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Characterizing Social Environments in the Physical and Virtual Worlds Using Digital Data

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Abstract

The study of social environments has typically revolved around interactions in the physical world. Here, a contemporary perspective of social environments weaves together multidisciplinary viewpoints and considers both physical and virtual spaces that offer opportunities for interaction. In the intersection where virtual and physical spaces collide, how does the structure of the social environment in the physical world affect that in the virtual world, and vice versa? How can abundant area-level digital data, produced at multiple locations and points in time, be used to study these social environments? This chapter examines the role that digital data plays in the study of human interactions, with considerations for context, in terms of physical proximity, history, and culture, as well as the advantages and challenges presented in using social media data for this type of study. The long-term goal is to examine how the social environment extends from the physical verse to the metaverse. This provides an unprecedented opportunity to characterize not only social environments using digital data but also to juxtapose them with the influence of physical environments.

Introduction

An important aspect of digital ethology is the role that digital data[1] can play in characterizing the *social environments* of an individual. The accelerating use of digital information technologies has allowed researchers to access and

[1] Digital data are data stored in digital form. In our context, digital data may refer to digital behavior (e.g., social media posts, number of followers/likes/shares on a social media platform, online search queries) or nondigital behavior (e.g., geolocation, census data, emergency room records).

analyze digital records about our behavior and interactions in the physical world (e.g., movement patterns, purchase history, mobile phone interactions). Traditionally, social environments were constrained to physical spaces such as neighborhoods or workplaces—the context in which people have the opportunity to interact by reflecting socioeconomic characteristics, including social networks[2] and levels of social support. These aspects of individuals' social environments determine their quality of life and collective behavior within their communities. While these aspects of the traditional social environment still hold true, the margins of the environment themselves have shifted through an increased impact by the virtual world.[3]

In addition to physical places, people interact online, and when they do, they leave many digital traces that encapsulate and define their collective behavior. Our understanding of the concept of social environment has been sharply modified by the advent of social media[4] and social media platforms,[5] which have been used to facilitate online communication and interactions. The social environments in which individuals live today consist of a combination of their physical and virtual environments. The emergence of this *new digital social environment* provides us with new opportunities and challenges to understand individuals' behavior and their interactions within their social environments. In this chapter, we attempt to characterize this new digital social environment in the context of the ongoing digital revolution. An individual's activities and their social interactions in the virtual world can influence and supplement their physical social environment, even covering some gaps or deficiencies in it. The online social networks[6] that an individual builds can become key factors in their social environments. In some cases, such as in augmented reality[7] and the metaverse,[8] the virtual and physical social environments intersect, thus blurring the boundaries between both social environments.

2 A social network consists of the connections and relationships made between individuals in the physical world. Social networks can consist of strong ties (i.e., close friendships) and weak ties (i.e., acquaintances, work colleagues).

3 The virtual world represents the online world and consists of interactions and connections made using online platforms. We use the term virtual world, or environment, as a contrast to the physical world.

4 Social media are communications between users in text, image, or video form shared over the Internet on a third-party platform (as opposed to direct communication using mobile phones).

5 A social media platform is a third-party software platform used to facilitate communications and connections between individuals and groups over the Internet.

6 Online social networks are social networks developed via social media platforms. In some literature, the terms online social networks and social media platforms are used interchangeably, but we make the distinction here.

7 Augmented reality presents an overlay of a virtual world or virtual objects onto a view of the physical world.

8 The metaverse is an emerging virtual world that combines simulated virtual reality (facilitated by 3D headsets) and elements of social interaction and connection to create an emotional and believable immersive experience.

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This chapter reflects our multifaceted discussions during the Forum, aimed at developing a framework to characterize social environments, both in the physical and virtual worlds, using digital data. We start by describing social environments from different viewpoints, including those based on ethology, social norms, geography and place, social epidemiology, and social networks. We then develop a view of social environments based on digital ethology, bringing in components of social environments from both the physical and virtual worlds. To be able to use digital data to study social environments, we must first consider how aspects related to the context influence social behavior. We emphasize factors related to physical proximity and human emotions as key aspects. We refer to the impact of context on the behavior of particular collectives (e.g., people who immigrate) and discuss how social bridges and social mobility can affect context. We then dive into how an individual's social environments can be influenced by the virtual world. This includes the effects of building social capital in the virtual world and considering how interactions in the virtual world can affect behavior in the physical world. In an attempt to understand our behavioral evolution in the near future, we discuss what ethology means in the metaverse and what implications the metaverse might have in our social environments and how they are perceived. We then turn to the various types of digital data that can capture traces of human behavior and provide a detailed discussion of social media data, which can be a rich source of information about the interactions in the virtual world. We discuss the advantages of using data extracted from social media (e.g., size, speed, capturing emergent knowledge) in comparison to more traditional sources (e.g., paper-based surveys) and the challenges of deriving knowledge from these data sources (e.g., making individual vs. group-level inferences, use of colloquial language, generalizability). We focus, in particular, on the various types of bias that might be present in social media data and discuss several studies that have used social media data to examine aspects of human behavior. Finally, we conclude with open questions to be addressed in the near future.

Describing Social Environments

There is not a singular definition of what constitutes a social environment nor a consensus across different disciplines, but there are overlapping elements. In addition, there is not one single social environment, rather, an individual can have multiple social environments that reflect the different aspects, spaces, functions, or interactions present in their life. Here we present several different, but related, views on social environments and conclude with a unifying view of social environments for digital ethology.

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Ethology View

We first consider social environments at the ethological level by considering the social behavior of nonhuman primates. In the wild, social environments vary according to species' characteristics and communicative system. They are not restricted to a particular defined physical environment and might change in scale, but they are related to the *opportunity that an individual has to interact socially with other individuals*. The social interactions do not necessarily have to take place, but the boundaries defining the social environment are delimited by the potential for the interaction. This potential varies among species, depending on their social structure and communicative system.

The social system of distinct animal species shape their social environments because it includes individuals with different characteristics (e.g., the prevalence of one sex over the other), and these individuals might use the physical environment in different ways and interact with different conspecifics (Mitani et al. 2012). For instance, social systems of nonhuman primates might vary from extended families organized around matrilineal hierarchies, where social interactions are more or less biased toward kin (Sueur et al. 2011), to troops that are organized within families. Families, in turn, are organized hierarchically across the troop, where friendships with immigrant males might be common (Smuts 2017). A species' social system shapes, therefore, the identity of the individuals with whom the interaction takes place in the social environment.

Different social systems can build different social environments according to the use that individuals make of it. For example, different ecological selective pressures can generate different social organizations, as in the case of species living in fission-fusion societies, which are characterized by a temporal and fluidly dynamic separation of the individuals in subgroups (Symington 1990). These dynamics challenge the opportunity to interact socially and moreover they create distinctive selective pressures affecting, in turn, the communicative system of the species (Aureli et al. 2008). The potential for communication between individuals shapes the physical space that allows the social interaction between the individuals of a community, concurring in defining a flexible social environment.

