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CAPSTONE PROJECT

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DYNAMIC PROMOTION OPTIMIZATION OVER SPARSE DEMAND REGRESSION

PROBLEM STATEMENT

WHY?

A **products** own **price**, as well as the **prices of other products** like itself, will heavily **impact** consumer **demand**

WHAT?

Maximize revenue for Matas by **placing products on promotion** at the **right time** with the **right amount of discount** to take advantage of cross-price effects

HOW?

Sparse Regression identifies **top cross-price effects** to include in **demand models**
Dynamic Promotion determines the **best price** to set items at **each time step** based on demand models

CLUSTER WHILE REGRESS PRODUCT DEMAND CLUSTERING

Optimization Formulation

For L clusters, we fit a demand model and assign products to the cluster they fit best.

$$\min_{z_{ik}, f_k} \sum_{i=1}^{n} L\left(y_i, \sum_{k=1}^{\ell} z_{ik} f_k(x_i)\right) + \lambda R(f_1, \ldots, f_\ell)$$ Minimize Loss

$$\text{s.t.} \sum_{k=1}^{\ell} z_{ik} = 1, \quad i = 1, \ldots, n$$ 1. Products can only belong to 1 cluster.

$$z_{ik} \in \{0,1\}, \quad i = 1, \ldots, n, \quad k = 1, \ldots, \ell.$$ 2. Binary decision

Iterative Algorithm with bounds

Implemented New Constraint to Improve Interpretability

$$\underline{L} \le \sum_{i=1}^{N} z_{ik} \le \overline{U} \qquad \forall k = 1, \ldots, l$$

Upper / lower bound on cluster size

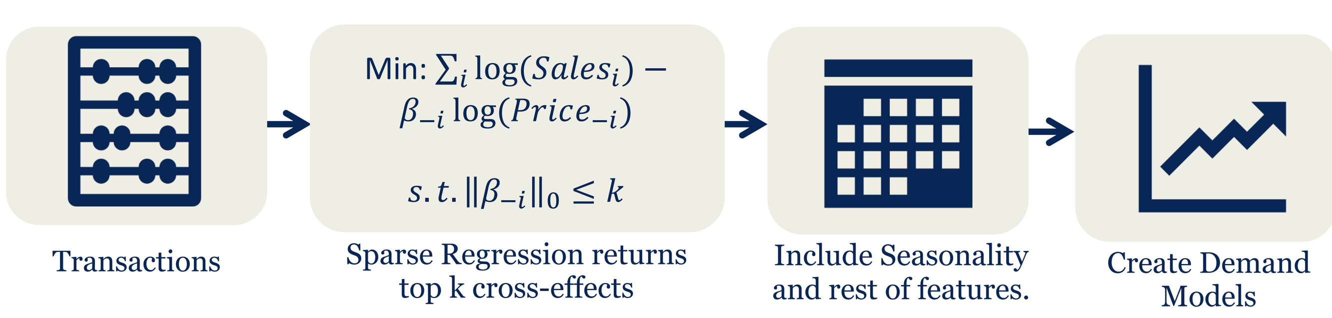
Optimality Gap with Constraint – 82 - 98%.

