Invite Your Friends and Get Rewards: Dynamics of Incentivized Friend Invitation in KakaoTalk Mobile Games

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ABSTRACT

Incentivized friend invitation is an efficient and effective user growth mechanism, more so when combined with social platforms, such as online social networks (OSNs) or mobile instant messengers (MIMs). KakaoGame, a two-year-old mobile game platform based on a dominant MIM called KakaoTalk, brought 5.2 billion sign-ups over 520 games with quota-based reward schemes. How does the reward scheme help the spread of services?

In this paper, we analyze the friend invitation logs from 4 mobile games on KakaoGame, consisting of 330 million invitations from 8.4 million users to 36 million users. Our analysis aims at answering the following three key questions. (a) How do quota-based reward schemes stimulate invitation behavior? (b) How many invitations trigger the invitee to sign up for the game or become an annoyance to make the invitee turn a blind eye? (c) How fast are the invitations sent out and how does the diffusion slow down? Based on the analysis, we provide practical insights for viral marketing.

Categories and Subject Descriptors

J.4 [**Social and Behavioral Sciences**]: Economics

General Terms

Economoics

Keywords

Word-of-mouth; viral marketing; incentive; social network

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1. INTRODUCTION

Word-of-mouth (WOM) is frequent and trustworthy. People talk about news, gossips, and products with friends all the time. Internet technologies, such as e-mail, online social networks (OSNs), and mobile instant messengers (MIMs) facilitate WOM, creating convenient forums for information sharing. According to Nielsen, 92% of consumers trust recommendations from their friends, while 67% do not trust online advertising [19]. WOM marketing is attracting attention from both the practitioners and the researchers, while traditional means of advertising is losing effectiveness [21].

Previous studies characterize WOM as an oral, person-to-person communication between customers, regarding a brand, a product, or a service [2, 5]. Businesses often exploit WOM by compensating social referrals with explicit incentives. Dropbox provides 250MB of bonus space for every successful referral. World of Warcraft gives one month of free game time when the user's recruit buys a month of game time. The auction site eBay provides a $5 voucher to recruiters. Moreover, such referral programs are becoming more powerful than ever before, being combined with social platforms based on OSNs and MIMs [9, 18, 22]. Accordingly, understanding user behavior under various reward schemes create opportunities for new designs in viral marketing.

KakaoGame, a mobile game platform based on a hugely popular MIM called KakaoTalk, is one of the most successful cases with 37 million users out of 50 million in Korea. KakaoGame users invite their KakaoTalk friends to a game by sending person-to-person private messages. The invitations are often compensated by quota-based rewards regardless of the success, *i.e.*, if a user invites 10, 20, and 30 friends cumulatively, then the user gets rewards, R_1, R_2, and R_3 respectively, no matter whether the invitee signs up for the game or not. In contrast to such a commercial success, the underlying incentive mechanism of WOM marketing has not received much attention.

In this paper, we analyze the friend invitation logs from four mobile games on KakaoGame. Our analysis aims at answering the following questions:

- *Inviter's behavior*: How do quota-based reward schemes stimulate spontaneous invitation behavior? How do users select whom to invite among their friends? How many friends do users invite comfortably?

- *Invitee's reaction*: Invitation even from a friend can be construed as spam and is controversial. How do invitees react to multiple invitations over time? When should the system stop or advise a user to stop sending invitations to a friend?

- *Propagation speed*: How quickly are the invitations adopted and reproduced?
- *Causes for saturation*: How does the diffusion process slow down and terminate?

The questions listed above are intuitive and yet the answers should bring novel and fundamental insight into quota-based reward schemes for online e-commerce. The remainder of this paper is organized as follows. Section 2 describes the KakaoTalk service, its game platform, and our datasets. Section 3 examines the inviter's behavior in terms of the invitation rate and count, the invitee selection process, and mental mechanics. Section 4 looks at the invitee's reaction. In Section 5 we investigate the temporal aspects of the invitation behavior and in Section 6 the slowdown of diffusion. We discuss related work in Section 7, then conclude this paper in Section 8.

Rank	Application	Publisher
1	Taming Monsters *for Kakao*	Netmarble
2	Cookie Run *for Kakao*	Devisisters
3	Candy Crush Saga *for Kakao*	King.com
4	Everybody's Marble *for Kakao*	Netmarble
5	Pokopang *for Kakao*	NHN
6	Anipang *for Kakao*	Sundaytoz
7	Everytown *for Kakao*	WeMade
8	KakaoTalk	Kakao
9	Anipang Mahjong *for Kakao*	Sundaytoz
10	Water Margin *for Kakao*	4:33
11	Five 2013 *for Kakao*	Netmarble
12	Zenonia Online *for Kakao*	Gamevil
13	Action Puzzle Family *for Kakao*	Com2us
14	Dragon Flight *for Kakao*	Next Floor
15	Atlan Story *for Kakao*	WeMade

Table 1: Top grossing applications on Korean Google Play Market captured on Jan 1, 2014. Except for KakaoTalk, all other applications are KakaoTalk mobile games.

2. BACKGROUND

Before presenting our analysis, we give a brief introduction about the MIM, KakaoTalk, and its mobile game platform, KakaoGame. Then we describe our dataset and the history of our game user growth.

2.1 KakaoTalk and KakaoGame

Google. FedEx. Xerox. These companies got so successful that their brand names became synonymous with the services they provide. KakaoTalk reached that level of success and Koreans say "KaTalk me!" instead of "Send me a text message!"

MIMs, such as WhatsApp, WeChat, LINE, and KakaoTalk, have emerged as a key medium for communication, along with the popularization of smartphones. KakaoTalk is the most widely-used one in Korea, claiming 37 million registered users from the population of 50 million. Everyday 27 million people send 4.2 billion KakaoTalk messages, which is equivalent to 156 messages per person a day [9].

