The Effect of Well-informed Minorities and Meritocratic Learning in Social Networks

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Abstract: A significant amount of information acquisition in human groups occurs through social learning, i.e., individuals learning through communication with their peers. Since people communicate what they know and their information is not completely accurate, such peer-to-peer learning can lead to the spread of both knowledge and misinformation over social networks. How much of each occurs depends on many factors, including the quality of knowledge in the group as a whole, its initial distribution over the network, and the learning styles of individuals. The number of configurations in which these factors can occur is infinite, but multi-agent network models provide a promising way to explore plausible scenarios. In this paper, we use such a model to consider the joint effect of two factors: 1) The proportion of initially well-informed and ill-informed agents in the population; and 2) The choice of each group to learn in one of two plausible ways. The simulations reported find that both factors have a large effect.

1 INTRODUCTION

The spread of misinformation in social networks has recently been a topic of major interest because of the increasingly important role social media is playing in politics and policy (Del Vicario et al., 2016; Allcott and Gentzkow, 2017; Shu et al., 2017; Waldrop, 2017; Vosoughi et al., 2018; Oliveira and Chan, 2018; Tambuscio et al., 2018). However, the social propagation of misinformation has been part of human society since time immemorial, and methods to counter it have become part of the social mores and codes in virtually all societies. The challenge being faced at the present time arises from the sudden, exponential, and non-geometric amplification of social networking with the advent of the Internet. It has, therefore, become very important to understand the factors that contribute to the spread of misinformation or can mitigate such spread. Of course, this is an extremely complex issue that can be addressed at many different levels using a variety of approaches. In this paper, we describe a simple, abstract multi-agent model called MANILA (Multi-Agent Network for the Implicit Learning of Associations) to explore the *implicit* social propagation of false conceptual associations. We apply this model to look at the effect of two factors on the spread of such misinformation: 1) The presence of an extremely well-informed minority in the population; and 2) The preference of individuals to attend to peers based on their perceived like-mindedness versus their reputation for being well-informed. The model considers both the quality and quantity of information, and attempts to capture the implicit nature of social learning as well as some of its cognitive complexities.

2 MOTIVATION

Human knowledge is necessarily imperfect, and the ubiquity of social learning makes it inevitable that false information would spread to some degree in human populations (Buntain and Golbeck, 2017; Mendoza et al., 2010; Castillo et al., 2013). However, not all individuals are equally well- or ill-informed, and it is interesting to consider how the presence of exceptionally well-informed individuals in a population influences the quality of knowledge in the larger, less well-informed sub-population. Here, one can consider varying degrees of being well- or ill-informed as well as a varying presence of each class in the overall population. Exploring this entire space of possibilities is practically impossible even in a computational model, but a few canonical cases can be considered. One of these is when the population is divided into those who only have accurate information and those

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whose information is tainted to some plausible degree by inaccuracies. The proportion of each group in the population can then be varied systematically, as is the case in the present study.

A second interesting factor is which peers the agents in each sub-population learn from. Again, there are many possibilities, but the MANILA model includes three pure strategies for accepting information received from a peer: 1) Based on the strength of the social connection; 2) Based on perceived like-mindedness; and 3) Based on the empirically observed reputation of the peer for having accurate information. Well-defined mixtures of these strategies are also possible. In this paper, we consider the canonical situation where well-informed agents prefer to learn from high-quality peers whereas the less well-informed agents prefer to learn from like-minded ones. We then consider whether the mixture of some quality preference in the latter population can have a significant effect.

3 BACKGROUND

The two main features of MANILA are the spread of information in the social network and the implicit learning of (true and false) associations that results from it. This section relates these features of MANILA to prior work.

The diffusion of information in social networks has been studied empirically for a long time, resulting in several models (Granovetter, 1978; Liggett, 1985; Kempe et al., 2003). Many other models have also been developed for the diffusion and spreading of ideas, innovations, information, and disease on social networks (Adar and Adamic, 2005; Leskovec et al., 2006; Leskovec et al., 2007; Watts and Dodds, 2007; Liben-Nowell and Kleinberg, 2008; Goldenberg et al., 2008). The effect of model structure on the spread of information (and misinformation) has also been studied (Weng et al., 2013). Lamberson (Lamberson, 2010) proposed the term "cognitive advantage" as a factor in how one should study idea propagation, and criticized previous models that took into consideration only the underlying structure of the social networks without looking at the cognitive and psychological profile of agents diffusing information or ideas through the social network. MANILA also incorporates the cognitive preferences and reputation of agents in the model.

Though learning and adaptation are not part of all multi-agent models (MAS), in most cases the phenomenon of interest does require the inclusion of adaptation – often in the form of reinforcement learning (Sutton and Barto, 1998), where agents learn to improve their choices based on positive or negative feedback from the environment or a critic. Learning in MAS is a natural extension of classic reinforcement learning, but adds a crucial social component, with learning depending not only on rewards, but also on communication, attention and information diffusion (Weiss (ed.), 1999). In almost all cases, however, reinforcement learning is explicit, with each action or sequence of actions eliciting a direct, visible reward from a critic. MANILA, in contrast, uses a type of reinforcement learning that differs from the classic paradigm because it uses reward only implicitly and indirectly.

