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EPISTEMIC NETWORKS AND POLARIZATION

Daniel J. Singer, Patrick Grim, Aaron Bramson, Bennett Holman, Jiin Jung, and William J. Berger

Introduction

Much of applied epistemology asks questions about how information moves in groups of individuals and institutions and how that dynamic influences individuals’ and institutions’ beliefs and actions. Political epistemology focuses on that dynamic with the aim of advancing our understanding of questions in political philosophy, but similar and related questions have been addressed by social epistemologists, philosophers of science, complex systems theorists, sociologists, political scientists, social psychologists, and marketing and management researchers. Among social epistemologists and philosophers of science, thinking in terms of epistemic network models has been fruitful for understanding the ways in which individuals’ beliefs can influence the beliefs of others and groups. This chapter will introduce the notion of an epistemic network model and discuss some of the ways that epistemic network models and implementations of them in computer simulations have contributed to our understanding of political polarization. In doing so, this chapter will serve as a non-comprehensive introduction to these topics that aims to inspire future work in political epistemology.

In Section I, we’ll introduce epistemic network modeling and contrast epistemic network approaches to thinking about political epistemology with more general aggregative approaches. Section II will introduce a result from Zollman (2007) about how the structure of epistemic networks influences how quickly and how accurately members of groups can come to have true beliefs. Section III begins to investigate polarization in epistemic networks by first looking at models of divided networks from Grim and Singer et al. (2015). Those models do not produce polarization despite seeming like they should. We’ll then turn to a model from Hegselmann and Krause (2002) that does produce polarization in similar networks. Section IV looks at two recent applications of the epistemic network approach to thinking about polarization in non-divided networks, those from Singer et al. (2019a) and Weatherall and O’Connor (forthcoming). The chapter concludes by briefly discussing some ways this framework can contribute to future work in political epistemology.
I What is an epistemic network?

To a first approximation, the guiding ideas of the epistemic network approach to questions in social epistemology are that

1. Beliefs, information, evidence, and other epistemic elements are held by *agents*, where “agents” is broadly understood to include individuals, but also families, small groups (like a Parent–Teacher Association), scientific lab groups, companies, journals, and other institutions;
2. The agents are connected to other agents in a (not necessarily fixed) network structure; and
3. The beliefs, information, evidence, and other epistemic elements are shared via network connections with other agents.

Let’s consider two simple examples.

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**Example 12.1: A racially divided city**

Suppose there is a city that is so deeply racially divided between White and Black people that there is literally no communication between the two races. The epistemic network of this city will contain two disconnected parts. Perhaps it looks something like Figure 12.1.

Here the individual agents (represented by dots) are connected to other agents (with the connections represented by lines). In this setup, beliefs, information, and evidence can move within the two racial groups, but because there are no links between the racial groups, no beliefs, information, or evidence is shared between them. Of course, the idea that two
subgroups of a population would be this disconnected is unrealistic, but here we’re simplifying. For a more realistic epistemic network model of a racially divided city, see Grim et al. (2012).1

Example 12.2: High school gossip

Charlie starts a rumor that Alex likes Sandy. Charlie tells one friend. That one friend tells the most popular person in the school, who proceeds to tell everyone else. In this situation, there’s an epistemic network on which the (misleading) information about Alex and Sandy travels. Figure 12.2 represents the network through time.

![Figure 12.2 Illustration of a high school gossip epistemic network through time.](image)

On the left, we see Charlie, who uses a piece of (mis)information to start the rumor. In the next step, that information has spread to Charlie’s friend. In the time step after that, the misinformation is spread to the popular student, who shares it with the rest of the group. Here the color of the agent represents whether the rumor has spread to that agent.

Both of these examples illustrate epistemic networks in which there are (1) nodes (agents) who have or do not have some information, belief, or evidence, and (2) links between agents that represent the connections between them. The second example also involves changes in the epistemic states of the group through time, which is another common element of epistemic network models. That particular example also uses a diffusion or infection dynamic, where information travels in the network by “infecting” neighboring nodes. Although that dynamic is commonly used in epistemic networks, it is not the only possibility, as we’ll discuss below.

