Professional Portfolio: Capstone Project

Maximizing Marketing Impact: Returns on investment optimization through Marketing Mix Modelling

Team members:

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Contents

1.0 Introduction

In the words of marketing pioneer John Wanamaker, "Half the money I spend on advertising is wasted. The trouble is I don't know which half." This sentiment reflects a longstanding challenge faced by businesses worldwide: the inability to accurately measure the effectiveness of their marketing efforts. In today's fiercely competitive landscape, where maximizing returns on investment (ROI) is paramount, this lack of insight presents a significant obstacle to success.

To address this challenge, our project focuses on leveraging Marketing Mix Modelling (MMM), a powerful analytical framework that allows businesses to dissect and optimize their marketing strategies. By delving into the intricate interactions between various marketing elements—such as channels, pricing strategies, and promotions—MMM provides invaluable insights into their individual contributions to sales performance. Armed with this knowledge, businesses can make data-driven decisions to allocate resources more effectively and maximize their ROI.

Through a combination of advanced statistical analysis and machine learning techniques, our project aims to develop a MMM framework tailored to the specific needs of our organization. By harnessing the power of MMM, we seek to empower our organization with the tools and insights needed to navigate the complexities of modern marketing effectively. Ultimately, our goal is to help businesses overcome the age-old dilemma highlighted by Wanamaker and unlock new opportunities for growth and success in today's dynamic marketplace.

2.0 Technical Analysis

2.1 Project Framework:

As taught in our professional portfolio course, most of the analytical projects can be solved using the CRISP-DM framework (Cross-Industry Standard Process for Data Mining). We have followed the same for our project as well. It consists of six phases:

1. Business Understanding
2. Data Understanding
3. Data Preparation
4. Modeling
5. Evaluation
6. Deployment

2.2 Hypothetical Problem Statement/ Business Understanding:

Skyline Technologies is an e-commerce company in Toronto-Canada selling electronic gadgets. They put a lot of money into marketing, sometimes running big sales events like "Tech Day Extravaganza." Now, they're planning their marketing budget for the next year, including spending on ads, online campaigns, and deals. But looking back over the last year, they see that their marketing money didn't really boost sales like they hoped. They're considering cutting the budget or spending it smarter to make more money next year.

As part of the marketing analytics team, our job is to figure out what went wrong and how to fix it. We're going to create a plan using a marketing model to see what worked and what didn't in the past year. Then, we'll use that info to suggest the best ways to spend the marketing budget next year, aiming for more sales and happier customers.

2.3 Business Data Understanding:

We had a limitation to procure publicly available data for our project, which has been stated in the proposal document. Hence, we found a medium.com website from where we could get simulated data, link for it has been provided in the References at last.

As per the 7Ps of Marketing we needed data from the below sources:

- Sales Transactions Data: Detailed information on product sales, including quantities sold, revenue generated, and transactional details.

- Marketing Expenses: Data on marketing expenditures across various channels and activities, such as advertising, promotions, sponsorships, and digital campaigns.
- Product Data: Attributes of the products being sold, such as SKU (Stock Keeping Unit) details, product categories, variations, and pricing tiers.
- Price Data: Historical pricing information for products, including regular prices, promotional prices, discounts, and pricing changes over time.
- Distribution Data: Data on the distribution channels used to sell products, including information on retailers, wholesalers, online platforms, and geographic coverage.
- Promotional Data: Details of promotional activities undertaken, such as discounts, coupons, special offers, and seasonal promotions.
- Competitor Data: Information on competitor activities, pricing strategies, promotional campaigns, and market share dynamics.
- Market Data: External market factors that may influence sales performance, such as economic indicators, consumer trends, seasonality, and demographic data.
- Customer Data: Customer demographics, preferences, purchasing behavior, loyalty program participation, and customer lifetime value.
- External Factors: Additional external factors such as weather patterns, holidays, events, and regulatory changes that may impact consumer behavior and sales performance.

We could get data for the following(These are not full data columns, only relevant have been listed down):

1. Product:

   •# of units sold •Delivery days and SLAs •Categories/sub categories & Transactions

2. Price:

   •Gmv •Product mrp

3. Place:

   •Pin code •Order Payment Type Place (& Time) •Weekofthe year– seasonality •Holiday/Events

4. Promotion:

   •Marketing Channel Investments •Customer sentiment (NPS) •Discounts •Adstock

2.4 Data Cleaning & Transformation:

Treating Duplicates and Ensuring Data Consistency: Duplicate values were meticulously eliminated to maintain data integrity, ensuring each entry remained unique. Columns underwent rigorous verification to uphold uniqueness, minimizing the risk of redundancy and inconsistencies. Non-numeric data within key columns like "GMV" and "Pincode" was removed to enhance data clarity and accuracy.

Validating Data Scope and Business Logic: Occurrences of '\N' and data falling outside the specified timeframe were filtered out, focusing solely on relevant data for analysis. Furthermore, columns with a high proportion of null values were eliminated, streamlining the dataset and aligning with business requirements.

