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Temporal patterns of reciprocity in communication networks

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Abstract

Human communication, the essence of collective social phenomena ranging from small-scale organizations to worldwide online platforms, features intense reciprocal interactions between members in order to achieve stability, cohesion, and cooperation in social networks. While high levels of reciprocity are well known in aggregated communication data, temporal patterns of reciprocal information exchange have received far less attention. Here we propose measures of reciprocity based on the time ordering of interactions and explore them in data from multiple communication channels, including calls, messaging and social media. By separating each channel into reciprocal and non-reciprocal temporal networks, we find persistent trends that point to the distinct roles of one-to-one exchange versus information broadcast. We implement several null models of communication activity, which identify memory, a higher tendency to repeat interactions with past contacts, as a key source of temporal reciprocity. When adding memory to a model of activity-driven, time-varying networks, we reproduce the levels of temporal reciprocity seen in empirical data. Our work adds to the theoretical understanding of the emergence of reciprocity in human communication systems, hinting at the mechanisms behind the formation of norms in social exchange and large-scale cooperation.

Keywords: Reciprocity; Temporal networks; Human communication

1 Introduction

Reciprocity, the tendency of entities to mutually interact, is a widespread feature of complex networked systems, central to social network analysis [1, 2], evolutionary game theory [3–5], and the economics of public goods and social norms [6, 7]. Already recognized in some of the earliest sociometrics studies [8], reciprocity is an emergent moral norm of human interaction [9] indicating stability, cohesion, and cooperation in social networks [10–13]. Reciprocity is also widely considered as a main contributor to tie strength [14, 15] and social influence [16].

Highly reciprocal patterns of connectivity have been found in static, aggregated data [17] from the world trade web, internet, and neurons, as well as in social networks of communication [18–20], kinship [21], and strategic partnerships [22]. This has prompted the development of reference models with tunable amounts of reciprocity within the framework of exponential random graphs [23–25], both in the absence [26] and presence [27, 28] of degree correlations. The resulting reciprocity measures have been extended to weighted [18, 29–31] and bipartite [32] networks, and used to uncover the role of reciprocal links in the world wide web [33, 34], the growth of Wikipedia [35, 36], synchronization in brain networks [37], and the dynamics of scientific reputation [38].

When inferring social network structure from repeated interactions like communication events [39, 40], reciprocity emerges as an inherently temporal property. A scenario in which individual A receives 10 messages from person B, followed by 10 messages from B to A, is structurally different from the case where 20 messages are exchanged in an alternating way ($A \rightarrow B$, $B \rightarrow A$, etc.). An appropriate notion to tackle this scenario is a temporal network [41, 42], where nodes are people and time-stamped edges are interaction events in one of potentially multiple forms of communication [43–45]. In contrast to the static case, reciprocity in temporal, non-aggregated network data has received less attention in the literature. Notable exceptions are the extension of reciprocity measures to spatio-temporal urban networks [46], as well as studies of the role of reciprocity in the temporal stability of non-human social networks [47], and in the dynamics of both collaboration [48] and organizational [49, 50] networks.

Here we explore the temporal patterns of reciprocity in social networks by analyzing time-stamped social interaction data in several communication channels (face-to-face, calls, text, email, online messaging, social media, etc.) [51–54]. We start by proposing measures of reciprocity that explicitly take into account the time ordering of events and are thus related to widely studied patterns of temporal inhomogeneity like burstiness [55, 56]. These measures give additional information than their aggregated counterparts [17, 31], particularly the overall balance between events in different directions over a social tie [20]. By separating each dataset into reciprocal and non-reciprocal temporal networks, we observe persistent differences between channels that point to their distinct roles in communication [57], in agreement with previous work on the structure of egocentric networks [58, 59] and daily patterns of communication [60]. Finally, we introduce a model within the framework of activity-driven, time-varying networks [61, 62], combining both heterogeneous node activity [63] and repeated interactions over established social connections [64, 65], which recovers the empirical levels of reciprocity seen in temporal communication networks.

2 Results

2.1 Multi-channel communication networks are reciprocal

We study temporal network data in several communication channels: phone-enabled social interactions via calls and messages in the Copenhagen Network Study [51, 52] (denoted calls & sms), private messages sent in an online social network at the University of California, Irvine [53] (msg), emails exchanged among members of a European research institution [54] (email), and our own crawl of retweets and mentions in Twitter with keywords associated to the anti-vaccination movement in Italy (retweets & mentions) (Fig. 1 and Table 1; for data description see Supplementary Information [Additional file 1] Section S2).

