Course Recommendation for University Environments

Boxuan MA
Kyushu University
ma.boxuan.611@s.kyushu-u.ac.jp

Yuta Taniguchi
Kyushu University
taniguchi@ait.kyushu-u.ac.jp

Shin'ichi Konomi
Kyushu University
konomi@acm.org

ABSTRACT

Recommending courses to students is a fundamental and also challenging issue in the traditional university environment. Not exactly like course recommendation in MOOCs, the selection and recommendation for higher education is a non-trivial task as it depends on many factors that students need to consider. Although many studies on this topic have been proposed, most of them only focus either on historical course enrollment data or on models of predicting course outcomes to give recommendation results, regardless of multiple reasons behind course selection behavior. To address such a challenge, we first conduct a survey to show the underlying characteristic of the course selection of university students. According to the survey results, we propose a hybrid course recommendation framework based on multiple features. Our experimental result illustrates that our method outperforms other approaches. Also, our framework is easier to interpret, scrutinize, and explain than conventional black-box methods for course recommendation.

Keywords

Educational Data Mining; Recommender Systems; University Environments

1. INTRODUCTION

Course selection in university is a crucial and challenging problem that students have to face. It is difficult to decide which courses they should take because there are a large number of courses opened each semester and students have to spend a lot of time exploring those courses. Moreover, the decisions they make shape their future in ways they may not be able to conceive in advance.

We collected a dataset during 2015 and 2018 from our university to gain a better understanding of the elective course enrollment patterns. Figure 1(a) presents the distribution of the enrolled course number of students on the left and the distribution of the popularity for each course of our university on the right. There are hundreds of elective courses offered by the university while averagely students only select a few of them to satisfy the requirements for their degree program. Figure 1(b) shows the distribution of the enrolled courses for each semester. We can also see that students may take courses in the first two years mostly (semester1~semester4), because they may potentially be busy with an internship or finding jobs in the third and fourth year.

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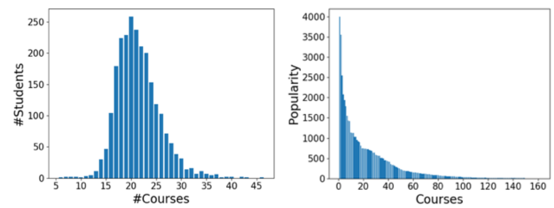
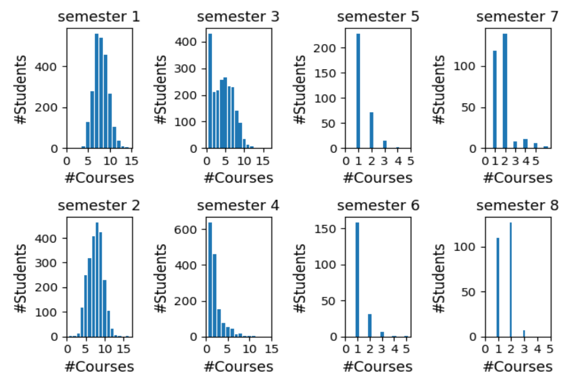


(a) #Course distribution.



(b) #Course distribution for each semester.

Figure 1. Distribution of courses.

From the discussion above, a safe conclusion could be drawn that due to a large number of available but unfamiliar courses, course selection is a critical activity for students.

With the increasing amount of available data about undergraduate students and their enrollment information, data-driven methods supporting decision making have gained importance to empower student choices and scale advice to large cohorts [14]. Many relevant studies on course recommendation focus on online learning platforms such as MOOCs. Other studies on course recommendation use datasets collected in physical university environments, however, they rely on approaches that are similar to the ones used in recommending MOOC courses without fully considering the different reasons involved in course selection process in physically-based university environments.

In fact, course recommendation for higher education can be more *"messy and unorganized"* [1] as it depends on many factors that students need to concern. Intuitively, the reasons behind course selection are manifold. Likewise, students who enrolled in the same course may have completely different orientations based on their own reasons, which serves as different criteria for course selection [34]. It inspires us to try to find more useful features for the recommendation.

To make the point clear, a survey is conducted on 81 students in our university to better understand student perceptions and attitudes for their course selection process. [10] Figure 2 shows the main underlying reasons for their course selection.

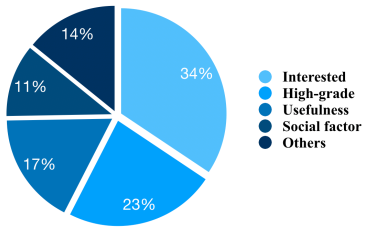


Figure 2. The distribution of main reasons for course selection.

