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# Social network analysis of the influences of educational reforms on teachers' practices and interactions

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**Abstract** In this chapter we present social network analysis in the context of recent educational reforms concerning teachers' instructional practices. Teachers are critical to the implementation of educational reforms, and teacher networks are important because teachers draw on local knowledge and conform to local norms as they implement new practices. We describe three social network approaches. First, we graphically represent network data to characterize the network structure through which information and knowledge about reforms might diffuse. Second, we use social influence models to express how teachers' beliefs or behaviors are affected by others with whom they interact. Third, we use social selection models to express how teachers might select with whom to engage in interactions about reforms. We discuss the implications for scientific dialogue, and for informing educational policy studies and the practice of educational policy makers and school administrators.

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## Soziale Netzwerkanalyse der Einflüsse von Bildungsreformen auf die Lehrpraxis und Interaktionen von Lehrkräften

**Zusammenfassung** In diesem Kapitel präsentieren wir die Soziale Netzwerkanalyse im Kontext aktueller Bildungsreformen, die sich auf Instruktionspraktiken von Lehrpersonen beziehen. Lehrpersonen spielen für die Implementation von Bildungsformen eine zentrale Rolle. Soziale Netzwerke von Lehrpersonen sind insofern von hoher Bedeutung, als Lehrpersonen im Zuge der Implikation neuer Praktiken auf lokales Wissen und lokale Normen zurückgreifen. Wir beschreiben drei netzwerkanalytische Ansätze: Erstens präsentieren wir Netzwerkdaten graphisch, um die Struktur des Netzwerkes zu charakterisieren, durch die Information und Wissen über die Reform verbreitet werden. Zweitens verwenden wir soziale Einflussmodelle, um darzustellen, wie Überzeugungen und Verhalten von Lehrpersonen von denjenigen Lehrpersonen beeinflusst werden, mit denen sie interagieren. Drittens verwenden wir soziale Selektionsmodelle, um darzustellen, wie Lehrpersonen die Personen auswählen, mit denen sie die Reform betreffend interagieren. Wir diskutieren Implikationen für den wissenschaftlichen Dialog, die Bedeutung für bildungspolitische Studien sowie die praktische Bedeutung für bildungspolitische Akteure und Schulangestellte.

Given that the implementation of reforms is one of the greatest and constant challenges for schools (e.g., Tyack and Cubin 1995), research communities have improved methods to probe policy implementation processes. Analyses of teachers' social networks are critical to these endeavors because it is teachers who implement new practices in classrooms (Cohen et al. 2003); and as they do so, teachers seek local knowledge and respond to local norms embedded in their collegial networks (Frank et al. 2004; Frank et al. 2011). Correspondingly, social network analysis (SNA) has been identified as one of the most direct approaches to map and measure how social interactions are shaped by, and shape the implementation of reforms (e.g., Datnow 2012; Moolenaar 2012).

In this chapter of the special issue, we anchor our presentation of social network analysis in examples of teachers who seek to implement reforms (see Frank 1998, for a more general review of social network analysis in educational settings). We will synthesize and discuss the applications of three SNA strategies: graphical representation, models of social influence and models of selection of network partners. In addition, we discuss the implications for scientific dialogue, and for informing educational policy studies and the practice of educational policy makers and school administrators.

**Fig. 1** Crystallized sociogram of collegial ties in Westville (Frank and Zhao 2005, p. 209)
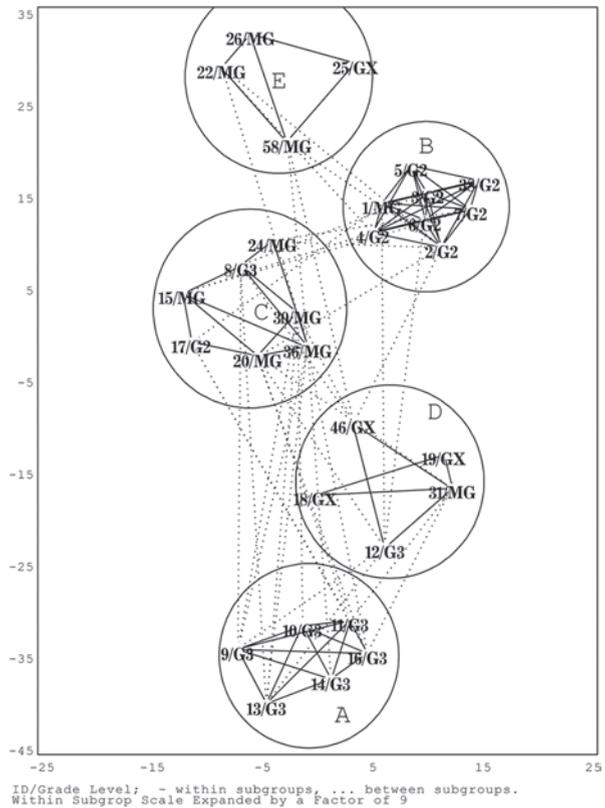


