Monetary Value of Customer Networks in Mobile Social Networking Services

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Abstract

Mobile Social Networking Services (SNS) are an emerging trend in which individuals of similar interests communicate with one another using mobile phones. In this paper, we calculate the monetary value of customers and their networks in mobile SNS using the official data provided by a service provider. The mobile SNS enable users to create their avatars to communicate with each other via blog comments and communities. The company sells various items for these avatars such as apparel and interiors. This service generates consumer purchase history data and user network data. In previous research, the value of the customer is often estimated using the purchase history, but the network value is neglected. In the field of computer science, the value of the network is evaluated via the network structure, but not much attention is paid to the economic aspect of each node. The aim of this paper is to incorporate the social factor with the customer purchase database and calculate the monetary value of each customer and his or her network. The results of empirical analysis show that our approach is useful in finding valuable customers for marketing activities and outperforms conventional metrics such as degree centrality.

Introduction

Mobile devices are more likely to be personal compared with other devices and have strong potential to become the best targeted, one-to-one digital medium (Chande, Gopalan, and Kurup 2009). One of the emerging trends for mobile devices is mobile SNS. Mobile SNS are internet-based social networking services for mobile phones. They enable users to set up their blogs, post a comment on bulletin boards, and send messages to other users using mobile phones. Recently, websites such as MySpace and Facebook have offered mobile versions of PC-based services.

Japan has a high usage rate of mobile social networks due to the spread of 3rd Generation mobile phones and flat rate data pricing. 19% of the mobile users enjoy mobile SNSs in Japan, and this number rises for teenagers. The usage rate of mobile SNS among female teenagers is 42.2%.

There are a number of mobile SNS providers striving for market share. Because they compete in sales of extra services and accessories for the avatars, it is important to understand the loyal customers.

The search for loyal customers has attracted much attention in the field of marketing. A frequently used analysis is called RFM analysis. RFM analysis ranks the customer by three aspects: the recency of the purchase, the frequency of the purchase, and the total monetary value. RFM variables provide the ground for sophisticated customer analysis.

Another approach to assess the value of customers is called customer lifetime value (CLV) (Blattberg and Deighton 1996, Blattberg, Getz, and Thomas 2001). Most of the CLV models determine advertising effectiveness by examining the effect of marketing communications on individual customers based on the premise that customers do not interact with each other. These models neglect the spread of word-of-mouth (WOM), but the consumer's purchase decision making is often influenced by WOM.

Recently, Hogan, Lemon, and Libai (2005) incorporated word-of-mouth effects into a model of customer lifetime value and quantified the advertising ripple effect. In their model, they calculated CLV using two parameters: customer retention rate (r) and average customer acquisition rate via WOM (w).

In the field of computer science, some studies incorporated economic aspects to the social network analysis. For example, Richardson and Domingos (2002) provided a method to calculate a network value of online customers. The network value of a customer is high when the customer is expected to influence other users' probabilities of purchasing the product both strongly and positively. Kempe, Kleinberg, and Tardos (2003) followed this problem using several widely studied models in social network analysis. The optimization problem of selecting the most influential customer was NP-hard. They provided a provable approximation for efficient algorithms. This is a useful approach to find the influential target, but they did not discuss the economic outcome of the optimization.

To summarize, in the field of marketing, the value of the customer is often estimated using the purchase history data of a single customer, and the network value is neglected. On the other hand, in the field of computer science, some studies incorporated economic aspects to the social network analysis, but the monetary value of the customer and his or her network is yet unknown.

The aim of this paper is to calculate the monetary value of each customer and his or her network on the mobile SNS by incorporating the social factor to customer purchase analysis. The customers spread word-of-mouth and they invite new customers. These invitations (electronic referrals) have been one of the driving forces for service providers to acquire new users. In this paper, we focus on these special customers, i.e., customers who contribute to the company's revenue by acquiring new customers.

This paper is organized as follows. First, we provide a model to calculate the monetary value of the customer and his or her network. Second, we present the data description followed by the empirical analysis. We close the paper with the conclusion and a discussion of future research.

