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Rise and decline process of online communities: Modeling social balance of participants.

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Abstract*—Some online communities like Friendster had declined, and some of the others are said to be declining. Recent research has revealed the mechanism of decline as well as that of rise in each community. However, no comprehensive research has yet revealed the difference in declining mechanisms of each communities. We considered the online communities as networks of users and topics and defined behavior of users using Heider's balance theory. Users in our model are in a dilemma, stuck between topic preference and the balance between neighboring users. How the user behaves in the dilemma, his/her strategy, disseminates to other users. We simulate online communities using the model and observe the rise and decline of different kinds of communities. As a result, we found that two types of communities tend to develop with many users: communities in which the topic changes dynamically (FreeTopic-type) and communities in which the topic changes gradually (Topic-type). However, the property of each community and behavior of users are different. We found by simulation that the collaborative behavior of users happens very frequently in the FreeTopic-type community, in which users consider the balance between each other rather than their topic preference. As a result, the FreeTopic-type communities do not often crash (i.e. quickly lose users). In addition, we confirmed that the postings about a topic are either negative or positive in the FreeTopic-type community. On the other hand, in the Topic-type community, simulation results indicate that users prioritize their preference for a topic. This causes the community to crash very frequently. However, users in such a community are found to obtain more benefits than in FreeTopic-type communities. It can be said that, after crashes occur, the community is still relatively beneficial for some users who remain.

I. Introduction

ONLINE communities and SNS services have become very popular. For example, in the USA, 67% of internet users use Facebook and more than 10% users use twitter and Pinterest [1]. Online communities demand the new kinds of media that can allow users to give each other the information they need [2]. However many communities, even large ones such as Friendster, have declined [3]. The number of users of Myspace has been decreasing [4], and some researchers argue that Facebook, which has more than one-billion active users, is also declining [5]. It is essential to reveal the mechanism of the declining process of online communities to stabilize them because they are of increasing social importance.

Online communities decline in various ways. The declining processes of Friendster and Myspace have been slower than their developing processes [5]. However, some content-oriented communities, such as small communities on YouTube, decline even more faster [6][7].

To reveal the declining process and estimate future trends, many models of online communities has been proposed. Most recently, Cannarella and Spechler have predicted the decline of Facebook using an irSIR model (recovery SIR model) [5]. They consider the entrance/stay/exit process of an SNS in the same way as the suspect/infect/recover process of the SIR model and calculate the probability of transitioning between states using the actual data. However, many critics, including a researcher working with Facebook, have argued against their conclusions because the research does not reveal the relationship between user behavior and the mechanism of decline. Other researchers have made a more detailed model of SNS. Liu et al. classified the users of SNS into four states: New Joining, Active, Active&Inactive, and Quiet)[8]. They estimate the property of bidirectional transition between each state and predict the number of users in the community. Furthermore, other researchers have focused on the developing process [9][10][11] and declining process [3] by investigating relationships in the macroscopic evolution of communities.

As shown above, researchers have revealed macroscopic dynamics of communities. However, the relationship between such collective dynamics and behavior of users is not clear. Furthermore, each research is ad-hoc and does not give a comprehensive interpretation of online communities. Online communities are very different in scale, network structure, range of topics, and so on. We thus propose a comprehensive model that can explain the evolution of a wide variety of communities and simulate the developing and declining processes.

In the model, we focus on the psychological state of users in a community. For example, researchers say Facebook users become tired of clicking the Like button, which expresses approval of other users' postings [12]. Even if your friend posts something that does not interest you, you sometimes push the Like button. In this case, the user is caught in a dilemma between their lack of interest in a friend's posting and the relationship with the friend. When you do not like your friend's posts, there are three solutions: going along with your friend, being silent, or giving your opposing opinion.

Such a situation is explained with Heider's balance theory [13]. In this theory, the psychological stability between three objects can estimated in a simple equation so that the three objects can behave more stably. In the online community, the three objects are a user, a user's friend, and a topic. Heider's balance theory has been verified in experiments [14] and improved with some small extensions [15]. Owing to the simplicity and correctness of model, the theory is used for describing the mechanism of group formation [16][17], predicting likes or dislikes between two users in a community [18], and investigating the process of forming opinions [19]. Thus, we use Heider's balance theory for describing user behavior in an online community.

In addition, we take into account the polarization of opinion in online communities. Cass Sunstein has claimed online communities cannot avoid this polarization without appropriate rules [20][21]. You can feel a unique atmosphere in online communities. For example, people talk only positively about things or only discuss in a serious manner. There are questions about how user interaction forms the atmosphere, what kind of conditions impact the formation of an atmosphere, and what kind of atmosphere is possessed by communities that do not decline.

We propose a comprehensive agent based model of an online community that can explain the developing and declining processes. Using the model, we first investigate what kinds of communities are likely to develop. Second, we investigate the mechanism of polarization of postings. Finally, we classify declining processes and estimate the probability of each process in different conditions (range of topics and affiliation of opinion).

II. Model

We describe the model of online communities using the network of the users and topics.

Balance theory, which was proposed by Heider in 1956 [13], is the generalization of an equilibrium between a person and surrounding objects. This theory considers the likes and dislikes of three objects. The objects can be three people or two people and a subject. The two attitudes, like or dislike, are represented by signs of + or - [(Fig.1). Shown in this figure, when the multiplication of the signs is +, the triangle is stable and people in the triangle also feel stable. For example, as shown in the upper half of [Fig.1], triangles composed of a three "likes" or two "dislikes" and one "like" are stable. The latter situation means you do not like what your rival likes. On the other hand, as shown in the lower half of Fig.1, when the multiplication of the signs is -, the triangle is unstable. For example, you like what your friend dislikes.

