

Paid Advertisement on Facebook: An Evaluation Using a Data Mining Approach

Jen-Peng Huang

Department of Information Management, Southern Taiwan University of Science and Technology, Taiwan

Genesis Sembiring Depari*

Department of Business and Management, Southern Taiwan University of Science and Technology, Taiwan

— *Review of* —
**Integrative
Business &
Economics**
— *Research* —

ABSTRACT

This paper focuses on evaluating the performance of paid publications (paid ads) on Facebook and proposes a managerial implication to maximize the paid publications' performance in reaching as many people as possible with the greatest possible engagement. Artificial neural networks, Garson's algorithm, and support vector machine weighting were used to analyze publication characteristics. The results demonstrate that in terms of number of people reached, paid publications are only 9.52% relevant, compared with 24.35% for post hour, 16.85% for total page likes, and 16.44% for type of publication. With regards to number of comments, likes, and shares, paid advertisement contributes 10.46%, 19.51%, and 15.55% relevance, respectively. Additionally, the real numbers of publication improvements from using paid ads and nonpaid ads are compared and calculated. This paper provides a managerial implication for marketing managers to improve the paid ad performance of company Facebook pages.

Keywords: Social media, Data mining, Paid ads, Artificial Neural Networks.

Received 20 July 2018 | Revised 1 November 2018 | Accepted 15 November 2018.

1. INTRODUCTION

In recent years, social media has been one of the most famous communication platforms among students (Pelling and White, 2009). Social media provides various opportunities such as reaching out to new customers, interacting with current costumers, promoting, and introducing special products or services (Curran et al., 2011). Use of social media as a marketing and promotion tool has been widely recognized as a proven, powerful tool to gain millions of customers (Hanna et al., 2011). Online advertising revenue increased from \$36 million in 2002 to \$6 billion in 2012 and is expected to increase further in the future (Yuan et al., 2013).

In early 2018, there were 132.7 million Internet users in Indonesia, and more than 90% of those Internet users were active on Facebook (wearesocial, 2018). This information reveals huge opportunities for online advertisement through Facebook in Indonesia. For companies that want to promote their products to Indonesia, using Facebook as an online publisher is probably a good strategy. Moreover, 27% of the surveyed respondents in recent studies indicate that Facebook is the most efficient marketing tool for companies with fewer than 500 workers (Needleman, 2014).

Furthermore, most private universities in Malaysia rely on social media to attract new students (Krishnan and Sajilan, 2014).

Facebook as an advertisement tool has two major methods to promote products or services: organic promotion and paid promotion. Through organic promotion, users can create free company pages or individual fan pages, group discussions, or even personal accounts without any charge. However, if companies decide to use organic promotion (without any payment), then the company fan pages must have numerous followers and Facebook mandates some specific publishing policies. By contrast, if companies are willing to spend money on Facebook paid advertisements (paid ads), the reach of the company to potential customers is wider and does not rely solely on the followers of company fan pages. Paid ads benefit the company because potential customers can be targeted without limitation. However, several researchers have discovered that Facebook paid ads do not reach new customers effectively (e.g. Margarida, 2013).

Because paid advertisements are not cheap, each decision must be controllable. The results of each decision should be easily measured. Data mining provides some excellent research methods for analyzing various data sets (Turban et al., 2011). Moreover, data mining is regarded as a powerful tool for extracting information from complex and copious social media data (Barbier and Liu, 2011). Machine learning is a set of data mining methods for analyzing such data sets. Artificial neural networks (ANNs) have been widely used as data mining tools for social media data (e.g. Krebs, 2017).

This research aimed to review the relevance of Facebook paid ads in terms of number of reached people and to gauge the publication engagement of each post by using ANNs. Garson's algorithm was used to interpret the ANN results. In addition, to help marketing managers in optimizing the performance of paid publications, a managerial implication regarding publication was proposed by using support vector machine weight (SVM). The managerial implications consist of a rank of the input variables based on their relevance to reach numerous people and boost engagement of each paid publication.

The results of the study reveal that paid ads accounts for only 9.52% of relevance to total lifetime post reach. Compared with other inputs, such as post hour, total page likes, and types of publications, the reach of paid ads in the post's lifetime was less effective. Paid ads have 10.46%, 15.55%, and 19.51% of the relevance of comments, shares, and likes, respectively. In this paper, a managerial implication strategy based on the importance of each subfeature (Table 1) is proposed to improve paid publication performance. The most relevant subfeatures are then considered as the most important factors in improving total lifetime reach and total engagement. Thus, this relevance rank of subfeatures would be considered when making a publication decision for publishing through the company's Facebook page. The publication decision would specify the post time, post type, post category, and other related strategies. Comprehensive explanation is provided in the managerial implications section.

2. RELATED WORK

Theoretically, a computer should work better than a human brain. Components inside the computer enable remarkable processing ability and memory. However, the human brain is adaptive and continues to learn and thus can manage itself during its long life (Kriesel, 2007). These versatile characteristics were implemented in ANNs for data mining operations (e.g., classification and prediction). ANNs consist of three types of layers: input layers, hidden layers, and output layers. These interconnected groups of artificial neurons propagate information through various connections.

