Who, when, and how long? Time-sensitive social network modeling using relational event data

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Who, when, and how long?
Time-sensitive social network modeling using relational event data

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Introduction

1.1 Motivation

Social interactions between people play an important role in society by, among other things, facilitating information exchange (Quintane & Carnabuci, 2016), shaping personal growth (Back, 2021), and fostering social connections (Fehr, 2008). Furthermore, social interactions are vital to the health and wellbeing of individuals (Umberson & Karas Montez, 2010). Hence, understanding what drives people to interact with one another and when is an important area of study in the social sciences.

The first challenge in studying what drives social interaction behavior is understanding the relational interdependence of social interactions. The behavior of individuals is influenced by the actions of other people around them. Statistical methods for dealing with such structural dependencies among concurrent, temporally extensive relational ties have a long history in the field of social network research (Robins, 2013). The study of social interactions is, however, further complicated by time sequencing. Unlike long-standing relational ties, social interactions take place in a successive flow of events between individuals. Previous interactions influence future actions taken by individuals in the network. Therefore, to understand what drives how social interaction behavior unfolds over time, statistical methods that can take the order and timing of the actions between individuals into account are essential.

The relational event model is a statistical framework that can be used to study how social interaction behavior evolves over time. A key element of this approach is that it allows researchers to examine how emerging patterns of prior interactions influence between who and when the next interaction is likely to occur. For instance, when do people tend to reciprocate the prior actions of their peers? Do more agreeable people tend to reciprocate prior actions faster than less agreeable people? Or, do people tend to reciprocate prior interactions that were evaluated as cooperative faster than prior interactions that were evaluated as hostile? Hence, the relational event model enables researchers to study the dynamic processes that drive how social interaction unfolds over time.

This dissertation presents an extensive introduction to the relational event model for applied researchers. Furthermore, we develop methods that further extend the toolkit of relational event models. One extension allows us to explore how the mechanisms that drive social interaction behavior change over time. This method can, for example, aid in our understanding of how dynamic processes underlying social interaction behavior change as people get to know each other. A second extension enables us to study how the duration of prior social interactions influences the occurrence of future social interactions, and vice versa. This method can answer questions such as "do people tend to reciprocate prior interactions that took longer faster than prior interactions that took shorter?" And, "do interactions that reciprocate prior interactions tend to take longer?".

1.2 Relational event history data

To study what drives social interactions between people, we use continuous-time social interaction data, also referred to as relational event history data. This type of data consists of a time-ordered sequence of events between actors in a social network. The definition of relational event history data is quite flexible and can encompass a wide range of data types. Examples of relational event history data include face-to-face interactions between people (Ejbye-Ernst et al., 2021; Génois et al., 2015; Geukes et al., 2019), e-mails between employees (Mulder & Leenders, 2019; Perry & Wolfe, 2013; Quintane & Carnabuci, 2016), phone calls between students (Stadtfeld & Block, 2017), radio messages between first responders (Butts, 2008), Twitter messages (DuBois, Butts, & Smyth, 2013), patient transfers between hospitals (Amati et al., 2019; Kitts et al., 2017), food sharing between animals (Tranmer et al., 2015), software developers fixing bugs (Quintane et al., 2014), Wikipedia users editing articles (Lerner & Lomi, 2020), members of congress that co-sponsor legislation (Brandenberger, 2018), and so forth. With relational event history data we can thus study questions about the temporal evolution of a wide range of processes that can be viewed as events linking entities.

Relational event history data may also include information about attributes of the actors in the network or characteristics of the environmental context. This information can be used to study exogenous influences on what drives people to interact with other. For example, we may be interested in the effect of personality, age, and gender on individuals' social interaction behavior.

1.3 Relational event models

In the last two decades, two major statistical frameworks have been introduced for the analysis of social interaction dynamics using relational event history data. The first is the Relational Event Model (REM), developed by Butts (2008). The REM framework uses techniques from event-history analysis to explain when the next event is likely to occur and why certain events are more likely to occur next than others. In brief, the outcome variable in a basic REM is the tuple with the time, sender, and receiver of the observed event. At a given time point, we observe an event between a sender-receiver pair (a dyad) that is a realization of a set of potential events. All dyads that can potentially be observed are collected in the risk set. Each dyad in the risk set has its own rate of occurrence, the event rate. The event rate is modeled as a log-linear function of exogenous and endogenous statistics. Exogenous statistics capture influences from outside the event history on the event rate for a given dyad. For example, we may use exogenous statistics to capture processes of "homophily", or the tendency of individuals to interact with others that are similar to them (Snijders & Lomi, 2019). Endogenous statistics capture the dependence of the next event on the event history. For example, we may use an endogenous statistic to capture the process of "routinization" of interaction, in which individuals tend to keep interacting with the same other individuals (Leenders et al., 2016). Or we may use an endogenous statistic to model the process of "transivitiy", which can be summarized as the "friends of my friends become my friends" (Leenders et al., 2016). The waiting time between subsequent events is assumed to follow an exponential distribution, with as rate the sum of the event rates for all dyads in the risk set. The probability for the each dyad in the risk set to be observed next follows a multinomial distribution. The event rate thus directly translates to the expected waiting time between events and to the probability for a given dyad to be observed next. Endogenous statistics are continuously updated as new events occur, resulting in a piece-wise constant function for the event rate. This enables researchers to investigate the manner in which interactions follow one another over time. The central question then becomes how the event history can be summarized in order to explain and predict when the next event will occur and who will be involved. While the REM is not the only statistical approach for modeling relational event history data that is available in the literature, it offers great flexibility and is therefore the focus of this dissertation.

The flexibility of the REM is showcased when we extend the definition of the basic relational event. For example, empirical analyses in this dissertation demonstrate that the REM is not limited to directed relational events with a sender and receiver, but can also handle undirected events. Furthermore, empirical analyses in this dissertation demonstrate that the REM can handle relational event history data with different types of events. This enables us to investigate how dynamic processes underlying social interaction behavior differ across and within different event types. For example, we could investigate whether a student who frequently initiates interactions with other students in a study-related setting is also more likely to initiate interactions with other students in a leisure setting.

An assumption of the REM is that the effects of the exogenous and endogenous mechanisms on the event rate operate in the same way throughout the entire observed event sequence. This may not always be a realistic assumption. In this dissertation, we discuss, develop, and evaluate extensions to the REM that relax this assumption and allow for dynamic network effects, i.e., effects on the event rate that change during the event sequence. Furthermore, the REM assumes instantaneous events, which implies that the occurrence of an event can be characterized by a single time point. However, streams of events with a duration are commonly observed. In that case, it is likely that previous events that took a long time are more important in predicting future interaction behavior than events that were shorter. In addition, we want to examine how the interaction history influences the duration of future events. Therefore, we present in this dissertation an extension to the REM that can account for the duration of relational events.

The second major statistical framework for the analysis of relational event history data is the Dynamic Network Actor Model (DyNAM), developed by Stadtfeld and Block (2017). The DyNAM is developed in the tradition of stochastic actor-oriented methods. Similar to the REM, the DyNAM enables researchers to investigate dynamic social interaction processes with endogenous statistics that capture the influence of emerging patterns of past behavior on future behavior. Compared to the REM, its emphasis lies more on modeling the dynamics of social interaction behavior from the perspective of the choices of the individual actor. The researcher specifies a model to explain and predict who will decide to start the next event and who they will choose as the recipient of the event. While the focus of this dissertation is on the REM, there are multiple parallels between the two techniques (Butts, 2017; Stadtfeld & Block, 2017; Stadtfeld et al., 2017b), and many of the concepts covered in this dissertation also apply to or are easily generalized to the DyNAM.

1.4 Outline of the dissertation

In **Chapter 2**, we provide an extensive introduction to the REM for psychologists and demonstrate how this statistical framework can be used to discover trends of social interaction behavior over time in a sample of freshmen university students. The study of social interaction processes between freshmen university students is especially intriguing because we can examine how they progress from zero-acquaintance to building social relationships through successive social interactions. The REM is used to investigate three fundamental research questions concerning how and why social interactions between freshmen students evolve over time. First, which important interaction processes drive students' social interaction behavior? Second, how and when do these interaction processes change over time? Third, how do the interaction processes influence the manner in which students interact with each other across and within different environmental contexts? The data and scripts to replicate the analyses in this chapter are accessible via https://osf.io/xjbm7/.

In **Chapter 3**, we develop an extension to the REM that allows us to study how the effects of the driving mechanisms that underlie social interaction behavior change over time. The basic REM assumes that network effects, i.e., the parameters that quantify the relative importance of the drivers of interaction, remain constant during the study period. We present a Bayesian approach to test this assumption. A simulation study is conducted to evaluate this method. Once time-variation in network effects has been established, we recommend using the moving window REM to investigate how the effects change over time. The moving window REM uses a fixed window width and slides that window across the entire sequence of events. We propose a method to empirically determine the window width, where a wide window is used during phases when the data show little or no change in the behavior and a narrow window when the data show ample change. The accuracy and precision of the existing moving window REM and our extension to discover dynamic network trends are assessed using a simulation study. The methods for testing and exploring for time-varying network effects are subsequently applied to a real-world data example, studying the temporal evolution of social interaction processes between employees of an organization. The data and script to replicate the analysis in this chapter are accessible via https://github.com/mlmeijerink/REHdynamics.

In **Chapter 4**, we develop an extension to the REM that enables us to investigate how the duration of previous events affects the future event rate, and vice versa. The standard REM weights all past events equally in their influence on the event rate. This might not always be realistic. For example, previous interactions that took a long time may be more important in predicting future interaction behavior than interactions that were shorter. We suggest a weight function of the duration of past events in the endogenous statistics. Furthermore, we present a method for estimating the non-linear impact of event duration on future interaction behavior from the observed event sequence. A numerical simulation is performed to evaluate parameter recovery using the proposed estimation procedure. Subsequently, we propose a methodology that enables us to study how past social interactions and individual characteristics influence future event duration. The methods presented in this chapter are applied to two case studies. In the first, we examine how emerging patterns of prior close-proximity contacts and their duration affect the rate and duration of future contact between hospital patients and healthcare workers. In the second, we investigate the influence of previous events and the duration of those events on the rate and duration of subsequent events between persons involved in a violent confrontation in a public setting. Data and scripts to replicate part of the analyses in this chapter are accessible via https://github.com/mlmeijerink/thesis-ch4-duration.

This dissertation includes two tutorial chapters to assist researchers with fitting REM models and testing scientific theories in R. In **Chapter 5**, we give a brief introduction in the use of the R software package BFpack (Mulder et al., 2020) for Bayes factor testing of exploratory and confirmatory hypotheses of REM parameters. In **Chapter 6**, we provide a tutorial for the R package remstats. This package assists researchers in the computation of statistics for relational event models. We created the remstats package to simplify the process of fitting relational event models and make it more accessible for a wide range of researchers. This chapter gives an overview of how the remstats package can be used to compute statistics for tie-oriented and actor-oriented relational event models. The remstats package is available for download via https://github.com/TilburgNetworkGroup/remstats.

Finally, **Chapter 7**, provides a reflection on the research in this dissertation. The main findings and implications of the research are discussed, as well as remaining limitations and several recommendations for future research. The chapter concludes with a final remark about the application of relational event models to study dynamic social interaction processes.

The chapters of this dissertation were written as separate journal articles and can be read independently of each other. As a result, some details about the relational event model appear in multiple chapters, creating some overlap.

2

Discovering trends of social interaction behavior over time: An introduction to relational event modeling

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This chapter is based on Meijerink-Bosman, M., Back, M., Geukes, K., Leenders, R., & Mulder, J. (2023). Discovering trends of social interaction behavior over time: An introduction to relational event modeling. *Behavior Research Methods, 55*, 997-1023. https://doi.org/10.3758/s13428-022-01821-8.

Abstract

Real-life social interactions occur in continuous time and are driven by complex mechanisms. Each interaction is not only affected by the characteristics of individuals or the environmental context but also by the history of interactions. The relational event framework provides a flexible approach to studying the mechanisms that drive how a sequence of social interactions evolves over time. This paper presents an introduction of this new statistical framework and two of its extensions for psychological researchers. The relational event framework is illustrated with an exemplary study on social interactions between freshmen students at the start of their new studies. We show how the framework can be used to study (a) which predictors are important drivers of social interactions between freshmen students who start interacting at zero acquaintance, (b) how the effects of predictors change over time as acquaintance increases, and (c) the dynamics between the different settings in which students interact. Findings show that patterns of interaction developed early in the freshmen student network and remained relatively stable over time. Furthermore, clusters of interacting students formed quickly, and predominantly within a specific setting for interaction. Extraversion predicted rates of social interaction, and this effect was particularly pronounced on the weekends. These results illustrate how the relational event framework and its extensions can lead to new insights on social interactions and how they are affected both by the interacting individuals and the dynamic social environment.

2.1 Introduction

Through social interactions we build and maintain social relationships, express and adjust our personalities, exchange information, communicate feelings, and satisfy our fundamental needs for social belongingness and social achievements (Back, 2021; Bakan, 1966; Baumeister & Leary, 1995; Hogan, 1983). Social interactions are a key source of well-being (Kushlev et al., 2018; Lucas et al., 2008; Mueller et al., 2019; Sun et al., 2019), and this appears to hold quite universally. However, the way in which we engage in social interactions and the antecedents that drive us to engage in (specific) social interactions or not appear much less universal and highlight differences on both the individual and interpersonal level in social interaction behavior (see Back, 2021; Echterhoff & Schmalbach, 2018; Hopwood, 2018; Sadler et al., 2011, for overviews). Conceptual models on the development of social relationships emphasize the key role of successive social interactions (Altman & Taylor, 1973; Back et al., 2011; Fehr, 2008; Knapp et al., 2014): People get to know each other, initiate, and build social relationships through the flow of shared social interactions over time.

Longitudinal empirical approaches to understanding what drives us to engage in social interaction, to repeat (or not) previous social interactions over time, and the eagerness or speed by which we reach out to others for interaction (or by which we respond to invitations to interact) are, however, scarce (Geukes et al., 2019). Without such approaches it is difficult to develop a fine-grained understanding of how and why social interactions unfold over time. Specifically, there are three key domains of substantive research questions that are to date difficult to investigate given the lack of truly dynamic longitudinal approaches (see Back, 2021; Back & Vazire, 2015). First, we need to better understand social interaction processes by which interaction partners influence each other's behavior and develop more or less intense forms of social relationships. Despite calls for a dynamic, process-oriented view on social interaction (Leenders et al., 2016; Back, 2021), the majority of research on social interaction is based on aggregated counts of social contacts, which provide a relatively static view of social interaction. This prevents us from understanding how important social interaction processes evolve and influence each other over time. Adopting a dynamic view on social interaction enables us to change focus from stable properties of social interaction ('Are more extraverted individuals on average involved in more interactions'?) to discovering social interaction processes ('Are, given their previous interactions with each other and other individuals until this time, more extraverted individuals more likely to interact together next?').

Second, we need a more continuous understanding of social interaction processes across acquaintance levels. Most research examines either zero-acquaintance contexts (i.e., getting-to-know scenarios like first freshmen interactions, speed-dates) or short-term acquaintance contexts (e.g., interactions among students or within network groups) or long-term acquaintance contexts (e.g., interactions among friends or romantic partners). What is currently missing are continuous analyses across time, showing us when certain processes are particularly important and when exactly other processes start to kick-in. That is, we are required to examine questions of stability and change of the driving mechanisms underlying social interaction, including when, how, and why change occurs. These questions are, for example, especially interesting in the context of newly acquainted individuals and the role of personality differences for relationship development. Previous research suggests that how personality drives social interaction changes when individuals become acquainted with each other (Leckelt et al., 2015, 2020) but this has not yet been properly tested in a truly continuous fashion.

A third domain of key open questions pertains to the role of interaction settings for social interaction processes. Here, we refer with a ‘setting’ for social interaction to its environmental context, i.e., whether the same individuals interact at home, at work, at a party, etc. It is widely recognized that both characteristics of individuals (e.g., personality) and the environmental context (e.g., situational features; Rauthmann et al., 2014) have important effects on behavior. It is shown that, while personality traits affect behaviors across many settings, an individual’s behavior in a specific setting is substantially dependent on the characteristics of the environmental context (Sherman et al., 2015). For example, extraverts behave more sociable in general, and people, and extraverts in particular, behave more sociable in leisure situations (Breil et al., 2019). It has, however, not yet been investigated in how far and how interaction settings together with individual characteristics influence interaction dynamics, that is, interaction processes over time (e.g., “Is the effect of extraversion on the probability to interact next more or less emphasized in leisure settings compared to study-related settings?”) To develop a deeper understanding of how social interaction unfolds over time, we need to examine how various driving mechanisms affect social interactions across and within different settings.

Here, we argue that the challenges involved in tackling these three domains of open research questions can be met by making use of recent advances in both the collection and the analysis of dynamic interaction data. Recent technological advances have increased the possibilities to collect samples of naturally occurring social interactions (Kozlowski, 2015). For example, we may collect email data to learn about patterns of digitally mediated communication between employees in an organization (Mulder & Leenders, 2019; Quintane & Carnabuci, 2016), or learn about real-life social interaction processes by recording naturally occurring social interactions by utilizing mobile phones (Geukes et al., 2019) or proximity sensors (Elmer & Stadtfeld, 2020). Rich data that contains detailed information on the flow of social interactions over time thus becomes increasing available. Pairing such data with data on traits and other characteristics of the individuals allows researchers to study what drives individuals to start, maintain, dissolve, and manage their social interactions over time and how others play a role in an individual’s interaction dynamic.

Following previous suggestions for a micro-analytic approach in which social interactions are observed and studied on a fine-grained timescale (Butts, 2008, 2009; Geukes et al., 2019; Kitts & Quintane, 2019; Kozlowski, 2015; Leenders et al., 2016), the current study proposes and illustrates how such data can be potentially analyzed using a fairly new analytic technique, called *“relational event models”*. As will be illustrated in the current paper, relational event models are especially suited to study how continuous social interaction data unfolds over time. First, since social interaction processes operate beyond the individual (Back, 2021; Geukes et al., 2019), observations are mutually dependent and assumptions of standard data analytic methods are violated. Relational event models, however, can take into account complex network dependencies. The researcher can utilize this functionality of relational event models to study how individuals' embeddedness in the overall dynamic network of interactions influences their interaction patterns (e.g., the more two individuals interact with the same others, the more likely it may be for them to interact with each other). Second, the order and timing of social interactions may contain important information on the dynamics of social interaction processes (Butts, 2008; Leenders et al., 2016; Quintane, Conaldi, Tonellato, & Lomi, 2014). When we have continuous-time interaction data, relational event models enable researchers to utilize this information in the data and study which factors influence the rhythm and speed of social interaction and how what happens next is influenced by what happened previously. Thus, in sum, relational event modeling approaches provide psychology researchers with the analytical tools to overcome the previously described challenges and develop from continuous-time interaction data a detailed understanding of how social interaction unfolds over time.

In this article, we introduce relational event modeling and illustrate how this statistical framework can be employed to gain important insights from continuous-time social interaction data. First, a general introduction of relational event modeling is provided. We illustrate that relational event models enable us to study what drives social interaction processes by providing an example analysis of the data from the CONNECT study (Geukes et al., 2019). The data consists of observations of the real-life social interactions between university freshmen at the start of their curriculum. Specifically, we illustrate how relational event models can be used to study how students' personality traits, demographic characteristics, the kind of situations they are in, their joint interaction history and their embeddedness in the overall dynamic network of interactions affect the way in which they develop and maintain social interactions with the other freshmen in a new community. Second, at the beginning of the observation period, the freshmen students are not yet acquainted with each other. As the students get to know each other, it is to be expected that what drives the social interactions between them changes (Leckelt et al., 2015, 2020). We illustrate how the basic relational event modeling analysis can be extended with a so-called "moving window" approach to study how the drivers of social interaction processes in the CONNECT data change over time. Third, we may distinguish between two settings for social interaction that the freshmen students move between: a leisure setting (e.g., an interaction in a restaurant or at a party) and a study-related setting (e.g., an interaction during class or as part of a learning activity). We further extend the analysis and model the setting (leisure versus study-related) as a dependent variable to study how the drives of social interaction processes in the CONNECT data behave across different settings for social interaction. Finally, we conclude with a discussion of the analyses in this paper and provide some outlook on future applications of relational event modeling in psychological research.

2.2 Modeling continuous-time social interaction data

Relational event models can analyze any type of continuous-time social interaction data that can be viewed as a so-called *relational event history* (Butts, 2008). The

Table 2.1.: The first few social interactions observed between freshmen students at the beginning of their new studies in the CONNECT study (Geukes et al., 2019). For illustration purposes, student IDs are replaced by fictitious names.

Time (min.)	Student 1	Student 2	Setting	Duration (min.)
1	Anne	Ben	Leisure	30
61	Anne	Chris	Leisure	20
121	Dan	Emma	Study-related	15
151	Ben	Dan	Study-related	300
...	...	...	...	...

term "Relational event history" refers to a sequence of successive social interactions between a set of individuals that contains information on *who* are involved in the interactions and the time (or order) *when* the interactions took place. See Table 2.1 for an example of an observed relational event history. Each row in Table 2.1 represents a so-called *relational event*, which is minimally defined as an interaction between two or more individuals at a specific point in time (Butts, 2008). Relational events can be, and often are, extended with more information on the social interaction, such as the "setting" for interaction or the "duration" of the interaction (see the rightmost two columns of Table 2.1).

Relational event models are especially suited to model relational event history data. They enable researchers to study how the complex interplay of individuals' characteristics, their environment, and their history of interaction influences the probability for future social interaction, thereby continuously updating the past. In recent years, a number of relational event modeling approaches have been introduced (Butts, 2008; de Nooy, 2011; Perry & Wolfe, 2013; Stadtfeld & Block, 2017). The current paper focuses on Butts' (2008) Relational Event Model (REM), which provides an especially flexible framework for modeling relational event history data. Many of the concepts that we describe in the current paper, however, also apply to other relational event modeling approaches. For a comparison between different approaches, we refer the interested reader to Quintane et al. (2014, pp. 28-30).

In a REM, the probability of relational events to occur at a certain point in time or in the sequence is modeled. The core of the REM is the event rate λ. At a given time t, the event rate determines both (a) *who* will interact next, and (b) *when* the next interaction will take place. Therefore, a so-called "risk set" must be defined. This risk set $\mathcal{R}(t)$ contains all the events that can potentially occur at time t. Often, it makes sense to define the risk set as all possible directed or undirected pairs (s, r) of individuals. For example, given N individuals and undirected pairs, the risk set consists of $\frac{N(N-1)}{2}$ relational events. In principle, the events in the risk set can potentially occur at any point in time. It is possible, however, that the size of the risk set varies over time. For example, if an individual is not available for interaction for a certain time-interval during the study period, the events with that individual should be excluded from the risk set for the time points t that fall within that interval.

Hence, we can flexibly account for individuals' availability for social interaction to accurately model the social interaction processes among a set of individuals (see also Quintane et al., 2014).

While the event rate for a pair of individuals is assumed to change over the course of the study period, the event rate is assumed to remain constant from the time of the current event until the time of the next event. Given this piecewise constant hazard assumption, the waiting time from the current event at time t until the next event follows an exponential distribution, where the rate parameter is the sum of all the event rates for the pairs at time t:

$$\Delta t \sim \text{Exponential}\left(\sum_{\mathcal{R}(t)} \lambda(s,r,t)\right). \tag{2.1}$$

Thus, higher event rates at time t decrease the expected time until the next relational event (compared to lower event rates at time t).

Under the piecewise constant hazard assumption, the probability that the next observed relational event at time t is of the pair (i,j) is equal to

$$P((i,j)|t) = \frac{\lambda(i,j,t)}{\sum_{\mathcal{R}(t)} \lambda(s,r,t)}, \tag{2.2}$$

i.e., the event rate of the pair (i,j) relative to the event rates of all the pairs (s,r) in the risk set $\mathcal{R}$ at time t, including (i,j) (Butts, 2008). Thus, pairs with a higher event rate at time t are more likely to be observed next than pairs with a lower event rate at time t.

The REM enables researchers to study the predictors that explain how an observed relational event history evolves over time by modeling the event rate. The event rate is modeled as the outcome variable on which predictors are regressed through a log-linear function:

$$\log \lambda(s,r,t) = \sum_{p} \beta_p x_p(s,r,t). \tag{2.3}$$

Here, β_p refers to the model parameters that denote the magnitude of the effect of predictor x_p on the event rate. In this article, we follow Butts (2008) and refer to these predictors as *statistics*, but they are also sometimes referred to as "Sequential Structural Signatures (SSS)" in the literature (Leenders et al., 2016; Pilny, Schecter, Poole, & Contractor, 2016). Statistics can encode both exogenous and endogenous predictors of the event rate. First, exogenous predictors refer to any kind of variable that is external to the relational event history itself, such as individuals' personality traits, age, or gender, or the environmental context (e.g., whether interaction occurs in a leisure or study-related setting). By including exogenous predictors of the event rate in the model we can study research questions like 'Are more extraverted pairs more likely to interact next?' or 'Are pairs more likely to interact next if they are similar in age or gender?'. Second, it is assumed that each event in the observed sequence depends on the history of events. This assumption allows us to model the events independently, conditional on the history of events. How an event depends on the past is summarized by the endogenous predictors that are included in the model to explain the event rate. Endogenous predictors summarize characteristics of past interactions (Leenders et al., 2016), e.g., the volume of past interactions for a given student pair or the number of interaction partners with whom both students in a given student pair have interacted in the past. By including endogenous predictors of the event rate in the model we can study potential important research questions related to social interaction processes, like 'Does the time between subsequent interactions decrease if individuals have interacted more together in the past?', or, interacting an endogenous predictor with an exogenous predictor, 'Are less extraverted pairs more likely to interact together next if they have interacted more together in the past compared to more extravert pairs?'. Estimation of the model parameters β_p associated with the predictors allows us to make inferences about the effects that drive how the sequence of social interactions evolves over time. For example, a positive parameter estimate for the exogenous predictor 'extraversion' indicates a tendency for more extraverted pairs to start interactions at a higher rate than less extraverted pairs.

A REM can be fitted both when the exact time points for the relational events are considered (e.g., $t_1 = 1,\ t_2 = 61,\ t_3 = 121,\ \ldots$) and when only the order of the relational events in the sequence is known (e.g., $t_1 < t_2 < t_3 < \ldots$). In the first case, the full likelihood is used, while in the second case the full likelihood reduces to an ordinal likelihood (Butts, 2008, pp. 163-165). In case the exact time points are available, it is recommended to use the full likelihood because using the ordinal likelihood instead would result in a loss of information (Quintane et al., 2014). When the ordinal likelihood would be used in such cases, nothing can be inferred about time-related concepts such as the speeding up or slowing down of social interaction. An advantage of using the ordinal likelihood, however, is that a REM can still be fitted when the timing of relational events is only known up to the order of the events in the sequence and the exact time points are unavailable.

2.3 Analysis I: The basic relational event model

2.3.1 Data

We show how to use the REM by providing some exemplary analyses of the CONNECT data (Geukes et al., 2019). The CONNECT study is an extensive research project into the joint development of personality and social relationships among freshmen students. Participants were 126 freshmen students who enrolled for the bachelor study in psychology at a university in Germany. Part of this study is an experience-sampling observation of the social interactions between these freshmen students. Our aim is not to fully analyze this dataset, but to show how the statistical approach of the REM can be used to study topics of psychological interest. The CONNECT data used in the following analyses as well as the code for all analyses can be found at https://osf.io/xjbm7/.

Over the course of the first 23 days of their new studies, the participating freshmen students used an app on a smartphone to report every face-to-face interaction longer

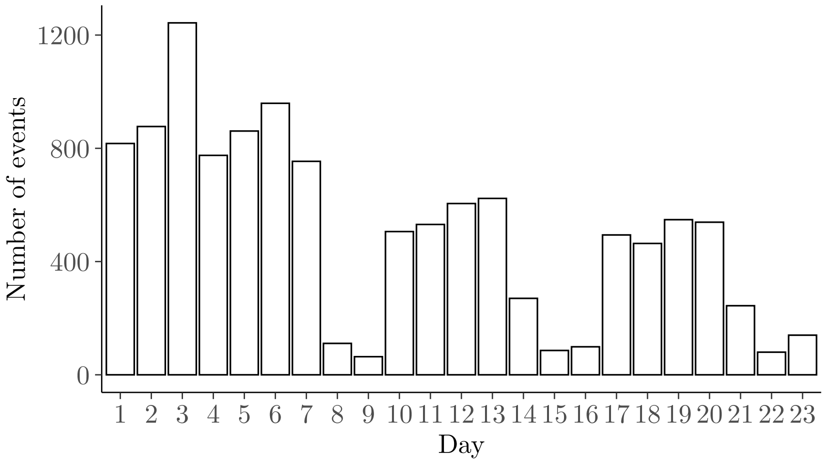

Figure 2.1.: Frequency of observed relational events in the CONNECT study over the course of the observation period.

than five minutes as well as every digitally mediated interaction. See Table 2.1 for the first four observed relational events and Figure 2.1 for the frequency of the observed events over the days. The specific time points for the relational events are defined in minutes relative to the onset of the observation period. The exact time points are available; thus we will use the full likelihood in our analysis. The relational events in the CONNECT study are undirected: we do not distinguish between sending and receiving students in a relational event. This means that, at any point in time, $\frac{126 \cdot 125}{2} = 7875$ potential relational events can occur among the 126 students.

2.3.2 Theoretical background

Previous research indicates that extraverted individuals are more likely to select friends (Feiler & Kleinbaum, 2015; Selden & Goodie, 2018; Selfhout et al., 2010) and to have larger social networks (Wagner et al., 2014). Furthermore, extraversion is linked to a stronger motivation for affiliation in peer groups (Neel et al., 2016), and to more sociable behavior particularly in social interaction (e.g., Breil et al., 2019). Extraverts also report to spend more time in social interactions (Asendorpf & Wilpers, 1998; Wilson et al., 2015). In general, extraversion most strongly relates to quantitative indicators of “getting ahead” in social groups such as the amount of social contact and social status (e.g., see Back, 2021; Back & Vazire, 2015; Grosz et al., 2020, for overviews). Agreeableness is shown to be related to being selected more as friend (Selden & Goodie, 2018; Selfhout et al., 2010). Similar to extraversion, agreeableness is linked to a stronger motivation for affiliation in peer groups (Neel et al., 2016). Agreeableness tends to be particularly related to qualitative indicators of “getting along” such as fewer social conflict (Asendorpf & Wilpers, 1998), particularly in long-term relationships, and less to the amount of social contact in newly emerging social relationships (e.g., see Back, 2021; Back & Vazire, 2015, for overviews). In the current analyses, we extend our understandings of the effects of the personality traits extraversion and agreeableness on social interaction behavior by studying their effects on the rate of continuously occurring social interactions. Specifically, we include personality traits (extraversion and agreeableness) to our model to understand how the personalities of two students affect the extent to which they choose each other as interaction partners.

Besides people's personality traits (such as extraversion and agreeableness), another important human trait that affects behavior over time is habituation or routine–the tendency of humans to repeat past behavior (Leenders et al., 2016). Within the context of relational event models, this is often termed *inertia*. Inertia captures the tendency to repeat past interaction, and to repeat more those interactions that were more frequent in the past. In essence, inertia captures the routinization of social interaction choices (Leenders et al., 2016). Pilny et al. (2016) suggest that, following general theories of social networks, an inertia effect may be essential to include in any REM. A tendency for inertia is found in previous REM analyses of directed social interactions between students (Pilny et al., 2017; Stadtfeld & Block, 2017). Therefore, we add inertia to our model to study the tendency of the students in the CONNECT study to develop interaction routines and keep interaction with past partners.

Closure is the tendency of individuals to interact with others with whom they share past interaction partners, i.e., the friends of my friends become my friends (Leenders et al., 2016). The tendency for closure is often found to be an important feature in forming social networks (Robins, 2013). A tendency for closure goes beyond the pair and describes the social embedding of individuals in the larger network. Evidence for a tendency for closure is found in previous REM analysis of directed social interactions (phone calls) between students (Pilny et al., 2017; Stadtfeld & Block, 2017). There are several reasons why this might be expected (see also Leenders et al., 2016). Having communication partners in common can be the consequence of having similar preferences and behavior, which might make the students more attractive to each other (similarity attracts). Another driver can be that having joint communication partners increases the opportunity to meet or to learn about each other. Either way, we would expect that the closure or shared partner effect may be an important predictor of social interaction in the CONNECT study. We add a shared partner effect to our model to study whether students who interact with the same others are also quicker to interact among each other. A further question to explore is whether the effects of inertia and shared partners on the event rate act the same across students' personality trait levels. In order to study this question, we add interactions between the endogenous mechanisms ('inertia' and 'shared partners') and students' personality trait effects ('extraversion') and ('agreeableness') to our model.

Homophily, or the tendency to interact or form relationships with others who are similar on one or more features, such as sex or age, has found to be an important mechanism in forming social networks (McPherson et al., 2001; Snijders & Lomi, 2019). Previous research showed that demographic similarity, including having the same gender and age, positively predicts friendship formation among adolescents (Rivera et al., 2010; van Zalk & Denissen, 2015). It is therefore important to account for effects of gender and age similarity on the probability for students to interact in our analyses of the CONNECT data.

The students in the CONNECT study recorded their interactions with fellow students both during weekdays and weekends. However, from Figure 2.1 we can see that the number of events between students is considerably and consistently higher on weekdays (when they have classes and other obligations) than the number of events on weekend days (when they are entirely free to do as they wish). Previous research among university students has found evidence for differences in communication patterns during weekdays compared to weekends (Masuda & Holme, 2019). Therefore, we introduce a weekend effect in our model to control for this difference in event rate and investigate if students interact differently during weekdays compared to weekend days. Finally, these freshmen regularly interact in groups, rather than in pairs. We will show a way to deal with that within the confines of the REM and analyze whether group interaction differs from dyadic interaction.

2.3.3 Model specification

A typical relational event model includes characteristics of the individuals, of the pairs of individuals, and of the way they are embedded in the network at large. In our example below, we will include a selection of effects to study the research questions that we described above. Of course, many more kinds of variables are possible to analyze social interaction dynamics. For an overview, see, for example, Butts (2008), Leenders et al. (2016) and Vu et al. (2017).

In this first model, we assume that effects are constant over time. We will relax this assumption later.

Baseline

We include a baseline (intercept) effect to capture the baseline rate for starting social interactions. The baseline simply is a statistic that is always equal to 1 for every dyad. It plays the same role in the REM as an intercept in a linear regression model: it captures the average tendency of student pairs to start interactions when all other statistics are zero.

Gender similarity

Two statistics are used to measure similarity in the gender of interaction partners. First, the statistic $x_{\text{both.male}}(s, r)$ is equal to one if both students in the pair (s, r) are male and equal to zero if not. Second, the statistic $x_{\text{mixed.gender}}(s, r)$ is equal to one if one student in the pair (s, r) is male and the other is female and equal to zero if not. The student pair (s, r) in which both students are female acts as the reference category. In the CONNECT sample, the majority of the students is female (80%) and thus the majority of the potential student pairs (64%) consists of students who are both female. Student pairs of mixed gender make up 32% of the potential student pairs and the remaining 4% are student pairs where both students are male. A positive model parameter $\beta_{\text{both.male}}$ would indicate that male student pairs (s, r) interact at a higher rate than student pairs with another gender composition. Similarly, a positive model parameter $\beta_{\text{mixed.gender}}$ would indicate that mixed-gender student pairs (s, r) tend to interact at a higher rate than other student pairs. Comparing these effects helps analyze gender preferences in the developing of social interaction.

Age similarity

Based on previous research, we include similarity in age in our example model to test if it positively affects social interaction for freshmen students. One approach is to calculate the difference in age between students and use that difference as an explanatory variable in our model. In this specific dataset, age differences are, however, limited. When a population is quite homogeneous with respect to a personal characteristic like age, students who are older than the common age can be seen as "outsiders" and be interacted with differently–a phenomenon connected to surface-level diversity (Thatcher & Patel, 2012). Therefore, in this analysis we dichotomize the age of students in a "young" category (age 24 or younger) and a "comparatively old" category (age 25 or older). Two statistics are used to summarize similarity in age. The statistic $x_{\text{both.older}}(s, r)$ is equal to 1 if both students are aged 25 years or older and equal to 0 otherwise. The statistic $x_{\text{mixed.age}}(s, r)$ is equal to 1 if one student in the pair is "young" and the other is "older". The student pair (s, r) in which both students are aged younger than 25 years acts as a reference category. The majority of the students in the CONNECT sample is classified as "young" (82%) and thus the majority of the potential student pairs (67%) consists of students that are both "young". Student pairs of mixed age make up 30% of the potential student pairs and the remaining 3% are student pairs in which both students are "older". A positive model parameter $\beta_{\text{both.older}}$ would indicate that "older" student pairs are likely to interact at an event rate than student pairs with a different age composition. Similarly, a positive model parameter $\beta_{\text{mixed.age}}$ would indicate that mixed age student pairs are likely to interact at a higher rate than student pairs with another age composition. This allows the researcher to discover any possible age-related faultlines and the tendency of older students to interact in a different manner from younger students (or mixed-age pairs).

Extraversion

Students in the CONNECT study provided self-report measures on personality traits by completing the GSOEP Big-Five Inventory (BFI-S; Hahn et al., 2012) that was part of an online survey. To obtain a measure of extraversion, the three BFI-S items that measure extraversion were averaged ($\alpha = .85$). Responses to these items were allowed to range on a scale from 1 (does not apply at all) to 7 (applies perfectly). Almost all of the 126 students filled out these items. The responses for two students were missing and we replaced those by the group mean. The other 124 participants scored an average of 5.1 and a standard deviation of 1.1. Finally, the extraversion scores were standardized.

There are two ways in which a trait like extraversion can be included in an analysis. One approach is to include it as a fixed sender effect, where it can be assessed whether extraverted students start more interactions. However, since the dataset only includes undirected interactions (so we cannot distinguish whether the more extraverted person was the sender or receiver of specific interactions), we cannot show this here.

An alternative approach in the case of undirected pairs is to study whether interaction is driven by higher extraversion levels for the most extraverted student or least extraverted student in the pair. In particular, we want to study whether it takes a minimum level of extraversion to interact with others and whether overly extraverted students are attractive interaction partners or not. We do this by computing two extraversion scores for each student pair. The first measure is the minimum level of extraversion of the two students in a pair. The statistic $x_{\text{extraversion.min}}(s, r)$ is equal to the standardized extraversion score for the student with the lowest extraversion score in the pair (s, r). This statistic tells us that both students have *at least* a level of $x_{\text{extraversion.min}}(s, r)$ on extraversion. The higher this value, the extraverted the student pair can be considered to be. A positive model parameter $\beta_{\text{extraversion.min}}$ would indicate that the higher the extraversion of the least extraverted student in the pair, the higher their interaction rate. So, if interacting with a (largely) unknown individual requires to have at least some minimum level of extraversion, this would follow from this analysis. This is a relevant question, considering that most students in the dataset were unfamiliar to each other at the beginning of the study.

Our second measure, $x_{\text{extraversion.max}}(s, r)$, is equal to the highest standardized extraversion score for the students in the pair (s, r). This captures an upper bound for extraversion: both students are not more extraverted than $x_{\text{extraversion.max}}(s, r)$. The lower this statistic, the less extraverted the students in the pair are. If we observe a positive model parameter $\beta_{\text{extraversion.max}}$, this would indicate that student pairs with at least one highly extraverted member interact at a higher rate than pairs where both students are less extraverted.

Agreeableness

Students' personality trait agreeableness is measured in the online survey with three BFI-S and two additional BFI statements (Rammstedt & John, 2007). Responds to these statements ranged from 1 (does not apply at all) to 7 (applies perfectly). To obtain a measure of agreeableness, the three BFI-S items and the two additional BFI items were averaged ($\alpha = .56$). Again, two students did not fill out these items and their scores were replaced by the overall mean. Agreeableness had a mean of 5.0 and a standard deviation of 0.8. Finally, the agreeableness scores were standardized.

