Analyzing the Phase Transition Dynamics in Social Contagion by an Agent-Based Inverse Simulation

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Abstract: This paper attempts to clarify the critical factors that determine the phase transition dynamics occurring in social contagion by an agent-based inverse simulation equipped with genetic algorithm. Previous studies have already shown that structural features such as network topology or social norm, affect significantly the macroscopic dynamics of complex social phenomena. We still need, however, a quantitative analysis of the decisive factors which could yield some particular phase transition in a society, e.g. the emergence of an epidemic. Thus we explore, by utilizing genetic algorithm, the vast parameter space of an agent-based model that represents social contagion, so that we might identify the specific values of parameters resulting in phase transitions. With the results, we will seek to describe their implications for either preventing or enhancing the contagion.

1. Introduction

The inquiry into the effects of network topology on the socially spreading phenomena has always been a topic attracting a large number of researchers since the last century. Several previous papers have demonstrated that social contagion such as the spread of obesity as well as happiness is greatly influenced by the structure of network in which individuals are interacting with others. These previous studies, however, appear to assume a network being its static status when they analyze the network effects on the spreading.

Recently, some prior studies have suggested investigating networks based on their dynamic, evolutionary or adaptive conditions in order to realize the genuine dynamics in a society. Especially, Sayama et al. has proposed adaptive networks in which the co-evolution of 'dynamics *on* networks' and 'dynamics *of* networks' plays a key role. Such networks whose states and topologies coevolve sequentially still need modeling realistically and analyzing systematically.

Thus, we attempt first to model such an adaptive network in the case of obesity spreading in order to really represent the complex social phenomenon. Secondly, we try to explore the model's parameter space by means of inverse simulation, so that we might identify the decisive factors which could yield some particular phase transition within the society.

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2. Overview of the model

We will describe the outline of our model based on the ODD protocol which is prevalent among researchers exploiting agent-based modeling, except the 'details' part we are just in the middle of elaborating.

2.1 Purpose

The present model aims at identifying the key factors that determine the dynamics of phase transition occurring in the social contagion. We begin by modeling the obesity epidemic as a complex social system where agents and networks co-evolve through growth, adaptation and interaction, so that we might represent realistically the dynamics of spreading phenomenon in a society. We will ultimately rely on the inverse simulation equipped with genetic algorithm in order to clarify the critical societal conditions which lead to particular phase transitionss, e.g. epidemic or outbreak of obesity like infectious diseases.

2.2 Entities and scales

In this model, agents correspond to individuals who consume an amount of food at each time step. The quantity of food consumption is determined by the dual system constituted of 'affective system' and 'deliberative system' which are operating competitively within an individual

The agents are situated in a network which grows gradually as new agents are added to the network and linked with existing nodes, i.e. agents, at every time step.

The way the network develops is essentially regulated by the "preferential attachment" algorithm: the embedded nodes' probability of obtaining a new link from added nodes is basically proportional to their current degree in the network. In the present model, however, this probability is fashioned differently based on two distinct considerations which we will describe later in detail.

Each time step corresponds to a week in the model. The simulation starts with a network constituted of 15 agents. The overall process ends up by counting 500 agents. When it takes 160 time steps for a simulation to finish, it means the simulation continues for approximately 3 years in the model. As regards the space, no particular, concrete space structure is assumed except network topology the design of which we are very involved with.

2.3 Process overview and scheduling

Since agents interact with each other in the network, their decision as to the amount of food consumption should be affected by their conformity to the social norm recognized through networked interactions. Thus, agents vary their balancing on dual system adaptively, according to the difference between their current weight status and perceived norm weight. Agents' adaptive behavior successively affects their weight values.

The oscillations of each agent's weight are reflected in the node's 'suitability', measured by the comparison between its current state and the objectively ideal one. As the suitability is parameterized in the growing network algorithm, its fluctuations affect the development of network topology, which in turn influences agents' interactions.

