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SENSING CLOSE-RANGE PROXIMITY FOR STUDYING FACE-TO-FACE INTERACTION

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Introduction

Face-to-face interaction is an archetype of interpersonal behavior and a building block for microsociology. As a fundamental human behavior, it shapes how we build and maintain our social identity while forming groups or segregating ourselves from others. This impacts virtually all aspects of people's lives (cf. "Social Interaction" and "Face-to-Face Interaction"). Studying face-to-face interaction is therefore important, however, at the same time, quite challenging. For example, self-assessments in surveys give people's perception of their activity that might be different from the actual one, resulting in a self-reporting bias. Similarly, manually observing face-to-face interactions in a large group and capturing all interactions is a) biased towards the observer, that is, the human encoding the interactions, and b) cumbersome and often unfeasible, if there are too many people to observe.

In today's digitized world, there are many opportunities for digitally "sensing" human behavior, including sensors for detecting interactions in situ – in a given (physical) space and environment – to focus on empirical evidence of face-to-face interactions between individuals. Mainly because of such new tracking devices providing fine-grained data on human behavior, the study of face-to-face interaction has advanced considerably in recent years. These devices apply different technologies, such as Bluetooth and radio-frequency identification (RFID), to capture proximity between humans in social occasions that is then interpreted as interaction between individuals. This non-intrusive data retrieval creates a unique opportunity to assess face-to-face interactions with a remarkable temporal granularity, allowing researchers to obtain data that can render a better understanding of the spatial and temporal dynamics of individual as well as group behavior (cf. "Close-Range Proximity Sensors"). Combined with individual-level information (e.g., sociodemographics), it also helps to untangle intricate social and psychological patterns in human behavior.

Such experimental studies of unmediated human interaction are the main contributions to social research with this new type of data. Current work has been done on linking (and theorizing the link between) microsociology to group behavior and on addressing substantive questions from the social sciences, for example, friendship, organization (hierarchies, formation of teams), social preference, and group formation, as well as inequality (cf. "Contribution of Sensor-Based Studies to the Social Sciences"). Furthermore, it allows for testing behavioral hypotheses like

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homophily, attractiveness, or polarization or for analyzing how different social areas or settings (schools, hospitals, workplaces, events) are being structured through interaction and how they, in turn, shape behavior.

The main problem with sensor technology is that it is merely a proxy for human behavior. This bears some challenges, such as the alignment between the signal captured by the sensor and the social construct researchers want to measure (Müller, Fàbregues, Guenther, & Romano, 2019). For example, close-range proximity between two sensors is often interpreted as an interaction between the humans wearing these sensors, where it is rather a co-location of these individuals. A related challenge lies in the nature of the definition what a face-to-face interaction exactly is and to which extent sensors can measure it. Across current literature studying this and similar social constructs, the articles' authors use different wording, including *in-person contacts* or *person to person communication* (Malik, 2018), which rather creates confusion on what exactly sensors can and cannot be used for.

Therefore, the main contribution of this chapter is to comprehensively illustrate the ongoing work on sensor-based face-to-face interaction studies. The goal is to set a common understanding of the underlying social construct and to which extent sensors can be used to measure it, by providing

- an outline of the social construct *face-to-face interaction*,
- the alignment of this social construct to a physical entity that can be detected by sensors,
- an extensive overview which types of sensors are rather useful to measure which type of social construct, that is, face-to-face interaction or co-location,
- a review of existing research using sensors to study face-to-face interaction and related social constructs,
- a list of challenges researchers must be aware of when conducting sensor-based studies.

Constructs of interaction

Social interaction

Human interaction is a prerequisite, a means and an end to social relations, which are at the core of sociology. Therefore, interaction – be it as an explicit label or an implicit concept – is featured in a broad range of theories and approaches. Microsociology cannot be conceived without the notion of action (J. Turner, 1988) which is directed towards others or includes the relation to others in shaping the individual's behavior, values, opinions, or communication strategies. Even if personality is at the center of a research interest, the social dimension comes into perspective (R. Turner, 1988).

Interaction offers a link between the individual and the social spheres; that is, while (inter-)action produces social structure, (inter-)action is also the enactment of supraindividual properties and patterns, such as roles, rituals, or norms. Therefore, studies on social interaction allow for analyzing a) how people build and maintain ties via, for example, mechanisms of integration and separation, and b) self-definition and reproduction of groups and their boundaries. Simmel (1890) states that society emerges from interaction whereof the interaction between individuals is the most basic one. From a phenomenological point of view, it is argued that the intersubjectivity of alter and ego is rooted in day-to-day interaction (Schutz, 1932). In their work, Berger and Luckmann (1967) show how interaction makes for a shared perception of reality.

Interaction defines the relation between the interacting entities and is necessary for recognition (of the other) and formation (of the self). Mead (1934) pointed at this reciprocity and the expectation of the generalized other as a constitutive feature of human action. The entrenchment of interaction in language is central not only for Mead and symbolic interactionism in his succession (Blumer, 1969) but also for ethnomethodology (Garfinkel, 1967) and the method of conversational analysis (Sacks, Schegloff, & Jefferson, 1978). This also applies to the much later and comprehensive account of deliberation processes in society, Habermas' "theory of communicative action" (Habermas, 1984) which is a theory of interaction (Habermas, 2002).

More recently, interaction figures in "relational sociology" (Crossley, 2011) and the prolific area of network studies (Borgatti, Mehra, Brass, & Labianca, 2010) that build on the "inter" for analyzing the temporal development of relations, social centrality, paths of influence, attraction, and so on.

Face-to-face interaction

While interaction might be well theorized in sociology from many angles, this does not imply that face-to-face interaction is as frequently addressed. We can argue that face-to-face interaction is the most basic and ubiquitous form of interaction, even in today's digitized world. We can also assume that people mentioning interaction often refer to face-to-face interaction. Still, we cannot equate one with the other. Interaction is a much broader term and not confined to interpersonal encounters; face-to-face addresses the dynamics that occur between people in detail (Bargiela-Chiappini & Haugh, 2009; Duncan & Fiske, 1977; Goffman, 1967; Kendon, Harris, & Key, 1975; Turner, 2002). Face-to-face interaction more specifically refers to an action as being embedded in a situation and requests the co-presence – both in time and space – of more than one human actor. It is "the prototypical case of social interaction" (Berger & Luckmann, 1967) and, although technically mediated interaction has been gaining ground, remaining "still primal and primary" (Turner, 2002): humans interact with other humans face to face in their everyday life (Goffman, 1978).

With "On Face Work" in 1955, Erving Goffman started approaching the concept of face-to-face interaction, which was included in his book *Interaction Ritual* (Goffman, 1967) in 1967. "Face" is the public image of the self; with their "face work", individuals strive for status and position in social situations. Hence, interacting with others is strategic and entangled in presuppositions, expectations, rules, and rituals. Compliance with this "interaction order" is enacted in encounters; Goffman's emphasis is on talk and conversation in a spatio-temporal situation (Goffman, 1981). Therefore, face-to-face interaction is further defined by its focused nature (Goffman, 1961), meaning that co-location is not enough.