A. User Dilemma in Online Communities

In online communities, users behave in accordance with the balance of Heider's triangles and with preferences for different topics. If these preferences are different, the user is caught in a dilemma. We make a model that can illustrate this situation.

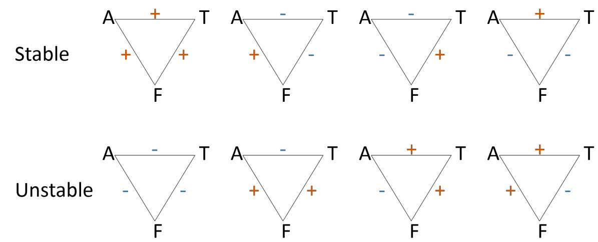


Fig. 1. Heider's balance theory. The model is composed of A (Person A), F (Friend), and T (Topic). The upper and lower rows show stable and unstable situations.

The balance theory is suitable for online communities because they are composed of users and topics. Online communities can be described as networks composed of topics and users (Fig. 2). In this figure, the three topics and seven users are connected. The edges between users can be described as the value of + or -. The edges between a user and a topic mean the user is a participant of the topic and may take the value of P (post positive), N (post negative), or S (silent).

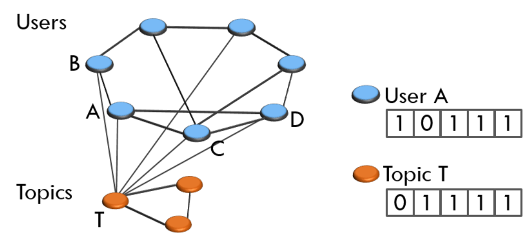


Fig. 2. Network structure of online community.

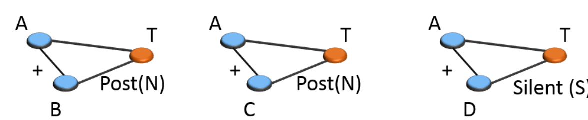


Fig. 3. Example of Heider's triangles related to User A.

A user recognizes all triangles to which he/she belongs. In Fig.2, user A recognizes the three triangles in the network. The networks are shown in Fig. 3. User A calculates the balance of his/her postings, the friend's posting, and the relationship with the friend. Thus, if the friend does not post about the topic, user A does not calculate the balance (right triangle in Fig.3). User A estimates that he/she can obtain better balance in the two triangles, P (post positive) or N (Post negative). In this case, N is the solution in both triangles, so users tend to post N.

However, a user also considers his/her preference to the topic. The user's interest and content of the topic are defined by L-length bits. A user's interest and content of topics are the same length. To represent the conversation in real communities, the L-length bits of a topic change at each step. The similarity of both L-length bits means the user's preference to a topic. This is defined in Eq.1 using the Kronecker productδ in the range -1 to 1.

$$pr(A,T) = \frac{\sum_{i=1}^{L} \delta_{I_A I_T}}{L} * 2 - 1 \tag{1}$$

In Fig.2, user A's preference to topic T is $pr = 0.2 (> 0)$. Therefore, user A is satisfied when he/she posts positive (P). However, user A is under pressure to post negative (N) in the balance of triangles, so he/she is caught in a dilemma. In this case, he/she has three solutions: post positive (P) to prioritize the preference to the topic, stay silent (S), or post negative (N) to prioritize the preference to balance.

B. Strategy in the Dilemma

To generalize the dilemma discussed above, agents are placed in four states, considering the balance of Heider's triangle and preference to topics (in the status section in Table I). The former is described as + or - corresponding to the preference to the topic defined in Eq.1. If $pr > 0$, the state is + and - in the opposite case. The latter is also described as + or -. This means which is a better balance in Heider's triangles. If P (Post Positive) is better than N (Post Negative), the state is +. Each user has a strategy corresponding to the four states. In each state, a user can behave in three ways: P, S, or N. Therefore, the number of combinations of the strategy is $3^4 = 81$. The strategies are shown in Table I. For example, when status = 3, the agent with the NNSP strategy selects (S).

TABLE I
STATUSES (#1-#4) AND EXAMPLES OF STRATEGY.

	#		1	2	3	4
Status	Preference to topic		-	-	+	+
	Balance of Triangle		-	+	-	+
Strategy	NNPP	Self	N	N	P	P
	NSPP	Self	N	S	P	P
	SSPP	Self	S	S	P	P
	NNNP	Coll	N	N	N	P
	NSNS	Coll	N	S	N	S
	NSNP	Coll	N	S	N	P
	NSSS	Coll	N	S	S	S
	NSSP	Coll	N	S	S	P
	NPNP	Coll	N	P	N	P
	NPSP	Coll	N	P	S	P
	NPPP	Coll	N	P	P	P
	SSSS	Coll	S	S	S	S
	SPPP	Coll	S	P	P	P
	NNSN	Irra	N	N	S	N
	NNPN	Irra	N	N	P	N
	NNPS	Irra	N	N	P	S
	NSNN	Irra	N	S	N	N

The 81 strategies are classified into three groups: selfish (Self), collaborative (Coll), and irrational (Irra). The agent with a Coll strategy prioritizes the balance rather than its topic preference. For example, an agent with an NPNP strategy posts Positive when it recognizes balanced triangle, even if the agent has a negative opinion. On the other hand, the agent with a Self strategy such as NNPP prioritizes its topic preference. For example, the agent who has an NNPP strategy behaves only on the basis of its preference to topics. However, a PPNN strategy is irrational, because the agent with a PPNN strategy will post (P) in state #1 but post (N) in state #3. These strategies are classified below.

