Evolutionary Analysis on Online Social Networks using A Social Evolutionary Game

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ABSTRACT

In this paper, we propose a social evolutionary game to investigate the evolution of social networks. Through comparison between simulation and empirical analysis on the social networks of Twitter and Sina Weibo, we validate the effectiveness of the proposed model and estimate the evolutionary phases of the two networks. We find that the users of Sina Weibo can withstand comparatively more costs than the users of Twitter. Therefore, they can perform more positive behavior and consider more about their reputation than Twitter users. Moreover, the evolutionary time of Sina Weibo to a stable state is longer than that of Twitter.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social & Behavior Sciences

General Terms

Experimentation, Human Factors, Algorithms

Keywords

Social Evolutionary Game, Reputation, Social Network

1. INTRODUCTION

Social ties in online social networks, including stable ties and temporary ties, emerge and vanish through users' interactions due to the change of their internal or external factors, causing the topological variation of social networks. Therefore, it is of great importance to study and understand the dynamic and evolutionary nature of social networks [1]. We propose a *social evolutionary game (SEG)*

in which each player aims to improve its short-term utility and long-term reputation by imitating its partners' strategy and adjusting its social ties, respectively. Through simulations on SEG, we investigate the underlying mechanisms of how players' short-term utility and long-term reputation affect, and co-evolve with, the topology of social networks. Comparative analysis is conducted between the simulation results and empirical studies of two datasets collected from Twitter and Sina Weibo, in order to validate the underlying mechanisms and investigate the evolutionary process of the social networks in Twitter and Sina Weibo.

2. SOCIAL EVOLUTIONARY GAME

The proposed **social evolutionary game** is an evolutionary game played by a group of selfish players in periods $t = 1, 2, 3, \ldots$. Let $G = (V, E; U, R)$ denote an SEG, where $|V| = n$ is the set of players, $|E| = m$ is the set of edges among players, $U = \{U_1, U_2, \cdots, U_n\}$ and $R = \{R_1, R_2, \cdots, R_n\}$ are the sets of utility and reputation functions corresponding to the players in V, respectively. **Utility** indicates a player's short-term concern that is mathematically the sum of payoffs it earns from all of its opponents in a game period with the current strategy profile. **Reputation** is actually a player's long-term concern suggesting the opinions of other players to it, which is determined by the evaluation of other players on the behavior history of this player. Each player $i \in V$ has two alternative strategies: $s_i \in \{C, D\}$, where C represents its positive strategy that causes i to pay a cost c and its partner to receive a benefit b, while D represents its negative strategy that does not cause any cost to player i and doest not cause any benefit to its partner. The payoff matrix A is a simplified Prisoner's Dilemma and the parameter is the cost-to-benefit ratio, $\boldsymbol{c/b}$. The utility of player i is $U_i = \sum_{j \in N_i} A(s_i, s_j)$, where N_i is the set of i's partners.

The evolutionary dynamics of SEG is built on the results of players' myopic decisions, as any player can only be aware of the local information about its current partners and the partners' partners. At each time step t, the player is randomly chosen to either adjust its interaction partners or update its current strategy with probabilities τ
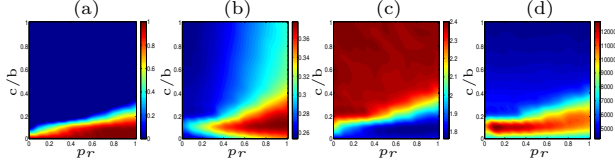
Figure 1: The final evolutionary states of social networks with c/b and p_r. (a) the average final fraction of players adopting positive behavior (f_c), (b) and (c) the clustering coefficient (cc) and the exponent (α) of power-law distribution of the emergent social network, respectively, (d) the evolutionary time of social networks to reach stable states.