Empirical data on face-to-face interaction are mainly observational data (Duncan & Fiske, 1977) obtained in field research or experiments. Especially conversational analyses often use manually encoded audio and video recordings. However, the characteristics of face-to-face interaction – namely its focused nature, the communicative, spatial and temporal dimensions, the co-presence in person in a situation – impose physical limitations on such a data collection. This makes it difficult to get reliable, unbiased, and comparable data on interpersonal behavior by any means. Observational data might suffer from observation or coding biases and are inclined to be intrusive; self-reports (from interviews, questionnaires, surveys) entail their issues of memory and bias, which might be aggravated when it comes to the minutiae of face-to-face interaction.

Sensible proximity

In this situation, research could benefit from including proximity sensors to study face-to-face interaction. Like log data from online activities, sensor data are non-reactive and – comparatively –

non-intrusive and thereby minimize the Hawthorne effect. With sensors, it is possible to maintain the conceptual unity of the interaction while at the same time widening the measurement in type, size, and scale. For instance, it is possible to better monitor multi-person interaction or simultaneously occurring interactions in gatherings, which allows for analyzing groups, subgroups, or networks.

Broadly speaking, sensors measure some physical constructs, such as position or distance. Researchers in the field of social sciences use sensors and relate such measurements of physical quantity to sociological constructs; for example, geographical location of smartphones can be used for studying group dynamics and proximity between sensors for studying face-to-face interactions.

As the technical overhead decreases with time, more and more researchers use sensors for studying human behavior and interaction. However, relating the physical measurements of sensors to social constructs must be performed with high caution. Malik (2018) and Müller et al. (2019) both provide an extensive and highly valuable overview of various sensor-based social science studies on human interaction. They state that these studies have no clearly articulated frames for the use of sensors analyzing networks, behavior, and/or interactions. For example, many kinds of sensors are not precise enough to capture face-to-face interactions, for example, Bluetooth; still they are used to measure this construct. In all studies, proximity between the sensors is used and related to face-to-face interactions. However, it is important to distinguish which sensors can be used to relate their physical measurement to face-to-face interaction and which sensor measurements are encoding solely co-location of individuals.

Proxemics

According to Goffman (1967), studies on human interactions are not about the individuals and their psychology but rather about the syntactical relations among the acts of different individuals. Face-to-face interactions occur in co-presence of other individuals verbally and non-verbally (Goffman, 1967). Non-verbal behavior is a combination of facial expressions, gestures, and body movements, whether intended or not (Mehrabian, 1968). Verbal, or speech-related, behavior comprises the speech itself but also the speech rate and speaking time, as well as tone and pitch of the voice. Therefore, while in a face-to-face interaction, individuals observe, that is, see and/or hear, such behavioral aspects when interacting with others. This means, to have a face-to-face interaction, a) the distance between individuals must be rather small, and b) the visual confrontation between individuals must be provided.

Proxemics describe the effects how different space and density influence human behavior, communication, and social interaction (Hall, 1963). For one, proxemics include the body distance, that is, the distance between at least a pair of individuals. The spaces around an individual describe the distance of an individual to other individuals. These spaces are categorized into four distinct zones: a) intimate space (up to 45 cm), b) personal space (up to 1.2 m), c) social space (up to 3.6 m), and d) public space (up to 7.5 m) (Hall, 1963). Figure 14.1 (a) shows the different spaces surrounding an individual. The personal space, that is, the region imminently surrounding an individual, is rather reserved for close family members, very close friends, and relationship partners, the latter also being part of the intimate space. The social space is reserved for conversations with friends and/or associates or for group discussions. The public space, on the contrary, is reserved for strangers or newly formed groups. Essentially, the personal and social space define the area in which a face-to-face interaction is likely to happen, whereas the public distance defines an area for larger audiences, in which a face-to-face interaction is less likely to happen (Hall, 1992). Second, the eyes are considered one principal

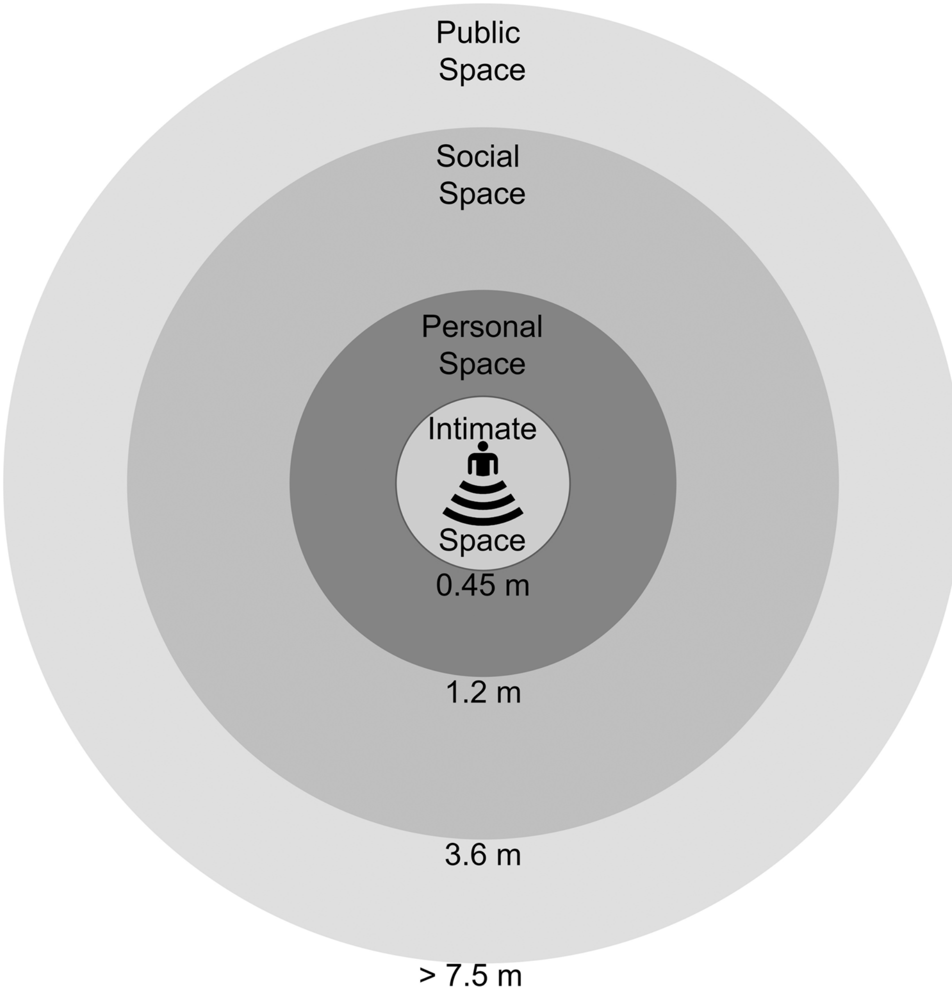

Figure 14.1 **Proxemics.** Distances surrounding an individual forming the interpersonal spaces. The curved solid lines indicate that the individual is looking in this direction. (a) Interpersonal spaces defined by proxemics, (b) examples of occurring face-to-face interactions, illustrated with solid lines (dotted lines mean "not a face-to-face interaction")

means by which an individual gathers information (Hall, 1963; Mehrabian, 1968). Gaze and gestures can encourage, punish, or establish dominance, a true non-verbal face-to-face interaction. This means if individuals are in a face-to-face interaction, they both must be at an angle towards each other, such that they can see the individual they are interacting with. In social interaction, this is defined as the individual's visual space (Hall, 1992). Figure 14.1b depicts examples where face-to-face interactions are happening (solid lines) and where they are not happening (dotted lines).

