Recommender Systems for University Elective Course Recommendation

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***Abstract*- Recommender Systems are an ongoing research that is applied in various domains. Course recommendation is considered a challenged domain that has not been explored thoroughly. It benefits undergraduate students who need suggestion and also enhances course selection processes during the pre-registration period. This paper introduces a recommendation system for university elective courses, which recommends the courses based on the similarity between the course templates of students. This paper utilizes two popular algorithms: collaborative based recommendation using Pearson Correlation Coefficient and Alternating Least Square (ALS), and compares their performance on a dataset of academic records of university students. The experimental results show that applying ALS in this domain is superior to collaborative based with 86 percent of accuracy.**

I. INTRODUCTION

Nowadays, there are recommender systems in various domains that facilitate daily livings of individuals such as product recommendation in online shopping stores, movie and music recommendations, hotel recommendation, and so on. These kinds of recommendation both attract and assist users to enter the websites, which may also result in increasing purchase transactions of products and/or services. Among these well-known domains, course recommendation is considered a challenged domain that has not been explored thoroughly. The recommender systems developed could aid students in suggesting suitable courses for them as well as reducing time to explore courses that they will take. Since there are many elective courses opened in each semester, students have to spend a lot of time for exploring those courses, and they may not be able to explore all of them. Apart from assisting the student, recommender systems could help the university registrar by recommending enough sections for a course.

According to our investigation, there are a couple techniques and/or algorithms introduced for course recommendation. The techniques and/or algorithms are varied from content based recommendation [1], collaborative filtering [2] and rule mining [3]. Our work focuses on designing and developing the recommender system that recommends elective courses for university students to assist them to make decision for enrolling courses in each semester. In particular, we propose a recommender system that builds user profiles based on student academic records. Then, the system applies two well-known algorithms to find similarity among students and finally suggests elective courses that are suitable for them. The two algorithms are collaborative filtering algorithm using Pearson Correlation Coefficient and Alternating Least Square (ALS). In addition, our work compares performance of the two algorithms using a real dataset of academic records of undergraduate students at Assumption University to justify the superior algorithm to serve elective course recommendation.

The rest of the paper is organized as follows. Section II describes related works of course recommender systems using various approaches. Section III provides details of the proposed recommender system for elective course recommendation. Section IV and V describes experimental results and conclusion, respectively.

II. RELATED WORKS

Students' course enrollment recommendation is one of the issues that universities tend to achieve. It does not only help the students decide what they should study, but it also leverages their full performance if they could study what they like or are interested in. The methods popularly implemented for the recommendation are content-based filtering, collaborative filtering and rule mining approaches.

Content-based filtering approach recommends an item to a user by considering the description of the item and clustering the item and the user into groups to gain similarity between them. The mechanism is suitable for the system that does not store the personal information of each user and merely keeps the information regarding items. Queen Esther Booker, Minnesota State University creates a prototype of a system that helps students select courses to enroll in a semester [4]. The system requires users enter their interests as keywords, current GPA and SAT or ACT score. It then takes the input from the student and match it with the description of courses to be offered. For example, a user enters 'coding' as the keyword of interests, the system would recommend courses that their description contains 'programming', 'writing programs', etc.

Collaborative filtering approach recommends an item to a user by investigating the user's similarity with the user's information in a system and predict the item that the user would be interested in. Hana introduces a mechanism based on this approach to recommend courses for a student by

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exploring the student's academic record and matching the record with others' ones to gain the similarity [5]. Then the system figures out and recommends which course he is good at or interested in so that he could pass the course. Elham S.Khorasani et al. proposes a Markov Chain Collaborative Filtering model to recommend courses based on historical academic data with concerns of the sequence of each course being taken [6].

Rule Mining approach focuses on recommending a series of items to a user by discovering the interrelation between each item such as selling amount as a rule. In terms of course enrollment, recommendation could be a series of courses that students prefer taking those courses. Itmazi and Megias develop a recommendation system using this approach to recommend learning objects [7]. They recommend series of courses for university students by investigating the factors relating to each student, e.g., demographics, and the factors relating to each course offered, e.g., instructors responsible for the course. Amer Al-Badarenah and Jamal Alsakran propose an elective course recommender system for students based on their similarity along with grades [8]. The system finds a set of courses that are taken with grades by the students like the targeted student so that he can select the courses suitable for him.

