



# Opportunistic mobile social networks: From mobility and Facebook friendships to structural analysis of user social behavior



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## ABSTRACT

In the last few years, several real-world mobility traces for opportunistic networks have been collected in order to explore node mobility and evaluate the performance of opportunistic networking protocols. These datasets, often including online social data of the mobile users involved, are increasingly driving the research towards the analysis of user social behavior. Within these challenged infrastructureless networks where connectivity is highly intermittent and contact opportunities are exploited to allow communication, node mobility is basically driven by human sociality. As such, understanding node sociality is of paramount importance, especially for finding suitable relays in message forwarding. This paper presents a detailed analysis of a set of six different mobility traces for opportunistic network environments including nodes' Facebook friendships. Using a multi-layer social network approach and defining several similarity classes between layers, we analyze egocentric and sociocentric node behaviors on the two-layer social graph constructed on offline mobility and online social data. Results show that online and offline centralities are not significantly correlated on most datasets. Also online and offline community structures are different. On the contrary, most of the offline strong social ties correspond to online social ties and in some cases, online and offline brokerage roles show high similarity.

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## 1. Introduction

The vision of a near future in which a multitude of human-driven mobile devices can easily create local wireless networks outside the public Internet is increasingly attracting several groups of researchers in the areas of Delay Tolerant Networks (DTNs) [13,24,44], opportunistic networks [39] and the more recent *Do-it-yourself* (DIY) networks [2]. Considering the wide diffusion of these mobile devices (e.g., smartphones, tablets, etc.) and the impact their use has in the social life of every individual, the study of infrastructureless networks allowing short-range (e.g., Bluetooth and Wi-Fi) wireless communication between nodes is generating a particularly hot research trend. When there is no suitable network architecture like the Internet one, for example, an alternative option for communication is necessary. DTNs were designed to allow communication between devices distributed within a networking scenario without fixed network infrastructure, forming sparse network topologies and having intermittent contacts. Using the *store-carry-forward* communication paradigm, the mobile

DTN node first stores the message, then carries it while moving, and then forwards it to an intermediate node or to the destination. A similar strategy is used in *opportunistic networks* where mobile hand-held nodes forward messages during an encounter opportunity. However, while in DTNs there are also cases where the points of disconnections are known and routing can be performed in an Internet-like fashion, opportunistic networks routes are always computed dynamically.

Opportunistic networks have been shown to be the suitable architecture for several applications in scenarios where network coverage is poor (e.g., dead spots, disaster-recovery situations, etc.) or network access is expensive. Through an opportunistic network and cooperative sensing, for example, it is possible to build sensing maps of air quality, noise, temperature, CO<sub>2</sub> concentration, etc., satisfying a specific sensing quality with low delay and energy consumption [50]. Another interesting opportunistic networking application refers to recommender systems. Such solution tracks users' activities and mobility patterns, and utilizes the user's contextual information to provide recommendations on a variety of items [33]. Opportunistic networks are also used for mobile data offloading in order to reduce the load on 3G networks [31]: with the increasing number of smartphone users, in fact, most of the 3G networks have been shown to be often overloaded. Another well-known application proposed for such networks is *MobiClique* [41]:

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a mobile social networking middleware exploiting ad hoc social networks to disseminate content and leveraging existing social networks to bootstrap the system. More recently, opportunistic networks have been proposed as a promising technology also for big data computing [48] and for connecting smart things in IoT exploiting the social side of things linked to human mobility [30].

It is a common belief that opportunistic networks are characterized by a social-based nature that can be exploited to exchange information. Recent works on opportunistic social routing have shown that message delivery can be optimized selecting the best relay nodes considering both their real-world (i.e., offline) wireless encounters and their online social interactions with the other nodes [5,15,16,21,36,41,45,47]. Similarly to wireless encounters from which extracting the offline social behavior of nodes, online social networking services like Facebook, Twitter and LinkedIn, just to provide some examples, are fostering the availability of additional data useful for analyzing the overall social behavior of the opportunistic network nodes. From this perspective, we believe that the analysis of sociality derived both from wireless encounters and online data becomes a fundamental aspect within these networks.

There are a lot of works studying encounters of people and social relations. However, while many of these works focus on analyzing the offline sociality extracted from encounters self-reported or detected from wireless proximity, or online social relations such as Facebook friendships or Twitter interactions, few of them analyze both aspects. Moreover, the few works analyzing both offline and online sociality in order to understand how a user behaves within the two contexts, often rely on self-reported meetings that differently from detected Wi-Fi or Bluetooth contacts, may be erroneous because a user may not recall meetings correctly or decide to provide wrong information. *This work*, differently from the aforementioned works, *explicitly focuses on analyzing the relationship between offline sociality built on wireless encounters and online sociality, where both socialities are built on the same set of users.*

In these last years, several real-world mobility traces for opportunistic network environments have been collected to explore human-driven motion and sociality. These traces, including in some cases nodes' online social data/profiles, are usually acquired through experiments tracking a set of participants carrying small portable wireless devices in campuses, conferences, entertainment environments, etc. Most of these data can be obtained through the CRAWDAD<sup>1</sup> repository. Although the work done so far analyzing these traces evinced many important aspects on mobility data, the relationship between the sociality built on mobility and the other social dimensions has not been fully discovered yet. In our view, the knowledge about the whole social behavior of mobile users is essential for designing effective social-based algorithms for opportunistic networks. As such, *the core of the analysis proposed in this work is represented by the use of a multi-layer network approach for comparing different kinds of social network layers extracted by an heterogeneous set of six mobility traces covering several networking environments: academic, conference and urban scenarios.*

Sociologists, anthropologists and psychologists have largely studied human behavior using two different approaches. One approach, being *egocentric*, focuses on the individual, taking into account his personal network composed by the other individuals to which is directly connected. The other approach, being *sociocentric*, focuses on large groups of individuals, quantifying internal relations and highlighting any interaction pattern that influences group dynamics. *The aim of this work is to study opportunistic nodes' social behavior using both sociocentric and egocentric network measures [46].* Specifically, we present a detailed analysis of six datasets for mobile social opportunistic networks containing two layers of so-

ciality: the social network graph built on offline wireless encounters and the online social network graph built on Facebook friendships. Exploiting a multi-layer social network approach, we aim to contribute to enlarge the knowledge about the similarity between online and offline worlds in different opportunistic networking environments. This is a much more advanced analysis compared to other recent studies such as [43,46]. Firstly, we consider a representative collection of six different datasets thus extracting more meaningful conclusions with respect to one single dataset. Secondly, we propose a novel analysis methodology based on egocentric and sociocentric measures for examining the datasets considered. Finally, we define several similarity layers that will be used to uniform the results obtained through the different analysis approaches thus making easier an overall comparison between social network layers.

As a preliminary step, we focus on node centrality (i.e., the contribution of network position to the importance of an individual in the network), thus answering to the challenging question whether online and offline node centralities are correlated and hence, the two social behaviors are similar. Later, we focus on communities, analyzing the similarity between online and offline groups. Starting from this analysis, we exploit the communities detected for investigating online and offline brokerage roles (i.e., nodes that act as brokers between communities) and perform a correlation analysis between online and offline brokerage values. Finally, motivated by recent studies [15,17,35,43] demonstrating that mobile nodes encounter other online socially connected nodes with high probability, we compute offline *tie strength* in order to find matchings between strong ties and Facebook friendships.

The paper has been organized as follows. **Section 2** provides background information on multi-layer social network models and analysis. **Section 3** describes the datasets analyzed. **Section 4** briefly details the social network model adopted. **Section 5** and **6** describe the sociocentric and the egocentric measures used to perform our analysis. Finally, in **Section 7**, we present our results, provide an overall comparison between the analysis methods used in **Section 8** and draw the main conclusions in **Section 9**.

## 2. Related works

The relationship between human encounters and online social relations has been the focus of several researches in these last years. In [32], for example, Hossman et al. analyze two datasets of self-reported data about social, mobility and communication ties of online social network users (Facebook, Twitter and Gowalla) showing that social ties are tightly coupled with mobility and also with communication. Dunbar et al., [23] explore the layered structure of the nodes within two Facebook datasets and a Twitter dataset to determine whether this structure is similar to the offline face-to-face interactions previously studied on other datasets. The results of such analysis show that the absolute size of layers and the mean contact frequency with alters within a layer in Facebook and Twitter match very closely to the observed values from offline networks. In addition, online communities have structural characteristics very similar to offline face-to-face networks. Similarly, Arnaboldi et al., [3] present a detailed analysis of a Facebook dataset finding that the number of social relationships an individual can actively maintain is close to the Dunbar's number (150) found in other examples of offline social networks. Moreover, they present a number of linear models to predict virtual tie strength from a set of Facebook variables.

Although the above studies analyze the relationship between online and offline sociality, they do not explore the offline sociality built on Bluetooth or Wi-Fi encounters. As such, the results provided within these works may not reflect the typical social

<sup>1</sup> <http://www.crowdad.org/>.

**Table 1**  
Characteristics of wireless contacts data.

Experimental dataset	UNICAL	UPB	LAPLAND	SASSY	Social Evolution	SIGCOMM
<b>Environment</b>	Academic	Academic	Conference	Academic/Urban	Academic/Urban	Conference
<b>Device type</b>	Phone	Phone	I-mote	T-mote	Phone	Phone
<b>Radio range</b>	~10 m	~10 m	~10 m	~10 m	~10 m	[10–20] m
<b>Granularity</b>	180 s	[5–30] min	[120–600] s	6.67 s	360 s	[120 ± 10.24] s
<b>Overall Duration</b>	7 days	35 days	3 days	70 days	352 days	5 days
<b>Analyzed week</b>	from 28/01 to 22/02 2014	from 18/11 to 24/11 2011	from 09/08 to 11/08 2009	from 08/03 to 14/03 2008	from 02/03 to 08/03 2010	from 17/08 to 21/08 2009
<b>Overall # of nodes</b>	15	22	17	27	70	76
<b># of analyzed nodes</b>	15	15	17	24	55	67

behavior of a mobile user within an opportunistic networking environment where many wireless encounters take place and those encounters will be used for exchange messages. Moreover, the analysis methodologies proposed within these works focus only on some social metrics (e.g., in [32], degree and betweenness as hubs characterization) not providing a wide view of user social behavior. Our work, on the contrary, analyzes a larger set of social metrics clarifying also the implications of the results for opportunistic networking. In the following sections, we thus review the works that explicitly rely on sociality built on wireless mobility and considering that we exploit a multi-layer approach for analyzing our data, we first briefly describe the multi-layer social network models present in the literature.

### 2.1. Multi-layer social networks models

Social networks show a nontrivial topological structure where more than one kind of connection may exist between any pair of nodes. Think, for example, to individuals having social links with friends in real-life, Facebook social links with virtual friends, LinkedIn links with co-workers, and so on. As a matter of fact, for this type of networks there is not a unique word identifying them. Terms as *multi-layer networks*, *multi-relational network*, *multidimensional network* and *multiplex network* are considered synonyms [10]. To represent the variety of link types that may exist between nodes belonging to these networks, different architectural definitions have been provided. Bródka et al., [11] define a multi-layer social network as a set of single-layered social graphs where each graph has the same set of nodes and only the set of edges between them may vary. A similar model is proposed by Magnani and Rossi [34], where a *pillar multi-network* in which every user has exactly one account on each layer is proposed. In the same work, authors define also a *ML-model* mapping a group of nodes belonging to one social network layer onto a single node belonging to another social network layer. Berlingerio et al., [4] perform a flattening of the different network layers resulting in a single network layer where links belonging to different social dimensions are represented by separated labels.

