Do-it-yourself Local Wireless Networks: A Multidimensional Network Analysis of Mobile Node Social Aspects

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Abstract: The emerging paradigm of Do-it-yourself (DIY) networking is increasingly taking the attention of research community on DTNs, opportunistic networks and social networks since it allows the creation of local human-driven wireless networks outside the public Internet. Even when Internet is available, DIY networks may form an interesting alternative option for communication encouraging face-to-face interactions and more ambitious objectives such as e-participation and e-democracy. The aim of this paper is to analyze a set of mobility traces describing both local wireless interactions and online friendships in different networking environments in order to explore a fundamental aspect of these social-driven networks: node centrality. Since node centrality plays an important role in message forwarding, we propose a multi-layer network approach to the analysis of online and offline node centrality in DIY networks. Analyzing egocentric and sociocentric node centrality on the social network detected through wireless encounters and on the corresponding Facebook social network for 6 different real-world traces, we show that online and offline degree centralities are significantly correlated on most datasets. On the contrary, betweenness, closeness and eigenvector centralities show medium-low correlation values.

1 INTRODUCTION

Do-it-yourself (DIY) networks (Antoniadis et al., 2014) have been recently proposed new generation networks where a multitude of human-driven mobile devices can create local wireless networks outside the public Internet. In January 2014, 32 people with expertise in Delay Tolerant Networks (DTNs) (Fall, 2003) (De Rango et al., 2008) (De Rango et al., 2013a), opportunistic networks (Pelusi et al., 2006), human-computer interaction, community informatics, urban interaction design, ethnography, media studies, arts and design grouped together in Dagstuhl to discuss the use of such networks from an interdisciplinary perspective.[1] Considering the wide diffusion of today mobile devices (e.g. smartphones, tablets, etc.) and the impact their use has in the social life of every individual, the study of infastructureless 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.

DIY networks are intrinsically social-based due to human mobility and this feature is well suitable for exchanging information in an ad hoc manner. Hence, the analysis of sociality derived from wireless encounters becomes a fundamental aspect within these networks. Moreover, online social networks like Facebook and Twitter, for example, offer additional data concerning online social relationships between people, that can contribute to the analysis of the social behavior of the DIY network nodes.

Sociologists, anthropologists and psychologists have largely studied the social behavior of individuals using two different approaches: *egocentric* analysis and *sociocentric* analysis (Socievole and Marano, 2012). In the first approach, the analysis focuses on the individual, taking into account his personal network, in other words, nodes to which the individual is directly connected. In the second approach, the analysis focuses on large groups of people, quantifying internal relations and highlighting any interaction patterns that influence group dynamics. The aim of this work is to apply these two approaches to DIY net-

[1] http://www.dagstuhl.de/de/programm/kalender/semhp/?semnr=14042

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works modeled as *multi-layer social graphs* (Bródka and Kazienko, 2012) composed by two layers:

- a DSN (Detected Social Network) layer built on the wireless encounters between devices
- a OSN (Online Social Network) layer built on online social ties.

In particular, we analyze nodes' centrality (i.e., the contribution of network position to the importance of an individual in the network) and the communities formed by these nodes within the online and the offline contexts in order to understand the implications these two aspects have on DIY networking. Specifically, we study the similarity between the online and the offline worlds of DIY network users. With the study of complex networks, the notion of centrality (Freeman, 1978) became an important parameter to estimate the relevance of a node within a network. In a DIY network, the study of the most central nodes is an important aspect since it allows the identification of the nodes that may act as preferred relays for message forwarding. Also the community formed by nodes are able to drive message dissemination. The human-driven nature of these networks, in fact, makes network centrality and community important forwarding metrics as shown for example in (Hui et al., 2011) (De Rango and Monteverdi, 2012) (De Rango et al., 2013b) (Socievole et al., 2013) (Socievole and De Rango, 2015) (Socievole et al., 2015).

