Efficient Sharing of Conflicting Opinions with Minimal Communication in Large Decentralised Teams

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Abstract

In large decentralised teams agents often share uncertain and conflicting information across the network, and it is a major challenge for team members to reach accurate conclusions individually. Previously, this problem was approached by introducing a communication overhead in order to reason about the accuracy of information or to reach agreements interactively. We address the more challenging problem of improving the accuracy in settings where communication is strictly limited to sharing opinions about the real state of the common subject of interest. We do so by presenting a novel decentralised algorithm, AAT, which reaches the settings of emergent behaviour in a team where agents' opinions becomes dramatically more accurate. We show that our solution significantly outperforms the existing algorithm, DACOR, and delivers an accuracy of opinions close to a team pretuned for the highest performance by empirical exploration of its parameters. Moreover, in contrast to the message-passing DACOR, our algorithm has a minimal communication requirement, where only opinions are shared, as well as significantly lower computational expenses. Finally, AAT delivers a high accuracy of opinions in settings where up to half of the team does not participate in optimising sharing parameters.

1 Introduction

The success of any individual in a large communication network, such as a sensor network or an online social community, heavily depends on its access to timely and accurate information. Naturally, to overcome uncertainty in the observations of different team members, the ultimate goal for a cooperative team is to share information efficiently. Although not every agent in the team may be able to make its own observations about the common subject of interest, the whole system can benefit from its collaboration in opinion sharing processes. Specifically, agents can reduce uncertainty by fusing information from a number of sources and propagating it to more distant team members. Thus, the common aim is to filter out inaccurate information in the process of its dissemination.

In this paper we specifically focus on the problem of efficient information exchange in a large communication network in order to improve the accuracy of agents' beliefs about a common subject of interest. Existing solutions are based on interactive agreement protocols [Olfati-Saber *et al.*, 2007] or require annotating communicated information to enable reasoning about its accuracy [Moreau, 2009]. However, these techniques require a communication overhead to operate. We address the more challenging problem when agents have to form accurate beliefs in a setting where communication is strictly limited. In order to minimise communication, each agent must filter and abstract all incoming information and communicate only its *opinion* about the true state of the common subject of interest. This restriction can be found in many real world communication networks, such as sensor networks where it is expensive to share raw data; or social communities where people rely on the conclusions of others when they do not have enough resources or skills to analyse the original information. We model these settings in which a small subset of agents have access to the sensors, while others have to rely only on opinions of their network neighbours. Since sensors are noisy, opinions in a team may conflict and agents have to decide which to support. Such settings expose the team to the *double counting fallacy*, when the same opinion may arrive via different paths and an agent is not able to identify this, that indicates on the complexity of the problem. By studying the information dynamics in social networks, Bikhchandani et al. [1992] show that an opinion propagation occur in the form of *opinion cascades* (or avalanches) when a single new observation may trigger a large number of agents to change their opinions and cause a sudden change in the system's state. Subsequently, it was shown that such systems exhibit complex emergent behaviour in dissemination processes [Watts, 2002] that in some cases can be exploited.

Specifically, researchers recently have studied an impact of this emergent phenomenon on the accuracy of shared opinions. Glinton et al. [2009] offered the corresponding model of propagation and fusion of conflicting opinions where agents form their public opinions based on their private beliefs about the real state of the subject of interest. In this model agents inform their beliefs by observing a small number of noisy sensors, and receiving opinions from their network neighbours. Each agent uses formal reasoning and updates its belief with a certain *trust level* in the received opinions. A trust level represents the number of the same opinions that an agent has to receive to adopt this opinion and propagate it further. Clearly, this is a key factor in influencing the dynamics of the opinion sharing process. It was found that in a particular range of trust levels, the opinions of agents are dramatically more accurate. The analysis showed that in this critical state, the sizes of opinion cascades are distributed by a power law. The frequent smaller cascades prevent the team from overreacting to inaccurate opinions, however, through less frequent, large cascades occur and disseminate the locally vetted opinions to the rest of the team. However, the range of these parameters necessary to achieve the desirable properties is very narrow and very sensitive to the configuration of the team.

To achieve optimised performance in a complex communication network, Glinton et al. [2010] proposed the Distributed Adaptive Communication for Overall Reliability (DACOR) algorithm. DACOR adjusts the agents' trust levels according to the estimated local *branching factor* – the expected number of neighbours that would change their opinions following the change of an agent's opinion. In particular, it was found that in the area of optimised parameters the branching factor is close to 1. However, actually performing a decentralised estimation of the branching factor requires significant message overhead compared to the number of messages used to share opinions itself. Additionally, as our empirical evaluation reveals, the internal parameters of DACOR are sensitive to the team's configuration and DACOR has to be tuned individually for different domains.

To address these shortcomings, we present a decentralised algorithm for Adaptive Autonomous Tuning (AAT) of agents' trust levels. The approach is based on our observation that the team becomes dramatically more accurate when the agents' trust levels are minimally sufficient for disseminating opinions on the team scale. Thus, in contrast to DACOR, it is possible for an agent to rely solely on observing its local information dynamics, rather than resource-intensive estimations of the branching factor. In more detail, the contributions of this paper are:

1. We develop a novel decentralised algorithm, AAT, that improves the accuracy of the opinions in a large team with a complex communication network. It does so by tuning the dynamics of opinions sharing processes to reach the area of optimised parameters. This is the first solution that has the minimal communication requirement and thus, communication is strictly limited to the sharing of opinions. In contrast, DACOR communicates 4-7 times more messages than is required to share the conflicting opinions in the area of optimised parameters.
2. We empirically evaluate AAT and show that it significantly outperforms the state-of-the-art solution, DACOR. Specifically, using AAT, 80-90% of the agents' opinions correspond to the real state of the common subject of interest. This figure is significantly higher than 65-75% for the existing algorithm, and close to 90-95% of the team pre-tuned for the highest accuracy by an expensive empirical exploration of its parameters. Moreover, AAT introduces less computation expenses and requires 10^4 times less agents' actions.
3. We show that AAT is the first decentralised solution designed to improve accuracy in teams with indifferent agents that do not participate in the optimisation process. Specifically, it significantly improves the accuracy when up to 50% of the agents in the team are indifferent.

