Multi-value opinion sharing based on information source influence in agent-based network

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Abstract. This paper proposes the information sharing algorithm for preventing propagation of wrong information in the agent-based network such as SNS, and aims at investigating the effectiveness of the proposed algorithm through the complex network such as a small world network. Towards practical applications, this paper extends the conventional opinion sharing model (OSM) to cope with the multi-value opinion from the binary opinion, and proposes the new algorithm for preventing propagation of wrong information to cope with the multi-value opinion. The intensive simulations of three types of the complex network have revealed that the accuracy of the correct opinion of agents in the proposed algorithm (called Self-information Weight Tuning (SWT)) reaches around 80% which is not affected by the number of opinion states in the multi-value opinions, while that of the conventional algorithm (called Autonomous Adaptive Tuning (AAT)) is lower than the proposed algorithm and decreases as the number of opinion states increases.

1. Introduction
In social network system, wrong information might be shared if some persons misunderstand something and sent the wrong information to their neighbors. To tackle this problem, the information sharing system for preventing propagation of wrong information is highly demanded. For this issue, Glinton proposed Opinion Sharing Model (OSM) [1] where the agents in the network update the belief of their opinions according to the surrounding information (e.g., the environment information or the information received from neighbors), form their opinions when the belief value exceeds its threshold, and tell their opinions (i.e., send the information based on the opinions) to their neighbors to share them, and Pryymak proposed the correct opinion sharing algorithm (called Autonomous Adaptive Tuning: AAT) [2] that prevents propagation of wrong information in the framework of OSM. As the feature of AAT, AAT is robust to the network topology and a scale of the number of agents.

However, the opinions in OSM are represented by the binary value, which means that OSM can be only applied in the limited situation. For example, OSM may be enough when a certain person wants to tell the information of “You should [stay at home, or come out of a house]” (binary representation) when a disaster occurs, but it is not enough when s/he wants to tell the information of “You should run to [school, park, downtown, or mountain] to escape from the dangerous area” (multi-value representation). This suggests that it is quite important to extend OSM for the multi-value opinion sharing.
To address this issue, this paper starts to extend OSM to Multi-value Opinion Sharing Model (MOSM) where the agents update their belief of the multi-value opinions, form them, and send one of them to their neighbors. However, AAT does not work well in MOSM when the number of opinion states \( \text{i.e.} \), the number of types of opinions) increase in the multi-value opinions, which means that the accuracy of the correct opinion significantly decreases in proportion to the number of opinion states. This is because the search space of AAT becomes large in proportional to the number of opinion states, which makes it difficult for the agents to form the correct opinion among a lot of opinions (In other words, the agents becomes difficult to select one correct opinion from the “\( n - 1(\gg 1) \)” number of wrong opinions as the “\( n \)” number of the opinions increases).

To overcome this shortcoming, this paper proposes the correct opinion sharing algorithm for the multi-value opinions, Self-information Weight Tuning (SWT) which forms groups with some number of the agents according to the self-information of the opinions of neighbor agents. This approach is based on the notion that the wrong opinions are limited to be propagated if the opinions are only propagated in the group. To form appropriate groups of the agents, SWT increases the weights of the agents who provide new information from the viewpoint of its self-information, which corresponds to find the agents who are close to the information sources. Such an approach contributes to forming the group of the agents with the high weights by separating the agents with the low weights. Concretely, SWT divides the propagation range of the information sources, which limits the propagation of wrong information.

The remainder of this paper is organized as follows. Section 2 describes OSM as the existing model, and Section 3 extends OSM to MOSM. Section 4 proposes SWT and Section 5 empirically evaluates SWT against AAT. Finally, our conclusion is given Section 6.

2. Opinion Sharing Model

We begin by presenting an overview of the formalized information cascade \[3\] agent-based network model, Opinion Sharing Model (OSM) \[1, 4, 5\] which has a large number \( N_A \) of agents \( A = i^1 \ldots i^{N_A} \) and the environment. The agents have neighbors and can communicate information to them. In OSM, information are represented as discrete values opinion for simplicity. Each agent \( i \in A \) has its own opinion \( o_i \) and it aims to match its \( o_i \) with the correct opinion, \( b \) of the environment. In OSM, \( b \) only takes a value from \( B = \text{White, Black} \) which is the opinion subset. Only a small subset \( S \subset A \) of the agents are sensor which can directly observe the environment. Sensors are sources of opinion propagation in the network of agents.

