Leveraging Big (Geo) Data with (Geo) Visual Analytics: Place as the Next Frontier

Alan M. MacEachren

Introduction

Place matters. It is a fundamental component of everyday life and has been a core topic of Geography since Aristotle (Morison 2002). GIScience, however, has directed much more attention to "space" than to "place" in its approaches to information collection, organization, analysis, and decision-support. This focus on formal approaches to space and precise location specification has served GIScience and related geographical information technology developments well, in leveraging the dramatic increases in geo-referenced data for a wide range of applications, But, the lack of attention to place has created a gap between the methods and tools now available and the needs of science and society for multifaceted understanding of the world. Plus, lack of attention to non-traditional geospatial data has left a vast resource of untapped place-relevant data that is unstructured and thus not accessible by current spatial database, analytical, and other tools.

Big Data matter—they have the potential to enable GIScience to move beyond the current spatial focus to address scientifically and societally important questions of place. It has been nearly a decade since the term "Big Data" gained prominence as a popular label for the challenge | opportunity that our instrumented world is prompting | providing. Big Data is a somewhat misleading term, since the concept is typically characterized as being about more than just data size (Volume). It is also about Velocity (the speed at which new data arrives) and Variety (the heterogeneity in type, quality, and other characteristics); and as outlined below, some argue for even more components.

A.M. MacEachren (✉)
GeoVISTA Center, Department of Geography, The Pennsylvania State University,
University Park, PA 16802, USA
e-mail: maceachren@psu.edu

C. Zhou et al. (eds.), *Spatial Data Handling in Big Data Era*,
Advances in Geographic Information Science,
DOI 10.1007/978-981-10-4424-3_10

Government agencies, businesses, and other organizations are gearing up to meet the Big Data challenge | opportunity with strategies to both generate and leverage Big Data; and science funding organizations have initiated a range of calls for Big Data research. For Geographical/Spatial Information Science, the big data challenges and opportunities require a fundamentally new perspective on geospatial data, one that treats geospatial data as an integral component of an information ecosystem in which (geo)spatial may still be special, but in which geospatial data cannot be considered independently from other kinds of data, … or from the context of use, … or from the knowledge and needs of users.

The argument presented in this paper is that the advent of big geospatial data (and development of data science methods to leverage those data through connections to other data, context of use, and knowledge/needs of users) offers an opportunity to address questions of place in fundamentally new ways. The view presented focuses not on formalizing place in ways that support application of existing modeling and analysis methods from GIScience, but on embracing the complexity inherent in conceptions of place as socially constructed and imprecisely delineated entities and leveraging advances in data availability and methods to explore that complexity.

Many industry estimates suggest that 80% (or more) of big data are unstructured (Andriole 2015). Much of these data are likely to contain some form of geographical reference through place names, descriptions of geographic-scale events and behavior in places, and other relative indications of location. But, that geographically relevant data is often ignored because our existing methods and tools take a 'space' focus while much unstructured data reference 'place' through natural language. Thus, understanding place, as it is reflected in language (as both an entity talked about and as a context within which described events and behavior happen), is a fundamental question in Geography and essential to developing geographical information retrieval (GIR) methods that leverage the wealth of geographical data embedded in text and related unstructured sources. In complementary fashion, developing geographical methods and tools for retrieving place-based information from unstructured text data sources and enabling users to leverage that information together with more traditional data sources offers new opportunities to connect place and space.

This paper presents an argument for a "human-in-the-loop" (geo)Visual Analytics approach to leveraging big (geo)data as a means to understand and enable experience of place as a dynamic construct. A focus is put on leveraging unstructured geographical data found in text sources. The approach contrasts with those that rely exclusively on computational methods to produce information and generate answers. (geo)Visual Analytics (gVA) is presented as both a science and set of methods/tools that are focused specifically on support of human analytical reasoning with big, heterogeneous, dynamically changing, and often 'messy' data that include geographical components. And, an argument is presented that gVA applied to these rich and dynamic data offers new windows to understanding place in ways that are not provided through traditional Geographical Information System (GISystem) methods applied to structured geospatial data.

Place: A Snapshot

Place is a complex concept that it is impractical to discuss in depth here. For those interested in in understanding the concept more fully, a comprehensive introduction is provided by Cresswell (2014). Some additional book length treatments of place from a social science and humanities perspective include: Agnew and Duncan 2014; Carmona 2003; De Blij 2008; Duncan and Ley 1993; Ellard 2015; Hubbard and Kitchin 2010; Massey 2013; Nairn et al. 2016; Relph 1976; Tuan 1977. Here, I will sketch just an outline of some of the complex issues about place for which big data have a potential to enable insight.

