Chapter 14
Understanding and Assessing Collaborative Processes Through Relational Events

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Abstract Effective teams are characterized by how skillfully they collaborate, coordinate, and interact while working towards their collective goals. These processes are inherently dynamic, and are best represented as a series of events (i.e. interactions). Whereas other methods for studying teams focus on the properties or structure of the group, an event-focused framework has potential to yield unique insights about the nature of collaboration. We therefore introduce the relational event framework, which is a statistical tool designed specifically to take advantage of event data. This method makes statistical inferences about what sequential patterns of collaboration ties form and how these patterns perform. In this chapter we introduce the reader to relational event modeling, including an overview of the necessary data, measures, and statistical models. We also provide insights on how this statistical technique can be utilized to assess and understand collaboration.

Keywords Relational events · Teams, team process · Social network analysis · Event history models · Structural signatures · Generative mechanisms

14.1 Introduction

Complex tasks are achieved through the efforts of highly productive, highly skilled teams. These specialized groups collaborate to produce outcomes well beyond the capabilities of any individual. Teams are present in all facets of life, from science to medicine, engineering to business. Increasingly, the sole practitioner cannot compete with a well-balanced, skillful group. However, we are often at a loss for explaining what makes a successful collaboration. The teams that work towards these collective tasks are living, breathing units with a character all their own, and

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A.A. von Davier et al. (eds.), *Innovative Assessment of Collaboration*,
Methodology of Educational Measurement and Assessment,
DOI 10.1007/978-3-319-33261-1_14

consequently studying them requires a level of sophistication on par with the complex nature of group behavior.

The implications of research on teams are straightforward; if we have a better team, we can expect better collaborations. Yet, this seemingly benign problem has no easy answer. Therefore we pose the simple question: why do some teams fail while others succeed? Often, it is not the inputs to the team that are problematic; by design, each individual can be highly skilled and/or knowledgeable of the task at hand. Rather, failure is rooted in poor interactions or a lack of "chemistry." While interpersonal chemistry has its own colloquial meanings, team chemistry is poorly understood. To truly understand what makes an effective team, we need to look deeper than inputs and outputs; specifically, it is the actions and interactions that unfold over time that represent the nature of a team.

A number of theories explain the nature and quality of team interaction and the relationship between collaborative skill and the final product. Kozlowski and Klein (2000) analyzed a team by its emergent properties, which are characteristics of the team and the individuals within it, as well as the configuration of attributes within the unit. For example, a team may be assessed by how much planning behavior they took part in during their collaboration. As an extension of this framework, Marks, Mathieu, and Zaccaro (2001) incorporated time into the analysis of teamwork. A collaboration will naturally move through phases, during which different types of interactions are necessary. For instance, at the beginning of a project, individuals may focus on defining goals and delegating roles, while during later phases they may focus more on coordinating specific tasks or managing the team's mood. More recently, Crawford and LePine (2013) proposed a configural view of teamwork suggesting that the pattern and structure of teamwork influences outcomes. For example, teams that centralize work around one individual may perform differently than teams that use a distributed collaboration.

Building on these frameworks for assessment of teamwork, Leenders, Contractor, and DeChurch (2015) have proposed a new paradigm to studying team process—relational events—that focuses on individual interactions over time. This approach frames collaboration and communication as a sequence of events; the unfolding of these events may be explained endogenously (prior actions taken by members of the team) or exogenously (changes in the team's environment). The relational event framework identifies emergent patterns of behaviors between individuals, as well as other factors which contribute to the generation of future actions (Butts, 2008). As a result, relational event models (REMs) answer the "what events should happen when" question posed by Marks et al. (2001), while also answering the "who talks to whom" question posed by Crawford and Lepine (2013). In contrast to prior approaches, a REM is multilevel, capturing in a single model the influences of individual, dyadic, triadic, and group-level characteristic on the dynamic unfolding of collaboration processes As a result, the assumption of homogeneity, both among team members and over time, is no longer needed.

In this chapter, we describe the relational event framework and illustrate how it can be applied to the assessment of collaboration. In particular, we specify the data structure required for this type of analysis and describe the development of event-based statistics for testing hypotheses. Next, we give a brief overview of how to fit relational event models and how to use these results to assess a collaborative effort. Finally, we give a brief example of a scenario in which REM is applied.

