What's the lift: Predicting Promotion Impact for Smarter Replenishment

MIT MANAGEMENT BUSINESS ANALYTICS

Coca-Cola SOUTHWEST BEVERAGES

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Overview

Problem Statement

- **CCSWB is the 3rd largest Coca-Cola bottler in the U.S., supplying over 1,500 beverage products to more than 88,000 retail locations.** Weekly replenishment decisions are supported by a machine learning-based Suggested Order (SO) system
- **Replenishers are frontline employees responsible for final replenishment decisions.** During each store visit, they restock shelves, assess inventory and shelf conditions, and determine how much of each product should be ordered
- **Today, the SO system has no awareness of when a promotion is running.** Replenishers rely on separate promotion planning sheets and manually estimate additional order quantities

Data

22 Key Accounts

26% Total Volume Covered

CCSWB to store

store to consumer

- **Customer (stores)**
- **Demographics**
- **Sales**

Find Similar Stores

- **Product (SKU)**
- **Promotion**

Quantify Lift and Train ML Models

How can we help replenishers make better ordering decisions during promotions?

Methodology

There was no existing module to quantify the sales effect (i.e., lift) of historical promotions. The lift is confounded by seasonality, baseline demand, and store-level variation, making it hard to isolate the true impact of a promotion from all other sales-driving factors.

Therefore, our solution is a 2-step process:

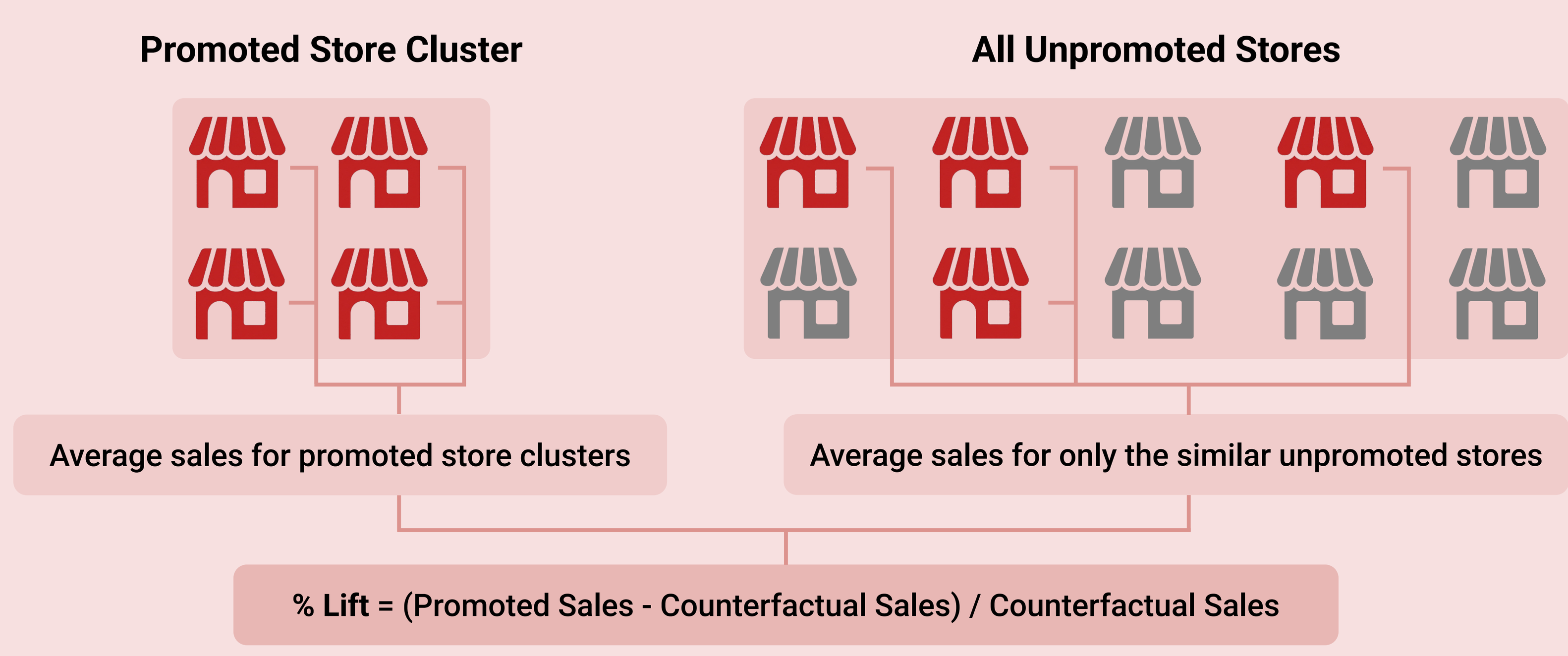
Step 1: Build a lift quantification module using historical promotions

Step 2: Train a lift prediction model for future promotions

Step 1: Quantify Lift

Lift Quantification Module

The no-promotion outcome is never observed. It is estimated from similar unpromoted stores, and promotion lift is calculated against this baseline.