Proxemics help us to distinguish face-to-face interactions in social gatherings in a technical manner. Co-location is not sufficient: individuals must be at least within the social space and turned towards each other.

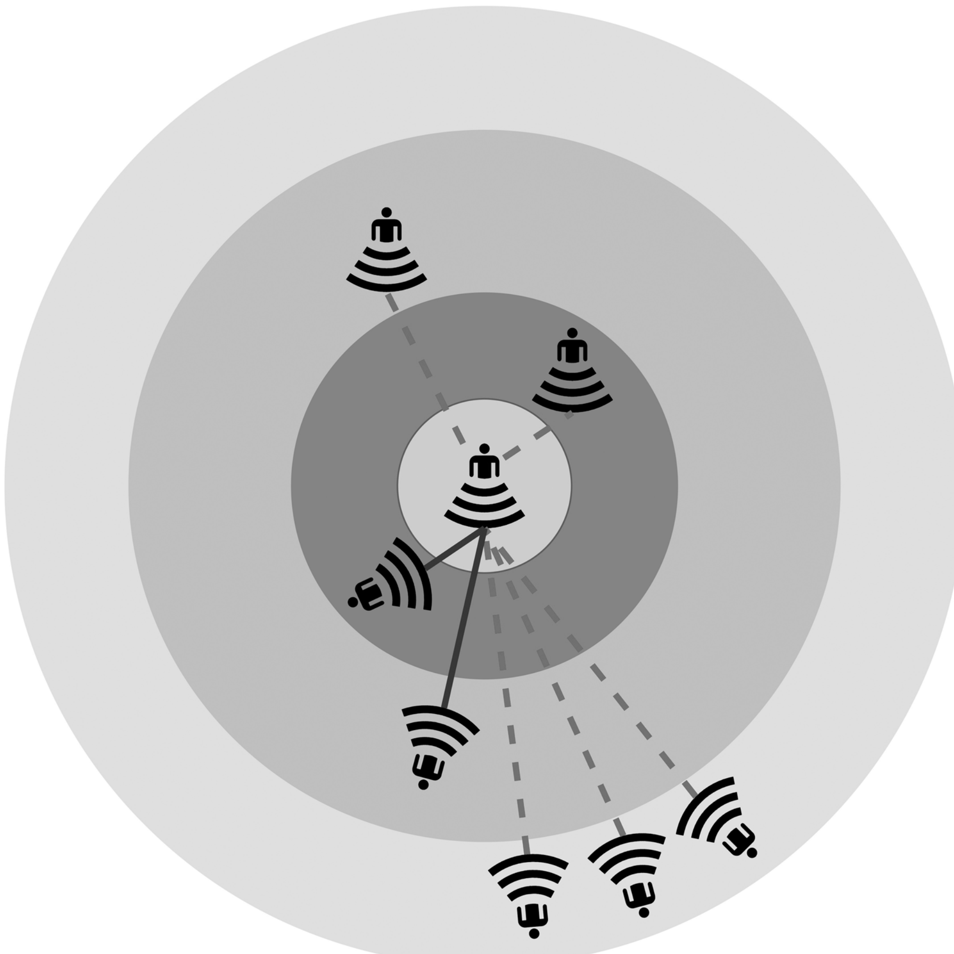

Figure 14.1 (Continued)

Sensing face-to-face interaction

Close-range proximity sensors

What is a sensor?

The term "sensor" refers broadly to a technological device that detects a physical, measurable signal. A thermometer, a camera, and a Geiger counter are sensors, designed and engineered to detect, respectively, heat, electromagnetic waves in the visible spectrum, and ionizing radiation. In the present context of face-to-face interactions, "sensor" refers more precisely to devices designed to detect and record interactions between individuals in the physical space.

By definition, a sensor *detects*, which means it returns a signal (from a simple binary present/absent cue to a full measure) if the event it is designed to detect is present. In other words, sensor data *do not need to be further coded* in order to extract the events from a data collection. As such, a camera, for example, is not a sensor for interactions, as it does not detect them. Video recordings of social context must be further coded (either by humans or automatic video analysis) to extract the interaction signal. We thus differentiate between *observational data*, produced by a global recording of a context that needs to be analyzed to detect and extract interactions, and *sensor data*, in which the interactions are by design detected and recorded as such, without the need for further extraction. In the present chapter, we focus solely on the latter.

An interaction is a social construct, not a physical one; therefore, sensors use proxy signals from which they infer the presence or absence of an interaction. For all setups that have been used in this context, the main criterion is always *proximity*. Indeed, an unmediated face-to-face interaction implies, by definition, some physical proximity between the individuals who are interacting.

A first family of sensors relies only on this criterion. As such, they are *co-location* sensors: they detect events when individuals are in the same physical location, that is, that the distance between them is less than a predefined threshold value. Different technologies are used to detect co-location: GPS tracking, which gives the location of individuals at any time and thus easily provides the interaction events; phone tracking, in which co-location is usually defined by two phones pinging the same cellular tower in the same time window; Wi-Fi tracking, similar to phone tracking but with Wi-Fi beacons; and Bluetooth detection, in which smartphones detect each other through the constant scanning of their surroundings for the presence of Bluetooth emitters.

Although proximity is necessary to have a face-to-face interaction, detecting it does not necessarily mean that an interaction occurred. A second class of sensors has thus been designed with added constraints on the simple proximity in the hope of narrowing down the detection of "true" *interactions*. The main criterion that has been implemented is the directionality of the interaction. The technology relies on electromagnetic signal detection similar to the Bluetooth setup but using frequencies that are blocked by liquids, such as the liquids within the human body. By having individuals wear sensors on their chest, one enhances the probability that the sensors can detect each other only if the individuals are facing each other. The technology generally uses RFID chips, but infrared beacons have also been used.

Choosing a sensor

The choice of a sensing platform always depends on the research question as well as the requirements for data collection. In particular, choosing a sensor means choosing a proxy for face-to-face interactions. The definition criteria are:

- What is the proximity threshold for interactions?
- Is co-location sufficient, or is directionality required?
- Are there other necessary criteria to define an interaction?

Aside from these, one must also consider the *practical criteria* of the data collection:

- Time resolution for the interaction recording.
- Deployment and management of the data collection system.
- Population sampling.
- Acceptability of the sensors.
- Privacy concerns.

