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Selecting Core Target Users for Online Social Networking Marketing with Target Marketing: A Preliminary Report

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ABSTRACT

This study proposes an approach to identify the core target group of users who will maximize the outcomes of online social network marketing (SNM) programs through a digitized Word-of-Mouth (WOM) marketing. We first compare methods based on topological measures such as random, in- and out-degree measures to evaluate the influence of a certain user to other users within the social network. Then a set of hybrid measures of two topological measures are calibrated and compared by varying the values of weights of each measure. Finally, we test the impact of the size of core target group on the outcome of the SNM, and suggest an optimal size of initial core target group for maximum return of SNM program.

Keywords

Social network marketing, knowledge score, optimal marketing size, core target users, net activated user

INTRODUCTION

With the advent of Web 2.0 technologies that allow users to interact with others via blogs, e-mail, instant messaging, and newsfeeds (Zhang et al., 2008), social network community sites such as Facebook, MySpace, Twitter, and Linkedln play a critical role in the success of commerce and change the way of social interactions of individuals (Redbridge marketing, 2011). Therefore, it is not surprising to observe that many marketers strive to leverage these social media sites as a new marketing channel by fully exploiting the fact that many users not only share their opinions but also make recommendations of certain products and services to others. According to a study (Stelzner, 2010), about 78% of consumers trust other people's recommendations for products and services more than any other medium, and the proportion of social network marketers increase 23% in 2009 to 31% in 2010. Social network marketers have been known to use this new marketing channel to mainly increase product and brand awareness (85% of all marketers), increase success Web traffic (63% of marketers), and increase customer loyalty at a relatively low cost.

In this paper, we consider a social network marketer who wants to increase the success of a new product launch by utilizing a social network marketing (SNM) combined with a more traditional target marketing approach. Note that users on social networking sites form a social network with other users with similar interests by mutually confirming a "friendship". The resulting social network can be a valuable information source for marketers to target users with similar interests and to infer the trends of users' preferences and interests (Mislove et al., 2007). The main objective of this study is then to present a feasible SNM strategy and measure its outcomes. In particular, we note that while all users of social networks act as both a supplier and a consumer of information content, the users who create early reviews can be highly influential to other users' adoption of a new product. Therefore, our paper focuses on estimating the outcomes of SNM strategy when social network marketers reach different groups of users who create early reviews as the initial core target users of a SNM program. We summarize our objectives as follows: (1) Compare several topological measures that can be used to determine the influence of each user and the strength of the trust relationships among users (2) Present a new hybrid measure that maximize the outcomes of a SNM program (3) Present a method of selecting an optimal size of the initial core targets either to maximize the exposure of a SNM program or to maximize the return of a SNM program.

The remainder of this paper is organized as follows. A brief introduction to our research framework and social network data sets are first presented. Then the outcomes of a SNM program with different topological metrics including a new hybrid metric are compared and discussed. Next we present two other metrics to measure the strength of trust relationships among users and suggest insights on how to determine appropriate thresholds. Finally, we illustrate how to determine an optimal size of the initial core targets where the exposure or the penetration of a SNM program is maximized, and conclude our paper with few future research directions.

RESEARCH FRAMEWORK AND DATA DESCRIPTION

SNM Research Framework

One of the main objectives of this study is to suggest and evaluate a feasible SNM program based on the pre-selected core target groups who will initiate digitized Word-of-Mouth (WOM) marketing. The users in this core target groups are most likely to be information (e.g., reviews) creators who are assumed to be influential to other users, and the social network marketers will be interested in identifying them. This study focuses on a realistic marketing scenario employing only well-known graph topological measures (e.g., random, in- and out-degree measures) to evaluate the influence of a certain user to other users within the social network. Note that in a graphical representation of the social network, it is not very difficult to imagine users with the highest in-degree edges (i.e., a user whom many other users trust) or out-degree edges (i.e., a user who outreach many other users) as most influential users.