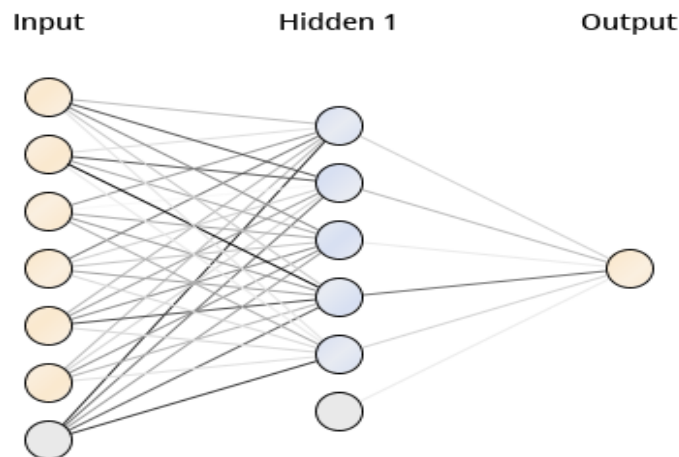


Figure 1 ANNs results using RapidMiner

The effectiveness of ANNs for the analysis of social media data has been proven by some researchers (e.g. Bollen et al., 2011). ANNs proved to be powerful tools in predicting users' emotions through social media post reactions (Krebs, 2017). In the data mining field, the nonlinear training capabilities of ANNs have been widely recognized as an excellent tool especially in large and complicated data set operations (Misra and Dehuri, 2007). Therefore, in this research we used ANNs to analyze the relevance of paid advertisements on Facebook. Because ANNs generate complex hidden layers and output weights, Garson's algorithm was used to interpret the hidden layers and output weights. Garson's algorithm was invented by Garson (1991) and then modified by Goh (1995). The present study used Garson's algorithm to obtain the relative importance of each network input. This relative importance is calculated by three major steps. The first step is to multiply hidden neuron weights and output weights. The second step is to calculate the relative contribution of each hidden neuron. The third step is to calculate the relative importance of the inputs by the relative contribution results. In this study, for determining the importance of each input and subinput of publication characteristics, SVM weighting was employed. SVM considers a data set as a two-group classification problem and determines the best hyperplane (Cortes and Vapnik, 1995).

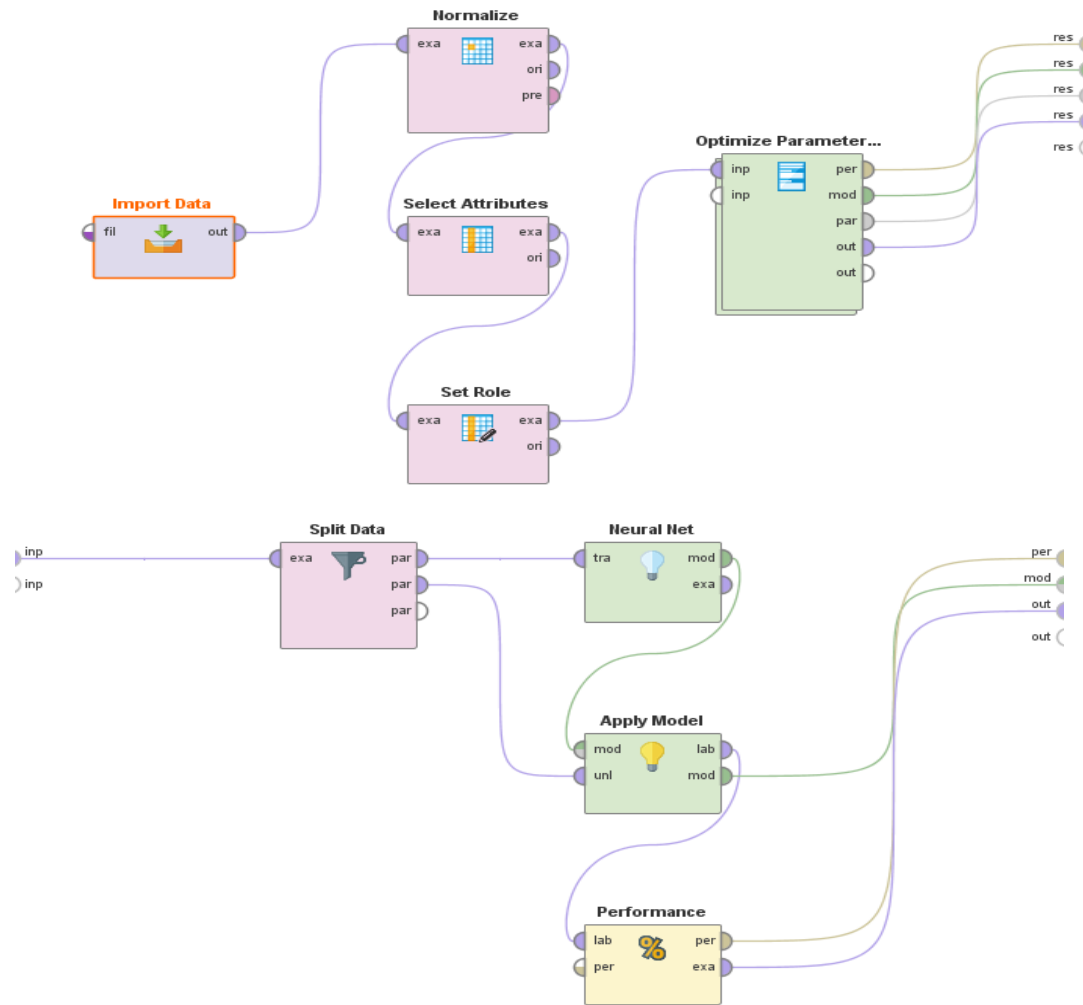


Figure 2. Data mining and optimize parameter processes Using RapidMiner (Grid)

3. DATA AND METHODOLOGY

The data was obtained from a UCI data set and consisted of 500 posts published from a famous cosmetic company (Moro et al., 2016). This data was processed with ANNs to measure the performance of paid ads. To interpret the results of ANNs, Garson's algorithm was used. To guarantee the accuracy of the ANNs, a grid method was used to determine the number of training cycles. Moreover, before the grid method was run, the data was split into two parts; the first part was used as training data (70%) and the second part was used as test data (30%). A complete data mining process using RapidMiner is shown in Fig. 2. Input variables consisted of seven characteristics of each published post and four label variables of company Facebook posts. Details are described in Table 1. First, seven input variables were standardized by using Z-transformation and the dependent variable (Y) was preprocessed into the range {0, 1} using the formula:

$$r_n = \frac{y_n - \min(Y)}{\max(Y) - \min(Y)}$$

Table 1. Features

Features	Role
Pages Total Likes	Input Variables
Type	Input Variables (Photo, Status, link, and Video)
Category	Input Variables (Action, Product, and Inspiration)
Post Month	Input Variables (January-December)
Post Weekday	Input Variables (Sunday-Saturday)
Post Hour	Input Variables (1-24)
Paid	Input Variables (1,0)
Total lifetime post reach	Output or label variable
Comments	Output or label variable
Likes	Output or label variable
Shares	Output or label variable
Total Interactions	Comments + likes + shares