Perfect setups that completely fit the "face-to-face interaction" construct do not exist. Therefore, a suitable approximation towards the research question and the data collection possibilities must be found. The usual tradeoff is between a) relying on an existing infrastructure (smartphones) but having less precise signal (co-location sensors) and b) having to develop, manage, and deploy a tailored setup in order to get information closer to the social construct (interaction sensors). Specifically noteworthy is the question of data privacy. It is a central one and can sometimes be a deciding factor in the choice of a sensor platform. However, whichever sensors are considered when designing a study, the researchers must follow the usual guidelines about informed consent, anonymity, and privacy, as it would be for any observational study in social sciences. In the following, both are described in more detail, as well as with respect to the aforementioned criteria. Figure 14.2 shows an overview of how Bluetooth as well as RFID and infrared sensors detect signals that are interpreted as interaction corresponding to the definition of proxemics. In Figure 14.2a, one can see that Bluetooth does not consider the direction individuals are facing,

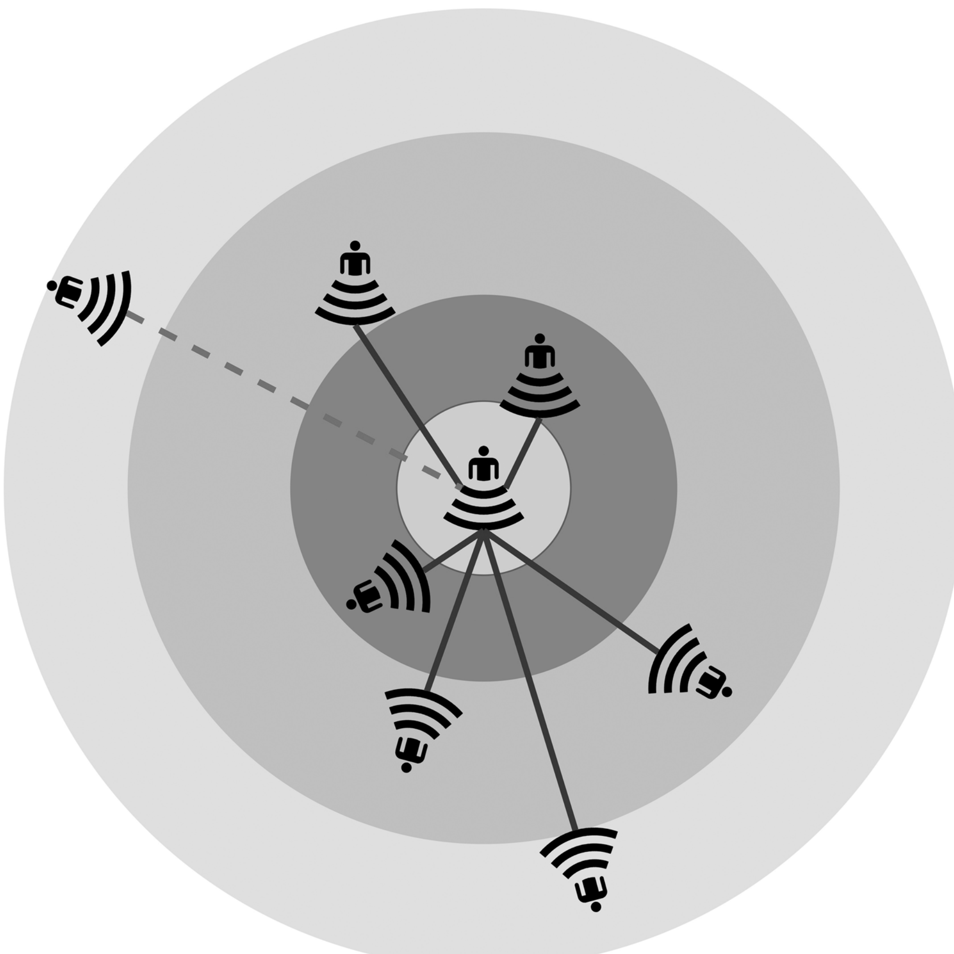

Figure 14.2 Bluetooth and RFID signal detection aligned to proxemics. Both sensors pick up different signals depending on the distances surrounding an individual and whether individuals are facing each other. The curved solid lines indicate that the individual is looking in this direction. Solid lines specify that an interaction is detected. Dotted lines mean no interaction. (a) Detected interactions using Bluetooth sensors, rather co-location; (b) detected interactions using RFID and IR sensors, rather face-to-face interaction

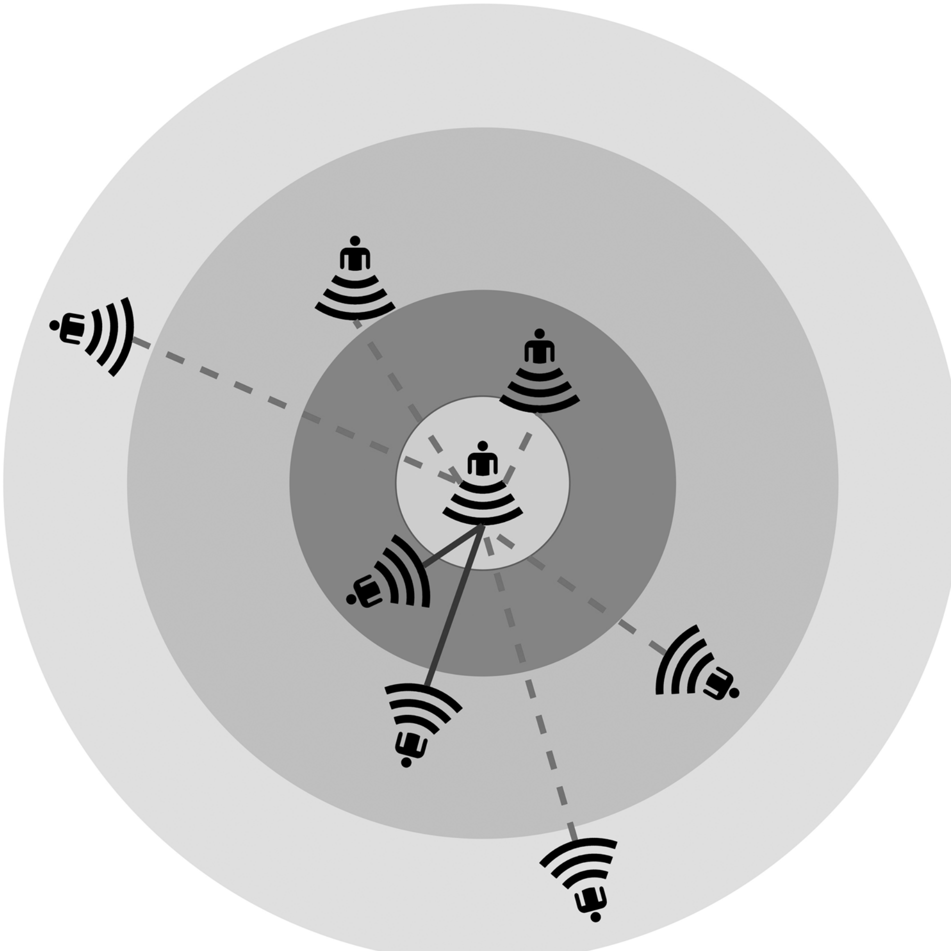

Figure 14.2 (Continued)

thereby detecting rather more "interactions", which thereby rather correspond to co-location. In (Figure 14.2b), one can observe that RFID and infrared take the individuals' line of sight into account, thereby detecting rather true interactions. However, as the transmission signal is rather low, it can happen that actual interactions within the social space are not detected. More detailed and highly valuable reviews on sensor-based interaction studies can be found in Huang, Kuo, Pannuto, and Dutta (2014), Müller et al. (2019), and Malik (2018).

