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Human Interactive Patterns in Temporal Networks

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***Abstract*—Modern information and communication technologies provide digital traces of human interactive activities, which offer novel avenues to map and analyze temporal features of human interaction networks. This paper explores mesoscopic patterns of human interactive activities from six real-world interaction networks with temporal-topological isomorphic subgraphs, i.e., temporal motifs. We discover two dominant mutual motifs, "Star," "Ordered-chain," and one dominant directed motif, "Ping-Pong," which characterize the interactive patterns of "Leader," "Queue," and "Feedback," respectively. Moreover, temporal dynamics shows that bursts are universal in human mesoscopic patterns, and the evolution of three dominant temporal motifs indicates the existence of characteristic time. Finally, we analyze temporal robustness and generalization to verify that 3-event temporal motifs are a simple yet powerful tool to capture the mesoscopic patterns of human interactive activities.**

***Index Terms*—Data-driven, human dynamics, interaction pattern, motifs, temporal networks.**

I. Introduction

UNDERSTANDING human interaction activities is essential in various implications [1]–[7], ranging from managing information spreading to tracking social contagion, evaluating individual/group performance and identifying social relationships. Today, human interactive activities are overwhelmingly digitized by a variety of modern information and communication technologies (e.g., Wi-Fi technology [8], [9], active radio frequency identification (RFID) technology [10], [11], internet [12], and mobile phones [13]), which record rich data to track human interactive activities and offer unparalleled opportunities to explore human interaction patterns beyond laboratories.

Recently, human interactive activities (e.g., online communications and face-to-face interactions) have witnessed non-Poissonian temporal bursts [13], [14], while temporal transitivity as well as reachability among interactive activities significantly influence social contagion and immunization strategies [15], [16]. Therefore, in temporal networks, the information of temporal dimension presents as an explicit element to characterize both topological and temporal dynamics of human interaction networks [8], [9], [12], [15], [17], and many statistical and topological measurements are extended [15], [18]–[22], e.g., path lengths, connectivity, degree centrality, and more close to the interests of this paper, temporal motifs.

Temporal motifs are extended from the concept of network motifs, which are defined as the isomorphic classes of subgraphs, and have been widely applied to capture mesoscopic structures of biological networks and specific dynamical functions [23]–[27]. For example, 3-node motif "feedforward loop" in the transcription network (*Escherichia coli*) performs the biological function of repressing sugar utilization systems in response to glucose, and shifting to anaerobic metabolism [23], [24]. By now, there exist two definitions of temporal motifs [28]–[31]. The direct definition is the equivalent classes of subgraphs in the weighted static networks after aggregating the edges of temporal networks over a period [28]–[30], which, however, fails to depict the time order of edges in the meso-scale. Here we apply the definition of temporal motifs based on temporal adjacency [31], which captures time sequences of edges, and enables quantitative analysis of temporal structures to infer human interaction patterns.

In this paper, we explore the mesoscopic patterns of human interactive activities with six datasets and find three dominant 3-event temporal motifs: "Star," "Ordered-chain," and "Ping-Pong," with the corresponding three interaction patterns: "Leader," "Queue," and "Feedback," respectively. The temporal dynamics of three dominant temporal motifs presents non-Poissonian statistics of bursts, which is universal in mesoscopic interactive patterns. The evolution of three dominant temporal motifs shows that there exists a characteristic time determined by the context of human activities. Finally, the temporal robustness of 3-event temporal motifs and the generalization to 2-event and 4-event temporal motifs verify that 3-event temporal motifs are a simple yet powerful tool to explore mesoscopic patterns of human interactive activities.

This paper is organized as follows. In Section II, we describe six datasets of human interactive activities, and introduce the definitions of temporal networks and motifs. In Section III, we find three dominant temporal motifs, and infer the corresponding interactive patterns. In Section IV, we present the

Manuscript received March 13, 2013; revised October 30, 2013; accepted June 16, 2014. This work was supported in part by the National Key Basic Research and Development Program under Grant 2010CB731403, in part by the National Science Fund for Distinguished Young Scholar of China under Grant 61425019, in part by the National Natural Science Foundation under Grant 61273223, in part by the Research Fund for the Doctoral Program of Higher Education under Grant 20120071110029, and in part by the Key Project of National Social Science Fund of China under Grant 12&ZD18. This paper was recommended by Associate Editor J. Lu. *(Corresponding author: Xiang Li.)*

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Digital Object Identifier 10.1109/TSMC.2014.2360505

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TABLE I
STATISTICS OF SIX EMPIRICAL DATASETS

Dataset	$\|V\|$	$\|E\|$	Type of events	Directed	Temporal resolution ϵ	Duration (day)	Reference
FudanWiFi09	17,881	209,137	proximity indoor interactions	N	1 min	84	[9]
Sex6yr	16,102	42,851	potential sexual contacts	N	1 day	2,232	[12]
HT09	113	8,641	face-to-face conversations	N	20 sec	3	[10]
SGinfectious	10,924	138,567	face-to-face conversations	N	20 sec	81	[10]
SMS1	9,259	22,771	short-message sending	Y	1 sec	1	[13]
SMS2	12,001	25,543	short-message sending	Y	1 sec	1	[13]

non-Poissonian statistics of three dominant temporal motifs, and analyze their evolution to uncover the characteristic time of each dominant interactive pattern. Section V focuses on temporal robustness and generalization of 3-event temporal motifs. Finally, we conclude this paper in Section VI.

II. DATASETS AND DEFINITIONS

A. Dataset Description

We use six empirical datasets of human interactive activities, which are introduced as below and summarized in Table I.

