Can Confirmation Bias Improve Group Learning?

Nathan Gabriel and Cailin O'Connor

April 27, 2022

Abstract

Confirmation bias has been widely studied for its role in failures of reasoning. Individuals exhibiting confirmation bias fail to engage with information that contradicts their current beliefs, and, as a result, can fail to abandon inaccurate beliefs. But although most investigations of confirmation bias focus on individual learning, human knowledge is typically developed within a social structure. How does the presence of confirmation bias influence learning and the development of consensus within a group? In this paper, we use network models to study this question. We find, perhaps surprisingly, that moderate confirmation bias often improves group learning. This is because confirmation bias leads the group to entertain a wider variety of theories for a longer time, and prevents them from prematurely settling on a suboptimal theory. There is a downside, however, which is that a stronger form of confirmation bias can cause persistent polarization, and hurt the knowledge producing capacity of the community. We discuss implications of these results for epistemic communities, including scientific ones.

1 Introduction

Chaffee & McLeod (1973) offered individuals a choice of pamphlets to read about upcoming elections. They found that individuals tended to choose those pamphlets that fit with their current preferences, rather than those that opposed them. Mynatt et al. (1978) presented subjects with a dynamic system on a computer and asked them to discover the laws governing this system. They found that once subjects generated hypotheses about the system they followed up with tests that would tend to confirm their hypotheses, rather than disconfirm them. Lord et al. (1979) conducted an experiment on individuals with strong views on the death penalty. They found that when these subjects were offered new information regarding the deterrent effect of the death penalty they were very resistant to changing their opinions. Sweeney & Gruber (1984) surveyed members of the public during the Watergate hearings and found that those who had voted for Nixon tended to ignore information about the hearings compared to those who had voted for McGovern.

This handful of studies are just a few of those outlining the pervasive impact of confirmation bias on human learning. Confirmation bias refers to a cluster
of related behaviors whereby individuals tend to seek out, to interpret, to favor, and to selectively recall information that confirms beliefs they already hold, while avoiding or ignoring information that disconfirms these beliefs. It has been widely implicated in the prevalence and persistence of false beliefs. Individuals exhibiting this bias often ignore information that might help them develop accurate beliefs about the world. Most notably, they are susceptible to holding onto false beliefs which have been discredited (Festinger et al., 2017; Anderson et al., 1980; H. M. Johnson & Seifert, 1994; Lewandowsky et al., 2012).

Confirmation bias has mostly been studied at the individual level—i.e., how does it influence individual beliefs and behaviors? Human knowledge and belief, though, are deeply social. Individuals influence the beliefs of those they interact with, and are influenced in turn. Ideas and evidence are shared via social networks in ways that impact further learning and exploration. This leads to a question: how does confirmation bias influence learning and belief in human groups? Is it harmful to groups in the same way it seems to be harmful to individuals?

We use network models to study this question. In particular, we draw on the network epistemology paradigm first developed in economics by Bala & Goyal (1998) to study learning in groups. Subsequently, this framework has been widely employed in social epistemology and the philosophy of science to study related topics such as the emergence of consensus in scientific communities (Zollman, 2007, 2010) and the impacts of social biases on group learning (O’Connor & Weatherall, 2018). Unlike some other sorts of network models, in this paradigm agents gather and share data and evidence with each other. This is an important feature in studying confirmation bias since this bias impacts the way individuals deal with evidence they receive.

We find that in models incorporating moderate levels of confirmation bias, surprisingly, groups do better than in models where individuals do not exhibit confirmation bias. Dogmatic individuals who do not easily change positions force the group to more extensively test their options, and thus avoid preemptively settling on a poor one. This result reflects claims from Mercier & Sperber (2017) who argue that confirmation bias might be a beneficial feature of reasoning in a group setting. Our results also echo findings from Zollman (2010) who shows that groups of “stubborn” individuals sometimes learn better than more individually rational learners. In our case, confirmation bias can function as a sort of stubbornness. It leads individuals to keep exploring theories that might otherwise seem suboptimal, and, in doing so, to sometimes discover that these theories are actually worthwhile.

There is a downside to confirmation bias, though. While moderate levels can promote accurate group-level learning, we find that a more robust type of confirmation bias leads individuals to entirely ignore theories they do not currently favor. In such cases, communities can polarize, and epistemic progress is harmed. This suggests that while we may have identified a useful function of confirmation bias, worries about its harms are still legitimate even when considered from the group perspective.

The paper will proceed as follows. In section 2 we describe relevant literature,
first focusing on empirical work on confirmation bias. We then briefly survey related modelling work. Section 3 outlines our model which incorporates a form of confirmation bias into epistemic network models. In section 4 we present two sets of results. The first considers models with a moderate level of confirmation bias, and shows how this bias can improve learning in a community. The second considers models where confirmation bias drives polarization, and prevents good group learning.