# 1 The basic approaches of network analysis

## 1.1 Graphical representations

Graphical representations of network data can give researchers, and potentially school leaders, a systemic overview of the social structure in a school. In turn the social structure can be related to the flow of resources that affects teachers' behaviors, such as the implementation of reforms. As follows, we will use Figs. 1 and 2, originally used in Frank and Zhao's (2005), to illustrate how new practices diffuse through the network structure of Westville (pseudonym) school.

In the mid-1990s, the district central administration made Westville switch from Macintosh computers to Windows. To illustrate how the informal network shaped the organizational response to change, Frank and Zhao (2005) first used Fig. 1 to illustrate the informal structure of collegial ties among the teachers in Westville. Each teacher is represented by a number, and the lines indicate close collegial relationships obtained from the survey question "who are your closest colleagues in the school?". Frank's *KliqueFinder* algorithm identified the subgroup boundaries in the image by maximizing the concentration of ties within subgroups versus between subgroups (see Frank 1995, 1996, for more details of the algorithm). The solid lines
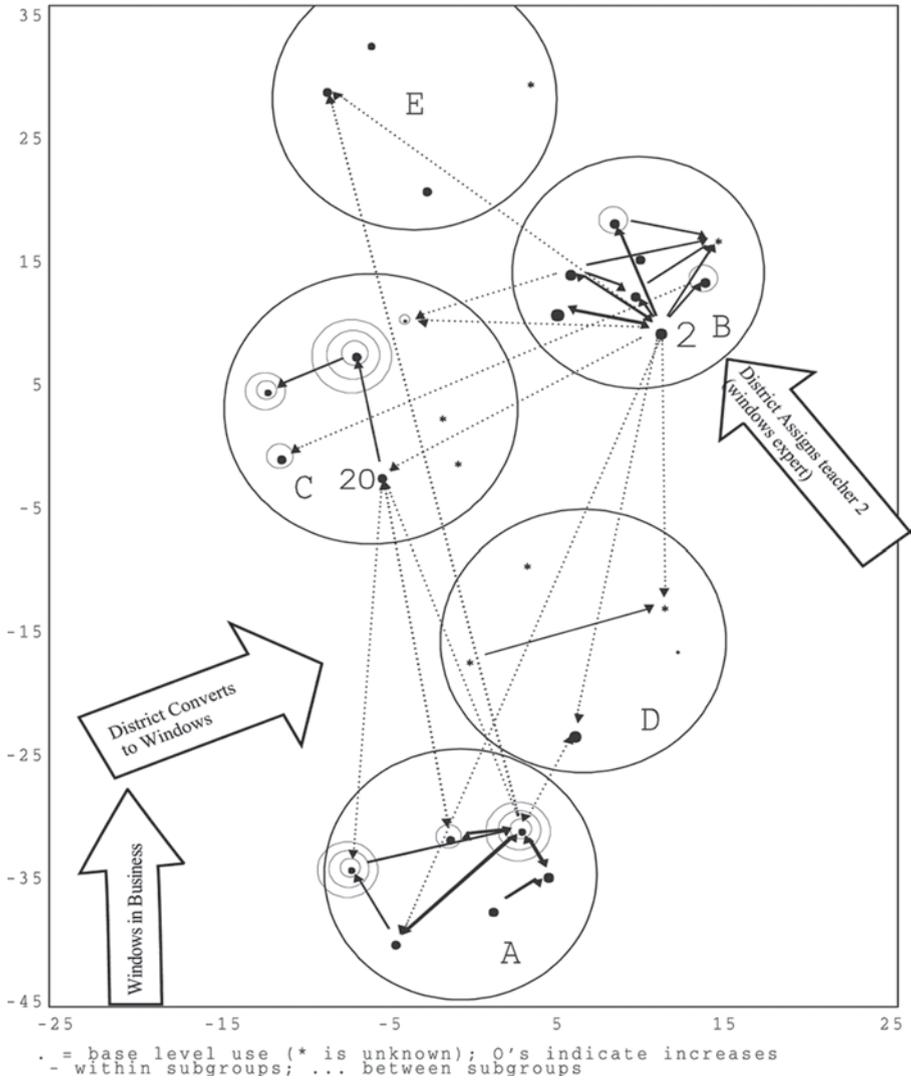
**Fig. 2** Ripple Plot of diffusion of technology implementation in Westville (Frank and Zhao 2005, p. 211)

indicate within-subgroup interactions, while dotted lines indicate between-subgroup interactions.[1]