Data Standardization and Integrity Maintenance: The format of essential columns such as "order_date" and "GMV" was standardized for uniformity, facilitating seamless analysis. Rows containing negative values or inconsistencies in product MRP, GMV, and units were systematically removed to uphold data integrity.

Categorization and Segmentation for Targeted Analysis: Discount percentages were computed, and items were categorized as Luxury or Mass Market based on pricing percentiles, enabling effective segmentation. Irrelevant columns were pruned to focus solely on key variables, enhancing the dataset's relevance and usability. Note here that we only have based the entire analysis on just one product category i.e. Camera Accessory just to limit our scope for targeted analysis.

Outlier Detection and Removal: Outliers falling below Q1-1.5IQR or above Q3+1.5IQR were identified and eliminated to ensure statistical robustness, enhancing the reliability of subsequent analyses.

Data Aggregation and Transformation for Analysis: Week identifiers were generated to facilitate time-based analysis, and daily Order Data was aggregated to a weekly level for a higher-level view of trends. Master data frames were scaled and partitioned into separate train and test datasets for comprehensive model training and evaluation processes.

By meticulously adhering to these steps, the dataset was cleansed, standardized, and prepared for subsequent analysis, ensuring robust insights and informed decision-making.

2.5 Feature Engineering:

In order to facilitate comprehensive analysis, several key transformations and calculations were applied to the dataset. Firstly, a "Week#" column was generated from the order date, allowing for the segmentation of data into weekly intervals, thereby aiding in temporal analysis. Additionally, products were categorized as either Luxury or Mass-market based on whether their GMV value surpassed the 80th percentile, facilitating segmentation for more targeted analysis.

Furthermore, various metrics were computed to provide deeper insights into sales dynamics. The List Price for each transaction was derived by multiplying the GMV by the Units, offering a comprehensive view of the monetary value of products sold. Additionally, the Discount% was calculated for each transaction, allowing for the quantification of applied discounts and their impact on sales performance.

Moreover, temporal patterns in sales behavior were identified by flagging Payday Weeks and Holiday Weeks. Assigning a value of 1 to weeks containing Payday or holidays, and 0 otherwise, enabled the analysis of sales trends around these significant temporal markers. Furthermore, the effectiveness of pricing strategies was assessed through the calculation of SMA# (Sales-Marketing Alignment), comparing List Price to product MRP and expressing the difference as a percentage.

To capture temporal dependencies in the data, Lag Variables were incorporated, including lagged values for key performance indicators (KPIs) by 1, 2, and 3 days. Additionally, 3-week and 5-week Simple Moving Averages (SMAs) were calculated for advertising media channels, Net Promoter Score (NPS), and Stock Index, aiding in the identification of trends and smoothing out fluctuations. Lastly, Adstock Values for all advertising media channels were determined by applying an ad stock rate of 60%, capturing the cumulative effect of past advertising efforts on current sales dynamics. These transformations and calculations collectively lay the groundwork for more robust and insightful analysis of sales performance and marketing effectiveness.

2.6 EDA & Visualization:

We have used Tableau desktop to create some EDA visuals for ease of access at later point in time to present the data well.

1. Weekly Net promoter Score(NPS) vs Discount %

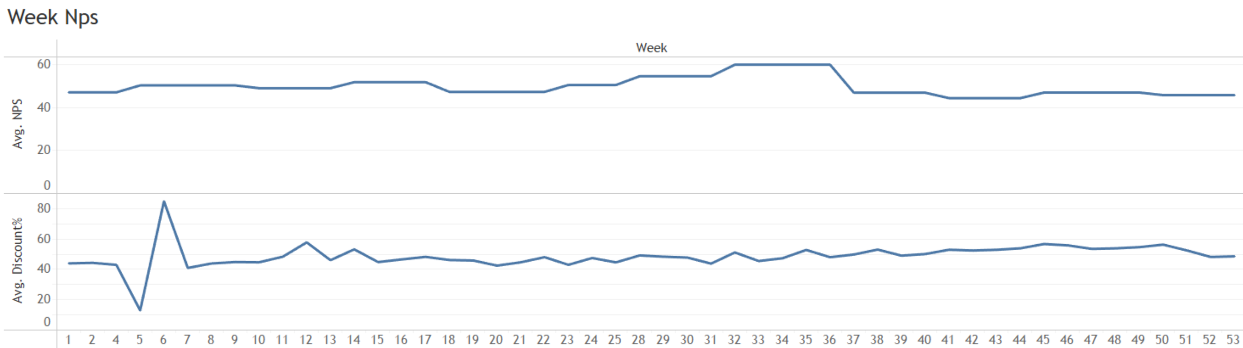


Figure 1

Nothing significant to note here while discounts can impact customer behaviour and potentially influence Net promoter Score(NPS). Not in our case.