Bayesian models of learning in social networks have been studied by several researchers (Gale and Shachar, 2003; Rosenberg et al., 2009; Acemoglu et al., 2011; Lobel and Sadler, 2012; Mueller-Frank, 2013). These models are complex, and focus mainly on proving the convergence of beliefs to the truth. However, most of them do not model the dynamics of learning and information diffusion, or the associative nature of knowledge. In contrast, MANILA takes into consideration the representation of knowledge as epistemic networks, the communication of this knowledge, and the flow of ideas over a social network with a specific structure – albeit in a simple, idealized way.

Implicit learning (Reber, 1967; Seger, 1994) refers to learning that occurs incidentally and without awareness of learning. Most work on this – including computational models (Dienes, 1992; Mathis and Mozer, 1994) – focuses on individuals without reference to social factors (Berry, 1997; Dienes and Berry, 1997). In MANILA, however, the term refers to the acquisition or loss of conceptual associations by agents as a side-effect of their communication with each other, and incorporates both social and cognitive factors.

4 MODEL DESCRIPTION

4.1 Overview

MANILA is a system with *cognitive and generative agents* who receive and learn associative information implicitly from interaction with their peers in a social network. The social network is assumed to have a small-world (SW) architecture as proposed by Watts and Strogatz (Watts and Strogatz, 1998). The *knowledge* of each agent, i, is represented as an *epistemic network* (EN), E^i, whose nodes represent *concepts* and edges indicate *associations* between concepts. Therefore, This system has a *network-of-networks* structure with two levels of networks: The social network connecting the agents, each of whom has an epistemic network. To mimic natural discourse, agents are assumed to communicate not in terms of concepts, but *ideas*, which are combinations of concepts, as postulated in most models of ideation (Campbell, 1960; Mednick, 1962; Brown et al., 1998; Paulus, 2002; Fauconnier and Turner, 2003; Simonton, 2003; Simonton, 2010). Formally, an idea is defined as a 0.5-quasi-clique (Brunato et al., 2008) of 6 to 10 concept nodes in the EN. Concepts and ideas are defined purely in abstract terms to perform systematic simulations, but a lexical network based on a text corpus could be used as well.

Agents in MANILA generate and express ideas, i.e., combinations of concepts, based *not* on their expectation of reward – which they have no model to calculate – but on their subjective assessment of the idea's coherence within their own mind, which they use as a surrogate for its value. This models the natural situation in human expression where individuals express ideas based on their own convictions rather than on a calculation of external reward, with the tacit assumption that those convictions, in fact, represent real value or truth.

Similarly, when an agent receives an idea from a peer, it assimilates that idea into its own mind based not on some explicit reward that the idea has visibly generated, but based on its esteem and regard for the peer from whom it came. This esteem, in turn, can be based on several factors, including those that have no bearing on the veracity of the idea or the agent.

The Oracle

Since the focus of this work is on false associations, there needs to be a criterion of true associations, and a mechanism by which the correctness or incorrectness of expressed ideas can be perceived in the social network. In keeping with the abstract nature of the model, we assume that there is a fixed large *ideal epistemic network* (IEN) of concepts and true associations known only to an *Oracle*, which thus represents the ground truth. Agents' initial ENs represent partial, noisy samples from the IEN, reflecting the fact that an individual agent's information is typically incomplete and possibly inaccurate. Whenever an agent expresses an idea, it is evaluated by the Oracle and elicits a *reward* to the agent based on the idea's consistency with the Oracle's IEN. Thus, the Oracle plays the role of the critic in classic reinforcement learning. However, in this case, the reward represents only the *implicit* benefit and reputation an agent acquires for being right, and is not publicly visible or linked explicitly to a specific idea in the generating agent's perception. Agents accumulate the rewards they receive with a decay factor, and the *cumulative* reward of an agent at a given time is visible to other agents as an indication of the agent's *merit status*. Thus, over time, every agent can see which of their peers are more (or less) well-informed in an aggregate sense.

In a real-world situation, the role of the Oracle would be played by fact-checkers, news reporters, experts, and the general social consensus on what is or is not acceptable as fact. In MANILA, the Oracle provides a purely abstract but fixed (and therefore objective) reference against which the correctness of assertions can be evaluated.

The Social Network

The social network in MANILA is defined by a symmetric small-world adjacency matrix $C = [c_{ij}]$, where $c_{ij} \in \{0,1\}$ indicates whether there is a social connection from A_j to A_i.

Epistemic Network Initialization

The initial EN for agent A_k is constructed in three steps:

1. A set of ideas is sampled randomly from the Oracle's idea repertoire.
2. The selected ideas are superposed to create an epistemic network with N edges, all of which are true by construction (because they came from the IEN).
3. Next, qN true edges are removed and the same number of false edges are added, giving the initial EN for A_k as a partial and noisy version of the IEN, with $q \in [0,1]$ controlling the degree of misinformation (incorrect associations) in the final EN.

4.2 Bayesian Model for Learning

Association Weights

For each Agent, A_k, if there is an edge $e^k_{ij} = 1$ between concept nodes i and j in its EN, it has a weight w^k_{ij}, representing the agent's *confidence* in the association between the concepts represented by nodes i and j. The weights are initially chosen independently from a uniform distribution between 0 and 1, and change based on an agent's learning process using a Bayesian formulation.