In a temporal network of social interactions via communication, two individuals i and j, or nodes, interact through a directed time-stamped event e_{ijt}, when source node i communicates with target node j at time t (e.g., calls, sends a message, etc.). The time-ordered

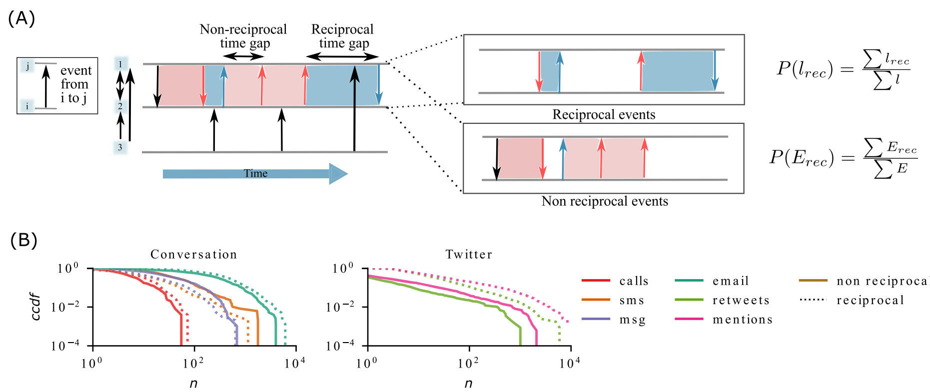

Figure 1 Reciprocal and non-reciprocal activity in empirical communication networks. *(top)* Schema for separating a temporal network of time-stamped, directed communication events between pairs of individuals (black arrows, left) into reciprocal and non-reciprocal components (right). A pair of consecutive events is a *reciprocation* if events have the opposite direction (blue areas), and a *non-reciprocation* if they have the same direction (red areas). (Non-) reciprocal time gaps are then the inter-event times within (non-) reciprocations (see Additional file 1 Section S1). *(bottom)* Complementary cumulative distribution function $P(n' > n)$ (ccdf), the fraction of nodes having strictly more than n reciprocations (solid) or non-reciprocations (dashed) in various communication channels. one-to-one communication channels tend to be more reciprocal than broadcasting channels (i.e. Twitter; see Table 1)

Table 1 Basic statistics of studied datasets. Temporal network data on calls and messages from the Copenhagen Network Study [51, 52] (calls & sms), online social network messages at the University of California, Irvine [53] (msg), emails at a European research institution [54] (email), and our crawl of keyword-restricted retweets and mentions in Twitter (retweets & mentions) (see Additional file 1 Section S2). Table shows the number of events E, links L, and nodes N, as well as the fraction of reciprocations over a link, $p(E_{rec})$, and the fraction of links having at least one reciprocation, $p(l_{rec})$ (see Additional file 1 Section S1). Most channels (apart from Twitter) show significant levels of temporal reciprocity

dataset	E	L	N	$p(E_{rec})$	$p(l_{rec})$
calls	2430	181	252	0.44	0.95
sms	23,779	473	482	0.74	0.99
msg	40,600	3343	941	0.67	0.87
email	306,529	6864	753	0.45	0.90
retweets	57,899	3142	1156	0.10	0.33
mentions	226,774	8292	1609	0.11	0.40

sequence of events of link l_{ij} is, e.g., $\{e_{ijt_1}, e_{jit_2}, e_{ijt_3} ... e_{jit_T}\}$ (with T the total number of events in the link) and one can display its directed events by arrows (Fig. 1 top; for definitions see Additional file 1 Section S1). Communication between a pair of individuals can then be divided into reciprocal and non-reciprocal components. Two consecutive events in opposite directions form a *reciprocation* $[(e_{ijt_1}, e_{jit_2})$ with $t_2 > t_1]$, while two in the same direction are a *non-reciprocation* $[(e_{ijt_1}, e_{ijt_2})$ with $t_2 > t_1]$. Other, less restrictive definitions of temporal reciprocity that do not require consecutive events are also possible (see Additional file 1 Section S7).

We compute the complementary cumulative distribution function $P(n' > n)$ (ccdf), i.e. the fraction of nodes having strictly more than n reciprocations or non-reciprocations in each of the 6 studied communication channels (Fig. 1 bottom). At this level of aggregation, calls and email are slightly more reciprocal, while sms and msg tend towards non-reciprocity. In both retweets and mentions, Twitter is markedly more non-reciprocal than other communication networks. This contrast is likely due to the different purposes for which these social networks are used [57]. Communication networks (msg, calls, email, sms) are primarily conversation channels where interactions are parts of a discussion, people reaching out to each other and responding throughout time. On the other hand, Twitter is mostly used as a broadcasting platform, where users post to reach the community and do not target specific users.

We begin to explore the temporal nature of reciprocity by measuring the number of reciprocations $E_{rec,ij}$ over link l_{ij}, relative to the number of consecutive event pairs on that link, $E_{ij} - 1$. By averaging over links, we obtain the reciprocation probability $p(E_{rec}) = \langle E_{rec,ij}/(E_{ij} - 1)\rangle_{ij}$. We also compute the number of links with at least one reciprocation (l_{rec}) relative to the total number of links (L), $p(l_{rec}) = l_{rec}/L$ (Table 1). We filter out links with less than five events, the lowest threshold value that starts showing relatively low variation in most quantities studied (for sensitivity analysis see Additional file 1 Section S3). This choice of filtering is motivated by previous studies on social network structure [14, 30, 66], which show that repeated interaction is a good proxy for tie strength. In our case, we remove the weakest ties to focus on more persistent patterns of communication.

