Network Epistemology:

Communication in Epistemic Communities

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Abstract

Much of contemporary knowledge is generated by groups not single individuals. A natural question to ask is, what features make groups better or worse at generating knowledge? This paper surveys research that spans several disciplines which focuses on one aspect of epistemic communities: the way they communicate internally. This research has revealed that a wide number of different communication structures are best, but what is best in a given situation depends on particular details of the problem being confronted by the group.

1 Introduction

Traditional epistemologists often assume a very simple model of knowledge acquisition. There is an individual inquirer who receives data from the world. Rarely does this data explicitly include other inquirers. If other individuals are included in the data they are treated as on a par with all other sorts of data. The now burgeoning field of social epistemology departs from this model. Its first, and probably most popular, departure incorporates other inquirers as different (potential) sources of knowledge. Doing so opens up many questions. How should one react to another inquirer who holds different beliefs? What is the epistemic ground for knowledge that comes exclusively from another inquirer? If two inquirers disagree, who should you trust? Etc.

This first departure retains the traditional focus on an individual inquirer but represents the inquirer's data as taking two different forms: data from the world and data from another inquirer. Scholars then ask whether these two are, in fact, different, and if so what epistemic norms govern the later.

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There is a yet more radical departure that focuses not on an individual agent, but instead considers a group of inquirers as the unit of analysis (Goldman, 2011). With the group as epistemic agent, one can now ask questions like what properties of groups make them better or worse epistemic groups? This question is important as much of our collective knowledge is generated by groups, not single individual inquirers. Juries decide guilt or innocence. Corporations must form something like beliefs so that they can make decisions for which they are (all too rarely) held liable. Science is increasingly becoming the collective endeavor of many individual scientists.

One might be inclined to conflate these two levels of analysis. Surely the best groups will be made up of the epistemically best individuals, and the epistemically best individuals will necessarily make the best groups. This is not always the case, however (Hong and Page, 2004; Mayo-Wilson et al., 2011). But even were it true, there remain many questions about how these individuals inside the groups should interact. There are many different dimensions on which groups might vary, but we will here focus on just one: the way they internally communicate amongst their members. This property of groups has received significant attention in economics and (to a lesser extent) philosophy. This paper will serve as an introduction to this literature.

Ultimately, what this literature has shown is two-fold. First, the best way for group members to communicate with each other depends critically on the epistemic problem with which they are confronted. There is no "epistemically best" structure for communication that holds across all groups and for all problems. As a result, one cannot criticize a group for communicating too little or too much or for having a hierarchical structure or not being hierarchical enough without having a detailed understanding of the type of learning problem this group aims to solve.

The second general lesson is that our intuitions can often be poor guides to optimal communication within a group. Mathematical analysis can show how an intuitive understanding of a problem is misleading, and it can point to a more precise way to develop answers to questions in social epistemology.

In this paper we will consider several different types of epistemic problems. In sections 2 and 3 we will consider how groups should be structured so as to maximize the use of information they already possess. Then in section 4 we will consider groups where the individuals are actively learning about the world as they share information with one another.

2 Information transmission

We will begin with a rather simple epistemic situation. There is a group of experts that each know something different about some underlying system – say a piece of machinery. Each individual must come up with a judgment about the effectiveness this machine, and so each individual would benefit from accessing the information of the others. We will suppose that each piece of information is independently valuable – getting one piece of information is useful – and that each is as valuable as any other. We will also begin by supposing that information can be communicated second-hand without any loss – i.e. you can learn about my friend's information from me without fearing that I have miscommunicated the information.

Establishing a line of communication might come with a cost, however. We will discuss three possibilities for how the communication might take place and how the costs (if any) are paid.

- *One way, one pays.* I can unilaterally visit you. I get all the information to which you have access, but you don't get mine. I pay the cost.
- *Two way, one pays.* I can unilaterally visit you. I get all the information to which you have access and you also get all the information to which I have access. I pay the cost.
- *Two way, both pay.* I can visit you but only with your permission. I get your information and you also get mine. We both pay the cost.

