Assortment Optimization

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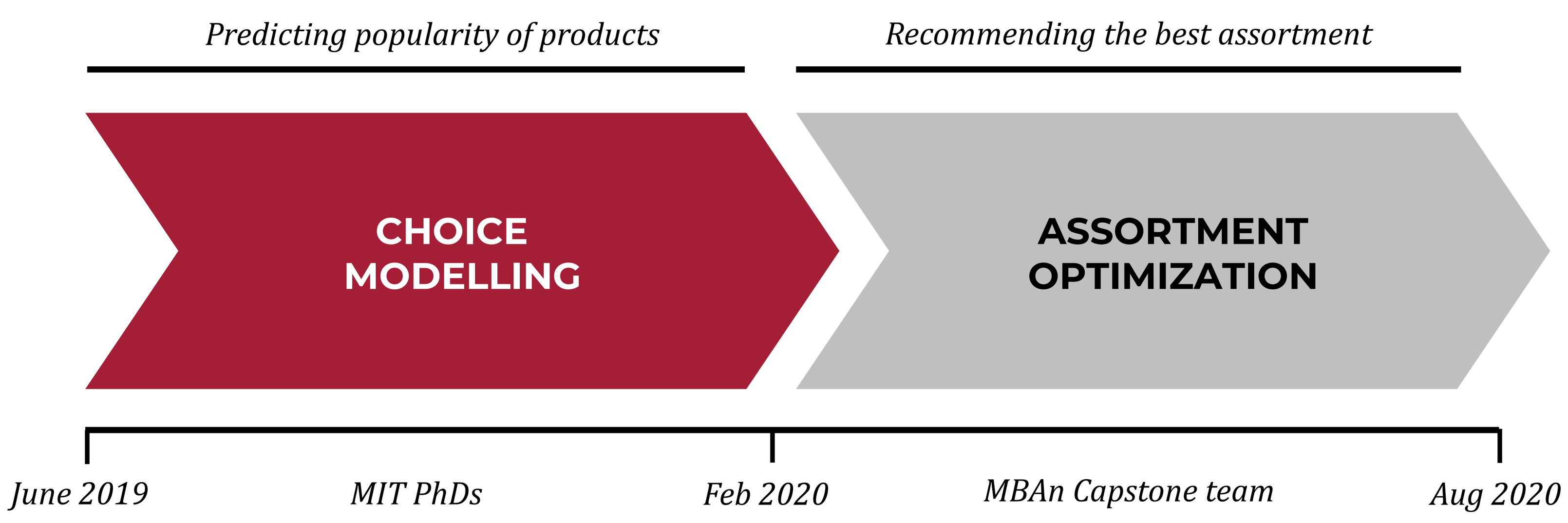
AB InBev

Introduction

- AB-InBev has 500+ unique products in North America and an average retailer has 10 to 50 products which are currently chosen heuristically
- AB-InBev and MIT aim to create a data informed technique to make product recommendations to retailers to increase their revenues
- The process involves two steps



Challenges

Limitation in visibility over Competitors' data: Visibility only on sales from wholesalers to retailers. No visibility on customer behaviour in retailers

Solution: Introduce imputed competition data from previous AB-InBev experiments as a proxy

Sensitivity to outliers: Niche products sold in few stores misguides the optimizer to recommend them more often