### 2.2. Analysis of multi-layer social networks with wireless encounter data

Some recent works on multi-layer networks have focused on multi-layer structures where one of the several social dimensions/layers is extracted by node mobility. Dong et al., [28], for example, explore a collection of data describing the relationships between students of a dormitory tracked using their smartphones' proximity and location sensors for a period of nine months. Their work highlights the existence of a relationship between the evolution of friendships and individual behavior in terms of space and time. In [6], Bigwood et al., analyze in terms of structural equivalence and role equivalence the Facebook social network and the social network detected through physical encounters of a group

of individuals carrying T-mote ZigBee sensors at the University of St. Andrews, showing that the two social graphs are different. Using the same dataset, Socievole and Marano [46] analyze the differences between the two networks using egocentric and socio-centric structural measures showing that the two networks differ except for betweenness centrality. In another work [15], Ciobanu et al., describe an experiment conducted at University Politehnica of Bucharest in 2011, where the Bluetooth wireless contact data and Facebook friendships of a group of students were collected. The gathered data were used to highlight key social aspects that can be exploited in opportunistic network routing and in particular, that nodes with more online social links belong to more communities (detected through mobility) and both the social and the logical grouping of nodes are in direct correlation with their interactions. In [27], Gaito et al., present the results of an experiment performed at University of Milano tracing the encounters and the Facebook friendships of a group of students. They find that people popularity is most likely to change in the two networks. More recently, in a work [43] analyzing the multi-layer social network constructed on Bluetooth contacts, Facebook friendships and interests of a group of students at University of Calabria, we show that Bluetooth contacts network layer and Facebook friendships layer are similar in terms of communities, closeness between the social graphs, and matching between strong offline ties and the other social ties.

The works described above, even if demonstrate the efforts that have been carried out to explore multi-layer sociality where one layer is built on wireless proximity, have been only focused on some datasets, some of which are not public, exploiting different analysis criteria and providing different conclusions. To the best of our knowledge, there has never been a clear description of user online and offline behavior in opportunistic networks followed by a comprehensive clarification on human offline mobility and online sociality and the implications these social dimensions have on opportunistic networking algorithms. To this end, we consider a wider set of datasets, propose a novel methodology for analyzing such data and provide more meaningful conclusions with respect to the implications these results have on opportunistic networking.

## 3. Datasets description

To analyze online and offline sociocentric and egocentric behaviors of mobile opportunistic nodes, we consider a collection of six real-world datasets including mobility data and online social data. Most of these datasets can be accessed on the CRAWLAD archive and will be shortly described in this section.

Table 1 summarizes the characteristics of the selected datasets in terms of wireless contacts data. For each experimental dataset, the group of researchers who carried out the experiments instructed the recruited participants to carry the wireless nodes (sensors or phones) in order to detect and log the nodes in proximity range for all the duration of the experiment. Since the various datasets have very different overall durations, we choose to

uniform them considering a maximum duration of 7 days or the whole trace if its overall duration is shorter. In particular, for the longer datasets, we focus on the week of wireless contacts having the highest contact durations (see the value represented by the row *Analyzed week* in the aforementioned table). Hence, we analyze parts of the wireless contacts data containing longer interactions between mobile nodes. As a consequence, the total number of nodes, indicated in the row *Overall # of nodes*, has been reduced (see the row *# of Analyzed nodes*) due to the absence of part of them during the considered week.

Choosing the links with the highest contact durations, we assume that they represent a suitable social situation where a message exchange can take place. Measuring, for example, centrality on a graph with links representing a high contact rate could be misleading. A node with high degree centrality would be considered more central and hence, a suitable relay. However, this node may have had many short contacts that do not reflect the sociality needed for the exchange of a message. As an example, think to an individual moving from work to home by bus. His smartphone may encounter many other devices in range for few seconds passing from a bus stop to another. These short interactions, however, do not make this node more socially suitable than others. Firstly, choosing this node as next hop, it may not have the time needed to setup a connection for exchanging messages if it detects a node with its Bluetooth and after few seconds this connection goes down. Secondly, even if having the time to setup a short connection, it may have to fragment the message thus leading to an overload of the network and node buffers with many message copies.

### 3.1. UNICAL

UNICAL [12] dataset contains Bluetooth proximity data collected by an ad-hoc Android application called *SocialBlueConn* and the social profiles in terms of Facebook friendships and interests of a group of 15 postgraduate students at University of Calabria campus (Italy). The experiment lasted one week during a specialistic course, from January 28, 2014 to February 5, 2014, including only the week days. To gather the proximity information, each participant was instructed to keep the device powered on from 12 AM to 8 PM. For collecting Facebook data, the participants were asked to log in with their Facebook credentials to an ad-hoc website accessing the Facebook API. Once the students were logged in, their friend lists and social profiles were collected and sent to a central server.

### 3.2. UPB

UPB [14] dataset is composed by a Facebook friendships trace and a Bluetooth contacts trace. These data were collected during an experiment of 35 days, from November 18, 2011 to December 22, 2011, performed in an academic environment at University Politehnica of Bucharest (Romania). The 22 recruited participants were instructed to install an Android application to log their Bluetooth contacts and keep alive their smartphone between 8 AM and 8 PM during week days.

### 3.3. LAPLAND

LAPLAND [49] is a dataset collected during the ExtremeCom09 workshop in Padjelanta National Park (Sweden). It contains Bluetooth co-location data of 17 conference attendees gathered during the four consecutive days of the experiment, from August 9, 2009 to August 12, 2009 (here, we consider only the first three days, since the fourth day results in few connections with low contact

durations). Each candidate was asked to carry iMotes with him detecting devices in proximity range. Moreover the dataset includes the participants' Facebook friend lists and interests in terms of scientific topics.

### 3.4. SASSY

SASSY [7] dataset consists of encounter records related to a group of 27 participants (22 undergraduate students, 3 postgraduate students and 2 members of the staff) carrying IEEE 802.15.4 sensors (T-mote invent devices), and their social network, generated from Facebook data self-declared by candidates at the beginning of the experiment. The experiment took place at University of St. Andrews (United Kingdom) for an overall duration of three months between February 15, 2008 and April 29, 2008.

### 3.5. Social Evolution

MIT Social Evolution [1] is a dataset related to an experiment performed to closely track the everyday life of a whole undergraduate dormitory of 70 students. The experiment duration covers about an entire academic year from April 6, 2009 to March 23, 2010. The dataset includes Facebook data, proximity, location, and call logs, collected through a mobile phone application that scanned nearby Wi-Fi access points and Bluetooth devices.

### 3.6. SIGCOMM

SIGCOMM [40] dataset includes Bluetooth co-location data of 76 conference attendees collected by an opportunistic mobile phone social application, called *MobiClique*. Each participant was also asked to log in to his Facebook profile in order to include the list of Facebook friends and interests. These data were collected during the SIGCOMM conference held in Barcelona (Spain), from August 17, 2009 to August 21, 2009.

## 4. Multi-layer social network model

Starting from mobility and Facebook data, we construct a multi-layer social network graph for each dataset and then, we use this structure to perform sociocentric and egocentric analysis. In this paper, we define a multi-layer social network as in [34], and consider unweighted graph layers since we have Facebook links (friendships) without weights.

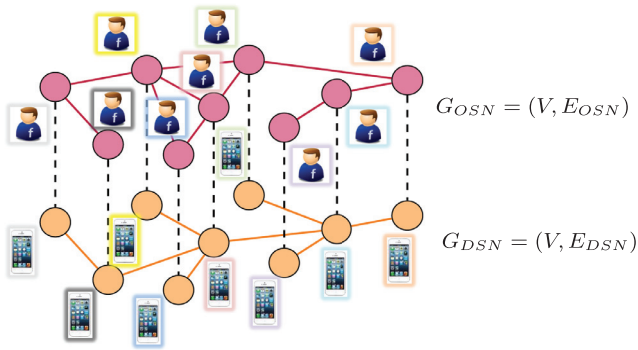
- **Definition 1** (SOCIAL NETWORK LAYER). A social network layer  $L$  is an unweighted graph  $G(V, E)$  with vertex set  $V$  corresponding to users on the social network and edge set  $E \subseteq V \times V$  corresponding to social links between users.
- **Definition 2** (MULTI-LAYER SOCIAL NETWORK). A multi-layer social network  $MLSN = (L_1, L_2, \dots, L_n)$  is a tuple where  $L_i = G_i(V, E_i)$ ,  $i \in 1, \dots, n$  are social network layers.

For each dataset, we form a two-layer social network composed as follows:

- a first social layer composed by the offline social network detected through wireless encounters, here called the *detected social network* (DSN) graph;
- a second social layer composed by the Facebook friendships network, here called the *online social network* (OSN) graph.

Using the participants' Facebook data in the form of a list with {#NODE ID1, #NODE ID2, #FRIENDSHIP FLAG} entries, where the friendship flag indicates whether two nodes are friends on Facebook or not, we generate an OSN graph, where an edge exists if two nodes are friends. As far as the wireless encounters data are





**Fig. 1.** Example of two-layer social network on a mobile social opportunistic network where each mobile node has a corresponding Facebook account. Nodes have different social connections at each social layer.

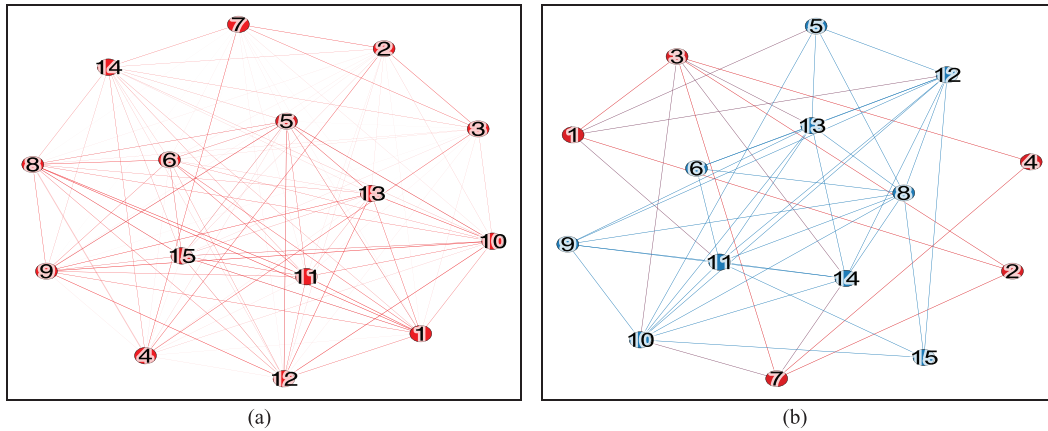
concerned, the modeling of a unique social graph from a temporal network is more complex and is still an open problem. In this work, we choose to form the DSN graph by setting an edge between two nodes if they had at least one contact during the analyzed week, by using the contact data in the form of {#NODE ID1, #NODE ID2, #CONTACT TIMESTAMP} entries. We underline that the DSN graph, even if unweighted, has been defined on a temporal window of a week where took place the highest contact durations. In other words, a link between two nodes in the DSN graph represents a high contact duration. As such, even if on one hand we loose some information on users' social behavior (i.e., how long

a contact is), on the other hand we preserve the aspect of long contacts and are able to easily compare the DSN and OSN graphs.