KakaoGame is a KakaoTalk-based mobile game platform launched in July 2012. It has brought 5.2 billion sign-ups over 520 mobile games, and generated USD 860 million in sales in 2013 [15], monopolizing the mobile application market as shown in Table 1. The games on KakaoGame have a few common characteristics. Most of them are single-player games, but users can interact with their friends by sharing activities via person-to-person private messages. Many are often score-based games providing each user with a personalized leaderboard involving only the user's friends. Also, most of them are *freemium*[1] games, and incentivize social referrals at a nominal cost by providing in-game items or coupons.

Quota-based reward schemes encourage users to invite friends and compensate for the act even when the invitations do not materialize to sign-ups. In order to prevent users from abusing the quota-based reward schemes, KakaoGame disallows inviting friends who have already joined a game or inviting more than twenty friends a day. Also a user cannot invite the same friend again to the same game within a month. The general convention in KakaoGame is to set the quotas at 10, 20, and 30 for reward schemes.

[1]Freemium is a pricing strategy by which a product or service (typically a digital offering, such as software, media, games or web services) is provided free of charge, but proprietary features, such as functionalities and virtual goods, are for fee.

2.2 Dataset Description

In this paper, we analyze the referral logs of four mobile games on KakaoGame. The datasets were provided by the game publisher, Netmarble. Per Netmarble's request we do not divulge the names of the games and instead refer to them as A, B, C, and D. All the games were launched on both Android and iOS in mid 2013, and we have logs for the first 20 weeks from the release dates. The datasets consist of user registration logs and friend invitation logs. The former includes the signed-up user's ID (encrypted) and the timestamp, and the latter has the inviter's ID (encrypted), the invitee's ID (encrypted differently), and the timestamp per invitation. Note that the IDs of the signed-up users including inviters follow different numbering schemes from the IDs of invitees. This idiosyncrasy of ID mismatch in the logs bars us from studying the cascading behavior of invitations. The game publisher has provided us with a mapping for a limited number of $10,000$ user IDs between the two encrypted IDs out of the 7 million invitees of C. We do not know the sampling mechanism for the $10,000$ users and cannot quantify the sampling error. But the sample size is large enough that we expect the error to be within a reasonable limit. We use these users in our analysis in Section 4 and part of Section 5 and 6.

All the games have similar, but slightly different quotas for rewards. All the games have quotas at 10, 20, and 30, but B and C have additional quotas at 3 and 5, and D has at 5, 15, and 25. There are reward resets that cleared all user's invitation counts to zero and users could get rewards again. A reset reward in the 15th week from its release, B in the 11th and 15th week, and C and D in the 6th week. Note that B changed the reward quotas to 5, 10, 20, 30, and 40 at the second reward reset. In Table 2 we summarize the dataset statistics and reward schemes.

	Dataset Statistics				Reward Schemes		
	n_{user}	n_{inviter}	n_{invitee}	$n_{\text{invitation}}$	Reward Quotas	Reward Resets	Notes
A	13, 413K	7, 762K	33, 668K	268, 123K	10/20/30	15th week	B changed the quotas to 5/10/20/30/40 at the 2nd reward reset
B	2, 510K	1, 270K	17, 111K	42, 419K	3/5/10/20/30	11th & 15th weeks	
C	872K	393K	7, 567K	12, 816K	3/5/10/20/30	6th week	
D	648K	253K	4, 934K	7, 680K	5/10/15/20/25/30	6th week	

Table 2: Dataset statistics and reward schemes.

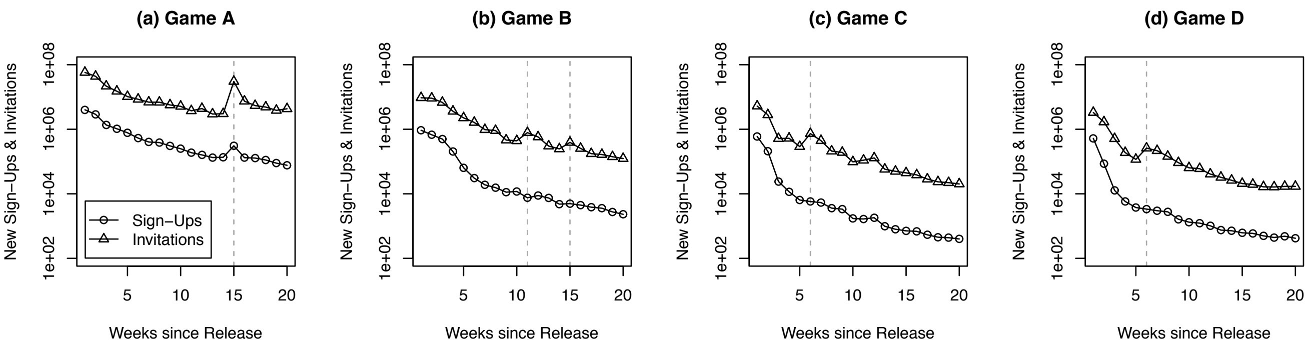

Figure 1: Weekly new sign-ups and invitations.

2.3 Friend Invitation and User Growth

KakaoGame has won its fame for its fast user growth mechanism. Figure 1 plots the weekly numbers of new sign-ups and invitations of the four games. The two numbers are highly correlated; the Pearson correlation coefficient is 0.94. Both numbers are the highest during the first week of the game release. In case of A, 4 million users joined the game and sent out 58 million invitations only in the first week. In contrast to the explosive growth in the early stage, both numbers drop exponentially (the y-axis of the graph is in log scale) over time. The dotted vertical lines represent reward resets. Even with the reward resets, the numbers of invitations and new sign-ups decrease by two orders of magnitude in 20 weeks after the initial release.

How does the quota-based reward scheme bring explosive user growth in the beginning? How does the user growth slow down exponentially over time? How do the inviters and invitees affect the diffusion dynamics? We answer these questions one by one in the following sections.

3. INVITER'S BEHAVIOR

3.1 Invitation Rate and Count

How do the quota-based reward schemes affect the invitation behavior? We begin by examining the *invitation rate*, the proportion of inviters among signed-up users, and the *invitation count*, the number of friends an inviter invites to a game. The reward scheme is not the only factor that affects the invitation behavior. For example, the player population of a game can limit invitation because users cannot invite friends who already signed up. Also, the reward resets that clear the quotas can stimulate invitations by encouraging users who have reached the maximum quota previously.

