How to Attract Customers to Your Website with Word-of-Mouth Communication in Social Media

Jieliang Zhou, Takashi Yamada, and Takao Terano

Abstract The social environment of a person has a high influence of his/her consumer behavior. Social networks transfer these social environments to the online world and enable a targeted influence on the customers purchasing behavior by word of mouth from their social contacts. In this paper, we present an agent-based simulation model that enables computational experiments of online media's management process using the word-of-mouth communication in social media. By comparing the number of customers' visits of two viral media in competitive setting, we confirm that following the market trend to make the contents and deliver them to the user who has more friends or relationships in social media is the effective way to gain customer's visit from social media.

Keywords Online media • Social network service • Word-of-mouth communication

1 Introduction

Rapid growth of the social media has not only changed the way people communicate and gather on the web but also affected the way of content discovery and navigation in a big way. According to "Reuters institute digital news report 2014" [1], more and more users, especially the young users, have become to choose social media as their gateway to make use of the online media contents. Meanwhile, the social media marketing which centers on creating content that attracts attention and encourages readers to share it across their social networks is grabbing a great deal of attention.

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“Viral media” is a new media style which employs the social media marketing to receive the majority of its traffic by creating content that is shared on social media websites. As a consequence, how to make the contents popular in social media is the most significant issue that the marketers there should take into consideration. The famous viral media site “BuzzFeed” reaches more than 130 million unique visitors per month which almost surpass most of the traditional online website [2]. On the other hand, compared to the traditional online website, because of the easiness to begin with a new one, varieties of viral media have been mushrooming, and the fierce battles among the viral media sites have been observed. For this reason, it is not easy for the viral media sites to survive under such business environment.

In this study, we construct an agent-based simulation model to reproduce the real-world management process of viral media to explore the feature of the viral media. By constructing two viral media in the competitive setting, we will indicate the effective contents of making strategy and targeting strategy to gain more customers from social media.

2 Related Work

To model and manage the word-of-mouth communication process effectively, Bampo et al. [3] proposed a decomposition approach of word-of-mouth activity consisting of three main aspects: (1) the particular structure of the social network, (2) the behavioral characteristics of its constituting members, and (3) the seeding strategy to initiate the viral process. We conceptualize our model by this approach to study the dynamics of viral media management process. However, our work differs from it by considering the change of the promotion contents, which can assist the online media marketer’s to decide how to update their contents in diffusion process. We also analyze the promotion strategy in the model ground with the reality.

3 Model Outline

We assume that there is a competitive environment with two online media companies utilizing the word-of-mouth communication to attract customers from SNS and wherein the user agents consume the contents the companies create based on their rules. Every user has an individual circle of friends consisting of other user agents. Figure 1 shows the outline of the proposed model. In our model, we have three kinds of agents, the news pool, the online media agent, and the consumer agent.

In every time step, the consumer users read and share the contents. After every several time steps, the news pool generates several media contents, and the online media agents select the new contents as the delivery contents and change the target SNS users. The behavioral rules for users and media agent are shown in Fig. 2.

