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Review mechanism promotes knowledge transmission in complex networks

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ABSTRACT

Knowledge transmission systems differ from epidemic spreading systems in that people who have forgotten knowledge can reacquire it through reviewing. In order to analyze the review mechanism, we propose a Naive-Evangelical-Agnostic (VEA) knowledge transmission model in complex networks. Specifically, we derive a knowledge transmission system in homogeneous and heterogeneous networks, respectively. Mean field theory is used to theoretically delineate the knowledge transmission systems. In homogeneous networks, the steady state solution of the system is obtained. In heterogeneous networks, we get the basic reproduction number R_0, in which the reviewing rate is an important parameter. Moreover, we analyze the system and prove that if $R_0 < 1$, the knowledge loss equilibrium of the model is globally asymptotically stable; if $R_0 > 1$, the knowledge is permanent. In addition, to complement the theoretical analysis, numerical simulations are performed in four representative network models: random regular, small world, random growth and scale free networks. The simulation results indicate that the review mechanism has a clear positive influence for the knowledge transmission in the four networks, i.e., a higher reviewing rate leads to a higher final density of evangelical nodes. In addition, the simulation results illustrate that scale free networks transfer knowledge faster than the other three networks.

1. Introduction

In the knowledge-based economy, knowledge is recognized as the driver of productivity and economic growth [1]. As the dominant resource, knowledge can create competitive advantage for firms, and the value of knowledge is closely related to its efficient propagation. At the individual level, after acquiring knowledge, people will apply it, then share it with others in order to increase the total value arising from the knowledge [2,3]. Argote et al. defined knowledge transmission as the process through which one entity is affected by the experience of another [4]. In a knowledge transmission process, people can communicate what they know to others, or actively consult in order to learn what others know [5]. Typical products of knowledge transmission are the spreading of ideas or opinions [6], practice, and know-how [7]. The knowledge transmission process results in sharing of knowledge assets by a large number of members of an organizational population [8]. Therefore, knowledge transmission, as an important part of knowledge management, has been studied for many years [9].

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In recent decades, complex networks have been widely applied to describe the features of complex systems in the real world, including in social, biological, and communication systems [10]. Subsequently, more and more researchers are using insights from the study of complex networks to analyze the dynamics of knowledge acquisition [6,11,12] and knowledge transmission [13–18]. For instance, Cowan et al. modelled knowledge diffusion as a barter process in regular networks, random networks and WS small world networks and found that the maximum performance is achieved in small world networks [13]. Tang et al. compared knowledge transmission in scale free networks and hierarchical networks, and found that the scale free structure is more effective for knowledge transmission [14]. Lin and Li studied numerically the knowledge innovation and diffusion process on four representative network models, and illustrated that the steady-state level of average knowledge is maximal in scale free networks [15]. Simultaneously, some researchers have been characterizing knowledge transmission in academia by applying network-based methodology to data such as records of scientific literature citation [16] and patent citation [17,18]. In addition, the patterns characterizing scientific collaborations [19] have been analyzed to infer features of knowledge transmission and development.

Based on the analogy between epidemic spreading and information and knowledge transmission, more and more researchers have been extending epidemic spreading models to research the spreading of scientific ideas [20–22], information diffusion (e.g. rumor spreading) [23,24], and knowledge transmission models [25–27]. Bettencourt introduced epidemic models to quantify the spreading of a specific research topic (Feynman diagrams in theoretical physics), and observed a good fit between suitably adapted epidemic models and data [20]. Further, Bettencourt et al. showed that this good fit does not depend on the particular chosen topic and determined that epidemic models provide good descriptions of the spread of other topics within different scientific disciplines [21]. Kiss et al. applied an individual-based epidemic model to records of citations between ISI subject categories (SCs) in order to capture the way in which a research topic spreads over an existing network of disciplines [22].

Knowledge transmission in networks of individuals occurs through a variety of mechanisms. Some research has been conducted using dynamical systems theory to reveal the effect of different mechanisms on knowledge transmission. For example, Cao et al. established a general SIS knowledge transmission model which included knowledge forgetfulness, in which the level of forgetfulness depended mainly on the number of neighboring individuals who possess knowledge [25]. Wang et al. analyzed the knowledge transmission in complex networks with self-learning mechanism and found that the self-learning factor has a clear positive influence on knowledge transmission [26]. Considering the effect of inspiration by leaders in the knowledge acquisition process, Li et al. constructed the knowledge dissemination model of the cooperative learning network by extending the classic epidemic model [27]. They found that inspiration mechanism of leaders can reduce the system threshold [27].

However, knowledge transmission is different from epidemic spreading. People who have forgotten knowledge can reacquire it by review. If one person has not reviewed learned knowledge for a long time, memory retention will gradually decrease over time. For example, unused words which are not reviewed could be lost from a vocabulary. That is, reviewing will help people retain the knowledge, while without reviewing, people have to re-learn. A review mechanism is an ongoing process of review to see how learned things are being put into practice, which is a good strategy that enhances and preserves learned material, thereby minimizing forgetting [28]. Research has shown that review at regular intervals does increase retention [29]. Motivated by the above literature, the current work aims precisely at addressing how the review mechanism affects the knowledge transmission process. As a matter of fact, knowledge transmission is a complicated system. Therefore, to consider the review mechanism, we analyze knowledge transmission dynamics from the perspective of theoretical and quantitative research. Specifically, based on the epidemic spreading models, we propose a Naive-Evangelical-Agnostic (VEA) knowledge transmission model and use mean field theory to analyze the dynamical systems in both homogeneous and heterogeneous networks.

The rest of this paper is organized as follows. In Section 2, we introduce the VEA knowledge transmission model with a review mechanism and analytically derive the mean field equations in both homogeneous and heterogeneous networks. In Section 3, numerical simulations are performed to investigate theoretical results. We give conclusions in Section 4.

2. Knowledge transmission model

The study of knowledge transmission is an important application of complex network theory. When discussing the modelling of knowledge transmission we should keep in mind two dimensions of this problem: network topology and design of interaction rules driving knowledge transmission [30]. In a knowledge network, the node actively processes knowledge and edges represent channels for knowledge relocation [31]. Specifically, we suppose that knowledge is transferred in a closed and mixed organization with N nodes, where the nodes represent the individuals and an edge represents a communication channel between two individuals. Moreover, we suppose the network is undirected. The whole population can be divided into three states: naive, evangelical and agnostic. Naive individuals (V) are those people who do not have the knowledge, but are susceptible to (i.e., enter the evangelical state) either by contact with evangelical individuals or by self-learning.[1] Evangelical individuals (E) are those who have acquired the knowledge; we assume that all the evangelical individuals are

[1] We use V to represent naive individuals, rather than the first letter of the word naive N, because N traditionally represents the number of network nodes.