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”Trust your neighbour”

Insights into Learning in Epistemic Networks

Introduction

Network models became an appealing tool of investigation amongst philosophers of science that want to replicate real world dynamics (Rosenstock, Bruner, and O’Connor). Some recent examples include studying the emergence and stability of structural groups of secondary-school students (Stadtfeld, Takacs, and Vörös), uncovering the phenomenon of epistemic network injustice in a toy political setting composed of ’masses’ and ’elites’ (Spiekermann), and investigating the effectiveness of the ’tobacco strategy’ through selective sharing and bias production (Weatherall, O’Connor, and Bruner).

This research paper follows closely the latter enumerated paper titled ”How to Beat Science and Influence People: Policymakers and Propaganda in Epistemic Networks,” but starts from a more fundamental setting. The learning dynamic in a network full of scientists is firstly considered, followed by an introduction of policymakers and journalists. A noticeable shortcoming of the Weatherall et al. paper lays in the size and configuration of the networks used. As such, the paper only considers cycle and complete networks of scientists with up to 20 nodes (Weatherall, O’Connor, and Bruner). As will be demonstrated, these configurations are less representative of the real-world networks in comparison to those described in the current paper. Thus, the main aim of this research paper is to discover valuable insights into learning in epistemic networks made of one or more of the following node types: scientists, policymakers, journalists.

Next sections will dive deeper into the field of network science in order to explain the choices behind the simulation settings. After choosing the values of the parameters for the simulation settings, the results will be presented and analysed. This paper concludes with a summary of the results together with a discussion and suggestions about possible future work on this topic.

Epistemic Network Model

Generally, the results obtained from simulations based on network models are highly sensitive to parameter choices (Rosenstock, Bruner, and O'Connor). To truthfully define the epistemic network model used in the simulations, two distinct matters need to be discussed in detail: the learning[1] model and the network structure.

Learning model

The learning model employed in this paper is the simplified version - two actions, two states - of the learning model based on neighbours, first described by Bala and Goyal in 1998 (Bala and Goyal). The model describes two actions - a_1 and a_2 - and two possible states - Θ_1 and Θ_2. Action a_1 yields a Bernoulli distributed payoff with parameter $p = \frac{1}{2}$, no matter the state. Action a_2 yields a Bernoulli distributed payoff with parameter $p = \frac{1}{2} + \epsilon$ in state Θ_2 and a Bernoulli distributed payoff with $p = \frac{1}{2} - \epsilon$ in state Θ_1. Each agent has a belief $\mu \in (0, 1)$ that dictates the state in which the agent thinks it is in. If $\mu < 0.5$, the agent thinks it is in state Θ_1 and, therefore, chooses the optimal action a_1. If $\mu \geq 0.5$, the agent thinks it is in state Θ_2 and chooses the optimal action in this case, which is action a_2. During the simulation, each agent chooses the

[1]The terms "learning curve," "belief propagation," and "belief update" will be used interchangeably throughout this paper.

optimal action based on its belief[2], then updates its belief based on the information gathered from the neighbours. The posterior belief for an agent is calculated using a Bayesian learning algorithm[3]. The process repeats itself for a fixed number of steps or until convergence.

Here, the two states represent two distinct scientific theories - Theory A and Theory B - from which the scientists need to choose the better one to agree on as a collective. The phenomenon of local independence is captured, as real scientists are highly influenced by other scientists from the same research team or research facility to believe a certain theory is the right one. The described learning process from above entails 'local independence' as the actions chosen by agents are only based on the immediate neighbours in the network. However, if the network is connected, no agent is totally independent as influences from further neighbours in the network are felt through transitivity (Bala and Goyal).

Another point worth mentioning here is that the desirable outcome of the scientists arriving at a consensus favoring the second theory (Theory B - translated in the model by state Θ_2) cannot be reached all the time under this model. A strong majority of initial beliefs less than 0.5 can generate a mistaken agreement favouring the worse theory; that is, the theory captured by state Θ_1. This is also mentioned in the Weatherall et al. paper (Weatherall, O'Connor, and Bruner).

Network Structure

Three different network structures from the network science literature are used for the simulations: Erdős-Rényi random networks, Watts-Strogatz networks, and Barabási-Albert networks. The first two are examples of static networks, while the last is a model for evolving networks.

