Design a Course Recommendation System Based on Association Rule for Hybrid Learning Environments

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Abstract: Course recommendation system is a help tool to provide suggestions for learners who have no sufficient experience to choose courses which they need. Different from MOOCs, the selection and recommendation for hybrid learning environments such as university are relatively difficult. Students who enrolled the same course may have very different purposes and with very different interest. Employing the enrollment record data from M2B, an e-learning system at Kyushu University, we conduct a systematic investigation on the problem of course-taking pattern for course recommendation. We then discuss the challenges to recommend relevant courses in 'hybrid' learning environments and propose a preliminary approach to address the challenges by designing a course recommendation mechanism based on the association rule. We also leverage the learner interest and social search to improve the performance by adjust the recommend results. Finally, we develop a course recommendation system based on the user interest, social search and previous course-taking pattern. Experiment results demonstrate that the proposed algorithm significantly helps improve the course recommendation performance comparing with the traditional data mining based recommendation system.

Keywords: Learning Analytics, Hybrid Learning Environments, Data Mining, Association Analysis, Recommender Systems

1. Introduction

The rapid development of Internet has led to great problem of information overload. Nowadays, there are recommender systems in various domains that facilitate daily livings of individuals to help them find their favorite content from the huge overloaded information. For example, the well-known e-commerce platforms such as amazon.com recommend products to users based on their browsing and purchase history; Netflix.com uses recommendation to help people find movies and videos that they are interested in by using collaborative filtering; Youtube.com builds personalized homepage that shows recommended videos for each user based on their access history. Recommendation system already becomes one of the most important and effective tools to help reduce the cost of information navigation. Besides these well-known domains, course recommendation is considered a challenged domain that could help students in suggesting suitable courses for them as well as reducing time to explore courses that they will take. The popularity of online education platforms has soared in recent years, which have increased the number of accessible learning opportunities. Massive Open Online Courses (MOOCs) are widely used all over the world. Lots of MOOCs platforms have been built to improve access to high quality educational content for anyone connected to the Internet. To provide suggestions to assist learners who have no sufficient experience to choose courses which they need, researchers have tried to develop various approaches to recommend relevant learning materials to learners in order to improve the effectiveness of studying, and we will introduce the popularly approaches in next section.

Although MOOCs have their own benefits they are inherently limited in supporting learners who want to master practical tools and technologies in the real world. We thus consider 'hybrid' environments that exploit e-learning systems in physically co-located environments such as classrooms and group/peer learning spaces. Indeed, e-learning systems and Learning Management Systems are increasingly used together in schools. One example is the M2B system which is used for supporting daily classroom teaching in Kyushu University. The selection and recommendation of 'hybrid' courses such as the ones at Kyushu University are often different from those in MOOCs. One of the most important challenges is the difficulty for diverse learners to find the right learning opportunities at the right time. Learners have to choose from a large number of courses that they are not familiar with. Just to give some examples, it is difficult for freshmen and other students to decide which courses they should take because there are a large number of courses to choose from, students' interests and goals can change as they explore and discover something meaningful on and off campus, and there are complex constraints and contexts that have to be considered in choosing courses. 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.

In this paper, we aim to discuss the difference between hybrid environment and MOOCs to recommend suitable courses for learners and study how to improve personalized course recommendation in such hybrid environment. Apart from assisting the student, recommender systems could help the university registrar by recommending enough sections for a course. Solving this problem has the following challenges:

(1) **Complex constraints**

Different from MOOCs, courses in such environments are closely interwoven with various types of physical, pedagogical and social contexts. For example, in Kyushu University, every major has required courses that students must take and elective

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courses which is one chosen by a student from a number of optional subjects. Elective courses usually have fewer students than the required courses. Students generally receive a grade and academic credit after completion of the course. They need to get enough credit to meet the requirements of graduation. Students usually do not choose many courses because learning a course is a time-consuming task. In Kyushu University, for instance, statistics show that each course usually lasts for several weeks and a student enrolls 14 courses on average each year. Another example, various courses are provided for each academic year, however, students may take courses in the first two years mostly, because they may busy for internship or finding job in the third and fourth year.

(2) **Anti-interest**

Students may not choose courses based purely on their interests in university environment. For example, some students would not enroll in a course which contains contents they are interested in, they just choose the course that allow them to get credits easily. In addition, student enrollment behavior may be influenced if they are not familiar with the contents of those courses. We want to develop an interest model from student feedback and social network to match the suitable course for students.