Model

In this section, we explain the model to calculate the value of each user using the friend invitation network. The topic of our analysis is the mobile SNS electronic referral system. If a user invites a friend and this friend subscribes to the service, the user can earn 1,000 Gold (G hereafter). Gold is the currency in this SNS with an exchange rate of approximately 100 G = 100 Japanese yen (approximately 1.1 US dollars as of December 2009).

Figure 1 represents a simple friend invitation network of mobile SNS. In Figure 1, user *a*, denoted U_a, invites user *b* and user *c* to the service. Similarly, user *d*, denoted U_d, invites user *e*, who has many friends and has invited user *f*, *g*, and *h*. The number in parenthesis is each user's gold expenditure, which is derived from the user database. In the example, U_a spends 50 G; U_b spends 100 G, and U_c spends 30 G.

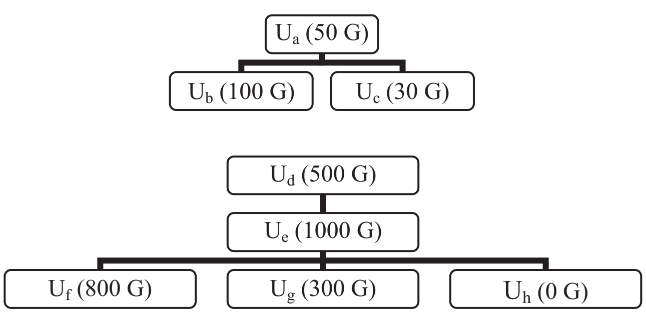

Figure 1. Friends invitation network

We calculated the monetary value of each user by calculating the direct and indirect gold expenditure. Let's assume that user *x* invited user *y*. The indirect gold expenditure ig_x can be calculated as the sum of direct gold expenditure of his/her invited friends (g_y).

$$ig_x = \sum_{y \in x\text{'s invited friends}} g_y \quad (1)$$

The monetary value of customer *i* can be expressed as follows:

$$mv_i = g_i + ig_i$$

mv_i can be considered as the value of the customer incorporating word-of-mouth. The direct gold expenditure (g_i) is the same as the monetary value of the customer, which is M in RFM analysis. The indirect gold expenditure (ig_i) can be considered as the monetary value of the customer's network. RFM analysis captures the monetary value of a single customer and neglects the power of his or her network. Our model enables calculation of the value of a single customer and also his or her friends' network.

Hogan et al. (2005) have incorporated word-of-mouth effects into a model of customer lifetime value. Their retention rate (*r*) and the successful referral rate (*w*) is the average rate of the total users. However, some customers manage to invite many friends while some customers don't. Their model fails to capture the heterogeneity of the customers. Their model can incorporate heterogeneity by evolving to a hierarchical Bayes model and estimating *r* and *w* for each customer. However, our model is more simple and straightforward because we can directly calculate the value of each user and his or her network.

The conventional marketer would consider U_e, who spent 1,000 G, as a "good customer" looking at the past purchase record. He would neglect U_d because this user spent only 500 G. However, U_d has friends who actively purchased items. By incorporating indirect expenditure into the calculation of the monetary value, the company can identify the most desirable customer (U_d) with a total value of 2,600 G.

In Figure 1, the network effect is considered at the friend level (*path length=1*) and friend's friend level (*path length=2*). We can generalize the network effect as follows. We denote matrix *M* as the user invitation network, which consists of *m* users (m x m matrix). The element $m_{ij} = 1$ if user *i* invites user *j*, otherwise $m_{ij} = 0$. We represent each user's gold consumption (g_m) as column vector *G*.

$$G = [g_1, g_2, g_3, \ldots g_m]^T \quad (2)$$

The monetary value of each user (MV_{total}) can be expressed as follows:

$$MV_{total} = (I + M + M^2 + M^3 + \ldots + M^{10})\, G, \quad (3)$$

where *I* is an m x m identity matrix.

MV_{total} is an m x 1 matrix. *i-th* row of MV_{total} corresponds to the monetary value of user *i*, i.e., $g_i + ig_i$. We stopped calculating the influence at path length = 10 for ease of calculation. Also, it is unreasonable to consider the WOM effect of a friend who is more than 10 steps away. The distribution of the path length is discussed in the following analysis section.