(1) Interest

As Figure 2 shows, the overall most important factor was students' interest and it is often taken as a main contributing factor to the recommendation. However, students may not choose courses based purely on their interest in the university environment. It is expected that students will be more inclined to choose courses that do not require too much effort or difficulty. For example, some students would not enroll in a course which contains contents they are interested in, they just choose the course that allows them to get credits easily.

(2) High-Grade

Improperly selecting courses would seriously affect the students' course achievements, which enforces students to drop out [12]. Getting relatively high grades for students is another factor influences student's choice especially for successful students. Some students even prefer to choose what they perceived would be an easier course for fear that a tougher course might lower their GPA.

(3) Learning goal and career plan

It is natural to recommend courses that align with student's learning goals and career plans as students consider the usefulness of courses as an important factor in their course selection process. However, first-year students may lack learning goals and career planning for the future, and the choice of courses is aimless. Also, student interest and goal can change as they explore and discover something meaningful on and off campus.

(4) Social Aspect

Social factor also plays a part in the course selection process. For example, some students prefer to enroll in a course with their friends or classmates together. Potts et.al [21] conclude that the risk of social isolation is a problem in the learning process especially for first-year students at university, who have difficulty navigating their new academic and environment. Tinto [22] concludes that participation in a collaborative learning group encourages student's attendance and class participation. Therefore, the classmates or friends based social links could be important information in course recommendation.

(5) Popularity

As shown in Figure 1(a), the long-tail distribution of course popularity indicates that students are more motivated to choose popular courses as their first choice. However, the popular courses will be filled up quickly while others will not be selected by students frequently.

In summary, all these discussions above indicate that there are complex constraints and contexts that have to be considered together to balance all those factors above, made more difficult by the multiple objectives that students want to maximize and risks they want to hedge against. For example, choosing challenging courses of value while maintaining a high GPA [16]. This suggests that recommendations that are aimed only at one or a few factors are likely not enough to help the students.

To address these challenges which have not been well explored in the research community, we propose our hybrid course recommendation framework, which incorporates different criteria in a modular way. Moreover, in our approach selection criteria can further be prioritized by the student. We believe that weaving those criteria could increase the usability of our recommendations compared to previous work focusing only on one of the two. Also, our framework is very efficient and easy to interpret.

2. RELATED WORK

2.1 Course selection

Some work has been done on analyzing the college students' course selection. Morsy and Karypis [23] investigated how the student's academic level when they take different courses, relate to their graduation GPA and time to degree. This study suggests that course recommendation approaches could use this information to better assist students towards academic success, by graduating on-time with high GPA. Also, understanding students' reasons for enrolling in a course provides key information for recommending courses and improving students' learning experiences [24-27].

Additionally, there is still a lack of study on the factors that influence students' course selection in university and how the course selection would impact the students' educational achievement.

2.2 Personalized Course Recommendation

Various approaches have been used in applications for course recommendation by learning from historical enrollment data [32, 33].

Content-based filtering approaches recommend a course to a student by considering the content of the course and clustering course and student into groups to gain similarity between them [2,3]. Collaborative filtering approaches recommend a course to a student by investigating student's similarity with the student's historical data in a system and predict the course that the student would be interested in [4-6]. Association rules based on frequent patterns are used to discover interesting relations that describe previous course selections from students [8,9]. Recently, other methods including sequence discovery and representation learning have been used in this domain [11,19,20]. However, those systems often behave like a "black box", i.e., recommendations are presented to the users, but the rationale for selecting recommendations is often not explained to end-users.

2.3 Grade Prediction

While some researchers have focused on between-course enrollment data, others have focused on models of predicting grades in future courses [13-6]. Based on what courses they previously took and how well they performed in them, the predicted grades give an estimation of how well students are prepared for future courses, then recommending courses to students that will help them to get relatively high grades [18,28,29,31].

However, these methods can be prone to recommending relatively easier courses in which students usually get high grades [17]. In addition, there are some students who like challenge difficult courses if they are interested in or think it is helpful for their future career, for those students, the grade prediction based recommendations are not enough.

Despite the significant success of various course recommendations, constraints on the number of student preferences in the university environment resulting in inflexibility where a student's requirements do not align perfectly with those built into the system. In contrast to the aforementioned approaches, our model combines the concerns of performance and interest together. Also, it has the benefit of allowing for a custom weighting of those components, as well as the increased explanatory value of the model itself.

3. PROPOSED METHOD

We first give the definition of our recommendation problem in Section 3.1. Then we propose our hybrid course recommendation framework with three subsections introducing our Interest-based Score, Timing-based Score, and Grade-based Score in detail. Finally, those different scores are used in our course recommendation algorithm introduced in Section 3.3.

