Human Mobility Models for Opportunistic Networks

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ABSTRACT

Mobile ad hoc networks enable communications between clouds of mobile devices without the need for a preexisting infrastructure. One of their most interesting evolutions are opportunistic networks, whose goal is to also enable communication in disconnected environments, where the general absence of an end-to-end path between the sender and the receiver impairs communication when legacy MANET networking protocols are used. The key idea of OppNets is that the mobility of nodes helps the delivery of messages, because it may connect, asynchronously in time, otherwise disconnected subnetworks. This is especially true for networks whose nodes are mobile devices (e.g., smartphones and tablets) carried by human users, which is the typical OppNets scenario. In such a network where the movements of the communicating devices mirror those of their owners, finding a route between two disconnected devices implies uncovering habits in human movements and patterns in their connectivity (frequencies of meetings, average duration of a contact, etc.), and exploiting them to predict future encounters. Therefore, there is a challenge in studying human mobility, specifically in its application to OppNets research. In this article we review the state of the art in the field of human mobility analysis and present a survey of mobility models. We start by reviewing the most considerable findings regarding the nature of human movements, which we classify along the spatial, temporal, and social dimensions of mobility. We discuss the shortcomings of the existing knowledge about human movements and extend it with the notion of predictability and patterns. We then survey existing approaches to mobility modeling and fit them into a taxonomy that provides the basis for a discussion on open problems and further directions for research on modeling human mobility.

INTRODUCTION

Recent analyses of the mobile phone market revealed an incredible penetration of pocket devices among the global population, estimating more than 5.3 billion people worldwide using cell phones,[1] with the smartphone market hitting 3 million devices sold to end users in 2010, accounting for 19 percent of total mobile communications device sales.[2] Added to the number of cameras installed on the streets, computing systems embedded into vehicles and equipped with wireless communication capabilities (e.g., Wi-Fi, Bluetooth, cellular, WiMax), they define an all-pervasive nature of opportunistic contacts between pairs of devices and thus give a strong background for developing opportunistic networks (OppNets) [1].

In OppNets we do not assume end-to-end connectivity between sender and receiver. Instead, the data is delivered based on pair-wise contact opportunities. The communication is thus *multihop* in the sense that each intermediate node is explored as a router that stores the message until a contact opportunity for further forwarding arises. The most challenging problem therefore lies in finding the route between two disconnected devices. Obviously, knowing the *context* of the network (which might include users' addresses, probability of meetings with friends, frequencies of visiting different locations, etc.) can help predict future contact opportunities and identify better candidates for relaying the data toward the destination. For example, consider a node A that aims to deliver a message to another node B with whome it does not directly communicate. Node A might be aware of frequent meetings between nodes C and B; thus, node A can decide to use node C as a relay [2]. The design of such context-aware protocols requires understanding habits in human movements and patterns in their connectivity (frequencies of meetings, average duration of a contact, etc.). Therefore, there is a challenge in studying human mobility and, specifically, its application to OppNet research.

A thorough study of individual movements became possible only recently with the availability of real-life *mobility traces* collected by cell phone operators [3, 4], academic experiments [5], and Internet communities [6]. The most accurate data come from systems that are directly designed to track location by either exploring satellites (e.g., GPS) or a system of radio emitters (e.g., RIPS). Another approach is based on utilizing nodes of communication systems such as GSM base stations or WLAN access points.
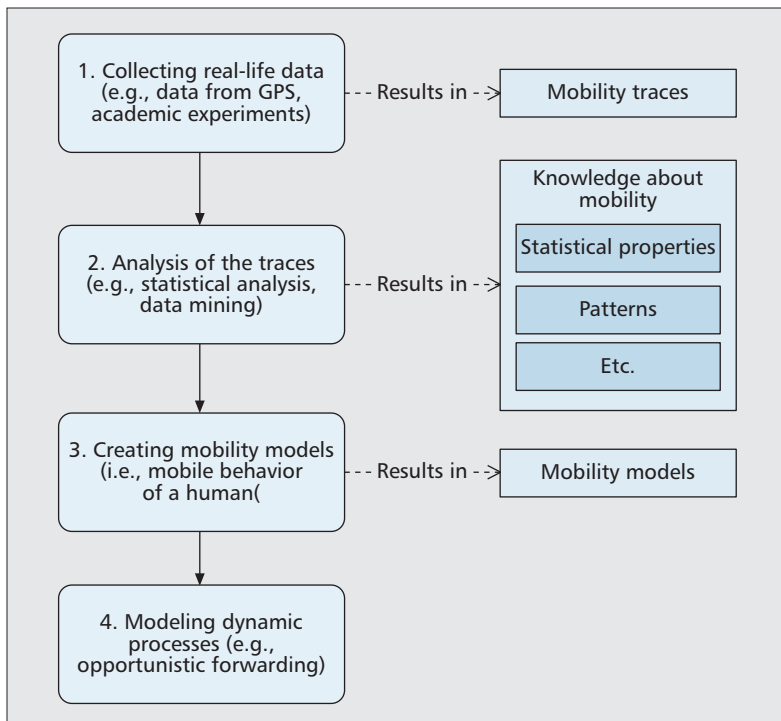
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Figure 1. *Human mobility: from data to models.*

The coordinates of the base station (e.g., UMTS Node B, WiFi router) can be approximately considered as the location of the users currently connected to it. Some useful characteristics of human connectivity can be derived from tracing Bluetooth or WiFi one-hop communications between handheld devices. Finally, the routes of items exchanged between humans, such as bank notes, can also be considered as a proxy of human mobility.