First, we describe the determination method of a Coll strategy. The order of this strategy is assumed to be $N < S < P$. If the strategy of #1 is larger than that of #2 and #3 and that of #4 is less than that of #2 and #3, the strategy is irrational (Irra).

Furthermore, the strategies other then $Irra$ are divided into $Self$ or $Coll$ in the following ways. We define the distance between two strategy strings as the sum of the distance between corresponding strings of each state #1 - #4. We assume the distances of N - S and S - P are 1 and that of N - P is 2. In addition, we assume the most selfish strategy is NNPP and the most collaborative one is NPNP. The strategy that is further from NNPP and closer than to NPNP is the $Self$ strategy.

The $Irra$ strategy seems to be rare in real communities. However, we use all 81 strategies to confirm that an Irra strategy is not suitable for any kind of community and that it will be eliminated within the process of community development. In the model, agents update the strategy in each step, and the strategy of an agent who gains many benefits tends to spread. For example, if the agent who has a $Coll$ strategy gains many benefits, the $Coll$ strategy will spread and the atmosphere of the community will be collaborative.

C. Steps

The flow of the model is shown in algorithm 1. First, a network with agents and topics is constructed. Subsequently, in each step, agents post, calculate benefit, exit, and update strategy in a random order. The steps of the model are described in detail in Algorithm 1.

Algorithm 1 Online communities

{**Initialization**} Making network of topic and agent
while $Number of Agent >= 10$ **do**
  for Each Agents by random order **do**
    {**Step 1**} Posting by strategy
    {**Step 2**} Calculate benefit B
    if $B < 0$ **then**
      {**Step 3**} Exit Agent
    else
      {**Step 4**} Update strategy
    end if
  end for
  {**Step 5**} Entrance of Agent
  {**Step 6**} Update Topic
end while

1) Initialization: At first, a perfect network with 10 agents and one topic is constructed. All have strong connections to each other at the beginning of the community. In this paper, we consider only one topic and all relationships between agents are good (+) for analyzing the fundamental behavior of the community.

The strategy of an agent is chosen randomly from the 81 strategies in Table I. Each L-length bit of a topic is 0 and that of an agent is defined as below. Interests of each user are determined completely at random if deviation is low ($dev = 0$) and permanently fixed if deviation is high ($dev = 1$). Initially, all bit sequences of all users are 0. Then, all bits of all users are changed to 1 in probability $(1 - dev)/2$.

2) Step 01 - Posting by Strategy: As defined in Section II-B, an agent recognizes state #1 - #4 by the topic preference and the balance of Heider's triangle and decides its behavior by its strategy. The behavior is post negative (N), silent (S), or post positive (P).

3) Step 02 - Calculate Benefit: Agents in a dilemma between topic preference and balance of Heider's triangle cannot gain much benefit. To express the benefit of such situation, we defined the utility function as below. When an agent posts N or P, the benefit for the agent is the sum of the benefit from its posting B_{po} and the benefit from its preference B_{pr} after subtracting the cost of writing C_{po} (Eq.2). If the agent is silent (S), the benefit is B_{pr}. Thus, the benefits B for the agent's behavior are shown as follows:

$$B = \begin{cases} B_{po} + B_{pr} - C_{po} & \text{(if agent posts (N or P))} \\ B_{pr} & \text{(if agent silents (S))} \end{cases} \quad (2)$$

B_{po} means the external balance of agent, friend, and topic. If the agent's post achieves a balanced triangle, B_{po} becomes higher. First, we describe the definition of $Po(A,T)$, $R(A,F)$, and N_t. $Po(A,T)$ take the values of -1 (when agent A posts positive (P) to topic (T)), 0 (when agent is silent (S)) and 1 (when agent posts positive (P)). $R(A,F)$ take the values of -1 (when A and F have a bad relationship) and 1 (when A and F have a good relationship). In addition, N_t is the number of triangles to which the agent belongs. B_{po} of agent A is the average of each Heider's triangle's balance, which is a multiplication of posting to the topic $Po(A,T)$, the relationship $R(A,F)$, and $Po(F,T)$ (Eq.). For example, if A belongs to one triangle, in which A posts positive (P) to T ($Po(A,T) = 1$) , A and F have a bad relationship and F posts positive (P) to T ($Po(F,T) = -1$). The benefit of A B_{po} is $1 \times 1 \times -1 = -1$.

$$B_{po} = \frac{\sum_{triangle} Po(A,T) \times R(A,F) \times Po(F,T)}{N_t} \quad (3)$$

B_{pr} means the internal balance of agent, friend, and topic (Eq.4). In this case, an agent considers his preference (Eq.1) for calculating his benefit. In the situation in which the agent posts negative (N) to a topic which it prefers, we assume that the agent obtains no benefits except for the cost of writing $-C_{po}$ on average. For this assumption, it is necessary to set $B_{po} + B_{pr} = 0$ on average. We assume the B_{pr} is doubled in Eq.4. This is because the average preference for topic ($E(Pr(A,T)) = 0.5$) in Eq.4 is half of the ($P(A,T) = 1$) in Eq.3 when comparing Eq.4 and Eq.3.

$$B_{pr} = \frac{\sum_{triangle} Pr(A,T) \times R(A,F) \times Po(F,T)}{N_t} \times 2 \quad (4)$$

As stated above, if an agent posts P or N, the benefit is the sum of the external balance calculated from its posting B_{po} and internal balance calculated from its preference B_{pr} from subtracting the cost of writing C_{po}. If an agent stays silent (S), the benefit comes from internal balance B_{pr}.