To observe the invitation behavior at an early stage with no reward reset, we use only the first 28 days of data after the sign-up for the first 100,000 users. Table 3 summarizes the statistics. The invitation rates vary from a low of 30%

	Invitation Rate		Invitation Count			
	n_{user}	n_{inviter}	1Q	Avg.	Med.	3Q
A	100K	87K	30	28.9	30	31
B	100K	40K	20	30.2	30	31
C	100K	32K	20	27.2	30	30
D	100K	31K	20	28.8	30	30

Table 3: Invitation rate and count statistics from the first 28 days of data after the sign-up for the first 100,000 users.

to a high of 90%, corresponding to popularity of the games. However, all the games show similar invitation count statistics, as they have similar reward schemes. For all four games, the median of invitation count is exactly 30, and the average and the 3rd quartile are also around 30, which is the maximum quota.

In Figure 2, we plot the complementary cumulative distribution function (CCDF) of the invitation count for each game. The CCDFs show marked discontinuations at quotas of the games. A is the most popular game with the total of 13 million signed-up users, and 75% of its users sent out the maximum quota or more. In all four games, more than half of the inviters have sent out equal to or more invitations than the maximum quota of 30. Beyond the maximum quota, A offers no more reward, while the other games give away a coin[2] per invitation. Possibly due to the coins, games other than A have heavy inviters who sent out hundreds of invitations.

So far, we have seen the invitation behavior at the early stage. How does the invitation behavior change over time, with growing gamer population and reward resets? In Fig-

[2]Users play a game with a coin. (Usually,) a user gets a free coin every 10 minutes, but cannot accumulate more than 5 coins at any point. When a user runs out of coins, the user must wait until a refill or purchase coins to continue playing.

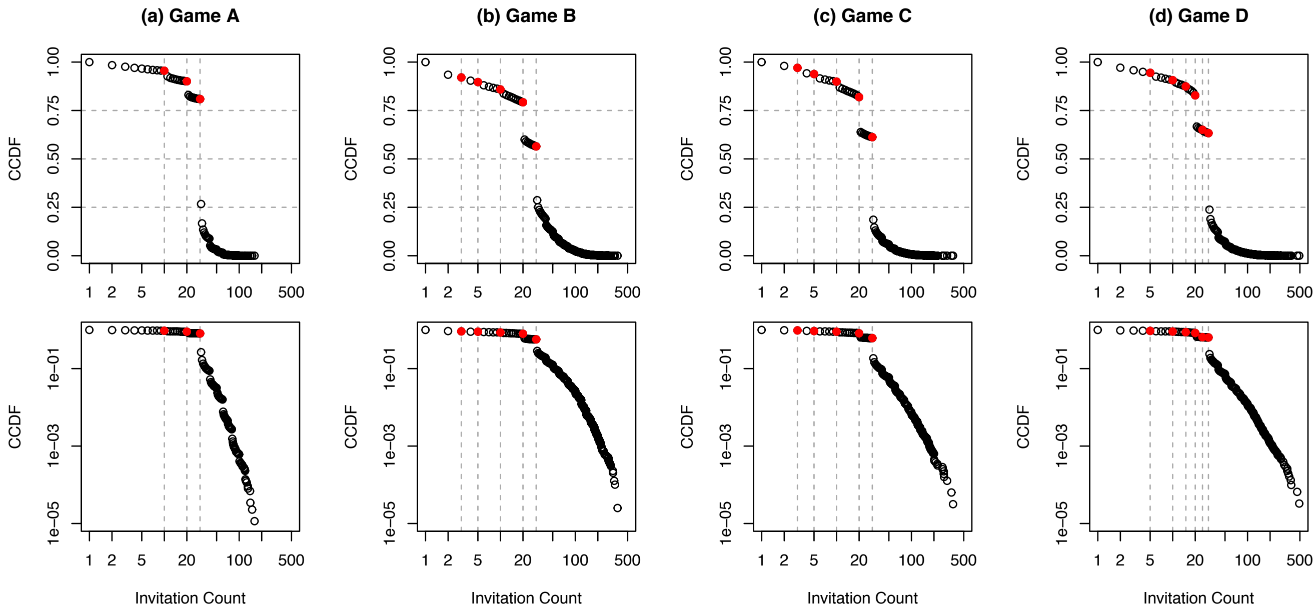

Figure 2: CCDF of invitation counts of the first 100,000 users in the first 28 days after each user's sign-up.

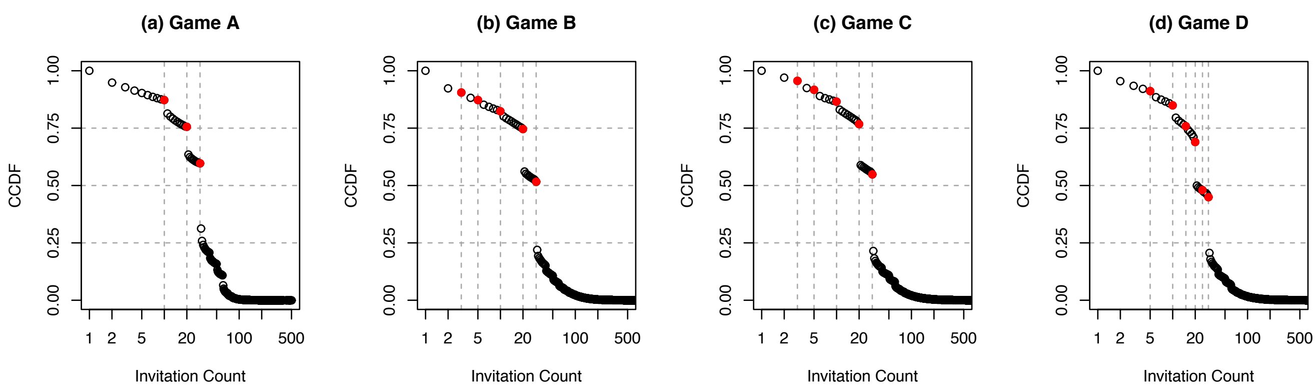

Figure 3: CCDF of invitation counts of all users in 20 weeks.

ure 3 we inspect the CCDFs of all users for the full 20 weeks of data. The percentage of users who have sent out equal to or more invitations than the maximum quota in game A decreases from 80% in Figure 2(a) to 60% in Figure 3(a). In the other games with less user growth, the drops are smaller but still manifest. The later a user joins a game, the more likely the user's friends have already signed up for the game and the more limited the user is in the choices of invitations. Thus less percentage of users have fulfilled the maximum quota of invitations compared to Figure 2. As the invitation count is reset to 0, users who have reached the maximum quota previously are encouraged to invite more. As a result in game A with reward intervals of 10, additional discontinuations appear between 30 and 60 in Figure 3.2(a).