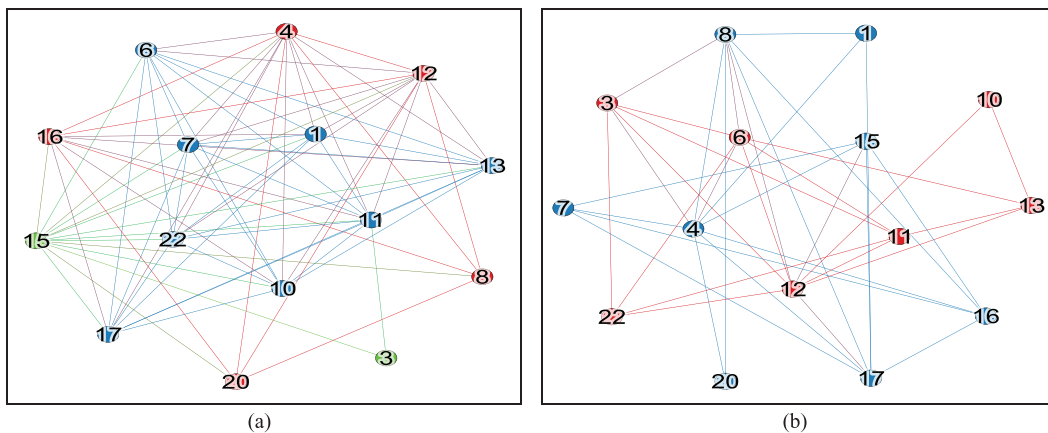
Fig. 1 shows an example of the multi-layer network structure adopted in this work. In Figs. 2, 3, 4, 5, 6, 7, we depict the two-layer graph for each dataset using different colors for nodes belonging to different communities. Here, we used the Louvain community detection method [8] (see Section 5).

### 5. Sociocentric analysis

Sociocentric analysis method extends and complements traditional social science by focusing on the quantification of interactions among a socially well-defined group of people and the identification of global structural patterns. In particular, the method analyzes sets of relationships among nodes that are considered as bounded social collectives. In this section, we briefly describe the sociocentric centrality measures and the community detection algorithms that we have chosen within this work to assess the similarities between the DSN and the OSN. Even if several centrality measures and community detection methods exist, we have chosen a subset of them that we consider more relevant for this analysis. The three centrality measures chosen, for example, are considered in the literature on network graphs main measures of the contribution of network position to the importance of a node within a network graph. As far as the community detection is concerned, we have chosen two algorithms representative of two different classes, one partitioning the network in non-overlapping communities and the other extracting overlapping communities.



**Fig. 2.** UNICAL (a) DSN and (b) OSN graph layers.



**Fig. 3.** UPB (a) DSN and (b) OSN graph layers.

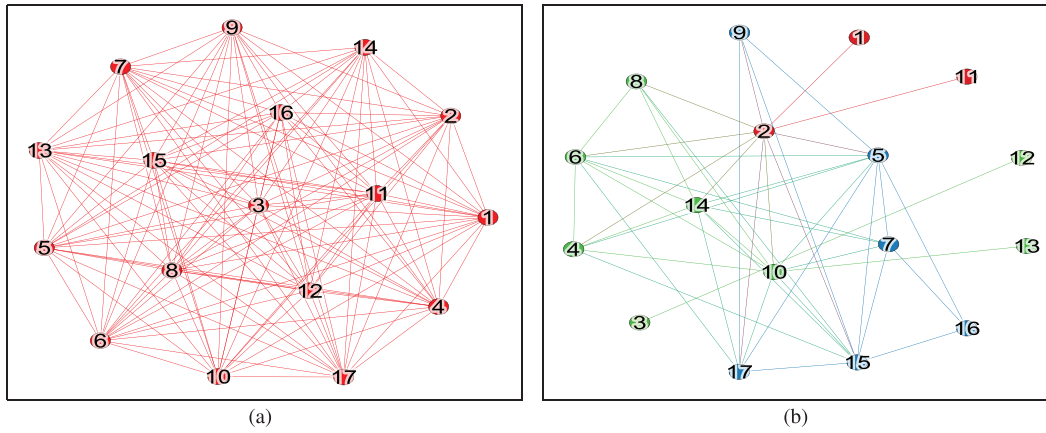


Fig. 4. LAPLAND (a) DSN and (b) OSN graph layers.

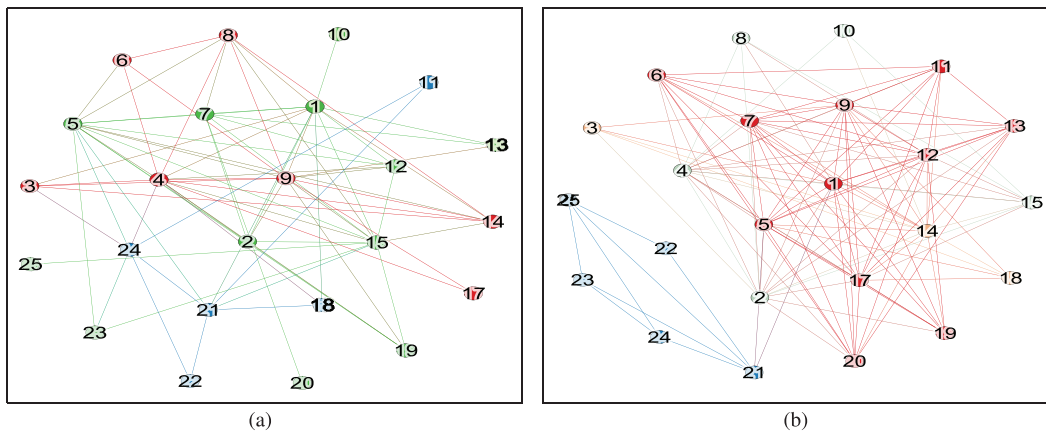


Fig. 5. SASSY (a) DSN and (b) OSN graph layers.

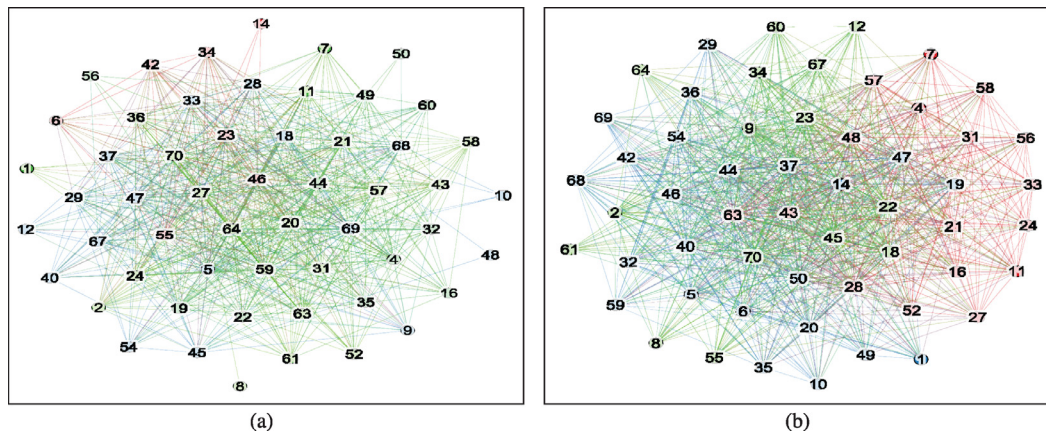


Fig. 6. Social Evolution (a) DSN and (b) OSN graph layers.

### 5.1. Betweenness centrality

Betweenness centrality [26], also referred to as sociocentric betweenness centrality, measures the frequency with which a node is present on the shortest path or geodesic connection between every couple of nodes in the network. This centrality measure is important in opportunistic networks and in social networks since it provides information concerning the influence a node has over

data flow. For node  $i$ , it is defined as:

$$C_b(i) = \sum_{i \neq j \neq k} \frac{g_{jk}(i)}{g_{jk}} \quad (1)$$

where  $g_{jk}(i)$  is the number of shortest paths from  $j$  to  $k$  passing through  $i$ ,  $g_{jk}$  is the total number of geodesic paths from  $j$  to  $k$  and  $N$  is the network size.

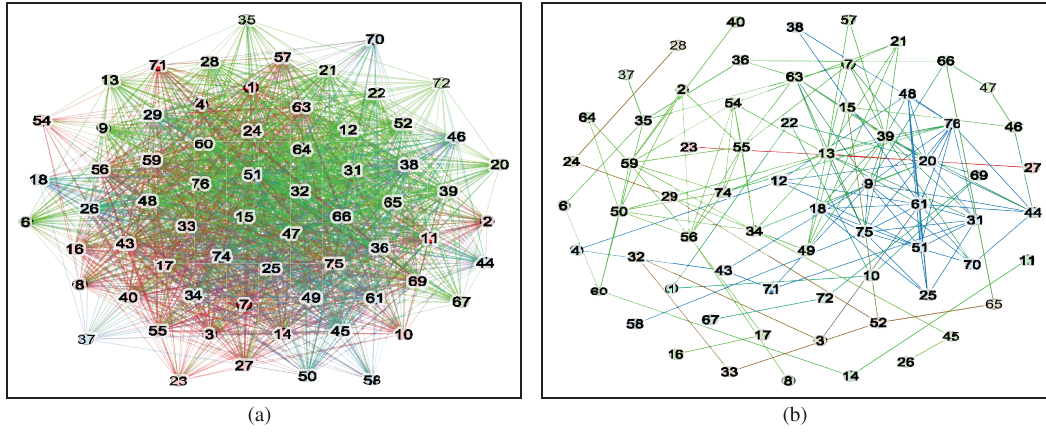


Fig. 7. SIGCOMM (a) DSN and (b) OSN graph layers.

## 5.2. Closeness centrality

Closeness centrality [42] measures the inverse of the sum of the shortest paths between a node towards each other node in the network. It is defined as:

$$C_c(i) = \frac{1}{\sum_{j=1}^N d(i, j)} \quad (2)$$

where  $d(i, j)$  is the weighted shortest path from the reference node  $i$  to each node in the network. This centrality measure assumes the value 0 if we consider a disconnected graph, since the distance between two nodes belonging to two distinct components in a graph has not a finite value. To overcome this problem, Danagalchev [19] redefined closeness as:

$$C_c(i) = \sum_{j \neq i}^N \frac{1}{2^{d(i, j)}} \quad (3)$$

## 5.3. Eigenvector centrality

Eigenvector centrality [9] measures the centrality of a node in a circular way. Starting from the assumption that a node is central if it is in relation with other central nodes, the centrality of a node is proportional to the sum of the centrality values of all its neighboring nodes. Using the adjacency matrix  $A$  of the graph, the eigenvector centrality for a node  $i$  is proportional to the sum of the eigenvector centrality values of its neighbor nodes, and is defined as:

$$C_e(i) = \frac{1}{\lambda} \sum_{j=1}^N A_{ij} C_e(j) \quad (4)$$

where  $\lambda$  is the largest eigenvalue.

## 5.4. Louvain community detection

Louvain method [8] partitions the network graph in disjoint communities and is based on a greedy optimization technique that attempts at optimizing the modularity of a partition of the graph. Initially, the method searches small communities by locally optimizing modularity. Then, it aggregates nodes belonging to the same community and builds a new network whose nodes are the communities. These steps are repeated iteratively until a maximum of modularity is attained and a hierarchy of communities is produced.

## 5.5. $k$ -CLIQUE community detection

This method, also known as Clique Percolation Method (CPM) [38], finds overlapping communities where a community is defined as the union of all  $k$ -cliques (complete subgraphs with  $k$  nodes) that can reach each other through a series of adjacent  $k$ -cliques, where two  $k$ -cliques are said to be adjacent if they share  $k-1$  nodes. Here, after several experiments, we have set  $k = 5$  both for the DSN and the OSN, being this value suitable for the datasets chosen.

## 6. Egocentric analysis

In the previous section, we focused on groups describing some measures that we will use to analyze user sociocentric behaviors in the DSN and the OSN. In order to understand the similarities between the two network layers focusing on the local behavior of individuals more locally, we need to take a closer look to their local circumstances. Egocentric networks are defined as networks of single actors together with the actors they are directly connected to. In this section, we focus on egocentric analysis methods that aim at describing and quantifying the variation across individuals in the way they are embedded in local social structures.

### 6.1. Degree centrality

Degree centrality [25,37] is an example of egocentric measure counting the number of connections a node has towards its neighboring nodes. Degree is considered a simple but fundamental centrality measure. For a node  $i$ , it is defined as:

$$C_d(i) = \sum_j^N a_{ij} \quad (5)$$

where  $a_{ij} = 1$  if nodes  $i$  and  $j$  are connected by an edge,  $a_{ij} = 0$  otherwise.