Similar to the extraversion measures we computed above, we define two agreeableness statistics. The statistic $x_{\text{agreeableness.min}}(s, r)$ is equal to the lowest standardized agreeableness score of the two students in the pair (s, r). This measure captures the minimal level of agreeableness of both students in a pair. A positive model parameter $\beta_{\text{agreeableness.min}}$ would indicate that the higher the agreeableness of both students, the higher their interaction rate. Second, $x_{\text{agreeableness.max}}(s, r)$ is equal to the highest standardized agreeableness score for the students in the pair (s, r). This value shows that none of the students in the pair score higher on agreeableness than $x_{\text{agreeableness.max}}$. A positive model parameter $\beta_{\text{agreeableness.max}}$ would indicate that student pairs with higher levels of agreeableness interact at a higher rate than student pairs who both have lower agreeableness.

Inertia

It is common to add an inertia effect to a REM model by defining $x_{\text{inertia}}(s, r, t)$ as the (relative) number of previous (s, r) interactions at time t. The more past interactions between a pair of students, the more likely it is that this pair will interact soon again. The CONNECT data enable us to refine this measure and describe the intensity of past interactions between a student pair with greater detail. Because the CONNECT data include information on the exact starting and ending times of the interactions, we can also include the duration of past events into the measure. It is reasonable to expect that past events that lasted longer will be more likely to be repeated than brief past events. Therefore, we account for the duration of past interactions in the inertia effect. Moreover, the CONNECT dataset has information on a second feature that is likely to affect repetition: group interactions. A fair amount (36%) of interaction among the students occurs in groups of more than two students. It is reasonable to expect that being together with person A in a ten-person group will be a less strong trigger for repeated interaction with A than when the interaction with A occurred in a small group or with A directly. Hence, we let the number of students involved in a past group interaction affect the weight with which past relational events are added to the inertia count. Let $e = \{t_e, s_e, r_e\}$ refer to an observed relational event e at time t_e between students s_e and r_e, let A_e refer to the set of students involved in the social interaction that relational event e was part of and let d_e refer to the duration of this interaction. We define the inertia statistic for the student pair (s, r) at time t as follows:

$$x_{\text{inertia}}(s, r, t) = \sum_{t_e < t, s_e = s, r_e = r} \frac{1}{|A_e| - 1} \cdot \ln(d_e), \tag{2.4}$$

The measure $x_{\text{inertia}}(s, r, t)$ captures the sum of the past interactions between two students, weighted to the duration of the interactions and the number of students involved in each past interaction episode. To get an intuition of how this statistic weights the intensity of different kinds of past events between a student pair, Figure 2.2 shows the weight of an event for increasing duration of interactions with 2 individuals (as in 64% of observed interactions), 3 individuals (as in 17% of observed interaction), or 8 individuals (97.5% of the observed interactions is with eight students or less). The duration of the interactions ranges from 5 to 1805 minutes, the median duration is 30 minutes, and 97.5% of the interactions lasted 240 minutes or less.

In the case of endogenous statistics that are counts of past events, it is advisable to perform some kind of scaling method to make the statistic comparable over time and obtain well-behaved model parameters (Butts, 2008; DuBois, Butts, McFarland, & Smyth, 2013; Schecter & Quintane, 2020). Here, we follow the recommendations of Schecter and Quintane (2020) and scale the weighted count by standardizing it per

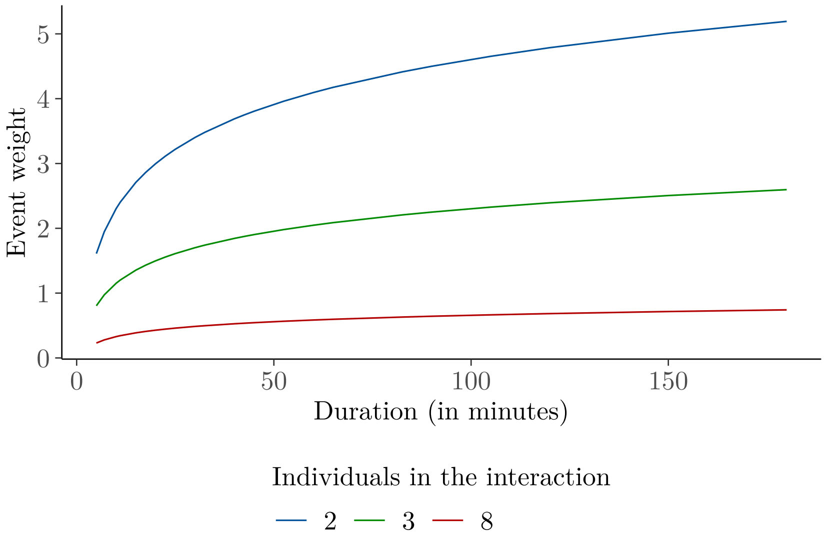

Figure 2.2.: The weight with which past events between student pairs are included in the inertia count for increasing duration and interactions with 2, 3, or 8 individuals.

time point t as follows:

$$X_{\text{inertia}}(s,r,t) = \frac{X_{\text{inertia}}(s,r,t) - \bar{X}_{\text{inertia}}(t)}{SD(X_{\text{inertia}}(t))}, \tag{2.5}$$

where $\bar{X}_{\text{inertia}}(t)$ and $SD(X_{\text{inertia}}(t))$ refer to, respectively, the mean and standard deviation of the inertia statistic at time t over all pairs (s,r). A positive model parameter β_{inertia} indicates that student pairs (s,r) who interacted more intensively in the past are likely to interact at a higher rate in the future than student pairs who interacted less intensively in the past. Of course, a researcher does not have to include event duration or group size and can use the common unweighted measure if preferred.

Shared partners

The statistic $x_{\text{shared.partners}}(s,r,t)$ is the number students h that s and r both interacted with before time t. We standardize the variable per time point in the same way as for the inertia statistic (see Equation 2.5). A positive model parameter $\beta_{\text{shared.partners}}$ indicates that student pairs (s,r) who have more past shared partners are likely to interact at a higher rate in the future than student pairs who have fewer past communication partners in common. This statistic helps us understand whether having third parties involved (i.e., statistical significance of the coefficient) matters for the building up of relationships among freshmen and how strong the effect is (i.e., size of the coefficient). Finding a non-significant effect is informative as well, as that signals that interaction does not depend on shared others but is driven purely by individual or dyadic traits (depending, provided, of course, on the other variables and coefficients in the model as well).

Weekdays versus Weekend

The statistic $x_{\text{weekend}}(t)$ is equal to 1 for all student pairs at time t if time t is in the weekend and equal to 0 if not. A negative model parameter β_{weekend} indicates that relational events in the weekend occur with at a lower rate in the weekend than interactions during the week.

Group interaction

None of the relational event models deal with group interaction in a fully natural way. Within the REM, there are two ways of dealing with group interactions. The first is to add potential groups as separate "actors" in the model (e.g., see Lerner et al., 2019), such that the individual actors can engage in interaction with these groups in addition to the interactions they can have with the other individuals (and even interactions between groups can be accommodated in this way). This is a useful method for relational events with a small set of actors, but can become computationally cumbersome for a large number of actors (and, hence, a larger set of potential groups). A possible refinement is to allow groups to come into existence (and dissolve) over the course of the observation period and include them as potential receivers during their existence (and exclude them when they are not active). This latter approach forms the basis of the recent DyNAM-i model of (Hoffman et al., 2020). Although elegant, this latter approach focuses on the choice of individuals to join and leave a group and does not naturally address the situation when a group gets together (and dissolves itself) *as a group*. In the context of the freshmen, groups get together for study or for social activities and are more naturally seen as group action, rather than as interactions between a group and an individual.

In this paper, we show a simple alternative that appears somewhat artificial, but appears to work quite well nonetheless. The approach considers a group interaction as a set of interactions between all individuals in the group, occurring jointly and during the same time period. Mathematically, we divide group interactions (i.e., interactions with more than two students) into the set of dyadic interactions between every pair of students in the group happening in random order.[1] Since relational events that are part of a group interaction have the same timestamp, which is not possible in a REM, a time difference between such relational events is induced before estimation (but after computation of the statistics, so the statistics are not affected by it). The time difference is such that these events are evenly spaced between the current time point minute t and the next minute $t + 1$. Since we induced a small time difference between relational events that were originally part of a group interaction, the rate of social interaction is artificially increased. We include a group effect in our REM to

[1] A sensitivity analysis with three different randomizations found no meaningful differences in results.

control for this artificial increase in the rate. The statistic $x_{\text{group}}(t)$ is equal to 1 for all student pairs in the risk set at time t if the relational event that we observe at time t is part of a group interaction and equal to 0 if not. Although somewhat artificial at first sight, this approach seems to work well in practice. It does make the underlying assumption that all students are aware of each other's presence in the group and consider all other participants in the group as potential communication partners while in the group. This may not be realistic for very large groups or for groups that are externally regulated in their communication. However, the fast majority (81%) of the interactions in the CONNECT study occurs in small groups with only two or three students.

The inclusion of the "group" variable not only takes care of the inflated interaction rates during times of group interaction, but it also allows the researcher to study the behavior of individuals vis-a-vis a group context. For example, a researcher can study whether extraverted student pairs are more likely to interact within a group context. Or one can analyze whether social similarity (such as having similar age, similar gender, or similar shared partners) affects the tendency to interact within a group. Just by itself, a positive model parameter β_{group} indicates that relational events tend to occur more in a group setting than outside of groups.

Interaction effects

Similar to the inclusion of interaction effects between predictors in linear regression or loglinear regression, we can also include interaction terms between variables in a relational event model. Interacting the "inertia" and "shared partners" with the four personality trait effects results in eight interaction effects. A positive model parameter $\beta_{\text{inertia.}\times\text{.extraversion.min}}$, for example, would indicate that the effect of inertia on the rate of social interaction increases for student pairs with a higher minimum level of extraversion. As in standard regression models, the interpretation of interaction effects requires a researcher to also include the main effects into the model.

2.3.4 Estimation

Appendix A.2.1 provides the reader with the script for the preparation and estimation of the REM analysis. First, the statistics are computed using the novel `R` software package `remstats`[2]. This software package has been developed to assist in the computation of commonly used REM statistics in an accessible manner. Second, estimation of the model parameters is realized using the `R` software package `relevent` (Butts, 2008). We build the models in a stepwise fashion, expanding the set of variables in consecutive steps. In total, we estimate five nested models (see Table 2.2).

[2]The `remstats` package for R is available via https://github.com/TilburgNetworkGroup/remstats.

2.3.5 Results

Model selection and goodness-of-fit

The five models we fitted vary in their fit to the data and in the complexity of the models. A straightforward measure that balances fit and complexity is the Bayesian Information Criterion (BIC). This value can be computed directly from the maximum likelihood. Better models have lower BIC values. As can be seen from Table 2.2, Model 4 is the model with the lowest BIC, i.e., according to the BIC, the model with the best balance of fit and complexity among the five models.

To assess how well the models explain the observed relational event sequence, we perform a goodness-of-fit analysis. For each event, we calculate the predicted rates for each dyad (by plugging the coefficient estimates into Equation 2.3). The probability of a specific dyad to host the next event is relative to its rate (see Equation 2.2). This means that the model expects that it is most likely that the next event is going to occur among the dyads that have the highest predicted rates. If the model captures the empirical reality well, we would expect that in a fair proportion of the events, the actual event would occur for a dyad that was among the dyads with the highest predicted rates. Hence, we define goodness-of-fit (gof) as the proportion of instances in which the next observed event was in the top 5% of dyads with the highest predicted rates. Recall that at any point in time, 7875 events can potentially occur, but only 1 actually does. The model aims to predict which of these 7875 events occur at every point in time, which is an extremely ambitious objective. Hence, any model that somewhat consistently ranks the actual event among the top 5% of 7875 possibilities can be interpreted as performing really well. A similar approach to evaluate goodness-of-fit is performed by Pilny et al. (2016) and DuBois, Butts, McFarland, & Smyth (2013). For an in-depth goodness-of-fit analysis, we refer the interested reader to the approach proposed by Brandenberger (2019).

For relational events that were originally part of group interactions, we determine whether the highest ranked relational event within that group is in the top 5%. This gof metric thus refers to the ability of the models to predict the most plausible student pair who takes part in the next interaction. For the baseline-only, Model 0, this means that goodness-of-fit is calculated as 14.2%, i.e., we expect that if interaction occurs completely random, that in 14.2% of the interactions at least one student pair is correctly predicted (as being in the top 5%).

Goodness-of-fit results in Table 2.2 shows that introducing the personality traits in Model 1 only slightly increases the gof compared to the baseline-only Model 0. Note that the personality trait variables do not vary over time and thus predict the same student pairs in the top 5% for all time points. Apparently, these student pairs do interact slightly more often on average in the sequence than would be expected on random. Subsequently, there is a large increase in goodness-of-fit when the endogenous effects (inertia and shared partners) are introduced in Model 2. Model 2 is able to correctly predict (as being in the top 5%) at least one dyad in over half of all of the 2886 interactions over the course of the three-week period. This large increase in goodness-of-fit for Model 2 indicates that these endogenous effects are very important in predicting

Table 2.2.: Relational event model parameter estimates with standard errors, BIC and goodness-of-fit (gof) results.

Effect	Model 0	Model 1	Model 2	Model 3	Model 4
Baseline	-9.99 (0.01)*	-9.81 (0.01)*	-9.89 (0.01)*	-10.93 (0.02)*	-11.01 (0.02)*
Personality trait effects					
Extraversion min.		0.26 (0.01)*	0.20 (0.01)*	0.14 (0.01)*	0.11 (0.01)*
Extraversion max.		0.07 (0.01)*	0.06 (0.01)*	0.03 (0.01)*	0.00 (0.01)
Agreeableness min.		-0.02 (0.01)	0.00 (0.01)	0.01 (0.01)	0.02 (0.01)*
Agreeableness max.		-0.22 (0.01)*	-0.21 (0.01)*	-0.19 (0.01)*	-0.15 (0.01)*
Endogenous effects					
Inertia			0.12 (0.00)*	0.14 (0.00)*	0.32 (0.01)*
Shared partners			0.12 (0.00)*	0.11 (0.00)*	0.06 (0.00)*
Demography effects					
Both male				0.60 (0.03)*	0.55 (0.03)*
Mixed gender				-0.08 (0.02)*	-0.11 (0.02)*
Both older				0.17 (0.04)*	0.20 (0.04)*
Mixed age				-0.88 (0.02)*	-0.77 (0.02)*
Event effects					
Group				2.15 (0.02)*	2.11 (0.02)*
Weekend				-0.75 (0.02)*	-0.78 (0.02)*
Interaction effects					
Inertia × extraversion min.					0.03 (0.00)*
Inertia × extraversion max.					-0.09 (0.01)*
Inertia × agreeableness min.					0.10 (0.00)*
Inertia × agreeableness max.					-0.06 (0.00)*
Shared partners × extraversion min.					0.04 (0.00)*
Shared partners × extraversion max.					0.13 (0.00)*
Shared partners × agreeableness min.					-0.15 (0.01)*
Shared partners × agreeableness max.					0.01 (0.00)*
BIC	256931	256004	249036	236133	234520
gof	14.2%	14.3%	52.0%	54.7%	51.7%

* $p < .05$

the social interactions among freshmen students. Introducing the demography (gender and age) and event effects (group interactions, weekdays-versus-weekends) in Model 3 further increases the goodness-of-fit metric slightly. Introducing the interaction effects in Model 4 leads to a slight decrease in the goodness-of-fit metric. This indicates that interacting the endogenous effects (inertia and shared partners) with the personality traits extraversion and agreeableness has little value and even harms the predictive performance of our model. The best performing model (Model 3) correctly predicts (as being in the top 5 %) at least one student pair in almost 55 % of all interactions, which is remarkable and lends credence to the idea that these variables capture the most important drivers of the social interaction choices these freshmen made in the process of getting to know each other and new study mates.

Interpretation

Table 2.2 shows the estimated relational event model parameters and their standard errors for the five different models. Below, we interpret the parameters for the model with the best goodness-of-fit results, Model 3.

Because the relational event model is a log-linear model (see Equation 2.3), we can take the log-inverse of the estimated model parameters to obtain a more meaningful metric for interpretation. For the baseline parameter the log-inverse refers to the average number of relational events per minute for a student pair with zeroes on all other statistics. After multiplication by the size of the risk set, we obtain the average predicted number of relational events per minute, $\exp(\beta_{\text{baseline}}) \times 7875 \approx 0.14$. The inverse of this number is the average expected number of minutes between two relational events: 7.08 minutes.

For all other effects, the log-inverses of the model parameters refer to baseline rate multipliers. For example, $\exp(\beta_{\text{inertia}}) \approx 1.15$ indicates that for student pairs who interacted with one standard deviation more intensively in the past compared to student pairs who interacted with average intensity, the baseline rate of starting a social interaction is multiplied by 1.15. Thus, for these student pairs, the predicted waiting time between the start of two social interactions is on average $\frac{1}{\exp(\beta_{\text{baseline}}) \times 7875 \times \exp(\beta_{\text{inertia}})} \approx 6.17$ minutes.

Figure 2.3 summarizes how the personality traits affect the time between interactions for a student pair. Results in Table 2.2 show that, after controlling for all the other effects, higher extraversion levels for both the least and most extraverted student in the pair positively affect the event rate. Higher extraversion levels for the students in the pair are related to higher event rates. The expected time between subsequent interactions is most strongly determined by the least extraverted student in the pair, as visualized in Panel 1 of Figure 2.3. The left column depicts student pairs where at least one member has an extraversion score of 1 standard deviation *below* the average. The cells in the table show the expected time until their next interaction. As can be seen, the extraversion of the most extraverted student in the pair has a small positive effect on the waiting time; the pairs with both students below the mean in extraversion tend to wait 0.41 minutes (5%) longer before they interact again than pairs with only one student below the mean and the other above the mean. The top row depicts student pairs where at least one member has an extraversion score of 1 standard deviation *above* the average. Here, we see that the extraversion of the least extraverted student in the pair has a larger positive effect on the waiting time; the pairs with one student above the mean in extraversion and the other below the mean tend to wait 1.92 minutes (32%) longer before they interact again that pairs with both students above the mean in extraversion. The results are subtle, but consistent: whereas the most extraverted communication partner has a small positive effect, the lowest extraverted partner most strongly determines the rhythm of social interaction.

Furthermore, results in Table 2.2 show a negative effect of agreeableness maximum and no effect of agreeableness minimum on the rate of interaction. As Panel 2 in Figure 2.3 shows, after controlling for all of the other effects, when at least one partner scores 1 standard deviation *above* the mean in agreeableness (top row), the student pair takes longer to activate than student pairs where both students are low in agreeableness. Agreeableness is often considered to be a superordinate trait that includes compliance, modesty, and tender-mindedness (Matsumoto & Juang, 2012, p. 217). Considering that the participants do not know each other at the beginning of the study period and find themselves in new territory (new university environment, new city to live, new people to get to know, new tasks), highly agreeable individuals may be more conscientious and particular in their interactions, whereas low agreeable individuals might be more progressive and impulsive in their interaction choices.

The results in Table 2.2 further show that both endogenous variables (inertia and shared partners) have a positive effect on the rate of interaction. The students show clear signs of habituation and the development of "preferred" communication partners to continue interaction with repeatedly. The inertia parameter is 0.14, showing that, after controlling for all of the other effects, student pairs who interacted more intensively in the past are likely to interact at an even higher rate in the future. Similarly, student pairs with more past communication partners in common tend to interact at a higher event rate than student pairs who had fewer shared partners.

The positive parameter estimate for both-male indicates that, after controlling for all of the other effects, pairs of male students tend to have a higher rate of interaction than other student pairs. Conversely, the negative parameter for mixed-gender implies that male-female student pairs tend to have lower interaction rates than other student pairs. However, the majority of the CONNECT sample is female, such that 2525 pairs of students have mixed gender, 300 are all-male, and 5050 are all-female. Therefore, mixed-gender pairs have a higher a priori opportunity for interaction than all-male pairs. Indeed, the predicted time between interactions is on average $\frac{1}{300\times\exp(\beta_{\text{baseline}})\times\exp(\beta_{\text{both.male}})} \approx 102.01$ minutes for male-male pairs, $\frac{1}{2525\times\exp(\beta_{\text{baseline}})\times\exp(\beta_{\text{mixed.gender}})} \approx 24.00$ minutes for mixed-gender interactions, and $\frac{1}{5050\times\exp(\beta_{\text{baseline}})} \approx 11.04$ minutes between female-female interactions. This shows that, despite the strong preference for same-gender interaction (and especially male-male interaction), interactions that involve one or two female students strongly outnumber interactions that are all-male.

In terms of the effect of age, Table 2.2 shows that, after controlling for all of the other effects, student pairs in whom both students are aged 25 years or older ("old") display

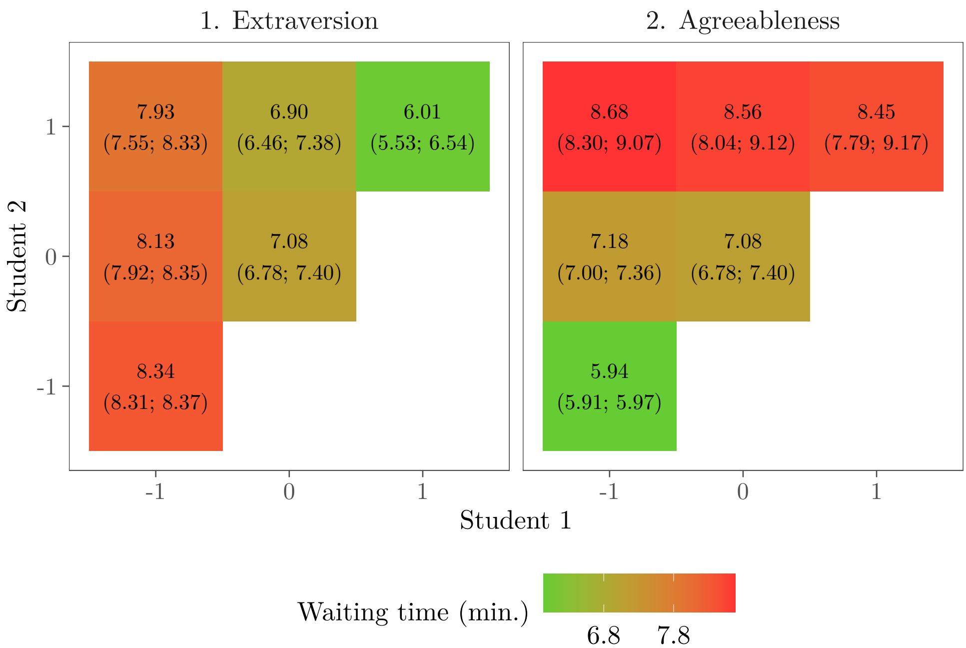

Figure 2.3.: Expected time (in minutes and with 95% confidence interval) between interactions for different extraversion and agreeableness scores, based on the estimated model parameters for the personality trait effects in Model 4 (see Table 2.2). A score "0" refers to an average score on the trait, "1" refers to being 1 standard deviation above the mean and "-1" to 1 standard deviation below the mean. Comparisons of the rows informs us on the effect of the personality traits for the, respectively, most extraverted ($\beta = 0.03,\ p < 0.05$) or most agreeable student ($\beta = -0.19,\ p < 0.05$) in the pair. Comparisons of the columns informs us on the effect of the personality traits for the, respectively, least extraverted ($\beta = 0.14,\ p < 0.05$) or least agreeable student ($\beta = 0.01,\ p > 0.05$) in the pair.

a higher expected rate of interaction than student pairs of another age composition. Student pairs of mixed age tend to interact at a lower rate than pairs of another age composition. This shows that there is a strong preference for same-age-group interaction (and especially for comparatively "old" student pairs). Like for gender, age is quite skewed, with 253 "old" dyads, 5253 "young" dyads, and 2369 dyads of mixed age. Hence, the expected time between interactions is calculated to be, on average, approximately $\frac{1}{253 \times \exp(\beta_{\text{baseline}}) \times \exp(\beta_{\text{both.older}})} \approx 186.85$ minutes for two older students, $\frac{1}{2369 \times \exp(\beta_{\text{baseline}}) \times \exp(\beta_{\text{mixed.age}})} \approx 56.66$ minutes for mixed-age students, and $\frac{1}{5253 \times \exp(\beta_{\text{baseline}})} \approx 10.62$ minutes for a pair of younger students.

The positive model parameter estimate for the "group" effect accommodates the increase in the event rate that was induced by dividing observed group interactions into dyadic relational events that follow each other rapidly. Considering that originally 2886 relational events were observed but 11690 relational events after the division of group interactions into dyadic relational events, the event rate was increased by a factor $\log(\frac{11690}{2886}) \approx 1.40$. Subtracting this number from the estimated group effect, $2.15 - 1.40 = 0.75$, gives us a “net” estimate of the tendency of freshmen to interact in pairs versus in groups. This positive effect indicates that, after controlling for all of the other effects, the freshmen engage in group interactions with a higher rate than in pairwise interactions.

The negative model parameter estimate for the “weekend” effect indicates a lower rate for engaging in social interactions during the weekend than during working days, after controlling for all of the other effects. On working days the predicted time between events is on average $\frac{1}{7875 \times \exp(\beta_{\text{baseline}})} = 7.08$ minutes and on weekend days the predicted time between events is on average $\frac{1}{7875 \times \exp(\beta_{\text{baseline}} + \beta_{\text{weekend}})} = 15.07$ minutes. This is in concert with Figure 2.1 where the number of events on weekend days is considerably and consistently lower than the number of events on working days.

From this first example analysis, we can see that the relational event model can highlight the effect of personality and personal and interpersonal characteristics on how these adolescents interact in a natural experiment: a situation where the students are unfamiliar to each other and are stimulated to find attractive interaction partners. In itself, this is a very straightforward model–essentially just a log-linear model–but it not only allows us to uncover the drivers of how these youngsters learn to interact with each other, but the REM allows a researcher to quantify the effects in terms of time and timing as well: how much longer does it take between two individuals in condition A versus individuals in condition B?

2.4 Analysis II: Relational event modeling with dynamic effects

In the analysis above, we made the underlying assumption that the effects are constant over the study period. However, the data concern freshmen who are starting a new life, with new people to get to know, a new place to live, and a new environment. As a result, we would expect to see some development of the way in which the freshmen develop their new persona as a student and learn whom to (not) interact with. Therefore, we now refine our model by dropping the assumption of constant parameter values and allow the parameters to vary over time. This allows us to study the second domain of key open questions outlined in the introduction, i.e., perform a continuous analysis of social interaction processes across acquaintance levels. Some of the interesting questions in this context are whether the effect of personality increases or decreases over time, how long it takes for inertia to kick in, or whether same-gender interaction may be considered a safe bet at the beginning of the period, while mixed-gender interaction gains attractiveness over time.

Our approach is to not put any constraints on the development of these effects (although that can certainly be done) and allow the parameter values to vary freely over the observation period. We do this by following Mulder and Leenders (2019) who extended the REM with a moving window approach. In this approach, a window of a pre-specified length slides over the entire observed relational event sequence. In each slice, the relational event model is fitted to the subset of relational events that falls within the window. Together, these slides create a picture of how the predictors of social interaction change over time. Following Mulder and Leenders (2019), a moving window REM can be fitted in the following steps:

1. Determine a window length.
2. Fit the specified REM to the subset of relational events that fall within the first window. Save the parameter estimates.
3. Move the window such that it partly overlaps with the previous window but also contains a new subset of relational events.
4. Fit the specified REM to the new subset of relational events. Save the parameter estimates.
5. Repeat Steps 3 and 4 until all relational events in the sequence are analyzed.

The choice of window length should depend on theoretical and statistical reasons. Ideally, the window length is chosen such that it corresponds to the empirically established or assumed temporal nature of the effects of interest (Mulder & Leenders, 2019). The smaller the window length, the more sensitive the results will be to each point in time (and the more estimates will reflect what happens on a given day or brief period of time). The wider the intervals, the smoother the development over time. Furthermore, the window length should be large enough such that it contains enough relational events to reliably estimate model parameters. The overlap between subsequent windows determines the smoothness of the results, where a higher number of events that overlap results in greater smoothness.

Since the interactions between the freshmen students in the CONNECT study are observed during the first three weeks of their acquaintance, we are interested to study how effects change over relatively short time intervals as the network develops during the getting-to-know-you processes. Therefore, we choose a window length of three days with two days overlap. This combination of window length and overlap between the windows allows us to study daily variation while also maintaining enough events in each window to reliably estimate model parameters. The number of events per window varies between 455 and 2937.

2.4.1 Model specification

The script for the moving window analysis of the CONNECT relational event sequence can be found in Appendix A.2.2. To study how student interaction behavior develops over time in the CONNECT dataset, we apply the moving window approach to the same five models as analyzed in section 2.3. However, it is no longer necessary to include a parameter to capture the difference in baseline event rate between the working days and the weekend; any weekday-weekend effect will be picked up automatically.

The endogenous statistics that were included in the model were slightly adapted to correspond to the expected dynamic nature of the social interaction processes in the CONNECT data. When interaction behavior is highly dynamic, it is important to consider how long past events influence future events (Brandes, Lerner, & Snijders, 2009; Leenders et al., 2016; Mulder & Leenders, 2019; Quintane, Pattison, Robins, & Mol, 2013). Unfortunately, little theory exists in the literature to make an informed choice on how long past interactions influence future interaction behavior. Brandes et al. (2009) propose that the influence of past events decreases exponentially over time and that how fast this occurs depends on a half-life parameter. Quintane et al. (2013) specifically compare short-term and long-term time frames along which interaction processes may develop. Mulder and Leenders (2019) included only those past events in the computation of the endogenous statistics that occurred at most a fixed time period ago, corresponding to the nature of the moving window. Here, we follow the approach of Mulder and Leenders (2019), and let the influence of past events decrease corresponding to the expected dynamic nature of the social interaction processes in the CONNECT data. Consequently, we study patterns of interaction that develop over a relatively short time period.

2.4.2 Results

Model selection and goodness-of-fit

The results of the analyses are shown in Figure 2.4. The BIC of Models 3 and 4 is consistently lower than that of the other models. Furthermore, we compute goodness-of-fit for the models over time in the same manner as before. Figure 2.4 shows that the goodness-of-fit drastically increases for the entire study period after inclusion of the endogenous effects (inertia and shared partners) in Model 2. Introducing the demography (gender and age) and event (group) effects in Model 3 and interaction effects in Model 4 on average slightly increase the goodness-of-fit further. Since Models 3 and 4 have consistently lower BIC values than the other models and are very similar in BIC and gof, we prefer the more parsimonious model of the two, Model 3, and will discuss that model's results below. Model 3 has a fairly stable and high goodness-of-fit over the course of the study period, ranging between 45.8% and 63.8%. For two-third of the study period, the goodness-of-fit for Model 3 with the moving window applied is higher than for Model 3 in the basic REM analysis (which was 54.7%, see Table 2.2). Thus, even though the estimates in the moving window REM are based on fewer events (per window) than in the basic REM analysis (which includes all events for a single model fit), we can better predict the events that are likely to occur next with the moving window.

Interpretation

Figure 2.5 shows how the effects on the rate of social interactions between freshmen students in the CONNECT study develop over time. Rather than interpreting every single effect, like we did above, we will highlight some interesting results. We can see from Panel 1 of Figure 2.5 that the freshmen students tend to more actively

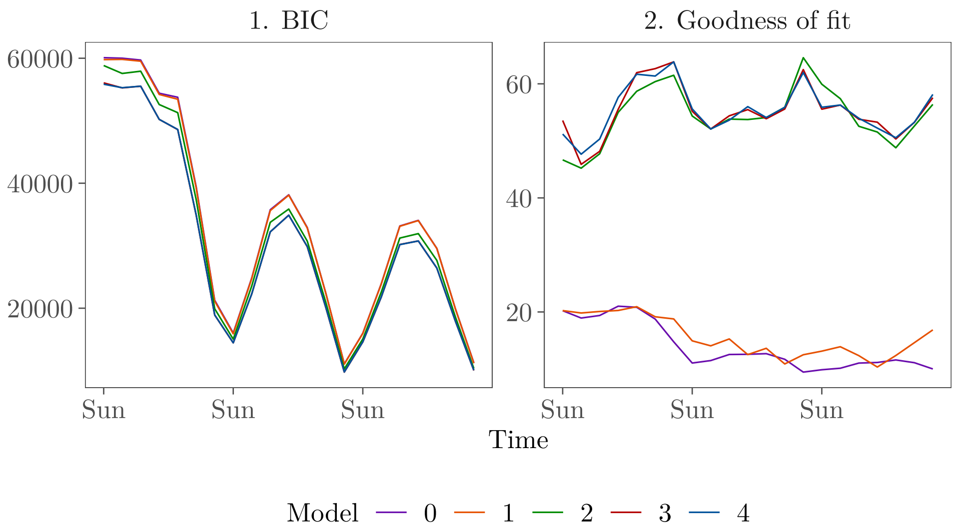

Figure 2.4.: BIC and goodness-of-fit for the five models over time for the moving window REM.

interact during the weekdays than during the weekends (controlling for all other effects). In the previous analysis we also found this, but we do not need to estimate a separate parameter for this in the moving window model. This not only allows us to estimate a more parsimonious model, but it also allows us to detect a timing effect without having to expect and specify it beforehand. In our previous approach, we found a weekday-weekend effect because we included a parameter specifically for that as we expected such an effect on theoretical grounds. Alternatively, the moving window approach allows us to spot timing effects we might not have anticipated before specifying our model.

Panels 2 to 5 in Figure 2.5 show the dynamic effects of students' personality traits on how their social interactions develop over time. The effect of extraversion minimum clearly affects interaction during weekends (controlling for all other effects). During the week it does not really matter, but on weekends interaction is favored in dyads where both members are extraverted enough. Dyads where at least one of the students scores very low on extraversion have much less intense interaction than dyads where the least extraverted student is also fairly extraverted. This fits with the idea that interactions on weekends probably require more individual initiative than interactions on weekdays where students meet around educational activities. The effect of extraversion maximum appears to be positive during the first week: highly extraverted individuals are involved in interactions at higher rates than others. However, this turns around after the first week. It may be that extraversion helps in creating interactions in the first week, when students barely know anyone yet, but after that first week of getting acquainted other students become more active in interacting and the most extraverted individuals may even become less attractive communication partners during the weekdays.

For agreeableness, we observe a weekend effect: during the weekdays at the university agreeableness does not affect interaction rate, but on weekends, outside of the university environment, it helps to have at least fair level of agreeableness to be an attractive communication partner (or, to seek out other, more agreeable partners to hang out with). Throughout the observation period, there is no benefit to being very agreeable, as student pairs tend to be less intensive with highly agreeable individuals than with lower agreeable others. This may be connected to the more timid nature of highly agreeable persons, or simply to highly agreeable individuals to “go with the flow” and not push themselves as interaction partners. Of course, more in-depth research is needed to draw more informed conclusions about these effects.

Results in Panels 6 and 7 of Figure 2.5 show that, after controlling for all other effects, the endogenous effects inertia and shared partners consistently positively affect the rate of social interaction throughout the observation period. Both these effects seem to develop in the first few days and remain relatively stable afterwards. These results suggest that such endogenous patterns of interactions develop early in a student network that starts at zero acquaintance. Moreover, the importance of these effects in explaining social interactions between freshmen students seems to remain relatively stable while acquaintance develops over time.

Results in Panel 8 of Figure 2.5 suggest that, after controlling for all other effects, student pairs who are both male tend to interact at a higher rate than other student pairs, given their opportunity for interaction. This effect is relatively stable in the first two weeks, but, after two weeks, its effect seems to disappear during the weekends. Panel 10 shows that older students do not particularly seek each other out during the first week (possibly because they do not know who they are yet), but a preference towards connecting with each other does appear to develop after this first week of becoming acquainted. Age may be less of a trigger during weekends. Overall, there is a negative tendency of the different age groups to connect, this effect is quite stable throughout the study period.

Panel 12 of Figure 2.5 shows the “net” group effect. Results show that connecting in a group context is very prevalent throughout the entire observation period.

Overall, the relational event model allows a researcher to draw conclusions of emergent behavior and how personality, demographics, social embeddedness, and human nature (i.e., human tendency towards habituation/inertia) drive how individuals interact and develop their social conduct. The moving window approach allows a researcher to not only study what the drivers are of the interaction choices these study participants make, but also uncovers how long it takes for the effects to kick in and for how long the effects then last. We believe this has the potential to add much detail to the development and refinement of theory of interpersonal human behavior.

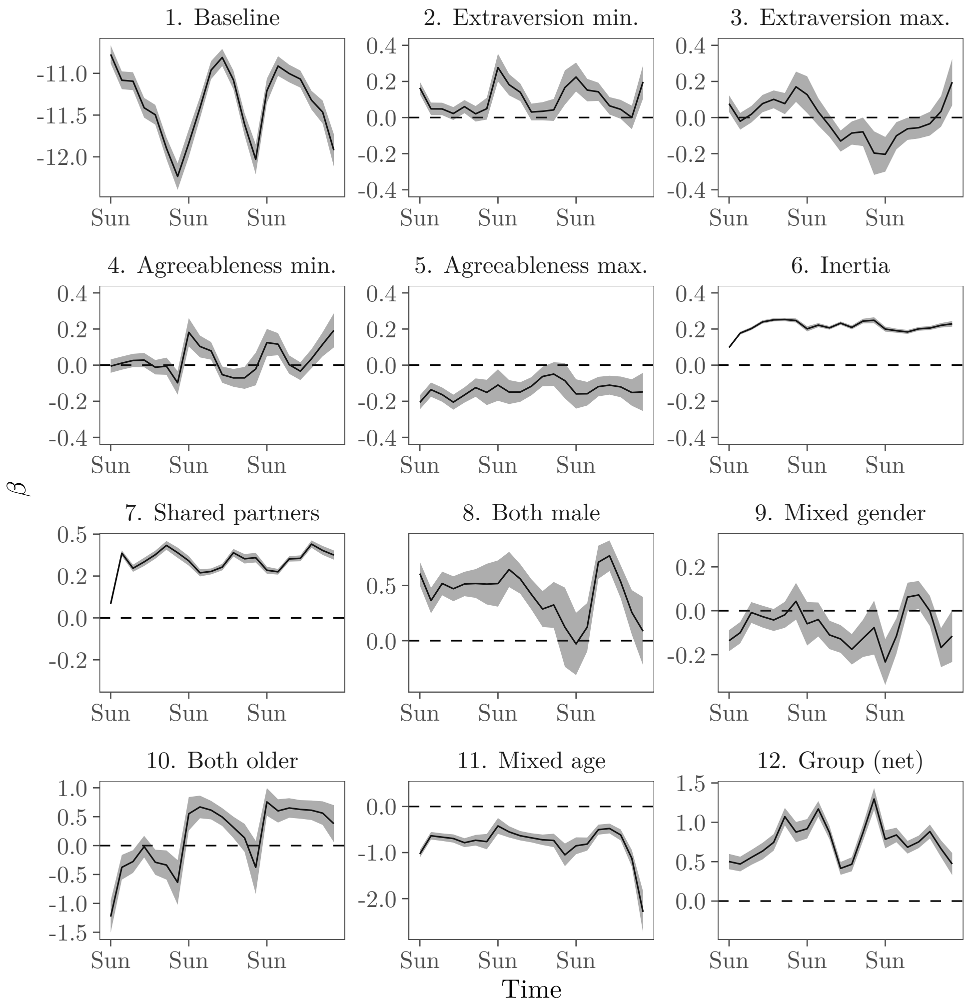

Figure 2.5.: Dynamic effects on the rate of social interaction (Model 3).

2.5 Analysis III: Relational event modeling with event types

In the models to this point, we consolidated the kinds of interaction the students could have into one. However, as outlined in the introduction, an important question associated with how social interaction unfolds over time is how various driving mechanisms affect social interaction across and within different settings. We now show a simple approach to address this question and check whether the variables we have found to drive social interactions between the students might actually have different effects for different kinds of interaction. This is done by including the setting for social interaction as an outcome variable in the analysis. In the CONNECT study, students report whether a given interaction occurred in a leisure or study-related setting. Letting c refer to the relational event type, Equation 2.3 becomes:

$$\log \lambda(s, r, c, t) = \sum_p \beta_p x_p(s, r, c, t) \tag{2.6}$$

Thus, the rate of social interaction for student pair (s, r) in setting c (leisure or work) is regressed on the set of model parameters β_p and statistics x_p.

