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

Jiwan Jeong / Sue Moon
KAIST
COSN’14, Oct 1–2, 2014, Dublin, Ireland
Top grossing apps on Google Play

Captured on Jan 1, 2014

<table>
<thead>
<tr>
<th>Rank</th>
<th>Application</th>
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<tbody>
<tr>
<td>1</td>
<td>Taming Monsters for Kakao</td>
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<tr>
<td>2</td>
<td>Cookie Run for Kakao</td>
</tr>
<tr>
<td>3</td>
<td>Candy Crush Saga for Kakao</td>
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<td>Everybody's Marble for Kakao</td>
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<td>6</td>
<td>Anipang for Kakao</td>
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<td>7</td>
<td>Everytown for Kakao</td>
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<td>8</td>
<td>KakaoTalk</td>
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<td>9</td>
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<td>FIFA Online 3</td>
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<td>10</td>
<td>Summoners War: Sky Arena</td>
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### Top grossing apps = KakaoTalk games

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KakaoTalk, a mobile instant messenger

- *De facto* standard MIM in Korea
  - 37M users among 50M population
  - Friendships based on smartphones’ contact book

- KaTalk as a verb in Korea
  - Google it!
  - FedEx it!
  - KaTalk me!

Text me! 👋

KaTalk me! 🙆‍♀️
KakaoTalk’s game platform

- **Sign-Ups**: 1M users per game
- **Games**: 14 games per user
Behind its rapid growth...

- **Quota-based reward scheme** for friend invitation
  - if a user invites 10, 20, and 30 friends cumulatively
  - then the user gets reward 💰, 💎, and 🚗, respectively
  - no matter whether the invitee signs up or not
Inviting friends
Inviting friends

Quotas and rewards for invitations
Inviting friends

List of KakaoTalk friends who did not sign up for the game yet
Inviting friends

Click
Inviting friends

[Taming Monsters]
Jiwan Jeong's invitation to Taming Monsters received.

"Please tame me softly."

Go to App

Click
Inviting friends

몽스터 길들이기 for Kakao
CJ Netmarble

UNINSTALL  OPEN
Social referrals are not only for games
This work

• We examine the inviters’ behavior and the invitees’ reaction in KakaoGame’s quota-based friends invitation

• Then, we see the dynamics of the game diffusion by looking at how the user behavior changes over time
## Datasets

<table>
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<tr>
<th></th>
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<th>user</th>
<th>inviter</th>
<th>invitee</th>
<th>invitation</th>
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<td>7.8M</td>
<td>33.7M</td>
<td>268.1M</td>
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<tr>
<td>B</td>
<td>10/20/30 + 3/5</td>
<td>2.5M</td>
<td>1.3M</td>
<td>17.1M</td>
<td>42.4M</td>
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<tr>
<td>C</td>
<td>10/20/30 + 3/5</td>
<td>0.9M</td>
<td>0.4M</td>
<td>7.6M</td>
<td>12.8M</td>
</tr>
<tr>
<td>D</td>
<td>10/20/30 + 5/15/25</td>
<td>0.6M</td>
<td>0.3M</td>
<td>5.0M</td>
<td>7.7M</td>
</tr>
</tbody>
</table>

for 4 games published by Netmarble / for 20 weeks since each game’s release date
Part I
Inviters’ behavior
Rewards stimulate invitation behavior by ...

1. Motivating users to invite friends
   - What proportion of users invite friends?

2. Pushing *motivated* users to max out invitations up to quotas
   - How many friends do they invite?
Rewards stimulate invitation behavior by ...

1. Motivating users to invite friends
   - What proportion of users invite friends? — invitation rate

2. Pushing *motivated* users to max out invitations up to quotas
   - How many friends do they invite? — invitation count
# Invitation rate and count

<table>
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<th>invitation rate</th>
<th>invitation count</th>
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<tr>
<td></td>
<td>user</td>
<td>inviter</td>
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<tr>
<td>A</td>
<td>100K</td>
<td>87K</td>
</tr>
<tr>
<td>B</td>
<td>100K</td>
<td>40K</td>
</tr>
<tr>
<td>C</td>
<td>100K</td>
<td>32K</td>
</tr>
<tr>
<td>D</td>
<td>100K</td>
<td>31K</td>
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for the first 100K users / for 28 days since each user's sign-up
Reward is not sufficient to motivate users

<table>
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<tr>
<td>user inviter</td>
<td>1Q avg median 3Q</td>
</tr>
<tr>
<td>A 100K</td>
<td>87K 30 28.9 31</td>
</tr>
<tr>
<td>B 100K</td>
<td>40K 30 30.2 31</td>
</tr>
<tr>
<td>C 100K</td>
<td>32K 20 27.2 30</td>
</tr>
<tr>
<td>D 100K</td>
<td>31K 20 28.8 30</td>
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</table>

invitation rates vary corresponding to popularity of the games for the first 100K users / for 28 days since each user’s sign-up
But highly affects *the motivated* users

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<td>B</td>
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All games have similar invitation count statistics regardless of popularity.

for the first 100K users / for 28 days since each user’s sign-up
CCDF of invitation counts

- Discontinuations at quotas at 20 and 30
- Users max out invitations up to achievable quotas
Motivated users max out their invitations up to achievable quotas. Then, how do inviters select invitees to achieve the quotas?
How do users select whom to invite?