Each of these three ways of describing social interaction have plausible real world analogues. Suppose that you are a book author who has written a book that I might buy. I don't need your permission to buy your book, nor can I transmit information to you by purchasing the book. Here we have a case of *one way, one pays.* Instead of buying your book, I might come visit you to discuss issues. If I come to your house or pay for your time, I incur the cost of the interaction but I can also transmit information to you. Here we have a case of *two way, one pays.* Finally, you and I might both incur a cost from interaction because we both travel to a third city (for a conference perhaps). Here we have a case of *two way, both pay.*

For each of these three ways that information might be transmitted we will first ask the question: how should individuals communicate in a way that makes the group as a whole the best it could be? We will then ask, if groups can't coordinate their actions, would they be expected to arrange themselves in an optimal way?

2.1 Optimal groups

If we begin by supposing that the cost to interaction is zero, one structure is optimal regardless of how individuals communicate with one another. In all groups if everyone talks to everyone else, everyone gets all the information. This is not the only optimal solution, however; there are others. More importantly, if there is any cost whatsoever to the interaction, this way of communication is not necessarily best. Often what is

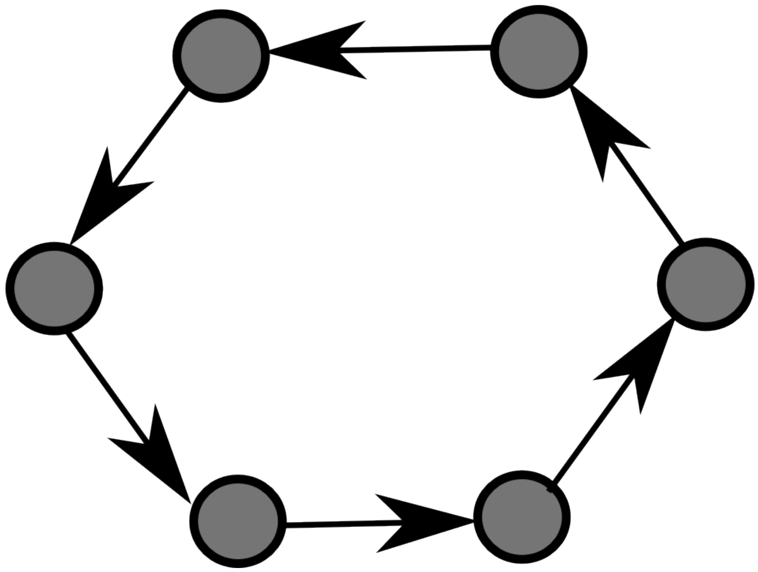

Figure 1: A directed cycle. Information flows in the direction of the arrows and the individual on the arrow side of the link pays the cost.

optimal represents another communicative extreme, there is very little direct communication at all. Exactly what sort of configuration is optimal depends critically on how communication takes place, however.

In order to best illustrate the structure of communication in groups, we will employ a graphical representation of the community. Each individual is represented by a circle and a line of communication is represented by an arrow from one circle to another. We will sometimes drop the arrow and instead represent two-way communication by an undirected line. This technique for representing communication is common in the literature, because it allows scholars to use the mathematical theory of graphs in order to represent groups.

If we first consider the *one way, one pays* model of communication, we find that there is a unique structure of communication known as the "directed cycle" (see figure 1, proof in Bala and Goyal 2000; Goyal 2007).[1] The directed cycle is the network with the fewest links that is strongly connected – there is an informational path from every individual to every other individual. This structure for communication is optimal because every individual secures the most information possible with the smallest cost possible.

Another important property of this network is that it is fair – every individual receives the same share of benefits and costs. Perhaps surprisingly this is not true when one moves from the *one way, one pays* to the *two way, one pays* model. In this second model of communication, there are a number of different optimal networks (some are pictured in figure 2, proof in Bala and Goyal 2000; Goyal 2007). All of these networks are minimally, *weakly* connected. Since information flows in both directions we only care that there is a path

[1] We are making one assumption: the cost for communication is worth paying if one can secure all information available. If the cost were higher than this, the optimal network would involve no communication and would not be terribly interesting.

