

## Code- Adaptive model of a consumer advice network

### Directed opinion learning model

On the basis of the DW bounded confidence model, the opinion that users hold on products in the process of product diffusion may become consistent, bipolar or multipolar through the bounded confidence mechanism. When the absolute value of the two users' opinion difference is lower than the confidence threshold, the users can exchange opinions; otherwise, the two users will maintain their original opinions. Therefore, this study selects the DW model as the basis for the construction of the directed opinion learning model.

On setting the size of the consumer advice network to  $N$ ,  $A = \{A_1, A_2, \dots, A_N\}$  is the users' set  $O^t = \{O_1^t, O_2^t, \dots, O_N^t\}$  is a set of opinions, and  $O_i^t$  represents the opinions held by the users  $A_i \in A$  at time  $t$ . User  $i$ 's and user  $j$ 's opinion values at time  $t$  are expressed as  $O_i^t$  and  $O_j^t$ , respectively,  $O_i^t, O_j^t \in [0, 1]$ .  $\varepsilon$  is the confidence threshold in the opinion learning process, and  $\varepsilon$  is a constant value in the range  $[0, 1]$ .

$G$  is a directed network, and  $G_i = \{G_{i1}, \dots, G_{ij}, \dots, G_{iN}\}$  represents the link set of user  $i$ . If user  $i$  follows  $j$ , then  $G_{ij} = 1$ . If users  $i$  and  $j$  follow each other, then  $G_{ij} = G_{ji}$ .

The opinion difference  $d_{ij}^t$  is calculated by the absolute value of the difference between user  $i$ 's opinion and user  $j$ 's opinion:

$$d_{ij}^t = |O_j^t - O_i^t| \quad (1)$$

The directed opinion learning model is shown in equation (2). At time  $t$ , if  $d_{ij}^t \leq \varepsilon$ , then user  $i$  updates the opinion based on his or her original opinion, user  $j$ 's opinion and parameters  $\mu$ . If  $d_{ij}^t > \varepsilon$ , user  $i$  maintains the original opinion.

$$O_i^{t+1} = \begin{cases} O_i^t + \mu [O_j^t - O_i^t], & d_{ij}^t \leq \varepsilon \\ O_i^t, & d_{ij}^t > \varepsilon \end{cases} \quad (2)$$

There are two important variables in the model,  $\mu$  and  $\varepsilon$ , which have a significant impact on user  $i$ 's opinion learning process. First,  $\mu$  is the opinion-convergence factor, which is generally a constant in  $[0, 0.5]$ .  $\mu$  plays an important role in the DW model and can be used to describe the different types of users. If  $\mu = 0$ , users will maintain their original opinions, that is, not change their opinions; if  $\mu = 0.5$ , the user's opinion is equal to the average value of both users' original opinions. Therefore, the smaller the  $\mu$ , the more the user tends to have his or her own opinion, and the larger the  $\mu$ , the more the user is inclined to the other's opinion. Second,  $\varepsilon$  is the confidence threshold, which is a constant in the interval  $[0, 1]$ . The value of  $\varepsilon$  indicates the individual's tolerance to other users' opinions, that is, the maximum opinion distance in which users can share opinions with each other.

### Network adaptive strategy

The current network structure forms the basis of future network evolution, and the opinion difference between users in the network affects the network evolution strategy. This study focuses on the impact of opinion differences (opinion distances) and influence differences (in-degree centrality) on the network structure.

The adaptive process of the consumer advice network includes two types of activities: disconnect edge (DE) and connect edge (CE). In the disconnect and connect process of the consumer advice network,

DE and CE strategies are based on opinion distance and node influence. Consistent with the bounded confidence model, opinion distance refers to the absolute value of the difference between the two users' opinions:  $d_{ij}^t = |O_j^t - O_i^t|$ . Node influence  $degree_i^t$  refers to the relative value of node  $i$ 's in-degree centrality. Although in the correlation analysis, there is a negative correlation between the opinion distance and the directed links and a positive correlation between the node influence and the directed links, in reality, the opinion distance and the node influence do not act independently on the network links. Therefore, opinion distance and node influence must to be considered in the strategy of an existing edge cancel (DE) and a new edge establish (CE).

#### 1) Disconnect edge (DE)

The basic hypothesis of edge disconnection is that at time  $t$ , if user  $j$  is connected to  $i$ , and  $|O_j^t - O_i^t| > \varepsilon$ , then the connection from  $j$  to  $i$  disconnects with probability DE at time  $t+1$ ; otherwise, the connection is retained (Su et al., 2014). Equation (3) is an expression of the disconnect edge probability DE, which reflects the marginal diminishing law, that is, the increase in the users' influence, or the increase in the ratio of the opinion distance to the confidence threshold, causing the marginal effect of the disconnect edge probability DE to decrease.

$$DE_{ij}^t = 1 - \left( degree_j^t \right)^{1 - 1/(d_{ij}^t/\varepsilon)} \quad (3)$$

$d_{ij}^t/\varepsilon$  is the ratio of the opinion distance to the confidence threshold, indicating the degree to which the two users' opinions deviate from each other in a given  $\varepsilon$ . When the opinion distance is outside the confidence threshold, this ratio is greater than 1; when the opinion distance is within the confidence threshold, this ratio is less than 1. When it is greater than 1, that is, the opinion distance is outside  $\varepsilon$ , DE is between 0 and 1, that is, the edge disconnects with a certain probability; when it is less than 1, that is, the opinion distance is less than  $\varepsilon$ , and if DE is less than 0, it is impossible to disconnect the edge.

