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Opinion dynamics in networks with common-neighbors-based connections

Huanjing Wang*, Lihui Shang

Information and Control Engineering Laboratory, School of Optical–Electrical and Computer Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China

HIGHLIGHTS

- We introduce common-neighbors rule in traditional HK model.
- The long-range neighbors can be adjusted through parameters.
- The robustness of network size in our model is strong.
- Communication between agents who have common friends prolongs system convergence.

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ABSTRACT

We investigate opinion dynamics of the model in which each agent can communicate with local neighbors whose opinions are inside the bound of confidence and meanwhile selecting long-range neighbors according to a common-neighbors rule. The common-neighbors rule means that two agents sharing more neighbors have larger probability to be connected. We find that increasing communication between agents who have common friends will prolong the time needed for the system to reach a consensus state. In contrast, the long-range connections between agents sharing no friends will promote the convergence of the system. The generality of this observation is tested against different system sizes. Simulation results also show that a large number of long-range connections help the system to reach a consensus fast.

1. Introduction

In daily life, our actions and decisions are usually affected and shaped by our opinions and beliefs. And scientists more and more realized the importance of the spreading of opinions in social networks. Therefore, the study of how beliefs are formed and how the structure of the social network impacts the formation of beliefs gradually developed into a relatively independent research field—social learning theory.

In recent years, social learning has attracted significant attention and many models of opinion dynamics have been proposed [1–6]. Understanding the emergence of system consensus involving a number of interacting agents becomes a fundamental issue [7–12]. In social learning, a system reaches consensus means that all agents in the system sharing the same opinions and beliefs. There are two important aspects to study opinion dynamics: social structure and updating rules. Generally, the social structure might be assumed to be fixed during the evolution process or co-evolved with the opinion dynamics [13–17]. For updating rules, some simple rules like taking a linear combination are prominent in existing models [18–24].

* Corresponding author. Fax: +86 21 55276042.
E-mail address: lhshang2003@163.com (L. Shang).

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One extensively studied model used for opinion dynamics is the Hegselmann–Krause (HK) model proposed by R. Hegselmann and U. Krause [12]. In traditional HK model, it is conventionally assumed that agents can communicate with each other only if their opinion distance is smaller than the bound of confidence. If the distance of two agents' opinion is out of the range, their contact will be cut off. Motivated by HK model, many extensions and improvements have been proposed and analyzed [25–29].

In our social life two individuals may be friends even if they have quite different opinions, or we want to communicate with those who hold different opinions. Based on this, Ref. [30] analyzed opinion evolution for short-range and long-range models, where some opinions out of the confidence ranges are considered with a weighted combination. It is showed that dynamical behaviors are different for the short-range and long-range models. Ref. [31] proposed a bounded confidence plus random selection model, where each agent can communicate with those whose opinions are inside her bound of confidence and meanwhile selects a few long-range neighbors outside the bound according to a similarity-based probability rule. This rule presents the homophily principle in sociology and proved that the opinions of all agents can reach a consensus in a bounded time due to the long-range neighbors outside the bound of confidence.

Considering a phenomenon that in our social networks, two people may also know each other if they have many common friends, we introduce a common-neighbors-based principle to select long-range neighbors in HK model, where a tunable parameter β introduces a preference in the neighbor selection. For $\beta > 0$ ($\beta < 0$), agent A have a relative larger (smaller) probability to choose agent B as her long-range neighbor if A and B have common neighbors. The opinion dynamics of such a system for different values of β are studied. It is found that the connection between agents having common neighbors will prolong the time needed for the system to reach a consensus state. The generality of this observation is tested against different network sizes. Furthermore, both a larger number of long-range neighbors and a large bound of confidence help opinions reaching consensus fast.

2. Model

Consider agents in a social network as a vertex set $V = \{1, 2, \ldots, n\}$. Each individual group member at any given time t, is assumed to be characterized by the opinion $u_i(t) \in [0, 1]$. All the agents are endowed with bounded confidence, and any pair of them are neighbors if their belief difference is smaller than a positive constant r, which is called the bound of confidence. Therefore, the set of short-range neighbors of agent i is defined as:

$$N_{i,1}(t) = \{j \in V, j \neq i : |u_i(t) - u_j(t)| < r\}. \tag{1}$$

Apart from selecting neighbors inside her bound of confidence, each agent also chooses m long-range neighbors according to a common-neighbors rule. If agent j is outside the bound of confidence, the probability that agent i chooses agent j as her long-range neighbor is as follows:

$$p_{i,j}(t) = \frac{e^{\beta s_{ij}(t)}}{\sum\limits_{k \notin N_i(t)} e^{\beta s_{ik}(t)}}. \tag{2}$$

Where $N_i(t)$ is the neighbor set of agent i, and $S_{ij}(t)$ denotes the number of common neighbors between agent i and agent j at time t. Moreover, a tunable parameter β introduces a preference in the neighbor selection. For $\beta > 0$, the agents having more common neighbors with agent i have larger probabilities to be selected. This implies that it is quite possible to find two neighboring individuals sharing common neighbors [32]. While for $\beta < 0$, the agents having no common neighbors with agent i are easy to be selected. In other words, we avoid making connection between two agents who have common neighbors. In the case of $\beta = 0$, the long-range neighbors are chosen uniformly at random irrespective of the number of common neighbors.

The set of agent i's long-range neighbors is defined as $N_{i,2}(t)$, so the neighbor set is $N_i(t) = N_{i,1}(t) \cup N_{i,2}(t)$. As for the opinion updating rule, we assume that agent i simply adopts the average opinion of all neighbors and herself as the new one:

$$u_i(t+1) = \sum_{j \in N_i(t) \cup i} \frac{u_j(t)}{1 + |N_i(t)|}, \tag{3}$$

where $|N_i(t)|$ is the cardinality of the set $N_i(t)$.

3. Simulation results

In this work we consider a social network with n agents. All the simulation results are the average of 200 independent runs, each with initial opinions randomly distributed in the interval [0, 1]. As the opinions are denoted by real numbers, we call that the system reaches consensus when the distance of the maximum opinion and minimum opinion is less than 10^{-4}, which means that all agents' opinions are so close that can be seen as the same. We measure the convergence speed of the whole group when it reaches consensus, the shorter the time steps for consensus, the faster the convergence speed.