CROSS-EFFECT IDENTIFICATION

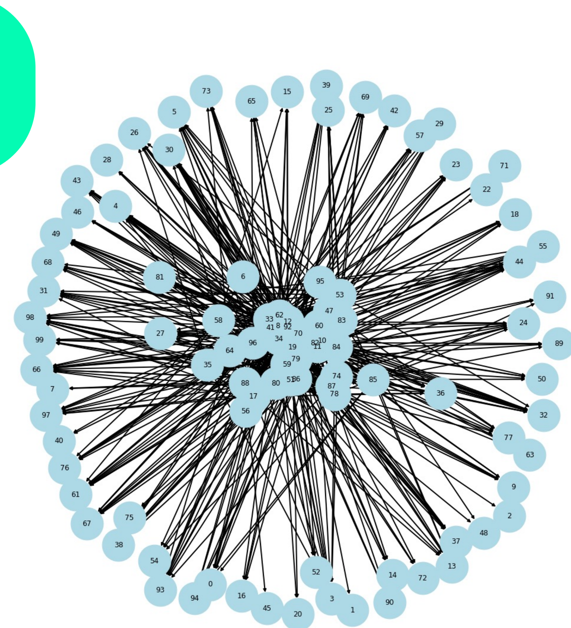
DATA

3 years of transactions of 100 health care products

METHOD



Complex Network of Cross-Price Effects



RESULTS

We use **Weighted Mean Absolute Percent Error** as the metric to evaluate, which gives a fair weight to each percent error based on its sales volume.

METHOD	IN SAMPLE MEAN	OUT SAMPLE MEAN
NO-EFFECTS	5.3%	11.9%
ALL-EFFECTS	**4.3%**	10.1%
SPARSE	4.6%	**9.6%**

DYNAMIC PROMOTION

Optimization Formulation

During a specific time horizon, we find the optimal promotion strategy considering the following restrictions

$$\max_{\gamma_{i,k,t}} \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{p_{i,t} \cdot d(p_{i,t}, p_{-i,t}, \ldots)}$$ Maximize Revenue

$$s.t. \; p_{i,t} = \sum_{k=0}^{K^i} q_{k,i} \cdot \gamma_{i,k,t} \qquad \forall i, t$$ 1. Define a Price Ladder per Item

$$\sum_{k=0}^{K^i} \gamma_{i,k,t} = 1 \qquad \forall i, t$$ 2. Pick 1 Price per Item / Time

$$\sum_{\tau=t}^{t+S^i} \sum_{k=1}^{K} \gamma_{i,k,\tau} \le 1 \qquad \forall i, t$$ 3. Separate Promotions by S periods

$$\sum_{t=1}^{T} \sum_{k=1}^{K^i} \gamma_{i,k,t} \le L^i \qquad \forall i$$ 4. Allow L total promotions per Item

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{k=1}^{K^i} \gamma_{i,k,t} \le L_T$$ 5. Allow L total promotions across all Items

$$\sum_{i=1}^{N} \sum_{k=1}^{K^i} \gamma_{i,k,t} \le C^T \qquad \forall t$$ 6. Allow C total promotions during period T

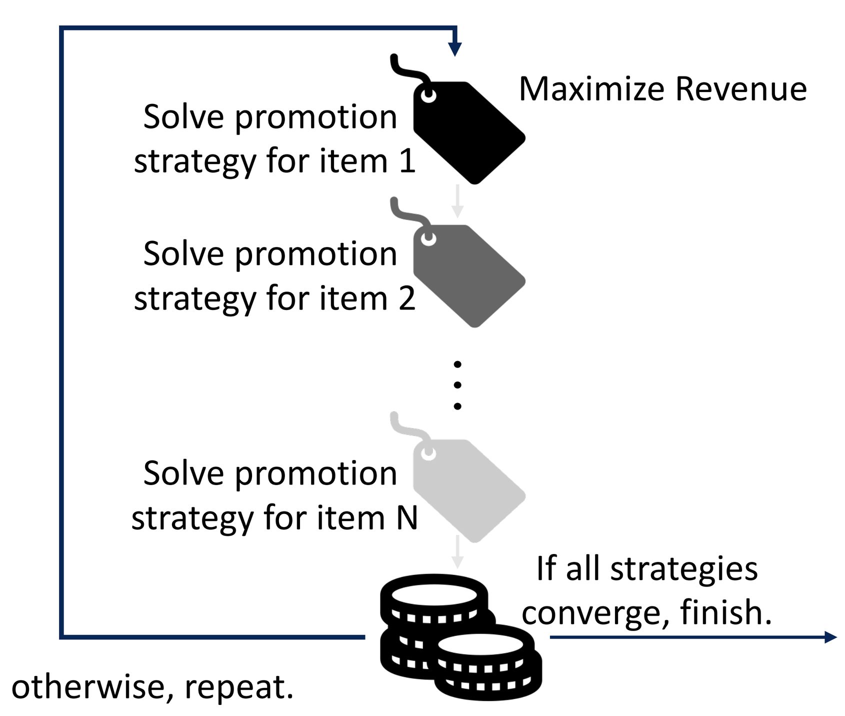
$$\gamma_{i,k,t} \in \{0,1\} \qquad \forall i, k, t$$ 7. A promotion must be only selected or not selected