In the current example analysis, we can assume that every student pair is able to interact in either setting throughout the observation period. It is straightforward to alter the model if this were not the case. At every point in time, there are now $\frac{126 \times 125}{2}$ dyads $\times$ 2 settings = 15750 possible interactions among the 126 students and the two settings.

2.5.1 Model specification

So far, not many studies have included event types to the dependent variable in their relational event modeling approach. Therefore, statistics that account for event types are limited in the literature and theory. In a study into the predictors of interpersonal communication in multi-team systems, Schecter (2017) defined several statistics that account for interaction types. Below, we suggest several statistics that draw some inspiration from Schecter's work.

Study-related setting

We include a dummy $x_{\text{study}}(s, r, c)$ that is 1 if the potential relational event (s, r, c) is in a study-related setting and 0 if it is in a leisure setting. A positive model parameter β_{study} would indicate that student pair (s, r) is more likely to interact in a study-related setting than in a leisure setting.

Setting inertia

An interesting question regarding interaction dynamics is whether student pairs tend to keep interacting within the same setting or whether they tend to switch between settings. In other words: does leisure-based interaction trigger new leisure-based interaction, or does it tend to trigger work-related interaction instead? Therefore, we include an inertia effect that captures the intensity with which student pairs have previously interacted in a specific setting. The statistic for this effect is defined as

$$x_{\text{setting.inertia}}(s, r, c, t) = \sum_{t_e < t \wedge s_e = s \wedge r_e = r \wedge c_e = c} \frac{1}{|A_e| - 1} \cdot \ln(d_e). \tag{2.7}$$

This statistic captures the intensity of all past relational events e between student pairs (s, r) in setting c at time t. The statistic is standardized for each time point t. A positive model parameter $\beta_{\text{setting.inertia}}$ indicates that the more intensely student pairs (s, r) interacted before in setting c, the higher their interaction rates in the future in this setting.

Setting shared partners

When studying interaction across settings, it becomes of interest whether the effects are specific to a particular setting or consistent across all settings. For this purpose, we include a statistic $x_{\text{setting.shared.partners}}(s, r, c, t)$ that is equal to the number of shared interaction partners for students s and r within setting c. The statistic is standardized per time point. If this statistic is included in a model with a shared partners statistic, it captures whether the likelihood for a student pair (s, r) to interact in a specific setting c increases with their past interactions with shared partners in that same setting above whether future interactions rates are driven by their shared partners regardless of the setting. A positive model parameter $\beta_{\text{setting.shared.partners}}$ indicates that shared partners in a specific interaction type stimulate student pairs to interact at higher rates in the future in this same setting.

Interaction effects

Student personality traits may have an effect on their preference to interact in specific settings. Therefore, we include interaction effects between the four personality trait effects and the study-related setting dummy. This allows a researcher to study if and how the effects of students' personality traits differ between the two settings. Interacting the four personality trait effects with the study-related setting dummy results in four interaction effects. A positive model parameter $\beta_{\text{study.}\times\text{.extraversion.min}}$, for example, would indicate that the effect of the minimum bound of extraversion in student pairs increases the tendency to interact in a study-related setting compared to leisure interactions.

2.5.2 Estimation

The script for the moving window REM analysis with event types for the CONNECT data can be found in Appendix A.2.3. We estimate three models (Models 3, 5, and 6), starting with the best model from the previous analyses (Model 3). In subsequent models (Models 5 and 6), we add setting effects as follows:

- Model 3: baseline, personality trait (extraversion and agreeableness), endogenous ("inertia" and "shared partners"), demography (age and gender) and event ("group") effects.
- Model 5: baseline, personality trait (extraversion and agreeableness), endogenous ("inertia" and "shared partners"), demography (age and gender), event ("group"), study-related setting and setting endogenous effects.
- Model 6: baseline, personality trait (extraversion and agreeableness), endogenous ("inertia" and "shared partners"), demography (age and gender), event ("group"), study-related setting, setting endogenous and interaction (stud-related setting with personality traits) effects.

2.5.3 Results

Model selection and goodness-of-fit

Figure 2.6 shows that the three models have very similar BIC values overall. Models 5 and 6 have higher goodness-of-fit than Model 3, with Model 6 not showing real improvement in fit over Model 5. This indicates that there is little evidence for the value of the interaction effects between personality and setting. For all three models the goodness-of-fit remains fairly stable over time, with the fit improving after the first week. This may indicate the existence of some (external) factors that influence freshmen interacting with each other during the first week that are not yet in our model. The generally higher goodness-of-fit for Models 5 and 6 (with setting effects) compared to Model 3 (without setting effects) during the weekdays of the second and third week suggest that the setting effects are especially important in explaining the drivers of social interactions between the freshmen during the weekdays and less during the weekends.

Interpretation

Given that the BIC and goodness-of-fit results suggest an approximately equal fit for Models 5 and 6, we interpret the model parameters for the more parsimonious model of the two, Model 5. Figure 2.7 shows the estimated model parameters along the observation period. We focus our discussion here on the three setting effects that were newly introduced in this section, since the effects of the other variables are virtually identical to the previous model.

From Panel 13 of Figure 2.7 we can see that there is a difference in the baseline tendencies for social interaction in a study-related and leisure setting (controlling for all other effects). During the first week, the students displayed no preference for interacting in one context of the other, but after that there is a clear tendency towards study-related interaction during the week and leisure-related interaction on the weekends. This is in itself not surprising (although students can also get together on weekends to work on class assignments or go on parties or hang-around during the week) and it shows that the relational event model can naturally pick this up. During

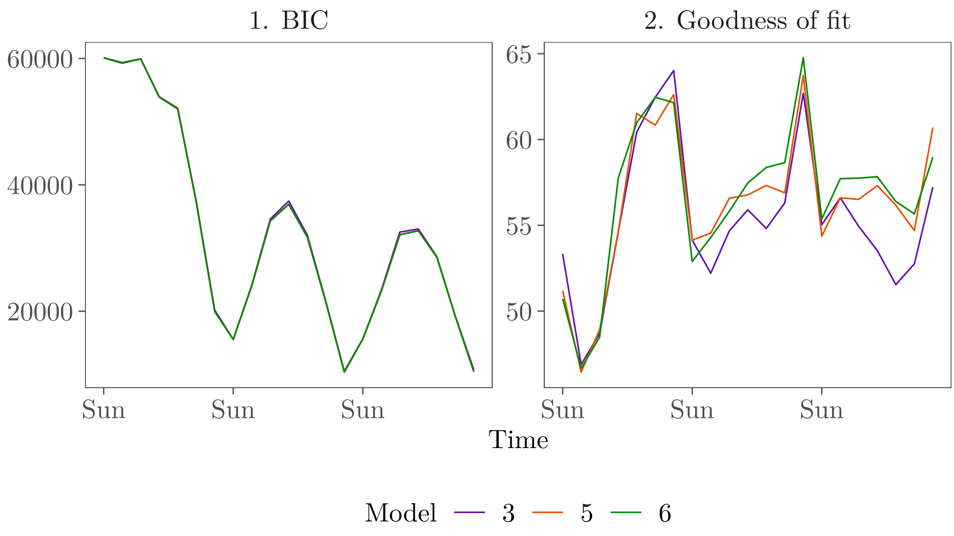

Figure 2.6.: BIC and goodness-of-fit for the three models over time for the moving window REM with event types.

the first week, it is to be expected that students are getting to know each other and switch a lot between study and leisure activities.

Results in Panel 14 of Figure 2.7 show that, after controlling for all other effects, the freshmen display a small preference to repeat interacting in a specific setting, this effect stays consistently positive and small throughout the entire study.

Results in Panels 7 and 15 of Figure 2.7 show that, after controlling for all other effects, student pairs with more shared partners are likely to interact at higher rates in the future than student pairs with fewer shared partners. This effect is enhanced by the setting in which the interactions with these shared partners occurred. Essentially, the more they studied with the same others in the past, the more they tend to study with each other in the future. Similarly, the more students engage in leisure activities with the same others in the past, the more they tend to do the same together in the future. While the shared partners effect suggests a tendency for clusters of students to form within the freshmen student network, the interesting implication is that these clusters appear to form especially within specific interaction contexts. This context-specific clustering seems to disappear during the weekends, because these are strongly leisure-driven for all students.

Together, this extension of the model shows that the dynamics and evolution of interactions among the freshman is affected by the context of the interaction and that the personality traits extraversion and agreeableness do not seem to interact with this.

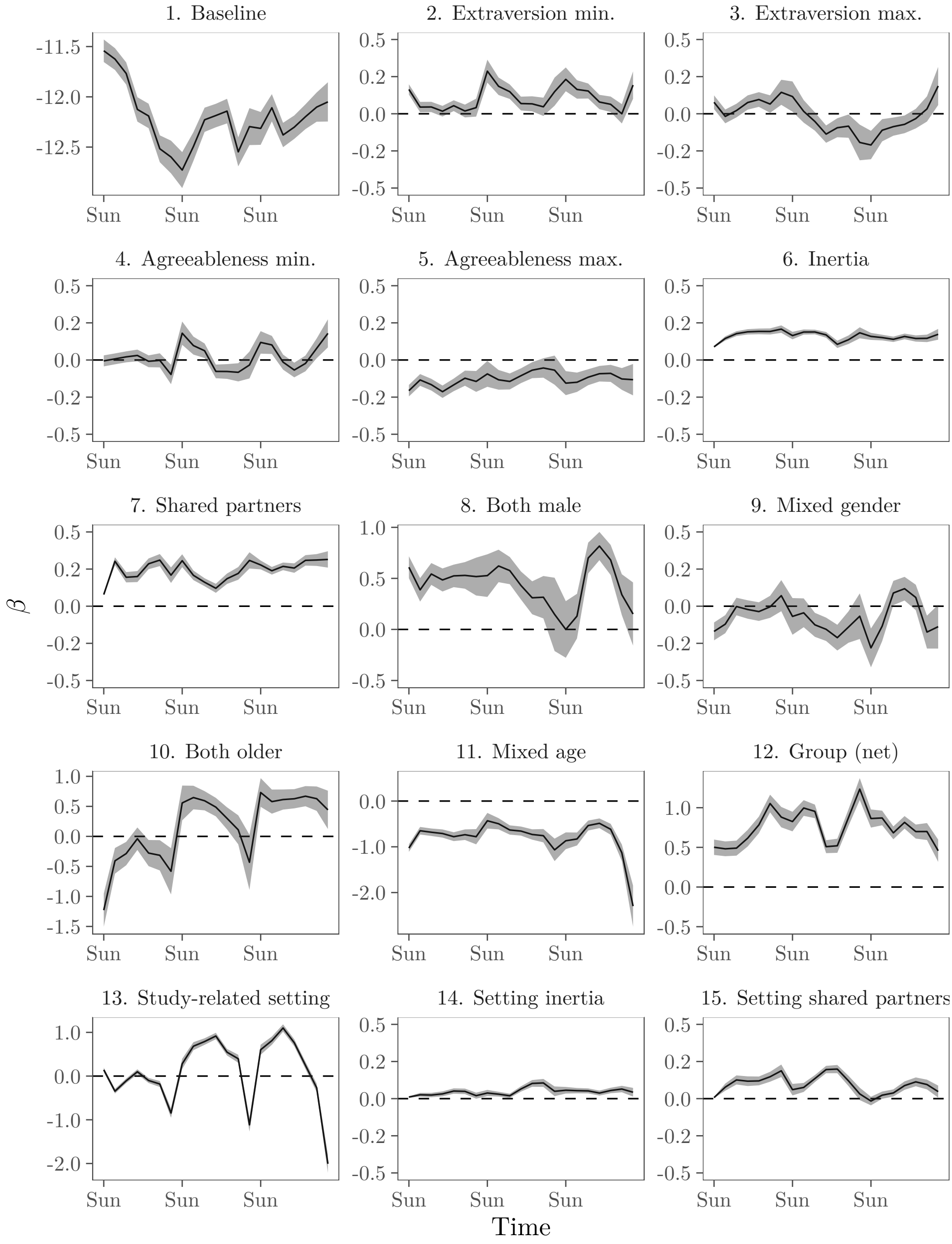

Figure 2.7.: Dynamic effects on the rate of social interaction, considering the setting for interaction (Model 5).

2.6 Discussion

With recent technological advances assisting real-life data assessment, relational event history data becomes increasingly available. This type of data has the potential to provide researchers with fine-grained information on social interaction dynamics and their role in social relationships and personality development (Back, 2021; Back et al., 2011; Bleidorn et al., 2020; Geukes et al., 2019). In this paper, we showed how such fine-grained social interaction information can be fruitfully analyzed making use of the REM modeling framework.

2.6.1 Illustrative REM effects in the CONNECT data

The REM framework was illustrated using an experience-sampling study on social interactions between freshmen students who start interacting at zero acquaintance. A basic REM analysis provided us with insights on how predictors affected the rate of social interactions between these freshmen students on average over the entire observed event sequence. The analysis showed that the rate of social interaction among the freshmen students was influenced by a combination of demographic similarities, students' personality traits, and endogenous effects. Regarding the latter, results underscore the relevance of including the history of social interactions as well as the broader social network (e.g., see Butts, 2008; Kitts & Quintane, 2019; Leenders et al., 2016) when trying to predict the occurrence of dyadic social interactions. Student pairs were more likely to interact in the future if they interacted more with each other in the past and if they had more past interaction partners in common. Results also point at the relevance of socio-demographic differences even within a highly selective and homogeneous sample of psychology students. Similarity in gender and age predicted the propensity to interact. Regarding the personality effects, results are in line with previously shown robust effects for extraversion (extraverts interact more) and more nuanced findings for agreeableness (e.g., see Back, 2021; Back & Vazire, 2015, for overviews). While agreeableness relates to better relationship quality (e.g., Asendorpf & Wilpers, 1998), it does not necessarily relate to a higher amount of social interaction. As shown in the present illustrative analyses, it can even go along with fewer social interactions. The REM allowed to investigate these basic effects of socio-demographic and personality within a joint framework, thereby controlling for the role of endogenous social interaction history effects and directly considering the timing of interaction events.

An extension of the basic REM framework with the moving window approach (Mulder & Leenders, 2019) allowed us to study how the role of predictors of the rate of social interaction changed over time. This is especially useful in situations where it is not realistic to assume that what drives social interaction is stable for the entire observed event sequence or when one is specifically interested in studying how the dynamics of social interactions unfold and change over time. This may not always be the case in lab-based studies, but this experience-sampling example study covered a three-week period, which allows a researcher to study dynamics over an extended period of time and uncover how effects emerge, disappear, or show a rhythm (such as the weekend effect, where interactions were governed by other dynamics than weekday interaction). By applying the moving-window REM in a second example analysis, we found that personality trait effects changed after one week of becoming acquainted with each other. The effects of extraversion and agreeableness on the rate of social interaction operated differently between working days and weekends, which was a stable pattern across the study period. Similarly, socio-demographic effects on the rate of social interaction changed after freshmen became more acquainted and results suggested a trend in which these effects operated differently between working days and weekends. However, this is only an example analysis and more research is warranted to study further details of these trends and whether they continue after the third week of acquaintance. Results from our study also showed that the tendency to repeat past behavior ("inertia") as well as the tendency to prefer interact with those with whom one many past communication partners in common ("shared partners") developed already in the early stages of acquaintance and remained relatively stable as acquaintance developed.

Social interactions are not only characterized by the time at which they occur and who is involved but also by other important features, that is, the sentiment, mode of communication, setting for interaction, and so forth. The REM framework allows us to differentiate between types of events to study what drives social interactions of different type and how they dynamically affect each other over time. For example, two important settings for social interactions between freshmen students are a study-related setting and a leisure setting. By differentiating between these settings in our exemplary study in a third analysis, we found that freshmen students have a tendency to interact more within a setting if they have interacted more intensively in the past within this setting. This tendency was small, but constant over time. Moreover, findings indicate that clusters of interacting students tended to form within a setting.

The current exemplary application of the REM approach to study real-life social interactions was limited to one specific relationship type, age-group and cultural context (peer-relations among fellow students in Germany) and to an illustrative analysis of selected person- and context-level predictors. The REM approach we outlined, is, however, extremely flexible and can be used to examine all sorts of social interaction dynamics including social interactions with friends, colleagues and clients, family members, team members, and romantic partners in both early and later stages of relationship development. In doing so, future research should test and explore the role of a range of further individual (e.g., attachment styles, leisure preferences, values) and contextual characteristics (e.g., face-to-face versus computer-mediated interaction).

2.6.2 Statistical considerations

Since the goal of the current paper was to provide an introduction into relational event modeling for psychology researchers, we had to make choices about the complexity of the analyses. Therefore, we choose a relatively simple solution to deal with group interactions. In this solution, all actors in an observed group were combined into all possible pairs. Since the goodness of fit results showed a remarkable recovery rate of about 55%, we are confident that this solution works well for the current data set. It should be noted, however, that other solutions exist that may be more appropriate in the case of modeling relational event history data with group events, see for example (Hoffman et al., 2020) or (Lerner et al., 2019). These approaches make different assumptions about how groups come to their existence. In Hoffman et al. (2020) actors join and leave groups one for one, while in Lerner et al. (2019) groups exists as entities that can also interact with each other.

Current studies in the literature that apply the relational event model mostly focus on directed relational events. Our exemplary analyses of the CONNECT data showcase that the flexibility of the REM framework is not limited to directed events, but can also handle undirected events. This is important because relational event histories with undirected events are commonly observed. For example, in recent years, wearable sensors are developed that allow the automated data collection of undirected face-to-face contacts (Cattuto et al., 2010; Olguín et al., 2009). Note, however, that the statistics that we used to summarize the embedding of the student pairs into the larger network are only a sample of the wide range of statistics that are available, especially for directed events (e.g., degree statistics, reciprocity, etc.).

Throughout our analyses, we showcased some aspects of the flexibility of the REM framework to incorporate past events. In typical relational event models, it is assumed that all past events are equally influencing the probability of next events. Some studies have relaxed this assumption. For example, it is reasonable to expect that the influence of past events decreases as time goes by, giving a higher weight to more recent events (Brandes et al., 2009; Mulder & Leenders, 2019). In our analyses with the Moving Window approach, we captured the decrease in the importance of events over time by including only the most recent events in the endogenous predictors. Other factors may influence the weight of past events as well. For example, the events in the CONNECT data differed in duration and number of actors involved, two factors that are likely to influence how important an event is for predicting future events. Therefore, we defined a detailed inertia measure that accounts for these factors. In doing so, we deviated from the more conventional measure of inertia that counts the number of past events for a student pair (i, j) in the risk set at time t, weighing each event equally. Table A.1 in Appendix A.1 shows the results of additional analyses in which we compare our measure of inertia to a more conventional measure. These results indicate that our weighted inertia measure outperforms the conventional measure in terms of model fit and prediction performance. These conclusions encourage future research into how the influence of past events is best integrated in, for example, an inertia statistic.

2.6.3 Neighboring approaches

Depending on the nature of the research question and the structure of the available data, a number of related statistical approaches may be appropriate for the data analysis. Current statistical approaches that are used in psychological research for the analysis of longitudinal social interaction (network) data (e.g., see Nestler et al., 2015, for overview) include the social relations model (SRM; Kenny & La Voie, 1984), continuous-time models (Voelkle et al., 2012), (separable) temporal exponential random graph models ((S)TERGMs; Hanneke et al., 2010; Krivitsky & Handcock, 2014; Lusher et al., 2013; Robins & Pattison, 2001) and stochastic actor-oriented models (SAOMs or SIENA models; Snijders et al., 2010). In comparison, relational event models (a) can take into account quite complex higher-order network dependencies, and (b) are especially suited for longitudinal social interaction data observed on a fine-grained time scale (e.g., with real-time timestamps). Most of the alternative models are best suited to analyze network dependencies that do not go beyond the dyad and/or work best with panel data (in which social network data is collected at multiple time points). While (S)TERGMs and SAOMs allow accounting for network dependencies in a way that is similar to relational event models, they would require the continuous-time data to be aggregated to a set of repeated networks; this creates artificial network observations and disposes of information on the time and order of the events in the aggregated sequences. Consequently, all information about social interaction dynamics is disregarded in the analysis. Instead, relational event models enable researchers to study how the history of interaction influences the probability for future social interaction, thereby continuously updating the past. Thus, when we have continuous-time interaction data (or interaction data in which the order of relational events is known), relational event models allows the researcher to perform the most detailed analysis, utilizing the full information available inside the data.[3]

Whereas the REM parameterizes the rate of interaction for a dyad, it is also possible to separate the dyadic activity by, first, modeling *who* is going to be the sender of the next relational event (including *when* the event is going to take place) and then, second, select who is going to be the receiver, *given who the sender is*. This approach is called the dynamic network actor model (DyNAM) (Stadtfeld et al., 2017a; Stadtfeld & Block, 2017). The DyNAM framework is in many aspects similar to the REM framework, with the difference that it models social interaction in a two-step approach. Since the two modeling steps are conditionally independent, two sets of model parameters can be estimated for the two different models. The DyNAM focuses on who is a likely receiver for a given sender, weighting every potential event relative to the other available choices for the active individual (Stadtfeld & Block, 2017). Alternatively, the REM focuses on which event of all possible events is likely to occur next, weighting each potential event relative to all possible events (Stadtfeld & Block, 2017). Hence, statistically, the differences between these two major statistical frameworks for modeling relational event history data result in a somewhat different interpretation of the estimated model parameters. Substantively, the DyNAM considers interactions to be driven by the sender, whereas the REM considers interactions to be driven by both parties involved alike. Both models can be setup to yield similar results to the other model, although some types of interaction and some drivers of interaction fit more naturally with one approach or the other. In this paper, we presented how the REM can be used to study how interaction develops among a new group of students. However, note that many of the ideas and approaches in this paper can also be used if a DyNAM model is chosen.

[3] For a detailed overview of the differences between the REM, (S)TERGMs and SAOMs, we refer the interested reader to Quintane et al. (2014).

2.6.4 Conclusions

This paper provided an introduction to the REM framework for quantitative psychological researchers who are interested in social interaction dynamics. Relational event modeling is currently an active field of study, constantly increasing its significance for the study of social interactions across research domains. With the tools provided in this paper, we hope that we can stimulate the application of the REM framework within diverse fields of psychological research to help developing a more precise and fine-grained understanding of social interaction dynamics and how they evolve in continuous time. Most of the well-developed and influential theories of human and interpersonal behavior are quiet about the speed by which effects occur. Similarly, they tend not to inform a researcher about how they develop (suddenly, gradually, perhaps plateauing along the way?), about how long effects are likely to last, of about how they wane (suddenly, slowly, etc.). Also, little is known whether the effect of one driver of interpersonal behavior occurs faster than another (let alone how much faster). Approaches like the relational event model enable researchers to get a better idea of these things. This allows us to further develop and refine existing theories and develop new ones, being informed by the type of empirical findings these models can provide. Considering that the world is not a static place and very few drivers of (interpersonal) behavior can be expected to kick in immediately and last indefinitely, we believe that much academic progress can be made by studying the temporal development/behavior of effects. Of course, researchers do not always have access to ordered or time-stamped interaction data, but technological developments do assist in making such data increasingly available. In this case, we believe that statistical models like the relational event model, provide researchers with the tools to achieve important theoretical and empirical progress in their quest to further understand our changing world.

3

Dynamic relational event modeling: Testing, exploring, and applying

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Abstract

The relational event model (REM) facilitates the study of network evolution in relational event history data, i.e., time-ordered sequences of social interactions. In real-life social networks it is likely that network effects, i.e., the parameters that quantify the relative importance of drivers of these social interaction sequences, change over time. In these networks, the basic REM is not appropriate to understand what drives network evolution. This research extends the REM framework with approaches for testing and exploring time-varying network effects. First, we develop a Bayesian approach to test whether network effects change during the study period. We conduct a simulation study that illustrates that the Bayesian test accurately quantifies the evidence between a basic ('static') REM or a dynamic REM. Secondly, in the case of the latter, time-varying network effects can be studied by means of a moving window that slides over the relational event history. A simulation study was conducted that illustrates that the accuracy and precision of the estimates depend on the window width: narrower windows result in greater accuracy at the cost of lower precision. Third, we develop a Bayesian approach for determining window widths using the empirical network data and conduct a simulation study that illustrates that estimation with empirically determined window widths achieves both good accuracy for time intervals with important changes and good precision for time intervals with hardly any changes in the effects. Finally, in an empirical application, we illustrate how the approaches in this research can be used to test for and explore time-varying network effects of face-to-face contacts at the workplace.

3.1 Introduction

Relational event history data consist of time-ordered sequences of events between individuals (Butts, 2008). For example, the relational event history in Table 3.1 consists of face-to-face contacts between employees in the workplace (Génois & Barrat, 2018). For each event in the relational event history we observe the time point and the individuals who are involved. Since relational event history data capture the timing and sequencing of social interactions on a fine-grained timescale, this type of data contain detailed information that helps us learn about interaction dynamics in social networks. The relational event model (REM; Butts, 2008) analyzes relational event history data in a direct manner without needing to aggregate over observational periods. The REM is therefore especially suited to study the drivers of the development of social interaction over time.

The REM models both *when* a social interaction occurs and *who* will be involved as a function of endogenous and exogenous variables. Temporal dependencies between the events in the relational event history can be introduced into the model by including endogenous variables that refer to characteristics of the past history of events (Butts, 2008). For example, triadic closure (Robins, 2013) is an endogenous driving mechanism of social interaction in which individuals are more likely to start an interaction with another individual if they have more past interaction partners in common, i.e., "friends of friends become friends" (Pilny et al., 2016). Exogenous variables refer to any factor outside the history of events that influences social interaction occurrence. For example, homophily, where individuals interact more with others with whom they share one or more individual attributes, such as sex or age, is a well-documented tendency for many social networks (Robins, 2013; Snijders & Lomi, 2019). In sum, the REM enables a researcher to study to what extent a combination of endogenous and exogenous variables drive the occurrence, rhythm, and speed of individuals interacting with each other over time.

An important assumption of the basic REM is that the effects on social interaction occurrence are constant over the study period. It is, however, often more plausible that effects change over time. Throughout this paper, we will refer to REM parameters that may change over time as "dynamic," "temporal," or "time-varying." In several articles, the importance of evaluating the assumption of constant effects in REM's has been emphasized (e.g., Amati et al., 2019; Leenders et al., 2016; Pilny et al., 2016). First, because the REM assumes that the effects act homogeneously over the course of the observed relational event history, the resulting parameter estimates average away any variation that may be present. Application of a basic REM may thus mask variation of effects over time and inferences drawn on the resulting parameter estimates may be erroneous as a result. Second, time-varying parameters may be intrinsically interesting. Insights in how effects change over time has the potential to progress the understanding of social interaction dynamics.

Studies that relax the assumption that effects are constant over the study period have indeed found evidence for time-varying effects. For example, Amati et al. (2019) propose to estimate separate models in which the dependent variable is segregated in discrete time-intervals of interest. In an empirical analysis of the drivers of patient referrals

Table 3.1.: The first 10 events from a relational event history with face-to-face contacts between employees in the workplace.

Time	Employee 1	Employee 2
08:00:40	0574	1362
08:00:40	0164	0779
08:01:00	0447	0763
08:01:00	0117	0429
08:01:40	0215	1414
08:01:40	0097	1204
08:01:40	0461	1245
08:01:40	0020	1209
08:01:40	0015	0020
08:02:00	0020	0985

between hospitals, the authors expected daily variations in the effects. Therefore, they estimated seven separate models, one for each day of the week. Results confirmed that drivers of patient referrals between hospitals operated differently for different days of the week.

The approach of Amati et al. (2019) is especially suited when time-specific variation of the effects can be expected beforehand based on theory. Unfortunately, since time is only limited accounted for in current social network theories (Leenders et al., 2016), it can be challenging to form theoretically informed hypotheses on time-specific variations in the effects. Moreover, effects in relational event history data may develop irregularly or more smoothly over time. If this is the case, it becomes infeasible to estimate separate models for different time periods. Hence, an approach that does not put any constraints on the development of effects could assist to explore how effects in REMs change over time.

The approach of Vu et al. (2011) allows for time-varying regression coefficients in REMs. On synthetic data, the authors illustrated that their model was able to accurately recover both underlying true fixed and time-varying model coefficients. Furthermore, Vu et al. (2011) compared the predictive power of a model with time-varying coefficients (the additive Aalen model) and a model with fixed coefficients (the multiplicative Cox model). Results from their prediction experiment on an empirical data set showed that the additive Aalen model significantly outperformed the multiplicative Cox model. These findings further illustrate the importance of testing and accounting for temporal dynamics of the effects in the analysis of empirical relational event history data.

A limitation of the additive Aalen model of Vu et al. (2011) for practical use is that the form of the model does not prevent against hazard functions that are estimated to be negative, which are not defined in practice. The moving window approach of Mulder and Leenders (2019) for estimating time-varying effects does not have this problem. In this extension of the REM, a moving window slides over the observed relational event history and provides a picture of how the drivers of social interaction develop over time. Mulder and Leenders (2019) show in an empirical analysis how the moving window approach can be used to uncover new insights about interaction dynamics. For example, results showed that homophily effects on the probability that employees send each other emails about innovation changed gradually over the course of a year.

The current paper develops an extension of the REM for testing and exploring time-varying effects in relational event history data. First, because of the importance of dynamic network effects, we propose a Bayesian method that tests whether network effects change over time. Such a test is currently missing in the literature. Second, because it is usually not known a priori how well a moving window REM is able to find dynamic network trends, we conduct a simulation study to investigate the accuracy and precision of the methodology. Third, because most theories of social network behavior do not inform researchers on how network effects may vary over time, we propose a data-driven moving window to appropriately balance between accuracy and precision of the moving window REM. Finally, we illustrate the proposed methods in an analysis of the drivers of face-to-face contacts between employees in a workplace (Génois & Barrat, 2018).

The remainder of this paper is structured as follows. First, we provide a general introduction to the basic REM and describes an extension with time-varying network effects. Subsequently, we introduce a Bayesian approach for testing for dynamic network effects. A simulation study is conducted to evaluate the ability of the test to distinguish between static and dynamic network effects. Next, we introduce the moving window REM, with pre-specified window widths and empirically determined window widths. A simulation study is conducted to study how well the approaches can recover the underlying true time-varying parameters. Subsequently, we describe the methods and results for the illustrative empirical analysis. Finall

3.2 A REM with time-varying network effects

At each observed time point t of the relational event history, the observed sender-receiver pair (s, r) is one out of a set of sender-receiver pairs that can potentially interact. We refer to the set of sender-receiver pairs (s, r) that can potentially interact at time t as the *risk set*, $\mathcal{R}(t)$. When every actor can be both sender or receiver of the relational events and self-to-self events are excluded, the risk set consists of $N \times (N-1)$ sender-receiver pairs that can potentially interact, with N referring to the total number of actors in the network.

Each sender-receiver pair (s, r) in the risk set $\mathcal{R}(t)$ occurs with its own rate in the observed event history. We refer to this rate of occurrence at time t for sender-receiver pair (s, r) as the event rate, $\lambda(s, r, t)$. In the REM (Butts, 2008), the event rate is modeled as a log-linear function of endogenous and exogenous variables:

$$\log \lambda(s, r, t) = \sum_{p=1}^{P} \theta_p X_p(s, r, t). \tag{3.1}$$

Here, $X_p(s, r, t)$ refers to statistic $p = 1, \ldots, P$ for the actor pair (s, r) at time t and θ_p refers to the model parameter related to statistic X_p. The statistics $X_p(s, r, t)$ are numerical representations of the endogenous and exogenous variables in the model.

The event rate determines both the waiting time until the next event and which pair (s, r) is most likely to occur next. Following (Butts, 2008), the waiting time Δt until the next event is assumed to follow an exponential distribution:

$$\Delta t \sim \text{Exp}\left(\sum_{(s,r)\in\mathcal{R}(t)} \lambda(s, r, t)\right). \tag{3.2}$$

The probability to observe the pair (s, r) next at time t follows from the categorical distribution:

$$P\big((s, r)|t\big) = \frac{\lambda(s, r, t)}{\sum_{(s,r)\in\mathcal{R}(t)} \lambda(s, r, t)}. \tag{3.3}$$

Throughout this paper, we consider a REM with dynamic network effects where the rate parameter is defined by:

$$\begin{aligned}
\log \lambda(s, r, t) = {} & \theta_{\text{baseline}}(t) X_{\text{baseline}}(s, r, t) + \\
& \theta_{\text{Z.of.sender}}(t) X_{\text{Z.of.sender}}(s, r, t) + \\
& \theta_{\text{difference.in.Z}}(t) X_{\text{difference.in.Z}}(s, r, t) + \\
& \theta_{\text{activity}}(t) X_{\text{activity}}(s, r, t) + \\
& \theta_{\text{inertia}}(t) X_{\text{inertia}}(s, r, t) + \\
& \theta_{\text{transitivity}}(t) X_{\text{transitivity}}(s, r, t)
\end{aligned} \tag{3.4}$$

Here, $X_{\text{baseline}}(s, r, t) = 1$ (i.e., an intercept), $X_{\text{Z.of.sender}}(s, r, t)$ is equal to the value of exogenous variable Z of sender s, $Z \sim \mathcal{N}(0, 1)$, $X_{\text{difference.in.Z}}(s, r, t)$ is equal to the absolute difference between the value of Z of sender s and receiver r, $X_{\text{activity}}(s, r, t)$ is equal to the standardized outdegree of sender s at time t, $X_{\text{inertia}}(s, r, t)$ is equal to the standardized number of past events sent by sender s to receiver r at time t, and $X_{\text{transitivity}}(s, r, t)$ is equal to the standardized number of past outgoing two-paths between sender s and receiver r at time t. The corresponding model parameters are referred to by θ and may vary over time.

We define the following four scenarios with time-varying parameters:

1. *Constant effects*; in this scenario we assume that the effects of the statistics on the relational event history are constant over time (i.e., they do not change). The corresponding model parameters $\boldsymbol{\theta}$ can be found in Table 3.2 and are visualized in Figure 3.1.

2. *Cyclic change*; in this scenario we assume cyclic changes in the effects of the predictors on the relational event history over time. Here, we focus on the cases in which cyclic patterns of change in the data are not necessarily expected beforehand, but are to be detected from the data. Alternatively, when time-specific variation (e.g., weekdays versus weekend days or daytime versus nighttime) can

Table 3.2.: Information on the model parameters in the four scenarios for time-varying effects.

	Constant	Cyclic		Gradual		Mixed
Effect	θ	a	b	c	d	Change
Baseline	-8.00	0.50	-8.00	1.00	-8.50	Cyclic
Z of sender	0.20	0.10	0.20	0.20	0.10	Constant
Difference in Z	-0.20	0.10	-0.20	0.20	-0.30	Constant
Activity of sender	0.10	0.05	0.10	0.10	0.05	Cyclic
Inertia	0.10	0.05	0.10	0.10	0.05	Gradual
Transitivity	0.20	0.10	0.20	0.20	0.10	Gradual

be expected to induce cyclic patterns in the effects of interest, these can be studied with the approach of (Amati et al., 2019). To let the model parameters change cyclically over time, we use the following sine functions:

$$a \sin\left(\frac{2\pi}{10000}t\right) - b. \tag{3.5}$$

The values for a and b per predictor can be found in Table 3.2, the resulting model parameters $\boldsymbol{\theta}$ are visualized in Figure 3.1.

3. *Gradual change*: in this scenario we assume that the effects of the predictors on the relational event history change gradually over time until they stabilize at a "new normal." To let the model parameters change gradually over time we use the following logistic function:

$$\frac{c}{1 + \exp\left[-0.001(t - 12500)\right]} + d \tag{3.6}$$

The values for c and d per predictor can be found in Table 3.2, the resulting model parameters $\boldsymbol{\theta}$ are visualized in Figure 3.1.

4. *Mixed change*: in this scenario we assume that some effects of the predictors on the relational event history stay constant over time, others change cyclically and the remaining effects change gradually. Table 3.2 shows per predictor the type of change for this scenario in which how the effects change over time is mixed.

These four scenarios for time-varying parameters were chosen to include a baseline scenario with no changes in the effects (constant effects), two scenarios in which effects change over time in a realistic way that may be encountered in empirically collected relational event history data (cyclic and gradual effects) and a scenario in which not every effect changes over time in the same manner (mixed effects). We assume that these four scenarios provide a thorough evaluation of the ability of the methods to capture a diversity of ways in which effects in a REM can vary over time.

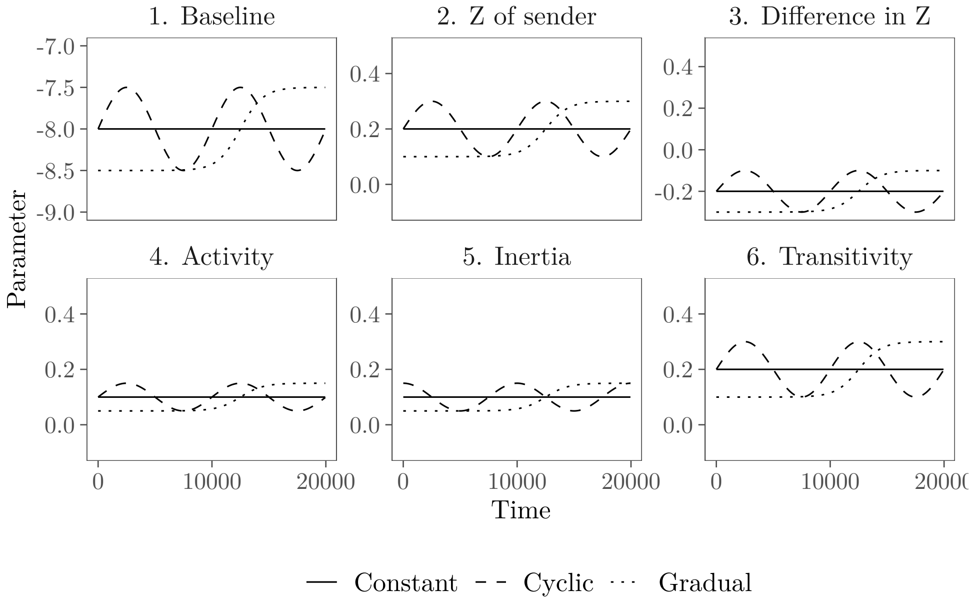

Figure 3.1.: Parameters in the four scenarios for time-varying effects. Solid lines show the parameters for the constant effects in the 'constant' and 'mixed' effects scenarios, dashed lines show the parameters for the cyclically changing effects in the 'cyclic' and 'mixed' effects scenarios, and dotted lines show the parameters for the gradually changing effects in the 'gradual' and 'mixed' effects scenarios.

For each of these four scenarios, we generate 200 relational event histories with $M = 10000$ events for a network with $N = 20$ actors. Sampling of the events starts at $t = 0$ and continues until 10000 events are reached. At a given time t, we sample the waiting time Δt until the next event from Equation 3.2 and the next observed dyad (s, r) from Equation 3.3. The script files to generate the data and reproduce the analyses performed in this article can be found at https://github.com/mlmeijerink/REHdynamics.

3.3 Testing for time-varying network effects

The first step in an empirical analysis of temporal network data is to test whether it is likely that the effects that drive the interaction between the actors can be assumed constant over the observation period. For this purpose, we formulate two competing hypotheses:

$$H_{\text{static}} : \text{network effects are static} \tag{3.7}$$

versus

$$H_{\text{dynamic}} : \text{network effects are dynamic.} \tag{3.8}$$

To evaluate the support in the data for these two competing hypotheses, we divide the observed relational event history into K sub-sequences that are evenly spaced in time, see Figure 3.2. For example, let τ define the time of the end of the observation period. Than, for $K = 2$, we obtain two sequences, one with the events observed in the time interval $[0, \frac{\tau}{2}]$, and one with the events observed in the time interval $(\frac{\tau}{2}, \tau]$, see Figure 3.2, upper panel. Subsequently, for each sub-sequence $k = 1, \ldots, K$, the vector with model parameters $\boldsymbol{\theta}_k$ is estimated. The hypotheses in Equation 3.7 and Equation 3.8 can now be re-written as

$$H_{\text{static}} : \boldsymbol{\theta}_1 = \cdots = \boldsymbol{\theta}_k = \cdots = \boldsymbol{\theta}_K \tag{3.9}$$

versus

$$H_{\text{dynamic}} : \text{not } H_{\text{static}}. \tag{3.10}$$

We propose to compute Bayes factor (Jeffreys, 1961; Kass & Raftery, 1995) for the evaluation of the two competing hypotheses in Equation 3.9 and Equation 3.10. In contrast to null hypothesis significance testing, the objective of hypothesis evaluation using Bayes factor is not to arrive at a dichotomous decision on whether a hypothesis is rejected or not, but to determine the probability of the data under one hypothesis versus another hypothesis (Hoijtink, Mulder, et al., 2019). For example, a Bayes factor of 10 for the comparison of H_{static} against H_{dynamic} indicates that there is 10 times more statistical evidence in the data for the hypothesis that effects are static compared to the hypothesis that effects are dynamic.