2. Weekly investment for Different Advertisement Channels

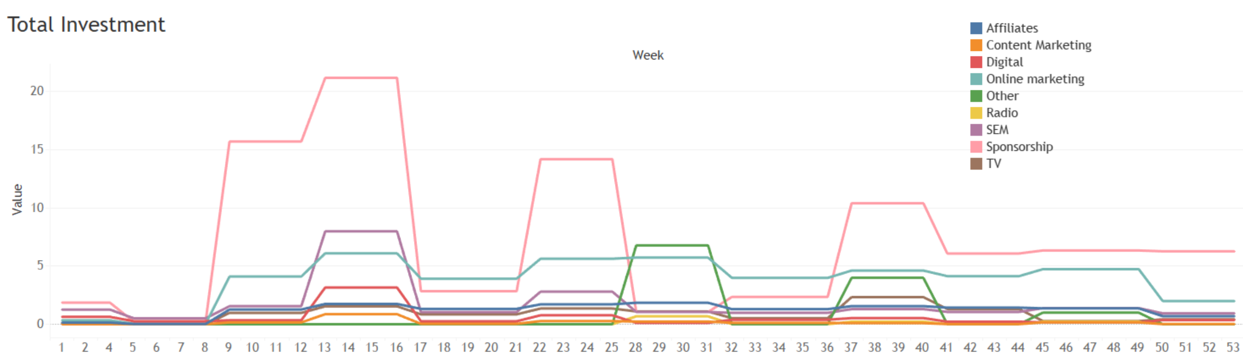


Figure 2

We can clearly see that the company spends a lot more on Sponsorship media for Advertising

Considering it might raise the revenue.

3. Product Types vs Units-Sold

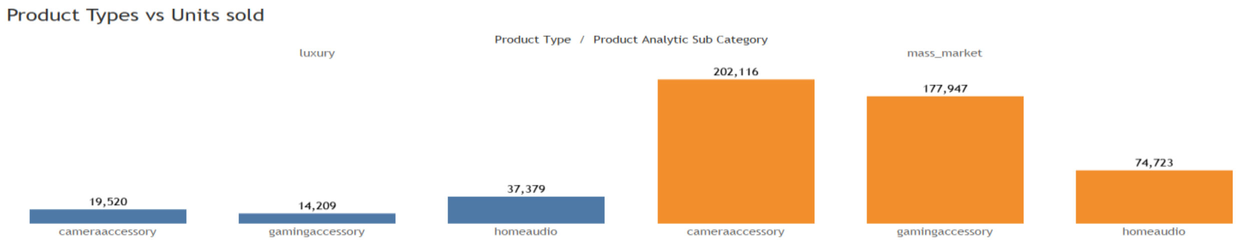


Figure 3

We can observe that there are two major product types i.e. Luxury and Mass-market which we created as an additional KPI earlier. For Mass Market we can see camera accessory sells the most and similarly Home Audio sells the most for Luxury brands.

4. Weekly Sales vs Monthly Sales

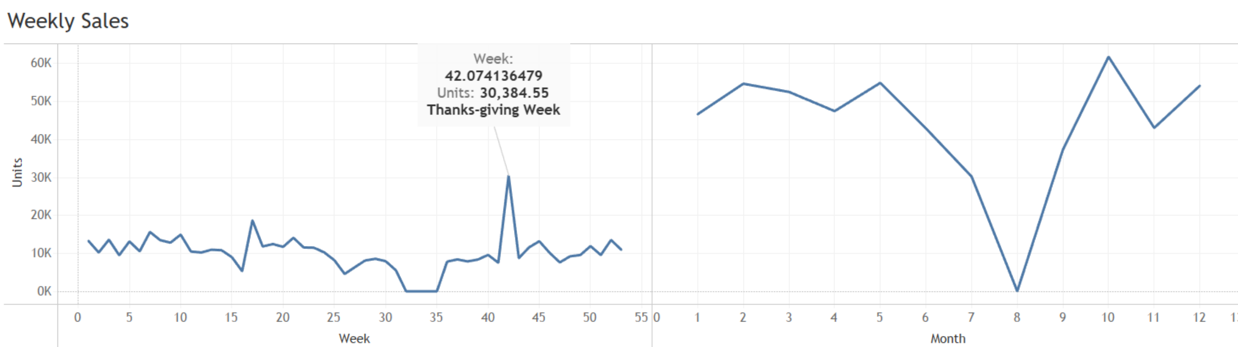


Figure 4

The week when the sales were the highest was week 42 and it was a thanks giving week. We can observe the monthly trend as well.