Idea Generation and Expression

Each agent potentially generates an idea at each time

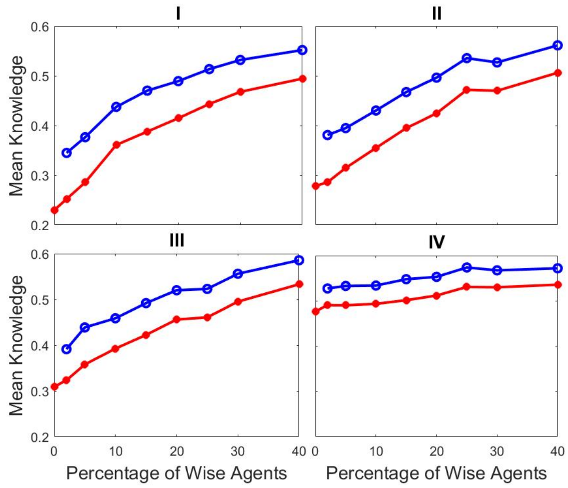


Figure 1: Mean Agent Knowledge after 1000 epochs for wise agents (upper blue curve) and normal agents (lower red curve) for various percentages of wise agents.

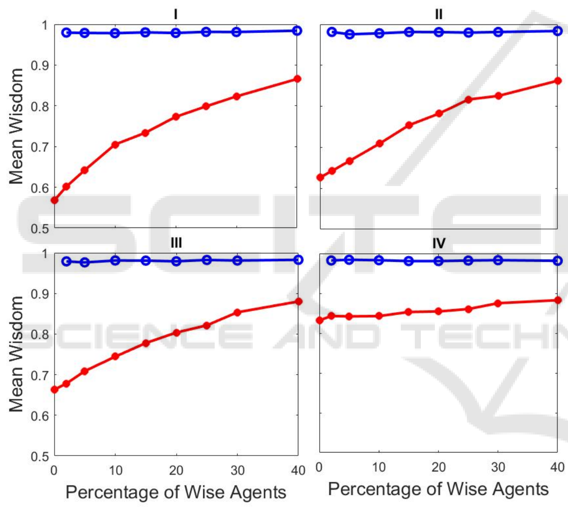


Figure 2: Mean Agent Wisdom after 1000 epochs for wise agents (upper blue curve) and normal agents (lower red curve) for various percentages of wise agents.

step by sampling its EN via an *attentional search* process. The edges in the generated idea are binary rather than weighted:The agent is asserting which associations exist or do not exist in the idea, and not indicating how strongly it believes each association in its own mind. However, the association weights are taken into account by the agent in the process of generating ideas. Idea generation and expression occurs as follows:

1. **Attentional Focus:** This step identifies the concepts and associations that agent A_s currently has in mind. A seed set of nodes is identified in the EN of the *source agent* A_s. This is then used to obtain the biased set of nodes via spreading activation. After removal of low-degree nodes, this gives the sub-network, $E^s_B(t)$, which is designated the current *attended epistemic network* (AEN) of the agent at time t, and represents the internal attentional focus of the agent (Iyer et al., 2009; Iyer et al., 2010).
2. **Generation of Potential Ideas:** This step generates the set $G^s(t)$ of all possible *potential ideas*, $g^s_i(t)$, within the AEN by applying the quasi-clique search algorithm, with the number of nodes per idea restricted to be between 6 and 10.
3. **Evaluation of Potential Ideas:** Once agent A_s has generated the set of potential ideas, $G^s(t) = \{g^s_i(t)\}$, it evaluates the *coherence*, $q^s_i(t)$, of each idea based on the density of its internal connectivity and weight of its edges in its AEN. For an idea g^s_i with nodes N^s_i and edges E^s_i, the weighted coherence is given by:

$$z^s_i = \sqrt[n]{\prod_{e \in E^s_i} w_e} \tag{1}$$

where w_e is the weight of the edge e and $n = |E^s_i|$ Thus, more densely connected ideas with higher weights are considered more coherent. Coherence is the agent's subjective assessment of the quality of an idea.
Coherence values below a threshold ϕ are set to 0. The result is a coherence vector $Z^s(t) = \{z(g^s_i(t))\}$ for the set of ideas in $G^s(t)$. If no idea meets threshold ϕ, the coherence vector is null, and the agent remains silent in that time-step.
4. **Idea Selection and Expression:** One of the ideas from $G^s(t)$ is chosen for expression by using a roulette wheel algorithm based on the coherence of the ideas, i.e., the probability of choosing idea $g^s_m(t)$ for expression is:

$$p_{comm}(g^s_m(t)) = \frac{z^s_m(t)}{\sum_{u \in G^s(t)} z^s_u(t)} \tag{2}$$

Once A_s decides to express the idea, it broadcasts it to all its immediate neighbors in the social network.

The seed set is also continually updated by the natural dynamics of the system based on recently generated ideas and what the agents hears from others (see (Shekfeh, 2017) for details.)

Idea Evaluation and Reward

Ideas expressed by agents are evaluated by the Oracle based on the number of true and false associations in it. If an idea g is expressed by agent A_s at time t, it generates a reward using the function R that is computed by the Oracle as follows:

$$R(\chi(g)) = \begin{cases} 0.5[1-(\chi(g))^{1-\mu}] & if\, \chi(g) \leq 0 \\ 0.5[1+(\chi(g))^{1-\mu}] & if\, \chi(g) > 0 \end{cases} \tag{3}$$

where μ is the *reward selectivity* parameter and $\chi(g)$ represents the Oracle's quality evaluation function for ideas. Given an idea g, its quality is calculated as :

$$\chi(g) = \frac{e_{true} - e_{false}}{e_{total}} \tag{4}$$

where e_{total} is the number of edges in g, e_{true} is the number of edges in g that are also present in the IEN, and e_{false} is the number of edges present in the g but not in the IEN.

