The SocioMetric Badges Corpus: A Multilevel Behavioral Dataset for Social Behavior in Complex Organizations

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***Abstract*—This paper presents the SocioMetric Badges Corpus, a new corpus for social interaction studies collected during a 6 weeks contiguous period in a research institution, monitoring the activity of 53 people. The design of the corpus was inspired by the need to provide researchers and practitioners with: a) raw digital trace data that could be used to directly address the task of investigating, reconstructing and predicting people's actual social behavior in complex organizations; b) information about participants' individual characteristics (e.g., personality traits), along with c) data concerning the general social context (e.g., participants' social networks) and the specific situations they find themselves in.**

I. Introduction

Studying organizational behavior over extensive periods of time has long been a challenge in social science [1]. Human observers have been employed in the past, but their observations are subjective and it is difficult for them to remain unobtrusive in an organizational environment. In addition, employing a large number of these observers for more than a short period of time is prohibitive in terms of costs. Surveys have been used extensively, but these too suffer from subjectivity and memory effects [15].

To mitigate some of these problems, e-mail, blogs, wikis, and more generally electronic communication have recently been employed to examine relationship structures (i.e. social network structure) [1]. However, while digital communication is important in the modern workplace, face-to-face interaction still represents a large and important share of organizational communication, information exchange, socialization and informal coordination [29].

Until recently, the prevalence of data from electronic communication (or any other systems exploited by people) was justified by the difficulties encountered in the collection of data concerning face-to-face communication at the same level of granularity as electronic communication. The increasing diffusion of devices with the capability of pervasive and ubiquitous sensing promises to radically change the picture and to allow for addressing face to face communication as efficiently, and with the same granularity, as obtained through electronic communication data.

Social sciences are currently being transformed by these possibilities and Computational Social Science is emerging as a new way to study and predict social behavior [17]. For this new trend to consolidate, common practices, approaches and tools are needed that permit easy capitalization on the results achieved, to quickly circulate new techniques and approaches across the community and to facilitate comparisons and benchmarking. As in many similar cases, sharable data sets are an essential ingredient of the picture. Data sets and corpora play the indispensable role of permitting extensive comparisons across approaches and techniques and of stimulating and enabling the tackling of new phenomena. This paper contributes to these goals by presenting the SocioMetric Badges Corpus, a new corpus for social interaction studies collected during a 6 weeks continuous period in a research institution and monitoring the activity of 53 people.

The design of the corpus was inspired by the need to provide researchers and practitioners with: a) raw digital trace data that could be used to directly address the task of investigating, reconstructing and predicting people's actual social behavior in complex organizations; b) information about participants' individual characteristics (e.g., personality traits), along with c) data concerning the general social context (e.g., participants' social networks) and the specific situations they find themselves in. Depending on perspective and intent of the researcher, data of type (b) and (c) can help in explaining, predicting and/or discovering relevant behaviors abstracted away from data of type (a), or they can play the role of the investigation target and provide the ground truth for attempts at automatically reconstruct individual traits and states from digital trace data.

In addressing the choice of the wearable device to use, we were guided by the requirement of achieving a multi-scale view of social interactions, from co-presence in a place (squares, buildings, rooms, etc.) to face-to-face proximity of individuals.

At present, Bluetooth and Wi-Fi networks allow the collection of data on specific structural and temporal aspects of social interaction [8], offering ways to approximate social interaction as spatial proximity (e.g., through GPS) or as the co-location of wearable devices, e.g., by means of Bluetooth hits [19], [7]. These means, however, do not always yield good proxies to the social interactions occurring between the individuals carrying the devices. Mobile phone traces suffer the same problem: they can be used to model human mobility [11] with the great advantage of easily scaling up to millions of individuals; they too, however, offer only rough approximations to social interaction in terms of spatial co-location.