Co-location sensors

The sole criterion for co-location sensors is detecting or calculating distance to other sensors, which defines "proximity" for the data collection. The most prominent sensors for co-location are GPS tracking, phone tracking, Wi-Fi tracking, or Bluetooth.

For Wi-Fi and phone tracking, the area of detection for beacons is around a few tens of meters. However, dense urban areas are much more precisely covered than rural or less connected areas, which can introduce a geographical bias in signal detection. These technologies were not designed to track individuals; their main purpose is solely signal transmission. As such, they often exhibit flickering or false detection. An example are cellular towers, which redirect signal to other towers nearby when they reach their full capacity. This gives a "false" location of some users. GPS tracking has detection errors as well. They range from a few meters to tens of meters, and proximity follows accordingly. On the contrary, all these systems have the great advantage of being pre-existing, meaning they are already built into smartphones or other smart wearables which are widely spread in the population. Provided that precision and geographical biases are not too much of a problem, and that the population sampling biases can be controlled or measured, they can give access to large-scale data about how individuals are co-located in a specific space at a specific time. This, however, results in another key limitation, the acceptability of these sensing platforms. In particular, regarding data privacy matters, a critical difference must be made between raw and co-location data. If using tracking methods such as GPS, the raw positioning data must be handled with much more attention than the final co-location data. The reason is that the raw data includes much more information about the behavior and whereabouts of participants, such that individuals can be recognized in the data. While the co-location data could in theory be shared following normal data privacy guidelines, the raw data could not.

Another setup for co-location sensing is Bluetooth. It has several advantages compared to the other co-location sensing platforms. As it uses peer detection, it does not have the coverage problems of Wi-Fi or phone tracking. Each individual carries a beacon in their smartphone, which detects the other individuals nearby, not having to rely on other infrastructure, such as cellular towers. Bluetooth uses radio waves and has a detection range of approximately 5–7 meters. This makes it relatively precise compared to other co-location platforms. However, it can be affected by the environment – walls, windows, obstacles, and so on (Müller et al., 2019). The detection range can, in theory, be refined using signal intensity (radio signal strength indicator, RSSI, which is measured by the sensor), but it proves difficult to calibrate (Huang et al., 2014). Furthermore, there exists a variability in the range of detection due to hardware differences (Huang et al., 2014). This explains why the largest example of data collection using Bluetooth, the Copenhagen Network Study (Stopczynski et al., 2014), gave identical smartphones to the studied population to tackle this issue.

Although such co-location sensing platforms are pre-existing, the software to collect and process the data still needs to be designed and implemented. GPS, Wi-Fi, and phone tracking rely on simple log data of the sensors. For Bluetooth, however, one needs to control the physical sensor and design a detection scheme. The detection system specifies the way two sensors communicate to ensure the detection of an interaction. It usually consists of setting cycles of sending/listening time windows. This is an important part of the setup, as it defines the temporal resolution of the interaction detection. The design also has an impact on the durability of the sensor through energy consumption: a detection program that drains the battery of a smartphones in a couple of hours is unpractical. One further critical aspect when using pre-existing smartphone sensors is the restrictions put in place by smartphone companies, essentially removing the possibility to access and control the needed sensor via self-developed applications. Maybe in the near future, the idea of using Bluetooth sensors to track social contacts in the case of epidemic spreading might give new opportunities to use this method in a broader way.

Interaction sensors

Historically, the first sensor specifically designed for tracking interactions was the sociometer (Choudhury & Pentland, 2003), which uses infrared (IR) to detect the presence of other sociometer sensors. IR detection depends on the line of sight between the transmitter-receiver pair. This means, if the sensors are attached to the front of individuals, they a) must face each other in close distance and b) must not have anything between the transmitter-receiver pair in order to produce a detectable signal. This setup was, however, not widely adopted in research (Malik, 2018). The later protractor sensor[1] uses the same technique, including measuring angles to detect interaction, as performed in (Montanari et al., 2018) based on the concept of proxemics.

Following the sociometer, several systems were designed, the most widely used being the SocioPatterns platform (Cattuto et al., 2010), which uses RFID chips for detecting close-range proximity. In comparison to IR-based sensors, RFID chips do not need to be in line of sight to each other. In order to maintain the aspect of directionality, the signal can be calibrated in such a way that the human body blocks the signal. This means individuals wearing the sensors at their front must still face each other to produce a signal. Besides the directionality, all these sensing platforms have the characteristic that proximity is much more constrained than with co-location sensors. In contrast to Bluetooth, which detects a signal up to 5–7 meters (which is already outside the social space according to proxemics), IR and RFID sensors have a threshold of detection of up to 2–4 meters. In addition, building on the fact that even co-location combined with directionality is not perfect in detecting "true" interactions, other systems have added further sensors, such as microphones to detect speech (Dai et al., 2019). This allows one to focus solely on interactions with oral communication. By combining ultrasound and radio waves, Huang et al. (2014) have been able to design Opo, a system with high temporal resolution of two seconds that also measures the distance between individuals with a good precision (5 cm).

The SocioPatterns platform has been by far the most widely used framework.[2] As such, we will use it as a typical example of this class of sensors, specifically to describe the accompanied challenges. Generally, using a designed sensing platform has the main shortcoming that they are not based on pre-existing infrastructures. This implies that researchers must purchase (or build) the devices first. Therefore, the number of sensors is limited, usually being far fewer than widely distributed pre-existing devices like smartphones. This means they can only be used in well-defined contexts with small populations, maximum a few hundred – in the case of SocioPatterns, the largest study gathered around 400 participants. Furthermore, the sensors must be deployed. For one, if relying on antennas receiving interaction signals, the conductors of the study must set up the antennas in strategic places covering the premises of investigation. Second, the sensors must be distributed to the participants. This requires setting up a deployment slot in the schedule, which can be challenging when studying events with a predefined schedule, such as conferences, for instance. Participants often forget that they are wearing a sensor. This is positive, as it mitigates the Hawthorne effect. However, this has also the consequence that they tend to forget to return the sensor. Therefore, the collection of sensors at the end of the study must also be carefully designed in order to limit the loss of equipment. In some studies, it is even mandatory to hand over and collect the sensors every day, which must be included in the daily routine without disturbing the social context. For studies with a long duration, there is even the need to charge the devices or replace batteries. Even prior to deployment, participants must be informed about the correct use of the sensors, as the directionality is a crucial factor. As with pre-existing sensors, specifically designed sensors also need a software component that controls the detection and processing of the signals.

