A Dynamic Clustering Approach to Data-Driven Assortment Personalization

Motivation and Objective. According to a study by eMarketer in 2014, worldwide business-to-consumer e-commerce sales will grow to $2.357 trillion in 2017. With the rapid growth of online sales, many tech entrepreneurs and traditional retailers find unprecedented opportunities for both enhancing the customer experience and increasing revenue. Assortment personalization is one such opportunity. The benefits of personalization are twofold: on one hand, it results in higher revenues for the retailer as the personalized offers increase sales by providing customers with a set of products that more accurately matches their preferences; on the other hand, it attracts customer attention and fosters customer loyalty and satisfaction.

As noted in a recent New York Times article, in personalized shopping “the magic comes from data.” Online retailers collect an abundance of customer data (e.g., demographic, transactional, etc.). However, given the broad range of customer profiles, collecting a sufficient amount of transaction data on each customer may not be possible. This, in turn, limits the retailer’s ability to accurately estimate the customer preferences and offer personalized assortments.

The goal of this paper is to explore the efficient use of data, achieved by pooling transaction information across customers with similar preferences, and study its benefits for assortment personalization in online retail operations.

Model. We consider an online retailer that sells multiple products over a finite selling season. Customers arrive sequentially and the retailer offers each arriving customer an assortment that consists of a subset of products. The retailer may face display or capacity constraints that limit the number of products that can be offered to each arriving customer. The customer then decides whether to purchase any product from the offered assortment. The retailer’s objective is to maximize expected cumulative revenue over the selling season.
Customers are exogenously divided into different profiles (types) based on their observable attributes, such as demographic information (e.g., gender, age, and location). Therefore, each customer profile is defined by a unique vector of customer attributes. This information is available upon arrival via the customer’s login information or internet cookies. We assume that customers with the same vector of attributes are homogeneous with respect to their product preferences. The retailer, however, has limited prior information on customers’ preferences. Personalized product offerings require estimation of such preferences by observing the customers’ purchasing decisions. There is a classic exploration (learning preferences) versus exploitation (earning revenue) trade-off associated with the retailer’s dynamic assortment selection problem. As such, we formulate the assortment selection problem as a multi-armed bandit with multiple plays per period (each product represents an arm and including a product in the offered assortment is equivalent to pulling that arm).

Given the broad range of customer attributes, it may not be feasible to estimate the product preferences for each customer profile accurately. At the same time, customers with different profiles may share similar product preferences. The retailer can exploit these similarities by pooling information across customer profiles with similar taste. To that end, we define a cluster as a set of customer profiles that have identically distributed preferences. This implies the existence of an underlying mapping from customer profiles to clusters that associates each vector of attributes with a cluster. Such a mapping is, however, unknown to the retailer.

**Main Contributions.**

1) **Prescriptive Approach.** We propose a dynamic clustering policy that adaptively adjusts the mapping of customer profiles to clusters and estimates the preferences based on the observed customers’ purchasing decisions. The advantage of the dynamic clustering policy emerges from the speed in learning (estimating) customers’ preferences as a result of pooling information.
We apply our proposed policy to a dataset from a large Chilean retailer. This dataset consists of 94,622 customer-tied click records for online ads of 19 different products (shoes in this study). We compare the performance of our policy with a benchmark which we refer to as the data-intensive policy. This policy treats each profile independently and therefore estimates the product preferences for each customer profile separately. We show that the dynamic clustering policy can result in more than 35% additional ad clicks compared to the data-intensive policy. We also demonstrate the scalability and efficiency of our proposed method in practice.

2) Theoretical Results and Insights. We consider a simplified version of the dynamic assortment selection problem in which the display constraint is of size one. In this setting, we analytically characterize scenarios in which pooling information across customer profiles is beneficial for the retailer in terms of revenue. We consider two policies that only differ in their assumption about the mapping of customer profiles to clusters: a semi-oracle that knows the true mapping (but not the customers’ preferences) and thus pools information within each cluster; the data-intensive policy that treats each customer profile independently and therefore does not pool information. We show that the semi-oracle outperforms the data-intensive policy, indicating that pooling information is beneficial for the retailer. We also show that the revenue gain from pooling information exhibits statistical economies of scale in the number of customer profiles - i.e., diminishing marginal returns from an increasing number of customer profiles. Finally, we characterize conditions under which a policy that pools information across all customer profiles outperforms the data-intensive policy, even if customers are heterogeneous with respect to their product preferences (and therefore pooling information across all customers may lead to erroneous estimates). This result speaks to the benefit of pooling information in the short-term, when there is insufficient data to accurately estimate preferences for each customer profile.