Preventing Incorrect Opinion Sharing with Weighted Relationship among Agents

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Abstract. This paper aims at investigating how correct or incorrect opinions are shared among the agents in the weighted network where the relationship among the agent (as nodes of its network) is different each other, and exploring how the agents can be promoted to share only correct opinions by preventing to acquire the incorrect opinions in the weighted network. For this purpose, this paper focuses on Autonomous Adaptive Tuning algorithm (AAT) which can improve an accuracy of correct opinion shared among agents in the various network, and improves it to address the situation which is close in the real world, i.e., the relationship among agents is different each other. This is because the original AAT does not consider such a different relationship among the agents. Through the intensive empirical experiments, the following implications have been revealed: (1) the accuracy of the correct opinion sharing with the improved AAT is higher than that with the original AAT in the weighted network; (2) the agents in the improved AAT can prevent to acquire incorrect opinion sharing in the weighted network, while those in the original AAT are hard to prevent in the same network.

Keywords: Multi agent system, Community computing, Learning communities

1 INTRODUCTION

In our society people sometimes communicate with the others in order to form their own opinions. They collect information of others, decide which information can be useful to make their opinions, and then form their opinions. For this issue, Gilinton proposed Opinion sharing model [1] as a multi-agent model to simulate such a decision making process. Since opinion sharing model focus on communication among people in the real world situations, this model regards the agents as people that communicate with the others in order to form their own opinions. Since this model aims at capturing the dynamics of opinion sharing in the decision-making process through communication among people, the agents have a simple style. In this model, a very limited number of agents in a community receive the correct information from an environment, while most of the agents can-not; then the agents convey their opinions after forming them,

adfa, p. 1, 2011.

while the other agents who receive the opinions from neighbors formed their opinions; the neighbor agents also convey it, which results in spreading out the opinions. What should be noted here is that the received opinions can be not only correct but also incorrect which derives the community of agents that wrongly share the incorrect opinions. To promote the agents to form the correct opinions by conveying their opinions including correct and incorrect ones, Pryymak proposed Autonomous Adaptive Tuning (AAT) algorithm [2]. The AAT algorithm can improve the accuracy of the correct opinion sharing in the various scale networks even including the incorrect opinions. However, this algorithm does not focus on the situation which is close real world, i.e., the weighted network where the relationship among the agent (as nodes of its net-work) is different each other. Such a situation should be considered because people in our society, have relationships such as kindness, trust, social standing or family, and most of them believe the opinions of others according to the relationships with others. To cope with such a relationship, this paper modifies the original AAT to propose the improved AAT which promotes the agents to form the opinions considering the relationships of neighbor agents connected to them. By employing the improved AAT, this paper aims at investigating how the relationships can help us (or the agents) to share the correct opinions. In this paper, the relationships among the agents are implemented by the weighted network where the weights give an influence to the decision making process of the agents. To investigate the effectiveness of the improved AAT, this paper compares an accuracy of the correct opinion sharing with the improved AAT with that with the original AAT in the weighted network.

This paper is organized as follows. Section 2 starts to explain the details of the opinion sharing model, and Section 3 describes the AAT algorithm. Section 4 proposes the improved AAT, and the experimental results are discussed in Section 5. Finally, our conclusion is given in Section 6.

2 OPINION SHARING MODEL

In this section, we describe in detail *Opinion Sharing model* for multi agent model (Glinton et al [1]). Opinion Sharing was formulated to capture dynamics of the decision making process which cooperating agents have in network. In this model, there are the agents can share their opinion by communicating with neighbors. In addition, some agents have noisy sensors that can only receive information which is related to environment. All agents aim to form the correct opinion by information from sensors and neighbors' opinions. As a result, the opinions of almost agents are unified correctly.

The agents aim for propagating the correct opinions in the following limitations [1]:

- The only few agents which have sensors in the network can observe environment.
- The observations of the agents which have sensors may form incorrect opinions since the sensors receive incorrect information.
- The agents can communicate with only their neighbors, while the agents compose network.