The text following each number in Fig. 1 indicates the grade in which the teacher taught (e.g., G3 indicates grade 3, MG indicates multiple grades, and GX indicates unknown grade). This information reveals an alignment of grade and subgroup boundaries embedded in the sociogram in Fig. 1. Subgroup A consists mostly of third

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[1] Directionality is not represented in Fig. 1 because close collegial relationships are used only to establish the underlying social structure. Arrowheads are used in Fig. 2 to show the flow of resources.

grade teachers and subgroup B consists mostly of second grade teachers.[2] But the subgroup structure also characterizes those faculty, administrators, and staff who do not neatly fit into the categories of the formal organization. For example, subgroup C contains the physical education teacher, a special education teacher, the principal, and two teachers who did not have extensive ties with others in their grades.

To relate the social structure in Fig. 1 to the flow of expertise about Windows and ultimately to changes in teachers' computer use, Fig. 2 represents interactions concerning use of technology (in response to the question: 'Who in the last year has helped you use technology in the classroom') with the location of the teachers still determined by the close collegial relations in Fig. 1. Generally technology talk was concentrated within subgroups, especially the grade-based subgroups A and B. To represent the flow of knowledge or expertise, each teacher's identification number was replaced with a dot proportional to his or her use of technology at time 1 (an * indicates no information available). The larger the dot, the more the teacher used technology as reported at time 1. The ripples indicate increases in the use of technology from time 1 to time 2.[3]

The intra-organizational diffusion essentially began when teacher 2 was assigned to Westville because of her expertise with the Windows platform. Teacher 2 immediately established collegial ties with the other teachers in subgroup B, and she supported those ties by talking with and helping others in subgroup B regarding computer technology. Thus she generated extensive discussions regarding technology in her subgroup, resulting in some increments in technology use.

The key to extending teacher 2's knowledge beyond her subgroup was the collegial tie which teacher 2 formed with teacher 20. Through teacher 20, the expertise of teacher 2 was disseminated to both subgroup C and B, because teacher 20 talked with members of her subgroup, C, as well as members of subgroup A, resulting in substantial changes in use (e.g., as can be observed in the ripples around school actors in subgroup C). In the aggregate, these interactions among teachers facilitated the diffusion of knowledge about how to use Windows which led to changes in classroom practices.

Graphical representations can intuitively demonstrate the information flow among actors in a social organization and illustrate the process of change. The application of social network analysis to educational research can go above and beyond these graphical representations by statistically testing the extent to which teachers are influenced through interactions with colleagues and what factors affect the ways in which teachers select with whom to interact. We discuss these models of influence and selection in the next sections (in the technical appendix we present an overview of the application of influence and selection models).

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[2] There is a strong alignment of subgroups and grades in Westville because it had been reconfigured shortly before the time of data collection, drawing most of the second grade teachers from one school and most of the third grade teachers from another. Furthermore, the teachers' room assignments reinforce grade assignments, as all but one of the second grade teachers are on one wing and all but one of the third grade teachers are on another wing.

[3] Because the metrics varied slightly between administrations of the instrument, each measure of use was standardized and then the difference was taken from the standardized measures. Each ring represents an increase of .2 standardized units.

## 1.2 The influence model

We begin the discussion of statistical modeling of teacher networks with the influence model, which is used to estimate a teacher's implementation of certain teaching practices as a function of the prior behaviors of others around her (as a norm), and her own prior behaviors. For example, Frank et al. (2013a) modeled a teacher's implementation of basic skills reading instruction[4] as a function of her previous implementation as well as the behaviors of those with whom she frequently interacted regarding professional matters. Formally, let *skills-based instruction$_i$* represent the extent to which teacher *i* implemented skills based instruction. This is modeled as

$$Skills\text{-}based\ instruction_i = \beta_0$$
$$+\beta_1\ previous\ skills\text{-}based\ instruction\ of\ others\ in\ the\ network\ of\ i_i \qquad (1)$$
$$+\beta_2\ previous\ skills\text{-}based\ instruction\ of\ i_i + e_i,$$

where the error terms ($e_i$) are assumed independently distributed, $N(0,\sigma^2)$. The term *previous skills-based instruction of others in the network of i$_i$* can be simply the mean or sum of the behaviors of those with whom teacher *i* interacted (e.g., as indicated in response to a question about from whom a teacher has received help with instruction). Using mean as an example, if teacher Ashley indicated interacting with Kim and Sam who previously implemented skills-based instruction at levels of 25 and 30 respectively (for example, these might represent the number of times per month the teachers used skills based instruction for the core tasks of teaching), then Ashley is exposed to a norm of 27.5 (=(25+30)/2) through her network.[5] Correspondingly, the term $\beta_1$ indicates the normative influence of others on teacher *i*. If $\beta_1$ is positive, the more the members of Ashley's network teach basic skills, the more she increases her use of basic skills instruction. Corresponding to Fig. 2, if $\beta_1$ is large, then one would observe many ripples associated with teachers who interacted with more others who had adopted the particular practice.

