# Retail & Marketing Analytics
# Individual Assignment

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## 1. Introduction

In today's competitive marketplace, effective marketing strategies are essential for brands to maintain their relevance and sustain growth. This report examines the marketing tactics employed by a high-priced premium juice brand, akin to Minute Maid, alongside its two primary competitors within the UK's juice industry spanning from 2019 to 2021.

The marketing problem addressed in this report revolves around optimizing the brand’s advertising strategy to maximize sales while maintaining brand positioning and profitability. To tackle this challenge comprehensively, the analysis commences with an exploration of pricing dynamics, consumer demand trends, and promotional strategies. Subsequently, a detailed examination of the statistical impact of various factors on sales is conducted through a regression model. Lastly, following an assessment of the statistical impact of the brand’s media investment on sales, the report evaluates the effectiveness of the brand’s current advertising approach and highlights potential areas for improvement.

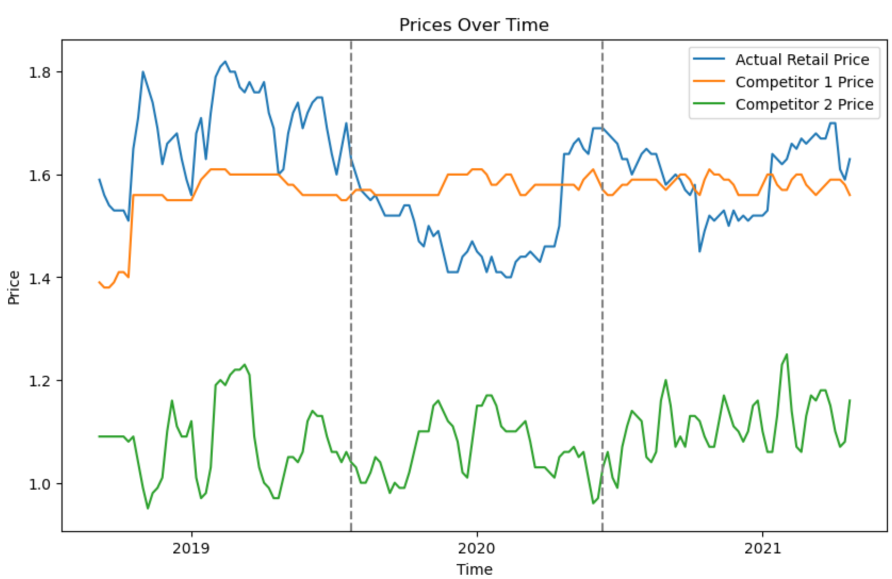
Through a comprehensive examination of data and rigorous analysis, we aim to uncover actionable insights that will guide our marketing efforts and capitalize on growth opportunities in the dynamic beverage market landscape.

## 2. Data Exploration

Our data set contains information on units sold, recommended and actual retail price, total media investment per week, as well as two competitors' price and their total media investment. Our juice brand, akin to a premium offering like Minute Maid, often shares price parity with the primary competitor, hinting at a shared market segment. Meanwhile, the second competitor is positioned as a general brand such as Sainsbury, with lower prices.

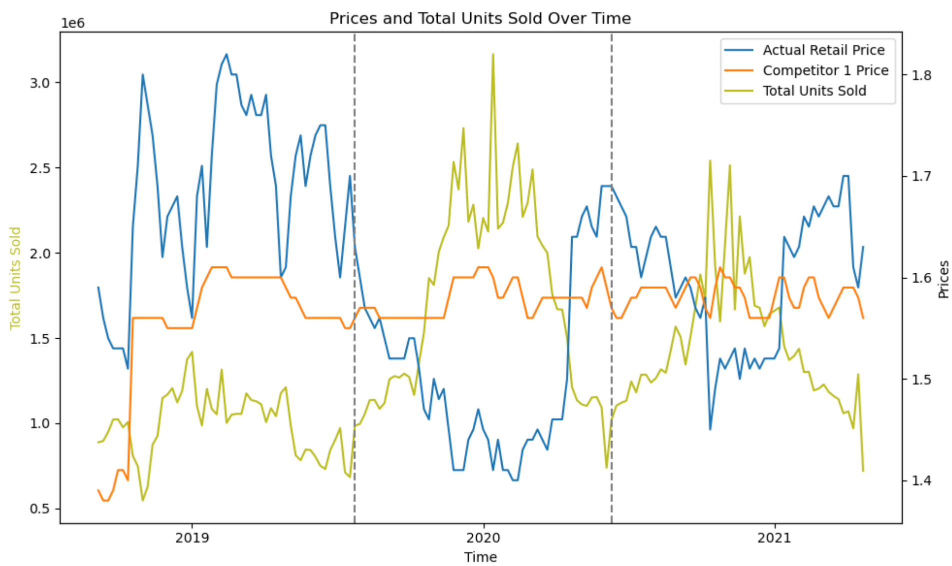
Exhibit 1 visually illustrates these pricing dynamics over time, providing valuable context for understanding sales variations and competitive positioning. Notably, our brand and the primary competitor show similar pricing trends, occasionally overtaking each other. Conversely, the second competitor consistently maintains lower prices. Despite our target customer base may differ from that of the second competitor, comprehensive insights into all market players aid in understanding the reason behind changes in our sales.