Imagine being at an office Christmas party when starting a new job. Naturally, in the beginning you tend to talk with people from your own department, but as the party progresses,

[2] It should be noted that the initial belief of each agent is random.

[3] The exact formula for calculating the posterior belief can be found in the original Bala and Goyal paper.

you start meeting new people. These random encounters of new people can be translated to an acquaintance network in which you are a node. Like the emergence of an acquaintance network through random encounters at an office party, a lot of networks seem random at the first sight. A random network of N nodes has each node pair connected with probability p[4] (A.-L. Barabási). Here, the random network model in the supercritical regime ($p > \frac{1}{N}$, where N is the number of nodes in the network) is chosen as a base model that might uncover interesting insights into the learning dynamics. The choice is guided by analysis which showed that most real networks are in the supercritical regime (A.-L. Barabási).

The second structure used in the simulations is generated using the Watts-Strogatz model. The Watts-Strogatz model is an extension of the random network model that tries to capture a high clustering coefficient and the existence of small worlds observed in real networks (A.-L. Barabási). To generate a Watts-Strogatz network, random links are extracted from a ring lattice network and rewired with probability p.

The final model used in the simulation is motivated by the characteristics of scientific collaboration networks. The scientific collaboration network has small worlds[5] (Newman). The scientific collaboration network is a scale-free network. Moreover, the evolution of the network is governed by preferential attachment (A. L. Barabási et al.). A scale-free network is a network in which a small number of highly connected nodes (hubs) exist together with a lot of other not so highly connected nodes. The Internet, the protein interaction network, and most social and online networks are also examples of scale-free networks (A.-L. Barabási). To generate such a network, the Barabási-Albert model is used. The model makes use of preferential attachment, which explains the phenomenon of highly cited papers that continue to receive citations from newly added papers in a particular domain, or highly popular individuals receiving new followers as soon as they join a particular social network. This might also be considered true not only for citation networks or social networks, but for scientific networks as well. For example, most universities and research institutes have individuals assigned as heads of departments. They

[4]This p is different than parameter p of a Bernoulli distribution.

[5]If two scientists are picked at random, there will be a path of just a few scientists between them.

coordinate and consult the other scientists in the department making them assume the role of the highly connected nodes in the scientist network. Following the same example, the head of the Computer Science department from University X might be in touch with the head of the Computer Science department from University Y, thus introducing a long distance tie in the network, highly facilitating the formation of small worlds. In addition, highly cited authors tend not to collaborate with each other directly, but cite each other extensively (Ding), it seems like a fair assumption to consider that highly connected individuals are not part of the same network community, but they interact with each other nonetheless. All the reasons above point to the fact that the Barabási-Albert model seems to be a good choice for shaping networks of scientists.

Simulation Analysis

Several simulations measuring the speed of belief convergence are run using different combinations of parameters. In each simulation, a single parameter is varied while keeping the other fixed. This is done in order to observe the impact of the varied parameter on the speed with which a consensus is reached. Each simulation has a deadline after 25 time-steps[6]. Three types of nodes can be present in the network: scientists, policymakers, and journalists[7]. Scientists are nodes which function entirely in conformity with the learning model presented in the *Learning Model* section. Policymakers are nodes which update their beliefs the same as scientists do, but they do not act. Journalists are nodes which act the same as scientists, but use a different process to update their beliefs. In accordance with the fair balanced manner in which journalistic information must be presented to the public, described in the Weatherall et al. (Weatherall, O'Connor, and Bruner), this paper implements the journalist to choose randomly with equal probability which theory to present. It then updates its belief by averaging over the beliefs of all the neighbouring scientists that trust the chosen theory at that point in time. It is interesting to

[6]This was chosen empirically in order to capture the overall trend of the simulation. For most simulations, a plateau is reached before the $25th$ step.

[7]From this point onwards, I will refer to scientists nodes, policymakers nodes, and journalists nodes as simply scientists, policymakers and journalists.

