Twitter as a Source of Global Mobility Patterns for Social Good

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Abstract

Data on human spatial distribution and movement is essential for understanding and analyzing social systems. However existing sources for this data are lacking in various ways; difficult to access, biased, have poor geographical or temporal resolution, or are significantly delayed. In this paper, we describe how geolocation data from Twitter can be used to estimate global mobility patterns and address these shortcomings. These findings will inform how this novel data source can be harnessed to address humanitarian and development efforts.

1. Introduction

Social programs, whether developmental, humanitarian or public health related, rely on knowledge of where vulnerable populations are located. People travel nationally and internationally for a variety of purposes including regular commuting, seasonal work, tourism or coerced migration. Data describing these movements allow for the development of statistical models and analyses and significant universal patterns have been found in human mobility patterns (González et al., 2008). Consider a few illustrative examples. In public health, epidemiological models of disease spread can forecast the course of an outbreak, allowing health workers to head-off infection transmission. These models rely on travel data to project disease transmission between geographic areas (Balcan et al., 2009; Bajardi et al., 2011; Parker & Epstein, 2011; Viboud et al., 2006; Sadilek et al., 2012). Human migration, whether caused by economic hardship or resulting from physical danger to a population, follows both geographically advantageous routes, as well as previously established transit patterns resulting from existing connections between populations. Tracking current and predicting future migrations, which allows governments and NGOs to respond to migrations and refugee crises, depends on global mobility patterns (Greenwood, 1985; Simini et al., 2012). A sudden change in established travel patterns may provide early-warning of crisis onset (Sönmez, 1998; Prideaux et al., 2003).

Researchers have utilized a diverse range of data resources for estimating global mobility patterns, each with distinct tradeoffs. These data sources can provide local travel patterns (within a metropolitan area) domestic patterns (travel within a country), and global patterns (international travel.) Airline travel dominates as a means for measuring long distance travel (Colizza et al., 2006; Khan et al., 2009). However, public air travel data is not timely, has poor coverage of local and domestic travel and may not accurately capture flights with connections (IATA). Anonymized mobile phone meta-data can provide coverage of travel at multiple levels (Sagl et al., 2012; Krings et al., 2009; Deville et al., 2014) especially throughout urban areas (Calabrese et al., 2013). As a result, mobile data has been used increasingly in epidemiological models of disease spread (Wesolowski et al., 2014; Bengtsson et al., 2015). However, mobile data is proprietary and can be privacy sensitive. Diverse providers throughout the world prevent the construction of a large, global dataset. Tourist statistics, available for many locations, do not typically reflect traveler origin and tourism reflects only one type of travel. Finally, travel diaries, where people manually log travel, are a traditional way of obtaining travel data (Axhausen, 1994). But such methods simply cannot scale beyond specialized purposes motivating new approaches.

Social media provides a new and mostly untapped resource
for obtaining travel patterns. Many social media platforms allow users to geotag their content. For example, Twitter allows users to geotag a tweet with a specific set of coordinates – using a GPS enabled device – or tag a location as being associated with the message. Additionally, local search and discovery services, such as Foursquare, allows users to check-in from different locations, creating geotagged tweets. The overall rate of geotagged tweets in Twitter remains low, roughly 2-3%, but continues to grow. Even at this relatively low rate, with roughly 500 million tweets per day, Twitter provides millions of geolocated data points on a daily basis. Since most tweets are publicly available, the result is a large, public geotagged corpus.

There have been numerous uses of geotagged Twitter data, such as in public health (Broniatowski et al., 2013; Sadilek et al., 2012), political science (O’Connor et al., 2010), linguistics (Eisenstein et al., 2010; 2014), disaster response (Tapia et al., 2011), event detection (Watanabe et al., 2011), topic discovery (Hong et al., 2012) and location recommendation (Noulas et al., 2012; Liu & Xiong, 2013). The importance of geotagged data has led to the task of geolocation, in which a system automatically infers the location of a user (Han et al., 2014; Rout et al., 2013; Compton et al., 2014; Cha et al., 2015; Jurgens et al., 2015; Osborne et al., 2014; Dredze et al., 2013) or a specific tweet (Osborne et al., 2014; Dredze et al., 2016). Compared to the extensive literature on inferring and using geolocated Twitter data, there has been less work on understanding aggregate location patterns. (Mocanu et al., 2013) used location data to understand the languages of Twitter. (Leetaru et al., 2013) used geotagged tweets to describe the geography of Twitter. Some have studied check-in data, such as that from Foursquare, which provided an early map of the emerging landscape of this type of data on Twitter (Cheng et al., 2011; Bauer et al., 2012). The most relevant work to ours is that of (Hawelka et al., 2014), who also derived global mobility patterns from Twitter. We contrast our work with theirs below.

