Subjective versus objective captured Social Networks: Comparing standard self-report questionnaire data with observational RFID technology data

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Abstract

Social network analysis provides insights into human social phenomena. Commonly, social network data is captured via surveys or newly via technical devices. In the described study, we combine subjective survey data with objective data from RFID tags in order to completely picture the closed network of an entire freshman students' cohort. RFID tags are small proximity sensing devices using radio frequency identification technology and can be worn as badges. Results indicate that the information of the two different data sources is similar but not entirely equal. Rather, they picture unique but complementing information and both should be considered in social network research.

Introduction

Social network analysis has become an important research perspective within various disciplines [4][14]. In particular, it enlarges the focus on individual attributes with the focus on interrelationships of people, which are present by nature as the individual is not living in isolation [6]. It offers the great possibility to study similarities, social relations, interactions, or flows between people [5], such as selection and influence processes [13]. For example, these processes are accountable for the formation of homogeneous subgroups in diverse teams, which may lead to subgroup polarization, increased conflicts and reduced performance [11]. The most common source of social network data is given by self reports [3]. However, some effort is done to examine social network patterns by means of observational data from sources such as emails [12], Bluetooth-enabled mobile phones [9], or Radio Frequency Identification (RFID) devices [1][3]. So far, the combination of both sources is used rather seldom, although this is promising for gaining a broader and more reliable insight into both, actually happened interaction and the emotional emphasis in this. Yet, Eagle et al. [9] combined and compared standard self-report survey data with observational data from Bluetooth mobile phones both regarding inter-individual proximity and found the information to be distinct and overlapping. Likewise, the goal of our study was to combine different sources of network data, in order to achieve an entire picture of social interaction including a comprehensive image of the occurred interaction and the underlying emotional weighting of the links between the examined actors. We followed a cohort of psychology freshman students during their first week at university and collected two types of network data (person-to-person interaction) using questionnaires and active Radio Frequency Identification (RFID) tags with proximity sensing. Hereafter, we will refer to data that was captured via surveys as 'subjective data' as opposed to behavioural data that is captured via RFID technology as 'objective data'.

Methods

Setting. The first week of freshman students at the examined degree program is usually organized as an introductory course before the regular courses. It was arranged over five days with a total attendance time of about twenty-five hours. The aim of the introductory week is to provide the newcomers with relevant information about the university, the degree program, and its contents as well as to introduce the professors and other lecturers, the departments/ chairs, and important committees. Moreover, this week as the first required course of the degree program offers a major opportunity to become acquainted with fellow students. In the year of data collection, three-fourths of the time (equals nineteen hours spread over five days) the week's events took place in a separate accommodation, which was suitable for the intended data collection and technically equipped for the purpose.

Sample. Seventy-eight students attended the introductory freshman's week (79.5% female). Sixty-seven of them belong to the new cohort of the psychology degree program. The remaining eleven students already studied two semesters at a different university and attended the week in order to get in easier. Those students were graded into the upper semester after the introductory course.

RFID technology. We employ RFID from the SocioPatterns consortium[1]. Worn as badges, RFID tags are able to identify face-to-face contacts by detecting other tags nearby. Criteria for contacts to be detected are (1) that the tags are facing one another (2) that they have a maximal distance of up to 1.5 meters, and (3) that this condition lasts for at least twenty seconds (see Figure 1).