In contrast to the focus in the literature on trust, here we discuss cooperative teams with indifferent agents. Instead of considering the reliability of peers, trust levels measure the optimal contribution of received opinions to agents' beliefs, assuming that any peer might be exposed to a misleading opinion. Therefore, accurate estimations of such trust levels based solely on local observations also contribute to the development of elaborate trust models. Specifically, this provides the initial trust values that improve the accuracy of opinions without any additional knowledge about the settings.

The remainder of this paper is organised as follows. In Section 2 the model of the environment, its properties and metrics are discussed. In Section 3 the agents' dynamics are analysed and AAT is presented. Then, in Section 4 AAT is empirically evaluated to demonstrate its advantages in contrast to DACOR and it is compared with a team pre-tuned for the highest accuracy. Finally, Section 5 concludes this work.

2 Problem Description

In this section, we formally describe a generic model of opinion sharing that was recently proposed and analysed by Glinton et al. [2009; 2010]. The aim of the model is to capture the complex dynamics of opinion sharing about the real state of the common subject of interest, in a network of cooperative agents. In this model, some agents have access to noisy sensors, and they introduce to the team conflicting opinions of which only one is correct. However, due to communication constrains agents can communicate to their neighbours only opinions without any additional information. Thus, each agent has to decide how much trust it has to put in the received opinions to form its own accurate opinion.

2.1 Model

Formally, the model consists of a large set of agents $A = \{i_l : l \in 1 \ldots |A|\}$, $|A| \gg 100$ connected by a undirected network $G(A, E)$ where E is the set of edges indicating which agents are neighbours and can therefore communicate. Each agent, $i \in A$ has a neighbourhood $N_i = \{j : \exists\,(i, j) \in E\}$ and the average number of neighbours is defined as the expected degree d, where $d = \sum_{i \in A} |N_i|/|A|$. Since agents do not have enough resources to support a large number of communication links, the network is sparse $d \ll |A|$.

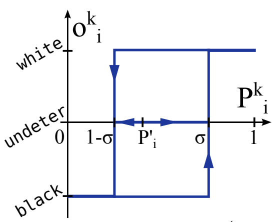
The aim of every agent, and eventually of the whole team, is to find the true state b of the common subject of interest, for example $B = \{\texttt{white}, \texttt{black}\}$, where $b \in B$. We support the assumption that B is binary following the argument that a binary choice can be applied to a wide range of real world situations [Watts and Dodds, 2007]. However, our approach, presented later, can be generalised for $|B| > 2$.

To recover the true state, agents rely on noisy sensors and their neighbours' opinions about the value of b. To decide which conflicting opinion to adopt, agent i forms its private belief $P_i(b=\texttt{white})$, which is the probability of $b = \texttt{white}$ (further denoted as P_i) and consequently $1 - P_i$ is the probability of $b = \texttt{black}$. The agent updates its belief starting from some initial prior P_i' and the ongoing belief is denoted by P_i^k where k is the current step of the belief update sequence.

Only a small subset of agents $S \subset A$, $|S| \ll |A|$ have noisy sensors and can make observations of the true state b. Each agent with a sensor $i \in S$ periodically receives an observation $s_i \in B$ with a low accuracy r, which is a probability of returning the true state b ($0.5 < r \ll 1$). To incorporate the new observation from the sensor into its belief, the agent uses formal reasoning based on Bayes' Theorem:

$$P_i^k = \begin{cases} \frac{rP_i^{k-1}}{(1-r)(1-P_i^{k-1})+rP_i^{k-1}} & \text{if } s_i = \texttt{white} \\ \frac{(1-r)P_i^{k-1}}{r(1-P_i^{k-1})+(1-r)P_i^{k-1}} & \text{if } s_i = \texttt{black} \end{cases} \quad (1)$$

After updating its belief P_i^k with a number of observations, the agent becomes confident enough to form its opinion o_i^k about the true state b once P_i^k exceeds thresholds, as follows:



$$o_i^k = \begin{cases} \texttt{undeter.}, & \text{initial} \\ \texttt{white}, & \text{if } P_i^k \geq \sigma \\ \texttt{black}, & \text{if } P_i^k \leq 1-\sigma \\ o_i^{k-1} & \text{otherwise} \end{cases} \quad (2)$$

where thresholds $(1-\sigma, \sigma)$ are the *confidence bounds* and $\sigma > 0.5$. The opinion update function has the shape of a sharp hysteresis loop, and because sensors are noisy, it is possible that later observations will support the opposite opinion, and the agent may change its opinion.