Mobility traces gave significant impulse to studying statistical characteristics and patterns of human movements, and have attracted researchers from different domains. Recent works in physics have revealed a number of scaling properties in human trajectories. More specifically, Gonzalez *et al.* [3] and Brockmann *et al.* [6] showed a truncated power-law tendency in the distribution of human jumps (i.e., the length of each segment composing a person's trajectory) along with the heterogeneity in human travel behavior (i.e., some people move in close vicinity of their homes, while others frequently take significantly longer trips). A long-tailed distribution was also revealed in the returning (to a previously visited place) time probability and the frequency of visits to different locations. Meanwhile, the computer science community conducted several experiments to study the temporal characteristics of human connectivity and found similar scaling tendencies in the distribution of contact duration and intercontact time (defined as the time between two consecutive contacts between two users) [7, 8]. This finding had a considerable impact on the opportunistic networking literature, because with heavy-tailed intercontact times the expected delay of messages could diverge [7].

Another important question addressed by recent works in human mobility is the feasibility of predicting the location of a person based on the history of his/her movements. Song *et al.* [9] tried to answer it by measuring uncertainty in human trajectories. The results revealed that, potentially, human moves are highly predictable. However, in order to give a precise estimation of the location of a person at a given point in time, it is not enough to consider only basic statistical properties (e.g., frequency of visits to the most popular places or returning time distribution); it is also crucial to take into account regular spatial and temporal patterns in the movements (i.e., repeated sequences of jumps). Obviously, this requires a more detailed analysis of the traces, and the application of advanced data mining and knowledge discovery techniques.

As highlighted in Fig. 1, the ultimate goal of the analysis of human mobility, as far as Opp-Nets are concerned, is the definition of a mobility model that allows us to evaluate the performance of forwarding protocols in realistic settings, by means of either simulation or mathematical analysis. One can imagine simulating city crowd behavior consisting of 1000 agents independently moving on a 2D map (the approach known as *multi-agent simulation*). The way the agents are distributed on the plane and the rules that govern their behavior define a *human mobility model*. Depending on the principle used to define these rules, we distinguish two classes of models. In *trace-based approaches* the mobility model is defined by the set of distributions that fit some statistics extracted from the traces considered. While, obviously, the agreement between the statistical properties of the traces and those obtained from the model is usually extremely good, these solutions do not propose a general mobility model that describes users' movements. Thus, their applicability outside the environment from which they have been derived is not clear. On the other hand, *synthetic models* aim to reproduce driving forces of individual mobility such as social attitude, location preferences, and regular schedules. Traces in this case might be explored for validation.

Depending on the scenario one would like to reproduce, synthetic approaches range from the basic random (e.g., Brownian motion) to more sophisticated models, which could incorporate a detailed map of the region, realistic individual schedules, and so on. In studying city crowd behavior or urban traffic, for example, one might be interested in microscopic movements and reproducing detailed motion along the predefined roadmap, and in conditions of static and dynamic obstacles. In contrast, if one is interested in modeling contacts between individuals only in the place where they stay together, it might be enough to approximate the movement between two such places as a movement along a straight line at some constant pace. Different approaches are also required to reproduce everyday city mobility, and model battlefields, evacuation, and other scenarios. Given that microscopic models are usually too complex for mathematical reasoning and formal analysis, in this article we neglect microscopic details of individual movements and focus only on regular (i.e., everyday) human mobility.

In this article we present the state of the art

in the field of human mobility analysis and a survey of human mobility models. Following the logic introduced above, we start by reviewing the most considerable findings in the physics of human mobility and from studying connectivity patterns in mobile ad hoc networks (MANETs). We discuss the shortcoming of the existing statistical knowledge on human movements, and extend it with the notion of predictability and patterns. We then introduce our approach to systematize repetitive tendencies in human movements in social, temporal, and spatial dimensions. This provides us with a taxonomy for surveying existing approaches to modeling mobility. Finally, we conclude with a discussion of open research directions.

STATISTICAL PROPERTIES OF HUMAN MOBILITY

In recent years, studying human mobility has been one of the major focuses of different disciplines. The main findings can be classified along the three axes of spatial, temporal, and connectivity properties (Fig. 2). Spatial properties pertain to the behavior of users in the physical space (e.g., the distance they travel), temporal properties to the time-varying features of human mobility (e.g., the time users spend at specific locations), connectivity properties to the interactions between users.