Contribution of sensor-based studies to the social sciences

Various studies have already been performed using sensor technology. Social science studies using proximity sensors specifically investigate patterns of co-location and face-to-face interaction to study human behavior and social topics and concepts such as friendship, inequality, status, group cohesion, or the organization of workplaces. All of this aims at deriving "social meaning" from physical data. In the following, we present work that has contributed to the investigation of human interaction in different areas and on different levels of social research. We focus on displaying sensor study design, types of collected data, and results in terms of social analysis.

Detecting and measuring social relations

Eagle, Pentland, and Lazer (2009) use interaction data based on Bluetooth and cellular tower data to infer a friendship network structure. They compare interaction data with self-reported survey data. Though they show an overlap between these two data sources, they reveal distinctions between them as well, suggesting that interaction data can be a complement to self-report surveys. In response to this paper, Adams (2010) argues that one should be careful on the type of social network being analyzed and what questions one can ask; specifically, behavioral networks versus social relationship. Oloritun, Madan, Pentland, and Khayal (2013) focus on close friendship ties. They investigate propinquity; that is, the proximity of people concerning physical and psychological aspects, which plays a main role in the formation of role relations. They show that interaction during the weekend and physical proximity explain close friendship ties. Usually, selecting a suitable RSSI threshold makes it possible to distinguish between strong and weak links. These signals correlate with friendship ties on Facebook, according to Sekara and Lehmann (2014). However, in today's digitized world, the question arises whether Facebook friends are real friends. Approaching this, Matusik et al. (2019) use self-reports among leaders in a large-scale research facility to establish the validity of Bluetooth RSSI thresholds for friendship and advice-seeking networks. They show that Bluetooth sensors can indeed assist researchers interested in studying actual friendship and advice-oriented relationships.

Individuals and interpersonal behavior

Sensor data have also been used to relate behavior to properties of individuals (e.g., personality traits, social status, or sociodemographic features like age or gender). The research mainly includes measuring the impact of individual traits on their interaction behavior as well as evaluating the validity of constructs, such as personality traits with empirical data. Typically, this is done by comparing self-reported and sensor-based data, for example, personality as expressed in a questionnaire or interview compared to personality as expressed in the interaction data. Olguin et al. (2009a) showed that personality traits could be identified via sensors; in particular, they used both proximity (Bluetooth) and interaction (infrared) data. Their results described the correlation between different interaction features with personality traits (i.e., Big 5 dimensions), showing that face-to-face interaction and proximity can predict these dimensions. Variation in face-to-face interaction duration time exhibits a positive correlation with neuroticism values. Staiano et al. (2012) examined how social networks can predict the Big 5 personality traits. They used a survey-based network and interaction networks based on calls and proximity (Bluetooth). They showed that the proximity network performs better than survey-based and call networks in personality classification. The authors categorize each personality trait (i.e., agreeableness, conscientiousness, extraversion, neuroticism, openness) into high and low labels based on the average of the individuals. They predict these labels using machine learning, more precisely the random forest algorithm. In general, Bluetooth is the best for this task; phone call network data are rather unusable. Similarly, Chittaranjan, Blom, and Gatica-Perez (2013) investigated whether sensors in smartphones (i.e., Bluetooth, SMS, Calls) can predict the Big

5, revealing specific gender differences. They show that higher extraversion and disagreeableness is associated with a lower number of contacts for male individuals. In the case of female individuals, higher scores for neuroticism and introversion are associated with a lower number of contacts.

Studies on mental health, psychological well-being, or creativity profit from sensor studies, as the data are collected non-intrusively and are therefore not based on self-assessment. Self-reporting on these topics is susceptible to bias as well as distortion. Similarly, an individual's state of mind or emotion might not always be accessible to self-analysis and reporting. In a small study, Gloor et al. (2011) investigate the relationship between interpersonal interaction patterns (close-range proximity) and individual creativity, finding two types of individuals: lonely genius and swarm creative. For the former, being near other individuals (face-to-face interaction distance or any proximity) is negatively associated with creativity, whereas the opposite occurs for the latter. Tripathi and Burleson (2012) analyzed the interplay of creativity with face-to-face interaction and movement. They find that creativity is associated with teammates' interaction and movement energy. The authors construct a model that predicts individuals' creativity based on face-to-face interaction (and movement) with 91% (87.5%) accuracy. Similarly, Parker, Cardenas, Dorr, and Hackett (2018) showed that perceived creativity (group and individual) is associated with face-to-face interaction. Pachucki, Ozer, Barrat, and Cattuto (2015) investigated the mental health of sixth graders and their social influence. They revealed that interaction networks of boys and girls are associated differently with self-esteem and depressive symptoms. Girls with more depressive symptoms present social inhibition, whereas boys show interaction patterns that match the depressive symptoms. In the StudentLife study, Wang et al. (2017) analyzed a class of 60 students via smartphones using different sensors: Bluetooth proximity, conversation (speaking) detection, GPS, and accelerometer, among others. They conducted pre- and post-surveys to capture the students' levels of depression and stress. They found that conversation frequency/duration is negatively associated with depression. Similarly, conversation frequency/duration is also negatively associated with perceived stress.

Indeed, social interactions can have positive or negative effects on participants' general subjective well-being. Alshamsi, Pianesi, Lepri, Pentland, and Rahwan (2016) have performed one study on the correlation between face-to-face interactions and such effects. The authors investigate how face-to-face interactions affect interacting people positively or negatively. They show that the participants' subjective well-being proved to have only rather low correlations with differentiating face-to-face interactions. Moturu, Khayal, Aharony, Pan, and Pentland (2011b) examined the relationship between sociability with sleep and mood. They define daily sociability as the number of interactions (Bluetooth) an individual has on a particular day. The participants fill in surveys about sleep duration and mood daily. They found that people who report poor moods have a significantly lower overall sociability. They failed to find a daily association between sociability and mood (i.e., changes on a day in sociability and mood). However, they found a non-linear association between sleep duration and previous day sociability. Short (less than six hours) and long (more than nine hours) sleep duration is associated with lower sociability in the previous day. Sleep duration around seven and eight hours is associated with higher sociability in the previous day. Though they found an association between sleep and the previous day's sociability, they failed to find a relationship between sleep and the following day's sociability. Social role relations might play a role in this relationship. The authors have shown that sleep duration and mood of an individual are affected by the sleep and mood of the spouse (Moturu, Khayal, Aharony, Pan, and Pentland, 2011a). Finnerty, Kalimeri, and Pianesi (2014) investigate face-to-face interaction in the work environment. They examine proximity (Bluetooth), face-to-face (IR), and electronic (e-mail) interactions. They also survey the participants to understand creativity, productivity, and affective states. They found that people interact more asynchronously (i.e., via e-mail) than synchronously. They also found out that interacting with more people face to face is associated with higher positive affect; also, having a higher number of face-to-face interactions with friends (survey-based) is negatively associated with self-reported measures of productivity and creativity. However, longer duration time interacting and proximity with friends is associated positively with productivity but not creativity; being co-located with colleagues and friends is associated with higher creativity.

