Modeling Dynamic Choice Behavior of Customers
(Extended Abstract)

Srikanth Jagabathula • Gustavo Vulcano *

1. Motivation

A central task in operations is demand estimation, which provides high quality inputs for assortment planning and revenue management (RM). For simplicity, many models in practice assume that each product has its own independent demand stream. However, if products are substitutes, then the demand for a given product will be a function of the set of alternatives available to consumers when they make their purchase decisions, and of the subset of products that may be on sale. Such choice behavior is a topic of great interest among researchers and practitioners alike because it has significant revenue consequences.

The building block for estimating customer choice is the specification of a choice model, either parametric or nonparametric. In this paper, we take a non-parametric approach. We use a simple, though quite general, non-parametric choice model in which customer types are defined by their rank ordering of all alternatives (along with the no-purchase alternative). When faced with a choice from an offer set, a customer is assumed to purchase the available product that ranks highest in her preference list – or she does not purchase at all if the no-purchase alternative ranks higher than any available product. Customers that share the same preference list constitute a type. With a finite number of alternatives, there is a finite number of rankings and hence a finite number of customer types. Demand is then described by a discrete probability mass function (pmf) on the set of customer types. This type of rank-based choice model has previously been applied in areas such as economics and psychology. One of the first applications in operational settings was the retail assortment problem studied by [4]. As they point out, several common demand processes studied in the literature can be modeled as special cases of a rank-based choice model (e.g., multinomial logit (MNL), Markovian second choice, universal backup, Lancaster demand, and the independent demand model).

Recently, with the rise of business analytics and data-driven approaches, there has been an increasing interest in demand estimation and revenue predictions derived from nonparametric choice models (e.g., [2] and [5]). However, these estimation proposals work on sales transactions and product availability data, or equivalently, on revealed preferences relating pairs of products. They all assume that every data point is an independent observation coming from different customers.

In this paper, we take a different perspective, and assume that a set of customers make repeated purchases from the firm. The canonical example is customers buying groceries on a weekly basis from a grocery retailer, but more broadly the setting includes any application in which customers exhibit loyalty through repeated purchases be it apparel, hotel, airline, etc. The goal of the retailer

*SJ and GV are affiliated with IOMS, NYU Stern. email: {sjagabat, gvulcano}@stern.nyu.edu
is to use the information from the repeated interactions to learn the preferences of the customer and customize the offering (both the assortment and the prices) in response to the learned preferences. We assume that the retailer has collected purchase transactions tagged by customer id. This type of data, popularly referred to as panel data, is very common in practical settings because of the proliferation of loyalty cards, personalized discount coupons, and other marketing programs.

Our goal in this paper is to use such panel data collected by the retailer to construct the preferences of the individual users. The additional information provided by panel data would allow to build models that have better predictive accuracy. At the same time, these models should be tractable enough to make practical operational decisions. Access to individual-level data as opposed to just aggregate data allows us to personalize assortment and pricing decisions. Our primary focus in this paper is estimating the model from data. We also briefly illustrate how our model can be used to make personalized decisions.

Our work also deviates from the work on preference learning from panel data in marketing in two ways: (a) we consider a non-parametric approach, and (b) we allow for stock-outs in data. The traditional approach in marketing is to fit hierarchical Bayesian models to panel data and estimate them in the form of customer choices (e.g., see [1]). Such a Bayesian approach imposes parametric restrictions on choice probabilities and priors on parameters for tractability reasons. These models are well suited to understanding how various co-variates affect individual choice behavior, but are not very proper for operational decision making: the assortments faced by the consumers typically change over time due to deliberate or unexpected stock-outs, or to the fact that a subset of product may go on sale, which also affects the consumers’ purchase behavior.

2. Summary of results

We assume that a fixed set of \( m \) customers visit a firm repeatedly, focusing on a particular category of products. The full assortment of the category is defined by a set of \( n \) products, together with the no-purchase option, which is always available. We assume that every customer belongs to exactly one of \( K \) customer classes, where \( K \) is a predetermined small number (e.g., \( K = 5 \)). Each class \( k \) is defined by a central preference list \( \sigma_k \). The preference lists of individual customers assigned to the same class may be different, but are assumed to be “close” (according to a well defined distance metric) to the central preference list.

An important component of our work is the modeling of the purchase behavior of each individual customer. We assume that the underlying preferences of an individual customer remain constant over time. A fully rational consumer when offered a subset of products, all at full price, chooses to purchase the product that ranks first in her preference list. However, customers are not fully rational and are influenced by price promotions. Existing literature has established several behavioral biases that are common in customer choice behavior [8]. We focus on one such bias that is relevant to the construction of consideration sets (i.e., the subset of products considered by customers as feasible) – namely inertia in choice. Inertia in choice – also referred to as short-term brand loyalty [8] –
is a common bias: customers tend to purchase what they bought previously rather than evaluate all products on offer in each purchase instance. We capture the effects of such inertia in choice and price promotions by assuming that customers always purchase what they bought previously or a product on promotion until there is a “trigger” event that forces them to re-examine all the products on offer. We focus on one important trigger event: stock-out of the previously bought product. Based on the behavioral assumptions, we define a set of behavioral rules that allow us to keep track of each individual customer purchase behavior and to build preferences over the \( n \) products. When the rules can properly explain the behavior of a customer, the preferences will define a transitive relation among the products. If so, a customer is characterized by a partial order, which can be represented by a directed acyclic graph (DAG). For tractability reasons, we cluster all the DAGs obtained into the aforementioned \( K \) classes, and for each class we build a single preference list (i.e., total order) as representative of the whole cluster. To this end, we formulate an integer program that achieves the two objectives simultaneously: 1) clustering, and 2) construction of the \( K \) total orders. Since the integer program has a poor linear relaxation, it is hard to solve to optimality using standard software packages. To overcome this, we present a heuristic that leads to high-quality solutions in polynomial time.

In order to demonstrate the predictive performance of our method, we performed numerical experiments using real-world panel data on the purchase of shampoo across 47 US markets in the year 2011. We observed that our method with behavioral rules and clustering outperformed the benchmark multinomial model by about 24% in prediction accuracy in predicting sales on the hold out sample.

References


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1The behavioral rules we posit may not explain all of the customer paths observed in real-world. Such paths may be discarded from the training data in fitting our model (not from test data and benchmark models). Discarding these non-explanatory customer paths did not significantly affect the performance of our method.