Due to prior sensitivity of Bayes factor, we propose to use the multiple population adjusted approximate fractional Bayes factor (from now on abbreviated to BF), which can be computed in an automatic fashion without having to formulate any substantive prior beliefs (Gu et al., 2018; Hoijtink, Gu, & Mulder, 2019; Mulder, 2014; O'Hagan, 1995). The BF uses a fraction b_k of the information in the likelihood for each sub-sequence k to construct an implicit default prior (Hoijtink, Gu, & Mulder, 2019; O'Hagan, 1995). We follow the recommendation in Hoijtink, Gu, & Mulder (2019), and choose

$$b_k = \frac{1}{K} \times J^* \times \frac{1}{N_k}, \tag{3.11}$$

where J^* refers to the number of independent constraints in H_{static} (i.e., $J^* = K - 1$), and N_k denotes the number of events in sub-sequence k. From Hoijtink, Gu, & Mulder (2019), it follows that the relative support in the data for H_{static} and H_{dynamic} can be quantified using:

$$\text{BF} = \frac{\int_{\theta \in H_{\text{static}}} \mathcal{N}(\boldsymbol{\theta} | \hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}}) d\boldsymbol{\theta}}{\int_{\theta \in H_{\text{static}}} \mathcal{N}(\boldsymbol{\theta} | \boldsymbol{\theta}_B, \hat{\boldsymbol{\Sigma}}^{\boldsymbol{b}}_{\boldsymbol{\theta}}) d\boldsymbol{\theta}}, \tag{3.12}$$

that is the ratio of the fit and the complexity of H_{static} relative to H_{dynamic}. Here, $\boldsymbol{\theta} = [\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_k, \ldots, \boldsymbol{\theta}_K]$, $\hat{\boldsymbol{\theta}}$ denotes the maximum likelihood estimate of $\boldsymbol{\theta}$, $\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}}$ denotes the corresponding co-variance matrix, $\boldsymbol{\theta}_B$ is the adjusted mean of the prior distribution, here, 0, i.e., a value of $\boldsymbol{\theta}$ on the boundary of all hypotheses under investigation (Mulder, 2014), and $\hat{\boldsymbol{\Sigma}}^{\boldsymbol{b}}_{\boldsymbol{\theta}}$ denotes the covariance matrix of the prior distribution of $\boldsymbol{\theta}$, which is

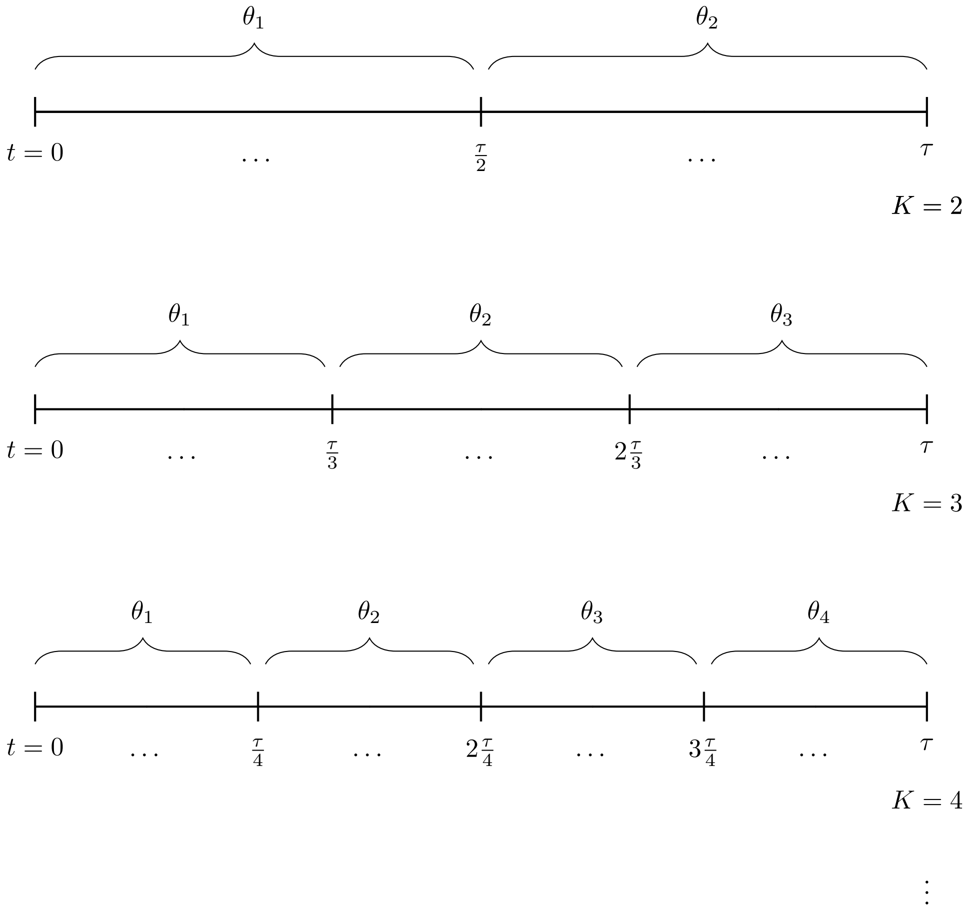

Figure 3.2.: Illustration of the procedure behind the Bayesian test for time-varying network effects in relational event history data. The observed relational event history is divided into K sub-sequences that are evenly spaced in time. For each sub-sequence $k = 1, \ldots, K$ the vector of model parameters θ_k is estimated. The statistical evidence in the data for $H_{\text{static}} : \theta_1 = \cdots = \theta_K$ versus H_{dynamic} : not H_{static} is evaluated by means of the BF.

based on a fraction $\boldsymbol{b}$ of the information in the data, where $\boldsymbol{b} = [b_1, \ldots, b_k, \ldots, b_K]$. Maximum likelihood estimates $\hat{\boldsymbol{\theta}}_k$, and, for each sub-sequence k, corresponding covariance matrix $\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}_k}$, are easily obtained from R software packages tailored for relational event modeling, and $\hat{\boldsymbol{\Sigma}}^{b_k}_{\boldsymbol{\theta}_k}$ is computed as $\frac{\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}_k}}{b_k}$. The BF factor shows consistent behavior, which implies that the evidence for the true hypothesis will increase to infinity as the sample size grows (Kass & Raftery, 1995; Hoijtink, Gu, & Mulder, 2019).

We recommend to compute the BF for increasing K from 2 to 10 (or more in the case of unclear results). By considering multiple values for K, we get insights into the time scale of the dynamic behavior of the network effects. Further, note that as K increases, the number of parameters under H_{dynamic} increases and thus the evidence for H_{static} will increase if the data suggest that the static REM fits bests.

In order to evaluate the ability of the proposed Bayesian test to prefer the true model (H_{static} or H_{dynamic}), we conduct a simulation study. We compute the BF factor for the evaluation of H_{static} versus H_{dynamic} with $K = 2, \ldots 10$ for the 200 generated relational event histories in the four time-varying effects scenarios. Results in Figure 3.3 show the mean log BF and its 95% sampling distribution across the increasing values of K. If the log BF is larger than zero, this implies most evidence in the data for H_{static}. If the log BF is smaller than zero, most evidence in the data is in favor of H_{dynamic}.

The upper left panel in Figure 3.3 shows that in the 'constant' effects scenario, the evidence is on average largest for the static hypothesis. In fact, the log BF is in favor of the true model (H_{static}) for all $K = 2, \ldots, 10$ in all 200 generated data sets, i.e., in all data sets the results of the test indicate that the relational event history can be best analyzed with a static REM. These results are what is wanted because the effects in the relational event histories don't change over time in this scenario. Furthermore, the results show that the evidence increases with increasing K. This shows that the BF functions as an Occam's razor that penalizes larger models. Results in the other panels of Figure 3.3 are indicative of time-varying parameters: for almost all K (except $K = 2$ and $K = 3$ in the "cyclic" scenario) the evidence in the data is largest for H_{dynamic}. These results are what one wants, because these three scenarios include time-varying parameters. Hence, based on these results, the proposed Bayesian test for time-varying parameters seems to be able to accurately distinguish between data with static and dynamic effects and to provide guidance as to whether the relational event history can best be analyzed with a static REM or whether a more dynamic approach is required.

3.4 Exploring time-varying network effects

3.4.1 Moving window REM

A few studies have explored time-varying network effects in relational event history data by fitting the model on different observational periods (Amati et al., 2019; Mulder & Leenders, 2019; Pilny et al., 2017). Here, we propose to use a moving window REM for exploring time-varying network effects. Algorithm 1 describes the steps in fitting a moving window REM. In summary, a REM is fitted on the sub-sequence of

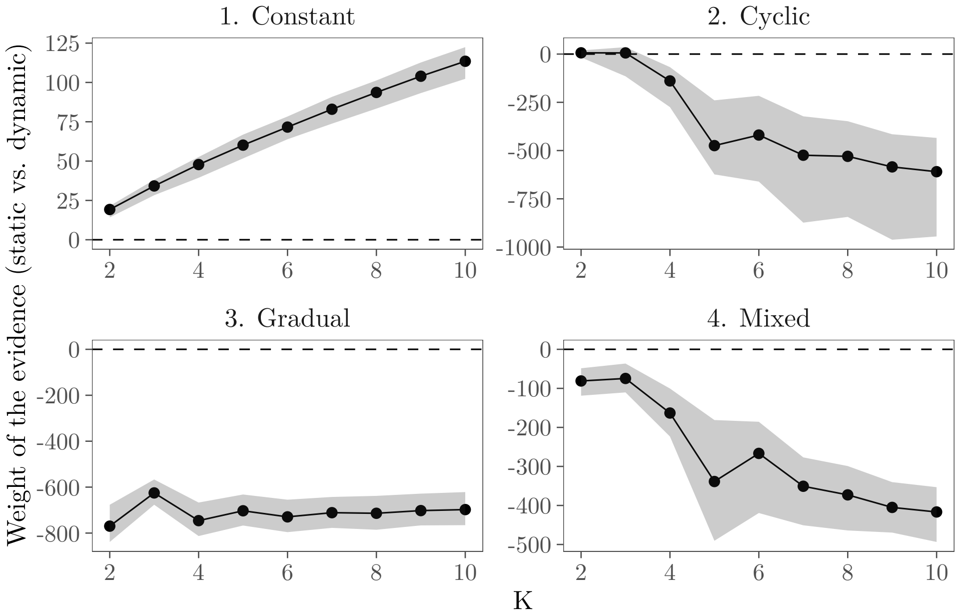

Figure 3.3.: Results for the numerical evaluation of the Bayesian test for time-varying parameters. The y-axis shows the size of the log BF, i.e., the weight of the evidence for the static hypothesis versus the dynamic hypothesis. Black dots and solid lines show per effect scenario the mean log BF with increasing K. The gray area shows the 95% sampling distribution of the log BF.

events that fall within a pre-specified time-interval or 'window.' By sliding this window over the relational event sequence and estimating the REM for each corresponding sub-sequence of events, a view of the trend in the parameter estimates over time is obtained.

As Algorithm 1 states, the researcher has to define the window width and the proportion of overlap between subsequent windows. A higher number of events that overlap between subsequent windows results in greater smoothness of the results. Numerous factors play a role in determining the window width, including the following:

1. Social theory or field knowledge. In certain situations, social theory or field knowledge can suggest how fast social interaction behavior changes over time. In these situations, the window width should correspond to the expected rate of change of the effects, i.e., a narrow (wide) window should be used when theory dictates that interaction behavior is highly (hardly) dynamic.

2. Research question. A window width should be chosen corresponding to the research question at hand, e.g., are researchers interested in daily, monthly, or annual dynamics?

Algorithm 1: Moving window REM

input : A relational event sequence with M events between $t = 0$ and $t = \tau$.

Set the window width ℓ;

Set the proportion of overlap between subsequent windows π;

Start at the first window $w = 1$;

while $(\ell + (w - 1)\pi\ell) \leq \tau$ **do**

  Select the set of events observed in the time-interval between $[(w - 1)\pi\ell,\ \ell + (w - 1)\pi\ell]$;

  Compute the statistics $X(s, r, t)$ for the selected events in the window w;

  Estimate the vector of model parameters $\boldsymbol{\theta}_w$ for the selected events in the window w;

  Continue at the next window $w = w + 1$;

output: Vector of estimated model parameters $\boldsymbol{\theta}_w$ for each window w.

3. Resolution of the data. In certain situations, the possible window widths may be limited by the resolution of the data, e.g., whether the time of the events is available in seconds, hours, or days.

4. Precision/accuracy trade-off. A window should be wide enough so that enough events fall within each window to estimate effects with sufficient precision. At the same time, a window that is too wide may average out small or moderate changes in the effects, resulting in loss of accuracy of the estimates. Unfortunately, studies into the power, accuracy and precision of REMs are currently limited. The results of one study suggest 100 events per actor to achieve good power (Schecter & Quintane, 2020).

3.4.2 A data-based method for balancing precision and accuracy in moving window REMs

One challenge of the moving window approach is to determine the window width that can best capture how the effects on social interaction develop over time. The moving window REM uses a fixed window width and slides that window across the entire event sequence. However, in certain situations the time-varying parameters may change quite fast and quite a lot in some parts of the observation period and a lot less in in other parts (e.g., see the “gradual” time-varying effects scenario). In these situations, an optimal precision/accuracy trade-off can only be achieved by allowing the window widths to themselves vary over time. Unfortunately, considering that most research on relational event histories is still fairly exploratory, there is little theory yet to guide us how to set the window width in which part of the observation period. For this reason, we propose a method to empirically determine the window width based on the observed event history, where a narrow (wide) window is used during phases when the data show important (hardly any) changes in social interaction behavior, balancing precision and accuracy of the parameter estimates.

The steps in the procedure for the data-driven moving window REM are described in Algorithm 2. We make use of the BF to determine the window width around a given time point. Due to the Occam's razor, the BF is very suitable to optimize the window width around a given time point by balancing between precision and accuracy. More events will be preferred when possible, and fewer events when necessary. First, at a given time point t, a small window width is proposed. We evaluate if the effects around t change during the proposed window width by computing the BF for the evaluation of H_{static} (Equation 3.9) versus H_{dynamic} (Equation 3.10) with $K = 3$ for the events in this window. If the log BF is larger than zero, there is more evidence in the data for the static hypothesis, i.e., the BF indicates that the effects do not change during the proposed window around t. Subsequently, we repeatedly increase the window width, i.e., repeatedly select more events to estimate the effects around t. For each increased window width, we evaluate if the effects change during the window around t by computing the BF with $K = 3$. As long as the log BF is larger than zero, we can conclude that the effects during the window do not change. In the algorithm, we implement a stopping rule to increase its computational efficiency. That is, we stop increasing the window width around t when the log BF is smaller than $\log \frac{1}{10}$, i.e., there is ten times more evidence in the data in favor of the dynamic hypothesis. When this happens, we set the window width around t equal to the window width for which BF was maximum, i.e., there was most evidence in the data for static effects. This allows us to estimate the vector of model parameters at t with more events when possible (when effects do not change) and fewer events when necessary (when effects change), hence with maximum precision and accuracy. The algorithm for the data-driven moving window REM only requires a *minimum* window width to be set.

3.4.3 Numerical evaluation

We conduct a simulation study to assess the accuracy and precision of the moving window REM with fixed (Algorithm 1) and data-driven (Algorithm 2) window widths. First, we fit a "static" REM to the 200 generated relational event histories in the four time-varying effect scenarios. Second, we fit a moving window REM with fixed window widths. To study the accuracy and precision across window widths, we apply three different window widths ($1000t$/'small', $2000t$/'medium', and $4000t$/'large'). We slide the windows such that they have a two-thirds overlap with the previous window. Finally, we fit a data-driven moving REM. The minimum width is set equal to $1000t$. Statistics are computed with the R package REMSTATS, estimation of the model parameters is done with the R package REMSTIMATE. Both these R package are available for download on https://github.com/TilburgNetworkGroup.

Figure 3.4-3.6 show the results of the numerical evaluation for the 'transitivity' effect. Results for the other effects show similar patterns and can be found in the Supplementary Materials via https://doi.org/10.1371/journal.pone.0272309.s001. Furthermore, Figure 3.7 shows the average data-based window width per time point

Algorithm 2: Data-driven moving window REM

input : A relational event sequence with M events between $t = 0$ and $t = \tau$.

1 Set the minimum window width $\ell_{\min}$;

2 Define the set of time points T around which an optimal window width will be determined as follows: $T = \{\frac{1}{2}\ell_{\min},\ \frac{1}{2}\ell_{\min} + \frac{1}{3}\ell_{\min},\ \frac{1}{2}\ell_{\min} + \frac{2}{3}\ell_{\min},\ \dots\}$;

3 **for** $t \in T$ **do**

4   Set the window width around t equal to $\ell = \ell_{\min}$ around t;

5   Select the set of events observed in the time-interval between $[t - \ell, t + \ell]$;

6   Compute the statistics $X(s, r, t)$ for the selected events in the window around t;

7   Compute the BF with $K = 3$ for the selected events in the window around t;

8   **if** $\log \mathrm{BF} \geq \log \frac{1}{10}$ **then**

9   Increase $\ell = \ell + \frac{2}{3}\ell_{\min}$;

10   Start again at line 5;

11   **else**

12   Set the window width around t equal to the ℓ for which BF was maximum;

13   Estimate the vector of model parameters $\boldsymbol{\theta}_t$ with the events in the window;

output: Vector of estimated model parameters $\boldsymbol{\theta}_t$ for each time point $t \in T$.

as determined by the data-driven moving window REM.

Figure 3.4 shows the average estimated model parameter over time. First, results in the top row of Figure 3.4 show that the "static REM" averages out any time-variation that is present. Furthermore, results in Figure 3.4 show that the moving window REM, both with fixed and data-driven window widths, is able to provide an informative view of the underlying trend in parameters over time. The accuracy and precision of this view, however, depend on the window width and the extent and kind of time-variation of the parameters, as shown in more detail in Figure 3.5 and Figure 3.6.

Figure 3.5 provides some insights in the accuracy of the moving window REM. We use the bias of the estimated parameters as a measure of accuracy. The bias quantifies how well the true underlying parameter θ is quantified by the estimator on average. For time t, it is calculated as

$$\mathrm{bias}(t) = \frac{1}{n_{\mathrm{sim}}} \sum_{i=1}^{n_{\mathrm{sim}}} \hat{\theta}_i(t) - \theta(t), \tag{3.13}$$

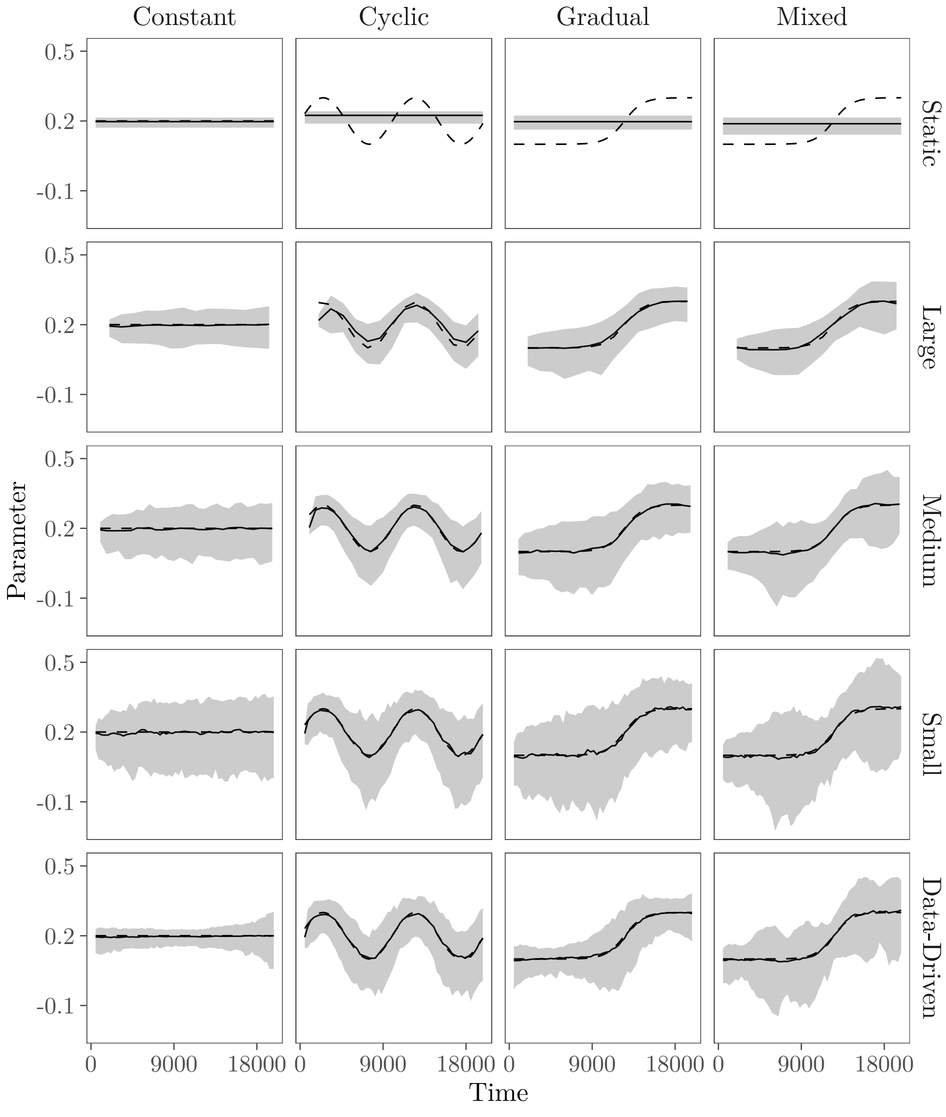

Figure 3.4.: Results from the evaluation of the (moving window) REM for the 'transitivity' effect. Rows show results for estimation of the 'transitivity' effect with the 'static' REM, large ($4000t$), medium ($2000t$), small ($1000t$), and data-based window widths, respectively. Columns show results for estimation of the 'transitivity' effect in the four time-varying effects scenarios. Solid lines represent the mean estimated parameters over 200 datasets over time. The gray area represents the range with 95% of the estimates for the 200 datasets. Dashed lines represent the parameters used for data generation.

where n_{sim} denotes the number of simulated datasets - here 200, $\hat{\theta}_i(t)$ denotes the estimated parameter in dataset i at time t and $\theta(t)$ denotes the true parameter at time t. We highlight three interesting results that follow from Figure 3.5. First, the results for the data generated in the 'constant' scenario (upper left panel) indicate that the bias of the estimates in the moving window REM, both with fixed and data-driven window widths, is generally very low. The moving window REM is able to estimate effects with good accuracy. Second, results indicate that the bias of the parameter estimates can become quite large if effects do change and the window widths are too large to capture that change. For example, the upper right panel of Figure 3.5 shows that the largest window widths are clearly too large to accurately estimate the highly dynamic transitivity effect in the data generated in the 'cyclic' scenario. Third, since smaller window widths signify greater model flexibility, it follows that bias is lower for smaller window widths. For all three time-varying effects scenarios, the bias is estimated to be reasonable small for medium, small and data-driven window widths. In sum, when effects are quite stable, bias is low for all window widths. When effects are highly dynamic, however, smaller window widths clearly outperform larger window widths by having lower bias. The algorithm for data-driven window widths enables us to find out when effects are highly dynamic, and thus window widths should be small.

Figure 3.6 provides insight into the precision of the moving window REM. We use the average estimated standard error (SE) of the parameters as a measure of precision. Following Morris et al. (2019), it is calculated as

$$\text{average estimated SE}(t) = \sqrt{\frac{1}{n_{\text{sim}}} \sum_{i=1}^{n_{\text{sim}}} \widehat{\text{Var}}(\hat{\theta}_i(t))}. \tag{3.14}$$

As expected, Figure 3.6 shows that the average estimated SE is larger for smaller windows in all four scenarios. While smaller windows may provide higher accuracy of the estimated parameters when effects are highly dynamic, this comes at the costs of lower precision since fewer events are contained inside each window. The upper left panel of Figure 3.6 shows that in the 'constant' scenario, the average estimated SE increases over time, even though the effects do not change. This is most likely due to the increased variability in the statistics over time, as the network that is observed grows. A similar pattern is also observed in the other time-varying effect scenarios. The upper right panel of Figure 3.6 shows the average estimated SE in the 'cyclic' scenario. As can be seen, the trend in size of the average estimated SE mirrors the trend of the parameters over time. This is mainly due to the fact that, when the baseline and other effects in the model are smaller, fewer events are generated/observed, leading to an increase in the estimated SE. A similar pattern is also observed in the 'gradual' and 'mixed' scenarios. Finally, from Figure 3.5 we could conclude that when effects were highly dynamic the bias was reasonably low for medium, small and data-driven window widths. The advantage of the data-driven window widths was that they enable us to find out when effects are highly dynamics and small(er) window widths are therefore required to estimate effects with enough accuracy. From Figure 3.6, we see another advantage from the data-driven window widths: they allow us to find out when

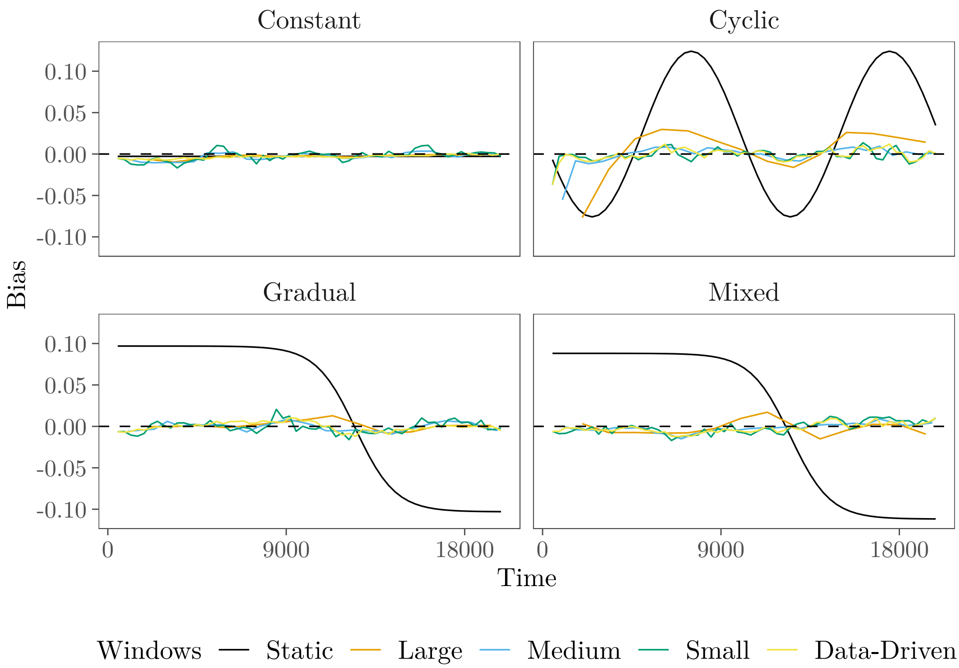

Figure 3.5.: Bias for the 'transitivity' effect in the evaluation of the moving window REM. Panels refer to the four time-varying effect scenarios. Solid lines represent the bias of the parameter estimates over time, with colors representing estimation with large ($4000t$), medium ($2000t$), small ($1000t$) and data-based window widths.

effects are stable enough to increase the window widths to estimate effects with greater precision (smaller SE). This becomes especially apparent in the "gradual" change scenario, depicted in the lower left panel of Figure 3.6. Here, the SE is considerably lower for the data-driven window widths compared to the small and medium fixed window widths for the first half and towards the end of the study period, i.e., when effects are more stable.

In sum, results from the numerical evaluation show that the moving window REM is able to provide a clear view of the trend in parameters over time. However, the window width influences the accuracy and precision of this view, depending on how much the parameters vary over time. Results further show that we can use the proposed algorithm for data-driven window widths to find out when effects are highly dynamic and we should decrease the window widths to estimate effects with greater accuracy, and when effects are stable enough to increase the window widths to estimate effects with greater precision.

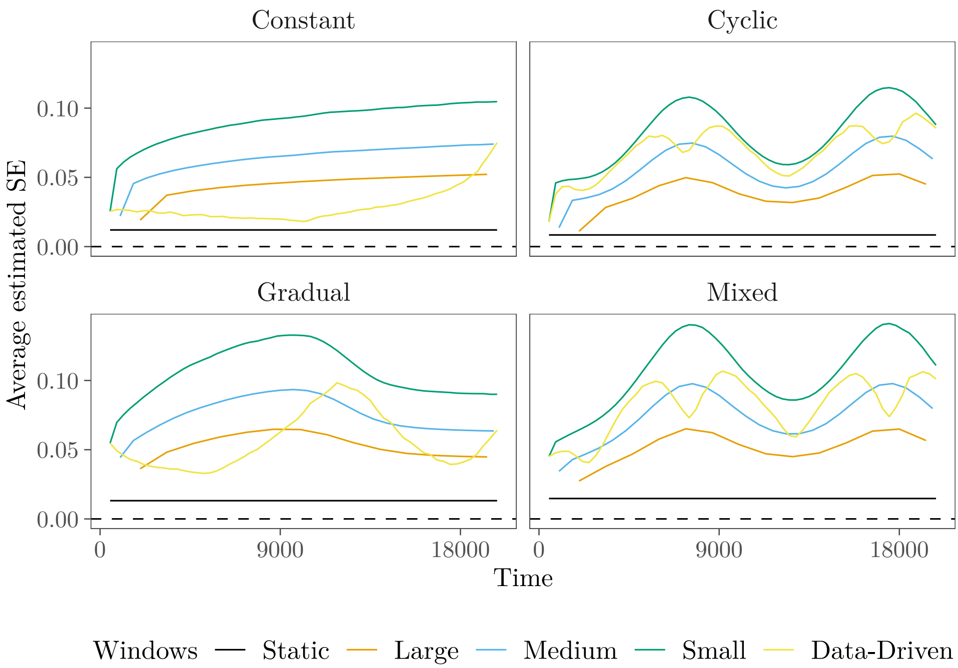

Figure 3.6.: Average estimated standard error (SE) for the 'transitivity' effect in the evaluation of the moving window REM. Panels refer to the four time-varying effect scenarios. Solid lines represent the average estimated SE of the parameter estimates over time, with colors representing estimation with large ($4000t$), medium ($2000t$), small ($1000t$) and data-based window widths.

3.5 Application: Time-varying network effects in workplace contacts

With the methods in place, we now perform an illustrative empirical analysis to demonstrate 1) the use of the Bayesian test for time-varying network effects and 2) the moving window REM with fixed and data-based window widths for exploring time-varying network effects. In particular, we focus on how past interaction behaviors (i.e., endogenous mechanisms) affect future contacts between the employees and how these effects change over time.

3.5.1 Data

The data set contains the face-to-face contacts between 232 employees of an organization in France, measured during a 2 week time period in 2015 (Génois & Barrat, 2018). These face-to-face contacts were measured with close-range proximity sensors. Following Génois and Barrat (2018), a contact between two employees is defined as "a

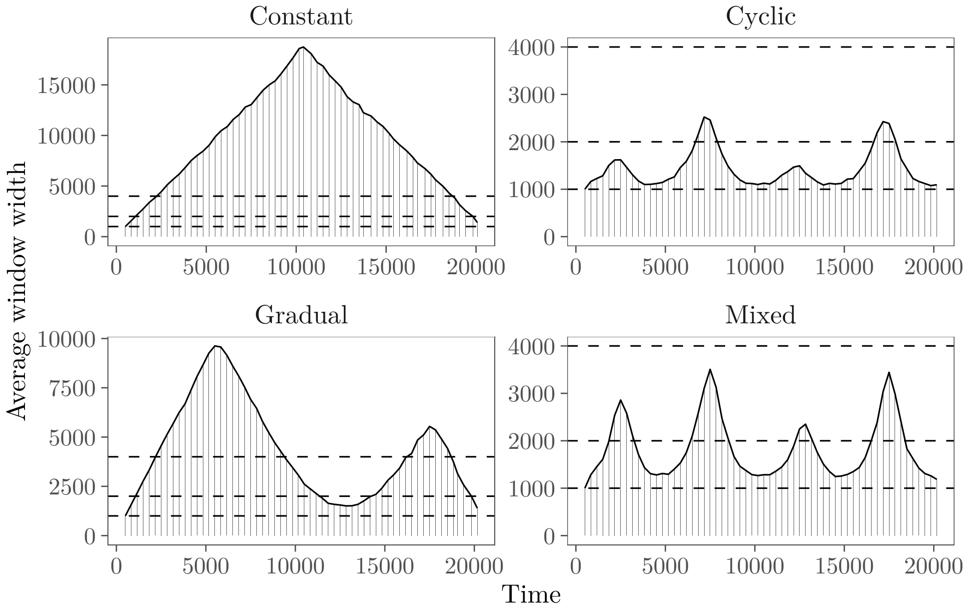

Figure 3.7.: Average data-driven window width found in the data-driven moving window REM for the four time-varying effect scenarios. Horizontal dashed lines refer to the different fixed window widths evaluated for the moving window REM, i.e., large ($4000t$), medium ($2000t$), small ($1000t$).

set of successive time-windows of 20 seconds during which the individuals are detected in contact, while they are not in the preceding nor in the next 20 second time window." We formally represent a relational event between two employees as the triplet (s, r, t), where s and r refer to the employees who are in contact and t refers to the start time of the face-to-face contact in seconds since onset of observation. The events do not distinguish between a sending and receiving individual, i.e., the relational events are undirected. The first ten events in the sequence are shown in Table 3.1. In total, 33751 relational events are observed over the course of the study period. The top panel in Fig 3.8 shows the distribution of events over time. The number of events per day ranged from 1778 to 5905 with a mean of 3375 (SD = 1166). In the analysis, idle periods, such as non-working hours and weekends, were discarded from the data. Between events that have a same timestamp, a time difference is induced such that these events are evenly spaced in time between the current time unit and the next time unit. The risk set consists of every undirected employee pair that can potentially interact, i.e., $\frac{232 \times 231}{2} = 26796$ pairs. Across the entire relational event history, the number of events per employee ranged from 0 to 1147 with a mean of 291 (SD = 206). The majority of actors (217, 94%) were involved in at least one event during the study period. The number of events per employee pair ranged from 0 to 506 with a mean of

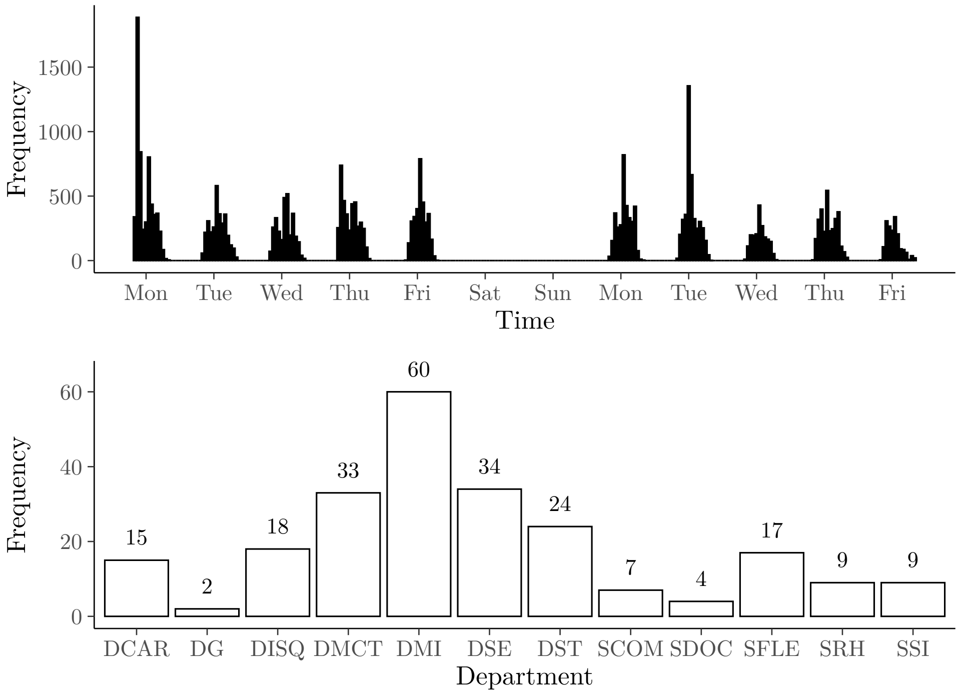

Figure 3.8.: Descriptive information of the empirical data. The top panel shows the frequency distribution of the events in the relational event sequence over time. The bottom panel shows the frequency distribution of the employees over the departments.

1 (SD = 8) and there were 4274 employee pairs (16% of the risk set) with at least one event during the study period. Besides the face-to-face contacts, information on the departments in which the employees work is available. The bottom panel in Figure 3.8 shows the frequency distribution of study participants over the departments.

3.5.2 Model specification

The following describes the statistics that are used to model the rate (see Equation 3.1) at which the employee pairs start face-to-face interactions.

Intercept

Firstly, an intercept is included in the model to capture the baseline tendency for interaction in the employee network. The statistic $X_{\text{intercept}}(s, r, t)$ is equal to 1 for all (s, r, t). The corresponding effect $\beta_{\text{intercept}}$ refers to the log-inverse of the average number of events per time unit (here, seconds) for an employee pair that scores zero on all other statistics in the model.

Same department

Previous research has shown that the number of contacts between employees is strongly influenced by the departmental structure of the organization (Génois et al., 2015). Since employees who work in the same department are likely to have a greater opportunity to interact, the statistic $X_{\text{same.department}}(s, r, t)$ is included in the model to capture whether the employees of the pair (s, r) work in the same department (1 = yes, 0 = no). A positive effect $\beta_{\text{same.department}}$ implies that employees who work in the same department start future interactions with a higher event rate with each other compared to employees who work in different departments.

Recency

A previous REM analysis of email communication between employees of an organization showed that individuals were more likely to send an email if the last email sent was more recent (Mulder & Leenders, 2019). Here, we are interested in the question whether such recency effects transfer to face-to-face interactions. Moreover, previous research into the validity of using sensor-based measures of face-to-face interactions has shown that merging interactions that occurred close to reach other in time improved the accuracy (Elmer et al., 2019). It is possible that individuals physically move away from each other during a face-to-face interaction in such a way that a longer interaction is recorded as two or multiple shorter interactions by the sensors. Hence, the speed of interaction is possibly confounded by this specific source of measurement error. By including a recency effect, we can control for this in the estimated sizes of the other effects in the model. Since we have undirected events, we include an effect to control for the effect of how recently the employee pair (s, r) interacted last. Let $\tau(s, r)$ refer to the time of the most recent event between the employee pair (s, r), then

$$X_{\text{recency}}(s, r, t) = \frac{1}{(t - \tau(s, r)) + 1}.$$

A positive effect β_{recency} implies that employee pairs who interacted more recently tend to engage in future interactions at a higher rate than employee pairs whose last interaction was less recent.