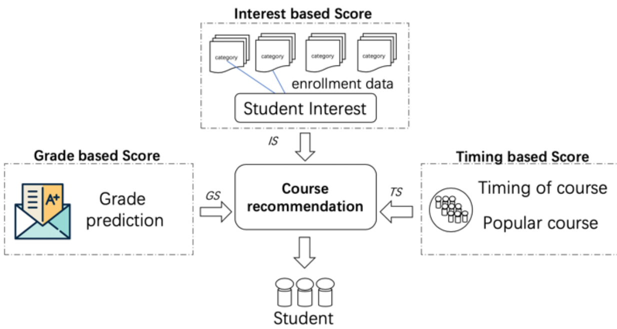


Figure 3. Overview of the proposed course recommendation.

3.1 Problem Formulation

Like every classic recommendation task, there are two basic elements *user* and *item* in our course recommendation task, where a user represents a student and an item represents a course. We use S to denote a set of students and C to denote a set of courses. Each $s \in S$ has enrolled some courses denoted by $C_s \subseteq C$ and each $c \in C$ has its enrollment set denoted by $S_c \subseteq S$. Let T denote a set of all available semesters, and t to denote a specific semester. Generally, there are 8 semesters for 4 academic years degree program. Let G denote a set of grades that student could get, and each $g \in G$ denote a specific grade that student obtained for a course. Let $E = \{(s,c,g,t) | s \in S, c \in C_s, g \in G, t \in T\}$ be the set of all enrollment relations, which means student s enrolled in course c in semester t, and got the final grade g.

Given enough students enrollment data (S, C, E), our goal is recommending courses to a specific student s which are not in C_s for next semester.

3.2 Framework

According to the result of the survey shown in Section 1, students may concern different factors while they choose courses. Inspired by that, we propose our hybrid course recommendation framework that considers student interest, the timing of taking the course and the predicted grade of the student together. Figure 3 shows the overview of the proposed course recommendation.

For each pair of student and course (s,c), we need to understand how suitable the course is for the specific student. We use three different aspects to calculate the $Score(s,c)$ for each pair of student and course:

(i) $Interest\ based\ Score\ (IS)$, which is to measure how interesting the course is for a specific student. (ii) $Timing\ based\ Score\ (TS)$, which is to measure how suitable students enroll in the course at a specific time (semester) since different courses may have different suitable time periods. (iii) $Grade\ based\ Score\ (GS)$, which is to predict students' performance for the course.

We propose our approaches to estimate IS, TS and GS, respectively. Then, they are fused by a student-specific weight parameter as the $Score(s,c,t)$. Once all of the $Score(s,c,t)$ have been computed, the k courses with the highest score are selected.

3.2.1 Interest-based Score

Let s and c be a student and a course, respectively, the goal of interest score estimation is to calculate $IS(s,c)$.

In our framework, we extract user interest from student historical enrollment behaviors. Since each course of university belongs to a category, let $CATE$ denote the set of all categories, $cate$ to denote a specific category, then $CATE = \{cate_1, cate_2, \dots, cate_{|CATE|}\}$. We think that there is a strong relationship between student interest and course categories. For instance, a student frequently enrolls in courses which belong to "Computer Science" may imply that the student has an interest in this category or he may have personal learning goal in this domain. Hence, it is appropriate to recommend the student the courses such as "Python Programming" and "Data science".

For a student s, the idea is to count the number of courses that he enrolled in and belongs to a category, i.e., $Num(s, cate)$. Then, all of the values are normalized as the preference score from 0 to 1, denoted as $p(s, cate)$, which is defined as equation (1).

$$p(s, cate) = \frac{Num(s, cate)}{Max_{cate' \in CATE}\left(Num(s, cate')\right)} \quad (1)$$

For a student s, the preference vector $\boldsymbol{P_s}$, is obtained by the preference score of each category, which is defined as equation (2).

$$\boldsymbol{P_s} = \left(p(s, cate_1), p(s, cate_2), \dots, p\left(s, cate_{|CATE|}\right)\right) \quad (2)$$

We can further use $\boldsymbol{P_s}$ to calculate the similarity between student s and other students. Let s_i and s_j be two students, the similarity between s_i and s_j can be measured by the cosine similarity measurement as shown below.

$$sim(s_i, s_j) = \frac{\mathbf{p}_{s_i}{}^T \cdot \mathbf{p}_{s_j}}{\left\|\mathbf{p}_{s_i}\right\| \times \left\|\mathbf{p}_{s_j}\right\|} \quad (3)$$

For the convenience of computation, we use a matrix form representation $P = (\mathbf{p'}_{s_1}; \mathbf{p'}_{s_2}; \dots; \mathbf{p'}_{s_{|S|}})$ to denote the interest of all students where $\mathbf{p'}_s = \mathbf{p}_s / \|\mathbf{p}_s\|$ means the normalization of $\mathbf{p}_s$. Then the similarity matrix Sim can be simply written as:

$$Sim = P^T \times P \quad (4)$$

where $Sim_{i,j}$ is the result of $sim(s_i, s_j)$.