Many types of human interaction, such as phone calls, e-mails, sexual relationships, and OSN friendships follow power-law distribution [1, 11, 17]. Recent studies of friend invitation counts report highly skewed distributions similar to power-law [18, 22]. Also, person-to-person product recommendations show power-law [16]. In our datasets there are a good number of users who continue to invite beyond the maximum quota of rewards. Unsurprisingly, the tails of the CCDFs in Figures 2 display power-law behavior.

The reward scheme alone does not motivate users to start inviting friends as the proportion of inviters varies from a game to another. Yet, we confirm that the quota-based reward scheme is quite effective in pushing users to invite up to the quotas, irrespective of game popularity. That is, *motivated* users who found the game interesting enough to entice friends and made up their minds to invite friends max out invitations to get rewards. Therefore we conclude that quota-based reward schemes are effective in exposing the game to a great user population, often 5x or more than the signed-up users as shown in Table 2.

3.2 Invitee Selection

Now, how do users select whom to invite? There is a trade-off between the cost of invitation and reward, where the cost includes emotional pressure for sending unsolicited messages to friends. How does a user minimize the cost? Here we present the following two possible strategies.

- **Strategy #1:** Users invite the same set of friends to different games repeatedly, thereby limiting the damage to a small circle of friends.
- **Strategy #2:** Users invite different sets of friends to different games, thus spreading the damage widely and imposing less on individual friends.

Which is a more dominant strategy? To answer the question, we examine the overlap between a user's invitees between games. For a user u who invites friends to games X and Y, let u_X and u_Y be the invitees for games X and Y, respectively. We define the user's invitee similarity for the game pair X and Y, $\mathcal{S}^u_{XY}$, as following:

$$\mathcal{S}^u_{XY} = \frac{|u_X \cap u_Y|}{\min(|u_X|, |u_Y|)}$$

Since users cannot invite friends who have already signed up for the game, the invitee selection can be severely restricted in popular games. A stands out among the four games with its popularity claiming 36% of all KakaoTalk users. To have a fair comparison of the user's emotional pressure, the two games under examination should have comparable rate of adoption. Therefore we exclude the game A in this analysis and consider only the remaining three.

For every pair of games, we select the users who have invited friends in both games. B and C have 179K common inviters, C and D have 55K, and D and B have 104K. Then we calculate $\mathcal{S}^u_{XY}$ for all three game pairs. Figure 4 shows the CCDF of the invitee similarities. For all three game pairs, about 80% of users invite more than 60% of same friends to two different games, and for about 50% of users more than 80% of invitees are the same. In summary, users are highly likely to invite the same set of friends to different games. Also, the distributions of users' invitee similarity for all three game pairs are analogous to each other.

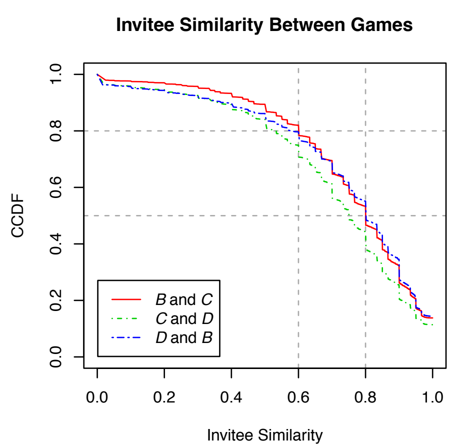

Figure 4: CCDF of invitee similarity.

Our observation above supports Strategy #1, but why do people use Strategy #1? One possible explanation is that gamers' preference to those games are similar. To examine the preference similarity among games, we compute the member and inviter overlaps between games as follows. Let $\mathcal{M}_{XY}$ be the member similarity and $\mathcal{I}_{XY}$ be the inviter similarity between games X and Y,

$$\mathcal{M}_{XY} = \frac{|\mathcal{M}_X \cap \mathcal{M}_Y|}{\min(|\mathcal{M}_X|, |\mathcal{M}_Y|)}, \mathcal{I}_{XY} = \frac{|\mathcal{I}_X \cap \mathcal{I}_Y|}{\min(|\mathcal{I}_X|, |\mathcal{I}_Y|)}$$

where $\mathcal{M}_G$ is the set of members in game G, and $\mathcal{I}_G$ is the set of inviters in game G. Not all members have invited friends, and thus $\mathcal{M}_G \supset \mathcal{I}_G$.

Table 4 summarizes the member similarities and inviter similarities among the three games, and compares them with average invitee similarities. The member and inviter similarities vary from a low of 0.2651 to a high of 0.5891. Yet, the average invitee similarity remains high, over 0.7. Therefore, we conclude that users invite the same set of friends, regardless of the preference for games.

X	Y	$\mathcal{M}_{XY}$	$\mathcal{I}_{XY}$	Avg. $\mathcal{S}^u_{XY}$
B	C	0.5214	0.4544	0.7529
C	D	0.3280	0.2177	0.7388
D	B	0.5891	0.2651	0.7022

Table 4: Similarities between games.

For the curiosity for the personal motivation behind Strategy #1, we conducted an informal survey among 50 gamers and 47 of them answered that they invite closest friends regardless of the game. We leave a rigorous user study for the motivation for future work.