Then, 500 posts' data were used to obtain the hidden layers and output weights. To further analyze the paid ads' effectiveness, we used a sampling method to select and compare 139 paid and 139 nonpaid ads. At the conclusion of this research, a managerial strategy on how to publish a publication was obtained by feeding the seven inputs into the system and analyzing them in terms of SVM weight. This managerial implication is aimed to help marketing managers in selecting ad type, ad category, and ad time, when publishing their company Facebook pages. Because the purpose was to find the best strategy for paid publications, 139 publications that used paid ads were considered.

Table 2. Hidden-output ANNs results

Variable	HN A	HN B	HN C	HN D	HN E
Pages Total Likes	1.567	5.285	-2.702	0.808	-1.696
Type	1.923	4.876	0.373	3.192	-1.809
Category	1.118	1.778	-0.157	2.779	-0.679
Post Month	-1.005	-2.93	3.275	1.324	1.675
Post Weekday	-1.617	-0.026	-0.713	3.272	0.97
Post Hour	-3.627	-1.017	3.061	5.216	-3.438
Paid	-0.065	-1.514	-2.702	0.387	-1.846
Output	-0.477	1.265	-0.726	-0.271	-0.967

4. DISCUSSIONS AND RESULTS

4.1 Paid Ads and Total lifetime post reach

We analyzed the weight of each input variable by using ANNs. To achieve the best possible results, grid search was performed to find the optimal parameters. In grid search analysis, the number of training cycles was set in the range 500–10,000 cycles. The result revealed that the configuration with 1070 (Table 3) training cycles had the smallest root mean squared errors. This observation was used as the specified number of training cycles for analyzing the weights of the seven inputs in relation to the total reach of a post over its entire lifetime. The results are shown in Table 2.

Table 3 Optimized parameters of input variables with respect to total reach (Grid)

Iterations	Training cycles	Root Mean Squared error
1	500	0.15
2	548	0.15
.	.	.
.	.	.
.	.	.
12	1023	0.17
13	1070	0.12
14	1118	0.28
.	.	.
.	.	.
.	.	.
.	.	.
200	9953	0.22

Because the results of ANNs only consist of hidden neuron weights and output weights, we applied Garson's algorithm to interpret the hidden neuron weights. The results of Garson's algorithm are shown in Figure 3. Overall weighting results reveal that the hour of the publication is more important than other inputs (Fig. 3). Post hour makes a 24.35% contribution to total lifetime post reach; total page likes of publications is in second place with 16.85% relevance; type of post is in third place with 16.44% relevance; and post month is in fourth place with 14.57%. Based on these results, we discovered that paid ads through company Facebook pages only have 9.52% relevance to lifetime total reach of a post. Post hour, page total likes, type, post month, and post weekday were determined to have more relevance than paid ads to total lifetime post reach. These results demonstrate that paid ads contribute little to lifetime total reach and post hour was the most relevant factor that enabled publications to reach numerous people. The implication is that a company should pay attention to timely publishing; a company should not randomly publish a post and promote it through paid ads.

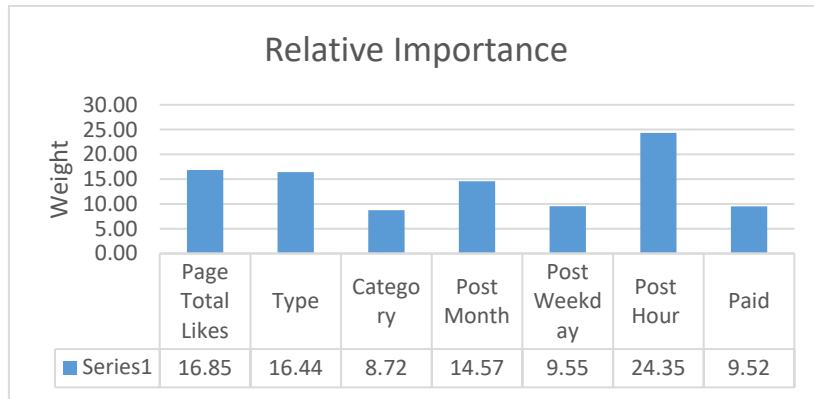


Figure 3. Relative importance of input variables with respect to total lifetime post reach

Furthermore, we compared the total reach values of 139 posts published with paid ads and another 139 posts published without paid ads. The comparison revealed that in terms of total lifetime post reach, publications promoted with paid ads work better than publications without paid ads. The number of people reached with paid ads was 2,681,054 and the number of people reached without paid ads was 1,068,650 (Fig. 4). The publications that use paid ads reach 19,288 people on average; the publications that do not use paid ads reach only 7,688 people on average. Thus, by choosing to pay for ads, a manager can reach more than 150% more potential customers. However, this accomplishment is not enough, because number of people reached does not guarantee transformation to number of real sale of products. The improvement is not solely caused by paid ads, but also supported by some factors such as type, post hour, category (content), post month, pages total likes, and post weekday. Moreover, this research discovered that the post hour and total page likes have more relevance than paid ads in reaching people. Therefore, if the right type of post is published at the right time, it will probably reach more people than a post that solely relies on paid ads without regard for timing or appeal. Extrapolating from the overall weighting process using ANNs, only 9.52% of paid ads support the total lifetime reach of a post. Thus, the contribution of paid ads to number of people reached is not better than the contributions of other inputs such as post hour, pages total likes, and type of publication. Thus, if companies gauged type and time correctly their published posts would probably perform much better in reaching more people than the posts of firms that only rely on paid ads.