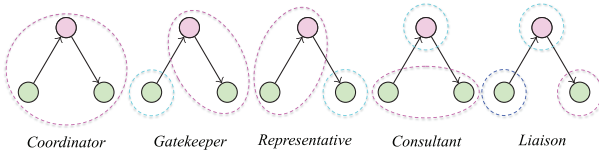
### 6.2. Ego betweenness centrality

Ego betweenness centrality is computed considering just the ego network of a node, and hence, the shortest paths between every pair of non-adjacent nodes will have length 2. Given the adjacency matrix  $A$ ,  $A_{i,j}^2$  contains the number of walks of length 2 connecting nodes  $i$  and  $j$ . It follows that  $A^2[1 - A]_{i,j}$ , where 1 is a matrix of all 1's, gives the number of shortest paths of length 2 joining  $i$  to  $j$ . The sum of the reciprocal of the entries gives then the ego betweenness.



**Table 2**  
Correlation between OSN and DSN centrality measures.

Experimental dataset	Correlation				
	Betweenness	Closeness	Eigenvector	Degree	Ego Betweenness
<b>UPB</b>	0.2151	0.0988	−0.015	0.1541	0.2587
<b>LAPLAND</b>	0.1446	−0.1454	−0.1498	−0.098	0.1455
<b>SASSY</b>	0.05	0.5791	0.5135	0.5251	0.6224
<b>SOCIAL EVOLUTION</b>	0.0492	0.0278	0.1058	0.089	0.0816
<b>SIGCOMM</b>	0.0533	0.1052	0.0268	0.0573	0.0012



**Fig. 8.** The five types of brokerage roles: the pink nodes are brokers, ellipses/circles correspond to community boundaries.

### 6.3. Brokerage

Gould and Fernandez [28] explored the roles that ego plays in connecting groups (i.e., communities) as broker. They listed five types of brokerage roles (see Fig. 8):

- *coordinator*: the broker mediates the contacts between two individuals from its own group;
- *gatekeeper*: the broker mediates the incoming contacts from an out-group member to an in-group member;
- *representative*: the broker mediates the outgoing contacts from an in-group member to an out-group member;
- *consultant*: the broker mediates the contacts between two individuals from a different group;
- *liaison*: the broker mediates the contacts between two individuals from different groups, neither of which is the group to which it belongs.

The *brokerage score* for a given node with respect to a role is the number of ordered pairs having their group memberships brokered by that node. Note that in this paper, considering undirected graphs, we do not take into account the representative score since it is not different from the gatekeeper score.

### 6.4. Tie strength

Tie strength [18,29] is a quantifiable property characterizing the link between two nodes (here, the ego and its neighbor). The notion of tie strength was introduced by Granovetter in 1973 stating that this measure may deal with four different aspects: the frequency of contacts, the contact durations, the history of relationships and the number of transactions. Here, we consider contact durations computing for each node pair the total contact duration had during the experimental period.

## 7. Results

### 7.1. Centrality correlation

We initially show the results obtained by computing sociocentric and egocentric centrality measures on the multi-layer networks built on the datasets presented in Section 3. Specifically, within each multi-layer network and for each centrality measure considered, we computed the Pearson's correlation coefficient between the centrality values of the nodes on the OSN and their centrality values on the DSN. The Pearson's correlation coefficient is

defined as  $\rho_{X,Y} = \frac{COV(X,Y)}{\sigma_X\sigma_Y}$  where  $COV(X, Y)$  is the covariance between the two random variables  $X$  and  $Y$ , and  $\sigma_X$  and  $\sigma_Y$  are the standard deviations. Correlation analysis aims at finding linear relationships between the same centrality measure over the two social layers. In Table 2, we show the correlation values obtained for each dataset, while in Figs. 9, 10, 11, 12, 13 we depict the relationship between DSN and OSN centralities. Note that we do not report the correlation values for UNICAL dataset since the DSN centrality values are 0 for betweenness and ego betweenness (see Figs. 9 and 13), and constant for the other centrality measures (see Figs. 10, 11 and 12). This results in covariance and standard deviations product between OSN and DSN centrality that are 0. In the case of betweenness and ego betweenness, we can observe from Fig. 2(a) that in the DSN graph, being complete, every node can be directly reached by each other node, hence, no shortest paths where one node is between couple of nodes exist and this results in a centrality value which is 0. UNICAL mobile users, in fact, were frequently co-located in a classroom during lessons and this resulted in mobile nodes able to easily detect all the other nodes of the experiment. The constant values for closeness, eigenvector centrality and degree are obviously related to UNICAL complete structure as well. On the contrary, UNICAL OSN graph (see Fig. 2(b)) is more sparse considering that not all the students involved were Facebook friends (the participants were postgraduate students coming from different degree courses and academic years) and results in non-zero values for all the considered centrality measures. Here, we conclude that UNICAL online and offline user centrality behaviors are different for all the measures considered because of the wireless co-presence between all the participants where many of these are not online friends. Looking at the other datasets, we note that LAPLAND shows also different online and offline behaviors having low correlation values for all the centrality measures. Here, the network size and the DSN structure is similar to UNICAL (17 nodes in LAPLAND and 15 nodes in UNICAL) and even if the network environment is different (conference in an extreme environment vs. university campus), online and offline behaviors are again different because the participants are basically conference members working on complementary research areas, not always co-located and not all Facebook friends. Also UPB, with a low network size (15 nodes) and dealing with an academic environment as UNICAL, shows low structural similarity between online and offline centrality. Unfortunately, for this dataset, there are not details concerning the type of participants to the experiment (e.g. students of the same courses, undergraduate, postgraduate or PhD students, etc.), hence, we hypothesize that UPB participants may be students following different academic courses considering that not all the DSN nodes are connected and with few online connections (see Fig. 3). As far as SASSY is concerned, we observe that this dataset is characterized by the highest correlation values, having strong correlation for closeness, eigenvector centrality, degree and in particular, for ego betweenness (0.6224). Here, the group of tracked participants shows interesting similar online and offline capabilities of locally influencing data flow. SASSY betweenness correlation values, on the contrary, are very low. However, even if this



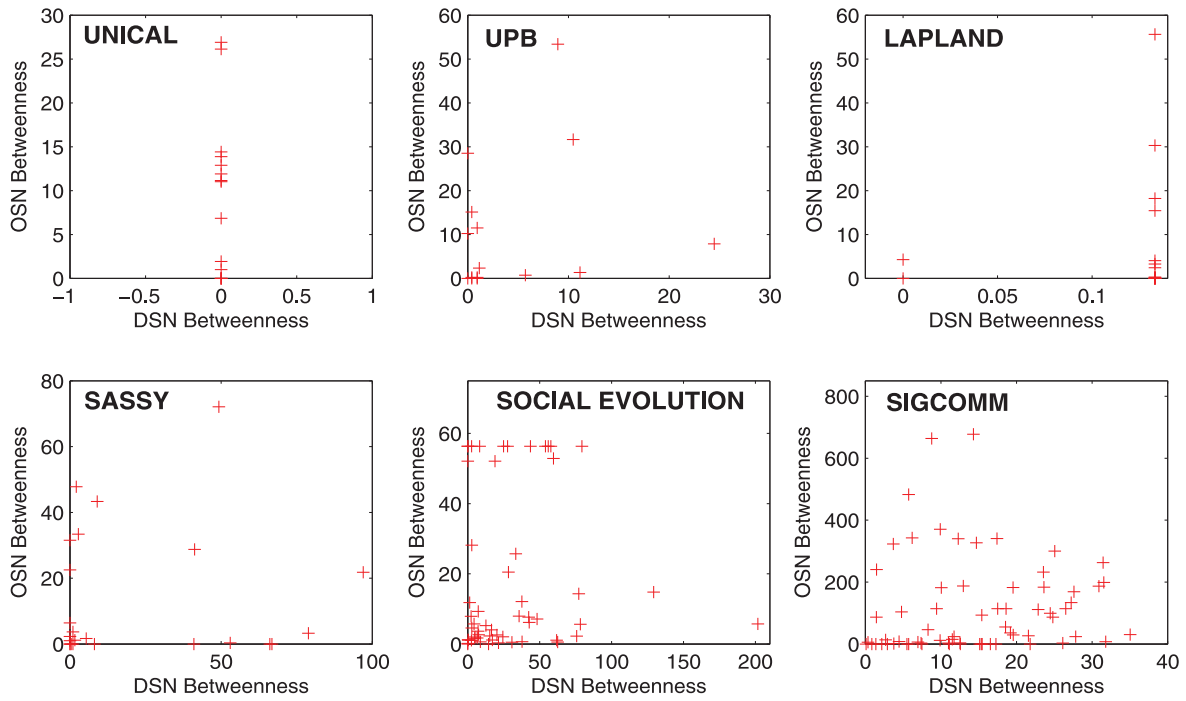


Fig. 9. Correlation between OSN and DSN betweenness centrality values.

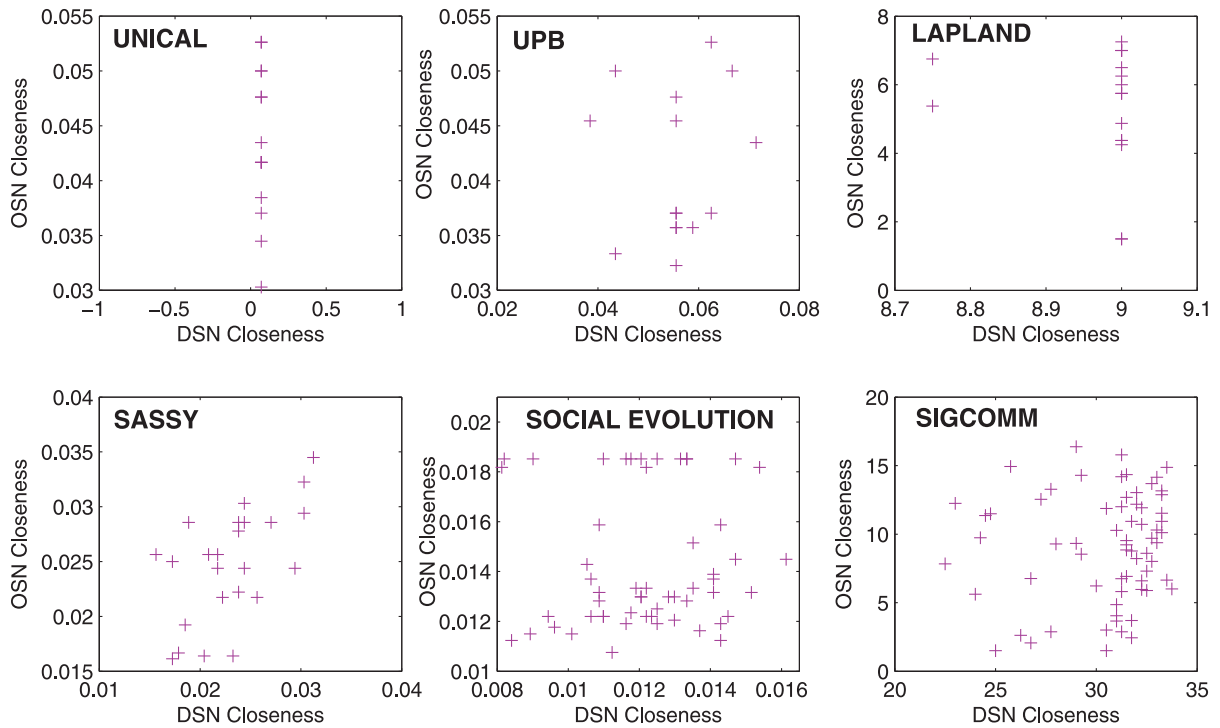


Fig. 10. Correlation between OSN and DSN closeness centrality values.

dataset shows similar online and offline behaviors for most of the centrality types probably due to the group of undergraduate students that may be friends, if we consider all the other datasets, we can conclude that, in general, there is a weak correlation between OSN and DSN centralities. The obtained low correlation values, in fact, reflect online and offline behaviors different, both in the sociocentric and the egocentric case. In particular, we note that for SIGCOMM and Social Evolution datasets, characterized by a higher number of nodes (67 and 55, respectively), the correlation between

each centrality measure assumes values very close to 0. In the first dataset, for example, the participants are members of a big conference mostly working on different research topics that were located in different areas during the experiment due to the different sessions they attended, and few of them were Facebook friends (see the very sparse OSN graph compared to the DSN graph in Fig. 7). In the second dataset dealing with undergraduate students of a dormitory, on the contrary, many of the participants are Facebook friends as can be observed by the denser OSN graph in Fig. 6(b).