4) Step 03 - Exit Agent: The agent exits from the community when the benefit of past steps B_{tot} (Eq.5) is less than 0. B_{tot} is not a simple totaling of B. The agent will forget the benefit of past steps by a constant factor of d. In Eq.5, $B(i)$ is the benefit in the i step and $step$ is the current step.

$$B_{tot} = \sum_{i=0}^{step} B(i) \times d^{step-i} \quad (5)$$

When an agent exits, the edge that contains the agent and the triangle to which the agent belongs will disappear from the model.

5) Step 04 - Update Strategy: Each agent updates its strategy to make it similar to that of users who obtain large benefits. An agent chooses one agent with a probability proportional to the past benefit (B_{tot}) and imitates its strategy. The previous strategy is crossed with the strategy of a chosen agent in accordance with the genetic algorithm (GA). In addition, a strategy changes 1 bit randomly with a probability of P_m. This probability means sensitivity to exogenous effects.

6) Step 05 - Entrance of Agent: In this model, agents enter the community at each step. At every step, four new users enter the community. All new joiners are connected to the topic. To reproduce the heavily linked node in the real communities, they connect to A_d friends in accordance with the BA [23] model. Users choose A_d agents with a probability proportional to the number of links that the existing agents already have.

7) Step 06 - Change Topics: If people do not lost interest in the same topic, the communities will continue for a very long time. However, the topic is changed by internal and external effects. To describe this phenomenon in the model, the L-length bits of a topic will be changed by T bits at each step. All randomly selected T bits of a topic will change the probability of 0.5. If T is not the integer, the selected number of bits of a topic is the sum of the number of T and 1 at the probability of a fraction less than one. With this, the model reproduces the dynamics, the balance collapses due to the transition of topics, and the balance is reconstructed by an agent's adaptation of its behavior and strategy.

III. Simulation and Verification

IN this section, we simulate the community using the model for examining whether it exhibits the same behavior of real online communities.

A. *Parameters and Simulation Conditions*

To simulate various types of communities, we observe the evolution of a community by changing the parameter of changeable bits of topics at each step T. If T takes a lower value, the topic changes gradually. Thus, we name this a Topic-type community. On the other hand, if T takes a higher value, the topic of the community changes greatly at each step. This means the agents of a community change the topic easily, so we name this a FreeTopic-type community.

In this paper, for studying basic behavior of the model, the number of topics is set at one. Other parameters are shown in Table II.

The deviation of user interest dev is set to 0.1 considering online communities in the real world. This is because users in the real online communities such as LinkedIn, Facebook, and Myspace specify their age, nationality, and academic qualifications in addition to their interests. [24].

TABLE II
FIXED PARAMETERS OF SIMULATION

Parameter		Value
T	Transition of topics (Changable bits of topic at each step)	Variable(1-15)
dev	Deviation of user interest	0.125
A_{degree}	Average connecting ratio	12
C_w	Cost of Writting	0.07
U_{add}	Number of users added at step	4
d	Decay ratio of past benefit	0.75
$P_{mutation}$	Mutation ratio of strategy	0.01

B. *Example of Simulation Results*

We simulate the model under the conditions defined above and observe the process of rise and decline of communities. The simulation results are shown in Figs.4 and 5, where the horizontal axis shows the step from the start and the vertical axis is the number of agents.

As shown in Figs.4 and 5, the rise and decline of a community is observed under the conditions of $T = 1$ and $T = 15$. In addition, the number of agents under the condition of $T = 1$ (Topic-type) seems to have larger variations than that of $T = 15$ (FreeTopic-type). We will verify their mechanisms in the next section.

The distribution of the number of posts is shown in Figs.6($T = 1$) and 7($T = 15$). The horizontal axis indicates the number of postings and the vertical axis indicates the number of corresponding users. The distributions of the posting counts follow power-low distribution, which is observed in real online communities [25].

C. *Elimination of Irrational Strategy*

Users who have an irrational strategy (Irra), defined in Table I, are considered to be uncommon in real communities. We confirm that an irrational strategy (Irra) is not suitable for a community by the following simulation. We observe the ratio of an agent that has an irrational strategy (Irra) through the entire step as the topics T transition from 1 to 15 by 0.5. In the results, the average ratio of an Irra strategy is $34 - 38\%$.

