Dynamic Facts in Large Team Information Sharing (Extended Abstract)

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ABSTRACT
In this paper, we extend the large team information sharing problem to consider *dynamic facts*, where the value of facts about the environment being observed can change over time. Dynamic facts are challenging because the team must repeatedly converge to consistent, accurate beliefs over time, without necessarily knowing if or when the fact changes values. We discover an interesting, emergent phenomenon: *institutional memory*, where the team as a whole becomes stuck remembering outdated beliefs. We demonstrate that controlling the trust placed in new information from neighboring agents does not adequately control belief convergence with dynamic facts, which previously was shown to benefit the team when working with static facts.

Categories and Subject Descriptors
I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *intelligent agents, multiagent systems*

General Terms
Performance, Experimentation

Keywords
Information Sharing; Dynamic Facts; Large Team

1. INTRODUCTION
For multiagent systems in complex environments, one important but challenging task is maintaining correct beliefs about the environment. Agent sensing has received increased attention in the recent literature, especially in robotics (e.g., [9]), human-agent interactions (e.g., [1]), and wireless sensor networks (e.g., [6]).

One interesting related problem is **large team information sharing** (LTIS) [2, 3, 4, 7], where many agents (e.g., 1000) work together as a team to observe the environment. Making this problem challenging and unique: only a small proportion of the agents (e.g., 5%) have sensors used to *directly* observe the environment. Moreover, these sensors are inaccurate, only producing correct observations according to accuracy probability r (e.g., 55%). All other agents rely on information shared throughout the team to form beliefs. Because the team is so large, agents cannot directly communicate with everyone. Instead, agents are localized within small, overlapping neighborhoods of average size $\bar{d}$ (e.g., 8).

In particular, agents are tasked with observing a fact F describing the environment, which is often binary (i.e., $True$ or $False$), although the problem can be easily extended to more values [7].

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Using sensor observations or information shared by neighbors, each agent forms a probabilistic belief b about F. Each agent starts with an initial belief of pure uncertainty, then uses Bayesian updating to incorporate new information, where new information is weighted based on its source: either using r for sensor observations or m_j for trust placed in agent a_j's neighbors. To filter noisy observations and minimize communications, agents only share information when they become reasonably confident that a fact is either $True$ or not. Specifically, an agent uses a confidence threshold $\sigma \geq 0.5$ (e.g., 0.8) to discretize its belief into confident opinions that are shared with its neighbors: it shares $True$ if $b(True) > \sigma$, and $False$ if $b(True) < 1 - \sigma$.

In the prior LTIS research [2, 3, 4, 7], the fact F observed by the agents has been assumed to be *static* and does not change during observation. This assumption is valid in many environments where the observed fact either does not change or changes slowly enough that the team will never notice a change while performing LTIS. Furthermore, studying static facts simplifies the problem and enabled prior research to form a good understanding of the fundamental properties of LTIS, creating both useful analytical models (e.g., [2, 3]) describing the effects of various team parameters on emergent behavior, as well as distributed algorithms for controlling information sharing (e.g., [3, 7]).

However, in many multiagent environments, the environment itself is *dynamic* and thus agents can experience **dynamic facts** that change values over time. Since a fact can change while under observation, dynamic facts could greatly reduce the ability of agents to converge to consistent, accurate beliefs. For instance, older beliefs might no longer reflect the current value of the fact in the environment, (1) causing incorrect beliefs (that might have been correct previously) and (2) requiring additional information gathering and sharing throughout the team. Moreover, because neighborhoods are relatively small, there is a delay between when a fact is observed and when information reaches agents far from sensors. Thus, after a fact change, information being propagated could be both *accurate* (due to recent observations from the sensors) and *inaccurate* (due to older observations still being communicated deep in the team), making it difficult to know what information to believe and what to discard.

2. IMPACT OF DYNAMIC FACTS
Due to dynamic facts, we have discovered an interesting emergent behavior that we call the **institutional memory phenomenon**: the team correctly converges its beliefs to the fact's initial value, but then fails to properly revise its beliefs over time. Specifically, agents primarily *remain stuck* with their initial belief and *do not even become uncertain* as conflicting information is received.