1) The dataset of "FudanWiFi09" was recorded by the Wi-Fi system in Fudan University in 2009–2010 fall semester (from October 18, 2009 to January 9, 2010). When members of the university (students, teachers, office staffs, and visiting scholars) use their unique accounts to access to the campus Wi-Fi system, the accessing information, e.g., the MAC addresses of their devices and the Wi-Fi access points (APs) being accessed, as well as the accessing on/offline timestamps, are automatically recorded by the campus Wi-Fi system (the details of our data see Appendix). Since each Wi-Fi AP is deployed inside a campus building and covers a small indoor region, we assume that all members accessing to the same Wi-Fi AP at the same time represents spatial proximity indoors, which is similar to the assumption in [32].
2) The dataset of "Sex6yr" was collected from an internet online forum in Brazil from September 2002 to October 2008, which records the sexual trading activities among the sellers and buyers. This dataset is available in [12], and for more details refer to [17].
3) The datasets of "HT09" and "SGinfectious" were from the SocioPatterns Program, with active RFID tags embedded in badges. The exchange of radio packets between badges within 1–2 m can be recorded by one of the closest readers, which detects face-to-face conversations between individuals. The dataset of HT09 was collected in the ACM Hypertext 2009 conference, hosted by the Institute for Scientific Interchange Foundation in Turin, Italy, from June 29 to July 1, 2009. The dataset of SGInfectious was collected during the art-science exhibition "INFECTIOUS: STAY AWAY" at the Science Gallery of Dublin, Ireland, from April 17 to July 17, 2009. Both datasets are available on the website of SocioPatterns (http://www.sociopatterns.org/datasets). For more details on the two datasets refer to [10] and [11].

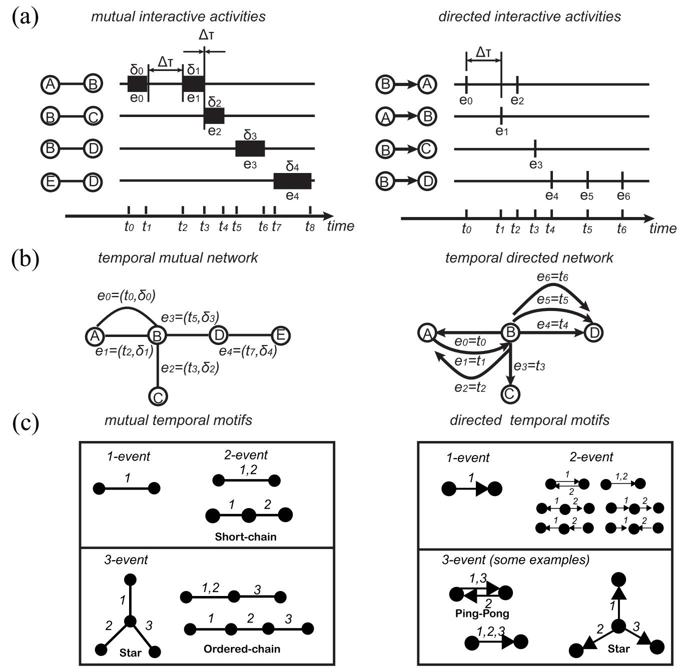

Fig. 1. (a) Mutual (left) or directed (right) interactive trajectories represent human mutual or directed interaction events, respectively. The bold lines pertain to the interactive duration or the time of events. The intervals between the end of one interaction event to the beginning of the consecutive one sharing the same persons are indicated by $\Delta\tau$. (b) Temporal network $G = (V, E)$ gives a reduced picture of interactive trajectories, where the vertices in V are individuals, and the edges in $E = e$ illustrate the interactive events $e = (v_1, v_2, t, \delta)$, which consists of two individuals v_1, v_2, the beginning time of event t and its duration δ. When $(v_1, v_2, t, \delta) = (v_2, v_1, t, \delta)$, the edges of temporal network are mutual (left), otherwise, the edges of temporal network are directed (right). (c) Mutual (left) or directed (right) temporal motifs with a given size of events (i.e., "1-event," "2-event," and "3-event"), where the numbers stand for the temporal order of the events.

4) The datasets of "SMS1" and "SMS2" were both from the charging accountant bills provided by two Chinese mobile operators. Each record comprises a sender mobile phone number, a recipient mobile phone number, and the timestamp with a precision of 1 s for their short-message communication [13].

B. Definitions

The six datasets cover two categories of interactive events: mutual interactive events and directed interactive events. Mutual interactive events are illustrated by the mutual interactive trajectories as shown in the left part of Fig. 1(a), where the bold lines pertain to the interactive duration δ. The interval between two consecutive mutual interactive events (sharing the same individuals) is the duration from the end of the former

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event to the beginning of the latter one (indicated by $\Delta\tau$). The mutual interactive trajectories can be mapped into a temporal mutual network $G = (V, E)$ as shown in the left part of Fig. 1(b), where vertices represent individuals, and edges between two individuals represent a set of events $E = \{e\}$. Each event $e = (v_1, v_2, t, \delta)$ consists of two individuals v_1, v_2, the beginning time t of the interaction and its duration δ. In a temporal mutual network, the order of individuals in an event is insignificant, i.e., $(v_1, v_2, t, \delta) = (v_2, v_1, t, \delta)$, and two individuals interact with each other simultaneously. As summarized in Table I, the events in the datasets of FudanWiFi09, Sex6yr, HT09, and SGinfectious interact mutually, which generate temporal mutual networks. Directed interactive events are described by the directed interactive trajectories as shown in the right part of Fig. 1(a). The difference between mutual and directed interactive events is that the order of two vertices in the latter events determines the direction of interaction. The events in the datasets of SMS1 and SMS2 generate temporal directed networks. Generally, a temporal mutual/directed network can be aggregated into a static mutual undirected/directed network, where the temporal information of interaction events is ignored, and only the connections (including directions) between vertices are retained as the edges of static networks.

