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Social Networks and Computational Social Science[1]

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A landmark article in *Science* (Lazer et al., 2009) presented computational social science (CSS) as a new domain for social science research based on novel data sources. This discussion highlighted how our locations, activities, interactions and transactions are increasingly monitored by sensors and location-aware devices, from transit cards and toll transponders to credit cards and security cameras. It also highlighted ubiquitous data collection on media consumption and interpersonal communication by telephone, email, or social media. This presentation of CSS included two branches that target distinct sources of relational data: first, those that study face-to-face networks using electronic devices; and, second, those that study computer-mediated social networks using email, social media and other telecommunication technology.[2] In either case, CSS encompasses the collection, processing and analysis of 'digital breadcrumbs' recorded through our everyday lives.

Researchers acknowledged from the start that these new data were relevant to scholarship on social networks, but the link from the new data to the body of conventional social network theory has often been absent, implicit, or unrigorous. This chapter extends recent efforts (Kitts, 2014; Kitts & Quintane, 2020; Lewis, 2022) to enrich the dialogue between the new CSS data sources and conventional social network concepts and theories. We will build on their analytic framework, which distinguishes four basic approaches to defining social ties as theoretical objects: *sentiments*, *role relations*, *social interaction* and *access*. Each of these four approaches represents a set of assumptions about the nature of social ties, which make it applicable to scope conditions for distinct domains of social network theory.

Classic theories of network dynamics often interpret social ties as interpersonal *sentiments*, which are thoughts or feelings directed from one social actor to others. Sentiments may be positive (liking, esteem, or trust), negative (hatred, disrespect, or distrust), or neutral (acquaintance, familiarity). In all of these cases, the 'tie' exists in the subjective thoughts or feelings of one actor towards another, so the resulting data are inherently directional and any tendency towards mutuality (e.g., shared feelings of liking or antipathy between two parties) is an empirical question.

Other classic social network research has measured social ties as *role relations*, socially recognised labels assigned to dyads (such as a friend, romantic partner, or family member), where the label represents distinct role expectations for the parties. These may go beyond dyads to represent shared involvement in a group that implies or imposes roles on members (such as teammates, officemates, housemates, or co-authors). These relations operate primarily as norms, expectations and repertoires for how actors behave towards one another within their roles (Kitts & Quintane, 2020; Fuhse & Gondal, 2022). For example, recent research on the meaning of friendship among adolescents (Kitts & Leal, 2021) shows that friendship is typically construed as *relational norms* (e.g., friends are expected to defend, help, or support one another, and to refrain from telling each other's secrets) as well as *structural expectations* (e.g., mutuality, transitivity, homophily). Role relations may also be directed, with norms and behavioural repertoires applying asymmetrically within the relation. For example, lawyers and clients, doctors and patients, or teachers and students follow particular scripts and respect particular expectations for role-related behaviour. Role relations are by definition socially recognised; the relationship exists insofar as the parties are aware of their roles and employ the associated behavioural repertoires. This social recognition makes role relations easy to measure, as researchers may simply ask individuals to identify their friends, or may obtain archival records of relationships such as co-authors of articles or co-sponsors of congressional bills.[3]

Research depicting network position as a source of power or social capital is often predicated on a definition of network ties as *access* to resources or information. Knowing the set of alters accessible to any given ego for a particular purpose (such as borrowing money or hearing about a job opportunity) allows a researcher to construct a graph of possible paths through which resources might flow among actors. This graph may support inferences about individuals based on their network position: an actor connected to others by shorter paths is assumed to have high-fidelity access to timely information, and an actor who is an intermediary on many paths of access among peers may derive power by controlling flows of resources. This work regards ties as providing opportunities for exchange or interaction, whether or not those opportunities are actually realised.