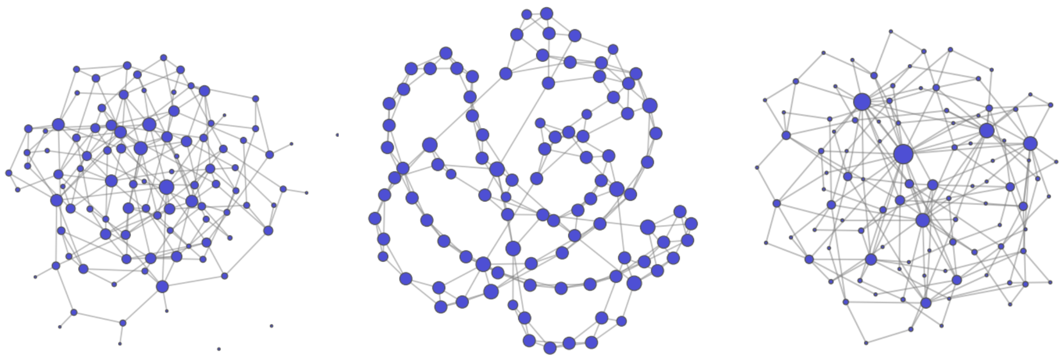


Figure 1: (a) Random Network (b) Watts-Strogatz Network (c) Barabási-Albert Network

notice that if the journalist would gather all possible information on both theories and share the resulting belief, this would influence the learning process in the network in the same manner as a scientist would from the point of view of the policymaker.

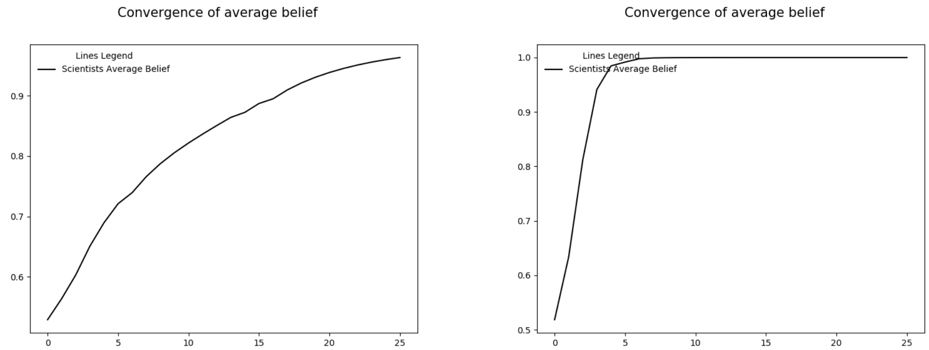
Scientists only

The following discussion analyses the results obtained from simulations on a network containing only scientists. By keeping p fixed at $\frac{1}{N} + \epsilon_0$ and m[8] at 2, the speed of convergence is compared using between 20 to 500 scientists in the network for each of the three previously described network types. Figure 1 shows three different networks of 100 nodes, each generated using one of the three network models introduced above. The size of each node is proportional to the number of neighbours it connects to - or in other words, its average degree.

The effect of increasing the number of nodes is similar for each of the three network types. Higher number of nodes result into a faster and steeper belief convergence, and, thus a quicker learning. The most noticeable difference happens in the case of the random networks. Figure 2 best depicts this difference. At time-step 5, in the network with 500 nodes, the scientists already reach consensus, while in network with 20 nodes the average belief reaches just around 0.7.

As expected, the ϵ - which is fixed at 0.05 for all the other simulations - from the Bernoulli

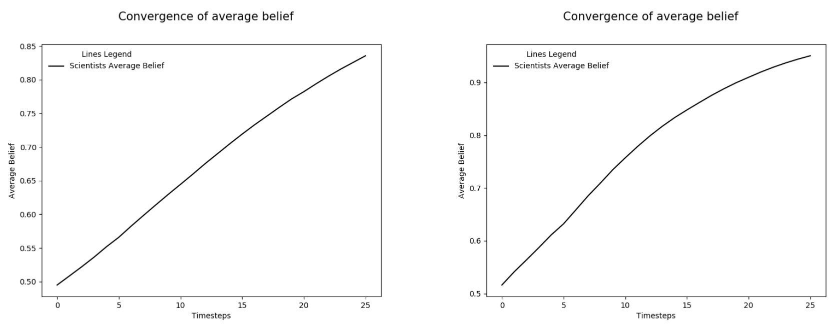
[8] m will be more exstensively detailed in a later paragraph.