2.1 Overview of the Opinion Sharing Model

In this model, the network $G(A, E)$ consists of a large set of agents $A = \{i^l : l \in 1 \cdots N\}, N \gg 100$ connected by E (set of edges). Each agent $i \in A$ can only communicate with their neighbors $D_i = \{j: \exists (i, j) \in E\}$. The average number of neighbors is defined as the degree $d = \sum_{i \in A} |D_i|/N$. The network is sparse because the degree is small number for all agents size, which $d \ll N$. The state of environment is either of value, for example $B = \{\text{correct}, \text{incorrect}\}$, where $b \in B$. The B following the argument that a binary choice can be applied to wide range of real world situations is supported by the paper[1]. The aim of the community which is comprised of every agent is to find the true state b where observed by some agents which have sensor. The aim of each agent is to form the opinion o_i that is the real state of environment, such that $o_i = b$. Each agent form its opinion by relying on their neighbors' opinions. Then agents which have noisy sensor also rely on the sensor. In order to decide the own opinion, the agent need to have its private belief $P_i(b = \text{correct})$. P_i corresponds the probability of b=correct (further denoted as P_i) and consequently $1 - P_i$ corresponds the probability of $b = \text{correct}$. The agents' belief is updated starting from some initial prior $P_i^{\prime}$' and the ongoing belief is defined as P_i^k , where k is the current step of update sequence for belief. Only some agents in the network $S \subset A, |S| \ll N$ have noisy sensors and can observe the state b of the environment. Those agents are defined as sensor agents. Each sensor agent $i \in S$ periodically reserves an observation $s_i \in B$ that is low accuracy $r(0.5 < r \leq 1)$. To incorporate observations from sensors, the agent use formal updating based on Bayes' theorem: [1]:

$$P_i^k = \frac{c_{upd} P_i^k}{(1 - c_{upd})(1 - P_i^k) + c_{upd} P_i^k} \tag{1}$$

$$\text{where } \begin{cases} c_{upd} = r & \text{if } s_j = \text{correct} \\ c_{upd} = 1 - r_i & \text{if } s_j = \text{incorrect} \end{cases}$$

The agents may be confident the opinions with updating its belief and forms these opinions about the true state b of environment. Forming own opinions of the agents follow the opinion update rule about its private belief P_i^k. It dose that its belief P_i^k exceeds thresholds:

$$o_i^k = \begin{cases} \text{undeter., initial, if } k = 0 \\ \text{correct, if } P_i^k \leq \sigma \\ \text{incorrect, if } P_i^k \leq 1 - \sigma \\ o_i^{k-1} \text{ otherwise} \end{cases} \tag{2}$$

Thresholds $\{1 - \sigma, \sigma\}$ are the confidence bounds, and the range is $0.5 < \sigma < 1$. The Figure.1 indicates the function of updating opinion has sharp hysteresis loop, Pryymak et al [2].

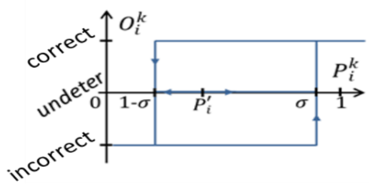

Fig. 1. The update rule of the opinion

If new observation support opposed state, the agents may change its opinion because received opinions may be incorrect.

The agents send new opinions to their neighbors only when they change own opinion. Subsequently, neighbors update their own beliefs and form their own opinions. To receive their neighbors' opinions, the agents use formal updating that is similar to sensor. When the agents receive new opinions from their neighbors $\{c_j : j \in D_j\}$, they uses the same belief update rule for each opinion c_j:

$$\text{where } \begin{cases} c_{upd} = t_i & \text{if } o_j = \text{white} \\ c_{upd} = 1 - t_i & \text{if } o_j = \text{black} \end{cases} \tag{3}$$

where $t_i \in [0,1]$ is defined as the importance level. This is the measure of influence of neighbors' opinion, and it is conditional probability. The importance level is collateral to the accuracy such that Equation 1. However, unlike the accuracy of sensor r, each agent must find own importance level t_i because it is unknown. We describe off algorithm that select t_i in Section 3. With regard to the importance level t_i, the agents should consider only its range $t_i \in [0.5,1]$. When $t_i = 0.5$ indicates, the agents ignore the received opinions. On the other hand, when $t_i = 1$ indicates, the agent changes the own belief to $P_i^k = \{1,0\}$ regardless of its previous value P_i^{k-1}.