Note that the inference of influence is indirect—we do not directly ask people who influenced them. Instead, influence is assumed if teachers change their behaviors in the direction of the average behavior of those in their network. A positive coefficient of $\beta_1$ indicates that the higher level of average implementation of a particular reform initiative of those in one's network the greater the likelihood of increasing one's own level of implementation. As an example, consider a teacher Lisa, who has comparable practices to Ashley at the beginning of the diffusion process, but Lisa's network implements basic skills at lower levels than the members of Ashley's network. Under

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[4] The skilled-based instructional practices include that teachers read stories or other imaginative texts; practice dictation (teacher reads and students write down words) about something the students are interested in; use context and pictures to read words; blend sounds to make words or segment the sounds in words; clap or sound out syllables of words; drill and practice sight words (e.g., as part of a competition); use phonics-based or letter-sound relationships to read words in sentences; use sentence meaning and structure to read words; and practice letter-sound associations (see Frank et al. 2013a, p. 12–13 for details).

[5] In this sense, the exposure term extends basic conceptualizations of centrality (e.g., Freeman 1978) because the exposure term is a function of the characteristics of the members of a network, whereas centrality is a function only of the structure of the network.

these conditions, Ashley and Lisa's practices will diverge as they conform to the norms in their respective networks. The network influence can accentuate any initial fragmentation in a network, as teachers respond to different norms in their own localized networks.

Note that model (1) is a basic regression model, with $\beta_1$ representing the network effect (Friedkin and Marsden 1994). As such, and given longitudinal data, the model can be estimated with ordinary software once one has constructed the network term[6]. Furthermore, one can include covariates of a teacher's attitude toward instructional practices representing a key predictor from the diffusion of innovation literature (Frank et al. 2013a; Frank et al. 2004; Rogers 2010).

Note the use of timing to identify the effects in model (1). The individual's outcome is modeled as a function of her peers' *prior* characteristics. This would be natural if one were to model contagion. For example, whether A gets a cold from B is a function of A's exposure to B over the last week and whether B had a cold *last week*. We would not argue that contagion occurs if A and B interacted in the last 24 hours and both A and B got sick today (see Lyons 2011 and Cohen-Cole and Fletcher's 2008a, b of Christakis and Fowler's 2007, 2008 models of the contagion of obesity; see also Leenders 1995).

## 1.3  Extensions of the influence model

**Multiple sources of influence.**  The basic model in equation (1) can be extended to estimate multiple sources of influence. For example, Sun et al. (2013a) modeled a teacher's use of skills based instruction as a function of influences of formal leaders from whom they received help with reading instruction (e.g., coaches, reading specialists, designated mentors) versus regular teachers from whom they received help with reading instruction. The models used in this study can be simplified as:

$$
\begin{aligned}
\textit{Skills-based instruction}_i &= \beta_0 + \\
&+ \beta_1 \textit{ previous skills-based instruction of formal leaders in the network of } i_i \\
&+ \beta_2 \textit{ previous skills-based instruction of informal leaders in the network of } i_i \quad (2)\\
&+ \beta_3 \textit{ previous skills-based instruction of } i_i + e_i
\end{aligned}
$$

The terms $\beta_1$ and $\beta_2$ then represent the influences of formal leaders (e.g., principals, assistant principals, instructional coaches) and of informal leaders (e.g., regular teachers who enact influences on other teachers' behavior) respectively.[7] Sun et al.'s (2013a) estimates of model (2) showed that informal leaders influenced teachers' specific classroom practices such as skills-based instruction while formal leaders were more likely to influence teachers' general practices (e.g., setting learning standards,

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[6] see https://www.msu.edu/~kenfrank/resources.htm: influence models for SPSS, SAS and STATA modules and PowerPoint demonstrations that calculate a network effect and include it in a regression model.