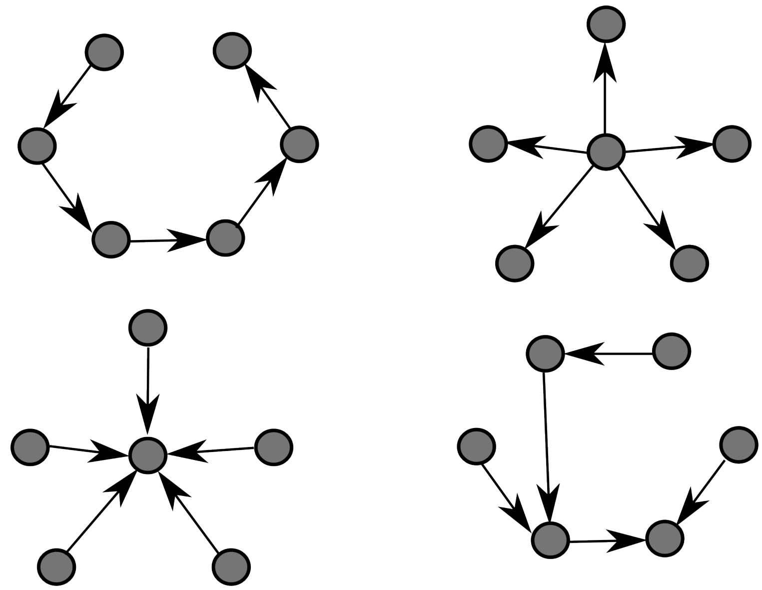

Figure 2: Four minimal weakly connected graphs. Information flows in both directions, but the individual on the arrow side of the link pays the cost. The top left graph is called "the line", the top right is called the "periphery sponsored star", and the bottom left is called "the centered sponsored star."

(regardless of direction) going from every individual to every other. But, because the costs must be borne by someone, necessarily at least one person will not pay any costs in this network.

In this model optimal communities can be almost fair, as is the case in the top two graphs in figure 2, where everyone but one individual pays the cost of maintaining a link. Or it can be radically unfair, as it is with the bottom left graph in figure 2 (known as the center sponsored star), where a single individual bears the cost of maintaining communication with everyone.[2]

When we finally turn to the *two way, both pay* model, we find similar graphs are optimal but now the arrows are totally meaningless – both individuals pay the cost (Jackson, 2008; Jackson and Wolinsky, 1996). Like the *two way, one pays* model, some optimal graphs are fair and some are not.

Suppose we relax one of the assumptions that we began with – that information can be transmitted without error between two individuals. If we assume there is even a very tiny probability that information is transmitted incorrectly based on the social "distance" that it must travel, only stars – where a single individual is connected to everyone – become optimal (Bala and Goyal, 2000; Jackson, 2008; Jackson and Wolinsky, 1996; Goyal, 2007).[3] These are interesting because they have very unequal distributions of benefits. Either the person at the center gets all the benefit without paying the cost (periphery sponsored star) or

[2] It is worth nothing that the notion of optimality we are using does not consider fairness to be an aspect of optimal configurations. We are instead maximizing the sum of benefits minus the costs. Other networks might turn out to be optimal if one were to use a different notion of optimality. Some other notions of optimality have been considered, although many have not been analyzed in the context of these models.

[3] It is possible, if information is sufficiently valuable and the loss from second-hand transmission is sufficiently high, that the complete graph (where everyone communicates with everyone) might again turn out to be optimal.

the center person bears the vast majority of the cost in maintaining communication (center sponsored star or undirected star).

What general lessons might we draw from these models? There is an widely held assumption that communication is beneficial in groups. One might, without reflection, judge an epistemic group whose communication structure follows a star or cycle patten to be absurdly sparse. Insofar as the assumptions of the models are appropriate, these groups are in fact structured in an optimal way. Criticizing these groups for their lack of communication would be unfair, and attempting to increase communication within them would be counterproductive.

Similarly one might worry about the uneven structure of these models. For instance, there are situations where only a star pattern is optimal. This represents a group with a single central person who mediates all the communication in the group. An uncritical examination of this group might suggest that some strange sociological forces have resulted in a single person becoming central in the group. While this might be the case, the mere presence of a central person does not provide evidence that a group (like a scientific group) is being unduly influenced by sociological forces.

Of course, one can criticize these communication patterns in other ways. For instance, many of these models don't account for the possibility that links might fail. As a result, the networks that turn out to be optimal are not robust to failures of individual links.[4] Alternatively, the notion of optimality is explicitly utilitarian. One might want to consider other notions of optimality. This might result in different networks being regarded as optimal.

So far, we have only asked what networks are optimal for the group as a whole. As many of us are all too aware, if one leaves individuals to do as they please they will often not find their way to socially optimal states. We will now turn to the more complex issue of whether we should expect individuals to find their way to optimal organizations.