and $1 - \tau$, respectively. **Adjusting social ties**: Player i creates a connection to a new partner and breaks an existing tie depending on its and its partners' reputation scores. Upon i's current reputation score r_i, there are three subranges: $r_i^+ = \{R|R > r_i + \lambda\}$, $r_i^\sim = \{R|r_i - \lambda \le R \le r_i + \lambda\}$ and $r_i^- = \{R|R < r_i - \lambda\}$, where λ is a threshold. Player i finds a new partner by two different ways, either searching a new partner with the highest reputation score among its partners' partners whose reputation score falls into r_i^+ with probability p_r, or just randomly selecting a new partner from its partners' partners with probability $1 - p_r$. $\boldsymbol{p_r}$ indicates the tendency of personal preference on the basis of reputation. Meanwhile, i breaks up the social tie with the one having the lowest reputation among its partners whose reputation score falls into r_i^-; **Updating strategy**: Player i imitates the strategy with the maximum utility among those used by its partners, according to a probability φ, which depends on the utility difference $\Delta u = u_j - u_i$. Specifically, we adopt the Fermi function and have $\varphi = \frac{1}{1+e^{-\beta \Delta u}}$[2], where β indicates a player's willingness to imitate others' strategy. Whenever a player is chosen to update its strategy, its reputation is updated simultaneously.

A set of Monte Carlo simulations were conducted with different c/b and p_r for investigating the evolution of social networks, which are characterized by four metrics, namely, the fraction of players performing positive behavior (f_c), clustering coefficient (cc) of the corresponding social network, the exponent (α) of the power-law distribution of players' degrees and the evolutionary time of social networks. Figure 1 presents the final states of simulations under one of three constraints: full positive behavioral players, full negative behavioral players, and the deviation of f_c under a tiny threshold in a large time steps. The final states of the four metrics suggest that the reputation mechanism encourages and speeds up the emergence of positive behavior, and promotes the dense of network more closely. Meanwhile, a larger p_r can enhance players' ability to withstand a greater c/b.

3. EVOLUTIONARY ANALYSIS

Two datasets containing user profiles and messages of more than $250,000$ user accounts were collected from Twitter and Sina Weibo in October 2011 and October 2012. By considering two-way interactions rather than one-way follow relationships, the networks were reduced to undirected ones. As the aforementioned four metrics, we calculated the average values of f_c, cc and α of both Twitter and Sina Weibo: $f_c = 0.610$, $cc = 0.2883$ and $\alpha = 1.7484$ of Twit-
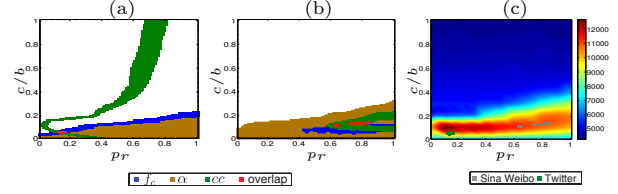
Figure 2: (a) and (b) the mapped areas of empirical analysis of Twitter and Sina Weibo on the simulation results, respectively. (c) the estimation of evolutionary phase of Twitter and Sina Weibo, according to the overlap in (a) and (b).

ter; $f_c = 0.935$, $cc = 0.3716$ and $\alpha = 1.9455$ of Sina Weibo. Comparing to the final states in Figure 1(a)-(c), we observed that the three calculated metrics of both Twitter and Sina Weibo are partly mapped to the evolutionary patterns of the conducted simulations. The four subgraphs in Figure 1 depict the four aspects of the evolution of social networks, and the metrics of a social network should have the same value interval of c/b and p_c, respectively. Based on this hypothesis, we could estimate the evolutionary phase and the corresponding characteristics of Twitter and Sina Weibo, according to the calculated metrics.

We merged the intersection areas of both Twitter and Sina Weibo from Figure 1(a)-(c) with the three corresponding calculated metrics. The existence of the overlapping areas in Figure 2(a) and (b) validates the effectiveness of the proposed framework and the evolutionary patterns in Figure 1. By comparing the overlap in Figure 1(a) and 1(b), it can be observed that the users of Sina Weibo can withstand comparatively more costs than the users of Twitter to perform more positive behavior (e.g., retweet, comment, etc.), and consider more about their reputations. The intervals of $\overline{c/b}$ and $\overline{p_r}$ of both networks are obtained from their overlap, and are substituted in Figure 1(d) to estimate the uncomputable evolutionary phase of both networks. Based on Figure 2(c), we obtained the average evolutionary time $t_{Twitter}$ and $t_{SinaWeibo}$. The ratio $\frac{t_{SinaWeibo}}{t_{Twitter}} = 1.0373$ shows that the evolutionary time of Sina Weibo is longer than that of Twitter to reach a stable state.

4. ACKNOWLEDGMENTS

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