In the conclusion we draw some more general lessons for social epistemology and philosophy of science. One relates to the independence thesis—that irrational individuals can form rational groups, and vice versa (Mayo-Wilson et al., 2011). Our models provide one more vein of support for this claim. Another relates to the rationality or irrationality of ignoring data as a Bayesian learner. Another regards models of polarization. It is increasingly clear that there are many causal pathways that can lead to community polarization. Which prompts the question: what can simple models of polarization tell us? We also consider, generally, how our models should influence our understanding of ideal structures for scientific communities.

2 Previous Literature

2.1 Confirmation Bias

As noted, confirmation bias is a blanket term for a set of related behaviors involving actors who are unresponsive or resistant to evidence challenging their currently held beliefs (Nickerson, 1998). Sometimes this bias is referred to as “myside bias”, since it is not a general preference for confirmation, but a preference for confirmation of one’s own beliefs specifically (Mercier & Sperber, 2017). The models we present here will not adequately track all forms of confirmation bias. They do, though, reflect behaviors seen by those engaging in what is called selective exposure bias, as well as those who selectively interpret evidence.

Selective exposure occurs when individuals are more likely to select or seek out information confirming their beliefs. For example, a person might believe that moonstones cure cancer. If she shows a preference for reading articles that confirm this belief over articles that contradict it, then she exhibits selective exposure bias. Describing the bias in this way allows for some neutrality between researchers who describe it as an avoidance of dissonant information (Hart et al., 2009) and those who describe it as a pursuit of consonant information (Garrett, 2009; Stroud, 2017).

1 The study by Chaffee & McLeod (1973) where participants chose pamphlets to read about an upcoming election is an example of selective exposure bias. The study where Sweeney & Gruber (1984) found that participants had been seeking out information about the Watergate hearings if they preferred McGov-
ern likewise illustrates selective exposure. While selective exposure has been most frequently studied in the context of politicized information, it need not be. Johnston (1996) observes selective exposure in participants seeking information to confirm their stereotypes about doctors. Olson & Zanna (1979) find selective exposure in participants’ art viewing preferences. Stroud (2017) gives a wider overview of these and related results.

As will become clear, our models can also appropriately represent confirmation bias that involves selective interpretation or rejection of evidence. Recall that in the study by Lord et al. (1979)—where subjects received information both supporting and opposing the efficacy of the death penalty as a deterrent to crime—this information did little to change subjects’ opinions on the topic. This suggests that they were selectively rejecting information that opposed their point of view. Gadenne & Oswald (1986) demonstrate a similar effect in subject ratings of the importance of information confirming vs. challenging their beliefs about a fictional crime. Taber & Lodge (2006) gave participants pairs of equally strong arguments in favor of and against affirmative action and gun control. They found that subjects tended to shift their beliefs in the direction they already leaned, indicating that they were relatively insensitive to counter-evidence. In each of these cases, individuals were exposed to multiple types of information, but seemed to selectively reject only the information challenging their views.

As noted in the introduction, previous authors have argued that various forms of confirmation bias may be epistemically harmful. Nickerson (1998) writes that, “Most commentators, by far, have seen the confirmation bias as a human failing, a tendency that is at once pervasive and irrational” (205). It has been argued that confirmation bias leads to irrational preferences for early information, which grounds or anchors opinions (Baron, 2000). In addition, confirmation bias can lead subjects to hold onto beliefs or delusions which have been discredited (Festinger et al., 2017; Anderson et al., 1980; H. M. Johnson & Seifert, 1994; Nickerson, 1998; Lewandowsky et al., 2012). Another worry has to do with “attitude polarization”, exhibited in Taber & Lodge (2006), where individuals shift their beliefs in different directions when presented with the same evidence.

Further worries about the harms of confirmation bias have focused on communities of learners rather than individuals, including scientific communities, social media sites, and more general groups. Attitude polarization, for example, might drive wider societal polarization on important topics (Nickerson, 1998; Lilienfeld et al., 2009). For this reason, Lilienfeld et al. (2009) describe confirmation bias as the bias, “most pivotal to ideological extremism and inter- and intragroup conflict” (391).

When it comes to scientific judgments, researchers may be irrationally receptive to data consistent with their beliefs, and resistant to data that does not fit. Koehler (1993) and Hergovich et al. (2010), for example, find that scientists rate studies as of higher quality when they confirm prior beliefs. If so, perhaps the scientific process is negatively impacted by these irrational responses to new evidence.
In the age of social media, it has been argued that confirmation bias may contribute to the formation of “filter bubbles” and “echo chambers”. Pariser (2011) argues that filter bubbles occur when recommendation algorithms are highly sensitive to content that users prefer. In the presence of confirmation bias, this may predominantly involve information that confirms already held views. “Echo chambers” are a related concept wherein online users seek out digital spaces—news platforms, followees, social media groups etc.—that mostly confirm the beliefs and worldviews they already hold. While there is some debate about the impact of these effects, researchers have argued that they promote polarization (Conover et al., 2011; Sunstein & Sunstein, 2018; Chitra & Musco, 2020), harm domain specific knowledge (Holone, 2016), and lead to worryingly uniform information streams (Sunstein & Sunstein, 2018; Nikolov et al., 2015) (but see Flaxman et al. (2016)).