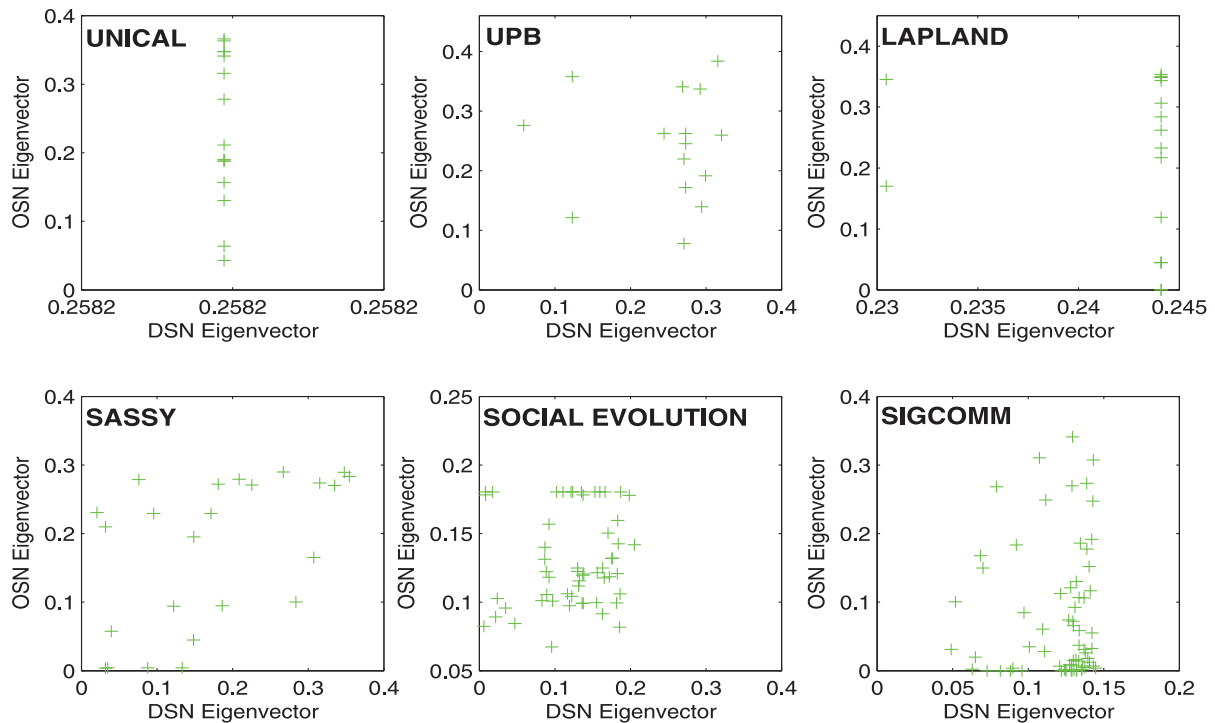


Fig. 11. Correlation between OSN and DSN eigenvector centrality values.

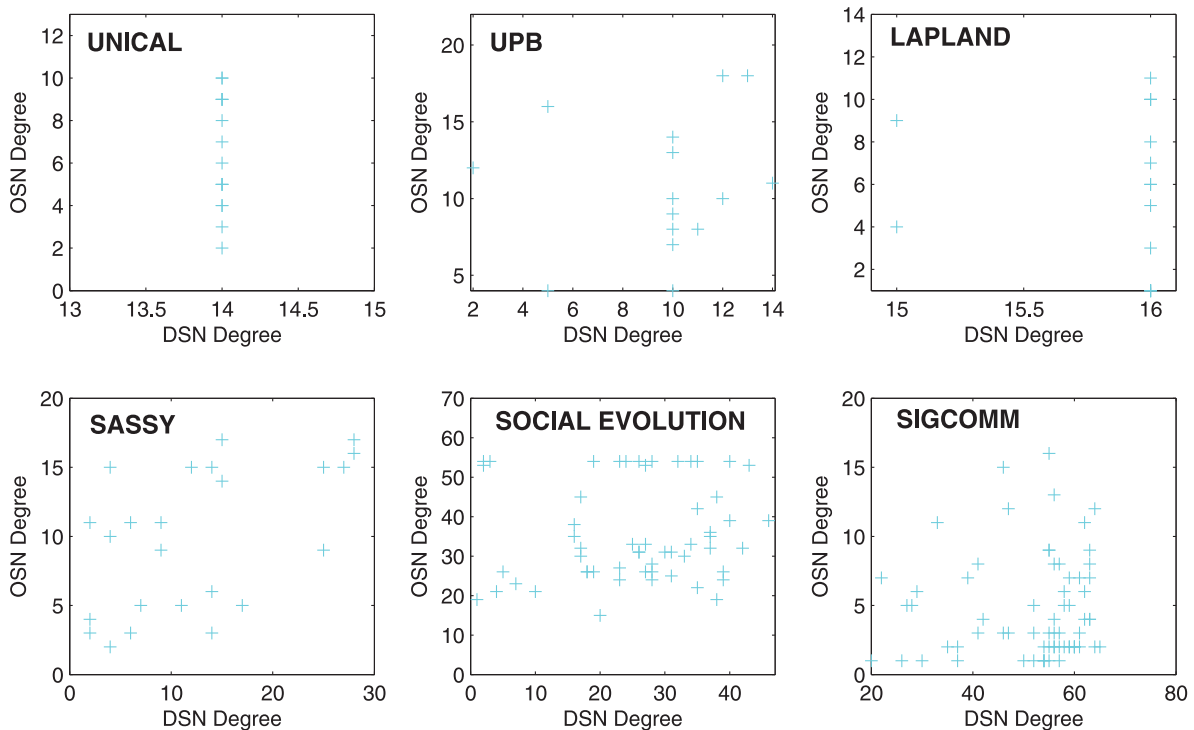


Fig. 12. Correlation between OSN and DSN degree centrality values.

However, OSN and DSN graphs are significantly different considering centrality. Here, the students involved have more virtual relationships than physical encounter opportunities as can be observed in Fig. 6.

The results of this analysis clearly show that the centralities of the Bluetooth-based social networks differ from those of the Facebook social networks. This happens because the co-location in a wireless environment implies both connections between nodes

carried by individuals having an interaction (i.e., people knowing each other and talking together) and connections between nodes that are just in proximity (e.g., strangers in the same room). In the Facebook case, on the contrary, a node has only connections that have been established intentionally. As such, the DSN and the OSN result in structures that are different and leading to different node centralities. From the results of this analysis, we conclude that in the design of opportunistic networking algorithms, this low

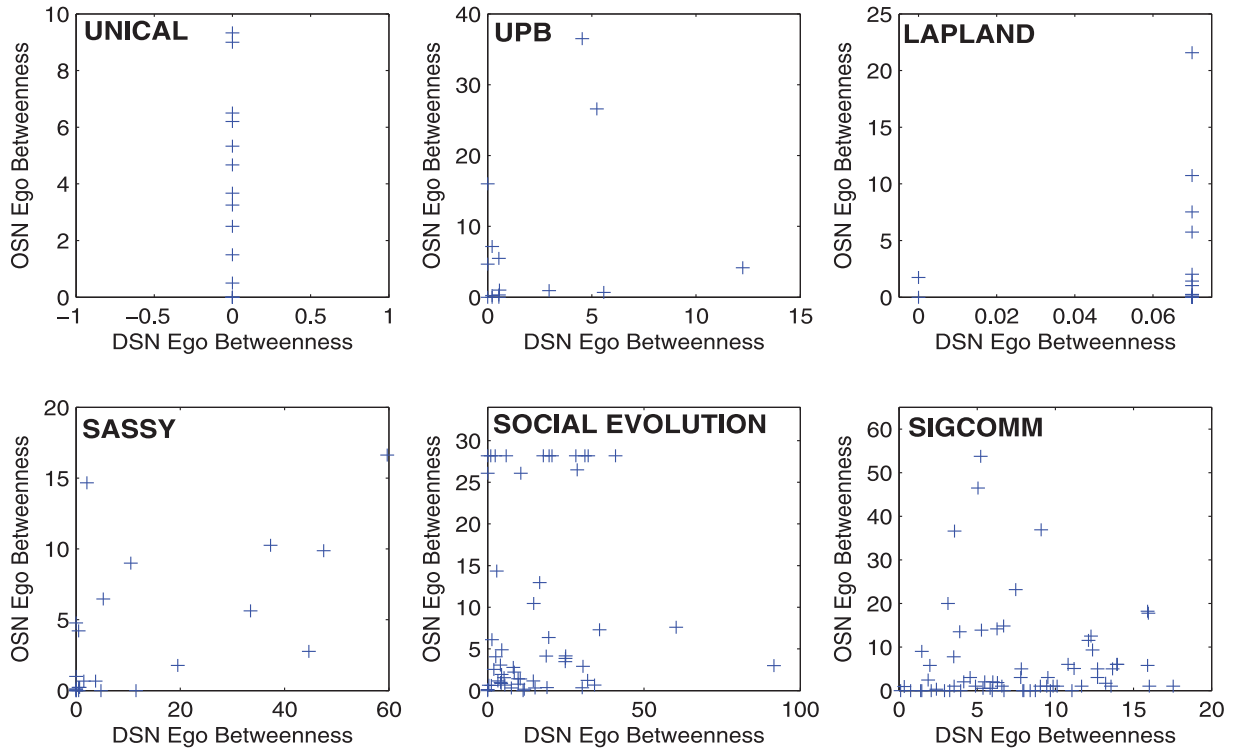


Fig. 13. Correlation between OSN and DSN ego betweenness centrality values.

Table 3  
Similarity (Normalized Mutual Information) between OSN and DSN communities.

		Experimental datasets					
		UNICAL	UPB	LAPLAND	SASSY	Social Evolution	SIGCOMM
NMI (OSN , DSN)	Louvain	0.3975	0.5738	0.3192	0.2521	0.0864	0.3466
	k-CLIQUE	0.5026	0.3849	0	0.1611	0	0.0103

correlation between online and offline behavior should be taken into account. As an example, when a social-based forwarding algorithm needs to initialize the social behavior of a node in the bootstrapping phase of the network, no information or partial social information is available because of the short history of contacts. In this case, the algorithm needs time to reconstruct the social behavior of a node in order to exploit this feature for improving message delivery. Hence, the node's online behavior could be considered. However, considering the results of our analysis, this node's online centrality should be conveniently leveraged with the available offline social centrality in order to find good forwarding paths and obtain improvements in message delivery.