*Exhibit 1 – Prices Evolution from Year 2019 to 2021*



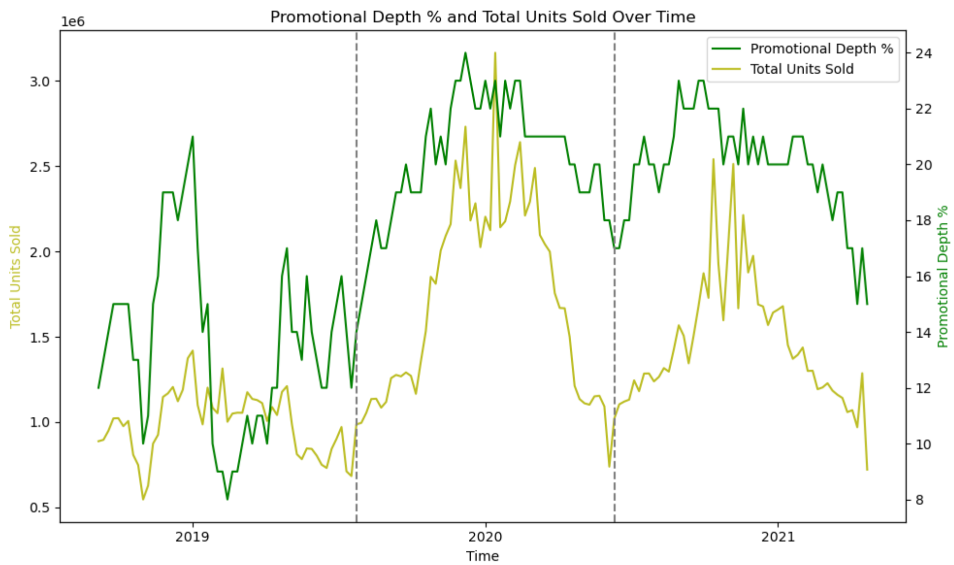
If we delve further into our data, an important pattern emerges: whenever our prices dip below those of our primary competitor, our sales experience a significant uptick, as evidenced by the occurrences in 2020 in Exhibit 2. This observation provides valuable insights into the price elasticity of demand within our target market. It suggests that our customers are particularly sensitive to price differentials relative to our main competitor, demonstrating a willingness to switch brands in response to perceived value.

*Exhibit 2 – Comparative Price Analysis and Units Sold*




Finally, I calculated promotional depth % (i.e. (1-ARP/RRP)*100), reflecting the discount level our brand offers weekly. As shown in Exhibit 3, a decrease in promotional depth, indicating a higher product price, correlates with reduced sales during the years 2020 and 2021. However, in 2019, with already low promotional depth, this effect is less evident. This suggests that the relationship between promotional depth and total units sold may be nonlinear. While it is possible that other factors beyond promotional depth played a more significant role in driving sales in 2019, taking this into account, along with other contextual factors and market dynamics, is crucial for comprehensively analyzing sales performance and recommending effective strategies.

*Exhibit 3 – Promotional Depth and Units Sold Comparison*



## 3. Regression Analysis and Price Elasticities

Our exploration of the data showed that there are various factors impacting sales performance. To gain a comprehensive understanding, I conducted an Ordinary Least Squares (OLS) regression analysis. The findings, presented in Exhibit 4, indicate an R-squared value of 0.899. This suggests that roughly 89.9% of the variance in the dependent variable (units sold) can be explained by the independent variables included in the model.