In the model, there is possibility of converging false state. Accordingly, the agents are identified with theses neighbors in themselves. In regard to this model, we consider that the agents are not equated with these neighbors since it may be quite natural.

2.2 Performance Metrics of the Model

The model is simulated until rounds $M = \{m_l : l \in 1 \cdots |M|\}$. Every round, the new true state $b^m \in B$ of environment is selected randomly. At the end of each round m_l, the conclusive opinions are observed. Each round is limited by the enough step which the agents converge the own opinion. When each round finishes, the current true state expires. After the new round start, the agents reset their opinion and belief.

In order to measure the average accuracy of the agents' opinions at the end of each round, Glinton et al proposed the proportion of the agent numbers that form correct opinion in the community is accuracy metric.

$$R = \frac{1}{N|M|} \sum_{i \in A} |\{m \in M : o_i^m = b^m\}| \cdot 100\% \tag{4}$$

Furthermore, [2] proposed performance index for single agent. When its opinion is formed correctly, the agent can't perceive. Therefore, the agents should be conscious of how often own opinion is formed correctly. Pryymak et al denote it as an agent's awareness rate h_i[2].

$$h_i = \frac{|\{m \in M : o_i \neq \text{undeter.}\}|}{|M|} \tag{5}$$

This myopic metric can be calculated locally by each agent and it is important metric for AAT algorithm that is descripted in Section 3.

3 AUTONOMOUS ADAPTIVE TUNING (AAT) ALGORITHM

In this section, we explain Autonomous Adaptive Tuning (AAT) algorithm. The algorithm is designed for improving the accuracy R by communicating the agents' opinions each other in the various complex network. In this algorithm, the agents automatically update these belief relying on only the local information. Especially, this algorithm is based on the observation as follows. The accuracy R increases when the dynamics of the opinion sharing is in phase change between the stable state (when the opinions are not shared out in the community $\forall i \in A: h_i \ll 1$) and an unstable one (when the opinions are propagated on a large scale $h_i = 1$). Accordingly, it is necessary that the agents share each opinion in smaller groups before large cascade occurs without reacting to the incorrect opinions in surplus. In order to set optimum parameter of the issue, this algorithm regulates importance level of the agents severally.

This algorithm has three stages for tuning that.

- The each agent running AAT has candidates of the importance level to reducing the search space for the following stages. This step runs only one at the first time of the experiment.
- After each dissemination round, the agent estimates the awareness rates of the candidate levels that are described in Section 2.2.
- The agents select the importance level by estimated the awareness rates of the candidate levels for next round. Then the agents consider how close it is to the target awareness rates. It is necessary that the importance levels are tuned gradually while considering an influence of own neighbors.

In the following sections, we describe three stages of AAT algorithm in detail.

3.1 Candidate Importance Levels

In this section, we describe how the agent running AAT estimates the candidates of importance levels T_i. By estimating the set of candidate importance levels, the agent reduces the continuous problem of selecting an importance level to use t_i from the consecutive values with the range $[0.5,1]$.

Through the number of sensor is much smaller than the total number of agents, we focus on the agents that update their belief using only neighbors' opinions without sensors. Pryymak et al describe the sample dynamics of the agent's belief, where the agent i has the opinion of black change it after receiving more white opinions [2]. Starting from its prior P_i'(black), the agent update own opinion 'white', because of an increase of belief after receiving the 'white' opinion continuously. The most important point of this dynamics is the update step that the agent changes its opinion newly, because it is only time the agent sends new opinion with its neighbors. Consequently, we focus on how many times the agent update its belief until changing the own opinion.

According to the opinion update rule in Section 2.1, we consider the case when the agent's belief match one of the confidence bounds $P_i^k \in \{\sigma, 1-\sigma\}$. If we consider that the maximum number of opinions that the agent can receive is limited to the number of its neighbors, $|D_i|$, we can pare down the candidate importance levels. The agent should find the importance levels as its belief coincides with one of the confidence bound $P_i^l \in \{\sigma, 1-\sigma\}$ in $l \in 1 \cdots |D_i|$ updates (see Eq.3). After solving this problem, the agent can get set of the candidate of importance levels that lead to opinion formation by receiving $1 \cdots |D_i|$ opinions.

$$T_i = \left\{t_i^l : P_i^l\left(t_i^l\right) = \sigma, l \in 1 \cdots |D_i|\right\} \cup \left\{t_i^l : P_i^l\left(t_i^l\right) = 1-\sigma, l \in 1 \cdots |D_i|\right\} \quad (6)$$

Consequently, the set of candidate importance levels is limited to twice the number of neighbors, $|T_i| = 2|D_i|$. This is the necessary and sufficient set of candidate importance levels in which the agent forms an opinion after different update steps and it should be initialized only once.