[7] The difference between the estimates of $\beta_1$ and $\beta_2$ can be tested via a standard test of the difference between two regression coefficients (Cohen and Cohen 1983, p. 111). Or the difference can be tested by including a main effect for types of peers (e.g., an indicator of whether the peer is a formal leader) and then an interaction effect between peers and types of peers: peer$_{ii}$' x formal leader.

choosing curriculum materials, or selecting tests). The findings empirically contribute to the literature of distributive leadership by showing how teachers exhibit informal leadership as they influence their colleagues' practices (e.g., Spillane et al. 2001; Spillane and Kim 2012; Supovitz et al. 2010).

**Multiple levels of influence.** Networks can also be extended beyond direct interactions. For example, one could construct a network term based on others whom a teacher observed, members of a teacher's cohesive subgroup (where interactions are concentrated within cohesive subgroups, but not all members of subgroups have interactions with each other—see Fig. 1), or her department. That is, the network can extend beyond direct ties with whom one is close colleagues.

These network effects beyond those of direct relations will quickly become difficult to measure and differentiate, especially in the small closed communities of elementary schools or high school departments which feature extensive opportunities for casual interaction and observation of all in the system. One way to model the influence of the community is through multilevel models. For example we can extend equation (1) to a multilevel framework (e.g., Raudenbush and Bryk 2002) for teacher $i$ nested within subgroup $j$:

*At Level 1 (teacher i in subgroup j) :*

*Skills-based instruction$_{ij}$ = $\beta_{0j}$*

*$+\beta_{1j}$ previous skills-based instruction of formal leaders in the network of $i_{ij}$*          (3)

*$+\beta_{2j}$ previous skills-based instruction$_{ij}$ + e$_{ij}$,*

At the subgroup level (level 2), $\beta_{0j}$, the adjusted mean behavior for a subgroup is modeled as a function of the previous subgroup norm:

*Level 2 (subgroup level j) :*

*$\beta_{0j} = \gamma_{00} + \gamma_{01}$ subgroup average of previous skills-based instruction$_j$ + u$_{0j}$,*          (4)

where the error terms (u$_{0j}$) are assumed independently distributed, $N(0,\tau_{00})$. The parameter $\gamma_{01}$ then represents the extent to which new practices are affected by old practices of subgroup members. Using a model such as defined by (3) and (4), Frank et al. (2013a) found that teachers responded to members of their subgroup, even those from whom they did not directly receive help. In fact, Frank et al. (2013a) estimated that the influence of other members of the subgroup was about as strong as a teacher's own prior skills based instruction, suggesting that teachers were highly responsive to the normative behavior of their subgroup. One can even extend the influence model to nested individuals within subgroups within schools (e.g., Frank et al. 2013a).

**'Spillover' effects.** Data from more than two time points can be used to illustrate complex dynamics of information diffusion and policy implementation. For instance, utilizing three years of data, Sun and colleagues found a "spillover" effect in which the expertise a teacher gained from a professional development program was diffused

to others with whom she interacted in her school (Sun et al. 2013b). For example, if Ashley attended professional development, the total effect of professional development can be augmented if Ashley spilled over what she had learned from this program to other teachers (e.g., Sam or Kim) who might not have directly participated in the program. Effective professional development programs for teachers can be designed to both increase the individual teachers' expertise in enacting high-quality instruction and facilitate the diffusion of new expertise among teachers (see also Penuel et al. 2012 and Cole and Weinbaum 2010, for similar indirect effects on changes in attitudes).

**Heterogeneous influence.** The strength of influence may depend on one's prior state of behavior. For example, Penuel et al. (2012) discovered a developmental theory of change in which teachers whose prior implementation were far from the desired practices responded more to direct participation in organized professional development, while teachers whose prior implementation were more advanced responded more to the sharing of promising practices and engaging in in-depth discussion with colleagues. The findings are fruitful to think of designing different features of programs for teachers with different prior practices (see also Coburn et al. 2012; Frank et al. 2011).

**The selection model.** While the influence model represents how actors change behaviors or beliefs in response to others around them, the selection model represents how actors choose with whom to interact or to whom to allocate resources. For example, the choices a teacher makes in helping others can be modeled as:

$$\log\left[\frac{p(help_{ii'})}{1 - p(help_{ii'})}\right] = \theta_0 + \theta_1 close\ colleague_{ii'}\ , \tag{5}$$

where $p(\text{help}_{ii'})$ represents the probability that actor $i'$ provides help to actor $i$ (similar to the influence model, these data can be obtained in response to a question about from whom teacher $i$ received helped with instruction) and $\theta_1$ represents the effect of being close colleagues on the provision of help. For the data in Figs. 1 and 2, the term $\theta_1$ would be large and positive if most of the help shown in Fig. 2 was to those who were close colleagues as shown in Fig. 1. As in the influence model, other terms could be included such as common grade taught, level of knowledge, etc. (e.g., Frank 2009; Frank and Zhao 2005; Spillane et al. 2012):

$$\log\left[\frac{p(help_{ii'})}{1 - p(help_{ii'})}\right] = \theta_0 + \theta_1\ close\ colleague_{ii'} + \theta_2\ same\ grade_{ii'} \tag{6}$$