One of the first significant findings in human traces, which highlighted the difference between our movements and random motion, was documented by Brockman *et al.* [6], who analyzed a huge data set of records of bank notes circulation, interpreting them as a proxy of human movements. They showed that travel distances Δr (frequently called *jump size*) of individuals follow a power-law distribution $P(\Delta r) \sim \Delta r^{-(1+\beta)}$, where the exponent β is smaller than 2. This fits the intuition that we usually move over short distances, whereas occasionally we take rather long trips. Known as Lévy Flight, a random model with such distance distribution was previously observed in dispersal ecology as an approximation of migration trajectories among different animal species. Studying data collected tracing mobile phone users, Gonzalez *et al.* [3] complemented the previous finding with an exponential cutoff ($P(\Delta r) = (\Delta r + \Delta r_0)^{-\beta} exp(\Delta r/\kappa)$, where $\beta = 1.75 \pm 0.15$, $\Delta r_0 = 1.5$ km, and κ a cutoff value varying in different experiments) and showed that individual truncated Lévy trajectories coexist with population-based heterogeneity. This heterogeneity was measured in terms of the *radius of gyration* (r_g), which depicts the characteristic distance traveled by a user. It was shown that the distribution of the radius of gyration can be approximated by a truncated power-law ($P(r_g) = (r_g + r_g^0)^{-\beta_r} exp(-r_g/\kappa)$, where $\beta_r = 1.65 \pm 0.15$, $r_g^0 = 5.8$ km and $\kappa = 350$ km). In other words, most people usually travel in close vicinity to their home location, while a few frequently make long journeys.

As for the temporal properties of human movements, Gonzales *et al.* [3] detected the tendency of people to return to a previously visited location with a frequency proportional to the
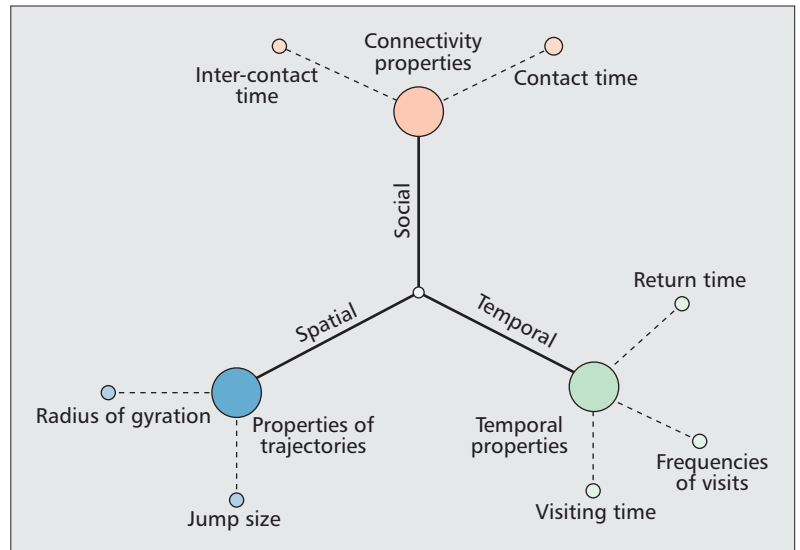

Figure 2. *Properties of human mobility.*

ranking in popularity of the location with respect to other locations. The authors also computed the *return time* probability distribution (probability of returning at time *t* to a selected place) and concluded that prominent peaks (at 24, 48, 72, ... hours) capture the tendency of humans to return regularly to the location they visited before. Song *et al.* [4] extended the experiment to a larger data set and measured the distribution of the *visiting time* (i.e., the time interval Δt a user spends at one location). The resulting curve is well approximated by a truncated power-law with an exponent $\beta = 0.8 \pm 0.1$ and a cutoff of $\Delta t = 17$ h, which the authors connected with the typical awake period of humans. Additionally, improving the result in [3], the authors found that f_k, the frequency at which a user visits its *k*th most visited location, follows a Zipf's law ($f_k \sim k^{-\zeta}$) with parameter $\zeta \approx 1.2 \pm 0.1$. This also suggests that the probability of a user visiting a given location a number of times equal to f (i.e., *visitation frequency*) follows $P(f) \sim f^{-(1+1/\zeta)}$.