(3) **Cold start**

Cold start is a classic problem in recommendation system. One common practice is using popular courses regardless of students' interest when we are short of education big data. However, if we use some other information besides user's enrollment activities, we may get better results.

In this paper, we discuss the challenges to recommend relevant courses in hybrid learning environments and propose a preliminary approach to address the challenges by designing a course recommendation mechanism based on the association rule. In particular, we first analyze the records of university student course-taking patterns in 'hybrid' environments by using the association rule analysis. Besides, learner interest and social contexts are also used to better reveal users' potential choice and increase the diversity and abundance of recommendation results. They are also used to deal with the cold start problem.

The rest part of this paper will be organized as follows. Section 2 lists previous studies closely related to our work and briefly introduces our contribution. In section 3, we present the framework of our recommendation. Section 4 is our experiment and results with discussion. In the last section, we conclude with a summary of our work and an outlook to future work.

2. Related Work

Course enrollment recommendation will 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. Various algorithms such as content based filtering, collaborative filtering and rule mining approaches have been used in applications. We review previous literatures which popularly implemented for the recommendation.

2.1 Content-based recommendation

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.

Minnesota State University [1] creates a prototype of a system that helps students select courses to enroll in a semester. Users are required to enter their interests as keywords. The system then recommends courses based on user's keywords. Piao and Breslin [2] propose a strategy to extracts user profile text from their LinkedIn pages and calculates the similarity with course profile text, then gives the recommendation results by the similarity. Apaza et al. [3] use LDA to train two different topic models on both college course syllabus and online course syllabus then a content-based match algorithm is used to estimate the ratings from a user to all courses.

2.2 Collaborative filtering

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 [4] introduces a mechanism based on this approach to recommend courses for a student by exploring the student's academic record and matching the record with others' ones to gain the similarity. 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. [5] 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. X.Jing and J.Tang [6] use LDA to extract user-specific latent information from their historical access behaviors to represent their interest profile. Then the similarity is calculated from above interest profile, and recommend outcomes are given based on the similarity. Kiratijuta et al. [7] developed an elective course recommendation system which investigates each student's academic records to find the similarity with the targeted student.

2.3 Association rule mining

Association rules based on frequent patterns are often used to discover interesting relations between variables in databases. The concept is first proposed by Rakesh Agrawal et al. [8] for discovering regularities between products in transaction data records of customers' shopping behaviors, and it is widely used in many application areas today, such as medical diagnosis and web usage mining. In terms of course enrollment, the objective is to extract rules from data that describe previous course selections from students in higher education.

Aher and Lobo [9] use association rule mining together with clustering to recommend courses by using historical data. Narimel Bendakir and Esma A¨ımeur [10] presented a course recommendation system, which incorporates association rule and user ratings in recommendation. Itmazi and Megias [11] develop a recommendation system using association rule mining to recommend series of courses for university students by investigating the factors relating to each student, such as demographics, and the factors relating to each course offered, e.g., instructors responsible for the course.

Parameswaren et al. [12] propose a course recommendation mechanism for university students, which consider complex constraints. However, existing course recommendation systems do not fully consider the potential of hybrid learning environments including the large-scale data they generate.

Compared with previous studies, the main contribution of our work is that we exploit student interest from e-portfolio and use that interestingness to improve the traditional association rule algorithm. In addition, we use other information including course relation and social contexts to boost the recommendation performance. We designed our framework to combine them in order to make better use of available information from our hybrid environment in Kyushu University.

3. Framework

In this section, we first introduce M2B system briefly, which is an e-learning system in Kyushu University. Then we propose our framework with a subsection introducing our student interest model and a subsection introducing how we leverage social information to boost our model. At last, we introduce how we use association rule together with student interest to recommend courses.

3.1 M2B System

Moodle, BookRoll, and Mahara, the learning environment encompassing all three of these systems is called M2B (Mitsuba) system, which is used for supporting daily classroom teaching and providing online courses in Kyushu University [13].

(1) Moodle is a Learning Management System which could manage student attendance, provide quizzes, and record educational and learning activities of teachers and students during class. These data and the access logs on Moodle are also used as a part of the educational big data.

(2) Mahara is an e-Portfolio system. Both teachers and students are asked to write journals after each class on Mahara, which is helpful to get feedback and to evaluate class's quality for improving the context of learning materials.

(3) BookRoll is an e-Book system. Students can access to digital materials through Web interface anytime, anywhere. Their activities on materials, such as flipping pages, writing notes, highlighting, are stored in activity logs.

