Metaheuristic for the Personalized Course Sequence Recommendation Problem

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1 Introduction

Scheduling problems have been studied in various domains, such as machine scheduling, staff scheduling, transportation and sport scheduling. In this paper, we focus on a novel scheduling problem in the university context, namely personalized course sequence recommendation. Many universities today offer courses in such a way that gives students more flexibility in selecting courses. The universities offer not only compulsory courses but also elective courses that students can choose based on certain criteria, such as majors, specific programmes, specialized courses and elective courses. Students are expected to take a required number of courses over a sequence of terms. Among the factors considered by students when selecting courses, course instructors, academic preference, relevance to career plan, and GPA (Grade Point Average) are often the important ones. GPA is commonly used in a university in Singapore. This scoring system refers to a student's academic performance and reflects it as a number - the higher the better.

Recommender systems become an important research area since it helps users to find the right content, products, or services [4]. Much of the research pertaining to recommendation systems has been conducted in the domain of e-commerce. [5] describe a recommender system as follows:

In a typical recommender system, people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases the primary transformation is in the aggregation; in others the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations.

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The application of the recommendation system in the education sector has recently gained popularity. [6] summarized the main challenges of developing recommendation systems. Unlike most existing recommender systems, such as movies or products to buy, course sequence recommender system generates sequences of courses rather than a single item at a time. The complexity increases when the number of courses offered is large. Other factors such as considering the student's performance and the university (or school) requirements simultaneously further add challenges to the task. [2] developed an application, namely SUcheduler, for helping students to plan their personalized course schedules by considering their preferences over sections, instructors and other factors. The application utilizes a declarative problem solving method based on Answer Set Programming, for generating course schedule plans. However, the model assumes that students have selected their courses before hand. Basically, it generates possible candidate solutions, using choice rules and eliminates the candidates that violate predefined constraints.

In this paper, we develop a personalized course sequence recommendation system with the main objective of generating a sequence of courses for all subsequent terms, i.e. until the final graduation term. [6] highlighted that prolonged graduation time may arise when courses are only taken myopically, without a clear plan. Therefore, it is important to tailor course sequences to students since students may not have the same learning path. We first analyze the past data that covers course titles and grades from previous terms of undergraduate students from a university in Singapore. From the data, we have learnt that students may achieve better GPA if they choose suitable sets of courses and order them in certain sequences. Performance of a student evolves in the process of learning [6]. Based on past courses taken by a student and the course grades, we design an objective function that returns a course sequence which maximizes the student's GPA. We propose an algorithm based on simulated annealing to determine the optimal course sequence. We conduct experiments based on a real-world student record dataset to verify the efficacy of the proposed algorithm.

2 Personalized Course Sequence Recommendation Problem

For a particular degree with a given set of courses $C = \{1,2,...|C|\}$, C_c and C_e are defined as sets of compulsory and non-compulsory (elective) courses respectively ($C_c, C_e \subset C$). Each student must complete C_c and take a subset of C_e in order to fulfill the graduation requirements. Assume that a student has completed the first T terms. The set of courses taken in term t is denoted as $C'_t (t \in T)$, and the actual grade received for the course i in term t is denoted as $G_{it} (t \in T, i \in C'_t)$. In our problem, there are five possible grades for courses $G = \{A,B,C,D,F\}$. They are converted to scores of 4, 3, ..., 0 respectively. Every student can take a maximum of C_{max} courses in each term, and is expected to complete C_{total} courses for graduation.

The main objective of the course sequence recommendation is to recommend a sequence of courses to a student, based on his first T terms information, such that all of the graduation requirements and prerequisites of courses are satisfied, and his overall GPA is maximized. In this work, we have chosen to maximize the overall GPA which has been highly valued among students within the highly competitive education systems [1]. Therefore, selecting what courses to be taken in their following terms should be done very carefully. For example, students who perform well in programming courses tend to perform well in advanced programming and data analytics courses. For such students, recommending both advanced coding and data analytics courses to be taken within the same term would not be a problem. However, for students who had performed badly in programming courses, it will be more challenging for them to take both advanced programming and data analytics courses within the same term.