Therefore, the influence of the social structure and the communicative system of a species creates a specific social environment at many levels (e.g., groups, species, orders), which is reflected in the potential for the individuals to interact. Examples range from cultural differences in the responsiveness during joint attention interactions (Bard et al. 2021) to the variability in the behaviors used to communicate in different but phylogenetically close species in relation to the evolutionary history (bonobos vs. chimpanzees, Gruber and Clay 2016; different macaques' species, Maestripieri 2005). Both human infants and young chimpanzees show a significant cultural variability when they interact socially with an adult female to share attention toward an object (joint attention); this highlights that different forms of engagement need to be contextualized to be fully understood in their expression (Bard et al. 2021).

Whatever the selective pressure, the social environment and its complexity influence the evolution of the social traits of a species in a feedback loop that redefines the social environment itself and the social interactions that characterize it.

Norm-Based View

Humans, like all other social animals, spend most of their lives in proximity to and in interaction with conspecifics. We largely live in "nests" built by others, eat food harvested and prepared by others, engage in conversations about knowledge created by others, and develop new ideas in cooperation with others, in a full behavioral synchrony. These interactions build a basis for a social environment that is both influenced by and influences social norms. Social norms guide our interactions, technologies (whether engineering or social), rules, laws, and how we perceive the universe around us. This broader societal context is a key component of our social environments and includes prevailing cultural norms, religious beliefs, structural racism, legal frameworks, political institutions, and other factors that may shape human attitudes, behaviors, and opportunities. We live in complex social networks, whether we are hunter-gatherers (Apicella et al. 2012) or live in modern societies (Dunbar and Spoors 1995). There are often consequences for individuals who violate social norms, including reduced opportunity for interaction or even being ostracized from the community (Kam and Bond 2009; van Kleef et al. 2015; van Leeuwen et al. 2012). In fact, perhaps the most important factor in the human brain, being of such an exceptionally large size, is the need to manage the cognitive demands of interacting with others inside complex social environments (Dávid-Barrett and Dunbar 2013), whether it is the task of computing strategic social action (Dunbar and Shultz 2007) or coordinating to achieve behavioral synchrony (Dávid-Barrett and Dunbar 2012).

Place-Based View

Social environments are the social settings or contexts in which people live and potentially interact with others. Interactions can occur in both physical settings (i.e., occupying physical space with a geographic location) and virtual settings (e.g., an online community). A place-based view focuses, however, on physical settings: the places people inhabit and live their lives. In human geography, "place" is traditionally defined as a location that has been constructed by human experiences; it is distinguished by the sociocultural or subjective meanings through which it is created and differentiated (Relph 1976; Tuan 1977). In this place-based view, an individual's social environment begins at home (i.e., where one sleeps at night). Here, an individual may interact regularly with other members in the household (family or unrelated roommates) and is both influenced by, and helps shape, the social norms of others who occupy the same home. People are also influenced by the social environments of their respective workplaces and/or educational centers, where they interact with their friends, colleagues/classmates, and supervisors/teachers. In these places, there are rules (explicit), social norms (implicit), and power relations (both explicit and implicit) that influence social relations and an individual's behavior within these social environments (Cresswell 2004). These social environments are typically experienced several times per week. In addition, other influential places make up one's social environments, such as places of worship, commerce, and recreation. These places, typically located within one's immediate neighborhood or are at least geographically accessible within one's settlement or population center (e.g., city, town, village), are usually accessed less frequently than home and work/school, but vary according to personal, cultural, and geographic factors. Balsa-Barreiro and Menendez (this volume) describe several ways in which geography and population density in urban versus rural settings impact the opportunities for and types of social interactions. Furthermore, an individual's social environment extends to their neighborhood, city, state, and country of residence. These administrative/governmental entities influence human behavior in that they exert power over society through, for example, laws and norms.

Social Epidemiology View

Following seminal works from Durkheim (1897) and Villermé (2008), social environment refers to social interactions and relations among people at different levels of analysis determined by the household, the family, the school, the workplace, the neighborhood, the society in which one lives (Berkman et al. 2014), as well as more recently the digital environment where people evolve in, willingly or not. The key idea is that these social relations, organized in networks, are essential for individuals' well-being and behavior, as well as for other outcomes. While we generally think of social environments as being resources, they can also be sources of negative interactions and exposures, such as conflict, violence, and incentives to engage in unhealthy or dangerous behaviors (Villalonga-Olives and Kawachi 2017). One of the questions that arises with recent changes in social interactions, increased by the dissemination of digital media, is the extent to which virtual social interactions replace, compensate, or augment face-to-face interactions. Moreover, the social environment also refers to the hierarchy of social relations in a society, which conditions access to socioeconomic resources related to education, employment, occupation, housing, and place of residence, which determine individuals' status in society.

Social Network View

If an individual's social environments are based on the opportunity for interaction, then they depend necessarily on the individual's social network (i.e., the network of personal connections that the individual has with others). Not all personal connections are equal in weight. These connections, or ties, have been generally classified as strong ties (e.g., close friendships with frequent meaningful interactions) or weak ties (e.g., acquaintances with fewer meaningful interactions). The importance of social ties in well-being has been recognized for a long time, both in terms of number (Dunbar and Spoors 1995; Hill and Dunbar 2003; Shultz and Dunbar 2010) and quality of ties (Granovetter 1973; Seyfarth and Cheney 2012). It was previously assumed that the well-being effect comes from the intensity of the relationships, which is usually determined by the frequency of meaningful interactions (Pollet et al. 2013; Roberts and Dunbar 2011). There is, however, a further effect that stems from the level of interconnectedness of the social network itself (Brondino et al. 2017; Dávid-Barrett 2022a; Dunbar 1998). For us to feel safe, we need to perceive a highly integrated social network around us, despite the fact that some studies on complex systems have demonstrated how networks with many interdependences tend to be more unstable (Balsa-Barreiro et al. 2020b). This integration (or lack thereof) can highly shape how we view our social environments, either as a benefit or a drawback. An organizing principle of social networks is also the notion of structural diversity, which suggests the number of connected components and their influence in forming the network connection (Dong et al. 2017b). For example, just being from the same larger physical space (zip code) might imply a more diverse common neighborhood between two connected nodes in a network, as each of those nodes may have their own friends or workplace connections; nonetheless, two close college friends may have more similarities in their connections, thus creating a less diverse common social neighborhood. Such diverse or common neighborhoods create the spectrum of social resources available to an individual.

Through much of human history, the primary organizing principle of all human communities was kinship. The fall in family size, especially when combined with urbanization, has led to the rise of friendship as the dominant form of social relationships (Dávid-Barrett 2019). Friendship is fundamentally different in its nature to kinship, in that the latter is mostly preset (and in a network sense, prewired), but the former is flexible. Such flexibility poses, however, a network organization problem, as friendship groups, if organized randomly, have a much lower level of integration (lower clustering coefficient, in network science terms) than kinship groups (Dávid-Barrett 2022a). One possible solution to this problem is the use of trait similarity (homophily) in friendship choice (Dávid-Barrett 2020). This mechanism explains the importance of homophily in friendship choice, a well-established phenomenon (Kossinets and Watts 2009; Laakasuo et al. 2020; McPherson et al. 2001). The presence of

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homophily in social networks reflects the interplay of selection, where an individual may choose to form ties with others who have similar characteristics or interests, and social influence, where an individual's existing ties contribute to the development of new interests (Easley and Kleinberg 2010).

