The Dynamics of Opinion Evolution in Gossiper-Media Model with WoLS-CALA Learning

Extended Abstract

Chengwei Zhang
School of Computer Science and Technology, Tianjin university
chenvy@tju.edu.cn

Xiaohong Li
School of Computer Science and Technology, Tianjin university
xiaohongli@tju.edu.cn

Jianye Hao*
School of Computer Software, Tianjin university
jianye.hao@tju.edu.cn

Sandip Sen
The University of Tulsa
Tulsa, Oklahoma
sandip-sen@utulsa.edu

Wanli Xue
School of Computer Science and Technology, Tianjin university
xuewanli@tju.edu.cn

Zhiyong Feng
School of Computer Software, Tianjin university
zhiyongfeng@tju.edu.cn

ABSTRACT

In social networks, media outlets such as TV, newspapers, blogs adjust their opinions to cater to the public's interest to increase the number of followers. Meanwhile, the evolution of the public's opinions are affected by both the media and the peers they interact with. In this work, we investigate how the interactions between mainstream media affect the dynamics of the public's opinions in social networks. We propose a reinforcement learning framework to model the interactions between the public (*aka* gossipers) and the media agents. We model each gossiper as an individually rational agent, which updates its opinion using the Bounded Confidence Model (BCM). Each media agent is interested in maximizing the number of following gossipers competitively, and an adaptive WoLS-CALA (Win or Learn Slow Continuous Action Learning Automaton) algorithm is proposed to achieve that goal. We theoretically prove that WoLS-CALA can learn to Nash equilibria for two-agent games with continuous action space. Besides, the opinion dynamics of both gossipers and media are theoretically analyzed. Extensive empirical simulation reveals the opinion dynamics of our framework facilitates the consensus of opinions and confirms the theoretical analysis.

KEYWORDS

Multiagent learning; Analysis of agent-based simulations

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*Corresponding author

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1 INTRODUCTION

The study of opinion dynamics using agent-based simulation techniques in social network has received much attentions [2, 5, 7, 9, 12, 13]. One key research objective is to seek a comprehensive understanding of the dynamics of opinion evolution and obtain insights into effective techniques for evolving consistent opinions [1–3, 6, 8–11, 14].

We propose a novel multiagent reinforcement social learning model to investigate the opinion dynamics consisting of two classes of agents, i.e., gossipers and media. Each gossiper's opinion is influenced by its interacting peers or the medium it is following, and its behavior is modeled using the Bounded Confidence Model (BCM) [4]. The media agents compete with each other for maximizing the number of gossipers following them and an adaptive WoLS-CALA (Win or Learn Slow Continuous Action Learning Automaton) algorithm for media agents is proposed. The WoLS-CALA algorithm is designed to learn a Nash equilibrium in continuous action space games. Then we investigate how the competitive interactions between two media agents influence the evolution of the gossipers' opinions. By theoretical analysis and experiment simulation, we reach a conclusion that competitive media would promote the consensus of public opinion.

2 GOSSIPER-MEDIA MODEL

In the Gossiper-Media model, gossiper agents' opinions are influenced by both its peer gossipers and the media agents, while media agents update their opinions to attract as many followers as possible. We consider a population N of agents which consists of a set G of gossiper agents and a set M of media agents ($N = G \cup M$). The overall interaction framework is summarized in Algorithm 1.

At each time step, each gossiper first selects one agent to interact with as follows: with probability ξ, it randomly selects one neighbor gossiper within its neighborhood; and with probability $1 - \xi$ the medium it currently follows is selected (Step 4). After that, the gossiper updates its opinion and chooses a new medium to follow according to distance of opinions between each media and the gossiper itself (Step

Algorithm 1 The gossiper-media framework

1: Initialize gossipers and media's opinion randomly.
2: **repeat**
3:   **for** each gossiper in G **do**
4:     Randomly select an agent from the network.
5:     Update its opinion according to BCM strategy.
6:     Follow the media that has the closest opinion.
7:   **end for**
8:   Randomly select a sample subset $G' \subset G$ of gossipers.
9:   Broadcast their opinions $\{x_i | i \in G'\}$ to all media.
10:   **for** each media in M **do**
11:     Find its best opinion according to WoLS-CALA s-trategy.
12:     Broadcast its opinion to the network.
13:   **end for**
14: **until** the repeated game ends

5-6). Next, each media receives the sampled opinion of a subset $G' \subset G$ of gossiper agents. Intuitively this step models media agents' ability (e.g., sampling survey) of collecting the public's opinion in practice (Step 8-9). Based on the sampling information, each media agent then updates its opinion following WoLS-CALA strategy and then broadcasts it to the public to attract more followers (Step 9-13).