The *merit* of agent k is then computed as follows:

$$\xi^s(t+1) = (1-\sigma)\xi^s(t) + \sigma R(\chi(g)) \tag{5}$$

where $\sigma \in (0,1)$ is the *merit adaptation rate* parameter and is set to a small value. Thus, the more accurate the ideas expressed by an agent, the more merit it acquires over time.

Idea Reception and Assimilation

Idea Reception: When a *receiving agent* A_r receives an idea from source agent A_s, it can choose to ignore it or assimilate it into its own EN, thus learning that idea. The idea is assimilated with a probability based on the receiving agent's general *receptivity* to ideas and its specific *attentiveness* towards the sending agent A_s. The attentiveness of A_r towards A_s depends on three possible factors: 1) The *social weight*, φ_{rs}, between the agents; 2) The empirical *epistemic affinity*, ψ_{rs}, that A_r has inferred with A_s (see below); and 3) The *merit differential*, $\xi_s - \xi_r$, of A_r and A_s. The attentiveness of agent A_r towards agent A_s is represented by the *esteem* of A_r for A_s:

$$\Lambda_{rs} = c_S^r f_S(\psi_{rs}) + c_E^r f_E(\varphi_{rs}) + c_R^r f_R(\xi_s - \xi_r) \tag{6}$$

where $f_S(\ )$, $f_E(\ )$, and $f_R(\ )$ are monotonically increasing sigmoid functions with range 0 to 1, and c_S^r, c_E^r and c_R^r, are parameters representing the social, epistemic, and perceptual components of the attentiveness function, respectively. These are defined on the simplex $c_S^r + c_E^r + c_R^r = 1$, so that the tuple (c_S^r, c_E^r, c_R^r) defines the *learning style* of agent A_r. There are three pure learning styles:

1. *Social* Learning Style (1, 0, 0), where the agent learns preferentially from those to whom it has strong social connections. The social selectivity function determines how esteem depends on social weight with the source agent. It is defined as:

$$f_S(\varphi) = \begin{cases} 0.5[1-(1-2\varphi)^{1-\alpha}] & if\, \varphi \leq 0.5 \\ 0.5[1+(2\varphi-1)^{1-\alpha}] & if\, \varphi > 0.5 \end{cases} \tag{7}$$

where α is the *social selectivity* parameter. If $\alpha = 0$, f_S has linear dependence on social weight. As α increases towards 1, $f_S(\varphi(r,s))$ approaches a threshold function at $\varphi(r,s) = 0.5$, so the agent accepts ideas only from peers with social connection $\varphi(r,s) > 0.5$.

2. *Like-Minded* Learning Style (0, 1, 0), where the agent learns preferentially from agents that have previously expressed ideas similar to its own. This function determines how esteem depends on epistemic affinity that the receiving agent perceives with the source agent. It is defined as:

$$f_E(\psi) = \begin{cases} 0.5[1-(1-2\psi)^{1-\beta}] & if\, \psi \leq 0.5 \\ 0.5[1+(2\psi-1)^{1-\beta}] & if\, \psi > 0.5 \end{cases} \tag{8}$$

where β is the *epistemic selectivity* parameter. If β = 0, f_E becomes a linear function of epistemic affinity. As β increases towards 1, $f_E(\psi(r,s))$ approaches a threshold function at $\psi(r,s)$ = 0.5, so the agent accepts ideas only from peers with epistemic affinity $\psi(r,s) > 0.5$.

3. *Meritocratic* Learning Style (0, 0, 1), where the agent learns preferentially from those who have higher accumulated merit than itself. The f_R function determines how esteem depends on the *difference* between the merit status of the receiving agent and the source agent. It is defined as:

$$f_R(\Delta) = \begin{cases} 0.5[1-|\Delta|^{1-\gamma}] & if\, \Delta \leq 0 \\ 0.5[1+|\Delta|^{1-\gamma}] & if\, \Delta > 0 \end{cases} \tag{9}$$

where the *differential status*, $\Delta = \xi_s - \xi_r$ is the difference in current merit status between the receiving agent and the source agent, and γ is the *merit status selectivity* parameter. If γ = 0, f_R is a linear function of reward status. As γ increases towards 1, $f_R(\Delta)$ approaches a threshold function at $\Delta = 0$, so ideas from an agent with higher status are always accepted and those from agents with lower status are not.

The probability of agent A_r accepting an idea from agent A_s is:

$$P_{accept}(r,s) = \kappa_r \Lambda_{rs} \tag{10}$$

where $\kappa_r \in [0,1]$ is the general receptivity of agent r to ideas from others. We use $\kappa_r = 1$ for all agents.

Idea Assimilation: Once the receiving agent A_r has decided to accept an idea, g, from the source agent A_s, it must be assimilated into A_r's EN. The process of assimilating a new idea involves updating the weights of edges using a Bayesian model. The process for updating the edge between concept nodes i and j in the received idea comprises the following steps:

- If i and j are connected (disconnected) in both g and E^r, they remain connected (disconnected) in E^r. However, in the connected case, the edge weight is adjusted according the weight adjustment rule which is described in the following section.
- If i and j are connected in g but not in E^r, A_r connects them with a small weight, w_ε, with probability $p_{add} = \Lambda_{rs}$ – the esteem for agent A_s.
- If i and j are not connected in g but are connected in E^r, the weight in E^r is decreased by an amount Δw_{ij} which is also described in the Learning Rule section

Thus, the result is to make E^r more consistent with the received idea g. Both addition of associations and weight adjustment of edges is possible, which is crucial for improving initially noisy ENs.

