An illustration of the relational event model to analyze group interaction processes

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Abstract

A fundamental assumption in the study of groups is that they are constituted by various interaction processes that are critical to survival, success, and failure. However, there are few methods available sophisticated enough empirically analyze group interaction. To address this issue, we present an illustration of relational event modeling (REM). A relational event is a "discrete event generated by a social actor and directed toward one or more targets" (Butts, 2008, p. 159). Because REM provides a procedure to model relational event histories, it has the ability figure out which patterns of group interaction are more or less common than others. For instance, do past patterns of interaction influence future interactions, (e.g., reciprocity), do individual attributes make it more likely that individuals will create interactions (e.g., homophily), and do specific contextual factors influence interaction patterns (e.g., complexity of a task)? The current paper provides an REM tutorial from a multi-team system experiment in which two teams navigated a terrain to coordinate their movement to arrive a common destination point. We use REM to model the dominant patterns of interactions, which included the principle of inertia (i.e., past contacts tended to be future contacts) and trust (i.e., group members interacted with members they trusted more) in the current example. An online appendix that includes the example data set and source code is included in order to demonstrate the utility REM, which mainly lies in its ability model rich, time-stamped trace data without severely simplifying it (e.g., aggregating interactions into a panel).

An illustration of the relational event model to analyze group interaction processes

Introduction

A fundamental assumption in the study of groups is that they are constituted by various interaction processes that are critical to survival, success, and failure. Indeed, interaction was the first feature in DeLamater's (1974) notable definition of groups as the "interaction between individuals, perceptions of other members and the development of shared perceptions, the development of affective ties, and the development of interdependence or roles" (p. 39). Moreover, classical theoretical works such as Bale's (1950) interaction process model and Schneidel and Crowell's (1964) spiral model of group development both emphasize the intricate dynamics of group interaction processes and how they influence group outcomes. As such, if "temporal patterns of interaction are central to the study of groups, then to understand groups fully, it is important to have methods for characterizing and testing theories of group interaction" (Hewes & Poole, 2012, p. 358).

As the word process implies, there is a continuous, developmental, and unfolding spirit to *process*, one that deviates from static, cross-sectional, and snapshot approaches. For instance, when groups make decisions, manage conflict, or simply communicate with one another, they are engaging in series of ongoing events and changes that occur continuously over time (Rescher, 1996). As such, to better capture this trend, we follow Marks, Matheiu, and Zaccaro (2001) and define group interaction processes as "members' interdependent acts that convert inputs to outcomes through cognitive, verbal, and behavioral activities directed toward organizing taskwork to achieve collective goals" (p. 357). That is, when groups act, their interdependent acts (i.e., processes) are influenced by a variety of factors brought into the group (i.e., input). Typical interaction processes include communication, coordination, and conflict management (Williams & Mahan, 2006). When groups engage in various processes, an output is generated, for better or for worse (e.g., performance outcomes, perceptions, affective ties, roles, etc.).

However, because group process inherently brings time into the equation, this poses a dilemma regarding: (1) appropriate ways to measure the nuanced concept; and (2) what methods can be used to analyze them. For instance, a large amount of measured group processes are arguably not processes, instead better conceptualized as *emergent states* (Marks et al., 2001), better known as attributes or properties of groups that were perhaps themselves influenced by various interaction processes. Emergent states are often measured through gauging group member's perceptions via a survey. For instance, when collective efficacy is hypothesized to influence group performance (Bandura, 1997), there is an implicit assumption that collective efficacy should be conceived of as a process that leads to high group performance, when in fact, collective efficacy may simply be an output of various ongoing interactions among group members. Thus, when processes are measured as emergent states, researchers neglect the actual fine-grained interdependent acts occurring over time that make up the heart of group interaction processes.

A second problem regarding the study of group interaction processes is method. Most methods used to study process are based on *variance theory*, which simply analyzes the relationship between a set of independent and dependent variables (Poole, 2012; Mohr, 1982). Such a method, even with longitudinal extensions, may not be sufficiently nuanced enough to capture how a series of interdependent interactions produce some sort of outcome. Indeed, traditional methods under the guise of variance theory make limiting assumptions about the nature of social reality, what Abbott (1988) referred to as *general linear reality*. General linear reality neglects sequential processes because it assumes “the social world consists of fixed entities (the units of analysis) that have attributes (the variables)” and “interact, in causal or actual time, to create outcomes, them-selves measurable as attributes of the fixed entities” (p. 170).

The purpose of this paper is to describe a newly developed method that can help ameliorate the problem of measure and method regarding group interaction processes: relational event modeling (REM). REM is a blend of social sequence and network analysis (e.g., Cornwell, 2015). It addresses the measure problem by producing a set of sufficient statistics that capture patterned and interdependent interaction over time, and the method issue by using continual and longitudinal inference to model a history of group interactions. The paper is organized as follows. First, we present a general relational event framework for analyzing group interactions processes. Next, we describe the data used for the tutorial analysis. Finally, we demonstrate best practices for using, reporting, and interpreting REM, concluding with some of the limitations affecting REM.

A general relational event framework for group interaction processes

At a basic level, a relational event can be defined simply as a “discrete event generated by a social actor and directed toward one or more targets” (Butts, 2008, p. 159). For instance, when group member *A* sends a message to group member *B*, at time *T*, there is the necessary information required for one relational event. Other REMs can take into account more information, such as the weight of the interaction to reflect level of influence or importance of the events (Brandes et al., 2009) and different types of receivers (Vu, Pattison, & Robins, 2015).

Though still quite young, several studies have implemented REM in various contexts. For instance, Welles and colleagues (2014) used it to understand how individuals form friendship ties in *Second Life*. Lerner and colleagues (2013) used it to analyze political interaction between nation-states, testing the old adage that the *enemy of my enemy will be friend*. And Quintane and colleagues (2014) used REM in a comparative analysis between two organizational teams and their email patterns. Because one team was high performing and the other low, this allowed to others begin an inquiry into whether some relational event patterns might lead to success more so than others.

In all these studies, the sequential aggregation of relational events forms what is called an event history. The overall purpose of REM is to model that event history. In traditional terms, the dependent variable here is the next relational event. As such, what are the independent variables? Or in other words, how and why do relational events happen? Figure 1, drawing from Lusher et al.'s (2013) cross-sectional network framework, presents a schema to conceptualize the factors that can influence the probability of an event occurring along three factors: (1) past relational events, (2) actor attributes, and (3) exogenous contextual factors.

