APPLICATION OF SOCIAL COMPUTING TO COLLABORATIVE ONLINE LEARNING RESOURCE RECOMMENDER SYSTEM

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Abstract- Recently, e-learning has been paid much attention in the area of education. However, it is increasingly difficult for low-achievement students to remain focused when learning on the Internet owing to the vast amount of information online and the many distractions from social media. Meanwhile, these low-achievement students often lack of the related prior knowledge to determine if the website is useful. Accordingly, useful online learning resource recommender algorithms can suggest learning resources fitting the task the low-achievement learners are currently working on or trying to gain knowledge about. In this work, an intelligent collaborative online learning resource recommender system is proposed. A group grading module is presented to derive three parameters that are used to calculate the ranking of each website via the Support Vector Regression method. The effects of online learning resource ranking shortened the searching processes, and the learners can thus have more time to focus on comprehending the contents of the recommended online learning resources. The experimental results revealed that the proposed algorithm can effectively guide learners to access the appropriate online learning resources; accordingly, the target of self-learning assistance can be achieved and the learning performance of the students was enhanced.

Keywords- Collaborative Online Learning Resource Recommender, Intelligent Tutoring Systems, Information Retrieval, Support Vector Regressions.

I. INTRODUCTION

World Wide Web (WWW) is a crucial learning environment for learners solving problems with a variety of network resources. However, learner's cognition load is heavy because they must filter useful knowledge out of diverse information. On the other hand, e-learning has been highly regarded in the area of education. However, it is difficult for the low-achievement students to determine whether an online learning resource in the Internet is useful because these low-achievement students often lack of the related prior knowledge for judgement. Accordingly, they selected those learning resources based on their disorderly instincts.

Recommender systems assist users to select items they can locate relevant to their interest [1]. Thus, recommender systems have been designed to cover the gap between information collection and analysis by filtering all available data, and presenting the most appropriate items to the user [2]. Such systems improve the capacity and efficiency of this process. In the meanwhile, the major issue with recommender systems is obtaining the ideal match between those recommending and those receiving the recommendation; that is, indicating and discovering the relation between users' interests. Nowadays, recommender systems are widely adopted in various fields for the recommendation of research papers, articles, music, objects, videos, movies, and even people. Professional databases and portals such as Facebook, LinkedIn, IBM, Cisco, and Amazon use recommender systems to suggest items (e.g. products, contacts, and others) to their users [3]. To provide such suggestions, the most-used approaches employed in recommender systems are collaborative filtering and content-based systems. Collaborative filtering does not take into consideration the kinds of items or their attributes, but bases its recommendations solely on the expressed opinions/posts for other items. On the other hand, content-based filtering uses the information it has about the items and their attributes to make recommendations [3].

The most important objective of recommender systems is to estimate the ratings for the items that are new for a user [4]. Ultimately, after calculating the estimated rates for the yet unrated items, an ordered list of most related items can be prepared and suggested to the target user [5]. A number of previous studies have revealed the contribution of recommender systems in education. A collaborative filtering method was used in a research to recommend documents that will either encourage the users to expand their knowledge of a given topic or reinforce the knowledge which they already have [6]. Hsu et al. [7]developed an expert system for EFL English reading recommendation based on the opinions and domain knowledge of English teaching experts. Subsequently, they proposed a personalized mobile language learning system that included a reading material recommendation mechanism for guiding EFL students to read articles that meet their preferences [8]. In another study in this domain, the impact of collaborative recommender systems was examined on college students' use of an online forum for English learning [9].
Erdt and Rensing presented a concept for evaluating Technology Enhanced Learning (TEL) recommender

algorithms using crowdsourcing, as well as a repeated proof-of-concept evaluation experiment of a TEL graph-based recommender algorithm AScore that exploits hierarchical activity structures [10]. Results from both experiments support the postulated hypotheses, thereby showing that crowdsourcing can be successfully applied to evaluate TEL recommender algorithms. Parvathy et al. [11]proposed the collaborative social tagging exploration method that data from social tagging systems are extracted for every individual considering the correlations between users, items, and tag information. Tag information from users is the most decisive factor to predict the personalized suggestion for web users. They rank the available content based tag information with the inclusion of temporal decay of users' behavior over time and the centrality of every node in the network. Finally, the common preference metric is used for effective personalization. Results have been experimentally demonstrated with the empirical dataset MovieLens and provided the results as an alternative recommendation method with simplicity and efficiency.