An important starting point to understand place as distinct from space, is Agnew's (2011) direct analysis of the distinctions and interrelationships of these two fundamental geographical concepts. Agnew presents space as the more abstract concept, grounded in conceptions of location (both absolute and relative) and reflected in twentieth century perspectives of "spatial science". Place, in contrast underlies conceptualizations of geography as a "science of places", with a holistic approach to places as dynamic, thus defined by activities and processes. Prototypical of this view is Pred's (1984) argument for place as a complex time-space activity, replete with power relations, culture forms, biographics, and relationships to nature.

With this context, Agnew (2011) makes important distinctions about how "place" is conceptualized, either as location (thus "assimilated to space") or as occupation of location. He elaborates on this distinction by characterizing the location view "as nodes in space simply reflective of the spatial imprint of universal physical, social or economic processes" (thus a "mere part of space") and the occupation view "as milieux that exercise a mediating role on physical, social and economic processes and thus affect how such processes operate" (thus "a phenomenological understanding of a place as a distinctive coming together in space").

Even with the place as location conceptualization, however, Agnew (2011) points to the dynamic and interconnected nature of places. Specifically, he extends from his initial location-occupation distinction to define three 'dimensions' along which the meaning of place is defined within the various theoretical positions from which place is considered. The first corresponds to the place as location view, specifically the meaning of place along this dimension is characterized as a "… location or a site in space where an activity or object is located and which relates to other sites or locations because of interaction, movement and diffusion between them." Then, the occupation view is further parsed into two additional meaning dimensions.

The second dimension characterizes "…place as a series of locales or settings were everyday-life activities take place. Here the location is not just the mere address but where of social life and environmental transformation" (Agnew 2011). These locales provide the social setting of everyday life that can include workplaces, churches, schools, etc., but also non-fixed settings of activity, such as vehicles or chat rooms. As noted by Cresswell, one mechanism through which spaces can become places in this sense is through naming. Places of importance, due to activities that they support, are given names while ‘spaces’ that do not meet a need or support recurrent behavior are not (and thus do not become) places.

The meanings associated with the activity-based places vary with geographical scale. Small places have meanings related to self while big places have meanings associated with others or with the environment (Gustafson 2001). Massey’s (1994) perspectives on place seem relevant to this dimension of place meaning. In particular, she critiques a common view of place as “bounded entities” (with inside clearly distinguished from outside) and with single, essential entities. Places, according to Massey should always be regarded in relation to the outside world. Places can be special due to linkages to the outside world (rather than their own intrinsic qualities). Massey (1994, p. 154) argues that places “…can be imagined as articulated moments in networks of social relations and understandings, but where a large proportion of those relations, experiences and understandings are constructed on a far larger scale than what we happen to define for that moment as the place itself, whether that be a street, or a region or even a continent.”

The third dimension of place meaning focuses on “… place as sense of place or identification with a place as a unique community, landscape, and moral order” (Agnew 2011). This latter view might be thought of as the humanistic conceptualization of place in contrast to the more social science perspectives of the first two dimensions. Representation of place along this sense of place dimension is typically verbal or visual. Coordinates are not place, but a description or photos of what is near them can invoke a sense of place. But, from this sense of place perspective, the actions of individuals in ‘creating’ the place through various activities, particularly those that may be ‘unofficial’ is part of what generates a rich sense of place. One intersection between GIScience and sense of place is, perhaps, the many volunteered geographic information (VGI) activities that citizens are engaging in (Hardy et al. 2012). One example is a recent project by Quinn and Yapa (2015) to help communities in Philadelphia create greater food security by mapping the informal food resources in their communities (e.g., urban gardens, sources of compost or organic matter to support those gardens, farmer’s markets, food banks and soup kitchens).

Vasardani and Winter (2016), considering place from a GIScience perspective, argue that place “…is a location (in an environment, not in an empty space) with properties that give it ‘shape and character’ and which enable conversations about place.” Their perspective draws upon the “theory of centers” from architecture. Grounded in this theory are 15 structural properties proposed by Alexander (2002). An argument is made that having a ‘center’ and a gradient away from center is fundamental to places and that places are seldom considered independently of other places and relationships; thus there is an emphasis on interconnectedness that reflects the social science arguments outlined above.