Is it justified to infer from individual harms of confirmation bias to group harms? The results we present will complicate the idea that groups must necessarily do worse, epistemically, in the presence of confirmation bias. Before presenting these results, we will take some time to address previous, relevant modelling work.

2.2 Previous Models

To this point, there seem to be very few models incorporating confirmation bias to study its effects on epistemic groups. Geschke et al. (2019) present a “triple filter-bubble” model, where they consider the impacts of 1) confirmation bias, 2) homophilic friend networks, and 3) filtering algorithms on attitudes of agents. They find that a combination of confirmation bias and filtering algorithms can lead to segmented “echo chambers” where small, isolated groups with similar attitudes share information. Their model, however, does not attempt to isolate confirmation bias as a causal factor in group learning. In addition, they focus on attitudes or opinions that shift as individuals average with those of others they trust. As will become clear, our model isolates the effects of confirmation bias, and also models learning as belief updating on evidence, thus providing better structure to track something like real-world confirmation bias.

There are a wider set of models originating from the work of Hegselmann et al. (2002), where agents have “opinions” represented by numbers in a space, such as the interval \([0, 1]\). They update these opinions by averaging with others they come in contact with. Hegselmann et al. (2002) show that if agents are only willing to average with those in a close “neighborhood” of their own beliefs, polarization arises. Individuals settle into distinct camps with different opinions, and do not influence each other. This could perhaps be taken as a representation of confirmation bias, since individuals are sensitive to only those opinions close to their own. But, again, there is no representation in these models of evidence or of belief revision based on evidence.\(^2\)

\(^2\)There is also no way to distinguish in their models whether the agents ignore some other opinions because they 1) do not like opinions that vary from their own or 2) do not trust social sources with different opinions.
As noted, we draw on the network epistemology framework in building our model. While this framework has not been used to model confirmation bias, there have been some relevant previous models considering cases where actors devalue or ignore some data for various reasons. O’Connor & Weatherall (2018) develop a model in which agents update on evidence less strongly when it is shared by those with different beliefs. This devaluing focuses on the source of information, rather than its content (as occurs in confirmation bias). Reflecting some of our results, though, they find that devaluation at a low level is not harmful, but at a higher level eventually causes polarization. Wu (2021) presents models where a dominant group devalues or ignores information coming from a marginalized group. Wu’s model (again) can yield stable polarization under conditions in which this devaluation is very strong. In both cases, and, as will become clear, in our models, polarization emerges only in those cases where agents begin to entirely ignore data coming from some peers.

There is another set of results from epistemic network models that are highly relevant here. Zollman (2007, 2010) shows that, counter-intuitively, in network models communities tend to reach accurate consensus more often when the individuals in them are less connected. This occurs because in highly connected groups, early strings of misleading evidence can influence the entire group to preemptively reject potentially promising theories. Less connected networks tend to preserve a diversity of beliefs and practices longer, meaning there is more time to explore the benefits of different theories. As will become clear, a very similar dynamic explains why, in our model, moderate levels of confirmation bias actually benefit a group. Zollman (2010) finds similar benefits to groups composed of “stubborn” individuals, i.e., ones who start with more extreme priors and thus learn less quickly. In our model, confirmation bias creates a similar sort of stubbornness.

3 Model
3.1 Base Model
As discussed, our model starts with the network epistemology framework (Bala & Goyal, 1998), which has been widely used in recent work on social epistemology and the philosophy of science. Our version of the model builds off that presented in Zollman (2010).

There are two key features of this framework: a decision problem and a network. The decision problem represents a situation where agents want to develop accurate, action-guiding beliefs about the world, but start off unsure.

---

3 See also Fazelpour & Steel (in press).
4 Other papers have found similar results using NK-landscape models (March, 1991; Lazer & Friedman, 2007; Fang et al., 2010), and have confirmed these empirically (Mason et al., 2008; Derex & Boyd, 2016).
5 See Wu & O’Connor (2022) for an overview of network models considering how mechanisms that slow learning, and thus promote transient diversity of practice, improve group outcomes.
about which actions are the best ones. In particular, we use a two-armed bandit problem, which is equivalent to a slot machine with two arms that pay out at different rates. The problem is then to figure out which arm is better. We will call the two options A (or “all-right”) and B (or “better”). For our version of the model, we will let the probabilities that each arm pays off be $p_b = .5$ and $p_a = p_b - \epsilon$. In other words, there is always a benefit to taking option B, with the difference between the arms determined by the value of $\epsilon$.