Past relational events. Often referred to as endogenous mechanisms (Leenders, DeChurch, & Contractor et al., in press; Stadtfeld, 2012), the accumulation and sequencing of past relational events can influence the likelihood of the next relational event. For instance, *inertia* describes how the aggregation of past events to an actor will influence future rates of his or her behavior. Inertia reflects the degree to which group members' past contacts tend to be their future contacts. Other mechanisms are more sequential in nature. Take for example reciprocity, which examines the likelihood of group member B sending a message to A if B had recently received a message from A. More complicated sequences can go beyond the dyad too. Triadic closure examines a sequence of three members forming a clique-like structure: when group member A sends a message to B, and B sends a message to C, what is the likelihood that A will send a message to C?

Actor and event attributes. Sometimes the likelihood of a group interaction occurring is due to some attribute of either the sender or receiver, or an attribute of the event itself. The effect of sending or receiving, for example, represents the most basic type of effect that attributes can have on relational events. An extraverted individual might, for instance, send messages at a higher rate than somebody who is more introverted.

However, it is more complicated if the specified sequence involves more than simple sending and receiving. Attribute sequences represent instances when a specific sequence interacts with a particular attribute of those involved in the process. For instance, consider the concept of brokerage roles (Gould & Fernandez, 1989) involving team leaders in groups. In this scenario, the team leader can take up different roles depending on the sequences of relational events (e.g., coordinator, itinerant broker, gatekeeper, representative, and liaison). For example, when a non-leader sends a message to a team leader on the same team and then the said team leader relays that message to another team, they are said to play the role of a *gatekeeper*. Other statistics can simply measure the influence of past events contingent on some sort of attribute. For instance, reciprocity might be more prevalent within group members who are more demographically similar (e.g., homophily) or preferential attachment might be contingent on experience (e.g., older group members).

Exogenous contextual factors. Exogenous factors refer to characteristics outside the relational event history and individual attributes. These measures include the state or character of a relation as well as environmental events beyond the scope of the interaction system. As a result, behaviors derived from these factors are not well explained by endogenous mechanisms such as previous relational events.

Relational attributes refer to different kinds of ties individuals might have with one another like affinity (e.g., friendship, trust), flow (e.g., other forms of sending messages like texting), representational (e.g., endorsements), and semantic (e.g., shared interpretations) ties (Shumate et al., 2013). It might be the case for example, that individuals who share a friendship tie are more likely to interact in groups than non-friends. Generally, relational attributes capture the nature of the dyad itself and provide context for the type and timing of events that occur between that pair.

Environmental factors may refer to more ambiguous concepts that lie outside the system of group interaction, such as social context or team cohesiveness. Alternatively, environmental factors may encompass more readily measurable entities like the nature of the task, restrictions on communication channels, or availability of resources. Any of these elements might have an influence on patterns of group communication. For instance, some groups might be embedded in environments where there is much more uncertainty (e.g., lack of credible information) or with an infrastructure that makes it more difficult to accomplish goals (e.g., lack of information technology). Comparative analysis might be one way to estimate the effects of the environment.

The next section briefly articulates the statistical logic underlying the relational event model. It also deals with the operationalization of some of the above mentioned variables and how they can be employed in an actual analysis. We use the framework as an example to model relational events in an experimental setting within a multi-team system playing a virtual military-like simulation.

Overview of the relational event model

For a more statistical introduction on how exactly to model relational events, we refer the reader to Butts (2008), Stadfeldt (2012), and Brandes et al. (2009). A technical introduction is included in the online appendix, but we provide a general introduction below.

For any group process, there is a discrete set of interactions (i.e., relational events) that can occur during any given time frame. The frequency of each interaction in this set depends on a unique rate of occurrence. Commonplace actions happen more often so they have a higher rate of occurrence, whereas unusual events have a low rate. Further, the rate also determines the time between interactions – a model containing more common interactions will show less time between interactions than a model with more unusual interactions. This rate variation forms the basis of event history models (Blossfeld & Rohwer, 1995). In event history models, the rate variation is assumed to be the result of certain covariates that are context-specific. For example, how long it took for group members to vote in favor of a new bylaw amendment (e.g., an event) might be influenced by a variety of factors likes member age, personality, or ideological views. Butts (2008) amended this framework to interpersonal actions, giving rise to the relational event model. Given the social context, the covariates responsible for the variance in interaction rates represent behavioral and cognitive mechanisms that lead individuals to engage in certain events more often than others.

As a process unfolds over time, the likelihood for an action to occur may change. Consequently the rate of that event should adjust to reflect the influence of past actions. For instance, if two individuals repeatedly communicate with a third party, the propensity for them to communicate with one another may increase. In essence, the history creates the context for the present. We therefore model the rate as a function of historical information, in addition to other individual or relational-level covariates. As the sequence continues to unfold, the rates of events are continuously updated to reflect the new network structure. This allows group researchers to "understand how past interactions affect the emergence of future interactions, without assuming that they are completely determined by them" (Quintane et al., 2014, p. 533). Given this general modeling scheme, the likelihood of a specific event sequence can be computed as the probability of each action, multiplied by the probability of the time between actions, conditional on the entire realized history.

Perhaps the greatest utility of REM lies in the wide range of sufficient statistics that can be derived from event sequences. These measures are numerical representations of specific interaction patterns, similar to those encoded in ERGM's or stochastic actor-oriented models (Lusher et al., 2013). That is, like how conceptual models are translated into statistical models, sufficient statistics are the operationalizations of model parameters like the ones described in Figure 1 (i.e., past relational events, actor attributes, and contextual factors). Prior work on proportional hazards models provides us with a framework for parameterizing rate functions (Cox, 1972); this general methodology is utilized in REMs. Each sufficient statistic maps the network information to a real number; this value represents the frequency with which that particular interaction sequence occurs. The influence of a particular statistic on the frequency of a relational event is represented mathematically by a parameter vector, analogous to a logistic regression coefficient. The sign and magnitude of each coefficient determines how influential a particular network effect is regarding the generation of relational events across a given pair of individuals.

