Pace of Life in Cities and the Emergence of Town Tweeters

Alexander Jones Gross1, Dhiraj Murthy2, and Lav R. Varshney3

Abstract
Long-standing results in urban studies have shown correlation of population and population density to a city’s pace of life, empirically tested by examining whether individuals in bigger cities walk faster, spend less time buying stamps, or make greater numbers of telephone calls. Contemporary social media presents a new opportunity to test these hypotheses. This study examines whether users of the social media platform Twitter in larger and denser American cities tweet at a faster rate than their counterparts in smaller and sparser ones. Contrary to how telephony usage and productivity scale superlinearly with city population, the total volume of tweets in cities scales sublinearly. This is similar to the economies of scale in city infrastructures like gas stations. When looking at individuals, however, greater population density is associated with faster tweeting. The discrepancy between the ecological correlation and individual behavior is resolved by noting that larger cities have sublinear growth in the number of active Twitter users. This suggests that there is a more concentrated core of more active users that may serve an information broadcast function for larger cities, an emerging group of “town tweeters” as it were.

Keywords
Twitter, human dynamics, social media, urban studies, communication, culture, and technology

Introduction
Several studies have found that the pace of life in cities is much faster than in less populated areas. In a classical study, Bornstein and Bornstein (1976) found that the rate of pedestrian locomotion varies in a regular fashion with the size of the local population, regardless of cultural setting. Levine and Norenzayan (1999) studied how pace of life measures such as the work speed among postal clerks and accuracy of bank clocks varied between countries and which attributes of a location’s “personality” (including population and population density) were correlated. Such findings demonstrate that lifestyle differs qualitatively and quantitatively in different locations according to the nature of the place. Moreover, as Gieryn (2000) argues, “we make places,” an allusion to our social construction of place—partially mediated by architecture and design.

Bettencourt, Lobo, Helbing, Kühnert, and West (2007) more recently considered macroscopic quantities that are indicators of the creation of wealth and of new ideas as functions of city population size. These indicators include new patents, inventors, private R&D employment, “super-creative” employment, R&D establishments, R&D employment, total wages, total bank deposits, gross domestic product (GDP), total electrical consumption, new AIDS cases, and serious crime. All were found to grow superlinearly with city population, and mathematical models of social interactions have been proposed to explain these findings (Bettencourt, 2013; Bettencourt et al., 2007; Pan, Ghoshal, Krumme, Cebrian, & Pentland, 2013). However, measures of city infrastructure such as number of gasoline stations and road surface area grow sublinearly with city population, indicating economies of scale (Bettencourt et al., 2007).

Beyond productivity and innovation measures, one may also consider other sociological indicators of city personality such as prosocial behaviors that promote social well-being, including volunteering, giving money, donating blood, or voting. Arbesman and Christakis (2011) found that whereas political contribution rates and volumes increase per capita with city population (like productivity and innovation), voting rates and organ donation rates do not seem to change with city size, and census return rates decrease per capita. If the amount of effort to add another person to a population requires less prosocial effort—by the person or by the collective—than the previous person, then one might expect prosocial behavior to decrease per capita. Arbesman and Christakis (2011) suggest that whether a given behavior scales superlinearly, linearly, or sublinearly may depend on whether a behavior is limited to interacting with nearby individuals or allows

1University of Maine, Orono, USA
2University of Texas at Austin, USA
3University of Illinois at Urbana–Champaign, USA

Corresponding Author:
Dhiraj Murthy, Moody College of Communication, University of Texas at Austin, 300 W. Dean Keeton, A1000, Austin, TX 78712-1067, USA.
Email: dhiraj.murthy@austin.utexas.edu

Creative Commons CC BY: This article is distributed under the terms of the Creative Commons Attribution 4.0 License (http://creativecommons.org/licenses/by/4.0/) which permits any use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).
The social media platform Twitter allows users to share messages restricted to 280 characters—tweets—among an ecosystem of over 300 million monthly active users (Twitter, 2017). As a highly active marketplace of virtually mediated communication and ideas, particularly from 2010 to 2013, Twitter has drawn the interest of social science researchers as both a subject of study in itself as well as a rich qualitative and quantitative data source to discern microsocial and macrosocial, economic, political, and health interactions (e.g., Arceneaux & Schmitz Weiss, 2010; Burrows & Savage, 2014; Chen, 2011; Chunara, Andrews, & Brownstein, 2012; Golder & Macy, 2011; Hutkins, 2011; Lassen & Brown, 2011). Twitter has faced monetization and user adoption issues recently (Lynley, 2017), but the data we have collected and analyzed are from 2012, which many argue was the heyday of Twitter as a platform for mass information exchange and represents the platform’s run up to its 2013 initial public offering. Ultimately, Twitter at that time was a good representative of general social media phenomena (see, for example, Buettnner & Buettnert, 2016; Murthy, 2013; Olteanu, 2016).

Our research seeks to explore and identify tweeting trends across cities by examining the behaviors of individuals within them. The goal is to identify characteristics of social media behavior and usage patterns that are connected with population. We aim to understand whether social-psychological and community characteristics of cities identified in classical pace of life studies manifest themselves in virtual environments. Twitter provides detailed data regarding usage behavior that enables meaningful data-driven analysis. The study presented herein is based on a collection of tweets tagged with geo-data from 50 American cities. Our research begins to understand some of the complex dynamics of Twitter use in urban America. One may wonder whether Twitter, a service for technological intermediation, is delinked from geography and so notions of physical place like user city are irrelevant to behavior (Takhteyev, Gruzd, & Wellman, 2012). Moreover, drawing from previous work which found evidence of more frequent log ins to social media among rural rather than urban users (Gilbert, Karahalios, & Sandvig, 2010), we hypothesize the opposite.

Hypothesis 1 (H1): The physical phenomenon of pace of life in cities manifests in tweeting behavior.

As we will show, although a smaller fraction of the population tweets in larger cities, this core of tweeters has a faster pace. In some sense, these active tweeters may act as an information broadcast infrastructure for their city, an emerging social group of “town tweeters” analogous to historical town criers. Others have argued that local community-based services including support of “local products and educational awareness” and pace of life may be linked (Mayer & Knox, 2009). Given the possibility of Twitter serving as an information broadcast infrastructure for cities, we make a further hypothesis on aggregate Twitter usage in cities as a function of population.

Hypothesis 2 (H2): Aggregate tweet volume scales sub-linearly with city population, according to a power law.

Our research validates this hypothesis. As population grows, tweet volume does not increase linearly. Unlike productivity, innovation, or mobile telephony measures, our findings are reminiscent of infrastructure scaling (Um, Son, Lee, Jeong, & Kim, 2009) like the number of gas stations or certain pro-social behaviors such as census return rates. We further refine this in H3 as follows.

Hypothesis 3 (H3): Deviations from a power-law distribution can be explained, in part, by aspects of city demographics, culture, and/or personality.