(a) (b)

Figure 2: (a) Random Network with 20 nodes (b) Random Network with 500 nodes - the X-axis measures time-steps, while the Y-axis measures average belief

distributed payoff parameter described in section *Learning model* has a big impact on the speed of convergence. Informally, ϵ shows how much better Theory B actually is compared to Theory A. Thus, it makes sense that the speed of convergence grows with the value of ϵ. Figure 3 emphasises this by showing the belief convergence graph on a Barabási-Albert network of 100



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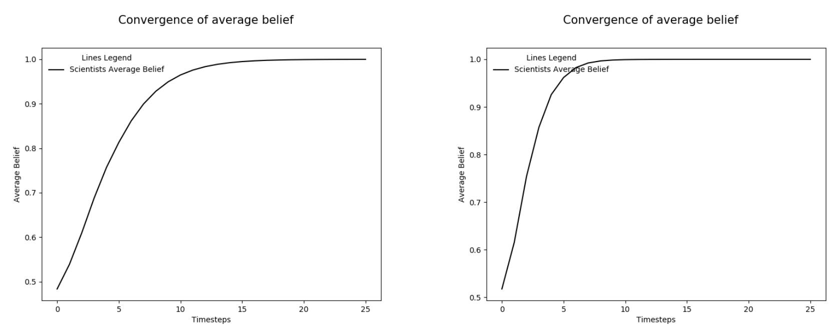


(c) (d)

Figure 3: (a) $\epsilon = 0.01$ (b) $\epsilon = 0.02$ (c) $\epsilon = 0.05$ (d) $\epsilon = 0.1$

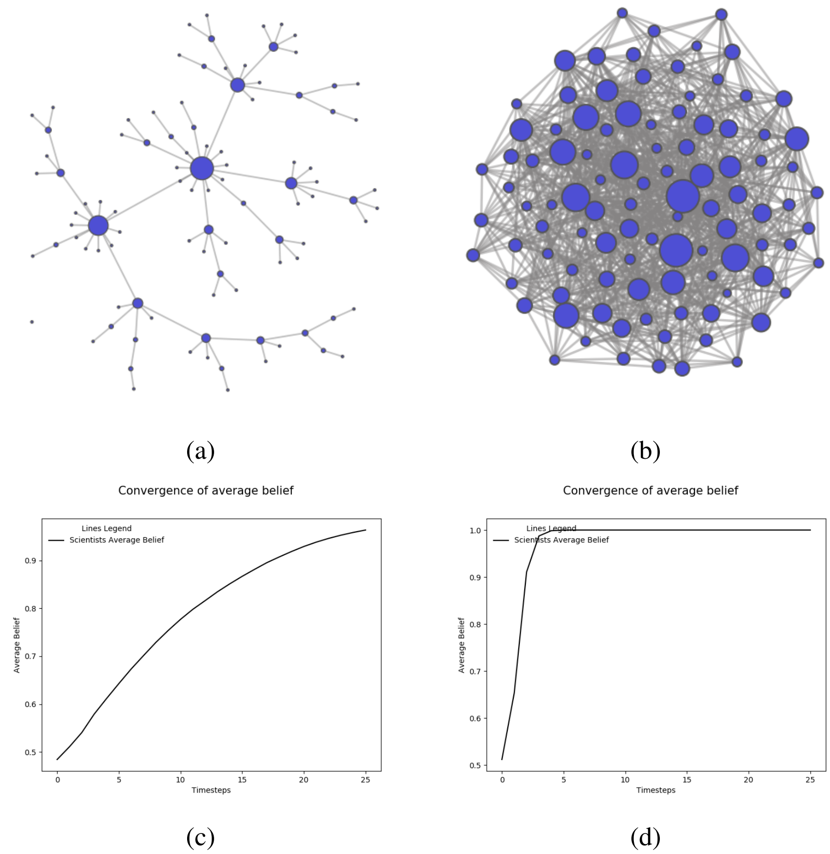


Figure 4: (a) Barabási-Albert Network with $m = 1$ (b) Barabási-Albert Network with $m = 10$ (c) Belief Convergence for $m = 1$ (d) Belief Convergence for $m = 10$

nodes, with $m = 2$ for an increasing ϵ value.