We present our research framework in Figure 1. As the first step of our analysis, we preprocess data sets to correct any measurement errors, combine related records, and remove irrelevant information. At the second step, we build SNM model after selecting evaluation metrics to identify an influential group of users, and identifying relationships among users through various trust metrics. Then a social network marketer offers them a free opportunity of trying a new product and hopes they write favorable reviews and recommend it to their friends on the network. At the third step, we measure the success of a SNM program using two metrics: the number of connected users and activated users. The number of connected users represents the number of users who are linked from any one of the initial core target users (and hence the marketers believe that they are exposed to the reviews of the new product by one of the initial core target users). This measure is optimistic because it does not consider the strength of the trust relationship. The number of activated users represents the number of users "activated" by the initial core target users via the digitized WOM processes. We imagine that a user within the social network is activated (i.e., becoming a customer) when her trust relationship to the initial information creator satisfies a minimum activation threshold based on three metrics. We also consider the order of WOM propagation level, 1st or 2nd order connected or activated users. The 1st order users will only include users who are "directly" connected or activated by any one of the initial core users, while the 2nd order users initially include all the users who are connected or activated by any one of the initial core users and 1st order activated users. However, to avoid the duplicate counting of the same users in the 1st and 2nd order users, we exclude all the users in 1st order users from the 2nd order users and ultimately count only newly identified connected or activated users for 2nd order users. Note that the total number of identified users includes not only 1st and 2nd order users but also the initial core target users. To exclude the number of initial core target users, we also define the (1st and 2nd order) "net" connected and activated users.

We also investigate whether a better hybrid metric can be developed to identify more influential initial core target users and to maximize the outcomes of a SNM program at the final step. Note that no single topological measures alone sufficiently represent the influence of a user (Cha et al., 2010). Practically, we will combine two topological measures, in- and out-degree measures, into a new metric by varying the weights of each measure and compare the outcomes. We also show that different trust metrics should be exercised with different threshold values to adequately estimate the outcomes of a SNM program. Finally, we study the effects of the size of the initial core target groups on the outcome of a SNM program. It is our goal to suggest an optimal size of the initial core target users where the return on a SNM program is maximized.

