University of California, Davis

Effectiveness of Advertising Expenditures on Cosmetic Sales

BAX 401: Homework 2

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Executive Summary

In this project, we developed a model to determine the effectiveness of all marketing activities using the campaign data for a cosmetic product as a proof of concept. We sought to optimize this firm's marketing strategies by recommending the adoption of an updated marketing versus sales model. To do so, we utilized the firm's focal model to investigate the relationship between relevant marketing channels and sales in different aggregation levels, as well as the robustness of this model. With the results, we provided managerial recommendations and insights on the limitations of the focal model. Specifically, we explored whether synergy exists in the firm's marketing mix and explained the reason for its absence. Discovering that the distributions of many potentially informative variables are not normally distributed, we suggest that the model be transformed and more data be included .

Introduction

The domain of our firm is in the cosmetic industry. They are currently facing difficulty in extracting information from marketing data for decision-making in allocating advertisement resources. Our goal in this project is to improve the model currently deployed by the firm by feature engineering and data transformation. We will do so by identifying variables with the best predictability, explaining limitations in the current model, and providing recommendations for future allocations of resources.

Problem Formulation

Dataset provided contains 42 observations of monthly sales and 15 columns of advertisement expenses. To develop our model, we screened useful variables from this marketing activities dataset. The company advertises both online and offline, with 10 channels, as shown in Figure 1in appendix.

Figure 2 shows that most offline marketing channels are negatively correlated with sales, with one exception being catalogs sent to customers who did purchase for at least six months. Conversely, all of the online marketing channels correlate positively with sales, in which the search and portal variables have a largely significant relation score. The strong correlation between portal and search expenditure is also worth noting. Multicollinearity will arise if both are included in the focal model.

To deal with diminishing returns to scales in the nature of advertising effect on sales, functional forms of the different marketing channels are required. A square root transformation is applied on independent variables to express this relationship.

Data Description

After our initial data exploration, we found that the social media column is composed solely of zeros, and limited data exists in the “banner” and “retargeting" columns. Because they have limited information on sales, we eliminated them from our suggested regression model.

As mentioned above, we are using a square root functional transformation on all predictors. Checking the distribution of each transformed variable further allows us to exclude three offline advertising variables that are extremely right-skewed, whose distribution is shown in Figure 3, because they may negatively influence the performance of our model.

After analyzing the correlations of the remaining variables with sales, we narrowed down seven independent variables detailed in Figure 4 as candidates to explain the sales volume for our focal model. The distributions for the square roots of these variables are illustrated in Figure 5. These shows the data included are normally distributed and may form a robust model. The five-number summaries for all candidate variables are provided in Figure 6.

Model Development

Since the data provided is hierarchical, we can investigate the effect of the advertisement from different levels of aggregation. The firm’s focal model prototype is structured as follows:

$$Sales_t = \lambda Sales_{t-1} + \beta_i \sqrt{Advertisement}_{it} + intercept + \epsilon_t$$

We viewed sales as dependent on the advertisement and its own lagged effect due to the cumulative nature of business reputation, goodwill and inherent seasonality in sales. Therefore, a dynamic model with sales in a one-period lagged form as well as the square root of advertisement expenses as independent variables was used for estimating the regressor.

We began by investigating the effectiveness of advertisements as a whole using the total advertisement amount. Our first model is as follows:

$$Sales_t = \beta_o + \lambda\, Sales_{t-1} + \beta_1 \sqrt{\text{Total Advertisement}_t} + \varepsilon_t \quad (1)$$

Next, we broke down the firm's advertising expenditures into two major segments: online and offline advertisement expenses. This formed our second model:

$$Sales_t = \beta_o + \lambda\, Sales_{t-1} + \beta_1 \sqrt{\text{Offline Advertisement}_t} + \beta_2 \sqrt{\text{Online Advertisement}_t} + \varepsilon_t \quad (2)$$

Finally, we partitioned each part of the advertisement into specific streams of marketing channels. We gradually picked up relevant variables via an iterative way to include explanatory variables and covariates that have the most predictability for the regressor. In addition, we dropped *Search* as it is highly correlated with *Portal.* With this, we have the following focal model:

$$Sales_t = \beta_o + \lambda\, Sales_{t-1} + \beta_1 \sqrt{\text{Cata\_Exist}_t} + \beta_2 \sqrt{\text{Newletter}_t} + \beta_3 \sqrt{\text{Portal}_t} + \varepsilon_t \quad (3)$$

Results

The results of our focal model are listed in Figure 7. In the first model, we discovered an overall insignificant negative influence of advertisement on sales. With the second model, we found that the offline advertisement may even negatively impact sales, while online marketing was positively influencing sales. The third model implies that *Portals* was the only effective marketing channel.