As such, the REM advances the measure and method of group interaction processes in two ways. First, the model is inherently longitudinal and takes into account every time-stamped interaction in groups into account. Thus, aggregating interactions into single or multiple time slices (e.g., combining emails with time-stamp information in weekly time slices) or asking members whom they communicate with, which has been shown to be not entirely reflective of who they actually communicate with (e.g., Corman & Scott, 1994), is no longer necessary. REM provides a statistical procedure that treats every minute group interaction as important. And second, the sufficient statistics can be interpreted as sequential structural signatures (SSSs) (Leenders, DeChurch, & Contractor, in press), providing maximum likelihood estimates for different group interaction processes, being able to take into account past relational events, individual attributes, and environmental factors. In essence, these estimates capture how different groups have similar and dissimilar interaction patterns. Thus, REM has the potential to answer several important research questions related to group dynamics, like:

1. Do some patterns of past interactions influence the probability of future interactions?
2. What types of individual attributes make it more likely that they will send or receive interactions?
3. What types of exogenous contextual factors influence patterns of group interactions (e.g., relationships between group members, nature of the task, information uncertainty)?

Example of REM

Data. The data come from a set of 12 MTS (Multi-Team System) experiments collected by two of the authors and is further elaborated in *Author citation (2014)*. MTSs are teams of teams that must often accomplish team and MTS level goals. Real life examples include emergency response systems and diverse military squads. Briefly, the experiment set up a small MTS of two teams of two. Each team (i.e., Phantom and Stinger) had a team captain and team driver. The military-like scenario was implemented in Virtual Battlespace 2 and requires that each team must make sure a path is safe for an emergency convoy to deliver medical supplies. In order to make sure the path is safe, the teams of must accomplish a variety of tasks that require communication between teams (some more so than others). These tasks include documenting artifacts, diffusing bombs, evading an ambush, collecting intelligence from a secret informant, and coordinating a convergence to battle a group of insurgence.

For the current example, we employed a chain network reflective of military chains of command. In the network, there was a line of communication available from each squad's captain and driver. As such, at any time, the captain and driver from each team can communicate. Next, there was a line of communication available to each squad's captain. That is, at any time, by switching channels, the captain from either squad could communicate to the other squad's captain.

The relational event data come from recording each interaction using Comm Net Radio (CNR), a radio software that each group member used in order to communicate with one another during the experiment. CNR records who sent a message whom and for how long (along with actual recording of the content). As such, the data can be easily converted into data exploitable by REM. A sample data snapshot includes three elements: (1) standardized time of the interaction, (2) a sender of the interaction, and (3) a receiver of the interaction (see Table 1).

The survey data come from an electronic survey administered immediately following the mission. Each MTS conducted two missions. For illustrative purposes, we choose to analyze a random MTS's interaction patterns in the second mission because we can exploit survey measures following the first mission and give detail on how to report results from REM. In other words, after the first mission, there is a brief history established by the MTS that may influence interaction processes in the second mission.

Sequential structural signatures. Table 2 describes the different SSSs used to model the group interactions. It describes the definition, visualization, and actual statistic used in the analysis. For past relational events, we include inertia and reciprocity. For attribute effects, we include sender effects for captains (i.e., are captains more likely to send message?) and the propensity for captains to relay messages to the other team (i.e., when a captain receives a message, what is the likelihood they will interact with the other team?). Finally, for environmental contextual factors, we include a trust network included in a survey after the first mission. The question simply asks on a Likert scale (1 – 5) “To what extent did you trust each member of the squad?” Thus, a valued trust network was extracted and entered in the model to determine if higher trust between team members predicts the probability of sending messages.

The SSSs used in this example are by no means exhaustive; various other structures may be encoded to capture specific behavioral patterns as needed. A sequential structural signature must be finite, affinely independent from other SSS included in the model, and must be a mathematical function of at least one type of antecedent as described in the previous section (Butts, 2008). For examples of how to operationalize simple structural signatures, refer to Table 2.

Reporting and interpreting results

Although there are no rule of thumb guidelines on what to report, we recommend at the minimum, following previous research using REM, the reporting of (1) pre-modeling descriptive statistics, (2) model adequacy of full and reduced models (i.e., AIC and BIC), (3) significant and insignificant estimates, and (4) goodness of fit metrics. Each is discussed below using the current example.

Pre-modeling descriptive statistics. Before modeling, it is important to get a glimpse of the data in order to get an initial idea of what may be driving the relational event history. Because this is more of a qualitative assessment, there are no specific statistics to report and will differ depending on the nature of the data (e.g., does it have attributes?), although simple metrics on amount of events sent and received by each actor can also be useful. One possible method is to aggregate or bin the event data in some way that generates a valued network structure (i.e., how many times each actor communicated with one another). From this data frame, various network methods of analysis can be explored to find out if there are dyads or cliques that interact on an unusually high or low frequency. This can also be seen visually by the weight of each tie from group member to group member. Other more dynamic visualizations can include creating animations of the event history in order to add some temporal aspects (e.g., ndtv, Bender-deMoll, 2015). Such an approach would better leverage the granularity of relational event data, relative to an aggregation method.

Table 3 provides a matrix of the raw number of messages sent and received by each team member. The data describes the aggregate total messages from each dyadic and number of messages sent and received by each member. In the current example, the Stinger team was more active with both members sending more messages (Captain N = 92, Driver N = 80) than both members of the Phantom team (Captain N = 75, Driver N = 51). Moreover, dyadic communication was much more prevalent within each team rather than cross team as the two Captains only exchanged 29 messages together out of the 298 total relational events (9.7%). As such, this information gives us some initial information about each team, namely, that the Stinger team was more active and that cross-team communication was not nearly as common as intra-team communication.

Model adequacy. Following REM, there is a need to determine which model provides the best fit. Like most modeling strategies, the goal should be a blend of parsimony (i.e., model with the fewest parameters) and accuracy (i.e., model that predicts events with the highest accuracy). As such, the use of the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are suggested to determine which model is more preferable. Moreover, if a reduced model is chosen, a comparison with the full model is recommended in order to understand the differences between the two.

As such, if the goal of the researcher is to develop the best predictive model in terms of a more inductive and exploratory approach, we recommend *forward selection* as a strategy for relational event model building. Forward selection, as in regression model building, is a bottom up approach, entering one variable in the model at a time and then dropping variables when they are highly insignificant (e.g., a probability value of above 0.20) and retaining significant ones. However, if the goal of the research is to develop the best theoretical model in terms of a more deductive approach, we recommend *theoretical selection* as a strategy for relational event model building. In this case, the researcher might investigate common mechanisms that can act as control variables (e.g., inertia, reciprocity), develop hypotheses on unique SSSs (e.g., cross-team relay) and include other SSSs that may be perceived as alternative explanations (e.g., intra-team relay).