In this work, we present a detailed multi-layer social network analysis of 6 mobility traces for DIY networks covering several networking environments (academic, conference and urban scenarios) containing two layers of sociality: the DSN built on offline Bluetooth encounters and the OSN built on Facebook friendships. As a preliminary step, we focus on node centrality answering the challenging question whether online and offline node centralities are correlated and hence, the two social behaviors are similar. Then, we focus on communities, analyzing the online and offline groups.

The paper has been organized as follows. Section 2 provides background information on the analysis of online and offline sociality. Section 3 describes the datasets analyzed. Section 4 briefly details the social network model adopted. Section 5 describes the sociocentric and the egocentric approaches used to perform our analysis. Finally, in Section 6, we present our results and draw the main conclusions in Section 7.

2 RELATED WORKS

The relationship between human encounters and online social relations has been the focus of several researches in these last years. In (Hossmann et al., 2012), for example, two datasets of self-reported data about social, mobility and communication ties of online social network users (Facebook, Twitter and Gowalla) are analyzed showing that social ties are tightly coupled with mobility and also with communication. In (Arnaboldi et al., 2013), a detailed analysis of a Facebook dataset is presented proving 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, the authors present a number of linear models to predict virtual tie strength from a set of Facebook variables. In (Dunbar et al., 2015), the layered structure of the nodes within two Facebook datasets and a Twitter dataset is analyzed 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.

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 behavior of a mobile user within a DIY environment where many wireless encounters take place and those encounters will be used for exchange messages. Other recent works such as (Bigwood et al., 2008), (Ciobanu et al., 2012), (Gaito et al., 2012) and (Socievole and Marano, 2012), on the contrary, have focused on multi-layer structures where one of the several social dimensions/layers is extracted by node mobility. However, these works 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 DIY networks followed by a comprehensive clarification on human offline mobility and online sociality and the implications these social dimensions have on DIY networking algorithms. To this end, we consider a wider set of datasets and provide more meaningful conclusions with respect to the implications these results have on DIY networking.

3 MOBILITY TRACES

We consider the following 6 real-world datasets including the mobility data and the Facebook friendships of sets of mobile nodes:

- UNICAL (Caputo et al., 2015)
- UPB (Ciobanu and Dobre, 2012)
- LAPLAND (Yoneki and Abdesslem, 2009)
- SASSY (Bigwood et al., 2011)
- Social Evolution (Madan et al., 2012)
- SIGCOMM (Pietiläinen and Diot, 2012)

Most of these datasets are freely available in the CRAWDAD[2] repository. Table 1 summarizes the characteristics of the selected datasets in terms of wireless contacts data. 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. For each dataset, we focus on the week of wireless contacts having the highest contact durations. 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. The choice of links with the highest contact durations has been driven by the consideration that these links are more significative since they represent the best 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 (i.e. a high number of contacts) 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. 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.

[2]http://www.crawdad.org/

4 ANALYSIS METHODOLOGY

In this section, we describe the methodology used to analyze the data. First, we shortly describe how we model a multi-layer social network starting from mobility and Facebook data. Then, we describe the centrality metrics and the community detection methods used to analyze node sociality.

4.1 Multi-layer Social Network Model

We define a multi-layer social network as in (Magnani and Rossi, 2011), and consider unweighted graph layers since we have Facebook links (friendships) without weights. Using the participants' Facebook data in the form of a list with {#NODE ID1, #NODE ID2, #FRIENDSHIP FLAG} entries, where the friendship flag indicates if 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 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.