Connectivity properties have been extensively studied in the context of MANET research. The reason comes from an engineering concern: given that messages are forwarded from node to node when they get in touch with each other, the time between two consecutive contacts of two devices contributes to the overall delay, while the duration of the contact bounds the size of the data that can be exchanged at each encounter. Since the behavior of human-carried mobile devices can be considered as a proxy of human movements, a contact between two devices implies that the corresponding users are close to each other. Thus, by extension, we take the *intercontact time* and *contact time* as measures of how frequently and for how long two users spend time together. More specifically, we define the contact time between two mobile devices as the time intervals during which two devices are in radio range of one another, while the intercontact time is the length of the time interval from the end of the contact to the beginning of the next one. Chaintreau *et al.* [7] showed that the distribution of intercontact time has a
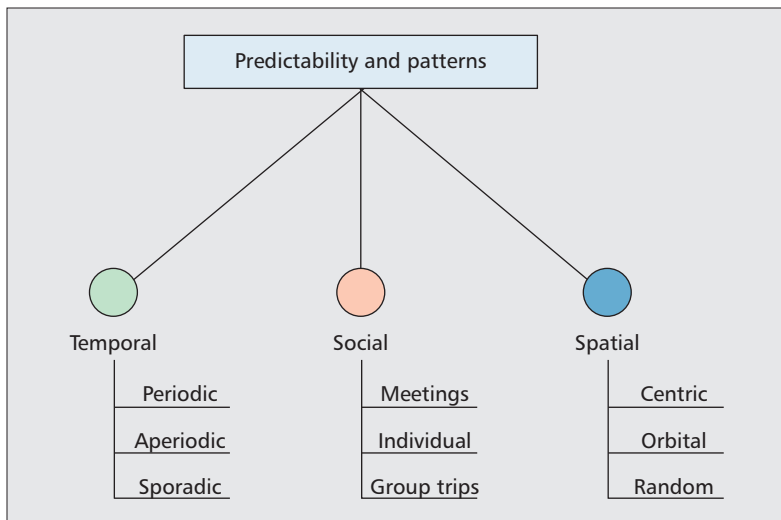
Figure 3. *Predictability and patterns in human mobility traces.*

power-law nature over a wide range of values from a few minutes to half a day. Later, Kara-giannis *et al.* [8] extended this result, suggesting that the power law decay should be complement-ed with an exponential cutoff. Although less attention was dedicated to studying the duration of contact times, it was also shown by Hui *et al.* [5] to follow an approximate power-law distribu-tion.

PREDICTABILITY AND PATTERNS

We have observed several metrics that depict regularities in people's movements. These met-rics, however, cannot capture some aspects of human mobility such as the distinction between periodic and frequent (but not periodic) trips. In this section we fill this gap by introducing the concept of human mobility patterns (Fig. 3). The motivation comes from the results of Song *et al.* [9], which provide a quantitative evaluation of the limits in predictability of human walks. The authors define some entropy measures (the met-ric used in information theory to evaluate uncer-tainty of random variables), ranging from one that depends only on frequencies of visits to one that considers the probability of finding particu-lar time-ordered subsequences in the trajectory. The study shows that if we rely only on hetero-geneous spatial distribution, as does the first entropy measure, the predictability across the whole population is insignificant and varies widely from person to person. Instead, if we take into account also a historical record of the daily mobility patterns, the potential predictability reaches 93 percent and does not vary a lot across the population (i.e., users who usually travel over long distances are as predictable as those who navigate within a narrow vicinity of their homes). This means that, knowing the history of a person's movements, we can potentially fore-see his/her current location with extremely high success probability.

When we talk about predictability or uncer-tainty, we usually connect it with some regularity or patterns in a structure or in the behavior of the phenomena. If we think of regularity in

human mobility the first association that springs into mind is the periodic (e.g., daily, weekly, monthly) nature of movements in time. For example, each single day in a working week includes a trip from our home location to the office, conducted at more or less similar time of the day. On a higher scale, we can think of repeated trips once every few weeks from a hometown to other cities to visit relatives or friends. These two examples, however, are dif-ferent: while the first case presents stronger periodicity, the second one also gives us a flavor of predictability, but in a weaker sense. On the other hand, there are always some completely random trips that might not repeat ever (e.g., a vacation spent on a desert island). All these types of movements are connected with the fre-quency of location visits, and thus with *some temporal patterns* in individual walks. More specifically, the first class represents *periodic* returns to the same location, the second charac-terizes frequent returns without strict regularity (let us call them *aperiodic*), and finally, the last one depicts unrepeated walks to new sites (let us name them *sporadic* trips).

We can also consider predictability in the context of patterns observed in the structure of trajectories. As mentioned by Song *et al.* [9], there is still a lack of knowledge in this area, and further development of the direction requires application of advanced data mining and knowledge discovery techniques. However, let us imagine the structure of mobility traces of an individual over a long time (i.e., years) and take the spatial grain at the level of a town. In other words, let us approximate the city (and human movements inside it) as a point and only consider trips between different localities (e.g., towns, cities). We can predict that for an average person, mobile trajectories would have an approximately star-like structure with a distinctly emphasized center (home town) and rays (depicting two-way trips) con-necting the home with other cities. If we look, however, at a smaller temporal and spatial scale (e.g., a work week of a student on a cam-pus), we can imagine the appearance of *orbits* in movements (e.g., from home to study room in the morning, from study room to gym in the evening and back home at night). We name these regularities in the structure of trajecto-ries *spatial patterns*.

Among the driving forces that define our mobility behavior, we should also consider the social aspect of predictability. For example, a substantial part of our free time is usually spent with our friends. Although this obviously gives a sense of predictability, it does not depend on some specific location (i.e., we might meet in different places) or other factors, but is only driven by the necessity to interact with our social contacts. In other words, knowing our social sur-roundings helps predict our location. We call these the *social patterns* of movements, and we distinguish three of them: *meetings* (when the trip is taken to meet social contacts), *group trips* (i.e., organized movements of a group of socially connected humans), and *individual trips*.

