

Effect of Monetary Reward on Users' Individual Strategies Using Co-Evolutionary Learning

Keywords: Consumer generated media, Game theory, Agent-based simulation, Monetary reward, Co-evolution

Extended Abstract

Background: *Consumer generated media* (CGM), such as social networking services (SNS) and review sites, are used by many people; however, these sites rely on the voluntary activity of users to prosper, garnering the psychological rewards of feeling connected with other people through comments and reviews received online. To attract more users, some CGM have introduced monetary rewards (MR) for publishing activity. However, the effect of MR on the article posting strategies of users, especially frequency and quality, has not been fully analyzed. Usui et al. [1] proposed a game theoretical-model, the *SNS-norms game with monetary reward and article quality* (SNS-NG/MQ), and investigated the dominant behavior of users by introducing a few strategies for providing MR (MR strategies) using the genetic algorithm (GA). They found that although MR increases the frequency of article posts, the positive or negative impact on article quality depends on the MR strategy.

However, the dominant strategies determined by the naive GA are almost identical for all users. We believe that appropriate strategies for CGM depend on the standpoints of users, such as normal users or *influencers* who have a large number of followers. However, such differences were ignored in their study although exploring the individual behaviors of users with different attitudes is crucial for CGM to infer the overall behavioral structure of all users.

Purpose and Method: The purpose of this study is to investigate the effect of MR on individual users by considering the differences in dominant strategies with respect to user standpoints. To this end, to determine the individual strategies of users in SNS-NG/MQ, we applied *multiple-world GA* (MWGA) [2] instead of GA. MWGA generates several copies of a CGM network with nodes as agents that correspond to users, and each agent in the multiple worlds selects different behavioral strategies to interact with its neighboring agents. Then, the agent with the larger reward is likely to be selected as one parent for the next generation, spreading the better strategies to agents at the same location in many worlds. As a result, each agent can have its own dominant strategy in CGM. The reader is referred to [2] for details of the algorithm.

We briefly describe SNS-NG/MQ. A CGM network represents the connections between agents, as expressed by graph $G = (V, E)$, where $V = \{1, \dots, N\}$ is the set of N agents, and E is the set of edges corresponding to friend relationships. Agent $i \in V$ uses three parameters to describe the behavioral strategy, (article) posting rate B_i , comment rate L_i , and quality Q_i ($0 \leq B_i, L_i, Q_i \leq 1$); these values are decided by MWGA for i 's own dominant strategy. Agent i also has a random value, $0 \leq M_i \leq 1$, representing the degree of the user's preference for MR, and is specified at the onset because it may be innate or acquired but underlying preference. Then, users are classified into two disjoint sets, $V_\alpha = \{i \in V \mid M_i < 0.5\}$ and $V_\beta = \{i \in V \mid M_i \geq 0.5\}$, which are the sets of agents preferring psychological and monetary rewards, respectively.

The flow of the game on this graph is illustrated in Figure 1, in which states transit depending on probabilities, as listed in Table 1. The effect of Q_i is that the articles with high Q_i requires more cost but increases the probability that the posted article will be read and hence,

likely to receive comments. A game round is defined as the round in which all agents have a chance for an article post. Note that s_j is the article number that i 's neighboring agent j can read in a game round. A generation of MWGA is four game rounds. A number of MR strategies can be considered for MR $\pi > 0$; however, due to the page limitation, we assume that agent i can receive π when i posts an article. Other parameters describing costs and rewards are identical to those in [1], which are also listed in Table 2.

Experimental Results and Discussion: The experimental setting is the same as in [1] and listed in Table 3, excluding that graph G is generated using the *connecting nearest neighbor model* [3] with the transition probability from a potential edge to a real edge set to $u = 0.9$, and $N = 400$. This model generates a well-known scale-free, small-world, undirected network with a high cluster coefficient. In Figure 2 and Figure 3, the values of B_i , L_i , and agent's degree, are plotted for GA [1] and our method with MWGA, respectively. The heat legend indicates the quality value Q_i .

The results of the previous study (Figure 2) suggest both acceptable and unacceptable behaviors of agents. First, agents, especially those in V_β , attempt to post numerous but low-quality articles. This behavior seems reasonable. Such articles receive few comments, and hence low psychological rewards, but the agents could gain more MRs from posting numerous low-quality articles. Another observation is that the strategies of all agents were almost uniform, i.e., they have similar values of B_i , L_i , and Q_i , regardless of their degrees. This result is somewhat counterintuitive because in actual CGMs, the strategies of influencers differ from those of normal users.

Meanwhile, Figure 3 indicates that agents have diverse strategies depending on their standpoints in the networks. The most remarkable difference is that the influencers, which have high degrees, behave such that they write as many high quality articles as possible at a high cost. We believe that this result is consistent with the actual behaviors of users in CGM. In particular, they indicate a situation where both psychological and monetary rewards are effectively used. In addition, the number of articles submitted by all agents increases while the quality of articles decreases. This depends on the value of the monetary reward π , and increasing π makes the situation worse; low-quality articles increased.

Conclusion: Experiments were conducted on SNS-NG/MQ [1] using MWGA to obtain more diverse realistic dominant strategies depending on user standpoints in the CGM network. We introduced a number of MR strategies and conducted the experiments other than those discussed here. These results will provide insight to CGM platformers regarding the MR strategies that can make CGMs thrive or fail. We plan on investigating different models of CGM with other reward structures.

References

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- [3] Alexei Vázquez. Growing network with local rules: Preferential attachment, clustering hierarchy, and degree correlations. *Physical Review E*, 67(5):056104, 2003.