Every time the agent changes its opinion, it communicates the new opinion to its neighbours. Consequently, these neighbours update their own beliefs and may form their own opinions. As with sensor observation, the agent uses Bayes' Theorem to update its belief, such that when the agent receives new opinions from its neighbours $\{o_j : j \in N_i\}$, it uses the following belief update rule for each received opinion o_j:

$$P_i^k = \begin{cases} \frac{t_i P_i^{k-1}}{(1-t_i)(1-P_i^{k-1})+t_i P_i^{k-1}} & \text{if } o_j = \texttt{white} \\ \frac{(1-t_i)P_i^{k-1}}{t_i(1-P_i^{k-1})+(1-t_i)P_i^{k-1}} & \text{if } o_j = \texttt{black} \end{cases} \quad (3)$$

where $t_i \in [0, 1]$ is the *trust level* that measures the importance of the neighbour's opinion. Note, the similarity with Eq. 1 such that the trust level is analogous to the accuracy of a noisy sensor. However, unlike the accuracy r of a sensor, trust level t_i is unknown and each agent must find its best value. We assume that agents in this model are cooperative and thus, we consider only the range $t_i \in [0.5, 1]$, where $t_i = 0.5$ indicates that the received opinion is ignored, and $t_i = 1$ is the maximum trust such that the agent changes its belief to $P_i^k = \{1, 0\}$ (depending on the received opinion) regardless of its previous value P_i^{k-1}. The model implies that the neighbours can be equally wrong in their opinions since sensor readings are introduced randomly. Therefore, the agent does not differentiate the sources of opinions and applies the same trust level t_i for all its neighbours.

If the agent changes its opinion following a received opinion from its neighbour, it participates in an opinion cascade where a number of agents change their opinions in a sequence after a critical sensor observation. It was found that the model exhibits emergent behaviour and agents' opinions converge to the true state b dramatically more often when the sizes of opinion cascades are distributed by a power law [Glinton *et al.*, 2010]. The trust levels are a key variable parameter which regulate the dissemination process and thus, impact the distribution of sizes of opinion cascades. Unfortunately, it was shown that it is infeasible in the general case to predict the critical trust levels t_{critical}, at which the emergent behaviour occurs, as it highly depend on properties of the network topology, the distribution of priors of the agents' and the properties of the sensors. If the team operates with trust levels lower than the critical $t_i \forall i \in A < t_{\text{critical}}$, agents cannot form their own opinions because they have insufficient neighbours to get their updated belief to pass one of the confidence bounds. Conversely, if $t_i > t_{\text{critical}}$, agents instantly propagate the first, possibly inaccurate opinion, and do not benefit from the presence of multiple sensors in the team.

2.2 Performance

In order to measure the performance of the team, we simulate a set of opinion dissemination rounds, $M = \{m_l : l \in 1 \ldots |M|\}$, with randomly selected the new true state $b^m \in B$. Then we observe the agents' final opinions, o_i^m, at the end of each round, m, which is limited by a number of sensor observations and agents with sensors converge to the correct opinion that is unlikely be changed any more. Thus, the end of each round constitutes a certain deadline when the current true state expires.

From its own perspective, a single agent i cannot determine when it has formed the correct opinion about the true state b^m. However, we assume that the common goal of the team is to share opinions since in many real world scenarios it is crucial for the agents' activities. To measure this, we define an agent's *awareness rate*, h_i, as the share of dissemination rounds where the agent held an opinion rather than being undetermined compared to the total number of rounds:

$$h_i = |\{m \in M : o_i^m \neq \texttt{undeter.}\}| \,/\, |M| \quad (4)$$

To measure an average accuracy of the agents' opinions, Glinton et al. [2010] proposed the reliability metric of the team that shows the ratio between the number of dissemination rounds when the agents' final opinions are correct versus incorrect. Thus, it heavily penalises the team for disseminating incorrect opinions. Therefore, this metric maximises even if a large share of the team does not form any opinion ($h_i \ll 1 \; \forall i \in A$). However, this contradicts our assumption, and we propose a new reliability metric that, unlike the existing one, is maximised when most of the team forms the correct opinion. Formally, our reliability metric measures how often an agent forms the correct opinion on average:

$$R_{\text{correct}} = \frac{1}{|A||M|} \sum_{i \in A} |\{m \in M : o_i^m = b^m\}| \quad (5)$$

Having introduced the model, we look next at algorithms which optimise the reliability R_{correct}.

3 Autonomous Adaptive Tuning of Trust Levels

As mentioned earlier, we cannot predict analytically the trust levels that introduce the desired emergent behaviour into complex communication networks. This limitation comes from the high complexity of the problem where the number of possible interactions between agents is combinatorial in the size $|A|$ of a large team and the range of trust levels $(0.5, 1)$.

In this section, we present our Autonomous Adaptive Tuning (AAT) algorithm, for improving the reliability R_{correct} of a complex communication network by exploiting its emergent behaviour. In contrast to the existing algorithm, DACOR, our solution does not introduce extra communication and agent share only their opinions. Specifically, DACOR implies that following a change of an agent's opinion, all its neighbours communicate on average d^2 additional service messages, where d is the expected number of neighbours. We address this shortcoming by developing a new solution that updates agents' trust levels autonomously, relying on their own observations of local information dynamics.

Specifically, AAT is built on our observation that the team's reliability dramatically increases when the trust levels are minimally sufficient to disseminate opinions, and the agents' awareness rates, h_i, indicate on this settings when they are slightly lower than the maximum, 1. This creates a condition where the team does not overreact to inaccurate opinions and the agents share opinions in small groups before a large cascade occurs. To reach this area of optimised parameters, AAT gradually tunes a trust level of each agent individually in three stages, described in the following sections. Firstly each agent running AAT builds a set of candidate trust levels to reduce the search space for the following stages. Then the agent estimates the awareness rates of the candidate trust levels after each dissemination round. Finally, the agent selects a trust level to use in the following round, considering how close its estimated awareness is to the target awareness rate.

3.1 Candidate Trust Levels

In this section, we analyse the dynamics and limit the search space for each agent from the continuous interval $t_i \in [0.5, 1]$ to the finite set of candidate trust levels. Since the number of sensors is very small, we analyse the agents that inform their beliefs only by their neighbours' opinions. Each such agent $i \in A \setminus S$ sequentially receives opinions from its neighbours and these opinions might be conflicting.

