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Differentiated Incentive Rewarding for Social Networking Services

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***Abstract*—Our ultimate goal is to develop an information diffusion system where individuals are motivated to create content and share it with public. As our first step, in this paper, we present an incentive-rewarding mechanism for social networking services and focus particularly on changing reward assignment ratio considering different risks users perceive when uploading content with different privacy settings: public-open and friend-limited. Our learning-based simulation allowed us to observe enlargement of social networks with different rewarding ratio. The result also suggested that there is an optimal reward assignment ratio to maximize social networks.**

***Keywords*-Social networking service; privacy setting; perceived risk; incentive; social graph**

I. Introduction

A social networking service (SNS) [1] is a service that allows users to exchange private information and organize communities on the Internet. In SNSs, users can customize and manage their own pages on which they upload content such as articles and photos. They can also register their friends on their pages and add links to their friends' pages, which forms what is called a social graph [2]. Users can assign the privacy settings for each content piece they upload: they might permit only their friends to browse private content, because they do not want their privacy to be exposed to public, while also uploading content for the public, which others including friends of their friends are permitted to browse. Studies have shown that most users tend to upload content only for friends [3] because they experience smaller perceived risk than uploading content open to the public. However, if users restrict their content to the private domain, the information available on SNSs is limited and opportunities to establish links with others drastically decreases.

We have therefore developed an incentive-rewarding mechanism specific to SNSs in which users receive incentive rewards in proportion to their number of page views (how many times their page is browsed by others) but alters the reward amount for public and private content to compensate for the different perceived risks experienced. We expect our mechanism to motivate users to upload content for the public as well as their friends, resulting in increased opportunities of link establishment with friends of their friends. This is the first attempt to model link establishment between two users who have a common friend via browsing content either of them have uploaded for the public, and we discuss how much risk users actually experience when they upload content to SNSs. Our design is also the first incentive mechanism that considers the different perceived risks associated with the uploaded content. Simulation results show the trade-off between the amount of uploaded content and the growth of social graph. They also suggests an optimal reward assignment that maximizes the number of page views.

II. Models

A. Service assumption

SNSs—including MySpace [3] and Facebook, which are two of the most popular SNSs—commonly have the following features:

- Users each have a personal page which only they are permitted to edit. They upload articles and photos onto the page.
- Users have links from their pages to those of their friends.
- Users can choose a different privacy setting for each content piece from two setting options: limited to friends or open to the public.
- Users can comment on their own uploaded content and the content uploaded by others which are permitted to browse.
- Users have the opportunity to meet the friends of their friends via content their friends upload with the limited-to-friends setting.
- Two users can establish a new link via browsing content either of them have uploaded for the public.

Users tend to choose "limited to friends" when uploading content that includes private diaries or photos in order to reduce the perceived risk involved.

B. Psychological factors

Psychological factors in human behavior can roughly be split into two: positive and negative factors called incentive and cost [4][5]. The former increases and the latter decreases the motivation to complete an action. In this paper, we discuss reward incentive and risk, which are two factors dominating SNSs (though there can be many other factors as well).

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Reward incentive People experience reward incentive when they receive money, gifts, points, or anything as equally valuable to them as their contributions. Reward incentives motivate people to upload content.

Risk People experience risk when they make content like diaries and photos open to others. Risk is categorized as cost because it decreases the motivation of people to upload content.

Since both incentive and cost can be represented quantitatively as an amount of money [6], they can be added and subtracted to and from each other. Therefore, the total satisfaction experienced by SNS user i is given as

$$SAT_i = W_i - C_i, \tag{1}$$

where C_i is the amount of risk experienced by user i and W_i is the amount of reward incentive experienced by him or her. We can assume user i is motivated to upload his or her content if $SAT_i > 0$ [5].

We surveyed fifty Kyoto University students who use an SNS, and 62% of them answered that they obviously feel larger perceived risk when they upload public content compared with content limited to friends. That is, $C_{\overline{f}}/C_f > 1.0$, where C_f and $C_{\overline{f}}$ are the risk amounts for uploading friend-limited content and public-open content.