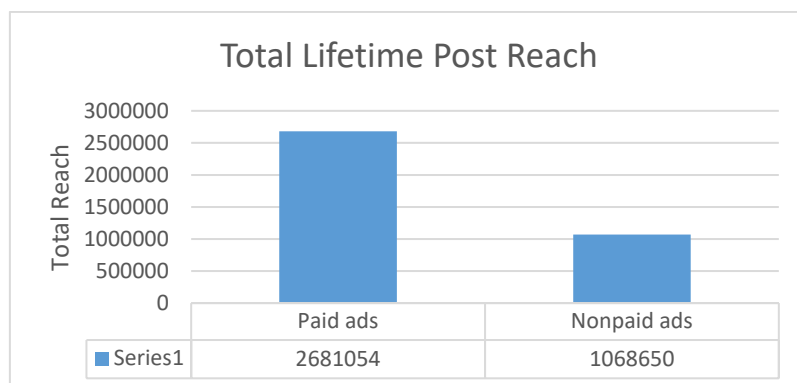


Figure 4 Contribution of paid ads to total lifetime post reach

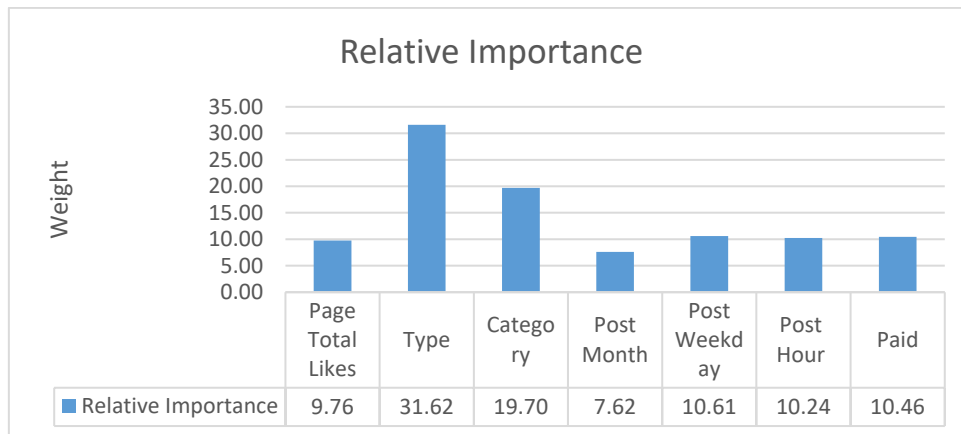


Figure 5 Relative importance of input variables with respect to number of comments

4.2 Paid ads and Comments

To calculate the weights of seven inputs with respect to number of comments, first we determined the number of training cycles using a grid search method. The results proved that 690 training cycles had the lowest error. Therefore, we implemented 690 training cycles to calculate weight with ANNs. Based on the ANNs weighting and Garson’s algorithm results, we understand that type of post has the highest relevance of all inputs (Fig.5). The type of publication has 31% relevance to the number of comments. This insight provides valuable information. To improve the number of comments, publications rely on the type of the publications. Photo, link, video, and status were the types in our research. Regarding the types of publications that contribute to number of comments, the results are discussed in the managerial implication section (section 5). The second most important factor is the category of the post. In our research, post categories were divided into action (special offer), product, and inspiration. Thus, based on these results, we conclude that to generate numerous comments, the type and category are essential. To understand which type and category contribute the most the number of comments, the weight of each subinputs was analyzed using SVM. Those subinput variables are discussed in the managerial implication section.

Table 4 Optimal parameters of input variable with respect to number of comments (Grid)

Iterations	Training Cycles	Root mean squared error
1	500	0.041026
2	548	0.053121
3	595	0.052383
4	643	0.039198
5	690	0.027391
6	738	0.049775
·	·	·
200	9953	0.091451

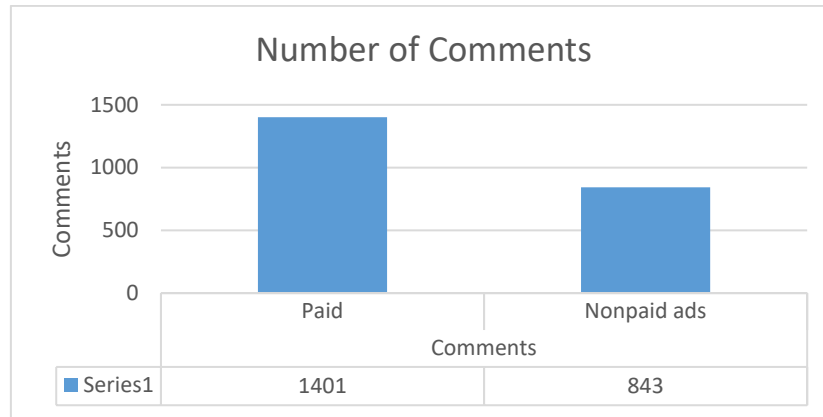


Figure 6 Contribution of paid ads to number of comments

Furthermore, comparing the number of comments between publications with and without paid ads, we observe that publications that used paid ads generated 1,401 comments from 139 publications, compared with 843 comments without paid ads (Fig. 6). Each of the posts that used paid ads generated 10.10 comments on average, and each nonpaid post generated 6.01 on average. This result indicates that paid ads contribute little to comment activity. This calculation is confirmed by the weight of each input variable in the context of the number of comments. Use of paid ads only has a relevance of 10.46 to encourage comments. Type and category are more effective factors that contribute more to encouraging comments.