Rohani et al. proposed a recommender algorithm, called Enhanced Content-based Algorithm using Social Networking (ECSN), which is applied in academic social networks to suggest the most relevant items to members of these online societies [5]. Considering user's own preferences, ECSN as well takes advantage of the interest and preferences of user's friends and faculty mates for providing more accurate recommendations. The research experiments were conducted by applying four different algorithms - random, collaborative, content-based, and ECSN, for 14 consecutive weeks. During this period, 1398 academic items were recommended to all 920 members of Malaysian Experts Academic Social Network (MyExpert). ANOVA tests indicate that the proposed algorithm significantly improves the prediction accuracy of algorithms.

There are software techniques and approaches that offer recommendations of items to be of interest to a user that exist in fields such as movie recommendations. However, building personalized recommendations in e-learning is more complicated than simply using existing systems [12]. One of the main challenges for an e-learning recommender system is that the items/services liked by learners could not be suitable for them. For instance, a learner without an extensive knowledge of the methods of web mining could be interested only in descriptions of the up-to-date web mining methods in e-commerce [2]. In this case, it should be suggested that he/she read some survey papers, for instance, an editorial article by two of the expert researchers in this field [13]; but there may be several quality technical papers associated with his interest. It should be noted that the recommendations are based solely on users' interests [14].

In this work, a collaborative online learning resource recommender system is proposed to tackle above-mentioned problems. We expect this platform can effectively guide learners to search for the appropriate online learning resource and achieve the purpose of self-learning assistance and enhance the students' learning performance. An experiment was conducted in a junior high school natural science course to investigate the following research questions:

(1) Does the proposed platformeffectively help guide learners to access the appropriate online learning resources?

(2) What sorts of information do the learners exchange during collaborative online learning resource recommendation process?

(3) Were students satisfied with the usage of the collaborative online learning resource recommender system?

The remainder of the paper is organized as follows. The details of the proposed collaborative recommender system are presented in Section 2. Section 3 addresses and discusses the experimental results. Conclusions and future work are set out in Section 4.

II. ARCHITECTURE OF THE COLLABORATIVE RECOMMENDER SYSTEM

The proposed platform consists of two major components, including a group grading module and an online learning resource ranking module. First, students issue their website search on the platform, and then the online learning resource ranking module is employed to evaluate the contents of the online learning resource that a student recommends. Notably, a well-known machine learning technique, Support Vector Regressions (SVRs), is adopted in this module to rank the online learning resource that the student recommends. Meanwhile, a group grading approach is adopted to derive three input parameters for the SVRs.

2.1 Group grading module

After a student browses a website on the platform, she/he is able to press "Agree", "Strongly Agree", "Disagree", or "Strongly Disagree" buttons in order to evaluate the quality of the contents of the websites to indicate whether it is qualified as a learning resource for the peers in the class. Notably, we also allowed students to press an "Uncertain" button on the Facebook-like platform, if they were not confident in terms of making a comment on the websites. The group grading module was then used to derive the required parameters for the SVRs to give a final evaluation of each website after enough peers' comments were collected. In addition, the system will adjust the weights of the students that commented on the websites based on their achievement. The detailed description of how the proposed group grading module operates is as follows.

Initialization: Each student's weight is first assigned by the teacher based on the student's past performance. The students' weights can be dynamically adjusted each time they comment on the websites.

Step 1: First, we sort the reliability of each student as follows,

$$w_1 \geq w_2 \geq \ldots \geq w_M, \tag{1}$$

where M denotes the number of peers.

