The Value of Data for Customer Acceptance in Attended Home Deliveries

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1. Introduction

Our work is motivated by the rapid growth of home delivery services in recent years. Creating a viable business model in this area is challenging, because profit margins are low, but customers' high service expectations increase logistics costs. This makes decision support in this area highly relevant. We use the example of an online supermarket that must accept or reject customers for delivery within a specific time window as their requests arrive. Since most online supermarkets are focusing on growth, accepting as many customers as possible is the foremost objective.

Each acceptance decision is a twofold challenge. First, the retailer has to give immediate feedback to the customer. Hence, simple but efficient routing mechanisms are required. Second, information about demand is gradually revealed over time. Knowledge of whether accepting the current request was beneficial or disadvantageous in terms of the final route plan's efficiency is revealed only in hindsight. Many online retailers, though, now have information from their historical order data. This work analyzes using this data in making better decisions for attended home deliveries.

To examine the value of historical order data, we propose a sampling-based online acceptance approach for attended home deliveries. Whenever a new request arrives, temporary routes are created that consist of already accepted requests and possible future requests sampled from historical order data. This can support decision making on whether the current request should be accepted or not. Sampling approaches that anticipate future events through historical data have been examined for a while (e.g., Hvattum, Løkketangen, and Laporte (2006), Voccia, Campbell, and Thomas (2017)); however, the characteristics and the value of historical data integrated within a retailer's

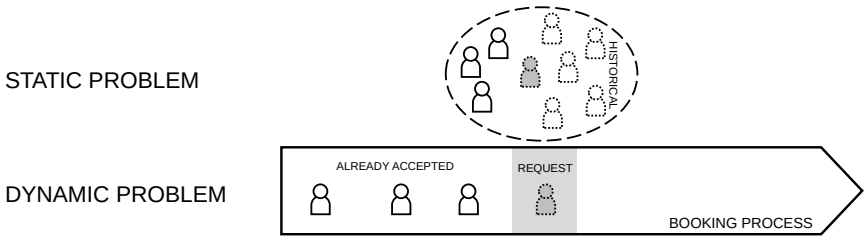


Figure 1 Sampling Approach for Request Acceptance or Rejection

acceptance decision has not yet been investigated. Especially for online acceptance, where computational time is scarce and the number of samples that can be solved is hence limited, the amount of historical order data and the methods used to create the samples should be chosen carefully.

We will consider historical order data from an online supermarket in Munich, Germany, for a period of one year. What we learn from this data is the following: (i) The number of orders varies often among days and weeks and can be on some days twice as high as on other days. As a result, capacity management is essential on some days and may not be helpful on others. (ii) Demand for time windows is highly imbalanced. From the eight two hour time slots offered by the online supermarket, one early and one after-work time window consume more than half of customer demand. (iii) Customer locations are not obvious, do not match population density, and are therefore challenging to anticipate. (iv) More than half of the customers order at short notice within 24 hours before delivery. This makes customer acceptance a highly dynamic problem.

2. Sampling Approach

We assume that customers can request service until a given cut-off time. Whenever a new request arrives, we have to make a decision on if we want to accept or reject the request within a time window chosen by the customer. To do so, we use historical order data to create samples as shown in Figure 1. Each sample contains the set of already accepted requests, the current request, and a set of historical requests that arrived at the same relative time or later than the current request in the historical booking stream. For each sample, we then create temporary routes using a team orienteering approach with the objective to include as many customers as possible given the available fleet. While we ensure that all already accepted requests are included in the routes, we do not prioritize including the current request and/or all historical requests. As a last step, we analyze how often the current request was included within the temporary routes and use this information to evaluate if we should accept or reject it.

To create the set of historical requests, we will first use historical order data from previous weeks for a specific weekday. This allows us to represent past ordering behavior as realistically as possible. However, this also requires more data from previous weeks if we want to create a larger number of

samples. If we randomly combine past requests from a specific weekday, we can more easily create multiple samples. Our second idea is to draw historical requests from all bookings regardless of weekday. By testing these different sample generation methods, we want to examine which and how much historical order data is beneficial for making customer acceptance decisions.

