BAX-401: Information, Insight and Impact

Homework 2: Multimedia Allocation

Group 14 (Section 1)

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Executive Summary

The question of how to evaluate advertising effectiveness and allocate marketing dollars has long puzzled senior management across different industries. This research uses 42 months of marketing spend data for a cosmetics firm's product launched about 4 years ago to assess the effectiveness of its advertising activities on sales through *attribution modeling*.

The final focal model is constructed by incorporating respective offline catalog expenditures, online search and newsletter ads expenditures, as well as the previous period sales, with a square root transformation applied to capture diminishing returns in advertising spending. The resulting model is statistically significant, indicating a linear relationship between the selected explanatory variables and sales, and possesses high AIC, a proxy for model quality. In addition, online advertising activities such as search and newsletters are found to have high, positive relationships with sales among all chosen channels, suggesting that the company should allocate more marketing budget to them in the future.

Introduction

The fact that consumers nowadays are involved in "an expanding, fragmented array of marketing touch points across media and sales channels" has made measuring advertising effectiveness more complex than ever (Nichols, 2013). Luckily, the recent advent of *attribution modeling* has provided companies with new abilities to accurately understand how marketing activities contribute to sales.

This report explores the effectiveness of a cosmetics company's advertising activities on the sales of a specific product it launched roughly 4 years ago. The process of selecting candidate variables and quantifying the contribution of various advertising touch points will be detailed, followed by an in-depth discussion about the results. A preliminary advertising budget allocation plan will also be proposed to help the firm adjust its marketing resources across multiple media for the given product as well as for similar products in the future.

Problem Formulation

The cosmetics firm has advertised in both offline and online channels. Offline broadly consists of catalogs and mailing. This channel can be further broken down into catalogs sent to existing customers, and catalogs sent to new potential customers. In terms of online advertising, this can be broken down into banners, search, social media, retargeting ads, and portals.

The level of awareness of brand and of product attributes may be built over time with advertising (Tull, 1965). This is represented in our model by including the effect of previous period sales. We also acknowledge that advertising expenditure has diminishing returns and this is represented by square root on the advertising variables considered in our model (Sasieni, 1971). This will be discussed in detail in our model development and further analysis done around this is discussed in the appendix.

Data Description

The data at hand consists of 42 months of unit sales and spending allocation on different ad categories. In terms of marketing channels not chosen for the model, the channels of winback catalogs, mailings, banners, social media, and retargeting had generated 0 sales in more than half of the periods, so they were discarded due to lack of data or effectiveness. We also chose not to include factors like the total amount spent on ads, the total amount spent on online ads, and the total amount spent on offline ads because including them would result in recommendations that were too broad (i.e. it is not overly helpful to know that more money should be allocated to offline ads because this raises the question of which offline channels).

Instead, we chose to include the channels within each of these categories which included catalogs sent to existing customers, catalogs sent to new customers, search ads spending, newsletter ads spending, as well as sales from the previous period. On average, the firm spent $567 on catalog-existing customers, $272 on catalog-new customers, $20 on newsletter and $69 on search, and sold a monthly average of 4800 units.

Model Development

The focal model was chosen on the basis of practicality, testing, and knowledge of theory behind monetary returns to advertising. It is well established that advertising has diminishing returns to scale, and even in the age of digital and social media marketing, companies are increasingly finding that despite growing costs digital ads are not leading to endlessly increasing returns (Zhang, 2022). In addition, we found that the best models that we tested incorporated past sales, which suggests that there is some form of carry-over effect where sales in the last period are impacting current sales in some way. As a result, the focal model accounts for both of these elements by incorporating the previous period's sales and taking the square root of the variables we used in our regression equation. The choice to use both online and offline marketing channels was motivated by the fact that a model with only one of these categories would be missing a large part of the company's ad spending. Instead, we provide a holistic view of the company's advertising efforts by combining the best channels from both offline and online advertising.