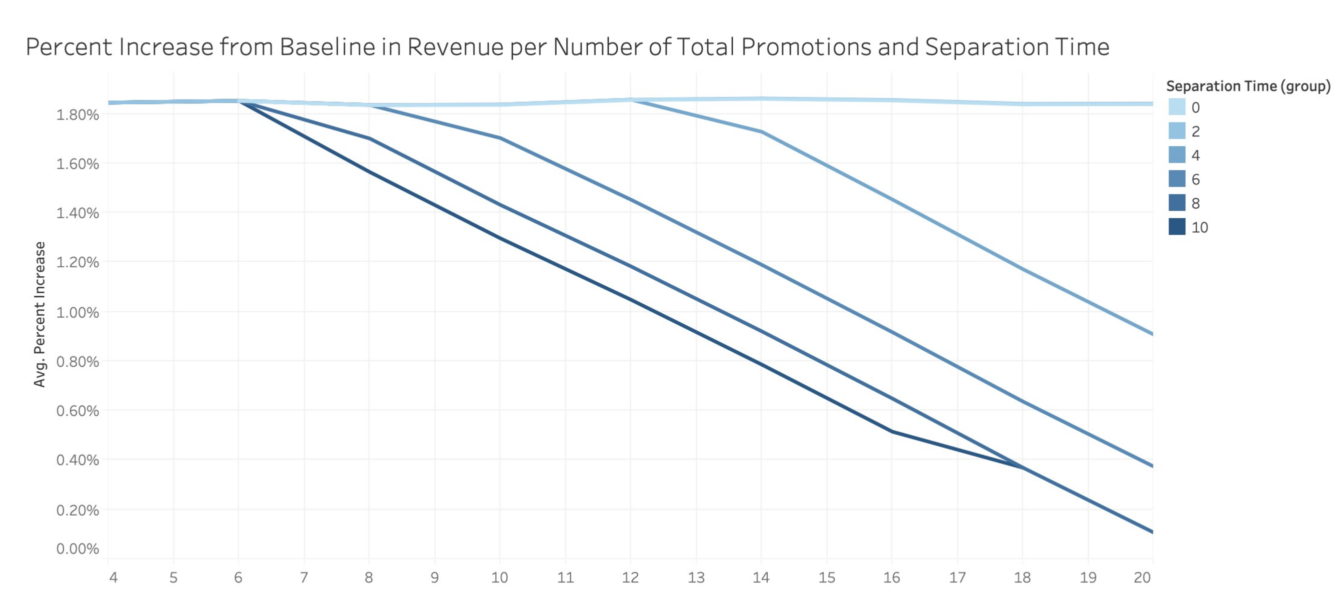
Greedy Dynamic Programming

OPTIMALITY GAP – 0%

BASELINE IMPROVEMENT – 1.8%

SCALABLE – Optimizes for 1000+ Products in 5 Hours





CONCLUSIONS AND RESULTS

IMPACT

- **Pipeline** converting readily available **transaction data** into **pricing strategies**
- **1.8% increase** in **revenue** per year
- Finds a pricing strategy for **1000+** products for the next year in only **5 hours** for 2 possible prices

TAKEAWAYS

- Cross price effects are **essential** to account for in **accurate demand models** and **pricing strategies**
- Optimization helps the most with **improving** pricing strategies with **fewer, strategically places promotions**

NEXT STEPS

- **Data Collection:** Matas plans to collect more pricing data to better train future demand models
- **Dynamic Promotion**: Possible prices per item will be better identified to optimize with using our greedy approach