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INTRODUCTION

Relational event models in network science

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Abstract
Relational event models (REMs) for the analysis of social interaction were first introduced 15 years ago. Since then, a number of important substantive and methodological contributions have produced their progressive refinement and hence facilitated their increased adoption in studies of social and other networks. Today REMs represent a well-established class of statistical models for relational processes. This special issue of Network Science demonstrates the standing and recognition that REMs have achieved within the network analysis and networks science communities. We wrote this brief introductory editorial essay with four main objectives in mind: (i) positioning relational event data and models in the larger context of contemporary network science and social network research; (ii) reviewing some of the most important recent developments; (iii) presenting the innovative studies collected in this special issue as evidence of the empirical value of REMs, and (iv) identifying open questions and future research directions.

Keywords: network models; network data; relational event models; social interaction; social networks; social relations

1. Introduction

The relational event modeling (REM) framework for studying social dynamics was introduced fifteen years ago by Butts (2008). Much has happened since then. Refinements and extensions of the original model have been developed to address new methodological issues, enable novel empirical questions, and expand the boundaries of our understanding of network dynamics in multiple directions.

This special issue on relational event models provides the opportunity to take stock of the field, looking both back at recent developments, as well as forward to the challenges that remain to be addressed. This editorial essay intends to highlight areas of progress—in particular, showcasing a number of cutting-edge contributions that appear in this issue—while also discussing open questions and untapped potential. It also aims at positioning relational event studies in the wider context of network science and empirical social network research. We conclude that the potential of relational event models remains considerable and that their future is bright: work to date has paved the way for many advances to come.

2. Relational event data

Relational data come in many forms. For readers of *Network Science,* the most familiar are records of ongoing social interactions either represented as a network observed at a single point in time or as a series of networks observed repeatedly at multiple points in time.

Implicit in such data is the notion of relationships as *spells*, which exist over a time period that is non-vanishing with respect to the phenomena under study. When network evolution is much slower than our phenomenon of interest (e.g., friendship ties in the context of rumor diffusion), we may indeed think of the network as fixed; when ties evolve on a timescale comparable to the process of interest (e.g., sexual contact networks and HIV diffusion), we may instead think in term of "dynamic networks." In both regimes, however, ties have duration, can be viewed as meaningfully simultaneous, and are generally characterized in terms of edge states over a predefined time interval.

Developing this example further, we may also consider what might happen when the spell length becomes very short compared to the dynamics of the process of interest. In the "short spell" limit, we are left with effectively instantaneous events—discrete interactions between social entities that can be approximated as duration-free, and (subject to regularity conditions) non-simultaneous. We refer to such interactions as *relational events*.

In data representation, relational events are typically characterized in terms of a single time point at which the event occurred (either as a quantitative "time-stamp" or an order within a series), an individual or group sender, and an individual or group receiver.

Relational events may also have other attributes, such as types (positive or negative, for example) or values (taking, for example, the form of "weights"). Think of the instance of a phone call record noting that, at time T, person A called person B. A relational event data set consists of a larger number of such events (an *event history*), typically defined within a well-defined set of actors. For example, it may represent all phone calls within an organization in a given time period. Although relational events often represent interactions of intrinsic interest (e.g., calls, speech acts, or transactions), it should be noted that we can also think of the onsets and termini of tie-spells themselves as relational events; this provides another important link between the "instantaneous" world of relational events and the "temporally extensive" world of social networks.

Relational event data are increasingly collected through electronic communication technologies or extracted from records produced and stored by open-source projects or social media platforms. Relational events may represent the instances of individuals calling each other, sending messages, trading electronically, interacting online, commenting, or liking social media content on a specific platform (e.g., Butts, 2008; Quintane et al., 2014; Stadtfeld & Geyer-Schulz, 2011; Vu et al., 2015; Leenders et al., 2016; Lerner & Lomi, 2017; Lomi & Bianchi, 2021; Lerner & Lomi, 2020b). Relational event data may, however, also stem from other sources such as historical archives or observational studies. In case of historical or archival records, relational event data may represent cases like the sequences of organizations or countries forming treaties or starting a conflict, individuals getting married or attending events, public records of interlocking directorates, or personal contact diaries (e.g., Brandes et al., 2009; Hollway, 2020; Brandenberger, 2020; Lerner & Lomi, 2022; Valeeva et al., 2020). In case of observational studies, relational event data may be produced by interaction between animals, interorganizational collaboration, acts of violence in criminal networks, or individuals starting and ending face-to-face conversations in social situations (e.g., Lomi et al., 2014; Tranmer et al., 2015; Patison et al., 2015; Niezink & Campana, 2022; Hoffman et al., 2020).

