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Epistemic Network Injustice*

Kai Spiekermann

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Abstract

To find out what is in one's own best interest, it is helpful to ask one's epistemic peers. However, identifying one's epistemic peers is not a trivial task. I consider a stylized political setting, an electoral competition of 'Masses' and 'Elites'. To succeed, the Masses need to know which alternative on offer is truly in their interest. To find out, the Masses can pool their privately held information in a pre-election ballot, provided that they can reliably find out with whom they should pool information. I investigate the process of finding the relevant peer group for information pooling by modeling this group formation process as dynamic network change. The simulations show that the Masses can succeed in finding the right peers, but they also suggest reasons why the Elites may often be more successful. This phenomenon generalizes to the notion of Epistemic Network Injustice. Such injustice arises when a subset of citizens is systematically deprived of connections to helpful epistemic peers, leading to their reduced political influence. Epistemic Network Injustice is a new form of epistemic injustice, related to but distinct from the notion introduced by Miranda Fricker.

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1 Introduction

If we are uncertain about which political choice is in our best interest, it is often helpful to consult with others and take their advice into account. But this strategy comes with a catch — it only works if one asks people with the same fundamental interests. Asking the wrong people can, at best, be a waste of time and, at worst, lead to choices against one’s best interest. Since people are epistemically dependent on others, finding one’s true epistemic peers matters. For example, registered Republicans voting in a primary may want to find out which candidate they should support to best promote their interests. It may be helpful to ask other voters, but not everyone will be helpful. A free-trade Republican, for example, should perhaps not listen to a Trump-supporting Republican. For information aggregation purposes it is pointless and often misleading to follow those who are not your true epistemic peers, i.e. do not share the same interests.¹ At the same time, listening to one’s true epistemic peers, if one is able to find them, can be very helpful and might substantially increase the chances for making the right choice. If a citizen is cut off from those who can help her to learn what is in her true interest, this person may experience what I will later introduce as ‘Epistemic Network Injustice’.

Identifying the alternative in one’s interest is not as simple as it might look. If the relation between means and ends is not transparent then, even if one is certain about the ends, the choice of means is non-trivial. Since political choices are rarely directly about ends but much more often about means to promote ends, knowing what one ‘really’ wants can be particularly hard in such contexts. This becomes important in elections or referendums. If all of one group – let’s call them the ‘Masses’ – knew which alternative best promotes their interest, they would easily beat the smaller but potentially more informed and more organized ‘Elites’. But if the Masses don’t know and their vote splits in the middle, then the Elites might well swing the vote to their advantage.

This is where asking one’s peers and pursuing one’s interest in solidarity might help. Solidarity is typically understood as a value appealed to in the context of collective action (Kolers, 2016; Sangiovanni, 2015). The Masses

¹There are, of course, many other good reasons for listening to those with differing or opposing interests. My question here is exclusively focused on information aggregation for predicting a correct choice under the assumption that different choices are correct for different individuals.

can overcome oppression or domination by the Elites if they act in solidarity in their joint pursuit of change. But there is a different aspect to solidarity that has been discussed less often, but which is in an important sense prior to collective action: solidarity can also help to identify what the Masses really want. To clarify their interests, the Masses can practice *epistemic solidarity*. They can pool the information they hold individually in a pre-election ballot and then successfully commit to vote for the result of their pre-ballot, making use of the dispersed information they hold. If they do, the Masses will not only have a good chance to identify what is in their interest (because of Condorcet's Jury Theorem and related results: Condorcet 1785), they are also likely to outvote the Elites because they coordinate their vote.

For a practical example, consider the Greek bailout referendum of 2015 called on the reform proposals of the 'institutions' (formerly known as the 'troika'). It might well be the case that the answer in the interest of the Greek Elites differed from the answer in the interest of the Masses (perhaps further austerity was good for the Elites but disastrous for the Masses, or, *vice versa*, perhaps risking default was disastrous for the Masses but the best option for the Elites, etc.; I do not intend to defend any view on this complicated matter). In the face of daunting complexity, the first challenge for the Masses is to find out whether it is better for them to vote Yes or No. That is not an easy task, but it may be a challenge they can meet if they practice epistemic solidarity: pool what they know individually, and then all vote along the lines of the pooling result.

The Masses are, in principle, able to outvote the Elites if the Masses succeed in pooling their information. More precisely, a majority of people who have the same interests but are individually not very competent in identifying their most preferred alternative can find out with great reliability which alternative is best for them if they take a majority vote among themselves. However, in order to identify their preferred choice in the majority vote, the Masses first have to find out 'who is with them', i.e. who their true epistemic peers are. This may well be the greater challenge for the Masses: if they are individually not very good at identifying which alternative is in their interest, they may also find it difficult to know who they can trust to provide information based on the interest of the Masses.

The Elites, by contrast, may have a few aces up their sleeves: they may be more competent individually, they might be able to spend more time and make an effort to find out who is 'with them', they tend to 'know people who know', they are probably socially more mobile, and they often dominate the

public discourse. This helps the Elites to identify their true epistemic peers, vote for their preferred alternative as a block, and perhaps even confuse the Masses about their choice. If the Masses remain divided while the Elites coordinate their votes, the Elites can impose their minority interests on the group.

In this paper I investigate how the search for true epistemic peers might turn out to be more or less successful for the Masses and the Elites, how this influences the practice of epistemic solidarity, and how these differential capacities to find peers can lead to what I call Epistemic Network Injustice. I will show that, when the playing field is level, the Masses are in a strong position. However, more often than not the playing field is not level. The Elites are often much better organized as a group, not only because they are smaller, but also because they have more resources available to identify their true peers and coordinate their votes. If the Elites are organized and the Masses are divided, the Elites have a good chance of winning. This phenomenon, I will show, links up with a renewed interest in structural injustice, especially the literature on propaganda and ideology. The notion of Epistemic Network Injustice captures settings in which individuals are disadvantaged by their inferior epistemic position in their communication network, which makes it harder for them to form beliefs about what is in their own best interest.

The paper begins in section II with an explanation of how groups form and change membership on a network. Section III introduces a simple baseline model, while section IV provides several extensions, showing that the competition between Elites and Masses depends on successful peer group formation. Section V offers a definition of Epistemic Network Injustice and explores the relation to other forms of epistemic injustice, while section VI concludes.

2 Finding Your True Epistemic Peers

What can individuals do when looking for a good epistemic peer group, a group of people with shared interests? Finding a good peer group would be easy if all the true peers were clearly marked, by green beards, for example. That is not particularly plausible. In practice, identifying one's true peers is tricky. This is for two reasons. First, even if individuals know what their fundamental interests are, they do not reliably know what these fundamental

interests entail for the concrete decision at hand. Second, when observing others they cannot (normally) see what their fundamental interests are, they only see their views about the concrete decisions to be made.