Big Data

Place has been a core concept of Geography for centuries, but one that has been difficult to formalize sufficiently in order to leverage digital data to support understanding of place as a dynamic construct. The structured digital data so well suited to supporting spatial analysis have been an impediment to analysis of place since they separate location from meaning. But, the advent of Big Data is creating a context within which new data-driven approaches to under-standing place may become possible. We now have: (a) an abundance of geo-located (or geo-locatable) data that serve as an input to geo-analytical reasoning and (b) many new map-based and other visual methods and technologies that purport to help people reason with and make decisions based upon these big data. To take advantage of these developments to address questions of place, we need to consider both the challenges and the opportunities that big data provide. In particular, I draw upon a characterization of the "5 Vs" of big data by Monroe (2013). They are:

- *Volume*: massive data scale due to sensors, electronic transactions and records, ubiquitous data generation via smarts phones & social media;
- *Velocity*: rapid data update due to continuously operating sensors and data generators + streaming technology;
- *Variety*: heterogeneity in types of data, many of them never before seen;
- *Validity*: varied and uncertain reliability of the data, its processing, its interpretation, and resulting decisions; a key is construct validity: the degree to which the technique measures what it claims to be measuring;
- *Vinculation*: to "vinculate" is to bind together, to attach in a relationship; it is about what might be described as the fundamental interconnectedness of all things (Richardson et al. 2012).

All of these components of big data are relevant to understanding place and to leveraging place-relevant data to support scientific and societal challenges. The fifth, vinculation is particularly relevant to the potential for leveraging big data to understand place and to conceptualizing place in an era of big data.

Place (from a theoretical, geographical perspective as outlined above) is an "experience-based dynamic construct" (Agnew 2011). Connectedness of places is also inherently dynamic, thus, big, streaming place-linked data, for the first time, make it possible to develop methods allowing insight into the geo-social dynamics of places and their massively interconnected, changing nature. But, if we are to leverage information about place from these largely unstructured and semi-structured data, we need to develop a better conceptual model of how place is signified in language (particularly in text) in order to recognize, retrieve, and analyze the wealth of references to place that have gone mostly untapped thus far. While more than a decade of research in GIR has made important progress, most of that work has focused only on the problem of recognizing and geolocating place names, thus turning place into space and/or on linking documents to a geo-graphic "footprint" for which they are determined to be relevant (again turning place into space to support integration of data derived from text into traditional spatial analysis). This space-centric work needs to be complemented by developing a rich characterization of what it means for a document to be "about" a place and how to recognize and interpret statements about place that lack formal place names. Here gVA is proposed as a method and suite of tools that can help achieve this objective.

(Geo)Visual Analytics

"Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces" (Thomas and Cook 2005). The initial focus of efforts in the field was on visual-computational support for assembling evidence, generating inferences and explanations from evidence, comparing /assessing those inferences and explanations, and reporting results (e.g., Andrienko et al. 2011; Keim et al. 2010; Kohlhammer et al. 2009; Malik et al. 2012; Robinson 2011; Tomaszewski and MacEachren 2012; Wang et al. 2008). As the field has developed, increased attention has been directed to big data (e.g., Andrienko et al. 2013; Keim et al. 2013). A 2010 Visual Analytics research agenda report from Europe proposed that "Visual analytics combines automated analysis techniques with interactive visualizations for effective understanding, reasoning and decision making on the basis of very large and complex datasets" (Keim et al. 2010). Building on these ideas, and focusing on geographical big data, I offer the following definition of gVA: *Geovisual Analytics is a domain of research and practice focused on visual interfaces to analytical methods that support reasoning with and about big, dynamic, heterogeneous, unconfirmed, hyper-connected geo-information—to enable insights and decisions about something for which place matters*.

The five "V"s of big data are reflected in the qualifiers on geo-information in the definition above as is the focus here on going beyond traditional spatial analysis to consider place. Since visual analytics was identified as a specific domain of research and practice, more than a decade ago, substantial progress has been made on developing new computational methods to deal with the challenges of big data and on visual interface methods to couple human knowledge, reasoning, and insight with these computational methods. But, although geolocated data is often a focus of these efforts (by GIScientists and others), place (in contrast to space) has been given only limited direct attention. The remainder of this essay presents an argument for, and selected early steps toward, taking advantage of advances in visual analytics, coupled with big data (in all its guises) to address place as a subject of specific attention.