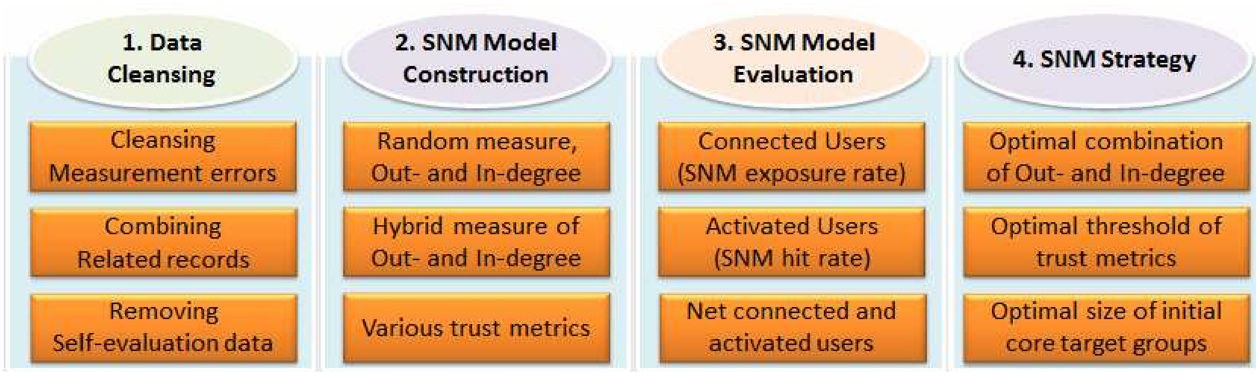

Figure 1. Research framework

Data Description

We use the datasets collected from Epinions Web site, a social network site where each user can freely write reviews about products as well as rate reviews written by other users. These datasets are ideal for this study because Epinions also allows users to explicitly state whom they trust or distrust, in effect, allowing them to form a Web of trust and distrust with trust ratings. While the datatsets and detailed description of the datasets are publicly available at http://www.trustlet.org/wiki/Downloaded_Epinions_dataset, we summarize them here for reader's convenience. The datasets consist of three main tables, "mc", "rating", and "user_rating". The "mc" table contains 1,560,144 reviews on a specific subject (e.g., a product) by 326,983 unique users, while the "rating" table contains 13,668,319 ratings for the reviews with information of object, rater, and rating (ranging from 1 to 5, and average value of rating is 4.6664). Note that we correct records with a rating value of "6" (96,287 ratings) in mc table so that all these records now have a rating value of "5". Note also that we remove duplicates (e.g., user "4294967295" issues a trust statement 469 times for user "295491") or self-trust statements (e.g., user "4294967295" issues 28,655 self-trust statements) from "user_rating" table. In the end, the "user_rating" table contains 613,988 valid trust (and no-trust) statements among 86,656 members, of which 65,161 are trust raters and 58,782 are trustees.

Trust Relationship Metrics

We utilize three trust metrics to determine the strength of relationships between users on the social network. The first metric we adopt is called knowledge score (KS) which reflects both the overall satisfaction of the relationship (R_{ij}) between users (e.g., an average of all user *i*'s ratings on reviews written by user *j*) and the relationship intensity measured by the number of interaction ($|R_{ij}|$). Practically, we use a sigmoid function to keep the intensity value in the range of [0, 1] and divide the value of KS by the maximum rating value (i.e., 5) so that the resulting KS value is between 0 and 1. We formally define KS in equation (1).

$$\textit{Knowledge Score (KS)} = \textit{intensity} * \textit{satisfaction} = \frac{1}{1+e^{-\alpha(|R_{ij}|-\mu)}} * \frac{\sum_{K \in R_{ij}} Sat_{iK}}{5*|R_{ij}|} \qquad (1)$$

where the values of two parameters of a sigmoid function are set as follows: $\alpha = 1$ and $\mu = \frac{1}{n}\sum_{k=1}^{n} Sat_k = 9.9549$.

The second and third metric we adopt to measure the strength of the relationship are called Matching coefficient (MC) and Jaccard coefficient (JC) (Han and Kamber, 2006), respectively. These metrics commonly transform the value of the structural similarity between two users (e.g., the number of users whom both user *i* and *j* trust) between 0 and 1. The only difference between MC and JC is that JC considers the number of common ratings to avoid such cases that two users with only few common ratings are rated as having a very similar and strong relationship. We formally define three metrics in equation (2) and (3), respectively.

$$\textit{Matching coefficient (MC)} = \frac{1}{1+e^{-\alpha(|\text{out-degree}(i) \cap \text{out-degree}(j)|-\mu)}} \qquad (2)$$

where $\alpha = 1$ and $\mu = \frac{1}{n}\sum_{k=1}^{n} Match_k = 13.8235$, and $|\text{out-degree}(i) \cap \text{out-degree}(j)|$ represents the number of users that are trusted by both user *i* and *j*.

$$\textit{Jaccard coefficient (JC)} = \frac{|\text{out-degree}(i) \cap \text{out-degree}(j)|}{|\text{out-degree}(i) \cup \text{out-degree}(j)|} \qquad (3)$$

where $|\text{out-degree}(i) \cup \text{out-degree}(j)|$ represents the number of users that are trusted by either user *i* or *j*, but not both. Note that these trust relationship metrics do not necessarily indicate whether or not a specific user will become an actual buyer. However, the strength of trust relationships among users has been regarded as one of the most important factors that affect the success of viral marketing. Therefore, it is reasonable to assume that users who keep a strong relationship with the recommender are most likely to become an actual buyer than those who have no relationship with the recommender.