The two categories of temporal networks above include two categories of temporal motifs, i.e., mutual temporal motifs and directed temporal motifs. We extend the definition of temporal motifs in [31] to both mutual and directed temporal motifs as follows.

1) Two mutual (or directed) interactive events are defined as $\Delta t -$ adjacent, if they share at least one individual, and the interval between them is less than a given time window Δt. As shown in the left part of Fig. 1(b), two events e_2, e_3 share the same individual B. When their interval $\Delta\tau = t_5 - (t_3 + \delta_2)$ satisfies $\Delta\tau \leq \Delta t$, they are $\Delta t -$ adjacent. Similarly, in the right part of Fig. 1(b), two events e_0, e_1 are also $\Delta t -$ adjacent if $\Delta\tau = t_1 - t_0 \leq \Delta t$.
2) Two mutual (or directed) interactive events are defined as $\Delta t -$ connected, if there is a sequence of $\Delta t -$ adjacent events between them. For example, in the left part of Fig. 1(b), two events e_1 and e_4 are connected by a sequence of events e_1, e_2, e_3, e_4. When e_1e_2, e_2e_3, e_3e_4 all satisfy $\Delta t -$ adjacent, e_1, e_4 are defined as $\Delta t -$ connected. Similarly, in the right part of Fig. 1(b), two events e_0, e_6 are defined as $\Delta t -$ connected, if e_0e_1, e_1e_2, e_2e_3, e_3e_4, e_4e_5, e_5e_6 all satisfy $\Delta t -$ adjacent.
3) A subgraph generated from a set of mutual (or directed) interactive events E, in which every pair of events are $\Delta t -$ connected, is defined as a $\Delta t -$ connected temporal subgraph. For example, the temporal mutual network in the left part of Fig. 1(b) is $\Delta t -$ connected if the time window satisfies $\Delta t \geq \Delta\tau_{\max} = \max(t_{i+1} - t_i)|_{i=1,4,6}$. Similarly, the temporal directed network as shown in the right part of Fig. 1(b) is $\Delta t -$ connected if the time window satisfies $\Delta t \geq \Delta\tau_{\max} = \max(t_{i+1} - t_i)|_{i=0\sim 5}$.
4) The maximal connected subgraph, which a given mutual (or directed) interactive event e belongs to, is defined as the maximal $\Delta t -$ connected subgraph containing event e while unable to accommodate any additional event. For example, the maximal connected subgraph that the event e_1 belongs to is the whole temporal network as shown in the left part of Fig. 1(b).
5) A temporal motif is such a maximal connected subgraph, where all $\Delta t -$ connected events of each individual are consecutive.

As shown in Fig. 1(c), we list all 1-event and 2-event temporal motifs and three 3-event temporal motifs for both mutual and directed cases, which are named as Star, Ordered-chain for two mutual motifs, and Ping-Pong, Star for two directed motifs, respectively. The details of the temporal motif detection method and its theoretical justification refer to [31].

III. Temporal Motifs and Human Interactive Patterns

According to the definition of temporal motif, time window Δt is critical to the definition and detection of temporal motifs in temporal networks. As illustrated in Fig. 2, with increasing time window Δt, all 3-event mutual temporal motifs and the top five directed temporal motifs gradually reach their invariant density. We clearly observe that in the datasets of FudanWiFi09, sex6yr, HT09 and SGinfectious, mutual motifs Star, and Ordered-chain [labeled as $1, 2$ in Fig. 2(e)] are prominent than others, and in the datasets of SMS1 and SMS2, directed motif Ping-Pong [labeled as 1 in Fig. 2(h)] prevails in the networks. In this section, we explore such three dominant motifs and uncover the interactive patterns of human activities: Leader, Queue, and Feedback.

A. Leader Pattern of Human Interactive Activities

As shown in Fig. 2(e), motif Star describes such a temporal structure that a center vertex connects the other three vertices in the temporal order, indicating that the central individual successively contacts his (her) neighbors. Note that such a centralized structure has been widely discovered [33]–[36], but not in a temporal version yet. For instance, in a multiagent networked system, the Leader agent commands the "follower" agents to reach consensus [33], [34]. In gene networks, a regulator can generate a temporal expression programme with the defined order of activation for each target promoter [35], as observed in *E. coli* for example [36]. Therefore, motif Star uncovers the Leader pattern of human interactive activities.

Fig. 2(a) and (b) tells that such a Leader pattern dominates both the proximity indoor interactions of Chinese students, and the potential sexual contacts in Brazil. Since the dataset of sexual contacts provides gender information of individuals, we further analyze 3-event mutual temporal motifs when identifying the gender of buyers/sellers (vertices) in the network. Fig. 2(b1) and (b2) not only verify that the Leader pattern is dominant, but also present that the female sex sellers play the leader role, indicating female sex sellers are more active (and important) than male sex buyers in such interactive activities.