Although this goes against intuitive sense, it may still be possible. Thus, we provide explanations and insights in the recommendation section. We also explore possible alterations for improving the current model, addressed in the extension section of the report.

Recommendations and Managerial Implications

Overall, the campaign for this cosmetic product is ineffective and may be counterproductive to the sales volume. To specify, offline marketing methods by sending catalogues to customers are most ineffective. This may result from incorrect customer segmentation, offensive campaign slogans etc.

The absolute elasticity values for all marketing channels are low. -0.0058 (Catalogs to Existing Customers), 0.1776 (Portals), and 0.0259 (Newsletter). Low elasticity suggests that the performance of the channel is relatively insensitive to the advertising input.

Currently, the most effective advertising method is through the portal channels, since it is the only statistically significant variable and it is comparably most elastic; thus, the company should prioritize allocating their advertising resources to their portal channels.

I. Robustness Check

We further investigated ways to test for the robustness of the focal model (3) of the company and seek improvement if needed. All of the results from the models we mainly explored are in Figure 8.

When we used a logarithmic transformation instead of square root to express the diminishing return effect, as shown in model (4), the R-squared and adjusted R-squared increased significantly. Thus, log transformations may be better for some variables in advertisement.

$$Sales_t = \beta_o + \lambda\ Sales_{t-1} + \beta_1\ Log(Catalog\ for\ Exisiting\ Customer_t) + \beta_2 \log(\text{Newletter}_t) + \beta_3 \log(\text{Portal}_t) + + \varepsilon_t \quad (4)$$

We then tried excluding the lagging effect with model (5), which showed that ruling out lagging effects worsens the model performance, indicated by higher AIC and BIC score. Thus, the sales amount is affected by the leftover effect from advertisement from previous periods, and will decay gradually.

$$Sales_t = \beta_1\sqrt{CatalogforExistingCustomer}_t + \beta_2\sqrt{News\ Letter}_t + \beta_3\sqrt{Portals_t} + intercept + \epsilon_t \quad (5)$$

Trying the regression from the origin, as specified in model (6), we found higher AIC and BIC scores, indicating the predictive ability deteriorates. It can be explained that when all marketing interventions are taken down, the sales will slowly decay, and eventually remain constant.

$$Sales_t = \lambda Sales_{t-1} + \beta_1\sqrt{CatalogforExistingCustomer}_t + \beta_2\sqrt{News\ Letter}_t + \beta_3\sqrt{Portals_t} + \epsilon_t \quad (6)$$

II. Synergy

We were inspired by the framework from "Advertising Analytics 2.0" (Nichols, 2013), so we introduced synergy to our models below as the most up-to-date technique.

$$Sales_t = \beta_o + \lambda\ Sales_{t-1} + \beta_1\sqrt{\text{Offline Advertisement}_t} + \beta_2\sqrt{\text{Online Advertisement}_t} + \beta_3\sqrt{\text{Offline Advertisement}_t} * \sqrt{\text{Online Advertisement}_t} + \varepsilon_t \quad (7)$$

$$Sales_t = \beta_o + \lambda\ Sales_{t-1} + \beta_1\sqrt{\text{Cata\_Exist}_t} + \beta_2\sqrt{\text{Newletter}_t} + \beta_3\sqrt{\text{Portal}_t} + \beta_4\sqrt{\text{Cata\_Exist}_t} * \sqrt{\text{Newletter}_t} + \beta_5\sqrt{\text{Cata\_Exist}_t} * \sqrt{Portal_t} + \varepsilon_t \quad (8)$$

However, we found all synergy terms to be insignificant on both the aggregate level (7) and individual marketing channel levels (8). These results can be found in Figure 9.

