Temporal Pattern of Communication Spike Trains in Twitter: How Often, Who Interacts with Whom?

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We evaluate complex time series of online user communication in Twitter social network. We construct spike trains of each user participating any interaction with any other users in the network. Retweet a message, mention a user in a message, and reply to a message are types of interaction observed in Twitter. By applying the local variation originally established for neuron spike trains, we quantify the temporal behavior of active and passive but popular users separately. We show that the local variation of active users give bursts independent of the activation frequency. On the other hand, the local variation of popular users present irregular random (Poisson) patterns and the resultant temporal patterns are highly influenced by the frequency of the attention, e.g. bursts for less popular users, but randomly distributed temporarily uncorrelated spikes for most popular users. To understand the coincidence in the temporal patterns of two distinct interactions, we propose linear correlations of the local variation of the filtered spikes based on concerned interactions. We conclude that the local variations of the retweet and mention spike trains provide a good agreement only for most popular users, which suggests that the dynamics of mention a user together with that of retweet is a better identity of popular users instead of only paying attention of the dynamics of retweet, a conventional measure of user popularity.

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I. INTRODUCTION

In recent years, online social media (OSM) have become a major communication channel, allowing users to share information in their social and professional circles, to discover relevant information pre-filtered by other users, and to chat with their acquaintances. In addition to their practical use for individuals, OSM have the advantage of providing a rich data set on collective social dynamics, as social relations between individuals, temporal properties of their interactions, and their contents are available. The study of these digital footprints has led to the emergence of computational social science, allowing for instance to quantify at large-scales our interests, such as political ideas and preferences [1], to discover roles in social network [2, 3], to predict our health [4] and personality [5], and to determine external effects on our online behavior [6]. Importantly, in OSM, users are at the same time actors and receivers, and the amplification of a trend originates from the interplay between influencing [6, 8] and being influenced [3, 9, 17].

A crucial aspect of OSM and, more generally, of human behavior is that the underlying dynamics is driven by complex temporal interactions [18–22], as the time series of user activities, e.g. posting a tweet, are strongly differ from Poisson processes, because of their burstiness [23, 24], correlations [6, 25–27], and non-stationarity [28, 29]. The deviation from a Poisson process has important implications, as diffusion on the network cannot be accurately described by models on static networks and the process tends to present non-Markovian features with a strong impact on the time required by the process to explore the system [30, 32]. Furthermore, this intrinsic dynamics is associated to a strong heterogeneity in terms of activity and popularity [33–50]. Specifically, in Twitter, the heterogeneity in popularity can be quantified in different ways, by the size of retweet cascades, as users re-transfer messages to their own followers with or without modifying them [36, 31–33], or by the number of mentions of a user name, identified by the symbol @, in other people’s tweets [50].

In this paper, we focus on the dynamics of social interactions taking place in Twitter. Our main goal is to identify statistical properties of temporal communication behavior of users associated to their activity and popularity. To this end, we investigate tweets including social interactions such as retweets a message (RT), mentions of a user name (@), and replies to a message (RE). For each type of the interactions, a user can either play an active, e.g. retweeting, or a passive, e.g. being retweeted, role. For this reason, we characterize each user by 8 time series of the 3 types of interaction and 1 full history composed of all interactions together with 2 for each communication channel, as summarized in Fig. I. Active time series are denoted as WHO and passive time series are identified by WHOM. We then investigate whether the properties of the temporal patterns of each signal is a good predictor for the activity and popularity of a user [31, 32, 50].

Main Sections are organized as follows. Section II describes the data set, quantifies the frequency of commu-
nication of who and whom users, and shows the diversity in the activity and popularity. Section III introduces the technique so-called local variation, originally established for neuron spike trains \cite{57, 62} and recently applied to hashtag spike trains in Twitter \cite{63, 64} to examine inter-event intervals of the underlying process, and describes the results of who and whom users. Finally, Section IV ranks the preferred interactions and the agreements of the active and popular users by constructing linear correlations of the temporal patterns suggested by the local variation. Section V highlights the important results and open questions.

