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Optimization and approximation methods for dynamic appointment scheduling with patient choices

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ABSTRACT

A well-designed appointment scheduling system in healthcare should take into account patient choices in order to improve patient satisfaction. A dynamic programming model is proposed to decide which slots should be offered for patients to choose from. We characterize optimal offer sets with a simple form by using the notion of "complete set", in which all slots with revenues higher than a certain value are offered. An approximate method making use of the complete-set policy is proposed for estimating the value associated with the system state. Experiments show that the complete-set policy is effective and efficient. The model is extended to handle a general appointment system, in which the reward depends on both patients and healthcare service providers. The complete-set policy continues to exhibit excellent performances.

1. Introduction

Healthcare delivery worldwide has been fraught with high cost, low efficiency and poor quality of patient care service. Appointment systems have been introduced into healthcare service management to obtain more information about patient needs and enable providers to improve patients' satisfaction, a main dimension of healthcare quality. A key issue in enhancing the patient satisfaction level is to offer more flexibility to patients. To this end, online appointment systems have been developed to allow patients to choose their preferred physicians and time slots. For example, the e-Referral Service is provided by the National Health Service in the United Kingdom. After patients log into the system, a list of suggested clinics together with basic information about them, including the approximate wait time and location, is displayed. Patients can choose their preferred clinics and times that best suit them (Green et al., 2008). In the US, Zocdoc.com provides a similar service (Zocdoc, 2015). In China, the Ministry of Health required hospitals to install appointment systems in 2009 (Wang and Fung, 2015a). Patients now prefer making appointments in advance, especially when they want to see a specialist (a senior physician), because that enables them to avoid long queues (Yu et al., 2013). Since complete flexibility results in unstable daily load in a clinic, systems are designed to determine which options should be offered (Feldman et al., 2014). This paper is motivated by the online appointment booking systems.

In our model, patients make appointments for a particular service day through an online interface. Appointment requests within a booking horizon arrive sequentially. When making an appointment, the patient is given a set of options to choose from, i.e., several physicians and their available time slots. If none of them is acceptable, the patient leaves without an appointment. The proposed online appointment scheduling system utilizes a dynamic programming (DP) model capable of deciding which available slots should be offered. The objective is to maximize the expected revenue from the service day. Note that our model is useful for the general capacity-demand relationship. First, strategical policies are needed even if the demand does not exceed the capacity, due to the sequence of appointment requests. Second, in the context where demands are much more than the capacity, some naive policy may also obtain the same revenue as that achieved by using strategical methods, e.g., DP model. However, the booking horizon must be much longer than that needed for strategical policy, since naive policies are more likely to refuse some appointments with large rewards. As a result, the cost of the long booking horizon for the service provider is high.

Wang and Fung (2015b) developed a decomposition-based approach to simplify the computations of the DP model. However, they do not investigate the property of the model, hence the benefit is limited. We identify a property of the DP model, which allows the optimal solution to be chosen from a much smaller

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number of candidate decisions. This is done by applying the notion of "complete set" developed by Talluri and Van Ryzin (2004), which is composed of all slots with revenue greater than a certain value. To reduce the number of system states in the DP model, we propose an aggregation-based approximation method. This method aggregates several time slots into a single slot and applies the complete-set policy to reduce the number of system states as well as actions. Numerical studies show that the new policy has demonstrated good performance at revenues with a maximum gap of −1.30%, compared with the policy using the results of the original DP model directly. Our policy is also efficient. For a system with 30 time slots, 1000 simulated instances can be finished within 34 s. In addition, we also consider a general reward case, in which the rewards are related to both patients and the healthcare service providers. The complete-set strategy continues to perform well in the extended model.

The contributions of this paper are as follows:

- In the context of online appointment scheduling system, we identify a policy which is optimal if certain conditions of patient choice probabilities are satisfied.
- Two common choice models are examined for the optimality of the new policy.
- For the general choice probabilities, we develop an approximation method capable of tackling the computational challenge associated. We show that the complete-set policy continues to be powerful even though the conditions for its optimality have not been satisfied strictly.
- We extend the existing model to deal with a case of the general reward system, in which rewards depend on both patients and healthcare service providers. Experiments show that the new policy we proposed continues to perform quite well.