Another parameter that is varied is the m parameter from the Barabási-Albert model. m depicts how many neighbours a new node added to the network connects to using preferential attachment. A higher m value results in a higher connectivity in the network. Figure 4 shows the two extremes from the range of tested m values. Each network has 100 nodes. The left images illustrate the network and convergence graph for $m = 1$ - each new node has just one neighbour which is chosen proportionally to its current number of neighbours - while the right images illustrate the network and convergence graph for $m = 10$. The results show that if connectivity is increased (higher m value), the convergence is accelerated. This is contrary to Zollman's findings that an epistemic community would benefit from having decreased connectivity (Zollman), but in concordance with the findings from Rosentstock et al., who focused more on parameter variation

(Rosenstock, Bruner, and O'Connor).

Policymakers and Journalists

The policymaker and journalist nodes are introduced after the network is generated. Here, the question of how to better introduce them into the model arises. The assumption is that scientists follow a taxonomic structure which has the most connected individuals at the top. These most connected individuals are directly connected to the policymaker. This is translated in the model as a parameter s, that dictates which percentage from the most connected scientists are linked to the policymaker. Assuming that a journalist's job is to uncover information, the assumtion is that the journalist should be connected to more scientists than the policymaker. In the model, the journalist is therefore connected to $2s$ scientists with a probability proportional to the number of neighbours of each scientist. The simulations uses $s = 0.1$, but also varies s to observe its impact on different networks. The focus here is on the learning curve of the policymaker.

Firstly, the number of nodes is varied between 20 and 500, while the other parameters are kept fixed. For both the random and Barabási-Albert networks, the influence of the journalist on the belief convergence of the policymaker is considerable in small networks (example $n = 20$). The influence is, however, negligible for networks larger than 250 nodes. Figure 5 shows the visual representations of two Barabási-Albert networks with 20, and, respectively 250 nodes together with a comparison between the resulted convergence graphs and the scientists only convergence graphs for the same network structures. The blue nodes represent scientists, the green node represents the policymaker, and the red node represents the journalist. The spikes as shown by the red line happen because of the manner in which the journalist updates its belief. At some point, the spikes cease to exist because the journalist has no neighbouring scientists that believe Theory A, thus it makes sense to also report only on Theory B.

For the Watts-Strogatz networks, the journalist slows the convergence of the policymaker even on large networks. This happens because, in this case, each scientist has a similar and small number of neighbours. Thus, the structure of the network still strongly resembles a ring lattice