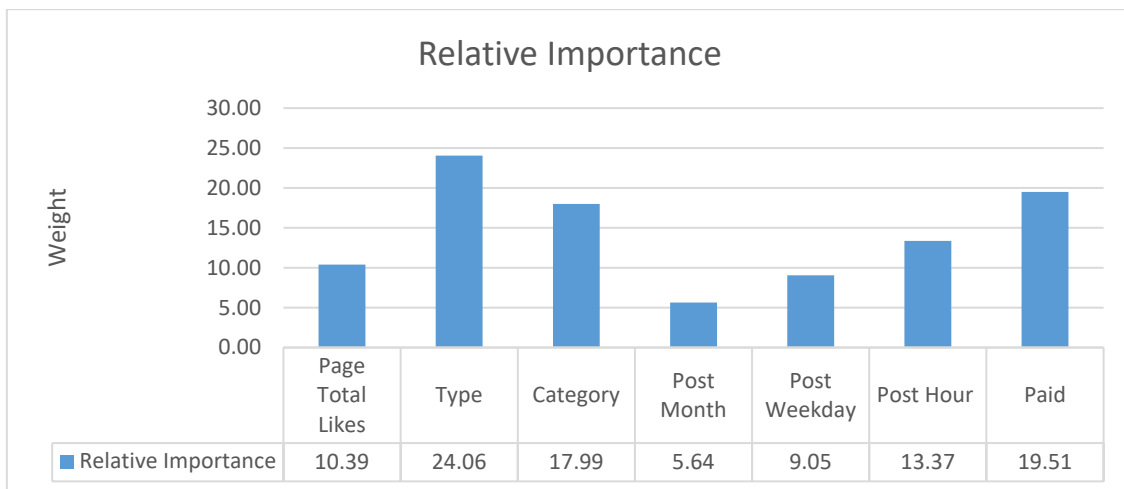


Figure 7. Relative importance of input variables with respect to the number of likes

4.3 Paid ads and Likes

On the basis of grid search optimization, 1,213 training cycles were found to be optimal (Table 5). After performing ANN analysis, we used Garson’s algorithm to interpret the data; the results are shown in Fig. 7. Type of publication was paramount for the number of likes. This result was proven by the ANN input variable weighting. Type of publication contributed 24.06% of the number of likes, followed by paid ads in second place with 19.51%.

Table 5 Optimal parameters of inputs with respect to number of likes (Grid)

Iterations	Training Cycles	Root mean squared error
1	500	0.041068
2	548	0.051143
3	595	0.053334
.	.	.
.	.	.
.	.	.
15	1165	0.06102
16	1213	0.038819
17	1260	0.069318
.	.	.
.	.	.
.	.	.
200	9953	0.091182

This result shows that in supporting number of likes, paid ads function better than supporting comments. Moreover, based on comparison results from 139 publications with paid ads and 139 publications without paid ads, publications with paid ads generated 32,755 total likes and earned 235 likes for each publication on average, compared with 20,458 total likes and 147 likes for each publication on average for publications without paid ads (Figure 8). This implies that paid ads provide 59% more likes. Category of publication provides 17.99% relevance for number of likes. Thus we can conclude that paid ads, type, and category of publication dominate the contributions to number of likes for each publication. Therefore, we conclude that using paid ads and selecting the best type and category of publication would considerably increase the number of likes.

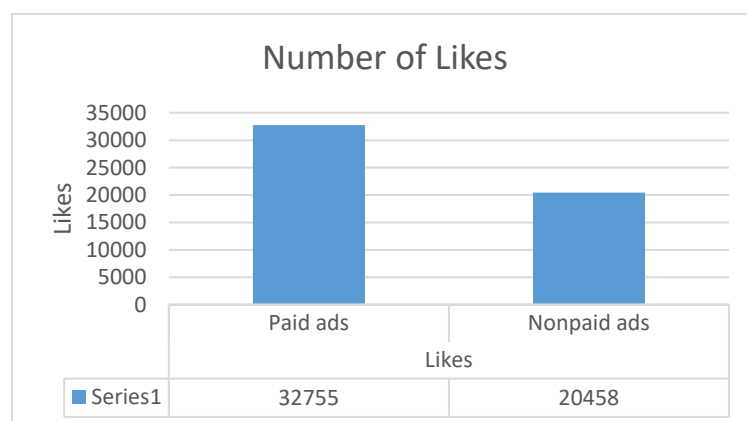


Figure 8. Contribution of paid ads to number of likes

4.4 Paid ads and Shares

Similar to the previous experiments, grid analysis was performed to find the optimal parameters. Thus, 1735 training cycles with 0.029 root mean squared error were determined to be optimal (Table 6). The weights of the seven inputs are shown in Figure 9. Category of publication had a vital role in supporting the number of shares of each publication. The relevance of category attained 21% importance; paid ads provided a 15.55% contribution to the number of shares.

Table 6 Optimal parameters of input variable respect to number of shares (Grid)

Iterations	Training Cycles	Root mean squared error
1	500	0.030315
2	548	0.039944
.	.	.
.	.	.
27	1735	0.029484
28	1783	0.058806
.	.	.
.	.	.
200	9953	0.087521

We considered 139 publications with paid ads and 139 publications without paid ads. The 139 posts with paid ads result in 4,517 shares, an average of 32.49 shares. For nonpaid publications, 3,489 shares were accumulated as organic share reach, an average of 25.01 shares (Figure 10). The percentages of paid and nonpaid publications were quite close. The difference between paid and nonpaid publications in terms of share numbers was 8 shares on average. The improvement of publication with paid ads was 29.46% relative to nonpaid publication. Paid ads had a 15.55% percentage of importance with respect to number of shares.

