# Networks Evolving Step by Step: Statistical Analysis of Dyadic Event Data

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## Abstract

*With few exceptions, statistical analysis of social networks is currently focused on cross-sectional or panel data. On the other hand, automated collection of network-data often produces* event data*, i. e., data encoding the exact time of interaction between social actors. In this paper we propose models and methods to analyze such networks of dyadic events and to determine the factors that influence the frequency and quality of interaction. We apply our methods to empirical datasets about political conflicts and test several hypotheses concerning reciprocity and structural balance theory.*

## 1. Introduction

Most social networks are inherently dynamic. Actors repeatedly create ties and break up others. Since the adjustment of ties is influenced by the existence and non-existence of other ties, the network is both, the dependent and the explanatory variable in this process. Methods designed to detect rules and regularities in network-dynamics can be distinguished by the type of data they work with.

The most common form of longitudinal data in network analysis are *panel data*, i. e., sequences of networks on the same set of actors, observed at two or more timepoints. Network panel data can be fitted to actor-based Markov-chain models [1], [2], where actors can change their ties at any moment between observations. Clearly, panel data do not represent these dynamics well, since the sequence of changes is not observed but has to be estimated by statistical methods. The prevalence of panel data in longitudinal network analysis is rather due to the fact that data are typically collected by the use of questionnaires.

Another form of longitudinal network data (typically called *event data*) consists of sequences of time-stamped events encoding interactions between actors. The availability of event data has grown considerably with the advent of automated data-collection facilities. Examples include log-data of computer mediated communication (e. g., email, Usenet-groups, or social network services), open collaboration in wikis, phone-call data, or events that are routinely observed and reported in the news. Note that event data typically do not encode affective relations, such as friendship, but rather dyadic interaction, such as communicating, working together, etc. However, apart from the advantage of a finer time-granularity, event data are often available in larger quantities and are independent of respondents' subjectivity in assessing their relations.

In this paper we propose models and methods for network data consisting of time-stamped, dyadic, weighted events, where the weight indicates the quality (hostile vs. friendly) of an event. Specifically our methods attempt to determine how the rate and quality of events is influenced by the state of the network.

In the remainder of this introduction we introduce a dataset used for illustration and present related work. Our newly proposed model is described completely in Sect. 2. The results of an illustrative application of the model and a summary are given in Sect. 3 and Sect. 4.

### 1.1. Exemplary Data: Political Events

We apply our newly proposed model to datasets from the Kansas Event Data System (KEDS) [3], which is a software tool that automatically extracts daily events from news reports. Events encode *who did when what to whom* and, thus, describe time-stamped dyadic interaction of specific types. The actors involved in events are political actors, such as countries, international organizations, or ethnic groups. Event types are classified using the World Event/Interaction Survey (WEIS) codes [4] and each event type is assigned a psychometrically determined weight (see [5]) from the interval $[-10, 8.3]$, where $-10$ stands for the most hostile and $+8.3$ for the most cooperative type of interaction. Examples or cooperative events are visits, agreements, and provision of military aid; hostile events include accusations, threats, and military actions against another actor. On those empirical event networks we test hypotheses concerning reciprocity and structural balance theory (e. g., "the enemy of my enemy is my friend"), see Sect. 3.

To evaluate how our method performs on networks of different size and density, we apply it to several datasets that are publically available from the KEDS website[1] and that have the following numbers of actors and events.

1. `http://web.ku.edu/keds/`

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| region | time period | act. | events |
|---|---|---|---|
| LEVANT | 1991/05/05 2007/01/31 | 699 | 171,000 |
| BALKANS | 1989/04/02 2003/07/31 | 325 | 78,000 |
| GULF | 1979/04/15 1999/03/31 | 202 | 304,000 |
| TURKEY | 1992/01/03 2006/07/31 | 429 | 20,000 |

### 1.2. Further Related Work

The analysis of event data (alternatively referred to as *time-to-event analysis*, *survival analysis*, or *lifetime analysis*) is an established area in statistics, see [6] for a general reference. Although, event data analysis is common in political science [7], network dependencies are rarely considered there. A notable exception is given by Goldstein et al. [8] who applied vector-autoregression to the dyadwise aggregated levels of cooperation/conflict over short time-intervals. The influence of common friends and enemies on dyads in political networks has been analyzed in [9], [10]. Both references do not use event data, but rather data coding the yearly state of the world system on the country-level in terms of alliances and wars (among others).

