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Ising-like agent-based technology diffusion model: Adoption patterns vs. seeding strategies

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ABSTRACT

The well-known Ising model used in statistical physics was adapted to a social dynamics context to simulate the adoption of a technological innovation. The model explicitly combines (a) an individual's perception of the advantages of an innovation and (b) social influence from members of the decision-maker's social network. The micro-level adoption dynamics are embedded into an agent-based model that allows exploration of macro-level patterns of technology diffusion throughout systems with different configurations (number and distributions of early adopters, social network topologies). In the present work we carry out many numerical simulations. We find that when the gap between the individual's perception of the options is high, the adoption speed increases if the dispersion of early adopters grows. Another test was based on changing the network topology by means of stochastic connections to a common opinion reference (hub), which resulted in an increment in the adoption speed. Finally, we performed a simulation of competition between options for both regular and small world networks.

1. Introduction

The model for statistical physics known as the ''Ising model'' was originally developed by Ernst Ising in 1925 to explain phase transitions in ferromagnetic materials [1]. It has been recently used in the simulation of several social processes [2], such as collective opinion formation [3–6] or adoption of new technologies [7].

The versatility of the Ising model lays on the fact that the interaction effects for any given object with its neighbors is considered to be proportional to the number of neighbors in each state. Those objects can be spins (in up or down states), individuals with political positions (A or B), adopters and non-adopters of a new technology, population members infected and not infected with a contagious disease, etc.

Social networks are the main channels for the interaction in social models [2]. In order to adapt the Ising model to a social context, we must add them to the original model [8]. Network nodes represent individuals and links represent the communication channels between them.

The topological characteristics of social networks have considerable influence on interaction dynamics — in this case, the diffusion of innovations. Different topologies have been discussed in the literature, such as the small world [9,10], scale-free [11–13], modular [14] and regular [7]. Any of these topologies maybe used with the Ising model in a straightforward

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way [15]. However, when physical proximity among nodes is important, a regular lattice provides a good approach. In our analyses, we will mostly consider regular two-dimensional lattice and in some cases, small worlds networks.

In the original Ising model, the change in the spin orientation occurs when a threshold is reached in the mean field of the node. In a similar way, a threshold of decision must be reached in order to change the decision-maker agent's state.

In most models of technology adoption (Delre, Jager and Janssen 2006) there are two basic terms which determine the threshold of decision: (a) social influence from a decision-maker's social network; and (b) the individual perception of a decision-maker agent about the benefits (or utility) of the new option. These two factors are combined into an "effective utility" that reflect the effects of both individual utility and social influence. The comparison of "effective utilities" (i.e., the relative effective utility) of both options leads to the selection of one option or another. The relative weight of the individual perception and social influence depends on the choice type [16]. For example, in fashionable markets (clothes, electronic gadgets) social influence has a strong weight, whereas on other choices (e.g., groceries), social influences are weaker.

As in physical systems, initial conditions have a strong influence on the evolution of a social system. In this particular case, technology adoption patterns are sensitive to the distribution of initial adopters (referred to as "seeding") in the network. This effect was illustrated by Libai et al. [17], who showed that marketing strategies leading to different spatial distributions of early adopters introduce differences in the speed of adoption of a new product. The same issue was addressed by Delre et al. [18], who explored diffusion patterns resulting from alternative (spread out or concentrated) distributions of early adopters. In this paper, we explore systematically the influence of spatial dispersion of early adopters on the subsequent adoption dynamics.

A close relation exists between the distribution of initial adopters and the take-off time of the new product. In another way, Delre et al. [18] concentrate on the targeting and the timing of the promotions in relation to the take-off. That is previous to the generation of the distribution of initial adopters. Moreover, they use an agent-based model with a slightly different decision algorithm (both the individual perception and the social influence must reach different thresholds independently, while in our approach the decision results from the effective utilities associated to each option). That decision is made in each time step, determining which option is adopted. Therefore the possibility of disadoption is introduced. This mechanism is useful when the adoption of a new product does not imply any investment (learning, technology or any other resource). If the last assumption is not satisfied, a model with no disadoption would be more appropriate. As our approach allows disadoption, it can be considered as a simple competition process.

In reference [7], the basic micro-structure of two or three initial adopters necessary to keep up diffusion was studied. In the present paper, we propose an extension by introducing many distributions of initial adopters with different dispersion degrees, in order to understand how the clustering of initial adopters affects the adoption speed.

In this paper, the simulations were performed using an agent-based model. Agent-based modeling is a way of doing thought experiments, obtaining, in many cases, non-obvious results and emergent patterns of the system [19]. The originality of this work does not lay in the introduction of a new statistical model (since the well-known Ising model has already been studied), but in the analysis of emerging evolutionary patterns associated to the adoption of a new product.

The paper is organized as follows. Section 2 presents a brief review of the Ising model and its application to modeling of innovation adoption in a social context. In Section 3 our specific implementation of the agent-based model is presented. Section 4 involves various experiments of technology diffusion including the study of adoption rate due to seeding effects, changes in the individual preference (both in space and time) and connection to a hub. Section 5 presents the conclusions.

2. A model of technology diffusion

2.1. The Ising model in the physical context

The Ising model was originally developed to explain phase transitions in ferromagnetic materials. For example, suppose we are interested on describing a phase transition process in a ferromagnetic material. We can envision the material as constituted by a lattice of micro-magnets called "spins" that can interact with their nearest neighbors and with an external field. We will identify the state of spin in the ith position of the lattice by discrete variable s_i that can take the values $+1$ or -1. If the system is constituted by N spins, its total energy is

$$E = \sum_{i=1}^{N} E_i = -\sum_{i=1}^{N} \left(\sum_{k=1}^{N} w_{ik} s_k + h \right) s_i \equiv -\sum_{i=1}^{N} m_i s_i, \tag{1}$$

where w_{ik} is the coupling strength between nearest neighbor spins, and h is a constant external magnetic field. E_i is the energy associated with spin i, where m_i is the magnetic field around spin i. From Eq. (1) it follows that

$$E_i(s_i = \pm 1) = \mp m_i.$$

The probability of finding spin i in state $s_i \in \{+1; -1\}$ is given by the Boltzmann–Gibbs distribution:

$$P(s_i = \pm 1) = \frac{1}{1 + e^{\mp 2\beta m_i}}, \tag{2}$$