Individual Assignment

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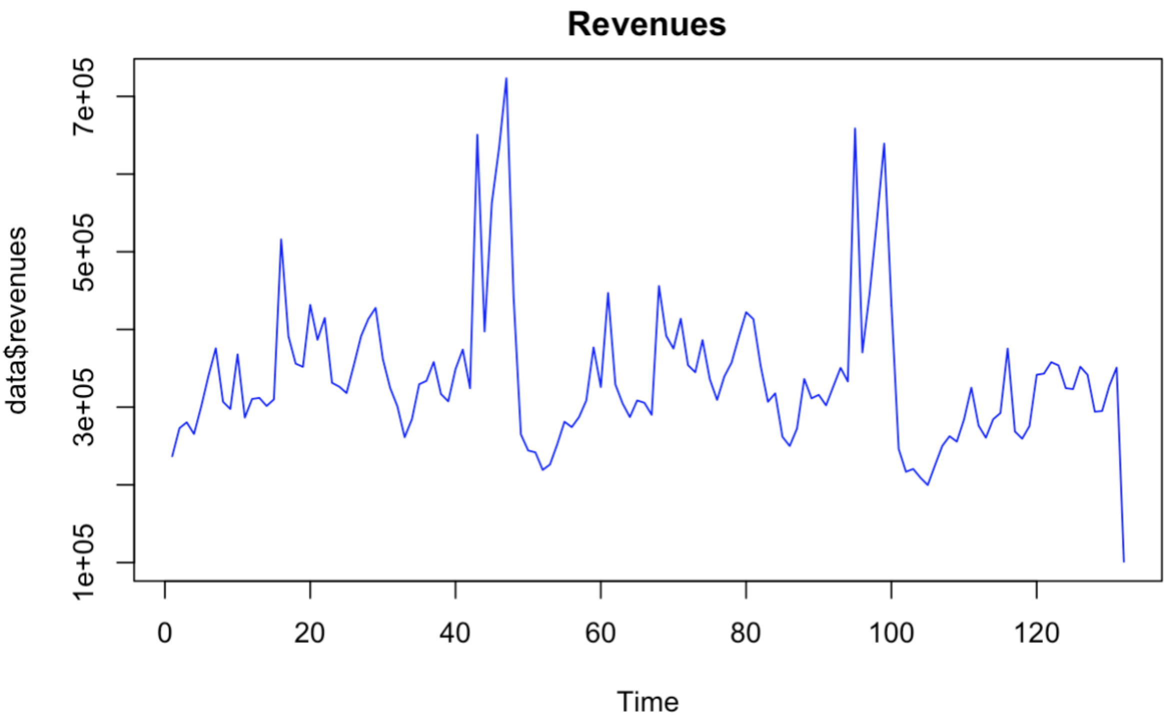
Problem definition

A) Goals and context

This assignment will explore the marketing opportunities offered by the advertising program of an online retailer as well as the importance of its social media community.

The objective will be to better target marketing to increase revenues. As seen in the graph below, over the 132 weeks of data (two and half years) the revenues seem to have an annual seasonality where between week 45 and 50 revenue is much higher than the rest of the year. If week 1 corresponds to the start of a year, these two peaks could represent Black Friday and Christmas, which are two events that generally lead to increased revenues.

Figure 1



If more years of data would have been available, it could have been interesting to see how to distribute marketing spending specifically in those holidays to improve even more revenues during those times. However, as two and half years of data is available, this report will focus on the whole year and will not differentiate between specific weeks.

As no background information is provided for this brand, a few assumptions/clarifications are made to contextualize this report:

- The retailer is selling one brand only, but multiple products from the brand.
- As the brand sells much more around Thanksgiving and Christmas, it is assumed that their products are high-end products bought at a discounted price (Thanksgiving) or as gifts (Christmas).
- The brand only sells online and thus only advertises for its online store.
- As it only has an online presence, and seems to be active on social media, its target audience is young to middle-aged (20-35 years old).

Specifically, this report will explore two different types of marketing. First, the number of social media conversations by topics will be used to understand the importance of the word of mouth on social media to drive revenues.

Then, the influence over the revenues of the three advertising channels that the brand uses and the optimal distribution of the spending will be modeled.

