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Encouragement Methods for Small Social Network Services

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Abstract

Recently, Social Networking Services (SNS) have become a social phenomenon on the Internet. There are many small SNSs, including campus SNS, company SNS, and regional SNSs. Such user-limited SNSs are not fully utilized yet. To solve this problem, we propose a SNS model to simulate effective SNS encouragement methods. Simulations based on our proposed model were performed to confirm the influences of the encouragement methods on small SNSs. The simulations show that encouraging existing users' logins effectively encourages small SNSs.

1 Introduction

New network communication tools continue to grow steadily. The social phenomenon of the continued expansion such Social Networking Services (SNS), as MySpace (USA) [1], Bebo (USA) [2], Cyworld (Korea) [3], Mixi (Japan) [4], is impacting societies all over the world.

As well as SNSs for general users, many examples of user-limited SNSs can also be found, such as campus, company, and regional SNSs that provide specialized services for limited users, which effectively activating user communication on the Internet. These user-limited SNSs are receiving attention for their business potential.

At the same time, since such small SNSs that include the user-limited SNSs are not well utilized, clarifying a method to encourage them is urgent. However, from the viewpoints of time and money, improving services without justification is unrealistic. Therefore this study uses agent-based simulation to clarify methods for encouraging insufficiently utilized SNSs.

[1]http://myspace.com/
[2]http://www.bebo.com/
[3]http://cyworld.com
[4]http://mixi.jp

In this paper, we propose a small SNS model by considering relationships and intercommunication among users.

We clarify an effective method to encourage SNSs using agent-based simulations based on the proposed model.

First, we propose a SNS model using an agent-based model. Second, we validate our proposed model by comparing it with an actual SNS, the Academic Community System (ACS) [7], from the viewpoint of network structures. Third, we clarify an effective method to encourage the use of small SNSs using agent-based simulations based on our proposed model.

2 Social Network Service model

2.1 Overview

In this study, we adapt an agent-based model to describe the common actions of users in SNSs. In our model, an SNS provides the following functions:

- Communication among users (diaries, BBS, and so on)
- Responses to the communications of other users (diary comments, BBS, and so on)
- Links for making new friends [5]

Each user can take a series of actions once a period, which is defined as one day in the actual world .

2.2 Social network model

2.2.1 Agent model

We define N agents in an SNS as $a_i (i = 1, 2, \cdots, N)$. Each agent a_i has the following two parameters:

[5]called "My Friend" in MySpace.

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- Login frequency l_i
- Communication frequency d_i

Login frequency l_i is the rate at which agent a_i logins to SNS during a certain period. Parameter l_i is the real number value that takes the following range:

$$0 \leq l_i \leq 1. \tag{1}$$

If login frequency $l_i = 1.0$, then agent a_i logins to SNS every period. On the other hand, if login frequency $l_i = 0.0$, then agent a_i never logins to SNS.

Communication frequency d_i is the rate at which agent a_i communicates in the SNS, such as writing diaries, posting messages on BBS, sending messages to other users, and so on. Parameter d_i takes the following range of real number values:

$$0 \leq d_i \leq 1. \tag{2}$$

If communication frequency $d_i = 1.0$, then agent a_i communicates with another agent every period. On the other hand, if communication frequency $d_i = 0.0$, then agent a_i never communicates with another agent.

Each agent changes login frequency l_i and communication frequency d_i based on the responses of neighboring agents.

2.2.2 Link model

We describe the friendship between agents a_i and a_j as non-directed link L_{ij}. Each link L_{ij} has a parameter f_{ij} that describes the strength of the friendship.

In general, friendships are strengthened when they have communicated more recently. Thus, by considering Weber-Fechner law[6], we define friendship f_{ij} as:

$$\begin{aligned} f_{ij} &= \alpha \log(c_{ij} + 1) + \beta \qquad (3) \\ & \quad \text{(Maximum value of } f_{ij} = 1\text{)}. \end{aligned}$$

Here, α is the rate of changes in the friendships, and β is a constant that defines the minimum value of the friendship[6]. Parameter c_{ij} is the number of communications between agents a_i and a_j in recent T periods.