For our data collection we resorted to the SocioMetric Badges, wearable sensors able to provide information about: (i) human movement, (ii) prosodic speech features (rather than raw audio), (iii) indoor localization, (iv) proximity to other individuals, and (v) face-to-face interactions [20]. The continuous (accelerometer, audio) and semi-continuous (e.g. infrared, Bluetooth) recording capabilities of the multiple sensors embedded in the SocioMetric Badges[1] make it possible to collect multiplex datasets, spanning over multiple dimensions, and provide a good match for many of the requirements discussed above. Up to now, SocioMetric Badges have been used in several studies to capture face-to-face communication patterns, investigate the relationship among individuals, collective behavior and performance outcomes, such as productivity and job satisfaction [20], [30].

Turning to the personal and contextual information collected, we targeted both stable and transient aspects: (i) *Stable and enduring individual traits (personality, dispositional affectivity and dispositional loneliness)*. These dimensions are expected to be among the (causal) antecedents of people's actual behaviors and therefore to have a good predictive value for them. They were collected by means of standard questionnaires; (ii) *The enduring social ties each individual is involved in and the social networks he/she is part of*. This information was also collected by means of questionnaires; (iii) *The transient states concerning personality, affectivity, creativity and productivity the person goes through in his/her daily life at work*. This information was collected by means of an experience sampling methodology; (iv) *Descriptions of the situations the person was in*. Provided by the person him/herself by means, again, of experience sampling.

The resulting data set comprises different types of data (digital traces as well as participant-provided assessments of personal traits, states and contextual aspects; data concerning social exchanges through electronic means and data about face-to-face interaction) allowing for a multilayer view of social interaction. It can be used to address many different phenomena ranging from the dynamics of personality and affective states, satisfaction and productivity at work, up to the formation and evolution of social networks, as well as to facilitate the integration of the perspective and tools of social and computational sciences.

[1] www.sociometricsolutions.com

II. Collection Methodology

Recruitment

A total number of fifty-three employees of a research center located in northern Italy were recruited on a voluntary basis to participate in the 6-weeks long study. During introductory meetings, they were provided with detailed information about: the purpose of the study; the data treatment and privacy enforcement strategies adopted; the devices they would be using and the measurements they provide. All participants signed an informed consent form approved by the Ethical Committee of Ca' Foscari University of Venice.

Forty-six out of the fifty-three participants were researchers in computer science belonging to four distinct research groups; the remaining seven participants were part of the full-time IT support staff. Eighty-nine per cent of the participants were male, with a mean age of 36.83 (SD=8.61) years and an average tenure in their current job of 7.48 (SD=6.75) years.

Each participant was assigned a unique ID and all related data were anonymized using these IDs.

Study Design

Stage 1 Before starting wearing the SocioMetric Badges, participants were given one week to complete an extended initial survey consisting of four sections addressing: (i) personality traits, (ii) dispositional affectivity, (iii) dispositional loneliness, (iv) network-ties at workplace.

Stage 2 During this six week period participants wore the SocioMetric Badges; putting it on at the time they entered the institution's premises and taking it off only when leaving. Issues concerning device maintenance - e.g., battery charging, data downloading, etc. - were taken care of by the study's staff. During this stage, an Experience Sampling Methodology (ESM) was employed to collect information about transient psychological states (personality, affectivity, perceived productivity) and situational aspects. A similar procedure of experience sampling strategy was adopted by [14] and [13] in social psychology studies. Participants completed a short Internet-based survey three times a day. Links to the surveys were automatically administered via email at fixed times and users were granted a temporal window of 2.5 hours to fill the survey before its expiration. Participants were asked to confirm their presence in the institute during the 30 minutes before starting the questionnaire; only if confirmed, their responses would be included in the database.

The experience sampling questionnaire included (i) BIG5 personality scale; (ii) fifteen items concerning affective states, loneliness and two basic emotions (anger and frustration); (iii) a single-item measure of self-perceived creativity and a single-item measure of self-perceived productivity; (iv) five situational items describing the social context. The questions in the experience sampling surveys referred to emotions, behaviors, states, etc., experienced over the 30 minutes prior to the survey.

Stage 3 Participants were asked to complete an extended questionnaire similar to the initial one, containing one addi-

tional item designed to derive self-perception of face-to-face interactions among participants during the course of the study.