**II. ACTIVITY AND POPULARITY OF USERS**

Our aim is to examine the dynamics of user communication in Twitter. We will investigate how frequently Twitter users talk to each other on a certain topic and identify how complex dynamic patterns of the communication evolve in time. To this end, we focus on the 3 different types of interaction between users, retweet (RT), mention (@), and reply (RE). Twitter uses can adopt a tweet of someone and use it again in their own tweet mentioning (@) the user names of whom users are recognizable. The observed unequal selection in the time series of who and whom users separately. We measure that 228,560 who and 41,400 whom users are present in RT whereas these numbers are less in @, e.g. 102,802 who and 31,477 whom, and even lesser in RE such as 27,227 who and 18,578 whom users. In each case, whom is much lower than who, which suggests that users are popular in what types of chosen interaction. To this end, we consider the Higgs Twitter data set \cite{63} providing us complete timestamps of users participating the spread of the rumor on the discovery of the Higgs boson via RT, @ or RE.

**Data Set.** We borrow the open Twitter data set of the Higgs boson \cite{63, 66}. The data set is composed of tweets containing one of the following keywords or hashtags related to the discovery of the Higgs boson, “lhcb”, “cern”, “boson”, and “higgs”. The start date is the 1st July 2012, 00:00 am and the final date is the 7th July 2012, 11:59 pm, which covers the announcement date of the discovery, the 4th July 2012, 08:00 am. All dates and timestamps in the data are converted to the Greenwich mean time. The full information related to the data collection procedure can be found in Ref. [65].

We are interested in quantifying the communication with the knowledge of the interaction. In total, there are 456,631 users (nodes) and 563,069 conversations talking about the Higgs boson in the given time period. Classifying the conversations based on the interaction, we detect 354,930 RT, 171,237 @, and 36,902 RE, which shows that the users apply RT more often. The majority of users also prefer RT. Introducing in Fig. 1 we examine the time series of who and whom users separately. We measure that 228,560 who and 41,400 whom users are present in RT whereas these numbers are less in @, e.g. 102,802 who and 31,477 whom, and even lesser in RE such as 27,227 who and 18,578 whom users. In each case, whom is much lower than who, which suggests that comparing to users showing their interests to messages and profiles of other users in Twitter only few identical users are recognizable. The observed unequal selection in the passive (whom) users makes the occurrence of popular users as a rare event and the restricted amount of

![Figure 1. Illustration of communication in Twitter. Users in who interact in time with users in whom by retweeting (RT) the messages and mentioning (©) the user names of whom in a message and replying (RE) to the messages from whom. Quantifying temporal patterns in time series of who users with various ranges of the activity of users $a_U$ and of whom users by increasing the popularity of users $p_U$ is the main scope of this paper.](image-url)
attention in both friendship network \cite{67,68} and online social media \cite{69,73} is given for a reason. Fig. 2 describes the heterogeneity of the frequency of the communication $f_U$ with marking the difference in the interactions. For who users, $f_U$ ranks how active users are and measures the activity of users $a_U$, on the other hand, for whom users, $f_U$ quantifies how often the users or their tweets are addressed and so gives the popularity of users $p_U$.

### III. LOCAL VARIATION OF WHO AND WHOM

**Communication Spike Trains.** We extract salient temporal patterns of the user communication time series. We evaluate each directed interaction (RT, @, and RE) of the users in the pool of who with any users in the whom class, shown in Fig. 1. We don’t check whether the whom users participate the conversation in a later stage and only construct independent time series of the who and whom users. The elements of the time series are the timestamps of the data \cite{55,60} providing us the exact time in second of the interaction and the user name or ID of the corresponding who and whom users. Ordering the timestamps from the earliest to the latest, we generate spike trains carrying full story of the communication of each user. The resultant user communication spike trains are grouped in eight: For each who and whom, the spike trains of all interactions together (i) and the spike trains of filtered timestamps of RT (ii), @ (iii), and RE (iv).

**Local Variation.** A standard way of investigating the dynamics of human communication is to examine the statistics of the inter-event spike intervals such as its probability distribution \cite{13a}, short-range memory coefficient and burstiness parameter \cite{19}, or Fano factor. However, recent works have showed that further detail analysis is required to resolve temporal correlations \cite{41,51}, bursts \cite{24,25}, and cascading \cite{13} driven by circadian rhythm \cite{28,29}, complex decision-making of individuals \cite{3,4,7,17}, and external factors \cite{8} such as the announcement of discoveries, as considered in the current data \cite{63}.