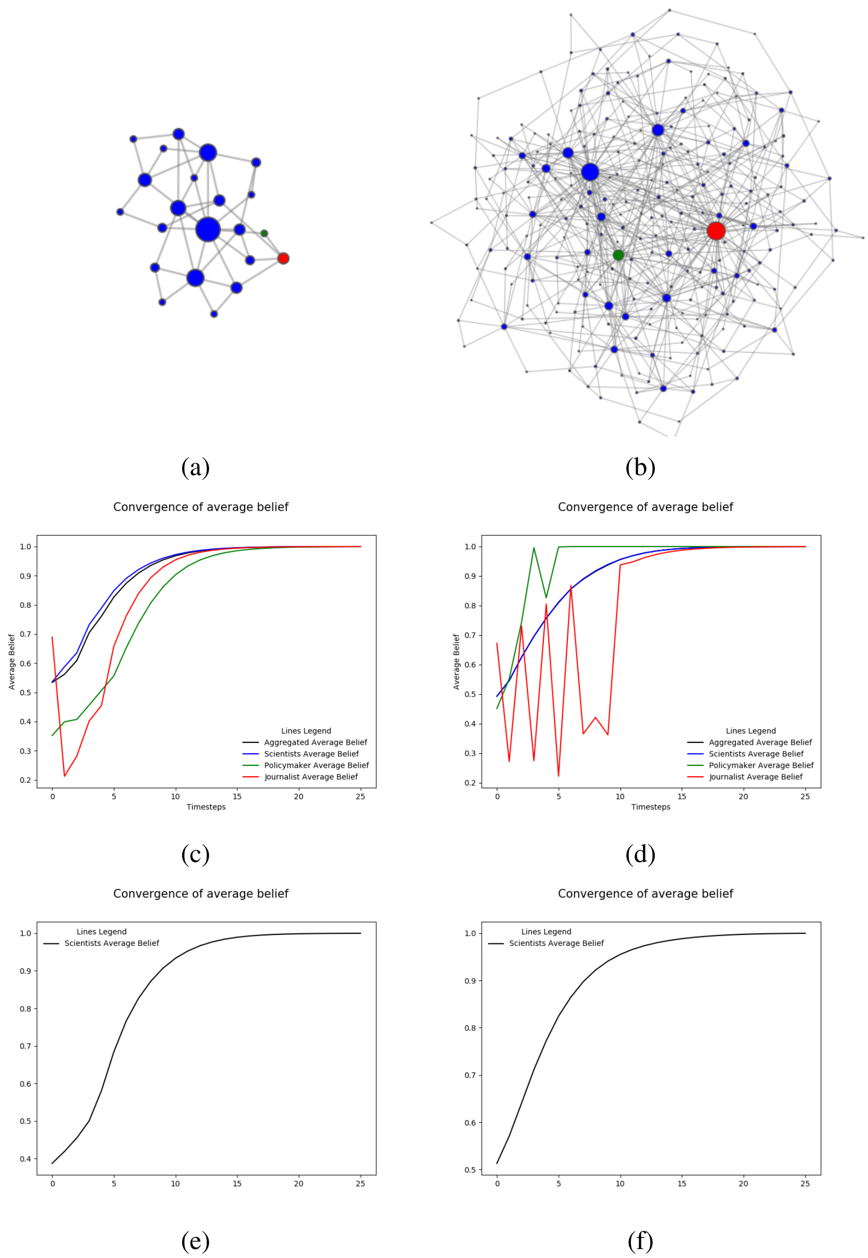
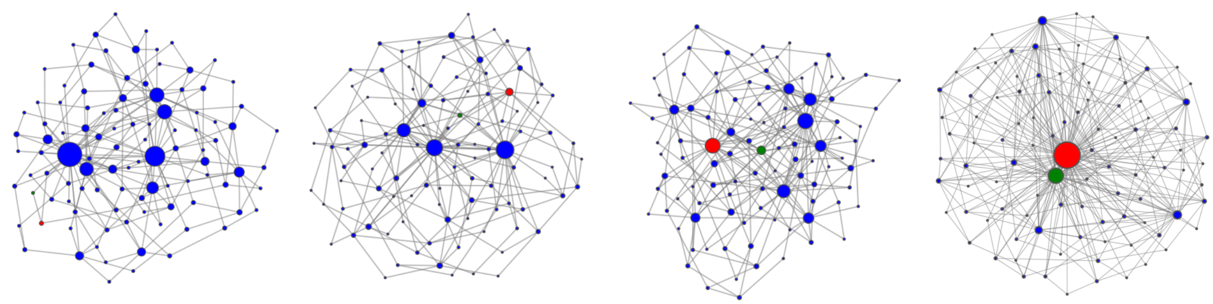


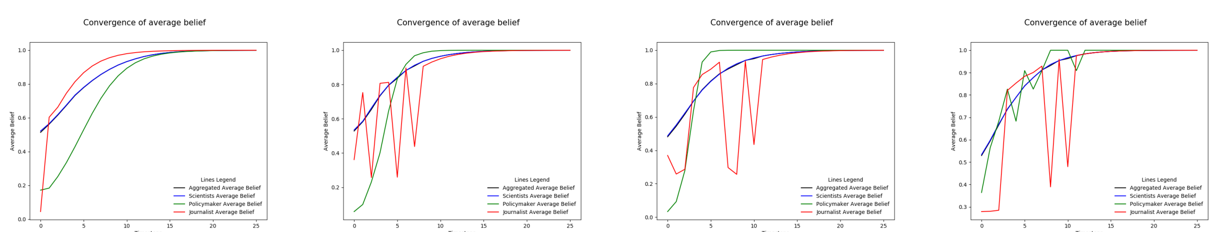
Figure 5: (a) Barabási-Albert Network $n = 20$ (b) Barabási-Albert Network $n = 250$ (c) Convergence Graph with Policymakers and Journalists for Barabási-Albert Network $n = 20$ (d) Convergence Graph with Policymakers and Journalists for Barabási-Albert Network $n = 250$ (e) Convergence Graph with only Scientists for Barabási-Albert Network $n = 20$ (f) Convergence Graph with only Scientists for Barabási-Albert Network $n = 250$

under the chosen parameters. This means that the belief propagation is slower - the phenomenon of local independence is at place - it takes more steps for a node to influence another node outside its neighbourhood in the network. This will influence the policymaker which, in turn, converges slower since it has more neighbours that believe in Theory A (including the journalist) early in the simulation.