For example, if individuals 1 and 2 agree on whether they should support alternative A or B that might be because they have the same fundamental interests and are both right (or both mistaken) in identifying the choice their shared interest entails, but it might also be because they have different interests and either 1 or 2 are mistaken about what their respective interests entail. Agreeing on the concrete alternative to be supported is therefore only very imperfect evidence for aligned fundamental interest.

The technical foundations of this paper go back to Condorcet’s jury theorem (see, for instance, Grofman et al., 1983; List and Goodin, 2001; Goodin and Spiekermann, 2018). Put very briefly, Condorcet’s jury theorem says the probability of a correct group majority grows with group size and converges to 1 if the voters are competent and the votes are independent.² However, unlike the Condorcetian setting, I allow for a person-relative standard of correctness, so that the correct answers for Elites and Masses can differ. This idea of multiple truth standards was first introduced by Miller (1986). Goldman (1999, chapter 10) independently linked diverging standards to social epistemology in a democratic setup. This idea was later formalized by List and Spiekermann (2016). The idea of epistemic solidarity stems from Goodin and Spiekermann (2015), but they only look at a static setting in which both groups know who their peers are. The present paper goes substantially beyond the static setup by making group formation endogenous.

I begin by introducing the fundamental building blocks of the model. Let there be a set of voters $V = \{1, \dots, n\}$. The number of voters is finite, so that $n < \infty$. In my simple model, each voter is either of the Elite (E) or the Mass (M) type. More formally, a voter i has one type $T(i) \in \{E, M\}$. The number of Elite voters is $e = \#\{i \in V : T(i) = E\}$ and the number of Mass voters is $m = \#\{i \in V : T(i) = M\}$, such that $n = e + m$.

To model epistemic dependence, the relationship between the individuals is represented as a network. A network consists of nodes, and some pairs of nodes are connected by edges (sometimes called links). Let the nodes represent individual voters, so that the set of nodes is V . We represent

²The problems with both assumptions, but especially the independence assumption, are discussed in detail in the literature on the Condorcet jury theorem. See Dietrich and Spiekermann (2015) for a brief review.

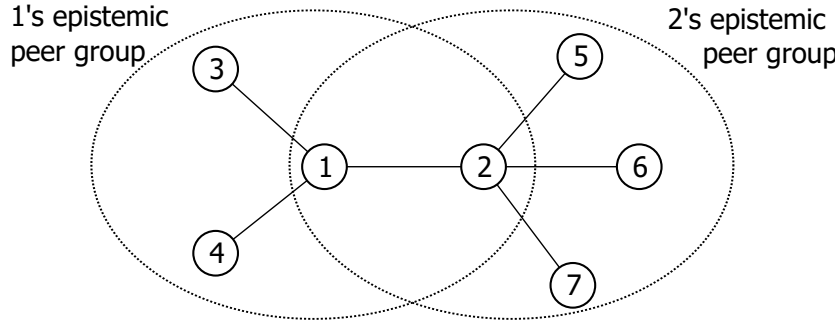


Figure 1: A simple network with epistemic peer groups.

the network as an undirected graph $G(V, L)$, with L being the edges in the graph. An edge (i, j) exists if and only if voter i communicates with j and j with i . The edges are symmetric (undirected), so that two connected agents always communicate in both directions. In other words, an edge between two individuals means that these two agents learn from their respective neighbour which alternative they think is the right one, prior to pooling any information.

The epistemic peer group of an individual is all the individuals that are directly connected, that is, the neighbourhood of the agent on the network. More formally, let the neighborhood of a voter $i \in V$ be $N_i = \{j : (i, j) \in L\} \cup \{i\}$. This means that all voters directly connected to i are part of the neighbourhood, and i is assumed to be part of the neighbourhood, too.

Note well that an epistemic peer group does not always consist only of true epistemic peers. Each individual may have members in their peer group that do not share the same fundamental interests. Figure 1 shows a small network. Individual 1 has 2, 3, and 4 as peers, as these are connected with edges to 1. Individual 2 has 1, 5, 6, and 7 as peers. While 1 and 2 have each other in their respective peer groups, this does not mean that their peer groups are identical; they listen to different peers.

The model rests on some core assumptions. First, as we have seen, all agents have a fixed type: either ‘Elite’ or ‘Mass’. This type determines their (fundamental) *interest*. For simplicity I assume that Elites and Masses always have diverging interests.

Second, prior to each vote, it is randomly determined which of the two available alternatives is the *correct alternative*, that is, the one in the interest of the Masses and the Elites, respectively. Formally, in each round an equiprobable state of nature $\theta \in \{0, 1\}$ is drawn that determines the correct

answer $c_E(\theta)$ for the Elites and $c_M(\theta)$ for the Masses:

	$\theta = 0$	$\theta = 1$
$c_E(\theta)$	1	0
$c_M(\theta)$	0	1

Third, the agents have *opinions* (private signals), which depend probabilistically on what is the right alternative for them in the present vote. In each round, each voter i receives a signal about the correct answer for them, and they form an opinion $o_i \in \{0, 1\}$ about the correct answer according to *competence* p_E for Elites or p_M for the Masses such that $p_E = \Pr(o_i = c_E(\theta))$ for each Elite voter i and $p_M = \Pr(o_j = c_M(\theta))$ for each Mass voter j with $p_E, p_M \in (0, 1)$. The competence is the probability to form the correct opinion about the alternative that is in the agent's objective interest, and these competence parameters remain the same for both possible states. This competence assumption is similar to the competence assumption of Condorcet's jury theorem, but in the present paper the individuals are competent if they are better than random at tracking their objectively best alternative (depending on their type), while in Condorcet's theorem the same external truth applies to everyone in the same way.