Nevertheless, this does not imply that the firm should account for synergy in its advertisement model. The reason for this insignificance is due to the firm's ineffective marketing campaigns, which cannot generate positive synergy. Cross-marketing channels advertising synergy does exist if marketing activities are conducted properly. Thus, it should be included and tested for existence in the model.

Conclusion

The company's marketing strategy is not performing optimally, with no significant effect detected for overall marketing activities of this cosmetic product. In addition, the company's current model for analyzing the relationship between various advertisements and sales is not ideal. The negative influence from offline marketing channels contribute to the absence of synergy effects.

Though we view our focal model as a relatively good fit in terms of AIC and BIC scores, it does have its limitations. For example, our model is unable to describe the power of missing channels, such as social media. This could see advancements through additional data collection. Our model also lacks seasonality analysis. Thus, we shall find possible lurking variables, such as holiday seasons, as cosmetic product sales are not solely dependent on advertising efforts.

Furthermore, the retargeting variable may exhibit significant effectiveness if using a regression discontinuity design. Since its occurrence depends on different time periods, we can find the average treatment effect by analyzing the difference between pre-retarget and post-retarget sales.

Finally, the diminishing returns to scale between variables can be better captured if using logarithmic transformations. Square root transformations, for instance, cannot correct for skewness. As noted by UCLA's Institute for Digital Research and Investigation, "Zero-inflated poisson regression is used to model count data that has an excess of zero counts. Theory suggests that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently." Therefore, the log transformation that we recommend for the model can be optimized through zero-inflated modeling.

References

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

“Zero-Inflated Poisson Regression | R Data Analysis Examples.” *Stats.idre.ucla.edu*, stats.idre.ucla.edu/r/dae/zip/.

Appendix

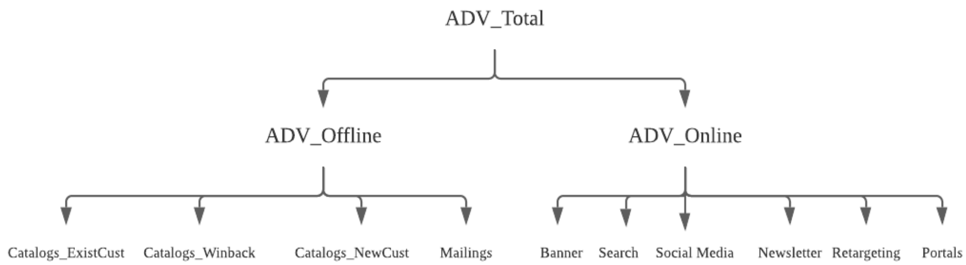

Figure 1: The Hierarchical Tree of Variables

	Sales (units)	ADV_Total	ADV_Offline	Catalogs_ExistCust	Catalogs_Winback	Catalogs_NewCust	Mailings	ADV_online	Banner	Search	SocialMedia	Newsletter	Retargeting	Portals
Sales (units)	1	-0.104	-0.2184	-0.2205	0.1048	-0.0277	-2.0E-04	0.3794	0.2178	0.4161	NA	0.0851	0.2384	0.492
ADV_Total	-0.104	1	0.9798	0.6204	0.6591	0.7608	0.2542	0.045	-0.1347	0.0611	NA	0.2292	0.0871	0.1001
ADV_Offline	-0.2184	0.9798	1	0.6888	0.6162	**0.7059**	0.2647	-0.0829	-0.2626	-0.0465	NA	0.208	-0.0021	-0.0104
Catalogs_ExistCust	-0.2205	0.6204	0.6888	1	0.0447	0.014	0.0645	-0.0193	-0.2122	-0.0188	NA	0.3204	0.0177	0.0107
Catalogs_Winback	0.1048	0.6591	0.6162	0.0447	1	0.7506	0.1587	-0.17	-0.0878	-0.1485	NA	-0.0783	-0.1344	-0.0555
Catalogs_NewCust	-0.0277	0.7608	0.7059	0.014	**0.7506**	1	0.1915	-0.0323	-0.1159	0.0126	NA	0.0494	0.0053	0.036
Mailings	#######	0.2542	0.2647	0.0645	0.1587	0.1915	1	0.0101	-0.2332	0.0916	NA	0.122	0.0497	0.0799
ADV_online	0.3794	0.045	-0.0829	-0.0193	-0.17	-0.0323	0.0101	1	0.6595	0.94	NA	0.1827	0.88	0.8521
Banner	0.2178	-0.1347	-0.2626	-0.2122	-0.0878	-0.1159	-0.2332	0.6595	1	0.4559	NA	-0.0978	0.4635	0.3917
Search	0.4161	0.0611	-0.0465	-0.0188	-0.1485	0.0126	0.0916	0.94	0.4559	1	NA	0.079	**0.8601**	**0.8903**
SocialMedia	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	NA	NA	NA
Newsletter	0.0851	0.2292	0.208	0.3204	-0.0783	0.0494	0.122	0.1827	-0.0978	0.079	NA	1	-0.0692	0.1378
Retargeting	0.2384	0.0871	-0.0021	0.0177	-0.1344	0.0053	0.0497	0.88	0.4635	**0.8601**	NA	-0.0692	1	0.7655
Portals	0.492	0.1001	-0.0104	0.0107	-0.0555	0.036	0.0799	0.8521	0.3917	**0.8903**	NA	0.1378	0.7655	1