2.2 Individual learning

Understanding what networks we might expect from a kind of organic process is a complicated matter. There are two related questions that one might ask. First, are the optimal networks consistent with individual choice? Would individuals who found themselves arranged in an optimal configuration stay there, or would they opt to change in ways that benefited them individually but hurt the group as a whole?[5] In most of the cases presented above the optimal networks are stable in this sense.[6]

[4]The models which utilize distance-based utility – where the benefit of connecting to someone via many intermediaries is much lower than connecting to someone directly – can be interpreted in this way.

[5]Such situations will be familiar from the Prisoner's Dilemma and other social dilemmas common in game theory.

[6]More formally, the networks comprise a Nash equilibrium of a appropriately defined game (Bala and Goyal, 2000; Goyal, 2007) or they are stable in a sense very similar to Nash equilibrium (Jackson and Wolinsky, 1996; Jackson, 2008). For a

Second, one can ask whether not an arbitrary group will find its way to an optimal configuration by the uncoordinated action of its members? This is a much more complicated matter that does not have a unequivocal answer.

For illustration, let us return to the *one way, one pays* model of communication. Suppose that the costs of communication are sufficiently high so that one would not be willing to pay the cost to secure only one piece of information. That is, Carlos would not talk to Jake unless Jake has also spoken with someone else that Carlos had not. Also supposing that the costs are low enough so that if one could receive more than one piece of information by speaking with another, the cost would be worth paying.

In this situation the directed cycle is the uniquely optimal network. This network is also stable; each individual is happy to maintain her single link because she is receiving information from the whole group for the cost of one contact. The empty network is also stable, however. If we start in the empty network, no individual could do better by unilaterally changing her behavior. If no one speaks to anyone else, then if a single individual opts to communicate with another, she only gains one piece of information and by hypothesis this is not worth the cost of communication. As a result, one might expect such a community to persist – at least for some short period of time – in this sub-optimal state.

Even if we could be assured that a group might escape this sub-optimal state, it is not guaranteed that it will find its way to an optimal state. It might end up choosing sub-optimal configurations forever. Research has revealed some cases where this occurs, but only if individuals change their behavior in certain ways. Even if we lower the cost so that the empty network is unstable, nonetheless some reasonable ways of modeling how individuals decide to choose communicative partners do not guarantee that groups will find their way to optimal configurations (Huttegger and Skyrms, 2008). There are other ways of modeling their change that do result in individuals finding their way to optimal communication, however (Bala and Goyal, 2000; Huttegger and Skyrms, 2008; Huttegger et al., 2012). So much depends on exactly how individuals change their behavior over time.

If we turn to the *two way, both pay* model, similar problems arise. If we return to the assumption that information might decay as it is transmitted over longer social distances, it can be almost impossible for a group to find the optimal social network (Watts, 2001)!

These results suggest that there is a deep and difficult problem that lies beyond identifying the epistemically optimal configurations. We must also figure out how to encourage groups to arrange themselves in optimal ways. The current research in this area is sparse, and there remain many open questions about how to help groups find their way to optimal configurations in these different situations.

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discussion of the case where the optimal configuration is not stable see Jackson (2008, pg 161).

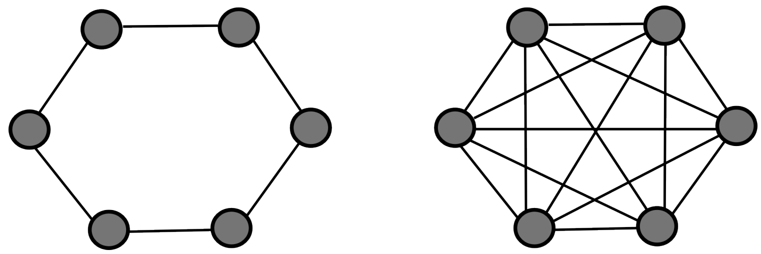

Figure 3: Two regular graphs. On the left is the cycle on the right is the complete graph.

3 Information sharing

3.1 Pooling models

Suppose there is a group of specialists who each have an estimate of a given quantity. This might be a value, say of a universal constant, or it might be a probability of a given event happening. Each individual is informed (with error) of the true value.[7] Each individual is interested in securing an estimate that is as close as possible to the truth.

If we suppose that estimates can be transmitted second hand, then this model is equivalent to the models discussed above. However, if I only change my opinion in response to others with whom I am directly connected, things are different. I can only learn what my friends' friends think by observing how my friends change their opinions.