3.3 Mental Mechanics of Inviters

If you are a compensation plan designer for a WOM marketing campaign with quota-based rewards, setting a proper quota is critical for the success. Too low a quota, for example, 5 friends to invite for the reward, may not bring enough exposure. On the other hand, too high a quota, for example 100, may actually discourage users and lead them to abandon the effort altogether. We investigate the time it takes for a user to invite friends to understand the mental mechanics of inviters.

In the previous section we have seen that most users invite the same set of close friends repeatedly. Then how big is the circle of close friends? Or to put it differently, how long does a person take to name the close friends? From the logs we mine the timestamps between invitations and plot them in Figure 5. The data points are grouped in 5 along the x-axis. The y-axis is the inter-invitation time between two consecutive invitations. The boxes represent the quartiles and the upper and lower marks represent the 5 and 95 percentiles of the inter-invitation time. Results from all four games are very similar, and here we only present the results from A.

Figure 5(a) pictures the inter-invitation time evolution of those who invited exactly 20 friends. The inter-invitation time dips if very minutely from the 5-th to the 10-th invitee in all three figures in Figure 5. We believe this slight decrease in invitation time is likely to be due to user's improved familiarity with the invitation mechanism. A conspicuous jump in the 95-percentile takes place from the 15-th to 20-th invitee in Figure 5(a). A bigger jump is from the 20th to 25-th in Figure 5(b). In Figure 5(b) the third quartile and median also increase, representing the extra mental cost users experience in listing 10 more friends beyond 20.

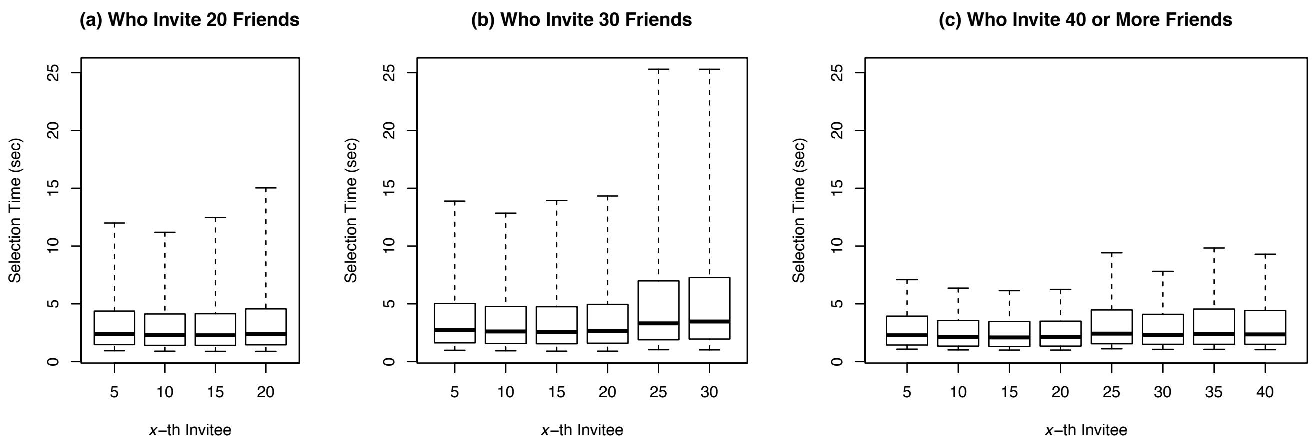

Figure 5: Time it takes an inviter to select x-th invitee in A. (a) For those who invited exactly 20 friends. (b) For those who invited exactly 30 friends. (c) For those who invited 40 or more friends. The x-axis is grouped in units of 5. The boxes represent the quartiles and the upper and lower marks represent the 5 and 95 percentiles.

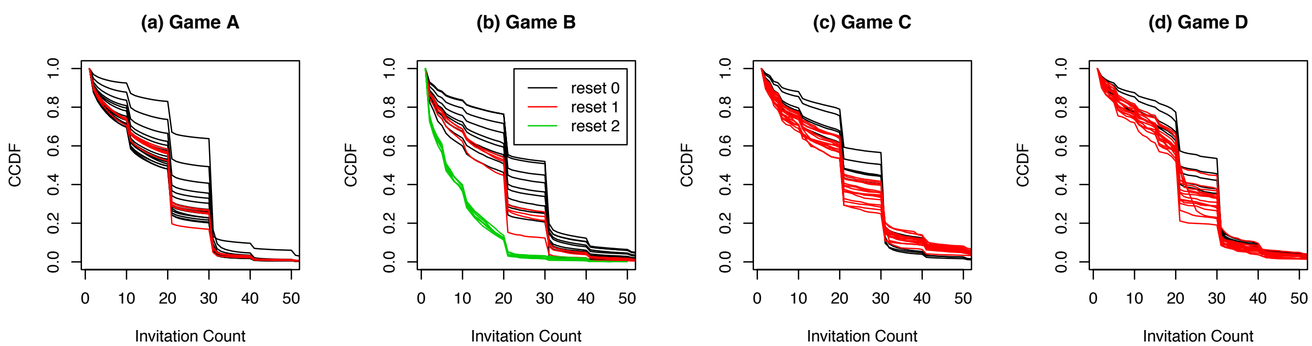

Figure 6: Weekly CCDF of the invitation counts. Black lines for the weeks before the first reward reset, red lines for after the first reward reset, and green lines for the weeks after the second reward reset for B (best viewed in color).

Apparently, those who invite beyond the maximum reward quota feel much less pressure about friend invitation. In Figure 5(c) for those who invite 40 or more friends, the selection time is much lower than the previous groups. Nevertheless, there is also a slight bump after 20. Thus we conclude that there is a mental hurdle somewhere between 21 to 30 in naming close friends.

Another angle to study the inviter's mental mechanics is to see the reaction to the quota over time. How has the user's invitation behavior changed? As more users sign up for the game over time, there remain fewer users to invite. Thus the number of friends a user invites should decrease over time. Is the change incremental? Figure 6 show the weekly CCDF of the invitation counts. As all games have had reward resets, we use black lines for weeks before the reset, and red for after.

During the course of our log collection, B had reset the quota in the 11th week and reset again with its maximum quota change from 30 to 40 in the 15th week. For B, we use a third color green for the weeks after the second reset.