EXPERIMENT 1: RANDOM, IN- AND OUT-DEGREE SELECTION METHOD

In our first experiment, three topological measures are compared to select the 100 initial core target users, and KS metric is used to determine the strength of relationships between users. The first topological measure is out-degree measure of a chosen user, reflecting the number of trust statements that she issues to other users and hence the outreach of her. The second topological measure we adopt is in-degree measure of a chosen user, which reflects the number of other users (or followers) who trust her. Therefore, out- and in-degree measure estimate the influence of a user in terms of how many users a user can outreach and how many users trust the user, respectively. To select the 100 initial core target users based on these two measures, we simply rank all the users in the descending order based on the scores of two measures and select the first 100 users for each measure. As a baseline measure, we also randomly select the 100 initial core target users among users with minimum five trust relationships with other users to avoid meaningless solutions. The threshold value of KS metric to determine whether or not a user is activated is subjectively set to 0.8 considering the average rating score among users is 0.92. Note that the trust strength from one of 2nd activated users to one of the 100 initial core target users is computed by multiplying two KS scores, KS (2nd to 1st) * KS (1st to core). We evaluate the success of a SNM program based on these three topological measures in terms of 1st and 2nd order connected and activated users, and summarize the findings in Table 1.

In Table 1, we use Node^1 and Node^2 to denote the users identified as 1st and 2nd order users (connected or activated) from the 100 initial core target users (Node^0) based on one of three measures, respectively. Note that we only count the newly identified nodes at each order, and hence there will be no duplicate users identified in the 1st and 2nd users. To have an insight on the market penetration, we also compute the proportion of identified connected users out of all the users in the social network. For example, according to Table 1, a total of 8,877 (10.24% of a total of 86,656 users) and 16,468 (19.00%) directly connected users (i.e., 1st order users = Node^1) are identified from the initial 100 core target users based on out- and in-degree measures, respectively. In contrast, a random method selection lead to only 492 1st order connected users, resulting in a market exposure rate of 0.56% of all the users on the social network. The last row, Total, is a sum of all identified users such as Node^0, Node^1, and Node^2.

Table 1. Identified 1st and 2nd order users based on random, out- and in-degree method

	Topological Measures	Connected nodes		Activated nodes	
		# of nodes	(%)	# of nodes	(%)
Node^0	Random, Out-, & In-degree	100	0.11	100	0.11
Node^1	Random	492	0.56	48	0.06
	Out-degree	8,877	10.24	1,664	1.92
	In-degree	16,468	19.00	2,991	3.45
Node^2	Random	9,949	11.48	219	0.25
	Out-degree	30,155	34.80	2,424	2.80
	In-degree	30,427	35.11	2,098	2.42
Total	Random	10,541	12.16	367	0.42
	Out-degree	39,132	45.16	4,188	4.83
	In-degree	46,995	54.23	5,189	5.99

We first note that the SNM program that uses in-degree measure identifies more connected and activated users from the initial 100 core target users than any other measures. A total of 46,995 users are at least connected through 1st and 2nd order trust relationships, and 5,189 users are considered activated users whose trust strength is greater than 0.8. According to the number of connected users based on in-degree measure, the digitized WOM on the social network has 47% of all the users exposed to a SNM program starting from the initial 100 core target groups. This finding is consistent with a well known small world phenomenon, which shows that any users on the network can be reached within maximum six hops on average (Milgram, 1967; Pool and Kochen, 1978). However, the fact that a user is directly connected to one of the initial 100 core target users (i.e., 1st order connected users) does not mean that the connected users will purchase a new product that the initial 100 core target users advertise. According to Table 1, 5.99% of all the users are activated users, which results in a SNM hit rate of 5.99%. We may also calculate how effective a SNM program is by dividing the total number of activated users by the initial core target group size, resulting in 51.89 (= 5,189 / 100). Overall, in-degree measure is the best, followed by out-degree and random method. Note that our finding is somewhat consistent with other findings (Cha et al., 2010) that popular users with the highest in-degree are not necessarily influential users in Twitter.

EXPERIMENT 2: HYBRID MEASURE SELECTION METHOD

In this section, we explore an optimal combination of two topological measures, in- and out-degree measure, to maximize the effect of a SNM program. A new hybrid measure, IO-degree, is easily represented as α * in-degree + (1 - α) * out-degree, where $\alpha \in (0, 0.1, 0.2\ldots..0.9, 1)$. Therefore, in- and out-degree measure is a special case of IO-degree when $\alpha = 1$ and $\alpha = 0$, respectively. Again, we will choose 100 initial core target users with the highest values of IO-degree measure for a given α, and count all the users who are directly connected (i.e., 1st order users) to one of 100 initial core target users or one of 1st order users (i.e., 2nd order users). To be a one of 2nd activated users, a user should maintain a trust relationship with a minimum value of KS (=0.8) with one of 100 initial core target users. We summarize out experimental outcomes in Table 2.