Digital Ethology View

Going forward, we take into consideration the various views on social environments that have been presented thus far. In doing so, we formulate a unifying definition of social environments that can encompass both the physical and virtual worlds and the various factors that impact an individual's social environments. When we include the virtual world, one's social environment also includes the interactions that can occur within personal online communities. For example, one can belong to, interact with, and be influenced by (and help create) the content within various social media platforms (e.g., Reddit, Twitter/X, Facebook). While these online social environments do not occupy a precise physical space, for those who spend a large amount of time on these platforms, they may exert a powerful influence over their real-life behavior.

In our view, and as related to digital ethology, *social environments are spaces where the opportunity for interaction occurs, whether physical or virtual, personal or societal*.

Context Can Affect Social Behavior

Societal context, in terms of physical proximity, history, and/or culture, is an important component of social environment as it can affect our social environments even when there are no direct interactions, such as the influence of proximity. For example, to understand the social and economic behavior of Mexican citizens, their proximity to the United States must be considered, even for those who do not travel to the United States or interact directly with Americans. Something similar happens in many Eastern European countries, where collective behavior is sharply influenced by recent history. For instance, even though more than 30 years have transpired since the Reunification of East and West Germany (Andor 2019), difficulties associated with converging the two populations are evident in terms of health disparities (Grigoriev and Pechholdová 2017), educational opportunities (Klein et al. 2018), and political attitudes (Weisskircher 2020). In this way, past history can lead to human emotions related to fear, mistrust, or guilt being mutually shared by whole communities.

When using data to study social environments, it is important to frame the data in the appropriate context and consider the source of the data. In some cases, what appears to be the same data points can lead to different conclusions (Balsa-Barreiro et al. 2022). This can happen even with indicators that can be quantified from an objective perspective. For example, how is poverty defined? The concept of poverty is contextual, varying according to different situations. An individual could be deemed impoverished within an affluent community while being relatively wealthy in a deprived neighborhood, even with an identical income in both settings.

Throughout history, humans have developed a series of survival strategies based on the simplification of information. An evident instance is the establishment of straightforward stereotypes about individuals from diverse countries, commonly held by many. Past relationships through history, popular traditions, books, and broadcast media contribute to spread and perpetuate these stereotypes. This societal survival strategy once made sense in terms of biological machinery for generations, yet such simple and binary thinking has become a problem in a society where the number of interactions and information available has grown exponentially over the last few decades (Dutton 2021). Therefore, properly contextualizing datasets is crucial to prevent biased outcomes and potentially misleading conclusions, which can result in weak and inadequate decisions. Incorporating context and a comprehensive grasp of spatial scales is vital, particularly given the extensive use of data-driven tools in decision-making processes.

Below, we discuss several examples that demonstrate how societal context can affect behavior in sometimes nonintuitive ways. These examples highlight the need to include context when drawing conclusions about group-level phenomena observed in data.

Impact of Context on the Behavior of People Who Immigrate

People who immigrate move from one context into another, often vastly different, context. Here, we consider, at a group level, how this change of location can affect behavior and the way in which these behaviors evolve over time. This provides important insights into the roles of different types of environments.

Research conducted as far back as the 1970s by Len Syme's group (Robertson et al. 1977) showed that over time, the behaviors of people who immigrate come to resemble those of the host population. For example, they found that men who immigrated to the United States from Japan had higher levels of cardiovascular disease than those living in Japan; further, levels of risk for cardiovascular disease varied depending on whether they resided in California or Hawaii. More recent research on this topic has shown that among persons who migrate from Ghana to Europe, dietary patterns change and cardiovascular risk is higher than if they had stayed in rural or urban Ghana, as well as across the destination cities (Galbete et al. 2017). Most notably, consumption of sugar, principally through soda drinks, varies greatly for a Ghanaian residing in London, Berlin, and Amsterdam, regardless of any other characteristics. Galbete et al. (2017) also showed that over time, Ghanaians who immigrated to Europe have an elevated risk of hypertension. The factors associated with that increased risk actually vary, however, across places of residence, further highlighting the role of context (van der Linden et al. 2022).

Moreover, the behavior of those who immigrate changes over time as well as across generations; differences are also possible across communities and contexts. For instance, research conducted in the United States shows that descendants of immigrants from Asia or South America follow similar diets as the host population, whereas South Asians appear to have distinct dietary patterns that resemble those of first-generation immigrants from South Asia (Rodriguez et al. 2020).

Sociological research has also shown that those who immigrate tend to converge with the majority population over time. Patrick Simon's group has studied the way in which individuals name their children in a nationally representative study of people who immigrate and their descendants living in France. Data show that while traditional French names are not common among descendants of immigrants, these children are also not given names that are most common in their parents' country or culture of origin either. Rather, they are given names that lie somewhere in-between the standards of the culture of origin and the French setting (Coulmont and Simon 2019). Consistent data have shown that persons who have a foreign, and particularly a Muslim-sounding, name are at high risk of experiencing discrimination with regard to education, employment, housing, and possibly other domains of life. Thus, giving a particular name to a child may shape the social environment and experiences of the child later in life (Simon 2017).

Impact of Social Bridges

Social bridges are individuals whose social networks serve to connect multiple communities and facilitate information exchange between the communities. Dong et al. (2017a) studied the impact of social bridges on purchase behavior between different communities when their social bridges worked at locations near each other. Their main assumption was that because they worked in proximity to each other, these social bridges had the opportunity to foster information exchange, which could then be transferred back to their home communities. The authors analyzed millions of credit card transactions and found more similarity in purchase behavior between communities that had higher numbers of social bridges linking them. This similarity was even present for nonbridge individuals in the communities. Further, the number of social bridges between two communities was a stronger indicator of purchase similarity than other factors, such as income, gender, or age.

Impact of Social Mobility

Studies examining the causal link between socioeconomic status and health/behaviors often evaluate this through investigations into the effects of social mobility, by considering both upward and downward shifts. Dohrenwend et al. (1992) conducted a key study by comparing the risk of psychiatric disorder to the level of educational attainment across two different ethno-racial groups in Israel. They showed that among young people who do not belong to a socioeconomically disadvantaged group, a low level of education was associated with a higher risk for a psychotic disorder. This effect was not observed among young people with similar level of education who came from a socioeconomically disadvantaged group. This suggests that downward social mobility can be related to poor health; that is, individuals are "selected" into a social group because of impaired mental health. In contrast, individuals who came from a socially disadvantaged group but achieved higher levels of education were at low risk for psychotic disorders, indicating that upward social mobility could be protective. Similarly, intergenerational upward mobility has been found to predict health habits (Mok et al. 2018) and mental health levels (Melchior et al. 2018) generally comparable to those of individuals who always experienced favorable socioeconomic conditions.

