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Abstract

With the rapid development of massive open online courses, peer assessment has played an important role in promoting social learning. According to social learning theory, peer assessment in online courses provides students a chance to learn from each other when they review other students' submissions, which motivates their participation in online social learning. However, existing peer assessment cannot generate satisfactory results in that a systematic approach to find peer reviewers for submissions is lacked. To address this problem, this paper proposes a reviewer recommendation system which can suggest appropriate reviewers for submissions during the process of peer assessment. This recommendation system is built by integrating information of learners and submissions. The integration of this reviewer recommendation system in the process of peer assessment may help to improve learners' satisfaction and their learning performance. Additionally, the reviewer recommendation system can also be used in many other fields such as enterprise training or language learning online.

Keywords: Social Learning, Reviewer Recommendation System, MOOC, Peer Assessment.

1 INTRODUCTION

Social learning theory has been proposed for decades of years and it has been widely used in many fields, such as medical(Rona L Levy, 2007), economy(Yu, Tian, Vogel, & Chi-Wai Kwok, 2010), pedagogy(Martínez, Dimitriadis, Rubia, Gómez, & de la Fuente, 2003).In learning context, social learning theory means that students can learn through observing, modelling or copying other students' behaviour to seek acceptance in society(Bandura, 1977). Besides traditional face-to-face learning mechanisms, online social learning enables students to learn from each other through the internet. According to social learning theory, peer assessment conducted online provides an opportunity for students to imitate the behaviour of each other when they review other students' submissions, which may encourage their participatement in online courses.

Peer assessment, as one of the most important parts of online courses, is used to describe the process that students assess the performance/contribution of themselves and their peers on the internet (Loddington, 2008).It has been proved that peer assessment in online courses can largely reduce instructors' burden, especially when those courses have complex and open-ended assignments such as mathematical proofs, design problems and essays(Piech C, 2013). With the emergence of the web 2.0 techniques since 2003, many kinds of online course platforms (e.g. Udacity, Coursera and EdX) have been designed. Courses distributed on those platforms are named MOOCs, which is short for massive open online courses. MOOCs is developed rapidly and the year of 2012 was called "The year of the MOOC" by New York Times(Pappano, 2012).These massive open online courses break the limitation of time and space, and realize the sharing of knowledge between large number of learners. However, how to grade huge number of learners' submissions in a short time becomes a problem. Peer assessment, as a promising solution, can efficiently grade complex assignments in courses which have tens of thousands of learners(Piech C, 2013).

Nevertheless, many researchers argued that existing peer assessment mechanism cannot always generate accurate results compared to human experts. For instance, it was estimated that 43% of student submissions were given a lower score by existing peer assessment system compared to human experts(Piech C, 2013).As a result, students' satisfaction with online courses and their attitude to learning online may be affected. It has been proved that personal attitude is a major factor to affect individual usage of information technology(Shu-Sheng Liaw, 2007).In order to use the online courses effectively, we have to pay more attention to the process of peer assessment to improve learners' satisfaction with online courses when we evaluate students' submissions. To optimize the process of peer assessment, this paper proposes a recommendation system which can recommend appropriate reviewers to submissions that are submitted by other learners. This reviewer recommendation system is based on integrating information of learners and submissions. Due to the fact that more than one question may be included in learners' tests every time, so we will design a recommendation system which can recommend reviewers to every question. Related literatures have proved that reviewer biases and reliabilities play important roles in peer assessment accuracy and it is also proved that reviewers with similar score tend to give the least biased score to each other's submissions(Piech C, 2013). Thus, this recommendation system is built based on the assumption that two learners who have the similar answer will get the similar score and they will give the least biased score to each other's submissions. Therefore, similarity of learners' answer is one of the dimensionality that we will consider. Another dimensionality that we must pay attention to is candidate's assessment ability which means that we must ensure the candidate has the ability to review other learners' submissions and this ability can be reflected by some other information which exists in learners' database. This reviewer recommendation system is suitable for those courses that have the peer assessment process but have no explicit answers for questions in the test.