Based on the similarity, we could estimate the user-based interest score. For a student s and a course c, the Interest Score denoted as $IS(s,c)$, is defined as (5), where $S_{s,k}$ indicates the set of top-k similar students of s as neighbors, and $I_{C_{s'}}$ is an indicator function whose value is 1 when $c \in Cs'$.

$$IS(s, c) = \frac{\sum_{s' \in S_{s,k}} I_{C_{s'}} \times sim(s, s')}{\sum_{s' \in S_{s,k}} sim(s, s')} \quad (5)$$

Furthermore, we try to utilize students' major information together with their similarity as equation (6).

$$sim_m(s, s') = \lambda sim(s, s') + (1 - \lambda) samemajor(s, s') \quad (6)$$

Where $samemajor(s, s')$ function equal to 1 if student s and student s' have the same major, otherwise, the function equal to 0. λ (limited from 0 to 1) is used to control the weight between similarity and major information. The underlying rationale is that each major has its owner preference on courses enrolling, students have the same major will generally make a similar choice in course selection. Also, students in the same major are more likely to be friends or classmates, which brings potential social link information into the course recommendation. Then equation (5) can be rewritten as below.

$$IS(s, c) = \frac{\sum_{s' \in S_{s,k}} I_{c_{s'}} \times sim_m(s, s')}{\sum_{s' \in S_{s,k}} sim_m(s, s')} \quad (7)$$

3.2.2 Timing and popularity based Score

Different courses may have different suitable time periods (semesters). For example, in each department, courses can be taken by students of different grades, e.g., freshman or sophomore. Previous studies showed that the timing of courses has a strong correlation with student graduation GPA and time to degree [23]. Based on that, we assume that the timing of courses is also important for course selection. The suitable timing of courses will help students for good grades and successful graduation in a timely manner.

For each course c, we define the $Timing\ based\ Scores\ (TS)$, denoted as $TS(c, t)$, where t indicates a specific semester. In our framework, TS is considered from two aspects:

(1) Which semester is more suitable for taking this course? For a specific course, we sum up the number of enrollments for every semester and normalize all of the values. The result is denoted as $T_t(c, t)$.

$$T_t(c, t) = \frac{Num(c, t)}{Max_{t' \in T}\left(Num(c, t')\right)} \quad (8)$$

where $Num(c, t)$ represents the number of enrollments of course c in semester t, and T indicates the set of all time periods, i.e., 8 semesters for 4 academic years degree program.

(2) Which courses are popular now? For a specific semester, we sum up the number of enrollments for every course and normalize all of the values. The result is denoted as $T_p(c, t)$.

$$T_p(c, t) = \frac{Num(c, t)}{Max_{c' \in C}\left(Num(c', t)\right)} \quad (9)$$

where C indicates the set of all courses. $T_t(c, t)$ and $T_p(c, t)$ are then fused by the harmonic mean since we want both of the two values are relatively high. The final $Timing\ based\ Score$, $TS(c, t)$ can be defined as:

$$TS(c, t) = 2 \times \frac{T_t(c, t) \times T_p(c, t)}{T_t(c, t) + T_p(c, t)} \quad (10)$$

Therefore, we can use $TS(c, t)$ to ensure that the semester t is suitable for taking the course c and the course c is suitable for taking in the semester t.

3.2.3 Grade-based Score

Improperly selecting courses would seriously affect the students' course achievements, which may decrease their GPA even enforce students to drop out. Accurately predicting students' grades in future courses has attracted much attention as it can help identify at-risk students early [30].

We use the grade prediction method called cross-user-domain collaborative filtering proposed by Ling et al. [12]. For predicting the score of each course $c \in C$ for each student $s \in S$, a small set of senior students who have already enrolled on course c and have the most similar previous score distribution to student s will be discovered by means of Pearson correlation coefficient. The underlying rationale is that students with similar scores in the previous courses will generally obtain similar scores in the subsequent courses.

