Fingerprinting temporal networks of close-range human proximity

André Panisson*, Laetitia Gauvin*, Alain Barrat†‡*, Ciro Cattuto*
* Data Science Laboratory, ISI Foundation, Torino, Italy
Email: {andre.panisson, laetitia.gauvin, ciro.cattuto}@isi.it
† Aix Marseille Université, CNRS, CPT, UMR 7332, Marseille, France
‡ Université de Toulon, CNRS, CPT, UMR 7332, 83957 La Garde, France
Email: alain.barrat@cpt.univ-mrs.fr

***Abstract*—Mobile devices and wearable sensors are making available records of human mobility and proximity with unprecedented levels of detail. Here we focus on close-range human proximity networks measured by means of wireless wearable sensors in a variety of real-world environments. We show that simple dynamical processes computed over the time-varying proximity networks can uncover important features of the interaction patterns that go beyond standard statistical indicators of heterogeneity and burstiness, and can tell apart datasets that would otherwise look statistically similar. We show that, due to the intrinsic temporal heterogeneity of human dynamics, the characterization of spreading processes over time-varying networks of human contact may benefit from abandoning the notion of wall-clock time in favor of a node-specific notion of time based on the contact activity of individual nodes.**

I. Introduction

The ever increasing adoption of mobile technologies and ubiquitous services allows to sense human behavior at unprecedented levels of details and scale. Digital traces from socio-technical systems have been used to study many specific aspects of human behavior, such as geographic mobility [1]–[7], phone communications [8], email exchange or instant messaging [9]–[14], and even human mobility and proximity in indoor environments [15]–[19]. Recently, inexpensive wearable sensors and short-range radio communication between personal devices [20]–[23] are providing new insights on the dynamics of close-range human proximity and face-to-face interaction patterns in indoor environments. This knowledge is important for a variety of pervasive applications [24], and brings forth novel challenges for the design and modeling of efficient protocols for ad-hoc communications and delay-tolerant networks [25]–[28]. A statistical characterization of high-resolution mobility traces is of great importance to understand the limits of such approaches [29], and a rich set of discriminative statistical features is critical for modeling realistic scenarios, as simulation is widely used to discover how mobile applications respond to heterogeneity in user activity [30].

Despite the several different types of temporal heterogeneity exhibited by human activity and contact patterns, to date most of the literature has focused on simple statistical features such as the distribution of inter-contact times between nodes, which is regarded as one of the key metrics in analyzing forwarding algorithms. Here we make a step beyond the characterization of empirical data by means of inter-contact times, and focus on designing statistical indicators that characterize the overall temporal structure of a time-varying contact network. We show that these statistical indicators, contrary to the inter-contact time distributions, allow us to tell apart datasets that would otherwise look statistically similar.

The paper is organized as follows. Section II provides some details on the measurement technique and describes the datasets we used for the present study. Section III characterizes the temporal properties of the proximity networks collected in different environments. In Section IV we discuss a simple flooding process that can be used as a probe to expose more subtle properties of the empirical temporal networks. In Section V we discuss a node-specific notion of time based on activity metrics, that we call "activity clocks". It allows us to expose temporal signatures that are robust with respect to the temporal heterogeneity of individual datasets and to the burstiness of human interactions. Finally, in Section VI we compare the delivery delay distributions of an epidemic process taking place of the empirical contact networks.

II. Datasets

Here we use time-resolved data on face-to-face human proximity collected by the SocioPatterns collaboration[1] in three real-world settings, two conference gatherings and a school. The collected data describe the room-level positions and face-to-face interactions of an entire community of a few hundred individuals during several days.

Participating individuals were asked to wear badges that contain active Radio Frequency Identification (RFID) devices (Fig. 1) that engage in bi-directional radio communication. We use the exchange of radio packets as a proxy for the face-to-face proximity of participants, as illustrated in Fig. 2 and reported in Refs. [15], [31]. The spatial range for proximity detection can be tuned by varying the power of the proximity-sensing packets, from several meters down to face-to-face proximity. At the highest spatial resolution, the exchange of radio packets is only possible when two persons are at close range ($\sim$ 1-1.5m) and facing each other, since the human

[1]http://www.sociopatterns.org

deployment	# participants	# days	Ref.
HT09 conference	112	3	[32], [33]
SFHH congress	415	2	[34]
school	251	2	[35], [36]

TABLE I
DATASETS USED IN THE PRESENT STUDY. FOR EACH DATASET, WE PROVIDE A REFERENCE TO A PAPER DISCUSSING IT AS WELL AS POINTERS TO DOWNLOAD IT (WHEN PUBLICLY AVAILABLE).

body acts as a RF shield at the carrier frequency used for communication. The operating parameters of the devices were chosen so that face-to-face proximity relations can be assessed with a probability in excess of 99 % over an interval of 20 seconds, which is a fine enough temporal scale to resolve human mobility and proximity at social gatherings.

