A Hybrid Peer Recommender System for an Online Community of Teachers

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ABSTRACT

In this paper we present a system that recommends online comments written by teachers –suggestions of teachers to their peers- about their experience conducting educational activities in an online educational community called Kelluwen. In Kelluwen, the teachers build, use and share collaborative didactical designs whose educational activities are based on Social Web tools. To generate the recommendations, we propose a hybrid peer-based recommender system that combines collaborative and content filtering, and is also enriched with contextual information. The results of a quantitative evaluation and a survey support the utility of the recommendation method to improve their work.

Author Keywords

Hybrid techniques, peer recommendation, collaborative filtering, context-based, educational, teacher

ACM Classification Keywords: H4.m. Information system applications: Miscellaneous.

INTRODUCTION

Improving the development of socio-communicative skills in poor students of middle schools from Southern Chile encouraged us to create a social platform that we called Kelluwen. The Kelluwen project has developed an educational community of students, teachers and researchers that aim to promote and evaluate didactical strategies and practices involving Social Web tools. The Kelluwen platform supports this educational community by allowing teachers to build, use and share collaborative didactical designs by means of educational activities [9]. Teachers' experience using the didactical designs in their own classes generates a considerable amount of feedback in the Kelluwen platform. However, supporting the teachers in finding the most relevant experience of their peer colleagues poses a challenge due to the increasing amount of educational activities and comments available in the platform. To solve this problem, the proposed peer recommender system promotes the experience sharing among teachers by performing two basic tasks: a) continuously recording feedback information, in the form of comments that teachers write while they are executing the educational activities, and b) generating a list of suggestions from the collected feedback, adapted to the needs of each teacher who will execute the same didactic activities. .The development of the recommendation method involves a heuristic which is an extension of the hybrid filtering technique and combines user and content information enriched with contextual data. We take into account the educational, social and cultural context of the teacher and also the quality of the suggested item in the recommendation procedure.

The rest of the paper is structured as follows: First, we contextualize our research with related work in hybrid recommender systems and technology enhanced learning (TEL). Then, we introduce the proposed recommendation algorithm based in our ad-hoc heuristic. In the next section, we present details on the system implementation, followed by the results of a preliminary evaluation. We finalize with our conclusions and some suggestions of future work.

RELATED WORK

In [5], Burke surveyed hybrid recommendation research and he distinguished 6 categories of recommendation techniques: content-based, collaborative, demographic, utility-based and knowledge-based. He showed that they have complementary advantages and disadvantages and he concluded that combining techniques allows the improvement of the algorithm performance. Given the characteristics of the Kelluwen platform and the items to recommend, we consider hybrid recommendation as the most suitable for our purposes. On the other hand, recommender systems for TEL have been developed extensively in recent years. A review in applications for TEL is presented in [7], highlighting their particularities compared to other application domains. In [10] a recommender system is developed for e-learning objects adapted to each student according to her learning style. In [4] a collaborative filtering technique is proposed where ratings are weighted according to the level of learning of the user. On the other hand, [8] presented a recommender system for teaching materials based on classification

SRS Workshop 2012, July 17, 2012, Montreal, Canada.

Variable	ID	Values
School socio-economical level	*NS*	Low: 1
		Mean low: 2
		Mean: 3
		Mean high: 4
		High: 5
School quality of TIC infrastructure	*CT*	Sumatoria de 3 valores
Size of school locality	*TL*	lower than 10.000 habitants: 1
		Between 10.000 and 100.000 habitants: 2
		Greater than 100.000 habitants: 3
Mean number of students by classroom	*N*	Mean number of students by classroom for each teacher
Number of ratings between teachers	*NRM*	Matrix of number of ratings that teacher *c* send to all the messages of teacher *t*, normalized to [0,1] interval
Number of response messages between teachers	*NNM*	Matrix of number of response messages that teacher *s* send to all the messages of teacher *t*, normalized to [0,1] interval

Table 1. User variables

Variable	ID	Medición
Number of didactical designs applied by a teacher *t* (sending de suggestion *s)*	NE_t	Number of didactical designs applied by a teacher t (sending de suggestion *s)*, normalized to the [0,1] interval
Activity evaluation from the teacher sending de suggestion *s*	AE_s	Very well: 0
		Well: 1
		Bad: 1
		Very bad: 0
Message nature	NM_s	Activity comment: 0
		Suggestion: 1
Number of rating of all messages from teacher *t* (sending de suggestion *s)*	NRT*t*	Number of rating of all messages from teacher *t* (sending de suggestion *s)*, normalized to the [0,1] interval
Number of rating of suggestion *s*	NRM_s	Number of rating of suggestion *s*, normalized to the [0,1] interval

Table 2. Content Variables.

models. To the best of our knowledge, no previous work has investigated the use of recommender systems for the recommendation of community comments in an educational context, specifically, peers' suggestions to lead educational activities.