Table 2. Identified 1st and 2nd order users identified varying values of α

		α										
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Node^0	Connected	100	100	100	100	100	100	100	100	100	100	100
	Activated	100	100	100	100	100	100	100	100	100	100	100
Node^1	Connected	8,877	10,848	12,492	13,823	14,702	15,744	16,098	16,324	16,370	**16,478**	16,468
	Activated	1,664	2,145	2,463	2,619	2,843	3,019	3,055	**3,061**	2,947	2,976	2,991
Node^2	Connected	30,155	31,014	**31,383**	31,280	31,130	30,667	30,589	30,292	30,503	30,425	30,427
	Activated	2,424	**2,457**	2,358	2,266	2,245	2,173	2,157	2,137	2,111	2,090	2,098
Total	Connected	39,132	41,962	43,975	45,203	45,932	46,511	46,787	46,716	46,973	**47,003**	46,995
	Activated	4,188	4,702	4,921	4,985	5,188	5,292	**5,312**	5,298	5,158	5,166	5,189

According to the Table 2, a hybrid measure with α = 0.5, 0.6, or 0.7 seems to work well in terms of the total number of activated users, while a hybrid measure with α = 0.8, 0.9, or 1.0 seems to work well in terms of the total number of connected users. Therefore, for the following experiments, we use α = 0.7 to combine out- and in-degree measure. To further investigate the performance of a hybrid measure, we also test with different trust metrics, MC and JC, to see if they may result in different outcomes in terms of the number of activated users. While finding an appropriate threshold for each trust metric to identify activate users requires a rigorous study, we use a rule of thumb to subjectively set the values of thresholds for each metric (e.g., 0.8 for MC and 0.05 for JC) by observing the mean values and overall distributions of metrics. We summarize the outputs in Table 3.

Table 3. Identified 1st and 2nd order users identified varying values of α

		α										
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
Activated (KS >= 0.8)	Node^0	100	100	100	100	100	100	100	100	100	100	100
	Node^1	1,438	1,866	2,133	2,241	2,405	2,548	2,581	2,606	2,497	2,518	2,537
	Node^2	2,424	2,457	2,358	2,266	2,245	2,173	2,157	2,137	2,111	2,090	2,098
	Total	3,962	4,423	4,591	4,607	4,750	4,821	4,838	**4,843**	4,708	4,708	4,735
Activated (MC >= 0.8)	Node^0	100	100	100	100	100	100	100	100	100	100	100
	Node^1	2,777	2,779	2,772	2,755	2,740	2,725	2,710	2,718	2,411	2,411	2,346
	Node^2	424	294	233	189	153	145	161	191	285	285	275
	Total	**3,301**	3,173	3,105	3,044	2,993	2,970	2,971	3,009	2,796	2,796	2,721
Activated (JC >= 0.05)	Node^0	100	100	100	100	100	100	100	100	100	100	100
	Node^1	1,224	1,480	1,718	1,856	1,962	2,118	2,189	2,279	2,059	2,089	2,107
	Node^2	2	1	1	0	0	1	1	8	0	0	0

	Total	1,326	1,581	1,819	1,956	2,062	2,219	2,290	**2,387**	2,159	2,189	2,207

We first note that KS and MC metrics return different numbers of activated users when the same threshold is applied to identify activated users. In particular, the number of 2^{nd} order activated users from MC metric is significantly smaller than that of KS metric, while the numbers of 1^{st} order activated users from both metrics are comparable across values of α except α <= 0.3. We attribute this difference to the fact that MC is heavily affected by out-degree measure, while KS is more affected by in-degree measure (refer to equation (1) ~ (3)). This notion is consistent with the finding that the largest number of activated users using MC metric is identified when α = 0, which, in turn, implies that MC metric considers only out-degree measure of each user. In comparison, JC metric follows a similar pattern as KS metric, finding the largest number of 1^{st} order activated users with α = 0.7. However, note that we use a much lower threshold value (0.05) than that of KS (0.8) to find a similar number of 1^{st} order activated users. Even so, the 2^{nd} order activated users from JC is much less than KS or MC mainly because the average value of JC is much smaller than other metrics and when two trust strength values (one between an initial core group to a 1^{st} order activated user and another between a 1^{st} order and a 2^{nd} order activated users) are multiplied, the outcome becomes very small and does not satisfy the minimum threshold of JC.