III. Data Collected: Personal and Situational Data

The measures related to personal and situational factors, as well as to self-perceived social interactions collected through surveys during the three stages of the study are detailed below.

Initial and Final Surveys

The surveys administered during Stage 1 and Stage 3 contained items relating to personality, dispositional affectivity and self-perceived relations with the other participants.

Personality. The Big Five Marker Scale (BFMS) [22] was used to assess personality traits. The BFMS scale is an adjective list composed by 50 items specifically designed to optimize the simplicity of the big-five factor solution in the light of results of psycho-lexical studies on the Italian language [5]. Our sample was composed of $\sim$ 90% Italian native speakers; the subject who were not Italian native speakers received a validated translation of the BFMS.

Dispositional Affectivity. In order to measure dispositional affectivity, a subset of Multidimensional Personality Questionnaire (MPQ) [26] was used with items rated on a 5 point scale from 1= "strongly disagree" to 5= "strongly agree". This subscale contained 14 items for Dispositional High Positive Affect such as 'everyday I do some things that are fun' and 'for me life is a great adventure' and 17 items for Dispositional High Negative Affect such as 'my feelings are hurt rather easily' and 'I often lose sleep over my worries'.

Network Ties. To reconstruct self-perceived ties among participants, they were asked to rate to what extent they agreed with the following statements about each of the other participants: 1) friendship; 2) task related advice; 3) competence; 4) warmth; 5) quality of interaction. A scale from 0 to 7 (0="Not Applicable"; 1="Strongly Disagree" to 7="Strongly Agree") was used.

Experience Sampling

As explained above, a set of short questionnaires were administered three times a day (excluding week-ends) during Stage 2 of the study.

Personality. The ten-item personality inventory TIPI [12] was used to assess personality states. A 7-point scale ranging from 1="Strongly Disagree" to 7="Strongly Agree" was used for responses.

Affect and Loneliness. Respondents were asked to report on a scale from 1 to 5 (1="Very Slightly Or Not At All" and 5="Extremely") to what extent they experienced High Positive Affect (HPA) and/or High Negative Affect (HNA) in the 30 minutes before starting to fill the survey. HPA and HNA were assessed by means of a 6-items shortened version of the Positive and Negative Affect Schedule (PANAS) [28], consisting of 3 items for HPA (α = .78) – "enthusiastic", "interested" and "active" – and 3 items for HNA (α = .83) – nervous, distressed, and upset. Three items were used to measure LPA (α = .70) – "sad", "bored", and "sluggish" – and two items for LNA (α = .77) – "calm" and "relaxed". Finally, two items – "lonely" and "isolated" – were used to measure states of loneliness (α = .87).

Self Perceived Creativity and Productivity. Participants were asked to report their self-perceived productivity (*"how productive were you during the last 30 minutes?"*) and creativity (*"How creative were you during the last 30 minutes?"*)in the previous 30 minutes on a scale from 1="Very Slightly Or Not At All" to 5="Extremely".

Situational Items. Following Fleeson [9], five items were included that described the interactional context of the previous 30 minutes. These items were: 1) *"During the last 30 minutes, how many other people were present around you?"* to be answered with one of *("0, 1-3, 4-6, 7-9, 10 or more")*; 2) *"I was continuously interacting with the other people around me"*, 3) *"What I was doing was freely chosen by me"*, 4) *"The deadline for what I was doing was very near"*, 5) *"What I was doing was extremely interesting to me"*. The last 4 questions requested answers on a scale from 1="Strongly Disagree" to 5="Strongly Agree".

IV. Data Collected: Digital Data

A large amount of data referring to participants behaviors was collected through the SocioMetric Badges during Stage 2 of the study.

Email and Phone Logs

For each email sent/received to/from another participant in the study, we collected information regarding who sent/received it. Moreover, we recorded the length of the message body, the time, and the list of recipients' IDs. To avoid privacy issues, no information about the content was stored. Phone logs were also collected for each landline telephone of the participants, by recording the phone ID, the timestamp, and the duration of each call. The phone ID was associated to the one or more participants (since in several cases more participants share the same phone). Again, to avoid any privacy issues no information about the content of the phone calls was stored.