## 7.2. Community similarity

To compute the similarity between communities belonging to the two network layers, we use the *normalized mutual information* [20] measure. Given two networks  $A$  and  $B$ , the normalized mutual information is defined as follows:

$$NMI(A, B) = \frac{-2 \sum_{i=1}^{c_A} \sum_{j=1}^{c_B} N_{ij} \log \left( \frac{N_{ij} N}{N_i N_j} \right)}{\sum_{i=1}^{c_A} N_i \log \left( \frac{N_i}{N} \right) + \sum_{j=1}^{c_B} N_j \log \left( \frac{N_j}{N} \right)} \quad (6)$$

where  $c_A$  is the number of communities in network  $A$ ,  $c_B$  is the number of communities in network  $B$ ,  $N_{ij}$  is the number of nodes in the intersection between community  $i$  from network  $A$  and community  $j$  from network  $B$ ,  $N$  is the total number of nodes, and  $N_i$  and  $N_j$  are the number of nodes in community  $i$  of network  $A$

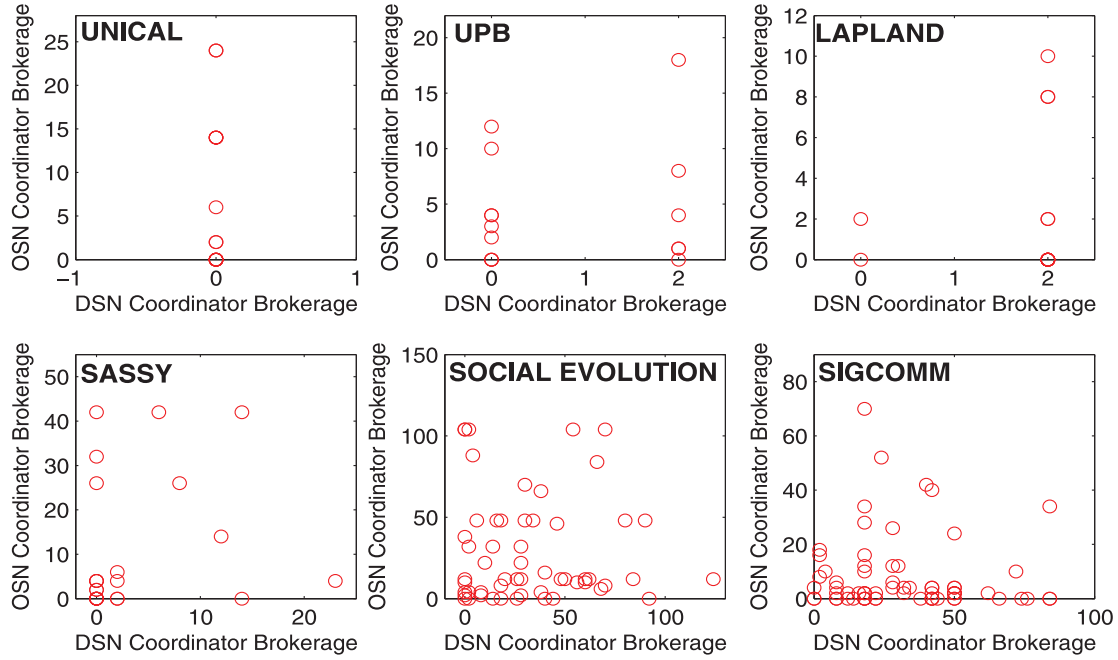
and community  $j$  of network  $B$ , respectively.  $NMI(A, B)$  ranges between 0 and 1, where different communities have a mutual information of 0 and identical communities have a mutual information of 1. The NMI quantifying the similarity between layers in terms of communities for each community detection method is shown in Table 3. UNICAL and UPB datasets, show a significant similarity degree in forming online and offline groups, both with Louvain (see, for example, OSN and DSN red communities in Fig. 3 containing both nodes 6, 22, 11, 13 and 10 and differing just for two nodes) and k-CLIQUE community detection methods, while, LAPLAND, SASSY and SIGCOMM datasets show an overall low similarity. Finally, Social Evolution shows OSN and DSN communities that are completely different. By focusing on the community detection method, we note that the two methods produce different NMI values. We thus conclude that the overlapping or non-overlapping communities assumption influences the similarity between online and offline communities for a given dataset. However, UNICAL, UPB and SASSY academic environments show near NMI values for the two community detection methods. This leads us to conclude that the three academic environments share a similar behavior even if the community detection methods are different. In general, by considering all the datasets, we can conclude that the structure of online and offline communities is different.

## 7.3. Brokerage

For evaluating nodes' brokerage roles, we computed the brokerage score corresponding to each role for each node in the DSN and

**Table 4**  
Correlation between OSN and DSN brokerage roles.

Experimental dataset	Correlation				
	Coordinator	Gatekeeper	Consultant	Liaison	Total Brokerage
<b>UPB</b>	0.1378	-0.1861	-0.1612	-	-0.0778
<b>LAPLAND</b>	0.0991	0.7619	-	-	0.0845
<b>SASSY</b>	0.1984	0.612	0.228	0.8036	0.6103
<b>SOCIAL EVOLUTION</b>	-0.038	0.0563	-0.0707	0.836	0.528
<b>SIGCOMM</b>	-0.0557	-0.0243	-0.0636	-0.0184	0.0199



**Fig. 14.** Correlation between OSN and DSN coordinator roles.

the OSN by grouping nodes with respect to Louvain community detection algorithm. Table 4 shows the correlation between OSN and DSN brokerage roles including also the *total brokerage score* computed as the total frequency of each role type. In Figs. 14, 15, 16, 17, 18, we also depict the relationship between DSN and OSN brokerage values. Overall, we found different behaviors for each dataset. Similarly to centrality analysis, we do not report the correlation values for UNICAL dataset since DSN brokerage values are 0. This absence of brokerage roles is basically due to UNICAL DSN complete structure (see Fig. 2(a)) and its resulting unique community detected. Also in other datasets like UPB and LAPLAND some roles are missing and we do not report the correlation values (see UPB liaison role and LAPLAND consultant and liaison roles). UPB and SIGCOMM show in general very different OSN and DSN roles, having negligible correlation values. On the contrary, SASSY shows a very strong correlation value for liaison role and strong correlation values for gatekeeper and total brokerage. Note that in the DSN and OSN graphs many nodes belonging to a certain community are connected with other node pairs belonging to distinct communities (liaison case) or a same community (gatekeeper case). Also Social Evolution shows for some roles an interesting similarity: liaison role has again a very strong correlation value and as a consequence, the total brokerage is characterized again by strong correlation. Finally, we observe that LAPLAND shows very strong correlation for DSN and OSN gatekeeper roles.

#### 7.4. Tie strength

After examining online and offline network centrality, communities and brokerage roles, we focused on analyzing strong ties. Specifically, we computed for each node pair within the two graph layers the total contact duration in terms of number of granularity intervals (i.e., using the dataset's granularity as time unit). Then, we ordered the node pairs for decreasing contact durations choosing the top-20 strong ties and analyzed the matchings between the found strong ties on the DSN and the Facebook friendships at the OSN layer for the same node pair. Figs. 19, 20, 21, 22, 23, 24, show that in most datasets, most of the strong ties correspond to Facebook friendships. Specifically, UNICAL, UPB, SASSY, Social Evolution, and SIGCOMM show 75%, 80%, 70%, 70% and 70% of matchings, respectively. Hence, differently from the other metrics and algorithms used for assessing the similarity between social network layers, the nodes' online and offline behaviors in terms of tie strength are common for many datasets. This result is interesting since by finding a good matching between the DSN strong ties and the links on the OSN layer, we are able to evaluate if a DSN link is a strong tie just considering the presence/absence of links on the OSN layer and thus avoiding the computation of contact durations.

## 8. Discussion

By proposing a novel methodology for analyzing data based on egocentric and sociocentric measures, we categorized some



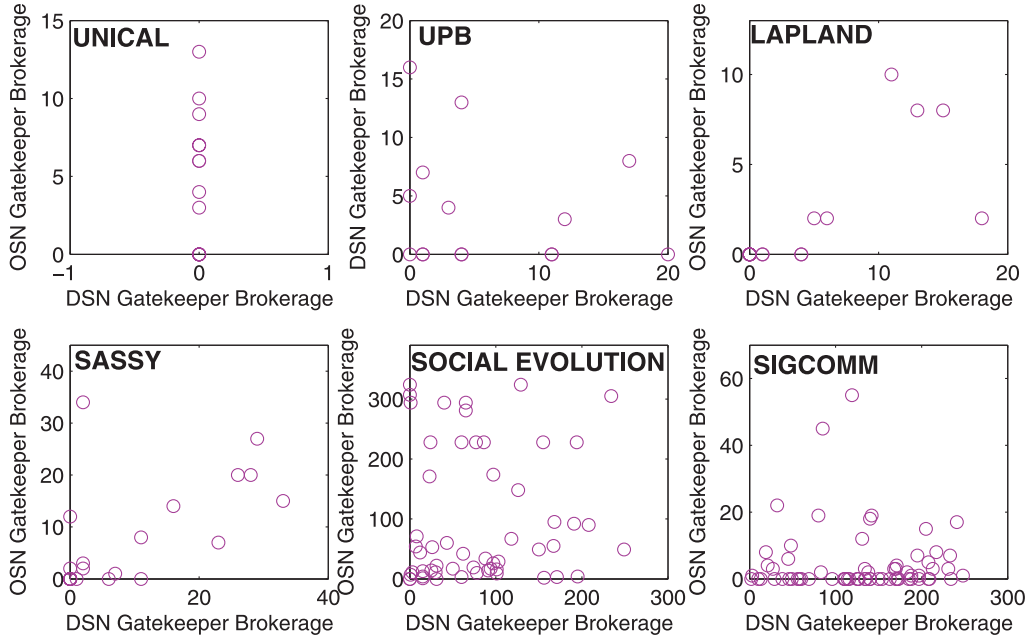


Fig. 15. Correlation between OSN and DSN gatekeeper brokerage roles.

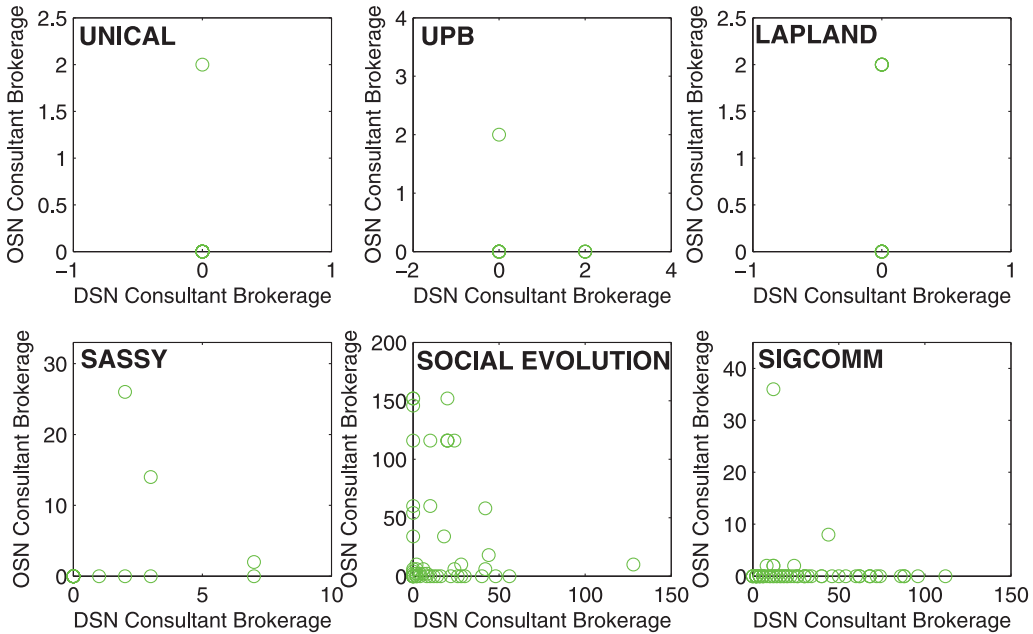


Fig. 16. Correlation between OSN and DSN consultant brokerage roles.

**Table 5**  
Segmentation of centrality correlation, community NMI, total brokerage correlation and percentage of strong ties values into several ranges for the assessment of similarity between OSN and DSN.