For demonstration purposes, in the current example, we only report the full model because removing non-significant parameters only marginally improved the AIC (57.985 for the model, and 54.553 dropping the insignificant term) and BIC (80.167 for the full model, 73.038 dropping the insignificant term). Moreover, for ease of interpretation and the tutorial, we build a rather parsimonious model as an introductory example, including sequences from all three factors in Figure 1.

Coefficient estimates. Users can interpret maximum likelihood estimates (MLE) as an indication of the odds or chance that an interaction (i.e., relational event) will happen given the conditions specified in each of the parameters entered. For instance, a MLE of 0.50 on reciprocity simply means that if A sends a message to B, then B is 1.64 times more likely to send a message back to A. The 1.64 is calculated by taking the exponential function of the MLE estimate, which in this case is 0.50 ($e^{0.50} = 1.64$). Moreover, the estimates are conditional on all other effects imputed in the model. Thus, they need to be interpreted not as independent, but as contingent on all other effects. As per traditional inferential statistics, we recommend reporting MLEs, standard errors, and probability values. Standardizing MLEs (e.g., z-score) may also be useful for comparing multiple models to see if some samples differ on estimates more or less so than others.

In the current example, there was a blend between positive, negative, and non-significant results (see Table 4). For instance, with respect to the influence of past events, using a threshold of 0.05, inertia was positive and significant ($MLE = 0.027$, $SE = 0.013$), but not reciprocity. This suggests, given all other effects in the model, there was a propensity for past contacts to remain as future contacts. This is not surprising as the descriptive statistics suggest that communication was primarily between each team's captain and driver within the team.

Likewise, the attributes of individuals had some mixed effects on relational event patterns. For example, contrary to our initial expectations, after accounting for all other effects, captains were *less* likely than drivers to send messages ($MLE = -0.274$, $SE = 0.125$). Moreover, cross-team relay, not surprisingly given information from the descriptive statistics, was not significant (*MLE* = -0.375, *SE* = 0.336), providing more evidence that communication was mostly intra-team related. Finally, for variables external to the communication system, trust was a significant predictor of relational events (*MLE* = 0.232, *SE* = 0.056). In other words, members were more likely to send messages to people whom they trusted.

Goodness of fit. The purpose of goodness of fit (GOF) analysis is to determine how well the statistical model explains the observed event history, similar to an R^2. Again, although there is no general rule of thumb, there are several techniques available to assess the overall predictive power of the model. A basic strategy is to compare the final model to a null model, which assumes events are predicted random chance or some sort of basic function (e.g., exponential function). Similarly to how we would assess a series of generalized linear models, we would derive the deviance, or log-likelihood value for both the null model and the fitted model. If the parameterized REM performed significantly better relative to the base model, then we should observe a statistically significant reduction in deviance. This difference may be tested using a Chi-square distribution. We find that the deviance of the null model is 224.46, while the deviance for the full model is 45.98 (see Table 5). This difference in deviance values gives us a test statistic of 178.47, which follows an approximate Chi-square distribution with five degrees of freedom; the corresponding p-value is < 0.001. Thus we may conclude that the full model performs significantly better than the null model.

Alternatively, goodness of fit could be assessed according to the misclassification rate of the final model. Using the estimated parameter values and the event history, we may generate a most likely event for each step in the sequence. Then, these predicted outcomes can be compared to the realized events; the misclassification rate is the proportion of events that were incorrectly predicted by our model. While there is no hard and fast threshold for fitting REM's, the misclassification rate may be used to compare several competing models, as well as indicate how accurate extrapolations may be. In the case of our model, the misclassification rate was 73.8%. Thus, there were only 78 instances out of 298 in which the most likely event as predicted by the fitted model was indeed the realized event.

Alternatively, the null model assigns equal probability to all possible events; because there are six possible dyadic events, the null misclassification rate would be 83.3%. Although, this result supports our previous conclusion that the parameterized model is a better fit to the data compared to a basic exponential model, it also represents a good example of when the researcher might want to explore with additional parameters in order to improve the accuracy of the model. Indeed, the framework provided suggests a number of theoretically informed event sequences might be useful, including but not limited to preferential attachment (i.e., past relational events), other brokerage sequences (e.g., representation), or other types of perceived network states from survey data (e.g., expertise).

When and how to use REM

The crux underlying the current illustration is that REM is a promising method to analyze group interaction processes. In other words, if researchers are interested in understanding the different patterns group members engage in during interaction, then REM is one way to empirical tease that out. Indeed, because of the unique trace data structure of REM, the most important factor determining when to use REM is the type of data available. Data on fine-grained interactions constitutes what is sometimes commonly known as Big Data because of the *velocity* at which interactions are exchanged and collected (Gandomi & Haider, 2015).

Perhaps more importantly, relational event data is sometimes difficult to collect. Nevertheless, the advent of new technologies like social media and crawling software make it a little easier and accessible to collect the type of trace data necessary for REM. Additionally, the software used in the current experiment, CNR, is great way to easily collect group interactions in real time.

To our knowledge, there is only one publically available package to conduct relational event dynamics, the *relevent* package in R (Butts, 2015). The current estimation was carried out in MATLAB through our custom estimation (see Appendix I for more detail), but we also provide a basic analysis in *relevent.* The main difference between the current analysis and the *relevent* package is the flexibility in parameter customization because *relevent* has a set of a priori sufficient statistics (though customization is available for those exceptionally skilled at R programming). We recommend thinking about the theoretical assumptions underlying the group task and structure in order to determine which program is more useful. For instance, if the researcher is primarily interested in group structure as a series of conversational norms and participation shifts, then *relevent* would be a good option.