The sensed proximity relations (or *contacts*, as we will refer to in the following) between individuals are relayed by radio receivers (RFID readers) to a centralized data collection system for post-processing, storage and subsequent analysis. Once a contact has been detected, it is considered ongoing as long as the involved devices continue to exchange at least one radio packet for every successive interval of 20 seconds. Conversely, a contact is considered terminated if an interval of 20 seconds elapses with no packet exchange.

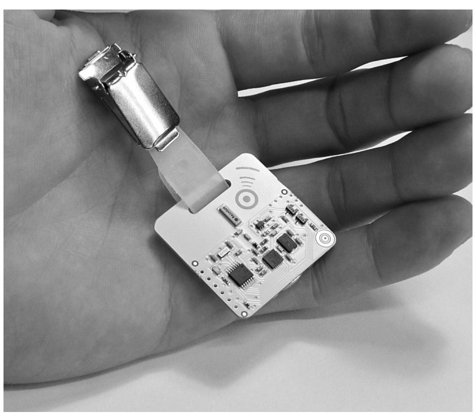


Fig. 1. Wearable proximity sensor used by the SocioPatterns collaboration to mine close-range encounters and face-to-face proximity in a variety of real-world settings.

The proximity-sensing platform described above was deployed in several different settings, yielding data on time-resolved human proximity in conferences, hospitals, schools and museums. The specific datasets we use for the present study are described in Table I. The first dataset we consider was collected at the 20th ACM Hypertext 2009 conference (*HT09*) in Turin, Italy, from June 29th to July 1st 2009 [32], and is available to the public (see Ref. [33]). The second dataset was gathered at the XXe Congrès de la Société Française d'Hygiène Hospitalière (*SFHH*) in Nice, France, on June 4th and 5th, 2009 [34]. The third dataset was obtained in a French primary school and describes the face-to-face contacts of children and teachers over two days of October 2010 [35].

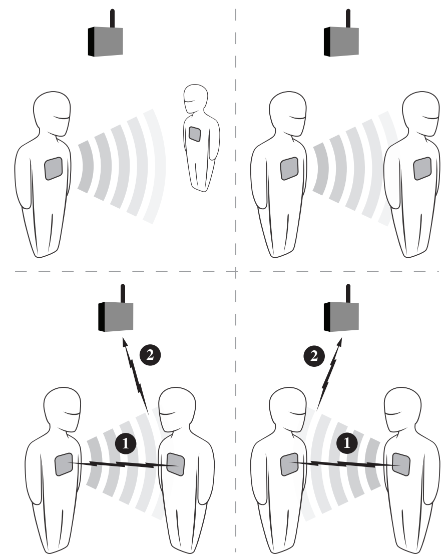


Fig. 2. Proximity sensing strategy. The wearable sensors engage in bidirectional ultra-low power radio communication (1). Packet exchange is only possible when two sensors are sufficiently close in space. At the lowest power used to sense proximity, packet exchange is only possible when the individuals wearing them are at close range (1-1.5m) and face each other (bottom panels). The sensed proximity relations are periodically relayed at higher power (2) to a centralized data collection system.

III. TEMPORAL PROPERTIES OF HUMAN PROXIMITY

The data we use provide for each pair of participants the detailed sequence of their contacts, with beginning and ending times. It is therefore possible to represent these data as time-varying proximity networks: nodes represent individuals and links represent face-to-face contacts between the individuals they connect.