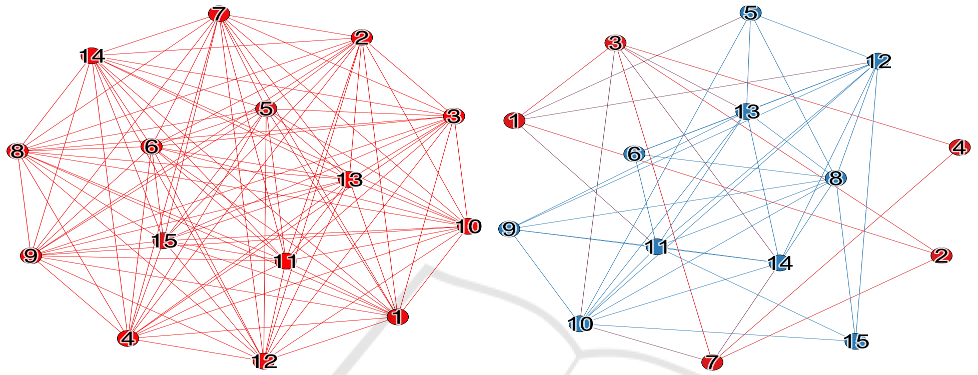
In Figs. 1 - 6, we depict the two-layer graph for each dataset using different colors for nodes belonging to different communities. Here, we used the Louvain community detection method (see Section 4.3).

4.2 Centrality Analysis

In this section, we describe the egocentric and sociocentric centrality metrics adopted in this work. Within each multi-layer network and for each centrality measure considered, we will compute 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 σ_X and σ_Y are the standard deviations. Correlation

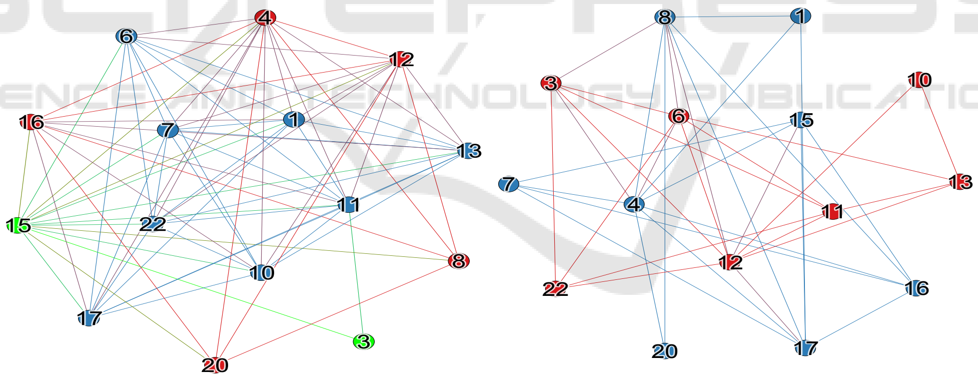
Table 1: Characteristics of wireless contacts data.

Experimental dataset	UNICAL	UPB	LAPLAND	SASSY	Social Evolution	SIGCOMM
Environment	Academic	Academic	Conference	Academic/Urban	Academic/Urban	Conference
Device type	Phone	Phone	I-mote	T-mote	Phone	Phone
Radio range	∼10 m	∼10 m	∼10 m	∼10 m	∼10 m	[10-20] m
Granularity	180 s	[5-30] min	[120-600] s	6.67 s	360 s	[120±10.24] s
Overall Duration	7 days	35 days	3 days	70 days	352 days	5 days
Analyzed week	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
Overall # of nodes	15	22	17	27	70	76
# of analyzed nodes	15	15	17	24	55	67



(a) (b)

Figure 1: UNICAL (a) DSN and (b) OSN graph layers.



(a) (b)

Figure 2: UPB (a) DSN and (b) OSN graph layers.

analysis aims at finding linear relationships between the same centrality measure over the two social layers.

4.2.1 Betweenness

Betweenness centrality (Freeman, 1977) measures the frequency with which a node is present on the shortest path. For node i, it is defined as:

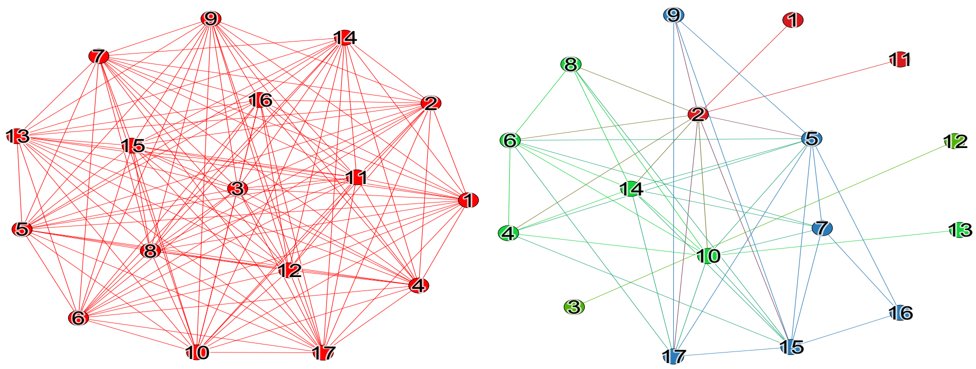
$$C_b(i) = \sum_{i \neq j \neq k}^{N} \frac{g_{jk}(i)}{g_{jk}} \qquad (1)$$

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.

4.2.2 Closeness

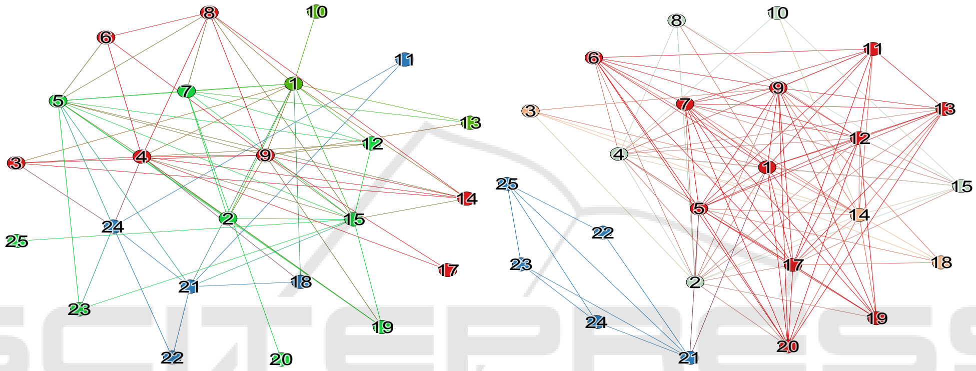
Closeness centrality (Sabidussi, 1966) is defined as the inverse of the sum of the shortest paths between a node towards each other node in the network:

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



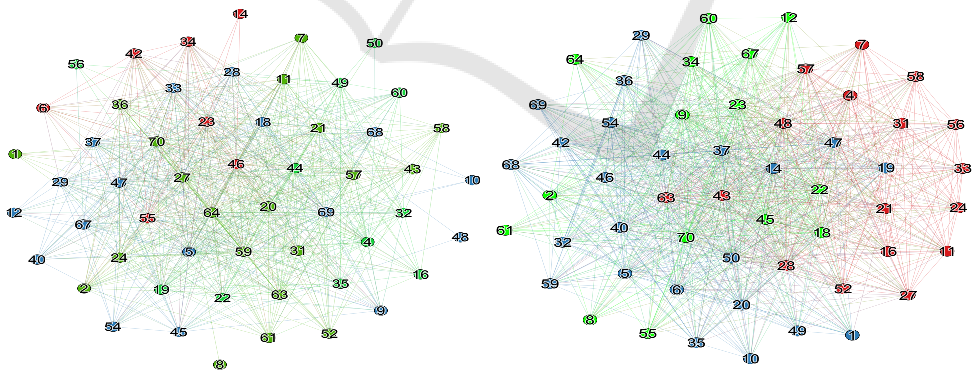
(a) (b)

Figure 3: LAPLAND (a) DSN and (b) OSN graph layers.



(a) (b)

Figure 4: SASSY (a) DSN and (b) OSN graph layers.



(a) (b)

Figure 5: Social Evolution (a) DSN and (b) OSN graph layers.