Finally, *votes* are the result of the opinions of the agents in the neighbourhood (the epistemic peer group) because we assume that individuals take into account the views of their neighbours before voting. In this simple model, individuals use the information their neighbours hold in a very straightforward manner: An agent connected to other agents votes for the opinion of the majority (including himself) in his immediate neighborhood, his epistemic peer group. If there is a tie of opinions in the peer group, then the tie is broken by the toss of a fair coin. One could say that each agent votes for the most supported alternative in his neighborhood. If an agent is unconnected (without peers), he votes according to his own signal, of course. Formally, this leads to the following rule to determine an individual i 's vote:

$$v_i = \begin{cases} 1 & \text{if } \sum_{x \in N_i} o_x > \frac{\#N_i}{2} \\ 0 & \text{if } \sum_{x \in N_i} o_x < \frac{\#N_i}{2} \\ \text{coin toss } \{0,1\} & \text{otherwise.} \end{cases}$$

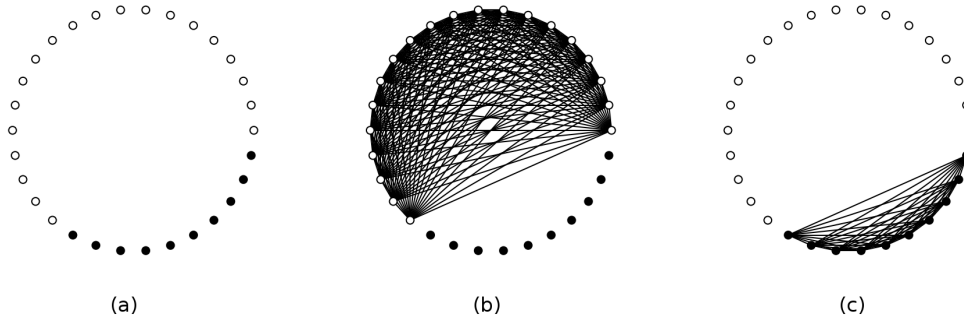


Figure 2: Examples of an unconnected graph, and complete subgraphs among the masses and the elites.

One nice feature of the network model is that it includes completely pooled and completely unpooled voting as special cases. If no opinions are pooled, the voters (nodes) are on an empty graph with no edges – everyone votes according to their own signals only, as in Figure 2a. (I represent the Elite voters as black, the Mass voters as white nodes.) If the Masses show perfect epistemic solidarity while the Elites do not, this can be represented as a complete graph of all Mass agents (a complete graph is a graph in which every node is connected to every node), and a separate empty graph with all Elite agents, as in figure 2b. And if only the Elites pool their votes perfectly, the Elite agents form a complete graph and all Mass agents are in a separate empty graph, as in figure 2c.

With all other central elements in place, it is time to consider how true epistemic peers find each other. I consider some simple but suggestive mechanisms for making the formation of peer groups endogenous. Looking at several dynamics of group formation provides us with clues which factors may enable the Elites or Masses to identify a good epistemic peer group to use for information pooling in order to win the vote.

What interests me is, in effect, a dynamic mechanisms of network change based on the information the individuals gather about their neighbours. I explore several simple processes for changing the network, i.e. for edge deletion and creation. To keep matters tractable, I assume that, while agents do not know with certainty what the best alternative for them is *ex ante*, they do know *ex post*, after each vote, what the best choice was (or would have been). In other words, the assumption here is that the correctness of

one's own decision can be assessed easily with hindsight. This means that a voter i knows, *ex post*, whether the opinions of i 's neighbours were correct or incorrect according to i 's standard of correctness. This is, of course, an important simplification, but, as we will see, the voters are still challenged to find their peers – weakening this assumption would make it even harder. One can think of this aspect of the model as a sort of learning about neighbours by trial-and-error.

Each simulation run consists of many rounds. A round starts with the determination of the correct alternative for the Masses and for the Elites. All agents then form opinions about which of the two alternatives is correct, in line with the competence parameters. Each agent (node) pools the opinions in the neighborhood and casts a vote accordingly. After this election, the network change process sets in: a subset of 10% randomly chosen agents has the opportunity to delete an edge to one of their neighbors. One can interpret this as a social process that lets some individuals respond to disagreements with the other individuals they interact with: after a disagreement, they sometimes cut the social connection and will no longer take the opinion of that individual into account.

I explore several simple rules that the individuals might use to decide which link to cut. In all cases, the deleted edges are replaced by new edges between randomly chosen individuals (thereby keeping the overall number of edges constant), assuming that new acquaintances are random encounters. I also assume that the link carrying capacity of nodes is only limited by the number of other nodes available, that is, if a node is linked with all other nodes, it cannot form more links. Self-loops and multiple edges between the same pair of nodes are ruled out.

My highly simplified network change process can be summarized in pseudo code. The decisive procedure to be defined is the **delete_edge_choice** procedure, the way how agents choose to which of their neighbors they want to cut their link:

```
set run_nodes as a random subset of 10% of all nodes
for each node in run_nodes:
  choose 0 or 1 adjacent edge by delete_edge_choice
  if 1 edge chosen:
    delete this edge
    draw new edge between two unconnected random nodes in network
```

In the next two sections, I investigate several possible renderings of the delete edge choice procedure and explore under which conditions Elites and

Masses manage to find suitable epistemic peer groups, and how that influences their likelihood to win votes.

3 A Simple Baseline Model

To obtain a simple baseline model, suppose, unrealistically, that after each vote individuals do not only learn which alternative was the correct one for them, all individuals also learn about which alternative was best for all other individuals. Who is with you and who is against you is then fully transparent.³ This is clearly a much too optimistic assumption about what the agents know about themselves and each other, and I will investigate more realistic and interesting settings below. Nevertheless, it is a useful starting point for understanding the dynamics of the model.

Given what the individuals know, it is clear what they will do: if it's an individual's turn to delete an edge, they will choose to cut a link to an agent with different interest (and not delete any edge if all their neighbors have the same interest). That way all individuals try to create a more homogeneous neighborhood in which the pooled votes are more likely to track their correct alternative in the next round.

Here and in all following simulations I begin with a random network constituted by 100 nodes and 300 edges, so that the edges are initially randomly arranged between the nodes.⁴ Multiple edges between the same two agents, and self-loops (edges to oneself) are not allowed. Of the 100 nodes, 30 represent Elite and 70 Mass voters.

Unsurprisingly, the network dynamics arising from the baseline model lead to a very quick separation of Mass and Elite agents. Since all agents recognize each other's type and remove links to agents that are not their type, the network quickly separates Masses and Elites and divides into two separate components. Once that separation is completed, the network has reached a stable state, as no agent has an incentive to delete any further edges and consequently no new edges are added. Figure 3 shows a typical development after 0, 20, 40, and 60 rounds.

The stable state on the right of figure 3 is typical for the outcome in the

³What is not transparent is which alternative is in an agent's interest in the next round because which alternative is best for which type can change from round to round. This is why it is still useful to pool opinions with epistemic peers.

⁴This is a Erdős-Rényi $G(n,M)$ model after Erdős and Rényi 1959.