Epistemic network models are a subspecies of the broader class of agent-based models. Agent-based modeling is an approach to modeling complex high-level phenomena in terms of simple interactions of the small parts of systems that give rise to the phenomena. We can contrast agent-based models with more traditional kinds of models that we call “aggregative models.” In aggregative models, the relevant features of the smaller parts of the phenomena are typically summed up and represented as a single unit. For example, simple macroeconomic models of the sales price of goods might represent the price as a function of the aggregated supply and aggregated demand for the good. Facts about how much individual agents will pay for the good or how much individual suppliers will supply are aggregated into supply and demand curves that represent the collection of buyers and the collection of sellers. An agent-based model of the same phenomenon would disaggregate the individual buyers and sellers and treat each as an independent actor that can contribute to changes in the good’s price.
Agent-based models (and epistemic network models, in particular) have made important contributions to our understanding of questions in political epistemology. To introduce the reader to some of these contributions and hopefully inspire future ones, we’ll use the next section to review an important general result about how the structure of epistemic networks can influence how quickly and how accurately members of groups of truth-seeking agents come to have true beliefs. After that, we’ll look at more recent work using epistemic network models to try to understand polarization.

II The impacts of epistemic network structure

It’s common in philosophical reasoning (and in scientific reasoning) to employ idealized abstract models of complex phenomena. Lottery and urn cases are used as paradigmatic idealized models of uncertainty in epistemology, for example, and Rawls uses a highly idealized model of group decision-making in his veil of ignorance argument. Similarly, one might think that political epistemologists can avoid the complexities of epistemic networks by idealizing them to completely connected networks. Work by Kevin Zollman (2007) shows this would be a mistake.

Zollman gives a model in which agents are trying to figure out which of two slot machines has a higher payoff. They do this by playing the two machines, collecting the outputs, and sharing their results with their neighbors in an epistemic network. Zollman uses this as a model of scientific inquiry, but it can easily be seen as a model of information sharing about the effectiveness of government policies, the justness of police action, and many other kinds of information. In Zollman’s model, agents start out with random credences (degrees of belief) about which of the two slot machines is better. They then play the slot machines in ways that balance maximizing their expected payoff (by playing the machine they think is best) and exploring the other machine (to get more information in case they are wrong). The agents share their information with their neighbors and update their credences based on their experience and the experience of those with whom they are connected. Zollman compares how different communities of researchers perform on different types of epistemic networks, including ring networks (where agents are connected in a circle), wheel networks (where agents are connected in a circle but also to a central hub), and complete networks (where all agents are connected).

Using computer simulations of this model, Zollman shows that the more connected a network is, the worse the agents can be expected to perform in the long run. In the complete network, even though the agents tend to converge on an answer quickly, they tend to converge more commonly on the wrong answer, since the group tends to react too quickly to misleading information. In less connected networks, when part of the group is misled, the more distant parts of the group still have a chance to turn the misled part around. This general point was explored in more detail and with a different model by Grim and Singer et al. (2013). What these arguments show is that the structure of epistemic networks might have an important effect on outcomes of interest to political epistemology. For example, if epistemic democrats are right that democracies are stronger partly as a function of how epistemically good they are (e.g. Landemore 2013), these epistemic network models point toward thinking that less connected democracies might be better. Care must be taken in working from highly theoretical and idealized models like Zollman’s to real-world implications, and unfortunately, exploring that further is beyond the scope of this chapter.

Epistemic network models are often too complex to explore from the (computer-free) armchair. So analyses of epistemic network models are typically done with computer
simulations. The way this works is that the model is implemented in a simple programming language like Python (a general-purpose high-level programming language) or NetLogo (a program designed specifically for agent-based model simulation). A “run” of the model starts with some initial conditions. In Zollman’s model, these would include the network of agents, facts about the payoffs of the slot machines, and an initial distribution of beliefs about the payoffs among the agents. The simulation then proceeds in “time steps,” in which the model’s primary dynamic is repeated. In Zollman’s model, in each time step, the agents play the slot machines to collect new data, share that data with their network neighbors, and update their beliefs about which machine is best. Many runs are performed, and data from those runs is statistically analyzed. Typically thousands to millions of different runs are performed (depending on the complexity of the model and available computational resources) so contingent initial conditions and stochastic elements of the model don’t affect the analysis.