For example, Figure 1 illustrates the sample dynamics of the agent's belief, P_i^k, where the agent participated in at least 2 opinion cascades of conflicting opinions. During each step, k, of its belief update, the agent has a number of opinions, u_i^k, received from its neighbours that support belief $b^m = \texttt{white}$, and a number of received opinions, $\overline{u}_i^k$ that support the opposite belief $b^m = \texttt{black}$. Following this, during the whole dissemination round, m, there is some belief update step k when an agent observes the *strongest support* in favour of one of the conflicting opinions. We denote the ongoing support as the difference between the received conflicting opinions, $u_i^k - \overline{u}_i^k$, and the strongest observed support during round m as $u_i^m = \max_k |u_i^k - \overline{u}_i^k|$.

When the agent observes the strongest support, its belief is maximised or minimised and thus, it is most confident to form its most accurate opinion given its local view. To form the opinion when the strongest support is observed, the agent's belief should match one of 2 confidence bounds, $P_i^k \in \{1 - \sigma, \sigma\}$. Since the agent's trust level, t_i influences the dynamic of its belief, we can select such 2 optimal trust levels that

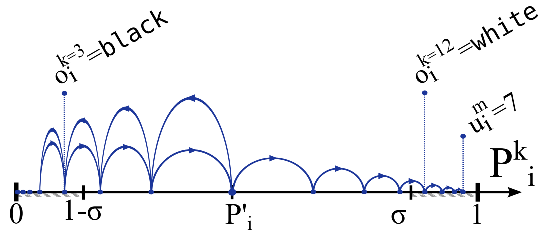


Figure 1: The sample dynamics of an agent i's belief with marked steps when i changed its opinion. Starting from its prior P_i', i updates its belief with 4 neighbours' opinions that support '$\texttt{black}$' after which i sequentially receives 11 opinions supporting '$\texttt{white}$'. The strongest support is $u_i^m = |4 - 11| = 7$.

meet the described condition given a specific value of u_i^m.

The number of received opinions that support one of the conflicting beliefs, u_i^k and $\overline{u}_i^k$, is limited to the total number of the neighbours, $|N_i|$. Following the definition of the strongest support, u_i^m is also limited by the number of agent's neighbours $u_i^m \leq |N_i|$, $u_i^m \in \{1 \ldots |N_i|\}$

Assume that the agents select its trust levels t_i before the dissemination round, m, and it is fixed till the end of round. If this case the belief update rule (Eq. 3) returns the same result regardless of the ordering of its update sequence. Thus, the agent's trust level is the only parameter that regulates the belief position. If the agent can predict the value of the strongest support, u_i^m, that it will observe in the upcoming round, the agent needs to consider only 2 trust levels to form the most accurate opinion given its local view. Specifically, a trust level t_i^- using which the agent's belief reaches the lower confidence bound $P_i^k = 1 - \sigma$ in u_i^m belief update steps to form its opinion $o_i^k = \texttt{black}$ when the strongest support is observed; or t_i^+ to reach the upper bound $P_i^k = \sigma$ and to form the opposite opinion. Since $u_i^m \in \{1 \ldots |N_i|\}$, we build the corresponding sets of trust levels: $T_i = T_i^- \cup T_i^+ = \{t_i^{l-} : l = 1 \ldots |N_i|\} \cup \{t_i^{l+} : l = 1 \ldots |N_i|\}$. Here T_i is a set of the *candidate trust levels* that the agent needs to consider in order to select the best trust level and form the most accurate opinion. Also, this is a complete set of distinct dynamics of agent's opinion formation.

We present Algorithm 1 that pre-calculates the candidate trust levels, $T_i = \{t_i^l : l = 1 \ldots 2|N_i|\}$, and thus, heavily reduces the search space from the continuous interval $[0.5, 1]$ to the finite set. Following this, we now present our algorithm for selecting the best trust level out of the candidates.

Algorithm 1 Candidate Trust Levels

Function CANDIDATETRUSTLEVELS$(P_i', \sigma, |N_i|)$
{Builds a vector of candidate trust levels}

$$P(t,u) = \begin{cases} P_i' & \text{if } u = 0 \\ \frac{tP(t,u\text{-}1)}{(1-t)(1-P(t,u\text{-}1))+tP(t,u\text{-}1)} & \text{otherwise} \end{cases}$$

{recursive belief update function, where t is a trust level, u is a number of updates (following Eq. 3)}

$U' := \{1, \ldots, |N_i|\}$ {the number of updates to consider}

$T_i^+ := \{t_i^{l+} : \text{SOLVE}\left(P(t_i^{l+}, u^l) = \sigma\right) \quad \forall u^l \in U'\}$

$T_i^- := \{t_i^{l-} : \text{SOLVE}\left(P(1\text{–}t_i^{l-}, u^l) = 1\text{–}\sigma\right) \quad \forall u^l \in U'\}$

$T_i = T_i^+ \cup T_i^-$

return T_i

3.2 Estimation of the Awareness Rates

In this section we present AAT that selects for each agent the best trust level to use from the candidates, T_i, and steers the team into the area of optimised parameters of opinion sharing when it becomes a large collaborative filter and its reliability significantly improves. The approach is based on our observation that the reliability, R_{correct}, is maximised when the trust levels are minimally sufficient to disseminate opinions in the team. In other words, AAT is based on the intuition that to filter out inaccurate opinions, agents have to gather as many neighbours' opinions as possible before forming their own opinion. However, if agents wait until all their neighbours communicate their opinions, a deadlock results where the opinion dissemination process stops. Therefore, each agent must apply a minimal trust level to the received opinions which guarantees that it actually forms its own opinion given the available number of neighbours' opinions, and thus, propagates this opinion further. In terms of the model, to maximise the reliability, R_{correct} each agent has to:

- form its opinion, and thus, reach a high level of its awareness rate, $h_i \forall i \in A$, since the agents with undetermined opinions decrease the team's reliability;
- form accurate opinion given its local view by crossing one of the confidence bounds when the agent observes the strongest support (following Section 3.1)

To meet these conditions, the agent has to use the minimal trust level, t_i^l, out of the candidates, T_i, that lead to an opinion formation given the strongest support, u_i^m, observed before the agent influences its opinion on the neighbourhood.