14.2 The Relational Event Framework

14.2.1 What Are Relational Events?

A relational event is any interaction or behavior that originates from an individual towards another individual or object (Butts, 2008). Relational events are encoded as units of data that include relevant information such as the sender, target, and time of the event. Additional information such as the type of event (e.g., phone call or text message), weight (Foucault Welles, Vashevko, Bennett, & Contractor, 2014), or valence (e.g., positive or negative interaction; Brandes, Lerner, & Snijders, 2009) may be observed and recorded (Marcum & Butts, 2015). A full relational event dataset is effectively a transcript of exactly what transpired during the course of collaboration.

Relational events may be applied in a number of different contexts. Perhaps the simplest example of such a behavioral event is a message, sent from one individual to another. For an example of a series of relational events in a three-person project group, see Table 14.1.

Table 14.1 could be converted to an event sequence in a straightforward fashion: $e_1 = (a, b, t_1), e_2 = (b, a, t_2),\ e_3 = (c, \{a, b\}, t_3)$. This process can be repeated for the whole dataset. However, events are not confined to messages. For example, events may be directed from an individual to a task or tool. Quintane, Conaldi, Tonellato, and Lomi (2014) used relational events to model the interactions between software developers and blocks of code over time. Vu, Pattison, and Robins (2015) studied the clicking behavior of students using online course material, as well as their interaction with chat rooms. Alternatively, events may be egocentric (i.e., focused on one individual); Marcum and Butts (2015) used this version of the model to track the behaviors of elderly individuals throughout the course of a day.

Table 14.1 Sample relational event sequence

Time (PM)	Sender	Receiver	Message
2:01:00	Adam	Bob	Did you finish your section yet?
2:01:05	Bob	Adam	No, not yet
2:01:14	Christina	Adam, Bob	I finished mine, can I help either of you?

14.2.2 How Are Relational Events Applied?

Relational event sequences differ from other social network techniques such as exponential random graph models (ERGMs; Lusher, Koskinen, & Robins, 2012) or stochastic actor-oriented models (SAOMs; Snijders, 1996). In ERGMs, the structure of a single graph is analyzed. The structure of ties between individuals is determined to be more or less prevalent than we would expect in a random graph. ERGMs are useful for studying structure of network ties that are relatively enduring states (such as trust) captured by concepts such as centralization or multiplexity (simultaneous occurrence of multiple ties), but are not suited for studying ties that are episodic events (such as a chat message). Snijders and colleagues modeled the evolution of network dynamics via a Markov process, with the state transitions dependent on the current network. These so-called SOAMs introduce time into the analysis of social networks. The models are actor-oriented because actors—who choose to create, maintain, and dissolve ties based on their current position within the network—drive changes within the network. These models are particularly appropriate when a snapshot of the network data is collected at discrete time intervals (such as a day, month, or year), but the underlying process cannot be observed.

Relational event models expand on both of these modeling frameworks to accommodate interaction data that is completely observable, and increasingly available, such as online chat logs or transcripts of conversations. Relational event data are used to posit what Leenders et al. (2015) termed as a sequential structural signature (SSS), which is a dynamic analog to the statistics used in ERGMs. SSSs are sequences of relational events that unfold in a particular pattern and are designed to represent theoretically interesting behavior sequences. SSSs characterize interactions of various types at multiple levels. In particular, they may be at the ego level, the dyad level, the triad level, or beyond. Additionally, SSSs can incorporate attributes of the actors, as well as the relations themselves.

To illustrate the notion of an SSS, we present a simple example. Preferential attachment is the tendency for individuals to communicate with others who have previously been epicenters of interaction (Barabási & Albert, 1999). Put simply, as individual A increasingly sends and receives messages from individual B, then individual C becomes increasingly likely to send a message to B. This mechanism captures the extent to which popularity drives future communication. In Fig. 14.1, we illustrate the preferential attachment SSS; solid lines represent past communication, while dashed lines represent the potential new communication. Arrows indicate directionality.