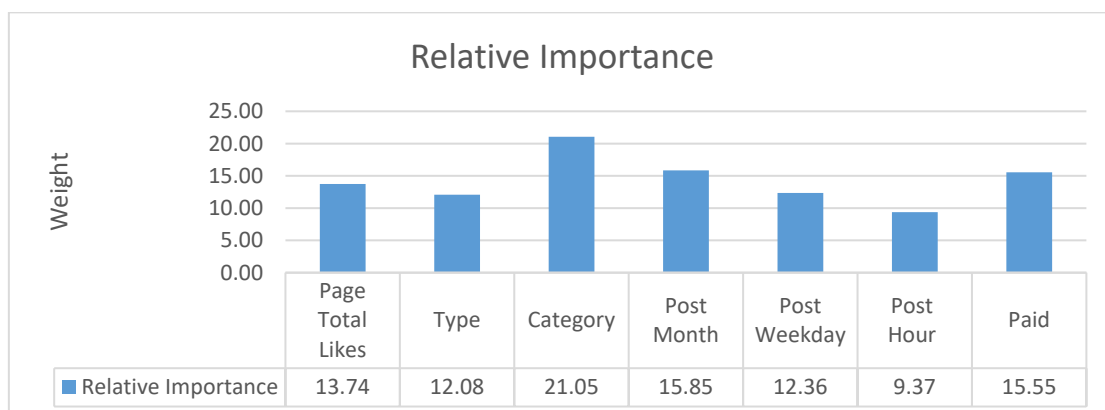


Figure 9 Relative importance of input variables with respect to number of shares

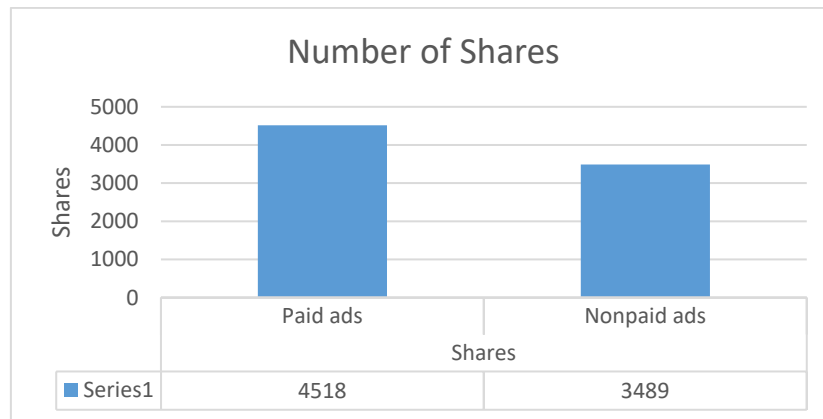


Figure 10. Contribution of paid ads to number of shares

We cannot conclude that paid advertisement is the only factor affecting how many people are reached by company Facebook pages. Other input variables have crucial roles in publications’ performance. In terms of the relevance of the seven inputs, paid ads were not the most relevant factor in supporting publications’ performance. Factors such as, type or category of publication, time of publishing, and the number of followers are important considerations. These results were supported by research conducted by Lee et al (2018). Using 782 companies around the world, they discovered that publications that contained humor and emotion tended to generate high engagement. Some research results demonstrated that Facebook paid ads attracted less user attention than did a friend’s recommendation (Margarida, 2013). Therefore, online advertisement through Facebook does not secure the success of promotional activity (Bačík et al., 2015). Facebook is equipped with a machine recommendation system that generates personalized ads addressing users’ interests; some users might be happy to get such ads (Anand et al., 2009) but also may feel unhappy when they know the company used their data as an advertising tool (Brad, 2010). In some cases, users prefer friend tagging to paid advertisement (Park et al., 2016). These research results suggest that companies should focus on selecting type, category, and time of publishing, instead of spending money on online ads for company Facebook pages. Total page likes were a vital factor in supporting number of reached people and engagement of a publication, thus maximizing the number of followers is necessary. The most important inputs are described in Table 7.

Table 7. Most relevant inputs

	No	Total lifetime post reach	Comments	Likes	Shares
The most relevance inputs	1	Post Hour	Type	Type	Category
	2	Page total likes	Category	Paid ads	Post Months