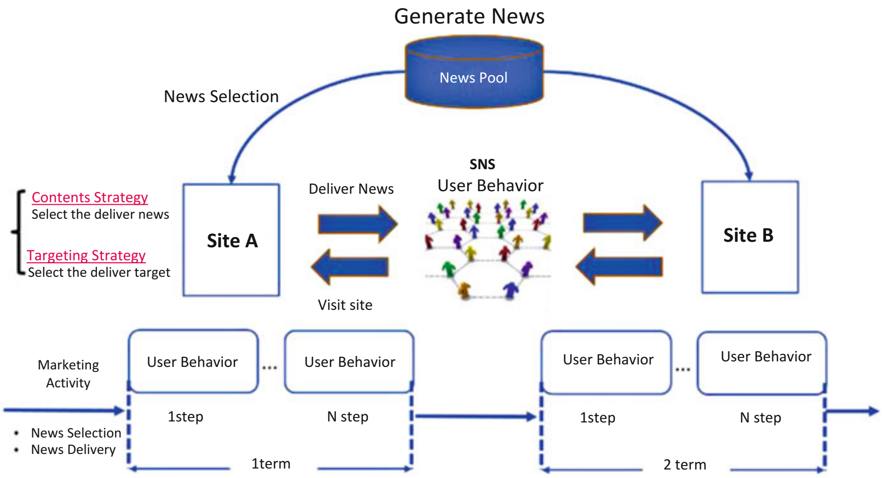

Fig. 1 Outline of the proposed model

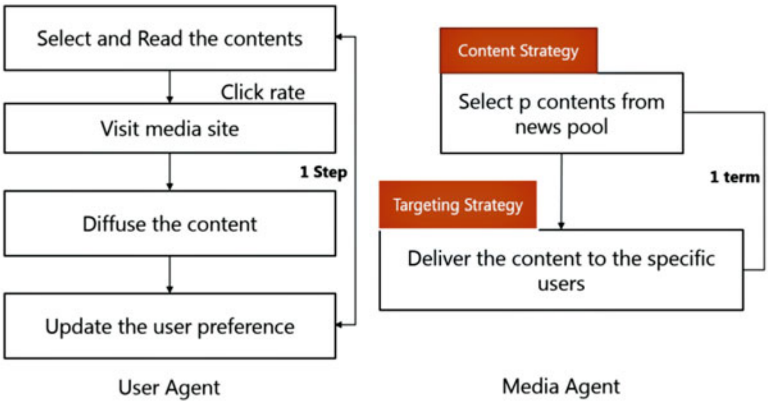

Fig. 2 Behavioral rules for each agent type

Media agents will (1) select the contents from the generated contents from news pool based on their content strategy and (2) transmit the contents to the target consumers based on their targeting strategy. Consumer agents select one content which can maximize their own utility from the received contents and then read and visit the media site according to the static click rate. Then, they diffuse the contents and update the personal preference.

The previous process of interaction between media agent and consumer agents is repeated over time. In addition, at the end of each time interval (i.e., terms), the media agents revise their content strategy.

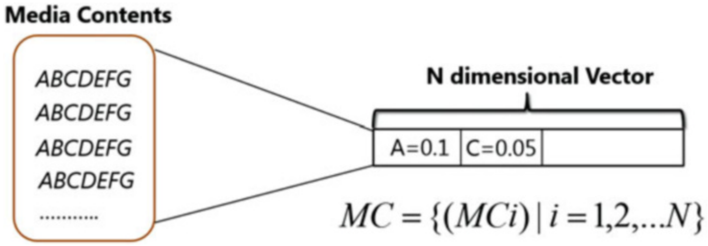

Fig. 3 Image of online media contents

3.1 News Pool

The news pool agent will generate M contents in every term (several steps). We use an N-dimensional vector to represent the online media content that is used by media agent. Each element of this vector indicates a keyword by which a user can reach the media content. In other words, each of the N elements can be conceptualized as one feature of the media content. The elements of the N-dimensional vector include not only the keywords but also a quantified weight. This weight shows the percentage of the media content in which the keyword is repeated or its synonym appears. Figure 3 shows the image of the online media contents in our model.

3.2 Consumer Agents

The same N-dimensional vector used for media content is considered to describe each user's preference. The segmentation set of keywords is defined as $UP = \{UP_i | \, i = 1, 2 \, \ldots \, N\}$. UP_i is the feature value of the user attribute i.

The consumer agents will receive the contents, adopt the contents, and diffuse the contents according to their own activity rules: the quality of the contents and the social impact from the adjacent users in social network.

We use utility to represent the extent of acceptance of the received content for each user. By summing up each agent's content utility and social utility, the weighted linear sum is determined as follows:

$$Ut_i(Mc) = W_i * Uc_i(Mc) + (1 - W_i) * Us_i(Mc) \tag{1}$$

where $Uc_i(Mc)$ is the content utility for the received content Mc, $Us_i(Mc)$ is the social utility, and W_i is the weight for content utility.