The M2B system provides a platform for both students and teachers in university for better education experience. On one hand, instructors could organize and manage teaching resources and learner records efficiently. On the other hand, students can conveniently access to the learning materials and even interact with it such as make a mark and create memos. Furthermore, it serves as a foundation of learning analytics (LA) providing the ability to collect activity logs and the seamless interface of LA tools.

3.2 Measures of interestingness

User interest is the most important target of our framework. We want to build a simple but universal representation of user interest which will be useful not only in course recommendation but also in other personalization tasks. Characterizing what is interesting is a difficult problem. The very definition of the word "interest" is elusive. A common solution in e-learning system is directly combining user enrollment and the tags of enrolled courses [6]. While this solution suffers from the small size of tag set and the sparsity of enrollment. In our framework, on the one hand, we utilize user activities courses instead of tags, on the other hand, we extract user interest from which contain much more abundant information.

In our framework, we use interestingness to reflect the different importance of each course to recommend suitable contents for students. The purpose is to recommend a wider range of courses to students, avoiding the problem of insufficient interest caused by traditional association rules. Measures of interestingness including objective measures and subjective measures. Objective measures of interestingness or objective interestingness criteria are measures of interest that depend only on the structure of the data and the patterns extracted from it. For example, the rating of a course from student. Subjective measures of interestingness or subjective interestingness criteria are measures that also depend on the specific needs and prior knowledge of the user.

First, we divided students into different clusters based on their department. Each cluster has its owner preference on courses enrolling according to the enrollment records. Then every student can take the average rating of students who belong to the same cluster as an interest weight on every course. Then, available information including student attendance, quizzes, learning activities during class and their final score in each course could be used to calculate the subjective measures. Moreover, both teachers and students write journals after each class on Mahara, which is helpful to get feedback. This kind of feedback will imply the interest of students for a specific course, which could be considered as objective measures. Let x_i be a course, subjective measures be $weight_s(x_i)$, objective measures be $weight_o(x_i)$, the total weight of interest of the course for a certain cluster can be written as:

$$w_{in}(x_i) = \alpha \times weight_s(x_i) + \beta \times weight_o(x_i) \quad (1)$$

where α, β are parameters to control the proportion of weights from different sources. $weight_s(x_i)$ and $weight_o(x_i)$ could be measured in different ways. In our framework, we simply use student attendance and final scores to rate the $weight_s(x_i)$, and the $weight_o(x_i)$ was defined by the keyword of student journals together with review's length, which both indicate student intent interest.

3.3 Social course search

In many physically-based learning environments, students would ask their peers, mentors, or senior students to recommend courses for them. Such word-of-mouth recommendations can be an extremely powerful means of acquiring useful information if one has knowledgeable friends and acquaintances. However, one could only obtain suboptimal recommendations without the availability of knowledgeable experts in his or her social networks. A systematic approach to remedy this limitation is what we call a social course-search mechanism.

Our social course-search mechanism extends the association rule-based recommendation mechanism by extending and integrating a model of social search engine proposed by Horowitz and Kamvar [14].

We assume that students create and update a "learning plan" document periodically (e.g., every year or every six months) as part of their learning portfolio. The mechanism we propose first derives learners' goals from their learning plans. Based on the learning goal g of learner l, we can compute the probability that learning topic t is relevant to the learning goal g, denoted by $p(t|g)$ by using the historical data in the digital part of 'hybrid' learning environments.

Using the learning topic t as a latent variable, we can compute a probability that person x_i makes a successful recommendation regarding learning goal g, denoted by $p(x_i|g)$, as follows:

$$p(x_i|g) = \sum p(x_i|t)p(t|g) \quad (2)$$

$t \in T$, T is a set of learning topics with their probabilities $p(t|g)$ larger than a threshold value. $p(x_i|t)$ is the probability that x_i successfully recommends courses for learning topic t.

Social closeness of learner l and x_i, denoted by $sc(l, x_i)$ can be computed as the reciprocal of the network distance d between l and x_i.

$$sc(l,xi) = 1/d(l,xi) \quad (3)$$

The social network data can be extracted from e-Portfolio systems such as Mahara as it has a built-in social networking feature. Additionally, we compute the profile similarity $ps(l,x_i)$ between learner l and person x_i by computing the distance between the goals of l and x_i.

$$ps(l,x_i) = |P \cap Px_i| / |Pl \cup Pxi| \quad (4)$$

Pl and Px_i are sets of topics related to the goals of l and x_i, respectively. Finally, we obtain score $s(x_i,l,g)$ to construct a ranking of best people to contact for course recommendations.

$$s(x_i,l,g) = p(x_i|g) \times sc(l,x_i) \times ps(l,x_i) \quad (5)$$

To avoid overloading some people with too many requests for recommendations, we consider delegation of requests to other people in the social network using a similar scoring function. In addition, we could reuse recommendations by constructing a repository of past recommendations as well as a hybrid network of human and computational recommenders.