The temporal tweeting behavior of regularly active individuals in urban America, whom we term town tweeters, could be affected by socioeconomic and other aspects of a city. As Shah, Kwak, and Holbert (2001) suggest, new media use is not homogeneous and seeks to “satisfy different goals, resulting in varied patterns of effects” (p. 142). Indeed, Barabási (2005) has suggested that most observable social, technological, and economic phenomena are driven by the dynamics and interactions of individual actions and has provided a mathematical model that generates experimentally observed bursty, heavy-tailed statistics of such human activity. Others have previously observed the burstiness of tweeting (Chalmers, Fleming, Wakeman, & Watson, 2011) and related social media activity (Zhao & Zhou, 2012). In particular, we hypothesize a power-law distribution for the distribution of intervals between tweets for individual users.

Hypothesis 4 (H4): The distribution of intervals between tweets for individual town tweeters is well-described by a power law.

Using formal statistical methods (Clauset, Shalizi, & Newman, 2009), we falsify this hypothesis and find that power-law behavior is not the best description of observed behavior.
data. Rather, other parametric forms which have finite mean for interevent intervals provide a better fit to data. The power law with exponential cutoff distribution and other distributions typically provide satisfactory fits, rather than power law. These distributions have finite mean but also suggest tweeting is a bursty activity, which echoes previous work that finds topics in Twitter bursty (Diao, Jiang, Zhu, & Lim, 2012) as well as posting of tweets (Raghavan, Ver Steeg, Galstyan, & Tartakovsky, 2014).

The actions and interactions of individuals are often said to generate city-level phenomena (Arbesman & Christakis, 2011; Bettencourt, 2013; Bettencourt et al., 2007; Pan et al., 2013), such as the sublinear scaling of tweet volume with city size that we observed. As we have access to Twitter data at the individual level, we are able to investigate the relationship between tweeting behavior of individual users and a population-centric notion of how they experience their city environment, informing our next hypothesis.

**Hypothesis 5 (H5):** The time between tweets for individual users decreases as a function of their city’s population density.

We verify this hypothesis. The effect is weak but strongly significant statistically. This indicates that individuals in denser cities tweet more frequently, which may seem contrary to the infrastructure-like tweet volume scaling we had observed. To explain this apparent contradiction between individual behavior and the ecological correlation, we make the following hypothesis on the number of people who tweet.

**Hypothesis 6 (H6):** A reduced number of people tweet in larger cities.

Contrary to telephony, which is point-to-point, Twitter has been designed to facilitate multicasting: the broadcasting of many to many (Murthy, 2013). Since people have limited time (Aral & Van Alstyne, 2011) and must allocate it to various activities that may be substitute goods with tweeting rather than complementary goods (Miritello et al., 2013), the general increase in pace of life in larger cities may, counterintuitively, inhibit participation by larger fractions of the population.

### Time, Pace of Life, and Town Criers

**Time and Pace of Life**

Time has been important to classical social scientific work and has been studied by Simmel (1950), Durkheim (2004), and Weber (Segre, 2000). Though Weber did not have a specific theory of time, he did observe how pace was socially constructed (Segre, 2000). For example, Segre (2000) describes how Weber saw factory workers change their pace based on solidarity with fellow workers or changes in institutional regulation. Unsurprisingly, scarcity of time in urban Western centers is correlated with pace of life (Garhammer, 2002). Simmel (1950) viewed the metropolis as having a constant flow of strangers. City life, from his perspective, breeds a rhythm of life which fosters detachment (Simmel, 1950). Veblen argued that constructions of time are associated with social structure (Southerton & Tomlinson, 2005).

Societally, gauging pace of life remains important as “being busy is symbolic of a ‘full’ and ‘valued’ life” in many cultures (Southerton & Tomlinson, 2005, p. 219). Durkheim famously argued that “Every disturbance of equilibrium, even though it may involve greater comfort and a raising of the general pace of life, provides an impulse to voluntary death” (Durkheim, 2004, p. 99). Ultimately, the notion of pace of life is a fundamental social question.

Indeed, Chicago School sociologist Robert E. Park (1929) classically measured urbanization by newspaper circulation. Park argues that “culture, since it is based firmly on communication, is always more or less a local phenomenon.” Park’s thesis is that towns and villages were losing their “independent character” and becoming “satellites of the cities.” We are more interested in sublinear versus superlinear distributions rather than “independent character.” However, Park’s argument that communication is local is important. Specifically, Simmel emphasizes locality when he argues that “The City is not a spatial entity with social consequences, but a sociological entity that is formed spatially” (Simmel, Featherstone, & Frisby, 1997). Of course, this formation of the urban spatially is also affected by localized social communication. Historically, places such as community clubs and neighborhood centers, for example, served this purpose (Guest & Oropesa, 1984).

**Town Criers and Information Flow**

Even with the pervasiveness of information flow in Twitter, we retain the need for some anchored locality in the city, even if that is relatively vague and blurred. With previous states of relatively sparse information, the town crier quietly died and disappeared from our cognitive space, replaced by broadcast media. Though the current state of surplus information has not resurrected the town crier as such, an opportunity for core groups of criers to virtually ring the bell and make proclamations has emerged as audiences appreciate a crier making noise over the rest of the crowd.

Hoshikawa (1994) argues that mass communication media has led to a “deterioration” away from the “community bell and town crier.” The town crier has been globally resurrected for ceremony. For example, Tony Appleton, town crier from Romford, proclaimed “Oyez, Oyez . . . the first-born of their royal highness, the Duke and Duchess of Cambridge” (Wright, 2013) at the birth of Prince George on July 22, 2013. In a state of information plenitude, the crier can provide a direct cognitive hook, as can be seen in Appleton’s case. Furthermore, the town crier has an almost haptic role, allowing us to be closer and perhaps touch and feel the news via its embodiment in the crier.
MacDougall (2011) argues that “the tradition of the town crier” has a “phenomenological feel” which can be seen in modern broadcast forms such as podcasting. Murdoch (2010) has also drawn a line between the town crier and bloggers, tracing an evolution of journalism. Twitter continues in this line. Miragliaotta (2012) argues that Twitter is important to the political public sphere; Bruns, Burgess, Highfield, Kirchhoff, and Nicolai (2011) conceive Twitter as part of a networked public sphere; and Ausserhofer and Maireder (2013) conceptualize a “national public Twittersphere.” Ultimately, the medium exhibits pace of life as well as notions of localized public life.

In terms of the latter, some aspects of urban life have been found to foster perceptions of anonymity and disassociation. New social media technologies may be encouraging geographically based connections. In the context of larger urban studies debates, this sheds light on the argument that the place itself matters and local information from the place therefore should be communicated. Studies of influence and Twitter tend to measure influencers, “alpha users,” by examining the most followed or mentioned users at the national or international level (e.g., Anger & Kitt, 2011). However, very active local Twitter users may be affirming dynamics of localized public life, ringing a bell like Appleton to draw in those in the local area to protests, people’s assemblies, or to read relevant local news stories.