Results

The final model is represented below:

$$Sales = 2604.1115 + 0.1563Sales_{t-1} - 19.7893\sqrt{Catalogs\_ExistCust}$$

$$- 1.6540\sqrt{Catalogs\_NewCust} + 166.3558\sqrt{Search} + 126.9976\sqrt{Newsletter}$$

The Adjusted R squared tells us how much of the variation in our data is explained by the marketing channels we have chosen, in this case roughly 16.58% of the variation in our data is explained by the channels we chose. The p-value represents whether or not there is a linear relationship between the marketing channels chosen and sales, and in this case our p-value of 0.03979 suggests that there is a linear relationship. Our AIC is a rough estimate of a model's quality and predictive power, and the higher the AIC the higher quality the model arguably is. In our case, this model had the second highest AIC of any model we tested. However, given the theory behind advertising that we discussed and the fact that the only other model to perform better did so by less than a point and only used two marketing channels meant that we chose our current model. A summary of the statistics from this model can be found in Table

1 in the appendix. In the equation above, the coefficients give us insight on the relationship between the marketing channels and Sales. According to the model, without any spending on advertisement, sales will be roughly 2604 units. The coefficients can be interpreted as for every one unit increase in each variable, sales will increase by the coefficient amount. For example, every increase of 1 unit in the previous period's sales leads to an increase in current average sales by 0.1563 units. A full summary of coefficient interpretation can be found in the appendix. We also examined the elasticity of sales with respect to each channel. Elasticity in this instance measures the change in sales for a change in the amount spent on a particular advertising channel, so a higher elasticity means that additional spending will drive more sales. A full summary of all elasticities can be found in Table 2 in the appendix.

Search advertising had the highest elasticity, and from the analyses we can say that a 10% increase in amount of money spent on search advertising will lead to a 3.55% increase in sales, which suggests that more money should be invested in search.

Recommendations and Managerial Implications

From our model, we can determine that the online advertising channels of Search and Newsletter are more effective at driving sales than offline Catalogs. Not only was the relationship between sales and the online advertising channels positive, the elasticities were higher, which suggests that investing more into online advertising will drive higher sales than investing in catalogs. We observe that the elasticity for catalogs sent to existing and new customers are negative. Therefore, allocation of large resources into these two offline advertising channels would likely not result in substantial increase in sales. Even though the overall model is significant, the relationship between both types of catalogs and sales is negative and insignificant (p-value > 0.05), hence we strongly recommend that we keep low allocations for these advertising channels. We recommend allocating those resources to newsletter and search because they have positive relationships with sales and positive elasticities.

We tried experimenting with how our final focal model (Catalogs_ExistCust, Catalogs_NewCust, Search, Newsletter) would perform in a situation where we have no previous sales or advertisement, such as if the business was to shut down or a completely new product was launched. We observed that the overall model becomes highly statistically significant having 0.9725 adjusted R square with an AIC of 688. However, since the situation we are investigating does not match either of these scenarios, we decided not to go with this model. Therefore, past sales and advertising are meaningful in this problem and removing it from the model does not represent the business reality.

We had used the square root function for the focal model to take into account the diminishing returns effect, but another possibility is the use of the log function to improve model performance. We observed that the robustness of logarithmic transformations over square root does a better job in terms of explainability and significance, despite lower predictive power for future sales (AIC = 675 compared to focal model AIC=682.184). The p value was also found to be more significant. We also tested for synergy by including different combinations of offline - online advertising channels and found no significant synergy. However, we did find synergy between the Newsletter and search advertisements, which makes sense from a practical perspective because it is likely that people regularly look up interesting products they see on a Newsletter. Hence, including synergy between Newsletter and Search advertisements in the model results in a better model in terms of explainability and predictability. Therefore, we recommend the business to incorporate this synergy into the model for a better understanding and accurate predictions in sales.

Conclusion

Considering all the important factors and investigating the effect of different advertising channels, we have formed a model that explains sales in the best possible manner with the given data. However, there are potentially significant improvements to be made in the existing model. For instance, the inclusion of seasonality is a factor that we did not have access to but likely has a large impact on sales. Additionally, the analysis done here is purely associative and not causal, mainly due to the fact that there are outside factors that could be influencing sales that we have not taken into account. As a result, we cannot say that a particular advertising channel is causing sales to increase or decrease, only that they are associated. An improved model should also take into account the synergies we discussed in the previous section because advertising channels interact to collectively drive sales.