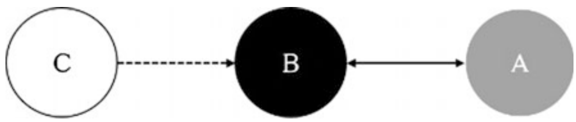

Fig. 14.1 Visual representation of preferential attachment SSSs

We now explain how to mathematically operationalize a signature such as the one presented in Fig. 14.1. Let n_{ijt} be the number of messages sent from i to j up to time t. As we stated in our description of preferential attachment, this signature represents an individual's level of activity, relative to the rest of the network. We provide a formula below (assuming N individuals):

$$s_{PA}(C, B, t) = \frac{\sum_{k=1,\ldots,N} n_{Bkt} + \sum_{k=1,\ldots,N} n_{kBt}}{\sum_{l=1,\ldots,N} \left(\sum_{k=1,\ldots,N} n_{lkt} + \sum_{k=1,\ldots,N} n_{ljt} \right)}.$$

The measure $s_{PA}(C, B, t)$ is the specific value of preferential attachment between sender C and receiver B at time t. The numerator is a sum of all incoming and outgoing messages involving node B up to the present time. The denominator is the sum of all messages sent and received in the network between any pair (l, k).

While the structure presented is straightforward, significantly more complex signatures can be developed. For instance, consider the case of two individuals collaborating on a software project. Let A and B be the individuals, and X is the software project they are considering working on. We represent this situation in Fig. 14.2. The solid line indicates that B has previously worked on the project, and that A and B have been communicating. The dashed line represents A's propensity to subsequently engage with the software project to potentially "redo" something just done by B.

We let the shading of A and B in Fig. 14.2 represent their relative experience; the grey circle represents the more knowledgeable member of the team. We would like to operationalize a statistic that captures the propensity for A to work on something B has already worked on, based on their prior communication, B's prior activity, and their relative skill difference. Using the same n_{ijt} notation as before and letting z_A denote the skill of individual A, we may create the following measure:

$$s_W(A, X, t) = n_{BXt} \times (n_{ABt} + n_{BAt}) \times (z_A - z_B).$$

This statistic will be large and positive if B has worked on software X more frequently, A and B have frequently communicated, and A is more skilled. If A becomes less likely to work on the software as s_W increases, then we would say that

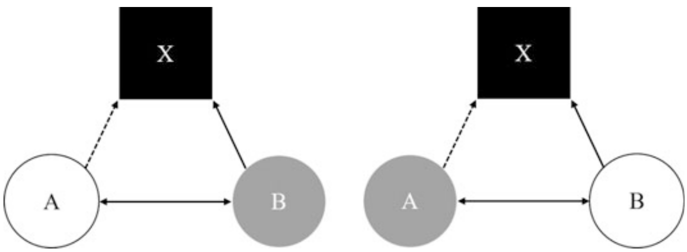

Fig. 14.2 Visual representation of communication and action

A has confidence in B's abilities to get the work done. Alternatively, if A becomes more likely to engage X, then we might infer that A lacks confidence in B's work, and decides to revise the item.

This approach to generating SSSs and operationalizing them can be applied to virtually any setting in which trace data are available. As with ERGMs or SAOMs, a visualization of the desired structure can be created, and accumulated interactions are used to represent the intensity of the hypothesized links. Attributes of the relationships or of the nodes themselves are easily incorporated, as illustrated above. The choice of statistics computed is based on theoretically motivated explanations for the emergence of events. Current research on relational events has used extensions of common signatures from ERGM or SAOM. Butts (2008) and Brandes et al. (2009) also provided a template for generating statistics. In general, the number and complexity of the terms are largely dependent on the theoretical explanation posited, as well as the context and availability of the data.

14.2.3 How Do We Fit Relational Event Models?

The foundation of REM is the specification of the rate function. The rate of an event represents its pace over time; more frequent events have a higher likelihood of occurring, relative to events with a lower rate. Event history analysis applies survival modeling to event data, and represents the event rate with a hazard function (see, for example, Blossfeld & Rohwer, 1995). The hazard rate for an event is the instantaneous likelihood of the action occurring, given its previous nonoccurrence. To account for the time between events, the survival function is used. The survival function is the likelihood that an event does not occur during a particular timespan. Survival functions may be directly computed from the hazard rate. As a result, determining a functional form for the hazard rate allows us to explicitly model a relational event sequence.