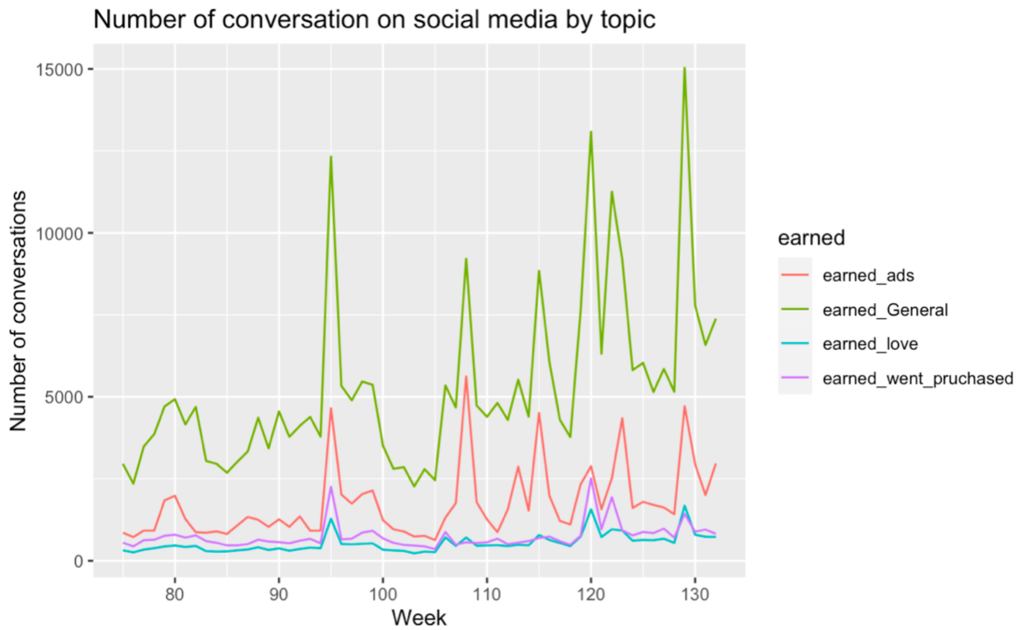
B) Social media conversations topics data

For the first analysis, the 4 following topics of social media conversations for week 75 to 132 (about one year) are counted:

- About the brand (named in the analysis "general"),
- Emphasizing "love the brand" (named "love"),
- Emphasizing "love the ad" (named "ads"),
- Emphasizing "purchased/went to the store" (named "went purchased").

The graph below shows that the brand generates generally little conversation on social media, except for a few specific moments during the year, which seem to follow specific spending in ads. This report will explore the link between the conversation on those 4 topics and revenues to understand the influence of individual topics on revenues.

Figure 2



Another option that this report will not cover is to explore the link between ad spending and the 4 topics of conversations to understand which ads create conversations about which topics.

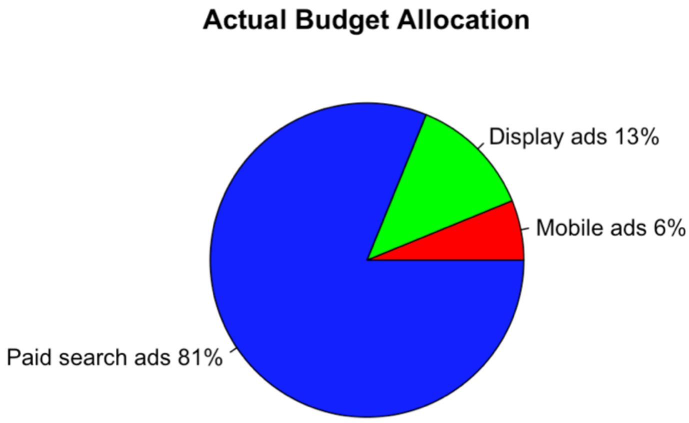
C) Online advertisements data

For the second analysis, 3 types of online advertisements spending are recorded over 132 weeks:

- mobile advertisements, which regroup mobile web and in-app advertisements,
- display advertisements, shown when browsing online, on social media or in YouTube videos,
- paid search advertisements from search engine results pages.

Currently, as the figure below shows, the retailer is spending far more on the paid search ads, since it spends 81% of its budget on it and spends 13% on display ads and 6% on mobile ads.

Figure 3



Performing an analysis to model how much the brand should be spending on each type of ad will show whether their current situation is optimal or can be improved.

Modeling and results

The detail of the code exposed in this section can be found in the linked R file.