C. Browsing model

Users browse friend-limited content uploaded by their friends and public-open content uploaded by friends of their friends. Survey results indicated users are limited in how many files they can browse within a certain period, they regularly leave comments when they browse content uploaded by their friends, they are not interested in old content, and they meet new friends through content on older friends' pages and then start visiting public-open content that the new friends upload.

Considering the above, we modeled how to browse the content of other users as follows.

1) Initialize: $p = 0$.
2) User i determines to browse content limited to his or her friends with probability P_i^f and then goes to the next step. Otherwise, he or she goes to step (4).
3) He or she randomly chooses content from pages that friends have uploaded most recently, $p = p + 1$, and goes to step (5).
4) He or she randomly chooses public-open content uploaded by users with whom he or she shares a common friend and has met before via the friend's page and $p = p + 1$.
5) If $B_i^{lim} \geq p$, the user goes back to step (2); otherwise, he or she terminates.

In the above, p is the number of content a user browse and B_i^{lim} is the limitation of how many files they can browse.

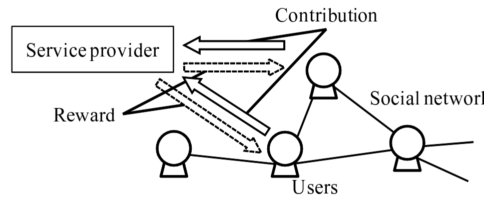


Figure 1. Incentive rewarding system

D. Link establishment model

Our survey suggests that it is natural for users to establish links with a new friend after they browse this new friend's uploaded content a couple of times. For simplicity, we just set a threshold, A_{th}; after user A browses user B's content more times than A_{th}, they establish a link between themselves.

III. Proposed mechanism

We assume a centralized incentive rewarding mechanism, as shown in Fig. 1. Users contribute their content to the SNS provider and the SNS provider distributes incentive rewards to them according to their contributions.

The simplest way to give rewards is to distribute them exactly proportional to the contribution result of each user [5], that is,

$$W_i = W_T \times \frac{R_i}{R_T}, (R_T = \sum_i R_i) \tag{2}$$

where W_i and R_i are the reward for user i and his or her contribution result, while W_T is the total amount of available reward source. In this paper, we consider the number of page views, which corresponds to how many times the content is browsed by others, to be R_i because the total page views in an SNS is commonly considered the metric of how active the SNS is.

Here, we propose a differentiated incentive rewarding mechanism that gives a different reward amount to friend-limited and public-open content. Let W_{ni} denote the reward amount given to user i when he or she attains the number of page views R_{ni} with privacy setting n (1 or 2), where $n = 1$ and $n = 2$ means "limited to friends" and "open to public," respectively. That is, Eq. (2) is extended to,

$$W_{ni} = \alpha(n) \times W_T \times \frac{R_{ni}}{R_T}, \tag{3}$$
$$(R_T = \sum_n \sum_i R_{ni}, \sum_n \alpha(n) = 1.0)$$

where $\alpha(n)$ is the differentiation parameter in our method.

IV. Simulation

A. Simulation method using learning algorithm

It is difficult to apply traditional approaches such as the game theory or network simulations to our system evaluation because the system we assume is very dynamic

Table I
CHARACTERISTICS OF CNN GRAPHS WITH PARAMETER u

u	avg. no. of links	clustering coefficient
0.3	5.36	0.217
0.5	7.92	0.392

and complicated: users dynamically change their behaviors according to the amount of rewards they obtain, while the social graph is constantly growing. Therefore, we introduce a learning-based simulation similar to one used in previous studies [5][7].

To apply a learning-based simulation, we assume that the time is slotted. Then, the behavior of user i is modeled as follows.

