Optimal Diffusion Strategy of Advertising Using a Facebook Application

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Optimal Diffusion Strategy of Advertising using a Facebook Application

ABSTRACT

In 2007, Facebook made a momentous decision to open its platform for independent applications. After that, numerous applications are designed and deployed. From a business perspective, a Facebook application has the characteristics of low development cost and strong word-of-mouth effect, which provide an ideal alternative to traditional advertising format. This paper reveals the diffusion pattern of three leading Facebook applications and concludes that the classic Bass diffusion model can be applied to the diffusion process. Based on Bass model, we further propose a diffusion strategy of advertising using a Facebook application. We find that for a given amount of advertising budget, to achieve a maximum percentage of user installations out of the target population of the application, there exists a unique solution to allocate the budget optimally between activities promoting innovation and imitation effects. Numerical examples are provided to illustrate the optimal solution.

Keywords (Required)

Diffusion, Social Network, Facebook Application, Advertising

INTRODUCTION

Established since 2004, Facebook as a social networking platform has attracted lots of popularity. The latest statistics report from Facebook claims that it has more than 175 million active users and more than 3 billion minutes are spent on Facebook each day. In May 2007, Facebook opened its platform that enables companies and developers to design applications that can be integrated with Facebook website and gain access to information of millions of its users. This means almost everyone can design an application and publish on the social network for free. Since then, Facebook has attracted more than 52,000 applications to the network and 660,000 developers from more than 180 countries. Further, more than 95% of its 150 million users have used at least one application (Facebook 2009).

From a business perspective, the possible exposure of an application in the social network can be a new format of marketing campaign, advertisement displaying, paid sponsorship, etc. Due to the low entry barrier and cost of developing Facebook applications, business with tight marketing budget are valuing Facebook platform as a new field to promote brand and test advertisement. For example, A&E Television Network built a Facebook application called “Parking Wars” to promote its new TV series. The application has users park virtual cars on friends’ profile pages, or “streets”, and users can also issue tickets on cars parked on the “streets”. After three months of launching the application, “Parking Wars” has attracted more than 198,000 unique users. Another example is from Sony. It promoted one of its sweepstakes in conjunction with a popular application and got 1 million participations (King 2008). Hagel and Brown (2008) claim that Facebook application provides a new format of interactive communication and advertising.

The general process of the diffusion of a Facebook application starts from author publishing the application on Facebook. Then the application link will appear in the application directory. Users of Facebook can check the applications via the directory and install them simply by clicking the link and following the consequent steps. After installation, each activity of the user will be listed in a mini-story feed to his/her friends. Friends of the user might get invitation from the user to install the application, or simply get curious about the application because of those mini-story feeds and install the application. This viral aspect of Facebook applications, which is highly valued by online advertisers, can easily diffuse advertising messages using the application through the network of friends.

Diffusion is formally defined as the “process by which an innovation is communicated through certain channels over time among members of a social system” (Rogers 2003). Here in the Facebook context, the innovation is the application and the social system is the network of friends in Facebook. We also decide to use the number of application installations as a proxy for successful communications. Therefore, diffusion process of a Facebook application instilled with advertising messages is basically the process of getting user installations over time.

Although Facebook applications have gained lots of practical deployments as a new social tool for diffusing advertisement, few formal studies exist to reveal a general diffusion pattern of applications. In fact, understanding the diffusion pattern is critical for business interested in investing applications for marketing and advertising. With the knowledge of diffusion...
pattern, applications developed for viral advertising can be measured for effectiveness at any given time point. As we have discussed, the diffusion of a Facebook application is realized through two approaches: direct installation of the application through links in application directory, and indirect installation through friends’ invitations usually in a personal notification list. These two channels can be improved through an advertiser’s activities such as giving rewards for inviting friends, promoting applications in the application directory, and so on. In this study, we empirically verified that the Bass model (Bass 1969) can be used to model the diffusion of Facebook applications. Then we utilize the Bass model to analytically derive an optimal diffusion strategy for advertising, so that an advertiser can maximize the user installation percentage of the target population for a specific advertising application within a given time period.

RELATED WORK
We use the classic Bass diffusion model to study the diffusion of Facebook applications. This model describes the process of how new products get adopted as an interaction between users and potential users (Bass 1969). It is widely used in forecasting, especially product forecasting and technology forecasting.

With regard to viral marketing, Leskovec, Adamic, Huberman (2007) is one of the latest works exploring the effectiveness of peer recommendations. They obtain a counterintuitive result that as peer recommendations increase, they actually lower the probability of a purchase. The maximum purchase probability is reached when there are exactly two recommendations.