Various underlying constructs may be measured as relational events. In many cases, however, these are instances of interaction, communication, transactions, tie formation, or dissolution. These events are directly observable behavioral data. They may be related to unobserved relational dimensions, such as roles (e.g., friendship), sentiments (e.g., liking), cognitive representations of social ties (e.g., being aware of another person), but they are typically not direct measurements of any of those dimensions. Such non-behavioral, perceived types of relationships are more commonly assessed by surveys.

Much prior social network research has been built upon such survey-based network measurements and has thus mostly focused on data collected at a single time point (cross-sectional data) or repeated static network measures (longitudinal panel data). As compared to such data, relational event data sets have a much higher time resolution, as often every single event or most events within certain empirical contexts can be recorded.

The connection between relational events and more stable types of social ties has been discussed both in recent reviews (Butts, 2009; Borgatti et al., 2009; Pallotti et al., 2022; Lewis, 2021; Bianchi & Lomi, 2022), as well as empirical studies (Kitts et al., 2017). Awareness of the distinction between relational "states" and relational "events" is not new in social network research (Freeman et al., 1987; Marsden, 1990) and continues to be central to current debates (Borgatti et al., 2009).

The distinct nature of relational event data—in terms of measured constructs and temporal resolution—suggests that studies employing REMs will partly focus on different research questions and rely on different theoretical assumptions than "traditional" social network analyses. When studying the dynamics of relational events, researchers might often want to focus on *micro-temporal mechanisms* and, for example, theorize about specific turn-taking patterns in conversation dynamics or the relevance of recent encounters in interpersonal communication. At the same time, relational event studies may also address questions on network-level structures and their emergence, similar to more traditional approaches in social network analysis. For example, they might investigate whether events are typically embedded within communication clusters or are more likely to occur between individuals who are similar. With relational event data, it is in general possible to simultaneously study micro-temporal and structural mechanisms.

3. Relational event models

Relational event models are parametric probability distributions defined over relational event data that consider both the timing of events and their structural position within a larger social network context.

Formally, they have been introduced building upon event history models (Blossfeld et al., 2014), expressing the hazards of any event to occur, given the history of previous events, and potentially additional nodal, relational, and global attributes (Butts, 2008). The hazard of an event to be observed may then, for example, be affected by the fact that similar events occurred in the past, the similarity of sender and receiver (nodal), their formal relationship (relational), and the time of the day (global attribute). When considering these endogenous and exogenous factors as the state of a stochastic process, relational event models are related to (and in some special cases reduce to) the continuous-time Markov chains used in some models of network dynamics (Butts, 2023). Markov models for tie changes have a long tradition in social network research as generative network models and are used in different model estimation routines (e.g., Holland & Leinhardt, 1977; Snijders, 2001). While REMs need not be Markovian, nor lead to stable long-run equilibrium behavior, REMs with such properties are thus another point of contact with traditional network modeling approaches.

The exact hazards of a REM may follow different functional forms and specifications. In most cases, the hazard is assumed to be piecewise constant, leading to conditionally exponentially distributed waiting times. The first REM papers specified rates by directly positing a functional form for the hazard of each competing event (Butts, 2008) (sometimes called "dyad-oriented" specifications), but it was later proposed to alternatively model them as a two-step process, similar to actor-oriented models for network panel data (Snijders, 2001; Stadtfeld & Geyer-Schulz, 2011; Vu et al., 2011; Perry & Wolfe 2013; Marcum & Butts, 2015; Vu et al., 2017). In each case, hazards are further specified by the inclusion of effects that consider how exactly previous events and nodal, relational, and global attributes are affecting the observed relational event dynamics. Each effect is associated with a parameter that is subject to statistical estimation.