Let S_s denote the set of senior students who have already enrolled on course c. For any senior student $s_s \in S_s$, the following Pearson correlation coefficient is used to measure the course score similarity between student s and the senior student s_s.

$$sim(s, s_s) = \frac{\sum_{i \in C_{ss_s}} (g_{si} - \bar{g}_{si})\left(g_{s_s i} - \bar{g}_{s_s i}\right)}{\sqrt{\sum_{i \in C_{uu_s}} (g_{si} - \bar{g}_{si})^2}\sqrt{\sum_{i \in C_{ss_s}} \left(g_{s_s i} - \bar{g}_{s_s i}\right)^2}} \quad (11)$$

where C_{ss_s} denotes the courses that are enrolled by both students s and s_s, g_{si} and $g_{s_s i}$ denote the grade of course i by students s and s_s respectively. $\bar{g}_{si}$ and $\bar{g}_{s_s i}$ denote the average grade of courses enrolled by students s and s_s, respectively. Accordingly, the grade of the course c by student s can be predicted as follows.

$$g_{sc} = \frac{\sum_{s_s \in S_{s,k}} (g_{s_s c}) \times sim(s, s_s)}{\sum_{s_s \in S_{s,k}} sim(s, s_s)} \quad (12)$$

where $S_{s,k}$ indicates the set of top-k similar senior students of s. It should be noticed that students often achieve inconsistent grades in the various courses they take, and different students may have varying grades deviations, i.e. the grades deviation compared with the average grades among all students. Similarly, different courses may have varying grades deviations, i.e. the score deviation compared with the average score among all courses. In order to deal with those variations. We use the grade deviation of student s and the grade deviation of course c to predict student grades. Accordingly, equation (12) could be rewritten as below.

$$g_{sc} = b_{sc} + \frac{\sum_{s_s \in S_{s,k}} (g_{s_s c} - b_{s_s c}) \times sim(s, s_s)}{\sum_{s_s \in S_{s,k}} sim(s, s_s)} \quad (13)$$

where $b_{sc} = \mu + b_s + b_c$ denotes the baseline estimate for g_{sc} with μ being the overall mean grade of all courses enrolled by all students, $b_s = \bar{g}_s - \mu$ being the grade deviation of student s and $b_c = \bar{g}_c - \mu$ being the grade deviation of course c, where $\bar{g}_s$ is the overall mean grade of student s and $\bar{g}_c$ is the overall mean grade of course c.

Finally, we could use the grades that students are expected to obtain in future courses to boost the performance of our recommendation. The final $Grade\ based\ Scores$, $GS(s, c)$ can be defined as normalized values of grades.

$$GS(s, c) = \frac{g_{sc}}{Max_{c' \in C}(g_{sc'})} \quad (14)$$

The total score of student and course pair $score\ (s, c)$ can be written as:

$$Score = \alpha \times IS(s, c) + \beta \times TS(s, t) + \gamma \times GS(s, c) \quad (15)$$

Where α, β, γ are parameters to control the proportion of weights from different sources. By taking those scores into account simultaneously, a course that the student interested in, and suitable for him to take to get a high grade could be ranked higher than other courses. Also, student could control the weighting of those components to have a better understanding of the data and decision-making.

3.3 Course Recommendation Algorithm

The whole framework can be written as Algorithm 1. Student set S, course set C, enrollment set $E(s, c, g, t)$ are input and output is a list of recommendations Rs for student's next semester that includes up to k recommendations per student.

Algorithm 1: Generating a list of course recommendations for student

Input：
Student set S, course set C, enrollment set $E(s, c, g, t)$;
Output：
Recommendation results for each student Rs.

```
Calculate student interest p_s for each s ∈ S by equation 1;
Calculate student interest similarity by equation 4;
Calculate student grade similarity by equation 11;
Calculate student deviation of each student;
Calculate course grade deviation of each course;
foreach s ∈ S do
    Calculate user interest-based score IS(s, c) by equation 7;
    Calculate timing-based score TS(c, t) by equation. 10;
    Calculate user grade-based score GS(s, c) by equation 13
    and equation 14;
    Calculate final score Score (s, c, t) by equation 15;
    Let Rs be the sorted list of C ordered by its Score (s, c, t) in
    descending order.
endfor
```

4. EVALUATION

In this section, we conducted a series of experiments to evaluate the effectiveness of our proposed method. We first describe the dataset and experimental settings. Next, the evaluation methodology and metrics are introduced in detail. Finally, the results are shown in Section 4.4.

4.1 Dataset

This work focuses on undergraduate students in a traditional educational institution. We used a dataset from our university that spans for 5 years. The dataset consisted of per-semester course enrollment information of 2,366 students from 12 departments, with a total of 38,968 pseudonymized enrollment records from 2014 through 2018. Each row of the course enrollment data contained semester and department information, an anonymous student ID and course information included course name, instructor and course category.

4.2 Experiment Settings

4.2.1 Data selection

The most natural approach to evaluate the model is to split the data by semesters. As shown in Figure 1(b), most of the undergraduate students may take courses in the first two years. Therefore, for students who enrolled in 2015, the semester of Spring 2015 was used for training, the subsequent semesters of Fall 2015, Spring 2016 and Fall 2016 are regarded as the testing semesters, each of which is tested separately. The results are evaluated by comparing the predicted courses and the ground-truth courses he/she has enrolled in.