The Learning Rule

The association weights in the ENs of individual agents change based on the ideas they assimilate from their peers, which increase or decrease the agents' confidence in each received association. A single weight update equation is as follows:

$$w^r_{ij}(t+1) = \bar{e}^s_{ij}\left[(1-\lambda)w^r_{ij}(t) + \lambda\frac{\rho_{sr}w^r_{ij}(t)}{(1-w^r_{ij}(t))+\rho_{sr}w^r_{ij}(t)}\right] + (1-\bar{e}^s_{ij})\left[(1-\lambda)w^r_{ij}(t) + \lambda\frac{w^r_{ij}(t)}{\rho_{sr}(1-w^r_{ij}(t))+w^r_{ij}(t)}\right]$$

where: $w^r_{ij}(t)$ is the belief at time t of agent A_r that the edge is True; $\bar{e}^s_{ij} \equiv$ the state of the edge in the message sent by agent A_s; $e^r_{ij} \equiv$ the state of the edge in the EN of receiving agent A_r: $e^r_{ij} = 1$ means the edge exists, else 0; λ is the *learning rate*; and ρ_{sr} is the odds ratio of A_r believing an association received from A_s. The last quantity is computed from Λ_{sr}, the esteem that Agent A_r has for Agent A_s, as follows:

$$\rho_{sr} = 1 - \log(1-\Lambda_{sr}) \tag{11}$$

Thus, an esteem of $\Lambda_{sr} = 0$ implies $\rho^1_{sr} = 1$, i.e., Agent A_r thinks that Agent A_s is just as likely to be wrong in its assertion of $e^*_{ij} = 1$ as it is to be right, it will learn nothing from Agent s and has no esteem for it.

Of course, it is necessary that $0 < \lambda < 1$. For the complete derivation of this equation, see (Shekfeh, 2017).

Two points should be noted here. First, that the esteem of A_r for A_s determines both whether the former accepts an idea from the latter and the degree to which the idea changes its own beliefs. Second, the learning happening here is implicit in that information elements (conceptual associations) are learned as a side-effect of assimilating ideas rather than individually, and that the agents are not trying explicitly to become wiser or more knowledgeable: It simply occurs as an implicit consequence of communication, attention, and influence among agents.

Activation and Forgetting

Not all knowledge in a person's mind is equally robust: Things must be brought to mind somewhat regularly, or may be forgotten entirely. This effect is modeled in the system by processes of activation and forgetting.

An association (edge) in an agent's EN is *activated* when it receives the agent's attention in the process of searching for ideas to express, or is updated via a received idea, that is:

1. If the two concepts occur in an idea received from another agent.
2. If the agent thinks of the two concepts as part of an idea it generates.

If the association is not activated at a time step, its strength changes as follows:

$$w_{ij}(t+1) = \begin{cases} (1-\varepsilon^-)w_{ij}(t) & if\ w_{ij}(t) \leq \theta_m \\ w_{ij}(t) & else \end{cases} \tag{12}$$

where ε^- is a small memory decay rate parameter.

Thus, if the absolute strength of the association between concepts i and j falls below θ_m, it begins to be forgotten and requires activation in order to survive. Through this process, both correct and incorrect associations can, in principle, disappear from the agent's mind – and from the entire population – over time. Recently activated concepts also provide the seed for idea search in the agent's mind.

Epistemic Affinity Update

The epistemic affinity, ψ_{sr}, that agent A_r perceives for agent A_s is based on the ideas it has seen from A_s, and quantifies the degree to which A_s says things that A_r agrees with. Initially, ψ_{rs} is set to 0.5 , i.e., neutral affinity. Every time A_r receives an idea, g, from A_s, A_r calculates the *raw similarity*, $S_r(g)$, of the idea with its own EN as:

$$S_r(g) = \frac{e_{present} - e_{absent}}{e_{total}} \tag{13}$$

where $e_{present}$ is the number of edges in g that are also present in EN_r, e_{absent} is the number of edges in g that are not present in EN_r, and e_{total} is the number of edges in g . Thus, if all the associations in g are already found in the receiving agent's EN, the raw similarity is +1, and if none are, the raw similarity is -1. A normalized *familiarity* value is then calculated as:

$$\Gamma(S) = \begin{cases} 0.5[1-(S)^{1-\nu_r}] & if\ S \leq 0 \\ 0.5[1+(S)^{1-\nu_r}] & if\ S > 0 \end{cases} \tag{14}$$

where ν_r is a small value $\in (0,1)$. A comparison with Eqns. (3) and (4) shows that the familiarity of idea g for agent A_r is a subjective version of the Oracle's objective reward metric: They represent an estimate of the *perceived truth* of the idea by the agent and the Oracle, respectively.

Then the epistemic affinity of agent A_r for A_s is updated as:

$$\psi_{rs}(t+1) = \psi_{rs}(t) + \eta[\Gamma(S) - \psi_{rs}(t)] \tag{15}$$

where $\eta \in (0,1)$ is a small adaptation rate parameter.

The $n \times n$ matrix $\psi(t) = [\psi_{rs}(t)]$ is defined as the *epistemic affinity matrix*.