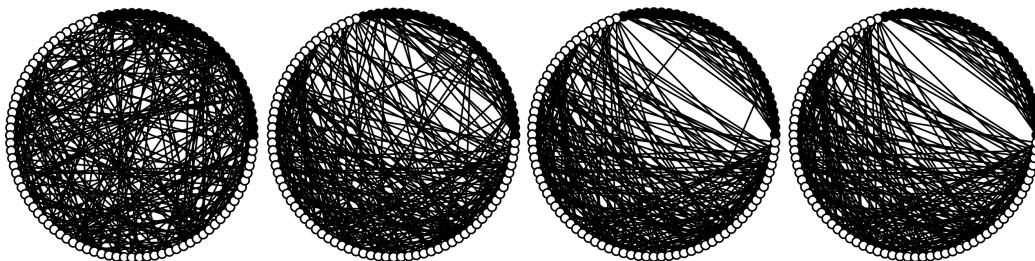


Figure 3: Development of the baseline model, showing network after 0, 20, 40 and 60 rounds (from left to right).

baseline model. Note that the Mass agents are now more strongly connected than the Elite agents and therefore pool their information in larger groups. To measure this effect systematically, we can investigate how the network topology affects the probability of Elite and Mass agents to vote for their preferred alternative.

I begin with the assumption that Elite voters recognize the alternative in their interest a bit more often than Mass voters do. I can then explore whether Mass voters can nevertheless beat the smaller but more competent Elites by practising epistemic solidarity. So suppose that an Elite voter on her own has probability $p_E = 0.7$ to vote for her preferred alternative, while a Mass voter has probability $p_M = 0.6$. Pooling opinions with voters of the same type increases (and pooling with voters of the opposite kind decreases) the probability of voting for the correct alternative.

Figure 4 visualizes the epistemic effect of pooling the votes in one such simulation. It shows the distribution of pooled competence for the initial (left) and the final network topology (right) after one simulation with 100 rounds. The distributions indicate how well the different voters are expected to do epistemically, given the neighbors they have. Each bar represents an expected pooled competence of the agent, given the distribution of types in their neighbourhood. It answers the question: how likely is it for an agent to vote correctly, given the peer group he relies on? The expected pooled competence is a measure of how large and how good the peer group is. Pooled competence is highest if an agent has found many true peers and avoids being connected to “false” peers that do not share the same interests. The formal statement of how pooled competence is calculated is not difficult but a little involved; it can be found in online Appendix A.

In the beginning, both Elite and Mass agents have a lot of variance in their

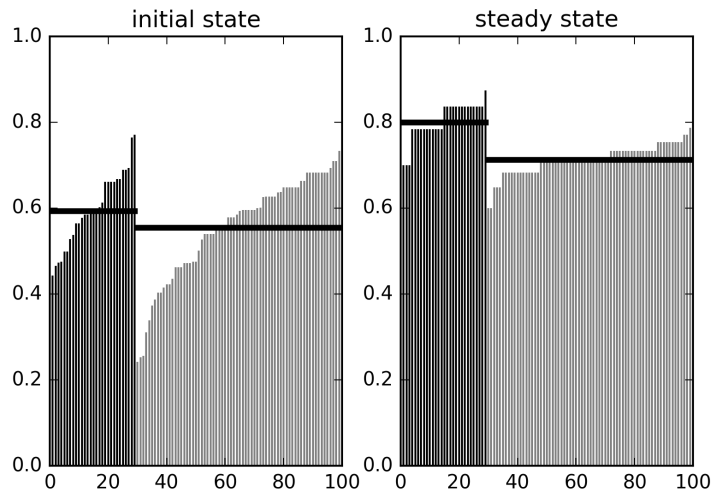


Figure 4: Distribution of pooled competence of Elites (black) and Masses (grey) with initial and steady state topology for baseline model. Bold lines are averages of the competence resulting from pooling, separately for Elites and Masses.

pooled competence because they tend to be connected to their adversaries to different degrees, dragging down the reliability of their pooled votes. The change in pooled competence, when drawing on neighbours, can be seen by looking at the averages of both groups, drawn as bold lines in figure 4.

After the network has gone through a revision process of 100 rounds, Elites and Masses are separated entirely and the network reaches a steady state. Both pooled competence averages increase compared to the initial state. The reason is that the separation of Mass and Elite voters benefits most voters, as they are now pooling exclusively with their own type. But the Elites benefit more, once they lose all edges to the Masses. In the steady state, most Elite agents have a higher individual competence, giving them an advantage.

The result for this one round is a typical outcome. Across 1000 simulations, the Elites end up with an average pooled competence of 0.79, the Masses with 0.72. However, in terms of the election, the Elites still do comparatively poorly. In 1000 simulations, the Elites win 24% of votes in the

steady states.⁵ This is actually worse than what the Elites could expect *without* any network change. Pooling with the initial random network gives the Elites electoral success in about 43% of cases. This is because the pooled competence for all agents in the initial state is so low that the Masses often ‘accidentally’ vote for the Elite interest. The result shows that a separation of the two groups is not necessarily in the interest of the Elites; an election in which everyone pools confusing and contradictory opinions allows the Elite minority to succeed more often than they would if their opponents were more unified. However, unless the Masses are totally incompetent in their edge deletion strategy, the Elites are probably not able to preserve the initial ‘pooling chaos’ of the random network.

4 Learning From Experience

The baseline model is unrealistic because it assumes that the correct alternative for each agent is perfectly visible to all agents after each vote. It is therefore no surprise to find a complete separation of Mass and Elite agents — they recognize each other without error. The next model variations come with less demanding assumptions about what the individuals find out about their peers. In the next set of simulations the agents perfectly know what was in their own objective interest after each vote (with hindsight), but they can only infer from the opinions expressed by a neighbor in the last round whether that neighbor shares their own interest (or whether she is of a different type). After all, the neighbor may have been wrong, *ex ante*, about his own correct alternative, expressing what the agent sees retrospectively as the ‘right’ opinion but not really share the agent’s interests; or vice versa. This makes it much harder to find ‘like-minded’ agents to pool information with, as previous opinions are not a very reliable indicator of their type, as long as the competence parameter is not close to 1.

To put this a bit more precisely, the `delete_edge_choice` procedure works as follows in this model:

1. Find all neighbors whose last opinion differs from one’s own correct alternative in the previous round;
2. If this set is non-empty, delete edge to one of those neighbors (random choice if there are several); otherwise do nothing.

⁵Votes that result in a tie are broken with the toss of a fair coin.

Using the other parameters as above, I find that Elites and Masses are now much less successful in separating into homogeneous groups. Even after letting the simulation run for a long time (1000 rounds), there are still many links between Elites and Masses. Consequently, the quality of the pooled results is reduced; average pooled competence hovers around 0.6 for both groups. This means that the Masses still win the elections most of the time: in 1000 simulations, they do so 58% of the time, doing about as well as they would without any network change.

The reason why information pooling failed in the previous model is the agents's very short memory, combined with their limited competence. Since Elites vote against their correct alternative 30% and Masses 40% of the time, looking merely at the last opinion expressed by their neighbours means that agents often keep links to the 'wrong' neighbors or sever links to the 'right' neighbors.