In the 1990s, vivid debates played out in the scientific literature between Michael Marmot's and George Davey-Smith's groups, regarding why social hierarchy and one's place within it influences behavior, with opposing views on the role of material versus psychosocial pathways. There is now evidence that both these mechanisms contribute to socioeconomic inequalities in behaviors and health (Fleitas Alfonzo et al. 2022). Moreover, extensive research has documented that social, economic, and the physical characteristics of places where individuals reside and spend most of their time contribute as well to condition certain behaviors (Daniels et al. 2021). Importantly, data from Ana Diez-Roux's group show that if one lives in a deprived neighborhood, the proximity to a wealthy area is also relevant (Auchincloss et al. 2006), indicating that the concentration of poverty is detrimental to health behaviors possibly because of reduced access to resources as well as higher stress resulting from spatial segregation.

Following the hypothesis proposed by Putnam (2000) and translated to epidemiology by Kawachi and Berkman (2014), social cohesion and social capital within communities and neighborhoods have been proposed to be protective in terms of health and health behaviors. This is based on the idea that tight social ties in a community provide a setting for individuals' supportive social networks and a source of social control, which can help taper unwanted behaviors. While much research has shown that a cohesive social environment can be positive, some evidence indicates that it is not, particularly when a person is excluded. Consistent research, primarily based in the United Kingdom and the Netherlands, show that members of ethno-racial minority groups who reside in neighborhoods populated primarily by members of nonminority groups have elevated rates of psychosis (Baker et al. 2021). The relative heterogeneity in findings across settings suggests that different social contexts exert varying effects. The main mechanisms that have been proposed to explain this counterintuitive finding relate to individuals' experiences of racism and discrimination in neighborhoods where members of ethno-racial minority groups are few, leading overall to experiences of social exclusion and elevated acute as well as chronic stress levels (Henssler et al. 2020).

Social Environments and the Virtual World

The social environment in a virtual world offers a large capacity to develop interactions that span neighborhoods, regions, and countries, which are things limited by the physical boundaries and constraints imposed by the physical world. In a virtual world, "travel documents" are not needed to communicate with someone across national borders, as there would be in the physical world. This creates fertile ground for unique social environments that may be particular to an individual and the development of communities and may even be of assistance to the individual. Nonetheless, the individual may also be exposed to risks that stem from the wide mix of social interactions that emerge in the virtual world. Virtual world and physical world interactions also intersect, however. Do virtual world interactions create strong ties, or are strong ties preordained as kinship or ties that originate in the physical world?

Social environment can also be a relative concept. If an individual is devoid of an accessible physical neighborhood for living or work, do virtual interactions create a complementary set of opportunities? If so, how do we develop a union or intersection of interactions between the virtual and physical environments that collectively build the social environment? What if an individual does not have good access to technology to enable a virtual social environment? Do these factors contribute further to inequities? Will an individual who is already facing disparities in the physical environment be further disadvantaged in the virtual world because of a lack of access to technology? As we imagine the construction of social environments, it becomes important to consider these questions and be able to develop a utility metric to characterize or measure the level of quality of social environments.

Social Capital and the Economy of Attention

One major element of the virtual world are online social networks that are facilitated by social media platforms, which take advantage of the Internet to allow interactions between individuals and groups in text, voice, image, or video format (Sarker, this volume). The emerging business model of social media platforms is to sell advertisements targeted toward specific groups of users based on behaviors tracked by the social media platforms. The longer a user stays engaged on a platform, the more advertisements they will see, so social media platforms have the incentive to hold users' attention for as long as possible. In essence, the use of social media platforms may be free for users, but it comes at the expense of providing extensive behavioral information to advertisers.

From the human behavioral perspective, online social networks are framed within the economy of attention. Franck (2019) outlines the shape of this new, quaternary sector of the economy, characterized by dematerialization and virtualization, where our attention is the main asset. Online social networks are presented as means or tools that allow us to connect with the world and communicate with our friends. They can be, however, somewhat more complex. For Wei (2019), online social networks are basically tools to extract and show status or social capital. This status is calculated as the sum of all the elements of prestige existing in our social life. In the past, this social capital was highly fragmented and difficult to estimate, at least until the advent of digital social media. Online social networks generate a new market where it is possible to quantify our social capital based on our communication and interactions on them, by checking the images we see/like/share, our comments, and our connections, among others. Competition in online social networks intensifies as more users seek increasing attention, but our limited attentional capacity means favoring some neglects others. Consequently, a paradox emerges: over time, all our online friends become competitors or adversaries in the medium to long term.

Interactions in Digital Spaces Can Affect Behavior

Some studies have explored how digital spaces can impact human behavior in real life. For example, in 2016, the first mobile phone-based augmented reality game, Pokémon Go, was released and became popular worldwide. Pokémon Go superimposed a virtual world based on augmented reality on top of the physical world; imaginary creatures called Pokémons could be seen and captured as part of the game. The game required players to walk around and explore the physical world in search of the virtual creatures. Althoff et al. (2016) showed that over a period of 30 days, engaged game players increased their average step count by 1,473 steps per day, approximately 25% more than usual. They estimated that within the brief time span of the study, the game resulted in a total of 144 billion additional steps to the overall U.S. physical activity. This was the first study that reported on the impact of augmented reality on the real-life physical activity of humans. Similar follow-up studies around the world (Laato et al. 2021; Ma et al. 2018) showed that connecting virtual spaces with physical world objects had the benefits of increasing physical activity and supporting social meetings.

Interactions on social media platforms can also change real-world behavior. A study of young girls who use the photo-based social media platform Instagram found more negative levels of body image than those who did not use the platform, likely due to social comparison. (Pedalino and Camerini 2022). Others found that cosmetic surgery consultations related to interventions similar to the filters used in social media increased (Maes and de Lenne 2022) and have demonstrated how social media can manifest a distorted view of physical reality (Hong et al. 2020; Perrotta 2020). In recent years, the idea has spread that online social networks function as echo chambers (Bail et al. 2018; Cinelli et al. 2021), where users interact exclusively with others (users and/or media) with similar ideologies and are no longer exposed to information that differs or contradicts their own ideas. In this way, it is hypothesized that online social networks are closed systems where one's own ideas would seem true due to amplification and continuous repetition of them.

In recent years, virtual reality technology has improved to the point where consumer devices are both affordable and provide a believably immersive experience. Combining virtual reality environments with elements of social interaction creates the opportunity for a new virtual space, the *metaverse*. An early example of such a community was the virtual world Second Life, released initially in 2003. Because the technology that powers these environments provides a more realistic experience, we can start to ask questions about how interactions in the metaverse could be different from physical interactions or interactions that take place on traditional online social media platforms. These platforms could allow individuals to break out from the social environments they experience in the physical world, which are influenced by culture, history, and social norms centered on a place. This is a new and exciting avenue for research. How will the metaverse impact an individual's social environments? What would digital ethology look like in the metaverse? What is behavior in the metaverse? Who is the actor, or who engages in the behavior? Who is the observer, or ethologist, in the metaverse? How might the ability to interact in ways that are impossible in the physical world, or to set up social norms and conditions that would take years to develop in the physical world, allow experimentation and incubation of ideas that could later be manifested in the physical world?