French, a social psychologist, developed an empirical model for these sorts of situations where individuals are influenced by one another (French, 1956). French supposed that each individual has a group of friends and that he repeatedly adopts the average of his and his friends' opinions. Because different people have different groups of friends, this procedure might continue for several (or even an infinite number) of steps as each person changes her mind in response to the changes of her friends. We can ask what will be the long run distribution of attitudes of this group.

This same model has been advocated as a normative model for belief change in situations where there is not any additional information on which to resolve the disagreement (DeGroot, 1974; Lehrer and Wagner, 1981). Although there are some concerns with interpreting these models as normative prescriptions, I will not delve into the issue of the appropriateness of this model from an individual perspective. Instead, I will ask what is the best arrangement for a group where the individuals modify their beliefs (rightly or wrongly) in this way?

One can show that the best networks are regular – every individual has the same number of friends (see figure 3, proofs in DeMarzo et al. 2003; Golub and Jackson 2010; Zollman 2012). All of these social

[7] One must make some assumptions about the error. In particular, it must be the case that the expectation of the signal is the truth, and that the distribution of initial beliefs has finite variance.

arrangements will, as time goes to infinity, do the best they can with the information available. However, the more connected the graph, the more quickly it approaches the truth. So if one is concerned with speed as well as long-run reliability, the complete graph is best. However, if connections come with a cost, there may be a more complicated trade-off between connections and speed.

Some have suggested that this model belief change is unreasonable because an agent's propensity to consider another's opinion is not dependent on the opinion itself (Abelson, 1964; Friedkin and Johnsen, 1999). It might be the case that my willingness to listen to your opinion depends on what your opinion *is* – if you are sufficiently similar to me I will listen to you, but if you are not I will ignore you.

A model has been proposed which accounts for this, where individuals average only with those friends who are within a certain "distance" of their beliefs (Krause, 2000; Hegselmann and Krause, 2002). Similar results hold for this model as well, although sometimes irregular graphs outperform some regular graphs. In all cases, however, the complete graph remains optimal (Zollman, 2012).

As we did above, one can ask about stability in these models. Not much is known. Holme and Newman (2006) have considered a model where individuals choose their friends based on similarity of belief, creating a situation where the network might break up into different "belief groups" which will allow disagreement to persist. In this model much depends on the relative speed of belief change and friendship change.

What is best for an epistemic group is very different in these models as compared to the models discussed in section 2. In the models from the previous section the optimal network often featured a very uneven distribution of connections – one person was responsible for most of the communication. In these models, regularity is very important – no one person should have a disproportionate share of the communication channels. The driving force between this difference is whether or not second-hand information can be transmitted or not. In the information transmission model of section 2 it can be, and as result unevenness is positive. In the information pooling models from this section, second-had information cannot be transmitted and so unevenness is a negative.

In this model individuals communicate about their beliefs about a single fact. It could be easily extended, with identical results, to a situation where individuals are communicating about several independent facts. Things become more complicated when they are communicating about facts that might be (logically or probabilistically) related to one another. Such a situation would more realistically model a situation where individuals not only share their attitudes, but also their reasons for believing a certain thing. There is a model of this sort of interaction (Betz, 2012), but it has not yet been used to model different structures for communication.

3.2 Specialized knowledge models

An assumption of all the preceding models has been that the information possessed by each individual is different and equally useful to each individual. This is the case when each individual has a different specialization or when each individual has different (probabilistic) information about the same thing. But not all epistemic situations are of this character. Sometimes different individuals know different, but overlapping, sets of propositions. One might now ask, how should networks be formed in this context?

We will begin by supposing there is a set of propositions that an individual might be informed about. We will assume there is no error, an individual either knows the truth or does not have a belief about the proposition. There is then a "relevant" set of propositions that each individual wants to learn. Each individual forms a connection to another individual who knows about propositions which complement her own, where each connection entails a cost.[8]

Consider the following example. Suppose that for some current project, I must know the truth values of three propositions p, q, and r. I know that p is true, but I know nothing about q and r. What would be best for me is to find someone who knows both q and r. This would minimize my cost while also allowing me to solve the problem. However, if no such person is available, I would also be willing to form two connections: one to someone who knows q and one to someone who knows r. I will not, however, form a connection to more than one person who knows q or more than one person who knows r, nor will I connect to anyone who doesn't know q or r.

Only a little can be said about the optimal network without knowing how knowledge is distributed in the community. Regardless of how knowledge is distributed, the optimal network is always stable – it is always consistent with individuals trying to maximize their individual welfare (Anderson, 2011).

