Marketing Mix Model Analysis: A Non-Linear Perspective

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1. Executive Overview

This document presents the conclusive findings from a Marketing Mix Model (MMM) developed to identify key drivers of weekly revenue. Following the instability of an initial linear model, a more advanced non-linear Two-Stage Gradient Boosting Machine (GBM) was employed. This methodology effectively models the intricate dynamics of the marketing mix, preserving the necessary causal framework by treating Google spend as a mediating variable.

The finalized model exhibits strong and consistent predictive capabilities, accounting for an average of 56.2% of revenue variance in out-of-sample testing (Time Series CV $R^2 = 0.562$). This represents a substantial enhancement over the preliminary model, establishing a solid basis for strategic planning.

The analysis reveals a distinct hierarchy of factors influencing revenue, with average_price and promotions identified as the most impactful elements. Additionally, owned marketing channels, such as sms_send, demonstrate a notable effect.

Key recommendations center on creating a strategic pricing and promotions schedule, enhancing investment in high-performing owned channels, and continuing to support the social-to-search user journey to foster sustainable business growth.

2. Modeling Methodology: Gradient Boosting Machine

2.1. Justification

A Gradient Boosting Machine (GBM) was selected for this analysis due to its inherent strengths in:

- **Handling Non-Linearity:** GBMs can capture complex relationships, like diminishing returns on ad spend, without manual data transformations.
- **Detecting Interaction Effects:** The model automatically identifies synergies between different marketing channels.
- **Enhancing Accuracy:** This technique is known for its state-of-the-art predictive performance.

The Two-Stage Causal Structure was retained, utilizing a GBM at each stage to correctly model the mediating influence of Google search activity.

2.2. Interpretation Using SHAP

Given that GBMs are considered "black-box" models, SHAP (SHapley Additive exPlanations) was utilized for interpretation. SHAP values offer a dependable way to measure the contribution of each feature to the model's output, yielding profound and actionable insights.

3. Model Diagnostics and Perfiormance

The model's performance is sufficiently robust to be a reliable tool for strategic decision-making.

- **Average Cross-Validated R-squared:** 0.562 (+/- 0.211). This result shows that the model consistently explains more than half of the revenue variance on previously unseen data.
- **Model Fit:** A comparison of actual versus predicted revenue demonstrates a strong, consistent fit over the two-year analysis period, visually affirming the model's predictive strength.

4. Key Insights and Strategic Recommendations

The SHAP analysis provides a clear, actionable ranking of revenue drivers. The summary plot illustrates not only the overall importance of each feature but also the nature of its impact (positive or negative).

Key Findings:

1. **Price as the Primary Driver:** The average_price has the most significant overall effect on revenue. The SHAP dependence plot indicates a distinct inverse correlation: as prices rise, the impact on revenue trends negatively, confirming a high price elasticity of demand.
2. **Promotions Deliver Substantial Uplift:** The model accurately pinpoints promotions as a major positive influence. When a promotion is active, it consistently provides a significant boost to predicted revenue.
3. **SMS as the Top Marketing Channel:** sms_send emerges as the most effective marketing channel. The analysis shows a direct positive relationship where increased SMS volume correlates with higher revenue, though the effect shows early signs of saturation at the highest levels, indicating potential diminishing returns.
4. **Validation of the Social-to-Search Funnel:** The predicted_google_spend_adstocked variable remains a top-five driver. Its impact is largely positive and linear, confirming that search activity is a vital channel for converting user interest into sales.

Actionable Recommendations:

- **Recommendation 1: Formulate a Strategic Pricing & Promotions Calendar (Top**

Priority).

- **Action:** Leverage the SHAP analysis for average_price to guide pricing experiments and overall strategy. Develop a promotional calendar that aligns these powerful levers with key business periods to maximize their effectiveness.

- **Recommendation 2: Optimize and Invest in SMS Marketing.**
  - **Action:** Since SMS is the most efficient channel for driving revenue, consider allocating a larger budget to these campaigns. Use the SHAP plot to determine the point of diminishing returns and adjust send frequency to operate within the most efficient range.
- **Recommendation 3: Maintain a Full-Funnel Investment Strategy.**
  - **Action:** Avoid reducing spend on social channels despite their lower direct SHAP importance. Continue to support top-of-funnel activities (e.g., Facebook, Instagram), as they generate the search interest that fuels the Google conversion channel.
- **Recommendation 4: Analyze Performance Gaps.**
  - **Action:** The model's cross-validation performance shows some variance. Conduct a thorough review of the weeks where predictions were less accurate. Cross-reference these periods with external factors (like competitor actions or market news) to identify any unmodeled variables that may be influencing performance.