After the preparation of the variables for modeling, the effects of social media conversations topics on revenues will first be explored, followed by the analysis of online advertisements spending, which will include its short to long-term effects on revenues, as well as the optimal allocation of the advertising budget to increase revenues.

A) Preliminary analysis

This section contains the preparation of the variables as well as the preliminary diagnostics performed on them before they are used in the later models.

I first took the log value of all the variables to balance out their volatility.

Then, I plotted the ACF and PACF of the variables to see if any of the variables are not stationary. As none of the plots gave very pronounced results (i.e., a large range of values above 0.3), I performed the ADF test for all the variables. For the ADF test, the null hypothesis is that the series is non-stationary. The results of the tests are in the table below:

Variable	Revenues	Mobile	Display	Paid search	general	Ads	Love	Went purchased
p-value	<0.01	<0.01	<0.01	0.01192	0.04394	<0.01	0.05	0.2293

Only the variable 'went purchased' for the social media conversations emphasizing "purchased/went to the store" has a p-value above 0.05, and does not have its null hypothesis rejected. Thus, to make the variable stationary, I will take its first difference, which results, after a new ADF test, in a p-value below 0.01, which allows to reject the null hypothesis and thus this new variable is stationary.

Now that all the variables have been transformed and that the Unit Root tests have been performed, the VAR model can be computed.

B) Social media conversations topics

The objective of the following section is to understand the effects of social media conversations topics on revenues through IRF plots for each of the social media conversation topics. To achieve this, I computed a VAR model as described in the next section.

a) Methodology

I computed the VAR model using the AIC criterion from the 76th week as there is no social media conversations data before week 75 and because the variable 'went purchased' has been differentiated by 1 week. This amounts to week 24 in the 2nd year of data.

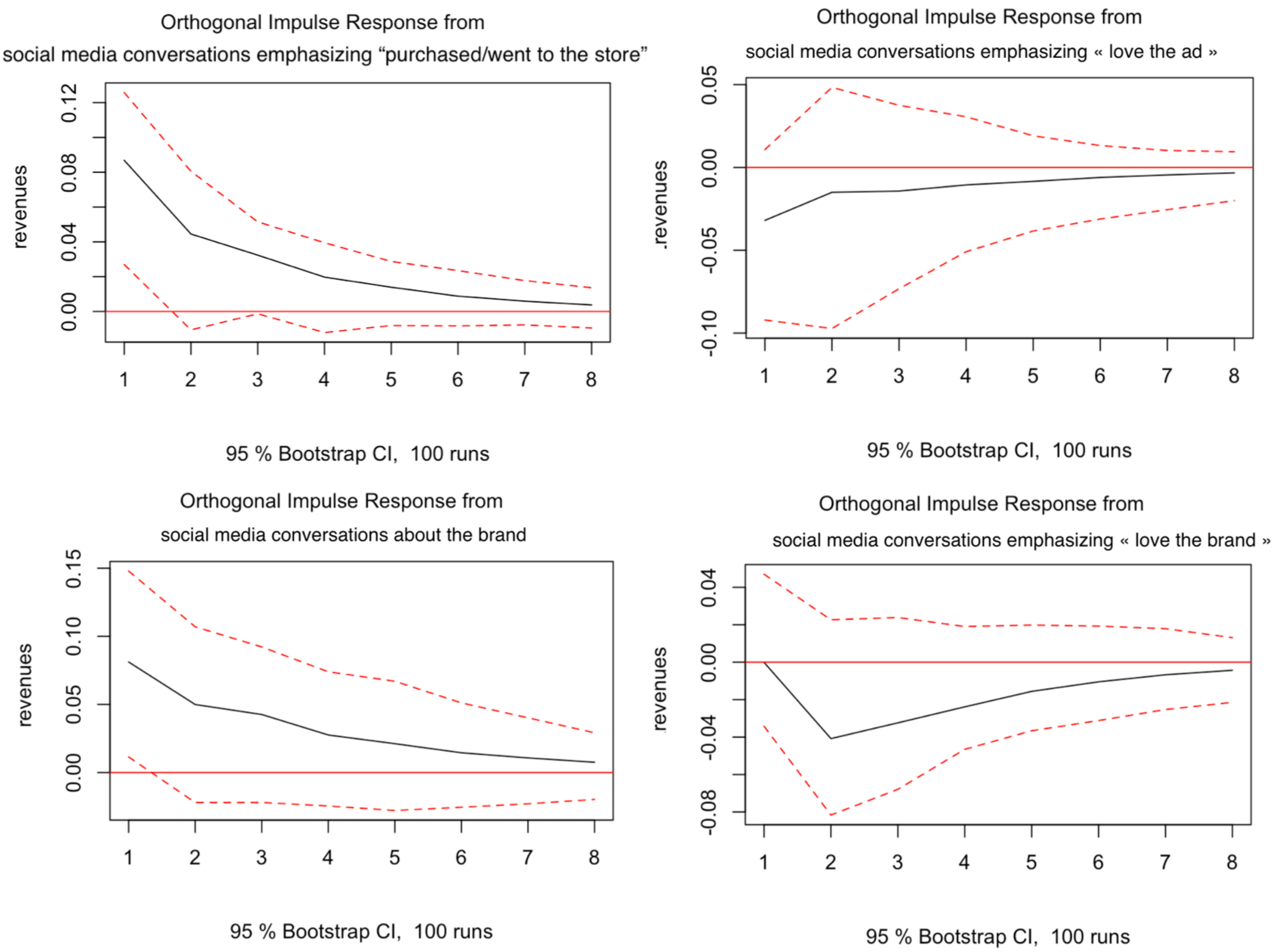
Then, I checked the residual's normality, which did not seem to have any issues as the mean of the residuals was 0, and checked their autocorrelation plot, which had values ranging from -0.5 to 0.5, which I considered showed some correlation but not excessive either.