The last aspect to consider is the scale of mobility. We distinguish three levels (*building-*

wide, *city-wide*, and *global views*), which characterize the mobility behavior of individuals. This is, however, only a spatial scale, which can also be extended with two other dimensions — *temporal* and social. The building-wide view characterizes our movements only during a short period of time (i.e., from a few hours up to one day) when we are located inside it. The scope of our social interactions is limited to a community of people staying with us simultaneously at the same location (e.g., colleagues from our office during the work day). On a higher city-wide scale, we spend considerably longer periods of time (between two trips to other cities) and operate in a wider social sphere. Finally, if we consider a worldwide (i.e., global) view, we talk about months long or years long tracks and interactions with the whole social network of our contacts. We are convinced that considering scale in modeling mobility is crucial due to the deviations in patterns and properties that can be observed at each of the layers. The driving forces behind our movements can also differ on different scales. For example, at the global level our movements significantly depend on country borders, travel cost (increasing with the distance), and so on. An interesting observation is that the duration of the visit to a location may significantly depend on the trip taken in order to reach it (e.g., if we pay the cost of travel from Europe to the United States, we probably want to stay there at least for a few days, as opposed to a one-day business trip to a nearby town). If we, in contrast, consider a daily circulation of a student on the university campus between library, study rooms, gym, and so on, probably the movements are defined by the function of the buildings, neglecting the cost of the walks. Now, if we think from a top-down perspective, we can imagine a hierarchical mobility model divided into layers. Thus, we can start by modeling a worldwide view and approximate all trajectories of movements inside the city with one point on the map, considering the whole time spent as a sojourn on a global scale and the cluster of our contacts inside it as a point. If we are interested in the details of human motion inside the city or in a particular building, we can zoom in on the map, as well as the social and temporal scales.

We explore these considerations in the next sections to classify the set of available mobility models, depict the properties and patterns they are able to reproduce, and discuss their applicability to modeling realilife scenarios.

EXISTING APPROACHES TO MODELING MOBILITY

As discussed so far, the spatial, social, and temporal axes have emerged as the main dimensions of people's movements. We therefore explore them in this section in order to classify existing human mobility models. More specifically, we distinguish solutions based on *exploring location preference*, *utilizing a social graph*, and approaches based on a *modeling agenda*. Please note that we do not consider here the class of random models (e.g., random waypoint, Gauss-Markov, random direction) because they do not exhibit the typical properties of human mobility, and thus are not able to reproduce the required patterns and statistical properties of real-life traces.

EXPLORING LOCATION PREFERENCE

In the previous sections we have seen that one of the main properties of human mobility traces is the regular reappearance at the set of preferred locations. Moreover, we discussed how the probability of returning to a specific place is correlated with its visitation frequency. These characteristics, along with a particular jump size distribution, significantly distinguish our movements from random motion. Mobility models that explore location preference are able to account for these properties. Their general approach is to store the maps (i.e., the sets) of preferred places for each of the users and to explore them while deciding on the next destination for their walks.

One of the first proposals in this class of models is the ORBIT model [10]. In ORBIT, the predefined sets of locations among which nodes move are generated at the beginning of the simulation. More specifically, each node selects a subset of these spots and moves between them based on a predefined customizable behavior. Another important aspect of human mobility — the hierarchy of the scale — is reflected in the appropriate structure of the preferred locations sets of ORBIT. More generally, movements of users can be described by a Markov chain where each state represents a specific location in the scenario. Realistic distribution of reappearance frequencies is then achieved indirectly by defining probabilities of transitions between places. The Time-Variant Community (TVC) model [11] is the most popular solution in this class. In TVC, node movements are slotted into time periods, during which different reference locations in the simulation area are associated with nodes. Then, within each period, a node can either move in a restricted area (its reference location) or freely in the whole simulation scenario. This behavior accounts for both returns to preferred places and random walks.

Lee *et al.* [12] extend this approach by proposing SLAW, which is also able to reproduce the preferences for shorter trips. This is achieved by exploring two coupled strategies. First, the meeting spots are scattered on the plane so that the distance among them features heavy-tailed distribution. Second, the daily routes of the users are formed from the jumps between a randomly selected subset of these spots according to the least-action principle (i.e., minimizing the overall trip length). Since part of this subset remains fixed for each user, SLAW is also able to capture regular returns to the same location.