4.3 Metrics of Agent Information

Agents are evaluated in terms of their information via two metrics:

1. **Knowledge:** This measures the *quantity* of correct information that the agent has in its EN compared to the Oracle's IEN, with a penalty for incorrect knowledge. The performance of agent A_k in time step t is computed as:

$$K_k(t) = \frac{e_{true} - e_{false}}{e_{total}} \tag{16}$$

where e_{total} is the number of edges in IEN, e_{true} is the number of true edges in EN_k, and e_{false} is the number of false edges in EN_k. Thus, if an agent knows all the true associations but no false associations, its knowledge is 1. If it has as many false associations as true ones, its knowledge level is 0, and when the number of false associations exceed true ones, knowledge becomes negative. This metric is similar in spirit to the standard *recall* metric, but allows for negative values.

2. **Wisdom:** This measures the *quality* of an agent's information regardless of its quantity. For an agent A_k, this is measured as:

$$W_k(t) = \frac{e_{true}}{e_{true} + e_{false}} \tag{17}$$

Thus, it is identical to the standard *precision* metric.

5 SIMULATIONS AND RESULTS

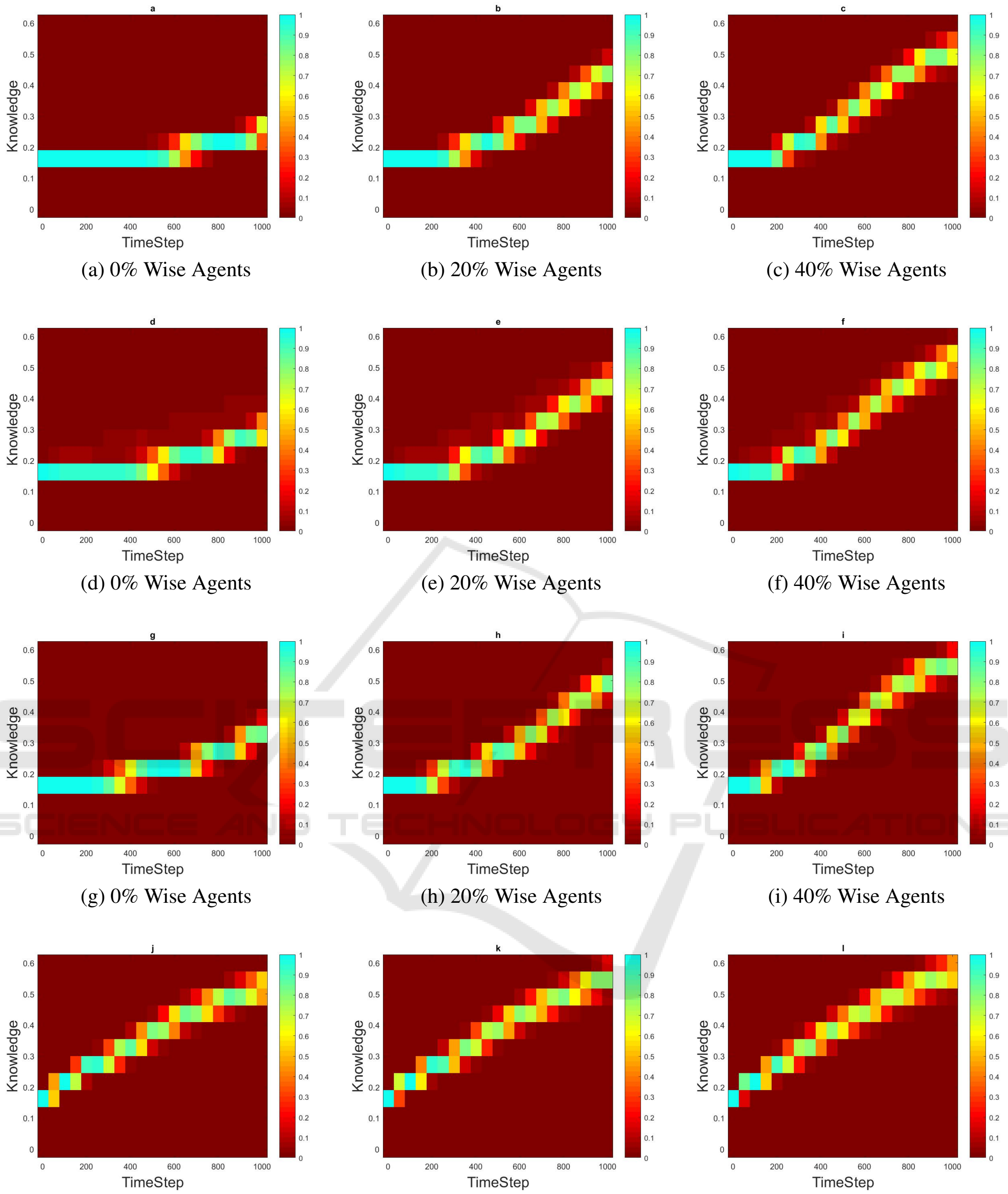
The simulations reported in this study use an undirected small-world social network with $n = 500$ agents and average degree of 20. All agents begin with ENs of approximately the same size, generated as described below. A fraction n_w of agents in the network are initialized as *wise* agents, i.e., $q = 0$ and all the associations in their initial EN are true. The remaining fraction $1 - n_w$ of agents are initialized as *normal* agents, with 5% false edges in their initial EN ($q = 0.05$). All the wise agents are assumed to always learn in the pure meritocratic style, while the learning styles of the normal agents are varied as described below.

