IDS 701 UNIFYING DATA SCIENCE, SPRING 2021

Facebook Promotional Strategy - AB Testing

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INTRODUCTION

Social Media has evolved as the most ubiquitous form of media today. Given this, advertising on social media has become one of the most effective ways to reach one's target audience. An important question that then comes up for businesses or organizations, is what promotional strategy to invest in.

In this project, we aim to gain basic insights into advertising on social media to help answer that question. Given that most of the advertisements on Social Media either take the form of a photo or a video, comparing the performance of these two generic types of advertising would be helpful by allowing us to understand which of the two is better and worth building upon.

To do so, we run two advertisements, photo-based and video-based, to promote the Facebook page of a musical band owned by one of our team members. We then attempt to answer the question which promotional strategy to invest in, by analyzing which of the two advertisements has higher popularity (provides more page likes) for the same amount of investment. We also further look at how the advertisements fare across genders, to gain deeper insight. Thus, we look at the cost per likes[1] and find the one with lower cost per likes. We then look at which of the two advertisements has a lower cost per like for male and female audiences respectively to understand the differences across genders[2].

Through the experiment, we find that compared to the photo-based advertisement, the video-based advertisement has a lower cost per like with high significance. Hence, the analysis finds that a video advertisement might be a good choice for music bands, or generally speaking organizations to invest in. Further, we find that the video advertisement seems to be a better strategy for audiences of both genders, especially females.

BACKGROUND

Brands grow by reaching out to widespread audiences. This is particularly so for Musical Bands, who grow by sharing their music to large audiences. A thorough understanding of the user persona is important when facing this enormous market. When promoting their music, learning which promotion strategy would yield highest number of page likes is of vital importance.

[1] Cost Per Like = Amount of Money spent to get 1 Page Like

[2] Based on the only information available via the experiment. Explained in the methodology section

Targeting the user preference will help us understand the way to best cost per page likes. Thus, we intend to figure out the persona to trigger further promotions based on the market.

For this, the most basic forms of advertisements on social media are either some sort of a picture or a video. We thus decide to use these basic forms for comparison and find which of the two should be enhanced further and advertised for promotions. Besides, as many businesses or musical bands are start-ups, keeping cost at a low level while attracting users as much as possible is equally important. Thus, we ran a small online test to understand what might be better and cost-effective to go with for real promotions.

DESIGN

We attempt to understand which promotional advertisement strategy between the two - photos and videos [3]- works better for promotion using a Musical Band's Facebook Page. We use the same to get insights into which form of advertisement gets more receptivity and would be worth investing in.

To understand the performance of each advertisement in getting more popularity/likes, we run a split test via the Facebook Ads Manager to compare the two. We create two Facebook advertisement posts - one containing a still photo and the other containing a video for the purposes of running this experiment. The two advertisements are then simultaneously released to the same audience. This allows us to compare the two as though the two groups were completely at par in all regards.

Further, we use the 'Cost per like' to be a good metric to compare their performances. Cost per like looks at what amount of money should an organization (Musical Band here) spend to get one like. The lower the amount spent to get one like the more beneficial it is for the organization. Thus, we decide to look at the metric of 'cost per likes' so as to understand which advertisement would allow us to create more popularity for lesser investment.

We choose the audience to belong to the countries United States of America, Canada, United Kingdom, and France and in the age of 18 - 65 years of age. We also ensure that the audience is a completely new one, to avoid any baseline differences or biases that could creep in otherwise due to the pre-existing fan base. We also turn off Facebook's advertisement optimization algorithm to make the audiences as random as possible; and avoid baseline differences, spill-over effects and differential treatment effects.

With the grace of the MIDS department at Duke University with a financial support of $500 for the project, we conducted this experiment with a total budget of $500.

We first undertake a couple of pilot experiments to get a basic sense of how the advertisements are performing and how to setup the final experiment. These mimic the actual tests to be run, but for much shorter periods. The first of the pilots works by creating a "Learn More" button (Fig. 1,Fig. 2), associated with each of those adds, clicking on which redirects the users to the Band's Facebook Page.The number of clicks are then monitored to gauge the interest among people. However, this button elicits a very lukewarm respondent turnover with only 0.001% of people interacting.