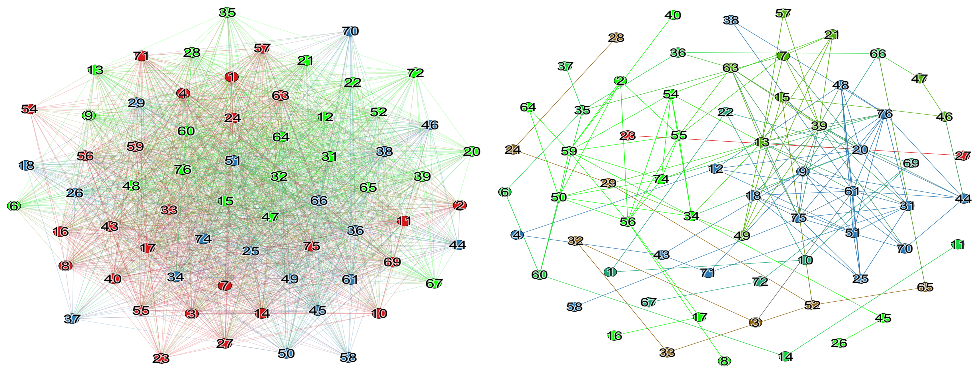
where $d(i,j)$ is the weighted shortest path from the reference node i to each node in the network.

4.2.3 Eigenvector

For eigenvector centrality (Bonacich, 1972), 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 defined as:

$$C_e(i) = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij} C_e(j) \quad (3)$$

where λ is the largest eigenvalue.



(a) (b)

Figure 6: SIGCOMM (a) DSN and (b) OSN graph layers.

4.2.4 Degree

Degree centrality (Freeman, 1978) counts the number of connections a node has towards its neighboring nodes. For a node i, it is defined as:

$$C_d(i) = \sum_{j}^{N} a_{ij} \tag{4}$$

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

4.3 Ego Betweenness

Ego betweenness centrality is computed considering just the ego network of a node. Given the adjacency matrix A, $A^2_{i,j}$ includes 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, while the sum of the reciprocal of the entries gives the ego betweenness.

4.4 Community Detection

To compute the similarity between communities belonging to two network layers, we use the *normalized mutual information* (Danon et al., 2005) measure. Given two networks A and B, the normalized mutual information is defined as follows:

$$NMI(A,B) = \frac{-2\sum_{i=1}^{c_A}\sum_{j=1}^{c_B} N_{ij}\log\left(\frac{N_{ij}N}{N_{i.}N_{.j}}\right)}{\sum_{i=1}^{c_A} N_{i.}\log\left(\frac{N_{i.}}{N}\right) + \sum_{j=1}^{c_B} N_{.j}\log\left(\frac{N_{.j}}{N}\right)} \tag{5}$$

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 community detection methods used in this work are described in the following subsections.

4.4.1 Louvain

Louvain method (Blondel et al., 2008) 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.

4.4.2 k-CLIQUE

This method, also known as Clique Percolation Method (CPM) (Palla et al., 2005), 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.

5 RESULTS

Table 2 shows the correlation values obtained for the centrality analysis. We do not report the correlation values for UNICAL dataset since the DSN centrality values are 0 for betweenness and ego betweenness and constant for the other centrality measures. This results in covariance and standard deviations product between OSN and DSN centrality that are 0. In the case of betweenness and ego betweennes, we can observe from Fig. 1(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. 1(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. 2). 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 betwenness (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 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 where they attended, and few of them were Facebook friends (see the very sparse OSN graph compared to the DSN graph in Fig. 6). 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. 5(b). 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. 5.

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 DIY networking algorithms, this low 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

Table 2: Correlation between OSN and DSN centrality measures.

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

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

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.

In Table 3, we show the NMI quantifying the similarity between layers in terms of communities for each community detection method. 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. 2 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.

6 CONCLUSIONS

In this paper, we have focused on the emerging concept of DIY networking, analyzing a set of real mobility traces for DIY networks using a multi-layer network approach. The aim of this initial study has been to better understand user social behavior in terms of centrality and communities not only focusing on the social network layer that can be built on mobility data, but also on the available additional information provided by the social network layer built on Facebook friendships. Our results show that network centralities and communities vary notably in the online and the offline social world. As such, in the design of future social-based algorithms for DIY networks, these features should be taken into account. For future works, we are planning to further analyze user behavior in multi-layer DIY networks focusing on other social aspects.

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