As a next step, I explore what happens if I give both Masses and Elites a memory of 5 previous rounds. To be more precise, all agents can recall the last 5 opinions of agents they were continuously connected with in the last 5 rounds (but forget all information about former neighbors as soon as they get disconnected).

The delete_edge_choice procedure is now this:

1. Rank all neighbors of agent i according to their rate of agreement with what were the correct choices for i in the previous 5 rounds;
2. If there are agents with a rate of agreement $< 1/2$, sever link to the agent with the lowest rate (or, in case of a tie, one of those agents chosen randomly).⁶

With a longer memory, both Masses and Elites are more successful in creating homogeneous pooling groups, and their epistemic performance changes accordingly. Figure 5 shows a typical competence distribution before and after one simulation with 1000 rounds.

The overall average competence after 1000 such simulations was 73% for the Elites and 65% for the Masses, showing that both groups are making (modest) gains compared to their individual competence. Since both groups gain epistemically, it is unsurprising that the Masses still win most of the votes (measured at the end of the 1000 rounds): the Masses succeed in 64% of those elections.

⁶The Python code for this approach is provided in online Appendix B.

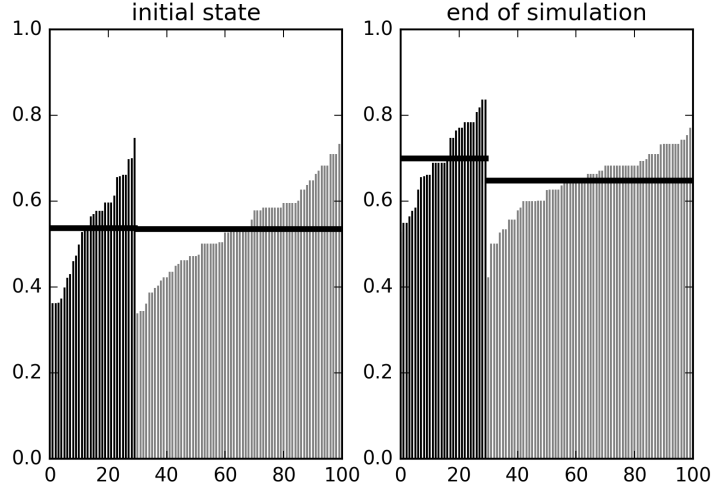


Figure 5: Distribution of pooled competence of Elites (black, competence 0.7) and Masses (grey, competence 0.6) with initial and end of simulation topology after 1000 rounds for memory of 5 for both Elites and Masses. Bold lines are averages.

However, this result changes quite dramatically if the difference in competence between Masses and Elites is more pronounced. With a higher level of competence, the Elites can recognize each other more reliably, as the Elites tend to vote more often in alignment with their objective interest. Figure 6 shows the pooled competence distribution before and after the network dynamics unfolding for Elite competence $p_E = 0.8$ and Mass competence $p_M = 0.6$. The difference between the pre- and post-simulation distribution is striking: the Elites see a sharp increase in their pooled competence (to 93% on average in 1000 simulations), while the Masses can increase their competence only modestly (to 63%). This increase allows the Elite to achieve majorities in 67% of cases.

An interesting variation of the memory parameter setting arises if one differentiates between Elites and Masses. In this next set of simulations, I give Masses a memory of 1 and the Elites a memory of 5. One can interpret this setting as a simulation of ‘more discerning’ Elites — they choose the agents they interact with more carefully, based on a longer period of experience.

Figure 7 shows a typical probability distribution of pooled competences

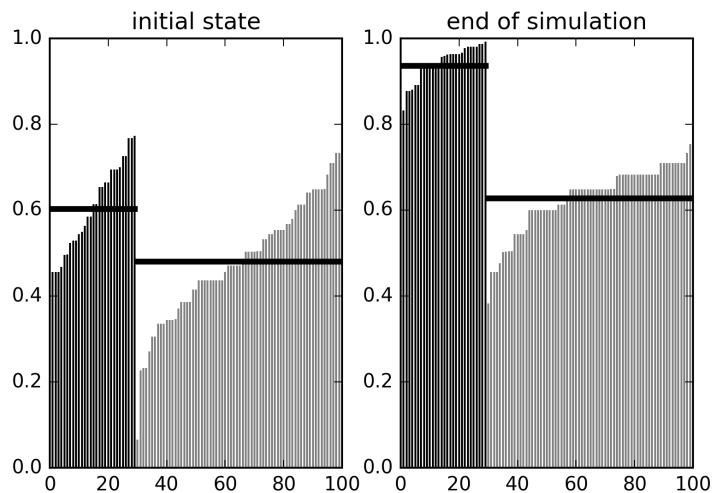


Figure 6: Distribution of pooled competence of Elites (black, competence 0.8) and Masses (grey, competence 0.6) with initial and end of simulation topology after 1000 rounds for memory of 5 for both Elites and Masses. Bold lines are averages.

before and after a simulation with 1000 rounds. Individual competences for the Masses are 0.6 and for the Elites 0.7. Compared to figure 4, we see an increase in the average competence of the Elites beyond their individual competence, while the Masses do not improve much compared to their individual performance. One can also note that at the end of the simulation almost all Elite agents do well epistemically, certainly better than $1/2$, and most of them better than their individual competence. Many Mass agents, by contrast, do poorly in their attempt to pool information. This is due to the fact that the Elites are now quite strongly connected between each other, while many Mass agents have a mix of links to Mass and Elite agents, which reduces their pooled competence.

In 1000 simulations, the Elites reach an average pooled competence of 75%, the Masses of 60%. This is also reflected when counting the winners of the elections at the end of the simulations: about 51% are won by the Elites, who are now punching much above their numerical weight, due to their successful information pooling. If I increase the memory of the Elites further, to 10 previous periods, the pooled Elite competence increases to 80%

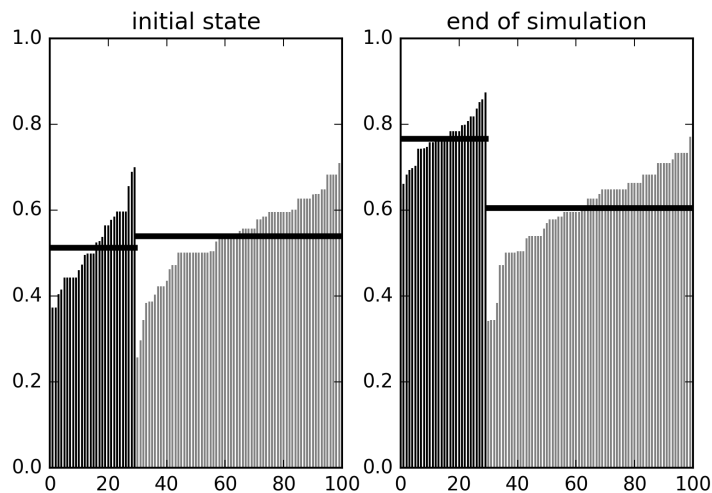


Figure 7: Distribution of pooled competence of Elites (black, competence 0.7) and Masses (grey, competence 0.6) with initial and end of simulation topology after 1000 rounds for memory of 5 (Elites) and 1 (Masses). Bold lines are averages.

