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Commentary

Contagion in Prescribing Behavior Among Networks of Doctors

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A foundational study regarding the diffusion of innovation involved the adoption of tetracycline by doctors in four Midwestern communities in the 1950s (Coleman et al. 1966), and it is not a coincidence that social scientists keep returning to this particular application of social network analysis (including to reanalyze this original study by Coleman and colleagues; see Van den Bulte and Lilien 2001). Studying the use of drugs by doctors involves the perfect mix of a discernable social network (among the doctors), a distinct innovation (a drug), an important area (patient care), difficult statistics (related to causal inference), and financial stakes (by pharmaceutical companies, insurers, and others).

Iyengar, Van den Bulte, and Valente, in their careful and insightful study (Iyengar et al. 2010), find that even after controlling for marketing effort and arbitrary systemwide changes, there is evidence for contagion in the prescribing patterns of doctors. The modeling is excellent, including controls for secular trends (such as the emergence of new drugs or clinical evidence or a change in prevalence of the disease), and the conceptual framework is innovative and comprehensive. And so this paper represents another important link in the chain stretching back to Coleman.

Like any social network, a network of doctors provides an opportunity to explore whether people who share a social connection exhibit similar behavior. However, even if we find that connected doctors do act in the same way, there are a number of possible explanations: (1) doctors might choose to associate with other doctors that they already resemble (known as *homophily*, or "birds of a feather flock together"—for example, infectious disease doctors might form ties with other doctors of the same specialty, or high-prescribing doctors might be connected to other high-prescribing doctors), (2) doctors might jointly experience unobserved contemporaneous events that cause their behavior to covary (omitted variables or *confounding*—for example, the doctors might jointly experience a marketwide ad campaign), and (3) doctors might exert social influence on each other (*induction*, or *social contagion*).

Of course, all three phenomena (homophily, confounding, and induction) are likely to be present in any social system, and the methodological challenge is to disentangle them, if possible. In our original work regarding the spread of obesity within social networks, we argue that the obesity epidemic could be understood, in part, as the adoption of the "innovation" of obesity, and, among other things, we propose a test for social influence involving the asymmetry of social ties (Christakis and Fowler 2007), an approach that we have since applied in other domains (Cacioppo et al. 2009; Christakis and Fowler 2008; Fowler and Christakis 2008; Mednick et al. 2010; Rosenquist et al. 2010a, b) and that has been explored and clarified by other scientists (Bramoulle et al. 2008, Anagnostopoulos et al. 2008, Shalizi and Thomas 2010). This approach can shed light on the existence of contagion, subject to certain assumptions about how people go about nominating friends (Shalizi and Thomas 2010). Moreover, alternative methods can help to parse how much of the observed association in adoption is due to homophily and how much is due to induction. (Aral et al. 2009) Among social network scientists, there is also a move to do more experiments with such processes, both off-line (Fowler and Christakis 2010) and online (Horton et al. 2010), and this may further help to clarify the extent to which contagion exists in social systems, by further enhancing the robustness of causal inference. But it is doubtful that experiments can capture the verisimilitude or scale necessary for the study of all social contagion processes, let alone for the special case of large networks of doctors caring for patients to whom they are administering drugs. This is why the current study is so helpful.

Iyengar et al. (2010) study the adoption behavior of a new drug designed to treat a chronic condition resulting from viral infection. To ascertain the social network, they surveyed doctors in San Francisco, Los Angeles, and New York City who were targeted by the pharmaceutical company that makes the drug, and they matched this information to commercially collected prescription data. Importantly, they collected information not just about the referral and discussion networks but also self-reported assessments of leadership. This allowed the authors to distinguish between the sort of subjective measures of leadership that are usually collected in regular surveys and objective measures of leadership that can only be ascertained in a sociocentric network study.

The availability of individual-level sales call data in this study is another compelling strength. This allows the authors to document evidence of social contagion net of overall marketing effort, an important source of possible confounding. And they show that more than geographic propinquity or shared group membership, self-identified ties between doctors are crucial to the spread of behavior.