Our proposed personalized course sequence recommendation approach is divided into two main stages:

Stage 1: Grade Estimation. The grade in course j after completing course i with grade g, denoted as E_{ij}^{g}, where $i, j \in C, g \in G$ is estimated. We define the probability of completing course j with grade g' after completing course i with grade g, denoted as $P_{ij}^{gg'}$, in equation (1). $S_j^{g'}$ is the set of students who have taken course j and obtained grade g', S_i^g is the set of students who have taken course i and obtained grade g, and S_j is the set of students who have taken course j.

$$P_{ij}^{gg'} = \frac{|S_i^g \cap S_j^{g'}|}{|S_i^g \cap S_j|} \tag{1}$$

The expected grade of course j after completing course i with grade g, E_{ij}^{g}, is defined by Equation (2). $GP^{g'}$ represents the grade point of grade g', where $GP^{g'} = \{4, 3, 2, 1, 0\}$.

$$E_{ij}^{g} = \sum_{g' \in G} P_{ij}^{gg'} \times GP^{g'} \tag{2}$$

Stage 2: Course Sequence Construction. The course sequence is constructed in order to maximize the overall estimated grade. For a particular student, an initial solution is constructed by recommending the next course j, starting from $|T|+1$, that satisfies the prerequisite requirements and Equation (3). The prerequisite requirement is defined as a certain list of courses that must be completed until term $|T|$ in order for a particular student is able to take course j in term $|T|+1$.

$$\underset{j \in C}{\operatorname{argmax}} \left\{ G_{j,|T|+1} = \frac{\sum_{t \in T} \sum_{i \in C_t'} E_{ij}^{G_{it}}}{\sum_{t \in T} |C_t'|} \right\} \tag{3}$$

We first recommend as many compulsory courses C_c as possible, before recommending C_e. Once we recommend C_{max} courses, we increase $|T|$ by one, update C_t' and G_{it}, and repeat the procedure until C_{total} is reached. The overall expected GPA, $E(GPA)$, of a student is defined in Equation (4). $E(GPA)$ is also the objective function to be maximized.

$$E(GPA) = \frac{\sum_{t \in T} \sum_{i \in C_t'} G_{it}}{\sum_{t \in T} |C_t'|} \tag{4}$$

A course sequence for a particular student, say student A, can be represented as a two-dimensional matrix $|T| \times C_{max}$, as illustrated in Figure 1. For example, in term

3 (see row 3), we recommend student A to take courses 166, 204, 37, 72, and 4. However, for cases where $|T| \times C_{max} \neq C_{total}$, -2 is added as a dummy value.

	Course_code				
Term	51	43	27	101	54
	114	41	108	212	15
	166	204	37	72	4
	238	262	240	288	33
	194	230	137	38	254
	155	224	214	394	157
	106	14	301	339	557
	281	536	245	-2	-2

Fig. 1: Example of solution representation with $|T| = 8, C_{max} = 5, C_{total} = 38$

To improve the initial solution, we propose an adaptive simulated annealing algorithm [3]. The algorithm includes parameters that control temperature schedule and the operator selections are automatically adjusted as the algorithm evaluates the later iterations. This makes the algorithm more efficient and less sensitive to user-defined parameters than pure simulated annealing. We adjust the probability of choosing the local search operators, such that operators with good performance in the past iterations will get a higher chance to be selected in the subsequent iterations. We implement six local search operators:

– **Swap**: choose two courses randomly from different terms and exchange their positions.
– **Move**: choose two courses randomly from different terms, move the position of the second course before the first course, and push back the courses in-between both courses.
– **2-opt**: choose two courses randomly and reverse the sequence between both courses.
– ***N*-replacement**: remove N courses (i.e. elective courses) from the solution, then, add other N unselected courses to the solution. We implemented $N = 1$, 2, 3.

3 Experimental Results and Discussion

We use a real dataset from a particular school of a university in Singapore. To perform grade estimation, we consider students who enrolled in years 2010 until 2018 with a total of 3905 students and 644 courses. We classify grades into 5 categories, $|G| = 5$. This grade estimation approach is tested on 572 students, we found that a mean absolute error of 0.32 with 172 (366) students' results are overestimated (underestimated). This ensures the fairness of the measurement conducted in the following experiments as the grade estimation is not always overestimated.