After this stage, the agent has to estimate the most optimal importance level from its set of candidate importance levels.

3.2 Estimation of the Agent's Awareness Rates

In this section, we describe criterions of selection the importance levels from candidates. As mentioned above, AAT algorithm is based on observation as follows, the accuracy R of the community improved when the opinion sharing dynamics is in a phase transition between stable state and unstable one. In order to estimate such optimal parameters, the agents have to procure the minimal importance levels to form their opinion.

In the opinion sharing model, there are two terms, such that in order to maximize the accuracy R.

- Each agent has to form its opinion. Consequently, each agent should reach a high level of its awareness rate h_i, because the agents without determined opinions drop in the accuracy of the community.
- Each agent has to form an opinion as late as possible with only local view, after the agent gathers the maximum number of neighbors' opinions.

To satisfy these terms, the agent has to select the minimal importance level $t_i^l \in T_i$ from the candidates, such that it can form its opinion ($h_i = 1$).

However, since sensors observe the value influenced by random noise, the dynamics of opinion sharing like phase transition behaves stochastically. The agents cannot form their opinion until the opinions are shared on the large scale, suffered by their awareness rates. The agents should select the minimal importance level, t_i^l, from the candidates T_i. Then the awareness rate imitates the target awareness rate h_{trg}. The target awareness rate is slightly lower than maximum, $h_i = 1$.

The each agent solves the following optimization problem:

$$T_i = argmin_{t_i^l \in T_i} \left| h_i\left(t_i^l\right) - h_{trg} \right| \tag{7}$$

In this problem, $h_i\left(t_i^l\right)$ shows the awareness rate of the importance level t_i^l that the agent achieves. It is optimal parameter, $h_{trg} = 0.9$ for versatile network dynamics [2].

3.3 Stratagem of Select Importance Levels

The agent affects the dynamics and awareness rates of all agents with the interdependence of the agents' opinion and neighbors' one. If the agent greedily select optimal importance level following the definition of its optimization problem (Eq. 8 shows), it may extremely change the local dynamics of the community. The agent has to select a strategy without dramatic changes in its dynamics, in order to estimate awareness rates of the community accurately and solve faster. To select such the strategy, the agent has to focus on the inference as follows. The agents' awareness rate for its importance levels increase monotonously. Because the minimum importance level t_i^{min}requires many updates against the maximum importance level t_i^{max}, if the importance levels are sorted in ascending order. In this inference, the agent employs a hill-climbing strategy. If the awareness rate of the current importance level $t_i = t_i^l$ is lower than the target $\widehat{h_i^l} < h_{trg}$, the agent employing the hill-climbing strategy increases the importance level to closet lager one (i.e. $l = l + 1$). If the awareness rate of the close importance level is lower than the target $\widehat{h_i^{l-1}} > h_{trg}$, the agent use this importance level in the next round (i.e. $l = l - 1$). The agents employed the hill-climbing strategy deliver the higher accuracy than the greedy strategy [2].

4 AAT with Weighted Network among Agents

Section 3 explains that AAT algorithm can improve the accuracy R in the various complex network. However, this algorithm does not focus on the situation which is close to real world, i.e., the weighted network where the relationship among the agents (as the nodes of its network) is different each other. Such a situation should be considered because people in our society, have relationships such as kindness, trust, social standing or family, and most of them believe the opinions of others according to the relationships with others. From this viewpoint, the relationships among people may help our communication smoothly. To cope with such a relationship, this paper modifies the original AAT to improve AAT algorithm to promote the agents to form the opinions considering the relationships of neighbor agents connected to them.