Agents learn about the options by testing them, and then updating their beliefs on the basis of these tests. Simulations of the model start by randomly assigning beliefs to the agents about the two options. In particular, we use two beta distributions to model agent beliefs about the two arms. These are distributions from 0 to 1, tracking how much likelihood the agent assigns to each possible probability of the arm in question. The details of the distribution are not crucial to understand here. What is important is that there are two key parameters for each distribution, $\alpha$ and $\beta$. These can be thought of as tracking a history of successes ($\alpha$) and failures ($\beta$) in tests of the arms. When new data is encountered, say $n$ trials of an arm with $s$ successes, posterior beliefs are then represented by a beta distribution with parameters $\alpha + s$ and $\beta + n - s$. It is easy to calculate the expectation of this distribution, which is $\frac{\alpha}{\alpha + \beta}$.

Following Zollman (2010), we initialize agents by randomly selecting $\alpha$ and $\beta$ from $[0, 4]$. The set-up means that at the beginning of a trial, the agents are fairly flexible since their distributions are based on relatively little data. As more trials are performed, expectation becomes more rigid. For example if $\alpha = \beta = 2$, then expectation is 0.5. Expectation is flexible in that if the next three pulls are failures, then expectation drops to $\frac{2}{2+5} \approx 0.286$. However, if a thousand trials resulted in $\alpha = \beta = 500$, three repeated failures would result in an expectation, $\frac{500}{500+503} \approx 0.499$ (which is still close to 0.5). In simulation, if the agents continue to observe data from the arms, their beta distributions tend to become more and more tightly peaked at the correct probability value, and harder to shift with small strings of data.

As a simulation progresses we assume that in each round agents select the option they think more promising, i.e., the one with a higher expectation given their beliefs. This assumption corresponds with a myopic focus on maximizing current expected payoff. While this will not always be a good representation of learning scenarios, it represents the idea that people tend to test those actions and theories they think are promising. Each agent gathers some number of data points, $n$, from their preferred arm. After doing so, they update their beliefs in light of the results they gather, but also in light of data gathered by

---

6The function is defined as follows.

**Definition (Beta Distribution)** A function on $[0, 1]$, $f(\cdot)$, is a beta distribution iff for some $\alpha > 0$ and $\beta > 0$

$$f(x) = \frac{x^{(\alpha-1)}(1-x)^{(\beta-1)}}{B(\alpha, \beta)}$$

where $B(\alpha, \beta) = \int_0^1 u^{(\alpha-1)}(1-u)^{(\beta-1)}du$.

7Kummerfeld & Zollman (2015) present models of this sort where agents also explore options that they think are suboptimal.
neighbors. This is where the network aspect of the model becomes relevant. Agents are arrayed as nodes on a network, and it is assumed they see data from all those with whom they share a connection.

To summarize, this model represents a social learning scenario where members of a community 1) attempt to figure out which of two actions/options/beliefs is more successful, 2) use their current beliefs to guide their data gathering practices, and 3) share data with each other. This is often taken as a good model of scientific theory development (Zollman, 2010; Holman & Bruner, 2015; Kummerfeld & Zollman, 2015; Weatherall et al., 2020; Frey & Šešelja, 2020) or the emergence of social consensus/beliefs more broadly (O’Connor & Weatherall, 2018; Wu, 2021; Fazelpour & Steel, in press).

In this base model, networks of agents eventually settle on consensus—either preferring the better option B, or the worse option A. If they settle on A, they stop exploring option B, and fail to learn that it is, in fact, better. This can happen if, for instance, misleading strings of data convince a wide swath of the group that B is worse than it really is.

### 3.2 Confirmation Bias

How do we incorporate confirmation bias into this framework? For each round of simulation, after trial results are shared according to network connections, agents have some probability of accepting and updating their beliefs based on the shared results. This probability is based on how likely they believe those results are given their prior beliefs, $\lambda$. This likelihood is a function of the agent’s current beta distribution parameters, $\alpha$ and $\beta$, as well as the details of the results, successes, $s$, per number of draws, $n$. An agent calculates $\lambda$ separately for each set of results shared via a network connection.

Additionally, the model includes an intolerance parameter, $t$, that impacts how likely agents are to accept or reject results for a given prior probability of those results occurring. The probability of an agent accepting a set of results is:

$$ p_{accept} = \lambda^t $$

When $t$ is low agents are more tolerant of results they consider unlikely, and when $t$ is high they tend to reject such results. For example, suppose an agent thinks some shared results have a 5% chance of occurring given their prior beliefs (i.e. $\lambda = .05$). Then for $t = 1$, the agent has a probability of accepting $p_{accept} = .05$. For $t = 2$, the agent is extremely intolerant with $p_{accept} = .05^2 = .0025$.