4.2.2 Comparison

We name our methods as Hybrid Course Recommendation (HCR). We compare our method with two group popularity approaches [14] and Random recommendation (Random). The two group popularity approaches including the department level (Grp-Pop-1), which recommend the most popular courses in the major, and the academic level (Grp-Pop-2), which recommend the most popular courses on the major and the academic level of the student ("freshmen", "sophomores", "juniors", and "seniors").

4.3 Evaluation Metrics

Like previous work [11,14,15,20], we used Recall@ns and Coverage as the evaluation metric for the performance.

Coverage is measured based on the percentage of courses that have been recommended at least once to students, which describes the ability of a recommendation system to explore the long-tail item.

Recall@ns is the percentage of actually enrolled courses of s in semester t that were contained in the recommendation list, where ns is the number of courses that the student took in the target semester. The reported metrics are averaged out across all students. Since our proposed course recommendation method considers both student interest and the grade he/she may obtain, we cannot only use the Recall metric, and instead, we use a variation of it. For the list of the courses R_s that recommended to a student s, Let T_s is the set of courses in the test set of s, A_s is the set of courses which student is expected to get the grade equal to or higher than his/her average previous grade. We use the ratio of $|R_s \cap T_s \cap A_s|$ and $|T_s \cap A_s|$ to measures the fraction of the actual well performed courses that are retrieved.

4.4 Results

4.4.1 Interest-based Score

In collaborative filtering strategy, taking how many similar students as neighbors is an important problem which is sensitive to the quality of the result. We investigate the performance of our interest model with different neighbor numbers. As shown in Figure 4, the performance of the model increases with the increase of neighbor number at first then decreases. According to the observation above, we pick a practical value 40 as the value of the neighbor number parameter in our follow-up experiments.

We also investigate the performance of our interest model with different weights between similarity and major information. As shown in Figure 5, we can observe that the performance of the model increases with the decrease of λ in terms of Recall. The reason is that the model considers not only the similarity but also the major information. That is, each major has its own preference for courses enrolling, major information will improve the performance of the algorithm.

However, 100% recall could be bad because the system just recommends what students do anyway. We noticed that the Coverage also decreases with the decrease of λ. The model seems benefit from the major information while scarifying the diversity of results. Recommendations for courses at other departments sometimes are useful to mine more long-tail student interest while students usually ignored that these courses existed or that their content matched their interests. To achieve the best performance of recommendation, we need to make a trade-off. According to the observation above, we set λ as 0.2 in our follow-up experiments.

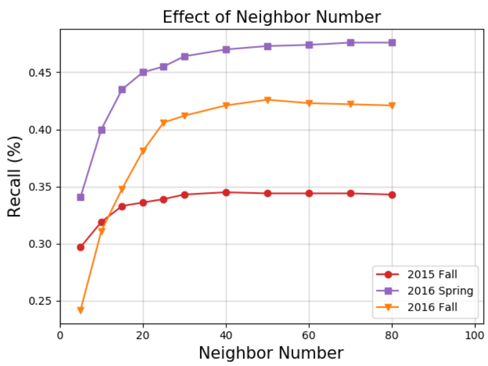


Figure 4. Performance of different neighbor numbers.

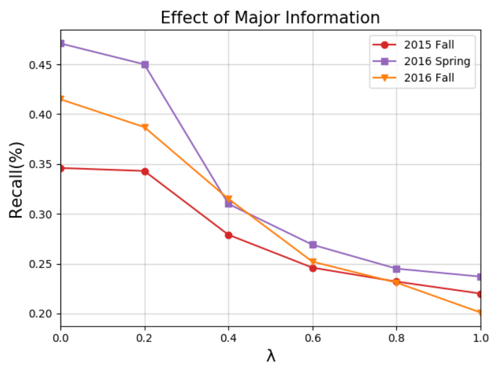


Figure 5. Evaluation of major information.

4.4.2 Influence of different factors

To illustrate the influence of different factors, we set each parameter α, β, γ from 0 to 1 with a step size 0.05 to find the optimal combination.

Table 2. Performance of different parameters

Model	(α,β,γ)= (1,0,0)	(α,β,γ) = (0,1,0)	(α,β,γ) = (0,0,1)	$(\alpha,\beta,\gamma)^*$
Recall@ns	0.380	0.412	0.341	0.434
Recall(a)@ns	0.311	0.315	0.332	0.322
Coverage	0.534	0.212	0.356	0.516

As shown in Table 2, the interest score and timing score has a good explanatory value for the recommendation than others. Also, the suitable timing of taking a course will help students to get a good grade. A recommendation only based on the grade has a good performance for recommending high grade courses. However, the results cannot help all the students. We reached the best Recall@ns with (α =0.4, β =0.45 and γ =0.15)*.