2 RELATED LITERATURE

2.1 Peer Assessment Systems in Online Courses

The existing peer assessment system mechanism of the online courses platform (e.g. Coursera) can be described as follows. Firstly, learners' submit their assignments to the system before the deadline of the submission. Secondly, at the beginning of the evaluation phrase, the system will randomly assign a small number of other learners' submissions to learners who have submitted assignments. Learners who receive this task will evaluate others' assignments according to a detailed scoring standard provided by their course instructor and then submit their evaluations to the system before the evaluation deadline. Finally, learners are able to see grades given by peers. Additionally, a training process or a self-evaluation may be included in the evaluation phrase which may help learners adjust their grading practices to match instructor's intentions for the assignment (http://help.coursera.org/).

In order to improve the accuracy of peer assessment in MOOCs, many researchers propose various approaches. Piech et al (2013) propose algorithms for estimating and correcting reviewers' biases and reliabilities to improve the accuracy of peer assessment. These biases relate to learners' factors, such as their comment styles, their performance and their engagement. They conduct the research by using a large number of data which is obtained from Coursera's HCI. While, Gillet et al(2014) propose a platform to deposit course materials and it has been proved that this platform plays an important role in immersing students into the course topic when assessing other's submissions. These literatures all propose approaches to optimize the process of peer assessment. Although they find the related factors or build a platform to set up peer assessment activity, some other information is ignored when they optimize the peer assessment process, such as learners' major, learners' education background and submission features. In this paper, we build a peer reviewer recommendation system which integrates the information of learners and submissions to generate the candidate list for each answer in submissions.

2.2 Recommendation System

Most of recommendation systems in e-learning field focus on recommending related materials(Salehi, Kmalabadi, & Ghoushchi, 2012; Salehi & Nakhai Kamalabadi, 2013) or courses to learners. Also some others focus on using it to optimize process. For instance, some researchers use recommendation system to accomplish personalization of e-learning activities(Rosaci & Sarne, 2010).In this paper, we optimize the peer assessment process by using a recommendation system. We can use many kinds of technologies and tools to develop a recommendation system. Collaborative filtering(J. Bobadilla, 2009), association rule mining(Civan Özseyhan, 2012), web mining and information retrieval(Mohamed Koutheair Khribi, 2009)and some other technologies all have been used in previous research to build recommendation systems. If we use a learner's submissions to represent his/her expertise in relevant areas, then the peer reviewer recommendation problem can be partially transformed into similarity measure problem of learner's and reviewer's submissions. In this paper, we use the text mining based on semantic analysis to get the similarity score for the final recommendation. The algorithm is adapted from Landauer, T.K.(2007). Due to the fact that in our recommendation system, learner cannot assess his/her own submission, therefore, we add a variable to control this condition.

3 AN OVERVIEW OF RRS AND ONLINE COURSE PLATFORMS

3.1 The Framework of RRS

This paper takes a profile-based approach to build the reviewer recommendation system (RRS). *Figure 1* illustrates the key framework.