By employing the improved AAT, this paper aims at investigating how the relationships can help us (or the agents) to share the correct opinions. In this paper, the relationships among the agents are implemented by the weighted network where the weights give an influence to the decision making process of the agents. In the weighted network, the agents have the weighted edge $w_j^i \in W$, where j is the neighbor $D_i = \{j: \exists(i,j) \in E\}$and the range of the weighted edges is $0.9 \leq w \leq 1$. The agents have weighted edges as many as neighbor agents, i.e. $|W_i| = |D_i|$. In order to combine the weighted edges into AAT algorithm, we modified it by multiplying the importance levels with the edges where the optimal importance levels T_i is the measure of influence of neighbors' opinion, while the weighted edges W_i implies the relationships for agents' neighbors. Note that the importance levels with the improved AAT are lower than that with original AAT, since it multiplies importance levels and the weighted edges together. The agents with the improved AAT may become cautious since they have the importance levels which is lower than original that.

The AAT algorithm with weighted edges is described as follow. [2]

AAT Algorithm with weighted Edges

Procedure UPDATE($\boldsymbol{i}$)

MULTIPLY each importance level by each weighted edges

{Revises the current importance level after each round}

if OPINIONS RECEIVED : $\boldsymbol{u_i^m} \neq \boldsymbol{0}$ then

  for all CANDIDATE LEVELS : $\boldsymbol{t_i^l} \in \boldsymbol{T_i}$ do

    if OPINION FORMED$(\boldsymbol{t_i^l}, \boldsymbol{t_i}, \boldsymbol{m}) = \textbf{True then}$

      $\boldsymbol{\widehat{h_i^l}}$ =UPDATE AVERAGE AWARENESS$(\boldsymbol{h_i^l}, \boldsymbol{1})$

    else

      $\boldsymbol{\widehat{h_i^l}}$ =UPDATE AVERAGE AWARENESS$(\boldsymbol{h_i^l}, \boldsymbol{0})$

  $\boldsymbol{t_i}$ =SELECT BY AWARENESS RATE$(\langle \boldsymbol{t_i^l}, \boldsymbol{\widehat{h_i^l}} \rangle : : \boldsymbol{l} \in \boldsymbol{1} \cdots |\boldsymbol{T_i}|)$

5 EMPIRICAL EVALUATION

5.1 Experimental content

In order to investigate the influence of weighted networks, we simulate multi-agent model of opinion sharing. We visualize the model on system to facilitate the analysis of the network model.

We validate the usability of our study as follows:

- The network topology of the community is adopted Small World Network since we motivate to simulate our study at the case which closes the real world.
- In order to validate the influence of the small community that share incorrect opinions easily, we set the number of the agents to 100.
- The number of the sensor agents that can observe the information of the true state *b* is only 5% for all agents. Then the community may form incorrect opinions, since the accuracy of sensor is low, about 55%

5.2 Evaluation criteria

In order to measure the influence of weighted networks, we use the accuracy *R* (number of the agents which have correct opinion in the community). We measure each average of the accuracy *R* in the 10 network (various network form and sensors') and compare original AAT algorithm and improved AAT (AAT with weighted edge). In order to analyze the network dynamics clearly, we also compare each number of the accuracy *R* of fixed network (same network form and same sensors' seed).

5.3 Experimental result

Fig.2 indicates the each average of the number of the correct agents in the 10 network as follows:

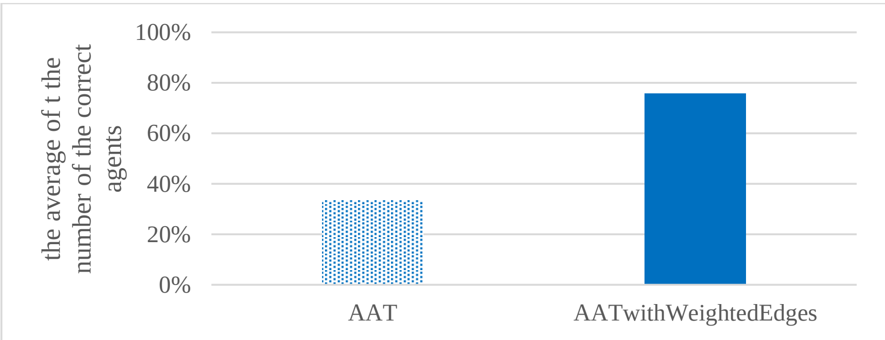

Fig. 2. The average of the accuracy *R*

The vertical axis and the horizontal axis, indicate the average of the accuracy *R* in the 10 network, and the respective method (AAT, improved AAT). Following Fig.2, the average of AAT is low, about 30%. However, the average of improved AAT is over than the average of AAT, about 70%.