This co-evolution between agents' adaptive behavior and varying network structure might yield several trends in the agents' average weight. This model attempts, ultimately, to identify the conditions that could generate the phase transition in the trend of agents' weight by means of the inverse simulation using genetic algorithm.

2.4 Design concepts

2.4.1 Basic principles

Our model presumes two fundamental theories, one of which is concerning the agent's decision process and the other is regarding the algorithm for generating networks.

An agent determines the amount of food to consume based on the balancing of internal dual system which is composed of the affective system and the deliberative system. The former system has a present-bias favoring the gratification obtained from over-eating. The latter one is, contrarily, oriented for the decision that takes into consideration the long-term consequences, e.g. health in future. Depending on the balancing of these two systems, an agent decides how much food to consume.

As regards modeling the network, we assume a well-known algorithm for generating networks, i.e. *Barabási–Albert model*, characterized by 'growth' and 'preferential attachment'. Then, we have differently fashioned the algorithm for preferential attachment based on two distinct considerations. First, the degree of each node is multiplied by a parameter η indicating agents' "suitability" which is measured by the deviation from the ideal weight status: as an agent's weight approaches the ideal weight, the value of her suitability increases. Second, an amount δ is added to each agent's degree in order to realize the equalization among agents through weakening the harshness of preferential attachment.

2.4.2 Emergence

The co-evolution of these two dynamics could generate different kinds of weight trends within the society. On the one hand, an upward trend might emerge when the network effects enhance the obesogenic mechanism in societies. On the other hand, a downward tendency could come out under the network influences restraining the obesity. Thus, we might be able to observe a phase transition where the weight trend changes suddenly, which is regarded as an emergent phenomenon in itself. Our model tries to demonstrate how these trends emerge by the simulations and, ultimately, to identify the conditions determining the occurrence of phase transition.

2.4.3 Adaptation

In our model, the way the network grows adapts itself to the weight statuses of nodes linked in the network. In a 'basic' *scale-free* network constituted of j nodes, the probability for an existing node i, whose degree is k_i, to receive an edge from newly added nodes is as follows :

$$p_i = \frac{k_i}{\sum_{j=1}^{n} k_j} \quad (1)$$

As noted above, we modify this basic form by adding the suitability η and equalizing factor δ.

$$p_i = \frac{\eta_i k_i + \delta}{\sum_{j=1}^{n}(\eta_j k_j + \delta)} \quad (2)$$

$$\eta_i = \xi \cdot \phi_i \quad (3)$$

,where ϕ_i represents the ratio of $i's$ current weight to the objectively ideal weight, and ξ indicates the significance given to the suitability. With this algorithm, the network develops while adapting to the oscillations of nodes' weight, which are in turn under the influence of networked interactions.

2.4.4 Objectives

In order to clarify the requirements for different weight trends to emerge, the present model defines temporarily the objective functions for genetic algorithm as follows:

$$\text{trend}_{up} \quad : \frac{avgweight\ at\ t_k - avgweight\ at\ t_0}{avgweight\ at\ t_0} = 0.2$$

$$\text{trend}_{down} \quad : \frac{avgweight\ at\ t_k - avgweight\ at\ t_0}{avgweight\ at\ t_0} = -0.1$$

$$\text{trend}_{level} \quad : \frac{avgweight\ at\ t_k - avgweight\ at\ t_0}{avgweight\ at\ t_0} = 0$$

,where $avgweight\ at\ t_k$ means the average weight of agents at time step k, while $avgweight\ at\ t_0$ indicates the one at the beginning of the simulation. We are exploring the parameter space with these distinct objective functions by running the multiple simulations.

Once we have identified the parameter values for these conditions separately, we will be able to shed light on the mechanism leading to the phase transition by graphically mapping out those parameter values.

3. Results of parameter sweep

We have run a series of simulations with our model in order to verify the basic model behavior. By varying the values of a few typical parameters, we were able to confirm some characteristics as to the dynamics of model.