This paper describes preliminary results from our investigation into Twitter as a data source of global mobility patterns for social good. We consider a massive dataset: over 8.5 billion tweets that represent almost four years of all publicly available geotagged Twitter data. We construct a global travel network for both cities and countries, which includes more than 87,856 cities and 248 countries, that reflects travel patterns over four years. We describe the construction of this travel network from Twitter data and a preliminary analysis of the resulting network.

2. Data Resources

**Twitter** We use a collection of every publicly available geotagged tweet from January 1, 2012 to September 30, 2015. The collection contains 8.578 billion tweets from over 50 million users. Users had a median of 10 tweets each, with a mean of 168.98 and standard deviation of 962.5. Each tweet contains text, a time the tweet was posted, the user id and a location. These tweets include those authored directly by the user, or those created by an automated service, such as FourSquare. No private tweets were captured.

There are two methods by which users can share location information with their tweet. First, a user can author a message from a GPS enabled device, such as a smart phone. If geotagging is enabled, then the device will attach the current latitude and longitude to the tweet. Second, a user can choose to tag their tweet with a location. For example, a user may identify their location as “Starbucks” or “Johns Hopkins University.” In this case, Twitter associates a known location with the tweet. Locations can be countries, administrative areas (e.g. US States), cities, neighborhoods and points of interest (e.g. stores, parks, buildings, etc.). These locations contain several fields, including a name, location type and bounding box. Tweets may have both a set of coordinates and an associated known location. We note that users can also attach a location to their profile, which indicates their primary location, but we did not use this information on account of ambiguities e.g. ‘NYC/LA’ or humorous locations ‘The World’.

**Geonames** While Twitter includes information about each location, we sought to map our data to an external knowledge resource. This will allow for future comparisons to other data sources, as well as inclusion of additional information about locations (e.g. populations, geographic administrative hierarchies, etc.) We use Geonames (Wick & Vatant, 2012), a geographical database that covers all countries and contains over eight million named locations. We used the file ALLCOUNTRIES.ZIP\(^1\) which contains 11,005,123 locations. Each location comes with a set of coordinates and associated metadata (e.g. population).

3. Computing Travel Statistics

For each user in the Twitter collection, we organized all of their tweets from the entire time period chronologically. We then examined successive tweets to identify possible travel events as indicated by different locations between two adjacent tweets. A travel event is defined using the following guidelines:

- The successive tweets must occur within 72 hours of each other.
- Both tweets must have a location as either a tagged location or specific coordinates.

\(^{1}\)Accessed April 25, 2016
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![Figure 1](image_url)

Figure 1. A histogram of the number of tweets (black) and events (blue) per user (y-axes in millions).

- The locations associated with each tweet are different, and one location does not contain the other. For example, a user may tweet first from Midtown Manhattan, and then from New York City. We would identify this as the same location.
- The tweets must have been authored more than 50km apart. Tweets closer than 50km are not recognized as a travel event as they likely indicate local travel, even when they are in different locations. When specific coordinates are not available, distance is measured from the centroid of the bounding box of the associated location.

Resulting travel events are associated with a timestamp (the time of the second tweet), a user, an origin and a destination location. Overall, we identified over 300 million travel events, with the number of travel events per user having a median of 0, mean of 3.6 and standard deviation of 250.7.

Some user accounts falsify location information for a variety of reasons. For example, a news aggregation account may list as its location the place most relevant to a tweeted story, or a spam account may attach false location information. We remove these accounts using several methods. First, we exclude travel events that require travel in excess of 1000km/hour (following (Hawelka et al., 2014; Compton et al., 2014)). Second, as can be seen from the distribution of tweets per user (Figure 1) there is a large skew in user activity. Therefore we remove users with more than 1000 geolocated tweets, roughly the top 4% of all users in our data. Finally, we remove users who have more than 100 travel events, roughly the top 0.4% of all users.

Geonames Matching We match every Twitter location to a Geonames location. We proceed in two passes. First, we attempt to match each location to a city with a population of at least 1,000 people (145,343 possible cities). Second, for unmatched places, we consider all possible locations in the database, which include administrative areas, roads, buildings, and other types of locations.