Step 2: Obtain the optimal combination of the students,

$$\hat{l} = \text{argmax}_l \left\{ \psi_0^1, \cdots, \sum_{i=0}^{\lceil l/2 \rceil - 1} \psi_i^l, \cdots, \sum_{i=0}^{\lceil K/2 \rceil - 1} \psi_i^K \right\}, \tag{2}$$

where K is the total number of students giving their opinions, and $argmax_l$ is the maximum of the elements in set $\hat{l}$. Each element in set $\hat{l}$ can be expressed by,

$$\psi_0^l = \prod_{j=1}^{l} w_j, \tag{3}$$

$$\psi_1^l = \prod_{j=1}^{l} w_j + \sum_{n=1}^{l} \left\{ (1-w_n) \cdot \prod_{j=1, j \neq n}^{l} w_j \right\}, \tag{4}$$

$$\psi_2^l = \prod_{j=1}^{l} w_j + \sum_{n=1}^{l} \left\{ (1-w_n) \cdot \prod_{j=1, j \neq n}^{l} w_j \right\} + \sum_{\ldots}^{l} \left\{ (1-w_n) \cdot \sum_{\ldots}^{l} \left[(1-w_r) \cdot \prod_{\ldots}^{l} w_j \right] \right\}. \tag{5}$$

In a similar way, we can obtain all the values of ψ_i^l. Notably, majority voting is adopted to make the final common consensus of the students. In addition, Eqs. (3) to (5) represent the probability that all peers who expressed opinions are correct, the probability that one out of all peers who expressed opinions is incorrect, and the probability that two out of all peers who expressed opinions are incorrect, respectively. The last element in set $\hat{l}$ as given in Eq. (4) denotes the probability that the comments given by $\lceil K/2 \rceil - 1$ out of *K* students are incorrect. For example, if three out of five students in a group gave opinions on a website, we would obtain $\hat{l} = argmax_l\{0.79, 0.66, 0.85\} = 3$ by using the above equations. We then can derive that the number of students achieving the best performance in terms of commenting is three.

Step 3: Next, we compute the group reliability of the optimal group combination,

$$Q_{mark} = \sum_{i=0}^{\lceil \hat{l}/2 \rceil - 1} \psi_i^{\hat{l}}. \tag{6}$$

Step 4: We then compare the group reliability of the optimal combination computed at Step 3 with the minimal group reliability of this combination obtained so far.

If the group reliability of the optimal combination is lower, we need to consult a student with good achievement from another group to assist in making the final decision. In case the system cannot get the reply from this student before the deadline, more students with good achievement in other groups will receive requests from the system in a round robin fashion.

Step 5: Derive the score for the website. Now we assume the number of the optimal combinations is three. The weights of the three students are w1, w2, and w3, and the comments given by the three students are $Arg = \{+, -, +\}$. Here the notations + and – reprensent that two students pressed the "Agree" button, whereas one student pressed the "Disagree" button, respectively.

Based on the given comments, the probabilities that the website is suitable for the learning topics, and that the website is unsuitable for the learning topics can be respectively expressed by,

$$P(+|Arg) = \frac{P(Arg|+) \cdot P(+)}{P(Arg)} = w_1 \cdot (1-w_2) \cdot w_3 \cdot \frac{P(+)}{P(Arg)}, \tag{7}$$

$$P(-|Arg) = \frac{P(Arg|-) \cdot P(-)}{P(Arg)} = (1-w_1) \cdot w_2 \cdot (1-w_3) \cdot \frac{P(-)}{P(Arg)}. \tag{8}$$

Step 6: After normalizing the two equations obtained at Step 5, we obtain:

$$\hat{P}(+) = \frac{P(+|Arg)}{P(+|Arg) + P(-|Arg)} = \frac{w_1 \cdot (1-w_2) \cdot w_3 \cdot P(+)}{w_1 \cdot (1-w_2) \cdot w_3 \cdot P(+) + (1-w_1) \cdot w_2 \cdot (1-w_3) \cdot P(-)}, \tag{9}$$

$$\hat{P}(-) = \frac{P(-|Arg)}{P(+|Arg) + P(-|Arg)} = \frac{(1-w_1) \cdot w_2 \cdot (1-w_3) \cdot P(-)}{w_1 \cdot (1-w_2) \cdot w_3 \cdot P(+) + (1-w_1) \cdot w_2 \cdot (1-w_3) \cdot P(-)}, \tag{10}$$

where $P(+)$ is the percentage of the sample websites in the database marked with "agree"(+) or "strongly agree"(++), and $P(-)$ is the percentage marked with "disagree"(−) or "strongly disagree" in the database.