We use the similarity between user preference vector and media content vector to define the content utility:

$$Uc_i(Mc) = \cos(Mc, Up_i) \quad U_c \in (0, 1) \tag{2}$$

Social utility can be defined as the following equation based on the information diffusion model proposed by Rand and Rust [4]:

$$U_s(Mc) = \frac{n_t(Mc)}{n} \quad U_s \in (0, 1) \tag{3}$$

where $n_t(Mc)$ is the number of content Mc received from adjacent node set S and n is the number of adjacent nodes.

3.2.1 Content Selection Rule

The consumer agent can only choose one content from received contents in every time step which means the agent who received several contents will select one content based on the following roulette wheel selection algorithm:

$$P_k = \frac{Ut_i\left(Mc^k\right)}{\sum_{k=1}^{Np} Ut_i\left(Mc^k\right)} Mc^k \in \ N\mathrm{pool}^i \tag{4}$$

where $Ut_i(Mc^k)$ denotes the utility value for the kth media contents received in current time which is stored in the media content's storage *Npool* for user *i*. *Np* is the number of received contents.

3.2.2 Content Diffusion

Consumer agents in the social network can diffuse the contents they receive from viral media based on specific rules. Here, we define the information diffusion cost, *Ci*, to control the user's diffusion probability based on the information diffusion model of Hildebrand et al. [5]. The consumer will diffuse the viral media content only when their utility for the content is bigger than their diffusion cost. The diffusion rule is written as follows:

$$\delta = \left\{ \frac{\text{Diffuse, } \mathbf{if} \ Ut_i(Mc) - C_i > 0}{\text{Do not diffuse, } \mathbf{otherwise}} \right. \tag{5}$$

3.2.3 Change of the User Preference

We consider the effect of user's friendship and external environment to the change of the user preference. We define the effect of user's social relationship as the local effect and update the user's preference as follows:

$$Up_i^k(t) = Up_i^k(t) + \sum\nolimits_{j \in s} \alpha_t \left(Mc_j^{kd}(t) - Up_j^{kd}(t)\right) \tag{6}$$

where UP_i^k (t) is the feature value for user i's feature k, α_t is the value of α in current step t, MC_j^{kd} is the feature value kd of media contents received from user j in current time step, UP_i^{kd} is the feature value kd of user i's user preference in current time step, and S is the set of users which has link with user i in social media.

Furthermore, in order to represent the process that the consumers are attracted by new information and get bored with the old one with the lapse of time, we define the local effect coefficient α as the following exponential decay function:

$$\alpha_t = \alpha_0 e^{-\gamma t} \tag{7}$$

where α_t is the value of α at step t, α_0 is the initial value of α, t is the elapsed step, and γ is the attenuation coefficient and set as 1 in this model.

Similarly, to represent the global environment like the mass media and trend of the society, we use the following equation to update the user agent's preference:

$$UP_i^k(t) = Up_{i\,i}^k + \beta_t \left(Mc_{\text{global}}^k - UP_i^k \right) \tag{8}$$

where $UP_i^k(t)$ is the feature value for user i's feature k, β_t is the value of β in current step t, and MC_{global}^k is the feature value k of global media contents. In each time step, the global media content MC_{global} is delivered to every user in social media.

3.3 Media Agents

Media agents can change their management strategy regularly in order to gain more visitors to their website. Here, we explain the targeting strategy and content marketing strategy as their management strategy.

3.3.1 Content Marketing Strategy

Media agents can change and update the delivery contents in each term to attract more visitors to the website. The following strategies are identified and developed in our interviews and discussions with online media that operates in Japan:

1. Learning Strategy

This strategy will select the contents from the news pool according to the number of customers attracted by the contents delivered by own company in previous term. This is comparable to the A/B test which is widely used in real-world website marketing. So, the media agent using this strategy will choose the contents which are most similar with the most attractive contents delivered by own company in previous term according to the following equation:

$$P_{\mathrm{del}}^{k}(t) = \frac{\cos\left(Mc^{O\mathrm{best}}\left(\mathrm{t}-1\right), Mc^{k}(t)\right)}{\sum_{i=1}^{M}\cos\left(Mc^{O\mathrm{best}}\left(t-1\right), Mc^{i}(t)\right)} \tag{9}$$

where $P_{del}^{k}(t)$ is the probability to select content k as the delivery contents from news pool, $Mc^{Obest}\,(t{-}1)$ is the contents achieved most of the customers from social media in own company, $Mc^{i}(t)$ is the ith contents in news pool, and M is the number of contents in news pool.