The results indicate that recommendations that are aimed only at one factor are likely not to be satisfied by every student. As we discussed before, different students may have completely different orientations based on their own reasons, which serves as different criteria such as their preferences, interests, needs, performance, etc. Such a hybrid system could provide explanations and user controls for different categories of target students to support the interpretation of the data and decision-making.

Table 3. Evaluation of course recommendation

Semester	Model	Recall@ns	Recall(a)@ns	Coverage
Fall 2015	Random	0.048	0.036	-
Fall 2015	Grp-Pop-1	0.374	0.306	0.272
Fall 2015	Grp-Pop-2	0.452	0.342	0.342
Fall 2015	HCR	**0.472**	**0.393**	**0.578**
Spring 2016	Random	0.025	0.020	-
Spring 2016	Grp-Pop-1	0.325	0.201	0.305
Spring 2016	Grp-Pop-2	0.423	0.372	0.237
Spring 2016	HCR	**0.431**	**0.402**	**0.342**
Fall 2016	Random	0.002	0.002	-
Fall 2016	Grp-Pop-1	0.326	0.243	0.213
Fall 2016	Grp-Pop-2	0.441	0.387	0.250
Fall 2016	HCR	**0.463**	**0.392**	**0.559**

4.4.3 Comparison result

We analyze the performance of different algorithms. The results in Table 3 show that our framework performs well when compared with other methods.

As the results show, both of the Recall and Recall(a) of Random recommendation strategies are very low since there are a large number of courses, but each student only averagely chooses a few courses per semester. Hence, it is difficult to recommend the right course. Popularity approaches are having considerably satisfactory performance in Recall since popular courses which are taken by students frequently usually attract most of students. However, Grp-Pop-1 and Grp-Pop-2 do not consider student preference, it is also difficult to mine more long-tail student interest as the Coverage is low. In addition, Grp-Pop-1 and Grp-Pop-2 are not good in Recall(a) since they only consider the popular courses, ignore the performance the student is expected to get in the recommended courses.

5. CONCLUSION

This research aims to recommend suitable courses for learners and study how to design a personalized course recommendation in the university environments. In this paper, we propose a hybrid course recommendation framework that considers student interest, the timing and popularity of courses, and predicted performance of students, simultaneously. Experiments are conducted to confirm the effectiveness of the proposed approach. The results show that the proposed hybrid course recommendation approach performed well compared to other methods. Also, the model itself is flexible in the sense that one can easily adjust or extend it by changing the recommendation formula and incorporate more information.

6. REFERENCES

[1] E. Babad and A. Tayeb. 2003. Experimental analysis of students' course selection. *British Journal of Educational Psychology*, 73(3):373–393.

[2] Piao G, Breslin JG. 2016. Analyzing MOOC Entries of Professionals on LinkedIn for User Modeling and Personalized

MOOC Recommendations. *In Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization*. ACM, 291–292.

[3] Apaza RG, Cervantes EV, Quispe LC, Luna JO. 2014. Online Courses Recommendation based on LDA. *In SIMBig*. 42–48.

[4] BYDŽOVSKÁ, Hana. 2016. Course Enrollment Recommender System. *Proceedings of the 9th International Conference on Educational Data Mining*. Raleigh, NC, USA: International Educational Data Mining Society. 312-317.

[5] Khorasani ES, Zhenge Z, Champaign J. 2016. A Markov Chain Collaborative Filtering Model for Course Enrollment Recommendations: *2016 IEEE International Conference on Big Data (Big Data)*. 3484 – 3490.

[6] Jing, X., Tang,J. 2017. Guess you like: course recommendation in Moocs. *In: Proceedings of the International Conference on Web Intelligence*, ACM, 783–789.

[7] Bhumichitr K, Channarukul S, Saejiem N, Jiamthapthaksin R, Nongpong K. 2017. Recommender Systems for university elective course recommendation. *14th International Joint Conference on Computer Science and Software Engineering (JCSSE)* (2017): 1-5.

[8] Aher SB, Lobo LM. 2013. Combination of machine learning algorithms for recommendation of courses in E-Learning system based on historical data. *Knowledge-Based Systems* (2013), 1–14.

[9] Bendakir N, Aïmeur E. 2006. Using association rules for course recommendation. *Proceedings of the AAAI Workshop on Educational Data Mining*. Vol. 3.

[10] Ma, B.X., Lu, M., Taniguchi, Y. and Konomi, S. 2020. Exploring the Design Space for Explainable Course Recommendation Systems in University Environments. *In Companion Proceedings of the 10th International Conference on Learning Analytics & Knowledge.*

[11] Polyzou A, Nikolakopoulos AN, Karypis G. 2019. Scholars Walk: A Markov Chain Framework for Course Recommendation. *International Educational Data Mining Society*. (2019 Jul).