Inertia

Inertia refers to the tendency of individuals to repeat past interactions, or the tendency of "past contact to become future contacts" (Pilny et al., 2016). Pilny et al. (2016) suggest that, following general theories of social networks, inertia is an important predictor of social interaction occurrence. Previous research on communication between employees has repeatedly found inertia to positively predict the event rate (Perry & Wolfe, 2013; Quintane et al., 2013; Quintane & Carnabuci, 2016; Schecter & Quintane, 2020). Hence, we may expect that inertia plays an important role in our data as well. We are especially interested in how the effect of inertia develops over time in the employee network. The statistic $X_{\text{inertia}}(s, r, t)$ is based on a count of past (s, r)

events before time t. Let $m = 1, \dots M$ refer to the mth event in the relational event history and let (s_m, r_m) and t_m refer to the employee pair and time of the mth event, respectively, then

$$X_{\text{inertia}}(s, r, t) = \sum_{m=1}^{M} I(t_m < t \wedge \{s_m, r_m\} = \{s, r\}).$$

To ensure that the statistic is well-bounded (e.g., see DuBois, Butts, McFarland, & Smyth, 2013; Schecter & Quintane, 2020), we standardize the statistic per time point t by subtracting the mean of $X_{\text{inertia}}(t)$ from $X_{\text{inertia}}(s, r, t)$ and subsequently divide by the standard deviation of $X_{\text{inertia}}(t)$. A positive effect β_{inertia} implies that employee pairs who have interacted more with each other in the past tend to engage in future interactions at a higher rate than employee pairs who have interacted less with each other in the past.

Triadic closure

Triadic closure refers to the tendency of 'friends of friends to become friends' (Pilny et al., 2016). Pilny et al. (2016) suggest that, following general theories of social networks, triadic closure is an important predictor of social interaction occurrence. Previous research on communication between employees has repeatedly found triadic closure to positively predict the interaction rate (Perry & Wolfe, 2013; Quintane et al., 2013; Quintane & Carnabuci, 2016; Schecter & Quintane, 2020). Hence, we may expect that triadic closure plays an important role in our data set as well. We are especially interested in how the effect of triadic closure develops over time in the employee network. The statistic $X_{\text{triadic.closure}}(s, r, t)$ is based on a count of the past interactions with employees h that employees s and r both interacted with before time t: Let A refer to the set of employees in the network, then

$$\begin{aligned} X_{\text{triadic.closure}}(s, r, t) = \sum_{h \in A} \min\{ & \sum_{m=1}^{M} I\left(t_m < t \wedge \{s_m, h_m\} = \{s, h\}\right), \\ & \sum_{m=1}^{M} I\left(t_m < t \wedge \{r_m, h_m\} = \{r, h\}\right)\}. \end{aligned}$$

We standardize the triadic closure statistic in the same manner as the inertia statistic. A positive effect $\beta_{\text{triadic.closure}}$ implies that the rate of interaction increases as employees have more common past interaction partners.

3.5.3 Testing for time-varying network effects

We first test for time-varying network effects as described in Section 3.3. Results in Figure 3.9 show that the BF indicates more evidence in the data for the hypothesis that the effects change over the course of the relational event sequence rather than remaining constant over time. This holds for every number of sub-sequences $K = 2, \dots, 10$. Hence,

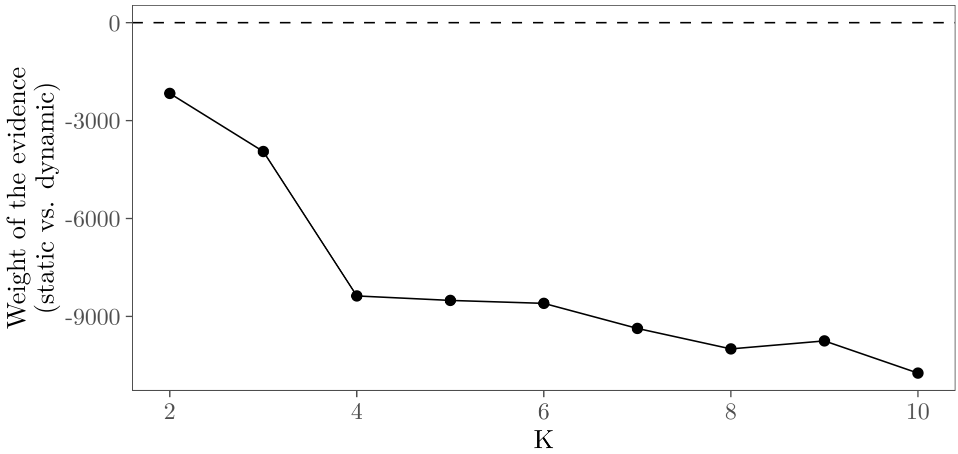

Figure 3.9.: Results for the tests for time-varying network effects in the empirical data. Weight of the evidence (log BF) for the static vs. dynamic hypothesis with $K = 2, \ldots, 10$ for the relational event history with face-to-face contacts in the workplace.

these results indicate the need to a dynamic analysis of the face-to-face interactions between these employees.

3.5.4 Exploring time-varying network effects

We implement the required dynamic model by means of a moving window REM; this allows us to study the time variation of the effects that influence employee interaction. We apply two different fixed window widths to explore the time-varying network effects: 6 hours and 2 hours. The number of events within the windows range from 375 to 4660 (mean = 1632, SD = 781) and 11 to 2877 (mean = 555, SD = 423), respectively. We also apply the algorithm for data-driven window widths (see Algorithm 2) with a minimum window width of 1 hour.

The results for the two moving window REM's with fixed windows widths and the REM with data-driven window widths are shown in Figure 3.10. These results show that the largest window (6h) shows the general trend of how the effects develop over time, but it does not pick up many nuances in them. The results suggest that some variations in the effects during the day exist. The smallest window (2h) show these daily variations in more detail, informing us about the magnitude in change of the effects during the day. The results of the data-driven window widths are mostly comparable to the results of the 2h window widths. For most time points, we see a fraction more detail for the data-driven window widths compared to the 2h window widths. For other windows, we see a fraction more precision, i.e., smaller standard errors, for the data-driven window widths compared to the 2h window widths. These results suggest that interaction patterns in the respective workplace are highly dynamic over the course of the study period (changing every $\frac{1}{3} \times 60 = 20$ minutes) and longer periods of stability of the effects do rarely exist.

Overall, results from the analysis with the moving window REM seem to suggest a basic level of importance of the effects throughout the study period. The smaller window width informs us that the general trends over time do not tell us the whole story. All effects show some variation in strength during the working days, through patterns that seem to repeat themselves for most working days.

The baseline rate of interaction seems to follow the same pattern every day, with less events during the beginning and the end of the working day and a small drop in the baseline rate around lunch. Working in the same department has a strong positive effect on the event rate throughout the study period. This effect seems to become an even more important predictor of interaction towards the end of each working day.

For recency, it seems that the effect increases somewhat in strength on the third day and then essentially stabilizes. Within these fairly stable period there are several times where recency is higher for awhile. This may be due to a number of reasons, for example because of tasks performed in teams or project work. When these periods of relatively high recency occur, they seem to be concentrated around the end of the working day.

The effect of inertia starts strong at the beginning of the study period, but decreases until the fourth day, after which it slowly increases again. This may be due to external influences, for example the end of a large project and the beginning of a new one. Throughout the days, inertia seems to be relatively more important in between the beginning of a working day and noon, and in between noon and the ending of the working day – i.e., the periods during the day when working in the same department was less important. This may point towards employees repeatedly working together on projects, regardless of the department they are in.

The results show some evidence that, aside from a baseline importance of the effect of transitivity throughout the study period, its effect on the event rate increases during the day and then resets again at the beginning of a new day. This pattern is especially observed on the first few days. Furthermore, there seems to be a drop in the importance of the effect around noon. Overall, it seems to be the case that around noon the pattern of work-related interaction may be broken up by the lunch break and, potentially, social interaction with other employees. However, the data set lack this type of contextual information to corroborate this explanation.

3.6 Discussion

The current research proposed three methods to progress the study of temporal effect dynamics in relational event history data. First, we proposed a Bayesian approach to test *if* effects truly change over time. Results showed that the approach is able to provide guidance on whether effects barely change (and a static REM can be applied) or whether effects change considerably (and a dynamic approach is required for the analysis). Second, we argued that the moving window approach enables us to study *how* effects in relational event history data develop over time. Results of a simulation study provided a proof of concept for the moving window approach. The moving window approach was able to recover the time-varying regression coefficients and

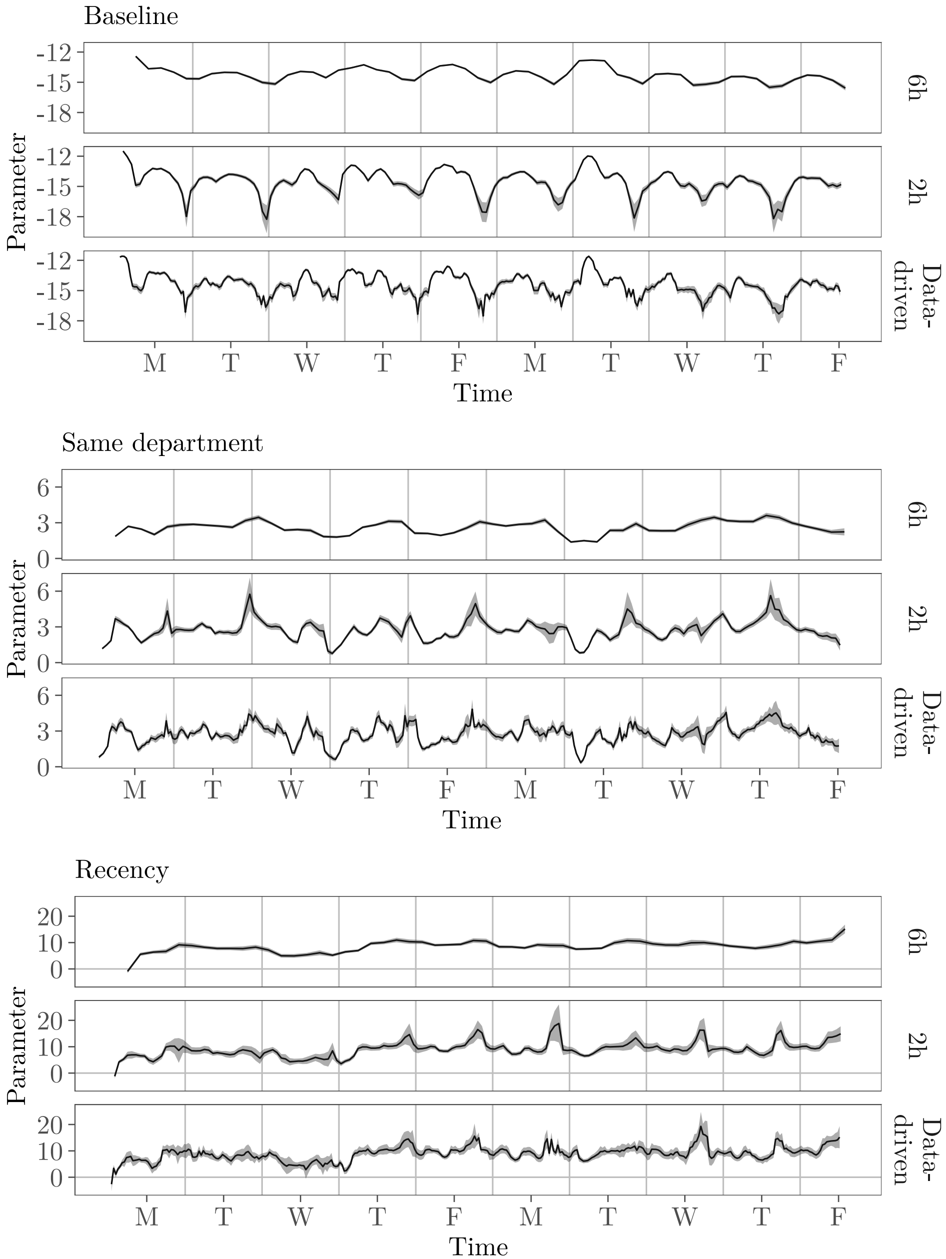

Figure 3.10.: Results for the moving window REM analysis of the relational event sequence with face-to-face contacts in the workplace, both with fixed and data-driven window widths.

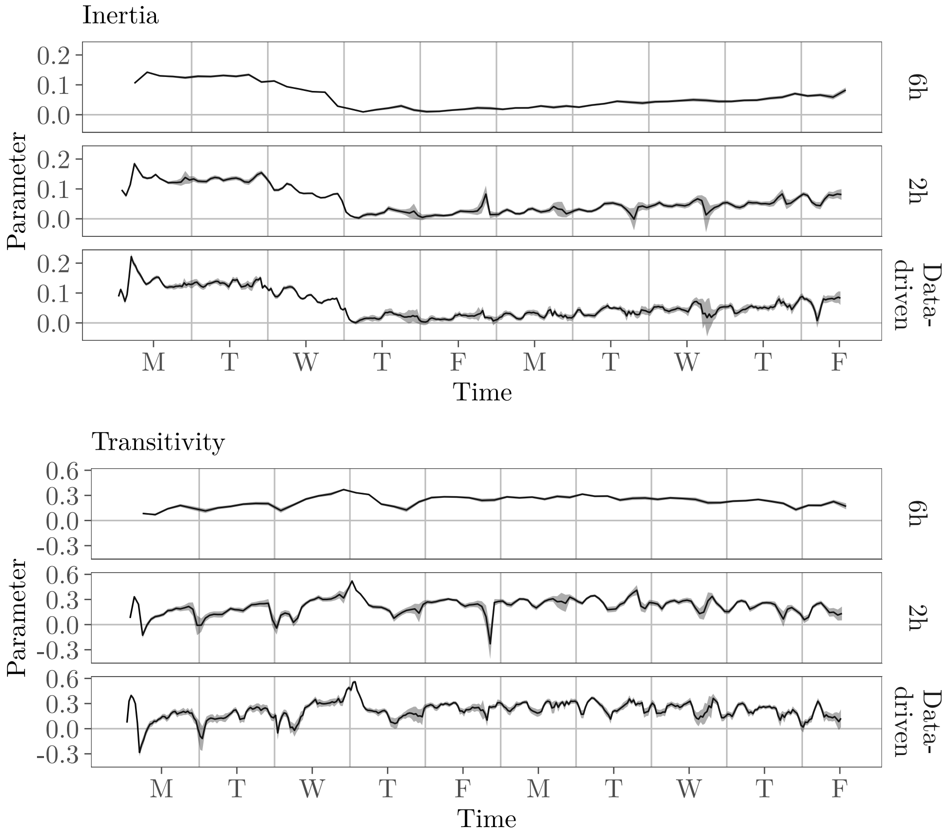

Figure 3.10.: Results for the moving window REM analysis of the relational event sequence with face-to-face contacts in the workplace, both with fixed and data-driven window widths. (Continued from previous page.)

provide a clear picture of how effects change over time. The accuracy and precision of this picture depend on the window width, with narrower windows resulting in greater accuracy at the cost of lower precision. Finally, since it can be challenging to determine the width of the window for the moving window REM, we propose an algorithm that finds flexible window widths based on the empirical data. The algorithm makes windows wider when effects are stable and narrower when they are dynamic. Results from the simulation study showed that the flexible windows lead to greater *precision* for time intervals in which effects were hardly changing and greater *accuracy* for time intervals in which effects did change greatly over time.

This was also highlighted in the empirical example. Wide fixed windows were able to uncover broad trends, but clearly lacked detail. Making the windows narrower increased this detail, but frequently led to windows that did not have enough observations in them to be sufficiently precise. This is fixed by the data-driven method with flexible window widths, although it will rarely be possible to precisely uncover dynamics in time periods with inherently few events anyway.

The illustrative analysis shows us that the models can indeed retrieve how the dynamics of social interactions change over time. The explanation of what is causing such changes may require additional data. In the empirical example, it appears that there is a lunch effect. To establish this with more certainty, one would like data about what indeed happens in this organization around noon. Do employees lunch together in a cafetaria? If so, it makes sense that interaction may then be driven by other factors than during the regular working hours. Or do the employees lunch with their own team? Or does the organization offer a different activity at noons? Similarly, we noted that recency is more important during short times (say, periods of 1-2 hours). It would be insightful to know what happened: did colleagues get together to jointly solve work-related problems in those periods? If so, that would (partly) explain the increased recency during those times. There may be other reasons for these effects as well. A dynamic REM approach that allows effects to vary over time is most informative when additional data are available to provide the context within which the interaction take place. Such data may often not be relational event type data and may not always be collected by a researcher who collects data that will be fed into a REM analysis. Our research, however, suggests that such additional data may be highly useful. For employees in an organization, a researcher would like to know at what times formal meetings are scheduled and who is supposed to attend. We would like to know how the work day is organized and which routines are built in (cf., Roy, 1959).

In the last decade, several approaches for modeling relational event data have been introduced (e.g., Butts, 2008; de Nooy, 2011; Perry & Wolfe, 2013; Stadtfeld & Block, 2017; Vu et al., 2011). Generally, differences between these approaches are small and affect mostly the interpretation of the estimated model parameters (Stadtfeld et al., 2017b). Therefore, while the current research focused on the REM framework of (Butts, 2008), we expect that the approach can generalize to other approaches for modeling relational events.

3.7 Conclusion

This paper has provided a tool set for testing for and exploring time-varying network effects in relational event history data. These methods enable researchers to gain insights into how driving mechanisms of social interactions develop over time; when their effects increase, decrease, or remain stable, when effects kick in, how long effects last, et cetera. In the social sciences, there is a dearth of truly time-sensitive theory. As a result, researchers have little guidance in theorizing about *when* events happen, *for how long*, and *what makes events happen* at some points in time but less so at others? We believe that empirical findings by models like the REM can inform the development of time-sensitive theory in the long run. In the current paper, we have suggested a way to make REMs even more informative, by acknowledging that the drivers of social interaction are unlikely to remain constant over time. If we find that organizational routines such as joint lunches break the interaction routines from the first half of the work day, this can inform more nuanced theory building to help us understand how time-specific institutions affect our work interactions. Similarly, it might help us understand how some disruptions (such as routinized lunch time) do not structurally impact employee interaction patterns (employees will likely “continue where they left off” after lunchtime is over), whereas other kinds of disruptions (e.g., the company internet going down, a visit by a boss, a joint company meeting, a fire drill, a visit to a customer, et cetera) do have the potential to completely reset the interaction dynamics for the day. This is both interesting from an empirical point of view and important for the development of theory of how human interaction is shaped, maintained, and developed.

4

A relational event approach for jointly modeling event rates and event duration

In collaboration with Joris Mulder, Roger Leenders, and Peter Ejbye-Ernst.

Abstract

Relational event models are used to study what drives actors in a social network to interact with each other and when. A key feature of these models is that they allow researchers to take the event history into account, resulting in a time-sensitive analysis. The central question is then how the event history can be summarized to explain social interaction behavior and predict when the next event is likely to occur and who will be involved. This chapter contributes to this central question by proposing a methodology that allows researchers to study how the duration of past events affects social interaction behavior. An estimation procedure is proposed to learn the non-linear impact of event duration on interaction rates. Additionally, an extension of the relational event model is proposed that can be used to study how the event history and other sources of information (e.g., individual characteristics) affect the duration of new events. The performance of the approach is evaluated using numerical simulations. Two case studies reveal that if we take the impact of past events on future interaction behavior into account, we can better predict who interacts when.

4.1 Introduction

The analysis of social interaction processes has contributed to a better understanding of important empirical questions on the transmission of infectious diseases (e.g., Vanhems et al., 2013), the development of interpersonal conflict situations in public (e.g., Ejbye-Ernst et al., 2021), transfer of knowledge between organizations (e.g., Tortoriello et al., 2012), and the well-being of individuals (e.g., Vörös et al., 2021), among others. In recent research, relational event modeling approaches are increasingly being used for this purpose. A key feature of these models is that they allow researchers to account for interaction history when studying how social interaction behavior evolves over time. As a result, relational event models enable researchers to develop a fine-grained understanding of temporal social processes.

Relational event models were originally developed for analyzing instantaneous events between individuals observed at a single point in time, such as radio transmissions (e.g., Butts, 2008) or emails (e.g, Mulder & Leenders, 2019) from one individual to another. These models use endogenous statistics to capture the temporal and structural dependency between events. Endogenous statistics summarize the event history up to a specific point in time. A typical example of an endogenous statistic is inertia, defined as the total number of past events that an actor A sent to another actor B until time t. The corresponding coefficient, which is estimated from the observed event sequence, then quantifies the relative tendency of actors to repeat previous behavior (i.e., a form of "habituation" or "routinization"; Leenders et al., 2016). Other typical examples of endogenous statistics include reciprocity and transitivity.

The basic quantification of endogenous statistics assumes that all previous events are equally important in explaining interaction behavior and predicting future events. However, this may be unrealistic because both more recent previous event and previous events with a long duration or high intensity are likely to have a greater impact on what happens next than previous events that occurred a long time ago or previous events of short duration or low intensity. The importance of memory decay of past events is becoming increasingly clear from previous research (e.g., Arena, Mulder, & Leenders, 2022; Brandenberger, 2018; Brandes et al., 2009; Perry & Wolfe, 2013; Quintane et al., 2013). However, the importance of the duration or intensity of past events has received little attention in the literature. Notable exceptions are Brandes et al. (2009) and Meijerink-Bosman et al. (2022), who assumed a fixed weight function that quantifies the relative importance (or "weight") of past events as a function of their intensity or duration, respectively. Their methods, however, do not allow us to investigate *how* the duration of past events influences social interaction behavior in the (near) future. For this reason, the current chapter extends the relational event framework by including a weight function of the duration of past events in the endogenous statistics that can be estimated from the observed event sequence, allowing us to improve our understanding of how the past affects future interaction behavior.

A second contribution of the current chapter is an extension of the model to investigate how previous social interactions and individual characteristics influence the duration of future events. Learning more about what explains event duration is useful for answering a variety of empirical questions. Interactions between patients and healthcare workers, for example, are one of the most important routes for the spread of hospital-acquired infections. The duration of these interactions, in addition to their frequency and temporal order, has important implications for the spread and control of infectious diseases in a population (e.g., Smieszek, 2009). By modeling event duration as an outcome variable, we can learn more about how emerging social interaction patterns, together with individual characteristics, affect the duration of interactions between individuals and develop targeted intervention strategies. Other important empirical questions about the drivers of event duration include, to name a few, how underlying social interaction processes affect the duration of violent behaviors (Ejbye-Ernst et al., 2021) or the duration of different types of interactions between team members (Morgeson & DeRue, 2006).

The remainder of this chapter is structured as follows. First, we outline the statistical model for jointly modeling event rates and event duration and the specification of the weight function of the duration of past events in the endogenous statistics. Subsequently, we describe a simulation study that evaluates the performance of our approach to learn the impact of event duration on the interaction rates. Next, two case studies demonstrate what we can learn about social interaction dynamics from the application of the proposed methodology. We end with a discussion of the research in the current chapter.

4.2 The relational event model using event duration

4.2.1 Model overview

The following notation is used in the chapter. A relational event sequence $\boldsymbol{E}_M = \{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_M\}$ is a time-ordered sequence of M relational events. A relational event $\boldsymbol{e}_m$ in $\boldsymbol{E}_M$ is defined as the tuple $\boldsymbol{e}_m = \{t_m, s_m, r_m, d_m\}$, where t_m is the time when $\boldsymbol{e}_m$ starts and s_m, r_m, and d_m are the sender, receiver, and duration of $\boldsymbol{e}_m$, respectively. Table 4.1 gives an example of a relational event sequence. The set of N actors that can send or receive events at time t is defined to be $\boldsymbol{A} = \{a_1, a_2, \ldots, a_N\}$. This set may change over time when actors leave or join the network. Actors can have (time-varying) attributes, which we refer to as $\boldsymbol{v}$. Further, the risk set $\boldsymbol{\mathcal{R}}_t$ contains the set of events that can potentially be observed at time t. The exact composition of the risk set depends on the research context. Often, the risk set is defined with all possible sender-receiver pairs (s, r), $s \in \boldsymbol{A}$ and $r \in \boldsymbol{A}$. The risk set may vary over time. The above outlined notation assumes directed relational events. Generalization to undirected events is straightforward, as will be illustrated later in this chapter.

Following previous relational event modeling approaches, we assume that each event $\boldsymbol{e} \in \boldsymbol{E}_M$ is only dependent on those events that happened earlier, i.e.,

$$p(\boldsymbol{E}_M) = \prod_{m=1}^{M} p_{\text{event}}(\boldsymbol{e}_m | \boldsymbol{E}_{m-1}). \tag{4.1}$$

We decompose the probability distribution for the event $\boldsymbol{e}_m$ in the sequence $\boldsymbol{E}_M$ into

Table 4.1.: The first six relational events between healthcare workers and patients in a hospital (see Vanhems et al., 2013). Time denotes the start of the event in seconds since onset of observation, duration denotes the duration of the event in seconds.

Time	Actor 1	Actor 2	Duration
140	1157	1232	20
160	1157	1191	20
500	1157	1159	40
560	1159	1191	140
680	1144	1159	20
700	1114	1191	240

two factors:

$$\begin{aligned} p_{\text{event}}(t_m, s_m, r_m, d_m | \boldsymbol{E}_{m-1}, \boldsymbol{v}, \boldsymbol{\beta}, \boldsymbol{\theta}) = & \; p_{\text{rate}}(t_m, s_m, r_m | \boldsymbol{E}_{m-1}, \boldsymbol{v}, \boldsymbol{\beta}) \\ & \times p_{\text{duration}}(d_m | t_m, s_m, r_m, \boldsymbol{E}_{m-1}, \boldsymbol{v}, \boldsymbol{\theta}). \end{aligned} \tag{4.2}$$

The first factor in Equation 4.2 is the probability distribution that the next event $\boldsymbol{e}_m$ starts at time t_m between actors $s_m \in \boldsymbol{A}$ and $r_m \in \boldsymbol{A}$. This probability is dependent on a set of model parameters $\boldsymbol{\beta}$ that quantify the association with the event history $\boldsymbol{E}_{m-1}$ and, potentially, a set of actor attributes $\boldsymbol{v}$. In the following, we refer to this first factor as the distribution for the event rate between actors. The second factor is the probability distribution that the next event $\boldsymbol{e}_m$ has a duration d_m, given the fact that the event started at time t_m between actors s_m and r_m. This probability is further dependent on a set of model parameters $\boldsymbol{\theta}$ that quantify the association with the event history $\boldsymbol{E}_{m-1}$ and, potentially, a set of actor attributes $\boldsymbol{v}$. In the following, we refer to this second factor as the distribution for the event duration.

4.2.2 Capturing event duration in the model for the event rate

For the functional form of the distribution for the event rate, we follow the Relational Event Model (REM; Butts, 2008). The REM frameworks draws upon techniques from event-history analysis to explain when the next event is likely to occur and why certain events (s, r) in $\boldsymbol{\mathcal{R}}_t$ have a higher probability of occurring next than others. Each potential event (s, r) in the risk set $\boldsymbol{\mathcal{R}}_t$ has its own unique rate of occurrence $\lambda(t, s, r)$ that is updated after a new event $\boldsymbol{e}$ is observed. Following other relational event modeling approaches, we assume that the event rates remain constant between observed event times. This corresponds to an exponential distribution for the waiting time until the next event where the rate parameter is the sum of the event rates of all potential events in the risk set, i.e., $\Delta t \sim \text{Exponential}\left(\sum_{(s,r)\in\boldsymbol{\mathcal{R}}_t} \lambda(t, s, r)\right)$. It follows that the estimated waiting time between events decreases when event rates at time t are higher (compared to lower event rates at time t). Furthermore, the probability for an event (a, b) in the risk set $\boldsymbol{\mathcal{R}}_t$ at time t to occur next is equal to its event rate relative to the sum of the event rates for all potential events in the risk set, i.e., $P\big((a,b)|t\big) = \lambda(t,a,b)/\sum_{(s,r)\in\boldsymbol{\mathcal{R}}_t}\lambda(t,s,r)$. It follows that the probability to be observed next is larger for events (a,b) in the risk set $\boldsymbol{\mathcal{R}}_t$ that have a higher event rate (compared to pairs that have a lower event rate).

Modeling the event rate allows us to investigate how an observed relational event sequence evolves over time. We assume a log-linear model for the event rate of pair (s,r) at time t, which is given by

$$\log\lambda(t,s,r) = \boldsymbol{x}'_{\text{rate}}(t,s,r)\boldsymbol{\beta}, \tag{4.3}$$

where $\boldsymbol{x}_{\text{rate}}(t,s,r)$ is a vector of length p containing the endogenous and exogenous statistics for pair (s,r) at time t that affect the event rate, and $\boldsymbol{\beta}$ is a vector of coefficients which quantify the relative importance of the effect of the statistics on the event rate.

We expect the impact of a past event on future interaction behavior to depend on on at least two factors: (1) The amount of time that has past since the event occurred, and (2) the duration of the event. First, we may assume that actors' forgetfullness causes the influence of past events on future interaction behavior to decrease over time (Brandes et al., 2009). In the following, we refer to this as a 'memory effect'. Second, we may assume that past events with a longer duration have more impact on future interaction behavior. Therefore, we extend the REM framework by presenting a joint method to take memory and event duration into account in the endogenous statistics and investigate these assumptions. We formulate a weight for the event history of each pair (s,r) in the risk set at time t:

$$w(t,s,r) = \sum_{\boldsymbol{e}_m:(s_m,r_m)=(s,r),t_m<t} f_{\text{memory}}(t_m,d_m)f_{\text{duration}}(d_m). \tag{4.4}$$

Here, $w(t,s,r)$ denotes the weight of the event history for actor pair (s,r) at time t. This weight is defined as the weighted sum of all past events e_m that occurred between the actors s and r. These past events e_m are weighted by a function that considers the effects of memory and duration. First, the function

$$f_{\text{memory}}(t_m) = \exp\left[-\big(t-(t_m+d_m)\big)\frac{\ln(2)}{\tau}\right]\frac{\ln(2)}{\tau} \tag{4.5}$$

causes the weight of event $\boldsymbol{e}_m$ to exponentially decrease when the time difference between the current time t and the time t_m+d_m since the event increases. In this function, τ denotes the half-life of the influence of an event: When the time since the mth event $\big(t-(t_m+d_m)\big)$ increases with τ, its weight is halved. The last factor, $\frac{\ln(2)}{\tau}$, ensures that $f_{\text{memory}}(t_m)$ has the interpretation of approximate "aggregate weight per time unit" (Lerner et al., 2013). Second, the function

$$f_{\text{duration}}(d_m) = d_m^{\psi} \tag{4.6}$$

captures the effect of event duration on the weight of event $\boldsymbol{e}_m$. By selecting a power function for considering event duration in the event history, we can study a wide variety of different ways how the duration of past events may affect future interaction behavior: When $\psi < 0$, the weight of past events decreases as their duration increases and when $\psi > 0$, the weight of past events increases as their duration increases. When $\psi = 1$, the relationship between the duration of a past event and its weight is exactly linear. When $\psi = 0$, the event duration has no effect on the weight of events in the event history for actor pair (s, r) and Equation 4.4 reduces to the formula proposed by Brandes et al. (2009) to account for memory effects.

4.2.3 The model for the event duration

Given that the duration of relational events is likely to depend on the event history as well as on actors' attributes, a model is proposed for the duration of the mth event so that it can be explained as a function of a set of predictor variables. Let D_m be a non-negative random variable representing the time from when the mth event is started until it is terminated, i.e., the duration of the mth event. Then, we can use a hazard model to explain the "risk" of terminating an event at a certain duration d with a set of predictor variables. We assume that the rate η_m of terminating event m remains constant for the duration of the event (i.e., an exponential model). A log-linear model is then used to explain the effect of a set of predictor variables on the event duration:

$$\log \eta_m = \boldsymbol{x}'_{\text{duration}}(t_m, s_m, r_m)\boldsymbol{\theta}, \tag{4.7}$$

where $\boldsymbol{x}_{\text{duration}}(t_m, s_m, r_m)$ is a vector of length q containing the endogenous and exogenous statistics for the observed pair (s_m, r_m) at time t_m that affect the event duration and $\boldsymbol{\theta}$ is a vector of coefficients which quantify the relative importance of the effect of these statistics on the event duration.

Algorithm 3 describes the data generating process for the full model. We assume a time-varying risk set to account for the effects of event duration on actors' availability for future events. Specifically, when at time t_1 a relational event of duration d_1 is observed between actors s_1 and r_1, potential events with these actors are removed from the risk set until $t_m > t_1 + d_1$. This also implies that the waiting time until the next event is assumed to be unaffected by the event rates of potential events with actors in ongoing events. Furthermore, note that the dimensionality of the set of predictor variables at a given time point t_m differs between the event rate and the event duration components of the model. We consider the statistics for all pairs (s, r) in the risk set at t_m in the model for the event rate, i.e., the set of predictor variables is contained in the matrix $\boldsymbol{X}_{\text{rate}}(t_m, s, r)$ of size $p \times |\mathcal{R}_{t_m}|$. For the event duration model, we consider the statistics for the observed pair (s_m, r_m) at t_m, i.e., the set of predictor variables is contained in the vector $\boldsymbol{x}_{\text{duration}}(t_m, s_m, r_m)$ of length q. Moreover, throughout this chapter we only update the event history with completed events. Thus, we assume that an ongoing event does not influence the tendency for future interaction until after it ended. For example, suppose that at time $t_1 = 1$ a relational event of duration $d_1 = 4$ is observed between actors $s_1 =$ "A" and $r_1 =$ "B". During this event, the next event is observed at time $t_2 = 2$ with duration $d_2 = 2$

Algorithm 3: Data generating process

Define N, M, $\boldsymbol{\beta}$, $\boldsymbol{\theta}$, τ_{rate}, τ_{duration}, ψ_{rate}, and ψ_{duration};
Initialize $t_0 = 0$;
Initialize $\mathcal{R}_{t_0}$;
Initialize $\boldsymbol{X}_{\text{rate}}(t_0, s, r)$ and $\boldsymbol{x}_{\text{duration}}(t_0)$;
for $m \in 1 : M$ **do**
  Compute $\lambda(t_m, s, r) = \exp\{\boldsymbol{x}'_{\text{rate}}(t_m, s, r)\boldsymbol{\beta}\}$;
  Sample $\Delta t \sim \text{Exponential}\left(\sum_{\mathcal{R}_{t_m}} \lambda(t_m, s, r)\right)$;
  Sample (s_m, r_m) from $P\left((s_m, r_m)|t_m\right) = \frac{\lambda(t_m, s_m, r_m)}{\sum_{\mathcal{R}_{t_m}} \lambda(t_m, s, r)}$;
  Compute $\eta_m = \exp\{\boldsymbol{x}'_{\text{duration}}(s_m, r_m, t)\boldsymbol{\theta}\}$;
  Sample $d_m \sim \text{Exponential}\left(\eta_m\right)$;
  Update $t_m = t_{m-1} + \Delta t$;
  Update $\boldsymbol{X}_{\text{rate}}(t_m, s, r)$ and $\boldsymbol{x}_{\text{duration}}(t_m)$;
  Update $\mathcal{R}_{t_m}$;

between actors $s_2 =$ "C" and $r_2 =$ "D". Then, at $t = 4$ (i.e., $t_2 + d_2$), the event history (and thus the endogenous statistics for all potential events) is updated with the event at t_2 between individuals C and D, and at $t = 5$ (i.e., $t_1 + d_1$), the event history is updated with the event at t_1 between individuals A and B.

4.2.4 Parameter estimation

Given that the rate model and the duration model each have their own unique sets of parameters and because the event duration is modeled (conditionally) independent from the time, sender, and receiver of each event, the parameters under both model components can be estimated separately but in a similar manner. The maximum likelihood estimates (MLEs) can be obtained by maximizing the log likelihood, e.g., for the event rate: :

$$(\hat{\tau}_{\text{rate}}, \hat{\psi}_{\text{rate}}, \hat{\boldsymbol{\beta}}) = \arg \max_{(\tau_{\text{rate}}, \psi_{\text{rate}})} \log p(\boldsymbol{t}, \boldsymbol{s}, \boldsymbol{r}|\boldsymbol{\beta}, \tau_{\text{rate}}, \psi_{\text{rate}}). \tag{4.8}$$

Because the MLEs of $\boldsymbol{\beta}$ can be obtained using the R packages RELEVENT (Butts, 2008) or REMSTIMATE (Arena, Lakdawala, & Generoso Vieira, 2022), the MLEs of τ_{rate} and ψ_{rate} can be obtained using a grid over these parameters and check which combination of values maximizes the log likelihood where the MLEs of $\boldsymbol{\beta}$ are plugged in conditional on the grid values of τ_{rate} and ψ_{rate}. The MLEs of τ_{duration} and ψ_{duration} can be obtained similarly, with the MLEs of $\boldsymbol{\theta}$ obtained using the R package SURVIVAL

(Therneau, 2020).

4.3 Numerical evaluation

4.3.1 Methods

The aim of this simulation study is to assess the recovery of the half-life parameter τ and the duration parameter ψ in the event rate and event duration components of our model. We assess parameter recovery by computing the bias, which is the deviation between an estimate's expected value and its true value. The expected value is calculated by averaging the parameter estimates across the generated relational event sequences per simulation scenario.

Using the method outlined in Algorithm 3, we simulate 100 relational event sequences with $N = 20$ and $M = 5000$ in six simulation scenarios. The model that we use for the event rate (see Equation 4.3) is

$$\begin{aligned}\log \lambda(t, s, r) = &- 8.0 \; + \; 0.2 x_{\text{activity.of.sender}}(t, s, r) \; + \; 0.2 x_{\text{inertia}}(t, s, r) \; + \\ &0.2 x_{\text{transitivity}}(t, s, r),\end{aligned} \tag{4.9}$$

and the model that we use for the event duration (see Equation 4.7) is

$$\begin{aligned}\log \eta_m = \; &1.0 \; + \; 0.2 x_{\text{popularity.of.receiver}}(t_m, s_m, r_m) \; - 0.2 x_{\text{inertia}}(t_m, s_m, r_m) \\ &- 0.2 x_{\text{transitivity}}(t_m, s_m, r_m).\end{aligned} \tag{4.10}$$

Table 4.2 contains a description of how the statistics for the endogenous predictors in Equations 4.9 and 4.10 are calculated. We standardize the statistics per time point to ensure that they are comparable over time and that we obtain well-behavior model parameters (e.g., see Butts, 2008; Schecter & Quintane, 2020). Furthermore, positive model parameters in Equation 4.9 are associated with an increase in the event rate (or a shorter waiting time between events), whereas positive model parameters in Equation 4.10 are associated with a decrease in event duration and negative model parameters with an increase.

The six simulation scenarios differ in the values for ψ and τ as follows. In the first five scenarios, the values of ψ and τ are equal for the event rate and event duration:

1. $\psi_{\text{rate}} = \psi_{\text{duration}} = 0.6$ and $\tau_{\text{rate}} = \tau_{\text{duration}} = 300$,
2. $\psi_{\text{rate}} = \psi_{\text{duration}} = 0.6$ and $\tau_{\text{rate}} = \tau_{\text{duration}} = 5000$,
3. $\psi_{\text{rate}} = \psi_{\text{duration}} = 0.6$ and $\tau_{\text{rate}} = \tau_{\text{duration}} = 7350$.
4. $\psi_{\text{rate}} = \psi_{\text{duration}} = 0.3$ and $\tau_{\text{rate}} = \tau_{\text{duration}} = 300$.
5. $\psi_{\text{rate}} = \psi_{\text{duration}} = 0$ and $\tau_{\text{rate}} = \tau_{\text{duration}} = 300$.

In the fifth scenario, we leave open the possibility that duration of previous events may have no effect on future events, which implies that all events have a similar level of “intensity", regardless of their duration. In the sixth and final simulation scenario, the values of ψ and τ differ for the event rate and the event duration:

Table 4.2.: Description of endogenous predictors for directed events used throughout this chapter.

		Interpretation	
Name	Formula	Rate model	Duration model
Activity of sender	$\sum_{h\in A} w(t,s,h)$	As the intensity of previous events initiated by individual s increases, they become increasingly more or less likely to initiate a future event.	As the intensity of previous events initiated by individual s increases, the duration of a future event initiated by them increases or decreases.
Activity of receiver	$\sum_{h\in A} w(t,r,h)$	As the intensity of previous events initiated by individual r increases, they become increasingly more or less likely to receive a future event.	As the intensity of previous events initiated by individual r in increases, the duration of a future event received by them increases or decreases.
Popularity of sender	$\sum_{h\in A} w(t,h,s)$	As the intensity of previous events received by individual s increases, they become increasingly more or less likely to initiate a future event.	As the intensity of previous events received by individual s in increases, the duration of a future event initiated by them increases or decreases.
Popularity of receiver	$\sum_{h\in A} w(t,h,r)$	As the intensity of previous events received by individual r increases, they become increasingly more or less likely to receive a future event.	As the intensity of previous events received by individual r increases, the duration of a future event received by them increases or decreases.
Inertia	$w(t,s,r)$	A future event from individual s towards individual r becomes more or less likely as the intensity of previous events from individual s towards individual r increases.	The duration of a future event from individual s towards individual r increases or decreases as the intensity of previous events from individual s towards individual r increases.