Groups, organizations, and institutions

As elaborated on previously, interaction is essential for cohesion in all areas of social life. It produces social structure and, in return, reproduces and enacts the "standards" social norms. Investigating behavior in workplaces, hospitals, schools, or at academic venues with sensors adds knowledge on the organization of these institutions, how they function on the micro level, and whether sub-groups interact differently (Chaffin et al., 2017). They also contribute to the evaluation of institutional goals, for example, productivity and job satisfaction in workplaces, proper care in hospitals, integration and equal attention in schools, or promotion of young scholars and collaboration in academia. Sensor data are a complement to existing approaches of data collection in organizational research, especially to investigate group dynamics of new teams (Kim, McFee, Olguin, Waber, & Pentland, 2012). Wu, Waber, Aral, Brynjolfsson, and Pentland (2008) study a work environment via face-to-face interaction networks, e-mail communication, tonal conversational variation, and physical proximity, aiming to uncover the characteristics of productive workers. The authors reveal that productive workers have e-mail networks structurally different from face-to-face networks. On the one hand, their results show that face-to-face network cohesion is positively associated with productivity; on the other hand, e-mail network cohesion is negatively associated with productivity. They also reveal that face-to-face networks have a higher cohesion effect in productivity than proximity networks; that is, actual face-to-face interaction is more important than just proximity. Olguin, Gloor, and Pentland (2009b) investigate job satisfaction and social interaction in a small organization. They examine networks of e-mail conversation, face-to-face interaction, and proximity, together with surveys about job satisfaction and group interaction satisfaction. Though they failed to find a relationship between these networks and job satisfaction separately, the authors found that the total communication of an individual (i.e., the combined network) is negatively associated with job satisfaction. This result suggests the need for multi-modal approaches to examine organization. Atzmueller, Thiele, Stumme, and Kauffeld (2018) characterize the dynamics of face-to-face interaction of the first week of first-year students in a university, revealing that the first and last days are determinant to the growth of stronger links. Examining the dynamics of teams, Montanari (2018) found that proxemics information can predict the role of an individual's task with 80% accuracy and identify the task timeline with 92% accuracy. Zhang, Olenick, Chang, Kozlowski, and Hung (2018) examined team dynamics of six individuals confined for a period of four months in a simulation of space exploration. They investigate individuals' affect states and group cohesion, as estimated via surveys, revealing that face-to-face interactions help predict both task and group cohesion. Parker et al. (2018) presented mixed-method studies in that survey and ethnographic data are combined with sociometric data, showing the interplay of social interaction, creativity, and events in social gathering (e.g., lunch, coffee break). Kibanov, Heiberger, Rödder, Atzmueller, and Stumme (2019) examined the social roles of students in university retreats. They characterize four roles, ambassadors, big fishes, bridges, and loners, in communities of face-to-face interaction networks. They found that male participants tend to be the ambassadors (i.e., providing connections to different communities) in cultural and research communities.

Topics and concepts

So far, we have illustrated that sensor data have been used to learn more about friendship, personality, gender differences, or job satisfaction. One concept which cuts across many topical areas of social research is homophily. Homophily refers to peoples' inclination to befriend or collaborate with similar others. It is thereby primarily used to explain alignment patterns and group behavior. Research on homophily is well established in the social sciences and has been widely adopted in relational studies and network analyses, including sensor-based studies

Stehlé, Charbonnier, Picard, Cattuto, and Barrat (2013) examined the influence of gender on face-to-face interaction in a primary school via an experiment that included 6- to 12-year-old children of different classes. The authors found evidence of gender homophily in all classes. They revealed that the effect of homophily strengthens with age and that boys tend to have a higher homophilic level than girls. Similarly, gender homophily is also found in universities (Atzmueller et al., 2018; Psylla, Sapiezynski, Mones, & Lehmann, 2017). More concretely, Psylla et al. (2017) found that women tend to form female-only triangles more often than men in networks of proximity, cell phone calls, and Facebook interaction. In schools, intra-class interactions tend to occur more often than inter-class interactions (Guclu et al., 2016; Stehlé et al., 2013). Guclu et al. (2016) suggested that the classes schedule play a fundamental role in these interactions. In elementary and elementary-middle schools, since they often have fixed schedules, students of the same class tend to interact more often. In middle and high schools, however, students tend to mix with other classes because of the free schedule in these schools (Guclu et al., 2016).

Madan, Farrahi, Gatica-Perez, and Pentland (2011) studied the dynamic homophily of political opinions in proximity networks. They investigated the interactions during the 2008 U.S. presidential election campaign, uncovering the relationship between interaction and political opinion changes among undergraduates. They found that individuals who decrease their interest in politics tend to interact face to face with individuals with little or no interest in politics (Madan et al., 2011; Madan, Cebrian, Moturu, Farrahi, & Pentland, 2012). Chancellor et al. (2017) found evidence of homophily with respect to well-being in the workplace. They showed that individuals sharing the same levels of connectedness tend to cluster in interaction network. They also found that individuals with dissimilar levels of depressive symptoms tend to cluster together.

Homophily also plays a role in health. Madan, Moturu, Lazer, and Pentland (2010) studied the dynamics of health-related behaviors by analyzing the face-to-face interaction of students in a residence hall. The authors showed that an individual's health behavior is associated with the health behaviors of the individuals who interacted with this individual, having an impact on weight changes (Madan et al., 2010, 2012). Notably, Madan et al. (2010) showed that self-reported friends are unable to explain individuals' health behavior.

Challenges of sensor-based studies

As mentioned before, using sensors to study co-location or face-to-face interactions creates fine-grained non-responsive data. It also comprises various limitations, as illustrated in "Close-range proximity sensors". However, there are further general limitations that affect both studies with co-location sensors and studies with face-to-face interaction sensors. In the following, we point out these challenges, including the introduction of new biases, shift in complexity, and specifying data that cannot be monitored by current state-of-the-art sensors. We also provide suggestions on how to approach these challenges.

Introducing new biases

Although mitigating self-reporting and human encoding biases, one major limitation with using sensors to study co-location and face-to-face interaction is that sensors introduce new types of biases. This includes biases due to technological aspects, the study design, the processing of the obtained data, or even biases created by the participants of a study.

As sensors are a piece of technology, they can break occasionally. Broken or generally non-functioning sensors do not record any signals during a study, which can create a possible bias in the data. For example, a larger number of broken sensors can skew the data of an interaction network. If such problems occur with sensors built into the participants' smartphones, there is hardly anything one can do to deal with this problem. When using dedicated sensors, though, it is of high importance to double-check that all sensors are working before the study.