To illustrate the significance of temporal information in characterizing human interactive activities, we calculate

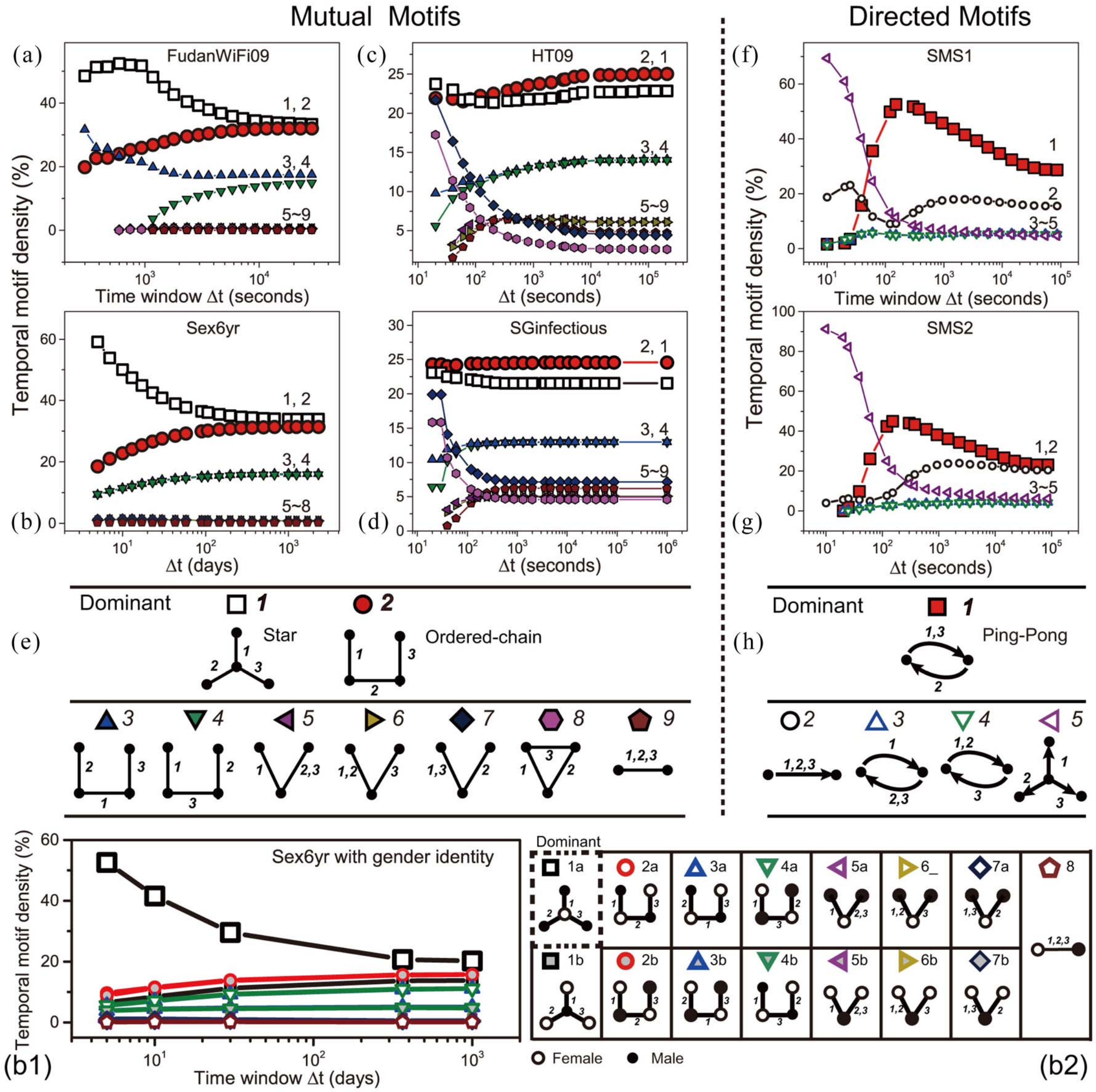

Fig. 2. Temporal motif density evolution. (a)–(d) Density evolution of 3-event mutual temporal motifs versus time window Δt in the datasets of FudanWiFi09, Sex6yr, HT09, and SGinfectious. (e) Temporal structures of 3-event mutual temporal motifs shown in (a)–(d), where the dominant motifs are Star (labeled as "1") and Ordered-chain (labeled as "2"). (f) and (g) Density evolution of top five 3-event directed temporal motifs versus time window Δt in the datasets of SMS1 and SMS2. (h) Temporal structures of 3-event directed temporal motifs shown in (f) and (g), where the dominant motif is Ping-Pong (labeled as 1). (b1) Density evolution of 3-event mutual temporal motifs versus time window Δt in the dataset of Sex6yr with gender identity. (b2) Temporal structures of 3-event mutual temporal motifs with gender identity plotted in (b1), where hollow circles represent female sex sellers, and solid circles represent male sex buyers.

the motif densities (using "FANMOD" [37], [38]) in the corresponding static networks where we neglect the temporal information. As collected in Fig. 3(a), for example, the chain static motif prevails over the Star static motif, indicating the observed Leader interactive pattern in the temporal version may be underestimated with only static contact information. Such difference mainly comes from the fact that after removing temporal information, the chain static motif represents the three chain temporal motifs [labeled as 2, 3, and 4 in Fig. 2(e)], whose density is therefore cumulated and dominant over that of Star motif.

B. Queue Pattern of Human Interactive Activities

There exists another dominant temporal motif, i.e., Ordered-chain motif, as shown in Fig. 2(c) and (d) in human interactive activities. Ordered-chain motif describes such a temporal interactive structure that a sequence of vertices consecutively connects one another in the temporal order, which prevails in the temporal networks generated from the datasets of HT09 and SGinfectious. Since both the datasets were recorded in such a rendezvous that a visitor/attendee may have face-to-face communication with one another, Ordered-chain motif depicts the Queue pattern of the social population's interactive activities. Note that in Fig. 2(c) and (d), both two dominant motifs of Star and Ordered-chain present minor density difference in four different datasets, which were collected as direct (HT09, SGinfectious) or indirect (FudanWiFi09 and Sex6yr) proxy of human interactive activities in different rendezvous with different data-collection technologies. Therefore, the dominance of Star and Ordered-chain motifs tells that both the Leader and Queue patterns characterize the centralized

