalize p_{2ia} .

Where, p_{2ia} is the indicator of learner u_a being more effective creator than learner u_i based on the interaction factor adequacy of remark. WP_{ai} is the web pages that were learned by both learner u_a and learner u_i .

3) The indicator of AoC (Agreement of comment)

$$p_{3ia} = \frac{\sum_{k \in WP_{ai}} \sum_{l \in Note_{ai}} AoC_{kla}}{\sum_{k \in WP_{ai}} \sum_{l \in Note_{ai}} AoC_{kli}} \quad (6)$$

Then, we use $p_{3ia} = p_{3ia} / \sum_{i \in U} p_{3ia}$ to normalize p_{3ia} .

Where, p_{3ia} is the indicator of learner u_a being more effective collaborator than learner u_i based on the interaction factor agreement of comment. WP_{ai} are the web pages that were learned by both learner u_a and learner u_i . $Note_{ai}$ are the notes that were wrote comments by both learner u_a and learner u_i .

D. Learner relationship identify

As our previous researches [4] [5] described, when learners are learning, the learning processes are changed by time and learning step, thus, we identify the

relationship of learners by using a Continuous-Time Markov Chain which includes the learning processes of every learner and we denote the relative learners' probability as the transition probability from learner a to learner i over s steps period.

Here the task is to generate Learner \times Learner matrix. The process of generating Learner \times Learner matrix is as follows.

1) Integrating

In order to combine the three indicators described in section C to obtain final result, there are several methods. For example we can use Bayesian or probabilistic networks. However, Bayesian network requires intensive data collection. In addition, computation of prior probabilities, conditional and joint probabilities and relationships among various learner interactions in real time is intensive especially if the network is large and updates are frequent. Therefore, here we adopt linear model to our approach.

$$\begin{aligned} p_{ia} &= \alpha \times p_{1ia} + \beta \times p_{2ia} + \gamma \times p_{3ia} \\ \alpha + \beta + \gamma &= 1 \\ \alpha, \beta, \gamma &\in (0,1) \end{aligned} \quad (7)$$

α, β, γ are parameter representing the sensitivity of indicator of CoW, the sensitivity of indicator of AoR and the sensitivity of indicator of AoC, repressively.

2) Relationship of learners

According to our previous research [4][5], here, we also adopt homogeneous Markov chain to our learner-learner matrix. And, we use approaches as [28] to adjust the matrix(8)(9).

$$\bar{P}_{ii} = \begin{cases} P_{ii} & \text{if } \sum_i \bar{P}_{ii} > 0, \\ \frac{1}{M} & \text{otherwise.} \end{cases} \quad (8)$$

Where, M is the number of the learners. \bar{P}_{ii} is the revised transition probability matrix.

$$\ddot{P} = \alpha \bar{P} + (1-\alpha) \frac{ee^T}{M} \quad (9)$$

Where, e^T is the row vector of all ones. \ddot{P} is the primitive stochastic matrix.

In this way, the learners' relationships can be identified in the group. Up to this step, the reputable learners are recommended. The learner can choose one or more reputable learners from the learner recommendation list. With these reputable learners the learner can initiate a cooperation step. Our system offers a tool that integrates synchronous cooperation, e.g. on a whiteboard, and text-based communication in form of a chat.

In addition, this result is utilized to multi dimensional collaborative recommendation phase to calculate the final learning materials recommendation.

IV. EXPERIMENTAL EVALUATION

A series of experiments which were participated by real-users, were constructed to evaluate our system and proposed approach. The experiments aim at comparing our approach with previous proposed LRMDCR.

A. Experimental condition

We implement the Collabo-eNOTE with two approaches: LRMDCR and the approach proposed by this research. And 10 learners that were students of masters' degree and postgraduate studied as a group participated the experiment.

The theme was "the problem of environment". The learners posted notes (web links, abstracts and remarks) after they sought useful web pages about this theme on the web. They also were allowed to post some comments to notes and respond to comments already posted in comment space. This theme was chosen, because it allows multiple perspective views on environmental issues such as pollution of the sea, global warming etc. In addition, this theme reflects that of the real world type of problems so that allows learners to bring in their experiences. Moreover, the learners expect to solve meaningful problems which their interests would encounter. Learners could expand the inquiry task based on these issues.

A total of 127 notes were collected. Each participant posted an average of 8.3 comments. The learners evaluated the first ten of ranking lists of the recommendations.

B. Experimental metric and result

The existing studies about recommender systems have used a number of different measures for evaluating the success of a recommender system. Those measures have been divided by Herlocker et al. into three categories [29]: (1) Predictive Accuracy Metrics which measure how close the recommender's predictions are to the true user ratings; (2) Classification Accuracy Metrics which measure how often a recommender system can decide correctly whether an item is beneficial for the user and therefore should be suggested to him; (3) Rank Accuracy Metrics which measure the proximity of a predicted ordering of items, as generated by a recommender system, to the actual user ordering of the same items.

The choice among those metrics should be based on the selected user tasks and the nature of the data sets. As above mentioned, since our experiment was participated by real users, we used Rank Accuracy Metrics. Breese et al. suggested a metric based on the expected utility of the recommendation list [30]. It is implemented as an exponential decay function, where the halflife value, α , is defined a priori as the rank of the resource in a recommendation list that had a 50% chance of being seen by the user. And this method evaluates an unbounded recommendation list that potentially contains all the items in the catalog. The Breese score is given by:

$$R = 100 \frac{\sum_a R_a}{\sum_a R_a^{\max}} \quad (10)$$

R_a^{\max} is the maximum achievable utility if all observed items had been shown at the top of the ranking list. In addition, R_a is an expression as below.

$$R_a = \sum_j \frac{\max(r_{a,j} - d, 0)}{2^{(j-1)/(\alpha-1)}} \quad (11)$$

In the above expression, $r_{a,j}$ is user a 's predicted vote to item j . d is the neutral vote and α is the viewing halflife. The halflife is the number of the item on the list, there is a 50-50 chance for the user to review that item.

We use this method and compare the learning materials recommendation results and evaluate proposed approach. In our experiment, we used a halflife of 5 items. A result of 72.11 was obtained by original LRMDCR, and a result of 76.16 by this research proposed approach. As expected, the proposed approach can improve the recommendation accuracy.

V. CONCLUSION AND FUTURE WORK

The recommendation mechanism which recommended the most relevant learning materials to learner according to not only learning process but also learning activity and analysis of learners' relationships is proposed.

In this paper, we focused our efforts on automatically inferring learners' social interaction factors and learners' relationships, based on data mining and nature language process technologies. We can quantify the quality of the knowledge construction process in online collaborative learning through analysis of social interactions among the participants. Since the design is implemented and the learning process starts, social relationships generate among participants. These social relationships control the learning outcomes. The relationship we proposed here takes into consideration both learners' social interaction and their cognitive relations with the knowledge points in a group, so as to assess their level of interest in individual knowledge points, and the extent to which they grasp each knowledge point (e.g. their learning experience). By using proposed approaches, it is possible to take individual relationship and reputation for recommendation.

The future work can be continued along the following directions:

(1) Our study with the interaction factors has some limitations. Although learner-content interaction is well recognized as a type of interaction, one major constraint of our study is a lack of learner-content interaction. We will do more discussion about learner-content interaction in the future.

(2) In our system, we have used Interaction Analysis Model (IAM) with the first two phases of coding categories: sharing/comparing of information, discovering/exploring of dissonance for analyzing some interaction factors. In future, we will consider the further three phases of coding categories: Negotiation of meaning, Testing tentative construction and Application of new knowledge.

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