2. Trend Strategy

This strategy will select the contents from the news pool according to the number of customers attracted by the contents delivered by both own and opponent company in the preceding term. This strategy can reproduce the imitation of other companies in the real world. So, the media agent using this strategy will choose the contents which are most similar with the most attractive contents delivered in market in previous term according to the following equation:

$$P_{\mathrm{del}}^{k}(t) = \frac{\cos\left(Mc^{M\mathrm{best}}\left(\mathrm{t}-1\right), Mc^{k}(t)\right)}{\sum_{i=1}^{M}\cos\left(Mc^{M\mathrm{best}}\left(t-1\right), Mc^{i}(t)\right)} \tag{10}$$

where $P_{\mathrm{del}}^{k}(t)$ is the probability to select content k as the delivery contents from news pool, $Mc^{M\mathrm{best}}\,(t{-}1)$ is the contents achieved most of the customers from social media in both own and opponent company, $Mc^{i}(t)$ is the ith contents in news pool, and M is the number of contents in news pool.

3.3.2 Targeting Strategy

This strategy encourages a certain number of user agents to immediately adopt their media contents. However, the most challenging problem for marketing manager to use this social media platform successfully is to have consideration about the privacy of users. Since the entire network structure is not available for the advertisers, they are forced to rely on the third-party information about the targeting consumers. In order to simulate this feature, we define a targeting strategy considering the network statistic characteristics instead of a whole network to find the most effective targeting strategy for the online media site's promotion under different situations. The possible strategies are as follows:

1. Degree Strategy

This strategy is to deliver the contents selected from the news pool to the target users according to the degree of the network. Higher-degree nodes influence more neighbors, directly encouraging more adoption. This strategy is comparable to marketing strategy choosing the user who has more friends to deliver the contents in the real world. So the number of neighbors of the target node normalized by the maximum possible value described as the equation below is calculated and delivers the contents to the users who have higher $w_d(i)$ value:

$$w_d(i) = \frac{\text{degree}_{(i)}}{\max\text{(degree)}} \tag{11}$$

2. Clustering Coefficient Strategy

This strategy is to deliver the contents selected from the news pool to the target users according to the clustering coefficient of the network. The lower the clustering coefficient of a node, the less overlap there is among its neighbors, encouraging wider adoption more quickly. So the 1.0 minus the fraction of neighbors of the node whose neighbors are also neighbors of the target node is calculated according to the following equation, and the media agent using this strategy will deliver the contents to the users who have higher $w_c(i)$ value:

$$w_c(i) = 1.0 - \frac{cc(i)}{\max(cc)} \tag{12}$$

4 Computational Experiments

In this study, we assume there are two viral media companies, Viral A and Viral B, in the competitive environment and attract the visitors to their website based on their management strategy. In this experiment, we set the content strategy and targeting strategy for each media agent according to the strategy described above and compare the number of attracted customers of the two companies to find the effective content selection and content delivery strategy for the viral media site to attract the customers. We use an improved version of Barabasi-Albert network [6] called DMS model which has the scald-free feature and small-world feature that is widely observed in social network as a static network to represent the real-world SNS network. The pair of the content strategy and targeting strategy is shown in Table 1.

The parameters setting for simulation is shown in Table 2.

Table 1 The pair of the strategy

	Degree strategy	Clustering coefficient strategy
Learning strategy	(1)	(3)
Trend strategy	(2)	(4)

Table 2 Simulation parameter

Parameter	Value
Ci: content diffusion cost	Uniform(0.25,0.5)
Wi: weight of the content utility	Uniform(0,1)
$\boldsymbol{\alpha}$: local effect of the change of the user preference	Uniform(0,1)
$\boldsymbol{\beta}$: global effect of the change of the user preference	Uniform(0,1)
number_population: number of the social population	10,000
Term_step: number of steps in one term	24
M: number of news generated in each step	10
P: number of contents selected from news pool in each tern	3
q: click rate for the reading contents	0.1
$\boldsymbol{\gamma}$: power index for the network	2
Step: simulation step	1000