*Exhibit 4 – OLS Regression Results*

| | | | |
|---|---|---|---|
| **Dep. Variable:** | Total Units Sold | **R-squared:** | 0.899 |
| **Model:** | OLS | **Adj. R-squared:** | 0.895 |
| **Method:** | Least Squares | **F-statistic:** | 188.9 |
| **Date:** | Mon, 01 Apr 2024 | **Prob (F-statistic):** | 1.91e-70 |
| **Time:** | 13:13:27 | **Log-Likelihood:** | -2091.8 |
| **No. Observations:** | 156 | **AIC:** | 4200. |
| **Df Residuals:** | 148 | **BIC:** | 4224. |
| **Df Model:** | 7 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 4.65e+06 | 8.53e+05 | 5.453 | 0.000 | 2.97e+06 | 6.34e+06 |
| **Actual Retail Price** | -3.39e+06 | 2.39e+05 | -14.183 | 0.000 | -3.86e+06 | -2.92e+06 |
| **Total Media Investment** | 0.0695 | 0.102 | 0.678 | 0.499 | -0.133 | 0.272 |
| **Promotional Depth %** | -3.18e+05 | 3.79e+04 | -8.397 | 0.000 | -3.93e+05 | -2.43e+05 |
| **Promotional Depth % Squared** | 1.006e+04 | 1190.241 | 8.448 | 0.000 | 7703.367 | 1.24e+04 |
| **Competitor 1 Price** | 2.392e+06 | 4.15e+05 | 5.764 | 0.000 | 1.57e+06 | 3.21e+06 |
| **Competitor 2 Price** | 7.035e+05 | 2.46e+05 | 2.859 | 0.005 | 2.17e+05 | 1.19e+06 |
| **Total Competitors Media** | -0.0267 | 0.006 | -4.641 | 0.000 | -0.038 | -0.015 |

When examining the impact of prices, we observe that a one-unit increase in our price leads to a decrease in sales by approximately $3.39 million. On the other hand, a one-unit increase in our competitors' prices corresponds to increases in our sales of approximately $2.392 million and $703,500, respectively.

To gain deeper insights into price dynamics, I utilized a methodology similar to the SCAN*PRO model. This involved applying a logarithmic transformation to both sales and prices, allowing for the computation of our brand's specific price elasticity and cross-price elasticity. The resulting model is presented below:

$$\ln(Sales) = 13.93 - 4.30 \cdot \ln(ARP) + 4.53 \cdot \ln(PCompetitor_1) + 1.47 \cdot \ln(PCompetitor_2)$$

The price elasticity of our brand indicates that our product is relatively sensitive to changes in price, with a 1% increase in our price leading to a 4.30% decrease in sales. This suggests that consumers perceive our product as somewhat price-sensitive, and small changes in price can significantly impact demand.

Regarding the cross-price elasticity, the relatively high value of 4.53 with the main competitor implies that our brand and the competitor's product are substitutes in the eyes of consumers. This means that when the competitor increases its price, consumers are more likely to switch to our product, leading to an increase in our demand.

Conversely, the cross-price elasticity with the second low-price competitor is lower at 1.47, indicating a weaker substitution effect compared to the main competitor. While an increase in the second competitor's price still leads to a rise in our demand, the effect is not as pronounced as with the main competitor.

The underlying goal of measuring the impact of prices is to understand how sensitive consumers are to a price change. This price elasticity analysis can help us optimize our price and promotional offerings. For instance, if our primary competitor has consistently raised prices recently, there may be less urgency to discount our product. Additionally, by capitalizing on our product's appeal as an alternative to competitors, we can design targeted marketing campaigns that emphasize our unique value propositions and resonate with consumers. Understanding our positioning relative to our main competitor is crucial for effectively capturing consumer attention and preference and hence driving the best marketing campaign.

Going back to the regression analysis on Exhibit 4, the negative coefficient for "Promotional Depth %" suggests that increasing the promotional depth tends to decrease total units sold, while the positive coefficient for "Promotional Depth % Squared" indicates that this effect diminishes as promotional depth increases, eventually reversing at higher levels of promotional depth. As both coefficients are significant, this confirms the nonlinear relationship between promotional depth and total units sold, which may have implications for optimizing promotional strategies. This conclusion aligns with our brand's perception as a premium, high-priced product: a small discount may not attract new customers but simply retain existing ones; however, a larger discount could attract a new customer segment seeking lower-priced options.

To offer actionable insights to decision-makers, I calculated the inflection point, which is 15.81. This indicates that at a promotional depth percentage of 15.81, the effect of promotional depth on total units sold shifts from negative to positive. Across the years 2019 to 2021, 72% of the weeks recorded a promotional depth exceeding 15.81%, suggesting that our promotional strategy is on the right track.