To better understand the properties of dynamical processes that take place over human proximity networks, it is important to characterize the temporal properties of contact behavior. To this end, the customary metrics used in the literature are the distribution of contact durations and the distribution of inter-contact times, i.e., of the time intervals between two successive contacts involving the same pair of nodes. These metrics are used to evaluate protocols using both empirical [26] and synthetic data [37]. It is known that inter-contact time distributions are broad [25], [29], with long-time tails controlled by circadian rhythms. Chaintreau et al. [26] report evidence suggesting that the (complementary) cumulative distribution of inter-contact times obeys a power-law. They investigate the viability and performance of ad-hoc communication algorithms, and show that, for any forwarding scheme, the mean packet delay is infinite when the power-law exponent of the inter-contact time cumulative distribution is smaller than or equal to 1. This is in sharp contrast with previous results obtained under the hypothesis of exponentially decaying inter-contact time distributions [19]. Furthermore, as exponential decay is implied by most mobility models, the authors point to the need for new models that yield power-law distributions.

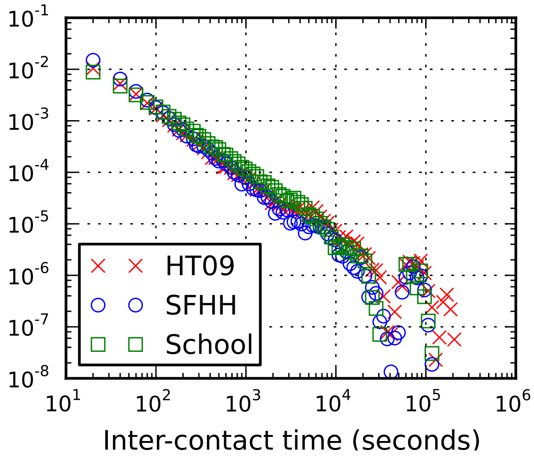


Fig. 3. Log-binned probability distribution of inter-contact times for the datasets under study.

Figure 3 reports the distributions of inter-contact times for the three datasets we consider. As expected, the three distributions have a broad shape which is compatible with a power-law-like behavior. Strikingly, the distributions look very similar: the distributions of inter-contact times do not represent a discriminating feature that can distinguish between the datasets under study. The robustness observed for inter-contact time distributions is consistent with a similar robustness across contexts observed for the distribution of contact durations [15]. Therefore, regardless of the social, spatial and demographic differences of the contexts in which the datasets were gathered, face-to-face contact patterns appear to obey the same bursty behavior.

IV. Epidemic processes as dynamical probes

As shown in the previous section, standard statistical observables used to describe human contacts fail to expose differences between the datasets under study. In order to achieve a better discriminatory capability, it is thus necessary to consider additional, more complex properties. To this aim, we propose to use a dynamical process, more precisely an epidemic process, as a probe for the temporal structure of the time-varying contact network. The dynamics of such a process, when simulated over the empirical contact sequence, may provide a way to uncover differences between the datasets that are not accessible by the direct analysis of the distributions of contact and inter-contact times.

Epidemic routing protocols have been commonly used in the literature to model the propagation of messages over ad-hoc networks and to study the spread of software viruses to mobile devices [38]. The discrete Susceptible/Infected (SI) process, as a simple model for the propagation of disease or information, has been investigated over time-varying interaction networks [39], and it was also used in Ref. [28] to investigate the topological and temporal properties of human proximity networks from wearable sensors. When simulating an SI process, nodes can be in either of two states, susceptible (S) or infected (I). Susceptible nodes have not caught the "disease" (or have not received the information), while infected ones carry the disease (or have received the information) and can propagate it to other nodes. The epidemic process is simulated by assuming that any entity that could be subject to spreading over the proximity network can be modeled as a message. In order to obtain generic results, we use a theoretical scenario where nodes have an infinite amount of resources and message exchanging delays are not considered.

We focus on the simplest, deterministic case in which each contact between a susceptible node and an infected one results in a transmission event ($S + I \to 2I$). In order to take into account the strong temporal and topological heterogeneity of empirical networks, we compute many different stochastic realizations of the SI process. The initial conditions correspond to a population of susceptible nodes with a single "seed" node which is infected at a given initial time. Each stochastic realization of the process involves the choice of a different initial time (over the entire empirical timeline) and of the initial "seed" node, chosen in turn among all nodes that are present at the initial time. The SI process is then simulated and the infection spreads deterministically over the network through the contacts between I and S nodes.