2.3 Social Network Service growth model

The structure of SNS networks changes when the following phenomena occur:

- New node (agent) is added
- New link (friendship) is generated

In our model, a combination scheme of a CNN-model[9] and a Fitness-model[3] is proposed to express network growth.

[6]When f_{ij} becomes smaller than β, agents a_i and a_j are no longer friends. But we do not define such situations in this model

2.3.1 New agent additions

When a new agent is added to the network, it is linked to another agent in the SNS. The linked agent is selected by a roulette selection. The selection probability of agent a_i is defined as:

$$\Pi_i = \frac{U_i k_i}{\sum_j U_j k_j}, \tag{4}$$

where parameter k_i shows the degree, which means the number of links of agent a_i. Parameter U_i, which shows the "SNS utilization" of agent a_i, is defined by

$$U_i = \frac{\sum_{n=1}^{H} h(t-n)}{H}. \tag{5}$$

In Equation (5), parameter H is a constant that shows the length of periods to determine SNS utilization. Function $h(t)$ is the history of communication defined as:

$$h(t) = \begin{cases} 1 & \text{(Communicated at turn } t\text{)} \\ 0 & \text{(Not communicated at turn } t\text{)} \end{cases}. \tag{6}$$

This model represents the invitation system often implemented on SNS.

2.3.2 New link generation

Each agent in SNS makes new friends at a constant rate. New friendship is expressed as a new link.

Based on the concept of the CNN model, a new link is generated by converting a potential link, which is generated between agent a_i and each neighbor of agent a_j, when agent a_i is added to the network and linked to agent a_j. This method is based on the adage that "a friend of my friend is friend." In this model, the potential link that is converted into a link is selected randomly.

2.4 Simulation Flow

In the simulation, each agent a_i sequentially performs the following 1-4 operations each period. The network is reconstructed after all agents finish their communications.

1. Login
2. Check responses
3. Response
4. Communication

Here, "communication" is an operation in SNS to which other users can respond, including making a diary entry, posting a message on BBS, and sending messages. "Response" signifies an answer to a "communication."

2.4.1 Login

In this model, agents login to SNS once a period at most. Based on the rate of login frequency l_i, agent a_i decides during the current period whether to login. When agent a_i logins to SNS, he/she sequentially performs the following communications. On the other hand, when agent a_i does not login, her/his actions for the current period are finished.

2.4.2 Check responses

After agent a_i logins to the SNS, he/she checks responses from other agents. Many responses from other agents increase their motivation to use the SNS.

Based on the number of responses $r_i(t)$, agent a_i changes the frequency of communication $d_i(t)$ based on the following equation:

$$d_i(t) = \begin{cases} d_i(t-1) - \rho & (r_i(t) = 0) \\ d_i(t-1) + \rho r_i(t)/k_i & (r_i(t) > 0) \end{cases} , \tag{7}$$

where parameter ρ is the rate of communication frequency change. Parameter k_i is the number of friends of agent a_i. Equation (7) represents that an agent that has frequent intercommunication with other agents actively uses SNS. On the other hand, an agent with little intercommunication decreases the communication frequency in SNS.

2.4.3 Response

Generally, the stronger a friendship becomes, the greater the chance for communication. Parameter $p_r(a_i, a_j)$ represents the probability that agent a_i will responds to agent a_j's communication. Probability $p_r(a_i, a_j)$ is defined as the following equation:

$$p_r(a_i, a_j) = f_{ij}. \tag{8}$$

For example, if $f_{ij} = 0.6$, the probability is 60% that agent a_i will respond to the communication of agent a_j.

Agent a_i changes login frequency l_i at period t as follows:

$$l_i(t) = \begin{cases} l_i(t-1) - \lambda & (c_i = 0) \\ l_i(t-1) + \lambda c_i/k_i & (c_i > 0) \end{cases} , \tag{9}$$

where parameter λ is the change in the login frequency rate. Parameter c_i is the number of friends of a_i that have been communicated with from the last logged-in period to the current one. From Eq. (9), this model can represent a situation where, as more friends use the SNS, the login frequency increases.