5. Product Category granularity with respect to Gross Merchandise Value(GMV)

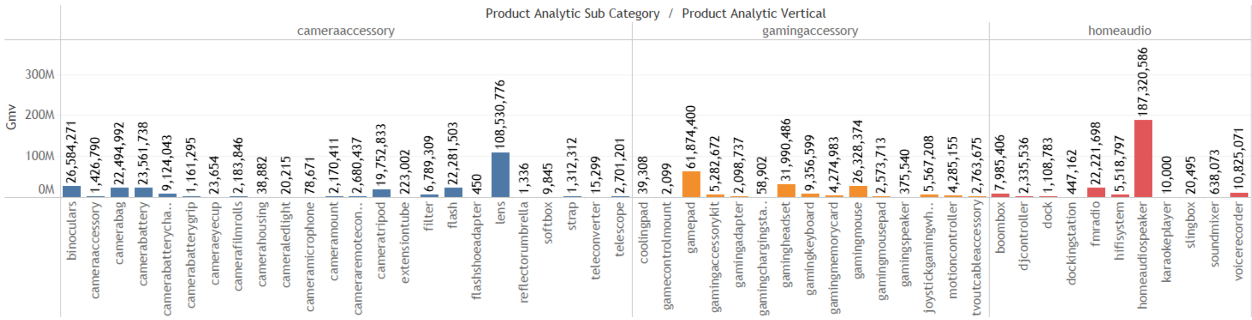


Figure 5

Lens , Gamepads and Homeaudio Speakers have the highest GMV amongst all products.

6. GMV vs Discount%

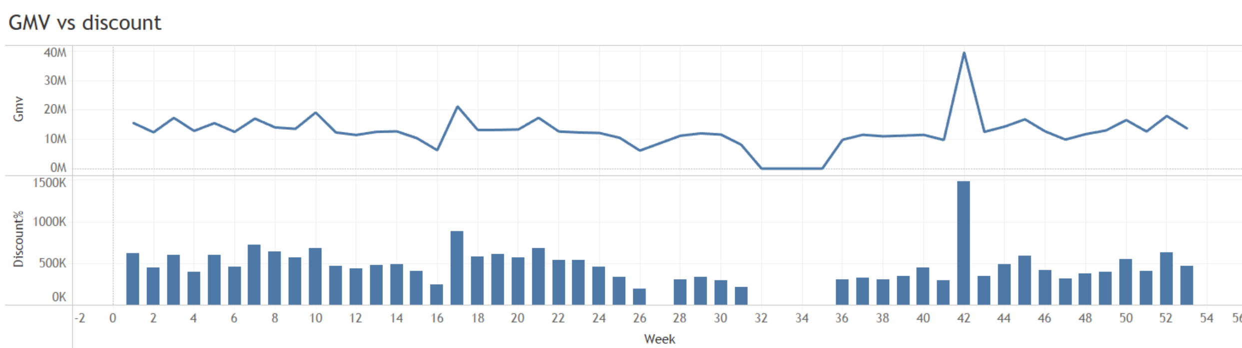


Figure 6

Higher the aggregated discount higher is the GMV as we can observe which holds true.

7. Discount bins vs GMV

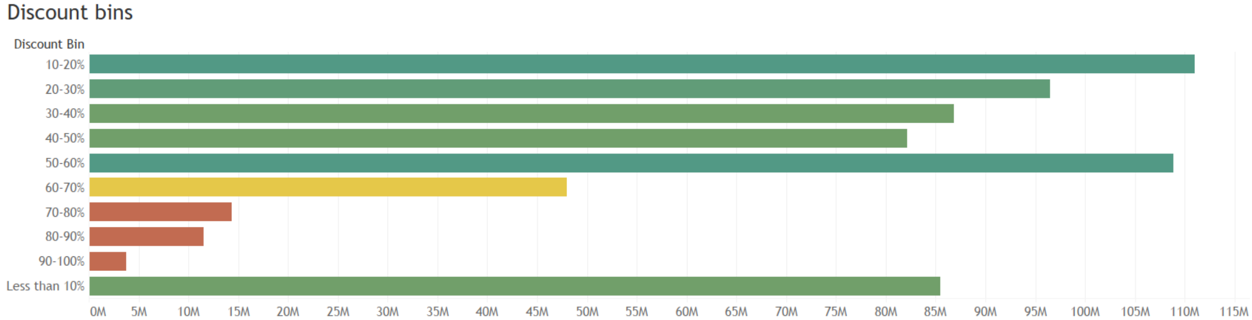
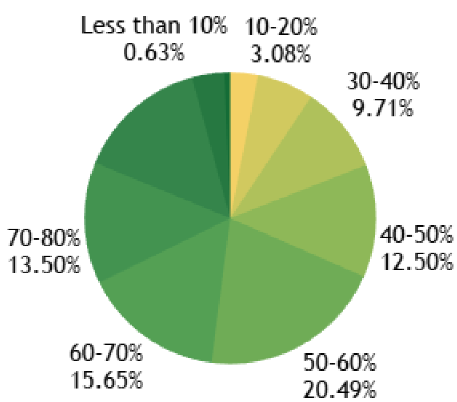


Figure 7

When the average discount percentage falls between 10% and 20%, the GMV is highest.