Using this type of model, several studies have found that teachers engage in extensive professional discussions with close colleagues as well as others who teach the same grade—both $\theta_1$ and $\theta_2$ are positive (e.g., Frank and Zhao 2005; Penuel et al. 2010;

Spillane et al. 2012). Help also tends to flow from experts to novices (Coburn et al. 2010; Frank and Zhao 2005; Penuel et al. 2009).

Using longitudinal data, Spillane et al. (2012) modeled the formation of new advice flows among teachers. Their results imply that the density of advice and information interactions within grades increases over time. On the one hand, this enhances resource flows within grades as grade members develop a common language and norms for knowledge sharing (Nonaka 1994; Yasumoto et al. 2001). On the other hand, without deliberate interventions over time (such a sending teachers in different grades to professional development together), teachers of one grade level may not be able to access the knowledge possessed by those in other grades (as is the case between subgroup A and C in Figs. 1 and 2). Such segmented social capital can inhibit learning because the knowledge necessary for successful teaching is not necessarily compartmentalized within grades (Frank et al. 2013a; Coburn et al. 2010).

## 1.4 Extensions of the selection model: modeling at the individual level

The selection model can be extended to model the characteristics of people that affect participation in ties or interactions. (Van Duijn 1995; Lazega and Van Duijn 1997; see Steglich et al. 2010; or Snijders et al. 2006, for alternatives). For example, Spillane et al. (2012) found that those engaged in professional development in a particular area were more likely to provide help to others in that area in their school. Similarly, Frank et al. (2008b) found that teachers who became National Board Certified were more likely to provide help to others in their school than similar teachers who did not become National Board Certified. This complements Sun et al.'s (2013b) findings regarding spillover: teachers who participated in professional development subsequently became more likely to help other teachers in the new school year. Professional development may either enhance teachers' content knowledge, or improve their ability to articulate knowledge to others, or merely signal the "expert status" of those who participated in professional development.

Finally, the effects of dyadic characteristics can be moderated by individual characteristics. For example, Frank (2009) found that the effect of being a close colleague on the provision of help was weaker if the provider of help identified with members of the school as a collective (e.g., "I matter to others in this school"; "others in this school matter to me"; "I belong in this school"). Frank (2009) interpreted the identification with the collective of the school as a quasi-tie, directing the allocation of resources without relying on a direct relation (e.g., close colleagues). Those who identified with others in the school *as a collective* developed a quasi-tie with all school members, directing their expertise equally throughout the school rather than just to their immediate networks. Thus factors that contribute to or compromise group identity (teacher turnover) can indirectly affect the flow of knowledge in a school; schools with high turnover rates may contain teachers who will help their closest colleagues but few others.

As a second example of how networks can be modified by individual characteristics, a recent study (Garrison et al. 2014) found that teachers who perceived pressure for their students to perform on tests were more likely to seek how others

who increased their students' test scores. In this way the external institutions associated with standardized testing changed not just teachers' practices, but their very networks. In turn, these changes in networks can affect a myriad of practices that may or may not be related to test scores. Thus the institutional forces may have powerful effects beyond the practices they target.

## 2 Discussion

The three basic techniques of graphically representing networks, and modeling influence and selection in networks can be employed to help researchers and policymakers better understand how schools and teachers respond to educational reforms. This section discusses the significance of social network analysis to educational research, implications for practice, and several directions for future inquiry.

### 2.1 Implications for research

Social network analysis provides a new set of tools for researchers to investigate the complexity of reform implementation and ask questions beyond traditional approaches based on characteristics of individuals or organizations. The graphical representations illustrated in Figs. 1 and 2 provide a systemic overview of how behaviors can diffuse unevenly among teachers as they respond to, and draw on, their social networks. Social network analysis also allows researchers to explore the variation of social contexts within school organizations, particularly relevant for individual teachers. While we can use multilevel models to examine how teachers are affected by the schools in which they teach (e.g., Frank 1998), teachers may experience the context of their schools differently depending on the particular local networks in which they are embedded. One teacher's network may present an unfavorable view of the principal and discourage teaching to standardized tests, while another teacher's network in the same school might favor the principal and encourage focusing on test scores. Thus the organizational culture is not monolithic as the teacher's particular network filters how she experiences the culture of her organization.