2.4.4 Communication

Agent a_i communicates at the rate of $d_i(t)$. Although there are many types of online communication in an SNS, a complete communication method is defined as "communication" in the proposed model.

After all responses and communications are finished, agent a_i finishes his/her operations in the current period.

3 Validity analysis

3.1 Simulation conditions

3.1.1 Simulation aim

To check the validity of the proposed model, we compared it with an actual SNS from the viewpoint of network structure [4][1]. Our actual SNS for comparison is the Academic Community System managed by Nagoya University. Additionally, we used three more artificial networks to compare with the actual SNS network structure. These three artificial networks were generated by "random graph [5]," the "BA model [2]," and the "CNN model [9][11]".

In this simulation, we used the following actual ACS data to analyze network structure and communication behaviors in the system:

- Date of first login
- Date of diary updates
- Links between users

3.1.2 Academic Community System

The Academic Community System (ACS), which was started in January 2006, is designed for communities such as universities that contain various human relationships [7].

As of September 2007, the total number of users was 586. Note that 265 users are not connected to other users. Additionally, the network is separated into two connected components: 249 users in the bigger connected component and 70 in the smaller. Thus we use the bigger component as an ACS network, which includes 249 users and 750 links.

3.1.3 Evaluation indices

The following three evaluation indices are used to compare network structures[8]:

- Cluster value [10]
- Average path length [10]
- Degree distribution [2]

Table 1. Simulation settings

Simulation period	350
Number of simulations	50
Rate of changes in friendshipsα	0.90
Minimum value of friendshipβ	0.10
Length of period$H$	14
Rate of communication frequency changeρ	0.02
Rate of login frequency changeλ	0.04

3.1.4 Simulation procedures

From the proposed method, we generate the following artificial networks, random graph, BA model, and CNN model, and compare them with the ACS network. In this simulation, the number of agents in each network changes identically as the actual ACS.

Each simulation was run 600 times, which corresponds to the number of days from January 2006 to September 2007. We simulated 50 times under identical situations. The results shown in Section 3.2 are the averages of each situation.

The random graph, BA model, and CNN model parameters are configured to generate networks with a similar number of agents and links, as the actual ACS network.

Table 1 shows the simulation settings.

3.2 Simulation results

Table 2 shows cluster values and average path lengths of networks generated by each model. From Table 2, the proposed method has the most similar values to the actual ACS data from the viewpoints of both cluster value and average path length.

Next, the degree distributions of the ACS network and a network generated by the proposed model are shown in **Fig. 1**. From these figures, the degree distributions of these networks seem similar. In fact, power indices γ of each network's degree distributions are -1.16 and -1.17, which are very close.

The power indices of each network are also shown in **Table 2**, which clarifies that the proposed method can generate the most similar network to the actual SNS from the viewpoint of power index γ.

Based on the above results, the proposed model's validity is confirmed from the viewpoint of the reproducibility of network structures.

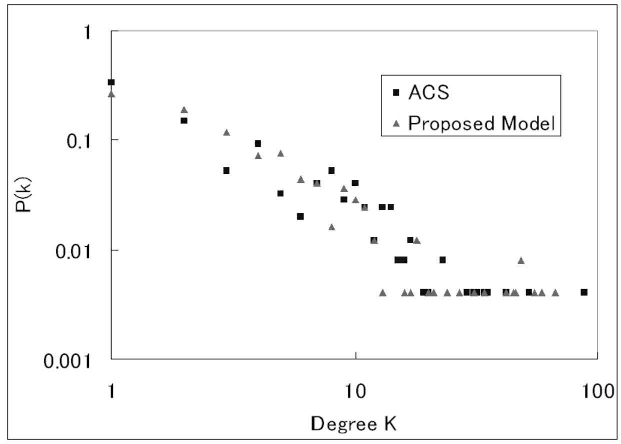

Figure 1. Degree distribution of ACS and proposed model

4 Simulation of utilization promotion

4.1 Simulation aim

Most small SNSs, including ACS, have a serious problem: decrement of user utilization. In fact, only a small number of daily diary entries are written in ACS. The changes in the number of diary entries in a day are shown in **Fig. 2**. This figure clearly shows that ACS utilization is decreasing.