Similarity layer	1	2	3	4
<b>Similarity percentage range</b>	0–25%	25–50%	50–75%	75–100%
<b>Similarity degree</b>	Low (L)	Medium-low (ML)	Medium-high (MH)	High (H)

well-known measures in distinct approaches in order to have a broader view of the user social behavior. Previous works only exploited a subset of the measures we have chosen thus providing partial results. In this section, we summarize the result of the different analyses. This will allow the reader to have an overall clear idea of the social behavior of mobile opportunistic nodes in the different networking environments considered in this work, thus

providing final meaningful conclusions based on the datasets used. In Table 5, we show the similarity layers with the corresponding percentage ranges and degrees that we defined to provide a final assessment of similarity between OSN and DSN graphs. In particular, we considered four similarity layers, converting each result (centrality, NMI and brokerage) in percentage values corresponding to low, medium-low, medium-high and high similarity

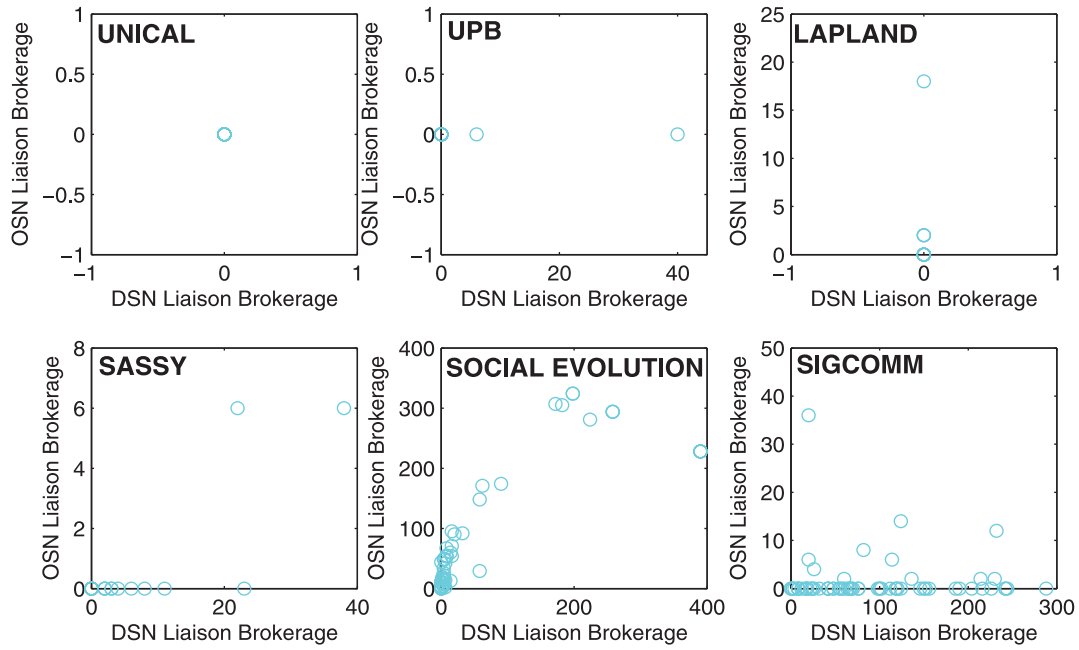


Fig. 17. Correlation between OSN and DSN liaison brokerage roles.

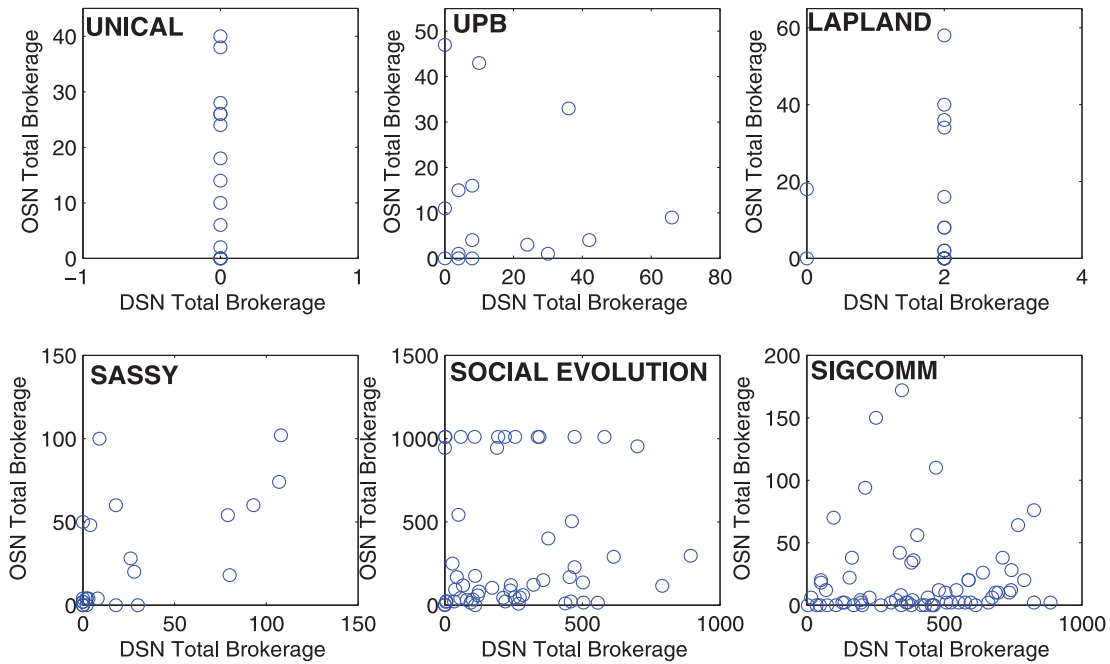


Fig. 18. Correlation between OSN and DSN total brokerage values.

Table 6

Summary of the similarity degree between OSN and DSN values according to betweenness (*Bet*), closeness (*Clo*), eigenvector centrality (*Eig*), Louvain method (*Lou*), k-CLIQUE method (*k-CLI*), degree (*Deg*), ego betweenness (*Ego Bet*), total brokerage (*Total Bro*) and tie strength (*Tie Str*).

Experimental dataset	Similarity									
	Bet	Clo	Eig	Lou	k-CLI	Deg	Ego Bet	Total Bro	Tie Str	
UNICAL	-	-	-	ML	MH	-	-	-	H	
UPB	L	L	L	MH	ML	L	ML	L	H	
LAPLAND	L	L	L	ML	L	L	L	L	ML	
SASSY	L	MH	MH	ML	L	MH	MH	L	MH	
SOCIAL EVOLUTION	L	L	L	L	L	L	L	MH	MH	
SIGCOMM	L	L	L	ML	L	L	L	MH	MH	

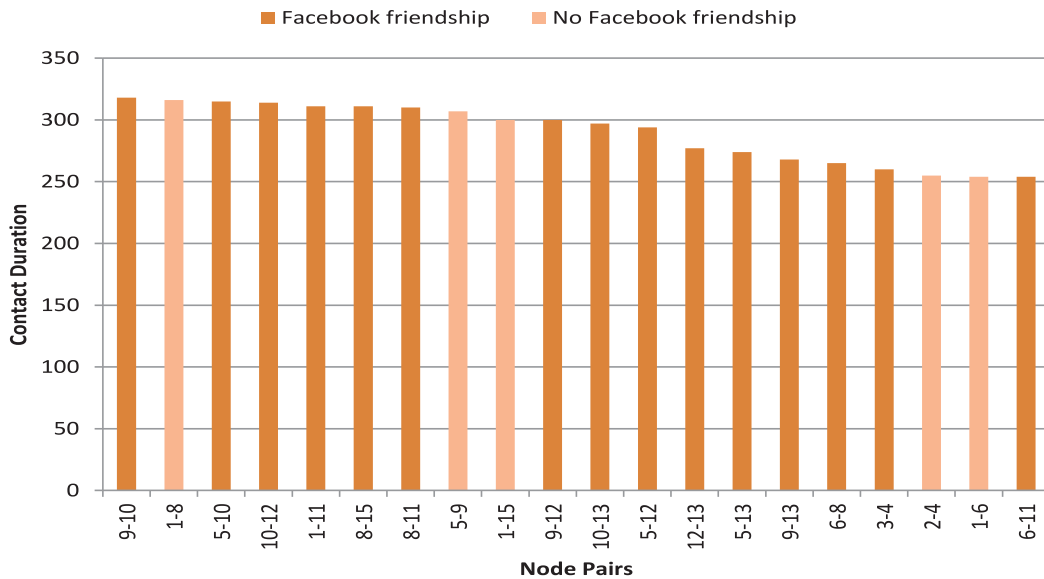


Fig. 19. UNICAL - Relationship between strong ties with high contact durations and Facebook friendship.

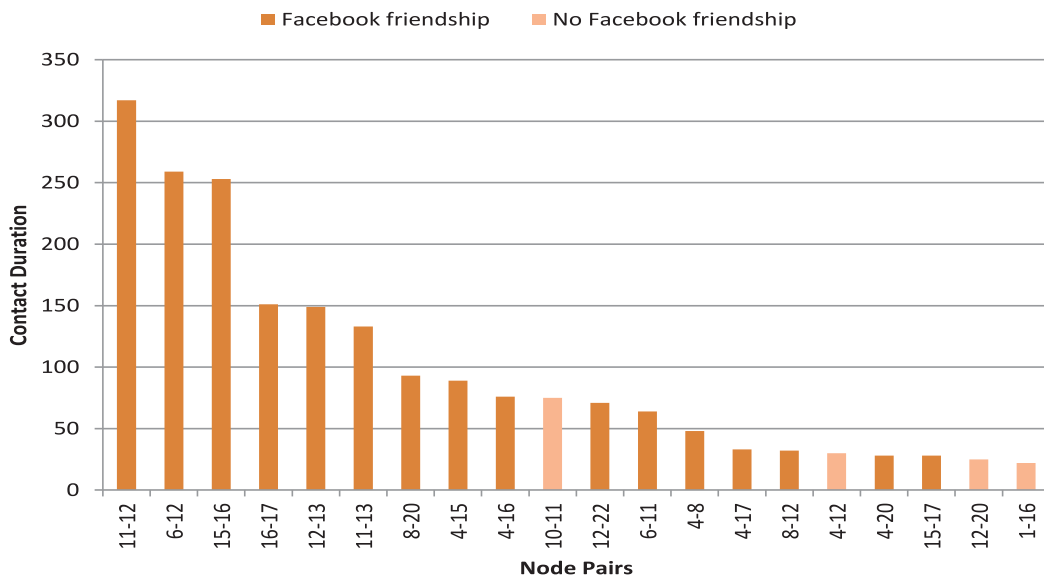


Fig. 20. UPB - Relationship between strong ties with high contact durations and Facebook friendship.

degrees. Table 6 shows a summary of the similarity degree between OSN and DSN values according to betweenness, closeness, eigenvector centrality, Louvain method, k-CLIQUE method, degree, ego betweenness, total brokerage and tie strength. As can be clearly noted, the social feature that results in a very significant similarity for five of the six datasets is DSN tie strength that is well predicted by OSN friendships. Even if some previous works highlighted that there can be a good matching between contact durations and friendships, this work offers a more complete view on this aspect, proving that on several datasets this feature is present.

## 9. Conclusions and future work

In this paper, we have presented a novel and detailed methodology for analyzing a set of real mobility traces for opportunistic networks using a multi-layer network approach. The aim of this study has been to better understand user social behavior in terms of egocentric and sociocentric behaviors that can be derived not only from mobility data (encounters' social network) but also from

the available additional information provided by the social network layer built on Facebook friendships. Our results have shown that online and offline social behavior computed in terms of centrality measures like betweenness, ego betweenness, closeness, degree and eigenvector centrality are not significantly correlated on most datasets. In other words, node popularity changes significantly on the online and offline social worlds. Also online and offline community structures are different. Analyzing the two-layer social network constructed on mobility data and Facebook friendships we have also shown that in some cases, online and offline brokerage roles show high similarity. However, the correlation between online and offline brokerage roles varies significantly from one dataset to another and it is not possible to extract a common trend with respect to this kind of similarity analysis. Finally, we have shown that in five of the six datasets considered, most of the strong ties in the social layer built on wireless encounters correspond to Facebook friendships.