(Masses: 60%) and the Elites win 60% of elections.

A more pronounced difference in competence (Elites 0.8 and Masses 0.6) leads to even more successful Elites. With a memory of 5 for Elites and 1 for the Masses, the 30 Elite agents dominate the elections after they successfully formed their pooling groups: they win in about 88% of cases, as compared to a baseline of 64% prior to any network changes.

Table 1 takes stock of the simulation results. The most important upshot is that the Elites have a chance of winning despite their minority position. This is likely to happen if they are either significantly more competent or more discerning due to their superior memory of past interactions. It can also happen if the Elites benefit from the confusion of the Masses, especially if the Masses do not manage to exercise epistemic solidarity. By contrast, if the Masses succeed in pooling the information they hold, they are very likely to win votes.

The model could be extended in many directions, making the network larger, starting with different constellations, thinking about the effect of di-

	p_E	p_M	Elites winning
Initial network	0.7	0.6	43%
Types recognised (Baseline)	0.7	0.6	24%
Memory 1 for both	0.7	0.6	42%
Memory 5 for both	0.7	0.6	36%
Masses Memory 1, Elites 5	0.7	0.6	51%
Masses Memory 1, Elites 10	0.7	0.6	60%
Initial network	0.8	0.6	64%
Memory 5 for both	0.8	0.6	67%
Masses Memory 1, Elites 5	0.8	0.6	88%

Table 1: Summary of Simulations, each estimate of Elite winning frequency based on 1000 simulations.

rected edges, or giving Masses and Elites different link carrying capacities.⁷ However, the main goal of these simple simulations is not realism but rather to help us see that the domination of the Masses by a smaller but well-informed and organized Elite is possible.

5 Epistemic Network Injustice

The simulations presented in the previous section give us a sense of how the Masses might become epistemically dominated by the Elites in specific circumstances. The simulations paint a suggestive picture, a picture that has been painted in other, less formal ways in the recent literature on ideology and propaganda. In this section, I briefly look at these recent contributions, with a special focus on their epistemic underpinning. I then state and explain a definition of epistemic network injustice.

Consider Jason Stanley’s (2017) observation that ‘[s]ome flawed ideologies will be democratically problematic, because they lead to widespread theoretical irrationality, which typically results in failure to track one’s own interest...’ (p. 216). Stanley presupposes an epistemic standard that determines one’s own interests and that one can fail to live up to that standard, just like the model framework in the present paper. He also thinks that it is the ‘Elite’ who can influence results to their advantage: ‘It is natural to

⁷I am grateful to a referee for pointing out this possible variation.

think that the elite maintain power by promulgating the flawed ideology that their interests are the interests of the society at large' (p. 232).

In that respect, Stanley is in agreement with Sally Haslanger (2017), whose 'epistemic critique of ideology reveals the distortion, occlusion and misrepresentation of the facts' (p. 150). Her work is but one example of a general shift of focus in political theory. An unjust society used to be conceived, at least in its most paradigmatic instantiations, as a society with unjust formal institutions. More recently, however, political theorists have turned towards the effects of informal arrangements, such as social norms, prejudice, or subtle forms of discrimination. What is needed to address these types of injustice, in addition to state action, is a change in culture. Specifically, cultural practices provide us with "resources for agency" (p. 154) that we will need to draw upon to resist ideology. A lack of such resources, by contrast, may "prevent us from appreciating what's morally relevant" (p. 159). This lack can constitute unjust structures, and the epistemic dimension of injustice connects to the political dimension.

The upshot from Stanley's and Haslanger's work in the context of this paper is twofold. First, both analyse the distortions of ideology at least partly in epistemic terms and appeal to a standard of correctness for that purpose. Second, they diagnose a structural epistemic problem. While they do not explicitly state the problem in terms of epistemic networks, the simple models presented in the previous section shed light on some aspects of the 'distortions' at play.

Advantaged groups might have many epistemic aces up their sleeve. They often already get born into a quality information network, growing up with family friends who are lawyers, doctors, academics, journalists, or politicians. They have every chance to maintain and improve on that network by getting to know more qualified peers. If necessary, they can buy expertise in the form of lawyers, financial advisors, or consultants.⁸ And finally, being advantaged typically means having time resources to investigate what is in one's own best interest, while less advantaged people often have their bandwidth absorbed by the necessities of life they cannot 'outsource' to others, from childcare to cooking or cleaning (Mullainathan and Shafir, 2014; Goodin et al., 2013).

The causal processes described just now stand for a certain sub-type of injustice, an injustice that arises due to specific mechanisms that lead to

⁸For a review of the sociology of elite networks and elite knowledge resources, see Khan 2012, with further references.

‘crippled epistemologies’ (Hardin, 2002) for some and richer epistemologies for others.

I suggest to call this particular type of injustice *epistemic network injustice* and define it as follows:

Epistemic Network Injustice. A society experiences *epistemic network injustice* if

- (i) there is a subset of citizens that, through no fault of their own, is systematically deprived of connections to helpful epistemic peers and/or is systematically misled by epistemic non-peers,
- (ii) due to the structure of the communication network;
- (iii) such that the ability of the subset members to identify their own political interests is compromised.

Conditions (i) and (ii) state the structural source of the injustice: a communication network structure that deprives a group of individuals of connections to peers that could help them make decisions in their own best interest. This could, in more extreme cases, also involve connections to non-peers that confuse or mislead.⁹ Condition (i) contains a responsibility caveat. Groups that deliberately *choose* to have disadvantageous peer connections do not experience injustice (though they do experience epistemic disadvantage). For example, a religious group that banishes any form of news media from their life might find that they are epistemically disadvantaged, but, given that their choices cause this network structure, they cannot claim to experience injustice. Condition (iii) spells out the implications of a problematic network structure. Compared to others, members of the group have a reduced chance to work out which political choices are in their best interest.

