Jones *EPJ Data Science* (2024) 13:5
https://doi.org/10.1140/epjds/s13688-023-00432-3

EPJ Data Science
a SpringerOpen Journal

COMMENTARY Open Access

What relational event models can reveal: Commentary on Thomas Grund's "*Dynamics of Denunciation: The Limits of a Scandal*"

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Abstract

This article provides a commentary on Thomas Grund's International Conference on Computational Social Science 2021 keynote "Dynamics of Denunciation: The Limits of a Scandal". The keynote presents results from research investigating the relational dynamics underpinning the denunciations provided in testimonies relating to a Canadian political scandal. Grund uses relational event models to test hypotheses about the social mechanisms driving the denunciations. Although denunciation should depend only on who is guilty and not on who has said what up to that point, Grund's study finds evidence in support of a number of relational mechanisms influencing the denunciation process. Grund argues that the apparent influence of past denunciations on testimonies reveals the limits of the inquiry process itself and what it can reveal about a scandal. This article reviews Grund's talk and puts the work in a broader context of using approaches rooted in event history modelling and social network theory to illuminate the processes defining social interaction data. It highlights ways in which the keynote can inform the development of computational social science approaches to analysing such data, and argues that the value of such an analysis has implications for scholarship beyond the social sciences.

Keywords: Social networks; Relational events; Event history models; Relational dynamics; Political scandal

1 Introduction

In "Dynamics of Denunciation: The Limits of a Scandal", Thomas Grund showcases the usefulness of relational event models for exploring how relational mechanisms shape social processes. Through a case study involving testimonies over the Canadian government's management of funding for a Québec-related spending programme, Grund explores how the nature of those testimonies appears to depend on the relational sequence of events. Ultimately, he argues that this reveals the limits of the inquiry process itself, as the likelihood of an actor denouncing another actor should in principle depend only on the facts of the case (whether the denounced actor was guilty) and not on who has said what up to that point.

While it is now commonplace in the social sciences to recognise the ways in which relational methods in general can help us understand social phenomena, Grund's keynote shows that relational *dynamics* in particular can help us gain an insight into the processes that shape those phenomena. As such, the talk represents one of the cutting edges of social network analysis theory and methodology, the development of which offers much needed tools and concepts for social scientists working with interaction data. Given the increasing prevalence of large-scale data consisting of time-ordered or time-stamped interactions between social actors (e.g. emails, tweets, wearable sensor contacts), social scientists now have "unprecedented access to contextualized and longitudinal action at the micro level" (de Nooy [10]:4) with which to analyse and theorise social processes. The kind of approach taken in this keynote is therefore particularly relevant for thinking about how computational methods can help uncover the dynamics of many different forms of typical and emerging relational phenomena embedded in these new event data streams. However, for the potential of the kinds of methods showcased in Grund's keynote to be fully realised, some key issues remain to be addressed. In this commentary, I will review Grund's talk and its key findings and arguments, consider some of the limitations of the work, and reflect on the broader implications for computational social science and digital humanities research.

2 Summary of the work presented

Grund's keynote presents a case study for thinking about how underlying social dynamics can shape a scandal, and how those social dynamics can be empirically explored as network mechanisms. The talk is concerned with the case of a political scandal in Canada relating to a government spending campaign designed to promote Canadian unity and identity. The spending campaign aimed to boost the profile of the federal government in the province of Québec following the extremely close 1995 independence referendum wherein the people of Québec narrowly voted to remain a part of Canada. Grund summarises the scandal as relating to the administration of this so-called "sponsorship program" and its funds, citing issues relating to inappropriate political interference, incompetence in program management, a lack of transparency over the contracting process, and financial kickbacks to elected officials and public servants overseeing the program. The scandal resulted in the Canadian government setting up a public inquiry in 2004, known as the Gomery Commission, to investigate the scandal. The sociological interest in this series of events lies in the testimonies presented to the commission by 172 witnesses, during which many denunciations were made. Grund sets out to explore the social mechanisms that drove the dynamics of these denunciations during the nine-month public inquiry.