The proposed algorithm is tested on a subset of students: students enrolled in years 2011 until 2014, from two different program tracks, Track 1 and Track 2. Since the final grade upon graduation are known, we are able to evaluate the performance of our proposed algorithm by: (i) the number of students enjoying grade improvement from the recommended course sequence compared to the actual course sequences. This is derived by the number of students with $E(GPA_{recommendation}) > GPA_{student}$ and (ii) the grade improvement obtained if students follow our recommended course sequences compared to their actual performance (measured by Equation (5)).

$$\%imp = \frac{E(GPA_{recommendation}) - GPA_{student}}{GPA_{student}} \times 100\% \tag{5}$$

From a total of 385 students, our proposed algorithm is able to improve the expected overall grade for 218 students, with an average improvement of 3.15%. Most of the improvement comes from students with low $GPA_{student}$ grades. It is harder to improve overall grades when the students have already obtained high actual grades (i.e. above 3.0).

To overcome this matter, we try other two scenarios: (i) to increase $|T|$ and (ii) to perform grade moderation. The results are summarized in Table 1.

Scenario (i) - to increase $|T|$. This approach is implemented such that we are able to ”know more” about the student’s past performance. Here, we use $|T| = 2$, meaning that we use student’s first and second terms information to recommend the course sequence for the following terms. By using this approach, we are able to improve the expected overall grade for 228 students, with an average improvement of 3.24%.

Scenario (ii) - grade moderation. This approach is implemented to ”adjust” our grade estimation, depending on student’s performance in their first term ($|T| = 1$). The moderation is done by deriving the performance index (PI) for each student, by Equation (6), where $\overline{x_s}$ is the average student’s grade in his first term and $\overline{x_d}$ is the average grade obtained by all students who have taken the same set of courses.

$$PI = \frac{\overline{x_s}}{\overline{x_d}} \tag{6}$$

$PI = 1$ indicates that the student is normal (performs as well as the average student), $PI > 1$ indicates the student has an academic ability above other students, and therefore we try to “upgrade” our grade estimation to match his ability, while $PI < 1$ indicates the student does not perform well compared with other students, and therefore we try to “downgrade” our predicted grade to match his ability. When applying this approach, Equation (3) is replaced by Equation (7). In our experiments, this new grade estimation scheme is shown to improve the expected overall grade for 236 students; but, the average improvement falls to 2.71%.

$$\underset{j \in C}{\operatorname{argmax}} \left\{ G_{j,|T|+1} = \frac{\sum_{t \in T} \sum_{i \in C'_t} E_{ij}^{G_{it}}}{\sum_{t \in T} |C'_t|} \times PI \right\} \tag{7}$$

Table 1: Results of different scenarios

	# improvement			Average of $\%imp$		
	Track 1	**Track 2**	**Both**	**Track 1**	**Track 2**	**Both**
Initial approach	76	142	218	1.62	4.14	3.15
Scenario (i)	77	151	228	1.90	4.10	3.24
Scenario (ii)	83	153	236	0.97	3.83	2.71

4 Conclusion

In this paper, we introduce a personalized course sequence recommendation system to suggest courses for students to achieve good academic performance. In our proposed model, the main objective is to maximize the expected GPA with respect to several constraints, such as the maximum number of courses taken in each term and prerequisite constraints. We propose an adaptive simulated annealing algorithm in order to solve the problem. The operator selections are dynamically adjusted. Our preliminary results show that the proposed algorithm is able to improve the expected GPA by recommending course sequences for 218 out of 385 students, with an average improvement of 3.15%. The current model only concerns about maximizing GPA while other factors that may affect the performance of students have not been considered yet, such as instructors, colleges of students, and so on. Furthermore, the popularity of a particular course has not been addressed in this work, e.g. courses with higher number of students enrolled are more likely to be recommended. Machine learning for education has recently gained attention in this recommendation system. For future work, we will focus on using machine learning techniques to further improve the grade prediction accuracy and develop a User Interface to allow students to use.

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