Increasingly, researchers measure actual social *interaction* as it occurs in relational behaviour between parties. Here they are concerned not with ties that could be activated, but where social contacts actually occur. Social interactions could be *directed*, as in giving a favour to a neighbour, sending a letter, or passing a syringe during drug use. Other forms of interaction are undirected by definition, as in sharing a dinner date or a phone conversation. Notably, interaction occurs in discrete social events at particular moments in time, which could at least in principle be represented as event histories (Kitts, 2014; de Nooy, 2015). To make interaction data conformable with traditional network lenses, researchers have turned event histories into timeless abstractions, such as social ties. An easy way to interpret social interaction events as relationships is to collect self-reports of implicitly aggregated interactions, such as typical or most frequent interaction partners (Paluck & Shepherd, 2012). Another way is to directly measure timestamped interaction events and then aggregate those events over time and compare the count to a threshold, inferring that a 'tie' exists if at least *k* interaction events occurred on the time interval (Huberman et al., 2009). For example, more than a certain number of phone calls or emails in a month indicates a friendship. This implicit or explicit aggregation is a common way to turn timestamped event data into *ties* that are abstracted from time and thus conformable to our concepts and theories of social networks.

This typology reflects qualitatively distinct approaches to thinking about network ties, as reflected in separate literatures addressing different theories. This is not a taxonomy of types of empirical ties, but a typology of approaches to defining ties. We consider the general category of *sentiment* ties, for example, but other work (e.g., Genkin et al., 2022) makes important empirical distinctions between specific sentiments captured by name generator surveys.[4] We build on work (Kitts & Quintane, 2020) that has interrogated the mapping from data to theory across these four types of network concepts, revealing some of the perils of using data representing one network concept (such as role relations or interaction) to investigate theories developed for another network concept (such as sentiments or access). Data sources are often selected for convenience rather than for their applicability to a given theoretical question. Much of the early research in social network analysis used role relations because of the ease of measuring those relationships using surveys or archival data. For example, network theories of all kinds have been applied to self-reported data on friendships. As the advent of computational social science brought unprecedented availability of data on interaction events, recently researchers have used interaction data (often aggregating events over time) as a proxy measure for various kinds of relationships, again applying all varieties of network theory to aggregated interaction data.

We focus here on the particular promise of CSS data for social network theory, and advocate for thinking more deeply about how to grapple with timestamped event data streams, rather than merely aggregating them and calling them relationships. Network researchers have had a variety of options to collect timestamped event data: human coding of observational or archival materials (Fuhse, 2022), retrospective self-reports (Vörös et al., 2021), experience sampling (Meijerink-Bosman et al., 2022), or time diaries (Zhang et al., 2021). While these methods are essential to our toolkit, they are typically challenging, expensive and prone to human error. In the following sections, we will review some ways that physical sensors and online platforms are vehicles to collect massive amounts of timestamped relational data. These have focused primarily on social interaction but, as we will see, can also measure sentiments, role relations and access.

DETECTING FACE-TO-FACE NETWORKS WITH DEVICES: SENSORS, LOCATION-AWARE TECHNOLOGY AND ACTIVITY RECOGNITION

A wave of early research in computational social science employed sensors, sometimes embedded in wearable badges or in handheld devices such as mobile phones. These sensors are used to automatically detect relational phenomena, often in fine time grain and over spans of time and space that would be difficult to observe with the human eye. For example, Bluetooth, GPS, Wifi, infrared (IR) and radio frequency (RFID) sensors can be used to infer location, orientation, or proximity of devices. Other sensor platforms have employed microphones to detect audio signals, accelerometers or gyroscopes to measure movement and physiological sensors to observe such features as heart rate, skin conductance, or hormone levels. These capabilities have been deployed over a broad range of contexts, including student communities in schools (Bahulkar et al., 2017; Vörös et al., 2021), employees or members in organisations (Chaffin et al., 2017; Müller et al., 2019) and children in families (de Barbaro, 2019).