Leveraging Unstructured Big Data to Understand Place: Taking a gVA Approach

There is a long history of spatial science and technology, both within geography and more broadly across the disciplines that coordinate research under the umbrella of GIScience. That history includes fundamental advances in how we collect spatial data and assess its fitness for use (e.g., Bharti et al. 2011; Martin 1998; Woodcock and Strahler 1987); in how we represent, store, and retrieve those data (e.g., Langran 1992; Mennis et al. 2000; Peuquet 1988); in spatial analytical methods (e.g., Anselin 1995; Charlton et al. 2006; Hubert et al. 1981); and in qualitative spatial reasoning (e.g., Egenhofer and Herring 1990; Klippel et al. 2012). In contrast to the focus on space, there is a very short history in GIScience (or gVA) of research directed to place (for a few examples, see: Agarwal 2005; Bennett and Agarwal 2007; Edwardes and Purves 2007). The relatively recent argument by Goodchild (2011) that attention is needed to formalize concepts of place for integration into work with GISystems has prompted some recent attention (nearly 50 citations as of October, 2016, e.g., Roche and Rajabifard 2012; Scheider and Janowicz 2014; Winter and Freksa 2012; Yang et al. 2016). But, only a very small proportion of that work addresses place in the rich sense that it is generally considered by human geographers, other social scientists and planners, or humanists.

An opportunity exists through the advent of big data, to address the nearly infinite complexity of place and its multifaceted connectedness. The challenge that must be met in order to take advantage of this opportunity is to develop strategies and methods to capture and reason about human concerns with place that are potentially represented within the complexity of big data.

My contention here is that three of the five “V”s are particularly central to moving attention in GIScience from ‘space’ to ‘place’. Place is a dynamic construct, thus data *velocity* increases that are associated with big data advances can enhance the granularity with which place can be understood and streaming data on its own (whether high velocity or not) provides a direct window on the dynamic nature of place. Place is also multifacected with multiple layers of embedded meaning. Data *variety*, therefore is an essential input to understanding the multifaceted structure of place. Place is also embedded in the context of the world and its diverse connections and complex relationships among entities; place is probably best understood as being hyper-connected. Thus, *vinculation*, with its focus on connection and relationships, complements data velocity and variety as a core component of the data needed to understand and enable behavior in place. Below, I sketch a few initial ideas about each of these aspects of big data, from the perspective of the role that gVA can play in leveraging big data to construct meaningful information about and enable activity in place.

Velocity: Dynamic Data to Represent a Dynamic World

Streaming data are changing the landscape of information technology and decision-making, with impacts across business, government, and science (Madia 2015). The new and rapidly increasing sources of streaming data, much with some kind of geolocation (or potential for geolocation through mechanisms such as geoparsing of place references in text), generates many possibilities for GIScience to consider place in new ways. The human-in-the-loop approach of gVA is well suited to leveraging large, complex streaming data to achieve insights about place, which is itself dynamic as outline above. The computational methods of gVA are needed to cope with the data flow and the visual interface to those methods is needed to both interpret output from the computational methods and steer the methods to cope with changes in data content and form over time, as well as changes in kinds of insights about place needed in a changing world.

More specifically, streaming data provide a key opportunity specific to understanding place because place (from a theoretical, geographical perspective) can only be understood through attention to the dynamic process of activities and events from which places are constituted. Integration of multiple sources and forms of streaming, place-linked data offers the opportunity to observe and analyze the dynamic processes and activities associated with a place. Connectedness of places is also inherently dynamic; across 4 theoretical perspectives on place, Agnew (2011) cites a "… stress on the fluidity and dynamic character of places as they respond to interconnections with other places." Thus, big, streaming place-linked data, for the first time, make it possible to develop methods allowing insight into the geo-social dynamics of places and their hyper-connected, changing nature.

Initial examples of the ways in which these new sources of streaming data can be used to develop a deeper understanding of places include research to leverage cell phone data (e.g., Ratti et al. 2010; Xu et al. 2016), Twitter (e.g., Jenkins et al. 2016; Wojcik et al. 2015), and photo sharing sites (e.g., Andrienko et al. 2015; Liu et al. 2015). As discussed above, places are created, exist, and change continuously as a result of human activity. Research by Kraft et al. (2013), as one example, demonstrates the potential of leveraging unstructured streaming text (from Twitter) within a gVA application to identify the dynamic creation and evolution of an informal place. They provide a use case example of their application in which an analyst is able to recognize a situation where political tensions led to a riot, thus an informal place was generated, and then through social media this informal place was connected across the globe to other places in which related events happened.