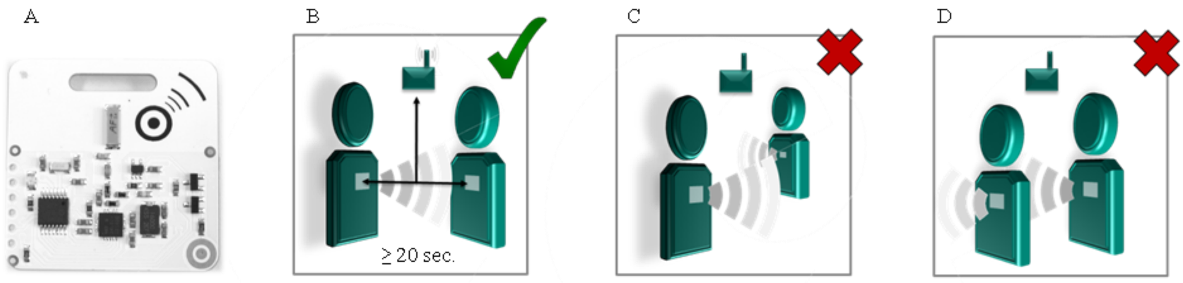

Figure 1. RFID-technology. (A) RFID-tag; (B) Accurate position of two RFID-tags to be detected as a contact; (C) Inaccurate position of two tags as they are not close enough to be detected as a contact; (D) inaccurate position of two tags as they are not facing one another.

When meeting these criteria, the tags send specific signals to RFID readers that are installed at fixed positions evenly spread all over the accommodation. The signals contain the unique ID of the sending tag, the ID of the detected tag as well as the time stamp of the contact between both tags. The readers then forward the signals to a server, where the information is stored and aggregated into a database, see Table 1 for a fictitious example. For detailed information about the functionality of RFID tags, see Barrat et al. [3]. With respect to the accuracy of the applied RFID tags, we refer to the results of Cattuto et al. [7] who confirm, that if the tags are worn on the chest, then very few false positive contacts are observed. In addition, according to Cattuto et al. [7] face-to-face proximity can be observed with a probability of over 99% using the interval of 20 seconds for a minimal contact duration.

Table 1. Data structure of RFID signals stored into a database with fictitious example data. SCR = sending RFID tag, DST = detected RFID tag, TSFROM = date and time the contact began, TSTILL= date and time the contact ended.

SCR	DST	TSFROM	TSTILL
1051	2987	21/10/2013 11:25:41	21/10/2013 11:26:51
1051	1652	21/10/2013 14:56:24	21/10/2013 15:01:04
1051	1652	22/10/2013 16:56:27	22/10/2013 16:58:57
[...]	[...]	[...]	[...]

Procedure. We asked each student to wear an active RFID tag while they were staying in the prepared accommodation. We combined the RFID tags with name badges to avoid multiple discomfort and to ensure unambiguous assignment during the five days of data collection. At the end of each day we requested the bagdes back so we could prepare them for the next day. In sum, we recieved 16780 data rows equal to the example in Table 1 via the RFID technology. These data include all detected contacts during the activities that happened

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

within the accomodation, also including breaks and intervening periods. Moreover, the near surrounded areas such as smoking areas, the garden and the outer entrance area could be reached as well.

At the very end of the week, we captured the egocentric communication networks of the student among their fellows via questionnaires. We asked the students to select those fellow students on an exhaustive name list, with whom they interacted much during the introductory course. We transferred these data into a common network matrix with all names in the rows (respondent) and columns (persons to be selected), filled with zeros ('0'=not selected) and ones ('1'=selected).

Comparison of subjective and objective captured networks. We conducted two different analyses to compare the subjective and the objective captured networks. Both sorts of data were present for seventy-seven of the seventy-eight students. First, we examined the extent to which subjective and objective network data are matching. For this purpose, we converted the objective dataset into a format that is comparable with the subjective one. Therefore, we needed to reduce information. That is, we aggregated the contact duration and frequency over the whole week for each tag couple. We defined a contact to be meaningful (identical to the '1' in the subjective data matrix), when it was frequent above-average or durable above-average, respectively. The average duration of all contacts was 00:13:19 (hh:mm:ss), the average frequency of all contacts was 5.17 times. All contacts between pairs of tags beyond these cut-off values were coded '1', the rest was coded '0', separately for duration and frequency. Second, to get a more detailed insight into the differences between the diverse captured networks, we compared specific network measures using all existing information of the objective networks. For the subjective network we considered the directed network, which contains information about the direction of a tie. Furthermore, we constructed an undirected network, neglecting the tie information about who is sender and receiver, analogously to the objective network. On the one hand, we descriptively compared overall network measures such as the average degree of a node (number of direct links to others), the diameter (max. distance between two actors), and the density (ratio of the number of existing links to the number of possible links). On the other hand, we correlated the values of the individual network measures degree (number of direct links to others), betweenness (number of shortest paths from all actors to all others that pass through that actor), and eigenvector-centrality (centrality of an actor weighted by the centralities of linked others) of the diversely captured networks.