It is important to see that there are potentially two different injustices at work. The *epistemic* injustice consists in the reduced ability of the disadvantaged subjects to work out what is in their own best interest, caused by the communication network they are embedded in. But while the problem starts

⁹A referee for this journal pointed out that the model runs shown earlier lead to epistemic disadvantage not only because of network structures, but also because the Masses were disadvantaged in other respects such as competence or memory. This is correct – the models show the emergence of Epistemic Network Injustice due to other initial disadvantages. But it is easy to imagine that, once the unjust network structures are established, they can persist to do harm even if the initial disadvantages that made them emerge disappear. More modelling work in that regard has to wait for another time.

with an epistemic inequality, this will likely lead to non-epistemic injustice in the form of political inequality. And being deprived of equal political power can have economic inequality in its tow. Political and economic inequality as a result of epistemic injustice are caused by epistemic injustice, but the epistemic injustice and the other injustices following from it are analytically distinct.

The main focus of the epistemic injustice literature has been on ‘discriminatory epistemic injustice’ (Fricker, 2013; Coady, 2010), especially testimonial and hermeneutical injustice (Fricker, 2007). But there is also a distinctly distributive form of epistemic injustice, concerned with the way epistemic goods are distributed. Epistemic network injustice is of this distributive kind. The epistemic resource at stake is the ability to access truth-conducive information in the network. Discrimination, by contrast, is not a necessary condition for epistemic network injustice because it is conceivable that the network structure is not the result of discriminatory preferences. Instead, it might be a coincidental side effect of other social processes. However, even though discrimination is not necessary, it is plausible that discrimination often plays a role in the emergence of the problematic network structures.

Finally, I will consider two objections to the definition of Epistemic Network Injustice as presented. One may object, first, that Epistemic Network Injustice is not a form of injustice, as there is often no perpetrator; the injustice arises from structural properties of the communication network. However, one needs to consider the notion of justice appealed to. As explained above, Fricker’s notion of epistemic injustice, and especially hermeneutical injustice, is based on a structural understanding of injustice (Young, 1990). This is closely analogous to the case of Fricker’s hermeneutical injustice, where there is often no specific person to blame for the systematic disadvantages that affect some groups (Fricker, 2007, p. 161). Epistemic Network Injustice is similarly structural. Admittedly, on a narrow understanding of justice, Epistemic Network Injustice is better described as a disadvantage and not an injustice. But such a narrow understanding of the notion of justice robs the concept much of its critical potential when it comes to the causal effects of structures.

A second, libertarian objection to Epistemic Network Injustice insists that structures arising from voluntary choices cannot be unjust.¹⁰ As the network structures arise from individual choices, the argument goes, no injustice has

¹⁰I would like to thank a referee for pressing me on this point.

occured. This is not the place to revisit this well-reheared debate in detail. But it is worth noting that Epistemic Network Injustice might affect agents who have not made any choices about network structures themselves. Individuals might find themselves in epistemically disadvantaged positions for purely structural reasons: because they cannot find or connect with their peers, because powerful influencers have confused their peers, or because someone else was able to influence network structures to their own advantage. More fundamentally, the concept of Epistemic Network Injustice shows that the voluntariness of choices alone does not ensure just outcomes. It also matters that individuals are in a good position to make choices that advance their own interests in the first place.

6 Conclusion

Epistemic solidarity can be a tool for the Masses to identify which alternative best promotes their interest and use their greater number to win elections. But this optimistic picture comes with a catch: before epistemic solidarity can work, like-minded agents have to find each other, and avoid including other agents with different interests in their pooling process. Collecting the input of one's true epistemic peers, and only those, is not easy.

The simple models presented here, while still far-removed from the complex reality of epistemic peer group formation, are nevertheless suggestive. They demonstrate that a reshaping of the epistemic peer network can change the epistemic success of different groups — sometimes dramatically so. Important factors for epistemic success are the ability to form a group of true peers and the size of that group.

One outcome is of special interest from a democratic perspective: the possibility that a smaller group of more knowledgeable or more organized individuals with a minority interest outvotes the majority. Normally, this should not happen: even if the Masses are less competent they should still be able to outvote the Elites, as long as they manage to organize a pre-vote *en bloc* and then stick to that pre-vote, practising epistemic solidarity. But there are good reasons to believe that the Elites are advantaged in many ways: they tend to 'know the people in the know', they tend to be well-connected, and they are smaller, which often makes collective action easier to organize. My simulations uncover several ways how the Elites might dominate the Masses. Even if the Elites are not more competent in recognizing each other directly,

they might have other advantages, such as a better memory to identify their peers, or a higher competence that makes it easier to recognize each other. Under such conditions the smaller group tends to succeed in coordinating their vote while the larger group is often divided and confused.

Exploring the dynamics of epistemic solidarity shows that there is an epistemic aspect to power and collective action that is often forgotten. The problem is not only to act collectively, the problem is to identify the best action, or, in more Marxist terms, to overcome false consciousness. If individuals are stuck in crippled networks, they can become victims of Epistemic Network Injustice. Being epistemically dependent on one's peers is thus a mixed blessing — only if one succeeds in finding one's true peers can one effectively identify one's own interests and make them heard.

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Appendix A: Calculation of Pooled Competence

A voter i has neighbourhood $N(i)$. Let the cardinality of that neighbourhood be $n(i)$. Let the number of Elite types in $N(i)$ be $e(i)$ and the number of Mass types be $m(i)$. The pooled competence of the neighborhood for voter i depends on the number of Mass and Elite voters in the neighbourhood. We are interested in the likelihood of majorities that identify the correct interest of i . Let there be a set K of all possible ordered pairs $\langle v_E, v_M \rangle$ with v_E representing the number Elite types in $N(i)$ voting in the interest of the Elites and v_M the Mass types voting in the interest of the Masses under the constraints that $0 \leq v_E \leq e(i)$, $0 \leq v_M \leq m(i)$. Each tuple represents a possible outcome of Elite types and Mass types voting in a specific way and the set of all tuples represents all possible ways for the Elites and the Mass votes in the neighbourhood to go.

Case 1: Voter i is a Mass Type

In this case we are interested in a subset of K , namely all elements in which the Mass interest gains a majority. Let this subset be

$$O_M = \left\{ \text{all } \langle v_E, v_M \rangle \in K : e(i) - v_E + v_M > \frac{n(i)}{2} \right\}.$$

Call the event of a majority for the Masses in that neighbourhood MW. For the calculations to follow, it is useful to recall the standard binomial formula for the probability of x successes out of n draws with success probability p :

$$\binom{P(n, x, p) = n x p^x (1 - p)^{n-x}.$$

The probability of all possible vote combinations from the Elites and Mass types in such that the Masses win is:

$$\Pr(\text{MW}) = \sum_{\text{all } \langle v_E, v_M \rangle \in O_M} P(e(i), v_E, p_E) \times P(m(i), v_M, p_M).$$

Since tied outcomes are decided by coin toss, we need to calculate the probability of making the correct choice for the Masses by coin toss. Call this event T. We are now interested in the subset O_T of K that leads to ties:

$$M_T = \left\{ \text{all } \langle v_E, v_M \rangle \in K : e(i) - v_E + v_M = \frac{n(i)}{2} \right\}.$$

The probability of a correct vote by coin toss after a tie is:

$$\Pr(\text{T}) = \frac{1}{2} \sum_{\text{all } \langle v_E, v_M \rangle \in O_T} P(e(i), v_E, p_E) \times P(m(i), v_M, p_M).$$

The pooled competence is $\Pr(\text{MW}) + \Pr(\text{T})$.

