Applications Of Customer Segmentation And Bayesian Modelling In MMM

20BBS0062, 20BBS0115, 20BBS0127 | Aditya Malpani, Rachita Singh, Akshita Jain | Anny Leema A. | SCOPE

Introduction

Businesses face the challenge of optimizing their marketing budgets across various channels to maximize sales impact. Utilizing Bayesian Market Mix Modeling, our project aims to accurately assess the influence of marketing efforts on sales, guiding budget allocation for optimal results while addressing the impact on diverse customer segments.

Motivation

Optimizing marketing budgets is vital for revenue protection and brand enhancement. Our Bayesian Market Mix Model optimizes allocation and fills segmentation gaps for improved effectiveness.

Scope of the Project

1) Data Collection: Gathering sales, marketing, and customer data.
2) Segmentation: Identifying customer groups and their response to channels.
3) Bayesian Regression: Analyzing channel impact on sales with lightweight MMM.
4) Budget Optimization: Maximizing sales within budget constraints.
5) Comparative Analysis: Contrasting Bayesian and OLS models.

Integration of digital and traditional media lacks coherence, hindering campaign impact. Businesses need effective measurement of online and offline media; Bayesian Models offer solutions for informed decision-making.

Methodology

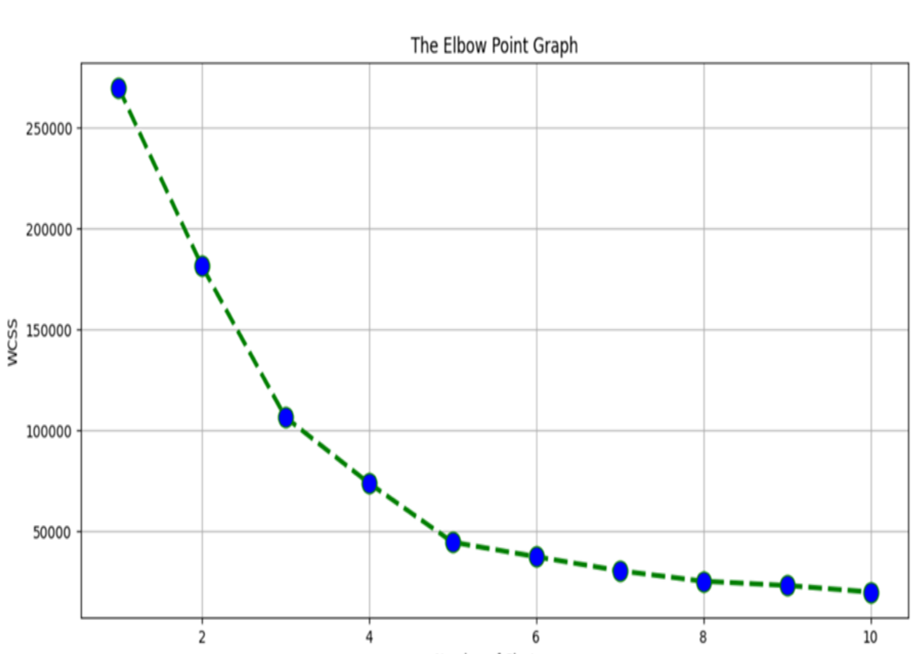
The project consists of four essential modules:

1) **Customer Segmentation**: Employing K-means clustering to categorize customers based on various attributes such as age, gender, income, and spending behavior.