1) User i uploads content with privacy setting 1 (limited to friends) and 2 (open for public) with probability E_{1i} and E_{2i}. Then, he or she suffers from either or both of perceived risks C_{1i} and C_{2i}.
2) The user browses content uploaded by users as modeled in Sect. II-C.
3) The user has opportunities to establish new links as modeled in Sect. II-D.
4) The user goes back to step 1 until duration T_p.
5) Rewards W_{1i} and W_{2i} are assigned to the user based on the R_{1i} and R_{2i} he or she gains within this T_p period. He or she updates E_{1i} and E_{2i} taking into account the experienced W_{ni} and C_{ni}.

We define steps 1–3 and 1–5 as an event and a period, respectively; E_{ni}, which is the effort level, is adjusted at every period so that SAT_{ni} is maximized. Note that E_{1i} and E_{2i} are determined independently of each other. To simplify our simulation, we consider only four discrete levels for E_{ni}: 0, $1/4T_p$, $1/2T_p$, and $1/T_p$. To pinpoint the optimal level in E_{ni} that maximizes SAT_{ni}, we let each user adopt learning automata [7]. With this algorithm, initially, the user chooses one of the four levels in E_{ni} with the equal probability. Then, the algorithm optimizes the selection probabilities of the four levels so as to maximize SAT_{ni} through a few tens of periods.

B. Simulation conditions

In our simulation, the initial social graph is generated based on the connecting nearest-neighbor (CNN) model [8], which has a density parameter u; as u increases, the average number of links per node and the clustering coefficient increases. Table I shows the characteristics of the 100-node CNN networks with the $u = 0.3$ and $u = 0.5$ we used for our simulations. These are consistent with the fact that the clustering coefficients in popular SNSs, including MySpace, are approximately 0.3 [9].

We evaluate the total number of page views after sixty periods. We assume that the total reward amount available for the SNS provider at each period, W_T, is in proportion to the total number of page views observed within the period,

Table II
SIMULATION CONDITIONS

Parameter	Value
$C_{\overline{f}}/C_f$	2
A_{th}	3
T_p	4 [events]
Content lifetime	2 [events]

that is,

$$W_T = \beta \times \sum_n \sum_i R_{ni}, \tag{4}$$

where coefficient β depends on how valuable one page view is. Other simulation conditions are shown in Table II. We uniformly set B_i^{lim} defined in Sect. II-C to $B_i^{lim} = 4$, which is the average number obtained from our survey results.

V. SIMULATION RESULTS

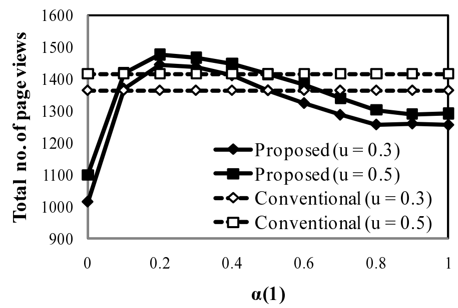
Figs. 2 (a) and (b) show the total number of page views for $\beta = 0.5$ and $\beta = 0.1$. We put the differentiation parameter $\alpha(1)$ in Eq.(3) on the horizontal axes. We compare our method with the conventional method using Eq. (2) the authors in [5] came up with.

In Fig. 2 (a), we can see the optimal value of $\alpha(1)$, which maximizes the total number of page views. The optimal $\alpha(1)$ was around 0.2 when $u = 0.3$ and $u = 0.5$. Let us consider two extreme cases. (A) If we increase $\alpha(1)$ to 1.0, a reward is assigned to users only when they upload content limited to friends; in this case, since no one uploads content open to the public, as described in Sect. II-C, users cannot establish new links with friends of their friends. (B) If $\alpha(1)$ is reduced to 0.0, a reward is assigned only to users uploading content open to the public; since users experience a bigger risk when they upload public content, they may upload less frequently, resulting in decreased page views. This explains why the optimal point exists in this figure.