As per studies on Facebook applications, Trung (2008) studies an application developed by the author. With the 648-user application, the author obtains the corresponding network structure, the adoption rates, and influence of friends. Here in this paper, we use three of the most popular applications from Facebook and study their diffusion pattern.

THE DIFFUSION MODEL
We use the data from Adonomics. Adonomics was a leading company in providing analytics of Facebook before late 2008. We randomly pick four of the top 10 applications in Adonomics’ leaderboard. One of them, with the name “Causes”, suffers from an obvious data inconsistency problem. Hence, we eliminate that application. Table 1 illustrates the basic data information for the remaining 3 applications.

<table>
<thead>
<tr>
<th>Application Name</th>
<th>Tracked Since</th>
<th>Data Valid till</th>
<th>Target Population</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Super Wall</td>
<td>June 25, 2007</td>
<td>August 29, 2008</td>
<td>38,345,630</td>
<td>Photo, Video</td>
</tr>
<tr>
<td>Movies</td>
<td>June 25, 2007</td>
<td>August 29, 2008</td>
<td>25,245,400</td>
<td>Just for Fun, Video</td>
</tr>
<tr>
<td>Texas HoldEm Poker</td>
<td>June 25, 2007</td>
<td>August 14, 2008</td>
<td>12,978,400</td>
<td>Gaming, Just for Fun</td>
</tr>
</tbody>
</table>

Table 1. Sample Facebook Applications

We use the classic Bass diffusion model (Bass 1969) to fit the number of installations on a daily basis:

\[ F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \]

We follow the timeline starting from the “tracked since” date to the “data valid till” date. Hence the total time unit in the above equation ranges from 438 to 469 days depending on the specific application. \( F(t) \) is the percentage of installations at a certain day based on the target population. Let us explain the target population for an application here. We assume that for each application, the potential reach of the application is the total target population. For example, if the target population of the application is “Female” with “College Degree” and residing in “United States”, the number of population satisfying the above criteria in Facebook is the target population. In fact, the number of target population can be obtained directly through Facebook after the criteria have been selected by the application developer. Here, we use the maximum number of installations during that period as the proxy for the target population because we believe for the given time period (438 to 469 days), the diffusion should have already reached the whole target population. The coefficient \( p \) is called the coefficient of innovation, external influence or advertising effect. The coefficient \( q \) is called the coefficient of imitation, internal influence or word-of-mouth effect. We use the actual installation data to compare with the calculated percentage by plugging in our time unit as well as the innovation and imitation coefficients. In order to fit the actual diffusion curve, we minimize the sum of squared errors for each daily record by changing the imitation coefficient.
We use different innovation coefficient and then find the corresponding optimal imitation coefficient. Table 2 shows the coefficients estimation for both innovation and imitation effect. Further, we provide correlations between the actual and estimated installation percentage to demonstrate the goodness of fit.

$$\varepsilon^2 = \sum (F_{\text{actual}}(t) - F(t))^2$$

We also plot the actual diffusion pattern versus the estimated diffusion in terms of the percentage of installations. Both the innovation and imitation coefficients are chosen when the correlation between actual and estimated installations reaches the maximum. For Movies, we choose to use $p = 0.004$ and $q = 0.00226$, because the maximum correlation reaches when $q = 0$. The chosen correlations are highlighted in bold text in Table 2.

Because the correlation between the actual and estimated percentage of total installations is high, we argue that Bass’s diffusion model can be a good fit to study the characteristics of Facebook applications.

**Lemma 1:** Facebook applications’ diffusion pattern can be modeled using Bass diffusion model with appropriate innovation and imitation coefficients.
OPTIMAL DIFFUSION STRATEGY

The applications studied in the above section are organic-grown applications. By saying that, we mean that those applications follow a natural diffusion pattern to gain user installations. Here we are further interested in a business strategy to intervene and improve the diffusion process. As mentioned in the introduction section, due to the low cost of creating and hosting an application on the Facebook platform, while, on the other hand, the attractiveness of the large potential audience on the Facebook platform, business are seeking advertising solutions via Facebook applications to raise brand awareness and engage audiences' involvements.