Fig.3 indicates the dispersion of the agents' opinions in the community running AAT when the community form incorrect opinion as follows:

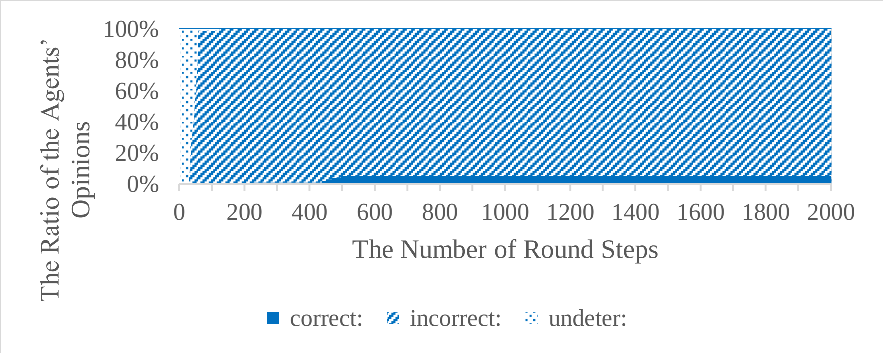

Fig. 3. The dispersion of the formed opinion by the all agents in the small community running original AAT

The vertical axis and the horizontal axis, indicate the ratio of the agents' opinions, and the number of round steps. Since the AAT cannot keep high performance in the situation that is refered to the Section 4, this small community spread the incorrect opinion to its members. In such a situation, we apply weighted networks and improved AAT to the community, where the weighted networks which the agents have for their neighbors are set up randomly.

Fig.4 indicates the dispersion of the formed opinion in the community which applied improved AAT.

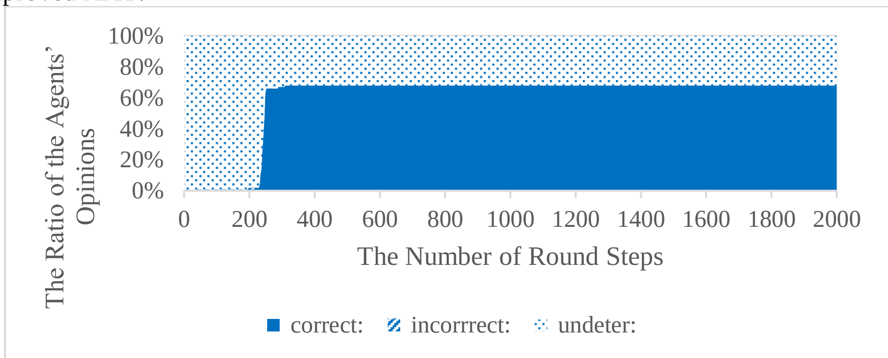

Fig. 4. The dispersion of the formed opinion by the all agents in the small community running improved AAT

The vertical axis and the horizontal axis, indicate the ratio of the agents' opinions in the community applied improved AAT and the number of round steps. The result indicates that the more agents succeeded forming the correct opinions in the similar community.

Now, we apply the AAT algorithm which is tuned the target awareness rate h_trg = 0.7 to same network. The target awareness rate is measure how much the agents form their opinions to receive neighbors' opinions. Following Fig.2, The average of the accuracy R in the community running improved AAT is about 70%. Fig.5 indicates the dispersion of the formed opinion in the community after application the AAT tuned by h_trg = 0.7.

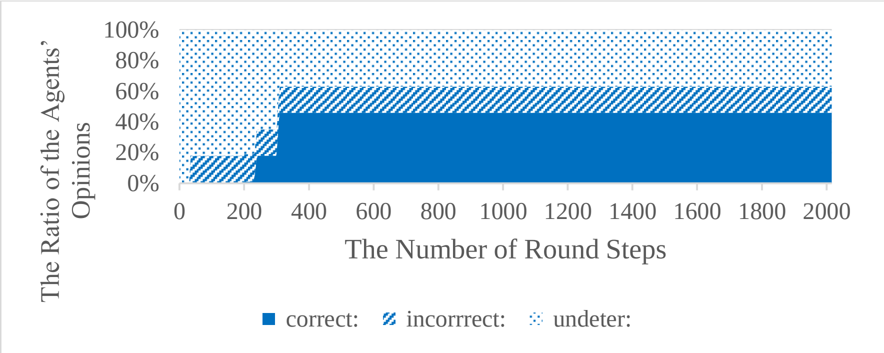

Fig. 5. The dispersion of the formed opinion by the all agents in the small community running AAT tuned by h_trg = 0.7