All conversation channels (calls, sms, msg, email) show high levels of temporal reciprocity. The fraction of reciprocations $p(E_{rec})$ ranges between 0.74 (sms) and 0.44 (calls, email) (Table 1). In contrast, low levels of temporal reciprocity in Twitter are likely due to the broadcasting, uni-directional nature of the platform, with $p(E_{rec}) \sim 0.10$. The aggregated weighted network of Twitter shows a significant negative correlation between in- and out-strengths (see Additional file 1 Section S5), meaning that communication between pairs of nodes is potentially unbalanced overall. As we describe in more detail below, if communication between two nodes is highly skewed in one direction, then temporal reciprocity [as measured by $p(E_{rec})$] cannot be high. We observe a similar behaviour with $p(l_{rec})$: most of the links (87–99%) in conversation channels have at least one reciprocation, while this is only the case for 33–40% of the links in retweets and mentions.

2.2 Balance is an upper bound of temporal reciprocity

A way of highlighting the temporal nature of reciprocity is by comparing it with the overall balance between events in different directions over a social tie. Following [20], we define balance between nodes i and j as $b_{ij} = \frac{\max(n_{ij},n_{ji})}{n_{ij}+n_{ji}}$, where n_{ij} and n_{ji} are the number of events from i to j and from j to i, respectively, for link l_{ij} in the aggregated network. In other words, balance quantifies how much the interaction between two individuals is skewed in one direction or another.

Communication data shows an inverse correlation between balance b in the aggregated network and the fraction of reciprocations $p(E_{rec})$ in the temporal network (Fig. 2). When $b \sim 1/2$ (the numbers of events from i to j and from j to i are equal, i.e. the social tie is balanced), $p(E_{rec})$ is large, meaning that the direction of the interaction between i and j changes repeatedly over time. Then, as b moves away from 0.5, $p(E_{rec})$ decreases, indicating that unidirectional interactions are more prevalent. Still, the fraction of reciprocations ranges from 0 to the approximate upper bound $2(1 - b)$ (for derivation see Additional file 1 Section S6), meaning there is variability in $p(E_{rec})$ among all datasets for a fixed value of b. Messaging, in particular, seems able to maximise reciprocity over balanced ties [i.e. $p(E_{rec}) \sim 2(1 - b)$ for $b \sim 1/2$ in msg and sms]. Thus, $p(E_{rec})$ complements balance as a measure of reciprocal relationships in communication networks, capturing its temporal nature more accurately.

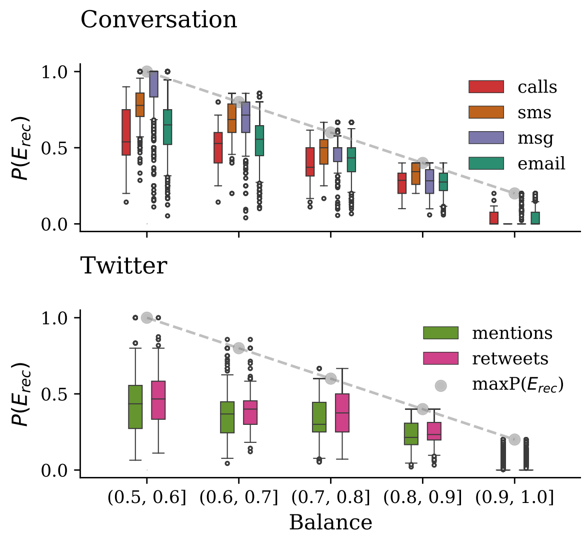

Figure 2 Balance as upper bound of reciprocity in temporal networks. Distribution of fraction of reciprocations $p(E_{rec})$ over nodes in dataset (box plot), and approximate upper bound $p(E_{rec}) = 2(1-b)$ (see Additional file 1 Section S6), both as function of balance b over nodes [20]. Balance is constrained to $0.5 \leq b \leq 1$, with $b = 1$ an unbalanced, unidirectional relationship from one node to the other, and $b = 0.5$ perfect bidirectionality between two nodes. $p(E_{rec})$ decreases as communication moves away from perfect balance, for both conversation (calls, sms, msg, email) and broadcasting (Twitter) channels. $p(E_{rec})$ is highest for balanced conversations ($b \in (0.5, 0.6]$), and smallest for severely unbalanced interactions between node pairs ($b \in (0.9, 1]$). As an aggregate measure, balance does not convey the same information as temporal reciprocity, since $p(E_{rec})$ varies greatly among the 6 datasets for the same interval of b; balance is a necessary but not sufficient condition for reciprocation. Outliers above the upper bound of balance are due to an approximation in its derivation (see Additional file 1 Section S6)