In the area of maximised reliability the trust levels have to be as low as possible to prevent overreacting to early and possibly inaccurate opinions. The awareness rates indicate on this when they are slightly lower than maximum, 1. However, during some rounds the opinions might not disseminate on a large scale and the awareness rates will suffer even further, since the sensor readings are introduced randomly producing randomness in opinion sharing dynamics. Therefore, to improve the overall reliability, each agent i has to compromise its own awareness rate, h_i, and find the minimal trust level, t_i^l out of candidates T_i that delivers the *target awareness rate*, h_{best}. Formally, each agent solves the optimisation problem:

$$t_i = \arg\min_{t_i^l \in T_i} |h_i(t_i^l) - h_{\text{best}}| \tag{6}$$

where $h_i(t_i^l)$ is the awareness rate that the agent achieves using trust level t_i^l. h_{best} has to be slightly lower than the maximum, 1, to indicate the moment when the team dynamics is changing, and we analyse the impact of its value on the reliability in the empirical evaluation (Section 4.1).

Given this intuition, in order to select the trust level, $t_i^l \in T_i$, the agent needs to estimate its awareness rate, $h(t_i^l)$, that would be achieved by using t_i^l. Since the agents opinions are highly interdependent, the choice of an individual agent eventually affects the dynamic of the whole team. By analysing the process of the agents' belief update, we propose the following approach to construct an estimator of the awareness rate, $\hat{h}(t_i^l)$, for the candidate trust levels $t_i^l \in T_i$ based on the observed local dynamics. Specifically, to estimate the awareness rate, the agent needs to decide if its opinion could be formed using a trust level, t_i^l, that is distinct from its actually used t_i, and we identify two evidences that indicate this:

Algorithm 2 Estimation of the Awareness Rates

Procedure UPDATE(i)
{Revises the current trust level after each dissemination round}
1: **if** $u_i^m = 0$ **then**
2:     **return** {no changes if new opinions did not arrive}
3: **for** $l \in \{1, \ldots, 2|N_i|\}$ **do**
4:     **if** $\text{Evs}(t_i^l, t_i, m) = \texttt{True}$ **then**
5:         $\hat{h}^m(t_i^l) := \frac{m-1}{m}\hat{h}^{m\text{-}1}(t_i^l) + \frac{1}{m}$ {add 1 to the average}
6:     **else**
7:         $\hat{h}^m(t_i^l) := \frac{m-1}{m}\hat{h}^{m\text{-}1}(t_i^l)$ {else add 0}
8: $t_i := \text{CHOOSET}(i)$

1. Consider the case that the agent used trust level t_i in round m and an opinion was formed ($o_i^m \neq$ undeter.). According to the belief update function (Eq. 3) all higher trust levels ($t_i^l \geq t_i$) would have led to the more confident belief, and thus, to opinion formation as well. We formalise this evidence of opinion formation as a boolean function that returns `True` if the agent would have formed an opinion with a candidate trust level, t_i^l:
$$\text{Ev1}(t_i^l, t_i, o_i^m) = (o_i^m \neq \texttt{undeter.}) \wedge (t_i^l \geq t_i) \tag{7}$$
2. Otherwise, the opinion should have been formed when the strongest observed support, u_i^m, is larger than it is required for the agent's belief updated with t_i^l to cross the nearest confidence bound, denoted as $u(t_i^l, P_i', \sigma)$. Additionally, we exclude the current trust level, t_i, which can be more accurately judged by the first evidence:
$$\text{Ev2}(t_i^l, t_i, u_i^m) = (u(t_i^l, P_i', \sigma) \leq u_i^m) \wedge (t_i^l \neq t_i) \tag{8}$$

Combining these evidences, we construct an indicator that returns `True` if the agent might have formed an opinion in the current round, m using trust level t_i^l with actual trust level t_i:

$$\text{Evs}(t_i^l, t_i, m) = \text{Ev1}(t_i^l, t_i, o_i^m) \vee \text{Ev2}(t_i^l, t_i, u_i^m) \tag{9}$$

Following the definition of the agents' awareness rate (Eq. 4), we formulate the empirical estimator of the awareness rate for each trust level out of the candidates $t_i^l \in T_i$ after the number of dissemination rounds $|M|$:

$$\hat{h}(t_i^l) = |\{m \in M : \text{Evs}(t_i^l, t_i, m) = \texttt{True}\}| \,/\, |M| \tag{10}$$

Algorithm 2 describes the core procedure of AAT that is executed after each dissemination round. In lines 3-7, AAT updates the estimates of the awareness rate for each of the candidate trust levels according to the procedure described above. If no opinions were observed ($u_i^m = 0$), the agent cannot form its own opinion with any of the trust level, and thus this case is limited by the condition on lines 1-2. Now, according to optimisation problem the agent solves (Eq. 6), it has to select the trust level (line 8) that delivers the awareness rate closest to the target, h_{best}, considering the high interdependence between agents' choices.