In this simulation, we clarified effective methods to increase the utilization rate and proposed the following two utilization promotion methods:

- Encouraging existing users
- Inviting new users

"Encouraging existing users" conducts campaigns to encourage utilization for users already using an SNS. For example, at ACS, students are given exercises that must use ACS lectures at Nagoya University.

"Inviting new users" attracts new users to participate in the SNS by promotion through other web sites, other media, and so on. .

We compared the effect of two promotion methods on the SNS Model generated by our proposed model using agent-based simulation.

4.2 Simulation procedures

4.2.1 Encourage existing users

The *Encouraging existing users* method is modeled as "During T_C periods, l_C percent of users are forced to login to the SNS independently from login frequency l_i".

Table 2. Structures of each network

Network type	Agents	Links	Avg. path length	Cluster value	Power index γ
Actual Social Network Service (ACS)	249	750	3.32	0.454	-1.16
Proposed model	249	751	2.94	0.408	-1.17
Random graph	249	748	4.09	0.02	
BA model	249	748	4.92	0.088	-1.64
CNN model	249	770	4.22	0.217	-1.11

The rate of promotion target agents l_C is varied from 0% (no users are encouraged) to 100% (all users are encouraged) in 10% steps. The effects of each situation are confirmed by 50 simulations.

4.2.2 Inviting new users

The *Invite new users* method is modeled as "During T_C periods, the number of agents increases at a constant rate."

The rate of agent increment I_C is varied from double to ten times of the existing agents. The effects of each situation are also confirmed by 50 simulations.

4.3 Simulation conditions

In this simulation, no promotion methods are applied until 600 periods (about two years) have passed. After that, each promotion method is applied to the generated SNS. The applicable span of encouragement promotions T_C is 30 periods (about one month).

The effect of the promotion method is analyzed using utilization rate U, which is the average of utilization U_i of each agent defined at Eq. (5) and is determined by the following equation:

$$U = \frac{\Sigma_i U_i}{N}. \tag{10}$$

When all users communicated in SNS every day, utilization rate U is 1.0.

Utilization value U is analyzed for 1000 periods (about 2.5 years) after the promotion methods are applied.

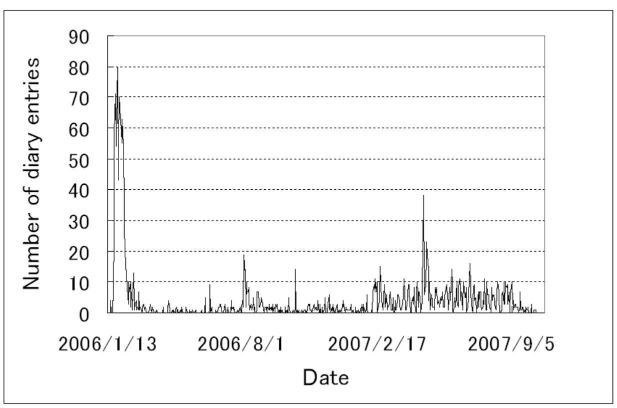

Figure 2. Changes in number of daily diary entries

4.4 Results

4.4.1 No utilization promotion

First, the change of utilization rate U without encouragement promotions is shown in **Fig. 3**. The X-axis shows the passing periods, and the Y-axis shows utilization rate U. The simulation was done 50 times, and the figure shows each simulation result.

From Fig. 3, certain SNSs are encouraged without any encouragement promotions, but not other SNSs ($U < 0.5$). Only 16% of SNSs are encouraged ($U \geq 0.5$) without encouragement methods, suggesting that some SNSs might be encouraged. However, most are not encouraged without encouragement promotion.

4.4.2 Effects of encouraging existing users

To analyze the effect of *encouraging existing users*, an encouragement promotion was applied to the artificial SNS from the 600th to the 630th day. The rate of promotion target agents l_C was varied from 0% to 100%. Based on the clarifications in Section 4.4.1, some SNSs were encouraged without any promotions. We assume that if an artificial SNS has utilization $U > 0.5$, it has already been encouraged.

