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Dynamical complexity in the perception-based network formation model

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HIGHLIGHTS

- We study how individual perception of the network affects strategic link formation.
- The stable link density shows discontinuous jumps according to the cost of linking.
- The effect of initial conditions of the network and the perception of it are investigated.

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ABSTRACT

Many link formation mechanisms for the evolution of social networks have been successful to reproduce various empirical findings in social networks. However, they have largely ignored the fact that individuals make decisions on whether to create links to other individuals based on cost and benefit of linking, and the fact that individuals may use perception of the network in their decision making. In this paper, we study the evolution of social networks in terms of perception-based strategic link formation. Here each individual has her own perception of the actual network, and uses it to decide whether to create a link to another individual. An individual with the least perception accuracy can benefit from updating her perception using that of the most accurate individual via a new link. This benefit is compared to the cost of linking in decision making. Once a new link is created, it affects the accuracies of other individuals' perceptions, leading to a further evolution of the actual network. As for initial actual networks, we consider both homogeneous and heterogeneous cases. The homogeneous initial actual network is modeled by Erdős–Rényi (ER) random networks, while we take a star network for the heterogeneous case. In any cases, individual perceptions of the actual network are modeled by ER random networks with controllable linking probability. Then the stable link density of the actual network is found to show discontinuous transitions or jumps according to the cost of linking. As the number of jumps is the consequence of the dynamical complexity, we discuss the effect of initial conditions on the number of jumps to find that the dynamical complexity strongly depends on how much individuals initially overestimate or underestimate the link density of the actual network. For the heterogeneous case, the role of the highly connected individual as an information spreader is also discussed.

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1. Introduction

Understanding the structure and dynamics of social networks is crucial to investigate social phenomena that emerge from interaction between human individuals [1–3]. Recent empirical analyses of large-scale datasets on social networks have revealed several common features or stylized facts [4], such as broad distributions of network quantities [5], existence of communities [6–8], and assortative mixing [9]. How and why social networks take such particular forms has been investigated in terms of link formation and/or deletion mechanisms, such as preferential attachment [10,11], triadic and focal closures [12–15], and link aging [4]. Although these link formation mechanisms have been successful to reproduce various empirical findings in social networks, they have largely ignored the fact that individuals make decisions on whether to create links to other individuals based on cost and benefit of linking. Thus, in this paper, we study strategic link formation mechanisms by considering cost and benefit of linking [3].

We also observe that the individual perception of the reality could significantly affect the individual behavior. Individuals embedded in a social network may have perception of the network. For example, Milgram conducted the small-world experiment to measure the distance between individuals in the social network [16]. In the experiment, each participant was asked to deliver a packet to the target person if he/she knows the target, otherwise to his/her acquaintance who is most likely to know the target. For the latter, the participants may use their own perceptions of the network. Precisely, the individual perception of the network can be straightforwardly represented by an adjacency matrix of the same dimension as that of the network, in alignment with Krackhardt's cognitive social structures [17]. Using this representation of perception, we can study how one's perception of the network could affect its decision making on whether to create a link to another individual.

We remark that compared to our modeling of individual perception of the network, one can find a number of relatively simple models for human perception or opinion, e.g., in opinion dynamics [18,19]. Here a perception or opinion of an individual has been mostly modeled by a spin having several choices or a low-dimensional vector. However, these approaches are often too simplified to properly represent human decision making, despite their successful applications.

In order to understand the evolution of social networks in terms of perception-based strategic link formation, we study the perception-based network formation model. This model was originally proposed in our previous work [20], where we mainly obtained analytic results of the model under restricted conditions. Some of analytic results will be presented in this paper whenever necessary. In this paper we study the model using numerical simulations for more general situations. In the model, each individual has her own perception of the actual network, and uses it to decide whether to create a link to another individual. The perception may not necessarily coincide with the actual network. Then, an individual with the least perception accuracy tries to benefit from updating her perception using that of the most accurate individual via a new link. This benefit is compared with the cost of linking for deciding whether to create a link. Once a new link is created, it affects how accurately other individuals perceive the network, hence their behavior. This might lead to further evolution of the actual network. In this sense, our model can be considered a coevolutionary or adaptive network [21]. As for initial actual networks, we consider both homogeneous and heterogeneous cases. The homogeneous initial actual network is modeled by Erdős–Rényi (ER) random networks, while we take a star network for the heterogeneous case. In any cases, individual perceptions of the actual network are modeled by ER random networks with controllable linking probability.

We introduce our model in Section 2. In Sections 3 and 4 for homogeneous and heterogeneous cases, respectively, we study the dynamics of the model to find that the link density of a stationary network shows discontinuous transitions or jumps according to the cost of linking. Here the structure of stable link density reflects how complex the dynamics of the model is, which we will call a dynamical complexity. Then we discuss the effect of initial conditions on the dynamical complexity in terms of the number of jumps. Finally we make conclusions in Section 5.

2. Model

Let us consider an undirected communication network of N agents who communicate with each other. For a pair of agents j and k, the link state $e_{jk,t}$ has the value of 1 if j and k are connected in a time step t, otherwise 0. We set $e_{ii,t} = 0$ for all i. The network G_t is a set of link states for all possible pairs, i.e., $G_t = \{e_{jk,t}\}$. We assume that an individual agent observes its own link states with $N - 1$ other agents, while guessing link states between other agents that are unobservable to it. Thus, guessed link states may not coincide with the actual link states. Precisely, an agent i's perception G_t^i of the actual network in time step t is a set of perceived link states for all possible pairs, i.e., $G_t^i = \{e_{jk,t}^i\}$, where $e_{jk,t}^i = 1$ if i thinks that j and k are connected, otherwise $e_{jk,t}^i = 0$. Since each agent correctly knows link states involving itself, we set $e_{ij,t}^i = e_{ij,t}$ for all j. A perception accuracy (or accuracy) of an agent i is defined as the aggregated quantity of correct link states in G_t^i:

$$\rho_t^i = \frac{1}{M} \sum_{j<k} \delta(e_{jk,t}, e_{jk,t}^i), \tag{1}$$

where $M = \frac{N(N-1)}{2}$ denotes the maximal number of possible pairs, and δ is the Kronecker delta function. Due to the fact that $e_{ij,t}^i = e_{ij,t}$ for all j, we have

$$\frac{2}{N} \le \rho_t^i \le 1. \tag{2}$$