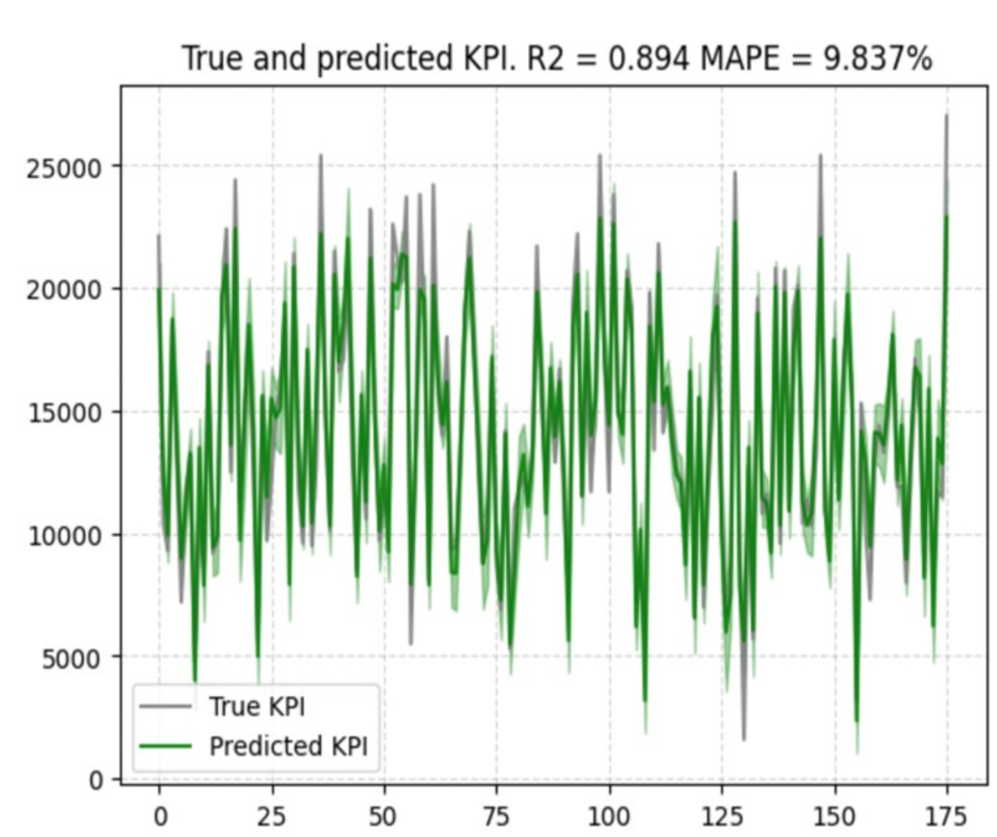
2) **Media Channel Impact Analysis**: Integrating customer segments into Marketing Mix Models to evaluate the influence of different media channels on each segment, aiding in targeted marketing strategies.

3) **Media Data Analysis**: Utilizing Bayesian regression techniques to estimate the contribution of media channels to sales and ROI, with options for flexible modeling approaches like Ad stock and Hill Ad stock.

4) **Budget Optimization and Allocation**: Implementing the Sequential Least Squares Quadratic Programming (SLSQP) algorithm to iteratively optimize budget allocation across media channels, ensuring maximum sales impact within defined budget constraints.



To determine the number of clusters, WCSS method is used to generate an elbow graph. To determine the number of clusters, WCSS method is used to generate an elbow graph. The WCSS is the sum of the variance between the observations in each cluster. It measures the distance between each observation and the centroid and calculates the squared difference between the two.



Markov Chain Monte Carlo construct a set of samples that can search over the range of possible outcomes. The density of the distribution should be proportional to the total amount of time spent in each interval.

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Optimization terminated successfully    (Exit mode 0)
            Current function value: -334577.88393752556
            Iterations: 6
            Function evaluations: 54
            Gradient evaluations: 6
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Gradient based Optimisation