Comparing datasets by $p(E_{rec})$ for a given value of b (Fig. 2), we find that conversation channels show higher levels of temporal reciprocity than Twitter. The datasets sms and msg show the largest $p(E_{rec})$, followed by email and calls, with Twitter mentions and retweets at the lowest level of reciprocation (see Table 1). There are several potential explanations for this behavior. Short phone messages (sms) and direct messages within an online social network (msg) are usually directed at specific people and not used for broadcasting, meaning high temporal reciprocity. Institutional communication (email) is often used both for sharing university-wide messages and talking among small groups of people, leading to heterogeneous values of $p(E_{rec})$. Phone conversations (calls) are inherently bidirectional irrespective of who initiates the call, so people can be reciprocal within conversations even when data shows lower values of $p(E_{rec})$. Twitter is consistently unidirectional mostly regardless of balance, in line with its use as a broadcast platform (see related results for aggregate in-/out-strengths in Additional file 1 Section S5).

2.3 Reciprocation is more bursty than non-reciprocation

Human communication is typically bursty (made up of short trains of intense activity separated by long silences [20, 56]), making us wonder about the relationship between temporal reciprocity and burstiness. We find, however, no significant correlation between $p(E_{rec})$ and standard measures of burstiness [55, 67] (see Additional file 1 Section S6). By separating communication channels into reciprocal and non-reciprocal temporal networks (see Fig. 1 top), we can also compute the time elapsed between successive interactions which

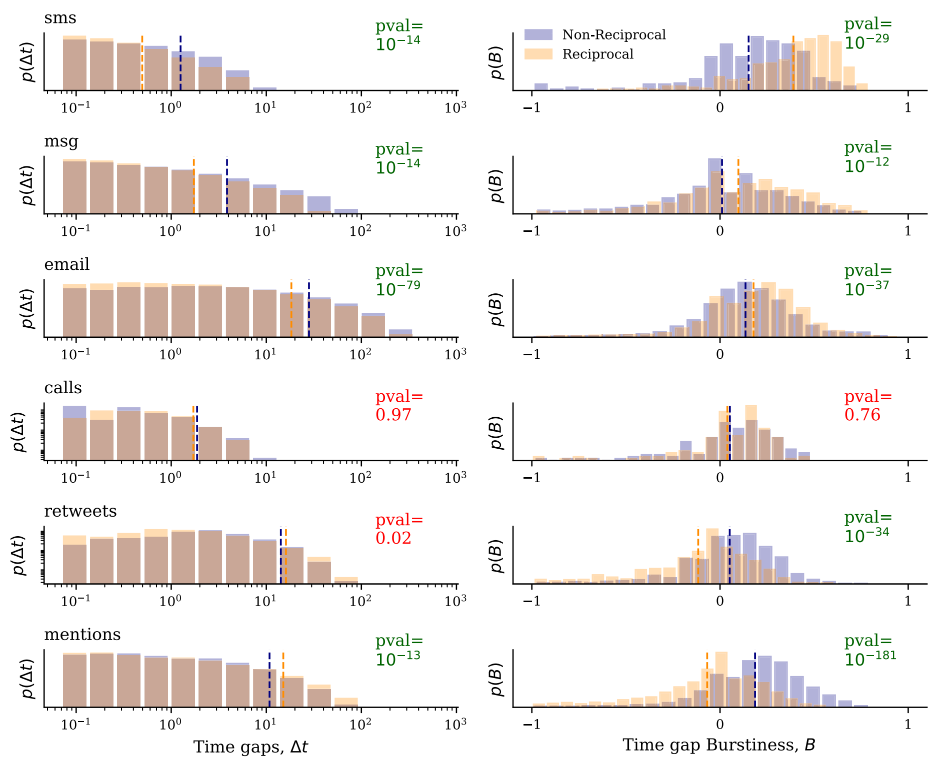

Figure 3 Reciprocation is more bursty than non-reciprocation in human communication, and varies across channels. Distribution $p(\Delta t)$ of the time gap Δt (in days) within (non-)reciprocations (left column), and distribution $p(B)$ of the time gap burstiness B (right column), both over links of all communication channels. Mean values $\langle \Delta t \rangle$ and $\langle B \rangle$ are marked by dashed lines (same colors as corresponding histograms). Reciprocations seem to be faster, showing smaller time gaps than non-reciprocations, for conversation channels (calls, sms, msg, emails), while the opposite holds for Twitter. Reciprocal communication is significantly more bursty (non-homogeneous) than non-reciprocity for sms, msg and email, and becomes less so for calls and the broadcasting channels retweets and mentions. We compute statistical significance of the difference between two distributions via a Kolmogorov-Smirnov (KS) 2-sample test; p-values (pval) < 0.01 are deemed significant (green, otherwise red)

are both reciprocal or non-reciprocal, which we refer to as the (non-) reciprocal *time gap* Δt (Fig. 3 left). The time gap is analogous to the well-known concept of inter-event time in temporal networks [41, 42], but limited to the inter-event times within reciprocations or non-reciprocations.