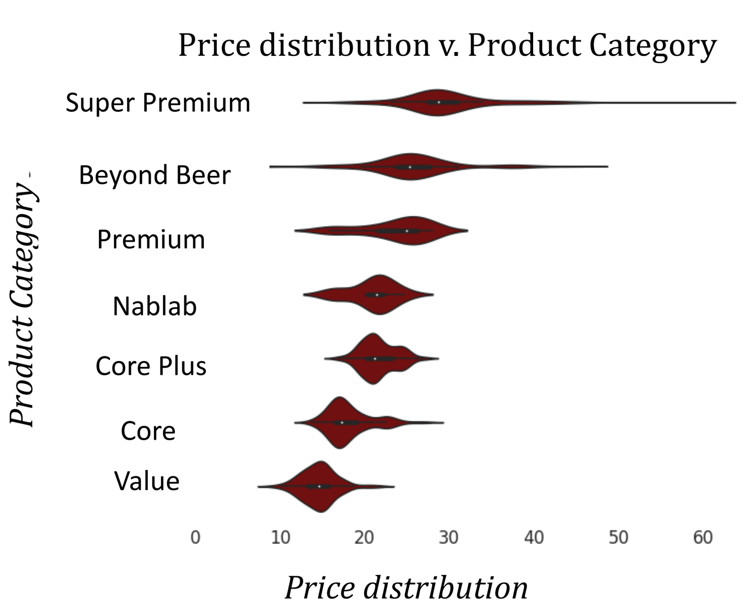
Solution: Bootstrapped choice model to get confidence intervals around our predictions. Introduced penalties and made recommendations robust

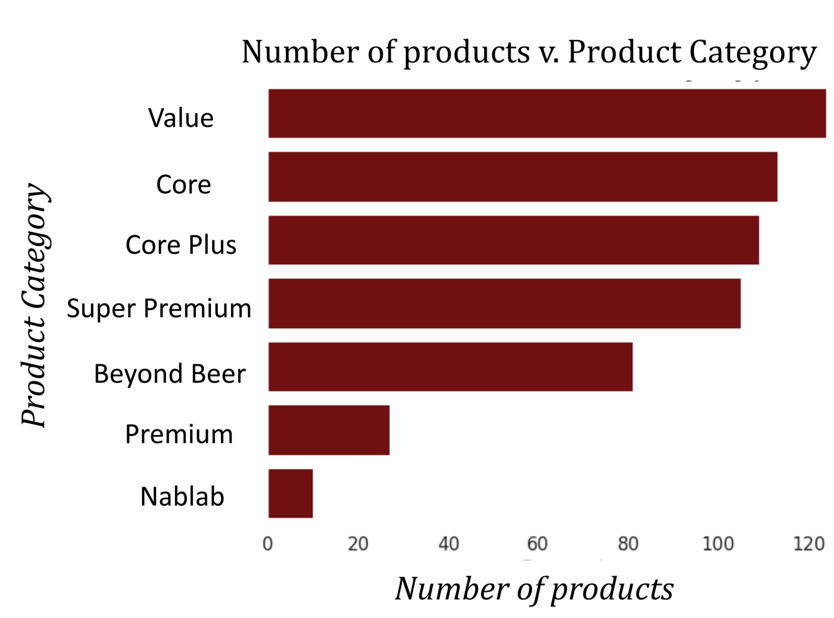
Low performing retailers: Certain stores have a market share of AB-InBev products that is lower than the regional average.

Solution: Expanded the assortment size based on historical data to increase AB-InBev market shares

Data

- There are 10 wholesalers, 10000+ stores and 550+ unique products
- AB-InBev products are divided in 7 categories based on price range
- Super Premium and Beyond Beer have the highest price
- Core and Value that have the widest range of choices at a relatively cheap price