We then run a second pilot which works by creating a "Like button" (Fig. 3, Fig. 4), that

[3]Click here for Video Link

Figure 1: Photo Ad Trial - Pilot 1

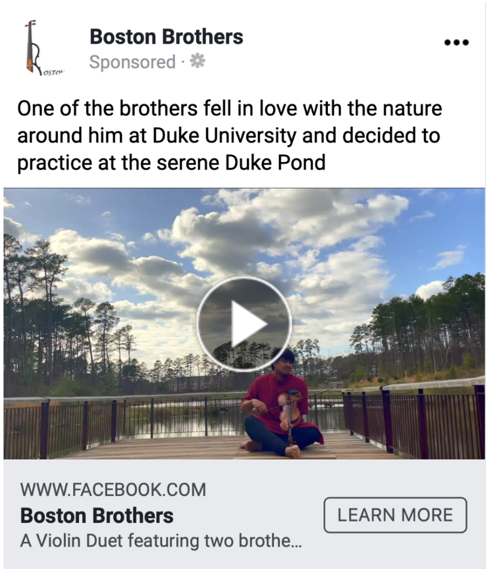

Figure 2: Video Ad Trial - Pilot 1

instantly allows users to like the Band's page instead of redirecting users. The second pilot shows substantial respondent interaction and hence, is chosen as a base for the final experiment.

Figure 3: Photo Ad - Pilot 2

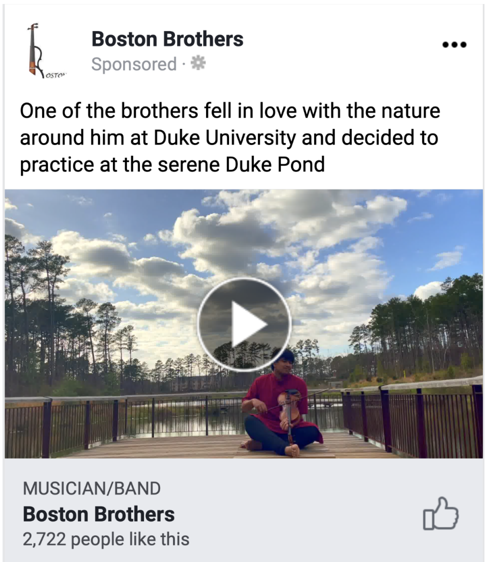

Figure 4: Video Ad - Pilot 2

We allocated \$80 from the total budget for running these pilot advertisements and decided to use the remaining \$420 to run the actual experiment. Based on the results of the second pilot, we then undertake power calculations, to find out the number of respondents that need to be reached in total to be able to conclude that the results from our final experiments are indeed statistically significant and sound. For the power calculations, we decide to use the standard values of alpha() as 5% (Percent of the time a difference will be detected, assuming one does not exist) and beta(β) as 5% (i.e. 100-5 = 95 Percent of the time the minimum effect size will be detected, assuming it exists). These define how accurate our model would be. We then use the lower of the two conversion rates (1.34%) and a 0.5% of Minimum

Detectable Effect (mde,the smallest effect that will be detected 95% of the time) on the absolute scale. We then calculate the total sample size as under using the online calculator (Sample-size calculator):

$$Samplesize = \frac{(t_{1-\frac{\alpha}{2}}\sqrt{2\beta(1-\beta)} + t_{\beta}\sqrt{\beta(1-\beta)+\beta(1+mde)(1-\beta(1-mde))})^2}{(\beta(1-mde))^2} \tag{1}$$

which gives us a total sample size of 14866 people per advertisement.

Facebook's Ad manager provides a range of estimated daily ad reach based on the daily financial investment spent. While designing the final experiment, Facebook estimated that $30 per day will have an ad reach 1.7K - 5.0K people. The trial runs indicated that while Facebook estimated this range of reach, in practice, the actual reach is below the mean of the estimated reach. Hence, given the financial budget at hand for the final experiment ($210 for each ad) and the calculations above, we realized that running an ad for $30 per day for 7 days would aptly fit our experiment (our power calculation sample size and the budget). We chose the same audience as before and with the same settings as in the second pilot project to consider parity between the two. Facebook show the ads to a randomized sample of population chosen from the selected demographic factors. Everyday, each ad (photo and video) costs $30 to run. The daily cost per like for a given ad is calculated by dividing $30 with the daily number of new page likes due to the particular ad. We then run the t-test calculations and regressions over it to find out the performance.

RESULTS

After running the experiments, we gathered the daily data in terms of cost per like, page likes, reach, impression, male and female likes. From these we first checked the balance between the two groups in terms of the daily reach and male-female likes. On running a t-test on the metrics above across the two advertisement groups, we find that the groups are near-to-being balanced with respect to reach and are balanced in terms of the proportion of male and female i.e. the proportion of male-female reach is balanced across groups. This provides weight to our analysis as the groups are at par.[4]

COST PER LIKES

We find that the average cost per like overall for the photo-based advertisement is 0.706 and the average cost per like for the video-based advertisement is 0.564. This indicates that video ads are likely to result in more likes when compared to photo ads with the same amount of financial investment. We vet this further through a T-test on the daily data of cost per likes for both the ads and observe that there is statistical significance[5] between the cost per likes for both ads. In a nutshell, the video-based advertisement seem to be a better investment.