3.4 Extended association rule

It is useful for taking advantage of the collaborative experience of the students who have finished their studies. However, in the traditional association rule method, the importance of each item in the database is the same, this kind of recommendation based on support threshold and confidence threshold is not enough. For example, some courses with good content are excluded because the amounts of selection are lower than the support threshold. Also, the popular course has been frequently extracted since it has been selected many times, but some students may not have much interest in it. As a result, most of the recommended courses come from the relatively popular courses. In a course selection database, what we really care about may not be which class is the most popular one, but which class can match the interest of the student and help the student to complete the learning goals.

If a recommendation system is simply based on the support threshold and the confidence threshold, it will have obvious shortcomings. The system will recommend those popular courses frequently since it has been selected many times, however, the most popular course is not necessarily the course that students are most interested in. Finally, students may be misled to choose those popular courses. For example, there are no rules come from language and culture courses, as well as comprehensive subjects. The reason is that those courses are not selected frequently, but that does not mean those courses are not important. As mentioned above, students have different interests in each course in the university. We are not only concerned about popular courses, but also about which courses are most suitable for student interests and which recommendation of courses can help students achieve their own learning goals.

In order to reflect the different importance of each course to recommend suitable contents for students, we propose our extended association rule method which considers student interest for the hybrid learning environment. The purpose is to recommend a wider range of courses to students, avoiding the problem of insufficient interest caused by traditional association rules.

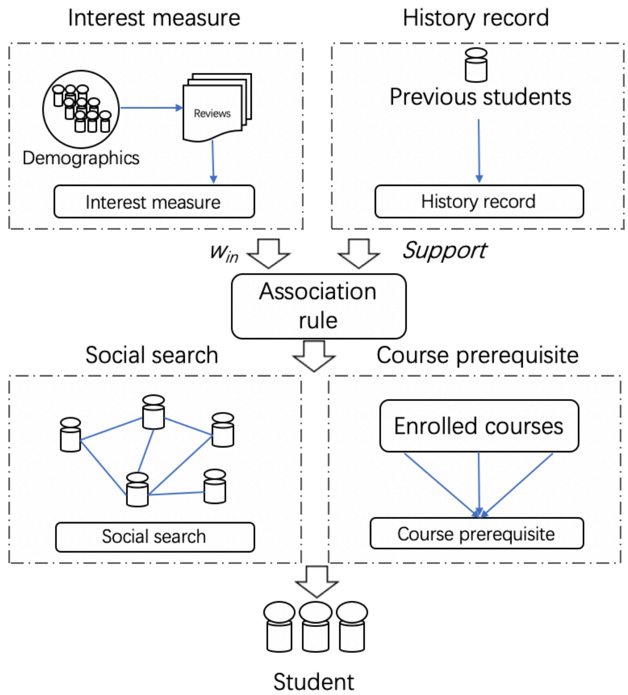

Fig.1 Overview of the hybrid recommendation framework

Let x_i be a course, $Support(x_i)$ is an indication of how frequently this course appears in the dataset. We assign interest weight for each cluster denoted by $w_{in}(x_i)$ to each course, which is calculated above according to the logs recorded in the learning management system (Moodle) together with student feedback in e-portfolio system (Mahara). Therefore, we obtain the $Weight(x_i)$ which could be represented as follows:

$$Weight(x_i) = w_{in}(x_i) \times Support(x_i) \quad (6)$$

Then, we could apply $Weight(x_i)$ instead of $Support(x_i)$ for association rule process. Figure 1 illustrates an overview of the recommendation system. We first use association rule together with student interest to get rules for a certain cluster. The rules' consequents determine a list of courses to be recommended. Then we use social search and courses prerequisite to adjust the final results. The data collected from M2B system will be used for the recommendation process.

4. Experiment

In this section, we introduce how to employ our framework into M2B system in Kyushu University to evaluate its performance.