Secondly, the s parameter introduced above is varied between 0.01 - which corresponds to a single neighbour for the policymaker and two for the journalist for networks with 100 nodes - to 0.5 - which corresponds to the policymaker being connected to half the scientists and the journalist being connected to all the scientists. Figure 6 shows the networks and learning curves for $s \in \{0.01, 0.05, 0.1, 0.5\}$. For $s = 0.01$ the learning is slow - at time-step 5 the belief of the policymaker is still under 0.6 and it plateaus only after passing time-step 15. For $s = 0.05$, the learning is already accelerated - on time-step 5 the belief of the policymaker already reaches around 0.8 and the plateau happens way earlier than in the $s = 0.01$ case. The $s = 0.1$ case is quite interesting. It might be deduced from the graph that the policymaker happened to be surrounded by scientists already believing Theory B - the convergence is quick and the journalist has low impact on the learning curve. In the last case ($s = 0.5$), as the journalist is connected to



(a) (b) (c) (d)



(e) (f) (g) (h)

Figure 6: (a) Barabási-Albert Network $s = 0.01$ (b) Barabási-Albert Network $s = 0.05$ (c) Barabási-Albert Network $s = 0.1$ (d) Barabási-Albert Network $s = 0.5$ (e) Belief Convergence graph for $s = 0.01$ (f) Belief Convergence graph for $s = 0.05$ (g) Belief Convergence graph for $s = 0.1$ (h) Belief Convergence graph for $s = 0.5$

all the scientists, it always finds a scientist that still believes in Theory A later in the simulation, which directly affects the learning of the policymaker.

Conclusion and Discussion

The simulations uncover interesting dynamics of belief propagation (or learning) in epistemic networks. Firstly, the results from the scientists only simulations reinforce the findings of Rosenstock et al. that the learning becomes more difficult in both of the following cases (Rosenstock, Bruner, and O'Connor):

- The number of nodes (or population size) is relatively small.
- Actions a_1 and a_2 have really similar payoffs; in other words, the ϵ from the Bernoulli distribution payoff parameter described by the learning model is really small or negligible.

Secondly, introducing the policymaker and the journalist into the simulations demonstrates that, indeed, the fact that fairness doctrine slows the learning process and, therefore, never improves the epistemic performance (Weatherall, O'Connor, and Bruner) remains true for larger and more complex networks. Additionally, highly connected journalists have a more substantial influence on the learning curve of the policymaker.

Under the presented learning model and network configurations, there are a lot of combinations of parameter configurations possible. Thus, an even more comprehensive analysis is achievable. Because of time and space constraints, there would have been impossible to thoroughly consider all of them. Also, this paper purposely omits reporting highly technical matters such as average degrees, clustering coefficients etc. as this is not designed as a network science paper, but a social epistemology one. More explicitly, a mix of relevant technical matters and general insights were preferred.

Finally, there are some discussion points and future directions that are worth mentioning. More network models could have been considered. For example, the Bianconi-Barabási was not considered because fitness was not taken into account during this implementation. The possibility of node or link deletion were also ignored. Future work could focus on any of these two points for improving the analysis. On a different note, the belief updating process might resemble the spreading phenomena used in epidemic modeling (examples are SI, SIS, SIR models) (A.-L. Barabási). However, they are not the same. An important difference lays in the fact that the spreading usually starts from a small number of nodes and evolves throughout the network, which is different than the uniformly distributed start from the model described in this paper. Another difference is that in the spreading case, nodes cannot transition the possible states in the reverse direction, which might be possible in the described model. Also, during the spreading phenomena, one link with a contagious other individual might be enough for an node to change states. In belief updating, the states do not change so abruptly. Nonetheless, this is still a debatable topic which is not the scope of this paper.

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