Research about event networks include the following. De Nooy [11] analyzed a network of literary authors and critics, where the interaction-events encode positive or negative literature reviews. In a paper closely related to ours, Butts [12] proposed a general framework for modeling the rate of relational events. Our paper extends this by modeling the conditional quality (weight) of events. Work dealing with the prediction of events in networks includes [13], [14].

Methods to visualize networks constructed from event data have been presented in [15], [16]. The contribution of the current paper is different, since here we propose methods for statistical testing of hypotheses in such networks.

## 2. Model Specification

We assume that the probability of events is dependent on previous events. It is the goal of the analyst to determine the form of this dependency and thereby establishing rules that govern the behavior of actors. For instance, the happening that an actor $a$ performs some hostile action targeted at an actor $b$ may increase the probability that $b$ acts hostile towards $a$. If this can be validated statistically, the analyst will have learned the rule that (in the specific context at hand) actors show a tendency to retaliate which, in turn, improves the ability to predict future events.

### 2.1. Model Overview

For modeling the probability of an observed sequence of events $E = (e_1, \ldots, e_N)$, we assume that each event $e_i$ is only dependent on events that happened earlier, i. e., $e_i$ is dependent on $(e_1, \ldots, e_{i-1})$. To obtain a tractable model, we further assume that this dependence is completely captured by a dynamic network encoding the past interaction among actors: The past events $(e_1, \ldots, e_{i-1})$ determine an *event network* $G_i$ (see Sect. 2.3) and, given the state of $G_i$, the next event $e_i$ is assumed to be conditionally independent on $(e_1, \ldots, e_{i-1})$. The probability of $e_i$, given $G_i$, is modeled parametrically so that the estimated parameters give the information which properties of $G_i$ increase/decrease the rate (frequency) of events and which properties of the network influence actors to act more friendly/hostile towards other actors.

More formally, let $E = (e_1, \ldots, e_N)$ be a sequence of events and let

$$\theta = (\theta^{(\lambda)}; \theta^{(\mu)}) = (\theta^{(\lambda)}_1, \ldots, \theta^{(\lambda)}_{k_\lambda}; \theta^{(\mu)}_1, \ldots, \theta^{(\mu)}_{k_\mu})$$

be the parameters of the model (where the *rate parameters* $\theta^{(\lambda)}$ stochastically determine the event rate and the *weight parameters* $\theta^{(\mu)}$ stochastically determine the event weight, as we shall see later). The probability density function for the event sequence $E$ (given specific parameter values) is

$$f(E; \theta) = f(e_1 \big| G_{e_1}; \theta) \cdot \ldots \cdot f(e_N \big| G_{e_N}; \theta) \ . \quad (1)$$

Here $f(e_i \big| G_{e_i}; \theta)$ denotes the probability density for the event $e_i$, given the network $G_{e_i}$ and parameter values $\theta$.

For a given observed sequence of events $E = (e_1, \ldots, e_N)$ we obtain a likelihood function on the space of parameters $\Theta$ by

$$L \colon \Theta \to \mathbb{R};\ \theta \mapsto L(\theta) = f(E; \theta) \quad (2)$$

and our goal is to determine those parameter values $\hat{\theta}$ that maximize $L$ (Maximum Likelihood Estimation (MLE), compare [17]).

In the next subsections we give details on the input format, the construction of $G_{e_i}$, the form of the probability density, and the estimation of the parameters.

### 2.2. Input Data Format

The input data we consider consists of *sequences of (dyadic, weighted) events* $E = (e_1, \ldots, e_N)$. An *event* $e \in E$ is defined to be a tuple $e = (a_e, b_e, w_e, t_e)$, where

- $a_e$ is the *source* (initiator) of $e$;
- $b_e$ is the *target* (addressee) of $e$;
- $w_e \in \mathbb{R}$ is the *weight* coding the quality of $e$; and
- $t_e$ is the *time* when $e$ happens.