Results

We tested the matching of the subjective and the reduced objective network data by computing Cohen's Kappa [8]. Typically, Cohen's Kappa is used to assess the average agreement of two observers for example concerning their ratings of behavior [2]. In this case, we transfer this common statistic to our purposes as we treat the subjective and the objective data sources as two independent observers (3239 comparable ratings). Cohen's Kappa yielded a value of κ =.507 (subj. versus $\text{obj.}_{\text{duration}}$; 84.8% agreement) and κ=.485 (subj. versus $\text{obj.}_{\text{frequency}}$; 83.5% agreement), suggesting a fair congruence [10]. Moreover, we find that the overall network parameters differ according to their source (see Table 2 left).

Table 2: Overall network parameters of the different data sources. #Nodes = Network size (number of actors); #Edges = Number of links; Dia = Max. distance; (Avg.) Degree = (Average) number of direct links; Density = Ratio of #existing links to #possible links; Betweenness = paths passing through; Eigenv.-centrality=weighted centrality; Spearman's rank order correlation coefficients: *p < .05. **p < .01, two-tailed.

	Overall network measures					Corr. of individual network measures		
	#Nodes	**#Edges**	**Dia**	**Avg. Degree**	**Density**	**Degree**	**Between -ness**	**Eigenv.-centrality**
objective	77	1622	3	42.13	0.55		objective	
subjective $_{\text{directed}}$	77	715	5	9.29	0.12	.281*	.333**	.262*
subjective $_{\text{undirected}}$	77	483	4	12.54	0.17	.267*	.265*	.272*

Naturally, the size of the networks (number of nodes) is the same. However, compared to the subjective network the number of connections, diameter, the average degree and the density of the objective network are rather different. We obtain a rather large deviation concerning the average degree of a node. Furthermore, the objective network is much denser than the subjective one. This indicates that the objective network covers more interactions during the observed time. On the individual level, we find significant but weak positive correlations of the subjective and the objective network measures (see Table 2 right). This indicates that the information of the two data sources is to a certain extent alike, but there is a substantial amount of uniqueness in the information of the diverse data sources.

Discussion

Results indicate that objective and subjective captured networks do not picture entirely the same, but can complement each other with respect to various aspects. Objective networks (RFID data) include all the contacts that took place in the equipped accommodation, which were not taken into account by the subjects in total when they filled the surveys. In contrast, the subjective networks (survey data) also contain interaction during the rest of the introductory week, covering places and times which could not be reached with the RFID technology. Simultaneously, the subjective data may be biased by several but relevant cognitive filters, for example by memory effects and emotional emphases. Our results suggest the complement use of both, self-reports and RFID technology. Advantages of this approach are formidable. First, it is possible to capture almost all interactions during the time of interest, no matter if the actors know each others names or even remember that they interacted with each other and no matter if the technical devices detected the interaction. Second, it is anyway possible to simoultaneoausly capture the subjective weighting of an interaction. That is for example, even if a pair of actors actually did not interact as much/long as another pair of actors, the interaction could be more meaningful to them, may resulting from the conversation's relevance or their interpersonal sympathy. Resultant, when it comes to capture the interaction network of large or newly composed groups and the researchers are interested in both a picture of actually happened interaction and the emotional emphasis of links between actors, both measures should be used. The use of each alone is to be considered in special situations of interest. When the group is very small, actors know each other and the emotional emphasis is of interest, subjective measures should be implemented. Contradictory, objective measures should be implemented when people do not know each other at all and the group is very large.

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