In a related note, depending on the nature of the data and goals of the researchers, other related models might be appropriate as well. For network evolution, where interactions are best modeled when they are put into different panels/waves rather than in timestamps or order from interaction to interaction (e.g., Barnett, Jian, & Hammond, 2015), stochastic actor oriented modeling (Snijders et al., 2010) may be useful to understand the factors that influence network reproduction and evolution. Similarly, if the researcher is interested in life cycles (e.g., Gersick, 1988) or different group phases (e.g., Moreland & Levine, 1998), than various longitudinal sequence analysis methods (Cornwell, 2015) might be useful too. The key difference is level of analysis. While most group sequence analysis focus on what the entire group is doing at a given moment of time, REM can be considered more of a micro sequence analysis, focusing on who interacts with who at a given time. Finally, Marcum and Butt's (2015) ego-centric REM model links an individual with the actions they are taking and models the different patterns of likely sequence combinations.

Furthermore, there are also some general rules of thumb worth mentioning for best practices on using REM. First, how many parameters can be modeled in a reasonable way? One key difference from REM than other methods like regression is that the addition of additional parameters does not mean an addition explanation in variance or in this case, the prediction of relational events. In fact, telling the model to look for parameters that are clearly not there in the data will most likely make the fit even worse. As such, we think that Miller's Law of seven plus or minus two might serve as a general rule of thumb for the maximum amount of test parameters a researcher should use because it represents a nice cognitive explanation for the amount of information an individual can handle at any given time. To that end, the model should make intuitive sense, not simply statistical sense. This suggestion, however, does not of course include control variables, which begs the question: which type of parameters should I always control for when using REM? Again, this is subjective to an extent, but following general theories of social networks (Robins, 2013), we suggest generally controlling for, if the data allows it, inertia (i.e., history always repeats itself), reciprocity (i.e., you scratch my back, I'll scratch yours), closure (i.e., the friend of my friend will also be my friend), and popularity (i.e., the rich get richer). The reasoning is that these are some of the most common explanations for forming social networks (Lusher et al., 2013) and thus, should translate well when networks are conceived as interactions via relational events.

Additionally, there is an issue of sample size. The key to an adequate sample size is not the amount of actors, but the proportion of the number of events to actors. For instance, 50 events would be good size for four actors, but not for 50 actors. Conversely, because the margin of error for REM parameter estimates is bounded by the square root of the ratio of events to possible events, larger datasets will generally have more power, but there is a diminishing benefit to observing more events for a fixed number of actors (e.g., heterogeneity of effects because of time). In practice, researchers have used a variety of samples sizes. For instance, Butts (2008) analyzed sequences with as few as 70 events for 28 individuals. On the opposite end of the spectrum, Quintane et al. (2014) used a sample of 4,348 events for 194 individuals. The authors of this paper have used datasets with 4, 8, and 20 individuals with the number of relational events ranging from around 200 to a maximum of 1,200. Thus, while there is no distinct minimum ratio, we recommend that researchers at the least observe more events than actors (i.e., a moderate ratio), and not include more parameters than events.

Finally, it is important to consider the overall analytical possibilities of REM. Theoretically, REM lends itself favorably to frameworks with constructivist leanings that have been difficult to implement empirically in the past because REM does not assume teams and groups are “well-defined, clearly bounded entities with a stable set of members” (Poole & Contractor, 2011, p. 194). Frameworks like the structurational perspective (Giddens, 1985) or bona fide group framework (Putnam & Stohl, 1990) can be used because REM has ability to take into account shifting/blurry group membership and interactional interdependence since the fundamental point of analysis is the interaction event, not group membership or individual level characteristics.

Contextually, REM is well suited to analyze how groups function and organize in the 21st century using technology given the amount of detailed recording in various new communication mediums (Lazer et al., 2012). Things like Tweets, Facebook posts, Wiki edits, blog postings, event check-ins, and text messaging all contain sufficient information that can be exploited by REM because they represent histories of interactions at specific time points. REM is one way to understand the patterns of how groups are using these technologies in similar or different ways.

Limitations of REM

In our view, there are three current problems researchers must think about when applying REM to analyze group interaction processes: (1) assumption of availability, (2) heterogeneity of effects, and (3) linking REM with group outcomes. Each is discussed below.

Assumption of availability. One of the basic assumptions of REM is that each actor has the availability to communicate with another. In many group settings, this assumption is fine, especially within single groups. However, when multiple groups are studied, as is the case with MTSs, this assumption might be problematic. One way to help remedy this problem is the incorporation of a structural zero file. A structural zero file simply lets the model know which dyads are unavailable to communicate with one another, as was the case with the current example in that the drivers were restricted to communication with their captains. As such, when researchers use REM, they need to take into account any barriers that would prohibit some members from communicating with others, otherwise estimates would surely be unreliable.

Heterogeneity of effects. Heterogeneity of effects refers to when individual effects (e.g., reciprocity) might differ depending on which time period is used for modeling the relational event history. That is, is there some reason to believe that some SSSs like reciprocity might be higher or lower depending on the time frame of which the analysis was carried out (i.e., portion of the relational event history). As it currently stands, REM can only analyze effect sizes for the entire time slice, not differentiating the magnitude in different slices of time. For example, as groups engage in the *initial stage* of a project, members may have a good deal of freedom to interact with one another, resulting in triadic closure being a common signature. Once the group has moved into its *performance stage*, members may be sufficiently occupied by the task and may not need as much time to interact freely, and thus, triadic closure may no longer be common. An REM run on the entire event history that includes both stages would have difficult determining if triadic closure was more common in one phase (e.g., initial stage) versus another (e.g., performance stage).

There have been a couple of strategies to remedy this problem. For instance, Quintane et al. (2013) used a nested time frame, running models on a short and long term frame to determine whether or not effects were heterogeneous. And Author citation et al. (2015) used a multi-panel approach, slicing a lengthy time frame not into nested waves, but discrete ones. In the above example, this would mean running REMs on the initial stage and performance stage separately to see if there were any differences in interaction patterns. Another option would be to include dummy variable that represents a time covariate, which would run an interaction effect on parameter estimates and different waves of time. The choice of how to handle the problem of heterogeneity of effects (i.e., nested models, discrete slicing, or time covariate) can be theoretically or data driven. For instance, slicing the event history based on some sort of environmental factor (e.g., change in the nature of the task) might be an effective way to delineate outside effects while slicing the event history using a data driven exploratory approach might give important insight to a previously unknown environmental factor influencing group interactions (e.g., it might challenge the researcher to explain why patterns were different in one time period versus another). One data driven approach is breakpoint analysis (Chiu & Khoo, 2005), which would statistically divide the event history into discrete waves of high and low activity depending on the effects put into the model (e.g., waves of high and low reciprocity).

