Introduction. In practice, retailers frequently utilize promotions as tools to encourage sales. Over a third of all fast-moving consumer goods spending is for items on offer, according to a recent report (Hill (2016)). Hence, strategically-employed promotions have the potential to increase sales significantly. However, the current process of promotion planning in the supermarket industry is still fairly manual and does not account for the long term effect of promotions on future revenue.

One of the most commonly employed promotional tactics is temporary price reduction, in which the retailer may choose to set a temporary lower price for a specific product in order to increase revenue. In this paper, we focus on the planning process of these temporary price reductions; for convenience, in the remainder of this paper we let promotion refer to temporary price reductions.

When planning promotions, retailers rely on demand predictions that allow them to understand the impact of promotions on current and future sales. Therefore, understanding the factors that affect a consumer’s purchasing decision is essential in order to design an effective promotion strategy. In particular, analyzing how changes in price influence current and future demand can lead to a more precise demand forecast, and in turn, to a better promotion policy that increases revenue. This implies that some of the past prices may be significant factors for demand estimation. However, as shown in Cohen et al. (2016) and in Chen et al. (2016), the complexity of the promotion planning optimization problem depends heavily on the number of such past prices. Incorporating too many past prices into the demand model may result in an intractable problem due to the Curse of Dimensionality (Bellman (1957)).

In the retail environment, where decisions are made by local managers, the tractability of the promotion planning optimization problem is vital. Thus, a good demand model would be able to balance between the prediction accuracy and the complexity of the promotion planning optimization problem.

In this work, we propose a new demand model that both improves the prediction accuracy and reduces the complexity of solving the promotion planning optimization problem. In particular, by altering the set of demand predictors, we make the promotion planning optimization problem tractable.

Utilizing the structure of the proposed demand model, we provide a mathematical formulation for the promotion planning problem. Furthermore, we study the structure of the optimal solution to this new formulation, and provide interesting structural properties on the optimal promotion policy. Based on these structural properties, we propose a polynomial Dynamic Programming (DP) formulation for the promotion planning optimization problem. We provide conditions for which this tractable DP can find the optimal promotion plan. In the cases where these conditions do not hold, we provide an analytical guarantee that indicates how good our near-optimal promotion pricing policies are.
Finally, working together with the Oracle Retail group, we tested our approach on real data from large retailers. We demonstrate that our suggested demand model achieves better prediction accuracy when compared to methods used currently in practice as well as in the academic literature in this area. In particular, we show that using the suggested demand model, we can provide a relative improvement in Weighted Mean Percentage Error (WMAPE) of $5.9 - 19.1\%$. Furthermore, we illustrate that the proposed DP works well not only in theory but also in practice. We show that using the suggested algorithm we can increase profit by $2 - 18\%$ relative to current practice.

**Contributions.**

1. *Improving demand prediction.* Our contribution to the demand estimation process is twofold.

   ⇒ *Anchoring Set and Features Reduction.* Motivated from the behavioral literature, we suggest a new set of past prices (namely, the last seen as well as the minimum price seen within a bounded number of past periods) as features in the demand model. We refer to demand models that use this set of past prices as Bounded-Memory-Peak-End models. This is a more compact set of past prices that allows for a better prediction accuracy compared to existing methods, including traditional reference price models such as Exponential Smoothing, Bounded Memory, and Peak-End. In addition, this compact demand model will also help us solve the optimization problem more efficiently.

   ⇒ *Novel Procedure for Demand Estimation.* Inspired by machine learning and consumer behavior, we develop a partially parametric demand prediction procedure. Our suggested procedure is a 2-stage approach, that utilizes the advantages of the Gaussian Process (GP) learning algorithm, as well as the log-log regression. We show that the demand prediction accuracy using the 2-stage approach with the suggested anchoring set, is consistently improved. We show that using the suggested prediction model, we can provide relative improvement in WMAPE of $5.9 - 19.1\%$ on real data.

2. *Insights and Structural Properties of the Optimal Solution.* We provide an interesting structural property on the optimal promotion policy when using our proposed demand model. In particular, we establish which prices in the price ladder are candidates for the optimal solution. In practice, for each product, at each time period, retailers select prices from a discrete set of prices. By analyzing the structure of the demand, we prove that in many cases the retailer uses an unnecessarily big variety of prices. Furthermore, by considering a small set of prices, we reduce the dimensionality of the promotion planning optimization problem while maintaining optimality.
3. **Optimal, Tractable Solution to the Promotion Planning Problem.** Using our demand model, we propose a new Dynamic Programming (DP) formulation that is more compact than existing literature. This further allows us to suggest an efficient solution to this DP model. This approach also captures the retailer’s need to obey several business rules, such as a limited number of promotions over the time horizon, and a minimum separation between promotion periods. Based on the structural properties we establish, we demonstrate conditions under which the proposed DP finds the optimal promotion strategy tractably. These conditions are satisfied by some of the most commonly used demand models in practice. Finally, when the conditions we introduce do not hold, we provide an analytical guarantee on the optimality gap achieved by the algorithm. We further show that the optimality gap is small with actual data.

4. **Testing our methods on realistic size instances using actual supermarket data.** By working together with the Oracle Retail group, we have access to data from large retailers. Using their sales data, we test our estimation process and illustrate significant improvement in terms of the estimation quality relative to a traditional estimation approach through a relative improvement in WMAPE by approximately $5.9 – 19.1\%$. Furthermore, we evaluate the effectiveness of our approach in terms of profit increase relative to the retailer’s existing practice and show significant increase in profit using our approach of $9.1 – 11.6\%$ on average.

5. **Insights on the Data.** Using the actual data, we drew interesting insights that can help the retailers understand the demand, and design promotion policies. We show how the length of the time that people remember prices changes for different categories and for the different demand models we introduce. We also discuss how the memory based demand models perform for different product categories.

**Literature Review.** This research lies in the intersection of three major research streams. The first stream of literature studies the effect of dynamic pricing on the behavior and purchase patterns of customers (see for example, Kahneman and Tversky (1979), Mazumdar et al. (2005), Macé and Neslin (2004), Dickson and Sawyer (1990) and van Heerde et al. (2000)). The second stream of literature focuses on non-parametric learning algorithms (see for example, Bishop (2009), MacKay (2003)). The last stream of literature is dynamic price optimization and retail operations (see for example, Blattberg and Neslin (1990), Talluri and van Ryzin (2006), Kopalle et al. (1996), Fibich et al. (2003), Popescu and Wu (2007), Cohen et al. (2017) and Cohen et al. (2016), Besbes and Lobel (2015), Chen et al. (2016) and Özer and Zheng (2015)).