3.1 Preferential attachment

Varying the parameters, ξ concerning the node's suitability and δ regarding the equalization of nodes, we observed the agents' average weight at the beginning as well as at the end of simulations. We investigated, then, different kinds of preferential attachment with respect to their effects on the agents' weight by calculating the ratio of change in the average weight.

Fig.1 shows the plotting of the relations between ξ, δ, and the ratio of change in the average weight. As the blue plane that visualizes the results of linear regression analysis suggests, the effect of δ on the ratio of change in weight is statistically significant, while ξ within the simulated range does not seem to influence the weight decidedly. While δ increases, the nodes' equalization multiplies the nodes having relatively many edges through transforming the degree distribution, as Fig.2 illustrates. So, we might be able to attribute the increased average weight to the emergence of agents linked with many 'friends' in the network.

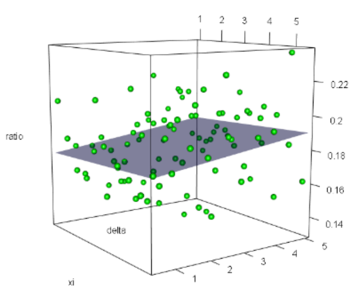

Fig. 1 ξ(x), δ(y), ratio(z).

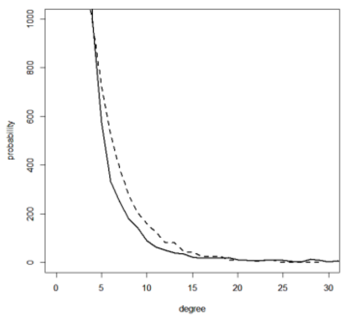

Fig.2 degree distribution

ξ as well as δ meaningfully boost the clustering coefficient of the network, as Fig.3 displays. However, the clustering coefficient in itself is proved, by regression analysis, to have no influence on the ratio of change in average weight. Therefore, the effects of δ on the weight may not be reducible to its effects on the clustering coefficient.

3.2 Adaptive behavior

By varying the λ indicating the threshold for beginning of agents' adaptive behavior, and the μ representing the breadth of change caused by the adaptation, we examined the effects of agents' adaptation on the ratio of change in the average weight. In Fig.4, the plotting of λ, μ, and the ratio of change in average weight is demonstrated. The blue plane resulting from linear regression analysis suggests that increasing μ, i.e. the breadth of an agent's adaptive alteration, significantly restrains the ratio of increment in the average weight. As for the threshold λ, it does not alter the agents' average weight meaningfully.

We could infer from these results that the frequency of adaptive behavior is less important than its range of change, at least in the case of agents linked with others in such a growing network as simulated.

3.3 Direction of future research

We have obtained some implication as to the effects of a few parameters on the agents' weight by running multiple simulations on our model. Especially, it is meaningful that in a growing network, a kind of degree distribution emerges under some parameter settings, and it appears to enhance the increasing trend in individuals' weight. However, it is quite evident that more extensive and thorough exploration

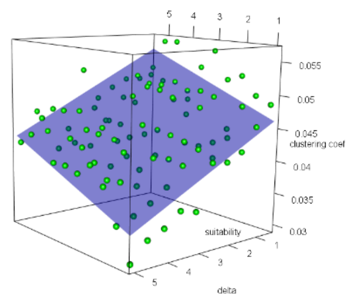

Fig.3 ξ(x), δ(y), clustering coef(z)

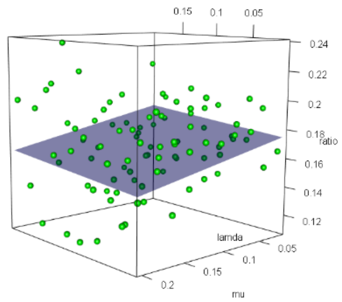

Fig. 4　λ(x), μ(y), ratio(z).

of parameter space (i.e. inverse simulation with genetic algorithm) will be needed in order to identify accurately the parameters and their range that decidedly influence the societal phenomena.

4. References

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