Here we consider two cases for the simulation of the SI process. In the first case, we choose two different starting times of the spreading $t_0 = 35$ hours and $t_0 = 45$ hours (for the *HT09* dataset), respectively when the contact density is low and when the contact density is high. This allows to understand how the global temporal patterns of the contacts between nodes impacts the arrival times. In the second case, we choose 100 initial times randomly distributed in the experiment timeline and we average the measures characterizing the SI process (described below) on all these runs. In both cases, for each starting time, we perform as many realizations of the SI process as the number of nodes, choosing a different "seed" node for each realization. We run each simulation until no node can become infected anymore.

Due to the deterministic nature of the process, the main relevant quantity to characterize the spreading dynamics is not the fraction of infected nodes over time (which quickly approaches 1, in general) but rather the time differences between the message injection and message arrival at all reachable nodes, i.e., the delivery delay of the message (infection). Therefore, we consider the average delivery delay of the message (or infection) at the various nodes, together with its standard deviation. Table II shows that, notwithstanding the high similarity of the inter-contact time distributions reported above, markedly different average delivery delays are observed across the datasets. Moreover, we remark that the standard deviations are of the same magnitude as the average values (or larger), pointing to strong heterogeneities in the epidemic dynamics that cannot be properly accounted for by simply computing the average arrival delays.

deployment	avg. delivery delay	standard deviation
HT09	$6.6h$	$8.5h$
SFHH	$5.4h$	$7.3h$
school	$3.5h$	$5.7h$

TABLE II
DELIVERY DELAYS: AVERAGE AND STANDARD DEVIATION.

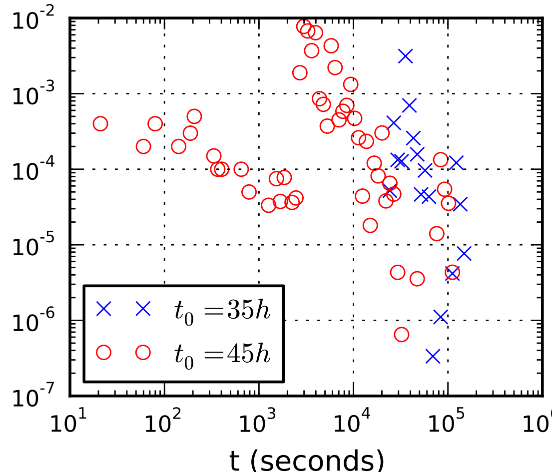
V. ACTIVITY CLOCKS

The most straightforward definition of the delivery delay, introduced above, is the elapsed time between the message (infection) injection and the delivery time at each node. Figure 4(a) shows the distribution of delivery delays for the conference HT09 dataset, for two different starting times of the SI process. The first starting time is chosen during a period of low contact density, while the second falls in a period of high contact density. The figure illustrates that different starting times can lead to dramatically different delivery delay distributions.

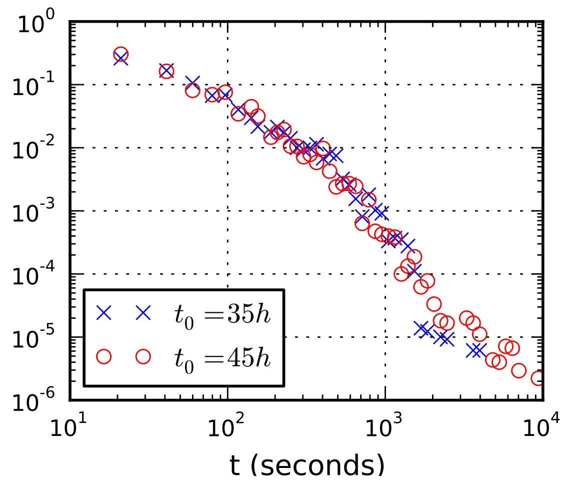
In fact, we observe that the distributions of the delivery delays, defined in terms of wall-clock time, do not exhibit any clear pattern and are extremely sensitive to details such as the initial time of the process. Such strong heterogeneities make it impossible to model the empirical arrival delay distributions by means of simple statistical models, and also impair any comparison across different datasets.