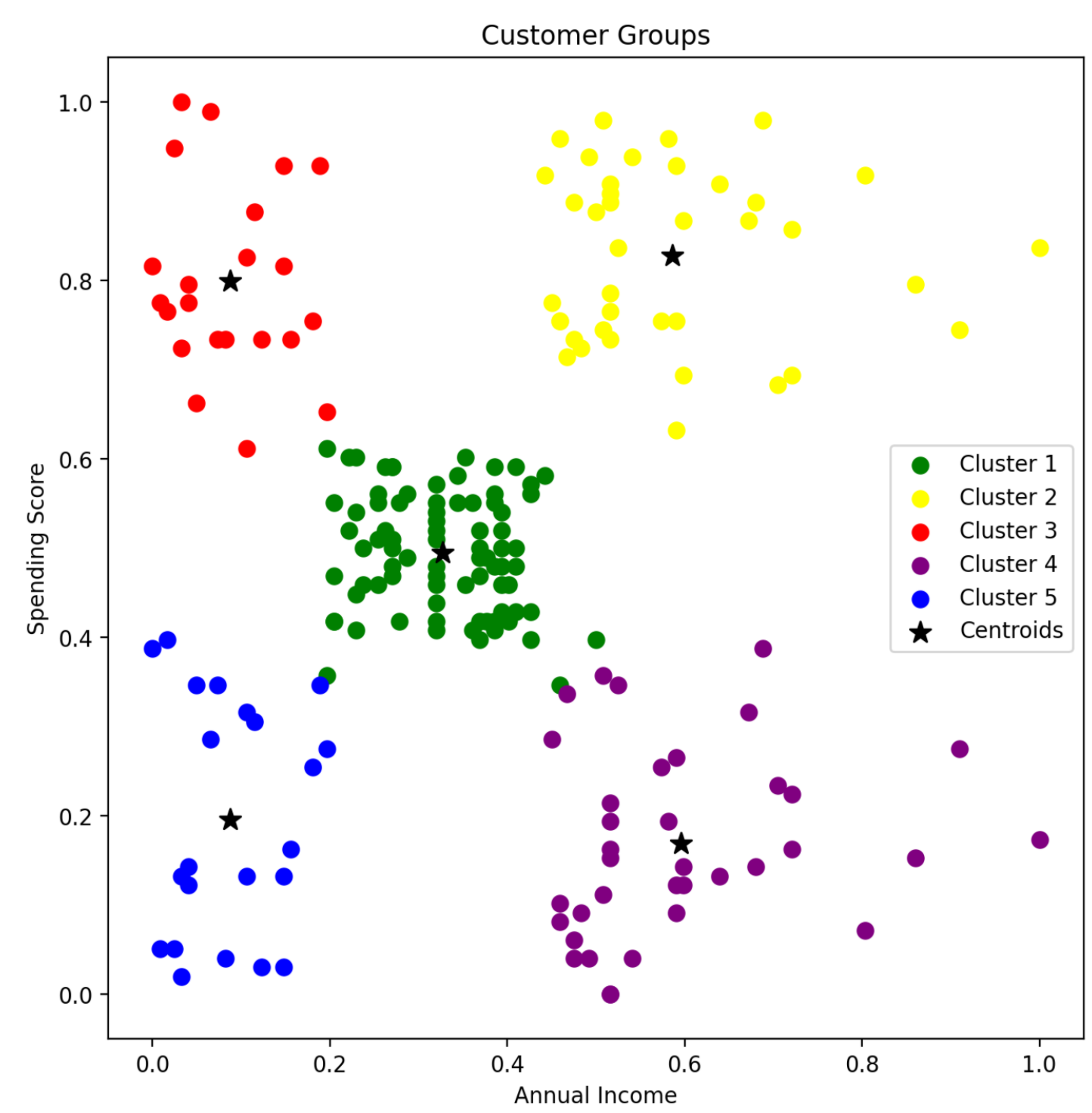
These modules collectively drive the project, involving meticulous data preprocessing, advanced regression analysis, and iterative optimization techniques to inform strategic marketing decisions effectively.

