Increasing Profits: Leveraging Consumer Behavior to Optimize Promotions; from Nonsocial to Social

Introduction. Trends play an important role in a variety of industries such as fashion and technology. Customers feel the need to purchase the newest gadgets and fashionable clothing. Next to keeping up with the general trend set by celebrity culture, customers are increasingly feeling the urge to keep up with their social circle. Social interactions and connections have always been important in creating a trend. However, today, its importance has surged due to the accession of social media such as Facebook, Twitter, and Instagram. Nowadays, every person creates a social trend by changing the purchase behavior of their social connections.

Working together with the Oracle Retail group, we notice that their retail clients have become interested in targeting promotions, and more generally in personalizing their services. At the same time, research on personalized pricing has received increased attention by the academic operations management literature. In order to target promotions and personalize pricing, it becomes inevitable to investigate how social trends impact customer purchase behavior. Mainly, retailers face two challenges in targeting their promotions. First, retailers need to learn how to estimate customer-to-customer-trend effects. Second, given the customer-to-customer-trend network, retailers need to be able to design an effective pricing strategy to improve revenue. Our goal in this work is to answer these questions: understand 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 how individual customer purchase behavior and customer-to-customer-trends affect demand, 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 demand models, access to social media data would be extremely useful. Unfortunately, often, retailers have a hard time acquiring detailed social data on their customers. This can either be caused by 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 that is able to measure customer-to-customer-trends 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 main contributions can be split into three parts as follows:

- **Customer-Trend Model and Estimation.** One of our major contributions is the proposal of an interpretable model to estimate customer-to-customer-trend effects and subsequently the construction of a promotion targeting tool. Furthermore, we show that when combined with a traditional demand estimation model, customer-trends improve the prediction quality.
– **Customer-Trend Model.** In the first part, we present an interpretable model that estimates how customers’ purchase decisions are driven by other customers or perhaps by other common trends that influence them. We envision customers (or groups of “similar” customers) as part of a network. The suggested customer-trend model explains how the customers are connected and how the probability of a customer to purchase 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.

– **Personalized Estimation.** Due to the difficulty in acquiring social media data, we do not assume that we have knowledge of the structure of the trend network. Hence, we solely use purchase transaction data in our estimation procedure. Our proposed estimation algorithm runs in a two stage procedure. We begin by considering a classical demand model, after which we standardize the purchase history according to this base demand. Finally, we fit the customer-trend model on the standardized purchase history. The customer-trend model is fit using a regularized version of Bounded Variables Least Squares.

– **Convergence.** To assess the consistency of the estimation algorithm, we prove that, under certain conditions, the estimated customer-to-customer-trend probabilities converge to the underlying true probabilities. This result is extended to a probabilistic finite sample guarantee on the gap between the estimated and the true customer-trend probabilities.

– **Causal Analysis.** Since we want to target promotions using a demand model that includes customer-to-customer-trend effects, we need to ensure that the estimated customer-to-customer-trends have a causal interpretation. First of all, we utilize Granger causality, an idea that if one customer usually purchases an item before a second customer, then there is an underlying pattern in the buying behavior of these customers. Additionally, using Instrumental Variables (IV), we show that our model naturally incorporates a strong instrument and would suffer from endogeneity problems if IV methods were not used. From this we are able to conclude that the customer-to-customer-trends are able to capture causal effect, and do not just capture a spurious correlation.

– **Personalized Promotion Targeting Optimization.** The goal in the Personalized Promotion Targeting Optimization problem is to develop 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.

– **Complexity.** Using a reduction from the set cover problem, we show that the Personalized
Promotion Targeting Optimization is NP-Hard.

- **Adaptive Greedy Algorithm.** We suggest an Adaptive Greedy Approach (AGA) to create personalized promotion policies. We identify 3 distinct cases:
  
  * In the case where the revenue function is linear in the promotion policy, we show that AGA finds the optimal solution.
  
  * In the case where the revenue function is sub-modular in the promotion policy, we provide a tight analytical guarantee. We also show that this case can be characterized solely based on the customer-to-customer-trend network, and identify when this is the case.
  
  * In the case where the revenue function is not sub-modular in the promotion policy, we provide a parametric analytical guarantee, that depends on the level of non-modularity of the revenue function.

- **Testing our methods on realistic size instances using real-world fashion data.** 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 are 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 over the retailer’s existing practice (for example, for most items, the retailer’s revenue is improved between 5 − 12% using our approach). Furthermore, we show that our customer-trend model improves the sales prediction quality by reducing 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 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 the first study that was able to provide a personalized estimation process together with personalized promotion strategies.