8. Discount Percentage distribution



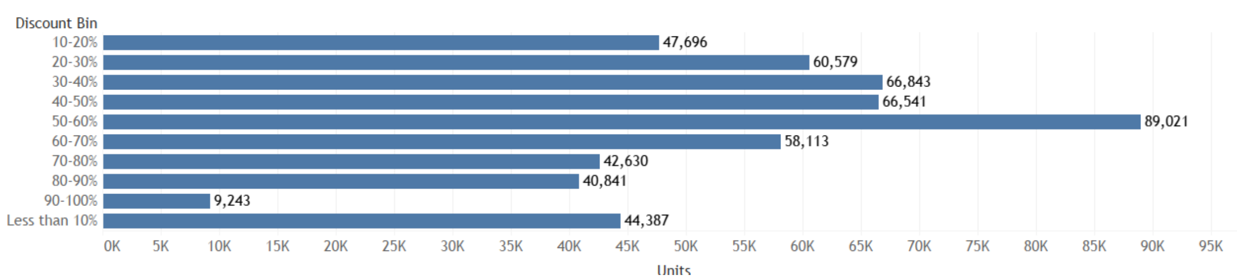


Figure 8

Discount % range of 50-60% is highly used with ultimately Number of units steadily increasing till that range and later steady decline in sales.

2.9 Model Building & Validation:

In the benefit of time, we built two different models and cross validated them for testing their accuracy.

2.9.1 Linear Regression Model

Linear model assumes an additive relationship between the different KPIs. Hence their impacts are also additive towards the dependent Y variable. The equation can be represented as:

$$Y = \alpha + \beta 1At + \beta 2Pt + \beta 3Dt + \beta 4Qt + \beta 5Tt + \epsilon$$

This framework allows for a clear understanding of how changes in each predictor variable affect the dependent variable, holding other variables constant. For example, an increase in advertising expenditure (At) by one unit will result in a change in Y by the corresponding coefficient β1, irrespective of the levels of other predictors like pricing or discount levels. The linear model simplifies the interpretation of relationships between variables, facilitating insights into their individual contributions to the overall outcome. In our case GMV was the predicted variable.

Results:

```
R2 Score: 0.855133435297494
Mean Squared Error: 0.17908377368019895
```

This is before cross validation which looks an adequate training accuracy of 85.5% with 0.19 as MSE.

Although after Cross-validation we got the below results:

```
Cross-Predicted Accuracy: 0.6767401112451525
Mean Squared Error: 0.32325988875484746
```

Sr No	Features	Coefficients
1	product_vertical_filter	0.307
2	product_vertical_lens	0.248
3	Snow on Grnd (cm)	0.19
4	product_vertical_camerabag	0.139
5	Total Snow (cm)	0.138

Table1

The above Table 1 shows top 5 KPIs/Features which contributed most for the success of the model

2.9.2 Koyck Lag Model

In the Koyck model, which accounts for lagged effects, the equation is stated below:

Yt = **α** + **μYt-1** + **β1X1** + **β2X2** + **β3X3** + **β4X4** + **β5X5** + **ϵ**

represents the relationship between the dependent variable Y_t at time t and the predictor variables X_1, X_2, X_3, X_4, X_5, along with the lagged dependent variable Y_{t-1}.

We had to calculate the coefficient of the lag variable "GMV_lag" separately.

The Koyck tells us that the current revenue generated is not just influenced by the different independent attributes, but also because of the revenue generated over the last periods. i.e. Current revenue(Yt) is also dependent on the past revenue values(Yt-1).

Yt = **α** + **β1X1** + **β2X2** + **β3X3** + **β4X4** + **β5X5** + **ϵ**

Yt = **α** + **μYt-1** + **β1X1** + **β2X2** + **β3X3** + **β4X4** + **β5X5** + **ϵ** -- (sale at time t is dependent on sale at time t-1)

*If X1 is the advertising effect, β1 is the current effect of advertising, carry over effect of advertising is β1 * μ/(1-μ).*

Therefore the total effect of advertising = Current effect + Carry over effect

= β1 + β1 * μ/(1-μ)

=β1/(1-μ)

Sr no	Features	Coefficients	Total Effect
1	product_vertical_lens	0.230	0.204
2	product_vertical_filter	0.218	0.193
3	product_vertical_camerabag	0.187	0.166
4	Snow on Grnd (cm)	0.164	0.145
5	Affiliates	0.151	0.134

Table 2

3.0 Conclusion & Recommendations:

For Camera Accessory Product Category:

- Sales peak when the discount percentage falls between 50-60%, yet this doesn't significantly increase revenue. Exploratory Data Analysis (EDA) reveals that an average discount percentage between 10-20% is most profitable, particularly among luxury items.
- Promote "Lens," "Camera Bag," and "Filters" for higher revenue.
- Sponsorship spending positively affects revenue, with each unit correlating to a revenue boost of 0.036 units.
- Content marketing spending has a negative impact on revenue.
- Mass-market products contribute more significantly to increased revenue than luxury items.
- Higher percentages of discounts within this product category tend to decrease revenue.
- Snow on Ground is another interesting metric which boosts revenue as people tend to shop online during that weather, but it cannot be controlled by humans!