Using Digital Data to Learn about Social Environments

Many of the interactions that make up our social environments can be characterized using digital data, yet there are distinctions to be made: digital data may reflect *digital* behavior (e.g., content of social media posts, number of social media followers) or *nondigital* behavior (e.g., census reports, hospital data), which in turn may reflect the consequences of human behavior or activities (e.g., traffic-related air pollution). Whatever the target, digital data offer a great potential for the study of human ethology. Some sources are, however, underused due to lack of knowledge about what is available, methodological complexity for using, and restricted access due to issues of user privacy and industry ownership. For a sampling of digital data sources that can be used to study human behavior, see Balsa-Barreiro and Menendez (this volume), with ethical considerations discussed by Lovasi et al. (this volume) and Medeiros et al. (this volume). We begin by considering two examples:

First, digital data can be used to study social networks in the physical world. For a relatively brief period of time, mobile phone networks provided an exceptionally useful source of social network data. Between the mid-2000s and the mid-2010s, when mobile phone usage became prevalent in the general population in most societies in the world, patterns extracted from mobile phone data created a rich and comprehensive image of human social networks. As the use of social networking apps for communication began to spread, however, much of the dyadic and polyadic digital communication shifted to platforms such as WhatsApp, Telegram, and Signal. Since the communication pattern on these apps tends to be opaque, the parallel use of several of these have made social network detection nearly impossible. Several mobile phone call studies allowed the recognition of a large number of social behaviors ranging from gender differences in social behavior (Bhattacharya et al. 2016; Palchykov et al. 2012; Yang et al. 2019), structural properties of social networks (Jo et al. 2014; Onnela et al. 2007), inference of demographics from communication patterns (Dong et al. 2014), and life course dependent social behaviors (Dávid-Barrett et al. 2016b). Although today it is far more difficult to acquire common behavioral patterns from mobile phone data, these can still be useful for extracting mobility patterns for some particular communities based on demographics and socioeconomic factors by using different aggregation levels of data (Pullano et al. 2020; Valdano et al. 2021).

Second, digital data can be used to unravel society's response to a pandemic. COVID-19 presented wide-ranging challenges (e.g., scientific, policy, economic, and behavioral), and there was variance in society's response to COVID-19 restrictions and expectations. As the scientific community raced to develop vaccines and therapeutics in record-breaking time, policy makers grappled with how to communicate and influence sociopolitical-economic decisions that could require individuals to take uncomfortable decisions. To inform the ethology of a society's response to a pandemic, it became important to leverage digital data. Krieg et al. (2020) leveraged several streams of digital data, including COVID-19 case data, demographic data, longitudinal news and web search trends, media bias data, and mobility reports to inform an understanding of society's response, norms, attitudes, and beliefs.

Social Media Data

We recognize the importance of digital data in general and their usefulness in learning about an individual's social environment. Here, however, we focus on social media data, which is a subset of the larger digital data, because of the relatively novel complexities involved in using such data to study human behavior. We consider social media data to be the traces of interactions between individuals and groups in text, voice, image, or video format taking place over the Internet (Sarker, this volume). These social media data consist of the posts as well as the metadata about posts and their authors obtained via application programming interfaces (APIs) offered by the social media platforms or via web scraping from the platforms' user interfaces.

There is a wide diversity in social media platforms in terms of the types of interactions that are enabled, the types of media that can be shared, and researcher access to that data and metadata. For instance, Twitter/X has a limit of 280 characters per post whereas Facebook, LinkedIn, Reddit have no character limits. While other platforms' main post type is text, Instagram is image based. Instagram users can include text captions, but they must accompany an image or video. Between platforms, there are also differences in how users can interact with each other. On Facebook, connections are largely bidirectional; if you "friend" another user, not only can you see their posts, but they also become your friend and can see your posts. On Twitter/X, however, relationships are unidirectional: you can "follow" another user, but they may not follow you back. In terms of access, Twitter/X had served as a favored platform for academic research due to its widespread accessibility as most posts are public. Additionally, Twitter/X offered a powerful API for accessing the posts and author and post metadata, including geolocation, though free use of this API on Twitter/X has been restricted. By contrast, Instagram has a much larger user base (1.5 billion vs. 425 million) (Statista 2022a) but offers only a limited API (via CrowdTangle) for researchers to access posts or metadata. Dong et al. (2017b) used some of the structural differences among social media platforms to uncover three main superfamilies of platforms, based on how users develop connections with each other. For instance, this explained how social networks developed via Facebook are different from those developed via LinkedIn.

Estimates suggest that globally over 4.26 billion people (around 58.4% of the global population) currently use social media (Statista 2022b). Consequently, the digital footprint of collective human behavior on social media is enormous, leading to a plethora of information on many topics of interest. The utility of such data was realized by the social media companies and the advertising industry as it provides insights about user-level and group-level interests and can be used to conduct targeted advertising. More recently, the utility of social media data has been realized by researchers with noncommercial interests. Data from social media sources have been used in different fields of knowledge, such as public health and social sciences. In public health, for example, social media chatter has been leveraged to study and detect infectious disease outbreaks (Hossain et al. 2016; Ting et al. 2020; Tsao et al. 2021) and adverse drug reaction patterns (Bulcock et al. 2021; Sarker et al. 2015).

Social media can present rich individualized or aggregated data about individuals, communities, and society at large. New data-harnessing technologies allow us to capture individual behavior and activities across a variety of social media platforms, and to link or integrate those with aggregated data generated from public record platforms (e.g., census records) or to combine the signals derived from social media with traditional survey instruments. This provides a unique opportunity to explore human behavior, attitudes, beliefs, and how they cascade, but it also opens possible pathways of risk (e.g., privacy invasion, bullying, or stalking). There are technical considerations involved in such linking and integration, as well as important ethical issues; for further discussion, see Lovasi et al. (this volume) and Medeiros et al. (this volume).

As researchers, we must ponder about how and when to use social media data, for what purposes, and what reliable methods and results could be derived. The normative question becomes: What is the focus of our study? Should we study the humans who create the content, and how attitudes, beliefs, and opinions develop or cascade as a result? Should we study the object of conversations (e.g., social media chatter on drugs) and the side effects that emerge? Or should we study some social network phenomena on how links emerge or how information flows on a social media platform?

Framing the normative question that guides data collection and research process is essential to determine whether the use or data sample derived from social media is sufficient for the research method and the conclusions that emerge. While social media holds the promise of large sample sizes (large *N*), it also presents the challenge of not knowing who (or what) it represents. We romanticize the idea of data availability at scale, but just because data are available and potentially accessible, it does not mean that data are sufficient to address the question being considered, and we lack a formal definition of sufficiency. We do not attempt to define this here, but rather aim to highlight that it is important to raise such a definition to inform the use of data. For a discussion of the use of such large-scale datasets, see Kum et al. (this volume).

Advantages to Using Social Media Data

From the perspective of research, social media data present several advantages compared with traditional data sources, as evidenced by the following examples:

- *Reach*: Social media potentially offers greater reach compared to other platforms or data sources. Social media adoption is globally at an all-time high. Many hard-to-reach populations (e.g., refugees, people without health insurance, victims of violence, people with disabilities who are unable to leave home) can make their voices heard through social media. Social media-based studies can include data generated from such populations, who may not be accessible through any other channels.
- *Size*: Social media data are massive. Thus, it is possible to generate reliable population-level insights for the population of social media users studied, though there are limitations to this, as will be discussed in the next section.