SocioMetric Badges' Data

SocioMetric Badges are equipped with a microphone, an accelerometer, a Bluetooth sensor and an infrared sensor.

Accelerometer Data. Accelerometer data were sampled with sampling frequency $f_s = 50$ Hz, in a three dimensional space. The accelerometer's signal vector magnitude $\mid a \mid$ provides a measurement of the degree of body movement activity by averaging the acceleration's signal power over the three axes. Consistency of body movement is obtained by calculating the standard deviation of the accelerometer's signal magnitude for all samples for every 60-seconds interval and subtracting this value from a constant (k = 1) that represents the zero-variation or 100% consistency.

Speech Data. The speech signal was sampled with sampling frequency $f_s = 8$ kHz. A number of basic speech measurements like the signal's amplitude, its standard deviation, minimum and maximum values, mean and variance, were

recorded over intervals of 50ms, along with the fundamental frequency and the first 16 mfcc coefficients.

Infrared Data. Infrared (IR) transmissions were used to detect of face-to-face interactions between people. In order for a badge to be detected through IR, two of them must have a direct line of sight and the receiving badge's IR must be within the transmitting badge's IR signal cone of height $h \leq 1$ meter and a radius of $r \leq htan\theta$, where $\theta = \pm 15^o$ degrees; the infrared transmission rate (TR_{ir}) was set to 1Hz.

Bluetooth Data. Bluetooth detection was used as a coarse indicator of proximity between devices. Radio signal strength indicator (RSSI) is a measure of the signal strength between transmitting and receiving devices. The range of RSSI values for the radio transceiver in the badge is (-128, 127). We also used 17 badges as base stations placing them at fixed locations of common interest like the hosting organization's restaurant, the cafeteria and meeting rooms; by detecting participants in close proximity this set up allowed enriching the tracking capability of our study. All SocioMetric Badges, including base stations, broadcast their ID every five seconds using a 2.4 GHz transceiver (TR_{radio} = 12 transmissions per minute).

V. A Few Statistics

Personal and Situational Data

We start by discussing the response rate to the surveys of Stage 1 and 3 and to the experience sampling of Stage 2.

Response Rates:

Initial and Final Survey. All 53 participants took the initial survey (response rate = 100%) while 51 responses were collected in the final survey. This is due to the fact that one participant withdrew from the study during the first week of Stage 2 and another one left the hosting organization during the fourth week. The following discussion considers only the 51 participants sample.

Experience Sampling. We observed that the majority of participants used to leave the organization before 5PM on Fridays afternoon, hence we decided not to consider those surveys in the analysis. To summarize, the 51 participants included in the final sample could complete 14 surveys per week (3 surveys from Mondays to Thursdays plus 2 surveys on Fridays) for a period of 6 weeks, thus 84 surveys in total per participant. Out of the 4284 possible responses (=51 participants * 84 surveys), participants reported not to be at work 536 times (because of meetings outside the institute, participation in conferences, illness, etc.), reducing to 3748 the total number of eligible responses. Out of them, we collected 3147 responses, which is equal to a participation rate of 83,9%. On average, we collected 37,5 responses per signal (SD = 4.2) and 61.7 responses per participant (SD=10.57), over the entire 6-weeks period.

Descriptive Statistics:

Initial and Final Survey. In Tables I and II, we report the descriptive statistics computed on the raw scores of the collected measures for the initial and the final questionnaire, respectively. Personality data are normally distributed with kurtosis values falling between -2 and +2, except for Agreeableness in the initial survey.

TABLE I
Descriptive statistics for the measures collected in the initial survey.