The authors note that the overlap between heavy users and influential users might be limited, suggesting a radical rethinking of how drugs are marketed. As shown in Figure 1, a heavy user might be peripheral or poorly connected in a network, and so, no matter how much his prescribing behavior were modified, he might not affect many other doctors within the network. Better to target a potentially lighter user who can induce more externalities. The authors write, "Because the correlation between prescription volume and sociometric leadership is only moderate, just focusing on heavy users will fail to leverage all potential influential seeding points" (Iyengar et al. 2010, p. 2).

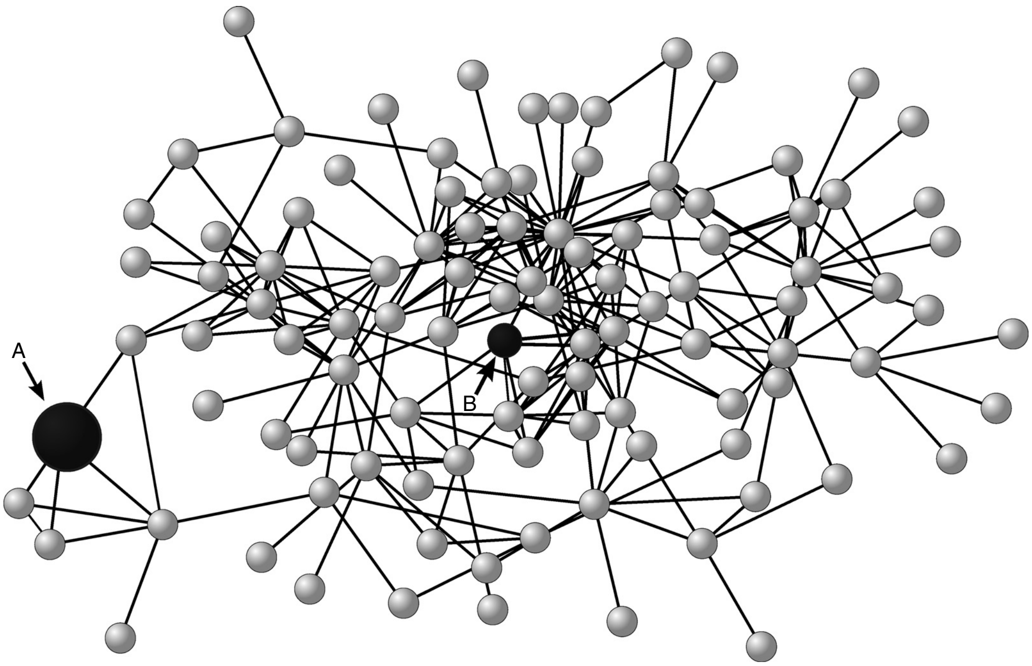
More generally, this observation is in keeping with one of the key intellectual claims of social network analysis (and, in fact, speaks to the whole debate between methodogolical individualism and methodogolical holism in the social sciences)—namely, that one cannot ascertain global properties of the network simply by knowing about the constituent parts. To know whether a doctor is central, one must map and study the whole network, not simply ascertain attributes of the doctors, such as their specialty or prescribing behavior, or even their own perception of where they sit in the network as reflected in self-assessed leadership measures. And, in fact, regression models that use individual attributes to infer network location may be very poor proxies.

It is one thing to identify opinion leaders within a network, according to whatever heuristic (for instance, by assuming that the most central or highest-degree nodes are the most influential). But an additional crucial consideration behind any network approach is that the intervention to change behavior works to begin with. There are two issues here: (1) if there is no contagion, then no matter how successful the detailing intervention is, it will not lead to cascade effects; and (2) if detailing does not actually modify doctors' practices very much (and evidence for the effectiveness of detailing is patchy), then a network-focused approach might again fail—but not because doctors do not influence their peers. To have contagion, one must first have individual-level adoption. In other words, a successful marketing campaign must identify not only who is *influential* but also who is *influenceable*. Interestingly, the authors are able to show that the individual-level sensitivity of physicians to being detailed does *not* vary with their network position—in itself, this is a valuable finding.