Linking REM with group outcomes. If, as the main argument of the paper has been, REM is a fruitful way of understanding group interaction processes, then a logical next step might be to determine if there are any individual or group performance outcomes related to those processes. By itself, REM cannot provide a direct inference to outcomes like group performance since it is only capable of predicting specific interaction patterns. However, with a creative blend of mixing methods, there is potential to link REM with a variety of group outcomes. For instance, simple independent t tests of sufficient statistics between low and high performing groups can provide one way of determining differences between high and low performing group interactions, especially if the sample size is not very large. Independent sample t-tests are robust to violations of statistical assumptions, so long as the groups being compared are independent of one another. For instance, are more successful groups more or less likely to have their captains relay information across teams? Or, are those captains who relay information more likely to be perceived as effective leaders by other group members?

Translating the level of analysis from group to individual outcomes is another challenge. Another option that is being explored is a multiplex REM. A multiplex REM investigates how patterns of one type of interaction (e.g., communication) predict another event (e.g., performance outcome). For example, if one type of event would represent an instance of high performance, like solving one problem or accomplishing part of a task, then the multiplex REM could explore whether or not different interaction patterns predict those successful or even unsuccessful events (e.g., friendly fire). This can answer how interaction patterns “scale up” to create positive or negative group outcomes.

Concluding remarks

Under the traditional lens of group process, performance is a consequence of emergent properties. The lower-level characteristics of the team, such as skills, cognition, or personality, will lead to higher-order outcomes. These phenomena are what drive the output of the group. Further, the pattern and timing of interactions among individuals simply contribute to the emergence of different properties of the team (Kozlowski & Klein, 2000).

The REM takes an alternative approach and suggests that both emergent properties and performance are consequences of complex group interaction processes that happen in real time. As such, group process should not be treated as aggregations of interactions or simple psychological constructs. What REM provides is a sort of *methodological requisite variety*, meaning that the method is nearly as complex as the phenomenon it is trying to analyze because there are few empirically methods that are sophisticated enough to analyze unfolding interactions over time. Under the lens of relational events, lower-level interactions are no longer viewed as elements of a broader phenomenon, but rather as realizations of process itself. Specifically, each interaction is driven by the situational context, the attributes of the individuals, and the preceding events. In our example, we can examine what are the *motors* that drive an individual to communicate; is it familiarity, or a sense of reciprocity? Do leaders take on roles as information brokers, or does trust predicate interaction? By asking these fundamental questions, we no longer focus on how actions form broader phenomenon, but rather focus on how action itself evolves.

The relational event model enables scholars to effectively identify patterns amongst the noise of the stream of interaction, which is well beyond the ability of qualitative observation to sort out. As a consequence, REM allows researchers to test and apply theoretical frameworks that were previously difficult to adopt because of the limitations of current methodological tools.

Theories such as discursive leadership (Fairhurst, 2007) or transactive memory systems (Wegner, 1987) can be operationalized and tested for because they both emphasize specific group interaction processes over time. The goal of this paper was to introduce that method to analyze group interactions processes and provide a more hands on tutorial for implementing REM for future work.

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Table 1

Data format for REM

Time	Sender	Receiver
0.61	4	3
0.66	3	4
0.90	3	4
1.45	1	2
1.53	2	1

Note: Time is standardized where the value 1 equals 1 minute.

Table 2

Sequential structural signatures in current example

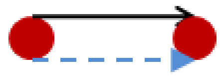
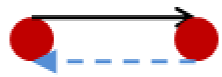
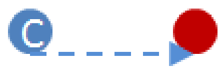
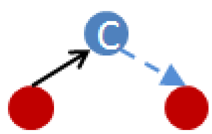
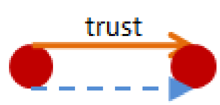
Sufficient statistic	Visualization	Statistic
Past events		
Inertia		$s_{INERTIA}(i,j,t) = \omega(i,j,t)$
Reciprocity		$s_{RECIP}(i,j,t) = \omega(j,i,t)$
Attributes		
Captain as sender		$s_{COMMAND}(i,j,t) = \mathbf{1}\{i \text{ is captain}\}$
Cross-team relay		$s_{RELAY}(i,j,t) = \mathbf{1}\{k \to i, i \to j\}$ $\times\ \mathbf{1}\{k, j \text{ not captain}\}$ $\times\ \mathbf{1}\{i \text{ is captain}\}$
Environment		
Trust		$s_{TRUST}(i,j,t) = trust(i,j)$

Table 3

Matrix of raw number of messages sent and received

	Phantom Captain	Phantom Driver	Stinger Captain	Stinger Driver	Total Sent
Phantom Captain	-	63	12	-	75
Phantom Driver	51	-	-	-	51
Stinger Captain	17	-	-	75	92
Stinger Driver	-	-	80	-	80
Total received	68	63	92	75	298

Note: N = 298 total relational events

Table 4

Relation event modeling results

Sufficient statistic	Maximum likelihood estimate	Standard error	p-value
Constant	0.027	0.243	0.909
Past events			
Inertia	0.027*	0.013	0.041
Reciprocity	-0.023	0.013	0.085
Attributes			
Captain as sender	-0.274*	0.125	0.029
Cross-team relay	-0.375	0.336	0.264
Environment			
Trust	0.232**	0.056	0.001
AIC	57.984		
BIC	80.167		

Note: * indicates a *p* value of < 0.05, ** indicates a *p* value of < 0.01.

