Learning from Close Ones: A Simulation Study

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Should people only receive information from like-minded individuals? Most would likely answer no. If individuals exclusively listen to those who share similar perspectives, they risk being insufficiently exposed to diverse sources of information. Such limited exposure can result in epistemic bubbles, namely communities in which certain pieces of information are ignored or dismissed. If specific conditions concerning the reliability of information sources are satisfied, these tendencies can further lead individuals into epistemic echo chambers. In these more entrenched structures, agents actively discredit information from outside sources, reinforcing existing beliefs and creating significant obstacles to accurate understanding. Real-world examples range from polarized political groups on social media to conspiracy theory forums that aggressively exclude alternative viewpoints. Yet it would also be unreasonable for individuals to accept radically different opinions without scrutiny. For instance, few would seriously consider the claims of Holocaust deniers or flat-earth proponents, nor revise their beliefs based on such views. This raises an intriguing question: where should we draw the boundaries of epistemic trust?

One way to explore this question is through computational modeling. By combining Bala Goyal's network model with the Hegselman-Krause model, we can capture the dynamics of restricted information exchange among agents and assess the effects of varying degrees of open-mindedness. In the simulation, agents update their beliefs in several stages. First, they conduct individual experiments on a target proposition, gathering evidence to determine its truth. They then revise their credences using Bayesian conditionalization. Next, they identify others whose updated credences fall within a predefined threshold, forming networks with those whose beliefs are sufficiently close. Finally, agents update their credences again based on the credences of their connected agents. This cycle continues until the community reaches a stable consensus.

The simulation focuses on two key parameters: the number of trials (n) and the accuracy parameter (epsilon). The parameter n indicates the number of experiments each agent makes before turning to social learning. A smaller value of n implies greater reliance on social input, while a larger value reflects more dependence on personal experimentation. Epsilon, on the other hand, represents the accuracy of each experiment. These two parameters jointly shape the balance between individual inquiry and social influence, revealing how different configurations affect a community's ability to converge on the truth.

Building upon initial results using Bayesian conditionalization, the simulation further explores how alternative averaging mechanisms such as linear averaging, geometric averaging, and multiplicative averaging influence belief convergence. In this extended analysis, agents again perform experiments, update their credences, and form networks based on credence similarity. Instead of conditionalizing, they adopt the average belief of those they are connected to. By comparing these distinct approaches, the study evaluates the effectiveness of each method in fostering epistemic communities that reliably reach accurate consensus.