It’s common to discuss epistemic network models as though they just are computational simulations, but we think it’s important to at least conceptually distinguish the models from their computational instantiations. Flaws or peculiarities in implementations of models need not be flaws or peculiarities in the models themselves, and often our understanding of the phenomena of interest (such as the spread of some idea or political polarization) comes from understanding the models and arguments about the models, not the details of their computational instantiations. So the simulations should be seen as a tool that helps us explore these models, not as the models themselves. We’ll turn now to discussing epistemic network models of polarized groups, but we encourage the reader to see Zollman (forthcoming) for a much deeper introduction to epistemic network research.

III Polarization in divided (“homophilous”) networks

The reader of this volume is probably aware of the polarization that characterizes contemporary political climates in most democratic countries. This polarization consists in persistent (and sometimes even violent) disagreement between groups, often two, and typically across an array of different issues regarding both factual and policy matters. For one recent collection of case studies, see Carothers and O’Donohue (2019). It’s a complex technical question how to define and measure polarization (see Bramson et al. 2016), but those technicalities won’t affect the discussion here. We’ll focus on models that purport to model very clear-cut cases of group polarization.3

In modeling polarization, it’s natural to think we should start with a divided epistemic network, perhaps representing connections inside and between different social groups. In “Germs, Genes, and Memes,” Grim and Singer et al. (2015) explore how information travels on divided networks of this sort. Grim and Singer et al. use five different types of sub-networks connected by varying numbers of bridging links. Figure 12.3 shows examples of these networks.

Their paper wasn’t about polarization. It was about the dynamics of different types of information transfer, including infection dynamics (like in the gossip example above), split-the-difference belief averaging, and the sexual reproduction dynamics of genes. They started the models with different information on each side of the network and explored how that information moved.

Although they weren’t focused on polarization, there’s a lesson for polarization in their work: every kind of information dynamic led to convergence across every network type. That is, given enough time, all of the forms of information dynamics destroyed any polarization that was originally there. What this means is that if we want to get a model that helps
us understand how groups can become and stay polarized, starting with a divided network
and a simple dynamic isn’t going to get us as far as we might have thought.

Another approach comes from Hegselmann and Krause’s (2002) Bounded Confidence
model (and related relative agreement models, e.g. Deffuant et al. 2002). Hegselmann and
Krause generate polarization with agents who update on others’ opinions only when those
opinions are already close enough to their own. Opinions in the model are mapped onto the
\([0, 1]\) interval, with initial opinions spread uniformly at random. Belief updating is done by
taking a weighted average of the opinions that are close enough to the agent’s own. What
counts as “close enough” is determined by a variable threshold in the model. As agents’ be-
liefs change, so do the other agents that count as close enough. In practice, what this means
is that the Hegselmann–Krause model has a \textit{dynamic epistemic network}, since who listens to
whom changes as the model runs. Unlike the static network models of Grim and Singer
et al., Hegselmann and Krause’s model does generate polarization for some thresholds.

When the threshold is too small (like 0.01), agents only talk to others who have be-
liefs very close to their own. In this case, the group doesn’t become polarized so much as
divided into lots of tiny groups. On the other hand, if the threshold is too big (like 0.25),

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{example_divided_networks.png}
\caption{Pictures of example divided networks.}
\end{figure}
everyone’s beliefs end up influencing everyone else’s, so the group converges onto a single average belief. In the middle though, there are some thresholds that give rise to polarized groups. When the threshold is 0.15, for example, the agents tend to divide into two groups both of which consolidate within themselves but to not eventually converge. Figure 12.4 illustrates this.