The fact that the distribution of delivery delays strongly depends on the temporal heterogeneity of the contact network calls for alternate definitions of "time" that are intrinsically more robust with respect to such heterogeneities. We therefore turn to a node-specific definition of time [28]: we imagine that each node has its own clock, and that this clock only runs when the node is involved in one or more contacts. Since the clock measures the amount of time a given node has spent in interaction with other nodes, we refer to this clock as an "activity clock". All activity clocks are set to zero at the beginning of the spreading process, when the initial seed is infected. In other words, the activity clock of a node measures the amount of time during which that node could have received a message propagated along contacts, i.e., it ignores the time intervals during which the node was isolated from the rest of the network. For each node i we define the "arrival time" as the value of its activity clock when it becomes infected, i.e., it is the elapsed time node i has spent in contact with others since the infection time of the seed.

The distributions of message delivery delays, measured in terms of *elapsed contact time* are shown in Fig. 4(b) for the HT09 dataset. Contrary to the case of wall-clock time (Fig. 4(a)) these distributions exhibit a well-defined pattern that is robust with respect to changes in the starting time of the process and is amenable to comparison across different datasets.



(a) $t_i - t_0$



(b) Elapsed Contact Time

Fig. 4. Log-binned probability distributions of message delivery delays. Panel (a): the delay is defined as the time difference between the delivery time t_i of the message at node i and the starting time t_0 of the spreading process. Panel (b): each node carries its own clock that ticks only when it is in contact with other nodes, i.e., we only count the time intervals during which messages could be exchanged.

VI. COMPARING DIFFERENT CONTACT NETWORKS

On inspecting the distributions of elapsed contact times obtained by simulating the SI process over the different empirical contact networks, we notice that the distributions for the two conferences (SFHH and HT09) approximately collapse, as shown in Fig. 5. This occurs despite the differences between the HT09 and SFHH cases: at the HT09 conference, a tightly knit community shared a small number of social spaces for several days and met according to a predefined schedule. Conversely, the SFHH case was a large-scale conference where many people did not know each other and very different social spaces coexisted, such as plenary rooms and exhibition spaces. In the case of the primary school, even though the inter-contact times distribution is similar to those observed for the conferences (see Section III), the distribution of elapsed times shown in Fig. 5 is actually very different from the conference cases. To quantify this statement, we compute the pairwise

	HT09	SFHH	school
HT09	0.0	0.026	0.675
SFHH	0.061	0.0	0.529
school	1.455	0.765	0.0

TABLE III
KULLBLACK-LEIBLER DIVERGENCES BETWEEN THE DIFFERENT DELIVERY DELAY DISTRIBUTIONS OBTAINED BY USING ACTIVITY-BASED CLOCKS.

Kullback-Leibler divergences [40] of the three distributions, defined as:

$$\mathrm{DIV}_{\mathrm{KL}}(D_i \| D_j) = \sum_t D_i(t) \log \frac{D_i(t)}{D_j(t)} \,, \tag{1}$$

where $D_i(t)$ and $D_j(t)$ are the distributions of elapsed contact times we want to compare, i and j indicate the SFHH, HT09, or school case, and t is the elapsed contact time. Since contact relations are assessed over consecutive 20-second intervals, the possible values of t are the discrete multiples of 20 seconds. Table III reports the computed Kullback-Leibler divergences, sho ery clo ool cas

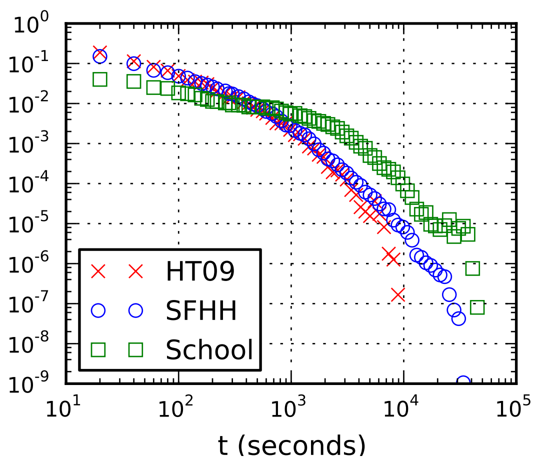


Fig. 5. Log-binned distributions of the elapsed contact time in a SI process simulated on the SFHH, HT09, and school datasets. Each distribution has been calculated by aggregating the elapsed contact times on several runs of the SI process (several starting times, several roots of infection).

VII. DISCUSSION

We used high-resolution time-resolved data on human proximity from wearable sensors to study some properties of time-varying contact networks that bear direct relevance to spreading processes and opportunistic routing.