The exact definition of hazards and the model specification will depend on the research questions and the empirical context. Their choices have implications for the computational complexity, the model fit, as well as the interpretation of the model (Schaefer & Marcum, 2017; Stadtfeld et al., 2017a; Butts, 2017; Stadtfeld et al., 2017b).

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REMs follow the tradition of multivariate mechanistic network modeling frameworks, such as the Exponential Random Graph Models and the Stochastic Actor-oriented Models (Robins et al., 2007; Snijders, 2001). These models are typically applied to cross-sectional and longitudinal panel data, respectively, to understand how network mechanisms, such as reciprocation, transitivity, homophily, or popularity relate to the emergence and change of empirically observed social networks.

Similar *structural patterns* can be studied in the context of relational event data. Indeed, some early applications of relational event models focused on testing such generic network mechanisms and presented evidence for inertia, reciprocation, closure, homophily, and degree-related effects across different empirical contexts (Butts, 2008; Brandes et al., 2009; De Nooy, 2011; Stadtfeld & Geyer-Schulz, 2011). Stadtfeld & Amati (2021) discuss how structural network mechanism can be studied with different models and how their interpretation may differ depending on the data being analyzed. Tonellato et al. (2023) link generic structural network mechanisms to the bipartite dynamic of attention allocation and problem-solving within a large open-source software project. Kitts et al. (2017) suggest that different network mechanisms may work differently over different time scale in the context of interorganizational coordination and exchange relations. Hoffman et al. (2020) emphasize how face-to-face interaction is shaped both by endogenous network mechanisms (such as, for example, popularity or repeated interaction), as well as exogenous factors associated, for example, with formal organizational roles or physical location.

More recently, applied research increasingly made use of the fine-grained temporal nature of relational event data to study *micro-temporal patterns*. Some recent work discussed and theorized about how network mechanisms may operate differently across time in the context of financial markets or patient transfers between hospitals (Amati et al., 2019; Bianchi et al., 2022; Lomi & Bianchi, 2021). Others built upon theoretical ideas of sequential constraints in conversation dynamics to study patterns such as participation shifts and turn-taking in group conversations (Gibson, 2005; Butts, 2008; Lerner et al., 2021). Yet others demonstrated how recently formed network structures that are captured within shorter time windows (e.g., emerging two-paths, events recently received, recently established institutional ties) may have a stronger effect on the probability of future events (Stadtfeld & Block, 2017; Mulder & Leenders, 2019; Stadtfeld et al., 2017a).

A number of additional methodological advancements and analytical tools have been proposed recently. Some researchers discussed temporal heterogeneity of parameters (Bauer et al., 2021; Meijerink-Bosman et al., 2022; Fritz et al., 2021), making use of the wealth of information typically available in relational event studies. Some work was concerned with relational events that are not purely dyadic and discussed multicast, group-related, and hyper event models (Perry & Wolfe, 2013; Hoffman et al., 2020; Lerner & Lomi, 2022, 2023). One promising attempt in scaling up relational event models to larger networks is the use of unbiased sampling strategies, as discussed in some recent work (Lerner & Lomi, 2020b; Overgoor et al., 2020). An improved assessment of model fit has been proposed recently, using the fact that relational event models have generative models at their core that can be used for tie prediction (Brandenberger, 2019). Further, statistical multilevel approaches to relational event models have been proposed (DuBois et al., 2013), as well as models for networks with latent interaction roles (DuBois et al., 2013). To date, several software packages are available that are continuously upgraded and taught at workshops around the world; among those are the R packages `relevent` (Marcum & Butts, 2015) and `goldfish` (Stadtfeld et al., 2017a). The `relevent` software provides a number of tools to fit and simulate REMs; `goldfish` has similar features and focuses particularly on the estimation and simulation of dynamic network actor models (DyNAMs), an actor-oriented variant of REMs. Finally, `eventnet` (Lerner and Lomi, 2020b) is a freely available software that may be adopted to compute a number of statistics typically included in empirical specifications of relational event and hyperevent models.

