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How to analyze dynamic network patterns of high performing teams

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Abstract

The dynamic communication network within teams affects the performance of teams. But how can we analyze these emerging networks? We identified three research areas that have to be included for this purpose. First we summarize empirical studies concerning team networks and performance to point out the need of longitudinal investigations. Second we present the multi-level multi-theoretical model by Monge and Contractor (2003) which provides a theoretical framework to explain the evolution of communication networks within teams. Third a stochastic model is introduced that allows analyzing event based data, like e-mail streams, using exponential random graph models. We propose to include these three research areas that enable researchers and practitioners to analyze dynamic network patterns of virtual teams.

Keywords: organizational network analysis; social network analysis; dynamic networks; teams; performance; exponential random graph models

1. Introduction

What is the ideal communication network for team performance? Bavelas and Leavitt already raised this question in the 1950s (Bavelas, 1950) and since then various empirical studies were carried out using static networks. But communication patterns emerge over time as actors decide continuously with whom they interact and these patterns affect the performance of teams. In this article we propose to use a theoretical framework to derive hypotheses about expected patterns that can be evaluated using a new exponential random graph model that is based on time oriented event data like e-mails.

People in teams do not act in isolation, but instead collaborate in organized relational patterns to collectively accomplish their intended objectives. The ways in which they collaborate therefore affect overall outcomes such as individual and group performance, degree of innovation and employee's satisfaction (Brass, forthcoming). Social network research combines concepts, methods and theories to study the micro and macro levels of such social systems. Over the last few decades, the amount of research being carried out into networks in organizations has increased rapidly (Borgatti & Foster, 2003; Zenk & Behrend, 2010), but still focuses primarily on the individual or organizational levels (Cummings & Cross, 2003). Very few studies address network patterns in teams (Katz et al., 2005), despite the fact that they are the basic units of collaboration in all organizations and, therefore, directly influence organizational performance. According to Balkundi and Harrison (2006, p. 63), "there is a new wave of interest in network effects on teams. At the same time, there is a lack of convergence or consensus about what is known about those effects and, hence, questions exist about where future theoretical and empirical resources should be spent."

From a time-oriented perspective, network structures evolve over time as particular patterns of social interaction (see Figure 1). In the case of virtual teams, e-mail logs represent these collaborative interaction patterns and provide event-based data for dynamic network analysis. Adopting such a time-oriented perspective again raises two main questions regarding the frequently assumed interdependency between network structure and performance: (1) Which dynamic interaction patterns predominantly shape the network structure of collaborative teams? (2) How do these interaction patterns affect the performance of teams? To answer these questions, we identified three research areas to empirically study dynamic patterns of teams.

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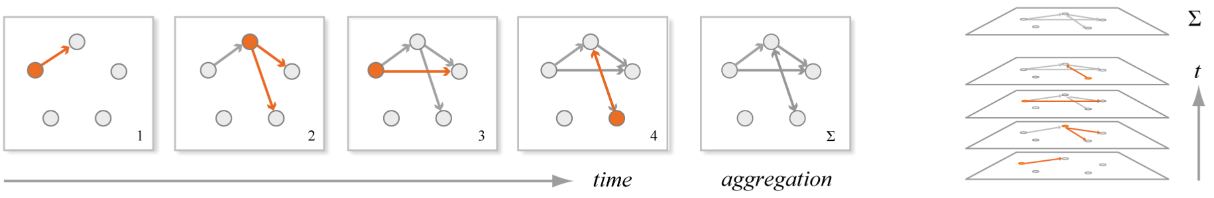

Figure 1: Networks as aggregation of social interaction patterns over time as parallel view (left hand side) and 2.5D-View (right hand side). Active interactions are orange, past interactions gray.

2. Empirical studies on team networks and performance

The first research into small group networks was carried out in the 1930s by Jacob Moreno (although he did not actually refer to it as network research at that time). One of the most famous network experiments was conducted in the 1950s by Bavelas and Leavitt (Bavelas, 1950), who were the first to examine what constituted the ideal network structure(s) for group performance. They determined that centralization, i.e. the extent to which an entire network is focused around a few central actors, is an important factor for performance: groups performed better in decentralized structures for simple tasks and in centralized structures for more complex tasks.

Katz et al. (2005) separate research into small group networks into two distinct periods: the early research carried out between 1930 and 1960 and the new era of research that began in the 1990s, perhaps as a result of the growing interest in social capital and the development of network software. In general, organizational network researchers traditionally focus their analyses on either the individual or the organizational level, while small group researchers in turn do not focus on relational aspects. "To demonstrate the extent of the disjuncture, we conducted a survey of all network and team articles published in the period 2000-2001 in five top management journals [...] We found 61 articles on networks and 105 articles on teams, but only four articles that involved both networks and teams" (Katz & Lazer, 2003, p. 6). However, over the last ten years a new wave of interest in team networks has evolved as network researchers have begun to analyze the group levels in organizations and small group researchers have become interested in team effects on the relational level. Thus, about half a century after Bavelas' first studies, the same question arises again: What is the optimal network structure for team performance?