The influence and selection models allow researchers to specify and test hypothesis derived from behavioral theories from economics, sociology, and psychological with regard to individual choice, decision making, and actions. For example, the tendency for teachers to be influenced by the others with whom they interact can be tested through the term $\beta_1$ in the influence model in equation (1). This can be used to identify the sociological theories of the social contexts under which teachers are *not* influenced by their colleagues versus when they are. Such models would also allow one to test social psychological theories about the effects of social identity on the tendency to conform (e.g., Tajfel and Turner 1979) and developmental theories of learning. The selection models can be used to identify how teachers choose to whom to provide help. This informs an economic or communications theory of how resources flow through a system (Frank et al. 2013b) and how the 'spillover' effect of human capital investment is generated via peer learning and norms (Sun et al. 2013b). Such analyses can then help school leaders select individual teachers to take

on special responsibilities to help others respond to change and thus add value to the development of organizational learning theories (Sun et al. 2013b).

## 2.2 Implications for practice

Acknowledging that policy implementation depends on local contexts, it is difficult for external researchers to propose "prescriptions" for how a particular school should organize its process for change, or "prescribe" uniform strategies for all schools. Therefore, our implications for practice are limited to the degree to which we can identify common features of policy implementation and school reforms across schools. Generally, we suggest that change agents (e.g., policy-makers, district administrators, principals, or teachers) should consider local contexts of individual teachers as they respond to external demands for change within the social organization of their schools (Frank et al. 2010; Youngs et al. 2012). 'Resistant' teachers might simply be ones whose immediate networks push against a new behavior, or who cannot access knowledge from colleagues to support new behaviors. Pushing too hard against such norms can place teachers in ambiguous roles which may contribute to burnout.

Moreover, change agents must consider themselves as changing *schools*, not individual *teachers* (Finnigan and Daly 2012). The model of identifying an effective practice and then training a few teachers in a given school in an isolated setting does not recognize the social context of the teachers; rather, change agents should engage the entire faculty and staff in a school with structured inventions (e.g., Purkey and Smith 1983). This can be facilitated by requiring a large buy-in of school faculty before implementing reform (e.g., Success for All's requirement of support from 75 % of a faculty). Change agents might also deliberately attend to how knowledge and support will be circulated throughout a school, for example, by targeting individuals well integrated into the networks of their schools (Frank and Fahrbach 1999; Sun et al. 2013b) or by cultivating help from subgroups of teachers who have already adopted new practices (Frank et al. 2013b).

## 2.3 New trends in social network analysis

We have attended carefully to the models of influence and selection because they are the bedrock of social network analysis and because there is an emerging consensus regarding their specifications and estimations. Here we present three extensions beyond the basic tools we presented above.

**Agent-based models.** One great challenge in understanding organizational responses to diffusion is to anticipate the organizational changes that will emerge as a result of the combined processes of influence and selection. To explore the combined effects one can use agent-based models which simulate processes based on rules for behavior and interactions among actors (e.g., Brown et al. 2005; Lim et al. 2002; Parker et al. 2003; Maroulis et al. 2010; Wilensky 1999, 2001). For example, one can use agent-based models to examine the ultimate distribution of teaching practices after diffusion through a network (e.g., Frank and Fahrbach 1999). Graphical representations of such processes can also be found in animated movies of network processes

**Fig. 3** Local positions of students focused around courses

(Moody et al. 2005). As such, agent based models hold great promise for educational research to explore the systemic implications of non-linear processes.

**Two-mode social networks.** Another new trend in social network analysis is the analysis of two-mode network data, or bipartite graphs (see the May 2013 special issue of *Social Networks,* 35(2), pp. 145–278). For example, Frank et al. (2008a) represented high school transcript data in terms of clusters of students and the courses they took as in Fig. 3 (p. 1655). In this figure each dot represents a student and each square represents a course, with lines indicating courses taken by students. The boundaries were identified by Field et al.'s (2006) adaptation of Frank's algorithm, which maximizes the concentration of event participation within ovals relative to between the ovals.

The analysis of two mode data can easily extend to analysis of teacher networks. One can imagine defining clusters of teachers based on committee memberships, participation in professional development, and grade level (Penuel et al. 2010). Thus the sense that a teacher makes of professional development in one area (e.g., basic skills) may well depend on other colleagues with whom she has participated in other common events, or whether she experiences professional development as an isolated experience.

The pattern of teachers' participation in professional development events as well as formal and informal entities within their schools can define leverage points for change agents. Administrators or providers of professional development may not be able to mandate specific interactions or practices. But they can provide venues that

define focal points of local positions. For example, professional development focused around basic skills may not merely serve as an opportunity to deliver content, but also for convening teachers among whom knowledge and influence might flow.