Time is given on some scale, e. g., by second, minute, hour, day, month, or year. In the datasets that we consider in this paper, time is given by the day. Several events may happen during the same time unit. The input event sequence is assumed to be in non-decreasing order with respect to time. The order of events that happen within the same time unit is considered as undefined.

The weight indicates the *quality* of the event, i. e., its level of *hostility* (negative weight) or *cooperativeness* (positive weight). We assume in this paper that event weights are normalized to the interval $[-1, 1]$. (So that, for instance, Goldstein weights of KEDS events are divided by ten.)

## 2.3. Explanatory Variable: Network of Past Interaction

Given a sequence of events $E = (e_1, \ldots, e_N)$ and a timepoint $t$ (denoting the current time), the *event network* $G_t = G_t(E) = (A;\ \omega_t^+, \omega_t^-)$ is a weighted network encoding the past interaction between actors. Here, $A$ is the set of actors that are involved in any event in $E$ (thus, $A$ does not change over time) and $\omega_t^+$ and $\omega_t^-$ are functions defined on dyads encoding cooperative respectively hostile interaction before time $t$.

The value of cooperative/hostile interaction of a particular dyad $(a, b)$ increases whenever $a$ initiates a cooperative/hostile event $e$ targeted at $b$. When the difference between the current time $t$ and the event time $t_e$ increases, the influence of $e$ diminishes. The latter property is motivated by the assumption that actors forget (or forgive) cooperative and hostile actions.

More precisely, let $D = \{(i, j) : i, j \in A,\ i \neq j\}$ denote the set of all dyads and $T_{1/2} \in \mathbb{R}_{>0}$ a given positive number denoting the *halflife* of the influence of events. Then, the function $\omega_t^+ : D \to \mathbb{R}_{\geq 0}$, is defined by

$$\omega_t^+(i, j) = \sum_{\substack{e:\ a_e = i,\ b_e = j,\\ w_e > 0,\ t_e < t}} |w_e| \cdot \frac{\ln(2)}{T_{1/2}} \cdot e^{-(t - t_e)\cdot \frac{\ln(2)}{T_{1/2}}} \quad .$$

The function $\omega_t^- : D \to \mathbb{R}_{\geq 0}$ is defined by the same formula, where the condition $w_e > 0$ is replaced by $w_e < 0$. (Note that $\omega^-$ still maps to the non-negative numbers, since the absolute value $|w_e|$ is taken.)

Thus, the function $\omega_t^+(i, j)$ is defined as the sum over all weights of events $e$ that involve $i$ as source ($a_e = i$) and $j$ as target ($b_e = j$), that happen before the current time $t$ ($t_e < t$), and that have positive weight ($w_e > 0$). Similarly, $\omega_t^-(i, j)$ is the sum over events with negative weight $w_e < 0$. How strongly an event $e$ is counted at time $t$ depends on the time-difference $t - t_e$: each time this difference increases by $T_{1/2}$ the factor for $w_e$ is halved. The choice of $T_{1/2}$ is dependent on whether the analyst is interested in short-term or long-term responses.

If $e$ is an event in $E$, we sometimes write $G_e$ for $G_{t_e}$. Note that $G_e$ is only dependent on events that happen *earlier* than $e$ (and not on events that happen in the same time unit as $e$).