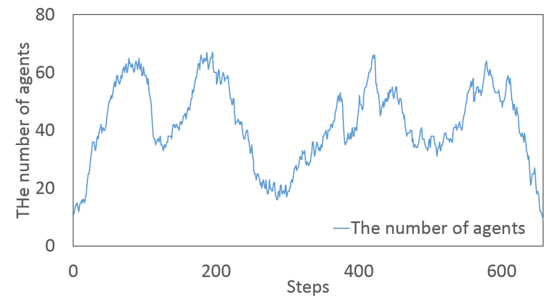


Fig. 4. The evolution of online community under the condition of $T = 1$ (Topic-type)

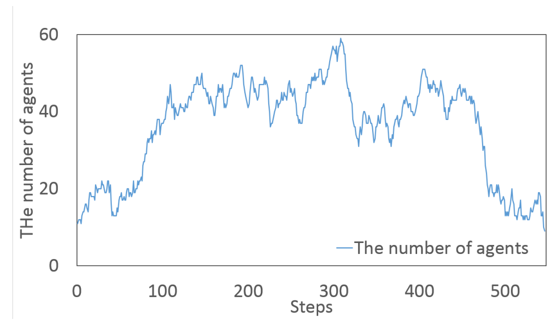


Fig. 5. The evolution of online community under the condition of $T = 15$ (FreeTopic-type)

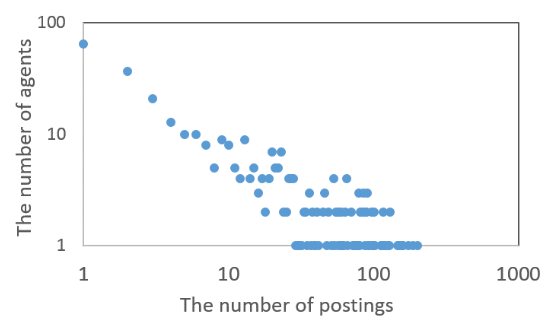


Fig. 6. Distribution of the number of postings of agents under the condition of $T = 1$ (Topic-Type)

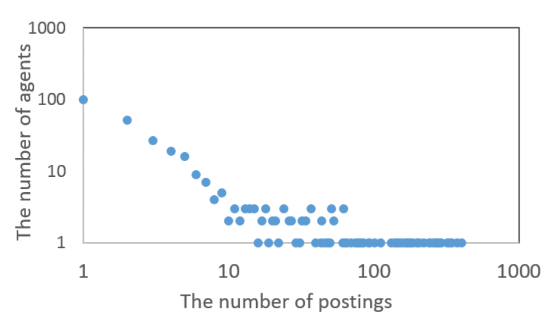


Fig. 7. Distribution of the number of postings of agents under the condition of $T = 15$ (FreeTopic-type).

The ratio of an Irra strategy is relatively low considering the percentage of the Irra strategy, $61/81 = 75\%$, in the initial users and users added at each step.

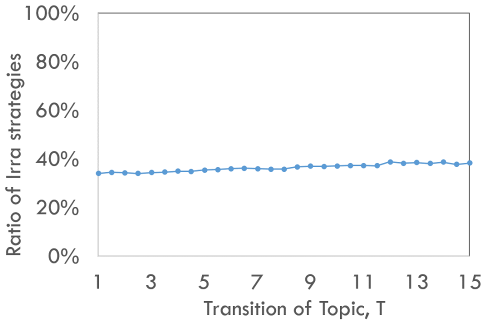


Fig. 8. Ratio of Irra strategy agents to all strategy agents

The users of Irra are considered to change their strategy or exit, since they cannot gain much benefit. In the real world, the proportion of the people who use such a strategy cannot be high. Thus, the model can illustrate the selection process of eccentric users.

According to the results above, this model based on balance theory reproduces the rise and decline of communities without cessation of adding new users or the explicit mechanism of losing interest. Power distribution of the number of users and the elimination of irrational strategy are characteristics of a real community.

IV. Rise and Decline of Community

To investigate the development and decline in different types of communities, we observe the communities' evolution process through changing the transition of topics T. The lower value T is a Topic-type community, such as a bulletin-board system for an exclusive community, and the higher value of T means a FreeTopic-type community, such as Facebook and Myspace.

In this chapter, we simulate the evolution process of communities through the entire step by changing the transition of topics T from 1 to 15 by 0.5. We did not simulate under the condition of $T = 0$, because the topics is not fixed to a specific one in real communities.

A. Average Number of Users and Duration of Community

First, we observe the average number of users and the duration of a community in a single simulation by changing the transition of topics T from 1 to 15 by 0.5. The duration is the number of steps between the first and final steps. The first step is defined as the step in which there are more than 10 users. A single simulation is finished when there are fewer than 10 users. The results are shown in Fig.9. In this figure, the horizontal axis indicates transition of topics T, and the vertical axes indicate duration (left) and the number of users (right).

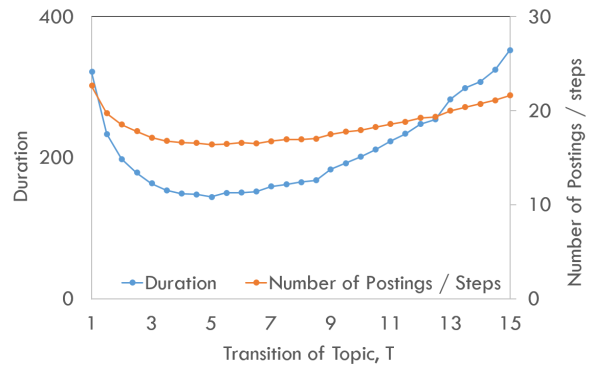


Fig. 9. Duration of communities and average number of postings per step. T is set from 1 to 15

When the transition of topics is high ($T = 15$) or low ($T = 1$), the duration of community becomes long and the average number of postings becomes high (Fig.9). The results show that there are two different conditions for growth of a community. This means the Topic-type ($T = 1$) and FreeTopic-type ($T = 15$) communities tend to exist over a long period.

B. Decline of Community

Subsequently, we observe the decline of a community with changes in the parameters of transition of topic T. In the preceding analysis, the two types of community, Topic-type or FreeTopic-type, both have a chance to grow large. We investigate the decline process of both types below. To investigate the decline process, we use two indexes: the ratio of the number of postings after / before peak and the probability of a crash. The peak is defined as the step that has the highest number of topics through all steps. When there are more than two steps that have the highest number of topics, the peak step is the last one.