Various studies have confirmed Bavelas' claim that centralization is an important factor for team performance (e.g. Brown & Miller, 2000; Sparrowe et al., 2001). Focusing on the figures for the most productive groups in their study, Reagans and Zuckerman (2001) found that the number of ties within teams that cut across demographic boundaries had a positive effect on performance. Other studies analyzed various network patterns that were negatively associated with performance, like core-periphery and hierarchical group structures (Cummings & Cross, 2003). Gloor et al. (2006) found that balanced communication in virtual teams (measured by number of e-mails sent and received) is positively correlated with performance. Hansen (1999) investigated inter-team interaction and distinguished between the weak ties that were beneficial for simple information purposes and the strong ties that were needed for more complex information sharing. Mehra et al. (2006) found that leaders' centrality in friendship networks was related to group performance. A meta-analysis by Balkundi and Harrison (2006) showed that high density within teams, leader centrality in teams and team centrality in inter-group networks were all positively related to team performance.

However, as far as team performance is concerned, there is still a clear lack of empirical analysis that focuses on longitudinal data and uses the available theoretical mechanisms to explain the communication patterns and aspects of virtual teams. According to Katz et al. (2004, p. 327) "one area especially deserving of future development is the longitudinal analysis of groups and networks." And Balkundi and Harrison (2006, p. 62) stated: "There is really no comprehensive theory about the interplay of networks, team processes, and team outcomes over time." Finally, Ahuja and Carley (1999, p. 741) note, that "virtual organizations that use e-mail to communicate and coordinate their work toward a common goal are becoming ubiquitous. However, little is known about how these organizations work."

3. Theoretical framework: Multilevel multitheoretical model

Social network analysis enables researchers to study a myriad of social interactions. In the field of organizational research, many studies have already been conducted into a diverse range of topics – from the antecedents (e.g. personality, human and social capital) to the consequences (performance, innovation, satisfaction) of networks (Brass, forthcoming). But the potential of organizational network analysis is by no means exhausted when it comes to the scientific and practical questions of collaboration and team work (Katz & Lazer, 2003). If anything, the reverse is true: organizational network analysis has really only just begun (Dandi & Sammarra, 2009).

As a result, there are still some challenging aspects in this young field of research that need to be addressed through appropriate empirical studies. Monge and Contractor (2003) maintain that there are three main gaps in organizational network research: (1) despite their prevalence, social theories are rarely used in empirical investigations and, therefore, cannot be used to construct hypotheses; (2) most research focuses on a single level of analysis, although network data would provide for the study of multiple levels; and (3) most network studies examine static networks, using cross-sectional data instead of dynamic networks using longitudinal event data.

To address these needs, Monge and Contractor (2003) propose a general analytical framework, the multitheoretical and multilevel (MTML) model, to study the evolution of organizational communication networks (Contractor et al., 2006). This framework combines a variety of social theories, thus allowing multiple complementary and contrasting perspectives to be incorporated into an individual study to assess their relative influence. It includes multiple levels and integrates the individual, dyadic, triadic and entire network levels. It also addresses the creation, maintenance, dissolution and re-creation of dynamic organizational networks.

Within the MTML-Model a wide range of social theories can be used that try to explain the emergence of communication ties. Each of these theories corresponds to specific theoretical mechanisms that can be translated in a graph theoretical notation to prove derived hypotheses in empirical studies (see Figure 2). A specific application of an exponential random graph model (ERGM) allows analyzing the event-based data at hand.

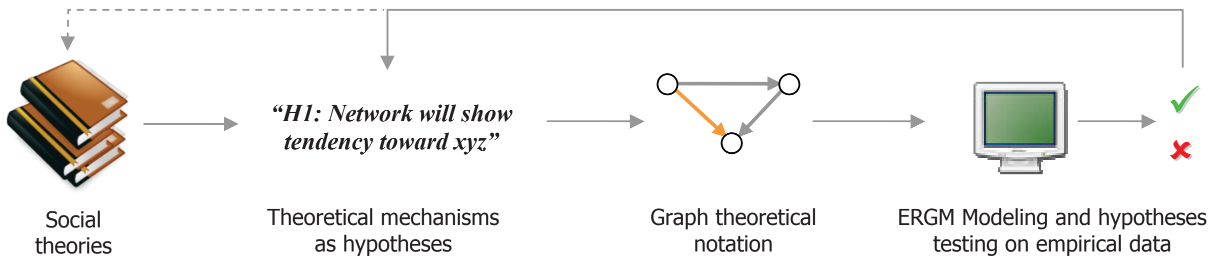

Figure 2: Translation of social theories via theoretical mechanisms into graph theoretical notations, which are available to test hypotheses on empirical network data by ERGM modeling.