Hegselmann and Krause’s models (and relative agreement models generally) use the simple belief updating mechanism of averaging with one’s interlocutors. One might worry that averaging of beliefs is neither realistic nor obviously rational, but averaging does capture the reinforcement learning effects and dissonance weakening effects that are characteristic of many forms of belief updating. To see that, imagine that you and your friends are discussing the weather last month. If you start out thinking it was unusually hot and your friends disagree, that will likely undermine your confidence in your own belief, making you less sure. This is dissonance weakening. On the other hand, if your friends agree with you, that agreement is likely to reinforce your original attitude. This is reinforcement learning. In models that use a belief averaging mechanism, the more an agent’s beliefs are like those of their interlocutors on the network, the less pressure there will be to change those beliefs, and the flip holds as well. So even though belief averaging is too simplistic to accurately represent belief change, it is convenient and methodologically advantageous because it captures key dynamics of belief change in a manageable way. For these reasons, it is probably the most common mechanism used in epistemic network models, and it’s definitely one of the earliest, dating back to some of the first epistemic network models from French (1956) and DeGroot (1974). Belief averaging is also one of the dynamics explored in the Grim and Singer et al.’s study discussed above. That mechanism fails to produce polarization in Grim and Singer et al.’s models, although it does produce it in the Hegselmann–Krause model. The difference is the flexible and changing network in Hegselmann–Krause as opposed to the static networks in Grim and Singer et al.’s work. The dynamic network of the Hegselmann–Krause model essentially disconnects each of the polarized subgroups from the other. While averaging continues to occur in the model, agents in each of the subgroups no longer have any averaging–connection to the agents in the other subgroup.

Bramson et al. (2017) critique the Hegselmann–Krause model and similar relative agreement models as being too unrealistic to be useful in understanding real polarization. This is because these models use a “peeling-back-from-the-edges” mechanism. Polarization occurs in these models (when it does) because agents at the extremes of the belief spectrum (very close to 0 or 1) don’t have neighbors who are more extreme than them. So those agents get “pulled” toward a more moderate position when they update with their more moderate neighbors. This results in there being two clusters of agents on either side of the mean belief,
which form the basis of the polarized groups. So when polarization is produced in this model, it’s because of the artificial edges of the belief spectrum in the model. This dynamic can be seen in Figure 12.4b. Bramson et al. argue that this mechanism doesn’t correspond to real-world mechanisms of polarization (2017:148). Despite this, the model might be able to help us understand polarization in other ways, as we’ll discuss more below.

We started this section thinking that we should use divided networks in models of polarization, and we saw that while Grim and Singer et al.’s divided models didn’t produce polarization, Hegselmann and Krause’s models did. There’s a methodological worry for any divided-network model of polarization though: If the goal is to understand polarization, models that start with a divided network will have a harder time producing any explanatory insight. That’s because the dividedness of polarization that we seek to explain is baked into the model from the beginning. Since the goal is to explain a kind of dividedness, the explanation will produce more insight if it doesn’t treat division as one of the explanans. In the next section, we’ll look at two epistemic network models of polarization where polarization is produced by how agents respond to each other, rather than division in the epistemic network.

IV Recent epistemic network approaches to polarization

Singer et al.’s (2019a) epistemic network model aims to be a general model of group deliberation. They use that model to show that for agents with limited memories, a deliberating group can become polarized simply by agents rationally managing their limited memory. They argue that because the polarization arises from what is epistemically rational for agents in light of their cognitive limitations, the polarization produced is, in that sense, epistemically rational. In their model, the epistemic network is a static and complete network (where everyone is connected to everyone else). So, the dividedness of the network being divided isn’t what explains the polarization. Instead, the agents polarize because of how they respond to each other.