We showed that empirical contacts measured in very different contexts exhibit similar statistical signatures in terms of customary observables such as the distributions of contact durations or of inter-contact times. These measures, while well understood and studied in the literature, are therefore not able to discriminate between datasets collected in different environments. On the one hand, this is a positive aspect for modeling purposes, as it means that any process that is known to depend only on such distributions can be assumed to behave similarly in all of the observed contexts. On the other hand, the lack of discriminative power of the distributions of contact durations and of inter-contact times points to the fact that they may be capturing robust but somehow superficial properties of the contact networks. This is not a surprise, as the characterization of the structure of time-varying networks, and even more so of the behavior of dynamical processes over them, lies at the frontier of our knowledge on complex networks. Here we provide a first step in the direction of devising novel statistical indicators that can tell apart environments that are known to have strong differences in terms of contact behaviors.

We use an epidemic-like process, in particular a susceptible-infected process, not so much to describe a routing protocol or a flooding process, but rather as a dynamical probe for the topological and temporal structure of empirical contact patterns. However, because of the strong heterogeneity due to circadian rhythm, bursty human dynamics, and coordinated human activity, extracting a clear signal that can summarize the behavior of a dynamical process over a time-varying network is a challenge in its own merit. We tackle this problem by shifting from wall-clock time to a distributed notion of time which is node-specific and depends on the (contact) activity of individuals nodes. We show that the delay distribution of delivery times for the epidemic process, once measured using this node-specific notion of time, displays simple patterns that are robust with respect to the starting time of the epidemic process, the identity of the seed node, and more. Remarkably, the distribution of delivery delays (in terms of activity clocks) for temporal proximity networks in a school is very different from the ones obtained for contacts gathered in conference settings (which turn out to be similar to one another), despite the overall strong similarity of the distributions of inter-contact times observed in the three cases.

Thus, the combination of a simple epidemic process and of activity-based clocks to measure arrival times yields an indicator that can successfully act as a “fingerprint” for the topological and temporal structures of the time-varying proximity networks, allowing us to tell apart cases (the school on the one hand, and the two conferences on the other hand) that we know are radically different in terms of behavioral patterns and interaction rhythms. The differences we observe may be due to a complex interplay of several factors at play in the school case: the community structure of the contact network, the correlated activity patterns induced by the school schedule, the synchronized activity of contacts across classes, and more. Relating these factors to the actual form of the observed distributions of elapsed contact times is a problem that goes beyond the scope of the present work, but it crucially hinges on the ability to have statistical indicators that reach beyond what is customarily used and capture more and more of the real-world complexity of human interaction patterns.

ACKNOWLEDGMENTS

We acknowledge the contribution of all partners of the SocioPatterns collaboration. We thank the organizers of the ACM Hypertext 2009 conference (HT09) and of the conference of the Société Française d’Hygiène Hospitalière (SFHH). We thank all the conference attendees who participated in the data collection. We are grateful to all children, parents and school staff who participated in the school deployment. This study was partially supported by EU grant 317532 (Multiplex).

REFERENCES

[1] G. Chowell, J. M. Hyman, S. Eubank, and C. Castillo-Chavez, "Scaling laws for the movement of people between locations in a large city," *Phys. Rev. E*, vol. 68, p. 066102, Dec 2003.

[2] A. De Montis, M. Barthélemy, A. Chessa, and A. Vespignani, "The structure of inter-urban traffic: A weighted network analysis," *Environmental Planning Journal*, vol. B, no. 34, pp. 905–924, 2007.

[3] D. Brockmann, L. Hufnagel, and T. Geisel, "The scaling laws of human travel," *Nature*, vol. 439, pp. 462–465, 2006.

[4] A. Barrat, M. Barthélemy, R. Pastor-Satorras, and A. Vespignani, "The architecture of complex weighted networks," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 101, no. 11, pp. 3747–3752, 2004.

[5] D. Balcan, V. Colizza, B. Gonalves, H. Hu, J. J. Ramasco, and A. Vespignani, "Multiscale mobility networks and the spatial spreading of infectious diseases," *Proceedings of the National Academy of Sciences*, 2009.