The architecture of the system is shown in Figure 2. Moodle manages student attendance, provide quizzes, and records educational and learning activities of teachers and students during class. It also keeps student information such as: the courses they followed, their profiles and their final score in each course. Also, both teachers and students write journals after each class on Mahara, which is helpful to get feedback. This kind of feedback will imply the interest of students for a specific course. In addition, the social network data can be extracted from e-Portfolio systems such as Mahara as it has a built-in social networking feature, students could cooperate and share with each other on Mahara. We then use those social contexts record to conduct our social course search. In addition, there are complex constrains and contexts that have to be considered in choosing courses, we rule based adjustment to address this problem. Therefore, the recommendation system could combine the benefits of available information including social course search and student interest in order to recommend the most relevant courses to its users.

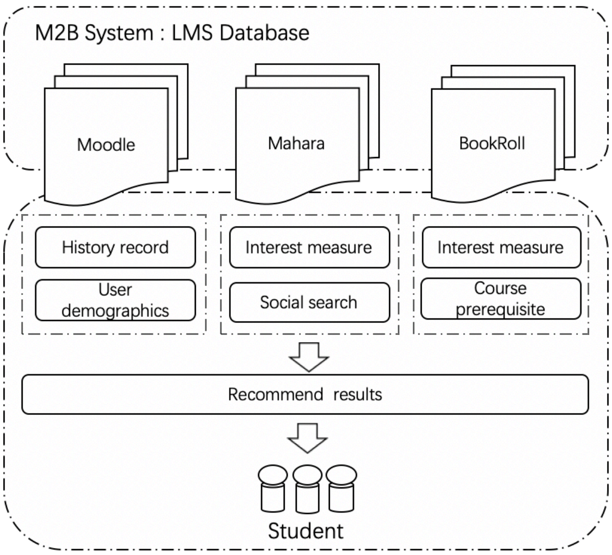

Fig. 2 Architecture of course recommendation system

4.1 Dataset

We analyzed approximately 38,968 pseudonymized enrollment records from 2,366 students via Moodle for this analysis. These students enrolled in 2015 at Kyushu University, so we have the records of course selection during their four years from freshman to senior students. These students are from 12 departments. Table I shows the number of students in each department.

Since each college has its own required courses, we extract electives that all students can choose according to the university's syllabuses. There is a total of 166 elective courses to choose from. They come from different fields to meet the needs of student interest and develop students' comprehensive knowledge. In addition, it is important to categorize elective courses for different field in order to detect or mine meaningful courses patterns for students efficiently. Therefore, we divide courses into six categories. Science includes basic courses in biology, chemistry, physics, architecture, and information science. The liberal arts include history, psychology, economics, and law etc. There are also language and culture courses, health and sports courses, and comprehensive courses.

Table 1 Collected Date by Moodle

Department	# of student	# of average courses taking
AG (School of Agriculture)	213	10.6
DD (School of Dentistry)	48	16.1
DS (School of Design)	174	13.8
EC (School of Economics)	222	14.6
ED (School of Education)	50	16.1
LA (School of Law)	171	16
LT (School of Letters)	152	13.9
MD (School of Medicine)	238	13
NC (The 21 Century Program)	23	15.7
PS (School of Pharmaceutical Science)	70	10.7
SC (School of Science)	264	15.1
TE (School of Engineering)	741	14.5

We also give each course a number based on its categories. In this way, we can find meaningful regularities easily, because courses from the same area will have adjacent numbers. The result of the categorization is shown in Table II. Most of the electives come from sciences and KIKAN educational courses (The academic curriculum at Kyushu University consists of the KIKAN educational curriculum and courses in one's major. The KIKAN educational curriculum gives students the skills and abilities necessary to develop a fertile and deep expertise in their given field and see and think about things in a way as to create new knowledge and solve unprecedented problems), each with 53 courses.

Table 2 Category of Elective Course

Category	Total	Course NO.
Language and Culture	29	1-29
Liberal Art	16	30-45
Sciences	53	46-98
Health and Sports	5	99-103
Comprehensive Subjects	10	104-113
KIKAN Educational Courses	53	114-166

On average, each student chooses 14 elective courses, and the average number of courses selected by different department is also different. The Dentistry department and Education department are the most compared with others, with an average of 16.1 courses each student. The Agriculture department is the least, with an average of 10.6. Most students choose electives from liberal arts and science. And we found that the most popular course has been chosen for 1,489 times.

In order to mine meaningful rules that associate elective courses followed by former students, the analysis of this paper was conducted following those criteria: Support 0.2, Confidence 0.7, Lift 1.5.