(To be continued)

Table 4.2 Continued

		Interpretation	
Name	Formula	Rate model	Duration model
Reciprocity	$w(t, r, s)$	As the intensity of previous events initiated by individual r towards individual s increases, the probability for a future event from individual s towards individual r increases or decreases.	As the intensity of previous events initiated by individual r towards individual s increases, the duration of a future event from individual s towards individual r increases or decreases.
Transitivity	$\sum_{h \in A} \min\{w(t, s, h), w(t, h, r)\}$	As the intensity of previous events from individual s towards an individual h and the intensity of previous events from individual h towards individual r increases, the probability for a future event from individual s towards individual r increases or decreases.	As the intensity of previous events from individual s towards an individual h and the intensity of previous events from individual h towards individual r increases, the duration of a future event from individual s towards individual r increases or decreases.

6. $\psi_{\text{rate}} = 0.3$, $\tau_{\text{rate}} = 300$ and $\psi_{\text{duration}} = 0.6$, $\tau_{\text{duration}} = 5000$.

Relational event sequences are simulated in R; the script with the code for the simulation study can be found on https://github.com/mlmeijerink/thesis-ch4-duration. Parameter estimates in the simulated sequences are obtained using the procedure outlined in Section 4.2.4.

4.3.2 Results and interpretation

The average estimated ψ and τ values and the resulting bias in our simulation scenarios are shown in Table 4.3. These results give some interesting new insights in estimating event duration and memory processes. First, results indicate that the parameter recovery in the first scenario ($\psi_{\text{rate}} = \psi_{\text{duration}} = 0.6, \tau_{\text{rate}} = \tau_{\text{duration}} = 300$) is good, with little bias in both the event rate and event duration components of our model. However, when τ increases in Scenarios 2 and 3, so does the bias in ψ_{rate}, τ_{rate} and τ_{duration}. This may be an indication that a certain length of the study period relative to τ is necessary for this parameter to be accurately estimated. In our simulation scenarios, time typically ran to approximately 45000 time units. This appears to be too short for $\tau = 5000$ to be accurately estimated. Inaccurate estimation of τ_{rate} also appears to increase the bias in ψ_{rate}. Conversely, the bias in ψ_{duration} does not appear to increase when τ_{duration} is inaccurately estimated. This is also found in Scenario 6. Changing ψ while keeping $\tau = 300$ in Scenarios 4 and 5 did not appear to affect the ability of the method to accurately estimate the parameters. In conclusion, based on the results from the numerical evaluation, we are confident that the proposed estimation method can be used to estimate ψ and τ. However, when we are interested in τ values that are relatively large in comparison to the length of the study period, we must be cautious about interpreting the size of the parameter estimates.

4.4 Application I: Hospital contacts

4.4.1 Data

In a first empirical application of the methods discussed in this chapter, we investigate the dynamic evolution of physical contacts between patients and healthcare workers in a hospital. The data were collected by Vanhems et al. (2013) to provide information on important routes of transmission of hospital-acquired infections. We use our model to investigate how a sequence of interactions between patients and healthcare workers evolves over time, with the frequency, time since, and duration of previous interactions influencing the rate and duration of future interactions.

Vanhems et al. (2013) used wearable sensors to record close-range (1-1.5m) proximity contacts between 75 patients and healthcare workers at a hospital's geriatric unit in France for four days in 2010. These records of close-range proximity contacts are assumed to provide a measure of the face-to-face interactions between individuals. The data has a time granularity of 20 seconds, which means we have information about the pairs of individuals between whom the sensors detected contact every 20 seconds. Similar to Vanhems et al. (2013), we define the beginning of a new relational

Table 4.3.: Per simulation scenario, the true ψ and τ values, the average $\bar{\psi}$ and $\bar{\tau}$ values across datasets, and the resulting bias ($\bar{\psi} - \psi$ and $\bar{\tau} - \tau$) for the event rate and event duration component of the model.

	Event rate					
	ψ	$\bar{\psi}$	$\bar{\psi} - \psi$	τ	$\bar{\tau}$	$\bar{\tau} - \tau$
1	0.60	0.58	-0.02	300	300	0
2	0.60	0.54	-0.06	5000	5682	682
3	0.60	0.51	-0.09	7350	8807	1457
4	0.30	0.31	0.01	300	300	0
5	0.00	0.00	0.00	300	300	0
6	0.30	0.30	0.00	300	300	0
	Event duration					
	ψ	$\bar{\psi}$	$\bar{\psi} - \psi$	τ	$\bar{\tau}$	$\bar{\tau} - \tau$
1	0.60	0.61	0.01	300	300	0
2	0.60	0.60	0.00	5000	5353	353
3	0.60	0.61	0.01	7350	8666	1316
4	0.30	0.31	0.01	300	300	0
5	0.00	0.00	0.00	300	300	0
6	0.60	0.58	-0.02	5000	5353	353

event when two individuals are detected in contact while they were not in contact in the preceding 20 seconds. The relational event is considered terminated if the two individuals are not detected in contact within the following 20 seconds.

Previous research about the validity of wearable sensors for recording face-to-face contacts has shown that these badges generally have high specificity but moderate sensitivity (Elmer et al., 2019). This research demonstrated that the sensitivity of the sensors can be improved by using a data processing strategy where two signals are merged into one when there is only a short interruption of at most 75 seconds between them. Based on these findings, we decided to merge relational events between the same two individuals that were no more than 75 seconds apart. Thus, when a relational event between individuals A and B is observed from $t = 300$ up to $t = 360$ and then again from $t = 420$ up to $t = 440$, these two events are merged into a single relational event between individuals A and B from $t = 300$ up to $t = 440$.

These data processing steps resulted in a relational event sequence with 10,607 events. The relational events are time-stamped. In some instances, multiple events started at the same time t. We analyze these events in a random order, with the time for the beginning of the events evenly spaced between t and $t + 1$. The first few events of the relational event sequence are shown in Table 4.1. Note that the relational events in this case study are undirected.

There are 46 healthcare workers (27 nurses, 11 medical doctors, and 8 administrative personnel) and 29 hospital patients among the 75 participants. The risk set is made up of all undirected pairs of individuals. Furthermore, in the construction of the risk set we took into account that most individuals would be unavailable for parts of the study period. First, patients were only available for interaction during their hospital stay. Therefore, patients are included in the risk set from the first time we observe an interaction with the respective patient until the last time. Second, hospital employees work in shifts. We define a new shift for employee A when we observe an interaction with this person and it is either the first interaction with employee A in the data or the most recent interaction with employee A was at least 7 hours ago. Similarly, the shift for employee A is considered to be over when there is no interaction with employee A for the next 7 hours. Hospital employees are present in the risk set for the duration of their shifts and removed otherwise. Third, for the duration of an ongoing event between two individuals, this pair is removed from the risk set to start a new event. Because the data suggested that it was possible to start a new event with already interacting individuals, individuals who are involved in an event are assumed to be still at risk for starting other events.

4.4.2 Model specification

The first research question that we investigate is how emerging patterns of past interactions (i.e., endogenous mechanisms) influence the rate and duration of future interactions. The research focuses on three types of endogenous mechanisms: “inertia", “transitivity" and “activity". Inertia describes a habituation process, or how the frequency, time since, and duration of previous interactions between two individuals affect the rate and duration of future interactions between them. Transitivity describes the tendency of individuals to interact with “friends of friends", or, to create a more direct flow of information. That is, it captures how the rate and duration of a future interaction between two individuals are affected when these two individuals have previously (separately) interacted more with the same third-party individuals. Activity captures the tendency of two individuals individuals to interact with each other if their combined intensity of previous events is greater. This endogenous mechanism combines common directed actor degree effects (“activity of the sender”, etc.) in order to be able to account for degree effects in an analysis with undirected events. In the literature, it is repeatedly reported that these three mechanisms are important for explaining the rate of social interaction between individuals (e.g., Butts, 2008; Stadtfeld & Block, 2017). However, little is known about how these mechanisms affect the event duration. Table 4.4 describes how the statistics for these endogenous mechanisms are calculated as well as the respective probabilistic mechanisms.

Since we consider both the event rate and the event duration in our analysis, we are able to investigate how currently ongoing events affect the rate and duration of the next event. As previously stated, the data suggested that individuals could start a new event with a person that is already involved in an event with someone else. The second research question that we investigate is therefore whether people are more likely (or faster) to initiate a new event with a person that is already interacting with someone else, and how this affects the duration of the event. Let A_{busy} denote the set

Table 4.4.: Description of endogenous predictors for undirected events in the application with face-to-face contacts in the hospital.

		Interpretation	
Name	Formula	Rate model	Duration model
Inertia	$w(t,i,j)$	Individuals i and j become more or less likely to interact in the future as the intensity of previous events between them increases.	The duration of a future event between individuals i and j increases or decreases as the intensity of previous events between them increases.
Transitivity	$\sum_{h \in A} \min\{[w(t,i,h)+w(t,h,i)], [w(t,j,h)+w(t,h,j)]\}$	As the intensity of previous interactions of both individuals i and j separately with actors h increases, the probability for a future interaction between them increases or decreases.	As the intensity of previous interactions of both individuals i and j separately with actors h increases, the duration of future interaction between them increases or decreases.
Activity	$\sum_{h \in A} w(t,i,h) + w(t,j,h) + w(t,h,i) + w(t,h,j)$	The intensity of previous events with either individual i or individual j increases or decreases the probability for a future interaction between them.	The duration of a future event between individuals i and j increases as the intensity of previous events with either individual i or j increases or decreases.
Join	$I(i \in A_{\text{busy}} \vee j \in A_{\text{busy}})$	The probability for an interaction between individuals i and j increases depending on whether either of them is already involved in an event (i.e., in A_{busy}).	The duration of a future interaction between individuals i and j increases depending on whether either of them is already involved in an event (i.e., in A_{busy}).

of individuals that are currently involved in an ongoing event. The "join" statistic is then equal to one for pairs (i, j) with either actor i or actor j in A_{busy} (see Table 4.4).

Furthermore, it must be assumed that the contacts between individuals in the current data are largely driven by professional rather than social motives. Therefore, the third research question that we investigate is how much the effects of the endogenous mechanisms on the event rate and duration are dependent on the (professional) roles of the individuals in the hospital. In short, we refer to the different professional roles of the individuals in the hospital (i.e., patient, nurse, medical doctor, or administrative staff) as the "class" to which the participant belongs. Since there are four different classes, we may observe interactions between individuals from 10 different class pairs. Let A_{PAT}, A_{NUR}, A_{MED} and A_{ADM} denote the set of individuals with class patient, nurse, medical doctor and administrative staff, respectively. As reference category, we select the patient-nurse class pair. For the remaining nine class pairs we include statistics of the type

$$X_{\text{NURMED}}(t, s, r) = I((s \in A_{\text{NUR}} \wedge r \in A_{\text{MED}}) \vee (s \in A_{\text{MED}} \wedge r \in A_{\text{NUR}})) \quad (4.11)$$

to our model for the event rate and event duration. Finally, we include interaction effects between the endogenous and exogenous parameters. This allows us to infer how endogenous mechanisms affect the event rate and event duration differently across the ten possible class pairs.

4.4.3 Results and interpretation

Estimation results indicate that the combination of the duration parameter $\hat{\psi}_{\text{rate}} = 0.42$ with the half-life parameter $\hat{\tau}_{\text{rate}} = 150$ seconds best explains the event rate and that the combination of the duration parameter $\hat{\psi}_{\text{duration}} = 1.00$ with the half-life parameter $\hat{\tau}_{\text{rate}} = 300$ seconds best explains the event duration. Figure 4.1 shows the event weights based on these parameter estimates as the time since the event increases for the 0.025, 0.500, and 0.975 quantiles of observed event durations (20, 40, and 280 seconds, respectively).

The estimated τ_{rate} value is very small, 150 seconds. This implies that only the immediate past is relevant in explaining the rate of future contacts between the individuals at the hospital. Further, the positive estimate for the duration parameter (0.42) suggests that the influence of emerging patterns of prior contacts on the future event rate increases as their duration increases. In the event duration component of our model, we find a slightly larger half-life parameter of 300 seconds. This means that, compared to the event rate, prior events that occurred longer ago remain relevant in explaining the duration of future contacts. Further, the large positive estimate for the duration parameter (1.00) indicates that the duration of prior contacts is important in predicting the duration of future contacts between individuals, i.e., emerging patterns of longer prior contacts between individuals are associated with longer future contacts.

By plugging the β estimates into Equation 4.3, we can calculate the event rate for each pair in the risk set at time t. The pair with the highest event rate has the highest probability of being observed next according to the model. Hence, we can

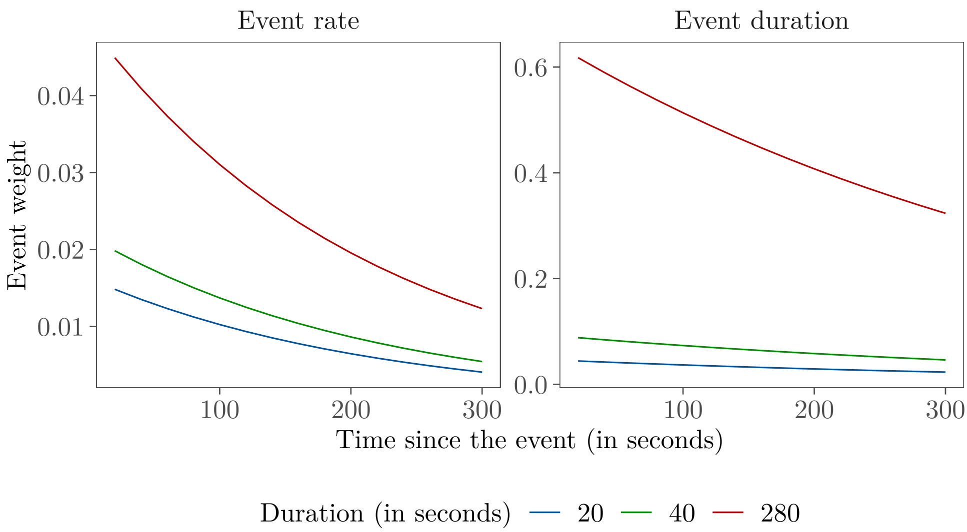

Figure 4.1.: In the first empirical application, the weight of past events is determined by the time since the events and their duration ($\hat{\psi}_{\text{rate}} = 0.42$, $\tau_{\text{rate}} = 150$, $\hat{\psi}_{\text{duration}} = 1.00$, and $\tau_{\text{duration}} = 300$).

assess the model's ability to predict the next event by examining the rank of the observed event rates. To evaluate the impact of accounting for event duration, we compare the predictive performance of our model with $\hat{\psi}_{\text{rate}} = 0.42$ and $\hat{\tau}_{\text{rate}} = 150$ to that of a "standard" REM model with $\psi_{\text{rate}} = 0$ and $\tau_{\text{rate}} = \inf$. We find average ranks of 59.1 and 69.2, respectively. These findings demonstrate that the model that takes event duration and memory effects into account performs better on average in terms of predicting the next event than the standard REM. Further inspection of the observed event ranks show that the extended REM can better predict the next event in a majority 6179 out of 10607 events (58.3%), the standard REM performed better for 3893 events (36.7%), and the models performed equally well for the remaining 535 events (5.0%).

Subsequently, Figure 4.2 displays the estimated regression coefficients in our log-linear model for the event rate and duration. We first discuss the results for the event rate, which are shown in the left column. Negative parameter estimates for the baseline effect on the top row refer to pairs of individuals who, on average, have a lower event rate than the patient-nurse pair, which is the reference category. For example, we can see that the event rate for contact between two patients is especially low. Contact between two patients is thus far less common than contact between a patient and a nurse. In fact, from all individuals, nurses are most likely to interact with patients, given their available interaction partners. Further, healthcare workers are relatively more likely to interact with others that have the same status in the hospital. Contact between two nurses, for example, is considerably more likely than contact between a patient and a nurse. The result for the "degree" statistic in the second row shows that the event rate of the patient-nurse pair decreases as their combined involvement in prior contact increases. Thus, patient-nurse pairs with more recent prior contacts are less likely to be involved in a new contact. For two-patient pairs, this effect is found to be even stronger. This could be explained if patients who have had many prior contacts with healthcare workers have less contact with each other (possibly because their condition is worse). Additional data is required to confirm such hypotheses. We can see in Figure 4.2 that for most other pairs of individuals, the effect of degree on the event rate is actually positive. In that case, individuals with more recent prior contacts are more likely to be involved in a new contact. This is, for example, especially found for contact between a patient and someone of the administrative staff. The result for the "inertia" statistic shows that the patient-nurse pair's event rate increases if they have recently interacted more together. For some pairs of individuals, we can see that recent prior contact has a larger effect on the event rate compared to the patient-nurse pair. For others, it has a smaller, possibly non-significant effect. The strongest positive effect is found for contact between two patients. Two patients who have recently been in contact together are thus more likely to be involved in new contact soon. This could be explained by the fact that these patients are in the same room, but unfortunately we do not have access to information about room assignments. According to the result for the "join" statistic, contact between a patient and a nurse is considerably more likely if one of them is already in contact with someone else. This effect is even stronger for patient-patient pairs. Again, this could be explained by patients being in the same room. For all other pairs of individuals, the effect is weaker than for the patient-nurse pair. Finally, the result for the "transitivity" statistic indicates that prior interactions with a shared communication partner increases the rate for contact between a patient and a nurse. This is also true for most other pairs of individuals.

The parameter estimates for the duration component of our model are displayed in the right column of Figure 4.2. These results inform us about when pairs of individuals are more likely to interact longer (negative effects) or shorter (positive effects). First, the baseline effect in the top row shows that contact between patients and nurses are, on average, relatively short. Most other pairs tend to be in contact for a longer period of time. Contacts between patients and doctors are an exception, lasting even shorter than contacts between patients and nurses. The result for the "degree" effect shows that for the patient-nurse pair, their previous combined activity does not affect the duration of contact between them. This is also found for the majority of other pairs. Contacts between two nurses and two medical doctors are exceptions, as they tend to interact for a longer period of time if they have recently had more prior contact with others. The result for the "inertia" statistic shows that previous contact between the patient-nurse pair is associated with a slightly shorter future contact on average. This effect is found to be even somewhat stronger in most other pairs of individuals. These pairs are even quicker to terminate a contact if they recently interacted more together. This is for example found for contact between two members of the administrative staff.

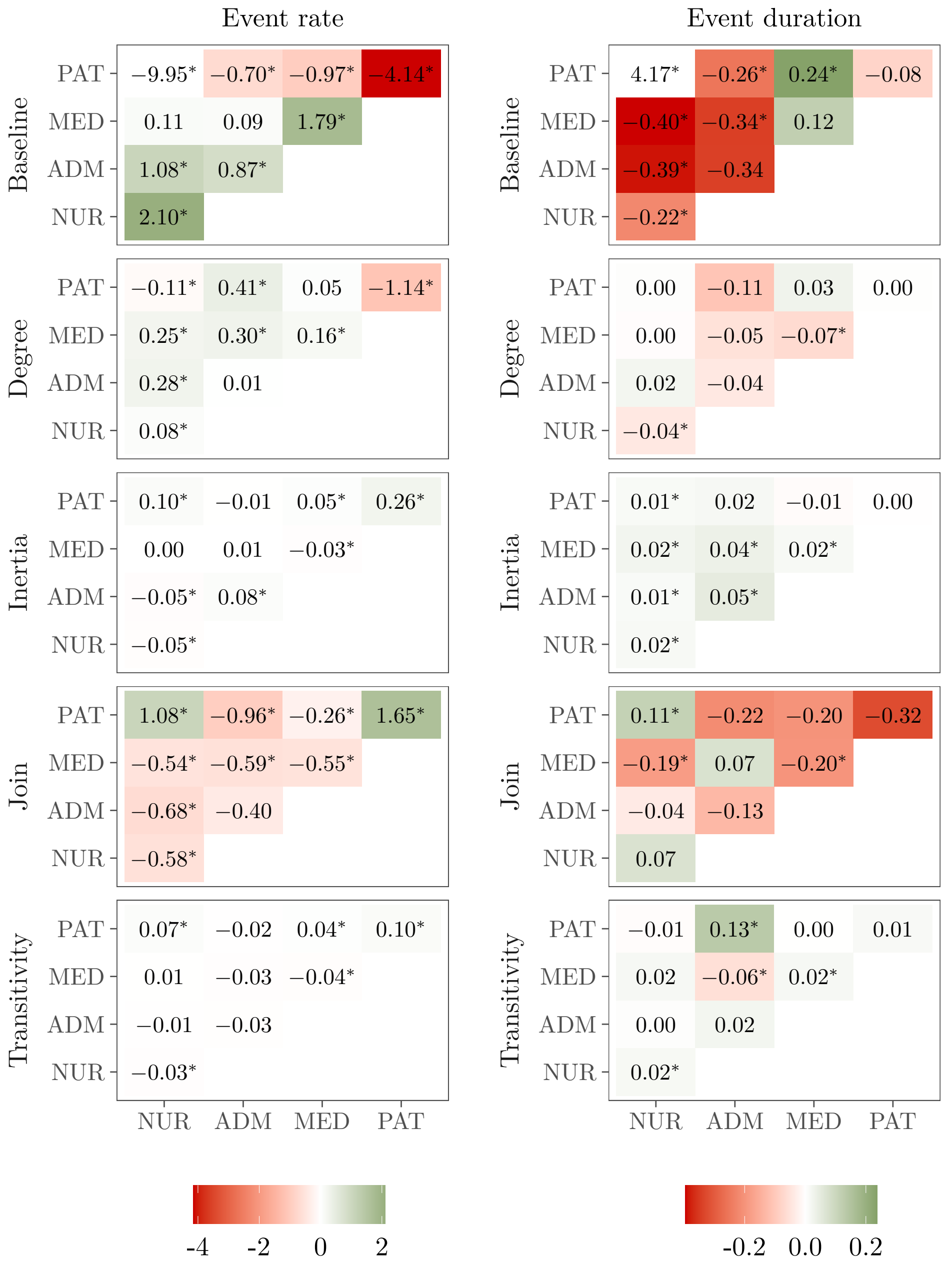

Figure 4.2.: Parameter estimates for the first empirical application. Note that the patient-nurse pair forms the reference category. $^*p < 0.05$.

Results for the “join” statistics indicate that a contact between a patient and nurse is, on average, terminated sooner if one of them is also in contact with someone else. This is also found for the majority of other pairs. For some pairs, the effect is found to be weaker than for the patient-nurse pair. These pairs are less quick to terminate a contact if they are also in contact with someone else, and may even interact for longer when this is the case. Finally, results for the “transitivity” effect show that recent prior contact with shared communication partners has no effect on the duration of a future contact between a patient and a nurse. This is also found for the majority of other pairs. Contact between a patient and a member of the administrative staff is a notable exception. These contacts are found to be shorter when they share more recent prior communication partners. On the other hand, in the case of an event involving an administrative staff member and a medical doctor, we find that more recent prior contact with shared communication partners lengthens the duration of a future contact.

Overall, these results provide an interesting picture of the dynamics of interactions between hospital patients and healthcare workers. Results showed that interaction dynamics change quickly, and that prior event duration has a strong effect on the rate and duration of future events. Further, results demonstrate how emerging patterns of prior interactions affect event rate and duration in this very specific setting. We observe clear differences in the size or direction of the effects between pairs of individuals. However, to interpret why these differences occur, further information is needed.

4.5 Application II: Violent conflict

4.5.1 Data

In a second empirical application, we examine the dynamic evolution of an interpersonal conflict in public space. This analysis is inspired by the interactionist approach to the study of aggression and violence. While many scholars argue that aggression and violence are caused by structural (e.g., racism, poverty, sexism) or individual (e.g., education, gender, genes) factors, the interactionist approach shows that these behaviors are also shaped by factors within the situation (Felson & Tedeschi, 1993; Jackson-Jacobs, 2013). Researchers within this theoretical tradition argue that, once a conflict has begun, the further development of the situation is mostly shaped by endogenous factors within the situation (Felson, 1984; Luckenbill, 1977). Aggression and violence are products of interactional processes, and to understand these behaviors, we need to account for their interactive nature. To explain how a person behaves in a conflict situation, we therefore need to account for not just the preceding behavior of this specific individual, but also the behavior of all the other people present (Felson & Steadman, 1983). Conflict behavior is thus reactive in nature, but this reactiveness has never been studied in a way that allowed researchers to systematically account for the complexity of preceding behaviors. We use the methods presented in this chapter to adapt a dynamic view and investigate the endogenous mechanisms that shape the development of interpersonal conflict over time. In particular, we investigate how much an individual’s behavior in a conflict situation is influenced by the frequency, time since, and duration of their own previous behavior and that of the other people present.

The data were collected by Ejbye-Ernst et al. (2021) and consists of records of violent interactions between individuals. These records are based on CCTV footage of an interpersonal conflict in a public space in Amsterdam, the Netherlands. This footage was systematically observed and coded by Ejbye-Ernst et al. (2021). Observed behaviors in the conflict situation on the CCTV footage were coded with timestamps for the beginning and end of the behavior, as well as identification numbers for the individuals who initiated and received the behavior. Over the course of the nine-minute conflict, 216 interactions between ten actors were observed. Four of these interactions had two recipients (rather than one). These four interactions were divided into two events for the analysis, one for each receiving individual in the original behavior. The order of these events in the sequence was chosen at random, with the time for event starts evenly spaced between the original event time t and $t + 1$. The resulting relational event history consists of 220 time-stamped, directed, and dyadic events.

The events' durations range from 0.02 to 26.70 seconds. Seven of the 220 relational events do not have a duration, e.g., an event with type "hitting". We decided to give these events an artificial duration of 0.02 seconds in order to include them in the analysis. All 220 relational events are then used to calculate statistics that capture emerging social patterns. For the model for the event rate, we include the occurrence of all 220 events. However, for the model for the event duration, we only consider the 213 events that have an observed event duration in the dependent variable.

At a given point in time, the risk set consists of all directed pairs of individuals who are available for interaction. Since inspection of the data revealed that it was possible to direct a new behavior towards an already interacting individual, we did not remove interacting individuals from the risk set.

4.5.2 Model specification

The first research question that we investigate is how endogenous mechanisms that describe an individual's own past behavior influence the rate and duration of new behavior initiated by this individual. This is investigated by incorporating statistics for "activity of the sender" and "inertia" into our model for the event rate and the event duration. Second, we investigate how the rate and duration of a new behavior initiated by an individual are influenced by the previous behavior of their current "opponent" (i.e., the receiver of the new behavior). Therefore, we include statistics for the "activity of the receiver" and "reciprocity" in our model for the event rate and the event duration. The third and final research question that we investigate is how the rate and duration of a new behavior initiated by an individual are affected by the previous behaviors of all their potential opponents. For this purpose, we include statistics for the "popularity of the sender" and "popularity of the receiver" in our model for the event rate and event duration. This leads to the following model for the log event rate:

$$\begin{aligned}\log\lambda(t,s,r) =&\beta_0 + \beta_1 x_{\text{activity.sender}}(t,s,r) + \beta_2 x_{\text{inertia}}(t,s,r)+ \\ &\beta_3 x_{\text{activity.receiver}}(t,s,r) + \beta_4 x_{\text{reciprocity}}(t,s,r)+ \\ &\beta_5 x_{\text{popularity.sender}}(t,s,r) + \beta_6 x_{\text{popularity.receiver}}(t,s,r)\end{aligned} \tag{4.12}$$

The model for the event duration is specified using the same statistics. Table 4.2 describes how the statistics in Equation 4.12 are calculated, as well as the corresponding probabilistic mechanisms.

4.5.3 Results and interpretation

Estimation results indicate that the combination of duration and half-life parameters $\hat{\psi}_{\text{rate}} = -0.2$ and $\hat{\tau}_{\text{rate}} = \inf$ best explains the event rate. The left panel in Figure 4.3 depicts the resulting event weights based on these parameter estimates for the range of observed event durations. The estimate for $\hat{\tau}_{\text{rate}} = \inf$ means that every event in the history weights equally in the explanation of the next event, regardless of the time since the event. Interestingly, the estimate for $\psi_{\text{rate}} = -0.2$ indicates that the impact of previous events on future event rates decreases as their duration increases. Given that these events take place in a conflict situation, one possible explanation for this finding is that more aggressive behaviors typically result in relatively short events (e.g., a hit or a kick).

We calculate the event rate for each pair in the risk set at time t by plugging the β estimates into Equation 4.12. Subsequently, we evaluate the model's ability to predict the next event by ranking the observed event rates. We compare the predictive performance of our model with $\hat{\psi}_{\text{rate}} = -0.2$ and $\hat{\tau}_{\text{rate}} = \inf$ to that of a standard REM model with $\psi_{\text{rate}} = 0$ and $\tau_{\text{rate}} = \inf$. The results indicate that the two models' average predictive performance is comparable, with average ranks of 14.1 and 14.3, respectively. However, further inspection of the observed event ranks slightly favors the model that takes event duration into account. This model can better predict the next event in 74 out of 220 events (33.6%), the models performed equally well for 81 events (36.8%), and the standard REM performed better for the remaining 65 events (29.5%).

The combination of the duration and half-life parameters $\psi_{\text{duration}} = 1.3$ and $\tau_{\text{rate}} = \inf$ is estimated to best describe the data generating process for the event duration. The right panel in Figure 4.3 depicts the resulting event weights based on these parameter estimates for the range of observed event durations. The estimate for $\psi_{\text{duration}} = 1.4$ indicates that, as the duration of previous events increases, so does their influence on future event duration. The estimate for $\hat{\tau}_{\text{duration}} = \inf$ indicates that, like for the event rate, the entire event history remains equally important in explaining future event duration.

The results of the fitted REM with the estimated duration and half-life parameters are shown in table 4.6. These results tell the following story about how the conflict situation evolved over time. In general, the frequency and duration of an individual's previous activity increases the likelihood that this individual will initiate a future

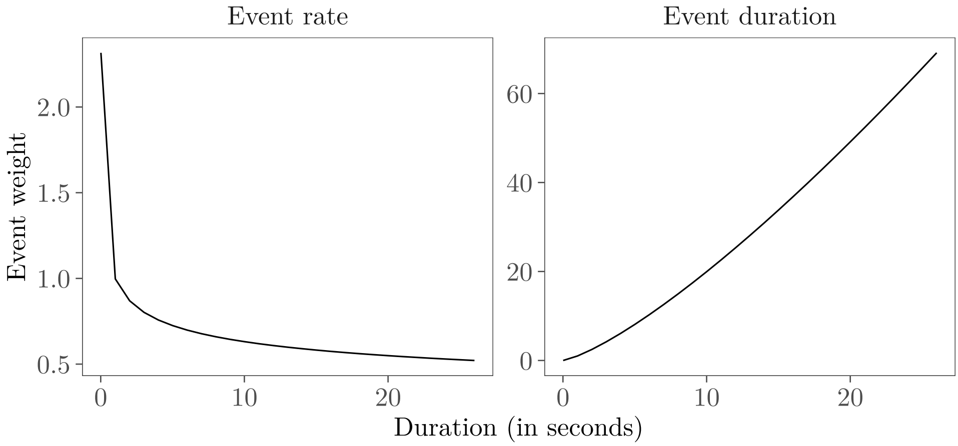

Figure 4.3.: In the second empirical application, the weight of past events is determined by their duration ($\hat{\psi}_{\text{rate}} = -0.2$ and $\hat{\psi}_{\text{duration}} = 1.4$).

event (activity of sender). Furthermore, the frequency and duration of their previous activity against a specific opponent increases the likelihood that this individual will initiate another event against the same opponent in the future (inertia). Hence, the same people tend to keep initiating new events in the conflict situation and people tend to keep initiating events against the same opponent. Furthermore, the event rate increases for future events directed at opponents who initiated (activity of receiver) or received (popularity of receiver) more and longer behaviors in the past. Hence, people tend to direct their behaviors towards others who were previously actively involved in the conflict. Surprisingly, we found no evidence for a reciprocity effect. Given the other effects in the model, individuals were not significantly more or less likely to initiate events towards others who had previously initiated events towards them.

In the duration model, we found evidence for a significant effect of the sender's previous activity, popularity, and reciprocity on the future event duration. Results indicate that the sender's previous activity reduces the duration of future events. Similarly, the duration of future events initiated by individuals towards others who had previously initiated more and longer events against them was typically shorter as well (reciprocity). Previous popularity of the sender was associated to a longer future event duration.

4.6 Discussion

In this chapter, we presented a relational event approach for analyzing how the length of social interactions affects future interaction rates, and vice versa. Building on the tradition of existing relational event modeling approaches, our model allows researchers to investigate how a combination of individuals' characteristics and emerging patterns of prior interactions between them influences who interacts when with whom and

Table 4.6.: Parameter estimates for the second empirical application.

	Event rate			Event duration		
Variable	$\hat{\theta}$	$\hat{\text{SE}}$	p-value	$\hat{\theta}$	$\hat{\text{SE}}$	p-value
Baseline	-6.13	0.11	$< .01^*$	0.87	0.12	$< .01^*$
Activity of sender	0.32	0.12	$< .01^*$	0.34	0.15	0.02^*
Inertia	0.19	0.06	$< .01^*$	-0.05	0.08	0.55
Activity of receiver	0.56	0.09	$< .01^*$	-0.02	0.09	0.80
Reciprocity	0.01	0.09	.91	0.24	0.09	$< .01^*$
Popularity of sender	-0.23	0.18	.21	-0.49	0.17	$< .01^*$
Popularity of receiver	0.58	0.08	$< .01^*$	0.14	0.09	0.12

$^*p < .05$.

for how long. Furthermore, the method we propose makes it possible to model how the impact of a prior interaction on future interaction behavior is dependent on its duration. The R code that we used to perform the analyses in this chapter is available on https://github.com/mlmeijerink/thesis-ch4-duration.

First, we argued that the impact of a prior event on future interaction rates is determined by both the amount of time that has elapsed since the event and its duration. We presented a method for learning the non-linear impact of time elapsed and event duration on interaction rates. In a simulation study, the ability of this method to recover the half-life and duration parameters, which quantify the effect of time elapsed and event duration, was briefly evaluated. Findings from the simulation study provided a proof of concept for the proposed methodology as they indicated that the half-life and duration parameters can be accurately estimated when the half-life parameter is relatively small in relation to the length of the study period. The latter is an interesting finding that gives new insights in estimating memory processes in relational event models.

Subsequently, we used the methodology we proposed in two case studies. In the first, we investigated the dynamic mechanisms underlying a series of physical contacts in a hospital between patients and healthcare workers. Specifically, we examined how emerging patterns of previous physical contacts drive the rate and duration of future contacts differently for different pairs of individuals. We found a small half-life parameter in this case study. Especially in the event rate component of our model, where it was as small as 150 seconds (compared to a study period of five days). This may suggest that interaction dynamics in the hospital changed quickly. However, we observed many events between the same two individuals that shortly followed each other. This may suggest that the wearable sensors lack a certain amount of sensitivity to detect that people are still in contact, something that is also found in (Elmer et al., 2019). Therefore, we do not know whether the small half-life parameter found in the first case study is something that reflects true rapid changes in interaction processes or is an artefact of using wearable sensors to detect contact between individuals. Future research into improving the sensitivity of wearable sensors to detect face-to-face contacts may aid in determining this. Furthermore, the duration parameter in our model is estimated to be large, particularly in the duration component. This implies that the length of previous contacts is important in explaining the length of future contacts. Prediction results revealed that, on average, the model that takes event duration and memory effects into account was better able to predict who will interact with whom next than the “standard” REM. Findings further indicated when certain pairs of individuals are more likely to interact and when they are more likely to interact longer. From the current data the cause of these effects is not clear. Instead, this information can be combined with knowledge about how hospitals work to guide future research into understanding why these things happen.

In a second empirical analysis, we investigated which dynamic mechanisms underlie the evolution of an interpersonal conflict in public space. We looked specifically at how emerging patterns in individuals’ own behavior and the behavior of their opponents influence the rate and duration of future events. In this case study, we found a negative duration parameter in the event rate component of our model. Prior events with shorter durations were thus more influential in determining future interaction rates than longer events with longer durations. Future research may consider the type or level of aggression of the behavior in the analysis and see if this can explain the negative duration parameter. Furthermore, results revealed that the entire history of events was important in explaining the rate and duration of future events. This finding may be explained by the fact that the conflict occurred in a relatively short time period of nine minutes. It appears that people did not forget what others had done to them in such a short period of time. This difference in results between the first and second case study highlights the importance of studying duration and memory effects in different empirical contexts to inform theories about social interaction behavior. Prediction results revealed that the model that considers event duration and memory effects correctly predicted who will interact with whom next more often than the “standard” REM. According to our findings, people who were previously more active in the conflict were more likely to be the initiator or target of new events. However, when these people started a new event, it was usually shorter. Those who had been the target of many events in the past were more likely to be targeted again. Furthermore, people tended to repeatedly initiate events against the same opponents. When the initiator was the target more frequently in the past, an event’s duration was frequently longer. Events that reciprocated previous events tended to be shorter. These findings reveal interesting details about how people’s behavior during a conflict influences how it evolves over time.

In our model we decompose the event probability into two components, one for the event rate and one for the event duration. The distribution that we present for the event rate in the first component is identical to that in the relational event model presented by Butts (2008). However, we extend the standard REM with a weight function that can account for the effect of event duration and memory on interaction rates. The event duration distribution presented in the second component is an exponential distribution, which is used to model effects on the time until an event is likely to be terminated. This two-step approach is similar to the method presented by Brandes et al. (2009). They do, however, use a normal distribution to model the level of hostility or cooperation in the event with the second component.

We assume an exponential distribution for event duration in our model. In other words, we assume that the hazard of event termination is independent of the time since the event began. Future research should test this assumption. Alternatively, a Weibull distribution can be used to determine whether the hazard of an event ending changes as time passes since it started. Furthermore, it would be useful for future research to extend the model to enable direct estimation of the duration parameter and half-life parameter. Direct estimation is likely to result in more stable estimates and allows us to assess the uncertainty of these parameter estimates. Additionally, for the effect of event duration on future interaction rates, we assume a power function. While a power function can encompass a wide range of different behaviors, future research should investigate methods to learn the shape of the impact of event duration from the observed data. For the effect of memory, this is for example discussed by Arena et al. (2022). It would also be useful to extend the model to allow for group events, i.e., events between more than two individuals. Such a model would allows us to draw inferences on with whom individuals interact when and for how long, potentially within a group context. This model must allow for the possibility for individuals to enter and leave groups at different times, and for groups to merge or split. Such a model might draw inspiration from the method proposed by Hoffman et al. (2020) for modeling group events and translate their model to a tie-oriented framework, where individual agency does not necessarily has to be assumed.

In conclusion, the current research contributes to the study of the interplay between event rate and event duration. We believe that it is important to develop ways in which the effects of event duration can be taken into account in relational event models. First, relational events with a duration are frequently observed. For example, proximity contacts and face-to-face interactions between individuals are automatically recorded on a large scale and in a non-intrusive manner by wearable sensors. Naturally, there is a duration attached to the records of interactions measured by wearable sensors. At the same time, the duration of each observed event is still short in relation to the time scale of the process being studied. Therefore, they are not suited to be analyzed with classical statistical methods for analyzing social network structure which assume temporally extensive relationships between the individuals in the network. Instead, they are better analyzed in the relational event modeling framework, which can deal with the continuous flow of events between the individuals in the network. Second, applications of relational event models typically ignore the duration of events in their analysis. That is, while we can learn about social interaction dynamics from considering event duration in the analysis. Understanding how interaction history affects the duration of future interactions helps to develop effective strategies aimed at, for example, limiting the transmission of hospital-acquired infections or preventing escalation of a violent interpersonal conflict. The model that we propose is tailored to facilitate such inferences. it is likely that event duration, besides event occurrence, influences future interaction behavior. Longer prior interactions with others may be easier to remember by individuals, something that is confirmed by previous research that finds that people tend to forget to report short contacts with others (Mastrandrea et al., 2015). Therefore, longer prior interactions with others are also likely more important in explaining future interactions. This is confirmed by our empirical applications, where we indeed see an effect of prior event duration on the future event rate and event duration. Thus, by accounting for how event duration affects the impact of the event history on future interaction behavior, we can better describe the underlying social processes.