3. Excerpt of Results

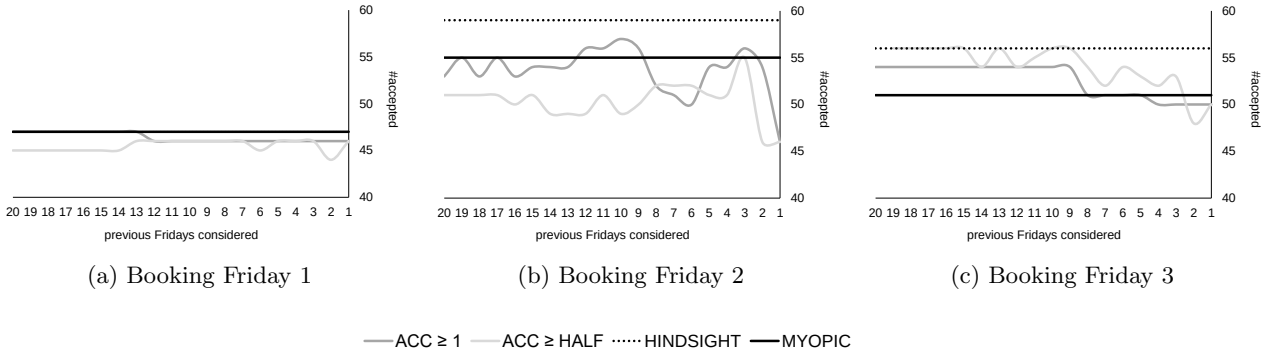
To test our approach, we will process requests consecutively from three actual booking streams for Friday deliveries. Each of these requests is characterized by its time of arrival, its delivery location, the chosen time window for order delivery. The three Fridays differ from each other as follows: Friday 1 shows only low demand; for Friday 2, most requests arrive earlier than normal; for Friday 3, most requests arrive within 24 hours before delivery. We will evaluate the value of historical order data for request acceptance for these three Fridays. When creating the historical requests for our samples, for each of these Fridays, we consider data from up to 20 previous Fridays. With the resulting samples, we build temporary routes for a delivery fleet of two vehicles.

We test two simple acceptance rules. With the first, we accept the current request if it is included in at least one of the temporary routes ($acc \geq 1$). With the second, the current request has to be included in at least half of the temporary routes to be accepted ($acc \geq half$).

In Figure 2, we present the results on how many customers we could accept (y-axis) when considering more historical data (x-axis), i.e. an increasing number of samples. We compare our results to a hindsight approach assuming all requests are already known for a given day at the beginning of the booking process. We also benchmark against a myopic approach in which we simply accept requests as long as capacity is available.

Due to low demand, hindsight equals myopic in Figure 2a, and we can see that our sampling approach does not add any meaningful information for request acceptance. In Figure 2b, we can see that our sampling approach performs even worse than the myopic approach. This is because customers order earlier than usual and we reject many early requests in order to accept more requests in the long run; however, since no late requests arrive for this Friday as they normally do, delivery capacity cannot be fully utilized. In Figure 2c, the benefit of sampling can be demonstrated clearly: we always achieve better results than myopic when considering nine ($acc \geq 1$) or even only three ($acc \geq half$) previous Fridays of historical order data. Furthermore, the sampling approach is often even able to accept 56 customers representing the same result as hindsight.

Interestingly, in general, using more samples is not always better, although this is often stated in the literature (e.g., Hvattum, Løkketangen, and Laporte (2006)). Here, the trade-off between overfitting and generalization comes into play, and sometimes learning from more historical data can create inferior results. This underlines the importance of analyzing historical order data and



(a) Booking Friday 1 (b) Booking Friday 2 (c) Booking Friday 3

Figure 2 How many customers are accepted if we consider more historical order data

considering the input carefully when making acceptance decisions for attended home deliveries. These results also show that sampling is more important when demand exceeds capacity, and that we need adaptive policies when an order day is experiencing lower demand or requests arrive at different times than normal.

4. Outlook

We plan to further discuss the interplay between the number of routes that need to be considered, the design of acceptance rules, and the amount of historical order data that should be included. We will discuss further sample creation methods and consider timeliness and representativeness of historical order data to show which features allow better decision making of customer acceptance. Further order scenarios and delivery areas will be considered to show how our conclusions change. For example, we may be able to establish that the value of data and best sample creation choices vary by geography and population or that results are stable with regard to various demand settings. We will present all of these results at the conference.

References

Hvattum L, Løkketangen A, Laporte G, 2006 *Solving a Dynamic and Stochastic Vehicle Routing Problem with a Sample Scenario Hedging Heuristic. Transportation Science* 40(4):421–438.

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