---

$^8$The likelihood for some agent of some set of results is given by a beta-binomial probability mass function:

$$ p_X(n, s, \alpha, \beta) = \binom{n}{s} \frac{B(s + \alpha, n - s + \beta)}{B(\alpha, \beta)} $$

where $B(\alpha, \beta) = \int_0^1 u^{(\alpha-1)}(1-u)^{(\beta-1)} du$, $X$ is the action (A or B) that generated the results, $\alpha$ and $\beta$ are the values corresponding to the receiving agent’s beliefs about action $X$, $n$ is the number of pulls, and $s$ is the number of successes in shared results. For further discussion of the beta-binomial probability mass function, see (N. L. Johnson et al., 2005, 282) or (Gupta & Nadarajah, 2004, 425).
For $t = .5$, the agent is more tolerant and $p_{\text{accept}} = .05^5 = .22$. And when $t = 0$ the probability of acceptance is always 1, i.e., our model reverts to the base model with no confirmation bias. Whenever evidence is accepted, agents update their beliefs using Bayes rule as described. Agents never reject evidence they generated themselves. This feature mimics confirmation bias by representing either, 1) a situation in which agents are selectively avoiding data that does not fit with their priors, or 2) engaging with, but rejecting this data and thus failing to update on it.

We consider several different simple network structures, including the cycle, wheel, and complete networks (see figure 1). We also consider Erdos-Renyi random networks, which are generated by taking some parameter $b$, and connecting any two nodes in the network with that probability (Erdős et al., 1960). In general, we find qualitatively robust results across network structures. For each run of simulation, we initialize agents as described, and let them engage in learning until the community reaches a stable state.

![Figure 1: Several network structures](image)

4 Results

4.1 Moderate Confirmation Bias

In the model just described, notice, actors can be very unlikely to update on some data set. But the structure of the beta distribution and our rule for rejecting evidence means that they always accept data they encounter with some probability. Whenever agents continue to test different theories, their data continues to reach networks neighbors and shape the beliefs of these neighbors. This mutual influences means that, as in previous versions of the model without confirmation bias, actors in our model always reach consensus eventually: either correct consensus that $B$ is better, or incorrect consensus in $A$. The question is: how does the introduction of confirmation bias influence the frequency with which correct vs. incorrect consensus emerges?

Surprisingly, we find that confirmation bias improves the knowledge producing capacity of epistemic networks, in that it increases the likelihood a particular network will reach correct consensus. This finding is robust across network

---

We do not actually consider values of $t > 1$ in our simulations because generally prior probabilities of evidence are fairly small to begin with.
structures, and variations in other parameters (network size, \( N \), number of pulls per round, \( n \), difference between the arms, \( \epsilon \)). Figure 2 shows this result for the wheel network with different numbers of agents. Results are averages over 1000 runs of simulation for each parameter value. Each trace tracks a different amount of confirmation bias, as modulated by \( t \). As is clear, the larger \( t \) is, i.e., the more confirmation bias, the more often the network of agents correctly concludes that B is the better option.

Figure 2: When agents use moderate levels of confirmation bias, groups tend to reach accurate consensus more often. This figure shows results for small wheel networks. Qualitative results are robust across parameter values. \( \epsilon = .001 \), \( n = 1000 \)

As noted this trend is robust across parameter values. In figure 3 we show similar results for larger graphs randomly generated using the Erdos-Renyi algo-

---

10 In all results presented we hold \( \epsilon = .001 \) and \( n = 1000 \). These choices follow previous authors. They also keep the difficulty of the bandit problem in a range where it is at least somewhat challenging to identify the better option. This reflects the fact that we wish to model the sort of problem that might actually pose a challenge to a community trying to solve it. If \( \epsilon \) is larger, or \( n \) larger, the problem is easier and more communities reach accurate consensus in this sort of model.

11 For all results displayed, we ran simulations long enough to reach stable consensus. To check replicability, the model was coded independently by two separate team members. Results were all highly similar, with some small variations based on exact details of algorithm implementation. Code is available at REMOVED FOR REVIEW.
rithm described above. Again, higher levels of intolerance correspond to better group learning.

Figure 3: When agents use moderate levels of confirmation bias, groups tend to reach accurate consensus more often. This figure shows results for moderate sized ER random networks with the probability of connection between any two nodes, \( b = .5 \). Qualitative results are robust across parameter values. \( \epsilon = .001 \), \( n = 1000 \)

As noted, this finding relates to results from Zollman (2007, 2010) showing that both lowering connectivity and increasing stubbornness can improve outcomes in this sort of model. This “Zollman effect” occurs when individuals influence each other too strongly, and, as a result, are prone to incorrectly settle on option A as a result of early strings of misleading data. By making agents less willing to accept data that might change their mind, confirmation bias decreases social influence in a similar way and leads to longer period of exploration for both theories. This, in turn, increases the chances that the entire group selects the better option B in the end.