• Strategy 1: Users invite same friends to different games
• Strategy 2: Users invite different friends to different games
Overlap b/w a user’s invitees in two games

• A user’s invitee similarity for a game pair

\[ S_{XY}^u = \frac{|u_X \cap u_Y|}{\min(|u_X|, |u_Y|)} \]

- \( u \): a user who invites friends to game \( X \) and \( Y \)
- \( u_X \): the set of invitees \( u \) invited to game \( X \)
- \( u_Y \): the set of invitees \( u \) invited to game \( Y \)
A user’s invitee similarity b/w two games

**Figure 4: CCDF of invitee similarity.**

![CCDF of invitee similarity](image)

Our observation above supports Strategy #1, but why do users use Strategy #1? One possible explanation is that users cannot invite friends who have already signed up for the game, the invitee selection can be severely restricted in popular games. Since users cannot invite friends who have already signed up, the two games under examination should have comparable rate of adoption. Therefore we exclude the game for the curiosity for the personal motivation behind Strategy #2: users invite different sets of friends to different games repeatedly, thereby limiting the damage. For every pair of games, we select the users who have invited friends to games. For the curiosity for the personal motivation behind Strategy #2: users invite different sets of friends to different games repeatedly, thereby limiting the damage. For every pair of games, we select the users who have invited friends to games. For the curiosity for the personal motivation behind Strategy #2: users invite different sets of friends to different games repeatedly, thereby limiting the damage. For every pair of games, we select the users who have invited friends to games.
Users invite same friends to different games

Figure 4: CCDF of invitee similarity.

Table 4: Similarities between games.

<table>
<thead>
<tr>
<th></th>
<th>A and B</th>
<th>A and C</th>
<th>A and D</th>
<th>B and C</th>
<th>B and D</th>
<th>C and D</th>
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<td>0.7529</td>
<td>0.7684</td>
<td>0.7588</td>
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<td>0.2651</td>
<td>0.2177</td>
<td>0.2458</td>
<td>0.0509</td>
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<tr>
<td>Y</td>
<td>0.3280</td>
<td>0.2651</td>
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</table>
Users invite same friends to different games
Users invite *closest* friends to regardless of the game

- I invite my closest friends regardless of the game (94%)
- I don't (6%)

Informal survey among 50 gamers
Most users invite the same set of close friends repeatedly to different games. Then how big is the circle of close friends?
Setting a proper quota is important

Invite 5 friends and get rewards! — Not enough exposure
Invite 100 friends and get rewards! — Discourage users

How many friends a user can invite comfortably?

Our approach — How long does it take to select \(x^{th}\) invitee?
Times it takes to select $x$-th invitee

* for those who invite exactly 30 friends in A
Users invite up to 20 friends *comfortably*

* for those who invite exactly 30 friends in A

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 at the 1st color for the week after the second reset. For A, C, and D, graphs in black for the 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.
Mr. Dunbar’s circles of acquaintanceship

- 150 – just friends
- 50 – trusted friends
- 15 – good friends
- 5 – best friends

Our social circle size for incentivized WOM

20 friends for comfortable invitation

150 – just friends

50 – trusted friends

15 – good friends

5 – best friends
Part 1 Summary

• In the quota-based reward schemes
  - The quotas affect *motivated* users to max out invitations
  - The invitations spread through the *closest* friendships
  - The *social circle size for comfortable* invitation is 20
Part 2
Invitees’ reaction
How do invitees react to multiple incoming invitations?
Different results from previous work

Probability of buying a book \textit{(Leskovec et al., EC’06)}
Different results from previous work

Probability of adopting a health behavior (Centola, Science, 2010)
Different results from previous work

Probability of joining a Facebook game (Wei et al., WOSN’10)

Figure 11 Acceptance rate over different number of invitations received by one user
Time intervals b/w invites are critical to sign-up

![Graph](image.png)

*10000 sampled invitees in game C*
We define \( p(n,d) \)

- \( p(n,d) \) to be ...

  - the percentage of signed-ups users among those who received \( n \) invitations spanning \( d \) days

\[
p(n, d) = \frac{\text{# sign-ups among them}}{\text{# those who received } n \text{ invites spanning } d \text{ days}}
\]

\( *d = \text{time interval between the first and the last invitations} \)
Table of $p(n,d)$

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<tr>
<th>$n$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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for 10K sampled users in game C
Shorter intervals, more likely to sign up

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for 10K sampled users in game C
Up to 4 invitations, more likely to sign up

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for 10K sampled users in game C
$p(1, 1)$ can be cut-off value for effectiveness

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\(p(1, 1) = \text{sign-ups among invitees who received only one invitation}\)

for 10K sampled users in game C
$p(1, 1)$ can be cut-off value for effectiveness

- a new invitee
- 2 invites in 3 days
$p(1, 1)$ can be cut-off value for effectiveness

- A new invitee: $p(1, 1) = 10.0\%$
- 2 invites in 3 days: $p(2+1, 3+1) = 12.2\%$
\(p(1, 1)\) can be cut-off value for effectiveness

- A new invitee: \(p(1, 1) = 10.0\%\)
- 2 invites in 3 days: \(p(2+1, 3+1) = 12.2\%\)

More effective!
$p(1,1)$ can be cut-off value for effectiveness

a new invitee

$p(1,1) = 10.0\%$

more effective!