We hypothesize that this problem could be caused by a lack of information flow through the team of agents. Recall that only a small proportion of agents can directly observe the dynamic fact, so the other agents in the team must rely on shared information to revise their beliefs over time as the fact changes. With respect to information flow, prior research in LTIS has primarily focused on the impact of the trust m_j placed in new information from neighbors. For example, Glinton et. al [3] discovered that too little trust results in a lack of flow, whereas too much trust results in oscillating beliefs as too much information is exchanged.

Moreover, for static facts, an *optimal* trust values exists, dependent on the team's parameters (especially average neighborhood size $\bar{d}$), that enables (almost) all agents to share just enough information such that the team converges to consistent, accurate beliefs [3]. In the following, we demonstrate that (for at least some teams), *no optimal trust value exists* for information sharing with *dynamic* facts. Instead, each trust value either leads to (1) the same institutional memory phenomenon, or (2) no convergence to accurate beliefs (i.e., too low trust, similar to [3]).

For this study, we use the example values given in Section 1 for our team parameters (i.e., 1000 agents, 50 agents with sensors, 55% sensor accuracy, 8 neighbors), which were also used in previous LTIS studies (e.g., [3, 7]). We vary the trust in neighbors' shared information within the range [0.5, 0.95] using 0.05 increments. We consider a dynamic fact that alternates values between $True$ and $False$ every 1000 ticks (initially $True$) and use 100 different randomly generated teams to average the results.

Fig. 1 presents the proportion of agents holding a correct belief at each point in time as the dynamic fact changes values. We observe that no matter how much trust was placed in neighbor's information, the team *always* failed to adapt to the dynamic fact's changing value. That is, each time the fact changed values to $False$ (e.g., 1001-2000, 3001-4000 ticks, etc.), which was different from the initial value of $True$, fewer than 17% of the agents ever achieved a correct belief.

Comparing different levels of trust, we note that (1) for very low levels ($m_j < 0.6$), very few ($< 25\%$) agents *ever* achieved a correct belief, (2) for medium levels ($0.6 \leq m_j \leq 0.85$), many agents achieved accurate beliefs whenever the fact was its initial value of $True$, but performed very poorly whenever the fact was $False$, and (3) for very high levels ($m_j > 0.85$), the largest proportion of agents held accurate beliefs after the fact changed to $False$, but this was due to forming and retaining *incorrect* initial beliefs that were unintentionally correct after a fact change.

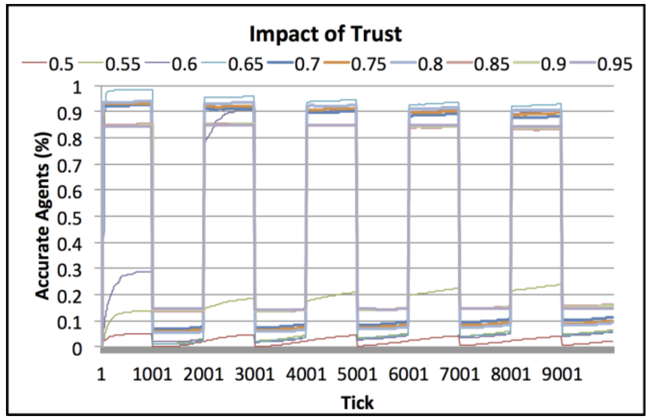

Figure 1: Impact of Trust

3. DISCUSSION

Overall, we conclude that not only do dynamic facts present an interesting challenge within LTIS, but no amount of trust placed in neighbors' shared opinions enables the agents to adapt their beliefs with the changing fact. This is much different from studying static facts, where optimal trust values do exist that lead to consistent, accurate beliefs. Moreover, since no appropriate trust value exists for dynamic facts, prior algorithms that choose a trust level (e.g., DACOR [3], AAT [7]) cannot inherently solve the problems associated with dynamic facts. Instead, we require different types of solutions to overcome institutional memory.

We are currently developing two novel solutions focusing on the flow of information between agents: (1) a distributed algorithm where agents cooperate to detect changes to the dynamic fact in their local neighborhoods and reset their beliefs to both quickly reach a new accurate belief and share more information, and (2) a forgetting-based solution, where agents independently use belief decay (e.g., [5, 8]) to forget possibly outdated information based on the amount of time since the last belief update.

We also intend to develop new analytical models (similar to [3]) in order to formally describe the effects of dynamic facts on information sharing and belief convergence as emergent behaviors within the team. Such models will increase our fundamental understanding of LTIS and could inform additional solutions to addressing dynamic facts.

4. ACKNOWLEDGMENTS

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