- *Speed*: Specific APIs make social media data available in real time or close to real time. These insights can be crucial for many studies, particularly in the space of public health, where it can be used to detect the outbreak of infectious disease faster than other sources. Social media is a compelling source for use cases that require scale and speed, which traditional surveys might not be able to provide.
- *Capturing emergent knowledge*: Social media data are constantly being updated, so emergent knowledge can quickly be captured. For example, if we are collecting streaming social media data and identifying the topics of discussion, we may suddenly notice a new topical construct that emerges. This can be a quick indicator of a change, possibly generated by an exogenous event of concern and can serve to be a leading indicator of a phenomenon. Kryvasheyeu et al. (2016) evaluated how online social media contributes to rapid assessment of disaster damage by improving situational awareness, facilitates dissemination of emergency information, enables early warning systems, and helps coordinate relief efforts. Similarly, Sarker et al. (2020) demonstrated the utility of social media in characterizing acute COVID-19 before widespread knowledge about its symptom spectrum was available.
- *Anonymity*: Social media often allows people to share information anonymously. Hence, discussions about sensitive topics (e.g., substance use, intimate partner violence) are frequently available on social media but often not available from other sources. Anonymous online data, such as Google search queries, can be more reliable indicators than answers to survey questions. For example, Google search queries were used to characterize the racial animus in the years leading up to the election of Barack Obama as president of the United States in 2008 (Stephens-Davidowitz 2013). Because of the sensitive nature of the behavior under study, it could be difficult to obtain truthful answers on a survey.
- *Cost*: Collecting data over social media is typically much cheaper than traditional methodologies (e.g., surveys). This is particularly true at the national or international level. Conducting national surveys, for example, can be very expensive, whereas social media data can be collected at little cost.
- *Breadth*: Traditional instruments, such as surveys, only collect information about the questions that are asked. Because the information shared over social media is not constrained by such questions, the breadth of the information can be much larger and may enable deep, longitudinal studies on the evolution of culture, behavior, opinions, and beliefs.
- *Discovery of knowledge using natural language processing*: Advances in the broader field of data science, particularly natural language processing and machine learning, have created new opportunities in social media-based research. Natural language processing may allow inference of knowledge that is not explicitly encoded in the metadata. For

example, even when geolocation information is not explicitly present, mentions of locations by a specific social media user can be identified and/or extracted using named entity recognition methods (Batbaatar and Ryu 2019; Chen et al. 2018). Meanings of expressions, including nonstandard or colloquial expressions, can be inferred by advanced natural language processing and machine-learning methods.

- *Collective information*: Social media can help identify common issues faced by groups or communities. For example, by understanding the challenges faced by individuals, we might be able to study substance use, depression, or drug side effects: what interventions work and how supportive communities form. In public health research related to substance use, insights derived from social media data in the United States have been validated against traditional sources of information, such as overdose deaths from the CDC Wonder database, the National Survey on Drug Use and Health (NSDUH), and the Nationwide Emergency Department Sample (Sarker et al. 2019; Yang et al. 2021). Compared with some traditional survey-based instruments, social media-based insights may be better representative of population-level behaviors because they integrate marginalized groups who may not complete surveys. For example, Yang et al. (2021) showed that gender distributions for opioid use, estimated from Twitter/X geodata in the United States, had better agreement with emergency department visits for opioid use related injuries compared with the NSDUH estimates. This ability to infer population-level insights for a specific geolocation has been shown to hold even for anonymous social media channels, such as Reddit (Harrigian 2018). At a country-level scale, Nigam et al. (2017) leveraged social media data to determine the outcome of the Colombian peace process and infer the underlying challenges or pain points of the population (Madan et al. 2010).

Challenges to Using Social Media Data

While the advantages described above make the use of social media data appealing, there are numerous challenges associated with the use of such data. We present a non-exhaustive sample below:

- *Presence of bots*: Digital data from social media can be used for prediction and analyses, but bots or fake posts can influence such tasks. At the individual level, particularly, bots can improperly influence analyses or predictions by contaminating the data collected. Relying on group-level data (e.g., posts from many users) can mitigate this problem. Some recent studies have also proposed methods for detecting bots automatically (Davis et al. 2016; Davoudi et al. 2020;

Sayyadiharikandeh et al. 2020), which may allow for their impact to be removed prior to analysis.

- *Making individual-level inferences*: Individual-level inferences should not be made from the data because data are incomplete and may even be false. For example, an individual post from a certain geolocation may be fake or posted by an automated account (i.e., a bot). At a group level, or with aggregated analyses, it is possible to mitigate some of these problems or risks. For example, if 10,000 posts from the geolocation are analyzed, it is likely that the number of fake posts, and consequently their influence on the overall inference, could be mitigated. Similarly, while missing data at the individual level can largely constrain our understanding of an individual, aggregation of large data can fill the gaps left by missing data at the individual level and help obtain more reliable population-level insights.
- *Natural language processing*: Most data available from social media are in free text format. The language of social media is often colloquial and contains nonstandard expressions and misspellings. While advances in natural language processing and machine learning have made it easier to derive knowledge from social media posts, the methods are not perfect, and in most cases, not even near perfect, especially with the nuance often present in communication using social media. As a result, knowledge is often not accurately detected or extracted from social media data.
- *Generalizability*: Conclusions derived from social media are typically not generalizable to the entire population of a given location. People on digital social media generally skew younger. Often, they are more tech savvy compared with the general population. The demographic representation also varies between social media platforms. For example, Facebook has a larger representation of older people, whereas TikTok is more popular among younger people (Auxier and Anderson 2021). These limitations must be established in any study and boundaries provided for the use of any insight or finding that emerges from the study. Further, social media data does not offer the opportunity of a deep understanding that might emerge from longitudinal ethnographic studies that stem from immersion into a community.
- *Representativeness*: Related to generalizability, representativeness refers to whether the characteristics of the sample population captured in the data are considered to reflect accurately the characteristics of a larger population from which it is drawn. Determination of sample representativeness is hampered by the fact that key demographic (e.g., age, sex, gender, ethnicity) and socioeconomic (e.g., income, education, employment status) information is often missing on the subpopulation captured in social media sources. In addition, to determine representativeness in social media data, one must carefully consider what

is the largest population that the data are meant to represent (e.g., a particular community or the society as a whole). Certain groups are excluded from access to social media, and thus no social media platform should be used to represent a population as a whole (Blank and Lutz 2017). In particular, individuals with a higher socioeconomic status and Internet use skills are typically overrepresented in social media (Hargittai 2020). Assessing the representativeness of social media is a moving target: social networks evolve continuously as do the populations that use them. While social networks were mostly popular among younger people, larger numbers of older people are gradually adopting them. Hence, a specific social media platform, such as Facebook, does not necessarily represent the same population now as it did five years ago nor will it represent a similar population five years from now. Unanswered questions about representativeness do not necessarily diminish the utility of social media in digital ethology research, but researchers need to be mindful of this when leveraging social media data.