2 invites in 4 days

$p(2+1,4+1) = 6.7\%$
$p(1, 1)$ can be cut-off value for effectiveness

<table>
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for 10K sampled users in game C
Part 2 Summary

• When a user receives multiple invitations
  - Time intervals are important as well as the # of invitations
  - More than 4 invitations are not persuasive

*K Use \( p(n,d) \) table for the utility of an invitation*
Part 3

Causes for Saturation
Diffusion explodes and terminates quickly

(c) Game C

Weeks since Release

New Sign-Ups & Invitations

Weeks since Release

Dataset Statistics

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<tr>
<th>Game</th>
<th>Invitations</th>
<th>Sign-Ups</th>
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<tbody>
<tr>
<td>A</td>
<td>762K</td>
<td>413K</td>
</tr>
<tr>
<td>B</td>
<td>872K</td>
<td>510K</td>
</tr>
<tr>
<td>C</td>
<td>668K</td>
<td>270K</td>
</tr>
<tr>
<td>D</td>
<td>419K</td>
<td>123K</td>
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</table>

In Figure 2, we plot the complementary cumulative distribution functions (CCDFs) of invitation count and sign-ups for four different games. The CCDFs are plotted on a log-log scale, with the x-axis representing weeks since release and the y-axis representing the number of new sign-ups and invitations.

The CCDFs show marked discontinuities at certain quotas, indicating that the majority of inviters have sent out a similar number of invitations. For example, in Game A, the 5th percentile of invitation count is around 10, the median is around 30, and the 95th percentile is around 90.

For all four games, the invitation count and sign-ups are highly correlated, with a Pearson correlation coefficient of 0.98. This suggests that the invitation behavior is stable over time.

In contrast to the explosive growth in the early stage, both the numbers of invitations and sign-ups decrease by two orders of magnitude from the 1st reward reset to the 2nd reward reset. Even with the reward resets, the numbers of invitations drop exponentially.

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 new sign-ups to a game. The reward resets can also stimulate invitations by encouraging friends who already signed up. Also, the reward scheme is reset to encourage more invitations.

In summary, the invitation rates vary from a low of 30% in the early stage to a high of 90% in the final stage, corresponding to the popularity of the games. The invitation rates are highly correlated with the proportion of inviters among signed-up users, and the invitation behavior changes over time.
There are still millions of people who didn’t sign up for the games. But why does it spread no more?
Diffusion = Decisions

- Whether or not to invite friends?
- How many friends to invite?
- Whether or not to join the game?

How these decisions change over time?
Causes for Saturation

• As time passes ...

  Possibility 1 — New sign-ups do not invite friends as before

  Possibility 2 — New inviters invite fewer friends than before

  Possibility 3 — New invitees do not sign up for the game
Constant % of new sign-ups invite friends

<table>
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<th>Weeks since Release</th>
<th>Invitation Rate</th>
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Figure 9: Time series showing the changes in the diffusion statistics of C. (a) The proportion of invitees 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.

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

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 limitations that they infer WOM rather than directly observe it. Investigating direct WOM is rare because of the lack in public data. Leskovec et al., report 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.
... and they invite a similar # of friends

![Graphs showing changes in diffusion statistics](image)

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Invitees’ acceptance rate drops rapidly

![Graph showing acceptance rate over time]

**Homophily? Possibly...**
Summary

• We study the friend invitation in KakaoTalk games
• The diffusion explodes at the beginning and soon decay
• Invitations spread through closest friendships
  - Social circle size for comfortable invitation is 20
  - Persuasive incoming invitation size is 4
  - Rapid drop in acceptance rate leads termination of diffusion
a mobile game analytics startup that launched in April this year, has been acquired at $40M by Tapjoy.
Weekly new sign-ups and invitations

(a) Game A
(b) Game B
(c) Game C
(d) Game D
CCDF of invitation counts

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.

Table 2: Signed-up users vs. exposed users.

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...
Time it takes an inviter to select x-th invitee

(a) Who Invite 20 Friends
(b) Who Invite 30 Friends
(c) Who Invite 40 or More Friends

Figure 5: Time it takes an inviter to select x-th invitee. 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. (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 shows 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 at third color for the week after the second reset.

For A, C, and D, graphs in black 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...
Weekly CCDF of invitation counts

Figure 5: Time it takes an inviter to select the $x$-th invitee in
(a) For those who invited exactly 20 friends.
(b) For those who invited exactly 30 friends.
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Timing of invitation cascading

(a) Invitation to Sign-Up

(b) Sign-Up to Invitation

(c) Inter-Invitation

(d) Inter-Invitation
Invitation rates and counts over time