4. Event-based analysis using exponential random graph models

An e-mail dataset provides very fine-grained information about how actors interact. This information can be exploited and different methodological approaches how to analyze this data have been developed recently (see Brandes et al., 2009; Butts, 2008; Stadtfeld & Geyer-Schulz, 2010). With the exception of any missing data, each individual e-mail interaction is logged. Prior to such interaction, the actors in this model have to make several decisions:

- How often do I want to interact?
- How many people do I want to send my e-mail to?
- Who are the recipients?
- Are the recipients members of my group and do they have certain attributes?

These decisions can be embedded in a Markov process as done in a similar approach by Snijders (2005) for longitudinal data. The states of this process are the states of a communication graph representing recent e-mail interaction. Transitions are defined for those changes in the graph that are caused by e-mails from one actor to another. Other changes also happen, but these are deterministic and describe time dependent processes. In general, the transitions are defined as follows:

$$\lambda_{i,J}(x) = \underbrace{\rho_i}_{*} \; \underbrace{p^{\#}(|J|,\tau)}_{\#\text{ of recipients}} \underbrace{\prod_{l=1}^{|J|} p^{?}(J_l; i, x, \beta, R \backslash \{J_1, .., J_{l-1}\})}_{\text{sequential choice of recipients}} \quad (1)$$

$*$: general activity of actor i

As explained in another paper (Zenk & Stadtfeld, 2009), this Markov transition rate models the first three of the above-mentioned prior decisions (how active sender i is in general; how many people he/she writes to; who the recipients are) in the communication graph x.

The first parameter rho_i is a Poisson parameter indicating the propensity of actor i to communicate. The higher this value, the greater the likelihood that the corresponding actor will write e-mails in a particular time span. The second parameter is a Poisson probability for choosing exactly |J| recipients given a Poisson parameter tau. The third part of the above given transition rate is a multiplication of probabilities for each individual recipient. Recipients who have already received an e-mail are removed from the set of possible recipients R. Since these decisions are all based on the same graph x (the process state immediately prior to the decision), they are assumed to be independent, like all other probabilities in this transition rate.

The fourth decision (are recipients members of my group and do they have certain attributes?) only plays an implicit part in our model. The transition rate may only be defined for certain recipient sets J, such as all actors in the same group as the sender if the group is high performing. This information is encoded in the set of possible recipients R.

In general, the parameters rho, tau and beta can be estimated using a maximum likelihood (ML) estimation. Since, for the purposes of analyzing high performing teams, we would only observe the choice of recipients of probability function $p^?$ in detail, we also only estimate the parameter vector beta. This probability is defined as:

$$p^?(j; i, x, \beta, R) = \frac{1}{c} \exp\left(\beta s(add(x, i, j))\right) \quad (2)$$

$$c = \sum_{k \in R} \exp\left(\beta s(add(x, i, k))\right) \quad (3)$$

The probability of actor j being chosen as recipient over all other possible recipients in R depends on the sending actor i, the process state x (the state of the communication graph), a parameter vector beta and R. This probability function is a non-linear regression model with network statistics in vector s as an independent variable and the decision regarding the recipients as a dependent variable. This regression model is in the class of exponential random graph models (see Robins & Pattison et al., 2007; Robins & Snijders et al., 2007).

Vector s includes functions that count certain weighted structures surrounding the sender and recipient. It could, for example, count whether the existence of a dyad between sender and recipient increases the probability of communication compared with a random tie occurrence. Prior to the evaluation of network structures of this kind, the communication value between i and j in network x is increased by 1 using the function add(x,i,j). Similar definitions of this model can be found in Stadtfeld and Geyer-Schulz (2010).

5. Discussion

In this article, we identified three research areas that have to be included to analyze dynamic network patterns of high performing teams. First, we summarized empirical studies on team networks and performance. By now, most of the studies focus on static networks and there is still a lack of empirical analysis using longitudinal data. Second, we presented a theoretical framework that can be used to derive relevant hypotheses from selected social theories. Based on both the empirical studies and this framework, we could hypothesize which dynamic network patterns explain high performing teams. Third, we introduced a new model based on exponential random graph models and its longitudinal extensions to analyze event-based data like e-mails.

Concerning future research, the authors plan to apply this integrated approach, using e-mail data of virtual teams (Zenk & Stadtfeld, 2009). Based on measured performance indicators, high and low performing teams will be distinguished. Thus, we will try to understand which dynamic network patterns lead to better team performance.

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