Table 1. The types of Geonames locations used. Travel events include the type of each vertex on the edge in the count. Parenthesis indicate the Geonames feature type code.

| Geonames Type          | Twitter Locations | Travel Events |
|------------------------|-------------------|--------------|
| Admin area (A)         | 672               | 115,163      |
| Water (H)              | 887               | 324,039      |
| Park (L)               | 221               | 18,387       |
| City (P)               | 84,982            | 156,273,217  |
| Road (R)               | 12                | 33,012       |
| Point of interest (S)  | 606               | 156,273,217  |
| Mountain (T)           | 405               | 156,273,217  |
| Undersea (U)           | 30                | 156,273,217  |
| Forest (V)             | 4                 | 339          |
| None                   | 26                | 352          |

(11,005,123 unique options). We match a Twitter location to a Geonames location by measuring the distance of the centroid of the Twitter location, as computed from the provided bounding box, to the closest possible Geonames location, which is defined by a single set of coordinates. We only consider matches closer than 50 km. Of the 1,128,662 unique Twitter locations 521 did not match to Geonames; these locations were dropped from the data.

Table 1 shows statistics on the number and types of matches of Twitter locations to Geonames locations. We provide statistics on the number of matches of unique Twitter location, as well as their coverage of the total dataset.

Travel Network Construction The final step is to construct the travel network from the individual travel events. We construct a graph, in which vertices are locations and weighted edges indicate the total number of travels between the two locations. We generate both a directed and undirected graph, where the undirected graph sums the weights of the two edges between a pair of vertices.

We construct two travel networks, where each has a directed and undirected version. First, we use the Geonames locations to construct a full global network between cities and other types of Geonames locations. This network contains 7,688,854 edges between 87,856 vertices. Second, we construct a global network between countries. This network contains 12,449 edges between 248 vertices. For this network, we rely on the country associated with each Twitter provided location, allowing for the inclusion of those few locations not successfully mapped to Geonames locations. Statistics on each network are shown in Table 2.

3.1. Comparison to Prior Work

The work of (Hawelka et al., 2014) also derived global mobility patterns from Twitter. We follow their approach with some modifications, such as mapping to an external reference (Geonames), the criteria for identifying travel events, and the spam removal method. The major difference from our work is the amount of data considered. They
Figure 2. Mobility as observed in the travel network between countries (left) and between cities within the same country (right).

**Table 2.** Statistics of the two travel networks.

| Continent   | Top edge           | Top penetration (penetration) |
|-------------|--------------------|-------------------------------|
| Europe      | UK-Spain           | United Kingdom (4.4%)         |
| Africa      | Botswana-Africa    | South Africa (2.9%)           |
| North America| US-Canada         | US (3.7%)                     |
| South America| Argentina-Brazil  | Chile (3.6%)                  |
| Asia        | Indonesia-Malaysia| Qatar (4.1%)                  |

use one year worth of geotagged tweets from 2012, which encompasses 944 million tweets. In contrast, our dataset is roughly nine times larger, and covers four years worth of data. The most immediate benefit of the increase in data size is our ability to consider cities, whereas their analysis only included countries. Additionally, their work presents methods for normalizing data by Twitter penetration (as in (Hawelka et al., 2014)).

**5. Discussion**

Our preliminary results suggest that Twitter may be a promising new data source for global mobility patterns and we plan to evaluate the suitability of this dataset for several applications. The most pressing consideration is the representativity of Twitter as determined by relatively low adoption of the service within low income countries. Careful calibration of movements aggregated from Twitter relative to the user base is required.

The benefits of Twitter as a mobility data source are clear. Firstly, data can be collected in real-time and are easily accessible through public APIs. Twitter can also capture movements on smaller spatial scales i.e. intra-urban, that are not captured by long distance travel records.

In this work we do not consider the content of tweets. While this content has been shown to be of great value in monitoring the opinions and topics of interest of vulnerable populations, further development of taxonomies and tools are required to analyze non-European languages and so provide insight in lower income countries. Analyzing these messages would allow us to consider the relationship between topic and travel. For example, do users who discuss climate change take fewer long distance trips, or are users who tweet about political activism less likely to travel to certain countries? We look forward to developing these ideas further in future work.

**Acknowledgements** We thank Adela Quinones and Mark Dimont for their insights and comments.

**References**

Axhausen, Kay W. *Travel diaries: an annotated catalogue*. University of London, Centre for Transport Studies, 1994.

Bajardi, Paolo, Poletto, Chiara, Ramasco, Jose J, Tizzoni, Michele, Colizza, Vittoria, and Vespignani, Alessandro. Human mobility networks, travel restrictions, and the global spread of 2009 H1N1 pandemic. *PloS one*, 6(1), 2011.