While it is surprising that a reasoning bias which is usually treated as worrisome can actually improve the performance of a group, this result reflects claims from Mercier & Sperber (2017). They point out that while confirmation bias is treated as irrational, and assumed to have largely negative epistemic effects, it might be beneficial in a group setting. In particular, they think that when peers
disagree about matters of fact, confirmation bias allows them to divide labor by developing good arguments in favor of opposing positions. They are then jointly in a position to consider these arguments and come to a good conclusion. This fits with a larger picture where reasoning evolved in a social setting, and what look like detrimental biases actually have beneficial functions for groups. Their mechanism for a possible group benefit for confirmation bias is not the same as the one we identify. Ours depends on the idea that confirmation bias leads to continued exploration and data gathering about multiple theories or actions, while theirs depends on interpersonal argumentation as a route to accurate belief. But both accounts suggest that confirmation bias might, counterintuitively, do something positive for epistemic groups.

To test the robustness of our general finding, we implement another version of the model. Confirmation bias in the first version responds to the likelihood of some data set given current beliefs. But confirmation bias often occurs in the context of fairly coarse-grained information. What if we suppose individuals ignore details of the data and ask simply: which general option does this data support? And: do I think that option is the better one? In deciding to accept or reject a set of data in this version of the model, the actor calculates their probability that B is better than A, or vice versa, and scales with an intolerance parameter as before.\(^{12}\) Actors accept any data set supporting B (or A) with probability \(P_{accept}\).

The qualitative results of this “coarse grained” model are similar to the previous one. Across parameters, increasing confirmation bias leads to improved group outcomes. Figure 4 shows results for ER random networks with different numbers of agents. As is clear, a higher value of \(t\) is again associated with a greater probability that the group adopts a consensus on the better option, B.

\(^{12}\)That is we calculate \(P_{accept}\) as

\[
P_{accept} = \left[ \sum_{i=0}^{999} \left( pmf_A(i, n, \alpha_A, \beta_A) \times \sum_{j=i+1}^{1000} pmf_B(j, n, \alpha_B, \beta_B) \right) \right]^t
\]

where \(pmf_X(s, n, \alpha, \beta))\) is the same as before.
Figure 4: Moderate confirmation bias increases epistemic success under a different operationalization of confirmation bias. This figure shows results for moderate sized ER random networks with the probability of connection between any two nodes, $b = .5$. Qualitative results are robust across parameter values, $\epsilon = .001$, $n = 1000$.

Our results to this point seem to suggest that confirmation bias is an unmitigated good in a group setting. It is true that the sort of confirmation bias modelled so far always improves group consensus formation in our models. There are a few caveats, though. First, for parameter settings where the decision problem is relatively easy—where the network ($N$) is large, agents draw more data ($n$ is large), and/or the two arms are relatively easy to disambiguate ($\epsilon$ is large)—most groups successfully learn to choose the correct arm. In these cases confirmation bias does little to improve learning.$^{13}$ On the other hand, confirmation bias as we model it always slows down consensus formation, sometimes very dramatically. This creates a trade-off between speed of learning and accuracy of consensus formation (Zollman, 2007, 2010). In cases where it is important for a group to quickly reach consensus, then, confirmation bias might cause problems. Second, as will become clear in the next section, stronger assumptions about what confirmation bias entails will shift this narrative.

$^{13}$See also Rosenstock et al. (2017) who point out that the benefits of network connectivity shown in Zollman (2010) are only relevant to difficult problems.
4.2 Strong Confirmation Bias

To this point, we have only considered models where agents always have some probability of updating on data they encounter, though this probability may be small. This means that all agents continue to exert influence on each other, regardless of what they believe and what sorts of data they gather. This influence might be small, but it ensures that given enough time the community will eventually reach consensus on one of the two options.

But what if agents sometimes entirely discount data that does not fit their prior beliefs? We now look at a much simpler version of confirmation bias. Agents calculate how likely some data set is given their current beliefs, as before. If that probability is below some threshold, \( h \), they discard the data. If it is above that threshold, they update on it.

In this version of the model, we now observe outcomes where groups do not settle on consensus. It is possible for subgroups to emerge which favor different options, and where data supporting the alternative position is unpersuasive to each group. This can be understood as a form of polarization—agents within the same community settle on stable, mutually exclusive beliefs, and do not come to consensus even in the face of continued interaction and sharing of evidence.\(^{14}\)

Figure 5 shows results for Erdos-Renyi random networks with different thresholds for ignoring discordant data, \( h \). As is clear, as the cutoff becomes more stringent, fewer simulations end up adopting an accurate consensus.