	Mean	Std.	Max.	Min.	Skew.	Kur.
Extr.	41.83	9.83	62	23	-.14	-.63
Agre.	51.6	6.03	62	29	-1.03	2.37
Cons.	50.44	8.61	66	34	-.19	-.77
Em. St.	41.02	6.92	54	23	-.19	-.34
Creat.	46.11	3.74	55	38	-.19	-.33
High PA	3.5	.55	4.9	2.2	.017	.048
High NA	1.76	.57	3.6	1	.911	.993
Low PA	1.78	.6	3.29	1	.725	-.291
Low NA	3.08	.56	4.4	1.8	-.016	-.225
Lone.	1.81	.81	4.2	1	1.029	.464

The mood data are not normally distributed as there is a natural skewed pattern to the data: if someone is high positive then it is normal for them to be low negative, as is known to occur with the PANAS scale [4]. Expectedly, the personality and the mood data are very highly correlated between the initial and the final questionnaire with values at least .6 for all measures. This shows that there is consistency in the measures of personality and mood traits of the participants and is confirm by the absence of statistical differences between the the initial and final measure measure for each considered dimension (as tested through ANOVA, $p < .05$).

Experience Sampling. For the transient states concerning personality and affectivity we computed the between-person variance and the within-person variance. More precisely, we define the between-person variance as the variance between each subject's mean and the sample mean, while the within-person variance is based on the difference between each of the subject's score and the subject's mean. Looking at values reported in III, we can see that with personality states the within-person variance tends to be higher than the between-person one, a trend that is stronger with Extraversion. These values are in line with findings in the literature on personality states [9] and emphasize the importance of shifting the attention to within-subject variations and their dependence on situational factors when addressing the interplay between personality and actual behavioral manifestations.

SocioMetric Badges' Data

We now turn to a few descriptive statistics of the data collected trough SocioMetric Badges. Some problems related to sensor malfunctioning were detected and addressed. In particular, the badges' clocks were found to accidentally lose synchronization, probably because of minor accidental shocks they were subject to. This problem was addressed through a data post-processing procedure in which each out-of-sync data slice was re-synced by cross-correlating its clock-time with the one of the most reliable alter detected by means of IR or BT sensors. More specifically, since we adopted a very strict data download procedure (intervals between two subsequent

TABLE II
DESCRIPTIVE STATISTICS FOR THE MEASURES COLLECTED IN THE FINAL SURVEY.

	Mean	Std.	Max.	Min.	Skew.	Kur.
Extr.	42.33	9.21	61	21	-.22	-.29
Agre.	51.67	7.98	65	27	-.9	.94
Cons.	51.71	8.18	66	32	-.18	-.59
Em. St.	41.79	7.53	60	24	-.16	-.02
Creat.	45.29	4.6	51	33	-.71	-.09
High PA	3.35	.54	4.6	2	.83	-.05
High NA	1.61	.5	3.2	1	1.06	1.27
Low PA	1.64	.54	3	1	.83	-.04
Low NA	3.04	.58	4.6	2	.62	-.04
Lone.	1.71	.68	3.8	4.68	1.08	.86

TABLE III
DESCRIPTIVE STATISTICS FOR THE EXPERIENCE SAMPLING MEASURES COLLECTED

	Mean	Between-person variance	Within-person variance
Extr.	4.099	0.428	1.136
Agre.	2.881	0.381	0.626
Cons.	5.54	0.434	0.564
Em. St.	2.455	0.489	0.686
Creat.	4.525	0.515	0.798
High PA	3.128	0.257	0.348
High NA	1.42	0.194	0.241
Low PA	1.368	0.174	0.146
Low NA	3.109	0.316	0.399
Lone.	2.238	0.103	0.126

downloads of the same badge were always no longer than 3), we could assign a specific time-window (derived from the recorded download schedule) to all out-of-sync badges. Was a out-of-sync badge found during the data post-processing stage, the records of its IR and BT detected alters were scanned to estimate the faulty badge's clock.

The other problem encountered was related to faulty sensors that would not either work or record data. We could not address this last problem, and we estimate 10% of the data to be missing due to occasional sensor malfunctioning.

Accelerometer and Audio Data. In total we registered 15725.35 hours of bodily activity and 15894.63 of audio data. The difference is explained by the occasional faulty behavior of some sensor leading to missing data.