The remainder of this paper is organized as follows. Section 2 reviews literature related to appointment scheduling and patient choices. Section 3 describes the booking process and system state and proposes a DP model. Section 4 examines the optimality of the complete sets if the choice probabilities satisfy certain conditions. Section 5 develops an approximate method to resolve the computation problem of the DP model, based on which a new policy is proposed. Section 6 extends the DP model to handle a case implementing a general reward system. Section 7 describes the numerical studies conducted. Finally, Section 8 presents the concluding remarks along with some suggestions for future work.

2. Literature review

Gupta and Denton (2008) broadly review appointment scheduling problems in healthcare. They identify some factors affecting the performance of appointment systems. It is pointed out that patient preference is one of the important challenges of outpatient scheduling. In this section, we first outline the appointment scheduling problem, and then review the literature concerning patient choices.

2.1. Appointment scheduling in healthcare

Appointment scheduling refers to the process of assigning appointment times to patients in advance of the corresponding service dates. It not only allows patients to obtain access to healthcare services efficiently, but also increases the utilization of facilities for hospitals (Cayirli and Veral, 2003). Numerous variables describing the patients' and the service provider's behavior make the appointment scheduling extremely complicated, e.g., no-shows (Parizi and Ghate, 2016; Samorani and LaGanga, 2015; Yan et al., 2015), walk-ins (Cayirli et al., 2012), cancellations (Liu et al., 2010; Schütz and Kolisch, 2013), and random service duration (Begen and Queyranne, 2011; Denton and Gupta, 2003). The decisions made by schedulers can be divided into two categories: those in the first category assign patients' requests to a particular physician or booking period, e.g., Wang et al. (2015) and Truong (2015) while those in the second category offer several options (physicians and time slots) for patients to choose from, e.g., Liu et al. (2015) and Feldman et al. (2014). Our paper belongs to the second category.

DP models are often used to deal with the sequential appointment scheduling problems, e.g., Patrick et al. (2008) and Patrick (2012). Owing to the high dimensionality of system state in DP models, different approaches have been used to approximate the values of the states, e.g., decomposition-based and simulation-based methods. Patrick et al. (2008) and Sauré et al. (2012) decompose the value of system states by using an affine approximate, and transform the DP model into a linear programming (LP) model. Schütz and Kolisch (2012) and Sauré et al. (2015) propose simulation-based approximate dynamic programming approaches capable of update the values of the system states dynamically.

2.2. Patient choices

Patient choice is a critical factor that should be taken into account seriously since it influences patient satisfaction level in the booking period and then the no-show rates (Bowser et al., 2010). Before patient preferences are researched explicitly, there is literature dealing with customer choices in revenue management (RM), which offers insights for researchers investigating patient choices in healthcare. For example, Talluri and Van Ryzin (2004) provide an exact and quite general analysis of a single-leg RM problem with consideration of customer choices. They arrive at an optimal policy involving an elegant form of an ordered family of efficient subsets. Our problem, however, differs from Talluri and Van Ryzin (2004), in that the candidate time slots in our model keep changing during the booking process, i.e., a time slot becomes unavailable once it is booked. However, in Talluri and Van Ryzin (2004), candidate products are always available. This model has been extended to the network RM problem. Different decomposition methods have been developed to obtain the approximate value associated with the system values in the DP models, e.g., Adelman (2007), Zhang and Adelman (2009) and Koch (2017).

Indeed, research on customer behavior in RM problems has already yielded some mature theories that are also applicable in the healthcare industry. However, Gupta and Denton (2008) identify two kinds of differences between the two. First, patient choice is affected by factors such as the provider, the date, and the time of the day. Second, price fluctuation is not usually a feasible method to control patient choice. A handful of researches have begun to concentrate on patient preferences and choices in healthcare. The closely relevant papers can be divided into two categories based on whether or not patients need to state their preferences before the scheduler makes decisions.

In the first category, patients state their preferred physicians or time slots first, and then the scheduler makes a decision. In Gupta and Wang (2008), patients suggest their preferred physician and the corresponding time slot. The scheduler then decides whether to accept or refuse the patient's suggestion. Two categories of patients are considered: regular patients who request appointments for more than one day in advance and same-day patients who arrive at the start of the workday. Wang and Gupta (2011) analyze a similar problem and propose a scheme that can dynamically learn and update patients' preferences with a view to improving booking decisions. Our paper is different from these two papers in the following ways. First, in the two papers, the booking state remains open for patients, whereas, in our paper,