Table 5

Goodness of fit metrics

Metric	**Null Model**	**Full Model**
Deviance	224.4623	45.9848
Misclassification Rate	83.3%	73.8%
AIC	226.4623	57.9848
BIC	230.1594	80.1674

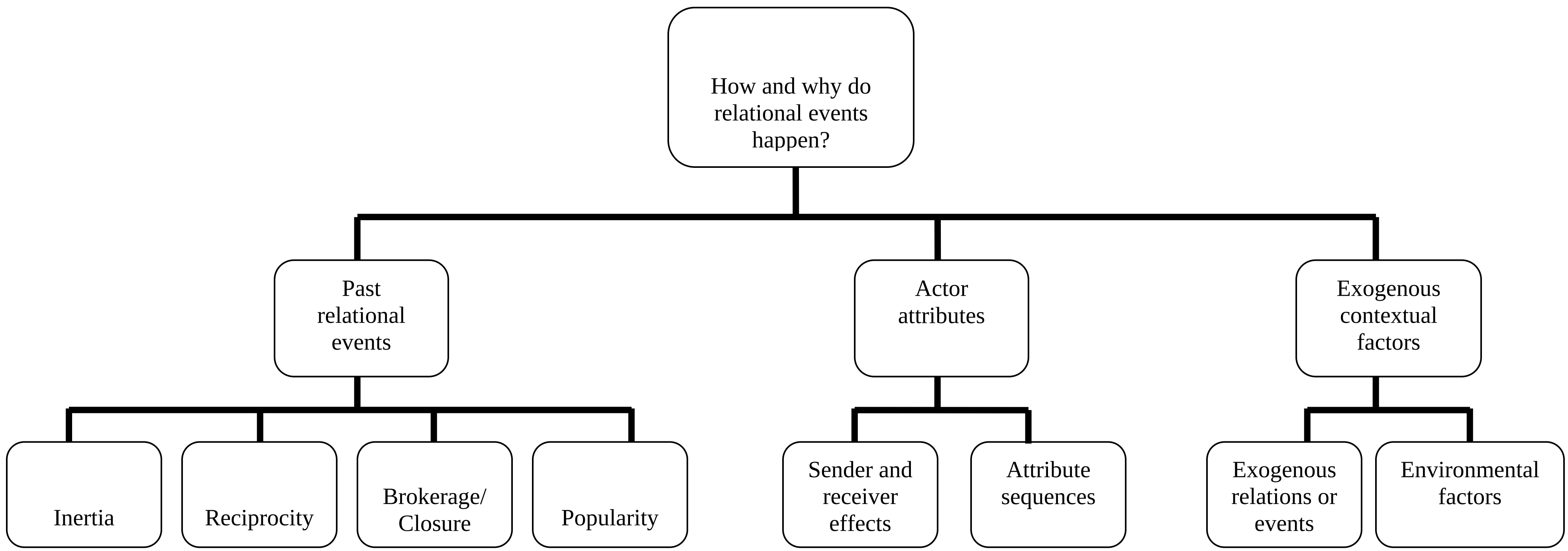


Figure 1. *Conceptual framework for the process of relational event occurrence.*

Online supplementary material 1: Technical Intro to Relational Event Modeling

Relational Event Data

The first type of observable data is the dyadic interaction. These behavioral events must be directed, may fall into a particular class, and are observed at a specific moment in time. Additionally, relational events may carry weight. Formally, a relational event is a tuple $e = (i_e, j_e, k_e, w_e, t_e)$ containing the sender i_e, receiver j_e, type k_e, weight w_e, and time t_e of an event; the full sequence of m events is the set $E = \{e_1, \dots, e_m\}$. Let $A = \{1, \dots, n\}$ be the set of all n actors, and $D \subseteq A \times A$ the set of all dyads. Events can fall into a set of K discrete classes. For each class k, we define the weight function ω_{kt} as the accumulated weight of all past interaction events (Brandes, Lerner, & Snijders, 2009). This function represents the relative strength of the directed relationship between each dyad, as measured by the frequency and intensity of interaction.

$$(\omega_{kt})_{ij} = \sum_{e: i_e = i, j_e = j, k_e = k, t_e < t} |w_e| \cdot exp\left(-(t - t_e)\frac{ln2}{T_{1/2}^{(k)}}\right) \quad (1)$$

In order to place a higher weight on more recent events, the accumulated relational event volume is decayed by some half-life parameter $T_{1/2}^{(k)} \in \mathbb{R}_{>0}$; this parameter can be consistent across all event types, or unique for each type. Refer to Leenders et al (in press) for a discussion of memory and a half-life in relational event networks.

The second type of observable data is attribute information; individual, such as gender, age, or institutional role; dyadic, such as friendship status or trust; environmental, such as information about the physical environment, the stage in a creative process, or the status of an emergency. Let $v_{ht} = (v_{1ht}, \dots, v_{nht})$ be the vector of individual covariates corresponding to attribute h at time t; let $u_{ht} = (u_{ijht})_{(i,j)\in D}$ be the matrix of dyadic covariate values for attribute

h at time t; finally, let z_{ht} be the state of environmental factor h at time t. The state values may hold constant over time, or may be variable. For simplicity of notation we combine all attribute information into the set G_t. Each of these attribute values may change over time, or may remain constant. We assume that at any given time t the values of each of these factors is known to the actors in the network. While it is possible to model a system in which actors control individual covariates (T. Snijders et al., 2007), we assume that actors do not directly control the value of the covariates or the environmental factors.

The Event Rate

Following the event history approach (Blossfeld & Rohwer, 1995), the probability of the sequence and timing of events can be defined by the hazard rate and survival function for each possible action. The hazard rate can be interpreted as the instantaneous likelihood of an event occurring, given that it has not yet occurred. Suppose that the random variable X has density function f and cumulative distribution function F; then mathematically the hazard rate for a particular value is:

$$h(x) = \frac{f(x)}{1 - F(x)}$$

The survival function can be interpreted as the likelihood of an event occurring after a given value x. Assuming the same density and distribution function, the survival function may be expressed as:

$$S(x) = 1 - F(x)$$

In the case of the relational event model, the hazard rate for a i directing an action of type k to receiver j at time t is some function of sufficient statistics and corresponding intensity parameters. The functional form is taken from the Cox proportional hazards model (Cox, 1972).

$$\lambda_{ijk}(\, t \mid G_t; \boldsymbol{\theta}\,) = \lambda_0(t)\, exp\big(\theta' s(i,j,k,G_t)\big) \qquad (2)$$

The parameter $\lambda_0(t)$ controls the relationship between the hazard rate and time; the simplest case is to assume that this value is constant, which corresponds to the Exponential model.

To fully define the relational event model, the set of sufficient statistics s needs to be explicitly defined; such variables should encompass the previous event history, as well as all other exogenous influences. Each sufficient statistic maps the network information G_t to a real number. This value represents the prevalence of a particular structure in the network. These structures may be single-relational or multi-relational. The sufficient statistics must be finite, dependent on past history (in terms of volume and timing), and are affine independent (Butts, 2008). To capture the influence of a particular statistic on the frequency of a relational event, define the parameter vector $\boldsymbol{\theta}$. The sign and magnitude of each element in $\boldsymbol{\theta}$ determines how influential a particular network effect is regarding the generation of relational events across a given dyad.