To uncover the dynamics of the communication spike trains elaborately, we apply the local variation $L_V$ originally defined to characterize non-stationary neuron spike trains \cite{57,62} and very recently has been used to analyze hashtag spike trains \cite{63,64}. Unlike to the memory coefficient and burstiness parameter \cite{19}, $L_V$ provides a local temporal measurement, e.g. at $\tau_i$ of a successive time sequence of a spike train $\ldots, \tau_i-1, \tau_i, \tau_i+1, \ldots$, and so compares temporal variations with their local rates \cite{61}

$$L_V = \frac{3}{N-2} \sum_{i=2}^{N-1} \left( \frac{(\tau_{i+1} - \tau_i) - (\tau_i - \tau_{i-1})}{(\tau_{i+1} - \tau_i) + (\tau_i - \tau_{i-1})} \right)^2$$

where $N$ is the total number of spikes. Eq. (1) also takes the form \cite{61}

$$L_V = \frac{3}{N-2} \sum_{i=2}^{N-1} \left( \frac{\Delta \tau_{i+1} - \Delta \tau_i}{\Delta \tau_{i+1} + \Delta \tau_i} \right)^2$$

Here, $\Delta \tau_{i+1} = \tau_{i+1} - \tau_i$ quantifying the forward delays and $\Delta \tau_i = \tau_i - \tau_{i-1}$ representing the backward waiting times for an event at $\tau_i$. Importantly, the denominator normalizes the quantity such as to account for local variations of the rate at which events take place. By definition, $L_V$ takes values in the interval (0:3) \cite{63}. It has been shown that $L_V$ classifies the salient dynamic patterns successfully \cite{57,58,68,60}. Following the analysis of Gamma processes \cite{57,58,60,63}, conventionally applied to model inter-event intervals and the neuron spike analysis \cite{62}, while $L_V = 1$ for uncorrelated (Poisson random) irregular spike trains, $L_V \approx 3$ proves that bursts dominate the spike trains and the presence of highly regular patterns in the trains gives $L_V \approx 0$.

We now investigate the $L_V$ analysis on the user communication spike trains. Eq. (2) is performed through the spike trains with the assumption of counting at most single spike in a second. The occurrence of multiple spikes in a second is rare and the validity of the results in this case is discussed in Ref. \cite{68} for hashtag spike trains. We confirm that the statistics on multiple spike occurrences of the communication spike trains is as comparable as that of the hashtag spike trains. Fig. 4 describes the distribution of $L_V$, $P(L_V)$ of full spike trains all together with RT, @, and RE for the who (a, b) and whom (c, d) users. Grouping $L_V$ based on the frequency $f_U$, e.g.
the activity of the who users $a_U$ and the popularity of
the whom users $p_U$, we examine the temporal patterns of
the trains in different classes of $a_U$ and $p_U$. For the real
data in (a, c), in Fig. 3(a), $L_V$ is always longer than 1 in
any values of $a_U$, suggesting that all who users contact
to the whom users in bursty communications. However,
in Fig. 3(c), we observe distinct behavior of the whom
users. By increasing $p_U$, $\log_{10}(p_U) \approx 2.5-3$, $L_V \approx 1$
indicating that there is no temporal correlations among the
who users referring the whom users and $L_V$ is slightly
lesser than 1 for the most popular users, $\log_{10}(p_U) \approx 3.5,$
showing slightly regular activation of applying the whom
users, as also observed for the hashtag spike trains [68].
These observations are significantly different for artificial
spike trains constructed by randomly permuting the real
full spike train and all distributions are centered around 1
independent of $a_U$ and $p_U$, as shown in Figs. 3(b, d).
The randomization and obtaining a null set follow the
same procedure explained in detail in Ref. [62].

Even though Fig. 3 represents $P(L_V)$ of full spike
trains, i.e. all interactions together, $P(L_V)$ of individual
RT, @, and RE communication spike trains describes
very similar temporal behavior for both the who and
whom users. Fig. 4 summarizes the detail of $P(L_V)$, the
mean of $L_V$, $\mu(L_V)$ with the corresponding standard de-
viations $\sigma(L_V)$ as error bars, comparatively. The results
highlight that to classify the communication temporal patterns
neither the position of the users, whether active or
passive, nor the types of the interaction, but the fre-
quency of the communication $f_U$ such as $a_U$ and $p_U$
plays a major role. All Figs. 3(a-d), we observe three regions:
Bursts in low $f_U$, $\log_{10}(f_U) < 2.5$, irregular uncorrelated
(Poisson random) dynamics in moderate $f_U$, $\log_{10}(f_U) \approx$
2.5-3, and regular patterns in high $f_U$, $\log_{10}(f_U) > 3$.
This conclusion supports the importance of frequency so
time parameter overall human behavior [18–22, 68].