## 2.4. Dependent Variable: The Next Event

Let $e = (a_e, b_e, w_e, t_e)$ be the $i$'th event in the observed sequence $E$ and and let $\Delta t_e$ denote the time difference between the $i$'th and the $(i - 1)$'th event. The probability density of $e$, given the state of the network $G_e$ (compare Eq. (1)), is decomposed into two factors

$$\begin{aligned} f(e \big| G_e; \theta) &= f_\lambda(a_e, b_e, \Delta t_e \big| G_e; \theta^{(\lambda)}) \cdot \\ &\quad f_\mu(w_e \big| a_e, b_e; G_e; \theta^{(\mu)}) \end{aligned}$$

Here $f_\lambda(a_e, b_e, \Delta t_e \big| G_e; \theta^{(\lambda)})$ is the probability density that the $i$'th event happens after a waiting time of $\Delta t_e$ and involves $a_e$ as source and $b_e$ as target—given the state of the network $G_e$ and the rate parameters $\theta^{(\lambda)}$. Likewise, $f_\mu(w_e \big| a_e, b_e; G_e; \theta^{(\mu)})$ is the probability density that event $e$ has weight $w_e$—given the network $G_e$ and values for the weight-parameters $\theta^{(\mu)}$ and given the fact that the next event involves $a_e$ as source and $b_e$ as target. Section 2.4.1 clarify the functional form of the density for the event weight (event quality); for space limitations we do not give details on how the event rate (frequency) is modeled (see [12] for how this can be done). We emphasize that the weight parameters and the rate parameters are uncorrelated and, thus, the former can be estimated even if the model for the event rate is unspecified.

**2.4.1. Event Quality.** We assume that the weight of an event $e$ from actor $a$ to actor $b$ has an expected value $\mu_{ab} = \mu_{ab}(G_e; \theta^{(\mu)})$ that is dependent on the current state of the network $G_e$ and the parameters $\theta^{(\mu)}$. The deviation of the actual (observed) weight from the expected value $\mu_{ab}$ is modeled as a normal distribution.

More precisely, for parameters $\theta^{(\mu)} = (\theta_1^{(\mu)}, \ldots, \theta_{k_\mu}^{(\mu)}, \sigma)$, the conditional distribution of the weight $w$ of event $e = (a, b, w, t)$ is modeled as

$$f_\mu(w \big| a, b; G_e; \theta^{(\mu)}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{[w - \mu_{ab}(G_e; \theta^{(\mu)})]^2}{2\sigma^2}} \quad .$$

The expected event weight $\mu_{ab}(G_e; \theta^{(\mu)})$ is postulated to be dependent on the parameters $(\theta_1^{(\mu)}, \ldots, \theta_{k_\mu}^{(\mu)})$ and the values of various *statistics* $s_h(G_e; a, b)$, $h = 1, \ldots, k_\mu$ that characterize the network around $a$ and $b$. More precisely, the average event weight is assumed to be a function

$$\mu_{ab}(G_e; \theta^{(\mu)}) = \sum_{h=1}^{k_\mu} \theta_h^{(\mu)} \cdot s_h(G_e; a, b) \quad . \tag{3}$$

The maximum likelihood estimates of the weight parameters $\hat{\theta}_h^{(\mu)}$ reveal dependencies between characteristics of the network and future event weights. For instance, if a certain statistic $s_h(G_e; i, j)$ encodes how much $j$ attacked $i$ in the past, then a (significantly) negative value for $\hat{\theta}_h^{(\mu)}$ would imply that actors show a tendency to initiate hostile events towards attackers. (This tendency to retaliate can indeed be observed, see Sect. 3.)

## 2.5. Network Statistics

The general model outlined so far can be applied to test many hypotheses concerning the interplay between network structure and the quality of dyadic events. The specialization is done by plugging various statistics into Eq. (3). The particular statistics that we define below are motivated by previous statistical models for cross-sectional [18] or longitudinal networks [2].

It should be noted that some of these statistics are used to test hypotheses (e. g., reciprocity or structural balance theory), while others mostly serve to control for certain trivial regularities (e. g., inertia). A control statistic that always has to be taken to obtain meaningful results is the *constant* statistic, defined by $\texttt{constant}(G_t; a, b) = 1$. The constant statistic just controls for possible deviation from zero of the average event weight. The function $\texttt{constant}(G_t; a, b)$, as well as the ones whose definition follows, correspond to the statistics $s_h(G_t; a, b)$ in Eq. (3).