3.3 Strategies to Select a Trust Level

The problem of selecting the best trust level out of the candidates, accordingly their estimated awareness rates, resembles the standard multiarmed bandit (MAB) model. In the MAB problem, there is a machine with $|T_i|$ arms (the candidate trust levels in our case), each of which delivers a reward

Algorithm 3 Hill-climbing strategy to select a trust level

Function CHOOSET($i, \epsilon = 0.05$)

$T_i := \langle \text{SORTASC}(T_i) \rangle$ {in order to use position indexes}
$l := \text{GETPOS}(t_i \in T_i)$
if $l < |T_i|$ **and** $\hat{h}^m(t_i^l) < h_{\text{best}}$ **then**
    $l := l + 1$
else if $l > 1$ **and** $\hat{h}^m(t_i^{l-1}) > h_{\text{best}} + \epsilon$ **then**
    $l := l - 1$
return t_i^l

(the awareness rate), that is independently drawn from an unknown distribution, when the machine's arm is pulled. Given this, we can apply the following widely recognised MAB strategies [Vermorel and Mohri, 2005] to select the trust level out of the candidates:

- **Greedy**: A benchmark that selects the trust level, which has the awareness rate closest to h_{best}.
- **ϵ-greedy**: Selects the trust level closest to the target awareness rate with probability $\epsilon - 1$, otherwise it selects a random one (let the random factor is $\epsilon = 0.1$).
- **ϵ-N-greedy**: The same as above but the random factor, ϵ decays in time as $(\epsilon - 1)/f(m)^2$ where $f(m)$ is selected such that it becomes insignificant after $m > 150$.
- **Soft-max**: Chooses each trust level with probability $\frac{\exp(q(t_i^l)/\tau)}{\sum_{v=1}^{|T_i|}\exp(q(t_i^v)/\tau)}$, where $q(t_i^l) = |\hat{h}^m(t_i^l) - h_{\text{best}}|$, and τ is the temperature that decays to 0 after $m > 150$.

The latter two strategies gradually decay their exploration in time. Following our note regarding the high interdependence of agents' opinions earlier, a trust level chosen by a single agent eventually affects the dynamics of the whole team. Thus, we expect the strategies with less dramatic changes in agents' dynamics to estimate awareness rate more accurately and converge to the solution faster.

MAB strategies assume that the distribution of awareness rates is unknown, however we note its shape can be estimated. For the candidate trust levels, T_i, sorted in ascending order the smaller trust level, t_i^1, requires more sequential updates to cross one of the confidence bounds, while the larger $t_i^{\max}$ requires less, and thus we expect $h(t_i^1) \ll h(t_i^{\max})$. Consequently, awareness rates are distributed as a hill with a peak for the largest trust level. Therefore, we offer the additional strategy that makes use of this observation:

- **Hill-climbing**: Select a trust level from the closest trust levels to the currently used. So, if the awareness rate delivered by the currently used trust level, t_i, is lower than target h_{best}, the agent must increase the trust level to the closest larger one. Conversely, if the closest lower trust level is estimated to deliver an awareness rate higher than h_{best}, the agent chooses to use it in the next round.

Algorithm 3 presents its definition with parameter ϵ that reduces the number of changes even further. We expect this strategy to deliver the highest reliability, since it introduces the least changes to the dynamics during the exploration.

4 Empirical Evaluation

To empirically evaluate the performance of AAT and the existing DACOR, we consider a wide range of parame-

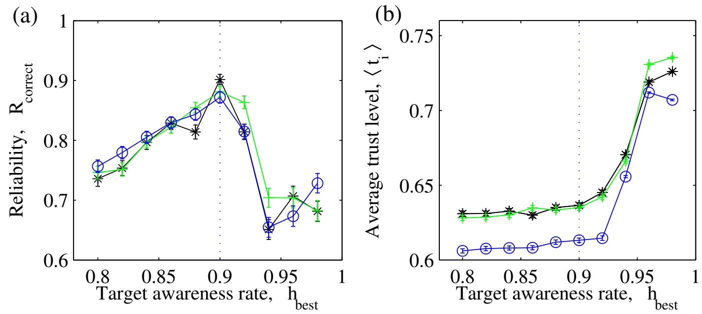


Figure 2: (a) The reliability of a team of 1000 agents, and (b) the average trust level achieved by AAT, both depend on the target awareness rate h_{best}. Each data point is averaged over the set of expected degrees.

ters in order to examine their adaptivity and scalability. Specifically, we evaluate the reliability of teams of $|A| \in \{150, 300, 500, 750, 1000, 1500, 2000\}$ agents on networks with a variable expected degree, $d \in \{4, 6, 8, 10, 12\}$. We consider the following network topologies widely used in the literature: (a) a connected random network; (b) a scale-free network with clustering factor $p_{\text{cluster}} = 0.7$ [Holme and Kim, 2002]; (c) a small-world ring network with $p_{\text{rewire}} = 0.12$ of randomised connections. [Newman, 1999]. We introduce new opinions through a small number of sensors ($|S| = 0.05|A|$ with accuracy $r = 0.55$), randomly distributed across the team. To simulate a gradual introduction of new opinions, only 10% of sensors make new observations after the preceding opinion cascade has stopped. Finally, all agents are initialised with the same confidence bound $\sigma = 0.8$, initial opinion $o_i^0 = \texttt{undeter.}$, and individually assigned priors P_i' that are drawn from a normal distribution $\mathcal{N}(\mu = 0.5, s = 0.1)$ within the range of the confidence bounds $(1 - \sigma, \sigma)$.