Figure 2: The Correlation Matrix of Sales and Marketing Channels

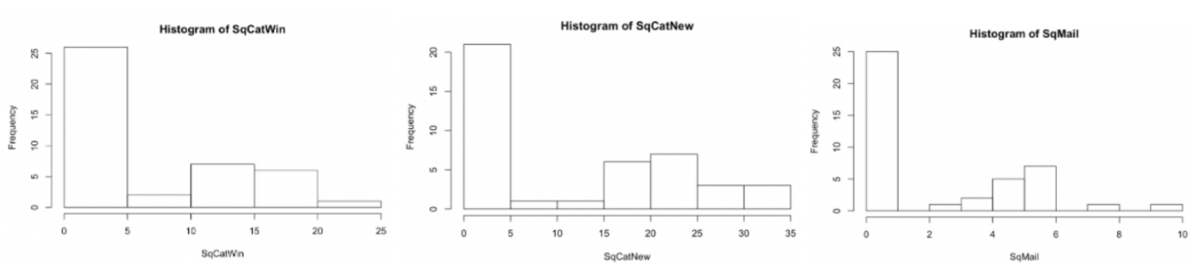

Figure 3: Histograms of SqCatalogs_Winback, SqCatalogs_NewCust, and SqMailings

Variable Name	Variable Description	Number of Observations	Dependent / Independent Variable	Categorical / Continuous Variable
Sales (units)	Sales of items in units in the month	42	Dependent	Continuous
ADV_Total	Total Advertising Spend in the month, comprises ADV_Offline and ADV_Online	42	Independent	Continuous
ADV_Offline	Total Offline Advertising Spend, comprises Catalogs_ExistCust, Catalogs_Winback, Catalogs_NewCust in the month	42	Independent	Continuous
Catalogs_ExistCust	Amount spent on Shopping Catalogs sent to existing Customers in the month	42	Independent	Continuous
ADV_online	Total Online Advertising Spend, comprises Banner, Search, SocialMedia, Newsletter, Retargeting, and Portals in the month	42	Independent	Continuous
Search	Amount spent on Search ads in the month	42	Independent	Continuous
Portals	Amount spent on ad portal advertising in the month	42	Independent	Continuous
Newsletter	Amount spent on Newsletter ads in the month	42	Independent	Continuous