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4. An overview of the papers in this special issue

This special issue includes seven new articles on relational event models. We believe that they showcase different applied and methodological research frontiers and that they will all have a long-lasting impact on the further development of the field. Collectively, the papers included in this special issue demonstrate the flexibility of the relational event modeling framework which can be adopted and adapted to address a variety of empirical problems in the context of very different disciplinary areas of research. Here, we present short summaries of these contributions in alphabetical order.

Arena, Mulder, & Leenders tackle the specification of the weight decay function. This addresses the fundamental issue in the application of REMs of determining how the rate of occurrence of events depends on the past. The paper elaborates the choice of the weight for three functions (exponential, linear, and one-step decay), with an estimated parameter in each. Estimation is done by maximizing the profile log-likelihood. In practical applications, often the weight decay function is chosen ad hoc. Simulations show that this may lead to serious biases and that such biases may be avoided by the proposed method.

Cannon & Robinson use the REM as a paradigm to incorporate insights from Expectation States theory about the emergence of status orders in the study of turn-taking in conversations. Using the language of relational events, they combine the formalized approach of the theory of Expectation States with the theory of Status Characteristics and extend this to a process model. This yields a theoretically based transformation of the past history of conversation events in a group to explanatory variables in a model for turn-taking events, leading to an emergent hierarchical structure. The model is empirically tested in a lab experiment and compared with a simpler model based on only performance expectations.

Measurement error—and what to do about it—is a vital and largely uncharted topic in the REM space. **Fritz, Mehrl, Thurner, & Kauermann** provide an important advance in this area, with detailed treatment of REMs with spurious events. While we often think of *missing* events during data collection, some of the same automated data systems that make REMs so appealing for many researchers are also prone to generating false positives—apparent events, that did not occur. As Fritz et al. show, this causes serious problems for REM inference. But all is not lost: the authors introduce a Bayesian data augmentation scheme that can help identify and control for the influence of spurious events in relational event data, increasing the robustness of estimation and also helping to detect possibly error-prone data. While there is no substitute for high-quality data, this research points the way to a broader class of error-robust models that can help us make the most of the data we do have and ensure that our conclusions are not unduly influenced by data limitations.

Gravel, Valasik, Mulder, Leenders, Butts, Brantingham, and Tita, specify and estimate relational event models to examine the network dynamics of inter-gang conflict in an urban area of Los Angeles. The study confirms that retaliation is a critical driver of gang violence. The study also goes beyond this result to demonstrate why and how gang violence may not be restricted to pairs of mutually retaliating gang, but can "spill over" to gangs that are not directly involved in conflict. Gravel and coauthors estimate models that explain how one violent incident can generate subsequent violence, and how this contagion process is sensitive to the timing of triggering violent events.

One of the great assets of the REM framework is to link the social dynamics across scales. **Haunss & Hollway**'s contribution exemplifies this potential, offering a detailed study of the 2011 policy "pivot" of the German government from supporting nuclear power to opposing it in the wake of the Fukushima disaster of March 2011. Using multimodal DyNAMs, the authors model the evolving political discourse surrounding nuclear energy in Germany, with events representing links between politicians and types of claims made or endorsed in public remarks. By connecting distinct periods within the history of the evolving debate with REMs capturing the microdynamics of discourse, the authors are able to show how multiple factors shaped the discussion—and how those factors waxed and waned over time. In addition to providing quantitative insights into an important political event, the paper serves as an excellent example of how REMs can be used to probe the ways in which the drivers of social dynamics themselves can shift in the face of exogenous shocks.

Renshaw, Livas, Petrescu-Prahova, & Butts revisit the dataset of emergency responses during the terrorist attack of the World Trade Center in 2001. A subset of these data was indeed the original demonstration case for the relational event models in Butts (2008). The new analyses demonstrate convincingly how REMs can be used to study the role and importance of specific social mechanisms. They investigate the emergence of *coordinating roles* in a self-organizing emergency response system that is faced with a disaster of unprecedented scale. The authors specifically compare the impact of different social mechanisms (e.g., preferential attachment and prior roles) on the formation of such coordinating hubs. They do so by simulating data from several models in which different subsets of mechanisms are included. This is a fantastic example on how relational event analyses can go beyond hypothesis testing of mechanisms. In particular, it demonstrates how REMs can be employed as empirically informed simulation tools to study the link between micro-level mechanisms and structural outcomes, such as emergent roles, on the network level.