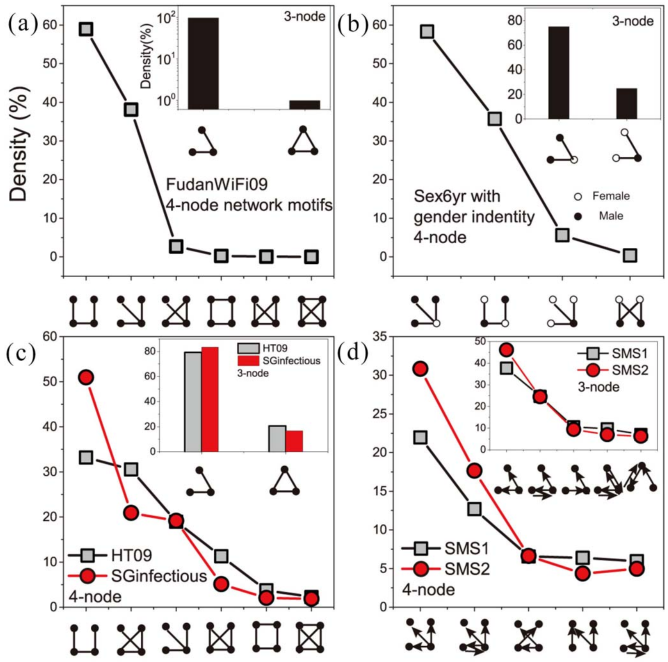

Fig. 3. Static motif density. (a) Densities of 4-node static motifs in the aggregated static network from the dataset of FudanWiFi09, and the inset shows the densities of 3-node static motifs from the same dataset. (b) Densities of 4-node static motifs with gender identity from the dataset of Sex6yr, where hollow circles represent females, and solid circles represent males, and the inset shows the densities of 3-node static motifs from the same dataset. (c) Densities of 4-size static motifs from the datasets of HT09 (black square) and SGinfectious (red circle), and the inset shows the densities of 3-node static motifs from HT09 (black bar) and SGinfectious (red bar). (d) Densities of 4-node static motifs from the datasets of SMS1 (black bar) and SMS2 (red bar), and the inset shows the densities of 3-node static motifs from the same datasets.

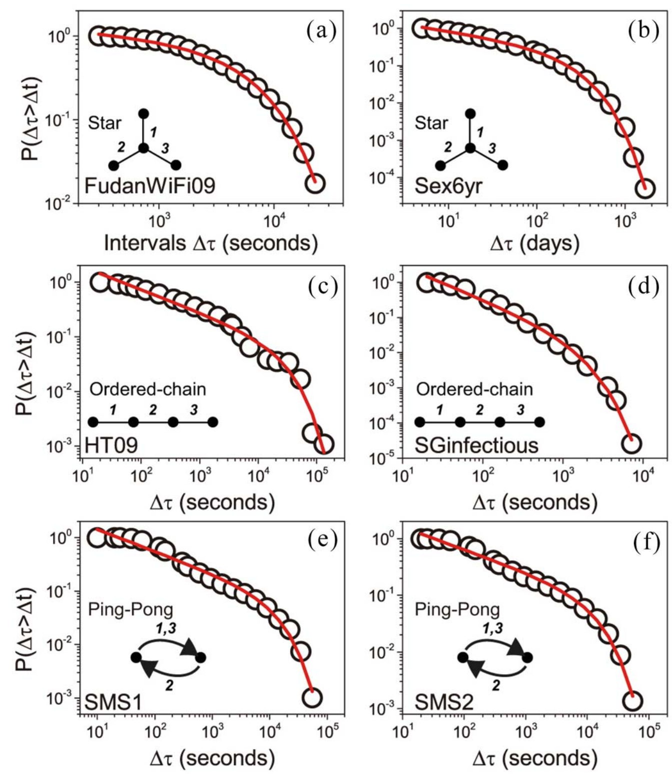

Fig. 4. Non-Poissonian statistics of bursts in the dominant 3-event temporal motifs. (a)–(f) Cumulative probability distributions of the intervals $\Delta\tau$ in the dominant temporal motif from the datasets of FudanWiFi09 (whose dominant motif is Star), Sex6yr (Star), HT09 (Ordered-chain), SGinfectious (Ordered-chain), SMS1 (Ping-Pong), and SMS2 (Ping-Pong). The red lines represent the fitted values based on power-laws with exponential cutoffs, and the details are summarized in Table II.

and decentralized interactive activities of a social population, respectively.

C. Feedback Pattern of Human Interactive Activities

In the case of directed interactive activities, where direction is not negligible, the outcome of dominant motifs presents new features. As shown in Fig. 2(f) and (g), both the datasets of SMS1 and SMS2 do not show similar patterns like before, while the so-called Ping-Pong motif prevails in the temporal networks. Ping-Pong motif is such a temporal structure that a pair of vertices consecutively repeat the directional events between each other, like the name of motif indicates. The dominance of Ping-Pong motif indicates the most frequent interactive activity in short-message communications is requesting-reply behaviors between two mobile phones' owners, which is named as Feedback pattern, and the loop of feedback in temporal order features such typical interactions.

As the comparison with the static motifs as shown in Fig. 3(d), the temporal loops disappear, while the directed Star static motif only tells that short-message broadcasting is popular in both the datasets of SMS1 and SMS2. Therefore, the significance of temporal motifs of Star, Ordered-chain, and Ping-Pong serves as a powerful indicator to uncover the Leader, Queue, and Feedback patterns featured in the interactive activities of human beings.