The time gap distribution $p(\Delta t)$ shows that time scales of communication vary widely among channels – sms has a fast dynamics with average time gap $\langle \Delta t \rangle \approx 0.5, 1.25$ days within reciprocations or non-reciprocations, respectively. Then we have calls, msg, mentions, retweets, and finally, emails as the slowest system with $\langle \Delta t \rangle \approx 28$ days within (non-) reciprocations. The broad distribution in the email channel seems to be consistent with its heterogeneous use for both sporadic institutional communication and more frequent personal exchanges. We also notice that reciprocation is faster than non-reciprocation in conversation channels (sms, msg, and email). The opposite is true for mentions, while calls and retweets show similar shapes of $p(\Delta t)$ between reciprocal and non-reciprocal exchange. Twitter as a broadcasting platform shows more non-reciprocations and less time between their events.

Following previous work on non-homogeneous patterns of communication activity over time [20, 55, 56, 67], we extend the notion of burstiness to time gaps by defining $B = (\sigma - \mu)/(\sigma + \mu)$, where μ and σ are, respectively, the mean and standard deviation of the time gaps within (non-)reciprocations. Time gap burstiness B ranges between −1 and 1, meaning time gaps are distributed either regularly or broadly in time. Explicitly, $B \sim 1$ corresponds to the most bursty time gap distributions possible ($\sigma \gg \mu$), $B = 0$ is a neutral case [an exponential distribution with $\sigma = \mu$], and $B = -1$ indicates identical time gaps ($\sigma = 0$) [67]. The difference between communication channels is even more evident when looking at the distribution $p(B)$ of time gap burstiness in both reciprocal and non-reciprocal components (Fig. 3 right). In conversation channels (sms, msg, email), reciprocal communication is significantly more bursty (i.e. less regular) than non-reciprocal exchange, while the broadcasting platform Twitter shows the opposite (non-reciprocity is more bursty). By explicitly separating communication into reciprocal and non-reciprocal components, sms comes out as the most non-homogeneous form of reciprocal communication among all channels considered. Overall, the consideration of temporal reciprocity, time gaps, and burstiness allow us to identify a spectrum of roles of communication (from one-to-one communication to uni-directional broadcast) not apparent from aggregated data alone.

2.4 Null models identify memory as mechanism for temporal reciprocity

Having established the presence of reciprocity and its temporal features in several communication channels, we turn to the question of how much of the reciprocation seen in data is explained simply by random processes, and how much is otherwise potentially due to specific mechanisms of social interaction, particularly memory [64]. In line with previous work on random models of reciprocity in static networks [26–28, 31], we focus on four null models that randomize (i.e. shuffle) the time of occurrence of events and/or the network topology. As a task of hypothesis testing via reference models of temporal networks [68], our null models correspond to the class of microcanonical randomized reference models, since we impose constraints on some network features (e.g., degree, number of events, etc.), while randomly shuffling others (e.g., time ordering of events, links, etc.).

The null models considered include two types of shuffling: a) *timestamp shuffling*, or b) *rewiring and timestamp shuffling*. Timestamp shuffling keeps the network topology fixed while randomly exchanging the times of event occurrence, thus randomizing the temporal aspects of communication only, not the underlying pattern of interactions. The rewiring and timestamp shuffling method randomizes both the network topology and timestamps of event occurrence, affecting temporal and structural patterns of information exchange. We implement the two shuffling methods at two levels of resolution: a) *node level* or b) *network level*. Shuffling at the node level is applied to the ego networks of each node independently, while shuffling at the network level is applied to all nodes at once. The combination of a shuffling method and a level leads to four null models, which we denote: (i) NTS (Network Shuffling Timestamps), (ii) NDS (Node Shuffling Timestamps), (iii) NTSR (Network Rewiring and Shuffling Timestamps), and (iv) NDSR (Node Rewiring and Shuffling Timestamps) (for a detailed description of each null model see Additional file 1 Section S4).

In line with the observation that humans remember past contacts and often repeat them over time [64], the analysis of our null models suggests memory as one of the underlying

Table 2 Null models identify memory as a mechanism for reciprocity. Signed (one-tailed) p-values of the temporal reciprocity measures $p(E_{rec})$ and $p(l_{rec})$ between the studied datasets and four null models shuffling interaction events. Symbols are ■ ($p < 0.03$), △ ($0.03 < p < 1$), and ○ ($p = 1$), with filled symbols indicating a statistical significant difference between model and data (significance level $\alpha = 0.03$). The sign of the p-value is chosen with respect to median values: for positive (green) p-values, empirical measures are higher than the median of shuffling results, and viceversa for the negative (red) p-values (see Additional file 1 Section S4 for details). Null models are denoted by NTS (Network Shuffling Timestamps), NDS (Node Shuffling Timestamps), NTSR (Network Rewiring and Shuffling Timestamps), and NDSR (Node Rewiring and Shuffling Timestamps) (Additional file 1 Section S4). The calls dataset is not included due to its small size after filtering (Additional file 1 Section S3). We see more positive than negative statistically significant p-values, implying that temporal reciprocity is not reproduced by random mechanisms. The NTSR model randomizes the timeline of social interactions of an individual and the identities of its neighbours, erasing its structural and temporal memory. Positive p-values for NTSR thus suggest memory as a potentially relevant mechanism for reciprocal interaction in social communication. There is also a notable difference in p-value sign between conversation (sms, msg, email) and broadcasting (retweets, mentions) channels, pointing to the distinct roles of bidirectional vs. unidirectional exchange