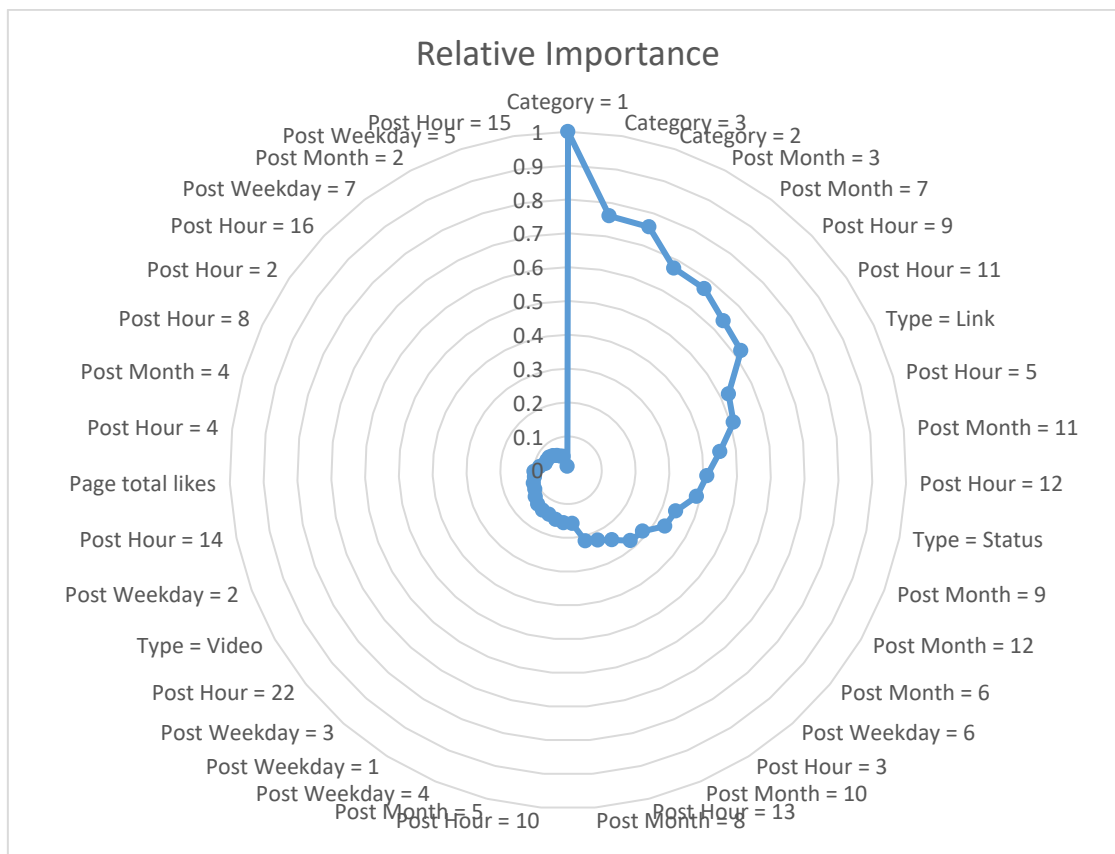


Figure 11 Relative importance of inputs toward total lifetime post reach (only for paid publications)

5. MANAGERIAL IMPLICATION

In this section, we consider 139 publications that used paid ads and we analyze the data through SVM weights. This strategy was implemented to create a managerial implication supporting paid publications. We infer from SVM weight results that special offer (Category 1) has the greatest relevance in supporting total lifetime post reach, followed by inspirations (Category 3), product (category 2), post month and other factors as depicted in Fig. 11. These results can support marketing decisions regarding how to post a publication to reach as many people as possible. Thus, we can conclude that a combination of paid ads and the ranking of the inputs (Fig.11) provides a robust strategy for reaching many people through company Facebook pages.

Furthermore, to understand how the paid publications can be improved to increase the number of engagements, total interactions were used as a label. The results are given in Figure 12. Based on these results, we can conclude that total page likes play a crucial role in number of engagements of each paid publication. These considerations can be used to decide how a publication should be posted and how to maximize engagement. In this case, total page likes is the most important input, followed by post month, type of publication (status), and other factors. Therefore to maximize engagement, a company should first focus on obtaining the greatest possible number of page likes. Generation of page likes could be a topic for future research.

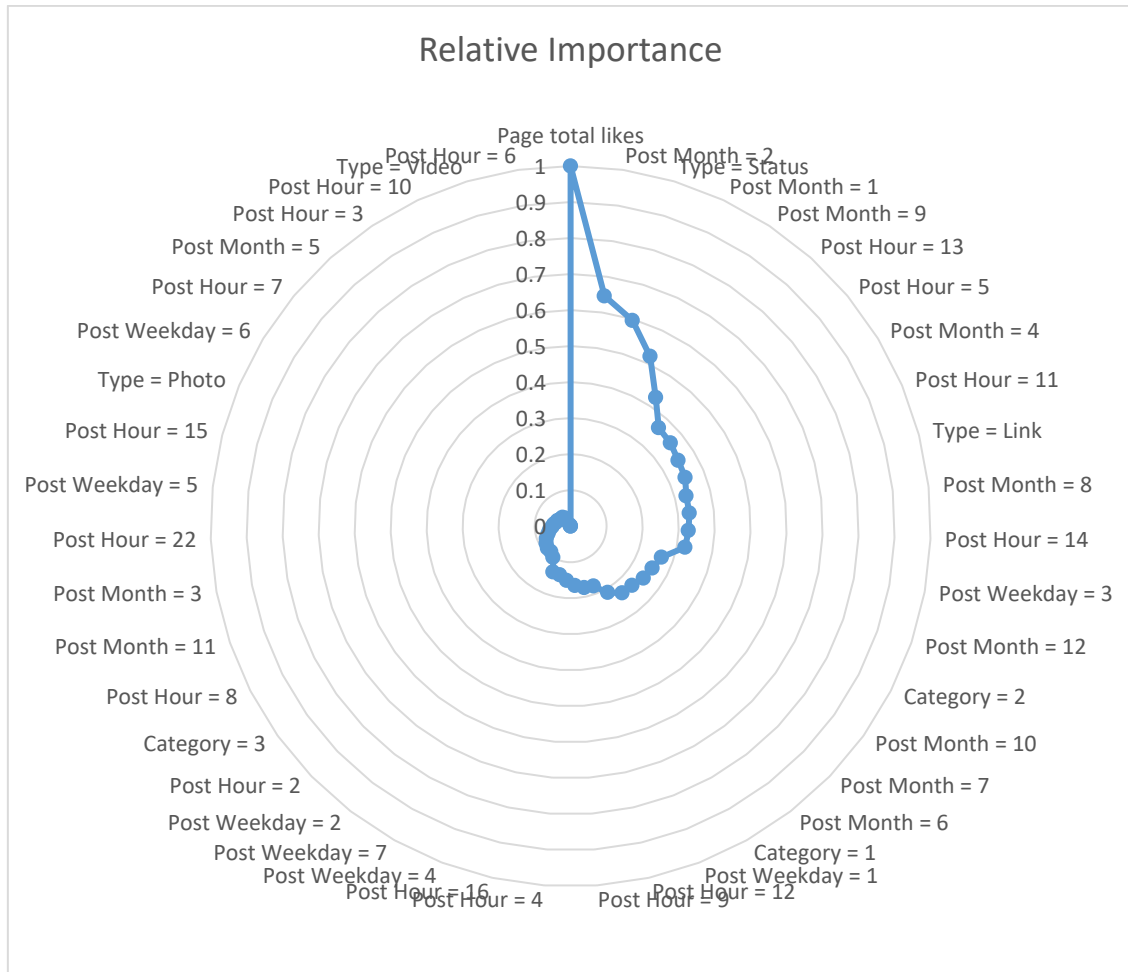


Figure 12 Relative importance of inputs toward total interactions (only for paid publications)