**2.5.1. Dyad Inertia and Reciprocity.** The most simple model would assume that actors just continue to act in the way they did in the past. For instance, if actor $a$ often initiated hostilities targeted at actor $b$, the dyad $(a, b)$ is likely to be a hostile one in the future. This effect is controlled for by the two statistics capturing the *inertia* of positive/negative events, defined by

$$\texttt{inertia}^{\pm}(G_t; a, b) = \omega_t^{\pm}(a, b) \ .$$

A non-trivial, but very reasonable, network effect would be that actors reciprocate, i. e., actor $a$ adapts its events towards actor $b$ dependent on how $b$ treated $a$ in the past. This is captured by the two statistics

$$\texttt{reciprocity}^{\pm}(G_t; a, b) = \omega_t^{\pm}(b, a)$$

equal to the positive/negative weights on the reverse ties. A positive estimate for the weight parameter associated to $\texttt{reciprocity}^{+}$ would imply that actors reward cooperation; a negative estimate for the weight parameter associated to $\texttt{reciprocity}^{-}$ would imply that actors retaliate when receiving hostilities. Interestingly, these two effects are not satisfied to the same extent in some datasets, compare Sect. 3.

**2.5.2. Structural Balance Effects.** Structural balance theory [19], [20] predicts that the relation of two actors $a$ and $b$ is (among others) dependent on their common friends and foes. In the following we take it as an indicator for being friends, if two actors cooperate (in either direction) and as an indicator for being enemies, if they exchange hostilities. Let $\omega_{t,\text{sy}}^{+}(i, j) = \omega_t^{+}(i, j) + \omega_t^{+}(j, i)$ denote the *symmetric positive weight* on a dyad $(i, j)$ and let $\omega_{t,\text{sy}}^{-}(i, j) = \omega_t^{-}(i, j) + \omega_t^{-}(j, i)$ denote the *symmetric negative weight*.

The *friends-of-enemies*-statistic for a dyad $(a, b)$ indicates whether there are actors who are enemies of $a$ and friends of $b$.

$$\texttt{friendOfEnemy}(G_t; a, b) = \sqrt{\sum_{i \in A} \omega_{t,\text{sy}}^{-}(a, i) \cdot \omega_{t,\text{sy}}^{+}(i, b)}$$

The square-root expresses the assumption that a second (third, forth, etc.) friend of an enemy has a decreasing marginal effect, compare [18].

By varying the plus/minus-signs, we obtain in a similar manner the statistics $\texttt{friendOfFriend}$, $\texttt{enemyOfFriend}$, and $\texttt{enemyOfEnemy}$.

**2.5.3. Activity and Popularity Effects.** As a matter of fact, some actors are more active than others, some do rather initiate hostile events (aggressive actors), others are more cooperative. Likewise, some actors are typical targets of hostilities, while others tend to experience cooperation. To control for such differences in actors' *position* or *power*, we introduce a set of statistics dependent on the degree of actors.

These statistics vary in three dimensions: (1) outdegree (activity) vs. indegree (popularity), (2) positive vs. negative weight, and (3) whether we want to analyze the influence of these degree statistics on the initiator of events (source) or on the addressee of events (target). Together we obtain eight different statistics, one of which is defined below (the others are implied by analogy). The statistic

$$\texttt{activitySource}^{+}(G_t; a, b) = \sum_{i \in A} \omega_t^{+}(a, i)$$

measures the *activity* of the *source* actor with respect to *positive* events.

## 2.6. Parameter Estimation

Given an observed event sequence, the log-likelihood function (compare Eq. (2)) on the parameters is

$$\begin{aligned} \log L(\theta) &= \log L_\lambda(\theta^{(\lambda)}) + \log L_\mu(\theta^{(\mu)}) \\ &= \left( \sum_{e \in E} \log f_\lambda(a_e, b_e, \Delta t_e \big| G_e; \theta^{(\lambda)}) \right) + \\ &\quad \left( \sum_{e \in E} \log f_\mu(w_e \big| a_e, b_e; G_e; \theta^{(\mu)}) \right) \ . \end{aligned}$$

Hence the maximum likelihood estimation of the rate parameters $\theta^{(\lambda)}$ is independent from the maximum likelihood estimation of the weight parameters $\theta^{(\mu)}$. This has the nice implication that a misspecification of one of the two submodels does not jeopardize the estimation of the other set of parameters.