RECOMMENDATION ALGORITHM

The items recommended by our system are comments and suggestions written by teachers about the activities they do in the Kelluwen platform. Also, the teachers are able to provide feedback over the recommended items (comments and suggestions) using a like button. Following [1], we define a utility function based on information about the users' and items' profiles as follows: Let *C* be the set of all users and let *S* be the set of all possible items to recommend. Let *u* be the utility function of an item *s* for user *c*. We also consider that the profile of user *c* is defined as a vector of *p* attributes,

$$a_c=(a_{c1}, a_{c2}, \ldots, a_{cp})$$

and the profile of an item *s* is defined as a vector of *r* features:

$$b_s=(b_{s1}, b_{s2}, \ldots, b_{sr})$$

Let $R = (r_{cs})$ be the rating matrix, were r_{cs} is the rating of suggestion *s* by the user *c* and $N = (n_{ij})$ the responses matrix, where n_{ij} is the number of responses to messages that user *i* has send to user *j*.

Hence the utility function has the following expression:

$$v_{cs} = u(a_c, b_s, R,N)$$

Moreover

$$u(a_c, b_s, R,N) = k_1 * u_1(a_c,R,N) + k_2 * u_2(b_s,R)$$

where u_1 is the utility function associated to the collaborative filtering focus and u_2 is the utility function corresponding to the content-based approach. We use k_1, k_2 for weighting each part such that $k_1+k_2=1$. In the user profile we consider information related to educational and cultural contexts of teachers and their classrooms: socio-economical level and infrastructure quality of school, locality size and mean number of student by class. From these variables we compute a similarity measure between teachers using the Pearson correlation statistic [4, 6] normalized to [0, 1] interval. The result is named NTM (normalized teacher matrix). Furthermore, from the collaborative approach, we consider the rating matrix R to compute the number of ratings that user *c* has done of suggestions (items) of user *t*, resulting after normalization to [0, 1] interval, the matrix named NRM (normalized rating matrix). Similarly, we normalize the matrix N to [0, 1] interval to obtain NNM (normalized messages number matrix). Then, the utility function corresponding to the collaborative filtering approach is written as:

$$u_1(a_c,R,N) = (NTM_{ct} + NRM_{ct} + NNM_{ct})/3$$

where t is the teacher that sent the suggestion s. In this way, the utility function u_1 considers the similarity between teacher who send the suggestion and the teacher who receive it, from three different perspectives: contextual information, number of ratings and interactions. A summary of involved variables in the utility function u_1 is presented in Table 1. On the other hand, from the content-based approach, we consider variables related to the quality of the item in the item profile. It is noteworthy that in this educational setting items correspond to comments provided by teachers on the platform Kelluwen and reflect the lessons learned by them in the application of didactical designs. Therefore, we distinguished item attributes from two perspectives: from the professor of origin (the commenter) we consider the number of didactical designs that she has applied, i.e. her experience, normalized to [0, 1] interval that we named NE_t and from the suggestion itself, we consider the corresponding activity evaluation (AE_s) and the nature of message: suggestion or comment (NM_s). Furthermore from the rating matrix we compute two other measures of the quality of an item s: the number of ratings received for all the items originated by the teacher who originate s, normalized to the [0, 1] interval (NRT_t) and the number of ratings received by the item s itself (by all the teachers who rated this item), normalized also to the [0, 1] interval (NRM_s). Then, the utility function corresponding to the based-content approach is written as:

$$u_2(b_s,R) = (NE_t + AE_s + NM_s + NRT_t + NRM_s)/5$$

where t is the teacher that writes the item s. A summary of involved variables in the utility function u_2 is presented in Table 2. For each active user, we calculate the value of the utility function of each of the items to be recommended, generating a ranked list. Only the top 10 recommendations are shown to the teacher while executing educational activities. As the project and platform Kelluwen encourage collaborative work and interaction among teachers, and moreover the peer recommendation system collects this information and uses it to calculate the utility function of each user, we decided to give greater weight to the collaborative filtering part of the utility function. Thus the assigned values for k_1 and k_2 were $k_1 = 0.8$ and $k_2 = 0.2$.

IMPLEMENTATION

The system implementation was conducted in two phases of development. The first focused primarily on the capture of the suggestions provided by the teachers during the activities. We first deployed the functionality sorting suggestions by time, i.e. the most recent showing first. We also included a feature to allow the users providing feedback to the comments that they considered relevant ('I like'). During the second phase of development, we focused on the design and implementation of the heuristics for ranking the suggestions. The new feature shows suggestions ordered adaptively for each teacher in the community according to the value of the utility function. Figure 1 shows how the suggestions are presented to teachers in Kelluwen platform. When the teacher starts an activity, all the suggestions made by other teachers in the past, regarding the activity, are ranked and showed on the right side. This is the first time that the teacher see the suggestions, related to the current activity, and it is possible that it is the only time doing this activity. Then, she has not had the opportunity to rate the suggestion yet. This implies that, in a pure collaborative filtering approach, our recommendation algorithm would always be applied in a cold-start situation.