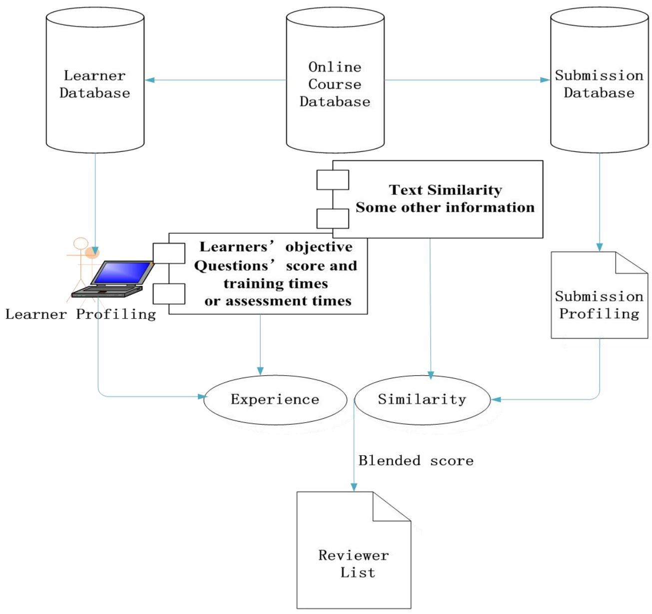


Figure 1. The framework of RRS

This reviewer recommendation system is built based on two dimensions of information. One is learners' experience and the other is submissions' similarity. We integrate information of these two dimensions then generate the candidate recommendation list which is based on learners' blended score.

3.2 Online Course Platforms

One of the most famous online courses is MOOCs. These courses are distributed on many large course platforms including Coursera, Udacity and Edx. Also, they are distributed on some other platforms recently. Due to the similarity of these course platforms' mechanism, our research is mainly based on those three platforms. From those large platforms, both learners' information and submissions' information can be obtained from related databases. Though we cannot obtain these data directly, we can obtain some courses' information through simulating part of these courses. Information that we want to obtain from these databases are learners' basic information and submission content. Learners' information includes learners' training/assessment frequency, learners' education background, learners' major and learners' objective answer records. All the information that we obtain will be used for building learner's profile and submission's profile.

4 PROFILING

In the process of building the reviewer recommendation system, two kinds of profiles are built: learner's profile and submission's profile. The examples of these two kinds of profiles are shown in *Figure 2*.

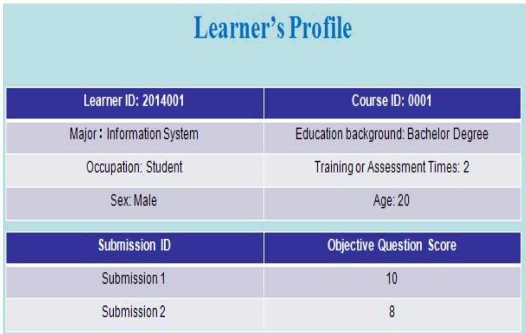
4.1 Building profile of learners

The learner's profile is composed of four dimensions: demographics, domain knowledge background, assessment ability and submission. Most of the above information can be found in majority of the peer assessment courses. Demographics mainly include the learners' basic personal information such as his/her age, education background, major, occupation. This kind of information can be obtained from the learner database. Knowledge background can be reflected from his/her major and his/her objective question score(besides subjective questions some tests also have objective questions) to some extent. Assessment ability can be reflected from the training process or times that he/she participating in the assessment process. Here we have an assumption that if learners who have taken part in the training process or have taken part in process of peer assessment more than one time, his/her assessment ability is stronger than those who haven't. Learner's submission is one of the most important parts of learner's profile because it reflects similarity between this learner's submission and other learners' submission. We will use semantic analysis to analyze the similarity of submissions(Some submissions may include pictures, here we ignore this condition and we will research it in our future work).

The learner's profile can be built as follows.

<Learner ID, Course ID, Submission ID, Major, Education Background, Occupation, Objective Question Score, Training or Assessment Times>

Here, Learner ID is used to specify the only one from all of the learners. Similarly, Course ID and Submission ID are used to specify the only one from all of the courses and submissions respectively. Due to the fact that some of the online courses have the objective question, therefore, its score can be a measure of learner's background knowledge partly. Training phrase may be included in some of the online courses. If some of the above items are not included in one course, then the score of that missing item will be set as 0. The above items all have contributions to the final recommendation, while different weights will be given to different items according to their contributions respectively.