I then plotted the IRF plots using 7 periods ahead and a 95% confidence interval as shown in the results part.

b) Results

The IRF plots for the four topics are shown below:

<u>Figure 5</u>



Moreover, it can also be noted that general conversation about the brand represents 63% of all conversations, conversations emphasizing "love the ad" 21%, "purchased/went to store" 9% and "love the brand" 6%.

It can be concluded that while conversations emphasizing "purchased/went to store" and conversation about the brand can cause an immediate increase in revenues, conversations emphasizing "love the brand" and "love the ad" seem to have an overall negative impact on the revenues. Specifically, conversations emphasizing "love the brand" seem to have a null impact on the first period, then a very negative impact on the second period to finally get back to a null impact at the end of the 8 weeks. These results need to be mitigated over the low number of data overall (only 1 year of data while online ads spending has 2.5 years) and specifically the low amount of data for conversations emphasizing "purchased/went to store" and "love the brand". If only the general conversations about the brand are considered as they are the larger proportion, the results seem to match what would be expected. Indeed, social media is generally considered are an ephemeral media where only recent publications are remembered and relevant. Thus, it is coherent that the largest impact of conversation about the brand on revenues is during the week of the conversations and that the impact decreases over time.

C) Online advertisements

The objective of the following section is to understand the effects of different channels of online advertisement spending on revenues through IRF plots and the computation of immediate and long-term effects. Finally, the optimal allocation of the advertising budget to increase revenues will be computed from the IRF analysis.

1. Effects on revenues

This section is initially very similar to the social media conversation topics section, as it follows through the same initial step to compute the VAR model and then the IRF plots. However, this section goes further as it computes the immediate and cumulative effects.

a) Methodology

I computed the VAR model using the AIC criterion over the whole data set.