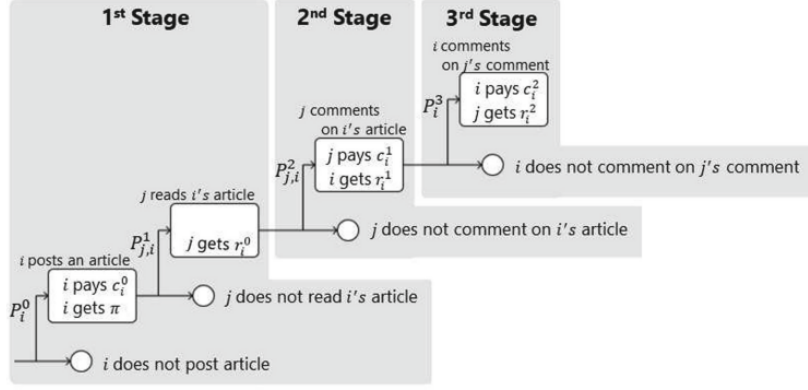


Figure 1: Flow of the SNS-norms game with monetary reward and article quality.

Table 1: Probabilities used in SNS-NG/MQ (Figure 1).

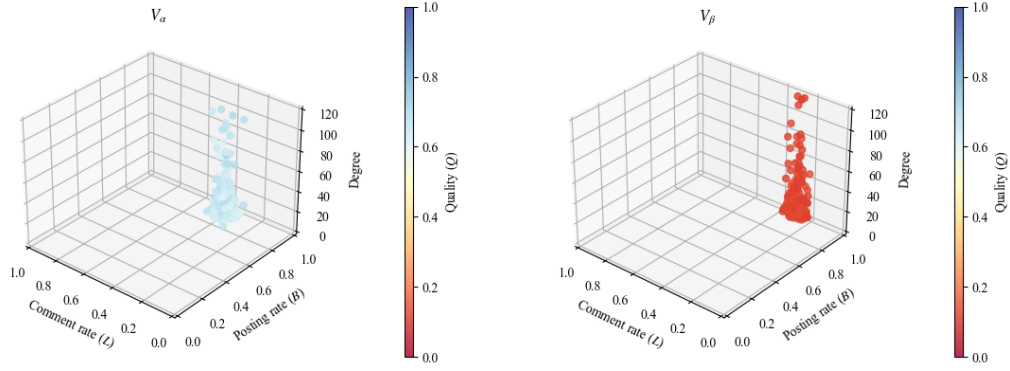
Description	Parameters	Value
Probability of article post	P_i^0	$B_i \times Q_{min}/Q_i$
Probability of article read	$P_{j,i}^1$	Q_i/s_j
Probability of comment post	$P_{j,i}^2$	$L_j \times Q_i$
Probability of posting a meta-comment	P_i^3	$L_i \times Q_i$

Table 2: Calculation of costs, psychological rewards, and utility in SNS-NG/MQ.

Description	Parameters	Formula
Cost of article post	c_i^0	$c_{ref} \times Q_i$
Cost of comment	c_i^1	$c_{ref} \times \delta$
Cost of meta-comment	c_i^2	$c_i^1 \times \delta$
Psy. reward of article read	r_i^0	$c_i^0 \times \mu$
Psy. reward of receiving a comment	r_i^1	$c_i^1 \times \mu$
Psy. reward of receiving a meta-comment	r_i^2	$c_i^2 \times \mu$
Utility	u_i	$(1 - M_i) \times R_i + M_i \times K_i - C_i$

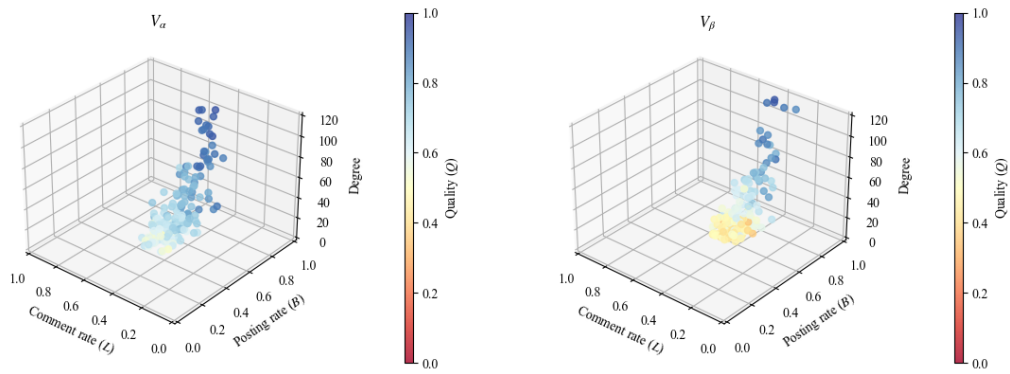
Table 3: Parameter values in experiments.

Description	Parameters	Value
Number of agents	$N = V $	400
Number of agents preferring psychological reward	$ V_\alpha $	200
Number of agents preferring monetary reward	$ V_\beta $	200
Reference value for cost and psychological reward	c_{ref}	1.0
Raito of cost to psychological reward	μ	8.0
Cost ratio between game stages	δ	0.5
Monetary reward	π	1.0
Number of worlds in MWGA	W	10
Number of generations	g	1000
Probability of mutation	m	0.01



(a) Agents preferring psychological reward V_α (b) Agents preferring monetary reward V_β

Figure 2: 3D scatter plots of strategy parameters and degree in GA.



(a) Agents preferring psychological reward V_α (b) Agents preferring monetary reward V_β

Figure 3: 3D scatter plots of strategy parameters and degree in MWGA.