# 3. Application to Political Event Networks

For illustration, we apply our newly developed method to test several hypotheses in political network analysis. The concrete datasets are introduced in Sect. 1.1.

Table 1. Estimated weight parameters and their standard errors (in brackets), computed with the halflife parameter $T_{1/2}$ (see Sect. 2.3) set to 30 days. Parameter values are bold if they are significantly positive (tendency towards cooperation) or negative (tendency towards hostility) at the 5% level. The rightmost column indicates which hypothesis predicts positive/negative values for which parameter.

| | LEVANT | BALKANS | GULF | TURKEY | *predicts* |
|---|---|---|---|---|---|
| *weight parameters* | | | | | |
| `reciprocity`$^+$ | 0.048 (0.120) | -0.129 (0.100) | **0.132 (0.014)** | 0.665 (0.758) | $H_1$ $(+)$ |
| `reciprocity`$^-$ | **-0.137 (0.013)** | **-0.225 (0.036)** | **-0.096 (0.003)** | **-0.729 (0.307)** | $H_2$ $(-)$ |
| `inertia`$^+$ | **0.272 (0.113)** | **0.718 (0.081)** | **0.252 (0.012)** | **4.184 (0.693)** | |
| `inertia`$^-$ | **-0.088 (0.008)** | **-0.368 (0.030)** | **-0.092 (0.003)** | **-0.657 (0.230)** | |
| `friendOfFriend` | **1.557 (0.073)** | **0.886 (0.122)** | **0.223 (0.023)** | **2.216 (0.620)** | $H_3$ $(+)$ |
| `friendOfEnemy` | -0.061 (0.044) | **-0.818 (0.084)** | **-0.134 (0.013)** | 0.518 (0.574) | $H_4$ $(-)$ |
| `enemyOfFriend` | -0.069 (0.040) | **-0.679 (0.081)** | **-0.157 (0.013)** | 0.091 (0.566) | $H_5$ $(-)$ |
| `enemyOfEnemy` | **-0.305 (0.015)** | **0.198 (0.051)** | **0.060 (0.007)** | **-3.110 (0.439)** | $H_6$ $(+)$ |
| `activitySource`$^+$ | **0.135 (0.019)** | **0.222 (0.022)** | **0.061 (0.003)** | **1.140 (0.169)** | |
| `activitySource`$^-$ | **-0.107 (0.003)** | **-0.058 (0.010)** | **-0.013 (0.001)** | **-1.272 (0.097)** | |
| `activityTarget`$^+$ | 0.008 (0.017) | **0.231 (0.021)** | **0.042 (0.003)** | **1.264 (0.163)** | |
| `activityTarget`$^-$ | **-0.045 (0.003)** | **-0.017 (0.008)** | 0.001 (0.001) | **-0.488 (0.095)** | |
| `popularitySource`$^+$ | **0.078 (0.017)** | 0.033 (0.018) | **-0.025 (0.004)** | **0.396 (0.166)** | |
| `popularitySource`$^-$ | **-0.017 (0.004)** | -0.009 (0.012) | **0.005 (0.001)** | -0.123 (0.090) | |
| `popularityTarget`$^+$ | **0.127 (0.014)** | **0.058 (0.014)** | **-0.028 (0.004)** | 0.080 (0.156) | |
| `popularityTarget`$^-$ | **-0.045 (0.003)** | **-0.061 (0.010)** | **0.004 (0.001)** | **-0.685 (0.078)** | |
| `constant` | **-0.087 (0.002)** | **-0.038 (0.002)** | **-0.078 (0.001)** | **-0.013 (0.004)** | |

### 3.1. Exemplary Hypotheses

One of the most widely satisfied hypotheses in network analysis is the one that actors tend to reciprocate; this has also been observed for political conflicts, see [8]. In signed networks, we got two types of reciprocation that need not to be fulfilled to the same extent.