2.1. Agent Description

Initially, all Agents has an undetermined opinion, thus \( o_i \in B \cup \{\text{undetermined}\} \). Also, sensors \( S \) is selected randomly from agents \( A \). When an agent is sensor, it receives new opinions from the environment with a constant rate \( \lambda \), which indicate the interval rate between the introduction of new opinions from the environment. Similarly, agents receives new opinions from their neighbors \( D_i = j^1 \ldots j^{d_i} \), where \( d_i \) is the number of neighbors, but when agent \( i \) is sensor, the neighbors become \( d_i \in D_i \cup \{e\} \) where \( e \) is the environment.

In order to decide which opinion is to be believed to the correct opinion \( b \), the receiving agent \( i \) updates its private belief \( p_i \) which indicate the probability that agent \( i \) believes White is \( b \). In contrast, \( 1 - p_i \) indicate the probability that agent \( i \) believes Black is \( b \). A private belief \( p_i \) starts from a prior belief. In the process of the belief update, agent \( i \) applies an aggregation function to new opinion received from the send neighbour or the environment with a certain weight \( w_{ij} \) attributed to each neighbour:

\[
p_{ik} = f \left( p_{ik}^{k-1}, o_j, w_{ij} \right)
\]  

(1)
where $k$ is a belief update step, and the weight $w_{ij}$ is the social influence of agent $j$ on agent $i$.

We illustrated the agent model in Figure 1. below. This agent design is proposed by Pryymak et al.

![Figure 1. The agent model](image)

- **Aggregation function** that update the agent’s belief based on Bayes’ theorem as:

$$p_k^i = f(p_{k-1}^i, o_j, w_{ij}) = \frac{wp_{k-1}^i}{(1-w)(1-p_{k-1}^i)+wp_{k-1}^i}$$

where $\begin{cases} w = w_{ij} & \text{if } o_j = \text{white} \\ w = 1 - w_{ij} & \text{if } o_j = \text{black} \end{cases}$

where $w_{ij}$ is a conditional probability that agent $j$ send the correct opinion. When agent $i$ received the opinion $o_j$ from agent $j$ or the environment, agent $i$ update its current private belief $p_k^i$ using prior private belief $p_{k-1}^i$, the received opinion $o_j$ and the weight $w_{ij}$.

- **Decision function** that is applied to the agent’s private belief $p_k^i$ after updating using Aggregation function because it has to decide whether it is confident enough to form its own opinion, $o_k^i$. In the model, Decision function is given by:
\[ o^k_i = F\left(o^{k-1}_i, p^k_i, \sigma\right) \]

\[
= \begin{cases} 
  \text{undeter. initial, if } k = 0 \\
  \text{white if } p^k_i \geq \sigma \\
  \text{black if } p^k_i \leq 1 - \sigma \\
  o^{k-1}_i \quad \text{otherwise}
\end{cases}
\] (3)

where thresholds \( \{1 - \sigma, \sigma\}, \sigma \in (0.5, 1) \) are the confidence bounds. When the private belief \( p^k_i \) crosses over the range, the agent are confident enough to form its own opinion. In the next step, when its opinion changed, it send the opinion to its all neighbors. The shape of Decision function is shown in Figure 2. The hysteresis curve of state switches is also known as Schmitt trigger [6].

![Decision function](image)

**Figure 2.** The decision function

2.2. Simulation Description

In the model, when the simulation starts, the step \( k \) proceeds from 0 and the agents’ beliefs and opinions are updated. If step \( k \) reaches the maximum number of steps \( K \), All agents’ beliefs and opinions are initialized. The process are defined one round. After repeating the number of rounds \( m \) to the maximum number of rounds \( M \), the simulation ends. the weights of agents update every round updating.

3. Multi-value Opinion Sharing Model

In OSM, the number of opinion states is defined as two, thus \( |B| = |\{\text{White, Black}\}| = 2 \). We extend the model from binary opinion to multi-value opinion (\( |B| > 2 \)). For the extension, we have to change the private belief and the opinion to multi-value, and Aggregation function for applying the multi-valued variables. In this section, we present our Multi-value Opinion Sharing Model (MOSM).