4.0 References

- Gupta, Sunil. (2019). "Marketing Analytics: Data-Driven Techniques with Microsoft Excel." John Wiley & Sons.
- Hanssens, Dominique M., et al. (2020). "Market Response Models: Econometric and Machine Learning Insights." Springer.
- Neslin, Scott A., et al. (2019). "Sales Promotion and Retailing: Allowance for Marketing Actions." Marketing Science.
- Wang, Wes. (2018). "Marketing Analytics: A Practical Guide to Real Marketing Science." Kogan Page.
- https://youtu.be/sYn1wuO9BDM
- Marketing Mix Modeling White Papers - MASS Analytics (mass-analytics.com)
- Essential Data for Marketing Mix Modeling | by David Scott | Medium – Data source
- Additional Data stored at Google drive which was exceeding 25mb – https://drive.google.com/file/d/18C7VPpeW514e1QudGf-wRKNwI1wrS-j4/view?usp=drive_link

Appendix:

Professional Portfolio: Capstone Project Proposal

Maximizing Marketing Impact: Returns on investment optimization through Marketing Mix Modelling

<u>Team members:</u>

Abhishek Rajendra Mahale

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Nehal Vadoliya

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1.0 Introduction

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To address this challenge, our project focuses on leveraging Marketing Mix Modelling (MMM), a powerful analytical framework that allows businesses to dissect and optimize their marketing strategies. By delving into the intricate interactions between various marketing elements—such as channels, pricing strategies, and promotions—MMM provides invaluable insights into their individual contributions to sales performance. Armed with this knowledge, businesses can make data-driven decisions to allocate resources more effectively and maximize their ROI.

Through a combination of advanced statistical analysis and machine learning techniques, our project aims to develop a MMM framework tailored to the specific needs of our organization. By harnessing the power of MMM, we seek to empower our organization with the tools and insights needed to navigate the complexities of modern marketing effectively. Ultimately, our goal is to help businesses overcome the age-old dilemma highlighted by Wanamaker and unlock new opportunities for growth and success in today's dynamic marketplace.

2.0 Project Description

In the realm of data-driven decision-making, businesses across industries face a common challenge to accurately quantifying the impact of their marketing strategies on sales performance. The ability to allocate resources effectively and optimize marketing channels hinges on a thorough understanding of how various marketing elements contribute to overall ROI. However, this task is often hindered by the complexity of analysing diverse datasets and extracting meaningful insights.

At this juncture, our project is poised at the initial stage of data acquisition, wherein we are actively seeking datasets that will enable us to delve into the intricate relationships between marketing inputs and sales outcomes. The industry focus of our analysis will be determined based on the availability and suitability of the acquired data. Our aim is to develop a versatile Marketing Mix Modelling (MMM) framework capable of providing actionable insights across different industry contexts.

The impetus behind our endeavour stems from the recognition that businesses stand to benefit significantly from a deeper understanding of their marketing effectiveness, irrespective of their sector. By leveraging advanced statistical analysis and machine learning techniques, our project seeks to unlock valuable insights into the contributions of various marketing components, including advertising channels, pricing strategies, and promotional activities.

Ultimately, our goal is to equip businesses with the tools and knowledge needed to make informed decisions, optimize marketing strategies, and drive sustainable growth. By addressing the universal challenge of marketing effectiveness through rigorous data analysis.

3.0 Project Objectives/Benefits (Research) Questions

We are proposing that we would analyse the real effects of different marketing variables over a year to suggest the best budget distribution for various marketing strategies in the upcoming year with the detailed objectives below:

1. Conduct a performance driver analysis aimed at identifying the key performance indicators (KPIs) that have the greatest impact on top-line performance within the business or organization. This analysis will delve into various metrics to uncover the specific factors driving overall revenue and growth, providing actionable insights for strategic decision-making and optimal resource allocation.

2. Conduct an impact analysis on marketing ROI to quantify the effect of each commercial lever on revenue. This analysis aims to determine the specific quantitative impact of various marketing strategies on revenue generation, providing actionable insights to optimize resource allocation and enhance return on investment.

3. Optimize marketing spends by strategically allocating the marketing budget to achieve the highest possible outcome. This entails identifying the most effective channels and initiatives to invest in, ensuring maximum impact and return on investment for the marketing budget.

Research Questions:

How do different marketing elements, such as advertising channels, pricing strategies, and promotional activities, contribute to overall sales performance?

What are the relative contributions of each marketing component to ROI, and how can businesses optimise their allocation of resources based on these insights?

4.0 Deliverables/Outcomes

1. Strategic allocation of the marketing budget to maximize outcomes and ROI. Example: Allocating a larger portion of the budget to social media advertising based on its higher ROI compared to traditional print advertising.
2. Actionable Insights Report: We will provide a detailed report summarizing the actionable insights derived from our analysis. This report will highlight key findings related to the effectiveness of marketing channels, pricing strategies, promotional activities, and customer segmentation, along with recommendations for optimizing marketing strategies and maximizing ROI.
   Example: When should promotional activities take place so that the revenue is maximized.

3. Interactive Visualization Dashboard: As part of our project, we will develop an interactive visualization dashboard using tools like Tableau Desktop. This dashboard will allow businesses to explore and visualize the results of the MMM analysis in an intuitive and user-friendly manner, facilitating decision-making and strategic planning.