Grund's dataset is drawn from the more than 25,000 pages of transcripts of the testimonies, from which information was extracted on who denounced whom and who knows whom. The primary research question is: how are testimonies affected by previous testimonies? In posing this question, Grund explicitly assumes that there are social dynamics underlying the denunciation process which ultimately bias what can be revealed in such an inquiry. The mechanisms which are assumed to drive these dynamics are expressed as a series of expectations relating to network structure. First, it is expected that Person A is more likely to denounce Person B if Person B already denounced Person A in the past. In network terms, this is commonly understood as reciprocity, and Grund argues that it captures the idea of "an eye for an eye" in this case study. The second mechanism is expressed as an expectation that Person A is more likely to denounce Person B if Person B has already received many denunciations before. In network terms, this is a receiver popularity effect, and Grund argues that it indicates a kind of scapegoating by witnesses of people already widely labelled as guilty. Third is the expectation that people who denounce many others will themselves receive more denunciations – a receiver activity effect in network terms. Grund acknowledges that the network structures which are represented by these mechanisms may also be produced by the fact that some people may simply be more inclined to talk, and others may be more likely to receive ties precisely because they are actually guilty. However, in those cases, their risk of being involved in a denunciation ought to be constant, and not dependent on the observed event history.

To test for the effect of these mechanisms on the denunciation process, Grund opts for a relational event model approach. Relational event models, as outlined by Butts [4], present a general framework for modelling events consisting of senders and receivers at a particular point in time. This framework allows the specification of models which estimate the risk of a relational event happening given the observed event history and a set of statistics about the actors involved in the realised and possible but unrealised events (ibid.). The relational event model approach draws on techniques from event history analysis, adapting and extending them to make them suitable for network data. In conventional event history models, the interest is in the hazard of an observational unit (e.g. a person) experiencing an event (e.g. death) within a given time period (e.g. since the onset of a disease). Including covariates in the model (e.g. the sex of the person) allows the researcher to test for the association between variables of interest and the hazard. In a relational event model, a similar approach is taken, but the observational unit is typically a dyad, the event that may occur is typically the sending of a tie or interaction, and the time during which a dyad is deemed at risk of experiencing the event can be captured in various ways depending on the context and the choice of model. Covariates may be included which describe the sender, the receiver, the dyad, or the local network structures that would result from the event. These covariates can be constant or time-varying, and allow the researcher to test for the association between hypothesised network mechanisms (e.g. homophily – the tendency for people to associate with similar others) and the hazard.

The particular type of model implemented in Grund's study is the multilevel discrete time event history model presented by de Nooy [9]. This type of model is chosen over continuous time alternatives such as the piece-wise constant hazard model (Butts [4]) to take into account that denunciation events can only take place in discrete temporal observation moments (the testimonies) and are thus not at risk of happening outside of these moments. It also allows for the flexible specification of the constraints on eligible pairs for involvement in a denunciation event. The model is defined in such a way that only the present witness at time point t is able to be the sender of the relational event at time t, and only individuals whom the witness knows are at risk of being denounced at time t. Crossed random effects account for heterogeneity in the propensity for certain actors to send or receive more denunciations. To test the mechanisms of interest, covariates representing reciprocity, receiver popularity, and receiver activity are all included as independent variables; positive coefficients indicate a positive association between these network structures and the observed occurrence of a denunciation event in the data.

Grund presents his results in four versions of the model. The first simply models the entire event history together as one sequence. In this model, the coefficients for all three mechanisms are positive and significant, supporting the hypotheses for what might be driving the denunciation process. The second version of the model splits the event history into two sequences (the first 100 testimonies and the remaining 72 testimonies chronologically) and estimates the model on each. In this version, the reciprocity and receiver popularity effects are significant in both timepoints, but the receiver activity effect decreases and becomes non-significant in the second timepoint. In the third version of the model, different moving windows are used to define periods of memory for each mechanism. So, for example, an outgoing denunciation would only be considered reciprocal if the prior incoming denunciation took place within k testimonies of the current testimony event, with the model being estimated for a number of different values of k. These results (which are based on observed events after the 100th testimony) find that the effects for reciprocity and receiver activity are essentially the same no matter how big the moving window of memory is, while the receiver popularity effect decreases for longer memory windows, suggesting that people are more likely to denounce people who have been denounced a lot *recently*.