Singer et al.’s model of group deliberation takes inspiration from Rawls’s conception of group discussion as “a way of combining information and enlarging the range of arguments” (1999:315). In Singer et al.’s model, agents have reasons for their beliefs, and they share those reasons with other agents. Reasons are modeled in terms of a content that is supported by that reason (e.g. that the defendant is guilty or that a particular tax policy will lead to less unemployment) and a (positive real-valued) strength of that reason. In the main kind of model run that Singer et al. consider, they assume that there are only two opposing contents in play in the discussion (e.g. the guilt or innocence of some defendant). They also assume that what reasons support and how strongly they support those contents doesn’t vary over time or between agents. They treat the agent’s over-all belief as the weighted sum of their reasons – i.e. agents believe the content that’s on balance supported by the reasons they have, which is required if the agents are to be epistemically rational. In the model, each agent starts with a random assortment of reasons. Agents are then chosen in a random order to share one of their reasons with the rest of the group. In their original model (2019a), agents choose reasons at random, but in the later version of the model (Singer et al. 2019b), the model is expanded to include different strategies agents might use to share reasons. When an agent hears a new reason, they add it to their stock of reasons and update their belief accordingly. If the agents’ memories and cognitive processing abilities are unlimited, as they are in the simplest versions of the model, then the agents eventually converge to the belief that’s supported by the total collection of held reasons.
When agents’ memories are limited, agents need a strategy to manage their memory. The authors consider several strategies. One strategy, which they call “coherence-minded,” has agents retain reasons with a slight preference for reasons that cohere with their collection of reasons as a whole. Although this model of memory isn’t intended to be descriptively accurate, it’s worth noting the similarity in mechanisms between coherence-minded agents and those posited by Lord et al. (1979) and discussed in the “myside bias” literature.

What Singer et al. show is that in many circumstances, groups of coherence-minded agents will polarize into subgroups and those subgroups will get tighter within themselves over time. Unlike in Hegselmann and Krause’s model, this happens in Singer et al.’s model even though every agent continues to be connected to (and listen to) every other agent. So, in this model, the polarization arises from how the individual agents react to new reasons, not a division in the network. Coherence-minded agents listen to any reason presented, one at a time, decide what’s most plausible on the basis of the reasons they already have and the newly presented ones, and then discard the weakest reason for the apparently misleading view. When agents manage their memory like this, they’ll disproportionately (but definitely not always) stick with the view they had before receiving new reasons.

Singer et al. argue that for epistemically limited agents, the coherence-minded memory management strategy is epistemically rational. If they’re right, then their model gives us a mechanism for understanding how groups of epistemically rational agents can get together, share their arguments for their views, but then end up more polarized than they were when they started. What the model brings out is a connection between individually rational management of one’s epistemic limitations and the distribution of beliefs in a group, and in doing so, it undermines a natural line of thought that polarization will be reduced by everyone calmly and collectively sharing their views.

This model, and the rest of the models discussed here, can be used in different ways to understand polarization. Singer et al. use the model for normative theorizing, since it’s supposed to tell us something about groups of rational agents. Singer et al. don’t argue that their model is empirically descriptively correct, but were it sufficiently similar to real groups, the model could also be used to try to understand some real cases of polarization. That is, the model could be used in descriptive research, similar to models in physics and biology, which help us understand and describe real systems. Finally, these models can serve a theoretical role. Rather than offering a way to understand particular real systems, the models can be used to help us understand what could happen by bringing out a mechanism for how polarization might arise. That is, they can offer what is sometimes called “how possibly” explanations.

Let’s consider another model of polarization that can also be used in each of these three ways. In real political polarization, individuals within polarized groups often agree with others in their group on a range of topics including apparently unrelated topics. In U.S. politics, for example, conservatives tend to share views on the permissibility of abortion as well as proper tax policy. The models discussed so far can’t account for cross-topic grouping, but that is the focus of Weatherall and O’Connor’s model of what they call “epistemic factionalization.”

To understand the model of epistemic factionalization from Weatherall and O’Connor (forthcoming), let’s start with the simpler model from O’Connor and Weatherall (2018). In the simpler model, agents gather and share evidence about the world. How much weight individual agents put on evidence shared with them is a function of how much they trust the sharer, and the amount of trust agents have in others varies over time. The model starts with a collection of agents in a complete network who are all trying to determine which of two slot machines has a higher payoff (following Zollman 2007). Agents start with a random
credence between 0 and 1 about whether the second machine is better than the first. On each round of the model, each agent plays the machine they think is best and updates their belief about which machine is best. When they update their beliefs, however, they don’t only use the evidence they collected. They also use evidence from their network neighbors (everyone, in this case, since it’s a complete network). If it’s a model run where everyone fully trusts everyone else, the group quickly converges onto a stable consensus (and so is not polarized). In runs where agents don’t fully trust their neighbors, agents treat the shared evidence as uncertain and the uncertainty increases the more the sharer’s belief differs from their own. So when an agent with a belief very different from their own offers them information, these agents don’t give it as much weight in their updating.