- *Unknown denominator*: While population-level behaviors can be studied using social media data, a major obstacle to conducting epidemiological studies using data from social networking platforms is that the denominator is typically not known. For example, while nonmedical use of prescription opioids can be detected from social media data and the relative volume of nonmedical use can be assessed, the total number of people who report using opioids for medical purposes remains unknown. Adding to the complexity, the proportion of people who consume opioids and report this on social media is also unknown. To date, we have no specific strategy to overcome this challenge and need to be mindful of this characteristic.
- *Ill-defined control groups*: Many studies require an intervention/experimental group and a comparison/control group. Currently, however, there is no well-defined mechanism for generating control or comparison groups from social media data. While observational studies of virtual cohorts can reveal group characteristics, there are no meaningful ways of comparing these characteristics with other groups. For example, while it is possible to create a virtual cohort of people who use opioids and study group-level patterns from the data posted by the cohort, the patterns may not be meaningfully compared with a control group. While a virtual cohort of people who never report using opioids can be created relatively easily, there is no guarantee that the members of the comparison group actually never used opioids nonmedically in real life. Rather this group would represent those that do not report on nonmedical use of opioids on social media. Nonetheless, it is also important to note that issues of gaps in reality and reporting are prevalent in most population studies (e.g., surveys only represent what participants choose to reveal, and emergency department data analysis

only represent those who went to the emergency service being studied) and measuring real truth is a fundamental issue in all research. Noting the limitations, learning what one can, and being thoughtful about the interpretation and inferences being made is most important.

- *Missing data*: Social media-based studies, behavioral or otherwise, can only incorporate information that is reported by individuals voluntarily. It is impossible to determine, particularly at the individual level, what information is and what is not reported. Additionally, many social media platforms allow users to edit or delete posts or may ban users, removing their posts from public view. This may not be an issue for studying group-level behavior, but many prominent public figures, including politicians, have deleted embarrassing or incriminating posts or have been banned from social media platforms. Especially for government figures, deletion of posts or account bans can impact the digital preservation of government public records (Kriesberg and Acker 2022). Some original social media posts may be found in web archives, but due to the prevalent use of JavaScript, many social media posts are difficult to archive (Bragg et al. 2023; Brunelle et al. 2016; Garg et al. 2021, 2023).
- *Self-editing*: Researchers should be cautious about taking social media data at "face value." In a personal profile, people may project their lives by posting what they want others to see, typically the most positive aspects of their lives (e.g., their most attractive photos on Instagram). Self-editing also means that people will share different pieces of data on different platforms, such as professional details on LinkedIn, but nothing about family (Hollenbaugh and Ferris 2015). Self-editing is not only restricted to limiting the type and amount of information that is shared; it also includes dishonesty. For example, photo filters can be applied to make one look more attractive, and people lie about various aspects of their lives (e.g., height, number of sex partners) to show that they are happier than they are in reality.
- *Legality/privacy*: The sociopolitical-legal structure informs the use of the social media platform. Different countries or cultures have different permissible uses or activities that can be done on social media platforms; this directly limits the replicability or reproducibility of the work. There are also risks involved when linking social media data that may have been considered by the author of a post to be anonymous with other sources of data that might personally identify the author. There is, thus, a particular need to study potential risks in parallel to any study utilizing social media data. It must also be noted that while academic researchers continuously regulate themselves from the perspective of ethics (e.g., through institutional review board reviews), the ultimate power lies with the companies that host the social networks and the ultimate risks perhaps lie with the commercial interests

of these companies. Little is known about how these companies use the data they host themselves. Perhaps there should be a greater push for transparency. For further discussion, see Medeiros et al. (this volume).

Issues of Bias in Social Media Data

Because there are many different types of bias that can be present in social media data, we have separated the challenge of bias from the above list. Even though data from social media might be large *N*, it might still be difficult to define the statistical power and mixing of potential biases. We provide an outline of different categories of bias below, though these categories are not exhaustive:

- *Selection bias*: Social media users do not typically represent the general population. As pointed out above, subscribers of social media platforms tend to be younger and tech savvy, and older populations are often underrepresented. Access to digital devices such as smartphones, digital literacy, and local policies (physical environment) also influence selection bias.
- *Behavioral bias*: Olteanu et al. (2019) described systematic distortions in how user behaviors are represented across different social media platforms and contexts. The same individual may express different behavioral traits based on the particular social media platform being used. Thus, data from one platform may contain quite different digital footprints compared with another network even though the underlying user base is similar.
- *Reporting bias*: The rate of reporting certain events on social media may deviate from their real-world frequencies. For example, social media posts may excessively amplify topics that receive coverage on traditional news media, while some topics can be underrepresented. Certain behavioral traits may also be overrepresented over social media, as people want to broadcast those behaviors to their networks (e.g., travel, exercise, dining), while others may be underrepresented (e.g., substance use). As another example, people using dating sites tend to represent themselves strategically and to behave strategically (e.g., women report lower age and lower weight than the reality, while men tend to report being taller and earning more than the reality) (Drouin et al. 2016). The distortion is so large, that despite the presence of exceptionally large datasets, the use of these for scientific understanding of human dating choice behavior is limited, apart from the fact, of course, that such dishonesty exists. Data from social media also often overrepresent extreme views on topics while underrepresenting non-extreme ones. Not all social media subscribers are equally active. Those who are most vocal are represented better by the data (Baeza-Yates 2020).

- *Group attribution bias*: This bias is more associated with the interpretation of behavioral data from social media rather than as a bias in the data itself. Often behaviors observed in individuals or groups of individuals are overgeneralized to a broader cohort to which they belong. There is also a tendency to stereotype individuals to groups in which they do not belong. Since insights from social media data are typically derived from aggregated cohorts, unique individual characteristics may be lost in favor of group characteristics.
- *Platform-imposed bias*: A significant limitation of social media data for research relates to the platform. For example, the sampling rate and algorithm that a platform provides can lead to a biased or uncertain sample, which directly impacts the method being considered and the result that emerges from the triangulation of data and methods. Thus, there is an accessibility versus representativeness dilemma.
- *Temporal bias*: Even on the same social network platform, data from different time periods can exhibit biases based on the user base of the platform, its usability, and constraints/rules imposed by it. For example, Twitter/X had a character limit of 140 per post at the beginning, which was increased to 280 characters later. The data generated on the platform, consequently, could change substantially over time. The evolution of social networking platforms, such as Twitter to X, lead to evolving biases. Thus, when using data to study human behavior, findings from one time period may not hold over time (Liu et al. 2014); it may only offer a snapshot from that specific time period.
- *Data processing bias*: Biases may also be introduced to the data when processing it to study human behavior. Over recent years, many studies have attempted to derive knowledge from user-generated social media data using machine learning and other data-centric methods. Machine learning algorithms themselves add biases when interpreting the data. Machine-learning models are vulnerable to, for example, algorithm bias (i.e., the algorithm favors specific data or is biased toward amplifying specific phenomena) as well as measurement bias (machine-learning algorithms are biased toward specific criteria).