We now perform more detail comparison in Fig. 3 how
$L_V$ of different interactions in the same frequency range
varies from each other. To this end, we calculate the
standard $z-$values in two ways. First, to compare $L_V$
of the full spike trains with $L_V$ of only RT and also with
$L_V$ of only @ spike trains, $L_V^{RT}$ and $L_V^{@}$, respectively,
we introduce

$$z(f_U) = \frac{\mu(L^k_V) - \mu_0(L_V)}{\sigma(L^k_V)/\sqrt{f_U^k}}$$

Here, $k$ in superscripts labels the interaction, e.g. either
RT or @. Precisely, $L^k_V$ is determined based on a filtered
spike train composed of the user timestamps of either RT
or @. In addition, $\mu^k$ is the mean of $L^k_V$, as presented
in Fig. 3(b-c), and $\mu_0$ is the mean $L_V$ of the full spike train,
shown in Fig. 3(a).
In Fig. 5(b) black squares show \( z \)–values of RT and black circles describes \( z \)–values of @. For the who users in Fig. 5(a) where \( L_V \) only presents bursty patterns (orange shaded area) and low \( a_U \), we have small \( z \)–values proving the agreement of the temporal patterns suggested by \( L_V \) in the same \( a_U \). However, for the whom users in Fig. 5(b) where we have rich values of \( p_U \) compared to the values of \( a_U \), while \( z \)–values are small in bursty patterns (low \( p_U \), orange area) as also observed in the who users and in regular patterns (high \( p_U \), yellow area), larger \( z \)–@ value (the black circle) is calculated in uncorrelated Poisson dynamics (moderate \( p_U \), purple area). The disagreement of \( L_V \) with large \( z \)–@ indicates that even though \( L_V \approx 1 \) in this region the results of @ are quite sensitive in the same \( p_U \), which is not observed in \( z \)–RT (the black square).

Furthermore, we repeat the comparison, but now between the temporal patterns of RT and @ as follows

\[
z(f_U) = \frac{\mu(L_V^a) - \mu(L_V^{RT})}{\sigma(L_V^a)/\sqrt{f_U}} \tag{4}
\]

The corresponding \( z \)–values are presented in green diamonds in Fig. 5. Unlike to the previous \( z \)–values given by Eq. 3, we now obtain very low \( z \)–values for the who users [Fig. 5(a)] showing a good agreement between RT and @ patterns. On the other hand, these \( z \)–@RT values (green diamonds) follow the similar trend of the previous cases (black squares and circles) for the whom users [Fig. 5(b)]. The bursts (orange area) and regularity (yellow area) depends on the frequency ranges with small \( z \), however, again less agreement is observed due to the large \( z \)–values in irregular random dynamics (purple area) as already observed in \( z \)–@ case (the black circle).

**IV. CORRELATION OF \( L_V \) IN USER COMMUNICATION HABITS**

We have analyzed the communication spike trains of the individual users and showed that the frequency of the communication of users \( f_U \) is an essential parameter. Both for the active (who) and passive (whom) individual spike trains, the overall \( L_V \) is independent of the types of the communication interaction and therefore the spike trains of the full, RT, @, and RE present the similar temporal behavior as a function of \( f_U \) [Fig. 4]: Only bursts in any \( a_U \) and bursts in low \( p_U \), \( L_V > 1 \), Poisson random (uncorrelated) dynamics in moderate \( p_U \), \( L_V \approx 1 \), and regular patterns in high \( p_U \), \( L_V < 1 \). In this section, our interest turns into building new measures to characterize (i) \( L_V \) of user pairs and (ii) \( L_V \) of interaction pairs of the same users. What extend temporal communication habits of two users in the same \( f_U \) ranges are dependent on each other is the first question we address. Second, we examine whether the temporal patterns of the interactions are consistent with each other for the same users and how the metric varies with increasing \( f_U \).