**The Importance of Twitter to Urban Life**

Twitter has been important both in shaping articulations of the urban but also influencing urban life socially, politically, and economically. This was seen in the Arab Spring with the platform broadcasting images of Neda Agha-Soltan dying in the streets of Tehran (Couldry, 2012, p. 26). Social movements such as Black Lives Matter (BLM) have used Twitter as a public sphere for youth of color (Carney, 2016), and previous work credited the platform as a key means of communication by localized urban black stakeholders (Freelon, Mcilwain, & Clark, 2016). Moreover, the platform has been used to broadcast important “hyper-local” urban news that does not generally cross to mainstream outlets (Agarwal, Vaithiyathanathan, Sharma, & Shroff, 2012). The medium has been used by major U.S. city governments to engage with citizens (Mossberger, Wu, & Crawford, 2013) and has been regularly used during disasters in concentrated urban spaces (Kogan, Palen, & Anderson, 2015). In urban spaces, where individuals are not necessarily interacting with each other in specific community places, such as community centers, farmers markets, swap meets, or other local municipal spaces (Putnam, 2001), Twitter has been found to help facilitate a “networked public” (Tierney, 2013). Moreover, in everyday urban life, users produce and consume locally geotagged tweets, which constitute “new ways of interacting with . . . cities” (Shelton, Poorthuis, & Zook, 2015, p. 199).

Ultimately, the platform is viewed as fundamentally important to urban life, given its historical utility in being an event-driven space where a community does not have to be consistent but can be formed around particular events, ad-hoc issues, or happenings affecting an urban population. Furthermore, Twitter use is part of larger processes involving social technologies and the “socially conscious urban citizen” (Foth, 2012, p. x) or, moreplayfully, through urban flash mobs (Brejzek, 2010).

**Technology to Mine Twitter**

It has been said that “we have, in Big Data, a vast new natural resource, as well as the means to mine it for value” (Rometty, 2013), and Twitter is one of the greatest such resources for insight into human behavior. Unlike many other social media services, Twitter provides a high level of access to its data. Collecting small amounts of data is straightforward and can be done via off-the-shelf free software, but collecting large amounts of data is not. Twitter has licensed several third-party organizations to provide serialized access to large amounts of filtered Twitter data, including the possibility of full access to the complete Twitter message stream, termed “Firehose.”

**Data Model and Collection Framework**

As per the recommendation of previous studies using geotagged tweets (Cheng, Caverlee, Lee, & Sui, 2011; Cranshaw, Schwartz, Hong, & Sadeh, 2012; Kamath, Caverlee, Lee, & Cheng, 2013), we rely on the Twitter Streaming API (application programming interface) to collect data. We collected Twitter data from major U.S. cities. In particular, we combined a list of the 45 U.S. cities with the most tweeting activity (Tweet Grader, 2012) with a list of the 50 most populated cities (according to the 2010 U.S. census) and selected 50 cities to cover a range of population sizes and geographic locations. Twitter allows specification of a set of unique locations using latitude–longitude bounding boxes. We created 10 individual collection scripts, each set to capture tweets from five of the 50 selected cities. The distribution of cities to scripts was guided by geographic location, population, and expected tweet volume (see Appendix A). This distribution provides some robustness to any temporary outages of collection scripts, as streams are designed to collect data continuously over time. This framework allowed us to collect between 400,000 and 1,000,000 tweets per day from these cities. Data collected with each tweet include the time, user’s name, and Twitter handle, the application used to post the tweet (web, Twitter for iPhone, Foursquare, etc.), location, user profile at time of tweet, number of friends and followers for the user, total number of tweets made by the user, and the text of the tweet itself. We store this data in a tabular data format (.csv) and analyze it using data analysis tools, primarily MATLAB.
Potential Limitations

Twitter-based research has innate limitations, and it is important to be aware of how these limitations affect the quality and robustness of the data collected. The Twitter API may sometimes experience data outages. Furthermore, our local collection database maintenance procedures required collection streams to stop for varying amounts of time. Twitter also makes no guarantees or estimates on the volume of tweets it will forward via Streaming data collection, only indicating that users should always expect to receive less than 1% of all tweets, and some fraction of tweets that match their query dependent on the strength of the chosen query filters. Since the process by which Twitter selects tweets to deliver on any individual stream is proprietary, it introduces unknown biases into the data. Our own experiments with a trial of the complete Firehouse as well as the results of others (Kamath et al., 2013), however, indicate that this sample is representative. There is also a potential procedural bias when using the Twitter Location Stream as tweets are collected only from users who use Twitter’s geo-location service, which is an opt-in feature. There are certain small but statistically significant biases in the Twitter users that elect to report their location (Graham, Hale, & Gaffney, 2014; Sloan & Morgan, 2015). Urban users often use geo-location-based apps such as Foursquare (Cranshaw et al., 2012; Seeburger, Foth, & Tjondronegoro, 2012), and there is greater rate of geocoding among urban users than rural users (Hecht & Stephens, 2014; Malik, Lamba, Nakos, & Pfeffer, 2015). Notably for our study, it has been found that when controlling for other factors, population has no effect on the number of geotagging users (Malik et al., 2015). Last, though query-based tweet sampling rates scale with total tweets, they may be influenced by factors such as tweeting frequency, retweet rates, or other criteria within Twitter’s API parameters.

Tweet Volume as a Function of City Population

The first step in our study is to look at total tweet volume in the various cities as a function of their population; we used approximately 2.5 million tweets collected between April and June of 2012. Using 2010 U.S. census data for metropolitan statistical area population, Figure 1 illustrates the relationship between tweeting volume and city population. Using least-squares regression, we find that tweeting volume grows sublinearly as a function of city population or, in other words, the per capita tweet volume decreases with city population. In particular, the power-law exponent from the least-squares fit is 0.952 (see Appendix B for formulas for least-squares fit of power law), which is between results for infrastructure indicators such as length of electrical cables and household electrical consumption in German cities, that have scaling exponents 0.87 and 1.00, respectively (Bettencourt et al., 2007), and is similar to results for the prosocial behavior of census return rates in American cities, with scaling exponent 0.988 (Arbesman & Christakis, 2011). These sublinear scaling results are contrary to superlinear scaling results for productivity, innovation, and telephony.

This result, by itself, validates H1 since it shows that geography influences aggregate tweeting behavior of a city population. It specifically validates H2. Examining deviations from the scaling behavior provides insight into the personality of cities (Bettencourt, Lobo, Strumsky, & West, 2010; García-Gavilanes, Quercia, & Jaimes, 2013). Figure 2 plots the regression residuals (see Appendix B for explanation of residuals). We observe that Los Angeles has a significant positive deviation from the power-law model. That is to say, there is more tweet volume in Los Angeles than would be expected from the population-based model. Other cities that deviate positively include San Francisco, Las Vegas, Boston, Austin, and Atlanta. Cities such as Washington, DC, Dallas, Tampa, Detroit, and Miami deviate negatively from the power-law model. There are several potential features of cities we can consider to explain deviations from the power-law model.

One potential explanation for deviations could arise from the role of media and entertainment in peoples’ lives and careers in a given city. It is plausible that cities with a strong media focus may produce greater cultural relevance of Twitter. Among our set of cities, New York, Los Angeles, Chicago, San Francisco, and Boston have been deemed top global media cities (Krätke, 2003). Technology adoption rates may also be a factor in city personality: some of the residuals may be explained by the time at which adoption of Twitter achieved critical mass in the cities and the percentage of users who were early adopters in the city (Toole, Cha, & González, 2012).
A third possibility is that Twitter usage in cities may be influenced by demographic factors such as age, race, and sex. In particular, survey results suggest that African Americans tweet more often than others, and areas with large percentages of African American residents tend to have higher tweet volume (Smith & Brenner, 2012). Furthermore, Twitter and other Internet-based social media platforms tend to have disproportionately young user bases. Age of city residents might be another factor explaining deviations from the observed relationship between tweet volume and population. Women are more likely to be social media users (Perrin, 2015), ceteris paribus, and individuals who have a serious interest in sports and entertainment are more likely to use Twitter (Hargittai & Litt, 2011, 2012). In addition, it has been suggested that Internet skill matters in Twitter adoption, even after controlling for age, race, and sex (Hargittai & Litt, 2011, 2012).