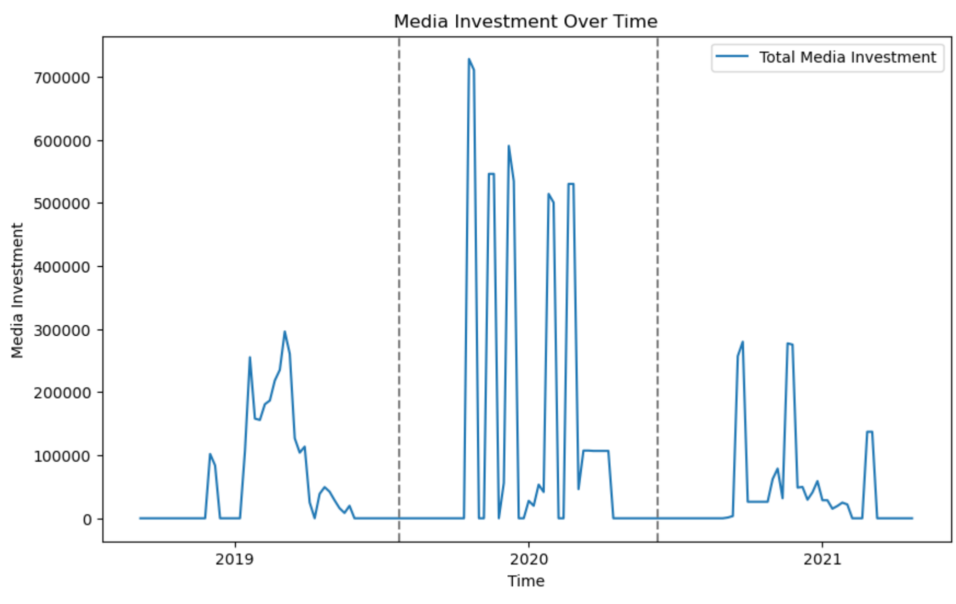
Lastly, OLS results show that an increase in competitors' media investment decreases our sales, while an increase in our media spending increases sales. The coefficients for both variables are very small and hence economically insignificant, as changes in these factors are unlikely to have a noticeable impact on sales. Moreover, our media investment coefficient has a p-value of 0.499, exceeding the typical significance level of 0.05, indicating its statistical insignificance. These findings raise concerns about our brand's media budget allocation, suggesting potential inefficiencies. In the subsequent section I will explore alternative models and strategies for improvement.

## 4. Advertising Effectiveness

Before jumping into the analysis of our media investment's effectiveness, I will first analyze our company's media spending patterns. Exhibit 5 provides an overview, revealing that media investment was absent in approximately 54% of the weeks. Moreover, there are fluctuations in media spending, with sharp spikes and declines. Notably, 2020 emerged as the year of highest media investment, contrasting with comparatively lower spending in 2019 and 2021.

These patterns suggest that our company may be employing a pulsing advertising strategy, characterized by maintaining low advertising levels throughout the year and intensifying advertising efforts during peak selling periods, which in the graph below appear to be during the summer months.

*Exhibit 5 – Media Investment Over Time*



To assess the efficacy of our advertising efforts, I will employ the model proposed by Gary Lilien, Phillip Kotler, and Sridhar Moorthy in their book "Marketing Decision Models" (Prentice-Hall, 1992). The model equation is outlined below:

$$Q_t = a + \lambda \cdot Q_{t-1} + b \cdot \ln(A_t) + c \cdot \max(0, \triangle A_t)_t$$

$Q_t$ and $A_t$ are the sales and advertising in period t, respectively. In addition, $\triangle A_t$ is the percentage increase in advertising for period t compared to period t–1.

λ represents the fraction of past sales used to predict current sales (as past sales have been built up by past advertising, this term incorporates the fact that past loyalty built up through advertising affects current sales). The logarithmic term incorporates the fact that the effectiveness of advertising diminishes as more advertising is done. Lastly, the max term gives an opportunity to model the effect of a change in advertising on sales.

To measure the effectiveness of advertising based on our company's data, I began by calculating the percentage change in advertising expenditure from the previous week ($\triangle A_t$). To prevent infinite values caused by zero advertising expenditure in some weeks, I first replaced these occurrences with a very small positive number, and then calculated the percentage change. Subsequently, I computed the lagged sales ($Q_t$).