In this paper, the recommender system focuses on the similarity amongst students based on their academic records. The system investigates each student's academic records to find the similarity with the targeted student. It then recommends the elective course that they used to take. It differs from the previously stated systems that it recommends individual courses based on the student's enrollment records similar to the targeted student only. In addition, ALS algorithm is used to improve the accuracy of the recommendation.

III. The Proposed Recommender System for Elective Course Recommendation

The definition of elective courses is any course that students can freely choose to study in a semester, which also depends upon the curriculum of the university. The goal of the system is to suggest elective courses to individual students based on their academic profiles. The system comprises 3 main processes. The first process is course template creation as user profiling for each student. The second process is recommendation model creation, and the third process is applying the model for course recommendation. The details of each process are as follows.

A. Course Template Creation (User Profiling)

A course template is a pattern of courses that a student studies in each semester. Creating a course template requires each student's academic records investigated for determining which course they each enroll. We construct the course template by specifying 1 to the course a student takes and 0 to the course the student does not. At last, each student has their own course template elaborating how one's learning style is.

B. Recommendation Model Creation and Course Recommendation

Once each's course template is constructed, we use the template to discover similarity amongst students in a university. That a student similar to others means that how the student enrolls courses is likely similar to how the others do. For example, student *A* takes the same 5 courses like how student *B* does. They are considered highly similar to each other because they identically take the stated courses. However, if the number of the taken courses of *A* is fewer than student *B*, the rate of similarity is lowered proportionally. It is noted that the students' course templates must be constructed from the same version of the curriculum because curriculum could be changed from time to time. For instance, if the targeted student is studying in the faculty of Marketing with the curriculum 2014, the students being compared must also be studying in Marketing with curriculum 2014.

The system uses collaborative filtering to recommend a student elective courses by comparing his course template to others' templates who have the same curriculum to find the pairwise similarity of students using Pearson's Correlation Coefficient. The similarity formula is given in Eq. 1.

$$sim(a,b) = \frac{\sum_{p \in P}(r_{a,p} - \overline{r_a})(r_{b,p} - \overline{r_b})}{\sqrt{\sum_{p \in P}(r_{a,p} - \overline{r_a})^2}\sqrt{\sum_{p \in P}(r_{b,p} - \overline{r_b})^2}} \quad (1)$$

where, *a* and *b* denote any two students that need to find the similarity. $r_{a,p}$ is the score of the course p for the student a and $r_{b,p}$ is the score of the course p for the student b. $\overline{r_a}$ and $\overline{r_b}$ are the average existence of the score of each course of the student a and b respectively.$\overline{r_a}$ After obtaining the pairwise similarities, the system recommends elective courses to a student by providing the elective courses enrolled by the top 3 of the most-similar-student. It should be mentioned that the recommended course is neither the already taken course nor the one that does not available in the upcoming semester.

The second algorithm is Alternating Least Square (ALS), which is one of the approached in matrix factorization proposed by Bell and Koren [9]. This approach is low rank matrix factorization in which the factorization is done by minimizing square error between the factors-based estimates and known ratings. In Eq. 2, rating r_{ui} is known from the set of user *u* and the item *i* for pairs *(u, i)*. The I_i is the i^{th} row of I, which associates to item *i*. The U_u is the u^{th} row of U, which associates to user *u*. The goal of ALS is to minimize the cost function, where *S* denotes the known ratings set.

$$\min_{U,I} \sum_{(u,i) \in S} (r_{ui} - I_i^T U_u)^2 \quad (2)$$

By calculating the weighted squared error, the approximation is low. Let *P* and *Q* denote the matrices composed of user and item feature vectors respectively where the associated function with the model is f_I. ALS algorithm is given as follows.

Algorithm 1. Alternating least squares (ALS)

Initialize Q with small random numbers
for E times **do**
  Compute the P that minimizes f_I for fixed Q.
  Compute the Q that minimized f_I for fixed P.
end

IV. THE SYSTEM IMPLEMENTATION

This section elaborates each significant process of the system for elective course prediction. Apart from the previous section stating the processes for the recommender system, the other processes such as data preparation are also essential. Decent data preparation may greatly help improve the accuracy of the recommendation. The followings are the processes to be implemented to this proposed system.