	$p(E_{rec})$				$p(l_{rec})$			
Dataset \Method	NTS	NDS	NTSR	NDSR	NTS	NDS	NTSR	NDSR
sms	+ ■	+ ■	+ ■	+ ■	○	○	+ ■	○
msg	+ ■	+ ■	+ ■	+ ■	○	○	+ △	- ■
email	+ ■	+ ■	+ ■	+ △	○	○	+ ■	- ■
retweets	- ■	- ■	- ■	- ■	○	○	- ■	- ■
mentions	- ■	- ■	- ■	- ■	○	○	+ ■	- ■

mechanisms for reciprocal interactions in temporal networks (Table 2). We measure the role of memory by calculating one-tailed p-values directly as the probability that the null hypothesis introduced by each shuffling method produces temporal reciprocity values at least as extreme as the empirical value in each dataset (further details in Additional file 1 Section S4). Both proposed measures of temporal reciprocity [$p(E_{rec})$ and $p(l_{rec})$] have many statistically significant positive p-values across null models, indicating that empirical communication channels have more reciprocation than randomized reference models.

In particular, the NTSR null model randomizes social contacts and their event times, thus erasing the memory of individuals in the structural and temporal sense, while preserving the in- and out-degree of each node in the network. This randomization results in decreased temporal reciprocity levels for both $p(E_{rec})$ and $p(l_{rec})$. The NTS model, which only shuffles event times –erasing temporal memory but preserving structural memory, i.e. the identity of social contacts– decreases only $p(E_{rec})$ but leaves $p(l_{rec})$ unchanged. Thus, a lack of reciprocation upon removing memory mechanisms, while preserving individual and network properties, suggests that the memory of past social interactions is one of the drivers for temporal reciprocity in social communication networks.

In the other two null models (NDS and NDSR), we see a similar trend in p-values for $p(E_{rec})$. As $p(l_{rec})$ is unchanged under event-time randomization (NTS and NDS), p values are trivially 1, while NDSR randomization produces higher $p(l_{rec})$ values than the empirical networks, across all datasets. A possible reason for the increase of $p(l_{rec})$ in NDSR could be that this null model homogenizes the strength of a node's connections to its neighbours, thus increasing the chance of at least a single reciprocal event with each neighbour when compared to a more skewed strength distribution. These results indicate that $p(E_{rec})$ is a useful measure of actual reciprocity in the network, in the sense that it reacts in similar ways to random events and noise from system to system.

A comparison of the values of $p(E_{rec})$ between empirical data and the null models also highlights the distinct roles of more traditional communication channels (sms, msg, and email, mostly used for one-to-one conversations) as opposed to the broadcasting platform Twitter (retweets, mentions) (Table 2). Conversation channels all have positive and statistically significant p-values, meaning that empirical values of $p(E_{rec})$ are higher than their randomized counterparts in all shuffling methods, while the opposite happens in Twitter. We interpret this behaviour as an increased tendency for reciprocal and bursty interactions in conversation channels. Communication on Twitter seems less reciprocal and bursty, possibly due to the intended use of the platform as a public setting dominated by unidirectional messaging aimed toward wider audiences.

2.5 Modeling reciprocity in temporal networks

Efforts at theoretically understanding the emergence of reciprocal interactions in temporal communication data include Bayesian inference via network models of Hawkes processes [69, 70] and stochastic blockmodeling of relational event data [71] in both directed [72] and temporal [73] networks. When posed as a machine learning task, the identification of reciprocal interactions has also been applied to the prediction of online extremism in Twitter [74]. Here, we attempt to model the temporal patterns of reciprocity seen in empirical data via a flexible framework of activity-driven (AD) temporal networks [61], used previously to explore several features of human communication dynamics, from cognitive constraints [75] to social contagion [62].

The AD model introduces a (typically broad) activity potential to describe the dynamics of structural heterogeneity in temporal networks [61]: active nodes are chosen more frequently to interact with other randomly selected nodes, with no memory of past interactions. Empirical communication data shows, however, a tendency of individuals to communicate preferentially over established social connections. Indeed, a previous analysis of mobile call networks [64] shows that, as time goes by and social circles evolve, individuals are more likely to re-contact someone they already know, and less likely to interact with new people. Ref. [64] extends the AD model to include a notion of *memory* (the ADM model), which promotes connections with past neighbours. Independently, the AD model has also been extended with a concept of *attractiveness* (the ADA model), by which an individual aggregates more incoming connections from active nodes than from others [63].