Our results refer to an heterogeneous set of datasets covering different experimental environments (academic, conference, urban)

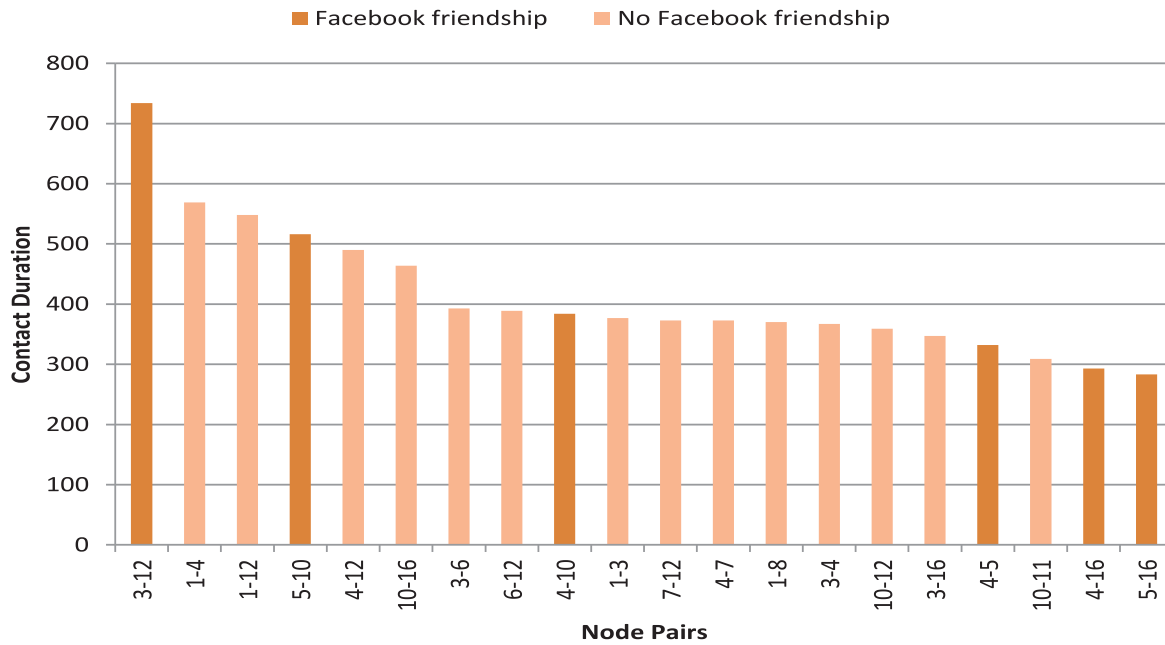


Fig. 21. LAPLAND - Relationship between strong ties with high contact durations and Facebook friendship.

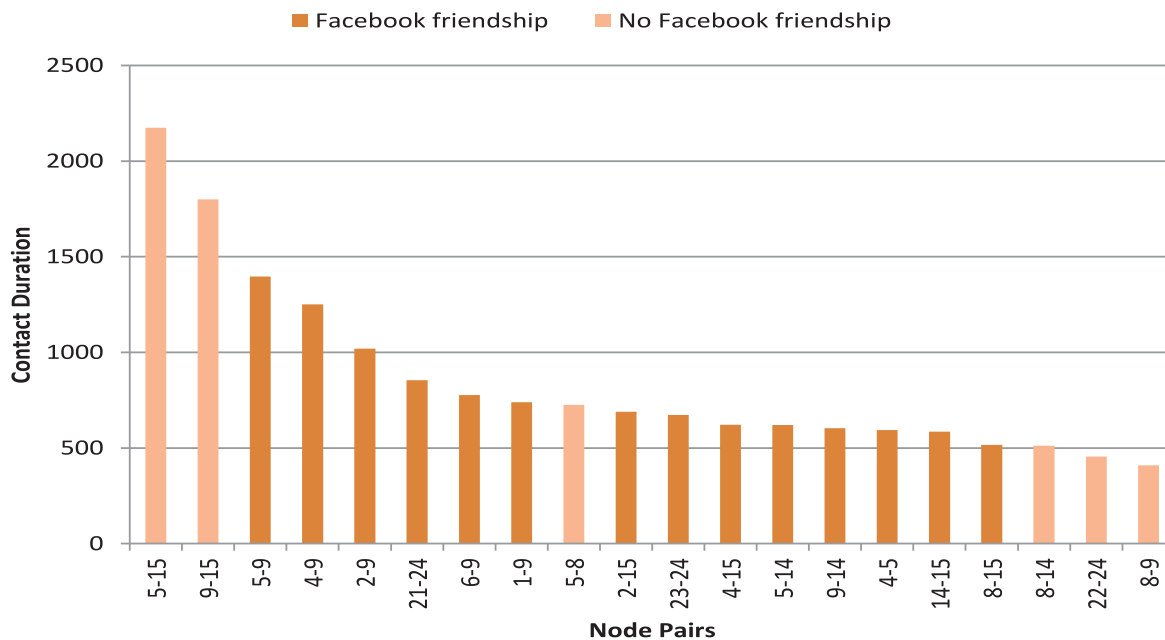


Fig. 22. SASSY - Relationship between strong ties with high contact durations and Facebook friendship.

with different mobility patterns, durations, number of nodes and Facebook friendship graphs. Choosing this set, our aim has been to analyze users' online and offline sociocentric and egocentric behaviors on social networks (specifically, the DSN and the OSN) extracted from the typical mobile social environments where opportunistic networking applications can be adopted as networking solution. Think, for example, to a city where running social collaborative monitoring and sensing, a conference where exploiting contextual information and sociality to provide recommendations on interesting events, or a university campus where running emergency social applications for launching SOS in case of terroristic attacks. In conclusion, we believe that our findings, being representative of several experimental environments, can be exploited

by the opportunistic networking research community when dealing with the social aspects of its target users. Having assessed that the network centralities and communities of a given user vary notably in his online and offline social worlds, in the design of future social algorithms, these features should be taken into account. For example, a social-based forwarding algorithm exploiting centrality and community as social metrics should properly leverage the online social information in the bootstrapping phase where the social information about the user's offline behavior is partial. On the contrary, the good matching between contact durations and Facebook friendships could be exploited, for example, for predicting strong DSN social ties just knowing if two users are Facebook friends or not. As such, if a forwarding algorithm exploits, for example, tie



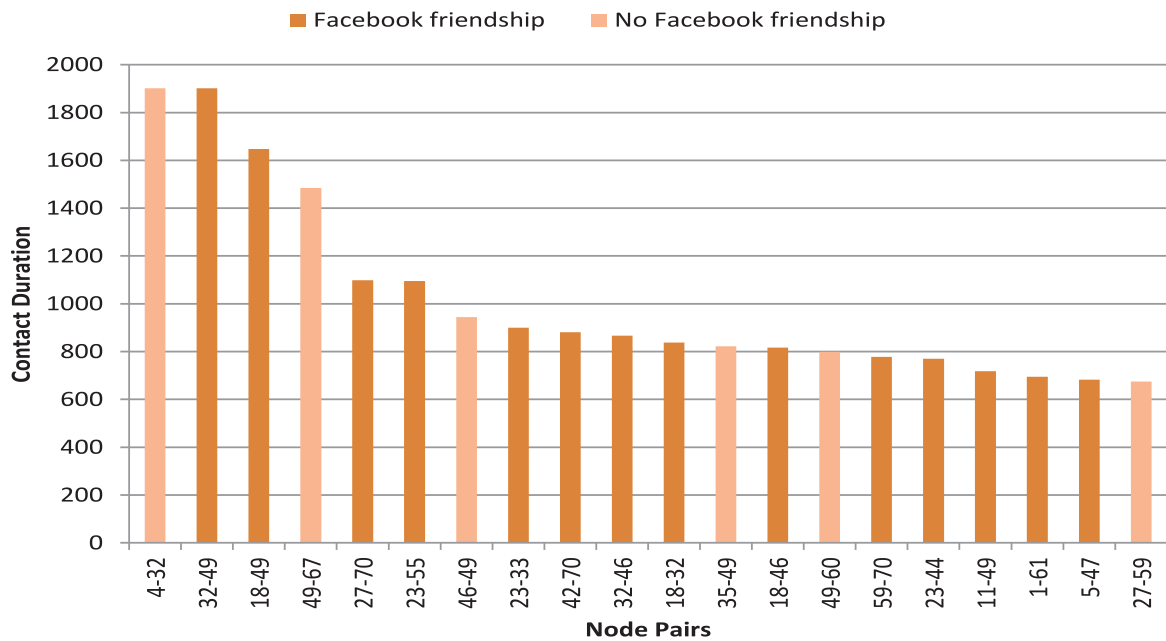


Fig. 23. Social Evolution - Relationship between strong ties with high contact durations and Facebook friendship.

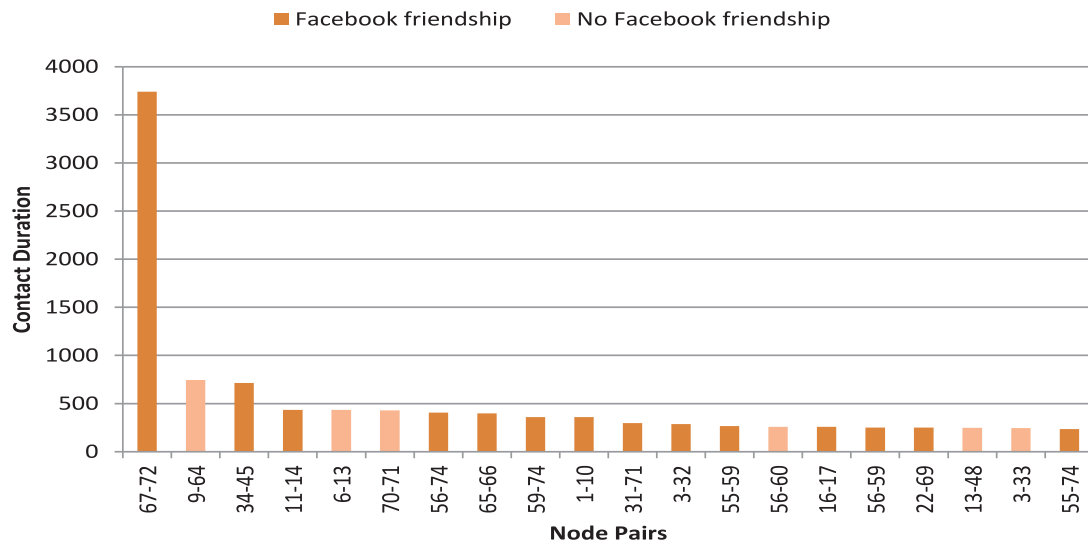


Fig. 24. SIGCOMM - Relationship between strong ties with high contact durations and Facebook friendship.

strength as social feature, the algorithm could avoid the computing of this metric on the history of the encounters by simply using the Facebook friendship information.

The results of this work, however, clearly need further investigation. The DSN model presented in this paper, for example, characterizes the entire experiment considering all the encounters observed between mobile devices without making differences between frequent and rare encounters and must be improved. Moreover, further investigation on larger datasets and other social dimensions may be interesting. As such, in the future, we will continue working on this research field including richer and larger network data containing also more than two social network layers and considering in greater detail the dynamics and the evolution of the social graph constructed on wireless encounters.

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