Figure 4 shows the change of utilization rate U when the target number of encouraged agents is $l_C = 50$. Note that the SNSs, which were already encouraged at period 600, were removed from the figure for viewing simplicity. From Fig. 4, the utilization rate rose during promotion periods. Then the level of utilization decreased. However, after a while, about 60% of the utilization of artificial SNSs increased without a promotion method being applied. This

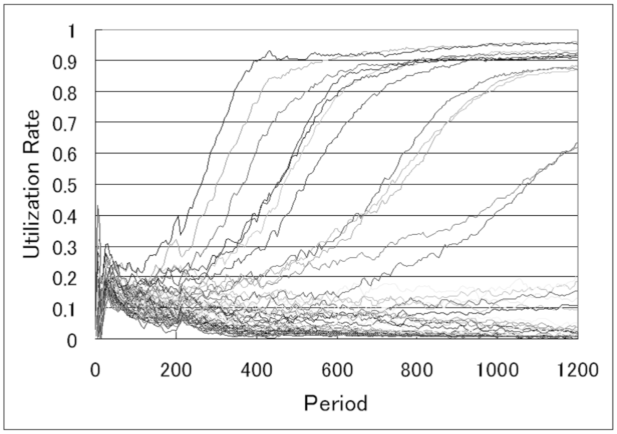

Figure 3. SNS utilization rate without promotion

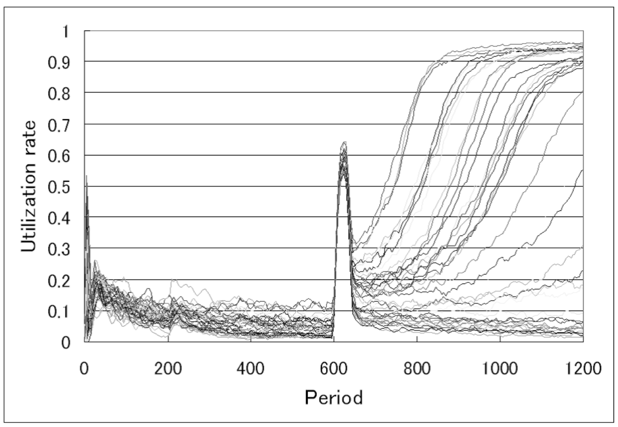

Figure 4. Effect of utilization promotion-target agent 50%

suggests that encouraging existing users to use SNS is effective for 70% of artificial SNSs.

Figure 5 shows the rate of encouraged artificial SNSs when the rate of promotion target agents l_C is varied from 0% to 100%. In addition, we defined "encouraged" as cases where utilization level $U > 0.5$. From Fig. 5, when the case of promotion target agents $l_C > 60\%$, more than 90% of artificial SNSs were encouraged.

4.4.3 Effects of inviting new users

Finally, we analyzed the effect of *inviting new users*. An invitation promotion was applied to artificial SNSs from the 600th to the 630th days. The rate of invited agents I_C varied from double to decuple of the existing agents.