3.1. Vectors of Opinion and Belief

In order to express a multi-valued opinion as vector, we defined the standard basis \( B_n \) of opinion vector as:
\[ B_1 = \text{White} = (1, 0, 0, \ldots, 0) \]
\[ B_2 = \text{Black} = (0, 1, 0, \ldots, 0) \]
\[ \vdots \]
\[ B_n = \text{Red} = (0, 0, 0, \ldots, 1) \]  

where White, Black and Red are the expressions of opinion in OSM, and \( n \) is the size of the opinion subset \( B \). In MOSM, The opinion vector \( (o_i) \) can be expressed uniquely as a linear combination of these as:

\[ o_i = (o_1', o_2', \ldots, o_n') = \sum_{l=1}^{n} o_l' B_l \]  

where \( x_n \) is the \( n \)th in the scalar components of the opinion vector \( o_i \). Similarly, we defined a multi-valued belief as:

\[ p_i = (p_1', p_2', \ldots, p_n') = \sum_{l=1}^{n} p_l' B_l \]  

3.2. Multi-valued Functions

We will discuss multi-valued functions based on vectors of opinion and belief in detail.

- Multi-valued Aggregation function

\[ p^k_i = f \left( p^{k-1}_i, o_j, w_{ij} \right) = \alpha \sum_{l=1}^{n} w_{ij} p_l' B_l \]  

where \( \{ \begin{array}{l} w = w_{ij} \quad \text{if } o_l' = 1 \\ w = \frac{1-w_{ij}}{n-1} \quad \text{if } o_l' = 0 \end{array} \) \n
\[ \alpha = \frac{1}{\sum_{l=1}^{n} w_{ij} p_l'} \]

where \( \alpha \) is the constant of proportionality.

- Multi-valued Decision function

\[ o^k_i = F \left( o^{k-1}_i, p^k_i, \sigma \right) = \sum_{l=1}^{n} x_l B_l \]  

where \( \{ \begin{array}{l} x_l = 0 \quad \text{initial, if other } x = 1 \\ x_l = 1 \quad \text{if } y_l \geq \sigma \end{array} \)
4. Self-Information Weight Tuning

In this section, we present our Self-Information Weight Tuning (SWT) algorithm, for improving the accuracy $R$ in MOSM. The existing algorithm, AAT, decreases $R$ as the number of opinion states, $n$ increases in the simulation because AAT searches for optimal weights from a range of weights that expands in proportion to the number of opinion states.

In contrast to AAT, our solution search the optimal weight relying on the uncertainty of received opinions for agents, and is not affected by the number of opinion states. Specifically, SWT is built on the observation that accuracy significantly increases when the network is equally divided by the range of opinion propagation of sensors because a part of incorrect sensor’s propagation does not spread throughout. Since the sensor’s observation include inaccuracy, the agents closer to the sensor are more likely to form various opinions. Therefore, when each agent preferentially weights neighbors that propagate more uncertainty opinions, each agent have stronger weights for neighbors connected to the nearest sensor, and weaker for other neighbors. Figure 3 illustrates how the sensors’ influences are divided for each nearest sensor.

![Figure 3. The influence is divided by the weighting of uncertainty](image)

4.1. Self-Information of Opinion

In order to evaluate the uncertainty of received opinions from neighbors, we introduce self-information of opinion, $I^m_{ij}$, that is the amount of information [7] of the agent’s final private belief $p^m_i$ about the received opinions $o_j$ from agent $j$ at the end of each round $m$ as:

$$I^m_{ij} = - \sum_{l=1}^{n} \log_2 p^l_{ij}$$

The self-information of opinion $I^m_{ij}$ shows the estimated distance between the neighbor and the nearest sensor.

We normalize $I^m_{ij}$ to a value greater than or equal to 0 that we called normalized self-information of opinion, $J^m_{ij}$, as blow:

$$J^m_{ij} = \log_2(I^m_{ij} + 2)$$

4.2. Weighting neighbors close to a sensor

At the end of each round $m$, each agent $i$ calculate the weight $w_{ij}$ for the neighbor $j$ following as:

$$w_{ij} = \frac{J^m_{ij}}{\max \left\{ J^m_{il} | l \in 1 \ldots |D_i| \right\}}$$

where $J^m_{ij}$ is divided by its maximum value in order to scale the range of estimated distances to $[0,1]$. In next round, each agent $i$ update $w_{ij}$ for each neighbor $j$. 