In Facebook applications, making recommendation of the application to friends is an essential part of installing the application. We use a simple example to describe the recommendation process in the following. User A finds a BMW Drive application via application directory and decides to install it. During the installation phase, the application will prompt user A a choice to choose friends to take a virtual ride together or have a race. The user can then choose zero to multiple friends to join the application. This installation activity is then turned into a mini-story feed and posted to the home page of each friend of user A. Friends who are chosen by user A to join the application will further receive additional invitation notifications. When user B, who gets the invitation from user A, decides to install the application, similar recommendation procedure is repeated and propagated to the network of friends of user B. Eventually, all users' activities with the application are recorded and feed to the networks of their friends.

From the above description, it is obvious that such word-of-mouth effect or imitation effect in the diffusion path can be easily captured by the developer of the application or the advertiser. In practice, Facebook does provide a detail traffic and usage report on the application to the developer of the application. Therefore, advertisers will be able to observe the diffusion process and improve either the innovation or the word-of-mouth effect. This characteristic is not observed in the traditional format of advertising. For example, for TV commercials and online display banner Ads, advertisers are only interested in the innovation effect, that is, how many people are watching the commercial directly or how many clicks have been generated through the banner Ads directly. Although people getting exposed to the advertisement might recommend it to others, the word-of-mouth effect usually cannot be easily captured by the advertiser.
To facilitate and improve the diffusion of a Facebook application, there are two different approaches. One is to enhance the innovation effect. Promoting an application is no different from promoting a webpage or a product. Advertiser can bid on the sponsor list in specified slots on Facebook platform or other online advertising inventory. They in general adopt either the tradition CPC (pay per click) or CPM (pay per thousand impressions) payment schema. The other approach is to enhance the word-of-mouth or imitation effect, the advertiser can pay viral experts and software developers in the field of Facebook applications to create applications with social network characteristics. Another way is to provide incentives to users for recommendations to friends, or encourage more activities associated with the application so that more stories (feeds) will be generated and posted to friends. For example, TravelBrain used to provide sweepstakes for users who had fulfilled five activities (such as recommending a place to travel, sharing travel tips, writing a review about a place, etc.) within a certain period of time.

Given these two different choices of promoting an application, our research question arises: for a given amount of advertising budget, what is the optimal strategy to allocate the budget wisely between enhancing innovation and imitation effects so that the application can reach a maximum percentage of target population within a certain time period? We hence propose a generalized model to gain insights for diffusion strategy used by advertising.

Most marketing campaigns are constrained by budget. We assume that an advertiser is interested in developing a Facebook application to promote one of its services or products. The traditional advertising approach will usually choose a direct advertising channel to post the advertisement. Hence, the entire advertising budget is used for direct channel. In a Facebook application, the advertiser has to choose appropriate magnitude of investing in both the direct channel – innovation effect and the indirect channel – imitation effect.

From the previous section, we already know that Bass model is appropriate for estimating the diffusion pattern of Facebook applications. Hence, we assume S-curve is appropriate in modeling the percentage of installations of a Facebook application. The goal for an advertiser is to maximize the percentage of installations of its application within a certain time period, T, and with a fixed advertising budget. Let us denote this total budget as C. Without losing generality, we assume that $C = 1$. The percentage of installations of target population at time $T$ is:

$$F = \frac{1 - e^{-(p(k)+q(1-k))T}}{1 + \frac{q(1-k)}{p(k)} e^{-(p(k)+q(1-k))T}},$$

where $p(k)$ denotes the innovation effect being a function of cost $k$ out of the total budget $1, 0 \leq k \leq 1$; and $q(1-k)$ denotes the imitation effect being a function of the remaining budget $(1-k)$. Both the innovation and imitation effects are now functions of cost. Spending money on directly advertising the application can immediately increase the innovation effect while encouraging viral word-of-mouth with monetary incentives can increase the imitation effect. Our purpose is to find a balance point to distribute the advertising budget appropriately. Again, let us make a clarification on the target population, which serves as the base for the percentage of installations. We assume that for each advertising application, the potential reach of the application is the total target population. In other words, the advertiser needs to decide the characteristics of the target population for a specific advertising application. For example, if the target population of the advertisement is “Female” with “College Degree” and residing in “United States”, the number of population satisfying the above criteria in Facebook is the target population. Therefore, the target population is not a generic value applying to all the advertising programs, instead, it is specific to each diffusion model, which can be determined by the advertiser.

we assume that both the innovation and imitation functions are non-decreasing and concave curves of cost, which is a common assumption for quality functions, i.e., $p'(x) \geq 0$ and $p''(x) \leq 0$; $q'(x) \geq 0$ and $q''(x) \leq 0$. In other words, the more budget investing in enhancing innovation (or imitation) effects, the higher the effect’s coefficient. Further, the marginal increase of the effect is decreasing with an increasing budget.