Table 3 Competition result (100 trails)

	①	②	③	④
①		79	84	23
②	21		44	11
③	16	56		18
④	77	89	82	

The value of upper triangular is the number of wins for Viral A, and the value of lower triangular is the number of victory for Viral B

4.1 Simulation Results

We observed winning percentage of each company in 100 simulation trials under each pair of the strategy. The win-loss records are shown in Table 3:

1. If the content strategy is set as the trend strategy and targeting strategy is set as the degree strategy, the company can win the match in the high winning percentage no matter what strategy pair the opponent uses.
2. If the two companies choose the same content strategy, the rank of the winning percentage for attracting visitors for each targeting strategy is
degree strategy > clustering coefficient strategy.
3. If the two companies choose the same targeting strategy, the rank of the winning percentage for attracting visitors for each content strategy is
trend strategy > learning strategy.

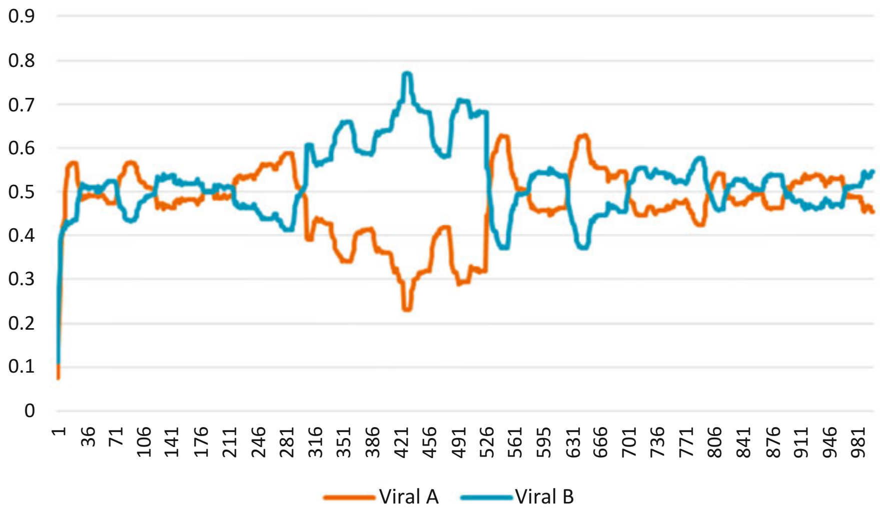

Fig. 4 The transition of the percentage of the latest customer visit

Table 4 The original company which produces the content

11th term	12th term	13th term	14th term	15th term	16th term	17th term	18th term	19th term	20th term	21st term	22nd term
A	B	B	B	B	B	B	A	A	A	A	B

From now on, we will focus on the competition between the two companies, Viral A and Viral B, using strategy pair (1) and (4) to analyze the detail of each strategy.

Figure 4 shows the transition of the percentage of the latest customer visit in the whole social population. From this graph, we can see that the share has rapidly changed from step 288 to step 528. We focus on this period and see what kind of contents each company delivers and how these contents attract the customers from SNS to their own website.

Table 4 shows the original company of the hit contents followed by media company B using the trend strategy as their content strategy from the 12th term (step 288) to the 22nd term (step 528). Figures 5 and 6 show the scatter plot of the similarity of delivered contents and user preference and the attracted customers through delivered contents.

From Table 4 and Figs. 5 and 6, we can observe that at the 12th term the media agent B imitated the contents delivered by media agent A at the 11th term. Furthermore, the media agent B delivers the contents which are highly similar with target users' preference from the 12th to 16th term and gain lots of customers. On the other hand, media agent A delivers the contents which have low similarity with target user preference from the 12th to 17th term and lost the market share rapidly.