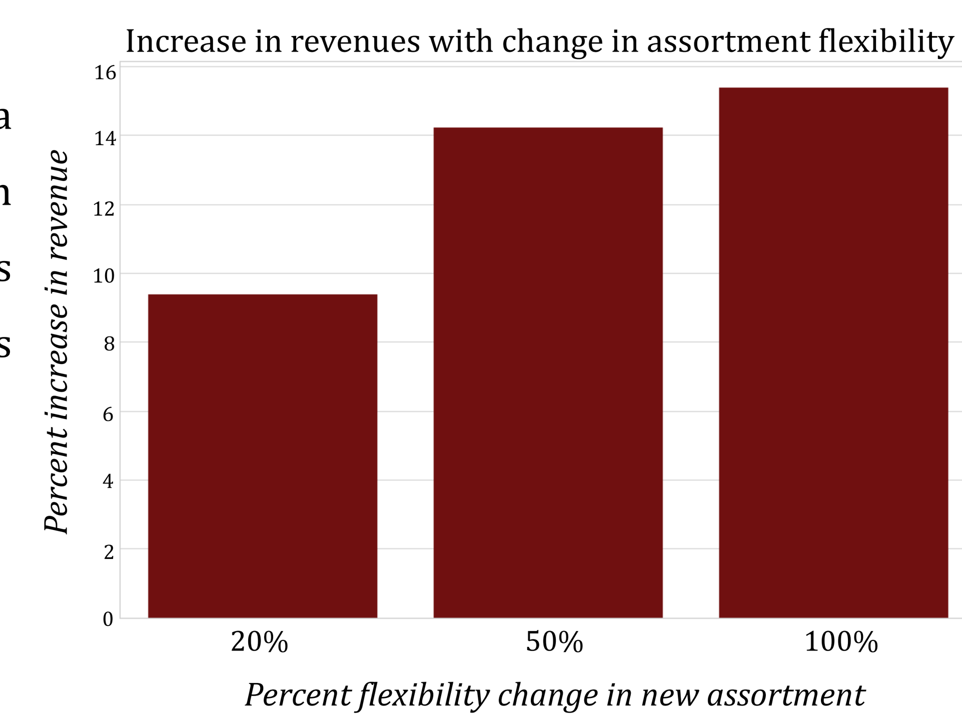


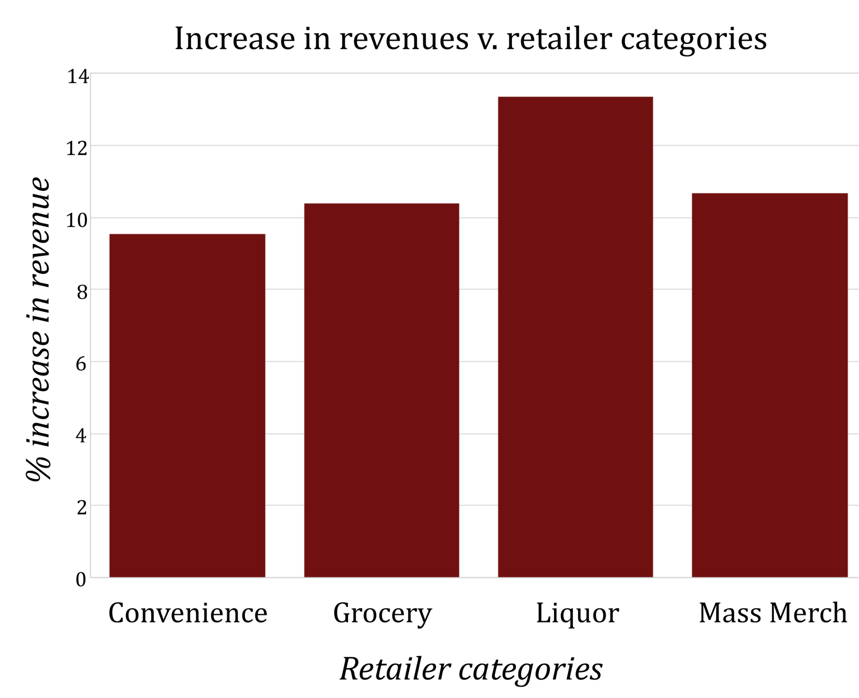


Results

- The optimizer was run on a sample set of 1700 stores with varying assortment flexibilities and a revenue growth of 10% was observed with the least flexibility