$H_1$ Actors behave more cooperatively towards those who cooperated with them in the past (*tendency to reward*).

$H_2$ Actors behave more hostile towards those who behaved hostile towards them in the past (*tendency to retaliate*).

Besides the dependency of a dyad on its reverse dyad, it is very reasonable to assume that interaction between two actors is influenced by their common friends or enemies. More precisely, *structural balance theory* [19], [20] (also compare [9], [10]) predicts that actors behave more …

$H_3$ …cooperatively towards the friends of their friends;

$H_4$ …hostile towards the friends of their enemies;

$H_5$ …hostile towards the enemies of their friends; and

$H_6$ …cooperatively towards the enemies of their enemies.

**3.1.1. Operationalization.** All hypotheses are operationalized by testing whether the estimated parameters of appropriate statistics are significantly positive (for the weight parameters this indicates a tendency towards cooperation) or negative (indicating a tendency towards hostility). The appropriate statistics for the event quality hypotheses $H_1$ to $H_6$ are given in Sect. 2.5. To control for other obvious network effects we include the inertia, activity, and popularity statistics in our model.

The choice of the value of the halflife parameter $T_{1/2}$ (see Sect. 2.3) depends on whether we want to test a tendency to, say, retaliate in the short run or rather in the long run. We estimated the model with $T_{1/2}$ being set to one day, seven days, 30 days, and 180 days; results were surprisingly consistent. Estimated parameters and their standard errors for $T_{1/2} = 30$ days are reported in Table 1.

### 3.2. Results and Discussion

A first observation is that, while hypothesis $H_2$ (tendency to retaliate) is consistently confirmed over all four datasets, hypothesis $H_1$ (tendency to reward) could only be validated for one of the four datasets.

Similarly, the four structural balance hypotheses are not satisfied to the same extent. The rule that "the friend of my friend is my friend" ($H_3$) indeed holds in all conflicts that we analyzed. The rules that actors fight the friends of their enemies ($H_4$), as well as the enemies of their friends ($H_5$) is validated in two datasets (BALKANS and GULF) while the other two yield non-significant parameters. Hypothesis $H_6$ ("the enemy of my enemy is my friend") is only validated in the BALKANS and GULF conflicts; by contrast, it has a significantly negative effect in the LEVANT and TURKEY conflicts. This might support the reasoning of Doreian and Mrvar [21], who argued that networks are often not perfectly balanced but might contain more than two mutually hostile subgroups. Saperstein [22] argued that application of the rule "the enemy of my enemy is my friend" often leads to undesirable political behavior.

It is interesting to note that the validity of hypotheses varies over conflicts of different type: the Gulf conflict is mostly a war among state actors, the Balkan conflict a civil war among ethic groups, and the Levant and Turkey datasets encode asymmetric conflicts involving state actors and non-state actors.

## 4. Conclusion

We propose a general model for longitudinal networks that are given as sequences of time-stamped, weighted events. The maximum likelihood estimates of the parameters of this model reveal how the network of past events influences the rate and quality of future events. Specializations of this general model—used to test hypotheses that are motivated by social science theory—are obtained by plugging specific network statistics into Eq. (3). In this paper we employed several statistics modeling dependencies of a dyad on its reverse dyad, on the network positions of its source and target, and on indirect relations such as enemies of enemies. It is straightforward to construct statistics modeling dependencies on actor or dyad *covariates* (see, e. g., [2]); in the case of political actors such covariates could encode, for instance, national capability, ethnic composition, level of democracy, trade relations, formal alliances, or geographic adjacency (compare [10]).

The concrete analysis of networks of political actors—although it has been included mostly for illustration purposes—yields interesting insight. Most notably are that, while negative reciprocity (tendency to retaliate) seems to be universally satisfied, positive reciprocity (tendency to reward) seems to be much rarer. Similarly, the four hypotheses resulting from structural balance theory ($H_3$ to $H_6$) do not seem to hold to the same extent. Clearly a sound validation of these hypotheses must control for certain covariates (see above and [10]).

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