Performing an ordinary linear least-squares regression on the power-law residuals with the following explanatory variables does in fact explain some of the variation: binary indicator of global media city (Krätke, 2003); Twitter critical mass achievement time (Toole et al., 2012); fraction of early adopters (Toole et al., 2012); age distribution in city (fractions of under 5, 5-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and over 85); race distribution in city (White alone, Black or African American alone, Asian alone, American Indian and Alaska Native alone, and Native Hawaiian and Other Pacific Islander alone); Hispanic or Latino origin percentage; and males per 100 females. The age, race, and sex data for each metropolitan statistical area are from the 2010 U.S. census. In particular, the $r^2$ value in the multivariate linear regression using all 20 features listed above is .558. The full regression table is given in Table 1. Although all the features do contribute, the most predictive feature in the presence of all others is the fraction of early adopters in a city, whose relationship to deviations from the power-law model is shown in Figure 3(a)—more early adopters predict positive deviations. Thus, we have verified H3.

Figure 3(b) shows the relationship between the fraction of a city population that is Black or African American only and the deviations from the power-law model. Contrary to national survey results (Smith & Brenner, 2012), once city population is taken into account through the power-law model, the tweet volume actually decreases as the fraction of Black or African American population increases. This is indicative of a “town tweeter” effect. These observations are an ecological effect rather than an individual one. Figure 3(c) shows the relationship for the fraction of young people (those between the ages of 15 and 24 years). Here, the tweet volume does increase as the fraction of young people increases, as expected.

We have seen that aggregated tweet volume scales sublinearly with city population. Moreover, much of the remaining variation is explained by factors of city personality, such as media centrality, technology adoption, and demographics. It
is important to note that tweet volume is an aggregate quantity consisting of entire cities and their generated tweets. Since our data are actually disaggregated to the individual level, the next step of our study is to investigate the tweeting dynamics of individual users in various cities.

**Individual Tweet Dynamics**

Returning to the roots of pace of life studies where the temporal dynamics of individuals in cities are examined (Bornstein & Bornstein, 1976), we now study the tweeting behavior of individual urban users. This provides a complementary view to the city-wide aggregated phenomenon we investigated in the previous section.

The temporal dynamics of various human activities have previously been found to obey bursty, heavy-tailed statistics for the time between events; models based on the prioritization of human attention specifically generate power-law distributions for interevent times (Barabási, 2005; Walraevens, Demoor, Maertens, & Bruneel, 2012). Specifically, the time between tweets has previously been argued to be governed by power-law distributions (Chalmers et al., 2011). Here, we draw on formal statistical methods (Clauset et al., 2009) to study the distribution of intervals between tweets for individual users in urban America. Rather than looking at all 50 cities in our data, we focus on users in nine cities with a range of populations and geographic locations: New York, Chicago, Los Angeles, Orlando, Minneapolis, Austin, Rochester, Louisville, and Boulder, as detailed in Table 2.

Though all tweets from a given user may not be collected, we can use information about the number of tweets made by a user to determine whether there were any uncollected tweets during a given interval between two collected tweets. For regularly active users, we have a fairly high number of identified true consecutive tweets (around 50% on average). For less active users, we see a lower percentage of observed true interval tweets. Intervals in which there was exactly one unobserved tweet are slightly longer than expected, and triple intervals are longer still. Shorter true intervals between tweets may make them more likely to be observed, that is, we may be collecting more tweets from regularly active users than from users who tweet less often.

### Intervals Between Tweets Analysis Methodology

We utilize a statistical methodology developed by Clauset et al. (2009) to determine the statistical distribution of events - here, the intertweet interval (ITI) of a given user. We consider regularly active users, that is, users from whom we have collected at least 200 total tweets, and select 16 users for each city at random from this group; in Boulder, we consider the 16 most active users since there were not enough regularly active users. We further restrict our ITI sample to data for true intervals rather than trying to infer ITI length from recorded double intervals, triple intervals, and so on.

Following Chalmers et al. (2011), we considered whether the ITI distribution of a given user is governed by power-law statistics. A power-law distribution has two parameters: \( \alpha \) which represents how quickly the tail of the distribution decays and \( x_{\text{min}} \) which is a lower cutoff for data points that defines where the power-law tail starts. The statistical methodology tests empirical data against power-law distributions with ranges of \( \alpha \) and \( x_{\text{min}} \) values, using the Kolmogorov–Smirnov goodness-of-fit test to find the best fitting (\( \alpha, x_{\text{min}} \)). A significance test is then used to determine whether this best fit is plausible for the empirical data. The same basic methodology is used to find the best fits for other parametric distributional forms and determine their plausibility. To compare various possibilities that pass the significance test above, we use log likelihood ratio (LLR) tests in a pairwise manner to see which distribution is a closer fit to the observed data. LLR tests yield two values: the LLR statistic and a \( p \) value. The LLR statistic indicates which of the two models is better, and the \( p \) value indicates the confidence in determining which is better. For each of the 144 users (16 users in nine cities), we applied this method.

### Intervals Between Tweets

Starting with our working hypothesis of power-law distributions, we find that it is plausible for 96% of the active users...
Table 3. Fraction of Users Best Modeled by Distribution Families.

| Distribution                  | Fraction |
|-------------------------------|----------|
| Power law                     | 0.0%     |
| Power law with exponential cutoff | 54.2%   |
| Exponential                   | 2.1%     |
| Lognormal                     | 25.0%    |
| Poisson                       | 0.0%     |
| Weibull                       | 18.8%    |
| Yule                          | 34.0%    |

to have power-law ITI behavior. However, the LLR tests show that other distributions are more likely. In particular, the majority of users have better fits with power-law with exponential cutoff distributions, and others have better fits with lognormal, Weibull, and Yule distributions. Results for the 144 users are summarized in Table 3. Note that of the users, 113 were individuals with more than 50 true intervals and were determined not to be automated “bot” accounts.

Given the variety in distributional forms that are most likely for the various regularly active users, there is no “typical” tweeting behavior, contrary to previous human dynamics findings (Barabási, 2005; Chalmers et al., 2011). This falsifies H4. Indeed, we find several natural groupings of temporal tweeting behavior. The prominence of power law with exponential cutoff and lognormal distributions, however, seems to indicate approximate power-law behavior with thinning in the tail of the distribution. To understand these dynamics further, we visually examine the empirical ITI distributions and see whether the shape of user distributions might indicate natural groupings of similar users.

The first natural grouping of users includes those that have power law with exponential cutoff forms, as shown in Figure 4(a). One possible interpretation for this group is that the underlying phenomenon is such that long gaps between tweets become unlikely. An alternative explanation is that biases in the capture of tweets may arise due to the finiteness of the collection period and the large gaps in tweeting behavior, causing reduced true tweet interval capture.