Proposition 1. For a given time period $T$, the optimal diffusion strategy of allocating the advertising budget between activities enhancing innovation and imitation effects should satisfy:

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1 There exist traditional advertising programs to promote products using word-of-mouth or referral incentives. However, the incentives are usually realized only with final purchase of the product instead of just being exposed to the advertisement. Therefore, it is quite unique for Facebook application serving as a media of advertising where the word-of-mouth effect of advertising (instead of purchasing) can be clearly tracked and managed.
\[
\frac{p'(k^*)}{q'(1-k^*)} = p(k^*) \left( \frac{(p(k^*) + q(1-k^*))T - 1 + e^{(p(k^*) + q(1-k^*))T}}{p(k^*)(p(k^*) + q(1-k^*))T + q(1-k^*)} - q(1-k^*)e^{(p(k^*) + q(1-k^*))T} \right).
\]

Proof: the advertiser’s maximization problem is:

\[
\max_k F = \frac{1 - e^{-(p(k)+q(1-k))T}}{1 + \frac{q(1-k)}{p(k)}e^{-(p(k)+q(1-k))T}}; \text{ s.t. } 0 \leq k \leq 1. \tag{1.1}
\]

Take the first order condition with regards to \(k\), we have:

\[
\frac{\partial F}{\partial k} = \frac{\partial F}{\partial p} p'(k) - \frac{\partial F}{\partial q} q'(1-k).
\]

In order to let the first order condition equals to zero (second order condition can be verified numerically), we have:

\[
\frac{p'(k^*)}{q'(1-k^*)} = \frac{\partial F}{\partial p} = p(k^*) \left( \frac{(p(k^*) + q(1-k^*))T - 1 + e^{(p(k^*) + q(1-k^*))T}}{p(k^*)(p(k^*) + q(1-k^*))T + q(1-k^*)} - q(1-k^*)e^{(p(k^*) + q(1-k^*))T} \right).
\]

Proposition 1 shows there exists a unique solution for allocating advertising budget wisely. We use a simple numerical example to visualize the result. Let \(p(x) = q(x) = \sqrt{x}\). Table 3 illustrates that, as the fixed time duration increases, the advertiser should shift the advertising focus from enhancing innovation effect to encouraging word-of-mouth effect. From this example, we can also see that the portion of budget investing in direct channel will be no less than 0.5. Overall, as long as innovation and imitation curves have the shape of non-decreasing and concave, the advertiser can use the result in Proposition 1 to derive the optimal budget allocation strategy and control the diffusion of the application.

**CONCLUSION AND FUTURE RESEARCH DIRECTIONS**

Facebook applications are everywhere. In the business world, attracted by the low cost and strong word-of-mouth effect, advertisers are also eager to experiment advertisements using Facebook applications. Our research presents a theoretical framework on how Facebook application diffuses over the network, and more importantly, for advertisers, how to utilize the diffusion pattern and exert efforts to influence the diffusion.

We find that the classic Bass diffusion model is sufficient to describe the underlying diffusion of Facebook applications. Then we use the model to derive an optimal advertising strategy. For a given amount of budget and a given time duration, in order to achieve a maximum percentage of user installations of the target population, an advertiser can find a unique balancing point to allocate the budget between activities enhancing innovation and imitation effects. Numerical examples are also provided to demonstrate the optimal solution.

Because this study is recent in the field, there are lots of future research directions. First, we only consider the total number of user installations of a Facebook application as a proxy for the effectiveness of advertising. In fact, there are also other measures we can consider. One of them is the number of monthly active users. Facebook keeps tracking not only the total installations of an application, but also the number of users who use the application every day. This can actually describes the extent of repeated exposure to the advertising information instilled in the application. Second, when using Bass diffusion model, we assume that both innovation and imitation coefficients are simply functions of advertising budget. In reality, those coefficients can surely be varied from time to time. A dynamic programming model should be able to capture the difference of coefficients at different time point and provide an optimal solution with a time path. Finally, we assume a homogenous network structure for Facebook while some studies point out that the social network is usually a heterogeneous network. This means that those innovation and imitation coefficients have to be node specific. Incorporating these factors might be able to provide a more in-depth analysis of the diffusion pattern.
Table 3. Visualization of the First Order Condition Curve from Equation (1.1)

REFERENCES