Topic of Analysis

The data was provided by MTI Ltd., which is one of the largest and oldest mobile SNS providers in Japan. MTI offer a service called *logtomo* (blog + friend in Japanese), a pure mobile-focused SNS service. A member can have an avatar and its room. A member can also create his or her blog, comment on other users' blogs, post a comment on community forums. It has more than 750 thousand members and attracts over 200 million PV per month as of October 2009. The users are 70% female, and approximately 50% of the users are in their 20's. The site offers over 20,000 items such as clothes, shoes, bags, interiors, and pets for avatars.

Logtomo is basically a free service, but users can purchase *gold* for better services. Gold (G) is a currency in this SNS. There are various ways to earn gold in this site. The site offers an electronic referral program. If a user invites a friend and this friend subscribes to the service, the user can earn 1,000 G. A user can also earn 300 to 1,000 G by becoming a member of other sites run by MTI. This expands the customer base of the company as a whole and creates synergy among the services.

More straightforward approach to earn gold is by purchasing it. A user can purchase special accessories for avatars that come with gold. Users can also earn gold by becoming paid members. There are various monthly payment courses, ranging from 315 to 2,100 yen per month. It is also possible to earn gold via activities on the website.

For expenditure, users can spend gold by purchasing blog templates, apparel and accessories for an avatar, interior for an avatar's room, joining in-site events such as tours, etc. For the service operator, a customer with a large amount of gold expenditure is a good customer.

Analysis

In this section, we apply our model to the actual data from the mobile SNS service provider. We were provided with customer data of 71,039 users. This includes 52,998 successful friend invitations by 23,989 users. We were also provided with gold acquisition/expenditure data from January 2009 to November 2009.

There were a total of 52,998 friend invitations in the dataset, which generates a secondary friends network of 12,733. These 12,733 users are indirect friends (*path length=2*) of the original user who invited the friend. The overall success invitation rate is 0.33. The frequency of friend invitation becomes 0 when path length is 11, confirming our assumption in formula 3 in the model section.

We applied our model and calculated MV_{total} of each customer using the friend invitation matrix M, which is 71,039 x 71,039. Table 1 is the result of the top 10 users sorted by monetary value of customer, MV_{total}.

ID	DF	IF	TF	g	ig	MV_{total}
11817xx	1	0	1	281,105	0	281,105
11246xx	1	0	1	271,545	500	272,045
9425xx	2	0	2	240,600	27,500	268,100
8xx	1	0	1	223,726	0	223,726
11398xx	12	4	16	136,820	85,228	222,048
12682xx	2	0	2	139,120	51,465	190,585
13142xx	1	0	1	187,420	0	187,420
11454xx	1	1	2	180,400	1,602	182,002
6449xx	219	60	279	0	178,727	178,727
10132xx	10	22	32	19,560	156,054	175,614

Table 1. Top 10 users by MV_{total}

The column *DF* indicates the number of direct friends the user invited, *IF* indicates the number of indirect friends, and *TF* indicates the number of total friends, which is $DF + IF$. g is the gold consumption of each customer; ig is the gold consumption by customer's friends. MV_{total} is the total monetary value of a customer, which includes both the customer's own expenditure and his or her friends' expenditure. Since gold is the currency in this SNS with an exchange rate of approximately 100 G = 100 Japanese yen, we use yen as the unit of MV_{total}. The ID of the users is masked to protect their privacy.

The conventional marketing analysis can only identify customers with high g. User ID 10132xx (ranked 10th) has a monetary value of 175,614 yen, but this user would be overlooked in the traditional marketing scheme because his or her individual monetary value is only 19,560 yen. Our model enables the capture of the true value of this user by calculating the monetary value of his or her network, which is worth 156,054 yen. If the company targets these users, it can expect not only the revenue from each user but also revenue from his or her network.

Table 2 shows the monetary value (*MV*) of the top 100 users by (1) number of direct friends (*DF*), (2) number of indirect friends (*IF*), (3) number of total friends (*TF*), (4) gold consumption (g), (5) friends' gold consumption (ig), (5) total monetary value (MV_{total}), and (6) 100 random users for comparison.