5.0 Scope/Constraints/Risks/Current Issues

Scope:

Our analysis will primarily focus on gathering data from the following channels:

- Sales/Subscriptions
- Price/Promotions
- Competitor Activity
- Economy/Seasonality

The analysis will cover a range of marketing elements, including:

- Advertising spend
- Pricing strategies
- Promotional activities
- Distribution channels

Furthermore, the scope may extend to include additional factors influencing sales performance based on the availability and relevance of data. This comprehensive approach ensures a thorough examination of key drivers impacting top-line performance, facilitating informed decision-making and strategic resource allocation.

Constraints:

Availability and quality of historical marketing data may pose limitations on the analysis.

Time constraints may impact the depth and breadth of the analysis and model development.

Resource limitations, including expertise, may restrict the scope and scale of the project.

Risks:

Data inaccuracies or inconsistencies could affect the reliability of the analysis and model outputs. Model complexity may lead to over fitting or misinterpretation of results. External factors such as changes in market conditions or consumer behaviour may impact the validity of the analysis and recommendations.

Current Issues:

Lack of standardized metrics for measuring marketing effectiveness may pose challenges in comparing and interpreting results.

Mitigation Measures:

To mitigate constraints, we'll focus on cleaning processes for data and diversifying data sources too, and prioritizing key metrics. Risks will be mitigated by implementing robust data validation protocols, regularizing models, conducting scenario analyses, and fostering stakeholder engagement to adapt to external factors and ensure transparent communication throughout the analysis.

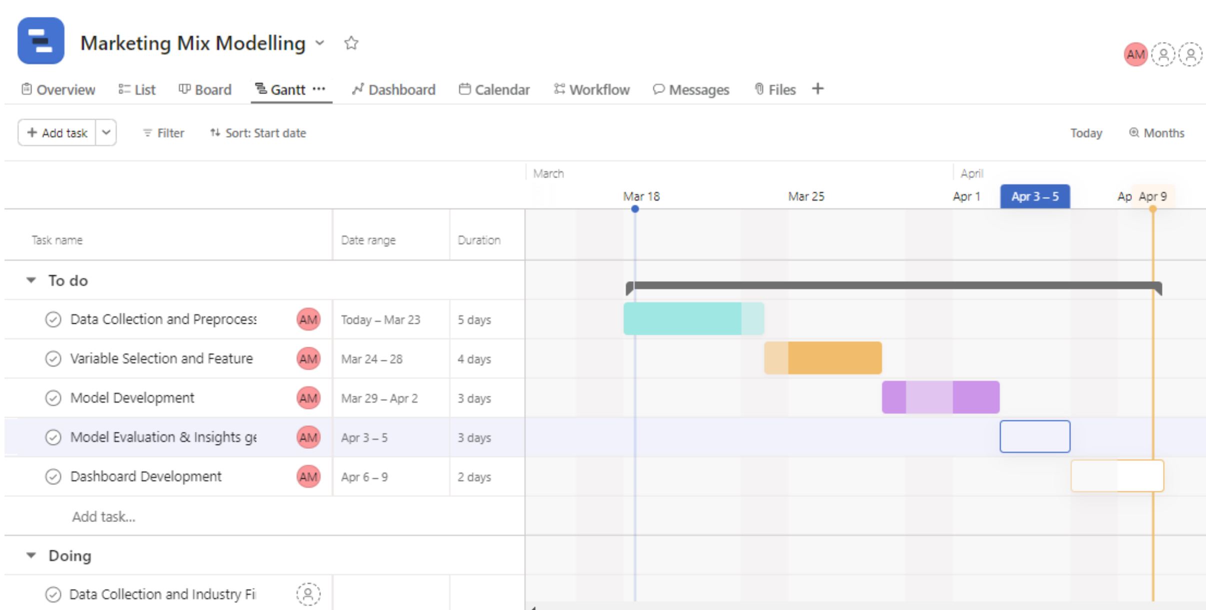
6.0 WBS/Gantt Chart

WBS:

Project Management				
1. Data Collection & Pre-processing	2. Variable Selection & Feature engineering	3.Model Development & Validation	4. Model Evaluation & Insights generation	5.Build Dashboard In Tableau/PowerBi
(i) . Identifying relevant Data Sources	(i). Identify key marketing elements and variables for analysis	(i). Develop initial Marketing Mix Modelling (MMM) framework	(i). Evaluate model performance metrics (e.g., R-squared, Mean Absolute Error)	(i). Design interactive visualization dashboard layout and interface
(ii). Gather historical Marketing Data	(ii).Conduct feature engineering to create meaningful input variables	(ii).Train and fine-tune the MMM model using historical data Validate odel performance using cross- validation techniques	(ii). Validate model assumptions and check for multicollinearity, heteroscedasticity	(ii). Test and validate dashboard functionalities and user experience
(iii). Clean and Pre-Process Data	(iii). Transform categorical variables, handle missing data, and normalize	(iii). Incorporate feedback and iterate on model refinement	(iii). Conduct sensitivity analysis to assess model robustness Perform validation testing using holdout datasets or out-of-sample testing	
(iv). Performing EDA	(iv). Select appropriate modeling techniques and algorithms			

This WBS outlines the breakdown of tasks and activities involved in each phase of the project, from project management and data collection to model development, insights generation & dashboard development.