Step 7: By Comparing $\hat{P}(+)$ and $\hat{P}(-)$, we can determine whether this website is suitable for the learning topics by,

$$O = \begin{cases} +, \text{if } \hat{P}(+) \geq \hat{P}(-) \\ -, \text{if } \hat{P}(+) < \hat{P}(-) \end{cases}. \tag{11}$$

Notably, $\hat{P}(+)$ includes the opinions expressing "agree"(+) or "strongly agree"(++) as given by the peers, whereas $\hat{P}(-)$ includes the options expressing "disagree"(−) or "strongly disagree".

Step 8: Compare the comment given by the *i*th student and the result obtained by Eq. (11). If the comment given by a student indexed by *i* is consistent with the result obtained by Eq. (11), the *i*th student's weight is adjusted as follows,

$$w_i = w_i + \rho \cdot \frac{Arg_i}{\sum_l Arg_l}, \quad (12)$$

Otherwise,

$$w_i = w_i - \rho \cdot \frac{Arg_i}{\sum_l Arg_l}, \quad (13)$$

Otherwise,

where $\frac{Arg_i}{\sum_l Arg_l}$ represents the proportion of this student's comments which were consistent with the proposed algorithm in the past.

Step 9: By using Eq. (6), we re-compute the group reliability of the current combination of the students, based on the collected sample websites in the database. We set the minimal group reliability of the current student combination as the smallest value of group reliability obtained thus far.

Step 10: Next we compute the impact factor of the website based on the keyword typed in by the *i*th student as follows,

$$Imf = \frac{1}{\sum_{i=1}^{M} \beta_i} \sum_{i=1}^{M} \beta_i C_i \quad (14)$$

Where C_i is a flag that is marked if the *i*th student gave a comment on the website. That is, $C_i = 1$if *i*th student gave a comment on the website. Otherwise, C_i is set to zero. β_i denotes the weight of the selected keyword that is predetermined by the teacher.

2.2 Online learning resource ranking module

The learning resource ranking module is used to compute the final ranking for the learning resource comparing with other sample learning resources in the database. Support Vector Regression (SVR) [15] is used to implement this module. Three parameters for the SVR are three equations obtained from Eqs. **Error! Reference source not found.**, **Error! Reference source not found.**, and **Error! Reference source not found.**. SVR is a kind of supervised machine learning method that recognizes patterns and analyzes data; it is mostly used for classification and regression analysis. The major difference between the SVR and traditional regression techniques is that the SVR employs the structural risk minimization (SRM) approach, rather than the empirical risk minimization (ERM) approach typically adopted in statistical learning. The SRM attempts to minimize an upper threshold on the generalization rather than minimize the training error, and is expected to perform better than the traditional ERM approach. Furthermore, the SVR is a convex optimization, which guarantees that the local minimization is the unique minimization. In the recent literature, numerous researchers have adopted SVR to deal with classification and regression problems. Wu et al. [16] used SVR to predict the time spent on driving according to the speed of vehicles, traffic flow, and weather conditions. Users can handle the overall schedule more efficiently with this method. In addition, Liu et al. [17] compared three regression approaches, including SVR, Back-propagation Neural Network, and Partial Least Squares, to predict the Cold Modulus of Silicon Ceramic, and the results showed that SVR obtained better performance in terms of root mean square error than the other two methods.

2.2.1 Support Vector Regression (SVR)

To solve a nonlinear regression or functional approximation problem, the SVR nonlinearly maps the input space into a high-dimensional feature space using an appropriate kernel representation, such as polynomials and radial basis functions with Gaussian kernels. This approach is utilized to build a linear regression hyperplane in the feature space, which is nonlinear in the original input space. The parameters can then be derived by solving a quadratic programming problem with linear equality and inequality constraints [18].

A training data set $D = \{(\mathbf{x}_i, y_i) \in \Re^n \times \Re, i = 1,..., l\}$ comprising l pair training data $(\mathbf{x}_i, y_i), i = 1,...l$, is given. The input x_i terms are n-dimensional vectors, and the system response y_i terms are continuous values. The SVR attempts to approximate the following function using data set D:

$$f(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^{N} w_i \cdot \varphi_i(\mathbf{x}) + b \quad (15)$$

where b denotes the bias term, and the w_i terms represent the subjects of learning. Furthermore, a mapping $\mathbf{z} = \mathbf{\Phi}(\mathbf{x})$ is selected in advance to map input vectors x into a higher-dimensional feature space F, which is spanned by a set of fixed functions $\varphi_i(\mathbf{x})$.