In the final version of the model presented, two additional triadic mechanisms are added to the moving window version of the model. The first is expressed as the expectation that Person A is less likely to denounce Person B if Person B has denounced a third Person C who has denounced Person A. This is based on the idea that an enemy of my enemy is my friend – I'm less likely to target someone who is denouncing one of my detractors. The second triadic mechanism is expressed as the expectation that Person A is more likely to denounce Person B if a third Person C has denounced both Person A and Person B. This is argued to capture the case of saving one's own skin, by deflecting attention onto a co-conspirator. The results show that there is some support for both effects, though the negative effect for the first triadic configuration is only statistically significant for some moving window sizes, while the saving one's own skin effect is positive and significant across all window sizes. Based on these collective sets of results, Grund argues that there is compelling evidence that previous testimonies matter for what is said next. Ultimately, this is a problematic finding for an inquiry process designed to capture the truth, which shouldn't depend on the social dynamics of who said what previously.

This keynote is part of Grund's broader body of work which uses a variety of methods for identifying how certain sociological outcomes are linked to the history of connection among those involved. For example, past research has examined how team experience relates to team success in the context of English football matches, in order to evaluate the broader proposition that "interaction patterns matter for success" in teams (Grund [13]:682, Grund [14]). A more criminological line of inquiry explores the role of dyadic dynamics in the co-offending trajectories of criminals. This work finds that people in street gangs that share ethnic identities are not more likely to commit the same types of criminal activity, but they are more likely to co-offend (Grund and Densley [15]). Further research with the same gang dataset uses an exponential random graph model approach to explore homophily and transitivity (and the interaction between the two) as mechanisms driving the formation of co-offending ties (Grund and Densley [16]). Here Grund and Densley find that ethnic homogeneity among co-offending ties is only partially explained by the dyadic homophily effect, with the tendency to co-offend with someone with whom you have a common co-offending tie also contributing to this homogeneity (ibid.). Furthermore, Grund and Morselli [12] explore an observed prevalence of both co-offending behaviours and dyadic specialisations in types of crimes committed for a large dataset of arrests in Quebec, finding that dyadic specialisation is largely driven by individual specialisation. In each of these strands of work, there is a clear commitment to bringing network mechanisms to the fore in the study of social processes, and especially finding methods which can highlight the relational *dynamics* of these processes. In the remainder of the paper, I critically reflect on the importance of this commitment and its implications in and beyond the field of computational social science.

3 What others can learn from the keynote

A little unusually for a keynote pitched at a general and cross-disciplinary audience, Grund's talk contains very little outward-facing reflection and ultimately chooses to limit its scope to its own case study. The keynote does not attempt to position the presented research among existing scholarship, nor does it offer suggestions for how social scientists who are not studying scandals might learn from or build on the work. This is not to imply that the talk ought to speculate on how scholarship based on other areas of theoretical expertise should proceed, but the lack of engagement with relevant literature disconnects the research findings from their significance for other related areas of inquiry. In this section, I offer some suggestions for where its impact might extend beyond the limited scope of the case study. I focus on Grund's innovative choice of methods and how those methods enable a novel and genuinely revelatory set of findings and arguments. Specifically, I propose that one of the key strengths of Grund's work in the paper is that it provides a neat example of a social process that should *not* depend on the relational event history of its participants. To find a dependency between the observed denunciations and past denunciation events is to call into question the purity of the inquiry process. As such, the case study cleverly illustrates the value of dynamic network methods for understanding the complex interdependencies in ostensibly individual actions. The implications of this point for research in and beyond this field are substantial, as I discuss below.

3.1 Implications for computational social scientists

Grund's work is certainly not the first to take a mechanism-driven and model-based approach to analysing relational processes. Relational event models have been used, for example, to demonstrate the temporal dynamics of interactions involving European jackdaws (Tranmer et al. [26]), health care organisations (Amati et al. [2]), open source software contributors (Quintane et al. [21]), attendees of meetings recorded in Margaret Thatcher's diary Lerner et al. [19], and participants in an online learning program (Vu et al. [28]). However, these examples are among relatively few studies applying relational event models, which are still relatively new and not yet fully understood. Grund's paper adds to these examples, and demonstrates how keeping an analytical focus on the role of social mechanisms in the process of producing macro-level social patterns can enable novel investigation of familiar social science topics of interest. The value gained by empirically unpacking the role of social mechanisms in dynamic network processes is significant for the current moment. The social research data landscape is now permeated with an unprecedented range and scale of dynamic interaction data, largely facilitated by online communications and advances in technologies for digitally gathering information from research participants. Grund's keynote aptly illustrates the promise of analysing relational data in their temporally disaggregated form, but it also highlights a key challenge for social network research in light of this new data landscape: the distinction between relational events and relational states.