Infrared Data. Hits from the infrared (IR) sensors were considered as a good proxy for face-to-face interactions; such dyadic interactions were weighted according to their duration. More precisely, the weight w of the face-to-face interaction between subjects X and Y was initialized at 1 at the first hit between their infrared sensors, and incremented of 1 at any subsequent detection happening after at least τ time units from the most recent one. Table IV reports statistics for $\tau = 10, 30, 60$ seconds over the 6 weeks of study.

Bluetooth Data. Bluetooth (BT) hits were used as a proximity measure for a) co-location with other participants, and b) co-location with base stations positioned in strategic places within the premises; BT detections of other machinery (e.g. personal laptops and smartphones) were discarded due to privacy concerns. We assigned a weight w to a tie between two participants or between a participant and a base station; such weight w was then processed following the same strategy detailed above for IR hits. Other approaches are possible, given the raw data in our availability, such as using the RSSI values in order to retain only detections above a threshold. Table V reports statistics for $\tau = 10, 30, 60$ seconds over the 6 weeks of study.

TABLE IV
STATISTICS FOR USER-TO-USER INFRARED FACE-TO-FACE DETECTION.

	τ =10s	τ =30s	τ =60s
mean	218.09	120.55	84.93
std	562.15	298.87	203.95

TABLE V
STATISTICS FOR USER-TO-USER AND USER-TO-STATION BLUETOOTH DETECTION.

user to user	τ =10s	τ =30s	τ =60s
mean	1076.24	653.515	464.93
std	3202.4	1860.78	1284.83
user to base station	τ =10s	τ =30s	τ =60s
mean	321.53	205.18	148.56
std	1377.7	832.75	575.08

VI. DISCUSSION AND FUTURE WORKS

In this paper, we have introduced and discussed the design, the methodology and some statistics concerning the SocioMetric Badges Corpus, a new corpus for social interaction studies collected during a 6 weeks contiguous period in a research institution, monitoring the activity of 53 people. The design of the corpus was inspired by the need to provide researchers and practitioners with: a) raw digital trace data that could be used to directly address the task of investigating, reconstructing and predicting people's actual social behavior in complex organizations; b) information about participants' individual characteristics (e.g., personality traits), along with c) data concerning the general social context (e.g., participants' social networks) and the specific situations they find themselves in. The resulting data set comprises a rich amount of different types of data: data concerning social exchanges through electronic means and data about face-to-face interaction as well as participant-provided assessments of personal traits, states and contextual aspects. The insights produced by the data remain to be demonstrated by future works. However, the multi-layer nature of the dataset shows the potential for addressing many different research issues. First of all, the joint collection of stable and enduring individual traits (through the questionnaires administered at Stage 1 and Stage 3), of transient states concerning subjects' personality (by means of the experience sampling of Stage 2) and of the raw data, provides the means to shift the focus from the prediction

of personality traits right away from actual behavioral manifestations as in [18], [2], [24] to their reconstruction on the basis of the distribution of transients personality states [10]. In socio-psychological literature, a personality state is a specific behavioral episode wherein a person behaves as more or less introvert/extravert, neurotic or open to experience, etc. This approach could be beneficial not only for the automatic computation of personality, but also for the long-term goal of predicting/explaining individual behavior from individual characteristics. Recently, some research efforts [25] have also tackled the explanation of the mutual influence between individual characteristics and network structure. Our dataset gives also the chance to trace the origin of network structure to its elemental relational and affective components: the ongoing micro-interactions between people in organizations, and the specific emotions they experience during those interactions. With existing research having demonstrated the importance of affect in network formation and individual performance, our data can be used to uncover the finer micro-structure of affect in organizations. Which interactions elicit different discrete emotions? How do these emotions shape subsequent interactions over time? And how do these ongoing micro-interactions result in aggregate network structure? Moreover, our dataset gives also the opportunity of testing how the spreading of emotions inside an organizations can influence performance, creativity and job satisfactions of the employees. Finally, the multi-layer longitudinal nature of the corpus described in this paper makes it highly valuable for network-based studies on organizational behavior.

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