1) Continuity of Community After Peak: We observe the ratio of the number of postings after and before the peak with changes in the transition of topics T from 1 to 15 by 0.5. The results are shown in Fig. 10, where the horizontal axis indicates the transition of topics T, and the vertical axis indicates the ratio of postings after and before the peak.

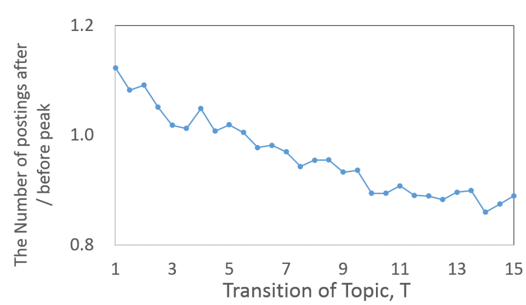


Fig. 10. Ratio of postings after / before peak

As shown in Fig.10, as the transition of topic T becomes larger, the ratio of postings after and before the peak becomes smaller. This means the Topic-type communities last longer than FreeTopic-type communities.

2) Probability of Crashes: Online communities occasionally lose many users in a short period. The causes are exogenous factors, such as server errors and holiday periods [26], and endogenous factors. We investigate the probability of endogenous factors of crashes by changing the transition of topic T.

A crash is defined as the number of users decreasing to less than half or 70% within 10 or 20 steps. We investigate the probability of crash in one simulation step by changing parameter T from 1 to 15 (Fig.11).

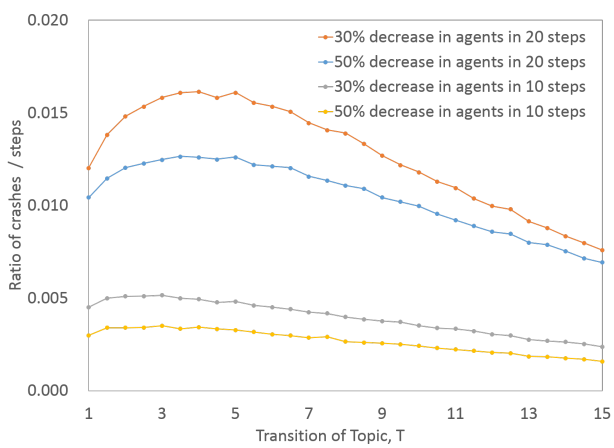


Fig. 11. Probability of crashes

As shown in Fig.11, in each four definitions of probability of a crash, the community with lower T (Topic-type) suffers crashes with high frequency. As the T becomes larger, probability of crash mostly becomes smaller under the condition of $T = 3$.

The above analysis clarifies that the Topic-type community and FreeTopic-type community both have a chance to grow large. However, the processes of decline are different. The Topic-type community has large amount of postings after a peak in spite of highly frequent crashes. Two questions remain in the results: 1) Why do the Topic-type and FreeTopic-type communities have different decline processes? 2) Why do topic-type communities continue long after a peak in spite of frequent crashes? In the next section, we analyze the mechanism of evolution of these communities.

V. The Mechanism of Rise and Decline of Topic-type and FreeTopic-type Communities

To investigate the difference between the decline processes of Topic-type and FreeTopic-type communities, we compare the distribution, selection of strategy, and the average benefit of agents of the Coll, Self, and Irra strategies.

As a result, in FreeTopic-type communities, the concentration of strategies occurs and agents stably gain benefits from the community. This lead to infrequent crashes. Furthermore, the average benefits of agents are larger in Topic-type communities than in FreeTopic-type communities, leading to the longer life of Topic-type communities in spite of their highly frequent crashes.

A. Concentration of Strategy and Stability of Community

In the model, the agent chooses its behavior by its strategy in the dilemma of the balance of Heider's triangles and topic preference. There are 81 strategies divided into three types: selfish (Self), collaborative (Coll), and irrational (Irra). We investigate the distribution of these three strategy types by the transition of topics T. The ratio of Self strategies to Self and Coll strategies is plotted in Fig.12.

Under the condition of less transition of topic T, the ratio of agents who have Self strategies is relatively higher (Fig.12). Agents with a Self strategy, which means they choose their behavior on the basis of topic preference, are eliminated under the condition of a larger transition of topic T. It is considered that the neighbor's postings dynamically change step by step and the balance of Heider's triangle is easily broken at each step. On the other hand, in the Topic-type community, the balance of Heider's triangle of agents who have a Self strategy is not easily broken.

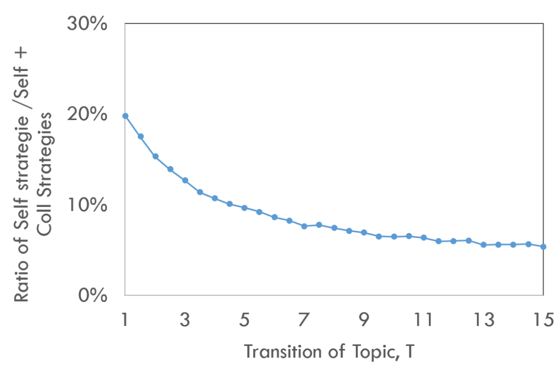


Fig. 12. Ratio of Self strategies to Self and Coll strategies

Subsequently, we investigate the concentration of strategies. The ratio of the top five selected strategies among all 81 strategies that have a higher ratio for the entire term is calculated by changing the transition of topic $T = 1, 8, 15$. In Fig.13, the vertical axis shows the ratio of top N strategies among all 81 strategies.