Before every round m we randomly choose the true state $b^m \in B$. Each round stops after 3000 sensors' observations and sequential opinion cascades. After this number of observations, opinions of the agents with sensors converge to the true state and are unlikely to change it any further, and thus, the dissemination process stops. The end of each round constitutes a deadline when the current true state expires, and agents reset their beliefs and opinions to the initial values. AAT and DACOR tune the trust levels in the first 150 rounds, then reliability is measured over the following 150 rounds

4.1 Selection of the Target Awareness Rate

We analyse the performance of our algorithm AAT based on the hill-climbing strategy with a regard to its single parameter – target awareness rate h_{best}. We support our discussion, that h_{best} has to be slightly lower than 1 to help agents to find the settings when the dynamics changes, and thus, to maximise the reliability. Figure 2 shows that the highest reliability achieved when $h_{\text{best}} = 0.9$ regardless of the topological properties, indicating on the adaptivity of AAT. The reliability significantly drops for the higher values of h_{best} since agents select much larger trust levels to form opinions out of smaller number of observations. Thus, they become overconfident and the whole team converges to the early opinion without fusing it with later observations that might be more accurate. Considering the results, in our further evaluation we use $h_{\text{best}} = 0.9$ since all strategies use the same approach to estimate the awareness rates.

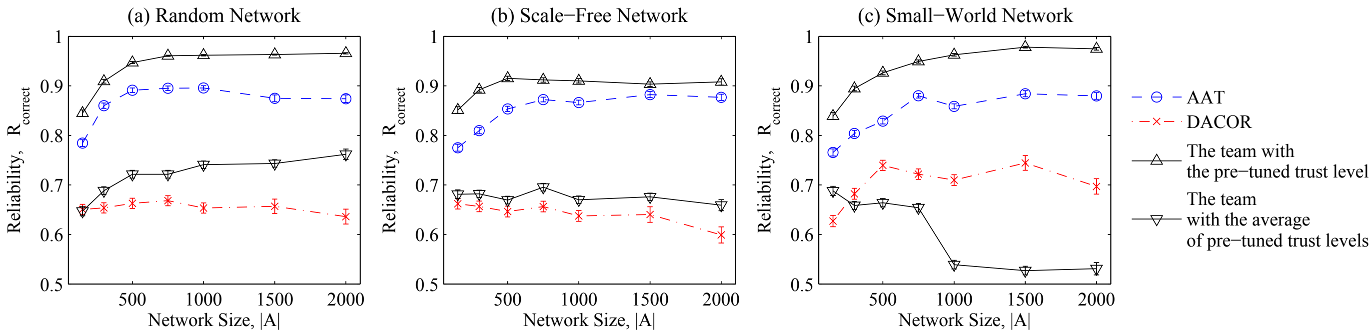


Figure 4: The reliability of a team with AAT, DACOR, and pre-tuned trust levels. Each network size is represented by 40 instances with variable expected degrees, the maximum size is limited by the large expenses of the pre-tuning process.

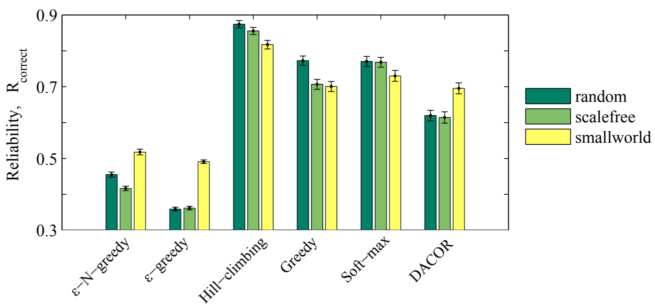


Figure 3: The reliability of a team of 1000 agents depending on the selection of strategy for AAT compared with DACOR. Each data point is averaged over the set of expected degrees.

4.2 Comparison of AAT Strategies

We test our hypothesis about the impact of the dynamics of different AAT strategies and choose the best one. Figure 3 presents the results with an additional comparison against DACOR. The ϵ-greedy strategy exhibits the worst performance since it introduces a large number of sudden changes to the opinions dissemination dynamics. Thus, due to the high interdependence in the team, AAT is not able to estimate awareness rates accurately and converge to the solution. Similar results are shown by the ϵ-N-greedy strategy with a slight improvement since its randomness decays with time. Despite its simplicity, the greedy strategy forces agents to keep an already selected trust level for a longer period, and with more stable dynamics the team converges to the better solution. However, a large number of agents change their trust levels simultaneously and thus, AAT fluctuates around the optimised parameters. The soft-max strategy provides better results by selecting the trust level with the awareness rate closest to the target with a higher probability, that introduces less sudden changes. And finally, the hill-climbing strategy introduces the least changes, estimates the awareness rates of the candidate trust levels accurately, and thus, exhibits the highest reliability. This experiment shows that the latter 3 strategies outperform the results achieved by DACOR, and in the following experiment we analyse this in wider settings.

4.3 Reliability of the System

Since the main objective of AAT is to improve the reliability of a team by helping agents to form accurate opinions, we benchmark its reliability against a team pre-tuned for the highest performance and against DACOR (with parameters $uA = 10, \gamma = 0.001, \beta = 0.1$ selected to maximise the reliability of a random network with $d = 8$). To pre-tune a team, we perform a resource intensive empirical exploration of each instance with fixed trust levels $t_i = t_{\text{f}}\ \forall i \in A$, where $t_{\text{f}} \in (0.5, 1)$ with a step of 0.05 over $|M| = 150$ rounds. Then we choose the trust level t_{best} at which the team exhibits the highest reliability. Note, that this is not the optimal solution, as it is infeasible to explore the whole domain where agents may have different trust values. Still, this approximation exhibits a high reliability of 0.9-0.97 and shows its level that can be achieved by a trust level tuning. However, t_{best} varies between different network instances since the area of optimised parameters is very narrow. Therefore, to show that it is hard to predict t_{best}, we provide the lower pre-tuned bound that shows the reliability of the team with the average $\langle t_{\text{best}} \rangle$ for the networks of the same size and topology.