Individuals participating in a study are likely to create a bias by themselves. If a study takes place over a period of several days (and sensors are not collected after each day), participants can forget to bring along their sensor on a few of these days. For instance, conference attendees can forget their name badge including the RFID sensor at their hotel, such that their interactions cannot be recorded on that day. Participants can also accidentally deactivate their sensor, for example, the Bluetooth or GPS on their smartphones, during a study. They can furthermore accidentally block the sensor's signal, for example, participants might hold a drink in front of the RFID sensors on their conference name badge, which blocks the signal just like the human body. Unfortunately, there are only limited possibilities to mitigate these problems. To make sure participants do not accidentally forget or turn off their sensors, the only option is to constantly remind them to keep the sensors activated or bring their sensors along the following day. This can be achieved via posters at specific points of interest, such as the entrance of a venue.

An insufficient study design can lead to a further bias in the data. As mentioned before, sensors are only proxies for the social constructs that are of actual interest. Such proxies have the limitations that they pick up signals where there should not be any signal, and vice versa. Building structures can interfere or even block sensor signals, such that actual co-location or interaction information is not recorded. For mitigating such biases, it is important to invest in the study design. This begins at testing the sensors intensively, that is, determining when a signal occurs and what blocks the signal. If possible, the sensors might need to be re-calibrated. The researchers should also test the sensors on the premises where the study takes place in order to detect building structures, for example, windows and walls, that can block signals. One should also think of how to attach a sensor to a participant, for example, by including sensors in the participants' conference name badges.

Finally, before using the obtained data for analysis, the "raw" data must be pre-processed to eliminate, or at least minimize, error rates in the measurements. Such pre-processing includes *filtering*, *aggregation*, and, in cases of large data collections, *sampling*. Each of these steps can create a bias, though, such that they need to be performed with high caution. For example, filtering out coincidental interaction signals can lead to filtering out real interactions if no care is taken. Wrongly assumed aggregations due to data privacy can even lead to unusable data for specific research questions. The same applies for bad sampling, which can create the well-known sampling bias. Mitigating this sort of bias requires cautious elaboration on how exactly to filter, aggregate, and sample the data, which includes double-checking obtained signals against a ground truth. Sometimes, a well-defined study setup can also help to minimize the amount of "junk data" (Kontro & Génois, 2020).

Complexity shift

Collecting data just for collecting data constitutes bad practice in research. A well-defined research question and study design, on the contrary, constitutes good scientific practice, as a social sensing study is only as good as the social science research question behind it. Defining a valuable research question and setting up the social sensing study requires a lot of effort, especially if the researchers intend to mitigate the aforementioned biases. In comparison to traditional observational or survey studies, performing sensor-based studies shifts the complexity towards a rather technical perspective. Beside sensor maintenance or calibration, it means developing and maintaining code for obtaining, processing, and analyzing the obtained data. Carrying out studies in the field, for example, preparing the sensors or assisting participants such that their sensors are working properly, requires further resources. Another major issue that cannot be stressed enough is regarding data privacy. At least the same standards must be applied to sensor-based studies as for traditional social science studies, specifically since tracking individuals can quickly lead to intruding on their privacy. This especially applies to studies where behavioral data are linked to further quantitative or qualitative information on the participants, for example, gender, age group, country of residence, and so on, that could be used to identify single individuals. Parker et al. (2018) provide a highly useful "Lessons from the Field" section on these and other aspects that researchers need to be aware of.

Data that sensors cannot detect

Different sensors detect different signals. If a social construct consists of various aspects, it is very likely that only one sensor cannot detect all signals to cover all these aspects. For example, from a social science perspective, proximity sensors do not capture the many facets of face-to-face interaction, for example, body language or facial expression, that contribute to the whole picture of human encounters. They also do not capture conversation as such, that is, what has been said or the nature of the conversation, or they cannot detect the motivation for an interaction. Typically, proximity sensors do not produce a directional network, such that it is impossible to see who approached whom or who is rather active and passive in an interaction.

Approaching these limitations is quite difficult. In the end, it is again highly important to clearly formulate the research question investigated in a study and which sensors are most likely to detect the corresponding signals. Studying sociological constructs for which co-location is enough, using Bluetooth sensors is sufficient. The same applies for face-to-face interaction, if the research question is whether there is a difference in interaction between different groups, for example, different age groups. In addition to the sensor data, interviewing the participants or obtaining further information via surveys alleviates the situation as well. For example, studying whether individuals are comfortable in very close-range conversations, a combination of sensors detecting the distance and a post-survey asking about the participants' well-being might be a possible solution. Another possibility is to use microphones and detect subtle changes in the sound and pitch of a person's voice.

Conclusion and outlook

In this chapter, we have elaborated on the usage of close-range proximity sensors to study face-to-face interaction. The field of social sciences can very much profit from quantitative sensor-based data on human interaction, as the obtained data are fine-grained and non-responsive, mitigating the Hawthorne effect. In addition, it is free from a self-reporting bias compared to survey studies as well as free from human encoding biases compared to traditional observational studies. Especially for mixed-methods research, sensor-based studies are of high interest and can contribute to a wide range of topical areas in the social sciences. However, researchers must be aware of the different types of sensors, as their measured physical entity must match according to the social construct under investigation. Sensors like GPS, Wi-Fi trackers, phone trackers, and Bluetooth are useful to study co-location. Sensors like RFID or infrared are rather useful to detect face-to-face interaction, as they also consider that the participants must be turned towards each other. The most important aspect is the study design! A well-defined research question gives insights on which kind of sensors to use for optimal results. The study design also sheds light on how exactly to conduct the study in all its details, from preparing and handing out the sensors or the corresponding app for smartphones, guiding the participants during the study, and pre-processing the data after the study.

The studies listed in "Contribution of sensor-based studies to the social sciences" show how sensor-based research can be performed and which social constructs can be measured. Nonetheless, it is rather a proof of concept and only a first step towards the possibilities that sensors can bring to research interest in social sciences. In the future, developing sophisticated machine learning algorithms can transform devices such as cameras and microphones into actual sensors, as manual encoding would be obsolete, for example, automatically detecting the distance between people in video recordings of open city cameras to observe peoples' reaction to COVID-19.[3] An even more appealing aspect includes bringing both the technological area and the social science area closer to each other. This implies, on the one hand, that social scientists should invest more effort in new technologies investigating which social constructs can be analyzed by which state-of-the-art sensors. On the other hand, technicians should invest more effort in investigating how to enhance existing sensors to measure more complex social constructs. For example, future possibilities can be exploited by advances mentioned in Chen, Zhao, and Farrell (2016), in which the authors specify that GPS can be used to detect proximity within the centimeter range.

Notes

1 https://github.com/robogao/Protractor, accessed November 2020
2 See https://sociopatterns.org for a list of all studies conducted, accessed November 2020
3 https://landing.ai/landing-ai-creates-an-ai-tool-to-help-customers-monitor-social-distancing-in-the-workplace/, accessed November 2020

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