Customized individual promotions: Model, optimization, and prediction

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Abstract

For a retailer, running personalized promotions is a means to overcome the negative effects of promotions offered to all customers (e.g., stockpiling effects on the customer side). These customized promotions rely on the heterogeneous preferences of individuals for products within a category, and their different sensitivities to price discounts. We consider the problem of predicting individual customer responses to promotion decisions over a category of products, and based on the predictions, optimizing the portfolio of products to put on promotion for a particular individual.

The data sources required by our methodology include historical purchase transactions data tagged by customer ID, information about the assortment available for the product category of interest at the moment of purchase, and the identification of the products that were on promotion by that time.

Our model builds on the proposal by Jagabathula and Vulcano (2017), where each customer is represented by a partial order or directed acyclic graph (DAG). The DAG is constructed from a set of rules that account for the revealed preferences of each customer through the history of past purchases. In a DAG, each node $i$ represents a product, and each arc $(i,j)$ represents the relation “$i$ is preferred to $j$”.

While processing the data source in the DAG construction phase, a customer may exhibit an apparent inconsistency in her purchase behavior that may imply the creation of a cycle. Different from the approach in Jagabathula and Vulcano (2017) –where all arcs of the graph-based customer representation
were deleted when identifying an inconsistency, here we run a de-cycling procedure based in a mixed-integer programming (MIP) formulation in order to keep a maximal number of arcs to describe the customer preferences through a DAG.

On the theoretical side, we provide tractable bounds to compute both the likelihood of partial orders (which in general is a \#P-hard problem) and the purchase probabilities from these DAGs.

Next, taking the collection of DAGs representing the customer basis as input, we calibrate a single class MNL model and a latent class MNL model following the procedure described in Jagabathula and Vulcano (2017). On the side, we also estimate two state-of-the-art parametric models: latent-class multinomial logit (LC-MNL), and random parameters logit (RPL) accounting for panel data, but without using the aforementioned DAG-based underlying structure.

Finally, our DAG-based MNL variants and both benchmarks were tested for designing personalized promotions. Via a MIP formulation, we consider the problem where the offer set faced by the customers in each store visit is given and the decision variables are which products to promote in order to maximize expected revenues.

Numerical experiments on real-world panel data for a grocery chain across 27 product categories show that as a result of our new DAG-based approach, we increased the percentage of individuals with non-empty structures from 38% to 100%. We observe that our approach allows more accurate, fine-grained predictions for individual purchase behavior compared to the state-of-the-art benchmarks. For the performance score functions that we computed, our DAG-based models could outperform the benchmarks by more than 10%. Furthermore, our MIP for running personalized promotions can increase revenues by 26% (on average) over the current practice reflected in the dataset.