By defining a linear loss function with the following ε-insensitivity zone:

$$|y_i - f(\mathbf{x}_i, \mathbf{w})|_\varepsilon = \begin{cases} 0 & \text{if } |y_i - f(\mathbf{x}_i, \mathbf{w}) \le \varepsilon \\ |y_i - f(\mathbf{x}_i, \mathbf{w}) - \varepsilon & \text{otherwise} \end{cases} \quad (16)$$

The w_i terms in Eq. **Error! Reference source not found.**) can be estimated by minimizing the risk:

$$R = \frac{1}{2}\|\mathbf{w}\|^2 + \frac{C}{l}\left(\sum_{i=1}^{l} |y_i - f(\mathbf{x}_i, \mathbf{w})|_\varepsilon\right), \quad (17)$$

where C denotes a user-chosen penalty parameter that determines the trade-off between the training error and VC dimension of the SVR model. Significantly, the VC dimension is a scalar value that measures the capacity of a set of functions.

Eq. can be further derived as the following constrained optimization problem:,

$$R(\mathbf{w},\xi,\xi^*)=\frac{1}{2}\|\mathbf{w}\|^2+\frac{C}{l}\left(\sum_{i=1}^{l}\xi_i+\sum_{i=1}^{l}\xi_i^*\right), \quad (18)$$

subject to constraints:,

$$\begin{cases} y_i-\mathbf{w}^T\mathbf{x}_i-b\le\varepsilon+\xi_i^* \\ \mathbf{w}^T\mathbf{x}_i+b-y_i\le\varepsilon+\xi_i \\ \xi_i,\xi_i^*\ge 0 \end{cases} \quad (19)$$

where ξ_i and ξ_i^* denote the respective measurements above and below the zone with the radius ε in Vapnik's loss function as given in Eq. **Error! Reference source not found.**).

Schölkopf et al. [15] developed a modification of Vapnik's original SVR algorithm, called ν-SVR, and claimed that it can automatically minimize the radius ε. Lagrange multiplier methods can be employed to demonstrate that the constrained optimization problem in Eqs. **Error! Reference source not found.**) and **Error! Reference source not found.**) maximizes the solution of the following equation:,

$$W(\boldsymbol{\alpha},\boldsymbol{\alpha}^*)=\sum_{i-1}^{l}(\alpha_i^*-\alpha_i)y_i-\frac{1}{2}\sum_{i,j-1}^{l}(\alpha_i^*-\alpha_i)(\alpha_i^*-\alpha_i)k(\mathbf{x}_i\cdot\mathbf{x}_j), \quad (20)$$

under constraints:,

$$\begin{cases} \sum_{i-1}^{l}(\alpha_i^*-\alpha_i)=0 \\ 0\le\alpha_i,\alpha_i^*\le\frac{C}{l},\ i=1,\ldots,l \\ \sum_{i=1}^{l}(\alpha_i^*+\alpha_i)\le C\cdot\nu \end{cases} \quad (21)$$

where (α_i,α_i^*) denotes one of l Lagrange multiplier pairs; C represents a regularization constant specified a priori; ν is a constant greater than or equal to zero, and $k(x_i \cdot x_j)$ denotes normally a Gaussian kernel or polynomial kernel.

The best nonlinear regression hyperfunction is then represented as:,

$$f(\mathbf{x})=\sum_{i=1}^{l}(\alpha_i^*-\alpha_i)\cdot k(\mathbf{x}_i,\mathbf{x})+b, \quad (22)$$

where b denotes the optimal bias.

III. EXPERIMENTAL RESULTS

To verify the effectiveness of the proposed collaborative recommender system, a total of 30 junior high school students participated in the study. One class related to natural science was assigned to be the experimental group in which the students were assisted by the website ranking mechanism, and the other was the control group in which the students used the ordinary search engine in the Internet. The experimental group included 30 students, while the control group had 30 students. After the teacher of a Natural Science course gave a detailed description of how to build a toy plane during a traditional classroom teaching activity, the students were asked to make a paper airplane using a plain piece of A4 size paper.