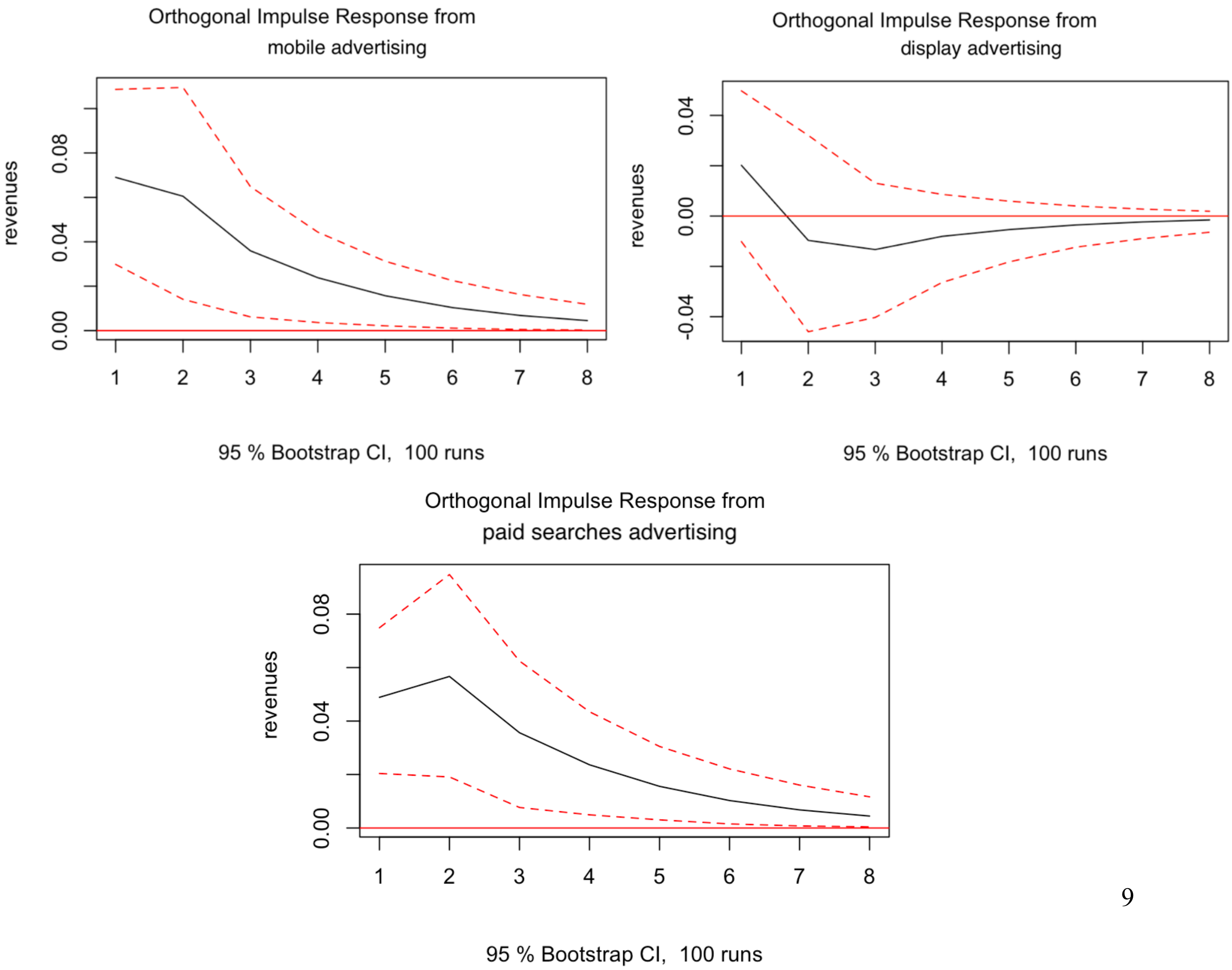
Then, I checked the residual's normality, which also did not seem to have any issues as the mean of the residuals was 0, and checked their autocorrelation plot, which had values ranging from -0.4 to 0.6, and similarly to the previous VAR model, I did not consider the correlation excessive. I then plotted the IRF plots using 7 periods ahead and a 95% confidence interval as shown in the results part.

Finally, I computed the immediate and long-term effects. To do so, I first calculated the t-statistics of the IRF coefficients, then, if a t-statistic of a coefficient was higher than 1 it was considered significant and otherwise the value of the coefficient became 0. Finally, the resulting coefficient in the first period will be the immediate effect and the cumulative effects over all the periods will be the long-run effect.

b) Results

The IRF plots for the three online advertising are shown below:

Figure 6



From the above graphs, it seems that an increase in mobile ad spending can cause an immediate boost of revenues over the first two weeks and then the effects of the mobile ads decrease slowly. However, paid search ads take longer to positively impact revenues as they impact revenues the most on the second week but then also decay overtime to almost reach 0 within the 8 weeks. Display ads also cause an immediate boost of revenues but hurt revenues from the second week to the 8th week. An explanation could be that display ads are generally more repetitively shown to a consumer and thus these ads would need to be displayed constantly for them to have an impact on revenues. Another explanation could also be that the ads displayed over these 2 years were not compelling ads for the high-end products that this retailer sells and were thus performing worse than other types of ads.