\(^{14}\)There are many ways the term polarization is used. Here we operationalize it as any outcome where the community fails to reach consensus, and where this lack of consensus is stable. This approximately tracks notions of polarization that have to do with failure of a community to agree on matters of fact.
Figure 5: Strong confirmation bias hurts group learning. This figure shows results for moderate sized ER random networks with the probability of connection between any two nodes, $b = .5$. Qualitative results are robust across parameter values. $\epsilon = .001$, $n = 1000$

As noted much of the reason that communities fail to reach accurate consensus in these models is because they polarize. When this happens, some actors adopt accurate beliefs, but others do not. Because actors with inaccurate beliefs develop credences where the accurate belief looks very unlikely to them, they become entirely insensitive to data that might improve their epistemic state. As figure 6 shows, polarization occurs more often the stronger the agents’ confirmation bias. Both accurate and inaccurate consensus become less common. For parameter values where only very likely data is accepted, polarization almost always emerges.
Figure 6: Strong confirmation bias leads to polarization. This figure shows results for ER random networks with the probability of connection between any two nodes, $b = .5$. Qualitative results are robust across parameter values. $N = 6$, $\epsilon = .001$, $n = 1000$

Another question we might ask is: how does this stronger form of confirmation bias impact the general epistemic success of agents in the network? Note that since polarization occurs in these models this is a slightly different question than how strong confirmation bias impacts correct group consensus. Given that confirmation bias leads to an increase in polarization, and a decrease in both correct and incorrect consensus formation, it is not immediately clear whether it is epistemically harmful on average.

In general we find that this stronger form of confirmation bias leads fewer individual actors, on average, to hold correct beliefs. As is evident in figure 7 for high levels of strong confirmation bias, fewer individuals hold true beliefs. In this figure notice that for lower levels of confirmation bias there is relatively little impact on average true belief. In fact, given details of network size, we find that there is often a slight advantage to a little confirmation bias for the reasons outlined in the last section—it prevents premature lock-in on false consensus.\footnote{In the simulations pictured here, the 20-30\% cutoff range does the best by a hair.} This slight advantage is eventually outweighed by the negative impacts of too much distrust. As confirmation bias increases, eventually too many agents adopt false beliefs, and fail to engage with disconfirmatory evidence.
Figure 7: Average correct beliefs under strong confirmation bias. This figure shows results for ER random networks of size 6 and 9, with the probability of connection between any two nodes, $b = 0.5$. Qualitative results are robust across parameter values. $\epsilon = 0.001$, $n = 1000$

At this point, it may seem that small differences in how confirmation bias is modelled have large impacts on how it influences group learning. As long as agents continue to have some influence on each other, no matter how small, confirmation bias improves consensus formation (and thus average true beliefs). Once this is no longer true, it generally harms average true beliefs. This picture is not quite right. Recall from the previous section that moderate confirmation bias always slows consensus formation, sometimes dramatically. When this happens, a network can remain in a state of transient polarization for a long period of time. If we stopped our models at some arbitrary time period, rather than always running them to a stable state, the two sorts of confirmation bias would look more similar. In both cases confirmation bias leads to polarization, but in one case that polarization eventually resolves, and this process improves community learning. The take-away is thus a complex one—confirmation bias can have surprising benefits, but these benefits are neither simple, nor unmitigated.
5 Conclusion

We find that confirmation bias, in a more moderate form, improves the epistemic performance of agents in a networked community. This is perhaps surprising given that previous work mostly emphasizes the epistemic harms of confirmation bias. By decreasing the chances that a group pre-emptively settles on a promising theory or option, confirmation bias can improve the likelihood that the group chooses optimal options in the long run. In this, it can play a similar role to decreased network connectivity or stubbornness (Zollman, 2007, 2010; Wu, 2021). The downside is that more robust confirmation bias, where agents entirely ignore data that is too dissonant with their current beliefs, can lead to polarization, and harm the epistemic success of a community. Our modeling results thus provide potential support for the arguments of Mercier & Sperber (2017) regarding the benefits of confirmation bias to a group, but also a caution. Too much confirmation bias does not provide such benefits.

There are several ongoing discussions in philosophy and the social sciences where these results are relevant. Mayo-Wilson et al. (2011) use network models to argue for the independence thesis—that rationality of individual agents and rationality of the groups they form sometimes come apart. I.e., individually rational agents may form groups which are not ideally rational, and rational groups may sometimes consist in individually irrational agents. Our results lend support to this claim. While there is a great deal of evidence suggesting that confirmation bias is not ideal for individual reasoners, our results suggest that it can nonetheless improve group reasoning under the right conditions.

This argument about the independence thesis connects up with debates about whether it is ever rational to ignore, or fail to update on, free evidence. According to Good’s theorem, it is always rational to update in such cases (Good, 1967). The proof relies on the idea that an individual who wishes to maximize their expected utility will not do worse, and will often do better, by updating on available, free information. In the models presented, our agents sometimes choose to ignore evidence, and doing so increases their chances of eventually holding true beliefs. Of course, in the meantime they ignore good evidence that should, on average, improve the success of their actions. Whether or not they “should” ignore evidence in this case arguably depends on what their goals are. But if the central goal is to eventually settle on the truth, we show that ignoring some data can help in a group learning setting.

It is worth noting that our results are also consonant with some lines of argumentation in philosophy of science regarding the value of stubbornness or dogmatism to the progress of science. Kuhn (1977), for instance, suggests that disagreement is crucial in science to promote the exploration of a variety of potentially promising theories. Some amount of potentially irrational stubborn-

---

16 We do not take a strong stance here about how to define rationality for a group. The main observation is that epistemically successful groups can be formed from irrational agents.