The students were asked to login to the platform after the cessation of classroom teaching activities. A question asking how to build an aircraft that would fly as long and as far as possible using a plain piece of A4 size paper was given to the students. The students were expected to surf on the Internet to address three main learning topics, including how to fly far, how to fly straight, and how to fly stably. The platform kept students' web search results in the database and evaluated the students' websites based on the students' comments. Each student was asked to take a pre-test and a post-test immediately before and after the learning activity, respectively.

We first compared the learning resource ranking results between the proposed algorithm and that of the teacher. Notably, the evaluation results of the students' learning resource recommendation were also provided by the teacher after the experiment, and were then compared with those given by the proposed algorithm. The correction rate for the proposed algorithm was up to 92.25%.

We next compare the students' achievement before and after the learning activity, as illustrated in**Error! Reference source not found.**.Ten multiple choice questions were included in the pre-test and post-test, respectively, to verify students' learning performance. The questions were related to the basic information related to flying, such as how to make the paper airplane fly straight, far, and stably. The statistical results were obtained by running a t-test with the SPSS software package. As shown inTable 1, the average score received by the 30 pupils whose learning activity was supported by the proposed website search mechanism was significantlybetter than the average score before using the mechanism. The evidence of a highly significant correlation between pretest and posttest obtained in Table 2,and the high significance level indicated by the results of the t-test in Table 3revealed that the learning effectiveness of the learners was indeed improved by the website search mechanism.

Table 1. Paired sample statistics.

	Mean	Standard deviation	Standard error mean
Pre-test	49.88	13.50	2.95
Post-test	68.92	15.20	3.01

Table 2. Paired sample correlations.

Correlation	Significance
0.802	0.000

Table 3. Paired sample test.

Mean Difference	t	df a	Sig.(2tailed)	95% C.I.b	
				Lower	Upper
-14.84	-5.20	30	0.000	-20.67	-9.01

[a] Degrees of freedom
[b] Confidence Interval

Table 4provides the ANCOVA analysis of the post-test results for the experimental group and the control group. Notably, we adopt ANCOVA analysis here by using the pretest as the covariance measure and the post-test as the dependent variable, since the students were not randomly assigned into two groups. It can be seen that the experimental group performed significantly better than the control group.

Table 4.
ANCOVA analysis of the post-test results for the experimental and control groups.

Group	N	Mean	S.D.	Adjusted Mean	Std. Error	F
Experimental group	30	68.92	13.50	67.86	2.47	4.65*
Control group	30	57.92	12.12	58.55	2.02	

*P<.05

To verify whether the online learning resource recommender was helpful, two short questionnaires were given to students in the experimental group that included the questions “Is the online learning resource recommender system able to provide you with appropriate guidance?” and “Are you satisfied with the usage of the online learning resource recommender system?” Among the 31 participants, 30 believed that the online learning resource recommender system was useful and all 30 students were satisfied with the usage of this system.

CONCLUSION

An intelligent online learning resource recommender system was proposed in this research. The proposed work is able to automatically evaluate whether or not the online learning resources the students search have addressed the related learning issues. The experimental results revealed that the online learning resource recommender system proposed in this study effectively enhances the achievement of the students from a junior high school who are participating in learning activities related to natural science. In future work, we will consider incorporating students’ learning styles into the experiments, in order to provide adaptive feedback tailored toward students with different learning styles.

One limitation of this study is that the 31 students participated in this experiment to assess their learning performance before and after using the proposed system for a period lasting only one-month, due to the limitation of course time. We only used t-test to analyze students' achievement before and after the conducted learning activity, and we will add more participants engaging in learning activity to explore the factors which may affect the learning performance via our proposed algorithm in future work. In addition, pre-existing personal friendships between the participants and how these relationships might affect learners’ social interactions have not been discussed in this study. Thus, further exploration of the impacts of social network interaction on enhancing collaboration and learning performance will be needed and considered in future work, as well.

ACKNOWLEDGMENT

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financially supporting this research under Contract NSC 102-2511-S-259-010-MY3.

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