10 %
Growth in revenue

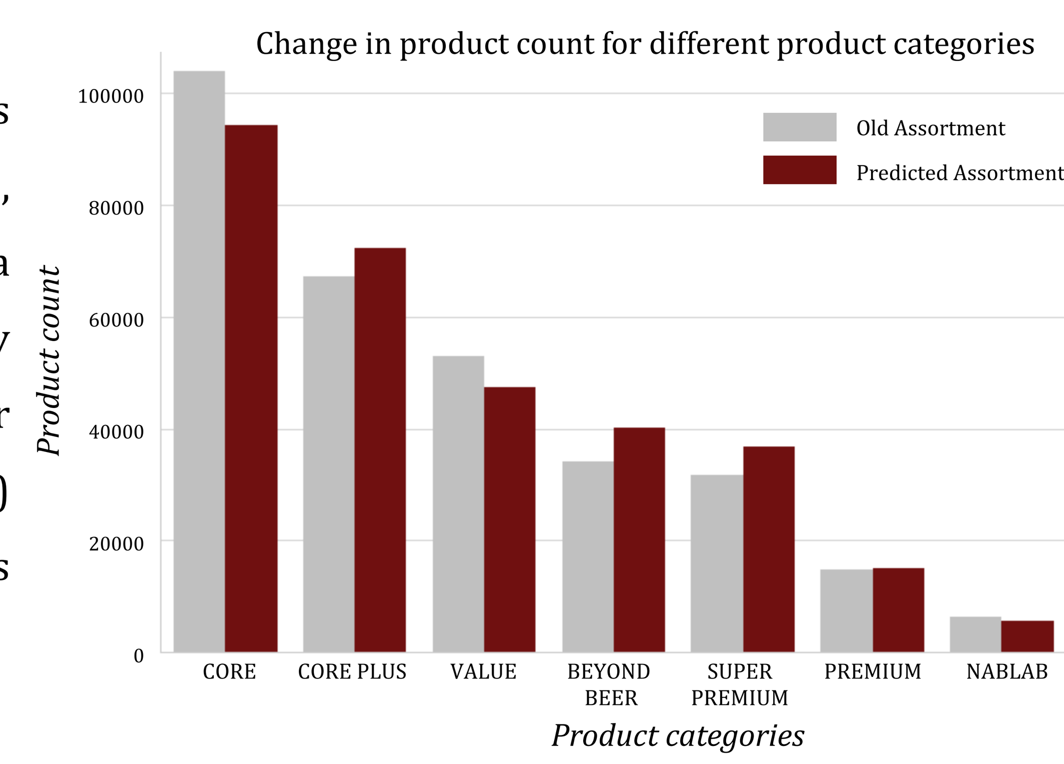




- Disaggregated results show that the growth in the revenues is the highest for retailers belonging to the liquor category, which is also the largest segment in the store

Liquor
Retailers have highest lift

- Though expensive products tend to get recommended, our optimizer ensured a good balance, i.e. not only pricy products (e.g. Super Premium, Beyond Beer) see a lift, so does Core Plus which is less expensive.



Modeling

Maximize assortment revenue → $F(A_s) = \sum_{i \in A_s} r_i P_{A_s}(i)$

Product assortment: A_s; Product price: r_i; Volume*: $P_{A_s}(i)$

- The optimization objective depends on the assortment A_s, the product price r_i, and the volume of the product sold $P_{A_s}(i)$ given assortment A_s
- The objective function is highly non convex and not continuous, and hence we had to develop our own solver using the Frank-Wolfe Method
- The optimizer takes into account the following constraints and business considerations:

Product preferences: Certain products need to be strictly included while others need to be excluded as per business constraints

Logistical constraints: Wholesalers have different supply chains and offer different products to different retailer segments

Change flexibility: The change allowed in recommended assortments needs to be fixed depending on retailer's tolerance to change

Market share targets: The recommended assortments need to meet the market share targets set by business

Future Steps

- **A/B testing**: Test the recommendations and get feedback to improve the optimizer
- **Introducing planogram data**: Leverage planogram data to have a better picture on the actual assortments on the shelves at stores.