IV. Temporal Dynamics of Three Dominant Interactive Patterns

A. Emergence of Bursts in Three Dominant Interactive Patterns

The definition of temporal motif shows that the interval $\Delta\tau$ between two consecutive events in a temporal motif is less than a given time window Δt. We assume the number of a temporal motif during time window Δt is $N(\epsilon < \Delta\tau \leq \Delta t)$, where ϵ represents the temporal resolution of the dataset. The calculation of N is as follows: when the time window is long enough ($\Delta t = \Delta t_\infty > \max(\Delta\tau)$), there is no artificial cutoff on temporal adjacency, i.e., any two consecutive interactive events sharing the same person are temporal adjacent, thus the number of the temporal motif is $N(\epsilon < \Delta\tau \leq \Delta t_\infty)$. Therefore, the (log-bin) cumulative probability distribution of the interval $\Delta\tau$ is

$$P(\Delta\tau > \Delta t) = 1 - P(\Delta\tau \leq \Delta t) = 1 - \frac{N(\epsilon < \Delta\tau \leq \Delta t)}{N(\epsilon < \Delta\tau \leq \Delta t_\infty)}. \quad (1)$$

The red lines in Fig. 4 represent the fitted values based on the model of power-law with exponential cutoff $f(x) = \alpha x^{-\beta} \exp(-x/\gamma)$; main parameters are summarized in Table II (all p-value < 0.01). We further give LR tests [39] between the model of power law with exponential cutoff and the exponential model. As shown in Table II, all LRs are

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TABLE II
LIKELIHOOD RATIO (LR) TESTS. THE MODEL OF POWER LAW WITH EXPONENTIAL CUTOFF IS $f(x) = \alpha x^{-\beta} \exp(-x/\gamma)$. THE LR TESTS COMPARE THE MODEL OF POWER LAW WITH EXPONENTIAL CUTOFF AND THE EXPONENTIAL MODEL $g(x) = \alpha \exp(-x/\gamma)$

Dataset	β	γ	LR (Exponential)
FudanWiFi09	0.12***	6377.55***	28.83***
Sex6yr	0.37***	215.48***	48.36***
HT09	0.42***	35087.72***	43.18***
SGinfectious	0.94***	1391.40***	46.11***
SMS1	0.41***	16051.36***	55.94***
SMS2	0.40***	15923.57***	61.21***

larger than zero ($LR > 0$ and all p-values < 0.01), indicating that the model of power law with exponential cutoff is better for fitting the cumulative probability distribution of the intervals compared with the exponential model. Therefore, the intervals in the dominant 3-event temporal motif Star, Ordered-chain, and Ping-Pong all follow the non-Poissonian statistics of heavy-tail distributions, indicating the bursts of rapid interaction events separated by long-time inactivities are popular in human mesoscopic interactive patterns.

B. Evolution of Three Dominant Patterns

We have observed that the three dominant 3-event temporal motifs, Star, Ordered-chain, and Ping-Pong correspond to the human interactive patterns of Leader, Queue, and Feedback, respectively. Note that the density evolution of the dominant 3-event temporal motifs is calculated from their cumulative numbers, which may not fully capture the leading pattern of human interaction activities. Therefore, we analyze the difference between the numbers of additional dominant and subdominant temporal motifs in each dataset with increasing time windows, and visualize the evolution of the dominant human interactive patterns.

When the time window grows from Δt_{i-1} to Δt_i, we assume that the number of additional dominant temporal motifs is $\Delta N^D(\Delta t | \Delta t \in (\Delta t_{i-1}, \Delta t_i]) = N^D(\epsilon < \Delta\tau \leq \Delta t_i) - N^D(\epsilon < \Delta\tau \leq \Delta t_{i-1})$, and the number of additional subdominant temporal motifs is $\Delta N^S(\Delta t)$. The dominant and subdominant temporal motifs in the six datasets are summarized in Table III. The time-varying normalized difference $\eta(\Delta t)$ between the dominant and subdominant temporal motifs is defined as follows:

$$\eta(\Delta t) = \frac{\Delta N^D(\Delta t) - \Delta N^S(\Delta t)}{\frac{1}{n}\sum_{j=1}^{n} \left\| \Delta N^D(\Delta t_j) - \Delta N^S(\Delta t_j) \right\|} \tag{2}$$

where n is the number of sampling time windows. Therefore, we define the characteristic time of the dominant temporal motif as

$$\lambda = \frac{\sum_{\Delta t \in \mathcal{T}} \Delta t \cdot \eta(\Delta t)}{\sum_{\Delta t \in \mathcal{T}} \eta(\Delta t)}, \left\{\mathcal{T} | \Delta t \in \mathcal{T}, \eta(\Delta t) > 0\right\}. \tag{3}$$

Fig. 5(a) shows that, when $\eta > 0$, $\mathcal{T} = (60\text{ s}, 2939\text{ s}]$. In other words, when the intervals between two consecutive events are less than 50 min, the number of additional dominant temporal motif Star is larger than that of the other temporal motifs. This tells that the students attending a class (45 min) in the same classroom interact more frequently with those Leader student. Fig. 5(b) shows that when $\eta > 0$, $\mathcal{T} = (1\text{ day}, 7\text{ days}]$, i.e., intervals between two consecutive potential sexual contacts of an active female sex seller are less than one week. Besides, Fig. 5(c) shows that there are two epoches $\mathcal{T}$ for $\eta > 0$, where the former epoch is calculated from over 60% of data, thus we only list this epoch in Table III. Table III tells that the characteristic time of each dominant interactive pattern, e.g., Leader, Queue, and Feedback, is independent on races, countries, and culture backgrounds of populations, but only dependent on the context of activities. For instance, Leader pattern prevails in the proximity indoor interactions and the potential sexual contacts, but their characteristic time is different. Moreover, Queue pattern dominates face-to-face conversations with the characteristic time around 20 min, while conversations occur among persons with different backgrounds and collected from different countries. Similarly, Feedback pattern prevailing in both datasets of short-message communications presents the characteristic time of 3 min, i.e., people are used to replying the requesting messages in minutes.