The second major grouping of users we observe have good power-law fit in the head, followed by a significant hump from the power-law line, and finishing with a cutoff around the same location as many of the distributions from the first grouping. Examples are shown in Figure 4(b). A hump might arise due to periodic tweeting behavior. If a person often tweets in the morning but then is unable to tweet again until midday or evening and this behavior repeated over the working week, a hump at 4- or 8-hr intervals would arise. This is similar to the time it takes for someone to respond to an e-mail or a phone call. The identification of this pattern is significant as it signals a hybrid that is not a fully Poison nor power-law distribution. Such bimodal distributions have been found in various forms of human communication that has an “interplay between processes of different time scales” (Wu, Zhou, Xiao, Kurths, & Schellnhuber, 2010). This also further emphasizes the importance of time and gaps in time to understanding social media behaviors.

There is also a third grouping of ITI behavior which differs from power-law behavior, exhibiting strong periodicity (as shown in Figure 4(c)). These types of users are generally automated Twitter bots set to send certain messages at fixed intervals. For example, Minneapolis User 12’s tweet intervals are very nearly either ~600 or ~1,200 s, with some small variation. This corresponds to 10- and 20-min tweet intervals. Indeed, this user is a bot programmed to tweet weather updates every 10 min; the 20-min intervals may be the side effect of the bot missing its regular tweeting time slot.
Disaggregating Tweet Volume

In the previous section, we saw that the tweeting behavior of regularly active individual urban American Twitter users is often well-modeled by distributions other than power law, contrary to what we would expect based on the literature (Barabási, 2005; Chalmers et al., 2011). Distributions such as power law with exponential cutoff, lognormal, Weibull, or Yule, unlike power law, have a finite first moment, which justifies the use of the average ITI.

In this section, we look at relationships between mean ITI and city characteristics such as population. To calculate mean ITI for users, we find the first and last tweets for each user with at least two tweets. The difference in timestamps and the difference in total tweet count at the time of the tweets yield the mean ITI for a given user. Note that the mean ITI metric is unaffected by potential biases in per-user tweet sampling rate or by problems of unobserved tweet intervals. We can therefore consider a much larger pool of users. We experimentally determined that for a 3-month collection...
window, a 10-day observation envelope is sufficient to have a significant number of users in each city, while controlling the variance in user ITIs. We limited our analysis to users who were observed to have tweeted at least twice and the difference in time between their first and last observed tweets was between 80 and 91 days.

In the “Tweet Volume as a Function of City Population” section, we had looked at the aggregate volume of tweets for all users in a city, as a function of city population. Some have raised the issue of whether ecological fallacies (Robinson, 2009) are present in pace of life studies (Fleiss, 1990), especially when interpreting results for individuals. Previous studies only had access to aggregated behavioral statistics (Arbesman & Christakis, 2011; Bettencourt, 2013; Bettencourt et al., 2007; Bettencourt, Lobo, & West, 2008; Pan et al., 2013), but our data can be disaggregated to the level of individual behavior. In this section, we consider mean ITI at the individual level. Furthermore, in this section, we first consider population density, rather than population as in the “Tweet Volume as a Function of City Population” section. This is because population density is locally experienced by people, as compared with population which is harder to experience. Note that Pan et al. (2013) have developed a generative model for innovation and productivity indicators in cities based on social interaction, which is parameterized by population density.

Using metropolitan statistical area population density data from the U.S. census, we look at the mean ITI for each individual user. Figure 5 shows a standard linear regression (despite being depicted on logarithmic axes using box plots), which indicates that as the population density increases, the mean ITI of an individual user decreases. In other words, the denser a city, the more individuals tweet. This is an individual correlation rather than an aggregated ecological correlation and is seemingly contrary to what we had observed about cities as a whole in the “Tweet Volume as a Function of City Population” section, where greater population led to less per capita tweeting. This verifies H5.

We understand this phenomenon and connect the results here to results from the “Tweet Volume as a Function of City Population” section. Even though individual users are tweeting more frequently in more populated cities, there are fewer of them. Figure 6 illustrates the number of users who are tweeting in the various cities, as functions of population and of population density, together with power-law fits. The power-law exponent is 0.944 for population and 0.791 for population density, which is strongly sublinear.

Though individuals in denser cities tweet more often, the aggregate volume of tweets decreases in larger cities because there are fewer people tweeting. This verifies H6 and contributes to the literature in terms of furthering our understanding of social media use in large urban environments. It also renders visible differences in urban life as not all urban people are the same in their social media habits or even their use or adoption of social technologies.

We may interpret this concentrated core of tweeters within denser and more populated cities as the emergence of a social group we term “town tweeters” that serves an information broadcast function. One might also conjecture that in dense
populations, there may be desires to strongly affiliate with some subidentity to preserve individuality and yield guidelines for who is within the homophilous group. People may be drawn to specific fandoms or race/ethnicity and religious affiliations. Microcommunities may need more synchronous communication similar to “naturally occurring talk” among members to sustain themselves (Giles, 2006). Of course, these processes can be understood through a social constructivist view.

**Conclusion**

We analyzed tweeting behavior and found it to be an indicator of pace of life. The temporal dynamics of tweeting are bursty rather than periodic, displaying a few different kinds of statistical distributions. Tweeting volume per capita decreases with city population size. This indicates the presence of economies of scale with Twitter, much like with city infrastructure. Remaining variation unexplained by city population is partially explained by aspects of city demographics and personality. However, an individualized (rather than ecological) look at tweeting behavior indicates that individuals in denser cities generally tweet more frequently. This apparent contradiction is explained by the fact that there are fewer active tweeters in larger cities, and, indeed, one may say that this active core of users acts as a broadcast infrastructure for a city, an emergent, concentrated group, we term “town tweeters.” This echoes the town criers in Spanish America who made public announcements via repetition (sometimes up to 30 times; Rappaport & Cummins, 1994). Ultimately, Twitter is a sociotechnical system which affords important forms of local communication that we might think are overshadowed in an age of information abundance. Our findings about people in cities of different sizes indicate that population is not the only factor. People post to Twitter in some cities in ways that deviate from expected statistical models. This tells us that the culture and demographics of a city do matter. Whether urban citizens are part of strong media or digital technology cultures could be influencing city-level dynamics on Twitter. Particular demographic factors such as disproportionately young citizens or unique racial composition also likely shape a city’s aggregate tweet personality.

Although tweeting is a significant aspect of Twitter, it is not all that Twitter is used for. Twitter has experienced “declining person-to-person communication”, with users opting to retweet more than reply (Liu, Kliman-Silver, & Mislove, 2014). It is difficult to judge how these types of behaviors contribute to the overall nature of Twitter’s social networking among various users, groups, and geographic areas. Further understanding of Twitter must include analysis of reading behavior, especially since Twitter is often said to be an important source for news.