5.1 Scenarios and Parameters

The simulations explore the effect of two factors on implicit learning in the network: 1) The fraction of wise agents, n_w; and 2) The learning style of the normal agents. The following 9 values of n_w are simulated: $n_w = 0$ (baseline case with no wise agents), 0.02, 0.05, 0.1, 0.2, 0.3, and 0.4. For each of these cases, four different learning style scenarios are simulated for the normal agents:

- **Case I:** All normal agents learn in the pure like-minded (0, 1, 0) style.
- **Case II:** 5% of normal agents learn in the pure meritocratic (0, 0, 1) style and the remaining 95% in the pure like-minded (0, 1, 0) style.
- **Case III:** All normal agents have a mixed (0, 0.95, 0.5) learning style: Mostly like-minded with a small degree of meritocratic learning.
- **Case IV:** All normal agents learn in the purely meritocratic (0,0,1) style – as do the wise agents.

Thus, in all there are 36 different simulation scenarios, with results averaged over 10 independent trials for each one. The *knowledge* and *wisdom* of each agent is tracked over time in each run. The structure of the social network is fixed across all simulations, but the positions of wise and normal agents



(a) 0% Wise Agents (b) 20% Wise Agents (c) 40% Wise Agents

(d) 0% Wise Agents (e) 20% Wise Agents (f) 40% Wise Agents

(g) 0% Wise Agents (h) 20% Wise Agents (i) 40% Wise Agents

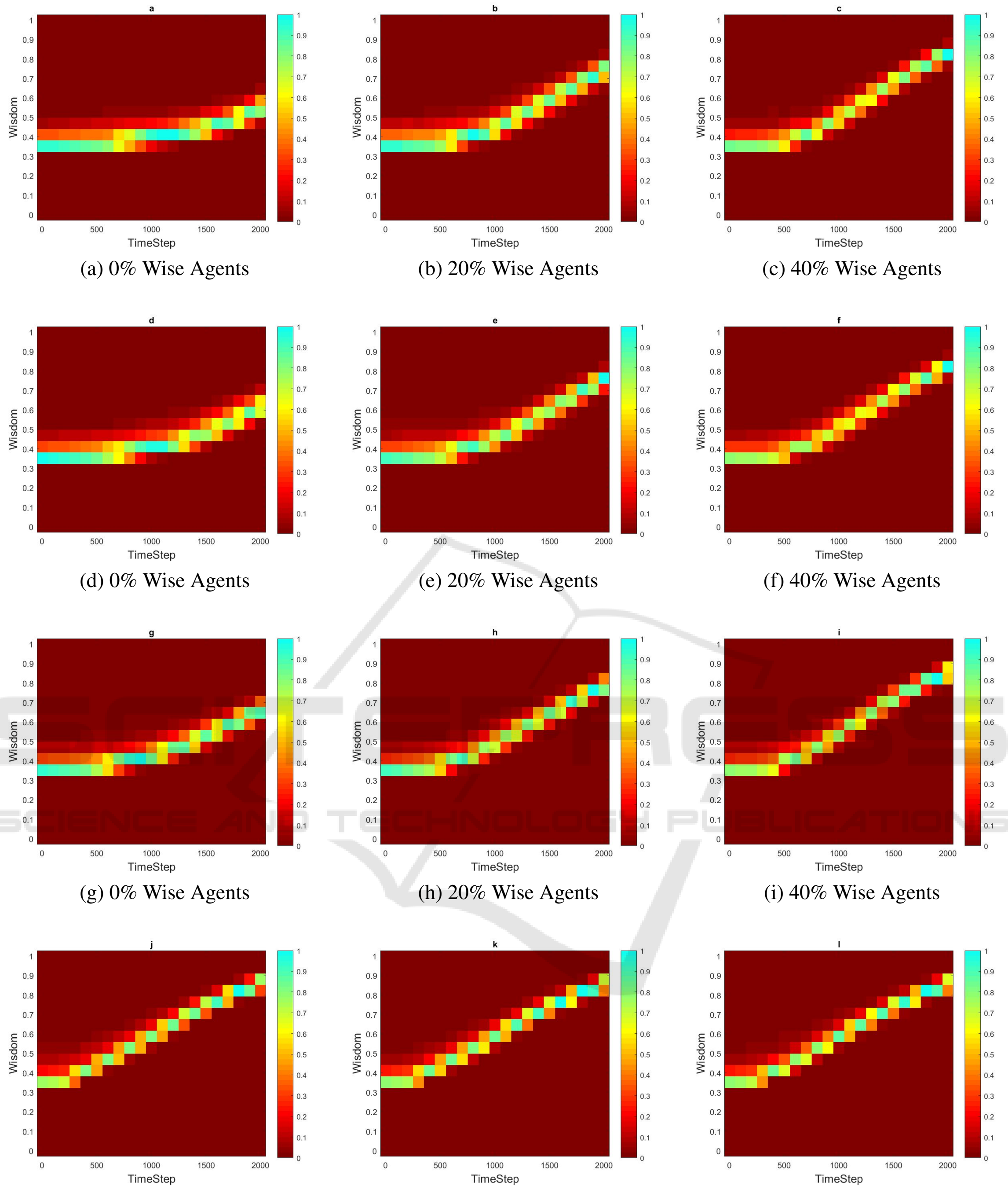
(j) 0% Wise Agents (k) 20% Wise Agents (l) 40% Wise Agents

Figure 3: Distribution of Knowledge in the *normal* agent population over time for Case I (top row); Case II (second row); Case III (third row); and Case IV (bottom row). In each image, the leftmost column shows the color-coded histogram of initial Knowledge distribution, and subsequent columns show the same at the end of successive a 50-epoch intervals.