If we consider a particular model of how knowledge is distributed more can be said. Suppose there exists a probability x such that for each individual i and each proposition p the probability that i knows p is equal to x, regardless of what other propositions i knows or how many other people know p.

Under this assumption for the initial distribution of knowledge, the optimal networks all share a particular feature: most individuals are contacted by very few people and a few people are contacted by a large number. This matches with a number of empirical studies of collaboration networks in science (Anderson, 2011).

An important consequence of this model (like the models from section 2), is that it shows high unequal distribution of communication links is not indicative of some sort of pathology. The fact that some individuals occupy very prominent positions in epistemic groups (like science) can be seen as a natural outgrowth of the distribution of knowledge amongst individuals instead of an indication of sociological factors distorting the

[8] This model was proposed by Anderson (2011). It is worth noting that Anderson's preferred interpretation of her model is different than the one I'm presenting here.

groups epistemically optimal configuration.

As with all the models in this paper, there are a number of assumptions of this model that one might like to relax. In this model, one cannot have an erroneous belief – one either knows the truth of a proposition or one has no belief about it. What if error was introduced into this model? In such a case it might be good to connect to several individuals who have a belief about a particular proposition to double check their veracity. Understanding what might happen in such a model remains an open question.

4 Active learning

In all the models considered thus far, individuals find ways to optimally use information which is already present. No new information arrives during the process of communication. This is reasonable for a number of epistemic situations, like a scientific conference or a business meeting, but not for all situations. Day to day communication takes place along with the discovery of new facts, and we would be remiss to ignore such situations.

4.1 Pooling with learning

First, we will return to the "pooling" model discussed in section 3.1. These models assume that at the beginning of the process of deliberation each individual receives information about the world and that no new information is forthcoming.

One might amend this model by assuming that each individual continues to receive new signals from the world, although it would difficult to determine how exactly the individual should treat this new information. Hegselmann and Krause (2006) suggest a more idealized setting. One might imagine when an individual averages her beliefs with those of her neighbors, some individuals are also "pulled" in the direction of the truth by some (perhaps very small) degree. This "truth pull" is a macroscopic idealization of a more complicated process of information gathering.

Modeling information accumulation in this way renders graph structure largely irrelevant. So long as the group contains at least one person who is pulled by the truth in this way (to any degree, however small), and so long as there is a path from every individual to that person (with any number of intermediaries), the network will eventually converge to the truth.[9]

As was the case in before, different graph structures will converge at different speeds, and some graphs might spend a very long time far away from the truth.

[9] A proof of this statement can be supplied by the author upon request.

Things become rather more complex if one turns to the bounded confidence model, where individuals ignore those who have sufficiently different opinions. Now one is not guaranteed to converge, unless everyone is pulled by the truth to some degree. Little is known about the effect of different network structures, although some particular ones have been considered (Hegselmann and Krause, 2006).

4.2 Learning in bandit problems

One feature of the above models of learning is that the evidence which arrives is independent of the beliefs or behavior of the individual scientist. Not all learning situations are of this type. Sometimes individuals must seek out evidence. Once they become sufficiently convinced about a fact they might decide to abandon inquiry about that fact altogether. Circumstances like this must be modeled differently.

One common set of models for this situation are bandit problems. The name comes from a rather simple analogy. Imagine a gambler who must repeatedly choose between two slot machines. She does not know the relative payoff rates of the different machines – she must learn by playing. If she only cares to learn the payoffs of the different machines a very simple policy will ensure she learns accurately: alternate between the two different machines. But we will assume that she does not care only for information, but she also wants to secure the highest possible payoff. Now the best policy becomes very complicated. She must balance her interest in playing the machine that currently appears best against her interest in learning about the different machines.

This model has been applied to a number of important epistemic problems including medical research (Berry and Fristedt, 1985; Robbins, 1952), choice of theories by scientists (Mayo-Wilson et al., 2011; Zollman, 2007, 2010), choice of experimental apparatus (Zollman, 2007, 2010), and technology choice (Bala and Goyal, 1998; Bolton and Harris, 1999; Ellison, 1993; Ellison and Fudenberg, 1995).

It is not hard to show that if each individual is choosing optimally, then more information cannot hurt. However, determining the value of the information is very complicated and depends on many different factors. In addition, the optimal policy for the individual is very difficult to determine.