Studies of the motivations behind Twitter usage have divided its population into three types: information sharing, information seeking, and friendship-wise relationship (Java, Song, Finin, & Tseng, 2009). Certain users have a high reputation that is not only contingent on how often they tweet but also on whether what they tweet is perceived as valuable. Such users who are important information sources would likely be “town tweeters.” Since Twitter is more concerned with information aggregation and dissemination than specifically with productivity or innovation, it is interesting to note the distinct scaling behavior with city size encountered in previous studies (Arbesman & Christakis, 2011; Bettencourt, 2013; Bettencourt et al., 2007; Pan et al., 2013). Twitter is perhaps a multicast communication infrastructure with economies of scale, rather than an emergent phenomenon like innovation, as measured through patents.

To further understand the distinction between the conversational point-to-point and the information-sharing broadcast possibilities of Twitter, one might look more deeply at the amount of @-mention tweets and retweets. Tweets with @-mentions may be more conversational, whereas retweets may lead to
greater information dissemination. Individuals who are not heavy Twitter users may be less likely to see and use @-mentions; instead, they may choose to post undirected tweets and be less concerned with tweet visibility by their followers.

Beyond investigating the notion of pace of life and describing the emergence of a core set of town tweeters, this study also concludes that urban American Twitter users exhibit bursts of activity on Twitter rather than continued engagement throughout the day. This helps counter mainstream media arguments that Twitter is “taking over our lives” (Meade, 2010). Rather than indicating a Twitter stranglehold, bursty behavior reveals that for some users, the medium has become a “normal” activity and an important part of one’s life. Of course, what is considered to be excessive use of Twitter varies by sociocultural contexts and bursty distributions may be at a time scale appropriate to their contextualized use. Users without a pattern of bursty behavior use Twitter in a fundamentally different way, most likely because they are spam-based or bots. These users could also be part of an increasing group who are not tweeting but are on Twitter to read the tweets of users they follow, particularly celebrities, news outlets, professional contacts, and family/friends.

There is high variation in tweeting behavior, perhaps due to the emergence of distinct social groups within the Twitter community. It should be noted that due to privacy concerns, some have multiple Twitter accounts to create a division between their professional and personal use of the platform (Vitak, Blasiola, Patil, & Litt, 2015). Others become more engaged or even have several different active accounts in operation. In addition, there is an increasing trend of short-lived parody/comedy accounts. Other bursty behavior could also be attributed to the fact that Twitter is used in lieu of blog posts by some users (Huston & Weiss, 2011).

Twitter activity has continued to grow as users find some level of social gratification from tweeting, which has been seen to be correlated with the average number of @-replies per week as well as the number of active months spent on the medium (Chen, 2011). Though users adopt different tweeting behaviors, the normalcy of bursty activity on Twitter suggests that our online social communication in this medium adds to our diverse forms of social communication, rather than dominating it. Ultimately, our social behavior on Twitter sheds light on the classic question of city life and pace of life. Unexpectedly, it also indicates the continuing power of spatially anchored “town tweeters” as well. Though we do not empirically study notions of community and Twitter, the presence of “town tweeters” does speak to the ways in which social media may be contributing toward localized (albeit globally networked) information distributors. Simmel (1950) saw the metropolis as having a constant flow of strangers and city life breeding a rhythm of life which fosters detachment. Perhaps the town tweeters are a response to this perceived detachment.

### Appendix A

#### Distribution of City to Unique Collectors.

| Collector 1       | Collector 2     | Collector 3     | Collector 4     | Collector 5        |
|------------------|-----------------|-----------------|-----------------|--------------------|
| Los Angeles, CA  | Chicago, IL     | New York, NY    | Atlanta, GA     | San Francisco, CA  |
| Minneapolis, MN  | Denver, CO      | Miami, FL       | Orlando, FL     | Las Vegas, NV      |
| Charlotte, NC    | San Jose, CA    | Columbus, OH    | San Antonio, TX | Pittsburgh, PA     |
| Cincinnati, OH   | Cleveland, OH   | Sacramento, CA  | Detroit, MI     | Milwaukee, WI      |
| Kansas City, MO  | Omaha, NE       | Oklahoma City, OK | Fresno, CA | Albuquerque, NM |

| Collector 6       | Collector 7     | Collector 8     | Collector 9     | Collector 10       |
|------------------|-----------------|-----------------|-----------------|--------------------|
| Boston, MA       | Dallas, TX      | San Diego, CA   | Seattle, WA     | Houston, TX        |
| Philadelphia, PA | Portland, OR    | Phoenix, AZ     | Austin, TX      | Washington, DC     |
| Indianapolis, IN | Nashville, TN   | Memphis, TN     | El Paso, TX     | Tampa, FL          |
| Richmond, VA     | Raleigh, NC     | New Orleans, LA | Baltimore, MD*  | Louisville, KY     |
| Boulder, CO      | Rochester, NY   | Salt Lake City, UT | Jacksonville, FL | Tucson, AZ        |

*Tweets from Baltimore, MD, were not regularly captured due to data errors and were removed from our analysis retrospectively.*

### Appendix B

#### Statistical Analysis in a Nutshell

In this appendix, we describe the basics of our statistical methodology for readers that may be unfamiliar with such procedures for inference from data. For more details, please see, for example, Clauset et al. (2009) or any survey-level literature.

To fit data to a power law hypothesis, we must find the least-squares estimates of the presumed parametric form. In particular, given a function of the form,

\[ y = Ax^B, \]

Least-squares fitting of \( n \) data points gives the coefficients as,
\[
\begin{align*}
b &= \frac{n \sum_{i=1}^{n} (\ln x_i \ln y_i) - \sum_{i=1}^{n} (\ln x_i) \sum_{i=1}^{n} (\ln y_i)}{n \sum_{i=1}^{n} (\ln x_i)^2 - \left( \sum_{i=1}^{n} \ln x_i \right)^2}, \\
A &= \frac{n \sum_{i=1}^{n} (\ln y_i) - b \sum_{i=1}^{n} (\ln x_i)}{n},
\end{align*}
\]

where \( B = b \) and \( A = e^a \).

Once data are fit to a model, we can look at the unexplained variation in the data. This is done by subtracting the power-law model predictions from the true data. These subtracted values are called the regression residuals. If there are features, for example, of city personality, that might explain these residuals, one can perform an ordinary least-squares regression to investigate. This tries to find a linear combination of the various factors to explain the variable of interest.

Another kind of analysis is concerned not with modeling a relationship as a power law but modeling the statistical distribution of some random variate according to a given parametric form, such as power-law distribution or power law distribution of some random variate according to a given parametric form.

\section*{Acknowledgments}

The authors thank Alex Pensavalle for help with data tabulation.

\section*{Declaration of Conflicting Interests}

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

\section*{Funding}

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Varshney’s work was funded in part by NSF grant CCF-1623821.

\section*{References}

Agarwal, P., Vaithiyanathan, R., Sharma, S., & Shroff, G. (2012). Catching the long-tail: Extracting local news events from Twitter. Proceedings of the Sixth International AAAI Conference on Weblogs and Social Media (ICWSM), Dublin, Ireland, June 2012.

Anger, I., & Kittl, C. (2011, September 7-9). Measuring influence on Twitter. Proceedings of the 11th International Conference on Knowledge Management and Knowledge Technologies, Graz, Austria.

Aral, S., & Van Alstyne, M. (2011). The diversity-bandwidth tradeoff. American Journal of Sociology, 117, 90-171.