Sensor technology has been applied most often to study social interaction, as it allows researchers to automatically collect timestamped data on interaction behaviour *in situ*, as it naturally occurs in time and space. Smartphones and other location-aware devices allow us to infer interaction among parties by observing colocation (Flamino et al., 2021; Lee et al., 2013) or by observing shared mobility patterns (Cranshaw et al., 2010). Specifically, several studies have used Bluetooth, RFID, IR, or wifi sensors to detect physical proximity or colocation (Eagle et al., 2009; Malik, 2018; Salathé et al., 2010; Guclu et al., 2016) and interpreted these as instances of social interaction. To refine simple colocation as a proxy measure of social interaction, researchers have used signal strength (Sekara & Lehmann, 2014), device direction or mutual orientation using infrared or RFID (Jang et al., 2017), and interaction duration (Oloritun et al., 2013). Researchers have also used microphones in either smartphones or dedicated sensor platforms to detect face-to-face conversations (Poudyal et al., 2021; Demiray et al., 2020; Harari et al., 2020; Wyatt et al., 2011), deployed sensors in clothing to monitor breathing patterns and detect conversations (Ejupi & Menon, 2018; Rahman et al., 2011), and even deployed sensors in seat cushions to measure meetings (Wang et al., 2004).

Note that sensors do not directly detect relationships or even social interaction behaviour, but detect some lower-level physical phenomena, such as Bluetooth signal strength or audio frequency. Researchers then take this sensor-derived data stream as an indirect measure of some meso-level construct, such as proximity between persons, and further infer a higher-order network construct like a social relationship. It is important to note that for each of these there are conceptual leaps between the fundamental property being measured (e.g., signal strength), the interpretation of that property (e.g., physical proximity and/or face-to-face orientation) and the theoretical construct it represents (e.g., social interaction). Partly to address the weak links between rich sociological concepts and the low-level physical properties monitored by sensors, some studies have aimed to triangulate by combining multiple sensor measures to study patterns of proximity, spatial positioning and verbal behaviour (Olguin et al., 2009; Onnela et al., 2014; Parker et al., 2018; Zhang et al., 2018).

Recent research has sought to collect electronic trace data on affective states using sensors. Affect can be measured as two distinct dimensions: *valence*, ranging from negative to positive, and *arousal*, or the intensity of feeling as indicated by activation of the sympathetic nervous system. Most sentiment-related sensor research has used sensing technology to monitor arousal by measuring physiological reactions such as galvanic skin response, heart rate, or pupil dilation (Palaghias et al., 2016). The work on inferring arousal from biometric sensors has often left valence unmeasured. In some cases, valence may be inferred by the researcher from the situation, or may be experimentally manipulated by the investigator (Kim et al., 2004). Other work has combined sensor measures of arousal with a more conventional measure of valence such as a self-report time diary survey deployed either periodically (Zhang et al., 2021) or using experience sampling (Zhang et al., 2018). In rare cases, researchers have attempted to measure affective valence using sensors; for example, Black et al. (2013) used audio recordings of conversations between couples in counselling, with the goal of using specific audio features to automatically classify communication in terms of positive and negative affect.

Other approaches have used sensors to detect events or activities that have an assumed relationship with particular sentiments. For example, researchers may employ sensors to monitor nonverbal behaviour, such as using accelerometers to detect laughter (Hung et al., 2013) or posture and body movement (Dragon et al., 2008), using video recordings to analyse patterns in eye gaze, body posture, or facial expressions (Dragon et al., 2008; Schmid Mast et al., 2015), using radio frequency signals to analyse breathing patterns and heartbeat (Zhao et al., 2016), using microphones to analyse response latency in speech (Iyengar & Westwood, 2015) or other acoustic features of spoken voices (Gu et al., 2017; Rachuri et al., 2010; Black et al., 2013) and using infrared thermography to infer emotions from facial microexpressions (Clay-Warner & Robinson, 2015). Such measures are then taken to reflect a related affective state.