For A, C, and D, graphs in black or weeks before the reset tend to be above the red lines. That is, the earlier users invite friends, the more they invite. In the case of B, we see a stark drop for the graphs in green. Since the second reset, almost no one has the heart to invite up to the quota and gave up around 20.

It is too premature to draw a conclusion on the mental capacity for human social networking from this data alone, and we only note the above as interesting observations that require further study.

4. INVITEE'S REACTION

Friend invitations arrive unsolicited, and that alone could trouble the invitee, whether it comes from a close friend or not. Worse yet, a user may get multiple invitations to the same game. It would be interesting to understand the user's reaction to multiple invitations. In this section, we analyze the invitee's reaction in 10,000 sampled invitees in C.

The response to social referrals has been studied in a few platforms, but the results are not consistent. In an online retailer's referral program, the probability of buying a book peaks at receiving two recommendations and then drops [16]. In an online social network experiment, the probability of adopting a health community activity increases up to four social signals [6]. In a social game diffusion case on Facebook, the probability of joining a game steadily increases as one gets more invitations [22].

All of the above studies only consider the number of incoming invitations per user. Yet, the temporal aspect in the invitation is another important factor. Receiving a number of invitations in a short period of time may be more attractive than receiving them staggered over time. Figure 7 shows the probability of signing up for C after receiving x invitations over time. When we do not consider the time interval between incoming invitations, the probability of joining decreases as one receives more invitations as in Figure 7(a), which is consistent to Leskovec *et al.*'s observation [16]. However, if we set the limit to a week, the probability of signing up for the game increases up to receiving 4 invitations, supporting Centola's observation [6].

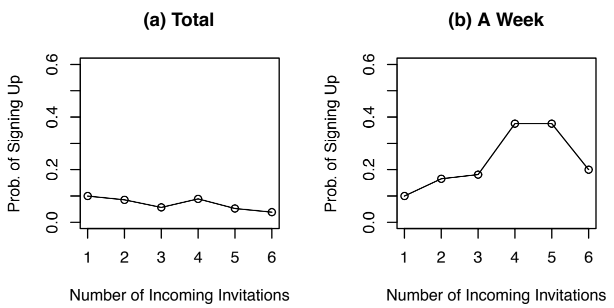

Figure 7: Probability of signing up given a number of incoming invitations for C. (a) In total. (b) In a week.

In Figure 7 we see that the time intervals between incoming invitations play a key role as well as the number of incoming invitations. In order to study the temporal aspect of invitations, we define $p(n, d)$ as the ratio of those who sign up over the total number of people who received exactly n invitations spanning d days. Then, $p(1, 1)$ means the ratio of sign-ups among invitees who received only one invitation. If $p(n, d) > p(1, 1)$, sending an invitation message to an invitee who received $n - 1$ invitations within d days is more effective than inviting a new person. If $p(n, d) < p(n-1, d)$, sending n-th invitation to an invitee is not that effective.

Table 5 shows $p(n, d)$ values, where the rows represent n and columns represent d. The first observation from the table is in a row the values increase when d decreases from right to left: invitations are more persuasive when they arrive in a shorter time span. Or for the same number of invitations, the longer it takes to receive them, the less likely the user signs up. At what point does it become not worthwhile to send an additional invitation? Using $p(1, 1)$ as the cut-off point, the dark shaded area represent the region of not effective invitation. If an additional invitation does not amount to the marginal utility of $p(1, 1)$, the invitation might as well be spent on a user never invited before.

More invitations for the same period of time do not always have a positive effect on the invitee. Except for $d = 1$, if the number of invitations goes over 4, the probability of sign-up starts to decrease. Why four invitations? Either

		d					
		1	2	3	4	5	$\geq$6
n	1	10.0	-	-	-	-	-
	2	29.2	23.2	12.3	9.2	6.8	2.9
	3	83.3	20.7	16.7	12.2	6.7	2.0
	4	100.0	88.9	50.0	20.0	25.0	2.2
	5	100.0	85.7	20.0	-	-	-

Table 5: Table of $p(n, d)$, the percentage of those who sign up over the total number of people who received exactly n invitations spanning d days. The shaded area represents not effective invitations.

by coincidence or not, our number is consistent with that reported by Centola [6]. We envision the need for controlled experiments to verify the psychological threshold of four and leave it for future work.

Based on the observations in this section, game companies can improve the effectiveness of friend invitations. For example, they can put recently invited people on top of the friend list as long as they have fewer than four invitations from friends. As time passes and if a user has received four invitations or more, the user should be demoted off the top in the friend's list of the recommended.

5. PROPAGATION SPEED

Previous sections describe how inviters and invitees behave in the quota-based reward schemes. Now we begin to examine how quickly the invitations are sent out and propagated. Our datasets are well suited for the study of game propagation, because the invitation and the act of sign-up are both explicit and timestamped with millisecond accuracy. In this section, we investigate the diffusion speed of game C. We divide the invitation cascading process into three phases, and examine the distributions of the time intervals for the three stages.

- t_1: Time interval from receiving an invitation to joining the game. (If a user received multiple invitations, we consider only the last one.)
- t_2: Time interval from joining the game to sending the first invitation.
- t_3: Time interval between consecutive invitations sent by a user.

We plot the distribution of each time interval in Figure 8. In Figure 8(a) about 20% of the sign-ups occurred within an hour after the last invitation received, 50% occurred within a day, and 80% occurred within a week. It seems like the CDF is linearly proportional to logarithm of the time intervals, $F(t_1) \propto \log t_1$, implying $P(t_1) \propto 1/t_1$.

After joining a game, users start inviting in very quick succession. As shown in Figure 8(b), about 50% of inviters start inviting friends within 5 minutes after joining the game, while only about 20% of users invite friends half a day after sign-ups. Most of the users invite friends right after the tutorial or a few additional plays.

After sending the first invitation, the users send consecutive invitations in a bursty manner. In Figure 8(c), about 50% of the invitations occurred within 6 seconds from the previous one, and more than 90% occurred within 1 minute.