The model described by Song *et al.* [4] does not fix the set of preferred places but allows them to emerge naturally during the evolution of the mobility process. To this aim, the authors introduce two different basic mechanisms, exploration and preferential return, that together describe human behavior. Exploration is a random walk process with truncated power law jump size distribution. Preferential return repro-

The spatial, social, and temporal axes have emerged as the main dimensions of people's movements. We therefore explore them in order to classify existing human mobility models.

duces the propensity of humans to return to the locations they have visited frequently before (e.g., home, workplace). Thus, an agent in the model selects between the two modes: with probability $P_{new} = \rho S^{-\gamma}$ (where S is the number of sites visited so far by the agent, ρ and γ are two model parameters), the individual moves to a new location, while with complementary probability $P_{new} = 1 - \rho S^{-\gamma}$, s/he returns to one of the S previously visited places (with the preference for a location proportional to the frequency of visits). As a result, the model has a warmup period of greedy exploration, while in the long run users mainly move around a set of previously visited places.

SWIM [13] is another approach based on location preference. The model assigns to each agent a so-called *home*, which is a randomly and uniformly chosen point on the plane. The agent then selects a destination for next moves depending on the weight of each site, which grows with the popularity of the place and decreases with the distance from the home (in this way the model captures power-law distribution of the jumps). The popularity of a location, however, does not depend on personal but on overall preferences, and it is calculated as the number of other people encountered the last time the agent visited the place.

Being able to satisfy the main spatial properties of the trajectories, the models described above, however, do not pay enough attention to the other — social and temporal — aspects of the movements, which are instead the focus of the models discussed in the next two sections.

MODELING AGENDA

This class of models focuses on reproducing realistic temporal patterns of movements by explicitly including repeating daily activities in human schedules. The most comprehensive approach of this group was presented by Zheng *et al.* [14]. The model incorporates detailed geographic topology, personal schedules, and a motion generator. It explores the data from the National Household Travel Survey of the U.S. Department of Transportation to extract realistic distribution of address type, activity type, visiting time, and so on. Streets and avenues are represented appropriately by horizontal and vertical lines. Their lengths, as well as the distances between them, are selected randomly. The database includes dozens of different types of addresses, each associated with a particular type of activities (selected from more than 30 available in the database), which in their turn define the time the user spends in the location (i.e., visiting time) and also influence travel time. The model also includes a motion generator that utilizes Dijsktra's algorithm to find the shortest path between two activities, also taking into account different speed limits assigned (at every particular time of the day) to each street. Finally, population heterogeneity in terms of occupation (and thus movements patterns) is also taken into account (e.g., the daily trajectory of an office worker is significantly different from that of a postman). Although the model gives an extremely thorough representation of human movements in a very particular scenario, its applicability to other scenarios (e.g., different demographic conditions) is difficult to establish. Moreover, relying on a huge statistical knowledge base, this model does not try to demystify the main driving forces of human movements. Finally, the model is too complex for analytical tractability.

The Working Day Movement model [15] is a lightweight and scalable approach, organized in the extensible framework of different types of activities. Additionally, this model incorporates some sense of hierarchy and distinguishes between interbuilding and intrabuilding movements. Hence, the authors introduce home, office, evening activities, and different transport submodels (walking, car, bus, etc.). An office model, for example, reproduces a kind of star-like trajectory around the desk of the person at the selected coordinates inside the office building, while a home model is just a sojourn in a particular point of a home location. Different social patterns are introduced in the model. For example, the evening activity submodel reflects a meeting with friends after work by modeling a random walk of a group along the streets. Being more flexible in its application to different scenarios than the model by Zheng *et al.* [14], this model, however, suffers from the same complexity problems.

UTILIZING SOCIAL GRAPH

The most recent and most rapidly evolving trend in modeling human mobility is based on incorporating complex network theory and considering human relations as the main cause of individuals' movements. Social relations are described as a graph, where nodes represent individuals and weighted edges the degree of the social connection between them. Complex network analysis revealed a number of significant properties in the structure of social graphs. For example, the number of edges connected to each user was shown to follow power-law distribution, and the average distance between two nodes to be bounded by a surprisingly small number (~ 6). These findings, along with the intuitive idea that our movements are highly influenced by the need for social interactions, led to the emergence of a new class of mobility models. The main idea is that the destination for the next move of a user depends on the position of people with whom the user shares social ties (Fig. 4a). Thus, if node B is connected with node A, B will influence the choice of A's destination proportionally to the weight of their social relationship (CMM [16]). The HCMM model [17] extends this idea by adding spatial attraction and incorporating power-law distribution of the jumps.