It is important to note that the above work using sensors to measure affect can serve as a proof of concept for measuring sentiments. However, even if the technology successfully measures affect, this typically applies to the individual rather than a dyad or relationship – that is, they are not generally network data. Whereas we could use traditional surveys to measure *interpersonal* sentiments, interpreting sensor measures of affect as directed at another specific person would require further analysis or contextual information. For example, we might analyse audio signals to detect features of a speaker's voice indicating arousal, but to derive meaningful sociometric inferences we may need to overlay these sentiments on more explicitly relational data, such as measures of social interaction. We might, for example, examine the *change* of speech features for a given speaker when interacting with particular conversation partners (Wyatt et al., 2008) and take those changes as evidence of relationships loaded with sentiments.

Sensors measure physical states at particular times and so cannot be used to directly detect or monitor socially constructed role relations. Researchers can use sensor measures of interaction behaviour or sentiments to infer or predict the existence of relations like friendship (Sekara & Lehmann, 2014), but the sensor measures alone do not directly detect friendship as a role relation. Similarly, Flamino et al. (2021) use hierarchical clustering of Bluetooth sensor proximity measures to infer undergraduate students' membership in groups, but strictly speaking these are only patterns of physical proximity in time; the sensors do not directly measure the role relation of group membership. Analysis of turn-taking patterns in classroom speech data would likely reveal the distinction between teacher and students. But the classification would be derived from our knowledge of relational norms for how teachers and students talk in class, not derived directly from the sensors. Similarly, sensor data have been combined with contextual data or knowledge of relational norms about how and when friends interact – such as characteristic locations and times of day for interaction – to predict friendships as self-reported in surveys (Eagle et al., 2009; Oloritun et al., 2013).

Sensors have not been widely used to study access. As location and physical proximity sensors are typically interpreted as revealing social interaction events, this assumed equivalence between sensed colocation and social interaction means that researchers cannot interpret colocation as opportunities or determinants of interaction. Instead, sensor measures of location and proximity could be used to model the opportunity structure for interaction at a particular moment, but this would require an independent measure of interaction to identify where this opportunity is realised in social behaviour. For example, combining sensor measures of colocation (such as Bluetooth, Wifi, or GPS localisation) with human observers of face-to-face conversations, one could examine the effects of physical location and proximity on patterns of realised face-to-face conversations. Researchers could replace human observers with sensor measures more finely tuned to detect face-to-face interaction, such as RFID or IR (Malik, 2018) or 'situated speech data' using audio sensors (Wyatt et al., 2011). Even if we can perfectly detect conversations and disambiguate them from colocation, it will be challenging to disentangle problems of endogeneity outside controlled laboratory settings. People may strike up conversations with others who happen to be standing nearby at cocktail parties or academic conferences, but they may also relocate themselves in the crowd to be near their regular or aspirational conversation partners – that is, the proximity may be a byproduct rather than a cause of the conversation.

Because sensor technology typically monitors properties that are quite remote from meaningful social network data, they are often used in tandem with more traditional network measures in order to aid interpretation. Some studies have combined surveys of affect with sensor measures of proximity and interaction to explore the relationship between social interaction and interpersonal sentiments (Zhang et al., 2018; Olguin et al., 2009). For example, Alshamsi et al. (2016) collect sensor (IR) traces from wearable badges to observe face-to-face communication (via a combination of proximity and facing), paired with logs of communication through mobile phones as a measure of social interaction, then combine both of those data sources with self-reported affect measured through experience sampling. This allowed them to analyse how different types of social contact correlated with positive and negative affect.

DETECTING COMPUTER-MEDIATED NETWORKS: SOCIAL MEDIA, TELECOMMUNICATION AND ONLINE LINKS

Our second focus is the collection of network data from computer-mediated contexts. In contrast to relational information that is inferred from wearable or fixed sensors, we are here referring to a class of data where network phenomena are not only recorded by but actually *enacted through* some kind of digital media (e.g., Facebook, Twitter, SMS, voice or video chat). Here, user activity on a platform leaves behind digital 'footprints' or 'breadcrumbs' that researchers may study. In many cases all objective features of the relational event itself are captured – for instance, exactly when a text message was sent and received as well as the entire contents of the message itself.