The vertical axis and the horizontal axis, indicate the ratio of the agents' opinions, and the number of round steps. Following this result, the agents which form incorrect opinion is over than the agents which form correct one.

Fig.6 indicates the each average of the accuracy R in the 10 network as follows:

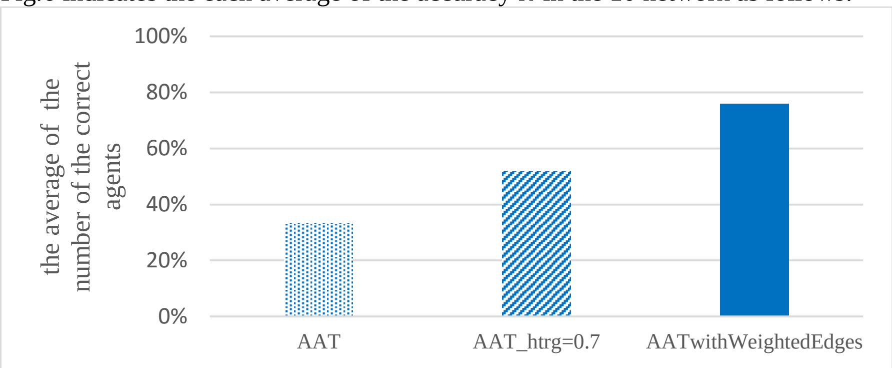

Fig. 6. The average of the accuracy R

The vertical axis and the horizontal axis, indicate the average of the awareness rate in the 10 network, and the respective method (original AAT, AAT with h_trg=0.7, improved AAT). Following Fig.6, the average of AAT with h_trg = 0.7 is 50%.

5.4 Discussion

Following Fig.6, the average rate of improved AAT is over than original AAT and AAT with h_trg = 0.7. Following Fig.3, Fig.4 and Fig.5, the accuracy of the correct opinion sharing in improved AAT is higher than that in the original AAT and AAT with h_trg = 0.7. Following these results, the agents running improved AAT can share a correct opinion in a certain small network, while those in the conventional method cannot share it in the same network. Additionally, the improved AAT prevent incorrect opinion in same community with weighted network, while AAT and AAT with h_trg = 0.7 cannot prevent it. The results indicates the agents with the improved AAT may be cautious, since they selects the importance levels with weighted networks which are lower than that with original AAT. These results indicate the weighted networks have influence on decision making of the agent and weighted networks help the prevention of incorrect opinion sharing in the difficult situation. There is some possibility of the weighted network which imply relationship among the agents may help the correct opinion sharing.

6 CONCLUSION

To promote the agents to share only correct opinions by preventing to acquire the incorrect opinions in the weighted network where the relationship among the agent (as nodes of its network) is different each other, this paper investigated how correct or incorrect opinions are shared among the agents in such a network, and improved the Autonomous Adaptive Tuning algorithm (AAT) to address the weighted network which is close in the real world. To investigate the effectiveness of the improved AAT, this paper compares an accuracy of the correct opinion sharing with the improved AAT with that with the original AAT in the weighted network. Through an intensive empirical experiments, the following implications have been revealed: (1) the weighted networks help the current communication, since the accuracy of the correct opinion sharing with the improved AAT is higher than that with the original AAT in the weighted network; (2) the agents in the improved AAT can prevent to acquire incorrect opinion sharing in the weighted network, while those in the original AAT are hard to prevent in the same network. What should be noticed here is that the effects of the weighted networks has not yet been shown in detail. Therefore, further careful qualifications and justifications are needed to generalize our results. Such important directions must be pursued in the near future in addition to the following future research: (1) to explore how the weighted network improves the correct opinion sharing; and (2) to explore how the weighted networks prevent incorrect opinion sharing.

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