Table 1. Parameter Setting

| Model parameter                  | Symbol | Value                        |
|----------------------------------|--------|------------------------------|
| Variable                         |        |                              |
| Network topology                 | -      | small-world, scale-free, square |
| Size of opinion state            | $n$    | $2 - 10$                     |
| Number of agents                 | $N_A$  | $100 - 1000$                 |
| Maximum number of opinion sharing rounds | $M$  | $100 - 1000$                 |
| Fixed                            |        |                              |
| Number of sensor                 | $N_s$  | $0.05N_A$                    |
| Weight of sensor                 | $sw$   | 0.8                          |
| Accuracy of sensor observation   | $sr$   | 0.5                          |
| Target awareness rate            | $h_{tar}$ | 0.95                      |
| Initial belief of agents         | $p_{init}$ | drawn from $N(\mu = 0.5, s = 0.1)$ |
| Confidence bounds of agents      | $\sigma$ | 0.9                         |
| Maximum steps of round           | $K$    | 2000                         |
| Number of Run                    | -      | 10                           |

5. Empirical Evaluation

5.1. Experimental setting

To empirically evaluate the performance of SWT as the proposed algorithm and AAT as the conventional algorithm, the following cases are tested:

- Case 1: Influence of the number of opinion states (AAT vs. SWT)
- Case 2: Influence of the network topology (AAT vs. SWT)
- Case 3: Influence of the number of agents (AAT vs. SWT)

5.2. Parameter setting

In our experiments, a wide range of parameters are employed in order to examine the adaptivity and scalability of the proposed algorithm (SWT). For this issue, the following parameters vary as shown in Table 1: (i) the types of network topology changes among the small-world network (WS) [8], scale-free network (BA) [9], and square network (Grid2D); (ii) the number of opinion states ($n$) varies from 2 to 10; (iii) the number of agents ($N_A$) varies from 100 to 1000.

In addition to these wide range of parameters, the following parameters are set as shown in Table 1: (i) for the sensor, the number of sensors is $N_s = 5\%$ of $N_A$; the weight of sensor is $sw = 0.8$; the accuracy of sensor observation is $sr = 0.5$; (ii) for the agent, the initial belief is represented by a normal distribution $N(\mu = 0.5, s = 0.1)$; the confidence bound is $\sigma = 0.9$, the initial opinion is set as $o^0_i = undeter$ (meaning “undetermined”); (iii) for AAT, the target awareness rate is $h_{tar} = 0.95$ which is the target of the agent’s opinion formation rate [2]; and (iv) for the network topologies, the randomised connections in the small-world network is $p_{rewire} = 0.01$; the attach edges in the scale-free network is $s_{attach} = 2$.

5.3. Evaluation criterion: Performance Metrics

The accuracy of the opinion sharing ($R$) in the complex network is calculated as follows, which shows how often an agent forms the correct opinion on average (i.e., the average number of the final opinions ($o^m_l$) of the agents, which is equal to the correct opinion ($b \in \{B_l : l \in \{1 \ldots n\}\}$) at the end of each round ($m$)).
\[ R = \frac{1}{N_{AM}} \sum_{i \in A} \left| \{ m \in M : o_i^m = b \} \right| \] (12)

5.4. Experimental results

5.4.1. Case 1: Influence of the number of opinion states (AAT vs. SWT) To investigate an influence of the number of opinion states, the results of AAT are compared with those of SWT by analyzing the accuracy \( R \) of sharing the correct opinion in the different number of opinion states \( n \) with changing the number of round \( m \). Figures 4a1 and 4a2 show the accuracy \( R \) of AAT and SWT, respectively. In these figures, the vertical axis indicates the accuracy of sharing the correct opinion while the horizontal axis indicates the number of rounds. The five lines in these figures indicate the accuracy of the different number of the opinion states. A comparison between Figures 4a1 and 4a2 suggests that the accuracy of AAT becomes high as the number of the round increases but is low in the small number of the round while that of SWT is more high and stable than AAT in any number of the rounds. From these results, AAT requires a lot of rounds \( m \) in proportion to the number of opinion states \( n \) to form the correct opinion while SWT does not require such many rounds to form the correct one.

In detail, Figures 4b1 and 4c1 and Figures 4b2 and 4c2 indicate the opinion formation rate of the correct, incorrect and undetermined opinions of agents of AAT and SWT, with \( m = 200 \), respectively as an example of the simulation runs. In these figures, the vertical axis indicates the rate of agents while the horizontal axis indicates the number of rounds, and the blue, orange, and green area in the figures indicate the agent’s rate that form correct, incorrect, and undetermined opinions. A comparison between Figures 4b1 and 4c1 and Figures 4b2 and 4c2 suggests that, in AAT the 100% of agents are formed when \( n = 2 \) (Figure 4b1) but the 60% of agents are formed when \( n = 10 \) (Figure 4c1), while, in SWT the 100% of agents are formed when \( n = 2 \) and 10 (Figures 4b2 and 4c2). Thus, in AAT, only some agents can form opinions before increasing the accuracy when the number of rounds is low, unlike SWT.