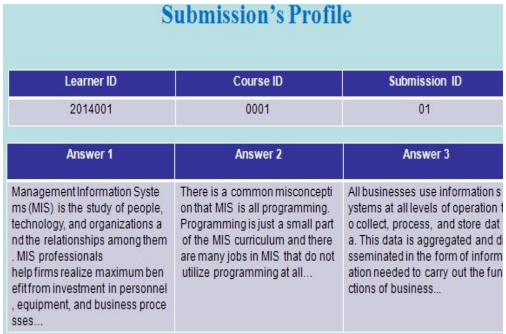


Figure 2. The examples of learner's profile and submission's profile

4.2 Building profile of submissions

In this paper, the submission's profile is a subset of the learner's profile. The submission's profile sequence can be as follows.

<Learner ID, Course ID, Submission ID, Answer *1*, Answer *2*, Answer *3*….>

In the process of peer assessment, one or more questions may be included. Thus, one learner's submission may include several answers to different questions. So we give every answer a space in the submission's profile. Here, Answer *i* means the answer to question *i*.

5 RECOMMENDATION

To generate the final recommendation list, many steps are designed. The recommendation process is illustrated in *Figure 3*.

The general process is as follows:

Step1: Extract attributes from the simulative online course databases to build the learner's profile and submission's profile.

Step2: Use text mining based on semantic analysis to analyze similarity between one learner's submission and other learners' submissions, and then generate the similarity score. At the same time assess every leaner's assessment ability based on the objective question score and his /her assessment times or training times, then give out the assessment ability score.

According to Kirill Kireyev(2008) LSA(Latent Semantic Analysis) can do better than other methods when calculate the similarity between two chunks of text, so we choose the following formular to calculate similarity between two learners' answers(Kireyev, 2008). Considering that learner cannot assess his/her own submission, so we change the original formular a little. The similarity between two answers can be calculated by the following formulars(Landauer & Kintsch, 2007):

$$S(T_1, T_2) = \frac{\left(\sum_{i=1}^{n} m_k a_i v_i\right)\left(\sum_{i=1}^{n} m_k b_i v_i\right)^T}{\left\|\sum_{i=1}^{n} a_i v_i\right\| \bullet \left\|\sum_{i=1}^{n} b_i v_i\right\|} \tag{1}$$

$$m_k = \begin{cases} 0 & if \quad T_1 \quad and \quad T_2 \quad belong \quad to \quad the \quad same \quad learner \\ 1 & others \end{cases} \tag{2}$$

Here n is the number of terms in space; v_i is the vector representation of term i; a_i is the number of times term i appeared in the answer T_1 ; and b_i is the number of times term i appeared in the answer T_2 .More details please find in (Landauer & Kintsch, 2007).

The assessment ability score can be calculated from two parts: learner's frequency of training or assessment and learner's objective question score. For instance, if one learner has taken part in training or assessment 3 times and his/her objective question score is 8 then his/her assessment score can be 3+8=11. In other words, the assessment ability score is partly decided by learner's training or assessment frequency and his/her objective score.

Step3: Calculate each learner's additional score according to his/her education background and major. When assessing learner's additional score, we can give different weights to different items according to their contributions to the final recommendation. The additional score can be calculated by many ways, for instance, if learner's education background or major is highly related to this course, then we can set this score as 1, others 0. The score calculated in this part will be discussed detailedly in the future research.

Step4: Calculate the total score by adding the additional score, the similarity score and the assessment ability score. Allocate every part a weight based on their contributions to the final recommendation, for instance, give the similarity score a ∂, the assessment ability score a **ß** and the additional score a **Ɵ**.

Final score=∂ Relscore+**ß** Asescore+**Ɵ** Addscore (∂+**ß**+**Ɵ**=1, **Ɵ** is obviously smaller than ∂ and **ß**)

Step5: Generate the recommendation list for each question according to their final score. And the example of calculating the blended score can be found in *Figure 4*.