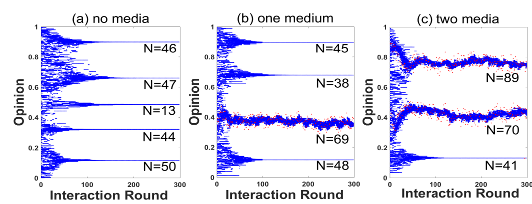
Gossiper's Strategy. Each gossiper agent's strategy consists of two steps: 1) how to update its opinion; 2) select which media agent to follow. In Step 1, each gossiper updates its opinion using BCM strategy [4, 9], which is a commonly used way of modeling the opinion change of the public. Specifically, a BCM gossiper agent adjusts its opinion only if the difference between its opinion and that of its interacting agent is below a given threshold d, which reflects its degree of tolerance. Formally, gossiper i's opinion x_i is updated by $x_i^\tau \leftarrow x_i^\tau + \alpha_g \left(x_j^\tau - x_i^\tau\right)$ if gossiper i interact with a gossiper j and $|x_j^\tau - x_i^\tau| < d_g$; or $x_i^\tau \leftarrow x_i^\tau + \alpha_m \left(y_k^\tau - x_i^\tau\right)$ if gossiper i interact with a medium k, where y_k^τ is medium k's strategy. For step 2, gossiper i determines which medium to follow based on the opinion distance between each medium and itself. The probability P_{ij} of gossiper i following medium k satisfies the following properties: (i) $P_{ij} = 0$ if $|x_i - y_j| > d_m$; (ii)$P_{ij} > 0$ only if medium j satisfies $|x_i - y_j| \leq d_m$; and (iii) P_{ij} decreases with the increases of the distance $|x_i - y_j|$.

Model Media Behavior with WolS-CALA . Given the sampled information of the public's opinion, each media agent adaptively changes its opinions to cater to the gossipers' interests and competes with each other for attracting gossiper followers. We propose a multiagent reinforcement learning algorithm WoLS-CALA to model medias learning strategy. The strategy of a WoLS-CALA agent is defined by a probability density function obeying normal distribution over the continuous action space. By learning over the mean u and variance σ^2 of the normal distribution, multiple WoLS-CALA agents can converge to a Nash equilibrium.

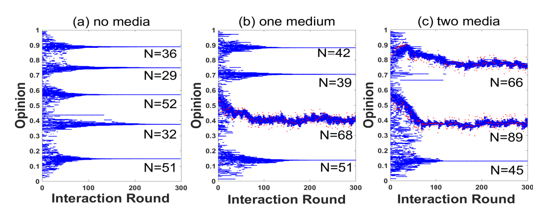
At each round t, a WoLS-CALA agent j randomly selects an action y_j^t according to normal distribution $y_j^t \sim N(u_j^t, \sigma_j^t)$, and then applys y_j^t and observes reward r_j from the environment. According to r_i and historical experience, the WoLS-CALA agent updates the expected reward value Q_{u_j}, $Q_{u_j}^{t+1} = Q_{u_j}^t + \alpha_{u_j}^t (r - Q_{u_j}^t)$, where $\alpha_{u_j}^t$ is the learning rate of agent j at time t. Then the mean action u_j and variance σ_j^2 are updated following $u_j^{t+1} = u_j^t + \alpha_{u_j}^t \left(y_j^t - u_j^t\right)$, $\sigma_j^{t+1} = \sigma_j + \alpha_{\sigma_j}(r_j - Q_{u_j}^t)\left(|y_j - u_j| - \sigma_j^t\right)$, where α_{u_j} and α_{σ_j} are learning rates of u_j and σ_j. The learning rate α_{u_j} of u_j and Q_{u_j} is defined as a variable value according to WoLS principle ($\alpha_{u_j}^t = \alpha e^{r_j^t - Q_{u_j}^t}$) to ensure the accuracy of Q_{u_j}, while α_{σ_j} is a constant. WoLS principle is designed to correctly estimate the expected payoff of action u, and guarantee the update of action u in the direction of increasing the agent's payoff. When the mean u of all agents no longer changes, this means that they have learn a Nash equilibrium.

3 EXPERIMENTAL EVALUATION

We consider a population of 200 gossipers and different numbers of media: (i) game with no media; (ii) game with only one medium; and (iii) game with two competitive media. For each case, two representative networks are considered: fully connected network (FCN) and small-world network (SMN).



(a) The Fully Connected network



(b) The Small-World network

Figure 1: Opinion dynamics for FCN and SWN Networks

Figure 1 shows the evolution dynamics of gossipers' opinions (the number of agents with different opinions) for the fully connected network and the small-world network. From the figure we can see: first, both networks share the same opinion dynamics among gossipers; Second the existence of a medium and two competitive media can improve the consensus of opinions; and third, WoLS-CALA learner can learn the global optimum when there exist only one medium, and can learn Nash equilibrium when exists more media.

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