Butts (2008) defined the hazard rate λ for a relational event to be an exponential function of a linear combination of sufficient statistics s and rate parameters θ. The sufficient statistics are simply mathematical representations of SSSs, as discussed previously. The rate parameters are analogous to the parameters of a logistic regression model; the sign and significance indicates what effect the corresponding pattern has on future events. The functional form of the hazard rate is as follows:

$$\lambda_{ij}(t;\, \theta) = \exp\left(\sum_{p=1,\ldots,P} \theta_p s_p(t)\right).$$

The mathematical form for the likelihood function for a sequence of events is equivalent to Cox's (1972) proportional hazards model. In order to recover the rate parameters for a particular sequence of events, maximum likelihood estimation can be applied directly to the log-likelihood function. Alternatively, Bayesian estimation methods may also be used, and empirically have proven to be more efficient; for more detail, see Butts (2008).

14.3 Relational Event Models as an Assessment Tool

Evaluating process requires insight into the structure and evolution of team interactions over time. The encoding of structural signatures provides an unprecedented high-fidelity quantitative measure of the frequency with which certain behavioral patterns repeat themselves in an event history. As a result, the dynamics of team communication and collaboration can be explicitly studied at a resolution heretofore unavailable. Relational event models determine the relative influence of each SSS on future behaviors; this output is a standard statistical metric that can be compared across teams. By using SSS as a metric for analyzing team actions, outcomes can be explained as an explicit and direct result of the structure and nature of team process.

At the group or network level, SSSs represent the prevalence of certain behavioral patterns in an interaction network. Differences in the emergence of these mechanisms across teams or across individuals are indicative of structural variations in the interaction patterns of individuals and/or teams. The variability in the estimated values of REM parameters for different teams can be used to explain variability in the outcomes of these teams. To capture this impact, standardized relational event parameter estimates are used as independent variables in a statistical analysis where team outcomes such as performance or creativity are the dependent variable.

14.3.1 Example Using Relational Event Models as an Assessment Tool

To illustrate how relational event models are used to assess the effectiveness of multiple collaborative efforts, consider our previous example of individuals working on a software project. Suppose that our metric of interest is the SSS from Fig. 14.2, which measures the propensity for a team member to redo another member's work, based on their communication and the discrepancy in their skills. Let us assume that there are a number of these teams working on different software projects, and there is some measure of output quality, such as reliability from crashes or number of downloads by users, that can be compared across the software projects.

Using REM, we can estimate the parameter associated with our hypothesized SSS for each team. This output represents the degree to which each group engaged in that particular behavioral pattern during the course of their collaboration. We may compare these values across teams and determine the extent to which variation in behavior explains variations in output. This form of analysis allows us to answer the following question: "If a team more frequently engages in behavior X, will their collaboration result in a better output Y?"

14.4 Discussion

The study of effective collaborations requires an understanding of how individuals express their collaborative fluency, or collaboration skill. Unfortunately, measuring these processes has been a challenge. A gap exists between theories of effective collaboration (Olson, Malone, & Smith, 2001; Olson, Zimmerman, & Bos, 2008) and the methodological frameworks available to articulate and test those mechanisms; however, given the increased availability of digital trace data, complex interpersonal interactions are now made visible. The relational event framework is a statistical tool designed specifically to take advantage of this newly available data to make statistical inferences about what sequential patterns of collaboration ties form and how these patterns perform.

Previous methodologies typically focused on the nature or quality of aggregated interaction, without factoring in the rhythm, pattern, or tempo. Encoding individual actions and relations as temporal events can capture dynamic team processes with high levels of precision. SSSs, which are functions of event histories, represent dynamic interaction patterns that explain emergent behavior. These metrics are highly flexible and customizable to the context of the collaboration.

The relational event framework reveals behavioral patterns that can be used to assess the quality of a team's process with regard to the desired outcome of the collaboration. In general, the relational event methodology is geared towards understanding how teams work together, how teams communicate, and how they interact with the tasks and tools at hand. Relational event modeling is an exciting new statistical tool that allows for the development and testing of theory regarding the nature and quality of collaboration.

Acknowledgements The preparation of this chapter was supported by the Army Research Institute for the Social and Behavioral Sciences under contract W5J9CQ12C0017. The views, opinions, and/or findings contained in this report are those of the authors, and should not be construed as an official Department of the Army position, policy, or decision, unless so designated by other documents.

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