Understandably, the advent of online social network sites was accompanied by a great deal of enthusiasm and research (e.g., Lewis et al., 2008b; Mayer & Puller, 2008), already the focus of recent review essays (e.g., Lewis, 2022; Tindall et al., 2022). These platforms appeared to offer large-scale, error-free and naturally occurring network data that potentially surmounts obstacles of prior work on face-to-face networks. In the time since, network studies of computer-mediated communication have encompassed a wide variety of platforms such as Facebook (Bond et al., 2012), Twitter (Tremayne, 2014), Wikipedia (Piskorski & Gorbatâi, 2017), online dating sites (Lewis, 2016) and massively multiplayer online games (Pham et al., 2022). They have examined interpersonal phenomena ranging from emails (Kossinets & Watts, 2009) and text messages (Igarashi et al., 2005) to 'friendship' or 'follower' relations on a variety of different platforms. And the boundaries of these networks have been defined in a variety of different ways, such as all communications among employees at a given organisation (Srivastava et al., 2018) or all tweets that include a given hashtag (Papacharissi & Oliveira, 2012). The activities recorded by these digital breadcrumbs can also have any manner of relationship with offline behaviour – at times preceding it (as when two singles who met online have their first date), at times succeeding it (as when two undergraduates meet in class and exchange phone numbers) and at times occurring entirely without it (as with anonymous participants in an online support group).

As with sensor research, computer-mediated contexts are most commonly used to study social interaction behaviours. For example, researchers examine timestamped logs of emails (Kleinbaum et al., 2013; Kossinets & Watts, 2009), instant messages (Leskovec & Horvitz, 2008), tweets (Boutyline & Willer, 2017), phone calls (Eagle et al., 2010; Onnela et al., 2007; Raeder et al., 2011; Stadtfeld & Block, 2017) and electronic calendar meetings (Lovett et al., 2010). They also analyse a variety of behaviours enacted within online platforms for gaming (Pham et al., 2022), resource sharing (State et al., 2016), dating (Lin & Lundquist, 2013), crowdsourced editing (Crandall et al., 2008) and cultural evaluation (Goldberg et al., 2016). Using network analysis tools to study the structure of interactions in these data requires some strong equivalence assumptions, such as treating nodes as interchangeable and treating interaction events as interchangeable in order to focus on the shape of the contact network. In contrast to the nuances of face-to-face interaction, digital interactions might seem well suited to formal network analysis, as the underlying behaviours may appear simple and even binary (such as 'swiping left' or 'swiping right'), thus easily translated to the binary sociomatrices employed by social network analysts. Even so, these contexts often provide rich additional information that could be used to observe the content or quality of communication and relationships. For example, researchers could use digital media data to record tie 'strength', such as the total time spent in phone calls (Onnela et al., 2007) or automated collection of measures of interaction intensity, intimacy, reciprocal giving, emotional support and relational duration (Gilbert & Karahalios, 2009).

Data that draw on computer-mediated communication to study interpersonal sentiments necessarily focus on *enacted* sentiments rather than direct measurement of psychological states; the correspondence between the two (especially given the performative nature of many such actions) warrants much more attention than it has currently received. As with digital interaction, sentiment data may also raise problems of interpretation insofar as superficially similar evaluations can mean many different things (e.g., Sumner et al., 2017). Enacted emotional evaluations become still more complex to study insofar as they provide the gateway to behavioural interaction (for instance, if two people have to ‘like’ each other on a dating site before they can interact, someone might strategically ‘like’ a lot of people to maximise romantic opportunities). Further, often what is ‘liked’ (or ‘disliked’ or ‘loved’ or ‘laughed at’) is not another person per se but a photo, link, comment, or other digital artefact they have uploaded. Other examples of online sentiment data include situations where users rate one another (or specific transactions between them), such as on Amazon, Etsy, or Airbnb (e.g., Leskovec et al., 2010; State et al., 2016), or give each other ‘gifts’ or other goods through the platform (Park & Kim, 2017). A final opportunity to study emotional expressions online is to apply sentiment analysis or other natural language processing tools to text in messages or posts (Pozzi et al., 2016). Such methods have been applied to social media data to identify emotional expressions and reveal temporal patterns in moods (Dodds et al., 2011; Golder & Macy, 2011) and also to analyse dyadic similarity in users’ sentiments towards social objects (Yang et al., 2017). Sentiment analysis of Facebook status updates (Coviello et al., 2014) allowed observation of emotional contagion on networks of Facebook contacts. The same tools can be applied to text sent from one actor to another to provide potentially rich and variegated measures of interpersonal sentiments.