Figure 6 shows the change of utilization rate U when

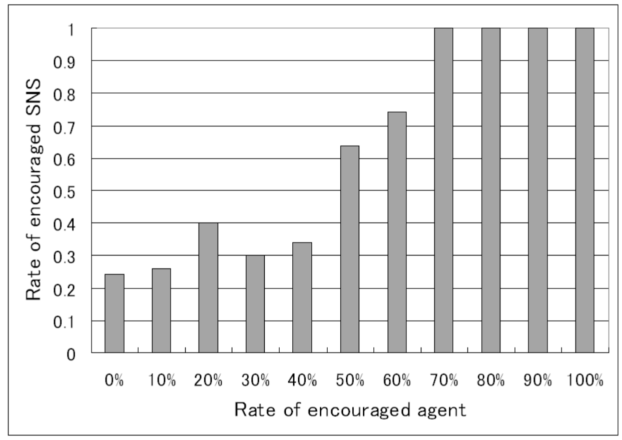

Figure 5. Effect of promotion utilization

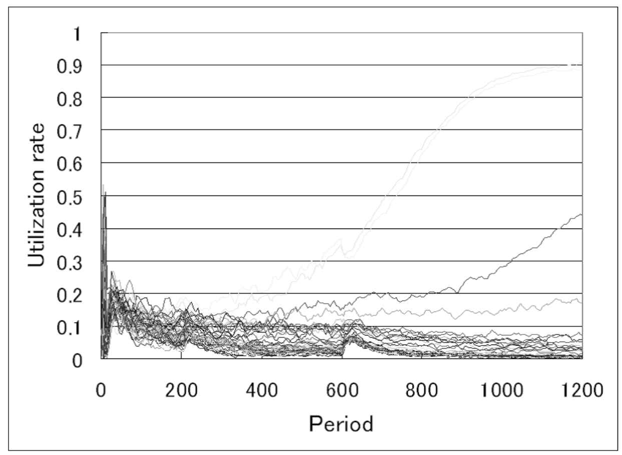

Figure 6. Participation of new users (doubled)

the rate of invited agents $I_C = 50$. As for Section 4.4.2 we omit artificial SNSs from Fig. 6 whose utilization is $U > 0.5$ before day 600. The invitation promotion to double the number of users does not effectively encourage the SNS.

Figure 7 shows the rate of encouraged artificial SNSs where the number of users increased by double to ten times. The X-axis shows the multiplying factor. For example, value $\times 2$ shows that the final number of users are double the existing users.

From Fig.7, despite user number incrementation, few SNSs were encouraged, suggesting that an invitation promotion does not effectively encourage SNS. The reason for this result is thought to cause the following phenomenon. That is, the low utilization of existing users causes the low frequency of communication of new invited users. As a consequence, the utilization of new invited users became low.

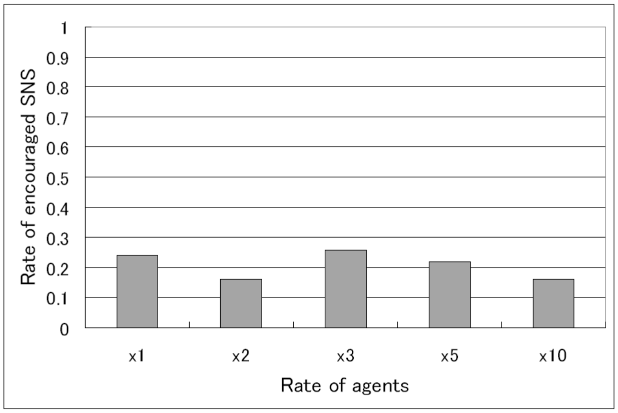

Figure 7. Effect of new user participation

4.5 Conclusion of simulation

We applied the following two encouragement promotion methods to artificial SNSs.

- Encouraging existing users
- Inviting new users

Simulation results clarified that the encouraging existing users promotion method more effectively encourage the utilization of artificial SNSs. On the other hand, the invitation promotion method barely affected encouragement.

We conclude that raising the utilization rate of existing users is an effective method to encourage the utilization of small SNSs.

5 Conclusion

In this study, we proposed an agent-based Social Network Service model.

To check the validity of the proposed model, the artificial SNS generated by the proposed model was compared with the Academic Community System (ACS), the actual SNS managed by Nagoya University. Comparison results confirmed the validity of the proposed method from the viewpoint of the reproducibility of network structures.

Using the proposed model, we simulated promotion methods to clarify effective methods to encourage the utilization of SNSs. Simulation results clarified that encouraging existing users is more effective than inviting other users to encourage small Social Network Services.

One future work is implementing a group model. Almost all Social Network Services have functions called *groups*, *forums*, or *communities* with which users can communicate with non-friend users. Since these functions are not currently implemented on the proposed model, we have to implement such a model on our proposed model.

Applying the proposed encourage methods to actual small Social Network Services is another crucial future work. We are planning to apply the proposed encourage methods to ACS in the future.

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