In social network analysis and theory, it is important to distinguish between stable relationships that, though mutable, can persist through time (e.g. friendship, kinship, trust) and ephemeral interactions that occur at particular moments in time (e.g. emails, money transfers, physical encounters) (Borgatti and Halgin [3]; Butts and Marcum [5]; Stadtfeld and Block [25]). Many of the theories and tools that have shaped social network analysis were designed with relational states in mind, and researchers often aggregate interaction data into one or more cumulative network snapshots in order to leverage the conventional network methods and frameworks that can be applied to static representations. However, there is widespread recognition that concepts, methods and measures developed for relational states are not always appropriate for relational events, at least not without modification (Foucault Welles et al. [11]; Lazer et al. [18]; Quintane et al. [21]; Robins [22]). When the network of interest is constituted by relational events, "the usual notion of network structure breaks down, while alternative concepts of *sequence* and *timing* become paramount" (Butts and Marcum [5]:52, emphasis in original). Thus, recognition of the difference between states and events matters not only for the choice of analytical method, but also due to the complexity of incorporating time and sequence into the conceptualisation of network mechanisms (Schaefer and Marcum [24]).

Grund's keynote encounters the problem of rethinking social mechanisms within an event-based framework when moving from simpler model specifications to those containing more complicated structural and temporal configurations. In particular, by extending the models to include triadic effects, Grund is forced to deal with those extra-dyadic mechanisms which are less easily translatable from the literature on relational states to relational events. Ideas such as transitivity (the notion that if i is connected to j and i is connected to k, j and k are more likely to become connected) do not neatly map over to the relational event-based framework for thinking about network mechanisms, and this raises issues. For example, transitivity in directed networks is typically associated with certain configurations from the mutual-asymmetric-null triad census (see Davis and Leinhardt [8]; Holland and Leinhardt [17]). However, the triad census for a relational event-based understanding of transitivity needs to account for not only the direction of ties but also their temporal ordering, which makes the configurations considerably more complex. Studies such as Grund's which aim to incorporate triadic effects into a relational event model ought to be clear about this complexity, because it has implications for how we understand the translation from mechanism to model.

In the case of transitivity, a key question to consider is how much time needs to have passed before a relational event between j and k should no longer be considered a transitive closure induced by earlier events involving i with j and i with k? Must the events be consecutive? Even for dyadic configurations, the salience of temporal considerations can complicate the translation of the mechanism. For example, how much time needs to have passed since an event $j \to i$ before the event $i \to j$ is no longer considered a reciprocation of the earlier event? There is no clear theoretical answer to these questions, as it is likely to vary across different contexts (and perhaps even among the actors within a particular context). Grund deals with this issue in his talk by applying a number of different moving windows representing the extent of a social actor's "memory", but the choice of the size of these windows is (necessarily) uniform and arbitrary. As such, one must specify many models using different values to observe in which cases the mechanism appears to be significantly linked to events' occurrence. This is an adequate solution, but it should be noted that for larger datasets, such an approach could be very computationally demanding.

In sum, as interaction data become more readily available, the issue of distinguishing relational events and states becomes increasingly important for computational social scientists working with network data. If computational social scientists refrain from aggregating the deluge of data into a static snapshot that can be more readily analysed using conventional methods for exploring social structure, they will be uniquely positioned to present new insights into how social actors interact with one another at different scales (de Nooy [10]; Lazer et al. [18]). However, as more empirical work is conducted in the relational event-based framework, more work is also needed to theorise and explore the temporal aspects of social mechanisms and their salience in different contexts.

3.2 Implications for computational research in the humanities

I note here that this commentary is written from my own perspective as a social scientist working in a digital humanities environment. From this standpoint, the implications of Grund's methods and arguments extend beyond the social sciences and into other areas of humanities research as well. Digital humanities has much in common with computational social science – in both cases, traditional research questions are combined with computational and quantitative methods to open up new avenues and scales of analysis. From my point of view, the primary distinction is whether the research questions are derived from arts and humanities or social scientific perspectives and traditions (a distinction which can itself be blurry at times). As such, it is worth closing this commentary with some reflection on how the arguments and methods presented in Grund's keynote might have implications for research on history, media and culture which often takes place outside of conventional social sciences fora.