As shown in Fig.12, in the FreeTopic-type community (larger transition of topic T), the certain strategies tend to predominate. In the community with middle-level transition of topic $T = 8$, the ratio of the concentration of strategies is also relatively high.

To summarize the analysis above, the ratio of selfish strategies (Self) is relatively higher in the Topic-type community, though diverse types of strategies remain. On the other hand, in the FreeTopic-type community, the agents are selected that use certain strategies but not Self strategies. It could be said that, in the FreeTopic-type community, agents collaborate by

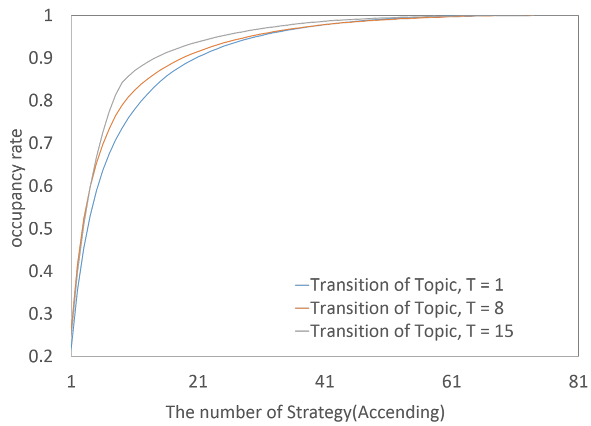


Fig. 13. The ratio of top N strategies among all strategies in a single simulation

considering the balance of Hider's triangle with their neighbors. This represents the process of a real online community in which the users cooperate with others and maintain their relationships by withholding what they want to post or offering an opinion they do not actually hold.

The benefits of agents are considered to be stable in the FreeTopic-type communities because certain strategies make up most selected strategies. In such situations, larger amounts of agents prioritize collaboration while neglecting their topic preference. Accordingly, they do not frequently change their posting behavior to the community and the frequency of crashes is low.

B. Average Benefits for Agents

We compare the average benefits of agents in Topic-type and FreeTopic-type communities or the entire period by changing the transition of topic T. The results are shown in the Fig.15, where the horizontal axis indicates the transition of topic T and the vertical axis indicates the average benefit of agents through the entire period.

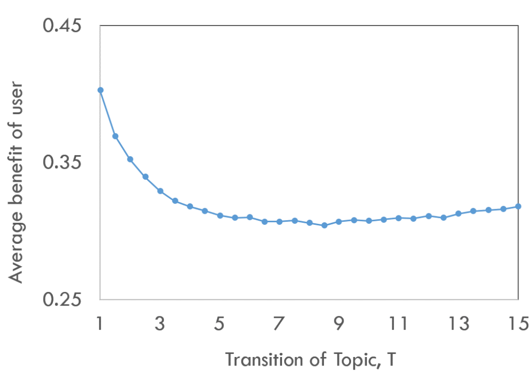


Fig. 15. Average benefit of agents

As shown in Fig.15, as the transition of topics T becomes larger, the average benefit becomes smaller. In Topic-type communities, the ratio of selfish users is relatively high (Fig.12). It is considered that agents tend to post considering their preference and that the positive/negative tendencies of neighborhood postings do not change dynamically due to low transition of topics. Thus, the agent obtains many benefits from its posting B_{po} and the benefit from its preference B_{pr}.

The results in the preceding section show the Topic-type community continues for a relatively long period after the peak in spite of highly frequent crashes. This long life is considered to be due to the many benefits for agents (Fig.15) and the diversity of strategies (Fig.13). Even if communities crash and neighborhoods exit from communities, some agents obtain more benefits and remain. This tendency can be observed in Fig.4. As shown in Fig.4, in the Topic-type community, some agents remain after a crash and the community rises again.

On the other hand, in a FreeTopic-type community, agents obtain relatively fewer benefits (Fig.15) and certain strategies predominate. The low ratio of postings after the peak (Fig.10) can be explained as follows: if some agents exit the community, a large number of neighborhood agents, which have the same strategies, lose the benefit of the balance of Heider's triangle. Therefore, the neighborhood agents are likely to exit subsequently.

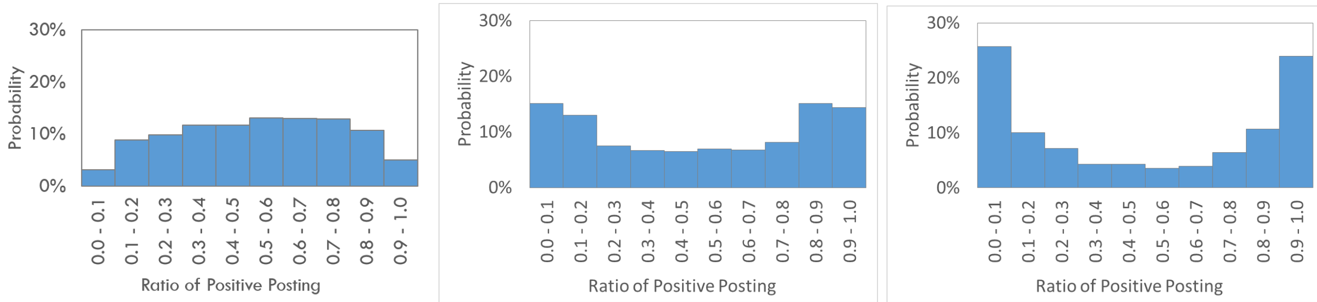
The reason for relatively fewer benefits in FreeTopic-type communities is conflict between agent's topic preference and the balance of Heider's triangles. There is a large cluster of certain strategies, and agents behave considering the balance of Heider's triangles rather than their topic preference. Therefore, the agent obtains benefits from its posting B_{po} in spite of the few benefits from its preference B_{pr}