Then, the IRF coefficients, including the immediate and cumulative effects for the three types of advertising are summarized in the table below:

	paid	**display**	**mobile**
Immediate effect	0.04887	0.020162	0.069034
week 2	0.056692	0	0.060509
week 3	0.035641	0	0.035948
week 4	0.023644	0	0.023825
week 5	0.015578	0	0.015711
week 6	0.010269	0	0.010355
week 7	0.006769	0	0.006826
week 8	0.004462	0	0.0045
Cumulative effect	0.201926	0.020162	0.226707

An increase in mobile ad and paid search ad spending will have the largest positive impact on revenues in the first and second periods.

A 1% increase in mobile advertising spending will increase the retailer revenues by 0.23% in the long run while a 1% increase in paid searches advertising spending will increase the retailer revenues by 0.20% in the long run.

An increase in display ad spending will have a positive impact (while small) on revenues only in the first period and a 1% increase in display advertising spending will increase the retailer revenues by 0.02% in the long run.

We can thus conclude that while mobile advertising has the biggest impact overall, as well as the largest immediate and cumulative effects, paid search advertising also has a large impact on the increase of revenues. However, display advertising seems to not have as much of an effect on revenues, which could mean that less spending should be used on this type of ad, or more spending should be used to improve the quality of the ad.

2. Optimal advertisements spending budget

This section explores the optimal advertisement spending budget that this high-end online retailer should spend to increase its revenues.

a) Methodology

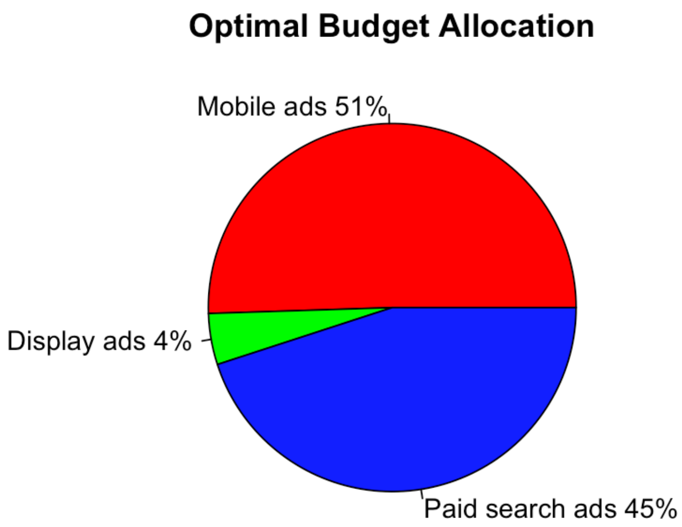
To allocate the budget, the cumulative effects computed in the previous sections are used. The sum of the cumulative effects for the three types of online ads will represent the whole budget. Then, each online advertisement channel will have the proportion of the budget corresponding to its cumulative effect.

b) Results

The resulting budget allocation can be seen in the pie chart below. It can be noted that mobile ads represent just more than half of the total budget at 51%, while they represented before 6% of the overall ad spending. As the total average weekly ad budget was $16,601 over the 132 weeks of the data, it means that $8,467 could be spent on mobile ads each week.

The paid search ads went from representing 81% of the budget to representing 45%. Display ads also decreased importance from 14% to 4%.

Figure 7



It can be noted that while this report considers a weekly spending budget, the historical data shows that ad spending was very different from week to week across all 3 channels.

Moreover, as I do not have the average price of each ad for each channel, I cannot compute how many ads could be bought in each channel. If paid search ads are largely more expansive than mobile ads, it would not necessarily make sense to decrease as much its budget as the number of ads that could be purchased with the new budget would not buy enough ads to have a real impact. On the opposite, if mobile ads are very cheap, increasing its budget by 45% could lead to an extremely large number of mobile ads send that could be too large for the target audience of this retailer. It would thus be necessary to balance the results from this part with the reality of the retailer the online advertising market.

Conclusion

This report underlined the fleeting effect of general social media conversations about the brand, as they led to an increase in revenue in the first week of the conversations, but this effect quickly decayed over time. While this online retailer currently spends most of its advertising budget on paid searches, it should also increase the importance of mobile advertising to increase its revenues. Display advertising however has a very disappointing effect on revenues, as its importance in the overall advertising spending should be decreased, or a new ad campaign should be created to increase its effect on revenues. It is thus important that analyses such as the one pursued in this report are computed regularly by retailers as they change their marketing strategy and spending.