V. ROBUSTNESS AND GENERALIZATION

A. Robustness Analyses of 3-Event Temporal Motifs

In this paper, the definitions of temporal motifs based on temporal adjacency request that any person can not interact with multiple persons simultaneously, i.e., a vertex can not interact with different vertices at the same time. Therefore, we preprocess all the six datasets by randomly conserving the interactive trajectories between two persons, in order to analyze the influence of missing data on our results. Firstly, when we randomly remove 90% of events in the datasets of FudanWiFi09, Sex6yr, HT09, and SGinfectious, the densities of all the temporal motifs are very close to the whole datasets with the corresponding time window [Fig. 6(a)–(d)], i.e., the densities of 3-event temporal motifs are robust to random sampling in preprocessing. Moreover, since all the datasets are the samples of human interactive activities during a finite period, we test the densities of 3-event temporal motifs in the (sub-)data collected from different periods. Fig. 6(a)–(d) shows that all 3-event temporal motif densities collected from different periods are identical to those of the origin datasets of FudanWiFi09, Sex6yr, HT09, and SGinfectious, which shows that the densities of 3-event temporal motifs are robust to the artificial cutoffs on the periods of data collections.

B. Generalization of 3-Event Temporal Motifs

We further generalize the case of 3-event temporal motifs to both the cases of 2-event temporal motifs and 4-event temporal motifs. We first analyze 2-event temporal motifs. The temporal structures of the dominant 3-event temporal motifs, Star, and Ordered-chain can be decomposed into the unique 2-event temporal motif Short-chain [see the left part of Fig. 1(c)], which characterizes two consecutive events sharing the same person. Due to the simple temporal structure of 2-event temporal motif, it is impracticable to distinguish the Leader and

TABLE III
CHARACTERISTIC TIME OF HUMAN INTERACTIVE PATTERNS IN SIX DATASETS

Dataset	Dominant motif	Subdominant motif	$\mathcal{T}$	Characteristic time λ
FudanWiFi09	'Star'	'Ordered-chain'	$(60, 2939]$(seconds)	20 minutes
Sex6yr	'Star'	'Ordered-chain'	$(1, 23]$(days)	7 days
HT09	'Ordered-chain'	'Star'	$(40, 3276]$(seconds)	26 minutes
SGinfectious	'Ordered-chain'	'Star'	$(0, 10657]$(seconds)	21 minutes
SMS1	'Ping-Pong'	'Star'	$(25, 600]$(seconds)	3 minutes
SMS2	'Ping-Pong'	'Star'	$(25, 375]$(seconds)	3 minutes

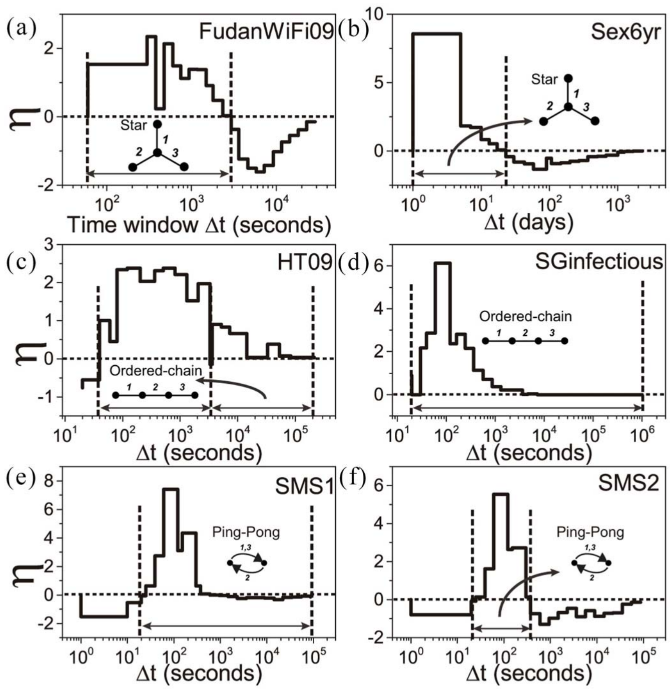

Fig. 5. Evolution of the dominant 3-event temporal motifs. (a)–(f) Difference η between the numbers of additional dominant and subdominant 3-event temporal motifs versus time window Δt from the datasets of FudanWiFi09, Sex6yr, HT09, SGinfectious, SMS1, and SMS2, respectively. The dominant and subdominant temporal motifs in the six datasets are summarized in Table III.

TABLE IV
DOMINANT 4-EVENT TEMPORAL MOTIFS

Datasets	Time window	Dominant 3-event motif	Dominant 4-event motif
FudanWiFi09	2 hours	'Star'	'Big Star'
Sex6yr	30 days	'Star'	'Big Star'
HT09	5 minutes	'Ordered-chain'	'Long Ordered-chain'
SGinfectious	10 minutes	'Ordered-chain'	'Long Ordered-chain'
SMS1	24 hours	'Ping-Pong'	'Big Ping-Pong'
SMS2	24 hours	'Ping-Pong'	'Big Ping-Pong'

Queue patterns. Next, we move to analyze 4-event temporal motifs. As shown in Table IV, the datasets which have the same dominant 3-event temporal motif also have the same dominant 4-event temporal motif. Fig. 7 shows that the dominant 4-event temporal motifs are linear combinations of the dominant 3-event temporal motifs. For example, Big Star motif is composed by two Star motifs, Long Ordered-chain motif is composed by two Ordered-chain motifs, and Big Ping-Pong