4.2 Result

The recommendation inference is done by checking the equivalence between the courses followed by students and the antecedents of the rules. The rules' consequents determine a list of courses to be recommended. Then we use social search and courses relationship to adjust the results. In order to evaluate the rule efficiency in recommendation, we take the subset of data as the training set of our framework and the remaining subset of data as the test set to validate the quality of course recommendation.

For each student x_i, we call F_i, the set of courses followed by this student. The main questions are: can this system recommend courses to that student knowing the first course, or the two first courses of F_i? And, also, are they contained in the remaining courses of F_i? In other words, we measure the recommendation *Coverage* and *Accuracy* [10].

If we denote by $R(s_i)$ the set of the courses recommended to a student S_i, and we denote by $T(s_i)$ the remaining courses followed in F_i, we define *Coverage* and *Accuracy* as follows: *Coverage* measures the ability of the system to produce all courses that are likely to be followed by the student. It is defined as:

$$Coverage = |R(si) \cap T(si)| \,/\, |T(si)| \qquad (7)$$

Accuracy measures the system's ability to provide correct recommendations. It is defined as:

$$Accuracy = |R(si) \cap T(si)| \,/\, |R(si)| \qquad (8)$$

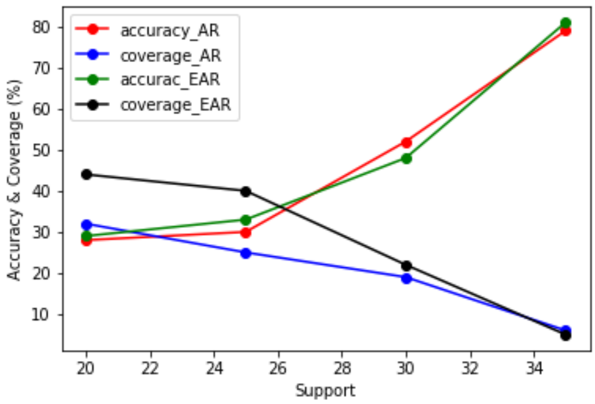

Fig. 3 Recommendation Accuracy and Coverage

As Fig.3 depicts, the results demonstrate the validity of our method compared to traditional recommendation based on association rule. A wider range of courses could be recommended to students, avoiding the problem of insufficient interest caused by traditional association rules. Our results also show that varying the value of the support and the confidence has an impact on recommendation coverage and accuracy. A low support gives the best coverage in contrast to the accuracy, which is better when the support value is high. In other words, the coverage decreases when we try to increase the accuracy. The reason is that when decreasing the support, more association rules are discovered. The system then proposes more recommendations, which explains the decrease in their accuracy.

To achieve the best performance of recommendation, we need a compromise between recommendation coverage and accuracy. Typically, as a starting point for an application like recommender systems, the initial support can be set to 10% [10]. Confidence should be set higher than 50%.

4.3 Comparison

Our recommendation system benefits from the basic knowledge that constitutes the extracted rules. Therefore, it displays a better performance under the cold start problem compared to Collaborative Filtering based recommendation system. Another important issue is scalability. When the amount of data is significant, recommendation systems based on collaborative filtering are more resource demanding than ours. For example, during a real-time recommendation, they have to compute the similarity between the current student and all the other students, or between the rated courses and all the other courses. In the case of our system, all the mining process is performed offline. Although the number of rules that are generated grows exponentially with the number of items [15], it is possible to produce a compact set of highly significant rules by appropriately tuning the weight. Therefore, deriving the rules during the offline phase can be time-consuming but scanning them during recommendation time is done quickly.

Our system still has some limitations when providing its recommendations. For instance, it does not yet consider student preference for personalized recommend.

5. Conclusion

In this paper, we discussed the challenges to recommend courses in hybrid learning environments and proposed a preliminary approach to address the challenges by designing a course recommendation mechanism based on the association rule.

In particular, we propose a hybrid algorithm framework which extracts user-specific latent interest from e-portfolio (Mahara) and combines association rule and student interestingness to give recommend results. Social course search and course prerequisite are also used to boost our method for the hybrid learning environment. We compare our framework with traditional data mining methods in offline dataset, result of experiments demonstrates the better performance of our framework. In addition, our extended association rule algorithm would be helpful in other personalization situations.

As future work, it would be interesting to boost recommendation performance according to the characteristics among different departments in courses selection. In addition, mining other information from user behaviors to match the contents of learning materials. It also would be interesting to study how to recommend the best learning path which means four years learning sequence of student to satisfy diverse personalized requirement in university.

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