5.4.2. Case 2: Influence of the network topology (AAT vs. SWT) Since Pryymak showed that AAT was robust to the network topology (i.e., the accuracy of sharing the correct opinion by AAT was not drastically affected in the different types of the network topologies) when the number of opinion states \( n \) was 2 (meaning that an opinion is designed by the binary representation) \[2\], the results of AAT are compared with those of SWT by analyzing the accuracy \( R \) in the different types of the network topologies as shown in Figure 5. In these figures, the vertical axis indicates the accuracy of opinion sharing in the different types of the network topologies. In detail, the red, blue, and green lines indicate the accuracy in the network of Grid2D, WS, and BA, respectively. Also, the bands around these lines represent the variance of accuracy.

Figure 5a as the result of AAT shows that the variances of the accuracy among three types of network topologies become large as the number of opinion states \( n \) increases, which means that AAT is not robust to the types of network topologies especially when the number of opinion states is large. In contrast, Figure 5b as the result of SWT shows that the variances of the accuracy among three types of network topologies are small and stable in the any number of the opinion states \( n \), which means that SWT is robust to the types of network topologies and the size of \( n \).

5.5. Case 3: Influence of the number of agents (AAT vs. SWT) To investigate an influence of the number of agents, the results of AAT are compared with those of SWT by analyzing the accuracy \( R \) with changing the number of agents \( m \) in the different numbers of opinion states \( n \) as shown in Figures 6a and 6b. In these figures, the vertical axis
Figure 4. The accuracy of (a1) AAT as the number of round increases. (b1) and (c1) the change of the opinion formation rate of AAT in $n = 2$ and 10, respectively. (a2), (b2), and (c3) are the same but in SWT ($N_A = 300$, $h_{tar} = 0.95$ and network topology is WS).

Figure 5. The Accuracy of (a) AAT and (b) SWT with each number of opinion states and the different types of the network topology. ($N_A = 300$, $h_{tar} = 0.95$) indicates the accuracy while the horizontal axis indicates the number of agents, and the five lines in the figures indicate the accuracy in the different numbers of opinion states ($n = 2, 4, 6, 8, 10$). From these figures, the accuracy of both AAT (shown in Figure 6a) and SWT (shown in Figure 6b) are stable (suggesting a robustness to the number of agents) but the accuracy of SWT is higher than that of AAT in any number of agents and opinion states.
5.6. Discussion: Why is SWT robust to the number of opinion state, the types of network topologies and the number of agents?

To investigate the robustness of SWT in terms of the number of opinion states, the types of network topologies, and the number of agents, this subsection visualizes the weights of agents in SWT as shown in Figure 7. In these figures, the squares and the lines between squares indicate the agents and the links between the agents, respectively. In detail, the color bordering of the agent indicates the opinion state that the agent forms. The agents bordered by orange are sensors. The black short lines on the green lines means the weights and the line thickness is proportional to the weight. Thus, SWT (and AAT) adjust the thickness of the black line in the visualized simulation.

Figure 7. shows the state during simulation in that the sensor at the bottom propagates yellow (incorrect) opinions around but stopped and the other sensors propagate red (correct) opinions throughout the network.

As you can see, agents split into those with red and yellow opinions. The reason is that SWT increase the weight to the nearest sensor and reduce the weights to the other, so the opinion propagation range of the yellow sensor is limited. In Figure 7b, the agents with the yellow opinion get weight to the agents closer to the yellow sensor.

6. Conclusions

This paper firstly extended the opinion sharing model (OSM) to propose the multi-value opinion sharing model (MOSM) which is based on the multi-value representation instead of the binary representation, and secondly proposed the Self-information Weight Tuning (SWT) algorithm by extending Autonomous Adaptive Tuning (AAT) for preventing propagation of wrong information in the multi-value opinions. The intensive simulations of three types of the complex networks have revealed that SWT outperforms AAT, i.e., the accuracy of the correct opinion of agents in SWT kept near 80% regardless of the number of opinion states, network size, and network topology, while that of AAT decreases as the number of opinion states increases.

What should be noted here is that the above implications have only been obtained from three types of the complex networks, which suggests that further careful qualifications and justifications (such as an investigation of SWT to other networks) are needed to generalize...
our results. Such important directions must be pursued in the near future in addition to the following future research: (1) an analysis of the effect of SWT in MOSM when the number of agents and/or the topology of the complex network changes; (2) an investigation of the effect of SWT in MOSM when the location/rate of the information sources change dynamically; and (3) an extension of SWT to actual application.

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