With this in mind, I suggest that a key way in which humanities scholarship could learn from this keynote is in recognising the value of illuminating relational and social processes where they might otherwise go overlooked. Grund's keynote shows that we cannot fully understand the observed denunciation patterns (as an indicator of guilt) in this case without taking into account the importance of the sequence of denunciation events. In doing so, the talk demonstrates that the macro-level patterns typically observed and studied by researchers could be the result of underlying dynamic processes. Thus, to fully understand the aggregate patterns, we need to also study the processes. This insight need not be restricted to the social sciences. Humanities research is full of scholarly interest in both event histories and the interconnectedness of artistic, cultural and historical entities. As such, the humanities could clearly benefit from methods such as relational event models which foreground the social mechanisms that characterise event history data. The rise of digital approaches in the humanities has further enabled scholars to piece together and document event histories of interest at unprecedented scales, opening up new avenues for analysis of the patterns characterising the resulting data. Recent debates in the digital humanities world have raised questions about what computational and data-driven methods are really adding to scholarship in the humanities (see, for example, Da [6, 7]; Underwood [27]; Weingart [29]). Being able to show in empirical terms how important relational and social dynamics are in arts, media and culture outcomes seems like an area where network methods have a clear contribution to make to computational humanities scholarship.

In particular, relational event models could be useful in those areas of humanities research interest where discourse is often focused on individual outcomes detached from social processes. For example, the quality of representation for female characters in fictional texts is often evaluated at the level of their individual depictions and characterisations; the success and generic positioning of authors is often discussed as a result of their own creativity and styles; and it is common to trace an artist's career trajectory and development in formal, aesthetic terms. However, there is surely a social dynamic to each of these phenomena – perhaps the macro-level patterns we observe are the result of processes guided by mechanisms of social organisation. This leads us to new ways of framing questions about familiar research problems: Can we understand the limited range of roles available to women in fiction as the result of certain relational mechanisms guiding how they interact with the other characters in the narrative? Do the patterns of correspondence between authors and other creative figures help explain their prominence and location within their cultural fields? Do the temporal patterns among the exhibition of artists' work in certain venues help us understand why those artists' careers and styles take the paths that they do? These kinds of questions are more tractable than ever before given the increasing availability of relevant data and the development of computational methods for analysing them.

To be clear, network perspectives and methods have already begun to spread into the digital humanities sphere (e.g. Ahnert et al. [1]; Moretti [20]; Rollinger et al. [23]; Weingart [30]). However, the approach taken by Grund offers two useful pointers for how such scholarship might proceed. Firstly, the work is based on a theoretically-motivated understanding of the social mechanisms which might be expected to influence the process at hand. Regardless of the area of application, social networks are *social*, and thus research questions should be based on (or at least informed by) theories of social organisation. However, the social part of "social network analysis" is not always retained when these analytical tools are used in the digital humanities. Often, more context-agnostic approaches to the study of graphs as representations of complex systems are preferred, inspired by claims of revealing universal laws of such systems. Second, the vast majority of network-based studies in the digital humanities are based on static graphs representing stable networks where connections between nodes either exist or do not. As noted in the previous section, this is not always an appropriate representation when the network one wishes to study is constituted by relational event dynamics. Network-based humanities scholarship could benefit from engaging more with some of the theoretical and methodological developments demonstrated in Grund's keynote in relation to relational events.

4 Conclusions

This commentary has attempted to outline the work presented in Grund's keynote and highlight its key implications for the wider research community. Empirically, Grund's finding that denunciation events seem to depend on the sequence of past denunciation events is an interesting finding for scholars interested in the role of public inquiries in political scandals. However, I have argued that the larger contribution of Grund's keynote is its demonstration that macro-level social patterns can be the result of dynamic network processes driven by relational mechanisms. Grund's methodological approach demonstrates that in order to understand how events of interest depend on the history of past events, we need to analyse relational events in their unaggregated state. While methods such as relational event models offer appropriate and useful tools for temporally disaggregated network analysis, questions remain concerning how best to account for the temporal aspect of social mechanisms in such a modelling framework. A more expansive sense of social networks which accounts for both relational states and relational events would thus enrich the ways in which network analytic approaches could contribute both in and beyond the social sciences.

Acknowledgements
The author thanks the two anonymous reviewers for their help in improving this manuscript.

Funding
Not applicable.

Data availability
Not applicable.

Declarations

Competing interests
The author declares no competing interests.

Author contributions
The author read and approved the final manuscript.

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Received: 22 February 2023 Accepted: 30 November 2023 Published online: 11 January 2024

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