RESULTS

The peer recommendation system was used by teachers in the community between October and December of 2011. A total of 314 recommendations were issued for activities, where 96 of them were rated by the users. More specifically, 89, 5 and 2 suggestions were rated one, two and three times respectively. To evaluate the peer recommender system we used Normalized Discounted Cumulative Gain metric (nDCG) [2, 3]. nDCG was applied on a sample of 39 sets of recommendations yielding the results shown in Figure 2.

Figure 1. Visualization of peer recommendations in Kelluwen. The yellow box on the right side lists the recommended items.

Most of the sets are concentrated at the value 1 or close to 1, indicating that the order of recommendations generated by the system is optimal. Furthermore, a sensitivity analysis to study the behavior of the factors k_1 and k_2 was carried out. This analysis allowed us to determine, using nDCG, which values provide the best results for ranking the items. Figure 3 shows the results obtained for weight values of $k_1 = 0.2$ and $k_2 = 0.8$. The variability of the results is low, however, the case marked with the letter D in the last two figures gives different results, being the original setting $k_1 = 0.8$ and $k_2 = 0.2$ the one that generates the best order of the suggestions. Furthermore, we conducted a user satisfaction survey consisting of five questions to be answered in the scale totally disagree, disagree, agree and totally agree. The survey was answered by 16 teachers out of 29 that used the platform. 70% of them said they made use of the recommendations. Although only 38% of users provided comments on the suggestions of their peers, a 68% said that the suggestions are useful in the educational process

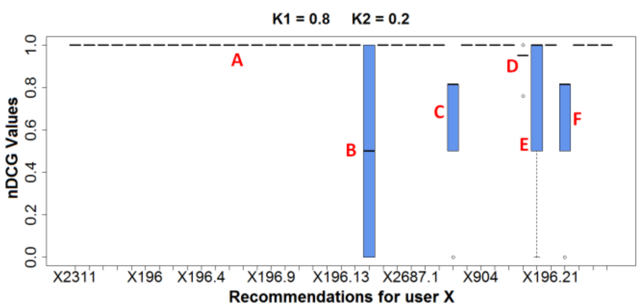

Figure 2. Peer recommender system assessment with nDCG metric for weights *k_1=0.8 and k_2=0.2.*

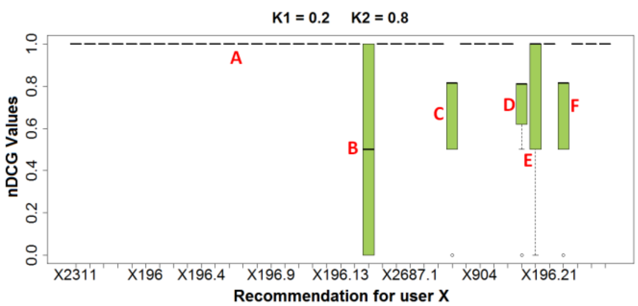

Figure 3. Sensibility analysis using nDCG metric with *k_1=0.2 and k_2=0.8.*

Finally, 70% of teachers said the peer recommendation system is a mechanism that significantly supports the work of teachers.

CONCLUSIONS

In this work we introduced a novel hybrid algorithm for a peer recommender system. On the one hand, from the collaborative filtering approach we built a utility function that considers the closeness between teachers. To compute the closeness we considered relevant variables that reflect the educational and socio-cultural context of the teachers and variables based on their participation in the platform. On the other hand, we used a content-based approach and built an additional utility function related with the quality of the suggestion (recommended items). In this case, we consider variables related to the teacher who sends the suggestion as well as attributes of the item itself. The whole utility is computed as a weighted combination of both collaborative and content based utilities. From these definitions we developed our peer recommender system to support teachers involved in the didactical innovation proposed by Kelluwen project. The tool was deployed and preliminary results showed that the ranking function is effective. It is worthy to note that the nature of the recommended items required a context-based recommendation strategy and dealing with the start-cold situation. Future work includes strategies to encourage the users to increase the number of ratings over items, in order to make a more robust validation of our heuristic.

ACKNOWLEDGMENTS

This work was partially funded by the project FONDEF D08i-1074 “Kelluwen: Investigación, desarrollo y validación de diseños didácticos colaborativos apoyados en servicios de la Web 2.0. Estrategias para el desarrollo de competencias socio-comunicativas en estudiantes de colegios vulnerables de la zona sur de Chile”. We appreciate the contribution of all the Kelluwen research team to this article, particularly Carolina Aros, carolinaaros@gmail.com.

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