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Estimating unconstrained customer choice set demand: A case study on airline reservation data

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Abstract

A good demand forecast should be at the heart of every Revenue Management model. Yet most demand models do not incorporate customer choice behavior under offered alternatives. We are using the ideas of customer choice sets to model the customer's buying behavior. The demand estimation method, as described in Haensel and Koole (2011), is based on maximum likelihood and the expectation maximization (EM) algorithm. The main focus of the paper is the application case on real airline reservation data. The reservation data, consisting of the airline's daily flight offers, is used to unconstrain the underlying customer demand in terms of price sensitivity. Using this demand information per choice sets, the revenue manager obtains a clear view of the real underlying demand.

Keywords: customer choice behavior; demand estimation and unconstraining; revenue management

1 Introduction

Accurate demand information is essential for the success of all kinds of sophisticated booking or pricing controls, short Revenue Management (RM). A non-scientific introduction to RM with its main concepts, tactics and execution steps is given by Cross (1997). Any successful RM systems needs customer information

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on the micro-market level. The information should not only contain the number of customers to expect, but also comprise information on customer behavior such as price sensitivity. Historical data mostly consists of sales information per price class or product. But customers who book the same price classes or buy the same products are not necessarily equal; possibly some of them are also interested in other products or would also buy the product at a higher price. As van Ryzin (2005) formulates on page 206: what is needed in RM research is a change from product demand models to models of customer behavior. Our focus is to estimate unconstrained demand per choice behavior from given sales data. Unconstraining methods, such as the ones compared in Queenan et al. (2007), are applied to estimate the true demand quantities in cases of stock-outs. We understand unconstraining in a broader sense: We are not only interested in the number of unobserved customers, but also in their specific choice behavior. Therefore, we apply the unconstrained demand estimation method described by Haensel and Koole (2011) to a dataset of real airline reservation data.
The article continues in the following section with the explanation of the airline dataset, followed by the choice set model in Section 3. The estimation results are presented in Section 4, and our general findings are concluded in the final section.

2 Airline Data

In our case study, we are able to work on real airline booking data of two routes provided by Transavia, which we will from this point simply call Route 1 and Route 2. Both routes are connecting the Amsterdam airport Schiphol (AMS) with a Spanish airport and there is only one competitor airline serving the same direct connection. Unfortunately, we have no information of historic competitor prices available for our analysis. The datasets consist of the booking information for 11 consecutive departure day of weeks, i.e., we fixed a certain weekday for each route and work with the data of 11 weeks. The separation of different weekdays is very common in the airline business and based on statistical test which show a higher dependency and more common characteristics for consecutive weekdays than for consecutive days. The total bookings per departure day and route are shown in Figure 1.

The usual possible booking horizon consist of several months and can span a period up to a whole year. Even so, we observe that most of the bookings are made in a much smaller time span, namely 12 weeks prior to departure. The average number of bookings per week are shown in Figure 2, where week 1 denotes the beginning of the booking horizon and week 12 the week including the departure day.

On both routes we have $F = 12$ fare classes which only separate in price, as given in Table 1.

There are no extra services or standards associated with different fare classes. Thus, the price is the only differentiator, so there is only one active fare class at