A. Data Gathering

Before the implementation, the appropriate and consistent data are needed so that the result generated by the system is acceptable. Similarities amongst students have to be calculated and then select the highest value for consideration. However, not all students are accounted for calculating the similarity since some may not have the same curriculum or course template. Therefore, we gather only the information of the students, who have the same course template as the concerned student. This means that those students are in the same faculty as well as the same department. We collect enrollment records from the university registration's database. The dataset contains the information of 3,614 students with 52 courses in the past 8 years.

B. Data Preprocessing

The data are also preprocessed to clean the data or delete unrelated ones. For instance, removing the course that is not opened in the semester because students are not able to take it.

C. Similarity Discovering

Once the clean and appropriate data have been gathered, the system discover the similarity amongst students. Supposing that it is trying to find the similarity between Student *S1* and the others who have the same curriculum. With the same course template, the system obtains the data regarding the hits of that each student takes a course by specifying 1 for the relation that the student enrolls the course and 0 vice versa, as illustrated in Table I.

According to the sample gathered data shown in Table I, the system calculates the similarity of both between student *S*1 and student *S*2, and student *S*1 and student *S*3 in order to determine which student should be chosen to make use of his information for recommending elective courses for student *S*1. The following expresses how the similarity is discovered.

TABLE I: THE EXAMPLE OF COURSE TEMPLATES OF EACH STUDENT

	MKT3210	**MKT3320**	**MKT3400**	**MKT3510**	**MKT3520**
*S*1	0	1	1	0	1
*S*2	1	0	0	0	0
*S*3	0	1	1	0	1
…	…	…	…	…	…

$$Sim(S1,\ S2) = \frac{\left(0-\frac{2}{5}\right)\left(1-\frac{1}{5}\right)+\left(1-\frac{3}{5}\right)\left(0-\frac{4}{5}\right)+\cdots}{\sqrt{(0-\frac{2}{5})^2+(1-\frac{3}{5})^2+\cdots}\ x\ \sqrt{(1-\frac{1}{5})^2+(0-\frac{4}{5})^2+\cdots}} \approx 0.29$$

$$Sim(S1,\ S3) = \frac{\left(0-\frac{2}{5}\right)\left(0-\frac{2}{5}\right)+\left(1-\frac{3}{5}\right)\left(1-\frac{3}{5}\right)+\cdots}{\sqrt{(0-\frac{2}{5})^2+(1-\frac{3}{5})^2+\cdots}\ x\ \sqrt{(0-\frac{2}{5})^2+(1-\frac{3}{5})^2+\cdots}} \approx 1.00$$

As the similarity calculated above, student *S*3 is more similar to student *S*1 than student *S*2 since the value of student *S*3 is more than student *S*2. Therefore, the enrollment records of student *S*3 are chosen to make the prediction regarding elective courses for student *S*1. In the system implementation, the number of nearest neighbors selected for assisting the prediction and recommendation is 3.

D. Prediction

Once the system has obtained the data, the system can predict elective courses for student S1 by determining the course that student S1 would be interested in based on the course student S3 has chosen. Table 2 is the extended version of the course template of each student, depending on the data in Table I.

TABLE II: THE EXTENDED SAMPLE COURSE TEMPLATE

	MKT 3210	**MKT 3320**	**MKT 3400**	**MKT 3510**	**MKT 3520**	**MKT 3550**	**MKT 3600**
S1	0	1	1	0	1	?	?
S2	1	0	0	1	0	0	1
S3	0	1	1	0	1	1	0
…	…	…	…	…	…	…	…

According to Table II expressed above, both MKT3550 and MKT3600 are not yet taken by student *S*1 and considered whether he should take them or not based on student *S*3. It is, thus, obvious that we will recommend MKT3550 to the student since student *S*3 takes it. However, MKT3600 will not be recommended because student *S*3 does not enroll it.

In this paper, the enrollment of each student is only taken into account as the initial work. Other information of students is also considered to be explored in the future work. However, some information might not be suitable to be used in this domain. For example, grade of each student may be useful at first but it could result in low prediction performance. The reason is that there are many grades in a university and each student could obtain various grades. With this consideration, the number of data may not be sufficient to find their similarities due to the diversity.