Balcan, Duygu, Colizza, Vittoria, Gonçalves, Bruno, Hu, Hao, Ramasco, José J, and Vespignani, Alessandro. Multiscale mobility networks and the spatial spreading of infectious diseases. *Proceedings of the National Academy of Sciences*, 106 (51), 2009.
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Bauer, Stefan, Noulas, Anastasios, Ségaudha, Diarmuid O., Clark, Spencer, and Mascolo, Cecilia. Talking places: Modelling and analysing linguistic content in Foursquare. In International Conference on Social Computing (SocialCom), 2012.

Bengtsen, Linus, Gaudart, Jean, Lu, Xin, Moore, Sandra, Wetter, Erik, Sallah, Kankoe, Reubandt, Stanislas, and Piarroux, Renaud. Using mobile phone data to predict the spatial spread of cholera. Scientific reports, 5, 2015.

Broniatowski, David, Paul, Michael J., and Dredze, Mark. National and local influenza surveillance through Twitter: An analysis of the 2012-2013 influenza epidemic. PLOS ONE, 2013.

Calabrese, Francesco, Diao, Mi, Di Lorenzo, Giuny, Ferreira, Joseph, and Ratti, Carlo. Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation research part C: Emerging Technologies, 26, 2013.

Cha, Miriam, Gwon, Youngjune, and Kung, HT. Twitter geolocation and regional classification via sparse coding. In International Conference on Weblogs and Social Media (ICWSM), 2015.

Cheng, Zhiyuan, Caverlee, James, Lee, Kyumin, and Sui, Daniel Z. Exploring millions of footprints in location sharing services. In International Conference on Weblogs and Social Media (ICWSM), 2011.

Colizza, Vittoria, Barrat, Alain, Barthélemy, Marc, and Vespignani, Alessandro. The role of the airline transportation network in the prediction and predictability of global epidemics. Proceedings of the National Academy of Sciences, 103(7), 2006.

Compton, Ryan, Jurgens, David, and Allen, David. Geotagging one hundred million Twitter accounts with total variation minimization. In IEEE International Conference on Big Data, 2014.

Deville, Pierre, Linard, Catherine, Martin, Samuel, Gilbert, Marius, Stevens, Forrest R., Gaughan, Andrea E, Blondel, Vincent D, and Tatem, Andrew J. Dynamic population mapping using mobile phone data. Proceedings of the National Academy of Sciences, 111(45), 2014.

Dredze, Mark, Paul, Michael J, Bergsma, Shane, and Tran, Hieu. Carmen: A Twitter geolocation system with applications to public health. In AAAI Workshop on Expanding the Boundaries of Health Informatics Using AI (HI4AI), 2013.

Dredze, Mark, Osborne, Miles, and Kambadur, Anju. Geolocation for Twitter: Timing matters. In North American Chapter of the Association for Computational Linguistics (NAACL), 2016.

Eisenstein, Jacob, O’Connor, Brendan, Smith, Noah A., and Xing, Eric P. A latent variable model for geographic lexical variation. In Empirical Methods in Natural Language Processing (EMNLP), 2010.

Eisenstein, Jacob, O’Connor, Brendan, Smith, Noah A, and Xing, Eric P. Diffusion of lexical change in social media. PloS one, 9(11), 2014.

González, Marta C., Hidalgo, César A., and Barabási, Albert-László. Understanding individual mobility patterns. Nature, 453, 2008.

Greenwood, Michael J. Human migration: Theory, models and empirical studies. Journal of Regional Science, 25(4), 1985. ISSN 1467-9787.

Han, Bo, Cook, Paul, and Baldwin, Timothy. Text-based Twitter user geolocation prediction. Journal of Artificial Intelligence Research, 2014.

Hawelka, Bartosz, Sitko, Izabela, Beinat, Euro, Sobolevsky, Stanislav, Kazakopoulos, Pavlos, and Ratti, Carlo. Geo-located Twitter as proxy for global mobility patterns. Cartography and Geographic Information Science, 41(3), 2014.

Hong, Liangjie, Ahmed, Amr, Gurumurthy, Siva, Smola, Alexander J, and Tsioutsiouliklis, Kostas. Discovering geographical topics in the Twitter stream. In International conference on World Wide Web, 2012.

IATA. International airline travel association. URL: www.iata.com.

Jurgens, David, Finethy, Tyler, McCorriston, James, Xu, Yi Tian, and Ruths, Derek. Geolocation prediction in Twitter using social networks: A critical analysis and review of current practice. In International Conference on Weblogs and Social Media (ICWSM), 2015.