Results

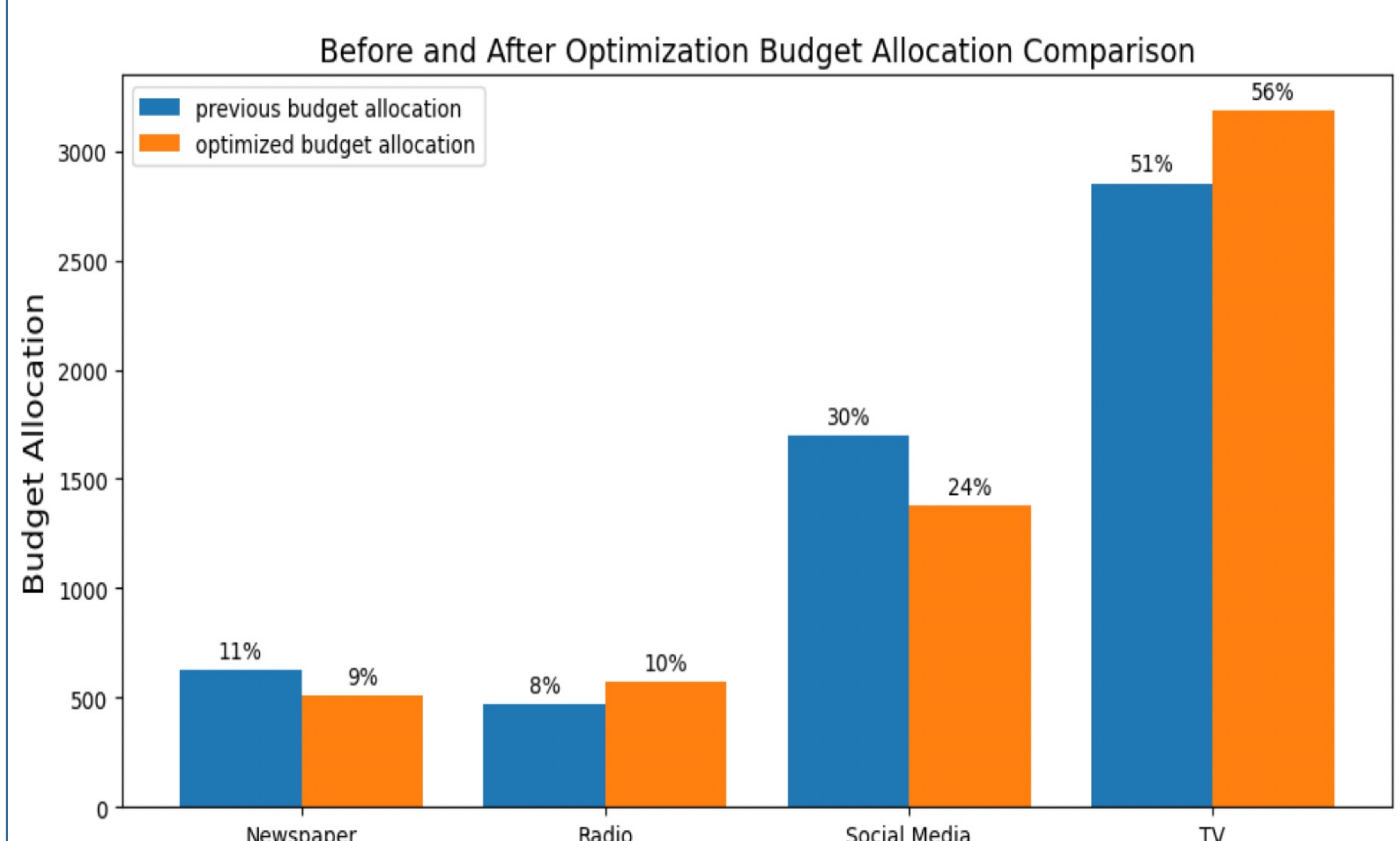
After performing customer segmentation in phase 1, five distinct clusters were identified, with clusters 2, 3, and 5 highlighted as crucial for maximizing sales. In phase 2, the impact of different media channels on these segments was analyzed, revealing positive and negative impacts across various channels and segments. Further analysis through MMM provided insights into media contribution, ROI, and response curves, highlighting TV's effectiveness in driving sales volume and radio's higher ROI.

Optimizing budget allocation based on these insights resulted in suggested adjustments across media channels to better target responsive customer segments. Bayesian regression outperformed linear regression, offering a more comprehensive understanding of uncertainties and incorporating ad stock and saturation advertising principles.

This approach allows for better estimation with fewer samples and provides distributions of expected values rather than single answers, enhancing decision-making in marketing strategies.



Cluster 1: Average earners with cautious spending.
Cluster 2: High earners, profitable with potential for increased spending.
Cluster 3: Higher income but low spending, potential for increased profit.
Cluster 4: Low earners with low spending.
Cluster 5: Low earners with high spending, possibly satisfied customers.



Conclusion

The thesis employed Bayesian Modeling to predict sales based on four advertisement media channels and consumer psychology impacting five customer segments. Utilizing algorithms like K-means and Bayesian Regression, along with Lightweight MMM, the model aimed to optimize budget allocation across media channels for maximizing sales. However, limitations included the inability to incorporate control variables like seasonality and holidays due to dataset unavailability, prompting suggestions for future work on multiplicative models and geo-level MMM for granular insights, as well as addressing selection bias for improved reliability.

References

[1] Yuxue Jin et al. "Bayesian methods for media mix modeling with carryover and shape effects". In: Google Research (2017)

[2] Sandeep Pandey, Snigdha Gupta, Shubham Chhajed, 'Market Mix Modeling-Concepts and Model Interpretation', International Journal of Engineering Research and Technology(IJERT), Vol 10 Issue 06 (2021)