6 EVALUATION

Generally, when we evaluate the performance of a new recommendation system, we usually put it into an experimental environment then collect related data to analyze the result. In the experimental environment two approaches can be used to evaluate a new recommendation system. One is that using existing reviewer recommendation system compares to this new recommendation system on peer assessment accuracy. The other is that conducting a survey to know about if learners' satisfaction is improved after adding this reviewer recommendation system into peer assessment process. Considering the fact that there is no reviewer recommendation system for peer assessment online courses ever before, therefore, we choose the second method to test the effect of the addition of the reviewer recommendation system. The evaluation of the proposed approach will be conducted as follows.

Before the addition of the reviewer recommendation system to the online courses, we carry out a satisfactory survey on some undergraduate students who are learning in one or many courses on online platforms. Learners are asked to complete a questionnaire designed to explore their satisfaction of the experience and to ascertain whether they felt the current form of assessment has improved their skills and interests tremendously or not. The questionnaire is consisted of a number of items rated on a 5-point Likert scale which is used to deal with students' general perceptions. Additionally, an open-ended question related to what they liked and disliked about peer assessment and the changes they would make to the process of peer assessment is also included. After the adding of the reviewer recommendation system, we will carry out a satisfactory survey on these undergraduate students again. Finally, we compare the two satisfactory results to ascertain whether the effect and efficiency is improved after the addition of the reviewer recommendation system.

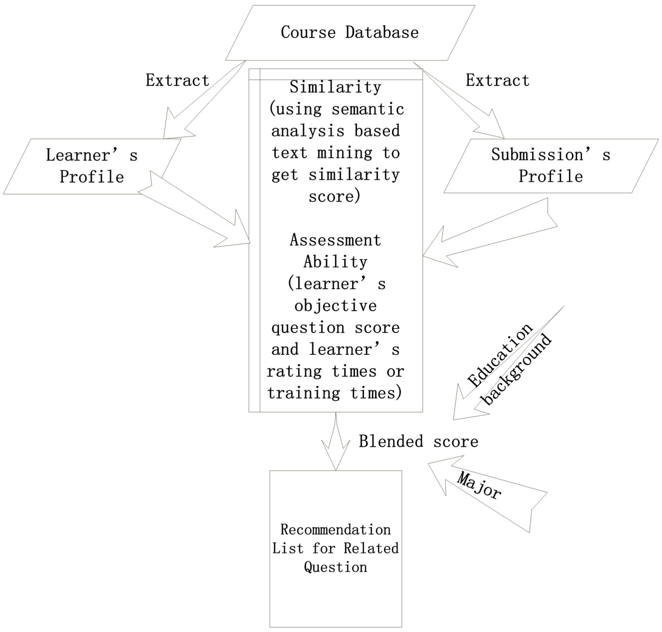


Figure 3. Recommendation processing

Learner's recommendation score for answer 1 of submission 1 of 2014001

Learner ID	The Blended Score	Similarity Score (60%)	Assessment Ability Score(20%)		Additional Score (20%)		
			Assessment or Training Times (10%)	Objective Answer Score (10%)	Education Background (5%)	Major (5%)	Mother Language (10%)
2014002	91	55	18		18		
2014003	75	40	17		18		
2014004	79	45	17		17		

Figure 4. The example of computing learner's recommendation score

7 CONTRIBUTIONS AND FUTURE WORK

Unlike some other researches which are trying to build models for peer assessment process or building platform to improve peer assessment accuracy, this paper proposes a new approach to optimize the peer assessment process. We try to integrate a reviewer recommendation system into the peer assessment process and this recommendation system will combine learners' information and submissions' information to generate the final reviewer recommendation list. If this research is proved to be successful, it can be meaningful for helping to improve learners' satisfaction and their learning performance. The theoretical contribution of this paper is that the integration of the reviewer recommendation system into peer assessment process can promote the development of online social learning by giving students a chance to learn from the appropriate peers when they review other peers' submissions. The practical contribution is that the reviewer recommendation system cannot only be used in the massive online open courses but also can be used in many other fields, such as business training and language learning which is conducted online.

For the future work, we will design this reviewer recommendation system and evaluate its performance.

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