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Information diffusion in networks with the Bayesian Peer Influence heuristic ☆

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ABSTRACT

Repeated communication in networks is often considered to impose large information requirements on individuals, and for that reason, the literature has resorted to use heuristics, such as DeGroot's, to compute how individuals update beliefs. In this paper we propose a new heuristic which we term the Bayesian Peer Influence (BPI) heuristic. The BPI accords with Bayesian updating for all (conditionally) independent information structures. More generally, the BPI can be used to analyze the effects of correlation neglect on communication in networks. We analyze the evolution of beliefs and show that the limit is a simple extension of the BPI and parameters of the network structure. We also show that consensus in society might change dynamically, and that beliefs might become polarised. These results contrast with those obtained in papers that have used the DeGroot heuristic.

1. Introduction

Repeated communication in groups and more generally in networks is often considered to impose large informational requirements on individuals. Individuals may be unaware of the structure of the network, so that while they know who they communicate with, they might not know their neighbours' neighbours. This implies that it may be very difficult to trace the path that a piece of information takes in an environment with repeated communication.

The network literature has typically taken one of two avenues. One avenue is the fully rational approach whereby individuals are fully aware of the network and the equilibrium and update using Bayes rule (see Acemoglu et al., 2014). The second avenue is to assume that individuals follow a particular heuristic when updating. A leading example is the DeGroot heuristic, where individuals average their's and others' beliefs, as in Golub and Jackson (2010) and De Marzo et al. (2003). These are two polar ways to model information diffusion, one based on full rationality and the other based on an adhoc heuristic.

In this paper we analyze information diffusion in networks by using a new heuristic which is based on rational foundations for all information structures which are conditionally independent. Specifically, we assume a simple model of

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communication in which individuals sincerely transmit their beliefs to each other.[1] Sobel (2014) and Levy and Razin (2016) show that if individuals believe that their marginal information sources generate (conditionally) independent signals, then upon communication, Bayesian updating yields a belief that is proportional to a simple multiplication of their posterior beliefs. Thus, if $p(\omega)$ is a common prior about a state of the world $\omega \in \Omega$ (finite), and $q^i(\omega)$ is the posterior belief of individual i that the state is ω following some signal realisation, the resulting belief following communication of posteriors in a group of n such individuals is

$$\frac{\frac{1}{p(\omega)^{n-1}} \prod_{i \in N} q^i(\omega)}{\sum_{v \in \Omega} \frac{1}{p(v)^{n-1}} \prod_{i \in N} q^i(v)},$$

where the formula can be easily extended to non-common priors, as well as to more general perceptions of correlation (Levy and Razin, 2016). In this paper we adopt this formula as an updating heuristic, which we term the Bayesian Peer Influence (BPI) heuristic. We analyze information diffusion in networks using the BPI.[2]

There are several advantages to using the BPI. First, it is a heuristic which is rational for all environments in which the information sources of individuals are truly (conditionally) independent. A benefit of using the BPI in these environments is that it is "information structure free": Both the modeler and individuals in the network do not need to know the exact information structures of others in order to compute the properties of beliefs in the network. We therefore do not need to make any specific assumptions about information structures. Second, in other, more complicated, environments, the BPI is simple to compute. The BPI is an order-free heuristic, which – as we show – lends itself easily to the computation of limit beliefs.

The BPI also allows us to isolate the implications of correlation neglect arising from repeated communication from other types of incorrect information processing biases. Correlation neglect has recently attracted attention in the literature and is a natural bias to arise in network communication.[3] As information flows in a network, individuals may be unaware that they are exposed to the same information they have been exposed to in the past, and thus if they treat information as independent, correlation neglect is likely to arise. When using the BPI to analyze repeated communication in a network, we are in effect assuming that correlation neglect is the only departure from rationality.

Our main results are the following. First, we characterise the limit beliefs of repeated communication in networks and show that they are easily computed. Similarly to Golub and Jackson (2010) and De Marzo et al. (2003) the limit beliefs depend both on the initial information in the network and the structure of the network. Beliefs converge to the mode of a belief that extends the BPI to account for the initial beliefs and the eigenvector centrality of the individuals in the network. In particular, beliefs converge to the mode of $\Pi_{j \in N}(q_0^j(\omega))^{\alpha^j}$ where $q_0^j(\omega)$ is the initial belief of individual j and α^j is the j'th element of the vector α that is parallel to the Perron–Frobenius eigenvector.

The result about the mode allows us to provide sharp predictions about the limit beliefs, which qualitatively differ from those obtained under the DeGroot heuristic. Specifically, a recent theoretical and experimental literature has focused on the question of whether polarised beliefs in society arise because of correlation neglect (see for example Glaeser and Sunstein, 2009; Schkade et al., 2000, and Sobel, 2014 for an alternative view). In our model polarisation arises as beliefs become degenerate in the limit. Using the BPI we show how polarisation depends both on the network configuration as well as on the nature of the initial belief. Relatedly, the BPI also implies that consensus might change dynamically; that is, even when all have the same beliefs – as long as these are not degenerate – individuals will continue to update from each other. These two results cannot arise within the DeGroot framework where limit beliefs are always in the convex hull of initial group beliefs and in which when consensus is reached there is no further updating. This implies that the BPI can account for phenomena such as "Groupthink" whereby even group homogeneity implies polarisation.

We show that with the BPI an individual's influence on the group depends both on his centrality but also on the quality of his information. In particular, the variance of an individual's belief is important. An individual holding beliefs with high variance has little effect on others' beliefs. Again, this contrasts with the DeGroot heuristic under which only the expectation of an individual's belief (or some exogenous parameters) can determine his influence. For example, a uniform belief will imply that an individual has no influence on others in our model, no matter his centrality in the network. In contrast, in the DeGroot model, such an individual will be influential as long as his expectation is different than others' and the higher is his centrality in the network.

Our paper relates to several strands of the literature. We contribute to the literature on information diffusion in networks (Golub and Jackson, 2010, 2012) by suggesting a new heuristic, which, as in machine learning, is motivated by a

[1] The assumption of sincerity is quite reasonable in the context of information diffusion in networks; as is the case in most of the literature, for such environment it is common to assume that individuals are not strategic (see the survey in Jackson, 2011). The assumption that people communicate their beliefs is motivated by the difficulty to remember and communicate the exact details of information structures.

[2] The BPI is used for the case of binary states and particular information structures by Duffie and Manso (2010) and Eyster and Rabin (2010, 2014).

[3] Ortoleva and Snowberg (2015) analyze the effect of correlation neglect on the polarisation of beliefs. De Marzo et al. (2003) and Gagnon-Bartsch and Rabin (2015) study how it affects the diffusion of information in social networks. Glaeser and Sunstein (2009) and Levy and Razin (2015a, 2015b) explore the implications for group decision making in political applications. Recent experimental evidence is in Eyster and Weizsäcker (2011), Kallir and Sonsino (2009) and Enke and Zimmerman (2013).