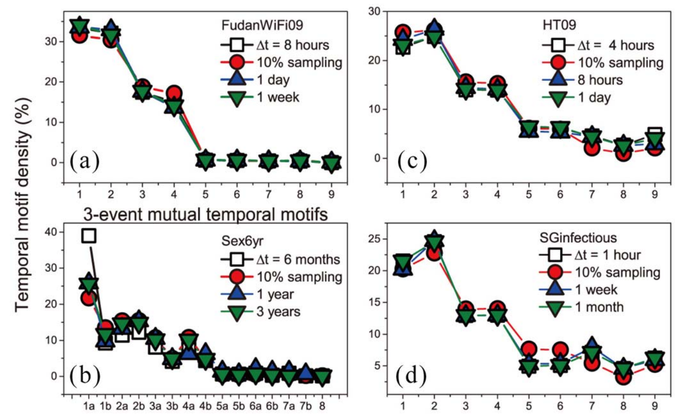

Fig. 6. Temporal robustness. (a)–(d) Densities of 3-event mutual temporal motifs detected from the origin datasets, 10% randomly sampled datasets, and two random period sampled datasets of FudanWiFi09, Sex6yr, HT09, and SGinfectious. The structures of 3-event mutual temporal motifs are shown in Fig. 2.

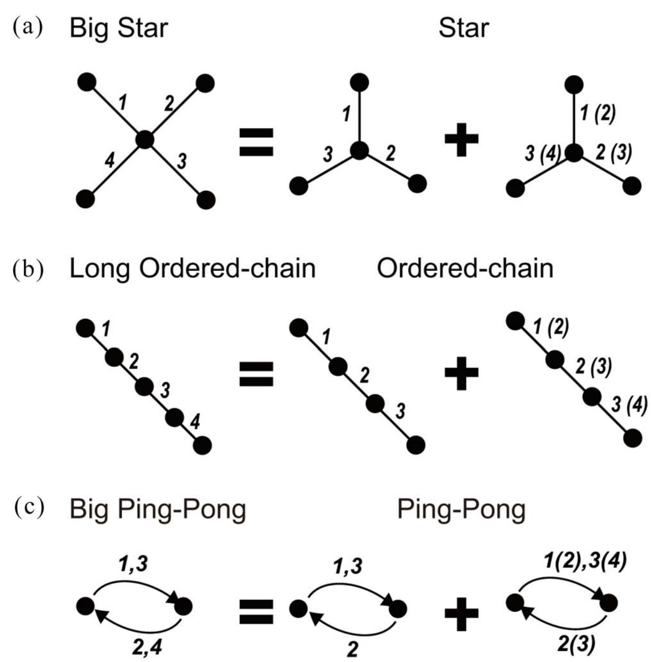

Fig. 7. (a)–(c) Temporal structures and decompositions of the dominant 4-event temporal motifs, Big Star, Long Ordered-chain, and Big Ping-Pong.

motif is composed by two Ping-Pong motifs. Therefore, the mesoscopic patterns of human interaction activities inferred by dominant 4-event temporal motifs are the same as those directly inferred by the dominant 3-event temporal motifs.

VI. Conclusion

In this paper, we have explored 3-event temporal motifs, whose edges consist of three temporal-adjacent interaction events, in six empirical datasets, and discovered three dominant 3-event temporal motifs, Star, Ordered-chain, and Ping-Pong, with the corresponding interactive patterns of Leader, Queue, and Feedback, respectively. With the comparison of static motifs after removing temporal information, we conclude that static motifs cannot fully characterize human interactive patterns. Furthermore, temporal dynamics of dominant temporal motifs present that non-Poissonian statistics of bursts are universal in human mesoscopic interactive patterns, whose characteristic time is dependent on the context of human activities. Finally, we have analyzed the robustness and generalization of 3-event temporal motifs to verify that 3-event temporal motifs are a simple yet powerful tool to help explore human interactive patterns.

Network motif as a mesoscopic connectivity pattern has been well recognized to successfully characterize functions of categories of biological gene networks [25], [35], and in recent years, new findings of social gene have uncovered how social behaviors affect (and are affected by) gene expression [40], [41]. Our efforts in this paper to uncover the significance of temporal motifs, on one hand, could help motivate the understanding of gene function from the viewpoint of embedding temporal information; on the other hand, the discovered mesoscopic temporal patterns of human interactive activities indicate the dominant temporal motifs may help detect/predict the emergent behavior features of a large-scale social population. Note that we are also a part of the social population at the same time, and the present understanding to human population behaviors is still only a tip of the iceberg. Creating a systematic view has a long way to go, and deserves more effort in the future.

Appendix

Open Dataset of FudanWiFi09

The dataset of FudanWiFi09 is formed by four data files, i.e., access logs, location data, interaction data, and sampled interaction data (used in this paper). These data files contain 18 715 Wi-Fi users' access logs, mobility trajectories and interactive records over 3 months (from October 18, 2009 to January 9, 2010) at one campus of Fudan University. All data files are saved as the *csv* or *txt* format, and for more details refer to the description document. The dataset can be obtained in the supplementary materials, or from the website of FudanWiFi09 [42], or by contacting the corresponding author. If you use the dataset, this paper should be cited.

Acknowledgment

The authors would like to thank the three anonymous reviewers for helping to improve this paper, and L. Wang for useful discussions. They would also like to thank SocioPatterns Project for sharing their data, the Informatization Office of Fudan University for the Wi-Fi Data collection, and the Archives of Fudan University for providing the blueprint of all six teaching buildings.

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