EXPERIMENT 3: EFFECTS OF THE SIZE OF INITIAL CORE TARGETS

Finally, we study the effects of varying the size of the initial core targets on the outcomes of the SNM. Note that for all previous experiments, we set the size of the initial core targets to 100, which is about 0.12% of all the users on the social network. Observing that the size of the initial core targets may be dependent on the marketing budgets and objectives of each firm, we decide to estimate the effects of various sizes of the initial core targets. For example, a firm with a limited marketing expense budget will be more interested in identifying a small group of initial core target users and its primary objective is to identify a reasonable number of activated users who actually become a customer. In contrast, another firm with a relatively sufficient marketing budget will be more interested in identifying a large group of users as an initial core targets and its marketing objective may be to raise the brand recognition by identifying many connected users. For this experiment, we vary the size of the initial core targets from 100 (0.12% of all the users) to 51,200 (59.08%), and summarize the outputs in Table 4 and Figures 2 & 3. Note that the proportion of identified connected and activated users represents their proportion out of all the users (86,656) on the social network.

Table 4. Identified 1st and 2nd order users (α = 0.7 & KS >= 0.8)

		Size of initial core targets									
		100	**200**	**400**	**800**	**1600**	**3200**	**6400**	**12800**	**25600**	**51200**
Connected	Node^1	16,324	19,022	21,540	25,490	29,874	33,781	37,396	**39,243**	35,354	24,076
	Node^2	30,292	29,401	27,992	25,118	21,382	17,239	11,876	5,558	1,268	0
	Total	46,716	48,623	49,932	51,408	52,856	54,220	55,672	57,601	62,222	75,276
	%	53.9	56.1	57.6	59.3	60.9	62.6	64.2	66.5	71.8	86.9
Activated	Node^1	3,061	3,691	4,148	4,990	5,688	6,136	**6,354**	6,035	4,780	2,951
	Node^2	2,137	2,003	1,862	1,586	1,082	672	242	35	0	0
	Total	5,298	5,894	6,410	7,376	8,370	10,008	12,996	18,870	30,380	54,151
	%	6.1	6.8	7.4	8.5	9.7	11.5	15.0	21.8	35.1	62.5

We note that as we increase the size of the size of initial core targets, the more 1^{st} order connected and activated users are identified but the less 2^{nd} order connected and activated users are identified. Note that the number of 1^{st} order connected users is maximized where the initial core target size is set to 12,800 (14.77% of all the users), while the number of 1^{st} activated users is maximized where the initial core target size is set to 6,400 (7.38% of all the users). The total number of connected and activated users also follow a similar pattern, increasing steadily but after a certain size of initial core targets (i.e., 12,800 for both connected and activated users), the number of these identified users start to grow fast as shown in Figure 2. While it is possible for the marketer to start her SNM program with 51,200 core target users and identify about 87% of all the users as connected users (i.e., users exposed to her SNM program), it is not cost effective if she offers free gifts to all users in core target users. In fact, the marketer may be better off if she decides to target only 100 initial core target groups, which results in having 54% of all the users exposed her SNM program.