Case 2: Voter i as an Elite Type

The same reasoning applied symmetrically. The subset O_E consists of all tuples of Elite and Mass votes voting according to their true interest in which the Elites obtain a majority:

$$O_E = \left\{ \text{all } \langle v_E, v_M \rangle \in K : v_E + m(i) - v_M > \frac{n(i)}{2} \right\}.$$

Call the event of a majority for the Elites in that neighbourhood EW. The likelihood of this occurring is calculated as above:

$$\Pr(\text{EW}) = \sum_{\text{all } \langle v_E, v_M \rangle \in O_E} P(e(i), v_E, p_E) \times P(m(i), v_M, p_M).$$

Again, results from tie-breaking coin tosses need to be taken into account. $\Pr(\text{T})$ is determined just as above. The pooled competence is $\Pr(\text{EW}) + \Pr(\text{T})$.

Appendix B: Python Code of Main Routines

In this appendix I reproduce the main part of the Python 3 code to calculate the results. This code is based on one simulation with memory. I have omitted auxilliary code to count votes, record and plot results.

```
import networkx as nx
import random as rd
from collections import Counter
from collections import deque

def modes(values):
    """function to return list of all modal values"""
    count= Counter(values)
    best = max(count.values())
    return [ k for k,v in count.items() if v == best ]

def indiv_opin(c):
    """return opinion according to competence c """
    return int(round(rd.random() + c - 0.5))

def group_opin():
    """ add opinion attribute for all nodes"""
    for n in network.nodes():
        network.node[n]['opinion'] = indiv_opin(comp_vector[n])

def vote_winner(votes):
    """for any given opinions or votes, determine winner, break ties by
    random choice"""
    return rd.choice(modes(votes))

def votes():
    """determine nbh including ego, collect all opinions, vote for winner,
    break tie randomly, set vote attribute for all nodes"""
    for n in network.nodes():
        nb = list(network[n]) + [n]
        nb_v = [network.node[i]['opinion'] for i in nb]
        # determine winner and break ties by random choice
        w = rd.choice(modes(nb_v))
        network.node[n]['vote'] = w

def mem_update():
    """ go through all edges and register the opinions of all neighbors in the
    memory attribute dictionary of network. Keep memory as a deque of length
    memlen so that old opinions are forgotten"""
    for e in network.edges():
        #check if there is a dict entry in memory of first node for 2nd node
        if e[1] in network.node[e[0]]['memory']:
            #if yes, then append opinion of 2nd node to memory of 1st node
            network.node[e[0]]['memory'][e[1]].append(network.node[e[1]]['opinion'])
        #otherwise create deque with that opinion, set deque max length
        else:
            network.node[e[0]]['memory'][e[1]] = deque(
                {network.node[e[1]]['opinion']},
                maxlen=network.node[e[0]]['memlen'])
        if e[0] in network.node[e[1]]['memory']:
```

```

        network.node[e[1]]['memory'][e[0]].append(network.node[e[0]]['opinion'])
    else:
        network.node[e[1]]['memory'][e[0]] = deque(
            {network.node[e[0]]['opinion']},
            maxlen=network.node[e[1]]['memlen'])

# initialize
rounds = 1000
network = nx.Graph()
elite = 30
mass = 70
nodes = elite + mass
edges = 300
elite_comp = 0.7
mass_comp = 0.6
# create vector of probability to vote for Elite option
comp_vector = [elite_comp] * elite + [1 - mass_comp] * mass
# define how many previous opinions from continuously connected nb
# the different types of agents remember
elite_memory = 5
mass_memory = 1
# make network; 1 stands for elite, 0 for mass
for n in range(elite):
    network.add_node(n, type=1, competence=elite_comp,
                    memory = dict(), memlen = elite_memory)
for n in range(elite, mass+elite):
    network.add_node(n, type=0, competence=1-mass_comp,
                    memory = dict(), memlen = mass_memory)
# add edges from an undirected random graph
network.add_edges_from( nx.gnm_random_graph(nodes, edges).edges() )

# main routine
for i in range(rounds):
    #do the opinion formation and pooled voting
    # note that, without loss of generality, it is assumed that Elites always
    #have correct answer 1 and Masses correct answer 0
    group_opin()
    votes()
    mem_update()
    # find 10% of nodes
    run_nodes = rd.sample(network.nodes(), int(round(nodes / 10)))
    #run through these node
    for n in run_nodes:
        max_disagree_list = []
        #only start deleting if a neighbor is wrong at least 50% of the time
        max_d = 1/2.0
        # run through all entries in memory
        for k, m in network.node[n]['memory'].items():
            #calculate neighbour rate of disagreement by comparing with type of
            #node deleting edge. Note that agents know correct answer with
            #hindsight so they can identify who was not voting correctly from
            #their perspective
            disagreement = (len(m) - m.count(network.node[n]['type'])) / float(len(m))
            #if this rate higher than all found previously, set nb as
            #nb with new highest disagreement
            if disagreement > max_d:
                max_d = disagreement

```

```

        max_disagree_list = [k]
        # if it is equal to what has been found previously, add nb to list
    elif disagreement == max_d and disagreement > 0:
        max_disagree_list.append(k)
if len(max_disagree_list) > 0:
    delete_target = rd.choice(max_disagree_list)
    network.remove_edge(n, delete_target)
    # when edge is deleted, delete memory of nodes about each other
    del network.node[n]['memory'][delete_target]
    del network.node[delete_target]['memory'][n]
    partner_list = []
    #ensure to look for an initiator such that an unconnected partner
    #exists (as no edge can be added to completely connected node)
    while not partner_list:
        # create new random edge
        # find random initiator
        initiator = rd.choice(list(network.nodes()))
        #find candidate partners not connected to initiator
        nb_init = list(network[initiator]) + [initiator]
        partner_list = [z for z in network.nodes() if z not in nb_init]
    partner = rd.choice(partner_list)
    network.add_edge(initiator, partner)

```