Customer-Trends for Personalized Demand Estimation and Targeted Promotions

Introduction. Inarguably, celebrity culture has played and still plays a significant role in the evolution of trends. People often feel the need to keep up with the most modern technical gadgets and fashionable clothing featured by celebrities. In the past, social interaction was useful in establishing customer-trends through word-of-mouth effects and social connections. Nevertheless, in the recent years social media (such as Facebook, Twitter, Instagram among others.) has sped up social communication tremendously. This rapid communication creates the urge for consumers to also keep up with trends in their social circle, and not just general trends. In a way, every person can create their own social trend by changing the buying behavior of their peers.

In collaboration with the Oracle Retail group, we notice that many of their retail clients have become interested in personalizing their services such as promotions and assortment offerings. We have also seen a surge in the academic operations management literature on personalized assortment and pricing research. Our goal in this work is to understand the consumer demand at a more personalized level and offer customers personalized promotions that fit their profile and needs better. In order to offer personalized promotions, the retailer needs to determine how to target the right customers with the right promotions at the right time. To accomplish this the retailer needs to understand individual customers’ behavior as well as customer-to-customer-trends, i.e., how they interact within their environment and also how they are “influenced” either by other customers or by other underlying social phenomena and socio-economic factors. In order to build personalized models access to social media data is important. Unfortunately, it is often the case that retailers have a hard time acquiring detailed social data on their customers. The reason is either privacy issues or simply cost. As a result, building and applying personalized recommendation models in practice can be a challenging task. To overcome this issue, we propose a customer-trend model to measure customer-to-customer-trend effects. Our model is based solely on transaction data that are readily available to a retailer. Applying this customer-trend model to a retailer’s data reveals insights into their customer base and allows us to propose personalized promotion targeting policies.

Contributions. Our major contributions include the proposal of an interpretable model to estimate customer-to-customer-trend effects and subsequently the construction of a promotion targeting tool. In the first part, we present an interpretable model to estimate how customer-to-customer-trends can improve the prediction of purchase behavior. We envision customers (or groups of “similar” customers) as part of a network. Due to the difficulty in acquiring social media data, we do not assume that we have knowledge of the structure of this network. Hence, we solely use purchase transaction data and show our model uncovers relationships as well as customer-trend effects. Furthermore, we show that when combined with a traditional demand estimation model, customer-to-customer trend effects improve the prediction quality.
In order to determine promotion strategies, we suggest an intuitive and simple greedy approach. We provide an understanding when this greedy approach solves the promotion targeting problem exactly and when this is not the case. In the latter case, we provide a tight analytical guarantee and illustrate that it works well even when not optimal.

Finally, working together with the Oracle Retail group, we have access to data from a large tier-one fashion retail client. Using their sales data, we were able to test our estimation process and illustrate significant improvement in terms of the estimation quality relative to a traditional estimation approach that ignores customer-to-customer trends. Furthermore, we evaluate the effectiveness of our approach in terms of revenue increase for the retailer’s existing practice (for example, for most items, the retailer’s revenue is improved between $5-12\%$ using this approach). Furthermore, we show that our customer-trend model improves the sales prediction quality by improving the WMAPE by 5%.

**Literature Review.** Although the question of diffusion over a network was studied for many years in different disciplines, models that incorporate diffusion ideas into a demand model are relatively recent. The network-based demand model and the promotion targeting over a network lie in the intersection of 4 major research areas. The first line of literature is promotion pricing (see, Blattberg and Neslin (1990)). The second stream of literature is personalization. In the intersection of personalization and promotion based pricing we find work that is focused on utilizing the individual response to promotions and pricing in order to find a pricing scheme that would maximize sales. (see Zhang and Krishnamurthi (2004), Golrezaei et al. (2014), Ferreira et al. (2015), Chen et al. (2016)).

The third branch of literature focuses on learning algorithms. In the intersection with personalization this type of work would focus on mining association rules from transaction history data. In the intersection with classic pricing and promotion optimization this type of work would focus on demand estimation.

The last related work is diffusion in social networks. This subject has been studied in many settings such as disease spread, and token passing in a computer network. In the area of revenue management, there have been a few studies that focused on diffusion optimization and revenue maximization using personalized pricing (see for example (Du et al., 2013), (Gomez Rodriguez et al., 2010), (Hartline et al., 2008), (Kempe et al., 2003)). To the best of our knowledge, this is perhaps the first study that was able to provide a personalized estimation process together with personalized promotion strategies.

**Results.** The main results in this work can be divided as follows:

- **Customer-Trend Model.** The goal in this part of the work, is the development of an interpretable model that estimates how customers’ decisions to purchase are driven by other customers or perhaps by other common trends that influence them. The suggested customer-trend model is a probabilistic demand model that explains how the probability of an individual
to buy an item can be changed in light of the purchase decisions of others. In order to capture classic demand features (such as price, seasonality, location etc.) the base of our model consists of a classical demand model. On top of the basic model we construct the customer-trend component. The core of the suggested customer-trend model is formed by the concept that the probability of a customer’s purchase can be conditioned on the buying behavior of other customers as well as on the features of the transaction.

- **Personalized Estimation.** In order to estimate such a model we suggest a two stage procedure. We begin by considering a classical demand model. Due to the probabilistic nature of our demand model, we logistic regression that considers all the features of the transactions from the purchase history. After estimating this base model we standardize the purchase history according to this base demand. Finally, we fit the customer-trend model on the standardized purchase history. We rely on Granger Causality, an idea that if one customer usually purchases an item before a second customer (or groups of customers), then we presume that there is an underlying pattern in the buying behavior of these customers. The idea of customer-trend resembles the spread of a disease, as it spreads from one customer (or group of customers) to another in a similar fashion. Finally, we use a regularized version of Bounded Variables Least Squares to fit the customer-trend model on the standardized purchase history.

- **Promotion Targeting Optimization.** The promotion targeting problem develops a personalized promotion strategy that maximizes the overall expected revenue while satisfying the business rules of the retailer. A personalized promotion strategy determines which customer should receive a special promotion price at what time. The main contribution of this part of the work to the field of promotion targeting, is the inclusion of the customer-to-customer-trend effect, which can have a large effect on the optimal promotion targeting policy in the underlying customer network. By offering a promotion price to the right customers, we can leverage the customer-to-customer-trend effect to increase the probability of a purchase, not only on the important customers that we target with a promotion, but also on the rest of the network. One good example could be targeting fashion bloggers, who create strong customer-trends in their followers’ community.

- **Greedy Approach.** We suggest a greedy approach to create promotion targeted policies. We demonstrate when this approach finds the optimal promotion strategy. Nevertheless, we also illustrate when this greedy approach is not optimal. In those settings, we prove that finding the optimal promotion strategy is NP-Hard. Furthermore, we show a tight analytical guarantee.

- **Impact in Retail.** Working together with the Oracle retail group, we apply our approach to a large retail client. We demonstrate that our personalized estimation approach consistently improves the WMAPE by close to 5%. In addition, our results suggest that our greedy approach to promotion targeting improves revenues by 5-12% over several product categories.