Here we combine both features (attractiveness and memory) into a single model, ADAM, and use it to reproduce the observed levels of temporal reciprocity in our six datasets. We define the activity a_i and attractiveness b_i of node i as

$$a_i = \frac{\sum_t k_{out}(i,t)}{\sum_{\ell,t} k_{out}(\ell,t)}, \qquad b_i = \frac{\sum_t k_{in}(i,t)}{\sum_{\ell,t} k_{in}(\ell,t)}, \tag{1}$$

where $k_{in}(i,t)$ and $k_{out}(i,t)$ are the empirical in- and out-degrees of node i at time t. In other words, the activation probability is proportional to out-degree and the attractiveness to in-degree. Then, the ADAM model follows the next rules recursively:

- At each discrete time step t the synthetic network starts with N disconnected nodes.
- With probability $a_i \Delta t$ each node i becomes an active source node and generates m out-stubs (or half-links). For each out-stub,

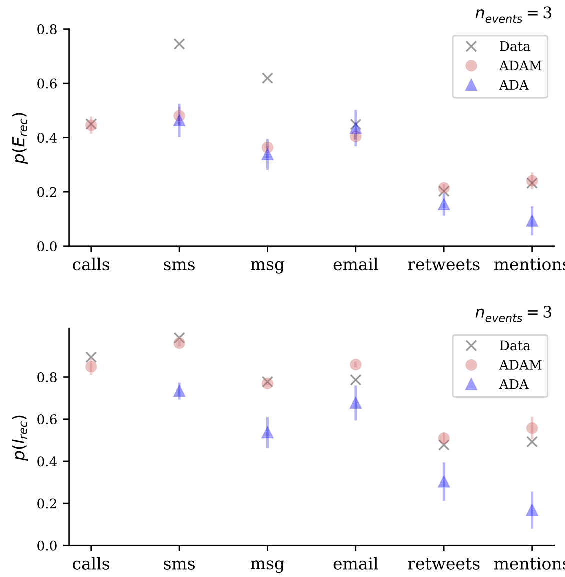

Figure 4 Memory drives temporal reciprocity in activity-driven network model. Fraction of reciprocations $p(E_{rec})$ (top), and fraction of links having at least one reciprocation, $p(l_{rec})$ (bottom), for several empirical communication channels (Data), as well as in synthetic temporal networks fitted by the ADAM and ADA models. The ADAM model, implementing both memory and attractiveness of nodes, reproduces empirical levels of temporal reciprocity in all datasets, outperforming the memoryless ADA model. We filter out links with less than $n_{events} = 3$ events. For calls, ADA does not produce any links with more than 3 events on them, so all edges are filtered out and the ADA symbol disappears. Qualitatively similar results are obtained for a different choice of filter, $n_{events} = 5$ (see Additional file 1 Section S8)

  - *(memory step)* with probability $c/(c + k)$, where c is a memory parameter, select target node j from the past contacts of node i, according to its attractiveness b_j. The memory parameter c is fitted from each dataset as in [64].
  - Otherwise, the target j is chosen randomly from the whole population with probability equal to its attractiveness b_j.
- At the next time step $t + \Delta t$, all edges in the synthetic network are deleted. Thus, all interactions have a constant duration Δt.

We numerically simulate the ADAM model, produce synthetic temporal communication networks and measure levels of reciprocity via $p(l_{rec})$ and $p(E_{rec})$ (Fig. 4). Comparison against an ADA model (i.e. lacking memory) serves as a baseline for testing the performance of our model. The ADAM model captures very well $p(l_{rec})$, consistently outperforming ADA across all channels considered. Values of $p(E_{rec})$ are well reproduced by ADAM for retweets, mentions and calls, while ADA fails for all but email. Our results are robust to the time scale of the observation period for all datasets. Indeed, we compare the levels of temporal reciprocity in data and models over increasing time windows, finding that ADAM systematically outperforms ADA (for details see Additional file 1 Section S9). Overall, a preference to preferentially interact with active individuals and previous social contacts, both within an activity-driven framework, seems enough to reproduce the temporal patterns of reciprocity observed in several communication channels.

Note that ADAM is not able to reproduce $p(E_{rec})$ for sms and msg, perhaps due to a more complex role of memory in these communication channels. The ADAM model does indeed account for memory of past contacts; however, it ignores the possibility that alters are treated differently by an ego. Namely, strong weight heterogeneity over the links of aggregated ego networks might cause discrepancies between data and ADAM. In any case, ADAM outperforms ADA even in the case of sms and msg, showcasing the relevance of some type of memory effect. Future research in the drivers of reciprocity in social communication networks might consider more involved implementations of memory, such as one where the number of past contacts with a given individual determines the frequency of future interactions.