Instead, a number of scholars have focused on "bounded rational" strategies in bandit problems. These are strategies which are computationally simpler (and thus plausible for an individual to follow), but approximate the optimal strategy in various ways.

We will begin by supposing that each individual keeps track of her own past successes and failures and also pays attention to the past successes and failures of a few others (her neighbors on a social network). Each individual updates her beliefs about the payoffs of the different bandits according to Bayesian reasoning and on each round chooses the option that seems best according to her current beliefs.[10]

[10]This response rule is known as "myopic best response" because individuals do not choose in order to gain information that

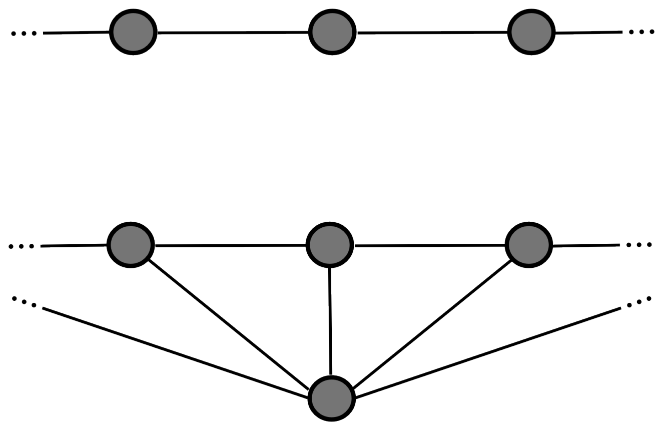

Figure 4: Two infinite graphs. The top graph is the "line" and the bottom is a line with a "royal family."

Bala and Goyal (2001) consider two different graphs pictured in figure 4. Both of these contain an infinite number of individuals. The top graph is the infinite line, where each individual only communicates with the individual to the left and right of her (and there is no second hand information). The bottom graph adds a single individual who communicates with everyone. Bala and Goyal prove that the top graph will certainly learn to choose the best bandit in the long run, but the bottom graph will not do so with certainty.

There are two differences between the graphs. The top graph has very little communication and is also regular. The bottom graph has more communication but has a central individual who is very influential. Bala and Goyal conjecture that it is the irregularity of the bottom graph which is the cause its inferiority.

Zollman (2007, 2010) showed that in finite graphs, it is not the unequal connections but rather the amount of communication that is detrimental to group learning. Utilizing computer simulation, I showed that in small finite groups, the best graphs are minimally connected. Unlike the models from above, minimally connected graphs are best even when communication is free! This occurs because too much communication causes groups to abandon inquiry too quickly, settling on a single best action which might not be optimal (Zollman, 2010).

5 Conclusion

There remain many open problems. While some is known about how the endogenous formation of epistemic groups, especially in the case of information transmission, there is also much that is unknown. These issues

they might use in the future (hence, myopic). When alone these individuals can converge to playing the sub-optimal bandit forever, which illustrates a limitation of Bayesian learning when supplemented with this response rule (Huttegger, 2011). A very similar response rule, known as ϵ-greedy, does better over the long run because it cannot be locked into sub-optimal actions (Huttegger, 2011; Mayo-Wilson et al., 2012; Sutton and Barto, 1998). Recent work suggests the relationship between ϵ-greedy individuals and network structure is rather complex (Kummerfeld and Zollman, 2012).

are critical if we are to understand the social forces that guide the formation of epistemic groups, and what might be done (by a funding agency or social planner) to improve the epistemic enterprise of these groups. These models are also restricted to particular type of learning situation. There remain many important learning situations that do not correspond neatly to one of these models.

Despite these limitations, the study of epistemic networks has shown that there are a number of interesting and nuanced issues that arise in the social epistemology of communication. A remarkable amount depends on the underlying learning problem. In some situations (like the pooling examples from section 3.1), more communication is better. In other situations (like the information transmission problems from section 2 or bandit problems from section 4.2) less communication is better. Sometimes increased communication is harmful because it comes at a cost and fails to improve the epistemic performance of the group. Even if a line of communication is free and non-redundant, increased communication is bad because it causes inquiry to be abandoned too early.

In addition, these models illustrate how the precise reasoning which is forced by mathematical modeling can provide insights into the structure of communities. Whether or not unequal connections are productive, counterproductive, or largely irrelevant will depend on the learning problem. This provides an explanation for these sorts of structures which does not depend on nefarious sociological factors interfering with the epistemic goals of the group.

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