![Figure 5](image.jpg) Detail comparison between the temporal patterns of different communications in each frequency range. While \( x \)-axis is the logarithmic average of frequency, e.g. (a) \( \log_{10}(a_U) \) for the who users and (b) \( \log_{10}(p_U) \) for the whom users, \( y \)-axis provides the calculation of three \( z \)–values (i) \( z \)–RT, the comparison of \( L_V \) of the full spike train with \( L_V \) of RT, in black squares, (ii) \( z \)–@, the same with \( L_V \) of @, presented in black circles, and (iii) \( z \)–@RT, the comparison between \( L_V \) of @ and RT, shown in green diamonds. All \( z \)–values are consistent with each other such that except moderate frequency range in (b), e.g. \( z \)–@ and \( z \)–@RT, we observe small \( z \) concluding that the temporal patterns in the similar frequency ranges are in a good agreement. Three distinct regions are colored due to the discovered patterns in calculating \( L_V \) in Fig. 4. Orange shaded area describes the ranges of the bursty patterns (\( a_U \) and low \( p_U \)), purple area is for the irregular uncorrelated -Poisson random- patterns (moderate \( p_U \)), and yellow area covers the regular patterns (high \( p_U \)).

We begin with introducing a Pearson correlation coefficient to investigate a linear correlation of \( L_V \) of two users. We consider \( r_{ij}^{kk'}(f_U) \), the correlation coefficient of \( L_V \) of two different users selected independently from the same \( f_U \) classes

\[
r_{ij}^{kk'}(f_U) = \frac{\sum_{i,j=1,j\neq i}^{N_U} [L_{ij}^k - \mu(L_{ij}^k)][L_{ij}^{k'} - \mu(L_{ij}^{k'})]}{\sigma(L_{ij}^k)\sigma(L_{ij}^{k'})} \tag{5}
\]
where $\sigma(L^k_{V_i}) = \sqrt{\frac{N_U}{\sum_{i=1}^{N_U} [L^k_{V_i} - \mu(L^k_{V_i})]^2}}$. Here, $L_{V_i}$ and $L_{V_j}$ are the local variations of user $i$ and $j$, respectively, $\mu$'s are the corresponding mean values, and $N_U$ is the total number of users. Moreover, $k$ and $k'$ represent all permutations among the full, RT, and $@$ spike trains. Furthermore, $r_{ij}^{kk'}(f_U)$ is evaluated for the who and whom users separately. Therefore, $i$ and $j$ are different users, but from the same (who/whom) pool and in the same frequency classes of $a_U$ and $p_U$, as grouped in Fig. 3.

Fig. 6 presents the results of $r_{ij}^{kk'}(f_U)$ for the who users in (a, b) and the whom users in (c, d). Similar to $z$-values done in the previous Section, we suggest three correlation coefficients: Red (left) triangles describe $r_{ij}^{\text{full,RT}}$, blue (right) triangles are for $r_{ij}^{\text{full,}@}$, and black and green diamonds show the values of $r_{ij}^{\text{RT,}@}$. The average frequency of the users $\langle f_U \rangle$ in the same class is similar but not equal and that is why Figs. 6(b, d) are plotted with respect to both the mean frequencies of RT and $@$ e.g. the average activity $\langle a_U \rangle$ and popularity $\langle p_U \rangle$ of RT and $@$. All correlations are above 0.85 proving the high dependency of the communication patterns of the users in the same $\langle f_U \rangle$, independent of the types of the interaction.

We now consider Eq. 5 with imposing the same user and repeat the procedure above for the correlation coefficient

$$r_{ij}^{kk'}(f_U) = \frac{\sum_{i=1}^{N_U} [L^k_{V_i} - \mu(L^k_{V_i})][L^{k'}_{V_j} - \mu(L^{k'}_{V_j})]}{\sigma(L^k_{V_i})\sigma(L^{k'}_{V_j})} \quad (6)$$

Fig. 7 summarizes the results of $L_{V_i}$ of user pairs. The standard Pearson correlation coefficient quantifies the dependency on the temporal communication habits of two different users independently chosen from the same frequency classes, as introduced in Fig. 3. The coefficient covers 3 potential relations in the communication interactions, e.g. full and RT spike trains, red (left) triangles, full and $@$, blue (right) triangles, and finally RT and $@$, black and green diamonds. These 3 coefficients are calculated for who (a, b) and whom users (c, d) separately. 6 coefficients in total prove that the temporal patterns present high consistency in each average frequency classes, the activity $\langle a_U \rangle$ and the popularity $\langle p_U \rangle$. In (b, d), the corresponding coefficients are described with the sensitivity of the frequency classes since the average frequency in the class of RT is so similar, but not exactly equal to that of $@$. The colored areas are as defined in Fig. 5 and characterize the three main regions of the temporal patterns of the individual user spike trains, e.g. bursts (orange), irregular random (purple), regular patterns (yellow).