Examples

Having discussed several advantages and challenges to using social media data to study human behavior, the following examples illustrate how social media data could be used in research.

To Test a Particular Social Behavior

In a Facebook profile picture study, social networking data collected in 2011 were used, for the first time, to evaluate whether a particular social behavior constituted a universal human behavior (Dávid-Barrett et al. 2015). Here, the aim was to assess the hypothesis that women have a larger number of close friends than men do. The study coded approximately 112,000 Facebook profile pictures for the number of people and the gender composition in profile pictures, which was used to determine close friendships. The assumption behind this methodology was that if the same behavior was detected in all populations, then it is likely to be universal, and thus it is valid to ask whether it is also genetically inherited. Finding universal human behaviors had been extremely difficult in the past, because for this to be the case, not only the same behavior should be observed in all human cultures, but manifestation of the behavior should also be within the same social context. Using Facebook allowed observation of behavior from an exceptionally large number of people in different cultures within the same platform, and thus solved both problems. A significant gender difference was found, in particular in the formation of close friendships. The pattern was the same on all continents, in line with the hypothesis that there might be an at least partial genetic underpinning behind the behavior. The dataset yielded results beyond the initial question, suggesting that life course drives social behavior on social networking sites (Dávid-Barrett et al. 2016a). The initial social media study was followed by a real-life observation of 1.2 million people in 46 countries across the world, which supported the original study's findings (Dávid-Barrett 2022b).

To Study Problems for Which Data Are Not Available from Other Sources

Social media serves as a valuable tool to study issues lacking data from conventional sources, thereby providing a voice to marginalized communities typically excluded from such data sources. A recent study focusing on opioid use disorder as discussed on Reddit (Spadaro et al. 2022) revealed insights about the concerns of patients receiving or looking to receive treatment through medications for opioid use disorder (e.g., buprenorphine). Specifically, the study revealed that people with opioid use disorder on Reddit discussed experiences and fear of precipitated withdrawal when initiating buprenorphine treatment. The study further showed that the Reddit subscribers had collectively discovered potential reasons for precipitated withdrawal, and the community discussed successful self-management strategies that worked better (according to their shared experiences) than the protocols followed in clinical settings. This study illustrated the utility of social media data for leveraging insights that addresses the true concerns of targeted communities.

Combining Social Media with Additional Data Sources

In the Tesserae project, Mattingly et al. (2019) studied how a suite of sensors could measure workplace performance, psychological traits, and physical characteristics over a one-year period. The study enrolled more than 750 information workers across the United States, who participated using sensors (e.g., smartwatch, beacons, phone agent). Shared data included measures such as heart rate, physical activity, activity patterns, and social context. Participants also shared access to their social media data (Facebook). The variety of such (unobtrusive) sensing streams for a diverse user group allowed a detailed understanding of patterns of life and activities in these people's natural environments (Robles-Granda et al. 2021). Based on naturalistic observation, this methodology was implemented to infer driving behavior, showing advantages such as the limited intervention of the researcher in the experiment (Balsa-Barreiro et al. 2019b, 2020a). The social media in this case presents an opportunity for verbal and social sensing, in addition to physical and environmental sensing which the smartwatches, beacons, and smart phones may provide. While social media sensing might be driven by an individual's self-selection bias on participating and sharing, the physical sensing could capture complementary contextual attributes that could explain or model the propensity to participate on social media or individual-/group-level outcomes (Saha et al. 2019).

To Measure Social Fragmentation

Social fragmentation refers to the breakdown in connectedness in a community. Dong et al. (2020) analyzed how income segregation determines social interactions both in the physical and virtual world. They checked preferred discussion topics in the online space according to income in some Western cities. Discussions in wealthy neighborhoods typically included lifestyle topics (e.g., travel, leisure activities), whereas in poor neighborhoods discussions were focused primarily on sports and TV shows. Balsa-Barreiro et al. (2022) investigated global communication patterns through data sourced from Twitter/X. They constructed a global network where edges linked locations when users mentioned others in different places, with edge weights indicating communication intensity between locations. Using the Louvain algorithm, they identified 14 major communities initially, expanding to 86 minor communities as the analysis scaled up, analyzing 70 million tweets by 4 million users worldwide between August and September 2019. Their study highlighted the intricate multiscale nature of social spaces based on human communication patterns. Bakker et al. (2019) implemented different measures extracted from mobile phone metadata for checking the level of integration of Syrian refugees in Turkey. Their integration was estimated based on three dimensions: social, spatial, and economic integration. This study found striking differences both in the distributions of these dimensions, but also in the relationships between them.

Open Questions

Based on our discussion of social environments and the challenges of using digital and social media data to study social environments, we list several open questions that should be considered in the future.

- Does the online social environment shape behavior as much as the physical social environment? How will the emergence of the metaverse change this?
- If an individual is devoid of an accessible physical neighborhood for living or work, do virtual interactions create a complementary set of opportunities? If so, how do we develop a union or intersection of interactions between the virtual and physical environments that collectively build the social environment? What if the individual does not have good access to technology to enable a virtual social environment?
- How does the particular online social media platform used relate to strength of relationship tie? For instance, being friends on Facebook may be more related to some physical interaction and may produce stronger ties, but connections on LinkedIn, Twitter/X, or Reddit may never meet physically, so those ties may be weaker. What factors are more relevant: time spent on the online social platforms, or number of online interactions with people that have physically met?
- How will the metaverse impact an individual's social environments? What would digital ethology look like in the metaverse? What is behavior in the metaverse? Who is the actor, or who is the behavior by? Who is the observer, or ethologist, in the metaverse?
- Could one calculate online inequality, similar to how income inequality is characterized with the Gini coefficient? What would be a meaningful metric for this inequality? Number of followers? Of likes? The scenes that someone is projecting on his/her social networks?
- Could one trace the variation in similarity (related to social fragmentation) across regions? In large regions where we collect abundant social media posts, greater diversity and heterogeneity of hashtags are expected. Yet, do these patterns unfold similarly in areas where people have varying income levels?

Conclusion

In this chapter, we have discussed the concept of social environments from various viewpoints, starting with a basic ethological definition and moving to more complex notions of social environments that humans may encounter in both the physical and virtual worlds. We considered how context, in terms of physical location, which then brings in that location's culture and history, can affect an individual's social environments. We also discussed how the virtual world can affect social environments through its impact on social capital and the ability of interactions in the virtual world to affect individuals' behavior in the physical world. This exploration culminated in a discussion of how the emerging metaverse could further affect individuals' behaviors and interactions, even more than interactions in more simple virtual worlds. With these considerations of social environments in hand, we then discussed how the vast amounts of digital data generated can be used to learn about social environments. In particular, we focused on social media data and various considerations for their use. Data scientists and others should be aware of the many challenges and potential pitfalls to using social media data to study social environments. The relative ease of data collection and volume of social media data make it an easy target for study, but researchers should be careful in making broad generalizations based on what could be individual-level data points. In closing, we hope that future studies will pursue the open questions that we identified to provide greater understanding in how digital data can be used to study social environments.

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