V. EVALUATION METHOD

To see how well the proposed idea works, we conduct an evaluation method by comparing the result of the recommendation from Pearson Correlation, and Alternating Least Square (ALS) with the course the students can take in a semester.

The data we use to evaluate the ideas are gathered from office of registrar from Assumption University so it contains the course enrollment records of each student in each semester. We select some of the students' records to let the system recommend elective courses for them by comparing with the records of the rest of the students.

VI. EXPERIMENT SET UP AND RESULTS

In this section, we illustrate the performance of the proposed system performed on the real dataset by comparing the recommended courses obtained from collaborative filtering algorithm using Pearson Correlation Coefficient and ALS algorithm with the courses each student registers to the registration system. Accuracy is used as an evaluation measure. However, we modify it so that it suits the domain in this paper by setting up a threshold involving in the accuracy calculation, called Threshold-Based Accuracy. For this paper, we set the threshold into the following model.

$$\boldsymbol{Score} = \begin{cases} \mathbf{0}: \textit{do not take any predicted courses.} \\ \mathbf{0.5}: \textit{take only one predicted course.} \\ \mathbf{1}: \textit{take more than one predicted courses.} \end{cases}$$

In the experiment, we choose to recommend elective courses for the 423 marketing students which are the batch of 561 to 592 studying in the same curriculum. Table III shows the result of the course recommendation of some marketing students. The reason we choose Marketing is that there are many students and courses, meaning that there are lots of data from them, for training the algorithms. With much data, the training set yields prediction more accurate.

We set up a threshold because there are limited number of courses that students can take in a semester. Also, the students cannot usually enroll all elective courses with the limited number of courses. The accuracy result would be too unreasonably low without having the threshold so the threshold is necessary. The threshold is configured to 2 for the full score since students usually take 2 elective courses in a semester.

TABLE III: THE COURSE RECOMMENDATION RESULT OF S1, S2 AND S3

	Recommended Course	Match
*S*1	MKT3515, MKT3530	1
*S*2	MKT3102, MKT3515, MKT3530	3
*S*3	MKT3823	0

According to the table shown above, the system recommends courses for each student which the course must be complying with the pre-condition described in the previous section. Besides, the system also summarizes the result of the number of courses that each student registers the recommended course. For instance, there are two recommended courses, MKT3515 and MKT3530, for the student S1 and the student takes only one of them. The system counts the student as 0.5 score and accumulates with the existing scores. Each student can yield 0, 0.5 or 1 as the score which the score is 1 if the student takes at least two of the recommended courses. Conversely, if the student does not take any recommended courses as their registration result, he yields 0 for the score.

Once all the 423 students' scores are computed, the accuracy of the collaborative filtering algorithm is approximately 67%.

Then, to compare the result with ALS algorithm, we firstly predict six elective courses for each student. After that we map the predicted courses with the course enrolled by each student in a semester. Then we collect the score of each student by counting the registered course and predicted course. The score is from the value that if a student takes at least two predicted courses, he yields full score or proportionally reduced. For instance, if a student takes only one predicted course, he yields only the half score. The experimental result shows that accuracy of ALS algorithm is approximately 86%. In other words, out of 423 students, 86% of them take at least two predicted courses.

This paper is just an initial work to explore the domain so we try to utilize the top technique in the field of Recommender system and find which one is better than another. However, we plan to dive deeper into the domain with other algorithms in the future work too.

VII. CONCLUSION AND FUTURE WORK

This paper proposes a course recommendation system that recommends elective courses by investigating the enrollment records of students to find the similarity and predict courses based on the information. It applies two well-known algorithms: collaborative filtering algorithm using Pearson Correlation Coefficient and ALS algorithm.

Based on the experimental results obtained It shows that ALS outperforms the other algorithms with 86% of accuracy. Therefore, ALS is selected to be deployed in the recommender system.

Although the experimental result of the proposed system is very good, the performance of the system may further be improved. For the current work, only student similarity based on their enrollment records is used, which might not be sufficient. In the future, we consider to use other information so that it would determine the behavior of the student for assisting further recommendation.

VIII. ACKNOWLEDGEMENT

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