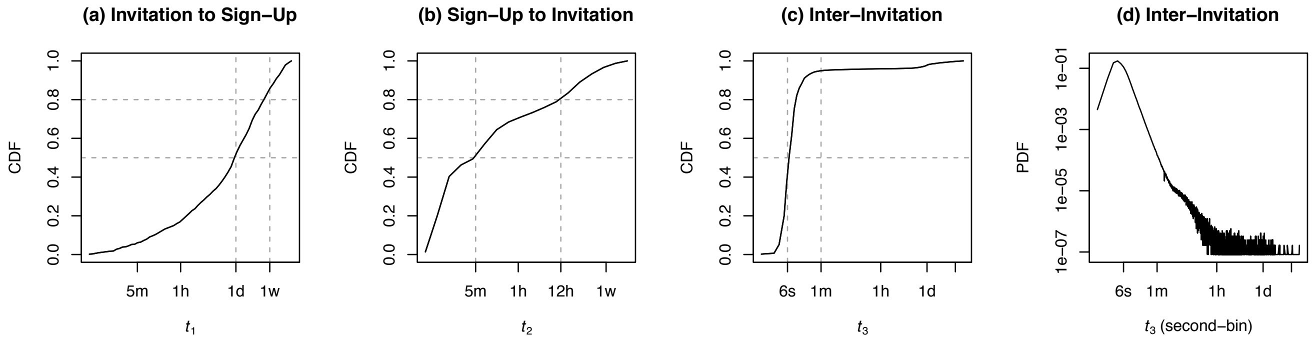

Figure 8: Timing of invitation cascading. (a) Time interval from receiving an an invitation to joining the game. (b) Time interval from joining the game to sending the first invitation. (c), (d) Time interval between consecutive invitations sent by a user.

As shown in Figure 8(d), the PDF of t_3 follows power-law, indicating that an individual's invitation pattern has a bursty nature. Barabasi models the bursty nature of human activities as a priority-based decision process [3]. In quota-based reward schemes, invitations up to reward quotas have high priority than the remainders. Users send several invitations during a single session in quick succession to meet the reward quotas, followed by a long period of no invitation activity. The immediate and bursty nature of the invitation behavior can be explained by the law of diminishing marginal utility. The utility of a reward is greater at the beginning of the game playing, because users have limited ability and experience to earn commodity such as game money or items.

Quota-based reward schemes not only motivate users to invite many friends, but also spur the pace of its propagation. This makes the explosive growth of the games at the very early stage, as we have witnessed new sign-ups and invitations occur in an explosive manner in the first week of the game launch as Figure 1.

6. CAUSES FOR SATURATION

In previous sections we have learned that friend invitations are a very effective mechanism for game advertisement and recruiting. However, the user growth soon reaches saturation regardless of the popularity (in Figure 1, new sign-ups decrease exponentially). Earlier studies characterize what drives ongoing WOM [4, 8, 10, 20], but none of them investigate what causes its termination. There are still millions of people not yet registered for the services, but why does the WOM spread no more? In this section, we study the causes for slowdown in the diffusion of the games, using data C.

The diffusion of the games arises from aggregation of each individual's decisions about the invitation. There are three decision points an individual faces. First, after signing up and playing a few matches, the user decides whether or not to invite friends. Then, the user decides whom and how many friends to invite. In next turn, each of the invitees decides whether or not to sign up for the game, and if so, the decision process repeats. To reveal where the slowdown occurs most at among the three decision points, we look at the temporal changes of the following measures.

- *Invitation rate*: what proportion of the signed-up users start inviting friends?
- *Average invitation count*: how many friends do the inviters invite on average?
- *Acceptance rate*: what proportion of the invitees actually sign up for the game?

Figure 9 shows the temporal changes of the invitation rate and the average invitation count for 10 weeks, and the acceptance rate for 3 weeks in C. Surprisingly, whenever users joined the game, constant proportion ($mean = 0.48, sd = 0.04$) of the users start inviting friends as in Figure 9(a). Also they invite a similar number ($mean = 24.21, sd = 1.32$) of friends on average as in Figure 9(b). However, the acceptance rate drops dramatically by the day. Invitees who did not sign up for the game are continuously exposed to additional invitations, while the signed-up invitees are not. This may cause the decreasing acceptance rate. Thus, we plot the acceptance rates for all invitees and new invitees who received the first invitation separately in Figure 9(c), and the acceptance rates for both groups drop rapidly.

With the sampled data, we could only check the acceptance rate for C. However, we show the time series of the invitation rate and the average invitation count of the other games in Figure 10. In A, the invitation rate decreases from 0.8 to 0.4, but still a significant proportion of users actually invite friends. The decreases in A arise from its popularity. Because most of the people have already signed up for the game, the users have limited friends to invite. Other games shows similar patterns to C, resulting in constant invitation rates and average invitation counts for ten weeks.

The result is striking because of the decrease in acceptance rate brings all the slowdown of diffusion. It is natural to expect that the termination of diffusion comes from a combination of three factors, but our analysis result points at only the acceptance rate.

One possible explanation for this result is homophilic nature of social network formation. In this incentivized WOM referral program, users invite closest friends as we have seen in Section 3.2. The diffusion of games may be initiated by a small number of the game fans at the beginning. Their close friends are likely to have similar preferences, and they are likely to accept the invitation. However the preferences