(and learning style assignments in Case II) are varied randomly over trials. A total of 1,000 epochs are run in each trial, where an epoch comprises giving each agent the opportunity to generate and express an idea.

5.2 System Initialization

The initial ENs are set up at the start of each simulation trial by randomly selecting a set of true ideas from the ideas pool gathered *a priori* by parsing the



(a) 0% Wise Agents (b) 20% Wise Agents (c) 40% Wise Agents

(d) 0% Wise Agents (e) 20% Wise Agents (f) 40% Wise Agents

(g) 0% Wise Agents (h) 20% Wise Agents (i) 40% Wise Agents

(j) 0% Wise Agents (k) 20% Wise Agents (l) 40% Wise Agents

Figure 4: Distribution of Wisdom in the *normal* agent population over time for Case I (top row); Case II (second row); Case III (third row); and Case IV (bottom row). In each image, the leftmost column shows the color-coded histogram of initial Wisdom distribution, and subsequent columns show the same at the end of successive a 50-epoch intervals.

IEN and collecting all possible ideas in it. The individual EN of a normal agent is then parsed again to remove some true edges and add as many false ones to reach the noise level q as defined in the agent parameters. Wise agents do not have any noise, so all their associations are true. Then, the initial status of each agent is computed according to the wisdom formula. So the wisdom of normal agents is initialized as the number of correct ideas after adding noise divided by the original number of correct ideas when the EN is created. Accordingly, the merit status of all wise agents is initialized to 1.

Finally, the initial epistemic similarity is computed between all pairs of agents by calculating the overlap between their initial ENs.

5.3 Results

Figures 1 and 2 plot the final levels of mean knowledge and wisdom attained by each agent group as a function of n_w and the learning cases for normal agents. The following observations can be made:

- In the absence of wise agents (left-most data point in each graph), by far the best strategy for normal agents is to learn from better informed peers (lower right graph in each figure.)
- Introducing even a small fraction of wise individuals into the population improves the learning of the whole community.
- Increasing the fraction of the wise minority in the population improves the learning of the normal population dramatically, except when the normal agents adopt a meritocratic learning strategy, in which case the presence of more wise agents makes only a modest difference. This suggests that the effect of more wise agents is not mainly due to the greater available volume of correct knowledge they bring, but due to the greater number of connections to wise peers available to normal agents.
- of the two non-pure learning cases for the normal majority (Cases II and III), it is better for all normal agents to have a small meritocratic element in their learning rather than having a small fraction of normal agents learn purely meritocratically.
- Interestingly, the wise minority shows exactly the same pattern of improvement in their final knowledge level with higher n_w as is seen for the normal majority – albeit with an increment reflecting their edge in initial knowledge due to the absence of false associations. This can be explained by the fact that, since the wise agents follow a pure meritocratic strategy, they learn mostly from their wise peers and hardly ever from the normal majority. As such, increasing n_w increases the pool of peers from whom each wise agent can learn, leading to faster learning. And since the normal agents do not pay much attention to the merit status of their peers (except in Case IV), the learning pattern for the wise minority simply passes through to the normal majority.
- The general pattern of knowledge and wisdom is similar for the normal majority across all scenarios. Of course, the wise minority always retains its perfect wisdom because wise agents learn with a purely meritocratic strategy, and thus hardly ever accept an idea from less well-informed peers. It will be interesting to see how wise agents fare if some of them adopt a different learning style.

Figures 3 and 4 show the time evolution of the distribution of knowlegde and wisdom among the normal agents when n_w is 0, 0.2, and 0.4. The most notable feature of all these plots is that normal agents all learn together: There are no stragglers or any bifurcation. The figures also show that the added benefit from a larger wise minority start showing up early. In the beginning, the distribution remains quite stable around the initial distribution for both knowledge and wisdom. But it then reaches a breakout point where learning suddenly takes off. Interestingly, the delay before breakout depends greatly not only on the size of the wise minority (horizontal comparisons) but also on the learning style of the normal majority (vertical comparisons). This effect is stronger with knowledge than with wisdom. The adoption of a purely meritocratic learning style by the normal agents leads to a qualitatively different learning pattern, with breakout occurring almost immediately, a very linear rise in performance, and much higher final level of both wisdom and knowledge. The latter effect is very small if the wise minority is larger.

Many other things can be analyzed based on the simulations (e.g., the spread or disappearance of individual true/false edges in the social network), but this will be discussed in future reports.

6 CONCLUSIONS

In this paper, a multi-agent network of generative cognitive agents was used to look at the effect of having a well-informed wise minority in a larger population of normal agents that carry a certain amount of false information. It was found that the size of the minority has a direct effect on the implicit learning performance of normal agents. The study also found that the performance depends very strongly on the learning style adopted by the normal agents. In particular, this is seen in the transition of learning from an initial flat phase to a breakout with rapid learning.

The MANILA model is versatile and powerful enough to be useful for exploring many other issues related to the spread and learning of information in human networks, including the spread of false information – a critical problem at this time. Such issues will be addressed in future studies.

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