5

Bayes factor testing of scientific theories for relational event models in R

This chapter is based on Section 4.8 “Relational event models" in Mulder, J., Williams, D. R., Gu, X., Tomarken, A., Böing-Messing, F., Olsson-Collentine, A., **Meijerink, M.**, Menke, J., van Aert, R., Fox, J.P., Hoijtink, H., Rosseel, Y., Wagenmakers, E.J., van Lissa, C. (2021). BFpack : Flexible Bayes Factor Testing of Scientific Theories in R. *Journal of Statistical Software, 100*(18). https://doi.org/10.18637/jss.v100.i18

5.1 Introduction

The software package BFpack is introduced in Mulder et al. (2021). This package contains functions for computing Bayes factors and posterior probabilities in R for many common testing problems. This chapter provides a brief introduction of how to use the BFpack functions for exploratory (zero vs. positive vs. negative effects) and confirmatory (competing hypotheses with equality and/or order constraints) hypothesis tests in relational event models. We direct the reader to the cited reference for the technical details on Bayesian statistical inference. We also refer the reader to the cited reference for a thorough introduction to using the BFpack for Bayes factor hypothesis testing in R for many common testing problems.

5.2 Application

5.2.1 Statistical model and exploratory hypothesis test

The Relational Event Model (REM) was introduced to analyze sequences of time-stamped relational events between actors in a social network (Butts, 2008; DuBois, Butts, McFarland, & Smyth, 2013). The REM can be used to understand what mechanisms drive interaction dynamics in a temporal social network (Mulder & Leenders, 2019). It builds on the survival (or event history) model with time-varying covariates where the dependent variable is the event rate between all possible dyads of senders in the network. For the technical details about the methodology, we refer the reader to the above references.

The relevent package can be used for fitting REMs in R (Butts, 2021). Adjusted fractional Bayes factors based on Gaussian approximations can be computed between constrained hypotheses for a REM using the default function of `BF()`. First the REM is fitted using the `rem.dyad()` function. Next, the (named) vector with the maximum likelihood estimates (MLEs), the error covariances matrix, and the sample size are extracted from the `rem.dyad` object, which are plugged in the `BF()` function. This calls the default `BF()` function from the BFpack package, which performs exhaustive exploratory tests on the separate parameters, i.e.,

$$H_1 : \beta_q = 0 \text{ versus } H_2 : \beta_q < 0 \text{ versus } H_3 : \beta_q > 0, \tag{5.1}$$

for $q = 1, \ldots, Q$. Constrained hypotheses can be specified using the names of the parameter estimates.

5.2.2 Confirmatory hypothesis test in communication networks

As was illustrated by Mulder and Leenders (2019), interaction behavior can be positively driven by past activity between actors and common attributes of actors (also known as homophily). To illustrate this, we consider a simulated event sequence consisting of 226 relational events (communication messages) in a small network of 25 actors (generated using the methodology in DuBois, Butts, McFarland, & Smyth, 2013) belonging to different cultures, and having different locations where they are based. The event rate of actor pair (s, r) a time t, denoted by $\lambda(s, r, t)$, is then modeled using a log linear model,

$$\begin{aligned}\log \lambda(s, r, t) =& \beta_0 + \beta_{\text{inertia}} x_{\text{inertia}}(s, r, t) + \beta_{\text{culture}} x_{\text{culture}}(s, r) \\ &+ \beta_{\text{location}} x_{\text{location}}(s, r)\end{aligned} \tag{5.2}$$

where β_0 is the intercept capturing the baseline of the event rate, β_{inertia} is the inertia effect (i.e., the general tendency for actors to keep sending messages to actors who they sent messages to in the past), $x_{\text{inertia}}(s, r, t)$ is the fraction of past events sent by s that were received by r until time t, $x_{\text{culture}}(s, r)$ and $x_{\text{location}}(s, r)$ are dichotomous variables that indicate whether actor s and r have the same culture ($1 =$ yes, $0 =$ no) and whether actors s and r are based at the same location ($1 =$ yes, $0 =$ no), respectively, and β_{culture} and β_{location} are the corresponding effects.

The following competing hypotheses will be considered:

$$\begin{aligned} H_1 &: \beta_{\text{culture}} = \beta_{\text{location}} > 0 \\ H_2 &: \beta_{\text{culture}} > \beta_{\text{location}} > 0 \\ H_3 &: \beta_{\text{location}} > \beta_{\text{culture}} > 0 \\ H_4 &: \text{neither } H_1, H_2, \text{nor } H_3 \end{aligned} \tag{5.3}$$

Hypothesis H_1 assumes that having the same culture and being based at the same location have an equal positive effect on the event rate. Hypothesis H_2 assumes that having the same culture has a larger effect than being based at the same location, and both effects are positive. Hypothesis H_3 assumes that being based at the same location has a larger effect than having the same culture, and both effects are positive. The complement hypothesis H_4 assumes that neither the constraints under H_1 nor the constraints under H_2 or H_3 hold.

5.2.3 Analyses using BFpack

To test the hypotheses in Equation 5.3, first the unconstrained REM is fit using the `rem.dyad()` function using the RELEVENT package (Butts, 2021).

```
# Load required libraries
library(BFpack)
library(relevent)

# Load the data
data(actors)
data(relevents)

# Prepare the data objects with covariates
CovEventEff <- array(NA, dim = c(3, nrow(actors), nrow(actors)))
CovEventEff[1,,] <- 1
CovEventEff[2,,] <- as.matrix(same_culture)
```

```
CovEventEff[3,,] <- as.matrix(same_location)
dimnames(CovEventEff)[[1]] <- c("baseline", "culture",
  "location")

# Run rem.dyad
set.seed(9227)
rd.fit <- rem.dyad(edgelist = relevents, n = nrow(actors),
  effects = c("FrPSndSnd", "CovEvent"),
  covar = list(CovEvent = CovEventEff),
  hessian = TRUE, fit.method = "BPM")
```

The MLEs and p values are given by:

```
## Relational Event Model (Ordinal Likelihood)
##
##                  Estimate     Std.Err Z value Pr(>|z|)
## FrPSndSnd    0.60034728  0.48674021  1.2334   0.2174
## CovEvent.1   0.00078987 89.50426628  0.0000   1.0000
## CovEvent.2   1.21939161  0.13587178  8.9746   <2e-16 ***
## CovEvent.3  -0.01028619  0.25387330 -0.0405   0.9677
```

Next, the estimates, the error covariance matrix, and the sample size are extracted from the fitted object and plugged in the `BF()` function, together with the constrained hypotheses:

```
# Give new names to the estimated values
names(rd.fit$coef) <- c("inertia", "baseline", "culture",
  "location")

# Define the constraints hypothesis
constraints <- "culture = location > 0; culture > location > 0;
  location > culture > 0"

# Extract the estimates, the error covariance matrix,
# and the sample size
estimates <- rd.fit$coef
covmatrix <- rd.fit$cov
samplesize <- rd.fit$m

# Run BF
BF.res <- BF(estimates, Sigma = covmatrix, n = samplesize,
  hypothesis = constraints)

# View results
summary(BF.res)
```

In the fist line new names are given to the estimated values with a clearer interpretation. These names are then used for formulating constrained hypotheses in the `hypothesis` argument. The estimates, the corresponding error covariance matrix, and the sample size ar then extracted from the fitted `rem.dyad` object `rd.fit`. Subsequently, these are plugged into the `BF()` function which then calls `BF.default()`.

For the exploratory analysis, the following output is then obtained:

```
## Bayesian hypothesis test
## Type: exploratory
## Object: numeric
## Parameter: general parameters
## Method: adjusted fractional Bayes factors using Gaussian
## approximations
##
## Posterior probabilities:
##          Pr(=0) Pr(<0) Pr(>0)
## inertia   0.778  0.024  0.197
## baseline  0.883  0.059  0.059
## culture   0.000  0.000  1.000
## location  0.882  0.061  0.057
```

The results clearly show that working at the same culture has a positive effect given the observed data. For the other parameters the null hypothesis of zero effect is most plausible.

Next, we discuss the results of the confirmatory test which are given by

```
## Bayesian hypothesis test
## Type: confirmatory
## Object: numeric
## Parameter: general parameters
## Method: adjusted fractional Bayes factors using Gaussian
## approximations
##
## Posterior probabilities:
##    Pr(hypothesis|data)
## H1               0.000
## H2               0.894
## H3               0.000
## H4               0.106
##
## Evidence matrix (Bayes factors):
##          H1    H2         H3    H4
## H1    1.000 0.000     46.092 0.001
## H2 6070.726 1.000 279808.924 8.412
## H3    0.022 0.000      1.000 0.000
## H4  721.686 0.119  33263.610 1.000
```

```
##
## Specification table:
##    complex= complex> fit=  fit> BF=   BF>    BF   PHP
## H1    0.136    0.500    0 1.000   0 2.000 0.001 0.000
## H2    1.000    0.082    1 0.484   1 5.921 5.921 0.894
## H3    1.000    0.185    1 0.000   1 0.000 0.000 0.000
## H4    1.000    0.733    1 0.516   1 0.704 0.704 0.106
##
## Hypotheses:
## H1: culture=location>0
## H2: culture>location>0
## H3: location>culture>0
## H4: complement
```

The Bayes factors and the posterior probabilities reveal there is most evidence for H_2 (with a posterior probability of 0.894), followed by the complement hypothesis H_4 (with a posterior probability of 0.106), and finally hypotheses H_1 and H_3 received a posterior probability of zero. This suggests that there is most support for the hypothesis which assumes that belonging to the same culture has a larger effect on interaction rates than being based at the same location and that both effects are positive. There is still a probability of 0.106 that the complement may be true after observing the data. This can be explained from the very small negative estimate of the `location` parameter of -0.0103 having a very large standard error of 0.2539. More data would be needed in order to draw more decisive conclusions.

6

Computing statistics for relational event models: A tutorial for the R package remstats

Abstract

Relational event modeling approaches enable researchers to conduct a fine-grained analysis of the dynamics of social interaction between actors in a social network. The current chapter introduces the R software package REMSTATS for computing statistics for relational event models. With the help of this package, researchers can compute a wide range of commonly used exogenous and endogenous statistics. Thereby, its aim is to simplify the process of fitting relational event models and make it more accessible for a range of applied researchers. The current chapter provides an overview of how to use the REMSTATS package to compute statistics for tie- and actor-oriented relational event models.

6.1 Introduction

Relational event modeling approaches enable researchers to perform a fine-grained analysis of relational event history data, i.e., time-ordered sequences of events between actors in a social network. The introduction of these type of models have greatly enhanced the analysis of social interaction dynamics. This chapter introduces the R software package remstats (Meijerink-Bosman et al., 2021). This package is developed to assist researchers in the computation of statistics for relational event models. Thereby, its aim is to significantly reduce the complexity associated with fitting relational event models and make it more accessible for a variety of applied researchers.

Throughout this chapter, basic knowledge of relational event models is assumed. For a technical introduction to relational event modeling approaches, the reader is referred to Butts (2008) or Stadtfeld and Block (2017). For an applied introduction to relational event modeling, the reader is referred to Leenders et al. (2016), Meijerink-Bosman, Back, et al. (2022), or Pilny et al. (2016).

While a detailed description of relational event models is beyond the scope of this chapter, the following provides a brief explanation of what is meant when we refer to "statistics" for relational event models. At the core of each relational event model sits the log-linear model for the event rate:

$$\log \lambda(t, s, r) = \boldsymbol{x}(t, s, r)'\boldsymbol{\beta}. \tag{6.1}$$

Here, $\lambda(t, s, r)$ and $\boldsymbol{x}(t, s, r)$ refer to, respectively, the event rate and the vector with statistics for a potential event between sending individual s and receiving individual r at time t, and $\boldsymbol{\beta}$ refers to the model parameters that quantify the effect of the statistics on the event rate. The statistics $\boldsymbol{x}(t, s, r)$ are numerical representations of exogenous and endogenous mechanisms that are hypothesized to drive the development of a relational event history. Exogenous statistics summarize attributes of the actors, e.g., the age of the potential sender or the difference in age between the potential sender and receiver. Endogenous statistics summarize the relational event history up to time t. For example, the 'reciprocity' statistic captures the number of past events initiated by potential receiver r towards potential sender s, thereby expressing the tendency for individuals to reciprocate events.

Based on the available actors in the social network at time t, a risk set is defined. The risk set contains the events that can potentially occur. Often, it is equal to all possible sender-receiver pairs (s, r). Each potential event (s, r) in the risk set has its own unique event rate $\lambda(t, s, r)$ that gets updated after each new event. Thus, for every potential pair (s, r) in the risk set statistics have to be computed and updated after a new event is observed. This means that for a specific pair (s, r) at time t, the vector with statistics has length P, the number of statistics in the model. For a specific time point t, we have a matrix of statistics equal to $D \times P$, where D is the number of potential (s, r) pairs in the risk set at time t. For the entire event history, the set of statistics grows to an array of size $M \times D \times P$, where M is the total number of events in the event history.

Especially the computation of endogenous statistics can become tedious, as the event history, and thus these statistics, are constantly updated with each new event. The REMSTATS software package offers a solution for this, enabling users to request the computation of a wide range of commonly used exogenous and endogenous statistics for their own relational event history data. As will be explained in this chapter, the required statistics are specified using the popular `lm()` formula syntax, to increase ease-of-use. Furthermore, the computation of statistics can become computationally complex, as the size of the data grows quadratically in N, the number of actors in the network. For that reason, the REMSTATS package makes use of the R software package RCPP (Eddelbuettel, 2013) that allows for an integration of R and C++. As a result, we can make use of the computational efficiency of C++ to assure that the computation of the statistics occurs relatively fast.

6.1.1 The tie-oriented vs. the actor-oriented approach

In the last two decades, two major statistical frameworks for relational event modeling have been introduced. The first is the Relational Event Model (REM), introduced by Butts (2008). The second is the Dynamic Network Actor Model (DyNAM), introduced by Stadtfeld and Block (2017). Both these approaches allow for a fine-grained analysis of relational event history data. The REM is often referred to as a tie-oriented approach, while the DyNAM is seen as an actor-oriented approach. This is because the REM models *who* will interact with *whom when* (i.e., the sender s, receiver r and time t of the next event) in one step. At each time t, all combinations of available senders s and receivers r in the risk set compete to create the next event. Here, the unit of analysis is the potential event (s, r), also referred to as the 'tie'. Conversely, the DyNAM uses a two-step approach. Here, the first step determines *who* will initiate an event *when* (i.e., the sender s and time t of the next event). The second step determines, given the active sender, *who* will receive the event (i.e., the receiver r of the next event). At the first modeling step, all potential senders compete to become active and send the next event. At the second modeling step, given the sender, all potential receivers compete to receive the event. Hence, the unit of analysis in the DyNAM in both steps is the 'actor', i.e., all potential senders in the first step and all potential receivers given the sender in the second step.

These differences in modeling approach require two distinct approaches for computing statistics. When fitting a REM, statistics have to be computed for all competing potential events (s, r) in the risk set. Assuming that all N actors in the social network are available for interaction at time t, the size of the statistic vector at this time is thus $N \times (N - 1)$. When fitting a DyNAM, two sets of statistics have to be computed for the two different modeling steps. First, a set of statistics is computed for all competing potential senders. The size of the first step statistic vector at this time is thus N. Second, a set of statistics is computed for all competing potential receivers, given the sender. Thus, the size of the second step statistic vector is $N - 1$. The REMSTATS package allows the computation of statistics for both the REM and the DyNAM approach.

The remainder of this chapter is structured as follows. First, we will explain how the

REMSTATS package can be used to compute statistics for a tie-oriented relational event model. This section will focus on the basic tie-oriented model. Included is a small overview of the entire process for fitting a relational event model in R, from processing the data to computing the statistics and estimating the model parameters. Further, computation of statistics for the model with undirected events and the model with event types are shortly discussed. Subsequently, we will explain how the REMSTATS package can be used to compute statistics for an actor-oriented model. Finally, future directions for the REMSTATS package are shortly discussed.

6.2 Compute statistics for the tie-oriented model

6.2.1 R Setup

The following guides the user through the steps for computing statistics for a tie-oriented model (Butts, 2008). Before using the REMSTATS package for the first time, it has to be installed once. This can be done with the following command:

```
install.packages("devtools")
devtools::install_github("TilburgNetworkGroup/remify")
devtools::install_github("TilburgNetworkGroup/remstats")
devtools::install_github("TilburgNetworkGroup/remstimate")
```

Note that we also install the REMIFY package (Arena et al., 2020). This package contains functions that will help us prepare the data before computing statistics. Further, we also install the REMSTIMATE package (Arena, Lakdawala, & Generoso Vieira, 2022). This package will be used to fit the model with the computed statistics. Subsequently, to enable us to use the packages' functionality, we load them in the environment with the following command:

```
library(remify)
library(remstats)
library(remstimate)
```

6.2.2 Data

The relational event history and the corresponding actor attributes used in this illustration can be loaded into the R environment with the command:

```
data(history)
data(info)
```

The data is a synthetic dataset to illustrate how to compute statistics for relational event modeling with the REMSTATS package. First, the `history` object contains the relational event history with 115 events between 10 “employees” of a fictive organization. The events between the employees were sampled in a completely random fashion, i.e., without an underlying statistical model. We can inspect the first six events in the synthetic relational event history with the following command:

```
head(history)
```

```
##   time actor1 actor2 setting weight
## 1  238    105    113    work   1.33
## 2  317    105    109    work   1.64
## 3  345    115    112    work   1.82
## 4  627    101    115  social   1.25
## 5  832    113    107  social   1.67
## 6  842    105    109    work   2.30
```

The first three columns are mandatory when computing statistics with REMSTATS for a relational event history. The first column holds the time when each event was initiated. Here, the time is denoted in time units since onset of the observation. The column with time information has to be named `time`. Next, the second column holds the id of the employee that initiated the event. This column has to be named `actor1`. The third column holds the id of the employee that received the event. This column has to be named `actor2`.

Besides the mandatory information about the time and the sender and receiver, the events in the `history` data.frame are additionally described by the variables `setting` and `weight`. The variable `setting` describes whether an event was related to work or occurred in a social setting. We will ignore this variable for now, but come back to it in the example for a dyadic model with event types. As the name suggests, the variable `weight` adds a weight to each event. This weight can for example refer to a metric of how the event was evaluated by the actors, or denote a metric for the duration of an event (e.g., see Meijerink-Bosman, Back, et al., 2022). Note that whenever a column named `weight` is added to a relational event history, the REMSTATS package will use this information to weight the events in the computation of the statistics. In the current example, we want each event to weight equally, thus we set the event weights to 1 with the following command:

```
history$weight <- 1
```

The `info` object contains attributes for the 10 employees between which events are observed. We can inspect the first six entries with the following command:

```
head(info)
```

```
##    id  time age sex extraversion agreeableness
## 1 101     0   0   0        -0.40         -0.14
## 2 101  9432   0   0        -0.32         -0.26
## 3 101 18864   0   0        -0.53         -0.45
## 4 103     0   0   0        -0.13         -0.65
```

```
## 5 103  9432    0    0           -0.43           -0.44
## 6 103 18864    0    0           -0.13           -0.43
```

The first column of `info` contains the id of the actors that interact in the sequence. Here, we see that the first two actors (101 and 103) both appear (at least) trice in the data.frame. That is because two of the attributes vary over time. The second column in the data.frame tells us when these attribute values change. For example, the extraversion value of actor 101 is equal to -0.4 from time 0 up to, but not including, time 9432. At time 9432, its extraversion value changes to -0.32. A column named `id` with the actor ids equal to the ids observed in the sequence should always be present in an attributes object used with REMSTATS. Similarly, a column named `time` that indicates when the attribute values change should always be present. When all attributes are fixed over time, this column only holds zero's. Subsequent columns in the attributes object hold the attribute values for the actors. Here, we have information about the actors for the attributes `age`, `sex`, `extraversion`, and `agreeableness`. A detailed description of these attributes can be obtained with the following command:

```
?info
```

6.2.3 A basic dyadic model

Step 1: Data preparation

The first step of computing statistics for relational event history data with REMSTATS is to prepare the event history with the `reh()` function from the REMIFY package. This function also prepares a risk set for our data. The definition of the risk set is an important aspect of relational event modeling: It contains all events that can potentially be observed in the relational event history. Statistics are computed for every event in the risk set for every time point.

For our dyadic model, we assume that all employees can interact with each other. That is, we define a risk set with all possible directed pairs of actors. This option is the default option in the `reh()` function, meaning that, if nothing is specified by the user, exactly this risk set with all possible directed actor pairs is created.

Alternatively, the user may specify a risk set with undirected events or consider event types. These options are illustrated in the examples for a dyadic model with undirected events and a dyadic model with event types, respectively. For other non-specific risk set situations (e.g., a risk set that varies over time), the user can use the `omit_dyad` argument of the `reh()` function.

After we inspect the data and decide on a definition for the risk set, we are ready to compute statistics for a relational event model. The `reh()` function from the REMIFY package prepares the data and risk set for computation of the statistics:

```
rehObject <- reh(edgelist = history)
```

Here, we supply the relational event history to the `edgelist` argument of `reh()`. Optionally, we may submit the ids of the actors in the sequence to the `actors` argument.

Since `reh()` extracts the interacting actors from the sequence, there is usually no need to explicitly use the `actors` argument. However, whenever we want our model to account for interacting actors that are present in the actor set but were not observed interacting in the sequence, we should use the `actors` argument.

Step 2: Model specification

The second step is to specify a model. The REMSTATS package for computing statistics for relational event models allows model specification in a formula syntax that is similar to the notation in the popular `lm()` function for fitting linear models (R Core Team, 2020). The formula is an object that specifies the independent variables (the statistics) that the dependent variable (the log event rate) is regressed on. The formula starts with ~ (tilde) and is followed by a set of functions that refer to the statistics that the user wants to compute. Statistics for main effects are separated with + (plus), statistics that form an interaction effect are separated with * (asterisk), , e.g., `~ stat1() + stat2() + stat3()*stat4()`.

The REMSTATS package provides an easy manner for users to compute a wide range of commonly used statistics for a relational event model. An overview of the available statistics is available in Appendix B. A more detailed description is available on the help page of the `remstats()` function, i.e., with the command

```
?remstats
```

In this illustration, we start with specifying a model with only two statistics: the baseline statistics (i.e., an intercept) and the inertia statistic. The statistics need to be called in the formula syntax with functions because most statistics in the REMSTATS package can be tailored to the user's need with the functions' arguments. For example, view the description of the inertia statistic:

```
?inertia
```

Here, we can read that the inertia statistic computes for every time point t for every pair of actors (s, r) in the risk set the number of past events between them. With the `scaling` argument, a method for scaling the statistic can be chosen. The `consider_type` argument is not yet relevant and will be discussed later in the illustration for a dyadic model with event types.

We choose to scale the inertia statistic by means of standardization. Standardization occurs per time point:

$$x_{\text{inertia}}(t, i, j) = \frac{x_{\text{inertia}}(t, i, j) - \bar{x}_{\text{inertia}}(t)}{\text{SD}(x_{\text{inertia}}(t))}$$

Here, $x_{\text{inertia}}(t, i, j)$ is the count of past events initiated by actor i and directed towards actor j at time t, $\bar{x}_{\text{inertia}}(t)$ and $\text{SD}(x_{\text{inertia}}(t))$ are, respectively, the and standard deviation mean of the counts of past events for every (s, r) pair at time t.

To request the model with the baseline and standardized inertia statistic, we define the formula as follows:

```
model <- ~ inertia(scaling = "std")
```

We do not need to explicitly define the intercept, because for an interval tie-oriented model, a baseline effect is automatically added with REMSTATS (unless removed explicitly by specifying `-1` in the formula).

Inertia is an example of an endogenous statistic, i.e., a statistic that is a function of the relational event history. The REMSTATS package can also be used to compute exogenous statistics, i.e., statistics that are a function of actors' attributes. For example, we extend our model with a statistic for the effect of actors' extraversion on their tendency to initiate events, i..e, a `send()` statistic. The description of this statistic can be viewed with

```
?send
```

Here, we read that we need to supply the variable for which we want to specify a sender effect and that this variable name should correspond to a column name in the attributes object that we supply. Thus, we specify a send effect of extraversion with `send("extraversion", attributes = info)`. We update our model with this new effect as follows:

```
model <- ~ inertia(scaling = "std") +
    send(variable = "extraversion", attributes = info)
```

Step 3: Compute statistics

Now, we have everything we need to compute our first statistics with the REMSTATS package. The main function to compute statistics is called `remstats()`. We can compute statistics for our simple model using the following command:

```
statsObject <- remstats(tie_effects = model, edgelist = rehObject)
```

Since we are computing statistics for a tie-oriented model, the formula that we specified in the `model` object is supplied to the `tie_effects` argument. Further, we supply the previously prepared relational event history object to the `edgelist` argument.

The `remstats()` function outputs a list with multiple objects. We can view the names of these objects with:

```
names(statsObject)
```

```
## [1] "statistics" "edgelist"   "riskset"    "actors"     "types"
## [6] "evls"       "adjmat"
```

First, the `statistis` object is a 3-dimensional array. On the rows of this array are the time points, the columns refer to the potential events in the risk set and the slices refer to the different statistics:

```
dim(statsObject$statistics)
```

```
## [1] 115  90   3
```

Our statistic object has 115 rows, corresponding to the 115 events/time points in the relational event history. Further, it has 90 columns, corresponding to the 90 potential events in the risk set. The object has 3 slices, one slice holds the baseline statistic, the second slice the inertia statistic, and the third the send statistic. We can view the names of the statistics that are in the statistics object with

```
dimnames(statsObject$statistics)[[3]]
```

```
## [1] "baseline"          "inertia"           "send.extraversion"
```

Here, we see that, indeed, a baseline, inertia, and send statistic are computed. If we want to view the statistics for actor pair 20 at time point 100, we can use the following command:

```
statsObject$statistics[100,20,]
```

```
##          baseline           inertia send.extraversion
##          1.000000         -1.093265          0.920000
```

For actor pair 20 at time point 100, the baseline statistic is equal to 1 (as for every pair at every time point), the inertia statistic is equal to -1.09 and the send statistic is equal to 0.92. We standardized the inertia statistic, thus its value means that the inertia count of pair 20 is -1.09 SD below the inertia count for the average pair at time point 100.

Since we did not request anything special for the risk set, it consists of every directed pair of actors observed in the relational event history, which is $10 \times 9 = 90$ pairs. These pairs are saved in the `riskset` object. We can ask for the first few entries in the risk set with the command

```
head(statsObject$riskset)
```

```
##   sender receiver type id stat_column
## 1    101      103    0  0           1
## 2    101      104    0  1           2
## 3    101      105    0  2           3
## 4    101      107    0  3           4
## 5    101      109    0  4           5
## 6    101      111    0  5           6
```

Here, we see that the first event in the risk set is the event where employee 101 sends an interaction directed towards employee 103. The `stat_column` variable denotes in which column from the `statistics` object we can find the statistics for this actor pair. Thus, if we want to know which actors are in pair 20, we can use the following command:

```
subset(statsObject$riskset, stat_column == 20)
```

```
##    sender receiver type id stat_column
## 20    104      103    0 19          20
```

The outputted `edgelist`, `actors` and `types` object are mainly control objects. They show the information used by `remstats()` to compute the statistics:

```
head(statsObject$edgelist)
```

```
##      time dyad weight
## [1,]  238   34      1
## [2,]  317   31      1
## [3,]  345   88      1
## [4,]  627    8      1
## [5,]  832   76      1
## [6,]  842   31      1
```

```
statsObject$actors
```

```
##  [1] "101" "103" "104" "105" "107" "109" "111" "112" "113" "115"
```

```
statsObject$types
```

```
## [1] "0"
```

The `adjmat` object is a helper object that is used internally by `remstats()`. Once obtained, this object could be supplied again to save computation time when the model specification supplied to the `tie_effects` argument is updated or altered. It contains per time point (on the rows) per dyad (on the columns) the number or weight of the past events.

Finally, the outputted `evls` object is a transformation of the edgelist into a format such that it can be used by the `rem()` function from the RELEVANT package (Butts, 2021) to estimate a relational event model. In this illustration, however, we will use a different estimation approach.

Step 4: Estimation

Different approaches exist for estimating relational event models in R. Here, we make use of the REMSTIMATE package (Arena, Lakdawala, & Generoso Vieira, 2022). We estimate our relational event model with the following command:

```
fit <- remstimate(reh = rehObject, stats = statsObject,
    method = "MLE", model = "tie")
```

The prepared relational event history data is supplied to the `reh` argument and the computed statistics to the `stats` argument. The `method` is set equal to Maximum Likelihood Estimation (MLE) and we specify that we are fitting a tie-oriented model.

A quick example

Before we continue with examples of other models, the steps for a relational event analysis with a basic dyadic tie-oriented model are summarized in a quick example:

```
# Load libraries
library(remify)
library(remstats)
library(remstimate)
# Load data
data(history)
data(info)
# Step 1: Prepare the data
rehObject <- reh(edgelist = history[,1:3], origin = 0)
# Step 2: Model specification
model <- ~ inertia() +
    send(variable = "extraversion", attributes = info)
# Step 3: Compute the statistics
statsObject <- remstats(tie_effects = model, edgelist = rehObject)
# Step 4: Estimate model parameters
fit <- remstimate(reh = rehObject, stats = statsObject,
    method = "MLE", model = "tie")
```

6.2.4 A dyadic model with undirected events

In the example analysis above, we assume directed events between the employees. That is, we assume that we know which actor in the event is the initiator and which actor is the receiver. In the case of undirected events, however, we cannot distinguish between an initiating and receiving actor for the events.

For a relational event analysis with undirected events, we follow the same steps discussed for the computation of statistics for a basic dyadic model. However, we need to change the definition of the risk set. The risk set now holds all possible undirected actor pairs, i.e., $(10 \times 9)/2 = 45$. When we prepare the data with the `reh()` function in the first step, we obtain the correct risk set for undirected events by setting the argument `directed` to `FALSE`:

```
rehObject <- reh(edgelist = history, directed = FALSE)
```

When we inspect the size of the risk set with the command

```
rehObject$D
```

```
## [1] 45
```

we see that this is indeed equal to 45.

All other steps for computing statistics are equal to the steps discussed for a basic dyadic model. However, when specifying the model, it is important to remember that not every statistic is defined for both directed and undirected events. For example, the AB-BA participation shift, where the receiver of the previous event becomes the sender of the next event, is only defined for directed events and not for undirected events. Whether a statistic is defined for undirected events can be viewed in the overview in its description.

6.2.5 A dyadic model with event types

In the example analysis for the basic tie-oriented model, we assume that all interactions between employees are of the same event type, or we were not interested in modeling the type of the event. However, relational event modeling approaches allow researchers to investigate how various driving mechanisms affect social interaction across and within different kinds of interactions (e.g., see Meijerink-Bosman, Back, et al., 2022). In that case, we extend the risk set.

For example, we could view the `setting` variable for the events in the `history` data object as an event type. Remember that interactions between employees occurred in two different settings: work and social. If we want to distinguish between interaction dynamics in work-related or social setting, we require two entries for every directed pair of actors in the risk set: One for the actor pair (s, r) interacting in the setting "work", and one for actor pair (s, r) in the setting "social".

When we prepare the data with the `reh()` function in the first step, we obtain the correct risk set with event types by adding a `type` column with the event types to the `edgelist` object that we supply to `reh()`:

```
history$type <- history$setting
rehObject <- reh(edgelist = history)
```

Optionally, we may submit the ids of the event types in the sequence to the `types` argument. This is needed when not every event type that can potentially be observede was observed in the event history.

The risk set now holds all directed actor pair twice, i.e., $(10 \times 9) \times 2 = 180$. We can check this with the following command:

```
rehObject$D
```

```
## [1] 180
```

For a relational event model with event types, a new set of statistics can be computed by using the `consider_type = TRUE` argument. For example, the `inertia()` statistic has the `consider_type` argument. When this argument is equal to `FALSE`, the count of past events for an actor pair (s, r) counts the number of past (s, r) events regardless of the event type. When the `consider_type` argument is equal to `TRUE`, however, the number of past events is count separately for events of the actor pair (s, r) of type "work" and events of the actor pair (s, r) of type "social". All other steps for computing statistics are equal to the steps discussed for a basic dyadic model.

6.2.6 Additional functionality

The former provides a brief introduction into computing statistics for tie-oriented relational event models with the REMSTATS package. There is still some functionality that we have not yet covered. First, it is also possible to compute statistics for a slice of the relational event sequence, but based on the entire event history. This can be done by using the arguments `start` and `stop` from `remstats()`. This is for example useful when the user first wants to train the statistics on a first subset of events and fit the model for the remaining subset of events. It can also be used to compute statistics for a moving window REM, where the change in the model parameters over time is estimated (see Meijerink-Bosman, Leenders, & Mulder, 2022; Mulder & Leenders, 2019).

Second, REMSTATS offers the possibility to account for two different types of memory effects. This can be done using the arguments `memory` and `memory_value` from `remstats()`. By default, the entire event history is taken into account when the endogenous statistics are calculated. Alternatively, the user can specify that the endogenous statistics are based on a subset of the most recent events within a specified time-interval. This is accomplished by setting the `memory` argument to `"window"` and supplying the respective time-interval to the `memory_value` argument. For example, this approach for calculating statistics is taken by Mulder and Leenders (2019) when they fit a moving window REM. Furthermore, the user can request the weight of past events to exponentially decline over time with a half-life paramater, as described by Brandes et al. (2009). This is accomplished by setting the `memory` argument to `"Brandes"` and supplying a half-life value to the `memory_value` argument.

6.3 Compute statistics for the actor-oriented model

The following guides the user through the steps for computing statistics for an actor-oriented model (Stadtfeld & Block, 2017). The procedure to compute statistics for the actor-oriented model is largely similar to the procedure for the tie-oriented model, except that statistics have to be specified and computed separately for the sender activity rates and the multinomial receiver choices.

Step 1: Data preparation

The data preparation step is exactly similar whether we want to compute statistics for the tie-oriented or actor-oriented model. The following command prepares the data and risk set for computation of the statistics:

```
rehObject <- reh(edgelist = history)
```

Step 2: Model specification

The second step is to specify a model. We have to specify a model separately for the sender activity rates and the multinomial receiver choices. First, we specify a simple model for the sender activity rate. We include only two statistics: the baseline statistic and an `outdegreeSender()` statistic. In the description for this statistic we read that, in the sender step of the actor-oriented model, the `outdegreeSender()` statistic computes for every timepoint t for every actor i the number of outgoing past events.

To request the model with the baseline and `outdegreeSender()` statistic, we define the formula as follows:

```
model_sender <- ~ outdegreeSender()
```

Again, we do not need to explicitly define the intercept, because for an interval sender activity model, a baseline effect is automatically added in REMSTATS.

Second, we specify a simple model for the receiver choice. For this illustration, we include only one statistic: the inertia statistic. We define the formula as follows:

```
model_receiver <- ~ inertia()
```

Note that for the multinomial receiver choices, a baseline effect is not added because it is not identified.

Further, it is important to remember that not every statistic is defined for both the sender activity rates and the multinomial receiver choices. For example, the `outdegreeSender()` statistic is defined for the sender and can thus be added to the model for the sender activity rates but not to the model for the multinomial receiver choices.

Step 3: Compute statistics

To compute statistics for the actor-oriented model, effects that are specified for the sender activity rate have to be supplied to the `sender_effects` argument of `remstats()` and effects that are specified for the multinomial receiver choices have to be supplied to the `receiver_effects` argument:

```
statsObject <- remstats(sender_effects = model_sender,
   receiver_effects = model_receiver, edgelist = rehObject)
```

The outputted list of objects is largely similar to the list outputted for the tie-oriented model:

```
names(statsObject)
```

```
## [1] "statistics" "edgelist"   "riskset"     "actors"      "adjmat"
```

The outputted `statistics` object is different:

```
str(statsObject$statistics)
```

```
## List of 2
##  $ sender_stats  : num [1:115, 1:10, 1:2] 1 1 1 1 1 1 1 1 1 1 ...
##   ..- attr(*, "dimnames")=List of 3
##   .. ..$ : NULL
##   .. ..$ : NULL
##   .. ..$ : chr [1:2] "baseline" "outdegreeSender"
##  $ receiver_stats: num [1:115, 1:10, 1] 0 0 0 0 0 0 0 0 0 0 ...
##   ..- attr(*, "dimnames")=List of 3
##   .. ..$ : NULL
##   .. ..$ : NULL
##   .. ..$ : chr "inertia"
```

It is now a list with two elements: `sender_stats` and `receiver_stats`. First, the `sender_stats` object contains the statistics computed for the sender activity rates. It is a 3-dimensional array. On the rows of this array are the time points, the columns refer to the potential senders of events and the slices refer to the different statistics. In the description of the object obtained with `str(statsObject$statistics)` we see that a "baseline" statistic and an "outdegreeSender" statistic is computed. If we want to view the statistics for employee 103 at time point 100, we can use the following commands:

```
id <- which(statsObject$actors == "103")
statsObject$statistics$sender_stats[100,id,]
```

```
##        baseline outdegreeSender
##               1              10
```

Here, we see that, for employee 103 at time point 100, the “baseline” statistic is equal to 1 and the “outdegreeSender” statistic is equal to 10, meaning that employee 100 was the initiator of 10 events before time point 100.

Second, the `receiver_stats` object contains the statistics computed for the multinomial receiver choices. Again, it is a 3-dimensional array. On the rows of this array are the time points, the columns refer to the different actors and the slice refer to the different statistics. In the description of the object obtained with `str(statsObject$statistics)` we see that an “inertia” statistic is computed.

Note that the computed values of the statistic for the multinomial receiver choices are equal to the values for this actor, given the current sender. For example, lets review the first six rows of this object:

```
# For ease of interpretation: set the column names equal to the
# respective actors and the row names equal to the sender of the
# current event
colnames(statsObject$statistics$receiver_stats) <- statsObject$actors
rownames(statsObject$statistics$receiver_stats) <- history$actor1
# View the statistic for the first six events
head(statsObject$statistics$receiver_stats)
```

```
## , , inertia
##
##     101 103 104 105 107 109 111 112 113 115
## 105   0   0   0   0   0   0   0   0   0   0
## 105   0   0   0   0   0   0   0   0   1   0
## 115   0   0   0   0   0   0   0   0   0   0
## 101   0   0   0   0   0   0   0   0   0   0
## 113   0   0   0   0   0   0   0   0   0   0
## 105   0   0   0   0   0   1   0   0   1   0
```

At the first time point, the inertia statistic for all actors given the current sender (actor 105) is zero because no prior events have occurred. At the second time point, the current sender is again actor 105. Now the inertia statistic is equal to one for the receiver of the first event (actor 113). At the third time point, the inertia statistic is again zero for all actors because now the sending actor is 115, who did not send any prior events.

Step 4: Estimation

We estimate our model again with the `remstimate()` function from the REMSTIMATE package. Note that we set the `model` argument to `"actor"`.

```
fit <- remstimate(reh = rehObject, stats = statsObject,
   method = "MLE", model = "actor")
```

A quick example

The steps for a relational event analysis with a basic actor-oriented model are summarized with a quick example:

```
# Load libraries
library(remify)
library(remstats)
library(remstimate)
# Load data
data(history)
data(info)
# Step 1: Prepare the data
rehObject <- reh(edgelist = history[,1:3], origin = 0)
# Step 2: Model specification
model_sender <- ~ outdegreeSender()
model_receiver <- ~ inertia()
# Step 3: Compute the statistics
statsObject <- remstats(sender_effects = model_sender,
   receiver_effects = model_receiver, edgelist = rehObject)
# Step 4: Estimate model parameters
fit <- remstimate(reh = rehObject, stats = statsObject,
    method = "MLE", model = "actor")
```

6.4 Conclusion

This chapter provided a brief introduction into computing statistics for relational event models with the R software package REMSTATS. The aim of this package is to increase the accessibility of relational event modeling by greatly reduce the complexity associated with computing statistics for relational event models. The package enables the researcher to compute a wide range of commonly used exogenous and endogenous statistics for the tie- and actor-oriented relational event model approaches.