On a variety of digital platforms (e.g., Facebook, Instagram, Twitter, LinkedIn), users may enter into formalised role relations, some of which parallel broader social categories of ties (e.g., ‘friend’) and others that are unique to digital space (e.g., ‘follower’). As with offline relationships, these ties may be undirected or directed and are governed by norms and expectations associated with the role relations. Unlike offline role relations, these online relationships may be explicitly constrained by the technical requirements of the platform software. For example, Facebook ‘friend’ relations must be mutually reciprocated, and are therefore undirected by definition, while Twitter ‘follower’ relations are directed and may or may not be reciprocated. However, these norms and expectations are also embedded within particular platforms and may not coincide with broader cultural meanings (e.g., a ‘Facebook friend’ may not be someone’s ‘friend’ offline). Additionally, whereas in the offline world there may be discordance in reporting role relations like friend or romantic partner, role relations online are typically hard-wired into the platform and observable without error or uncertainty. Further, whereas offline role relations entail relational norms and structural expectations, these may also be hard-wired into an online platform, where forms of interaction may be enabled only within certain kinds of relationships and disabled otherwise. In most cases, formal digital relationships also tend to persist until or unless they are actively terminated (whereas elsewhere role relations may fade unless they are actively renewed).

As with offline role relation data, these relations are often convenient to measure but may not correspond to theoretically motivated network concepts (sentiments, interaction, access). Given such ambiguous data on online relationships, scholars may use a variety of approaches to identify a subset of digital contacts that maps more closely to a social tie concept from conventional offline networks research. For example, Golder et al. (2007) make Facebook ‘friends’ more comparable to offline friendships by removing Facebook friends that are never observed to interact on the platform; Gilbert and Karahalios (2009) measure tie strength among Facebook friends by observing exchange of photos as well as public and private messages; and Wimmer and Lewis (2010) focus only on Facebook friends who have posted and tagged pictures of each other (and therefore have presumably spent time together offline). These approaches essentially add a measure of interaction to refine the definition of a role relation, blending the two network concepts together.

Kitts and Quintane (2020) point out that access networks are generally difficult to observe outside the laboratory, but well-defined online platforms may be an exception as digital media data present novel ways to study networks as access. For example, platform privacy settings may allow users to share or restrict profile information, updates, or direct messages to subsets of other users (or the public at large) and analysing these data allows us to see who has access to what information about peers (Anthony et al., 2017; Lewis et al., 2008a). For some platforms this is linked to role relations, as having a certain relationship with someone may be a prerequisite for accessing information about them or communicating with them. For instance, two people may have to be friends in order to post to each other’s profile; two dating site users may have to mutually ‘like’ one another before they can directly communicate; or a user may have to ‘follow’ someone (and have this request approved) before they have the opportunity to view that person’s post. Each of these provides the opportunity to rigorously measure channels of access to information or communication within a naturalistic setting, whereas direct investigation of access networks has been heretofore limited largely to experimental research (Centola, 2010). Although this approach contains a great deal of promise, there is one major caveat to keep in mind: these data on access are generally limited to a single platform. Just because two users cannot communicate on a given platform does not mean that they cannot communicate outside the platform. In this sense, it is a high bar to find interpersonal channels where the transmission of information is truly impossible. This is of course even more true for offline networks (where we typically observe only a small slice of access networks, fail to observe much interaction that actually occurred and never observe the potential interactions that failed to occur).