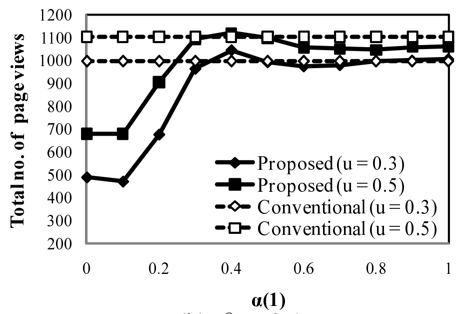
In Fig. 2 (b), it is not clear what the optimal $\alpha(1)$ is. The difference between Figs. 2 (b) and (a) is that in (b), since β was changed from 0.5 to 0.1, the reward became insufficient to compensate for the risk of updating public content. As seen in Fig. 3 (b), which shows the number of total links in the social graph as a function of $\alpha(1)$, there is still the optimal point. However, as seen in Fig. 4 (b) which shows the total number of uploaded contents as a function of $\alpha(1)$, when the reward source is not sufficient, simply increasing $\alpha(1)$ is also effective in increasing the total number of content because the risk of uploading content limited to friends can be compensated for by the smaller reward amount. Thus, when $\beta = 0.1$, the number of uploaded contents is dominant in increasing the total number of page views. For reference, we show Fig. 3 (a) and Fig. 4 (a), where $\beta = 0.5$.

VI. CONCLUSION

We developed an incentive-rewarding mechanism for SNSs that gives users incentive rewards in proportion to the number of page views but alters the reward amount to

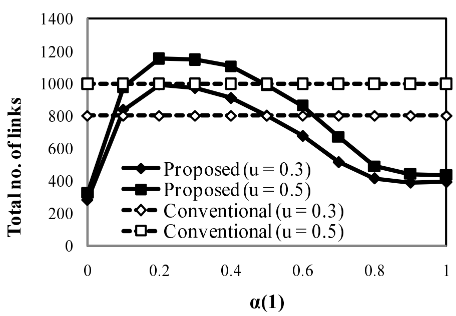


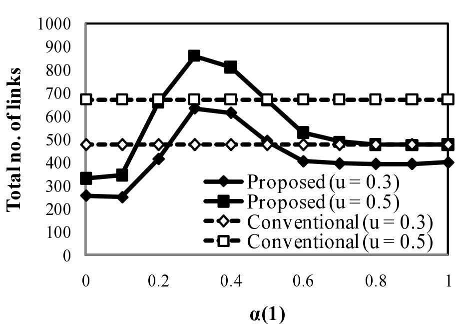
(a) $\beta = 0.5$



(b) $\beta = 0.1$

Figure 2. Total number of pageviews

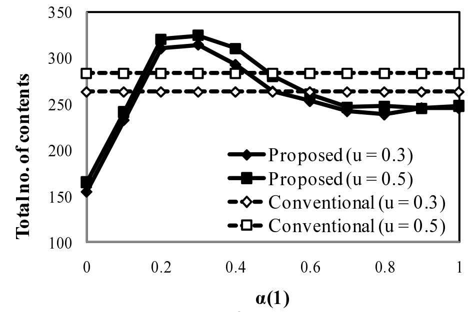




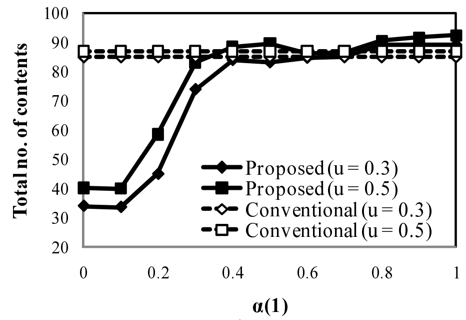
(b) $\beta = 0.1$

Figure 3. Total number of links

compensate for the different perceived risks users experience when uploading content with different privacy settings (limited to friends and open to public). We modeled psychological factors in SNSs and link establishment between two users via content browsing. Our learning-based simulation



(a) $\beta = 0.5$



(b) $\beta = 0.1$

Figure 4. Total number of uploaded contents

results showed the trade-off between the amount of uploaded content and the growth of the social graph and the optimal reward assignment that maximizes the number of page views. Future work includes experimental studies on our mechanism.

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