- WHO: Twitter users starting an interaction via $@$ or RE or RT with any other users,
- WHOM: Twitter users addressed by the who users such that their message is retweeted or user name is mentioned in a message by the who users or they get a reply from the who users.

Any relation between who and whom users such as the following-follower is not imposed.

V. DISCUSSION

In this paper, our interest is to quantify online user communication in Twitter. To reduce the complexity in the communication, the data studied here consider only a unique subject which users talk about such as the discovery of the Higgs boson on July 4, 2012 within a restricted time window, e.g. 6 days [65]. The main aim is to extract salient temporal patterns of communication
in various types of interaction observed in Twitter such as retweet (RT), mention (@), and reply (RE). Adopting the technique so-called local variation \( L_V \) originally introduced for neuron spike trains \[57, 62\] and recently has applied to hashtag spike trains in Twitter \[63, 64\], we perform detailed analysis on user communication spike trains. Showing strong influences of the frequency of the hashtag spike trains on the resultant temporal patterns in the earlier work \[62, 64\], in parallel we here examine the differences in the patterns induced by the frequency of the user communication spike trains, \( f_U \).

We investigate user communication spike trains in two categorizations, first set of users are the active ones, who users, and the other set is composed of the passive users, whom users, in the communication. For the who users, \( f_U \) simply gives what extend the users contact to the whom users and so it is the activity of the who users, \( a_U \). On the other hand, for the whom users, the generated spike trains present how often the who users refer the messages or the user names of the whom users and therefore, \( f_U \) is the popularity of the whom users, \( p_U \).

Providing comparative statistics on \( L_V \) of who and whom with increasing \( a_U \) and \( p_U \), respectively, we observe quite distinct temporal behavior of online users. First, when we consider the overall picture, \( a_U \ll p_U \) indicating that the most popular users are rarer than the active ones, only very few users are able to attract attention even though much more users participate to address someone in Twitter. Moreover, the who users only present bursty patterns, \( L_V > 1 \) in all \( a_U \), whereas, the whom users experience communication temporally in 3 different ways resembling hashtag spike trains \[63\]. While the least popular users with low \( p_U \) perform bursts, popular users with moderate and high \( p_U \) are contacted by temporarily uncorrelated who users and so show Poisson random spike trains \( L_V \approx 1 \), and the most popular users with the maximum \( p_U \) are referred regularly in time, e.g. \( L_V < 1 \).

These scenarios, for both the who and whom users, are independent of the preferred interactions, e.g. whether RT or @, suggesting that the frequency of the communication mainly itself designs the resultant temporal patterns compared to the function of the users, active or passive, and the types of the interaction. This conclusion is further proven by the high correlation coefficient of \( L_V \) on the user pairs in the same frequency classes. On the other hand, the linear correlation of \( L_V \) on the same users highlights the unfair temporal behavior in the interactions. A sparking distinction is observed in the correlation between RT and @ of the whom users. Having no significant correlation in the users with low \( p_U \), we observe that only popular users perform very similar temporal habits in both RT and @, which emphasizes the importance of @-network as well as RT cascades and suggests an alternative and maybe even a better metric to identify the influential users instead of only focusing on RTs.

The analysis can be improved by integrating the communication spike trains with the following-follower relation in Twitter. How the results are varied when we construct the who and whom spike trains composed of the users having this relation is a valuable question we could pinpoint. Another important concern is the time period of the data. The data starts 3 days before the announcement of the discovery and lasts 3 days longer than this date and therefore it has been shown that the dynamics of the communication is totally different before/after and during the announcement \[65\]. Our findings could gain an interesting dimension with including this difference in the dynamics. Our study shares the similar aims of the other research on the online user behavior and the influence of the frequency in online platforms such as Flickr, Delicious and StumbleUpon, which user profiles have been included in the analysis \[68\]. This understanding can be also applied to our analogy with considering further details in the data.

### A. Data Sharing

The full data studied in this paper has open access \[65\].
DISCLOSURE/CONFLICT-OF-INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

Conceived and designed the experiments: CS. Performed the experiments: CS. Analyzed the data: CS. Contributed reagents/materials/analysis tools: RL CS. Wrote the paper: CS RL.

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