Data Variety

As outlined above, place is dynamic and multifaceted, a concept conceptualized as having multiple dimensions. Thus, while data variety is a technological big data challenge, it is also essential to a rich characterization and understanding of places and to support for activities in those places. The variety of data needed to address questions of place goes well beyond traditional spatial data that existing GIScience methods and tools have been designed to collect, store, and process. As outlined in the introduction, unstructured data (in the forms of text, images, and video), are being generated at rapidly increasing rates and much of those data contain at least indirect reference to places. The unstructured data offer an important complement to traditional quantitative geospatial data that is critical to questions about meaning of place.

Here, I highlight two exemplar *data variety* foci that are central to developing new GIScience/gVA methods that can identify, characterize, and support understanding of place: (a) text analytics—extracting place references and meaningful information about place from unstructured, often fragmentary data from a wide variety of sources; and (b) "extreme" information fusion—constructing place characterizations through integration of structured and unstructured data.

Text Analytics

There is probably much more place-relevant data locked up in text data sources than in all forms of traditional geospatial databases. For example, we have found that more than half of all Twitter tweets have some form of place reference (which includes a location that the tweet is from, places mentioned in the tweet text, and/or places that the Twitter user specifies in their profile) (Pezanowski et al., submitted). Similarly, virtually all news stories have a location where the story was posted and also often mention places in the text of the story, particularly in any story about events.

An example of (partially) understanding the dynamic complexity of a place through gVA text analytics methods is provided in SensePlace, one of the first gVA tools developed in our research group specifically to leverage text data sources (Tomaszewski et al. 2011). SensePlace was built specifically to support document foraging and sensemaking designed to understand the seasonally dynamic nature of regional and national population patterns in Niger (as input to infectious disease modeling). Specifically, SensePlace enabled analysts to 'mine' a news archive in order to achieve multiple linked objectives: (1) see where events are and how they relate; (2) know when events happened; (3) visualize links between map/article/timeline/concepts; (4) explore multiple search strings together; (5) save searches and share; (6) focus on relevant documents by eliminating less relevant articles. A core capability of SensePlace was a set of computational methods that recognize and geolocate place names. As noted above, one thing that distinguishes 'places' from 'spaces' is that the former are given names due to their importance. Thus, recognizing and geolocating place names in text is a key step in the process of turning unstructured text into place-relevant data. But, it is a step that is both challenging to do (see Table 1) and that only partially captures the place references in text; recognizing and locating place description that does not include proper place names is an open problem.

Beyond determining the "where" of entities or statements in text, substantial progress has been made in natural language processing that is relevant to the "what" and "why" aspects of places. For example, Nelson et al. (2015) use computational methods integrated into a web-based gVA application to explore differences of opinion about political situations in the U.S. by Congressional district. While this research used existing Congressional boundaries as 'bins' into which twitter data were aggregated and opinions rated computationally, the methods could easily be extended to support identification of places with shared opinions. In related work, Liu et al. (2015) demonstrate methods that extract place semantics from photo tags, providing a means to characterize the sense of a city (using Paris as an example). They go on to propose a comprehensive approach to "social sensing" that complements ideas below on information fusion.

In addition to assessing the "sense" of statements (e.g., opinion, sentiment), a range of methods for topic modeling have been develop that computationally identify sets of discourse having semantic/thematic similarity. One recent example that applies these methods directly to deriving a "sense of place" from text sources is reported by Jenkins et al. (2016). These authors focus in particular on investigating the scale of places and find that (at least for Twitter and Wikipedia) particularities of places can be derived at neighborhood levels but that analysis at city scale provides more insight about the differences between text media than it does about the unique features of places. This finding relates to the above discussion of scale-dependent meanings associated with activity-based places.

Extreme Information Fusion

As noted in the snapshot on place (Section "Place: A Snapshot" above), place as conceptualized in human geography and other social sciences, is a complex concept that is multifaceted, dynamic, and with flexible geographical bounds. Characterizing place, thus requires both the application of multiple perspectives and the integration of multiple kinds of data. The challenge is what I label as *extreme information fusion*, a term intended to characterize the scale of data, the multiple kinds of data, the continually changing nature of data, and the need to build connections across data that are all needed to represent places. While few attempts have been made to apply information fusion methods to understanding place, there are advances in this domain that are relevant and that have the potential to be repurposed to focus more directly on place.

One exemplar is recent work by Cervone et al. (2016) focused on leveraging heterogeneous data in support of crisis response. The authors illustrate how multiple traditional geospatial data sources can be combined with novel unstructured data sources to better characterize events in places in order to support crisis response.