[12] Huang L, Wang CD, Chao HY, Lai JH, Philip SY. A score prediction approach for optional course recommendation via cross-user-domain collaborative filtering. *IEEE Access*. (2019 Feb 7);7:19550-63.

[13] Sweeney, M., Lester, J., Rangwala, H., and Johri, A. 2016. Next-term student performance prediction: A recommender systems approach. *Journal of Educational Data Mining* 8, 1, 22–51.

[14] Elbadrawy, A. and Karypis, G. 2016. Domain-aware grade prediction and top-n course recommendation. *In Proceedings of the 10th ACM Conference on Recommender Systems*. ACM, 183–190.

[15] Morsy, S. and Karypis, G. 2017. Cumulative knowledge-based regression models for next- term grade prediction. *In Proceedings of the 2017 SIAM International Conference on Data Mining.* SIAM, 552–560.

[16] Jiang W, Pardos ZA and Wei Q. 2019. Goal-based course recommendation. *In Proceedings of the 9th International Conference on Learning Analytics & Knowledge*. ACM, 36–45.

[17] Morsy S, Karypis G. 2019. Will this Course Increase or Decrease Your GPA? Towards Grade-aware Course Recommendation[J]. arXiv preprint arXiv:1904.11798.

[18] Okubo F, Yamashita T, Shimada A, Ogata H. 2017. A neural network approach for students' performance prediction. *In Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (2017 Mar 13). 598-599.

[19] Pardos ZA, Jiang W. 2019. Combating the Filter Bubble: Designing for Serendipity in a University Course Recommendation System. arXiv preprint arXiv:1907.01591 .2019.

[20] Pardos ZA, Fan Z, Jiang W. 2019. Connectionist recommendation in the wild: on the utility and scrutability of neural networks for personalized course guidance. *User Modeling and User-Adapted Interaction.* (2019 Apr 1). 487-525.

[21] Potts BA, Khosravi H, Reidsema C, Bakharia A, Belonogoff M, Fleming M. 2018. Reciprocal peer recommendation for learning purposes. *In Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (2018 Mar 7). 226-235.

[22] Tinto V. 1997. Classrooms as communities: Exploring the educational character of student persistence. *The Journal of higher education.* (1997 Nov 1).68(6):599-623.

[23] Morsy, S. and Karypis, G. 2019. A study on curriculum planning and its relationship with graduation gpa and time to degree. *In Proceedings of the 9th International Conference on Learning Analytics & Knowledge.* ACM, 26–35.

[24] Kinnunen P, Malmi L. 2006. Why students drop out CS1 course? *In Proceedings of the second international workshop on Computing education research* (2006 Sep 9). 97-108.

[25] Crues R, Bosch N, Anderson CJ, Perry M, Bhat S, Shaik N. 2018. Who They Are and What They Want: Understanding the Reasons for MOOC Enrollment. *International Educational Data Mining Society.* (2018 Jul 16).

[26] Kardan, H. Sadeghi, S. S. Ghidary, and M. R. F. Sani. 2013. Prediction of student course selection in online higher education institutes using neural network. Computers & Education. vol. 65. 1–11.

[27] Feng W, Tang J, Liu T X. 2019. Understanding dropouts in MOOCs. *Proceedings of the AAAI Conference on Artificial Intelligence.* 2019. 33: 517-524.

[28] Elbadrawy, A., Studham, R. S., and Karypis, G. 2015. Collaborative multi-regression models for predicting students' performance in course activities. *In Proceedings of the 5th International Learning Analytics and Knowledge Conference.*

[29]Hu, Q. and Rangwala, H. 2018. Course-specific markovian models for grade prediction. *In Pacific-Asia Conference on Knowledge Discovery and Data Mining.* Springer, 29–41.

[30] Hu, Qian and Huzefa Rangwala. 2019. Reliable Deep Grade Prediction with Uncertainty Estimation. *In Proceedings of the 9th International Conference on Learning Analytics & Knowledge.* ACM,76–85.

[31] Backenköhler M, Scherzinger F, Singla A, Wolf V. 2018. Data-Driven Approach towards a Personalized Curriculum. *International Educational Data Mining Society.*

[32] Morsomme R, Alferez SV. 2019. Content-based course recommender system for liberal arts education. *In Proceedings of the 12th International Conference on Educational Data Mining* 2019. Vol. 748, p. 753.

[33] Bydžovská H. 2016. Course Enrollment Recommender System. *International Educational Data Mining Society.*

[34] Esteban A, Zafra A, Romero C. 2018. A Hybrid Multi-Criteria Approach Using a Genetic Algorithm for Recommending Courses to University Students. *International Educational Data Mining Society.* (2018 Jul).