Sources

Dinner, I. M., Heerde Van, H. J., & Neslin, S. A. (2014). "Driving Online and Offline Sales: The Cross-Channel Effects of Traditional, Online Display, and Paid Search Advertising." *Journal of Marketing Research*, *51*(5), 527–545, https://doi.org/10.1509/jmr.11.0466

Loeb, Walter. "The Rising Costs of Digital Advertising Will Force Spending Shifts." *Forbes*, Forbes Magazine, 10 Dec. 2021, https://www.forbes.com/sites/walterloeb/2021/08/04/rising-costs-of-digital-advertising-will-force-spending-shifts/?sh=5bf6aa1b5a7c.

Nichols, Wes. "Advertising Analytics 2.0" *Harvard Business Review*, March 2013, https://hbr.org/2013/03/advertising-analytics-20.

Tull, Donald S. "The Carry-over Effect of Advertising." Journal of Marketing, vol. 29, no. 2, 1965, pp. 46–53., https://doi.org/10.1177/002224296502900212

W., M. W. (1959). "Optimal Advertising Expenditure." Management Science, 18(4-part-ii). https://doi.org/10.1287/mnsc.18.4.p64

Zhang, Jonathan Z. "How Paper Catalogs Remain Relevant in a Digital Age." *Harvard Business Review*, 19 July 2022, https://hbr.org/2022/07/how-paper-catalogs-remain-relevant-in-a-digital-age.

Appendix

Data Dictionary

Variable	Description
Months	Time in Months
Sales (units)	Sales of items in units in the month
lag_sales	Previous period's sales
ADV_Total	Total Advertising Spend in the month, comprises ADV_Offline and ADV_Online
ADV_Offline	Total Offline Advertising Spend, comprises Catalogs_ExistCust, Catalogs_Winback, Catalogs_NewCust in the month
Catalogs_ExistCust	Amount spent on Shopping Catalogs sent to existing Customers in the month
Catalogs_Winback	Amount spent on Shopping Catalogs sent to Customers (who have not bought for at least 6 months) in the month
Catalogs_NewCust	Amount spent on Shopping Catalogs sent to New Customers in the month
Mailings	Amount spent on Mailings (excluding Catalogs) sent to Customers. Mailing include flyers, postcards and letters in the month
ADV_online	Total Online Advertising Spend, comprises Banner, Search, SocialMedia, Newsletter, Retargeting and Portals in the month

Banner	Amount spent on Banner ads in the month
Search	Amount spent on Search ads in the month
SocialMedia	Amount spent on Social Media ads in the month
Newsletter	Amount spent on Newsletter ads in the month
Retargeting	Amount spent on Retargeting ads in the month (https://retargeter.com/what-is-retargeting-and-how-does-it-work/)
Portals	Amount spent on ad portal advertising in the month (https://www.marketingterms.com/dictionary/portal/)

Adjusted R-squared	**P-value**	**AIC**
0.1658	0.03979	682.184

Table 1

Channel	**Elasticity**
Catalogs_ExistCust	-0.01156538
Catalogs_NewCust	-0.0004843091
Newsletter	0.0147364
Search	0.0355406

Table 2

Interpretation of coefficients for focal model

- Without any spending on advertisement, sales will be roughly 2604 units.
- every increase of 1 unit in the previous period's sales leads to an increase in average sales by 0.1563 units.
- For every increase in 1 unit of spending on catalogs to existing customers, sales will decrease by 19.783 units.
- For every increase in 1 unit of spending on catalogs to new customers, sales will decrease by 1.65 units.
- For every increase in 1 unit of spending on newsletters, sales will increase by roughly 127 units.
- For every increase in 1 unit of spending on search, sales will increase by roughly 166.3558 units.