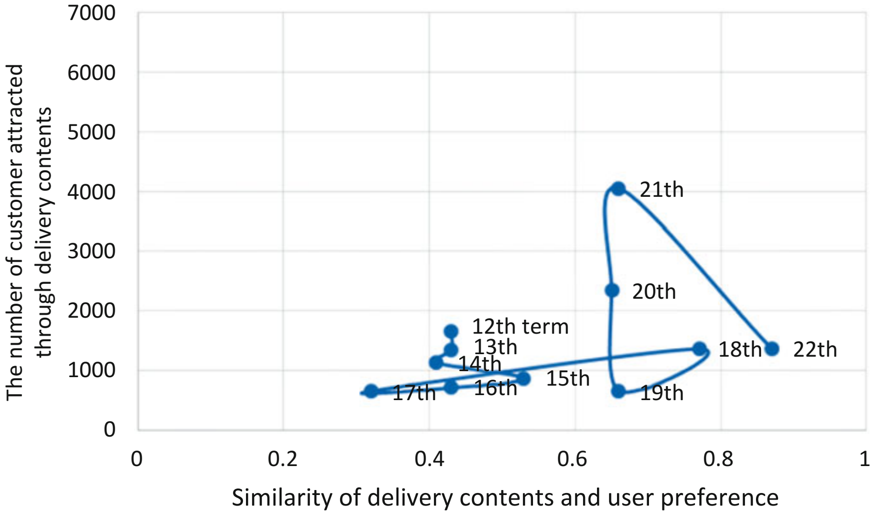

Fig. 5 The scatter plot of the similarity of delivered contents and user preference and the attracted customers through delivered contents (Viral A)

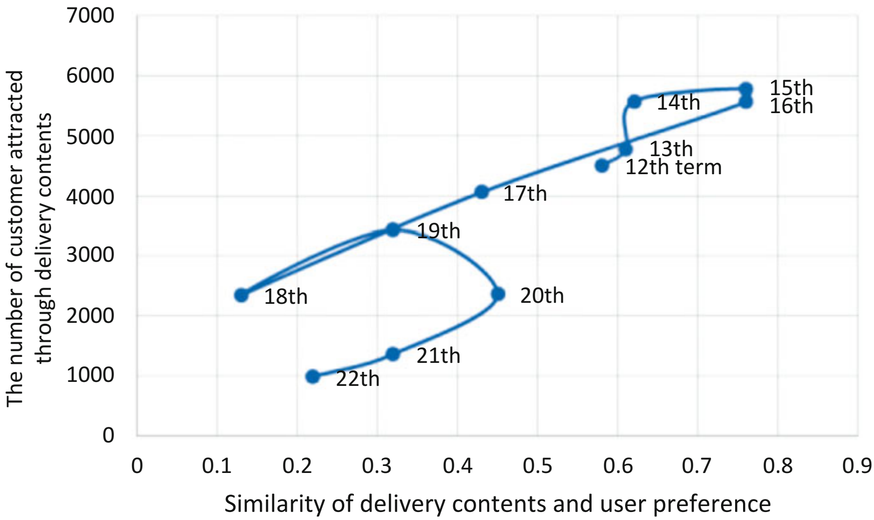

Fig. 6 The scatter plot of the similarity of delivered contents and user preference and the attracted customers through delivered contents (Viral B)

However, from the 18th to 21st term, the media agent A delivers the attractive contents and recovers the market share, but the growth has stopped at the 22nd term because of the imitation of media agent B using the trend strategy. From this result, we can say that if the company using trend strategy produces the attractive content itself, it will win the competition, and if the opponent company produces the attractive contents, it will imitate the opponent and block the increase of the opponent's market share.

So, we can conclude that if the market has the contents which can rapidly attract the customers, the trend strategy has a superiority in attracting more customers.

On the other hand, if the market has not delivered the contents which can attract lots of customers, the trend strategy does not have much superiority in attracting customers from SNS.

5 Discussion and Conclusion

In this paper, we present an agent-based model simulating the management process of viral media and attempt to find the best content selection and content targeting strategy for viral media to attract more customers. By comparing the two media sites' number of attracted customers in the competitive setting, we concluded that setting the content strategy as the trend strategy and targeting strategy as the degree strategy is the most effective strategy pair to gain customers from the social media. Meanwhile, we also successfully reproduce the phenomenon that the "plagiarizing viral media" has been increasing in real society. For the future work, we will increase the number of media agent to do the simulation. Also, the benefit and cost of the media agent should be taken into consideration in our model.

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