VI. Deviation of Posting for the Topic

THE above analysis reveals that the mechanism of the rise and fall of a community differs between the Topic-type and FreeTopic-type communities. In this section, we investigate agents' posts in the community, especially focusing on the deviation towards negative/positive postings. In real online communities, participants' posts sometimes deviate towards negative/positive. The reason for the deviation is considered to be that the strategy to post only negative/positive is spread or that many users who only post negative/positive stay in the community.

To investigate the probability of the occurrence of the deviation of posting, we observe the ratio of positive posts in a single simulation by changing the transition of topics $T = 1, 8, 15$ (Fig. 14). In Fig.14, the vertical axis indicates the ratio of positive posts and horizontal axis indicates transition of topic T.

As shown in Fig.14(a), the ratio of positive posting is close to 0.5 under the condition of $T = 1$. In such a community, agents post the same amount of negative and positive postings in a single simulation. On the other hand, as the transition of topics T becomes larger, the ratio of positive postings inclines



(a) Transition of topics $T = 1$ (b) Transition of topics $T = 8$ (c) Transition of topics $T = 15$

Fig. 14. Distribution of the ratio of positive posts through a single simulation under the condition of transition of topics $T = 1, 8, 15$

to 0 or 1. This means the FreeTopic-type community tends to be composed of only positive/negative posts for the topic.

The reason for deviation towards positive postings is that the strategy by which agents tend to post positive things spreads in the community. In this situation, the agents post only positive posts and the benefit from their postings B_{po} (Eq.2) remains stable. The same explanation is suitable for cases of the deviation towards negative postings.

The reason for large deviation of postings under the condition of large T can be considered to be the result of group adaptation. In such situations, the benefit from an agent's preference B_{pr} is unstable because the topic changes dynamically. The strong cluster of agents, who only post positive/negative things, stably benefit from their postings B_{po}. This is considered to the best way to survive in such situations.

According to the above results, the deviation towards negative/positive postings is more likely to occur in the FreeTopic-type community. In such a community, going along with neighborhoods is a good method for staying in the community. As a result, postings for the topic deviate towards negative/-positive. The model shows that peer pressure tends to spread widely in the FreeTopic-type community.

VII. Conclusion

We proposed a model on the basis of balance theory that reproduced the rise and fall of online communities and that clarified their general characteristics, such as the power distribution of postings and the elimination of irrational strategies.

The simulation results indicate two types of communities that will grow large: Topic-type and FreeTopic-type. However, both types of communities have different decline processes. Topic-type communities continue for a long time after they peak, even though they crash relatively frequently. We also investigated the evolution mechanism of Topic-type and FreeTopic-type communities.

The Topic-type communities contain many agents who have selfish strategies. Also, the opinions in postings are not disproportionately positive or negative. In such communities, the ratio of selfish strategies is higher than in FreeTopic-type community. This causes the highly frequent crashes. However, despite these crashes, there is a continuously large number of postings after the peak (Fig.10). In such communities, agents gain many benefits on average (Fig.15) and strategies are highly diverse (Fig.13). After a crash occurs, a relatively large number of agents gain benefits from the community.

On the other hand, FreeTopic-type communities contain a strong cluster of agents who share the same strategy. In this situation, even though the topic changes at each step dynamically, the opinions in postings are disproportionately positive or negative. The mechanism of this phenomenon can be explained by group adaptation to a community in a situation in which topic dynamically changes at each step. In such a community, the opinion of the post deviates towards being either positive of negative. Therefore, agents gain benefits stably. Accordingly, the community does not often crash. However, in such communities, the average benefit for an agent is low, because agents greatly consider the balance between each other rather than their topic preferences.

The simulation results can explain some phenomena that appear in real online communities. For example, on Facebook, the topics change dynamically and positive postings are more likely than negative posts to spread [12]. The simulation results indicated that such a community can be composed of negative postings. The Like button of Facebook could be considered to lead the user to positive postings. It is still doubtful whether Facebook would be composed of negative posting even if there were a ”Don't Like” button.

In this research, we clarified the mechanism of the rise and fall of online communities, especially focusing on the transition of topic. We found how communities decline and what conditions will decrease the probability of crash. However, we still do not know what conditions are sufficient for a crash, and these conditions are required to formulate indicators of an online community's decline. We plan to analyze this in the future.

Furthermore, the model we proposed is suitable for evaluating resilience under some different condition because the model can treat the relationship between users. For example, estimating the effect of the users who attack the community is important for considering how to improve the resilience of a community. In addition to this, the following factors are expected to be significant for estimating the rise and fall of communities.

- Setting the number of topics above two
- Setting the link between the agents to negative.
- Changing the initial conditions of distribution of user strategy
- Introducing stubbornness to each agent
- Introducing the symmetry bias of positive and negative postings to each agent

The final goal of this work is to provide the foundations for analyzing and predicting the behavior of agents in each kind of online community. We will simulate the online communities with the above extensions and confirm their consistency with data of real online communities.

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