Extended Appendix

Model without an intercept

As part of our analysis we also investigated using a model with no intercept. This would roughly correspond to shutting the business down for some time and then starting from scratch to investigate how advertising would affect sales when people haven't been exposed to or been able to buy the product for some time. We observe a sharp increase in adjusted R-squared and AIC, but the actual usefulness of using this model is questionable because it is not practical to shut the business down for a prolonged period of time.

Adjusted R-Squared	P-value	AIC
0.9725	0	688.2876

Equation:

$$Sales = 0.3004 Sales_{t-1} - 5.5973\sqrt{Catalogs\_ExistCust} + 1.1036\sqrt{Catalogs\_NewCust}$$

$+ \ 255.9499\sqrt{Search} + \ 306.3874\sqrt{Newsletter}$

Model With No Lagged Sales Term

We also considered the possibility that there is no carry-over effect to sales and that there is no need to include last period's sales in the model. The results are summarized below:

Adjusted R squared	P-value	AIC
0.1534	0.03688	681.9561

Equation:

$$Sales \ = \ 3090.696 \ - \ 26.302\sqrt{Catalogs\_ExistCust} - \ 2.399\sqrt{Catalogs\_NewCust}$$

$$+ \ 124.565\sqrt{Newsletter} + \ 216.587\sqrt{Search}$$

Because we saw a drop in both the AIC and adjusted R squared, we can infer that this model is worse than the model which included a lagged sales term and as a result we did not go with this model. From a theoretical perspective, it also makes more sense if sales possess some form of carry-over effect where sales last period impact sales this period in some way.

Model With Log Terms

Another way to address the principle of diminishing returns to advertising in a model is to take the log of terms instead of the square root, which is another regression we experimented with. The results can be seen below:

Adjusted R squared	P-value	AIC
0.2823	0.004002	675.86

Synergy

Based on past research, we expected to see some form of interaction between online and offline marketing channels (Dinner et al., 2013). The intuition behind this is that people might see a print version of marketing outreach, and then actually make the purchase through an online channel. As a result, using a model that does not take into account these kinds of interactions is arguably faulty. We have tried to portray synergy through several models, the equations and summary statistics are below:

1. $Sales = 255.661 * Search + 21.556 * Catalogs\_NewCust - 2.892 * Search * Catalogs\_NewCust$
    a. AIC: 683.0019
    b. p-value: 0.0558
    c. Adjusted R-squared: 0.1137
2. $Sales = 61.46 * Search - 79.74 * Catalogs\_ExistCust + 6.98 * Search * Catalogs\_ExistCust$
    a. AIC: 680.4511
    b. p-value: 0.01938
    c. Adjusted R-squared: 0.1659
3. $Sales =- 38.61 * Portals - 121.90 * Catalogs\_ExistCust + 42.28 * Portals * Catalogs\_ExistCust$
    a. AIC: 674.6128
    b. p-value: 0.001612
    c. Adjusted R squared: 0.2742

4. $Sales = 910.067 * Portals - 10.702 * Catalogs\_NewCust$
   $+ 3.439 * Portals * Catalogs\_NewCust$
   a. AIC: 679.4809
   b. p-value: 0.01289
   c. Adjusted R squared: 0.185
5. $Sales =- 141.39 * Catalogs\_NewCust - 167.91 * Newsletter +$
   $3.439 * Newsletter * Catalogs\_NewCust$
   a. AIC: 686.4507
   b. p-value: 0.2205
   c. Adjusted R squared: 0.03785

One of the notable takeaways from this experimentation was that the coefficient for the synergy term, which was the term in the equation where two variables are multiplied together, were almost all positive, suggesting that certain offline and online channels are working together in order to drive more sales. However, an interesting dynamic emerged. For synergy between newsletters and catalogs to new customers, the overall model was not significant, but it had the highest AIC and the synergy term was significant at the 5% confidence level. In contrast, every model was significant at the 5% level, but none of the coefficients for the interaction terms were significant. This calls into question whether or not synergy actually exists between online and offline marketing channels for this company, so I would argue that synergy between online and offline advertising channels does not need to be taken into account for this model. We also explored synergy within online elements:

1. $Sales = 0.139 * lag\_sales - 19.8680 * Catalogs\_ExistCust - 2.3688 * Catalogs\_NewCust$
   $- 194.2745 * Newsletter + 41.6680 * Search * Newsletter$
   a. AIC: 681.3453
   b. p-value: 0.02965
   c. Adjusted R squared: 0.1823

We found that the interaction term is statistically significant at the 5% level. the AIC dropped slightly to 681, but the adjusted R-squared improved. From an intuitive perspective, it also makes sense that synergy would exist between Search and Newsletter. If someone received a newsletter from the cosmetic company, they are likely to look it up if they are interested in the product to find out more, and when they do this they will be exposed to search ads which is where they are likely to buy the product.

Summary of Functional Forms Tried (Square Root)

The columns represent the variable used and the rows represent the model. * means that the variable is significant at the 0.05 level, ** means significance at the 0.01 level and *** means significance at the 0.001 level.

1=lag_sales, 2=ADV_Total, 3=ADV_Offline, 4=Catalogs_ExistCust, 5=Catalogs_NewCust, 6=ADV_online, 7=Search, 8=Newsletter, 9=Portals

Model	1	2	3	4	5	6	7	8	9	AIC
1	0.2950**									679.9786
2	0.2916*	-2.2303								681.9536
3	0.1027	239.3249**	-204.2738**							672.2603

4	0.1017	262.8307**	-232.5256**	17.9320						673.3395
5	0.1014	261.9849**	-233.4876**	19.3078	1.0676					675.3384
6	0.1070	286.4182*	-252.9929*	20.9204	-0.1720	-23.4473				677.1886
7	-0.02919	418.32920***	-359.64882***	24.22380	-9.47980	-429.20396*	610.49037*			671.5469
8	-0.03132	420.53680***	-351.09361***	10.23320	-16.50844	-479.22213**	679.31524**	136.17221		672.1462
9	-0.03518	390.78148**	-329.12031**	9.45362	-14.62756	-466.44687*	486.88000	117.12265	772.27319	671.4639

10	0.2705*			-10.8452						681.472
11	0.2702*			-10.8471	-0.4795					683.4694
12	0.1546			-15.2415	-1.2530		173.2777			681.1715
13	0.1563			-19.7893	-1.6540		166.3558	126.9976		682.1844
14	0.1378			-20.9245	-2.5547		-98.1596	93.4610	1090.6323	680.3274

Summary of Functional Forms Tried (Log)

1=lag_sales, 2=ADV_Total, 3=ADV_Offline, 4=Catalogs_ExistCust, 5=Catalogs_NewCust, 6=ADV_online, 7=Search, 8=Newsletter, 9=Portals

Model	1	2	3	4	5	6	7	8	9	AIC

1	0.2951**									679.978
2	0.2664*	-166.8								680.952
3	0.1302	967.21*	-495.83**							682.87
4	0.1201	1243.3*	-829.98*	265.05						683.17
5	0.1253	1133.8*	-918.30*	381.55	32.624					669.095
6	0.07791	819.56	-746.52	299.91	40.741	388.6				665.533
7	-4.816e-02	1.432e+03*	-1.094e+03*	4.250e+02	1.876e+01	-1.481e+03	2.295e+03*			667.365
8	-5.361e	1.450e	-1.005e	3.134e	-2.874	-1.960	2.784	3.71		667.257

	-02	+03*	+03*	+02	e+00	e+03*	e+03*	3e+02		
9	-6.405e-02	1.381e+03*	-9.436e+02*	2.750e+02	-1.034e+01	-2.137e+03*	2.121e+03	3.667e+02	9.974e+02	679.97
10	0.2034			-146.7376						677.89
11	0.2050			-151.9688	15.6231					679.69
12	0.05587			-182.42949	12.48573*		829.50974*			675.24
13*	0.06518			-195.60579	9.49103		768.90810	301.2529		675.86

				*			*	9		
14	0.05685			-192.0 7739*	5.1021 4		-109. 7440 2	250. 4443 8	1002. 2531 1	674.86