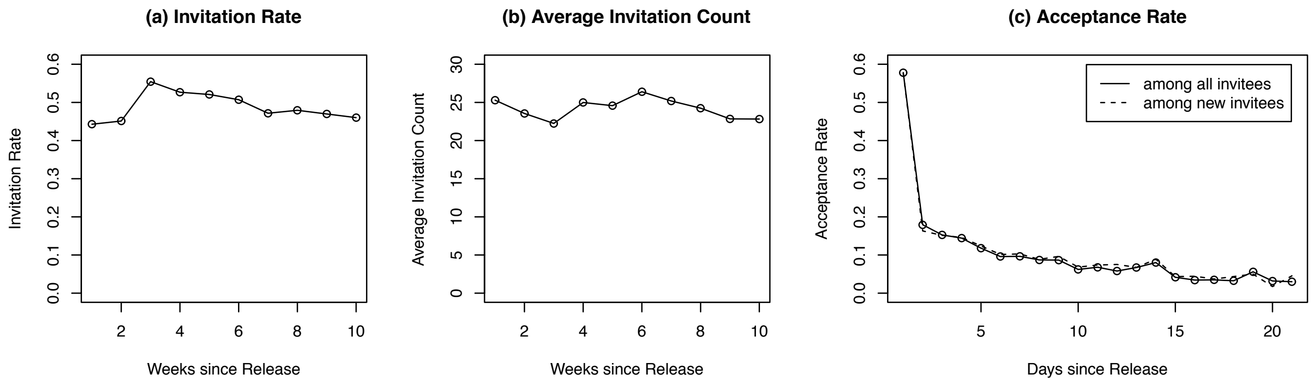

Figure 9: Time series showing the changes in the diffusion statistics of C. (a) The proportion of inviters among new sign-ups. (b) The average number of invitations a new inviter sent during a week. (c) The proportion of sign-ups among invitees. We plot the acceptance rate in daily binning to show its rapid decrease.

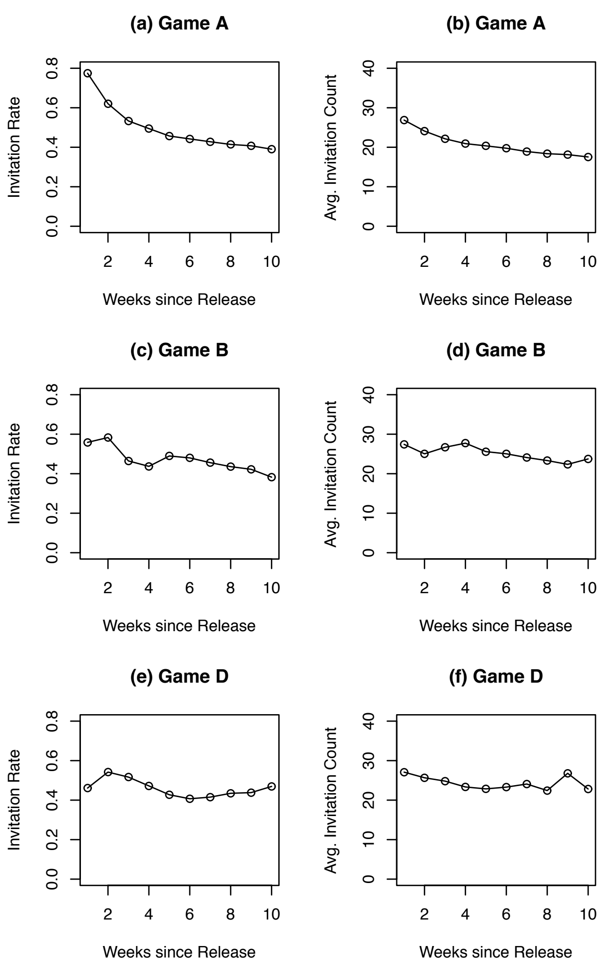

Figure 10: Time series showing the diffusion statistics of A, B, and D. (left) The proportion of inviters among new sign-ups. (right) The average number of invitations a new inviter sent during a week.

drop as the invitations spread through the network. Eventually, most of the incentivized friend invitation cascading terminates. Nevertheless, it is efficient and effective because it draws a large number of people explosively at the early stage of a game launch.

7. RELATED WORK

WOM marketing is attracting massive interest with emerging social platforms, but studies on the influence of WOM go as far back as decades. Earliest studies on WOM effect were survey-based, and reported that WOM affects not only purchase decisions, but also pre- and post-purchase perceptions [2, 12, 14]. Recently, the survey-based work begins to focus on the online and, in particular, the mobile environment [10, 20].

As OSNs have emerged providing venues for content sharing, a number of studies characterized content dissemination on OSNs. Guhl *et al.* studied information diffusion on blogspace based on keywords and links [13]. Cha *et al.* investigated the photo propagation on Flickr from favorite marking activities [7]. However, these works have limitation that they infer WOM rather than directly observe it.

Investigating direct WOM is rare because of the lack in public data. Leskovec *et al.*, reported an analysis of person-to-person recommendation via e-mail on an online retailer, as the first empirical study with large-scale data [16]. On the other hand, Centola designed an experiment about spread of behavior on artificially generated social networks [6]. With the recent advent of social platforms based on existing social networks such as Facebook, Wei *et al.*, studied diffusion of social games on Facebook platform via friend invitation [22].

8. CONCLUSIONS

In this paper, we analyze the user behavior and diffusion dynamics in friend invitation programs compensated with quota-based rewards.

The incentives motivate users to invite their friends up to reward quotas, only beyond which we start to see power-law tail behavior. Users tend to invite their closest friends to different genres of games, regardless of the game popularity or one's own preference. In general, users invite 20 friends *comfortably.*

The acceptance rate increases up to 4 incoming invitations, but more than 4 invitations are not effective. Also the time interval between multiple incoming invitations is critical to the success. Generally, 2 invitations within 3 days, 3 invitations within 4 days, and 4 invitations within 5 days are more effective than just a single invitation, and multiple invitations spanning longer than 5 days are regarded not as persuasive.

Once a user receives an invitation, the user signs up quickly, and starts inviting people in a few minutes. As they start inviting, the consecutive invitations are sent in a bursty manner, showing a power-law time interval distribution.

However, the diffusion of games soon terminates. We have found that only the acceptance rate decreases rapidly, but the invitation rate and the average invitation count remain constant. However, incentivized friend invitation still makes sense because it draws attention to potential sign-ups immediately after the game launch.

Mobile social platforms are growing rapidly. KakaoGame already has two-thirds of Korean population as registered users, and LINE and WeChat are following suit. Accordingly, understanding the user behavior in mobile social context has a far-reaching impact on marketing, psychology, sociology, and beyond. In this paper, we have analyzed a novel dataset from KakaoTalk mobile games. We have found practical insights for viral marketing which we hope will bring a new spin to the social network research community.

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