1. Motivation

Most models of consumer purchase process that are used in operations focus on purchases from a single channel, typically the offline brick-and-mortar store. However, there has been a proliferation of multiple retail channels, such as online and mobile. This proliferation has created the need for operational decisions to model consumer switching between different channels during the purchase process. Even when shopping for medium-priced items such as backpacks, furniture, or electronics, many consumers typically visit the store’s webpage to learn about product attributes, before potentially visiting the brick and mortar store. The purchase can now happen at any point: either online before offline store visit, in the offline store, or online after the store visit. Despite the higher variety and convenience that the online channel offers, consumers continue to visit the offline brick-and-mortar stores because they may have a hard time judging the value of certain attributes online. For example, consider a consumer shopping for a backpack. He may be certain about his utility for the color Black, but uncertain about his utility for colors “Pacific Blue” and “Safety Cone Orange”, or the value of a padded hipbelt and an AirMesh back panel. The consumer can learn about the available attributes from the store webpage and then form beliefs about his values for the attributes. However, he may need to physically examine a product with a particular attribute in the brick and mortar store to learn that attribute’s true value.

2. Problem setup

Products: We assume that there is a finite number of products in the universe that vary on a discrete set of attributes. We assume that the retailer sells through two different channels: online (e-commerce web store) and offline (brick-and-mortar store). The offline channel is capacity constrained while the online channel contains the entire product universe. The retailer faces the problem of finding the optimal offer set for the offline channel with the objective of maximizing sales across both the channels.

Consumer Decision Process: We assume that consumers behave according to a multi-attribute utility model: consumers purchase the product with the highest utility, where the utility of each product is the weighted sum of its attributes. We refer to the weights in the utility function as the attribute partworths, or simply the partworths, as is standard in the conjoint literature. The standard assumption is that the consumer knows the partworths. We deviate from this assumption in this paper, we assume the firm’s products are differentiated enough from other firms, such that there is no direct competition. Additionally, the firm is indifferent about which channel a sale comes from. A real world example is Crate & Barrel: all products can be ordered online, and only a subset is displayed in-store.

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by allowing the consumers to be unaware of some attribute partworths. We assume that consumer adopts the following purchase path:

1. Learn about the available product attributes and form beliefs about the attributes’ respective utility partworths by browsing online. Based on these beliefs, form utility partworths referred to as initial partworths.

2. Discover the true partworths of the attributes of the products offered in the offline channel by visiting the brick and mortar store. For the attributes not present in the store, keep the initial partworths.

3. Purchase the product (which could also be the outside alternative) from the entire universe that maximizes the utility based on the partworths from Step 2. Purchase could be made either through the online or offline channel.

4. Receive the purchased product, if any, and then return it if the realized utility is less than that of the outside alternative.

Population: The population consists of $K$ types of consumers, where each type is defined by a unique combination of initial and true partworth vectors.

3. Overview of results

We consider the problem of finding the sales maximizing assortment to offer in the offline channel. We assume that the retailer is aware of each consumer’s initial and true partworth vectors, which can be learned using existing preference elicitation tools $\Pi$. Our contributions are two-fold: (1) deriving insights about the structure of the optimal assortment (2) proposing and numerically testing an efficient heuristic for finding the optimal assortment.

We obtain the following main results.

1. The optimal assortment may include items that are not purchased by any consumers. Such items still generate sales by exposing consumers to new, previously undervalued, attribute levels. The following example illustrates the insight. Consider the backpack example above. For simplicity, suppose that the backpacks vary only on color (Black, Orange) and the type of back panel (Airmesh, Regular). Suppose there are two consumer segments, and both have an outside option with utility 1. The initial partworths for both segments are all zeros, so the utilities of all products based on the initial partworths are zero resulting in no sales if there is only the online channel. However, suppose the first segment likes Orange (true partworth +2) but dislikes Airmesh (true partworth -2). Conversely, the second segment of consumers dislikes Orange (true partworth -2) and likes Airmesh (true partworth +2). Assuming that the retailer can offer only one product in the offline store, it is easy to see that the optimal offering is an orange bag with an airmesh back panel. With this offering the offline channel sees no sales, but the online channel captures the entire market. Note that with only the offline channel, the optimal offering is different and can capture only one of the two segments.
2. We note that determining the optimal assortment to offer in the offline store may be computationally hard. We propose a natural greedy heuristic: based on the observation that only the attributes that are offered in the offline channel affect sales, the heuristic adds one attribute in a greedy fashion at a time until it either reaches a local optimum or hits the capacity constraint. The computational complexity of the heuristic scales linearly in the number of attributes and the number of products.

We performed a simulation study in order to demonstrate the impact of jointly optimizing the two channels. We considered a market with 10 segments of consumers. The products were described by two 4-level attributes. True partworths for each segment were generated as i.i.d uniform random variables, U[-3,1]. Initial partworths were generated by randomly setting each component of the true partworth vector to zero independently with probability $\rho$. Thus, $\rho$ captures the discrepancy between the true and initial partworth vectors. We draw the following conclusions from the results (see figure on the side):

1. The sales generated from using the optimal assortment from the classical method decrease as the discrepancy between the consumer’s initial beliefs about the utility partworth (in Step 1) and the true partworths that are revealed upon examining the product (in Step 2) increases.

2. The sales loss from using the classical method that does not capture the presence of two channels can be significant: of the order of 16% on average observed in our simulation study.

3. The greedy heuristic we propose performed well in our numerical experiments: an average loss of about 2% relative to the optimal observed in our simulation study.

We note that we made several simplifying assumptions in our model. In particular, we assumed that arrivals to the store are exogenous, consumers make at most one purchase, and retailers know the true and initial utilities with certainty. The model can be extended to relax these assumptions. We expect that most of the results will not change qualitatively.

References