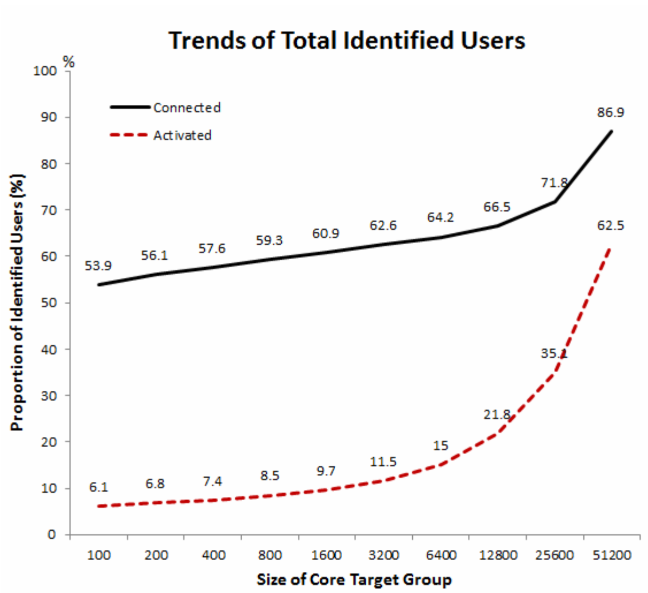

Figure 2. Trends of total identified users

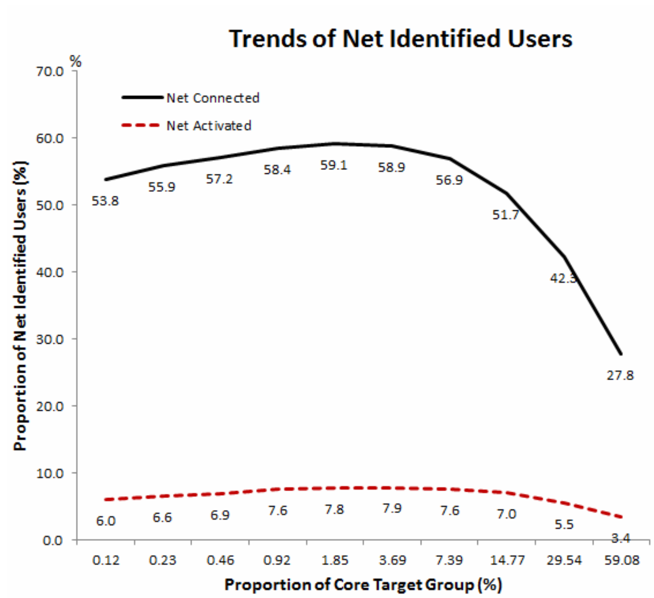

Figure 3. Trends of net identified users

However, if the market aims to maximize the market penetration rate, indicating the degree that she actually sells a new product to the users, the 100 initial core target users may not sufficient enough. In addition, the marketer needs to consider the cost of free gifts for the initial core target users. For this purpose, we present the trend of the number of net identified users (= total identified users – initial core target users) across various sizes of initial core target users in Figure 3. Note that the x-axis value of Figure 2 and Figure 3 is one-to-one mapped, the size of 100 of the initial core target group is equal to 0.12% of total users, and the size of 51,200 is equal to 59.08% of total users. According to the Figure 3, the net connected and activated users are slowly increasing, reach at maximum where the size of the initial core target users is set to 3.69% of total users, and then start to decrease sharply when more than 14.77% of total users are targeted as the initial target groups. Therefore, an optimal size of the initial core target users will be 3,200 users.

CONCLUSION

In this study, we first compare SNM strategy based on three topological measures of how influential each user is on the social network, and propose a hybrid measure to maximize the outcome of SNM by varying the weights of two most successful measures, out- and in-degree. Then, we adopt two other trust metrics to measure the strength of trust relationships among users and advise that the thresholds for each metric should be adjusted to accurately estimate the success of the SNM program. Finally, we show the trends of total and net connected and activated users to help marketers determine an optimal size of initial core target groups. We also observe that while the optimal selection of the initial core target users size is dependent on the marketing budgets and objectives of each marketing strategy, the total number of connected and activated users tend to increase as more users are regarded as initial core target users but the net number of connected and activated users tend to decrease after an optimal initial core group size. As an extension of the current study, we like to test the proposed method on different social community domains with additional topological measures (e.g., PageRank and Betweenness) while exploring higher order relationships among users. In particular, we will develop and examine a marketing scenario in which the main objective is to maximize the profit from the SNM program with given revenue and cost information of a chosen product and marketing budgets and costs.

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