CONCLUSION

Computational social science methods employing physical sensors and digital media have offered timestamped data streams with great potential for the extension of social network research and theory. We have discussed these new data sources in light of four approaches to defining social ties: sentiments, role relations, interaction and access. We have shown that both types of CSS data lend themselves foremost to observing behavioural interactions, though there are emerging methods for using either sensors or digital media to observe affect, with applications to interpersonal sentiments. It is difficult to measure role relations and access using sensors, though digital media offer some promise in these areas.

In discussing these new sources of data, we have amplified recent calls for researchers to pay close attention to how the observed social ties or other relational data fit into standard network concepts (enabling them to be connected to social network theories). Within computational social science, particular theoretical questions may also apply better to either sensor or digital media data, as these approaches are not at all interchangeable. For example, most applications of sensors can yield only undirected data (e.g., shared conversations, colocation) so research that requires directed data, such as investigations of reciprocity dynamics, could more fruitfully draw on digital media data. Given that node-level data on individuals (personal traits, identities and attitudes) are rarely detectable by sensors, research that requires such node-level data – such as on homophily, social influence and diffusion – is difficult to pursue with a sensor approach unless individual-level data are collected by some other means. Some node-level data may be available within a digital media platform (often as part of a user's public profile, including postings of likes, favourites, or status updates) and this may support research on homophily or social influence. However, such generally public declarations may reflect a user's self-presentation to friends or other audiences rather than private opinions or other details as might be measured by a confidential survey.

Data collection using sensors is typically designed by the researcher in order to detect and monitor naturally occurring relational phenomena, as when a researcher deploys wearable badges on a population of college students. This approach is often expensive but highly customisable. Although online platforms may be set up by a researcher for experimental purposes (e.g., Centola, 2010) they are typically created by firms for commercial purposes and observed passively by researchers, allowing for observation of much larger populations but with less control. In some cases, the online platform design may manipulate networks in ways that interfere with research objectives. For example, an online social networking platform may recommend friends for users based on their similar interests or attitudes, or based on their shared relationships with third parties (friends of friends), confounding research on homophily or triad closure. More generally, online data face profound challenges that observed relationships and relational behaviour may not correspond to offline counterparts. So for researchers interested in making this link the opportunity to collect timestamped relational data for face-to-face relationships using sensors is a pathbreaking frontier. The advent of sensors and location-aware devices also opens an unprecedented opportunity to understand the relationship between social networks and physical space, which remains a blind spot for much research on online networks. We thus see particular promise for research in computational social science that integrates both approaches in dialogue with social network theory.

Notes

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2 The term 'computational social science' has been used to describe other communities as well as the two branches described in this chapter. The oldest body of work under the CSS umbrella (as represented in the four-volume 2010 Sage collection, *Computational Social Science*, edited by Gilbert) involves the use of computational models to simulate social processes and elucidate social theory, typically without any reference to empirical data. Second, recent work in CSS has applied

computational analytical methods (e.g., machine learning) aiming to detect, classify and predict patterns in social data of any kind, typically without any reference to theory. While acknowledging the work on computational theory and computational methods, we focus on the bodies of work targeting new data sources.

3 Note that many network scholars define social ties as relationships of this kind and then regard interaction, sentiments and access as properties or features of ties, rather than as ties themselves.

4 Other work has discussed a superficially similar typology of name generator questions on surveys, as ways of measuring an individual's 'personal network' for social support (Marin & Hampton, 2007). In that work, there is one underlying support network and there are four kinds of name generators (role relation, interaction, affective and exchange) that may be used to capture the true underlying support network. Their distinct aim is to find a minimal set of name generator questions that adequately represent the 'true' support network without the expense and burden of asking many questions.

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