#### 2) Connect edge (CE)

The basic assumption of the new edge connect is that at time  $t$ , if user  $i$  is not linked to user  $j$ , the new connection from  $i$  to  $j$  is established with probability CE at time  $t+1$ ,  $CE \in [0,1]$ . Equation (4) is the expression of connect edge probability CE. For user  $i$ , if user  $j$  whose opinion distance is within the confidence threshold is selected, then user  $i$  is linked to user  $j$  with probability CE according to the opinion distance and in-degree centrality. Within the confidence threshold range, the larger the opinion distance, the smaller the edge connection probability.

$$CE_{ij}^t = 1 - \left( 1 - degree_j^t \right)^{1 - d_{ij}^t/\varepsilon} \quad (4)$$

Equation (4) shows that with the increase in opinion distance, the new edge connection probability CE decreases; with the increase in  $\varepsilon$ , the new edge connection probability CE increases; with the increase in in-degree centrality, the new edge connection probability CE increases. For the same opinion distance, the new edge is more likely to be established at high  $\varepsilon$  and high in-degree centrality.

### Adaptive model of a consumer advice network

In the consumer advice network, users with connections can interact with each other, and the network topology will change during the opinion interaction. As shown in Figure 5, when the opinion distance from  $i$  to  $j$  is greater than the confidence threshold, the two consumers cannot exchange opinions, and the link between them will disconnect with probability DE. Then, a link from node  $i$  to node  $k$  is

established with probability CE and node  $i$  learning opinion from node  $k$ .

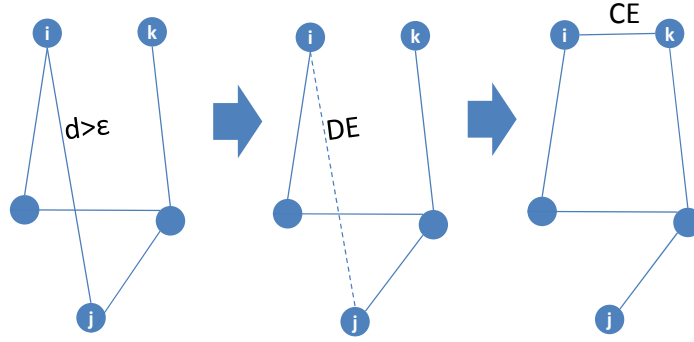


Figure 5. Edge disconnection and connection process in an adaptive network

This article adopts synchronous updating.

①Disconnect edge: If user  $i$  follows user  $j$  at moment  $t$ , that is,  $G_{ij}^t=1$ , the connection from  $i$  to  $j$  will disconnect with a disconnect edge probability DE at time  $t+1$ :

$$G_{ij}^{t+1}=0 \quad (5)$$

②Connect edge: If user  $i$  does not follow user  $j$  at moment  $t$ , that is, when  $G_{ij}^t=0$ , user  $i$  will establish a connection  $j$  with probability CE at time  $t+1$ :

$$G_{ij}^{t+1}=1 \quad (6)$$

③Opinion learning: User  $i$  follows user  $j$  at time  $t+1$ , that is,  $G_{ij}^{t+1}=1$ . Then, when the opinion difference between  $i$  and  $j$  is greater than the confidence threshold  $\varepsilon$ , that is,  $|O_j^t - O_i^t| > \varepsilon$ , user  $i$  will not change his or her opinion, as shown in equation (7):

$$O_i^{t+1}=O_i^t \quad (7)$$

When the opinion distance between user  $i$  and user  $j$  is less than  $\varepsilon$ , that is,  $|O_j^t - O_i^t| \leq \varepsilon$ , user  $i$  changes his or her opinion, as shown in equation (8):

$$O_i^{t+1}=O_i^t + \mu[O_j^t - O_i^t] \quad (8)$$

## Experimental procedures

The experimental procedures include the following.

The first step generates the initial network. According to the algorithms for generating the BA, ER, NW and WS networks, an initial network with network sizes  $N = 200$  and  $N = 1000$  is generated.

The second step is to set the opinions of individuals. In general, network members have different task-related knowledge, opinion, experiences and perspectives, and the opinion followed uniform distribution.

The third step is to set the confidence threshold  $\varepsilon$  and convergence coefficient  $\mu$  of the directed opinion learning model. The confidence thresholds  $\varepsilon$  are set to 0.1, 0.2, 0.3, 0.4, 0.5, and the opinion-convergence coefficient  $\mu$  is set to 0.5.

Under the above experimental parameter settings, according to the directed opinion learning model, MATLAB 2012 was used to conduct agent-based experimental analysis. In each experiment, one type of network was chosen, and the evolution round was 200 steps. For each group of experiments, the experiment was repeated 100 times, and then the average result was calculated.