In the first paper, O’Connor and Weatherall show that using this kind of updating on a single issue can lead to agents polarizing when there is enough mistrust between agents. In their later paper, Weatherall and O’Connor show how polarization can arise across multiple topics when hearers adjust their trust of sharers as a function of how much the sharer agrees with the hearer’s antecedent views on various topics.

In the model from the second paper, agents have beliefs about more than one set of slot machines. Which slot machine is best in one pair has no connection to which is best in another pair, so the second model can be thought of as a model of agents having beliefs about independent topics. Again here, agents play the slot machines they think are best and share their results with the group, and they again discount the input of those who disagree with them. This time though, disagreement is measured as disagreement across all of the beliefs, not just a single belief.

Interestingly, Weatherall and O’Connor show that with enough mistrust between agents, coordinated polarization can arise in this model—that is, the model can give rise to groups of agents who are polarized into subgroups that internally agree about unrelated issues. Why does the coordinated polarization arise? The correlation happens because once there is polarization about one set of slot machines, the disagreement between those polarized groups affects how the agents think of input about the other slot machines, representing other questions. In other words, since there is agreement about the first set of slot machines in one subgroup, members of that subgroup take insiders’ opinions about other questions more seriously than the opinions of outsiders. That results in correlation on the issues about which agents are polarized, even when the issues don’t bear any theoretical connection to each other. The upshot, the authors tell us, is that mistrust can lead to what they call “epistemic factionalization” even when there is no common cause for that factionalization such as a shared group ideology or desire to maintain group boundaries.

Like Singer et al.’s model, this model explains how polarization (and epistemic factionalization) can happen in virtue of how agents respond to each other’s input, rather than in terms of a communicatively divided network. Both of these epistemic network models can provide ways of understanding how political polarization might arise in highly connected societies.

V The prospects for epistemic network approaches for political epistemology

As the above examples make clear, epistemic network approaches are well-poised to help answer important questions about political epistemology. Here we’ve focused on group polarization in particular, but epistemic network models have already been used in many other areas of political epistemology, including (but certainly not limited to) understanding the epistemic aspects of democracy (Landemore 2013), the epistemic aspects of representative
democracies (Grim et al. 2018a), the role of diversity and expertise in group deliberation (Grim et al. 2019; Hong and Page 2004; Singer 2019), the influence of minorities in groups (Jung et al. 2018), the stability of political institutions (Grim et al. 2018b), and the impact of fraudulent actors and misinformation on groups (Holman and Bruner 2015; Weatherall et al. forthcoming). This methodology could easily contribute further to our understanding of other topics in political epistemology as well, such as the connection between group beliefs and political legitimacy, how judicial beliefs impact the positions of courts, how representative and constituent beliefs influence each other and policy, how social position affects access to knowledge and vice versa, and how epistemic and other injustices are perpetrated and become systematized.

The examples we discussed here were of relatively simple models with relatively high-level normative and theoretical implications. The question of how to apply the lessons from the models to real-world policy is complex, and in many ways, it’s analogous to the question of how to apply lessons from other parts of highly idealized and theoretical political philosophy to real-world policy. In both cases, doing so is hard, and it must be done only with a careful eye toward empirical results and the potential impacts of missteps.

The goal of this chapter was to introduce epistemic network models and discuss some of the ways they have contributed to our understanding of political polarization. We hope this discussion has also inspired some readers to use these tools for further research in political epistemology.

Notes

1 We don’t use this model for this here, but this model also shows how polarization can be produced from opposing information from religious, friend, and government sources.
2 For general history and defense of agent-based modeling, see Railsback and Grimm (2019).
3 We’ll discuss models of group polarization, the formation of groups of like-minded individuals. This is different from belief polarization, the phenomenon discussed by social psychologists involving two individuals’ opinions diverging after sharing evidence.
4 Weatherall and O’Connor actually consider two kinds mistrust, but we’re simplifying the model here.
5 One might worry that the O’Connor and Weatherall model implicitly uses a divided network like the Hegselmann and Krause model. That may be right, but it’s at least a degree version of division.

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