The first row shows the number of friends, i.e., degree centrality in the friend invitation network. Naturally, the top 100 users by number of direct friends have the highest value with an average of 103 friends. Compared to these users, the top 100 gold spenders have a relatively small network with 12 friends on average.

	Top 100 by *DF*	Top 100 by *IF*	Top 100 by *TF*	Top 100 by g	Top 100 by ig	Top 100 by MV_{total}	Random
Average DF	103	19	99	12	32	34	1
Average IF	10	32	21	1	22	13	0
Average TF	113	51	120	13	54	48	1
Average g	22,616	9,703	19,723	90,999	17,677	70,947	1,624
Average ig	25,851	49,919	37,661	8,022	70,805	46,915	715
Average MV_{total}	48,466	59,621	57,384	99,021	88,482	117,861	2,338
Average MV_{total} *per friend*	229	979	314	617	1,311	977	715

Table 2. Comparison of monetary value (*MV*)

The average number of friends for the 100 random users is 1 meaning the overall friend invitation rate is 1%. This indicates the rareness of friend invitation. There are various motivations for friend invitation. One is an affiliate fee, which is prominent for users with a large number of direct friends. The other reason for friend invitation could be recommendation due to customer satisfaction, and this motivation is the one that the service provider aims to stimulate.

The average gold expenditure (*g*) is 90,999 G for the top 100 big spenders, which is apparent. These users spend four times as much as the top 100 highest degree centrality users and more than 50 times as much as average users (based on 100 random users).

The average MV_{total} is the average monetary value of each user and his or her network. The result indicates that the average monetary value of the top 100 MV_{total} users is 117,861 yen, which is more than twice as much as users with high degree centrality.

The average MV_{total} per friend indicates the monetary value of a friend. This can be considered as a monetary value of word-of-mouth. The value of word-of-mouth depends on how much the newly invited friend spends. This value is the highest for the top 100 users with high *ig* at 1,311 yen. The top 100 users with high MV_{total} values also have big spending friends at an average of 977 yen per friend. Since MV_{total} is a monetary value of a customer, the result indicates that a friend of a valuable customer is also a valuable customer, since he or she is a big spender.

Trusov, Bucklin, and Pauwels (2009) calculated the monetary value of a WOM referral based on revenue from advertising impressions served to a new member. Their analysis reveals that by sending out ten referrals, each network member could bring in approximately $7.50 of incremental ad revenue for the site. The value of the referral is consistent in our survey, since the *Average* MV_{total} *per friend* for 100 random users is 715 yen (approximately $7.69). What we want to emphasize is that this value can be increased by better targeting. If the company targets users with a large number of indirect friends, the value of a WOM referral increases to 1,311 yen per user.

Although the top 100 users by # of direct friends have the largest number of friend invitations, these friends do not contribute much to the company revenue since each friend only spent 229 yen.

Conclusion

In this paper, we propose a new method to calculate the monetary value of a customer and his or her network using a unique data set from a leading mobile SNS in Japan. We incorporated the social factor of the network by using the referral network and examined the value of word-of-mouth.

The quantitative value of a node in networks is often examined by the well-studied notion of degree centrality. The qualitative value is examined at the level of a single customer, not the network. The contribution of this research is that our approach enables the capture of both quantitative and qualitative aspects of the customer and his or her friends network. Our approach expands the frontier of existing research on customer value analysis in marketing.

Past research argued the power of the hub, i.e., a node with a large number of edges. However, our analysis reveals that customers with the highest number of edges are not necessarily desirable customers for the service provider when the quality of the network is accounted for. If the focus is only on the direct invitation process, the company will end up targeting users whose main concern is to pursue affiliate fees.

The results of empirical analysis using the customer purchase history and friend invitation network show that our approach is useful in finding valuable customers for marketing activities.

Another contribution is that we calculated the value of the network on a monetary basis. This is a simple and straightforward outcome that offers rich managerial implications.

Future research includes churn prediction, dormant user prediction, and evaluation of social influence compared with other marketing activities such as TV commercials.

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