Sample Lift (2026-05-27 → 2026-06-02)

Supermarket Chain A

11 Stores

+

SSD 12oz 12pk

→

Without Promotion: 15 EQ

With Promotion: 23 EQ

↑53% Lift

Step 2: Predict Lift

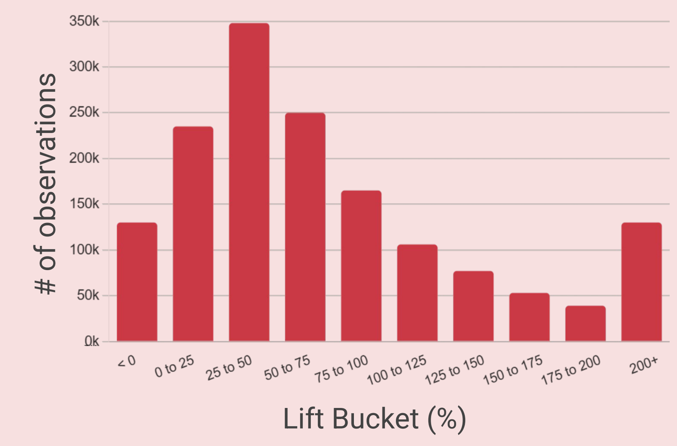
Feature Engineering

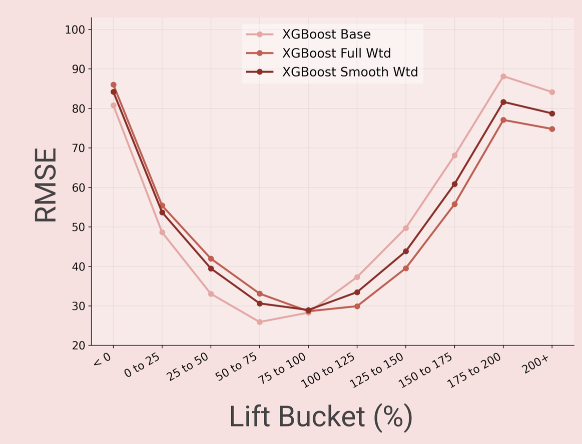
To capture the factors that influence promotional lift, additional features were created for each store-product pair. Key features include:

- Average historical promotion lifts
- Historical promotion frequency
- Seasonal timing of promotions

Smooth Weighted XGBoost

Lift buckets with fewer observations are harder to predict, so a **smooth inverse-frequency weighting** scheme was applied during model training.



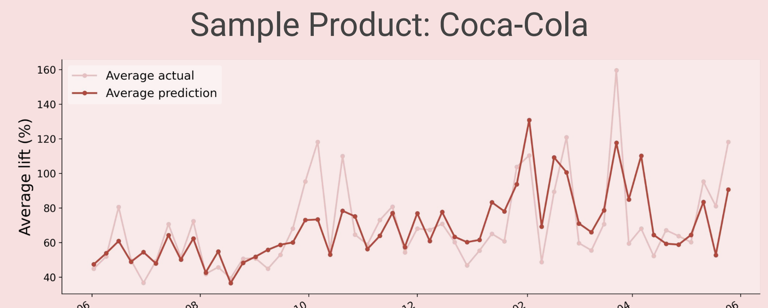


Result

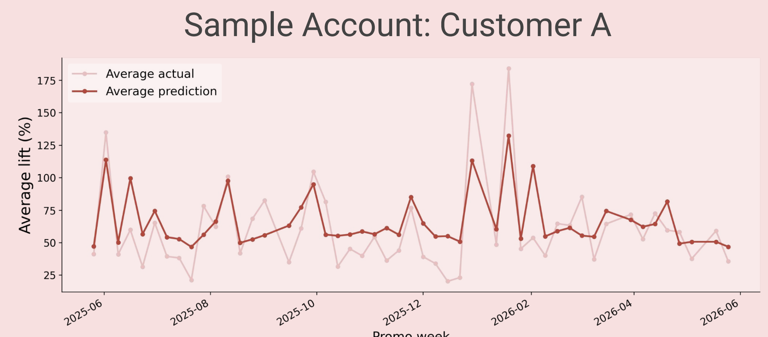
The final prediction model achieved a **test MAE of 43.7%**. The predicted lift closely matched the overall trend of the actual lift across products and customers.

Due to regularization, predictions **were smoother over time** while still capturing the overall trend.

Sample Product: Coca-Cola



Sample Account: Customer A



Impact

Coverage

25%
Total Volume

Promotions drive 25% of order volume, and this model targets exactly where the opportunity is

Revenue Captured

+400k
USD per week

Compared with current ordering behavior

+677k
USD per week

Compared with output of Suggested Order