Arbesman, S., & Christakis, N. A. (2011). Scaling of prosocial behavior in cities. Physica A: Statistical Mechanics and its Applications, 390, 2155-2159.

Arceneaux, N., & Schmitz Weiss, A. (2010). Seems stupid until you try it: Press coverage of Twitter, 2006-9. New Media & Society, 12, 1262-1279.

Aussenhofer, J., & Mairesse, A. (2013). National politics on Twitter. Information, Communication & Society, 16, 291-314.

Barabási, A.-L. (2005). The origin of bursts and heavy tails in human dynamics. Nature, 435, 207-211.

Bettencourt, L. M., Lobo, J., Strumsky, D., & West, G. B. (2010). Urban scaling and its deviations: Revealing the structure of wealth, innovation and crime across cities. PLoS ONE, 5, e13541.

Bettencourt, L. M. A. (2013). The origins of scaling in cities. Science, 340, 1438-1441.

Bettencourt, L. M. A., Lobo, J., Helbing, D., Kühnert, C., & West, G. B. (2007). Growth, innovation, scaling, and the pace of life in cities. Proceedings of the National Academy of Sciences of the United States of America, 104, 7301-7306.

Bettencourt, L. M. A., Lobo, J., & West, G. B. (2008). Why are large cities faster? Universal scaling and self-similarity in urban organization and dynamics. The European Physical Journal B, 63, 285-293.

Bornstein, M. H., & Bornstein, H. G. (1976). The pace of life. Nature, 259, 557-559.

Brejzek, T. (2010). From social network to urban intervention: On the scenographies of flash mobs and urban swarms. International Journal of Performance Arts and Digital Media, 6, 109-122.

Bruns, A., Burgess, J., Highfield, T., Kirchhoff, L., & Nicolai, T. (2011). Mapping the Australian Networked Public Sphere. Social Science Computer Review, 29, 277-287.

Buettner, R., & Buettner, K. A. (2016, January 5-8). Systematic literature review of Twitter research from a socio-political revolution perspective. 2016 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI.

Burrows, R., & Savage, M. (2014). After the crisis? Big Data and the methodological challenges of empirical sociology. Big Data & Society: Advance online publication. doi:10.1177/2053951714540280.

Carney, N. (2016). All lives matter, but so does race. Humanity & Society, 40, 180-199.

Chalmers, D., Fleming, S., Wakeman, I., & Watson, D. (2011, October 9-11). Rhythms in Twitter. 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third International Conference on Social Computing (SocialCom), Boston, MA.

Chang, R. M., Kauffman, R. J., & Kwon, Y. (2014). Understanding the methodological challenges of empirical sociology. Big Data & Society: Advance online publication. doi:10.1177/2053951714540280.

Chung, R. M., Kowalski, J. R., & Kwon, Y. (2014). Understanding the paradigm shift to computational social science in the presence of big data. Decision Support Systems, 63, 67-80.

Chen, G. M. (2011). Tweet this: A uses and gratifications perspective on how active Twitter use gratifies a need to connect with others. Computers in Human Behavior, 27, 755-762.

Cheng, Z., Caverlee, J., Lee, K., & Sui, D. (2011, July 17-21). Exploring millions of footprints in location sharing services. Proceedings of the Fifth International Conference on Weblogs and Social Media, Barcelona, Spain.

Chunara, R., Andrews, J. R., & Brownstein, J. S. (2012). Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak. American Journal of Tropical Medicine and Hygiene, 86, 39-45.
Clauset, A., Shalizi, C. R., & Newman, M. E. (2009). Power-law distributions in empirical data. *SIAM Review*, 51, 661-703.

Coudry, N. (2012). *Media, society, world: Social theory and digital media practice*. Cambridge, UK: Polity Press.

Cranshaw, J., Schwartz, R., Hong, J. I., & Sadeh, N. (2012). The livehoods project: Utilizing social media to understand the dynamics of a city. Menlo Park, CA: Association for the Advancement of Artificial Intelligence, ICWSM 2012.

Diao, Q., Jiang, J., Zhu, F., & Lim, E.-P. (2012, June 8-14). Finding bursty topics from microblogs. Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers—Vol. 1, Jeju Island, Korea.

Durkheim, E. (2004). *Readings from Emile Durkheim* (K. Thompson, Ed.). London, England: Routledge.

Feiss, J. (1990). Ecological fallacy. *American Scientist*, 78, 487-487.

Foth, M. (2012). From social butterfly to engaged citizen: Urban informatics, social media, ubiquitous computing, and mobile technology to support citizen engagement. Cambridge, MA: The MIT Press.

Freelon, D., Mcilwain, C. D., & Clark, M. D. (2016). Beyond the hashtags: #Ferguson, #Blacklivesmatter, and the online struggle for offline justice. Washington, DC: Center for Media & Social Impact, American University.

Garcia-Gavilanes, R., Quercia, D., & Jaimes, A. (2013, July 8-11). Cultural dimensions in Twitter: Time, individualism and power. Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media, Cambridge, MA.

Garhammer, M. (2002). Pace of life and enjoyment of life. *Journal of Happiness Studies*, 3, 217-256.

Gieryn, T. F. (2000). A space for place in sociology. *Annual Review of Sociology*, 26, 463-496.

Gilbert, E., Karahalios, K., & Sandvig, C. (2010). The network in the garden: Designing social media for rural life. *American Behavioral Scientist*, 53, 1367-1388.

Giles, D. (2006). Constructing identities in cyberspace: The case of eating disorders. *British Journal of Social Psychology*, 45, 463-477.

Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, 333, 1878-1881.

Graham, M., Hale, S. A., & Gaffney, D. (2014). Where in the world are you? Geolocation and language identification in Twitter. *The Professional Geographer*, 66, 568-578.

Guest, A. M., & Oropesa, R. S. (1984). Problem-solving strategies of local areas in the metropolis. *American Sociological Review*, 49, 828-840.

Hargittai, E., & Litt, E. (2011). The tweet smell of celebrity success: Explaining variation in Twitter adoption among a diverse group of young adults. *New Media & Society*, 13, 824-842.

Hargittai, E., & Litt, E. (2012). Becoming a Tweep. *Information, Communication & Society*, 15, 680-702.

Hecht, B. J., & Stephens, M. (2014). A tale of cities: Urban biases in volunteered geographic information. Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media (ICWSM), Ann Arbor, MI, USA, June 1-4, 2014.

Hoshikawa, T. (1994). On the structural change of the autonomous public—The possibility of media networking as the basis of civil society. *Shakaitakku Hyoron / Japanese Sociological Review*, 45, 18-31.

Huston, C., & Weiss, M. (2011). Gathering in digital spaces: Exploring topical communities on Twitter. In A. Datta, S. Shulman, B. Zheng, S. D. Lin, A. Sun, & E. P. Lim (Eds.), *Social informatics* (pp. 320-323). Berlin, Germany: Springer.

Hutchins, B. (2011). The acceleration of media sport culture: Twitter, telepresence and online messaging. *Information, Communication & Society*, 14, 237-257.

Java, A., Song, X., Finin, T., & Tseng, B. (2009). Why we Twitter: An analysis of a microblogging community. In H. Zhang, et al. (Eds.), *Advances in web mining and web usage analysis* (pp. 118-138). Berlin, Germany: Springer.