3 Discussion

In this paper, we have proposed measures of reciprocity that explicitly account for the temporality of social interactions in human communication, and used them to quantity the levels of reciprocation in multiple channels including calls, messaging and social media. We have shown that existing reciprocity measures on aggregated directed and weighted networks [17, 31], particularly the notion of balance [20], are actually an upper bound on temporal reciprocity measures like $p(E_{rec})$. Given a level of balance between pairs of nodes, temporal reciprocity can vary widely, highlighting differences across communication channels. Indeed, for conversation channels like sms, msg and email, the time gaps within reciprocations tend to be shorter than for non-reciprocations. This suggests that one-to-one channels [57] support quicker reciprocal communication than the broadcasting platform Twitter. We have seen a similar effect for time gap burstiness; conversation channels have more bursty reciprocal activity, while Twitter displays more bursty non-reciprocal dynamics.

While our measures of temporal reciprocity uncover a range of differences between conversation and broadcasting channels, it would be interesting to perform a similar analysis on channels combining features of both classes. For example, reply dynamics in Twitter may show similar levels of reciprocation as the conversation channels explored here. Implementing several null models based on event shuffling [68], we have also identified the memory of past contacts as a driver of temporal reciprocity. Upon adding a memory mechanism to a framework of activity-driven temporal networks [61, 63, 64], we were able to theoretically emulate the observed levels of temporal reciprocity in several communication channels.

Even if more granular than previous measures on aggregate data, the quantities $p(E_{rec})$ and $p(l_{rec})$ are themselves bounds on reciprocal activity over a social tie. We define temporal reciprocity as consecutive pairs of events in opposite directions across a tie, but less restrictive notions of reciprocity may apply to realistic scenarios of social communication. For example, a reciprocation could be a pair of events in opposite directions within a window of Δ events, regardless of the direction of other events in the window (see Additional file 1 Section S7). This definition increases temporal reciprocity with larger Δ, as expected, yet it maintains the observed difference between modes of comunication: in conversation channels, reciprocations are more bursty and closer in time, while in broadcasting channels, even these relaxed reciprocations have more events in between.

Our measures of temporal reciprocity do not explicitly consider the time elapsed between events. But if this time gap is too large, events are potentially not related to each other (e.g., correspond to different conversations, topics, or even people), meaning actual temporal reciprocity is equal or lower than $p(E_{rec})$ and $p(l_{rec})$. This effect might not be large given our observation that reciprocal communication is bursty, i.e. trains of reciprocations with small time gaps within them are common, notably in conversation channels

(Fig. 3). While we have measured the burstiness of reciprocal interactions and thus quantified the change in temporal reciprocity at the link level, considering temporal correlations may help further uncover periods of high reciprocation punctuated by intermittent non-reciprocal trains. Still, it remains an open question whether our measures could be extended beyond event directionality to reflect reciprocal human behaviour more closely, by, for example, integrating potential correlations between reciprocity, time gaps, and individual activity, or communication content via text analysis [76].

An interesting open question remains as to what extent temporal reciprocity is an indicator of the strength and persistence of ties in social networks, in line with long-standing hypotheses by Granovetter and others [14, 15]. A preliminar analysis shows that high and low levels of temporal reciprocity in communication channels can be found regardless of the amount of activity and structural cohesion around a tie, while in broadcasting channels, high communication frequency tends to be slightly more non-reciprocal (see Additional file 1 Section S6). These results are consistent with recent studies estimating the strength and persistence of social ties via temporal communication data, where similar low correlations have been found [40, 77]. In this sense, temporal reciprocity contains additional information and may be considered a complementary indicator of tie strength beyond aggregate topological measures.

Our exploration of patterns of reciprocity in human communication deals with the large-scale structure of temporal networks. We identify reciprocal interactions at the link level and then accumulate them over whole channels. This reveals a spectrum of modes of communication, from reciprocal, one-to-one conversation channels, to non-reciprocal platforms used mainly for broadcasting. The way temporal reciprocity is distributed across the ego network of an individual is, however, still unexplored. Social signatures, a ranking of alters by decreasing number of contacts with the ego, seem to persist in time and across communication channels [58, 59] and correlate with individual traits [60]. Alter turnover also grows as we go down the ranking, in agreement with generic behavior of rankings in open social systems [78]. By extending our measures to the dynamics of social signatures, we might find higher levels of reciprocal activity among top alters, further cementing the relationship between reciprocity and notions of stability and cohesion in social networks.

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1140/epjds/s13688-023-00382-w.

Additional file 1. Supplementary information (PDF 713 kB)

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Availability of data and materials
Code to reproduce the results of the paper is publicly available at github.com/dynamicalsystemsceu/codes. For data availability see Additional file 1 Section S2. Non-public data is available from the authors upon reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

Author contributions
SC, EA, AM, and LB contributed equally to this work, and are listed in order agreed by the authors. EA and AM analyzed the empirical data, and AM crawled the Twitter data. LB implemented the null models, and SC explored the reciprocity model. All authors conceived the research, discussed the results, and wrote the manuscript. All authors read and approved the final manuscript.

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