Khan, Kamran, Arino, Julien, Hu, Wei, Raposo, Paulo, Sears, Jennifer, Calderon, Felipe, Heidebrecht, Christine, Macdonald, Michael, Liao, Jessica, Chan, Angie, et al. Spread of a novel influenza a (H1N1) virus via global airline transportation. New England journal of medicine, 361(2), 2009.

Kring, Gautier, Calabrese, Francesco, Ratti, Carlo, and Blondel, Vincent D. Urban gravity: a model for inter-city telecommunication flows. Journal of Statistical Mechanics: Theory and Experiment, 2009(07), 2009.

Lee, Katep, Wang, Shaowen, Cao, Guosong, Padmanabhan, Anand, and Shook, Eric. Mapping the global Twitter heartbeat: The geography of Twitter. First Monday, 18(5), 2013.

Liu, Bin and Xiong, Hui. Point-of-interest recommendation in location based social networks with topic and location awareness. In SDM, 2013.

Mocanu, Delia, Baroni, Andrea, Perra, Nicola, Gonçalves, Bruno, Zhang, Qian, and Vespignani, Alessandro. The Twitter of Babel: Mapping world languages through microblogging platforms. PloS one, 8(4), 2013.

Noulas, Anastasios, Scellato, Salvatore, Lathia, Neal, and Mascolo, Cecilia. A random walk around the city: New venue recommendation in location-based social networks. In International Conference on Social Computing (SocialCom), 2012.

O’Connor, Brendan, Balasubramanayam, Rammath, Routledge, Bryan R, and Smith, Noah A. From tweets to polls: Linking text sentiment to public opinion time series. In International Conference on Weblogs and Social Media (ICWSM), 2010.

Osborne, Miles, Moran, Sean, McCreadie, Richard, Von Lungen, Alexander, Sykora, Martin D, Cano, Elizabeth, Ireson, Neil, Macdonald, Craig, Oum, Iabh, He, Yulan, et al. Real-time detection, tracking, and monitoring of automatically discovered events in social media. In Association for Computational Linguistics (ACL), 2014.

Parker, Jon and Epstein, Joshua M. A distributed platform for global-scale agent-based models of disease transmission. ACM Transactions on Modeling and Computer Simulation (TOMACS), 22(1), 2011.

Prideaux, Bruce, Laws, Eric, and Faulkner, Bill. Events in indonesia: exploring the limits to formal tourism trends forecasting methods in complex crisis situations. Tourism management, 24(4), 2003.

Rout, Dominic, Bontcheva, Kalina, Pretoj-Pietro, Daniel, and Cohn, Trevor. Where’s Wally?: A classification approach to geolocating users based on their social ties. In Conference on Hypertext and Social Media, 2013.

Sadilek, Adam, Kautz, Henry A, and Silenko, Vincent. Predicting disease transmission from geo-tagged micro-blog data. In AAAI, 2012.

Sagl, Günther, Resch, Bernd, Hawelka, Bartosz, and Beinat, Euro. From social sensor data to collective human behaviour patterns: Analysing and visualising spatio-temporal dynamics in urban environments. In Proceedings of the GI-Forum, 2012.

Simini, Filippo, González, Marta C, Maritan, Amos, and Barabási, Albert-László. A universal model for mobility and migration patterns. Nature, 484(7392), 2012.

Sommer, Sevi F. Tourism, terrorism, and political instability. Annals of Tourism Research, 25(2), 1998.

Tapia, Andrea H, Bajpai, Kartikeya, Jansen, Bernard J, Yen, John, and Giles, Lee. Seeking the trustworthy tweet: Can microblogged data fit the information needs of disaster response and humanitarian relief organizations. In Information Systems for Crisis Response and Management Conference, 2011.

Viboud, Cécile, Bjørnstad, Ottar N, Smith, David L, Simonsen, Lone, Miller, Mark A, and Grenfell, Bryan T. Synchrony, waves, and spatial hierarchies in the spread of influenza. Science, 312(5772), 2006.

Watanabe, Kazufumi, Ochi, Masanao, Okabe, Makoto, and Oua, Rikio. Jasmine: A real-time local-event detection system based on geolocation information propagated to microblogs. In Conference on Information and Knowledge Management (CIKM), 2011.

Wesolowski, Amy, Buckee, Caroline O, Bengtsson, Linus, Wetter, Erik, Lu, Xin, and Tatem, Andrew J. Commentary: containing the ebola outbreak-the potential and challenge of mobile network data. PLoS currents, 6, 2014.

Wick, Mark and Vatant, Bernard. The Geonames geographical database. http://geonames.org, 2012.