Course Offering Support System

Emergent Research Forum (ERF)

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Abstract

In this paper, preliminary needs and goals are outlined for a support system to provide a good default course sequencing and course schedule that is tailored to individual student needs. The basis of optimization will be finding optimal combinations of courses for each semester to maximize overall GPA and the probability of graduation within the college.

Keywords

Course recommendation, dynamic programming.

Introduction

While most college curriculums for a bachelor degree are designed to be completed in four years, only less than 31.9% of all students graduated within four years at public universities in the United States according to the latest published statistics (ACT). Not graduating on time results in cost for the students in form of increased opportunity cost as a result of lost income, in addition to greater out of pocket expenses when attending state universities beyond the required number of years. Students are often supported by scholarships that have funding limited to four years. One such scholarship program in Louisiana is TOPS Opportunity award. It provides students with assistance for up to 4 years, or 8 semesters (Assistance, 2018). Course scheduling and advising for choosing appropriate schedules are key to on-time graduation. However, many state schools have experiences severe budget cuts over the past decade, reducing the number of course offerings and the resources available for advising and it is unlikely that state universities will experience an increase of funding any time soon. Hence, universities must explore other way to provide proper advising within their limited budgets. This paper proposes a Decision Support System that can be used by students to guide them each semester to the most effective course schedule to achieve graduation in the shortest possible time with the highest grade point average possible.

Each major at a university has a course plan that consists of a number of required courses and electives. However, students often do not follow this course plan for a variety of reasons: a student may change major, may fail to meet grade requirements for a prerequisite class, may be unable to schedule a needed class or the course may not be offered. In reality, deciding on which courses, and when can be difficult. The fact that the course schedule is a guideline and not a requirement can make forecasting demand for classes imprecise. In addition, some students may wait until the last minute to schedule.

The basis for a student decision support system for class scheduling is an individualized course schedule for each student that takes into account the student’s prior education and abilities to optimize the GPA and time to graduation. This course schedule will be updated each semester to reflect courses completed and grades received. In our DSS we propose to implement Libertarian paternalism, as popularized by the book Nudge, and construct an individualized default schedule for each students, but give them the opportunity to change it themselves. (Thaler & Sunstein, 2008) This approach would give the administration in charge of scheduling some indication of the scheduling needs for students. We start with the premise that all students are not created equally. Some students may handle a difficult and higher course load than others, while some may need remedial instruction in subjects like math to bring them up to speed.
This research uses ten year of student data from a business college, which includes, demographics, ACT, high school GPA, courses taken in college, grades received and whether a student graduated and in which major. Upon completion, the proposed support system will be able to provide students with a default recommendation that is optimal and tailored for them, but will also provide a new potential method of forecasting for scheduling departments.

**Related works**

Course Recommendations that focus on the student have been widely studied. One of the more common methods for course recommendations implements collaborative filtering (Abu Sarhan, 2013) (Khorasani, Zhenge, & Champaign, 2016) (Al-Badarenah & Alsakran, 2016) (Lee, Kuo, & Lin, 2017) (Ray & Sharma, 2011). Collaborative Filtering would be possible here, as we have both historical course choices and outcomes of past students, in addition to demographic characteristics of the students. Collaborative Filtering tends to focus on the next upcoming term, so while that would address the success of a positive outcome in the next term, it does not address the larger goal of overall efficiency. Without looking at the big picture, it is entirely possible that due to constraints like pre-requisites, a student might get stuck with additional semesters because pre-requisites were not addressed in a timely manner. Other methods employed have involved Ant Colony Optimization (Sobecki & Filanowski, 2011) (Sobecki & Tomczak, 2010), Context Trees (Mi & Faltings, 2016) or sequential pattern mining (Tarus, Niu, & Yousif, 2017)

Instead of focusing on next term recommendations, turning the problem into a dynamic programming task can address the overall goal of successfully completing the program in a timely manner. Both (Uslu, Ozturan, & Uslu, 2016) and (Xu, Xing, & van der Schaar, 2015) create optimal schedules using different objectives. Uslu et al. worked with Mecanin, to build recommendations and schedules on the following semester based off user ratings, employing dynamic programming to come to a solution that gives the student the highest score for the semester. Xu and van der Schaar instead focus on the big picture, similar to our goal here. The objective of that study was to find a course sequence that helps with both GPA and time to graduation, but does not directly address the probability of graduation.

**Methodology**

If the university employs a default scheduler for the students, requiring them to opt out and modify the schedule on their own, they can better anticipate course demands. Collaborative filtering can be utilized to recommend courses for the next semester, taking into account the required courses and decisions of similar past students and their grades. We make grade estimates for the students, similar to the Performance Prediction employed by (Sweeney, Lester, Rangwala, & Johri, 2016). The objective is to find the optimal semester for core courses to be taken, not just courses for the upcoming term. A metric such as expected contribution to graduation is created which combines both the grade, and the probability of graduating on time or in the current major. This metric permits capture of scenarios such as difficult courses taken together. Focusing on either just GPA or just probability of graduation is not sufficient. Taking two difficult courses in the same semester could lower the student’s semester GPA, but provide a higher probability of graduation. Alternatively, the student could excel in that semester, but burn out. Both scenarios are shown in Table 1. It is also entirely possible that one course should be taken before the other. With expected contribution to graduation for all courses and every semester (taking into account pre-requisites) it is an optimization problem to ensure that we maximize the expected contribution of courses to graduation for each semester.

<table>
<thead>
<tr>
<th></th>
<th>Scenario 1 (Lower GPA, higher chance to graduate)</th>
<th>Scenario 2 (Higher GPA, lower chance to graduate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Math</td>
<td>3.0*0.9=2.7</td>
<td>4.0*0.6=2.4</td>
</tr>
<tr>
<td>Econ</td>
<td>3.0*0.8=2.4</td>
<td>4.0*0.5=2</td>
</tr>
<tr>
<td>Expected Contribution</td>
<td>5.1</td>
<td>4.4</td>
</tr>
</tbody>
</table>
Table 1

The steps to obtain the above figures are as follows:

1. Find a representative group of students similar to the incoming student.
2. For each course that pre-requisites are met, single and combinations of courses are evaluated to take the average course GPA, and overall semester GPA.
3. The above step is repeated to find the individual course and overall probabilities of graduation.
4. The course schedule is not finalized until the semester GPA multiplied by the probability of graduation is maximized for all required courses.

After each incoming student is given a default course plan, aggregating the students will give the department an indication of course demands for both the upcoming semester, and future semesters. This will hopefully limit the problem of students not being able to get into necessary courses in time to keep on track for graduation within scholarship limits. This forward looking view of student course demand can alert also decision makers if the need to alter the planned semester of a course that does not occur every semester. Implementation of such a DSS will require frequent updates, to capture changes in the students, both in performance and changes in major.

Conclusion

The benefit from the proposed DSS is largely due to the success of a well-informed default choice given to students (Thaler & Sunstein, 2008). Students may deviate from the default schedule for reasons such as time, difficulty, outside employment or popularity of a professor (Sobecki & Filanowski, 2011). If a sufficient number of students deviate from the default choice, the usefulness of the system may suffer. One issue with using historical data of past students to predict future outcomes may rise from changes in courses. For instance, if the way introductory economics is taught at the undergraduate level has less of a focus on mathematics, any assumptions based on the previous method of instruction would no longer be valid. Course requirements and changes must be monitored and accounted for in order to update any DSS.

References