Once I ensured the data was properly prepared, I developed a function to predict sales (forecast), calculate the sum of squared errors (SSE), and determine the optimal parameters a, b, c, and λ. The resulting equation is as follows:

$$Q_t = 1.19 + 0.99 \cdot Q_{t-1} + 1.45 \cdot \ln(A_t) - 1.24 \cdot 10^{-12} \cdot \max(0, \triangle A_t)_t$$

To accurately evaluate our company's advertising strategy, it is crucial to individually interpret each coefficient:

The intercept term (1.19) represents the expected value of sales when all other predictors are zero. It suggests a baseline level of sales that is not influenced by advertising or past sales.

The $\lambda$ coefficient (0.99) indicates the fraction of past sales used to predict current sales. A value close to 1 suggests that current sales are heavily influenced by past sales, reflecting the effect of past advertising efforts on current consumer behaviour and brand loyalty.

The b coefficient (1.45) quantifies the effect of the natural logarithm of advertising spending on present sales. Its positive value suggests that increased advertising spending correlates with higher sales, although this impact diminishes as advertising spending rises. A pulse advertising strategy allows us to focus our advertising efforts during critical periods when the impact on sales is maximized.

The final coefficient ($1.24 * 10^{-12}$) represents the influence of changes in advertising spending on sales following a positive change from the previous week ($\triangle A_t$). Its extremely small value suggests minimal effect. This implies that sudden shifts in advertising spending may not result in immediate impacts on sales and could lead to ineffective resource allocation. A pulse advertising strategy, featuring alternating periods of high and low advertising, enables more strategic resource planning, optimizing advertising efforts based on anticipated consumer responses over time. However, our first analysis revealed instances in 2020 where advertising expenditure dropped to zero even during peak seasons. Based on the c coefficient, our recommendation would be to avoid such fluctuations and instead maintain a consistent level of advertising expenditure during peak season as in 2019.

These findings confirm the suitability of our current advertising strategy compared to other alternatives such as continuous or event-based strategies. What's more, this approach aligns well with the characteristics of a high-priced premium juice brand, which typically has a sizable base of loyal customers throughout the year, while targeted advertising efforts are deployed to attract new customers during peak demand periods, such as the summer months.

Moving forward, further analysis should be done to determine the optimal allocation of advertising budget across various channels, including digital ads, television commercials, and influencer partnerships. Given our pulse strategy, prioritizing high-impact advertising campaigns is advisable, as they can leave a lasting impression on consumers despite limited exposure. However, comprehensive data analysis beyond the scope of this report is necessary to inform these decisions accurately.

## 5. Conclusion

In conclusion, our analysis has shed light on various aspects of our marketing strategy, providing valuable insights to guide future decision-making. Through rigorous examination of pricing dynamics, promotional strategies, and competitor analysis, we have gained a comprehensive understanding of our brand's positioning in the market landscape.

One notable finding is the confirmation of the effectiveness of our advertising strategy, particularly in the context of a pulse advertising approach. The model proposed by Lilien, Kotler, and Moorthy indicates that our current strategy aligns with optimal advertising effectiveness, despite the initial insignificance revealed by OLS results. To further evaluate this, additional testing using ROI analysis or the Adstock model could help refine our approach.

Competitor analysis has also been instrumental in understanding market dynamics and identifying areas for differentiation. By closely monitoring competitors' pricing strategies, media investments, and consumer behaviour, we can adapt our own strategies to capitalize on market opportunities and mitigate competitive threats.

Moving forward, there were several areas of improvement identified. Consistency in advertising during peak periods, as highlighted by the fluctuating media investments observed during 2020, is crucial for maximizing brand exposure and capitalizing on intense consumer demand. Additionally, exploring methods to measure and improve ROI will be essential for optimizing advertising effectiveness and ensuring efficient resource allocation.

In summary, while our current marketing strategy shows promise, there are opportunities for refinement and optimization. By leveraging the insights gained from our analysis and remaining vigilant in monitoring market trends and competitor actions, we can position our brand for sustained growth and success in the dynamic beverage market landscape.

## 6. Appendix

(1) Lilien, G., Kotler, P., & Moorthy, S. (1992). Marketing Decision Models. Prentice-Hall. Retrieved from link.

(2) Wittink, D., et al. (2000). Building Models for Marketing Decisions. Kluwer Publishing.

(3) All mathematical computations and models outlined during the report can be found in the Python file attached.