**Measuring the depth of teachers' interactions.** Marsden (2005) extensively reviews the measurement of social networks. Examples of network instruments for teachers can be found at https://www.msu.edu/~kenfrank/resources.htm#survey. Here we signal a new approach to measurement attending to the nature of teachers' interactions instead of merely the presence or absence of an interaction. Motivated by Coburn's attention to the importance and variability of depth of interactions (e.g., Coburn and Russell 2008), new social network instruments include items concerning the depth of collaborative activities about teaching, including "sharing how to use curricular materials," "discussion of why and how students can learn best," or "demonstrating a lesson or activity." Analyzing the psychometric properties of the measures of depth is challenging for conceptual and technical reasons. Conceptually, it is difficult for teachers, like many others, to parse their conversations into specific components. Technically, observations of teacher interactions are dependent on one another. One can address some of these dependencies by employing multilevel models of selection to cross-nested item analysis within the individuals who make nominations and the individuals who receive nominations in a network survey (Sun 2011). The conceptual challenges are as yet unresolved, but would be an important area for further work.

## 3  Conclusion

To sum up we encourage researchers, policymakers, school reformers, and school leaders to focus on individual teachers as embedded in their networks. It is the teacher's practices that significantly contribute to educational outcomes. But those practices are shaped by the others in a school who can provide local knowledge and who may expect local coordination. Thus we bring the tools of social network analysis to bear on the classic challenge of understanding the decision making of teachers within the social organization of their schools.

**On-line technical appendix**

**Table 1** Examples of the Components of Influence and Selection Models

| | Influence Model | | | Selection Model |
|---|---|---|---|---|
| | Basic Influence Model | Multiple Sources of Influence | Multiple levels of Influence | Basic Selection Model |
| Hypothesis | $H_1$: If teachers interacted with others with higher levels of skills-based instructional expertise, their own instructional practices would be positively influenced | What types of instructional practices most responsive to which types of leaders. For example, $H_{21}$: Teachers' general practices (e.g., setting ambitious goals, choosing assessment and curriculum) would be more likely to respond to the influence of formal leaders $H_{22}$: Teachers' specific pedagogical practices in classrooms are more likely to be influenced by informal leaders who are regular classroom teachers | $H_3$: Teachers' practices of skills-based instruction were increased if they belonged to a subgroup with a higher level of skills-based instructional expertise | $H_{41}$: Teachers who were close colleague were more likely to help each other in classroom instruction $H_{42}$: Teachers who taught in the same grade were more likely to help each other |
| Data | Longitudinal data | Longitudinal data | Longitudinal data with teachers nested in subgroups | Longitudinal aata with paired-level relationships between all possible pairs of teachers |
| Model | Regression | Regression | Multilevel modeling | Logistic regression |
| Dependent Variable | $Y_1$: Teacher's skills-based instruction | $Y_2$: Teacher's skills-based instruction | $Y_3$: Teacher's skills-based instruction | $Y_4$: at pair level, one teacher helped the other teacher |
| Independent Variable | $X_{11}$: Teacher's exposure to the skills-based instructional expertise of other teachers in her/his network $X_{12}$: Teacher's own previous skills-based instruction | $X_{21}$: Teacher's exposure to the general practices of formal leaders in her/his network $X_{22}$: Teacher's exposure to the skills-based instructional expertise of informal leaders in her/his network $X_{23}$: Teacher's own previous skills-based instruction | Level 1: $X_{31}$: Teacher's exposure to the skills-based instructional expertise of other teachers in her/his network $X_{32}$: Teacher's own previous skills-based instruction Level 2: $X_{33}$: The averages of teachers' skills-based instruction in the subgroups | $X_{41}$: The pair of teachers taught the same subject $X_{42}$: The pair of teachers taught in the same grade |
| Hypothesis Test | If the coefficient of $X_{11}$ is positive and significant, the hypothesis $H_1$ is retained | If the coefficient of $X_{21}$ is positive and significant, hypothesis $H_{21}$ is retained If the coefficient of $X_{22}$ is significant, the hypothesis $H_{22}$ is retained The comparison of coefficients between $X_{21}$ and $X_{22}$ implies the comparative influences on different types of instructional practices between formal and informal leaders | If the coefficient of $X_{33}$ is positive and significant, the hypothesis $H_3$ is retained | If the coefficient of $X_{41}$ and $X_{42}$ are positive and significant, the hypotheses $H_{41}$ and $H_{42}$ are retained |

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