17 Of course if data is costly, it is easy to see that even a rational agent might not be willing to pay the costs to update on it. But in our modeling set-up, we assume that data may be shared and updated on cost-free.
ness is acceptable in generating this disagreement. Popper (1975) is not too worried about confirmation bias in individual scientists because, as he argues, the critical aspect of science as practised in a group will serve to eliminate poor theories. He goes on to argue that, “...a limited amount of dogmatism is necessary for progress: without a serious struggle for survival in which the old theories are tenaciously defended, none of the competing theories can show their mettle” (98). On this picture, it is not ideal for scientists to abandon their currently preferred theories too easily. Some persistent disagreement or debate is necessary to ensure that a new theory is worthwhile. He goes on to add, though, that, “Intolerant dogmatism...is one of the main obstacles for science” (98). New theories must at least be entertained and given proper attention by the scientific community. Our results support this picture.

There is a question, though, about whether confirmation bias, or other forms of arguably irrational stubbornness, are the best mechanisms by which to improve group learning. Wu & O’Connor (2022) overview the literature looking at transient diversity of practice/beliefs in network models. They end up arguing that in scientific communities there are better ways to ensure this diversity than to encourage actors to be stubborn. For example, centralized funding bodies can promote the right amount of exploration across topics instead. By doing so, they allow all scientists to learn about all data rationally, but still prevent premature adoption of suboptimal theories. But Wu and O’Connor’s conclusions are specific to scientific disciplines where there are levers for coordinating exploration across a group. When it comes to more general epistemic groups, especially outside of science, such coordination may not be possible. If so, confirmation bias may provide benefits that are not available via more efficient routes.

One larger discussion that this paper contributes to regards the mechanisms that can lead to polarization in real communities. Such mechanisms often include a feedback loop wherein similarity of opinion/belief leads to increased influence between individuals, and vice versa. Individuals whose beliefs diverge end up failing to influence each other, and their divergent beliefs become stable. But under this general heading, theorists have identified a number of different such mechanisms. Hegselmann et al. (2002) show how this can happen if individuals fail to update on the opinions of those who do not share their opinions. Weatherall & O’Connor (2020) find polarization emerges when individuals conform with those in their social cliques, and thus ignore data from those outside. Pariser (2011) argues that algorithms can drive polarization by supplying only information that users like in the face of confirmation bias. Echo chambers function when individuals seek out and connect to friends and peers who share their beliefs (see also modeling work by Baldassarri & Bearman (2007)). Wu (2021) finds polarization arises when entire groups mistrust other groups based on social identity. O’Connor & Weatherall (2018), as noted, find that polarization emerges when actors do not trust data from peers who hold different beliefs. And in our models polarization can follow from confirmation bias because subgroups ignore different sets of disconfirmatory data.

Why does this diversity of mechanisms for polarization matter? It suggests
that identifying sufficient causes of polarization is very different from identifying necessary, or even likely, causes of polarization. It also suggests that in considering real instances of polarization researchers should be sensitive to many possible causes. Thus experimental/empirical research and modeling are both necessary in figuring out just what real causes are at work in producing social polarization.

As a last note before concluding, we would like to discuss limitations of our models. Of course the models we present are highly simplified compared to real social networks. This means that the results should, of course, be taken with a grain of salt. In particular, we only consider one type of learning problem—the one-armed bandit model. The question remains whether and to what degree these results will be robust. We suspect that models with other problems might yield similar results. The general benefit of slowing group learning, and promoting a period of exploration, has been established across a number of models with different problems and mechanisms (Wu & O’Connor, 2022). We leave this for future research.

Acknowledgements

Many thanks to the members of our NSF group meeting for discussion and feedback on drafts of this proposal—Clara Bradley, Matthew Coates, David Freeborn, Yu Fu, Ben Genta, Daniel Herrmann, Aydin Mohseni, Ainsley Pullen, Jim Weatherall, and Jingyi Wu.

References


Derex, M., & Boyd, R. (2016). Partial connectivity increases cultural accu-
mulation within groups. Proceedings of the National Academy of Sciences, 113(11), 2982–2987.


Fang, C., Lee, J., & Schilling, M. A. (2010). Balancing exploration and exploita-
tion through structural design: The isolation of subgroups and organizational

Fazelpour, S., & Steel, D. (in press). Diversity, trust and conformity: A simu-
lation study. Philosophy of Science.

and psychological study of a modern group that predicted the destruction of the world. Lulu Press, Inc.

Flaxman, S., Goel, S., & Rao, J. M. (2016). Filter bubbles, echo chambers, and
online news consumption. Public opinion quarterly, 80(S1), 298–320.

models of scientific interaction. The British Journal for the Philosophy of Science.


agent-based modelling to test a meta-theoretical framework for the emergence


applications. Marcel Dekker.