On running a regression model of Cost per Like by the type of ad (baseline is photo ad), it is found that the video ad has a -0.1414 coefficient and a p-value of less than 0.05, therefore suggesting that the cost per like for the video ad is lower than that of the photo ad by $0.14 in this particular case. This, however can't be generalized given the specifics used in the experiment.

[4] Refer Appendix.
[5] p-value less than 0.05. Refer Appendix

We further explored the results by separating the cost per likes by gender (for male and female) to understand the differences. A similar trend where the cost per like for the photo ad is more than the cost per like for the video ad is also noticed amongst the genders. For female, the average cost per like for the photo ad and video ad are 0.7843 ($\tilde{7}8$ cents) and 0.5814 ($\tilde{5}8$ cents) respectively. This difference is statistically significant with a p value of 0.012. For male, the average cost per like for the photo ad and video ad are 0.8114 ($\tilde{8}1$ cents) and 0.6328 ($\tilde{6}3$ cents) respectively. This difference is very close to the 0.05 statistical significant level with a p value of 0.06. From those, the video ad turned out to be a better pick with the female audiences when compared to male audiences. This suggests that with target audience as women, the video is more likely to be cost-effective strategy while not necessarily so for the male target audiences.

From these, we gauge that video-based advertisement seemed to be a better promotional strategy that allows the band to gain higher popularity for the same amount spent. Further, we find that it seems to be a good promotional strategy across genders. But, especially so for female audiences when compared to male audiences.

CONCLUSION

In a nutshell, we try to understand which promotional strategy works better to promote a brand (here a musical band). We analyze the strategy in terms of cost per like and find that the video-based advertisement promotional strategy seems to be a more cost-effective strategy to build upon. The video advertisement has lower cost per like and is more cost friendly. Further, we find that the strategy seems to be a good one irrespective of the genders, but especially so for women.

The project is further limited by a few more issues. We notice that there is some variation across the gender and age sub-groups. However, there is nothing conclusive that could be found across the subgroups suggesting that further investigation may be required with better data collection strategies and resources. Besides, due to the limited amount of information that could be gathered, we could not address the variation across the sub-groups and how it mattered. This could be a possible limitation to the experiment's internal validity and may be better addressed with a more thorough advertisement analytics with higher transparency. It is also to kept in mind that the audience may react differently in different cases, and hence, the results may not be very generalizable.

The result is for users within the United States of America, United Kingdom, Canada, and France. It is not applicable for users outside these four countries. For promotion in other countries, it is necessary to run the other experiment. Also, the focus of the main goal of the advertisement may change across organizations requiring a newer analysis. We should be wary of what matters in a particular situation before using these insights.

However, from the results of the project, a video-based advertisement can be considered as a promotional strategy worth investing in, enhancing it further to make it even more worthwhile!

Appendix

Data Dictionary

Facebook : Facebook is a social networking site with over 2.5 billion users (as of April 2021)
Facebook Ads Manager: It is an all-in-one tool for viewing current and former ad campaigns
Like : Users click on the Like Button to showing support for the Page want to see content from it.
Cost Per Like : The amount of money that needs to be spent to get 1 page like.
Facebook Page : Facebook pages are where artists, public figures, businesses, brands, organizations and nonprofits can connect with their fans or customers. When a Facebook user likes a Page, they can start seeing updates from that Page in their News Feed (For more info: www.facebook.com/help).

Regression Output

Dep. Variable:	Cost_per_Result	**R-squared:**	0.752
Model:	OLS	**Adj. R-squared:**	0.731
Method:	Least Squares	**F-statistic:**	36.30
Date:	Wed, 14 Apr 2021	**Prob (F-statistic):**	5.98e-05
Time:	22:53:07	**Log-Likelihood:**	24.971
No. Observations:	14	**AIC:**	-45.94
Df Residuals:	12	**BIC:**	-44.66
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.7057	0.017	42.517	0.000	0.670	0.742
Advertisement[T.Video]	-0.1414	0.023	-6.025	0.000	-0.193	-0.090

Omnibus:	2.611	**Durbin-Watson:**	0.597
Prob(Omnibus):	0.271	**Jarque-Bera (JB):**	1.235
Skew:	-0.726	**Prob(JB):**	0.539
Kurtosis:	3.092	**Cond. No.**	2.62