6. CONCLUSIONS AND FUTURE RESEARCH

1. Paid ads contribute 9.52% of total relevance for total lifetime post reach. Post hour, type of publications, and post month have higher contributions to total lifetime post reach. This result provides useful information; instead of solely relying on paid ads, marketers should post the right material at the right time.
2. Publications that used paid ads as a strategy do not have any perceptible impact on number of comments. Paid ads produce an average of 10.10 comments to each post and posts without paid ads average 6.01 comments per post. Type and category of publications have more significant effects on comments. Thus, understanding these aspects may increase comments.
3. In terms of relevance, paid ads support the number of likes better than total lifetime post reach, comments, and shares and improve likes by 59% on average.
4. The importance of paid ads toward number of shares is 15.55%; shares are improved 29.46% if paid ads are used. If we focus on the percentage of relevant inputs to number of likes, then category of publications is the most important factor to number of shares.

Therefore, to maximize shares, companies should understand the category of each post instead of only using paid ads as a publishing strategy.

5. This research results suggest that companies need to understand their publication. Having paid ads is not a bad strategy for reaching potential customers, but combinations of paid ad strategies and other content strategies (time of publishing, type, category, having more pages likes) are highly recommended.

Even if company Facebook pages reach many people and generate excellent engagement, such successes do not guarantee any real sales or revenue. Difficulties exist in measuring performance of such publications in terms of real sales because marketing touch points that affect customers' decisions are vague and hard to predict. The touch points that convert various customer behaviors into real sales should be studied. Based on such research, the allocation of budget to particular marketing strategies could be determined. This process is called marketing attribution. Marketing attribution for online advertising through company Facebook pages is a potential topic for future research.

ACKNOWLEDGEMENT

Author profoundly appreciated all parties for valuable advice and guidance during research process. A special gratitude to Prof Jen-Peng Huang for his efforts in teaching and guidance from the beginning to the end of this research. Moreover, author convey a ton of thanks to academic editors and reviewers of the RIBER's Journal for providing a space to collaborate in international research community.

REFERENCES

- [1] Anand, B.N. and Shachar, R., 2009. Targeted advertising as a signal. *QME*, 7(3), pp.237-266.
- [2] Bačík, R., Fedorko, R., Kakalejčík, L. and Pudło, P., 2015. The importance of Facebook ads in terms of online promotion. *Journal of Applied Economic Sciences*, 10(5), p.35.
- [3] Barbier, G. and Liu, H., 2011. Data mining in social media. In *Social Networks data analytics* (pp. 327-352). Springer, Boston, MA.
- [4] Bollen, J., Mao, H. and Zeng, X., 2011. Twitter mood predicts the stock market. *Journal of computational science*, 2(1), pp.1-8.
- [5] Cortes, C. and Vapnik, V., 1995. Support-vector networks. *Machine learning*, 20(3), pp.273-297.
- [6] Curran, K., Graham, S. and Temple, C., 2011. Advertising on Facebook. *International Journal of E-business Development*, 1(1), pp.26-33.
- [7] Garson, G.D., 1991. Interpreting neural-network connection weights. *AI expert*, 6(4), pp.46-51.
- [8] Goh, A.T., 1995. Back-propagation neural networks for modeling complex systems. *Artificial Intelligence in Engineering*, 9(3), pp.143-151.
- [9] Hanna, R., Rohm, A. and Crittenden, V.L., 2011. We're all connected: The power of the social media ecosystem. *Business Horizons*, 54(3), pp.265-273.

- [10] Krebs, F., Lubascher, B., Moers, T., Schaap, P. and Spanakis, G., 2017. Social Emotion Mining Techniques for Facebook Posts Reaction Prediction. *arXiv preprint arXiv:1712.03249*.
- [11] Kriesel, D., 2007. *A Brief Introduction on Neural Networks*.
- [12] Krishnan, K.S.T. and Sajilan, S., 2014. The Effects of Social Media on Gen Z's Intention to Select Private Universities in Malaysia. *Review of Integrative Business and Economics Research*, 3(2), p.466.
- [13] Lee, D., Hosanagar, K. and Nair, H.S., 2018. Advertising content and consumer engagement on social media: evidence from Facebook. *Management Science*.
- [14] Margarida Barreto, A., 2013. Do users look at banner ads on Facebook?. *Journal of Research in Interactive Marketing*, 7(2), pp.119-139.
- [15] Misra, B.B. and Dehuri, S., 2007. Functional link artificial neural Networks for classification task in data mining.
- [16] Moro, S., Rita, P. and Vala, B., 2016. Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. *Journal of Business Research*, 69(9), pp.3341-3351.
- [17] Needleman, S.E. and Marshall, J., 2014. Facebook ads become costlier choice for small businesses. *The Wall Street Journal*.
- [18] Park, J.Y., Sohn, Y. and Moon, S., 2016, March. Power of Earned Advertising on Social Networks Services: A Case Study of Friend Tagging on Facebook. In *ICWSM* (pp. 299-308).
- [19] Pelling, E.L. and White, K.M., 2009. The theory of planned behavior applied to young people's use of social Networksing web sites. *CyberPsychology & Behavior*, 12(6), pp.755-759.
- [20] Stone, B., 2010. Ads posted on Facebook strike some as off-key. *New York Times*, 3.
- [21] Turban, E., Sharda, R., Delen, D., & Efraim, T. (2011). *Decision support and business intelligence systems* (9th ed.). Pearson.
- [22] We Are Social, 2018, "Digital in 2018: World's Internet Users Pass The 4 Billion Mark", <https://wearesocial.com/blog/2018/01/global-digital-report-2018> (June 2018).
- [23] Yuan, S., Wang, J. and Zhao, X., 2013, August. Real-time bidding for online advertising: measurement and analysis. In *Proceedings of the Seventh International Workshop on Data Mining for Online Advertising* (p. 3). ACM.