In order to capture periodical events in agents' moves, recent works have explored the concept of time-varying social graphs (Fig. 4b). The idea comes from the following reasoning. During each part of the day, the social communities to which we belong influence our behavior differently. For example, during working hours a regular person tends to interact mainly with his/her colleagues at work, thus resulting in the person leaving home in the morning and spending part of the day in the office. On the con-
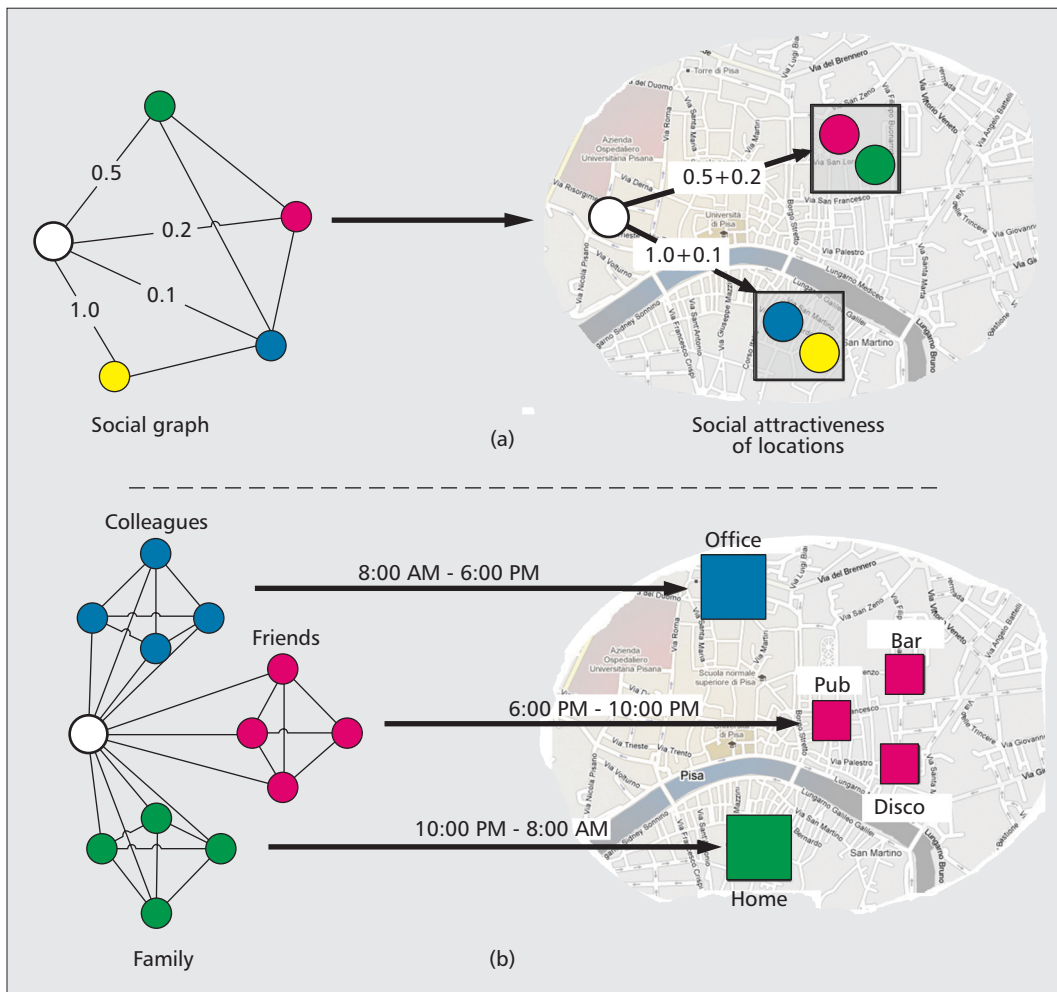
Figure 4. *Exploring social graphs in human mobility: a) calculating the social attractiveness of locations; b) the concept of a time-varying social graph.*

trary, our evening activities are usually connected with our family or friends, to meet whom we go back home or to a pub. In this scenario, the social strength of relationships between users (i.e., the weight of the edges connecting users in the social graph) changes with time, and the associated graph can thus be modeled as a time-varying graph. By appropriately tuning the weights of social links, we can easily reproduce the recurrent behavior of users. Then the movement decision process at time t for node A consists of choosing one community among those communities that are relevant at time t and moving toward the location associated with the chosen community. Although the concept was already mentioned in CMM [16] and HCMM [17], it has been fully developed in HHW [19] and GeSoMo [20].

In reality, social relations can not only aggregate nodes but also separate them. SIMPS [18] and GeSoMo [20] take into account this repulsion force between nodes. Thanks to this social repulsion, nodes spend some time in isolation, thus implementing the individual walk social pattern. Furthermore, GeSoMo also includes group trips, achieved by letting nodes form dynamic groups that select a common destination for the next movement.

DISCUSSION AND FURTHER DIRECTIONS

In the previous section we have shown the main three approaches used in modeling human movements. We also depicted the main existing solutions in each of the groups, and stressed the differences in their design. Table 1 compares these solutions according to the statistical properties and behavioral patterns considered earlier. Starting from this comparison, in this section we draw some conclusions and discuss future directions to be pursued in the area of human mobility modeling.