The REMSTATS package is developed as part of a larger collection of R software packages called REMVERSE that deal with a variety of aspects of relational event modeling. This collection further includes the REMULATE package for generating relational event history data (Lakdawala et al., 2022), the REMIFY package for processing relational event history data (Arena et al., 2020), and the REMSTIMATE package for fitting relational event models (Arena, Lakdawala, & Generoso Vieira, 2022). The packages are available for download at https://github.com/TilburgNetworkGroup. While the REMSTAS package and the collection of packages in REMVERSE already greatly enhance the ease of fitting relational event models in their current form, the packages remain in development. The user is encouraged to request extra functionality or report found bugs via https://github.com/TilburgNetworkGroup.

7

Discussion

7.1 Main findings and implications

This dissertation dealt with the use and development of relational event models to study the manner in which interactions between actors in a social network follow one another over time. A key feature of relational event models is that they allow researchers to take the event history into account to explain when the next interaction will take place and between whom. As a result, relational event models allow for a time-sensitive analysis of dynamic social network processes.

This dissertation focused specifically on the Relational Event Model (REM; Butts, 2008), which is one of the major statistical frameworks for modeling relational events. In Chapter 2, we gave an extensive introduction to the REM for psychologists. The REM was used in three empirical analyses to investigate how and why social interactions between freshmen university students evolve over time. First, we described how the standard REM can be used to investigate which important network processes drive students' social interaction behavior. The results from this analysis gave insights into how a combination of demographic similarities, students' personality traits, and endogenous effects affected the rate of social interactions between the freshmen students on average across the entire study period. The importance of taking the social interaction history into account was highlighted by the substantial increase in the model's ability to predict which dyad would interact next that followed from the inclusion of the endogenous effects. Second, we described the moving window extension to the REM (Mulder & Leenders, 2019) and demonstrated how this extension can be used to study how the interaction processes that drive students' social interaction behavior change over the course of the study period. This was an especially interesting research question in the sample of freshmen students because they progress from zero-acquaintance to building social relationships through successive social interactions. The findings from this analysis gave insights in when important driving mechanisms of social interaction (like inertia and transitivity) first emerged and how they evolved over time. Third, we described how the REM framework enables us to distinguish between different types of events. We demonstrated how this allows us to investigate what motivates students to interact with one another in both a study-related and leisure setting, and how interactions in these two settings dynamically affect each other over time.

The research in Chapter 2 demonstrated briefly that an interesting research question when studying social interaction behavior is how the effects of various driving mechanisms underlying the evolution of social interaction themselves change over the course of the observed interaction sequence. This question was investigated further in Chapter 3. First, we proposed a Bayesian approach to test whether the effects that drive interaction between individuals can be assumed to be constant over the observation period. Since this is an assumption of the standard REM, we believe it is important to investigate this in an empirical analysis of temporal network data. Findings from a simulation study indicate that the Bayesian test for time-varying effects can help determine whether effects are barely changing and the standard REM can be used, or whether they change considerably and a dynamic approach is needed. Second, we propose using the moving window REM (Mulder & Leenders, 2019) as a flexible method for exploring time-varying network effects. This technique requires researchers to determine a window width that matches the expected rate of change in the network effects. This can be a challenging task when the theory about the temporal evolution of network effects is limited. Therefore, we extended the existing moving window method with a data-driven algorithm that allows for flexible window widths. These windows become more narrow during periods of significant change in the effects, in order to capture these changes with sufficient accuracy. When effects are relatively stable, the windows become wider to capture the effects more precisely.

In a simulation study, we investigated the accuracy and precision of the estimates of time-varying network effects obtained with the moving window technique with fixed and flexible window widths. The results showed that the standard REM averages out any time variation in the parameters. The moving window REM with fixed and flexible window widths was able to provide an informative view of how the parameters changed over time. However, the accuracy and precision of this view are dependent on the window width and the extent and kind of time-variation of the parameters. The best balance of accuracy and precision was achieved by the moving window REM with flexible window widths. This was further demonstrated by the results of the empirical analysis. The findings from the empirical analysis demonstrated that the moving window methods were able to detect changes in the dynamics of social interaction between employees over time. Wide fixed windows were able to detect broad trends in the effects, but they lacked detail. If the windows were made more narrow, these details could be detected, but this frequently led to windows with insufficient observations to be precise. The data-driven method with flexible window widths performed better at finding this balance between accuracy and precision. The empirical analysis showed that the moving window technique is able to reveal some intriguing trends in how network effects change over time, which may inspire further research into why effects change at certain times but not at others.

In Chapter 4 we explored the effects of and on event duration in relational event models. We argued that it is often not realistic to assume that all prior events have an identical effect on future interaction rates, but that this is likely to depend on the duration of the event. For example, because longer prior events are more easily remembered. Therefore, we presented a method to learn the non-linear impact of event duration on future interaction rates. A simulation study provided a proof of concept for the proposed methodology. Furthermore, we presented a method for jointly modeling the rate and duration of future events dependent on the event history. The use of the proposed methodology in two case studies demonstrated what we can learn about interaction dynamics if we take event duration into account. We discovered that longer prior events between hospital patients and healthcare workers were more influential in explaining the future event rate and duration than shorter prior events. Conversely, shorter events were found to be more influential in explaining the future event rate for interactions between people in conflict. This last result was unexpected, but future research should investigate whether it can be explained if the aggression level of behaviors is taken into account. Furthermore, findings showed that the rate and duration of future interactions between hospital patients and healthcare workers are influenced by emerging patterns of prior interactions. The magnitude and direction of the effects varied between pairs of individuals. These findings give insights in hospital interaction processes. In addition, findings from the second case study revealed interesting details about how people's behavior during a conflict influences how it evolves over time.

We considered memory effects in several REM applications throughout this dissertation. In Chapters 2 and 3 we used a windowed version of memory, where the contribution of previous events to future interaction rates expires after a certain time interval. In Chapter 4, we use an exponential decay function to account for previous events' contributions to the interaction rate, allowing them to diminish exponentially as the time since their occurrence increases. In two empirical applications, we estimated the half-life parameter for the exponential decay function. Findings for one application showed that the influence of previous events on future interaction behavior diminishes quickly, while findings for the other application showed that the entire event history was equally important in explaining future interaction behavior. These findings demonstrate that the exploration of memory effects in relational event models can increase our knowledge about interaction dynamics across various empirical contexts. The essence of relational event models is that they make it possible to examine the temporal evolution of interaction dynamics. We believe that the change in the influence of the past in predicting the future must be recognized as part of the process of temporal evolution. Results from our simulation study in Chapter 4 did reveal that estimating the speed of memory decay from the observed data can be challenging, and must be done cautiously if memory decay is relatively slow in relation to the length of the study period. Methods that explicitly estimate the shape of memory decay in relational event models are, for example, discussed in more detail by Arena et al. (2022) and Perry and Wolfe (2013).

We hope that the research presented in this dissertation inspires researchers in a variety of field of psychology to use the REM framework to study social network dynamics. For this purpose, this dissertation also included two tutorial chapters to assist researchers with fitting REM models and testing scientific theories in R. First, in Chapter 5, we gave a brief introduction in the use of the R software package BFpack (Mulder et al., 2020) for Bayes factor testing of exploratory and confirmatory hypotheses of REM parameters. Second, in Chapter 6, we introduced the R software package remstats (Meijerink-Bosman et al., 2021) for easy computation of a wide range of statistics for the tie-oriented (Butts, 2008) and actor-oriented (Stadtfeld & Block, 2017) relational event models.

7.2 Limitations and directions for future research

Despite our efforts to extend the REM to address important empirical questions such as the temporal evolution of network effects and modeling the effects of and on event duration, a few points for discussion still remain. First, most current applications of the REM in the literature concentrate on modeling directed relational events. In this dissertation, we demonstrated through a variety of empirical applications that the REM framework can also handle undirected relational events. This is important because relational event histories containing undirected events are frequently observed.

However, it can be challenging to take into consideration characteristics or endogenous mechanisms that relate to the individual while modeling undirected events inside the REM framework. That is because, when modeling undirected events, statistics have to be defined at the dyad level. Moreover, statistics for endogenous mechanisms that underlie the development of a sequence of undirected events are not yet well researched within the REM framework. In this dissertation, we made a few suggestions for statistics that account for actor level processes at the dyad level. We combined statistics for the minimum and maximum agreeableness and extroversion of the two actors in a dyad in our model in Chapter 2. Using this approach, we were able to investigate the conditions under which the most or least agreeable or extroverted member of a pair had the greatest influence on interaction dynamics. In Chapter 4, we used the sum of the degrees of the individual actors in a pair. Using this statistic, we were able to investigate how actors' combined previous activity influences future interaction rates for the dyad. However, because the empirical applications mainly served as examples for the use of the presented methodology, this dissertation lacks a thorough examination of endogenous statistics for modeling undirected events in the REM framework. Thus, while this dissertation demonstrated that the REM is appropriate for modeling undirected events, we believe that further research into the development and evaluation of endogenous statistics that provide good representations of the dynamic social processes underlying the formation of undirected ties is necessary.

Second, across the empirical applications in this dissertation, we also occasionally had to deal with "group events", i.e., events between more than two actors. When this happened, we chose a simple, ad-hoc solution by dividing these events into events between all pairs of actors in the group. However, several statistical approaches have been presented in the literature that enable researchers to deal with the modeling of group interactions in a more elegant manner. First, Perry and Wolfe (2013) and Mulder & Hoff (2021) present a model for modeling directed relational events with a single sender and multiple receivers. A notable difference between these approaches is that the number of receivers for a relational event is determined a priori based on the observed data in the proposal of Perry and Wolfe (2013), whereas the number of receivers in the latent factor approach of Mulder & Hoff (2021) is determined by a generative model. Further, Hoffman et al. (2020) present an extension to the Dynamic Network Actor Model (DyNAM; Stadtfeld & Block, 2017) for group interactions, that can be used to analyze how individuals choose and change their interaction groups during social gatherings. The model focuses on individual actors' decisions to join or leave an interaction with other actors. Therefore, it requires detailed information about individual agency in group formation, which is not always available. To address this problem, the order and direction of individual actions could be determined at random. Finally, Lerner et al. (2019) propose the relational hyperevent model (RHEM) for dealing with multi-actor events. In this model, separate event rates are specified for all hyperedges (multi-actor events) in the risk set. However, preliminary analyses found a strong confounding effect of hyperedge size on the event rate. These findings suggest that it is necessary to constrain the risk set at the time of an event to hyperedges with the same size as the event (Lerner et al., 2021). The model is then consistent with the viewpoint that (groups of) actors compete for participation in events. To summarize, depending on the research question and type of available data, each of the modeling approaches discussed has advantages and disadvantages for modeling group events. Despite these limitations, these methods help answer questions about how mechanisms related to individual characteristics, group characteristics, and past interactions influence how individuals engage in social interactions while accounting for group structure. The appropriate modeling of group relational events across various environmental settings is currently an active area of research. Future research to generalize relational event models to multi-actor events could, for example, explore models that allow for the splitting and merging of groups.

Another issue that we haven't addressed yet for some relational event models, including the methods presented in this dissertation, is their computational burden. In general, the size of the statistics array grows with the square of the number of network actors N, which can quickly become computationally expensive. The R software package REMSTATS, introduced in Chapter 6, was design to provide relatively fast computation of the statistics in C++. Nevertheless, the computation of statistics is again slowed down when we want to account for more complex temporal dynamics, such as memory effects. In that case, we have to reconsider the contribution of all previous events for all dyads at each new observed event time. Issues like this can place a significant computational burden on solutions that extend the REM to address important but complex empirical questions. A solution that is sometimes proposed is to look into case-control sampling methods (Butts, 2008; Vu et al., 2015), where a partial likelihood is obtained that includes the case (i.e., the observed event) and sampled controls (potential, unobserved events) from the risk set. Results from a first study into the variability of parameter estimates obtained through sampling methods are encouraging (Lerner & Lomi, 2020). Future research into sampling methods may give more insights into the conditions that are needed to make this work. Another option worth investigating further is to fit separate models for first events and repeated events (Lerner et al., 2019). In many applications, a large portion of the potential events in the risk set are never actually observed. By using a different model for repeated events, the number of events at risk can be greatly reduced. Furthermore, from a substantive standpoint, it is interesting to investigate the differences between network effects that influence the first occurrence of events and those that influence repeated occurrences. Finally, efforts to improve statistics' computation algorithms could potentially reduce the computation times.

While the REM has been around for a few years now, research into its statistical properties has been limited. To our knowledge, only one previous study investigated the power, precision, and accuracy of the REM (Schecter & Quintane, 2020). According to the findings of this study, the REM's power and precision levels are generally adequate. However, the study's findings also indicated that, in some cases, REM parameter estimates can be quite inaccurate. The research in this dissertation contributed to our knowledge about the accuracy and precision of the REM parameter estimates with a simulation study in Chapter 3, where we evaluated this for both the moving window technique and the standard REM. Our findings indicated that, in our very specific case, the accuracy and precision of the standard REM were good. Together, these findings suggest that future research into the statistical properties of the REM to develop guidelines for the conditions under which good power, accuracy, and precision are achieved is needed.

In our experience, the study of the statistical properties of the REM is complicated by "process explosion" issues when generating relational event history data (DuBois, Butts, McFarland, & Smyth, 2013). Process explosion occurs when data generation results in the same event being sampled over and over again. This can already happen with small effects when endogenous mechanisms are used that reinforce each other (e.g., activity of the sender and inertia), leading to the sampler favoring the same few dyads. Mirroring the data generation model to findings from a real-world data example may appear to be a simple solution. Even then, we have observed that process explosions occur frequently. This is also an indication that we have not yet discovered the complete picture of what causes social interaction, which is often extremely complex. Other possible solutions include using a large model with many endogenous effects that do not all reinforce each other (which may not always be computationally feasible) or including a bunch of exogenous effects that force other dyads to be sampled. Regardless, it remains difficult to generate relational event histories that can help us understand the conditions under which good power, accuracy, and precision are achieved in REMs. To summarize, we believe that the issue of data generation and the related issue of studying the statistical properties of the REM are both important directions for future research.

Finally, throughout the empirical applications in this dissertation, we used a (variation of) the classification rate of observed events to assess how well the specified models predicted the observed data. The classification rate is equal to the proportion of observed events that were successfully predicted by the model to occur at the correct time. Variations of this technique are frequently used in the literature to assess model fit (e.g., see Pilny et al., 2016; Vu et al., 2011). This method is particularly useful when comparing models fitted to the same data. However, certain aspects of relational event models must be considered when interpreting the classification rate as a measure of absolute model fit. The first is that as the risk set grows, it becomes increasingly harder to predict the one event that is going to occur next because the model has more events to choose from. This issue also needs to be considered when modeling with a time-varying risk set. The second is the effect of the proportion of (regularly) active dyads in the risk set. When this proportion is lower, it might be easier for the model to select the correct event from among the few active dyads. The third point to consider is that we may want to account for temporal prediction errors, which occur when an event occurs one or a few time points earlier or later than predicted. The question then becomes how tolerant we want to be when this happens, which may vary depending on the empirical context. Brandenberger (2019) present an alternative approach for a more in-depth assessment of model fit. This method generates event sequences based on parameter estimates and compares them to the original sequence to assess model fit. Although this method has the potential to provide a comprehensive evaluation of model fit, it is computationally expensive. To summarize, we believe that future research into the development of methods for assessing model fit will benefit the field of relational event modeling.

7.3 Conclusion

The introduction of relational event models has greatly enhanced the study of dynamic social interaction processes. These models enable researchers to examine how characteristics of the individual (e.g., age, gender, personality) together with patterns of previous interactions (e.g., inertia, transitivity) influence how a sequence of interactions unfolds over time. Empirical research with relational event models has the potential to give insights into important questions about how a violent conflict develops over time, the development of effective strategies to prevent the spread of disease in a hospital, or encourage the spread of information among employees, et cetera. The field of relational event models is currently an area of active research. The research in this dissertation contributed in several ways. First, we gave a thorough introduction to the relational event model for psychology researchers. In this introduction, the relational event model is presented as a flexible model that can be used for studying a wide range of empirical questions concerning the evolution of social interaction dynamics, including how effects on social interactions change over time and how social interaction processes differ between and within different event types. Second, we developed two extensions for the relational event model that increase its applicability. With these methods, we can test for time-varying network effects, explore how these effects change over time, and examine the role of event duration in network effects. Third, we developed software that increases the ease of fitting relational event models in R. The discussion in the previous section made clear that some directions for future research still remain. Regardless of these limitations, we believe that relational event models, including the methods presented in this dissertation, provide researchers with the tools to further develop a fine-grained understanding of dynamic processes underlying social interactions and how they evolve in continuous time.

Appendix A

Additional material for Chapter 2

A.1 Results with different inertia statistics

Table A.1.: Relational event model parameter estimates with standard errors, BIC and goodness-of-fit (gof) for models with different inertia statistics. Results for Models 2 and 3 (as in the article, with an "inertia weighted" statistic), Models 2a and 3a (in which the "inertia weighted" statistic is replaced by a conventional "inertia" statistic), and Models 2b and 3b (with both the "inertia weighted" and "inertia" statistics). All endogenous statistics are standardized.

Effect	Model 2	Model 2a	Model 2b	Model 3	Model 3a	Model 3b
Baseline	-9.89 (0.01)*	-9.88 (0.01)*	-9.89 (0.01)*	-10.93 (0.02)*	-10.96 (0.02)*	-10.96 (0.02)*
Personality trait effects						
Extraversion min.	0.20 (0.01)*	0.21 (0.01)*	0.20 (0.01)*	0.14 (0.01)*	0.13 (0.01)*	0.13 (0.01)*
Extraversion max.	0.06 (0.01)*	0.05 (0.01)*	0.06 (0.01)*	0.03 (0.01)*	0.02 (0.01)	0.03 (0.01)*
Agreeableness min.	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Agreeableness max.	-0.21 (0.01)*	-0.21 (0.01)*	-0.21 (0.01)*	-0.19 (0.01)*	-0.18 (0.01)*	-0.19 (0.01)*
Endogenous effects						
Inertia	-	0.12 (0.00)*	0.03 (0.00)*	-	0.14 (0.00)*	0.06 (0.00)*
Inertia weighted	0.12 (0.00)*	-	0.10 (0.00)*	0.14 (0.00)*	-	0.09 (0.00)*
Shared partners	0.12 (0.00)*	0.12 (0.00)*	0.12 (0.00)*	0.11 (0.00)*	0.11 (0.00)*	0.11 (0.00)*
Demography effects						
Both male				0.60 (0.03)*	0.61 (0.03)*	0.60 (0.03)*
Mixed gender				-0.08 (0.02)*	-0.08 (0.02)*	-0.08 (0.02)*
Both older				0.17 (0.04)*	0.18 (0.04)*	0.16 (0.04)*
Mixed age				-0.88 (0.02)*	-0.87 (0.02)*	-0.88 (0.02)*
Event effects						
Group				2.17 (0.02)*	2.17 (0.02)*	2.17 (0.2)*
Weekend				-0.75 (0.02)*	-0.75 (0.02)*	-0.75 (0.02)*
BIC	249036	249189	249027	236133	236175	236028
gof	52.0%	47.5%	51.7%	54.7%	50.8%	53.9%

* $p < .05$

A.2 Scripts

The scripts in this section can be executed using REMIFY V2.0.0 and REMSTATS V3.0.0.

A.2.1 Script I: Basic REM

```r
# Install required R packages
install.packages("relevent")
remotes::install_github("TilburgNetworkGroup/remify")
remotes::install_github("TilburgNetworkGroup/remstats")

# Load the packages
library(remify)
library(remstats)
library(relevent)

# Load pre-processed data objects
load("CONNECT.RData")

# Specify the statistics to be computed
stats <- ~ (minimum("extraversion") + maximum("extraversion") +
  minimum("agreeableness") + maximum("agreeableness")) :
  (inertia(scaling = "std") + spUnique(scaling = "std")) +
  tie(both_male, "both_male") + difference("sex") +
  tie(both_old, "both_old") + difference("age") +
  event("group") + event("weekend")

# Call remstats to compute the statistics
out <- remstats(tie_effects = stats, edgelist = eventseq,
  attributes = info, actors = info$id, directed = FALSE,
  origin = 0)

# Extract the relevant objects from the output
statistics <- out$statistics
evls <- out$evls

# Induce a small time difference between dyads interacting in
# groups
rehObject <- reh(eventseq, actors = info$id, directed = FALSE,
  origin = 0)
evls[,2] <- cumsum(rehObject$intereventTime)

# Get the parameter estimates for the five models
fit0 <- rem(evls, array(statistics[,,1],
```

```
  dim = c(dim(statistics[,,1]), 1)),
  timing = "interval", estimator = "MLE")
fit1 <- rem(evls, statistics[,,c(1:5)],
  timing = "interval", estimator = "MLE")
fit2 <- rem(evls, statistics[,,1:7],
  timing = "interval", estimator = "MLE")
fit3 <- rem(evls, statistics[,,1:13],
  timing = "interval", estimator = "MLE")
fit4 <- rem(evls, statistics,
  timing = "interval", estimator = "MLE")
```

A.2.2 Script II: Moving window REM

```
# Load the packages (see for installation script I)
library(remify)
library(remstats)
library(relevent)

# Load data objects
load("CONNECT.RData")

# Define the windows
windows <- data.frame(
  begin = c(0, seq(from = 961, to = 28321, by = 1440)),
  end = seq(from = 3840, to = 32640, by = 1440))

# Find the event indices for when the windows start and stop
windows$start <- apply(windows, 1, function(x) {
  start <- min(which(eventseq$time > as.numeric(x[1])))
  ifelse(start == 0, 1, start)
})

windows$stop <- apply(windows, 1, function(x) {
  stop <- min(which(eventseq$time > as.numeric(x[2])))-1
  ifelse(stop == Inf, nrow(eventseq), stop)
})

# Specify the statistics to be computed
stats <- ~ (minimum("extraversion") + maximum("extraversion") +
  minimum("agreeableness") + maximum("agreeableness")) :
  (inertia(scaling = "std") + spUnique(scaling = "std")) +
  tie(both_male, "both_male") + difference("sex") +
  tie(both_old, "both_old") + difference("age") +
```

```
  event("group")

# Run a for loop over the windows to get for each window the
# parameter estimates
fit0 <- fit1 <- fit2 <- fit3 <- fit4 <- list() # saving space
evlsList <- statsList <- list() # saving space

for(i in 1:nrow(windows)) {
  # Call remstats to compute the statistics
  out <- remstats(tie_effects = stats, edgelist = eventseq,
    directed = FALSE, actors = info$id, attributes = info,
    memory = "window", memory_value = 4319,
    start = windows$start[i], stop = windows$stop[i])

  # Extract the relevant objects from the output
  statistics <- out$statistics
  evls <- out$evls

  # Induce a small time difference between the dyads interacting
  # in groups
  rehObject <- reh(eventseq[windows$start[i]:windows$stop[i],],
    actors = info$id, directed = FALSE, origin = windows$begin[i])
  evls[,2] <- cumsum(rehObject$intereventTime)

  # Get the parameter estimates for the five models
  fit0[[i]] <- rem(evls, array(statistics[,,1],
    dim = c(dim(statistics[,,1]), 1)),
    timing = "interval", estimator = "MLE")
  fit1[[i]] <- rem(evls, statistics[,,1:5)],
    timing = "interval", estimator = "MLE")
  fit2[[i]] <- rem(evls, statistics[,,1:7],
    timing = "interval", estimator = "MLE")
  fit3[[i]] <- rem(evls, statistics[,,1:12],
    timing = "interval", estimator = "MLE")
  fit4[[i]] <- rem(evls, statistics,
    timing = "interval", estimator = "MLE")
}
```

A.2.3 Script III: REM with event types

```
# Load the packages (see for installation script I)
library(remify)
library(remstats)
```

```
library(relevent)

# Load data objects
load("CONNECT.RData")

# Define the windows
windows <- data.frame(
  begin = c(0, seq(from = 961, to = 28321, by = 1440)),
  end = seq(from = 3840, to = 32640, by = 1440))

# Find the event indices for when the windows start and stop
windows$start <- apply(windows, 1, function(x) {
  start <- min(which(eventseq$time > as.numeric(x[1])))-1
  ifelse(start == 0, 1, start)
})

windows$stop <- apply(windows, 1, function(x) {
  stop <- min(which(eventseq$time > as.numeric(x[2])))-1
  ifelse(stop == Inf, nrow(eventseq), stop)
})

# Define the type column
colnames(eventseq)[4] <- "type"

# Specify the statistics to be computed
stats <- ~
  inertia(scaling = "std") + spUnique(scaling = "std") +
  minimum("extraversion") + maximum("extraversion") +
  minimum("agreeableness") + maximum("agreeableness") +
  tie(both_male, "both_male") + difference("sex") +
  tie(both_old, "both_old") + difference("age") +
  event("group") +
  inertia(scaling = "std", consider_type = TRUE) +
  spUnique(scaling = "std", consider_type = TRUE) +
  FEtype() : (minimum("extraversion") + maximum("extraversion") +
      minimum("agreeableness") + maximum("agreeableness"))

# Run a for loop over the windows to get for each window the
# parameter estimates for models 3, 5 and 6
fit3 <- fit5 <- fit6 <- list() # saving space

for(i in 1:nrow(windows)) {
  # Call remstats to compute the statistics
  out <- remstats(tie_effects = stats, edgelist = eventseq,
```

```
    directed = FALSE, actors = info$id, attributes = info,
    memory = "window", memory_value = 4319,
    start = windows$start[i], stop = windows$stop[i])

  # Extract the relevant objects from the output
  statistics <- out$statistics
  evls <- out$evls

  # Induce a small time difference between the dyads interacting
  # in groups
  rehObject <- reh(eventseq[windows$start[i]:windows$stop[i],],
    actors = info$id, directed = FALSE, origin = windows$begin[i])
  evls[,2] <- cumsum(rehObject$intereventTime)

  # Get the parameter estimates
  fit3[[i]] <- rem(evls, statistics[,,c(1:12)],
    timing = "interval", estimator = "MLE")
  fit5[[i]] <- rem(evls, statistics[,,1:15],
    timing = "interval", estimator = "MLE")
  fit6[[i]] <- rem(evls, statistics,
    timing = "interval", estimator = "MLE")
}
```

Appendix B

Additional material for Chapter 6

Table B.1.: Name and description of the exogenous statistics available in REMSTATS V3.0.0. Letters in the final four columns indicate whether the statistics are available for the tie-oriented (T) and actor-oriented model (A), and for a model with directed events (D) and undirected events (U).

Statistic	Description				
send	An exogenous actor attribute that affects actor s's rate of sending events.	T	A	D	
receive	An exogenous actor attribute that affects actor r's rate of receiving events.	T	A	D	
tie	An exogenous dyad attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model).	T		D	U
same	An exogenous actor attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model) or actor r's probability of being chosen as the receiver for the event send by the active sender s at time t (actor-oriented model) based on whether actors s and r have the same value on this attribute.	T	A	D	U
difference	An exogenous actor attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model) or actor r's probability of being chosen as the receiver for the event send by the active sender s at time t (actor-oriented model) based on the difference between the values of actors s and r on this attribute.	T	A	D	U
average	An exogenous actor attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model) or actor r's probability of being chosen as the receiver for the event send by the active sender s at time t (actor-oriented model) based on the average of the values of actors s and r on this attribute.	T	A	D	U
minimum	An exogenous actor attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model) or actor r's probability of being chosen as the receiver for the event send by the active sender s at time t (actor-oriented model) based on the minimum of the values of actors s and r on this attribute.	T	A	D	U
maximum	An exogenous actor attribute that affects dyad (s, r)'s rate of interacting (tie-oriented model) or actor r's probability of being chosen as the receiver for the event send by the active sender s at time t (actor-oriented model) based on the maximum of the values of actors s and r on this attribute.	T	A	D	U
event	An exogenous event attribute that is the same for all potential events in the risk set at time t and affects the waiting time between two events (tie-oriented model).	T		D	U

Table B.2.: Name and description of the endogenous statistics available in REMSTATS V3.0.0. Letters in the final four columns indicate whether the statistics are available for the tie-oriented (T) and actor-oriented model (A), and for a model with directed events (D) and undirected events (U).

Statistic	Description				
baseline	Refers to the baseline event rate, i.e., the average number of events per dyad (tie-oriented model) or actor (actor-oriented model) per time unit.	T	A	D	U
indegreeSender	Captures the number of previous events received by the potential sender s of the next event.	T	A	D	
indegreeReceiver	Captures the number of previous events received by the potential receiver r of the next event.	T	A	D	
outdegreeSender	Captures the number of previous events sent by the potential sender s of the next event.	T	A	D	
outdegreeReceiver	Captures the number of previous events sent by the potential receiver r of the next event.	T	A	D	
totaldegreeSender	Captures the number of previous events sent and received by the potential sender s of the next event.	T	A	D	
totaldegreeReceiver	Captures the number of previous events sent and received by the potential receiver r of the next event.	T	A	D	
totaldegreeDyad	Captures the number of previous events that involved at least one actor in the potential dyad (s, r) for the next event.	T			U
inertia	Captures the number of previous events initiated by the potential sender s of the next event and received by the potential receiver r of the next event.	T	A	D	U
reciprocity	Captures the number of previous events initiated by the potential receiver r of the next event and received by the potential sender s of the next event.	T	A	D	

(To be continued)

Table B.2 Continued

Statistic	Description				
otp	Captures, summed over actors h, the minimum of the number of previous events initiated by the potential sender s of the next event towards actor h and the number of previous events initiated by this same actor h towards the potential receiver r of the next event (i.e., outgoing two-paths).	T	A	D	
itp	Captures, summed over actors h, the minimum of the number of previous events initiated by the potential receuver s of the next event towards actor h and the number of previous events initiated by this same actor h towards the potential sender r of the next event (i.e., incoming two-paths).	T	A	D	
osp	Captures, summed over actors h, the minimum of the number of previous events initiated by the potential sender s of the next event towards actor h and the number of previous events initiated by the potential receiver r of the next event towards this same actor h (i.e., outbound shared partners).	T	A	D	
isp	Captures, summed over actors h, the minimum of the number of previous events initiated by actor h towards the potential sender s of the next event and the number of previous events initiated by this same actor h towards the potential receiver r of the next event (i.e., inbound shared partners).	T	A	D	
sp	Captures, summed over actors h, the minimum of the number of previous events with actor h and the potential actor i of the next event and the number of previous events between this same actor h and the potential actor j of the next event (i.e., shared partners).	T			U

(To be continued)

Table B.2 Continued

Statistic	Description				
spUnique	Captures the number of unique actors h with whom both potential actors i and j in the next event have previously interacted.	T			U
psABBA	Participation shift statistic. Is equal to one if the potential sender of the next event is equal to the current receiver and the potential next receiver is equal to the current sender (i.e., immediate reciprocation).	T	A	D	
psABBY	Participation shift statistic. Is equal to one if the potential sender of the next event is equal to the current receiver and the potential next receiver is not in the current event (i.e., turn receiving).	T	A	D	
psABXA	Participation shift statistic. Is equal to one if the potential sender of the next event is not in the current event and the potential next receiver is equal to the current sender (i.e., turn usurping).	T	A	D	
psABXB	Participation shift statistic. Is equal to one if the potential sender of the next event is not in the current event and the potential next receiver is equal to the current receiver (i.e., turn usurping).	T	A	D	
psABXY	Participation shift statistic. Is equal to one if the potential sender and the potential receiver of the next event are both not in the current event (i.e., turn usurping).	T	A	D	
psABAY	Participation shift statistic. Is equal to one if the potential sender of the next event is equal to the current sender and the potential next receiver is not in the current event (i.e., turn continuing).	T	A	D	
rrankSend	Is equal to the inverse of the rank of the potential next receiver r among the actors to which potential next sender s has most recently sent events.	T	A	D	

(To be continued)

Table B.2 Continued

Statistic	Description				
rrankReceive	Is equal to the inverse of the rank of the potential next receiver r among the actors from which potential next sender s has most recently received events.	T	A	D	
recencySendSender	Is equal to the 1 divided by the time that has past since the potential next sender s was last active as sender plus one.	T	A	D	
recencySendReceiver	Is equal to the 1 divided by the time that has past since the potential next receiver r was last active as sender plus one.	T	A	D	
recencyReceiveSender	Is equal to the 1 divided by the time that has past since the potential next sender s last received an event plus one.	T	A	D	
recencyReceiveReceiver	Is equal to the 1 divided by the time that has past since the potential next receiver r last received an event plus one.	T	A	D	
recencyContinue	Is equal to the 1 divided by the time that has past since the last event between the potential next sender s and the potential next receiver r.	T	A	D	U
userStat	Allows the user to add its own pre-computed statistic to the statistics object and, optionally, interact this statistic with other statistics in the model.	T		D	U

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Summary

Social interactions between people have an important role in society, and understanding social interaction behavior is thus an important area of study in the social sciences. The Relational Event Model (REM) is a statistical framework for modeling what drives actors in a social network to interact with each other and when. A key feature of this model is that it allows researchers to take the event history into account, resulting in a time-sensitive analysis. The central question is then how emerging patterns of previous interactions explain social interaction behavior and predict when the next event is likely to occur and who will be involved.

This dissertation contributes to the study of social interaction dynamics with the REM in several ways. First, we provide a thorough, non-technical introduction to the REM for psychologists and demonstrate how this method can be used to discover trends of social interaction behavior and the influence of personality over time in a sample of freshmen university students. The REM is used to investigate three fundamental research questions. First, which personality traits and important interaction processes drive students' social interaction behavior? Second, how and when do these interaction processes change as students get better acquainted over time? Third, how do the interaction processes influence the way students interact with each other across and within different environmental contexts? The main findings indicate that students develop stable patterns of interaction early in the acquaintance process, which play a significant role in predicting future interaction behavior.

Furthermore, we present two methodologies that expand the REM toolkit for studying social interaction. First, the standard REM assumes constant network effects, i.e., the parameters quantifying the relative importance of the drivers of interaction remain unchanged throughout the study period. However, this assumption may not always hold in reality. Therefore, we discuss, develop, and evaluate extensions to the REM that relax this assumption and allow for dynamic network effects, i.e., effects can vary over time. Second, the REM assumes instantaneous interactions, such as e-mails. However, real-life scenarios often involve interactions of varying durations, such as phone calls. In such cases, longer interactions are likely to have a stronger influence on predicting future interactions compared to shorter ones. Consequently, we need to account for the duration of previous interactions in our analysis and assess its impact on predicting future interactions. Additionally, we aim to analyze how patterns of previous interactions influence the duration of future interactions. To accomplish this, we propose an extension of the REM that incorporates the duration of social interactions. This extension enables us to gain a better understanding of the role of interaction duration in social dynamics and predictions of future social interaction behavior.

We evaluate the performance of the proposed methods through simulation studies and demonstrate how these methods can be applied in various empirical applications. In these applications, we examine how interaction patterns develop over time, aiming to gain insight into when the next interaction is likely to occur, who will be involved, and how long it will last. We investigate interactions between employees, between patients and healthcare workers, and in violent conflicts in these applications. These studies help us better understand the factors that influence the timing, participants, and duration of social interactions in different situations.

Finally, this dissertation includes two tutorials aimed at facilitating the estimation of REM and testing scientific theories regarding REM parameters in R. These tutorials provide step-by-step explanations and examples for researchers interested in applying REM to their own social interaction research. This allows researchers to more easily utilize REM and contribute to the further development of knowledge regarding the dynamics of social interaction behavior.

Nederlandse samenvatting

Sociale interactie speelt een cruciale rol in onze samenleving, waardoor het begrijpen en onderzoeken van de dynamiek en totstandkoming ervan belangrijke onderzoeksthema's zijn binnen de sociale wetenschappen. Het Relational Event Model (REM) is een statistische methode waarmee onderzoekers de drijfveren en timing van interacties tussen individuen binnen een sociaal netwerk kunnen analyseren. Een belangrijk kenmerk van dit model is dat het rekening houdt met eerdere interacties en hoe deze invloed kunnen hebben op toekomstige interacties. De centrale onderzoeksvraag is welke patronen van interacties zich in de loop van de tijd ontwikkelen en hoe deze patronen kunnen verklaren wanneer de volgende interactie zal plaatsvinden en wie daarbij betrokken zal zijn.

Dit proefschrift draagt op verschillende manieren bij aan de studie van sociale interactie met behulp van het REM. Allereerst geven we een toegankelijke introductie van het model en laten we zien hoe deze methode kan worden toegepast om de ontwikkeling van sociale interactie tussen eerstejaarsstudenten en de invloed van persoonlijkheid in de loop van de tijd te onderzoeken. Het REM wordt gebruikt om drie fundamentele onderzoeksvragen te onderzoeken. Ten eerste, welke persoonlijkheidskenmerken en belangrijke interactieprocessen beïnvloeden het sociale interactiegedrag van studenten? Ten tweede, hoe en wanneer veranderen deze interactieprocessen naarmate studenten elkaar beter leren kennen in de loop van de tijd? Ten derde, op welke manier beïnvloeden de interactieprocessen de manier waarop studenten met elkaar omgaan in verschillende omgevingscontexten; zowel binnen hun studie als tijdens hun vrije tijd? De belangrijkste bevindingen tonen aan dat studenten al in een vroeg stadium van het kennismakingsproces stabiele interactiepatronen ontwikkelen, die een belangrijke rol spelen bij het voorspellen van toekomstig interactiegedrag.

Vervolgens ontwikkelen we twee methoden die de REM-toolkit voor het bestuderen van sociale interactie verder uitbreiden. Ten eerste gaat het standaard REM uit van constant blijvende netwerkeffecten, wat betekent dat de relatieve invloed van verschillende drijfveren van sociale interactie gedurende de onderzoeksperiode gelijk blijft. Dit is echter niet altijd realistisch. Daarom bespreken, ontwikkelen en evalueren we uitbreidingen van het REM die deze aanname versoepelen en ons in staat stellen om veranderingen in netwerkeffecten in de loop van de tijd te onderzoeken. Ten tweede gaat het REM uit van interacties die op een specifiek moment worden waargenomen, zoals bijvoorbeeld e-mails. Echter, in de praktijk observeren we vaak interacties met een bepaalde duur, zoals telefoongesprekken. In deze situaties is het waarschijnlijk dat interacties die langer duren een grotere invloed hebben op het voorspellen van toekomstige interacties dan kortere interacties. We willen daarom rekening houden met hoe lang eerdere interacties hebben geduurd en onderzoeken in hoeverre dit van invloed is op hun relevantie bij het voorspellen van toekomstige interacties. Daarnaast willen we analyseren hoe de patronen van eerdere interacties de duur van toekomstige interacties beïnvloeden. Om dit te kunnen onderzoeken, ontwikkelen we een uitbreiding van het REM die rekening houdt met de duur van sociale interacties. Deze uitbreiding stelt ons in staat om een beter inzicht te krijgen in hoe de interactieduur een rol speelt in sociale dynamiek en voorspellingen van toekomstig gedrag.

We evalueren de prestaties van de door ons voorgestelde methoden door middel van simulatiestudies en laten zien hoe deze methoden kunnen worden toegepast in verschillende praktijkvoorbeelden. In deze voorbeelden onderzoeken we hoe interactiepatronen zich ontwikkelen in de loop van de tijd, met als doel inzicht te krijgen in wanneer de volgende interactie waarschijnlijk zal plaatsvinden, wie erbij betrokken zal zijn en hoe lang deze zal duren. We onderzoeken in deze toepassingen interacties tussen werknemers, tussen patiënten en gezondheidswerkers, en in gewelddadige conflicten. Deze onderzoeken helpen ons beter te begrijpen welke factoren invloed hebben op de timing, deelnemers en duur van sociale interacties in verschillende situaties.

Ten slotte bevat dit proefschrift twee tutorials die gericht zijn op het vergemakkelijken van het schatten van een REM en het testen van wetenschappelijke theorieën met betrekking tot REM-parameters in R. Deze tutorials bieden stapsgewijze uitleg en voorbeelden voor onderzoekers die geïnteresseerd zijn in het toepassen van het REM in hun eigen onderzoek. Hierdoor kunnen onderzoekers gemakkelijker gebruik maken van het REM en bijdragen aan de verdere ontwikkeling van kennis over de dynamiek en totstandkoming van sociale interactie.