The Likelihood Function

The likelihood function for the full event sequence and timing can be explicitly computed by combining the hazard rate for each realized event with the survival function for all possible events. Leaving out the time dependent parameter $\lambda_0(t)$, the partial likelihood function is given by Eq. 3:

$$f(E;\boldsymbol{\theta}) = \prod_{e\in E} \lambda_{i_e j_e k_e}\big(\, t_e \mid G_{t_e-1}; \boldsymbol{\theta}\,\big)\, exp\left(-\Delta t_e \sum_{k=1,\dots,K}\ \sum_{(i,j)\in D} \lambda_{ijk}\big(t_e \mid G_{t_e-1}; \theta\big)\right) \qquad (3)$$

The value Δt_e is equivalent to the time elapsed between events, or $t_e - t_{e-1}$. This expression represents the conditional likelihood of every event in the sequence, along with the conditional likelihood that no other events occurred in the period between observed actions.

Often it is the case that relational event data is simply ordinal; i.e. there is no specific timing data available. In this scenario, the likelihood function can be reduced to a product of multinomial probabilities derived from the same event rate as in (2).

$$f(E;\boldsymbol{\theta}) = \prod_{e \in E} \frac{\lambda_{i_e j_e k_e}\left(t_e \mid G_{t_e - 1}; \boldsymbol{\theta} \right)}{\sum_{k=1,\dots,K} \sum_{(i,j) \in D} \lambda_{ijk}\left(t_e \mid G_{t_e - 1}; \theta\right)} \tag{4}$$

Recovering Model Parameters

Coefficient estimates for relational event models – ordinal or temporal – are derived from the solution of the maximum likelihood problem:

$$\underset{\theta}{argmax}\, log\big(f(E;\boldsymbol{\theta})\big) \tag{5}$$

Common optimization techniques such as Newton-Rhapson are well-suited to solving this maximization problem. Standard errors for the coefficients can be computed from the Hessian matrix at the solution. Alternatively, Bayesian approaches may be utilized for parameter estimation. In some situations, it is actually suggested that this class of solution method provides more stable estimates of the standard errors (Marcum & Butts, 2015).

Online supplementary material 2: *Relevant* R code

Link do datasets: [Click here for zip file data]

R code

```
# Install and load the programs
install.packages("statnet")
install.packages("relevent")
install.packages("informR")
library(informR)

# Load datasets
#The "sample.csv" is the event history file. The 'read.csv' tells the program to read it and name it 'REM'
REM = read.csv("sample.csv")

# the "Event_Cov.txt" is the structural zero file. It tells the program which dyads cannot communicate. This line tells the program to read it as a matrix (as.matrix) and name it 'cov'.
cov = as.matrix(read.table("Event_Cov.txt"))

# "Intercept.txt" is the intercept file. This line tells the program to read it (read.table) and call it 'Intercept'.
Intercept = read.table("Intercept.txt")

# "Trust.txt" is the trust matrix after mission 1. This line tells the program to read it and call it 'Trust'.
Trust = as.matrix(read.table("Trust.txt"))

#Relevent requires the user to combine the two networks into an array. The array is defined by 2 networks, with 4 rows and 4 columns: c(2,4,4). 'abind' is the function that combines them. We are going to name it 'combmat1'.
combmat1 <- array(dim=c(2,4,4), data=abind(cov, Trust))

#Detail of effects
#CovSnd = This effect is for the Intercept. It answers, "what is the baseline tendency of an event to even happen?"
#CovEvent = Controls for structural zero and influence of trust network. It answers "what is the likelihood of a team member sending information to somebody if they highly trust them". The high negative values on the structural zero file tells the program to ignore ties between those dyads.
# FrPSndSnd = Inertia. This is the inertia effect. It answers, "what is the likelihood of a team member sending information to a member that they have sent information to in the past?"
# PSAB-BA = Reciprocity. This effect answers, "what is the likelihood of a team member sending information to a team member that they have just received a message from?"
# Cross-team relay = not available in relevant
#Captain as sender = not available in relevant

#Run the model
REMfit = rem.dyad(REM, n = 4, effects=c("CovEvent","CovSnd","PSAB-BA", "FrPSndSnd"), ordinal = FALSE, covar=list(CovEvent=combmat1,CovSnd=Intercept), hessian=TRUE)

#Display results
summary(REMfit)

Relational Event Model (Temporal Likelihood)

            Estimate     Std.Err Z value  Pr(>|z|)
FrPSndSnd   2.78675783  0.23083159 12.0727 < 2.2e-16 ***
CovSnd.1   -1.76238480  0.20094766 -8.7704 < 2.2e-16 ***
CovEvent.1  0.00133117  0.00076287  1.7449  0.080995 .
CovEvent.2  0.00041910  0.00010942  3.8302  0.000128 ***
PSAB-BA     1.07392130  0.12255721  8.7626 < 2.2e-16 ***
---
```

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Null deviance: 523.7979 on 298 degrees of freedom
Residual deviance: 7.982701 on 294 degrees of freedom
Chi-square: 515.8152 on 4 degrees of freedom, asymptotic p-value 0
AIC: 17.9827 AICC: 18.18818 BIC: 36.46817

Results in table format

Sufficient statistic	Maximum likelihood estimate	Standard error	p-value
Constant	-1.76	0.21	> 0.01
Past events			
Inertia	2.79*	0.23	> 0.01
Reciprocity	1.07*	0.12	> 0.01
Attributes			
Commander as sender	na	na	na
Cross-team relay	na	na	na
Environment			
Trust	0.0004*	0.0001	> 0.01
AIC	36.47		
BIC	17.98		

#See how much were not very well predicted, this simple model was correct 41.61% of the time for predicted event history
mean(apply(REMfit$predicted.match,1,all))

#A line by line assessment of events that were predicted correctly and incorrectly. TRUE means correct and FALSE means incorrect.
REMfit$predicted.match

# This displays the event history and tells us how “surprising” each event was. It uses a ranking scheme that asks “to what extent the events viewed most likely to occur are in fact those that are observed” (Butts, 2015, p. 6). A high ranking value indicates that the model was way off that event, while a low value indicates that it was what the model expected to happen next.
cbind(REM,REMfit$observed.rank)