The results of the reliability benchmark are shown in Figure 4. As can be seen, AAT shows reliability close to the results of the pre-tuned teams and significantly outperforms the existing solution, DACOR, for all network topologies. AAT scales well, since it reaches the stable reliability around of 0.86-0.88 for teams larger than 1000 agents. However, it declines as the team size becomes lower than 1000 agents, since all approaches improve the reliability by reaching the optimised settings when opinions are filtered on a team level, and these settings are less distinct on smaller teams. Analysis of the results showed that unlike adaptive AAT, DACOR is highly dependent on its parameters which have to be individually tuned for specific domains. And finally, the low reliability achieved by teams with $\langle t_{\text{best}} \rangle$ indicates a clear need for an algorithm that can efficiently tune each team individually.

4.4 Communication and Computation Expenses

AAT is designed to improve the reliability without introducing additional communication over opinion sharing described by the model. We compare the communication in Figure 5a as a number of messages that agents exchange while the team is tuned by AAT, DACOR, and the minimal number of messages required to share an opinion on a team scale in a single cascade. The latter represents the *minimal communication*, when agents share their opinions only once to the neighbourhood, and thus, communicate $d|A|$ messages. The average number of messages for a team with AAT is similar to the minimal communication, since during some rounds a team does not disseminate opinions on a large scale (as the result of $h_{\text{best}} < 1$). Thus, AAT is communication efficient and further reduction of the communication will harm the achieved reliability.

Also, AAT requires radically less changes of the trust lev-

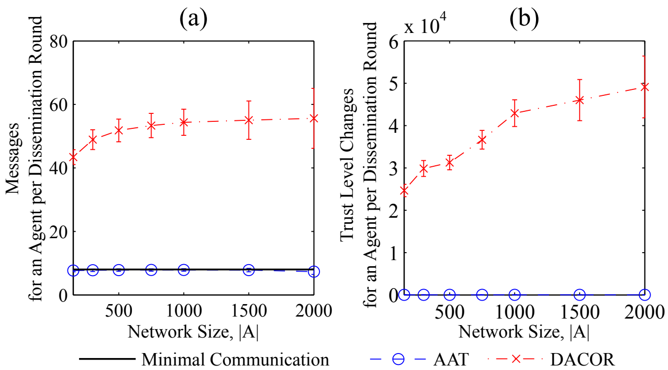


Figure 5: (a) Number of messages and (b) Number of trust level changes, for an agent per dissemination round. Measurements are averaged across all instances used in Fig 4.

els than DACOR in the process of tuning. AAT updates a trust level only once at the end of each round, while DACOR updates an agent's trust level if any of its neighbours has observed new opinion. The results that represent computational expenses, are shown in Figure 5b. Both expenses metrics confirms that AAT is a highly scalable solution.

4.5 Team with Indifferent Agents

Finally, AAT is robust and significantly improves the reliability when a large number of the agents are indifferent and do not participate in the optimisation process. To illustrate this, we evaluate a team with a variable number of indifferent agents that are randomly distributed across the team with trust levels that are not dynamically determined by AAT or DACOR algorithms, but fixed and uniformly selected from the range close to the critical trust level $[0.55, 0.75]$. The results in Figure 6 shows that AAT with up to 50% of indifferent agents delivers higher reliability than can be achieved by using $\langle t_{\text{best}} \rangle$. This shows the direct benefit from deploying AAT even on half of the agents in a team over the manual tuning by predicting the critical trust level based on the analysis of a number of similar teams. Similar results are obtained for the other topologies and team sizes.

5 Conclusions

We developed a decentralised algorithm, AAT, which significantly improves the accuracy of agents' opinions about the true state of the common subject of interest, and thus, improves the reliability of the team, in the settings where communication is limited to the opinion sharing. AAT reaches the parameters where a large team becomes a collaborative filter when early and possibly inaccurate opinions are shared amongst small groups to prevent overreacting, and only these locally vetted opinions are disseminated on a large scale.

We showed that AAT significantly outperforms the existing algorithm, DACOR, and delivers reliability close to the team individually pre-tuned by the resource expensive empirical exploration. AAT is the first solution that operates with the minimal communication requirement and it is computationally inexpensive, while DACOR requires a significant communication overhead and considerably more update cycles. We showed that AAT is scalable, adaptive and robust, and it significantly improves the reliability of team where up to half of the agents do not participate in the optimisation process.

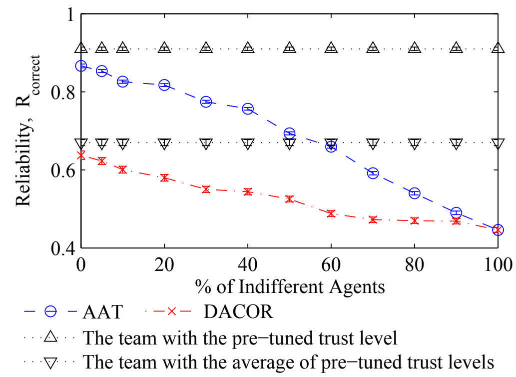


Figure 6: The reliability with indifferent agents averaged over 40 scale-free networks of 1000 agents with variable degree d.

Our future work in this area is to investigate the applicability of our algorithm to the continuous settings of opinions dissemination by relaxing the assumptions that information expires after a certain deadline and agents have to reset their opinions. Also, we plan to extend AAT with individual trust levels for each neighbour based on learning their dynamics to reduce the effect of the double counting fallacy.

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