Figure 5: Cost Per Like ~ Type of Ad Regression Model Output

OLS Regression Results

Dep. Variable:	Cost_per_Result	**R-squared:**	0.789
Model:	OLS	**Adj. R-squared:**	0.750
Method:	Least Squares	**F-statistic:**	20.54
Date:	Wed, 14 Apr 2021	**Prob (F-statistic):**	0.000193
Time:	22:53:27	**Log-Likelihood:**	26.108
No. Observations:	14	**AIC:**	-46.22
Df Residuals:	11	**BIC:**	-44.30
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.6778	0.026	26.446	0.000	0.621	0.734
Advertisement[T.Video]	-0.1617	0.027	-6.017	0.000	-0.221	-0.103
Daily_Reach	1.432e-05	1.03e-05	1.393	0.191	-8.31e-06	3.7e-05

Omnibus:	1.600	**Durbin-Watson:**	1.159
Prob(Omnibus):	0.449	**Jarque-Bera (JB):**	0.378
Skew:	-0.373	**Prob(JB):**	0.828
Kurtosis:	3.305	**Cond. No.**	7.11e+03

Figure 6: Cost Per Like ~ Daily Reach + Type of Ad Regression Model Output

OLS Regression Results

Dep. Variable:	Cost_per_Result	**R-squared:**	0.838
Model:	OLS	**Adj. R-squared:**	0.789
Method:	Least Squares	**F-statistic:**	17.18
Date:	Wed, 14 Apr 2021	**Prob (F-statistic):**	0.000285
Time:	22:53:54	**Log-Likelihood:**	27.943
No. Observations:	14	**AIC:**	-47.89
Df Residuals:	10	**BIC:**	-45.33
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.6997	0.027	26.143	0.000	0.640	0.759
Advertisement[T.Video]	-0.1569	0.025	-6.310	0.000	-0.212	-0.102
Daily_Male_Reach	8.844e-05	4.38e-05	2.017	0.071	-9.25e-06	0.000
Daily_Female_Reach	-5.965e-05	4.38e-05	-1.363	0.203	-0.000	3.79e-05

Omnibus:	2.676	**Durbin-Watson:**	1.316
Prob(Omnibus):	0.262	**Jarque-Bera (JB):**	0.964
Skew:	-0.608	**Prob(JB):**	0.617
Kurtosis:	3.416	**Cond. No.**	5.53e+03

Figure 7: Cost Per Like ~ Type of Ad + Male Reach + Female Reach Regression Model Output

OLS Regression Results

Dep. Variable:	Daily_Male_CPR	**R-squared:**	0.258
Model:	OLS	**Adj. R-squared:**	0.196
Method:	Least Squares	**F-statistic:**	4.177
Date:	Tue, 27 Apr 2021	**Prob (F-statistic):**	0.0636
Time:	22:39:44	**Log-Likelihood:**	6.5706
No. Observations:	14	**AIC:**	-9.141
Df Residuals:	12	**BIC:**	-7.863
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.8114	0.062	13.134	0.000	0.677	0.946
Advertisement[T.Video]	-0.1786	0.087	-2.044	0.064	-0.369	0.012

Omnibus:	2.251	**Durbin-Watson:**	2.163
Prob(Omnibus):	0.324	**Jarque-Bera (JB):**	1.407
Skew:	0.536	**Prob(JB):**	0.495
Kurtosis:	1.875	**Cond. No.**	2.62

Figure 8: Male Cost per Like ~ Type of Ad Regression Model Output

OLS Regression Results

Dep. Variable:	Daily_Female_CPR	**R-squared:**	0.418
Model:	OLS	**Adj. R-squared:**	0.370
Method:	Least Squares	**F-statistic:**	8.622
Date:	Tue, 27 Apr 2021	**Prob (F-statistic):**	0.0125
Time:	22:39:44	**Log-Likelihood:**	9.8583
No. Observations:	14	**AIC:**	-15.72
Df Residuals:	12	**BIC:**	-14.44
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.7843	0.049	16.055	0.000	0.678	0.891
Advertisement[T.Video]	-0.2029	0.069	-2.936	0.012	-0.353	-0.052

Omnibus:	1.453	**Durbin-Watson:**	1.600
Prob(Omnibus):	0.484	**Jarque-Bera (JB):**	0.816
Skew:	0.579	**Prob(JB):**	0.665
Kurtosis:	2.759	**Cond. No.**	2.62

Figure 9: Female Cost per Like ~ Type of Ad Regression Model Output