Gantt chart



7.0 Description of Team (Group Members)

Abhishek Rajendra Mahale (BE, MBA, PG Artificial Intelligence & Data Science (*pursuing*))

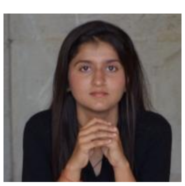
Project Manager & Data Scientist: Responsible for overall project coordination, stakeholder management, and ensuring project deliverables are met on time and within budget & Advanced statistical analysis and machine learning techniques, responsible for enhancing the MMM framework's predictive capabilities and model optimization with domain expertise in marketing analytics.

Sonjeet Kaur (BCA IT, Artificial Intelligence & Data Science (*pursuing*))

Data Analyst: Skilled in data collection, pre-processing, and analysis, responsible for developing the MMM framework and generating actionable insights.

Nehal Vadoliya (BSC Mathematics, Artificial Intelligence & Data Science (pursuing**))**

Dashboard Developer: Proficient in data visualization tools like Tableau or PowerBI, responsible for designing and implementing the interactive visualization dashboard.



Sukhdeep Singh (BCA IT, Artificial Intelligence & Data Science (pursuing))

Data Engineer: Proficient in data collection, data warehousing, and data pipeline development, responsible for managing the flow and storage of data, ensuring data quality, and optimizing data processing workflows.

8.0 Literature review

MMM has found widespread applications across diverse industries, ranging from retail and consumer goods to telecommunications and finance. Gupta (2019) highlights the utility of MMM in quantifying the impact of marketing activities on sales and profitability; enabling organizations to allocate resources effectively and optimize marketing spend. Neslin et al. (2019) emphasize the role of MMM in evaluating the effectiveness of sales promotions and retailing strategies, providing insights into the short-term and long-term impacts on consumer behaviour and sales performance.

Methodologies and Techniques

MMM employs a combination of econometric models, statistical analysis, and machine learning techniques to analyze the relationship between marketing inputs and sales outcomes. Hanssens et al. (2020) present insights into market response models, exploring the econometric and machine learning approaches for estimating the impact of marketing variables on sales. Wang (2018) offers practical guidance on marketing analytics techniques, including regression analysis, time series forecasting, and attribution modelling, which are instrumental in developing robust MMM frameworks.

Contributions to ROI Optimization

The primary objective of MMM is to optimize marketing strategies and maximize ROI by identifying the most effective marketing channels, pricing strategies, and promotional activities. By quantifying the contribution of each marketing element to sales performance, businesses can make data-driven decisions to allocate resources efficiently and drive sustainable growth. Gupta (2019) emphasizes the importance of continuous monitoring and refinement of MMM models to adapt to changing market dynamics and consumer preferences, thereby maximizing the long-term impact on ROI.

9.0 Tools & Resources

1.Python: Python will be used for data analysis, preprocessing, and model development. Libraries such as Pandas, NumPy, and Scikit-learn will be leveraged for data manipulation, statistical analysis, and machine learning.

2.Tableau or PowerBI: Tableau or PowerBI will be used for developing the interactive visualization dashboard. These tools offer robust features for creating dynamic and visually appealing dashboards to present the results of the Marketing Mix Modelling analysis.

3. Hardware requirements: High-performance CPUs, ample RAM for large datasets, and sufficient storage capacity. GPUs can accelerate computations, while fast network connectivity and backup systems ensure efficiency and data integrity. Scalability is essential for accommodating future growth in data volume and analysis complexity, for now we required a 16gb RAM machine with sufficient processing power.

10.0 Summary

The project aimed to revolutionize marketing analytics by developing a sophisticated Marketing Mix Modelling (MMM) framework to maximize marketing impact and optimize return on investment (ROI). Through the integration of advanced statistical analysis, machine learning techniques, and interactive visualization tools, the project sought to provide actionable insights for businesses to enhance their marketing strategies and drive sustainable growth.

Key achievements include:

1. Conducting a comprehensive literature review to understand the applications and methodologies of MMM.
2. Successfully collecting, pre-processing, and analysing historical marketing data to develop an initial MMM framework.
3. Training, evaluating, and refining the MMM model to ensure robustness and accuracy in predicting the impact of various marketing activities on sales performance.
4. Implementing an interactive visualization dashboard using Tableau or PowerBI to effectively communicate MMM analysis results and provide stakeholders with intuitive visualizations and actionable insights.
5. Providing training and support to enable businesses to implement recommendations derived from the MMM framework effectively.

11.0 References

- Gupta, Sunil. (2019). "Marketing Analytics: Data-Driven Techniques with Microsoft Excel." John Wiley & Sons.
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