Figure 4: Data Descriptions of Candidate Variables

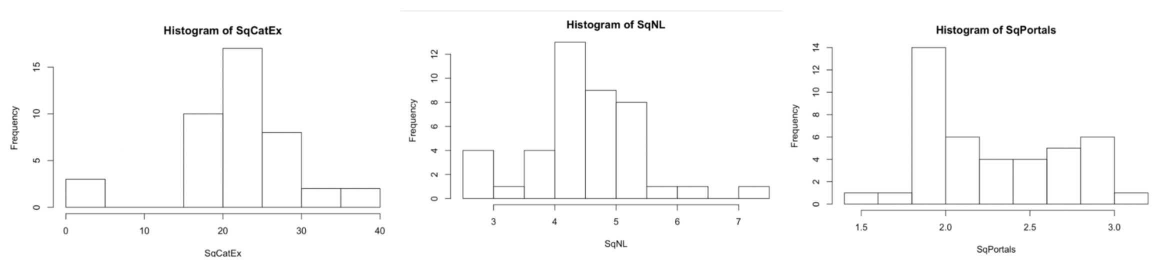

Figure 5: Histograms of SqCatalogs_ExistCust, SqNewsletter, and SqPortal

	Min.	1st. Qu.	Median	Mean	3rd. Qu.	Max
Sales	3355	4406	4690	4809	5195	6976
SqADV_Total	59.61	709.14	924.22	1047.16	1408.27	1971.53
SqADV_Offline	0	24.84	27.76	28.84	35.98	42.6
SqCatalogs_ExistCust	0	18.13	24.45	22.49	25.01	36.04
SqADV_Online	7.1	8.375	9.997	10.317	11.688	17.182
SqSearch	6.178	6.736	8.129	8.223	9.391	11.613
SqPortal	1.595	1.842	2.17	2.252	2.62	3.05
SqNL	2.656	4.086	4.447	4.466	5.013	7.322

Figure 6: Five-Number Summary for Sales and All of the Candidate Variables

	(1)	(2)	(3)
One-period Lagged Sales	0.290 (0.079)	0.113 (0.525)	0.008 (0.965)
Total Advertisement	-2.308 (0.884)		
Offline Advertisement		-12.535 (0.338)	
Catalogs_ ExistCust			-28.000 (0.102)
Online Advertisement		101.221 (0.072)	
NewsLetter			125.300 (0.352)
Portals			860.600** (0.007)
Intercept	3520.433** (0.002)	3613.060** (0.001)	3005.000** (0.005)
R^2	0.09645	0.1848	0.2966
Adjusted-R^2	0.04889	0.1187	0.2184
AIC	664.6756	664.6756	660.6297
BIC	673.2434	673.2434	670.9112
n	41	41	41

Figure 7: Regression Results for Focal Models

Significance levels: * = significant at 10%; ** = significant at 5%; *** = significant at 1%.

	(4) Log	(5) Without Lag Sale	(6) Without Intercept
One-period Lagged Sales	-0.185 (0.263)		0.314* (0.039)
Catalogs_ ExistCust	-251.313** (0.001)	-26.48 (0.079)	-5.543 (0.738)
Newsletter	384.112 (0.207)	92.09 (0.486)	250.208 (0.081)
Portals	1284.917** (0.002)	927.08** (0.001)	1019.131** (0.035)
Intercept	3861.790** (0.002)	2905.76*** (0.000)	
R^2	0.4313	0.3021	0.9774
Adjusted-R^2	0.3681	0.247	0.9749
AIC	651.9162	676.1568	667.8827
BIC	662.1976	684.8452	676.4505
n	41	41	41

Figure 8: Regression Results for Transformed Models

Significance levels: * = significant at 10%; ** = significant at 5%; *** = significant at 1%.

	(7) Aggregated Level with Synergy	(8) Focal Model with Synergy
One-period Lagged Sales	0.1129 (0.5296)	0.005 (0.9722)
Total Advertisement		
Offline Advertisement	-27.6696 (0.5763)	
Catalogs_ ExistCust		-195.6* (0.0386)
Online Advertisement	63.6220 (0.6272)	
NewsLetter		-188.1 (0.5958)
Portals		-177.2 (0.8238)
Intercept	4015.0212* (0.0189)	6708** (0.0044)
Offline Advertisement * Online Advertisement	1.4297 (0.7508)	
Catalogs_ ExistCust * Portals		44.01 (0.1600)
Catalogs_ ExistCust * NewsLetter		14.68 (0.3058)
R^2	0.1871	0.3627
Adjusted-R^2	0.0968	0.2502
AIC	666.5591	660.5825
BIC	676.8405	674.2911
n	41	41

Figure 9: Regression Results for Synergy Models

Significance levels: * = significant at 10%; ** = significant at 5%; *** = significant at 1%.