[6] M. C. Gonzalez, C. A. Hidalgo, and A.-L. Barabasi, "Understanding individual human mobility patterns," *Nature*, vol. 453, no. 7196, pp. 779–782, June 2008.

[7] C. Song, Z. Qu, N. Blumm, and A.-L. Barabsi, "Limits of predictability in human mobility," *Science*, vol. 327, no. 5968, pp. 1018–1021, 2010.

[8] J.-P. Onnela, J. Saramäki, J. Hyvönen, G. Szabó, D. Lazer, K. Kaski, J. Kertész, and A.-L. Barabàsi, "Structure and tie strengths in mobile communication networks," *Proc. Natl. Acad. Sci. USA*, vol. 104, p. 7332, 2007.

[9] J.-P. Eckmann, E. Moses, and D. Sergi, "Entropy of dialogues creates coherent structures in e-mail traffic," *Proc. Natl. Acad. Sci. USA*, vol. 101, p. 14333, 2004.

[10] G. Kossinets and D. J. Watts, "Empirical analysis of an evolving social network," *Science*, vol. 311, no. 5757, pp. 88–90, 2006.

[11] S. Golder, D. Wilkinson, and B. Huberman, "Rhythms of social interaction: Messaging within a massive online network," in *Communities and Technologies 2007*. Springer London, 2007, pp. 41–66.

[12] J. Leskovec and E. Horvitz, "Planetary-scale views on a large instant-messaging network," in *Proceedings of the 17th international conference on World Wide Web*, ser. WWW '08. New York, NY, USA: ACM, 2008, pp. 915–924.

[13] D. Rybski, S. Buldyrev, S. Havlin, F. Liljeros, and H. Makse, "Scaling laws of human interaction activity," *Proc. Natl. Acad. Sci. USA*, vol. 106, pp. 12 640–12 645, 2009.

[14] R. Malmgren, D. Stouffer, A. Campanharo, and L. N. Amaral, "On universality in human correspondence activity," *Science*, vol. 325, pp. 1696–1700, 2009.

[15] C. Cattuto, W. Van den Broeck, A. Barrat, V. Colizza, J.-F. Pinton, and A. Vespignani, "Dynamics of person-to-person interactions from distributed rfid sensor networks," *PLoS ONE*, vol. 5, no. 7, p. e11596, 07 2010.

[16] H. Alani, M. Szomszor, C. Cattuto, V. Wouter, G. Correndo, and A. Barrat, "Live social semantics," in *8th International Semantic Web Conference (ISWC'09)*, October 2009.

[17] W. Van den Broeck, C. Cattuto, A. Barrat, M. Szomszor, G. Correndo, and H. Alani, "The live social semantics application: a platform for integrating face-to-face presence with on-line social networking," in *First International Workshop on Communication, Collaboration and Social Networking in Pervasive Computing Environments (PerCol'10)*, April 2010.

[18] M. Salathe, M. Kazandjieva, J. W. Lee, P. Levis, M. W. Feldman, and J. H. Jones, "A high-resolution human contact network for infectious disease transmission," *Proceedings of the National Academy of Science*, vol. 1072, pp. 22 020–22 025, Dec. 2010.

[19] M. Grossglauser and D. Tse, "Mobility increases the capacity of ad hoc wireless networks," *Networking, IEEE/ACM Transactions on*, vol. 10, no. 4, pp. 477–486, aug 2002.

[20] M. Conti, S. Giordano, M. May, and A. Passarella, "From opportunistic networks to opportunistic computing," *Communications Magazine, IEEE*, vol. 48, no. 9, pp. 126 –139, sept. 2010.

[21] J. Farringdon, A. Moore, N. Tilbury, J. Church, and P. Biemond, "Wearable sensor badge and sensor jacket for context awareness," in *Wearable Computers, 1999. Digest of Papers. The Third International Symposium on*, oct. 1999, pp. 107 –113.