The first observation comes from the three-dimensional nature of human movements. Starting from the analysis of recent works in the field, we highlighted the focus on spatial, temporal, and social aspects in studying human mobility traces. As a result, we have observed three corresponding dominating techniques explored in the models: maps of preferred locations, personal agendas, and social graphs. Unfortunately, each of these approaches is designed to reproduce only a subset of patterns and properties of movements; therefore, a combination of different techniques is required to construct more realistic models. We believe that one of the most

Model	Scale			Mobility properties							Mobility patterns									Other			
											Temporal			Social			Spatial						
	Global view	City view	Building view	Inter-contact time	Contact-time	Jump size	Radius of gyration	Visitation frequencies	Return time	Visiting time	Periodic	Aperiodic	Sporadic	Group trips	Meetings	Individual	Highly centric	Orbital	Random	Uses social graph	Uses periodic event planning	Uses preferred location map	Analytical affordable
Location preferences																							
Song et al. [4]	o	o	o	o	o	√	√	√	—	√	—	√	√	—	—	√	—	—	√	—	—	√	√
Mei and Stefa [13] — SWIM	—	√	—	√	√	√	o	o	—	√	—	√	√	—	f	√	—	—	√	—	—	√	√
Ghosh [10] — Sociological Orbit	√	√	√	o	o	o	√	√	o	√	o	√	—	—	f	√	—	o	—	—	o	√	√
Lee et al. [12] — SLAW	—	√	—	√	o	√	√	o	o	√	√	—	√	—	f	√	—	√	—	—	√	√	o
Hsu et al. [11] — Time Variant Community	—	√	√	√	o	o	o	√	√	—	√	√	√	—	f	√	—	√	—	—	√	√	√
Modeling agenda																							
Zheng et al. [14] — Agenda driven	—	√	—	o	o	√	o	o	o	√	√	o	√	—	f	√	—	√	—	—	√	√	—
Ekman et al. [15] — Working Day Movement	—	√	√	√	√	o	o	o	o	o	√	o	√	√	f	√	—	√	—	—	√	√	—
Exploring social graph																							
Musolesi and Mascolo [16] — CMM	—	√	—	√	√	—	o	o	o	o	o	o	o	—	√	—	—	—	√	√	s	—	o
Boldrini and Passarella [17] — HCMM	—	√	√	√	√	√	o	o	—	√	—	√	—	—	√	—	√	—	—	√	—	s	√
Yang et al. [19] — HHW	—	√	—	√	o	—	o	o	o	√	√	√	—	—	√	—	—	√	—	√	s	s	o
Borrel et al. [18] — SIMPS	—	√	—	√	√	√	o	o	—	o	—	—	√	—	√	√	—	—	√	√	—	—	o
Fischer et al. [20] — GeSoMo	—	√	—	√	o	√	o	√	√	o	√	√	√	√	√	√	—	√	—	√	s	s	o

General: "√" — if the model satisfies the property, "—" — if not and "o" - for ambiguous cases. Patterns: "f" — meetings are modeled only based on the joint location preferences (i.e., model is not aware of social ties between persons). Periodic event planning: "s" — periodic event planning based on time-varying social graph. Preference location maps: "s" — preferred places are associated with the nodes or communities in the social graph

Table 1. *Comparison table of mobility models.*

promising approaches among those we have surveyed is that of time-varying social graphs. Not only they already account for two out of three mobility dimensions, the temporal and social ones, but they are also being extensively studied in the complex networks research community, whose results could be readily exploited. Future research efforts should then concentrate on how to incorporate the spatial dimension into a model based on time-varying social graphs. As a preliminary to this, the relation between movements and user sociality should be better investigated using traces of real human mobility. In fact, while it has been shown in the literature that the social structure of the network does influence user movements, the dynamics, both qualitative and quantitative, of this causal relationship are not yet clear.

Another aspect we would like to stress is the role of the scale in modeling human mobility. We introduced the three-level approach to classifying individual movements based on the building, city, and global scales, and discussed the differences between the patterns emerging at different levels. Therefore, we included the scale aspect in the analysis of mobility models. However, Table 1 shows that the majority of models concentrate only on the city-view level. These models usually apply a very simplified random model for the lower — building-view — level. In addition, mobility on a wider scale (i.e., outside the city) is almost never considered. Therefore, we believe that future work on mobility modeling should also take into account the different behavior of users at different scales. In particular, it might be the case that different behavior emerges from a different sensitivity to the movements' driving forces at difference scales. For example, a user is expected to be willing to visit a friend who lives close to his/her home even if their friendship relationship is not very strong, while he would hardly embark on a trip around the world to meet this friend.

Finally, we conclude by stating the need for better understanding of the correlations between the different statistical properties of human movements, as these correlations might positively drive the way such properties are incorporated into mobility models. Observing the similarity in the scaling nature of different properties, in fact, we argue that there might be (yet) uncovered dependencies between them. In this case, some properties could be considered as the most important (i.e., generative), and therefore should be included explicitly in the design of the model, while others could emerge naturally during simu-

lations as a side-effect of the generative properties being correctly reproduced. As an example, heavy-tailed intercontact times emerge spontaneously in the majority of the models, without explicitly forcing for them any specific probability distribution. Thus, the particular shape of intercontact times could be considered a side-effect of some major driving forces of human movements. As an example, heavy-tailed intercontact times could be the result of human sociability, which, essentially, makes us meet frequently with people who are socially close to us (thus implying short intercontact times in this case) and only rarely with people who are simply acquaintances.

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