REMs are usually specified under the assumption that the sending behavior of all actors, given the heterogeneity represented by covariates, is governed by the same parameters. This is clearly an implausible assumption. For large data sets, it often leads to unwarranted strikingly low p-values because unobserved heterogeneity is ignored. **Uzaheta, Amati, & Stadtfeld** develop models with random effects varying across actors or contexts. Bayesian estimation of the parameters in these models is proposed using Hamiltonian Monte Carlo methods as implemented in the well-known `Stan` language, with preprocessing using the package `goldfish`. They apply this random-effects model to "like" events in an online community of designers.

5. Looking forward: The future of relational event models

More than ever since their introduction fifteen years ago, relational event models are currently sustaining innovative empirical applications and important methodological progress by an ever-growing international community of researchers interested in the statistical analysis of dynamic network processes. As the analytical framework becomes more established and understood, it is possible to detect an increased level of sophistication and creativity in the theoretical narratives being developed, research questions asked, data collection strategies adopted, and statistical estimation techniques performed in studies based on relational event models (e.g., Kitts et al., 2017; Leenders et al., 2016; Lerner et al., 2021; Juozaitienė & Wit, 2022). It goes beyond the scope of this editorial to discuss all future developments that the editors hope to see over the next few years (and beyond the abilities of the editors to forecast all important future developments), but we propose a short overview of topics that we think might be particularly timely and important next steps.

As both computing hardware and high-efficiency algorithms improve, REMs can be fit to increasingly large data sets. This can place researchers in the historically unusual position of having sufficient statistical power to make traditional sources of uncertainty (particularly sampling/realization variability) negligible in comparison to approximation, specification, and even numerical error. In this regime, conventional tools such as standard null hypothesis tests and confidence intervals can be of limited use (since they report largely on precision), and questions related to detectability ("is there any measurable effect of X or deviation from Y") are often unproductive. This motivates greater attention to alternative ways of testing hypotheses and assessing models, for example, based on explanatory or predictive power, or on adequacy. Quantification of effects (rather than simple identification of direction) is also a concern, going hand-in-hand with parameterizations that facilitate consistent interpretation of effect sizes in terms of observables.

At the same time, it is also useful to consider when "going big" is a poor use of resources. With better methods for sampled event data, we may be able to draw strong conclusions from smaller, cheaper, and more readily collected data sets (Breiger, 2015; Lerner & Lomi, 2022).

REMs are generative network models, and as such, they can be used for (agent-based) simulations. This opens the potential of marrying statistical analyses of network data with theoretical agent-based models (ABMs). Researchers from empirical network research and ABMs for networks have called for better empirically calibrated, theoretically meaningful models (Snijders & Steglich, 2015; Flache et al., 2017; Stadtfeld & Amati, 2021; Steglich & Snijders, 2022). Relational event models seem like a promising framework to achieve this, in particular as simulation engines are already available in REM software packages. Deeper theory on the properties of different REM specifications (particularly long-run behavior) and on the connection between REMs and dynamic network models seems like an especially fruitful avenue for development.

Various theories about social networks are often concerned both with the tie perception of individuals (e.g., whom they define as a friend, whom they like or dislike), as well as their relational behavioral action (e.g., when they meet, how they interact) (Freeman et al., 1987). We hope that future research will be able to merge behavioral and perception network data in joint theoretically founded statistical analyses. The same holds for individual outcomes that are often not directly observable, such as political attitudes and psychological well-being. Additional efforts to integrate behavioral and perceptive data are necessary.

Some communities have found exciting new ways of how to describe and study relational event data without the use of REMs. There have been, for example, proposals of temporal clustering approaches and centrality indexes within the context of large, digital data sets (Aslak et al., 2018; Scholtes et al., 2016). We hope that some of these developments can inform future developments in relational event models and contribute to more sophisticated data description in empirical studies.

Research based on relational event models has proceeded at a fast pace over the past 15 years. The new articles that appear in this special issue are indeed good examples of the high level of innovation that we are currently witnessing in applied and methodological contributions based on relational event modeling frameworks. We believe that the papers in this special issue demonstrate that the potential of relational event models remains considerable, and their future looks very bright.

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