Kamath, K. Y., Caverlee, J., Lee, K., & Cheng, Z. (2013, May 13-17). Spatio-temporal dynamics of online memes: A study of geo-tagged tweets. Proceedings of the 22nd International Conference on World Wide Web, Rio de Janeiro, Brazil.

Kogan, M., Palen, L., & Anderson, K. M. (2015, March 14-18). Think local, retweet global: Retweeting by the geographically-vulnerable during Hurricane Sandy. Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, Vancouver, British Columbia, Canada.

Kräcke, S. (2003). Global media cities in a world-wide urban network. *European Planning Studies*, 11, 605-628.

Lassen, D. S., & Brown, A. R. (2011). Twitter: The electoral connection? *Social Science Computer Review*, 29, 419-436.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A. L., Brewer, D., . . . Van Alstyne, M. (2009). Computational social science. *Science*, 323, 721-723.

Levine, R. V., & Norenzayan, A. (1999). The pace of life in 31 countries. *Journal of Cross-Cultural Psychology*, 30, 178-205.

Liu, Y., Kliman-Silver, C., & Mislove, A. (2014). The Tweets they are a-Changin: Evolution of Twitter Users and Behavior. Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media (ICWSM), Ann Arbor, Michigan, USA, June 1-4, 2014.

Lynley, M. (2017, February 9). Twitter’s advertising business is stalling. *TechCrunch*. Advance online publication. https://techcrunch.com/2017/02/09/twitter-streamlining-efforts-still-arent-fixing-its-core-business-problems/

Macdougall, R. C. (2011). Podcasting and political life. *American Behavioral Scientist*, 55, 714-732.

Malik, M. M., Lamba, H., Nakos, C., & Pfeffer, J. (2015). Population bias in geotagged tweets. *People, 1*, 3,759,710-7,233,531.

Mayer, H., & Knox, P. L. (2009). Pace of life and quality of life: The slow city charter. In M. J. Sirgy, R. Phillips, & D. R. Rahtz (Eds.), *Advancing quality of life indicators: Best cases III* (pp. 21-40). Dordrecht, The Netherlands: Springer.

Meade, W. (2010, April 27). Hyperconnected. *Sarasota Herald Tribune*. Retrieved from http://www.heraldtribune.com/news/20100427/hyperconnected

Miragliotta, N. (2012). Politicians, Twitter and the limits of the virtual political public sphere. *Social Alternatives*, 31, 6-10.

Miritello, G., Moro, E., Lara, R., Martinez-Lopez, R., Belchamber, J., Roberts, S. G. B., & Dunbar, R. I. M. (2013). Time as a limited resource: Communication strategy in mobile phone networks. *Social Networks*, 35, 89-95.

Mossberger, K., Wu, Y., & Crawford, J. (2013). Connecting citizens and local governments? Social media and interactivity in major U.S. cities. *Government Information Quarterly*, 30, 351-358.

Murdoch, R. (2010). From town crier to bloggers: How will journalism survive the Internet age? Phoenix, AZ: McMurry.
Murthy, D. (2013). Twitter: Social communication in the Twitter age. Cambridge, UK: Polity Press.

Olteanu, A. (2016). Probing the limits of social data (Doctoral thesis). Lausanne, Switzerland: École Polytechnique Fédérale de Lausanne.

Pan, W., Ghoshal, G., Krumme, C., Cebrian, M., & Pentland, A. (2013). Urban characteristics attributable to density-driven tie formation. Nature Communications, 4, Article 1961.

Park, R. E. (1929). Urbanization as measured by newspaper circulation. American Journal of Sociology, 35, 60-79.

Perrin, A. (2015). Social media usage. Washington, DC: Pew Research Center.

Putnam, R. D. (2001). Bowling alone: The collapse and revival of American community. New York, NY: Simon & Schuster.

Raghavan, V., Ver Steeg, G., Galstyan, A., & Tartakovskiy, A. G. (2014). Modeling temporal activity patterns in dynamic social networks. IEEE Transactions on Computational Social Systems, 1, 89-107.

Rappaport, J., & Cummins, T. B. F. (1994). Literacy and power in colonial Latin America. In G. C. Bond & A. Gilliam (Eds.), Social construction of the past: Representation as power (pp. 89-112). London, England: Routledge.

Robinson, W. (2009). Ecological correlations and the behavior of individuals. International Journal of Epidemiology, 38, 337-341.

Rometty, G. (2013). Competitive advantage in the era of smart. New York, NY: Council on Foreign Relations.

Schläpfer, M., Bettencourt, L. M. A., Grauwin, S., Raschke, M., Toole, J. L., Cha, M., & Gonzalez, M. C. (2012). Geography of Twitter networks. Social Networks, 34, 73-81.

Tierney, T. (2013). The public space of social media: Connected cultures of the network society. New York, NY: Routledge.

Toole, J. L., Cha, M., & Gonzalez, M. C. (2012). Modeling the adoption of innovations in the presence of geographic and media influences. PLoS ONE, 7, e29528.

Tweet Grader. (2012). Top Twitter cities. Cambridge, MA: HubSpot.

Twitter. (2017). Company | About—Twitter. San Francisco, CA: Author. Retrieved from https://about.twitter.com/company

Um, J., Son, S.-W., Lee, S.-I., Jeong, H., & Kim, B. J. (2009). Scaling laws between population and facility densities. Proceedings of the National Academy of Sciences of the United States of America, 106, 14236-14240.

Vitak, J., Blasiola, S., Patil, S., & Litt, E. (2015). Balancing audience and privacy tensions on social network sites: Strategies of highly engaged users. International Journal of Communication, 9, 1485-1504.

Walraevens, J., Demoort, T., Maertens, T., & Bruneel, H. (2012). Stochastic queueing-theory approach to human dynamics. Physical Review E, 85, 021139.

Wright, J. (2013, July 23). Town crier Tony Appleton delivers news of a future king. The Sydney Morning Herald. Retrieved from http://www.smh.com.au/lifestyle/celebrity/town-crier-tony-appleton-delivers-news-of-a-future-king-20130723-2qfrz.html

Wu, Y., Zhou, C., Xiao, J., Kurths, J., & Schellnhuber, H. J. (2010). Evidence for a bimodal distribution in human communication. Proceedings of the National Academy of Sciences of the United States of America, 107, 18803-18808.

Zhao, Z.-D., & Zhou, T. (2012). Empirical analysis of online human dynamics. Physica A: Statistical Mechanics and Its Applications, 391, 3308-3315.

Author Biographies

Alexander Jones Gross is a researcher in Intermedia Arts at University of Maine, Orono, specializing in in natural language processing, and computational social science.

Dhiraj Murthy is an associate professor in the School of Journalism and the Department of Sociology at the University of Texas at Austin, where he also directs the Computational Media Lab. Murthy’s research explores social media, digital research methods, computational social science, qualitative/mixed methods, big data, and virtual organizations.

Lav R. Varshney is an assistant professor of electrical and computer engineering, computer science, and neuroscience at the University of Illinois at Urbana-Champaign. His research interests include information theory, data science, and computational social science.