[22] T. Choudhury and A. Pentland, "Sensing and modeling human networks using the sociometer," in *Proceedings of the 7th IEEE International Symposium on Wearable Computers*, ser. ISWC '03. Washington, DC, USA: IEEE Computer Society, 2003, pp. 216–. [Online]. Available: http://dl.acm.org/citation.cfm?id=946249.946901

[23] A. Förster, K. Garg, H. A. Nguyen, and S. Giordano, "On context awareness and social distance in human mobility traces," in *Proceedings of the third ACM international workshop on Mobile Opportunistic Networks*, ser. MobiOpp '12. New York, NY, USA: ACM, 2012, pp. 5–12. [Online]. Available: http://doi.acm.org/10.1145/2159576.2159581

[24] S. Giordano and D. Puccinelli, "The human element as the key enabler of pervasiveness," in *Ad Hoc Networking Workshop (Med-Hoc-Net), 2011 The 10th IFIP Annual Mediterranean*. IEEE, 2011, pp. 150–156.

[25] P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot, "Pocket switched networks and human mobility in conference environments," in *WDTN '05: Proceedings of the 2005 ACM SIGCOMM workshop on Delay-tolerant networking*. New York, NY, USA: ACM, 2005, pp. 244–251.

[26] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, "Impact of Human Mobility on Opportunistic Forwarding Algorithms," *Mobile Computing, IEEE Transactions on*, vol. 6, no. 6, pp. 606–620, june 2007.

[27] E. Yoneki, "The importance of data collection for modelling contact networks," in *CSE '09: Proceedings of the 2009 International Conference on Computational Science and Engineering*. Washington, DC, USA: IEEE Computer Society, 2009, pp. 940–943.

[28] A. Panisson, A. Barrat, C. Cattuto, W. Van den Broeck, G. Ruffo, and R. Schifanella, "On the dynamics of human proximity for data diffusion in ad-hoc networks," *Ad Hoc Networks*, vol. 10, no. 8, pp. 1532 – 1543, 2012.

[29] T. Karagiannis, J.-Y. Le Boudec, and M. Vojnović, "Power law and exponential decay of inter contact times between mobile devices," in *Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, ser. MobiCom '07. New York, NY, USA: ACM, 2007, pp. 183–194.

[30] M. Kim, D. Kotz, and S. Kim, "Extracting a mobility model from real user traces," in *Proceedings of the 25th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM)*. Washington, DC, USA: IEEE Computer Society, April 2006, pp. 1–13.

[31] W. V. den Broeck, C. Cattuto, A. Barrat, M. Szomsor, G. Correndo, and H. Alani, "The live social semantics application: a platform for integrating face-to-face presence with on-line social networking," in *Proceedings of the 8th Annual IEEE International Conference on Pervasive Computing and Communications*, Mannheim, Germany, 2010, pp. 226–231.

[32] L. Isella, J. Stehlé, A. Barrat, C. Cattuto, J.-F. Pinton, and W. V. D. Broeck, "Whats in a crowd? analysis of face-to-face behavioral networks," *Journal of Theoretical Biology*, vol. 271, pp. 166–180, 2011.

[33] http://sociopatterns.org/datasets/hypertext-2009-dynamic-contact-network .

[34] J. Stehlé, N. Voirin, A. Barrat, C. Cattuto, V. Colizza, L. Isella, C. Regis, J. Pinton, N. Khanafer, W. Van den Broeck, and P. Vanhems, "Simulation of an seir infectious disease model on the dynamic contact network of conference attendees," *BMC Medicine*, vol. 9, no. 87, July 2011.

[35] J. Stehlé, N. Voirin, A. Barrat, C. Cattuto, L. Isella, J.-F. Pinton, M. Quaggiotto, W. Van den Broeck, C. Régis, B. Lina, and P. Vanhems, "High-resolution measurements of face-to-face contact patterns in a primary school," *PLoS ONE*, vol. 6, no. 8, p. e23176, 08 2011.

[36] http://sociopatterns.org/datasets/primary-school-cumulative-networks .

[37] H. Cai and D. Y. Eun, "Toward stochastic anatomy of inter-meeting time distribution under general mobility models," in *Proceedings of the 9th ACM international symposium on Mobile ad hoc networking and computing*, ser. MobiHoc '08. New York, NY, USA: ACM, 2008, pp. 273–282.

[38] A. Vahdat and D. Becker, "Epidemic routing for partially-connected ad hoc networks," Duke University, Tech. Rep. CS-200006, 2000.

[39] P. Holme and J. Saramäki, "Temporal networks," *Physics Reports*, vol. 519, p. 97125, 2012.

[40] S. Kullback and R. A. Leibler, "On information and sufficiency," *Ann. Math. Statist.*, vol. 22, no. 1, pp. 79–86, 1951.