Educational Timetabling with Unconstrained Demand Forecasting

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Abstract. The University Course Timetabling Problem (UCTTP) often assumes that course enrollment is given a priori, though this is not always the case in practice. In this extended abstract, we outline our work to predict unconstrained course demand and student registration behavior using methods borrowed from airline revenue management, and to analyze the impact of these predictions within a timetabling optimization model.

Keywords: Educational timetabling · Demand forecasting · Overbooking.

1 Introduction

In the University Course Timetabling Problem (UCTTP), a set of courses is assigned to times, classrooms, students, and instructors. This problem has been studied extensively, with many variations and solution methods (see surveys [3, 4, 6]). Although most formulations of the problem are NP-complete [2], there exist methods for finding high-quality solutions to large-scale instances in practice [8].

In most of these studies, course enrollment is assumed to be fixed in order to meet classroom capacity constraints. In practice, universities must often estimate course enrollment when making room assignments without knowing the true course demand or how many students will add or drop the course. One such institution is the Georgia Institute of Technology (GT), the focus of our case study. At GT, the registrar assigns centrally-scheduled courses to classrooms before the first phase of registration opens to students. Most enrollment predictions are rolled over from the previous semester each course was offered; when this is not possible, the academic unit supplies its best guess. The registrar's goals are to use these numbers to maximize classroom utilization while satisfying the building preferences of each academic unit.

Given that this method has been in place for years, it provides a reasonable estimate for enrollment. However, this method does not account for constrained demand. If a course was assigned a room with a capacity of 30 last semester, and then enrolled 30 students, the final enrollment would not include the demand of students who wished to take the course but could not because of the limited capacity. Most work investigating unconstrained demand for timetabling has utilized student surveys to estimate course demand [9, 11], which doesn't capture students' actual registration behavior. Additionally, we have only found one paper that defines a mathematical model for the add/drop process [13]. If we knew how many students would enroll in a course during registration, we could assign classrooms while satisfying capacity constraints; and if we knew students' add/drop behavior, we could allow for overbooked classrooms.

Although largely unstudied in the context of education, demand forecasting and overbooking have been key areas of research in the airline industry for decades. In [10], we find a taxonomy of the various methods of demand unconstraining used in the literature over the years, bucketed into basic approaches (ignoring censored data, imputation, etc.), statistical methods (time series, linear regression, etc.), discrete choice models, and optimization methods (expectation maximization, nonlinear programming, etc.). The above survey also provides examples of how these techniques for unconstraining demand have been adopted by other industries, including rail, hotel, rental, and retail; we propose adding university operations to that list.

Student registration behavior over time also parallels airline passenger behavior. Students often over-enroll in courses and later drop them, thus artificially inflating the demand for a course. In a similar way, airline passengers often purchase tickets and then cancel their flight at the last minute or no-show altogether. With average no-show rates of 10% during regular operations and 20% during the peak holiday season, not overbooking means that these seats would remain empty when they could otherwise be filled with paying customers [1]. Similarly to demand forecasting, overbooking has been studied extensively in the context of airline operations [5], but the only applications of overbooking in educational institutions we have found study the institution-level yield rates, not course-level enrollments [12].

In order to make better use of university resources, we propose adapting demand unconstraining methods and overbooking models from the airline industry to better predict student enrollment and registration behavior and thus improve the inputs to our timetabling model. Our work therefore bridges the gap between stochastic enrollment behavior and traditionally deterministic course timetabling.

2 Methods

2.1 Initial Formulation

We base our model on the formulation in [7]. In the first stage of our analysis, we assume a fixed timetable and assign classrooms to maximize classroom utilization. We have a set of class sections $\mathcal{X}$, each with projected enrollment p_x. For every day-time pair in the set of start times $\mathcal{ST}$, we define $\mathcal{X}_{d,t}$, the set of sections that have a meeting on day d that starts at or before time t on that day and makes the classroom it is assigned to unavailable at that time. We also have a set of classrooms $\mathcal{R}$, each with capacity n_r. To allow for overbooking, we let M be the maximum percentage by which classrooms may be overfilled, and β be the factor by which overbooked seats are penalized compared to underbooked seats.

We define the following decision variables.

$$X_{x,r} = \begin{cases} 1 & \text{if section } x \text{ is assigned to room } r \\ 0 & \text{otherwise} \end{cases}$$

$$Y_x \in [0, M] : \quad \text{percent by which section } x \text{ is overbooked}$$

The primary objective is to maximize classroom utilization, which is equivalent to minimizing unused capacity. We add a penalty term proportional to the number of overbooked seats.

$$\min \sum_{x \in \mathcal{X}} \sum_{r \in \mathcal{R}} \max(0, n_r - p_x) X_{x,r} + \beta \sum_{x \in \mathcal{X}} p_x Y_x \tag{1}$$

Our constraints ensure that each room is assigned to at most one class section at a given time, and each class section is assigned to a room. We relax the room capacity constraints by adding a term to allow for controlled overbooking.

$$\sum_{x \in \mathcal{X}_{d,t}} X_{x,r} \leq 1 \qquad \forall r \in \mathcal{R},\ \forall (d,t) \in \mathcal{ST} \tag{2}$$

$$\sum_{r \in \mathcal{R}} X_{x,r} = 1 \qquad \forall x \in \mathcal{X} \tag{3}$$

$$p_x X_{x,r} \leq n_r + p_x Y_x \qquad \forall x \in \mathcal{X},\ \forall r \in \mathcal{R} \tag{4}$$

The initial dataset that we used to test the above formulation consists of approximately 2,000 course sections, 150 classrooms, and 125,000 total projected enrollments across all sections for a given semester at Georgia Tech.

2.2 Predicting Demand

While overbooking can allow for an improved objective value, overbooking too aggressively can incur costs that outweigh the benefits. While the airline industry can reroute passengers and accept the accompanying denied boarding cost, universities cannot force a student to unregister from a course due to capacity issues. They thus have two options: move the course to a larger room or change the course modality. The first is challenging and potentially not feasible, since the problem is already highly constrained. On the other hand, changing modality may incur technology costs, as well as frustration from students and faculty who were expecting an in-person course. We thus seek to control these over-enrollments in our model.

To conduct these analyses, we are acquiring student registration data from the last three years at GT, including add/drop behavior and the precise timing of these actions. In order to unconstrain demand for courses at capacity, we will use time series and discrete choice models to account for both the temporal and strategic nature of student registration behavior when considering alternatives throughout the registration period. Additionally, we will create models to predict the future enrollments of a given student based on factors like their course history and program of study. Finally, we will analyze patterns of student registration behavior over time to predict how many students will drop a course and how many students admitted from the waitlist will actually end up enrolling in the course. These predictions will allow us to recommend an overbooking level for each course, which we will then use in the above optimization formulation with relaxed capacity constraints. In a later step, we will drop the assumption that class times are fixed, and analyze the impact of better demand prediction on the overall university timetable. To our knowledge, this is the first work to incorporate demand unconstraining and overbooking methods into course-level educational timetabling.

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