But the result that is perhaps most compelling is that the tendency to adopt early is more pronounced among those who are known to be central based on the whole network map than it is among doctors who perceive themselves to be influential. This finding vindicates the utility (and the necessity) of mapping whole networks rather than just merely surveying doctors to find out their attributes. The authors also find that sociometric and self-reported measures of structural locations are distinct. The most immediate implication is that for us to know doctors' structural locations in a network, we, again, must map the whole network and not just rely on their own reports about how many contacts they have.

Not everything spreads in networks, of course. And we might find network contagion effects for some drugs and not others. The authors correctly and subtly argue that contagion may work differently for different products (e.g., those with more or less perceived risk) and that it may operate differently at different stages of product adoption (e.g., at the awareness versus evaluation stage). However, it is tantalizing to consider the possibility that the findings in this paper might generalize not only to other

Figure 1 **Difference Between a High-Prescribing and Socially Central Doctor**



Notes. In this hypothetical network of doctors (nodes) and their social relationships (lines), we have made the circle diameter proportional to how often doctors prescribe a drug. Node A is a high-prescribing doctor who is not very central to the network, and node B is a low-prescribing doctor who is very well connected and who is therefore better positioned to influence many other doctors.

prescription drugs but also to the adoption of medical devices, surgical procedures, guideline adherence (e.g., for harm reduction), and even nonprescription drugs like aspirin (for which there is little commercial incentive on the part of manufacturers, but much interest on the part of providers, given its utility in preventing heart attacks and strokes). As a result, the authors' work on the spread of medical innovations will undoubtedly be of interest not only to pharmaceutical companies, but also to diverse actors with group-level perspectives like hospitals, health systems, insurers, the military, and even the government.

As in all social network studies, defining the population of interest requires some assumptions. Here, the authors restrict the network of physicians to be studied to doctors in particular geographic areas (San Francisco, Los Angeles, and New York City) and with particular features (e.g., having previously prescribed certain drugs in the past). Other sorts of restrictions are also possible, such as the specialty or practice style of the doctors in question.

One significant limitation of this study is the response rate (which varies between 29% and 45% in the three cities studied and which is lower than is typical of physicians; see Asch et al. 1997) and the small sample sizes (just 67, 57, and 69 doctors, respectively, in the three city-based networks). These are, indeed, tiny data sets. The name generator only allowed respondents to identify up to eight physicians with whom they feel comfortable discussing the clinical management and treatment of a disease (discussion ties) and up to eight with whom they typically refer patients (referral ties). Nonetheless, the authors have previously published important work on the effect of missing observations in networks (Costenbader and Valente 2003), and they take great pains to discuss these limitations at length and to evaluate whether or not they would influence the results. The argument that they do not, in this particular case, is persuasive.

New techniques to identify the connections among entire networks of doctors will be required, perhaps involving administrative data, such that networks of thousands of doctors can be identified. One innovation we have been exploring is the use of shared patients. This involves taking the bipartite network of doctors and patients that is implicit in any large-scale data set involving prescriptions or medical claims and discerning which doctor is connected to which other doctor by virtue of the patients they have in common. Moreover, the strength of connection might be proxied by the total number of patients any two doctors share, thus allowing us to generate weighted networks. In addition to size, this approach offers the advantage of lower cost and vastly less missing data, because existing data rather than de novo surveys are all that is required.

Various complex strategies for targeting also need investigation, and not just the idea of targeting the most central or highest-degree nodes (Valente et al.

2003). Moreover, it may be important to pay more attention to the way in which prescribing behavior spreads, taking into account, for instance, the possibility that it spreads via "complex contagion" (Centola and Macy 2007, Centola 2009). This will be a key area for future marketing research, not just in the case of doctors, but more generally. Once a network of everyone in the health-care system is mapped and understood, then what? How do we know how best to intervene to foster the spread of desirable properties within a network? The massive/passive revolution in data collection and analysis (Lazer et al. 2009) is sure to help us make great strides in answering these questions, but it is the focused efforts of smaller studies like this one that will help to guide these future efforts.

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