Table 1 Place entity recognition is challenging due to the variability and imprecision of natural language. Below are a few representative examples of tweets containing place names with non-locational, ambiguous, or vague senses; the kinds of references that are challenging to process automatically

Examples of tweets with 'place names' used in ways other than to signify a place
• Noun adjuncts: here place names are used, not to specify the location but as a modifier of another noun, often a person or an organization; there are several variants, as illustrated, that need to be addressed differently by computational methods designed to decide when a statement is "about" a place – Qualifying/naming an event RT @miamivice_22: It is a photo at the time of the Great Hanshin-Awaji Earthquake. Picture hell. http://t.co/rwzzhexLgn – Qualifying a person: RT @ezralevant: Watch the riot videos. Listen to the victims of this violence. And then help me hire Calgary's best lawyer to sue the offen – Qualifying a more precise generic place: Iran: protest rally in front of Gilan governor office against the shutdown of Looshan Cemnet Factory http://t.co/8wkH2239CH – Metonymy: RT @Watcherone: South Sudan rebels have killed several Uganda soldiers in the Upper Nile in renewed fighting in the country – Regular polesymy: RT @we_support_PTI: All Pakistani's In USA - COME OUT to Protest #GoNawazGo, as the #FakePrimeMinister visits United Nations. #ImranKhan ht…
• Ambiguous: places are often contained within other places with the same name (as with Gaza, the city, that is within Gaza, the territory) – RT @saidshouib: #Gaza_Under_Attack | This is not the effect of an #earthquake, also it's not a #meteor. It's an Israeli Missile. http://t.c…
• Vague spatially: informal places are often described relative to formal places – Breaking M6.0 earthquake jolted the sea area near S. Sumatra Wed., the quake hit at a depth of 10 km.(CENC) http://t.co/E0NkG1mbkV
• Vague meaning of place: the meaning of a "place" depends on ones experience with that place; the two individuals posting the tweets below are likely to have extremely different conceptions of Beijing as a place – Getting ready to see @ladygaga!!!!!! I am BEYOND excited!… Back in HK but still high from the thrill of visiting Beijing. Here is me and the Great Wall. Yes – The latest Tweets from Amy Mathieson (@AmyWMathieson). Western trained architect living in Beijing and following building restoration, eco-tourism, and…

Specifically, they fuse multiple data sources over the cities of Boulder and Longmont, CO including: (a) Flickr ground photographs, (b) tweets, (c) Civil Air Patrol images, (d) Falcon UAV, and the (e) satellite water classification. The fusion of this information is shown to support accurate predictions about road closures in specific places. The process enables dynamic update of the continually changing nature of the places impacted by a natural disaster. In this case, the focus is on flooding, but the methodology would support understanding of the dynamic situation in particularly places as any kind of natural hazards or other emergency events evolve.

Vinculation: Extreme Connectedness

Perhaps the most important qualitative change that big data brings over traditional geospatial data is that related to vinculation, the inter-connectedness of all things. Prior data sources tended to put data into 'silos' by type, making it difficult to identify and leverage connections among disparate kinds of entity. But, as noted above, place is fundamentally interconnected at multiple scales. To investigate and understand place at a substantive level requires data and methods that can cope with and leverage the connections. As data about connections becomes increasingly available, geographers and others have begun to explore those connections. In one representative study, about the *Geography of talk in Great Britain*, Ratti et al. (2010) constructed data-derived delineations of places using cell phone call data. Specifically, they mapped the strongest 80% of links among areas within Britain, based on cell phone total talk time. The result is a data-derived division of Britain into social-geographic 'places' at a regional scale.

Advances in heterogeneous network mining have the potential to move beyond simple mapping or network statistics applied to interconnections among places derived from single data sets such as the cell phone data discussed above. Heterogeneous network mining represents multi-typed data as heterogeneous information networks and applies methods that can mine useful knowledge from these networks (Sun and Han 2012).

As one example of the potential for developing rich place-relevant information using this approach, Savelyev and MacEachren (2014, in preparation) have implemented a linked data structure and query mechanism in SensePlace3 (a follow-on to the system discussed above). The implementation supports complex queries across feature types extracted from Twitter data. In Fig. 1, the query for tweets containing the term 'refugee' has been filtered on the basis of a linked query for tweets by individuals who have a profile location of London and that mention Syria in the text of the tweet. The results provide a mix of perspectives from individuals who live in or associate with London. The links on the maps signify all connections among locations mentioned in any of the tweets by individuals from London or any of the tweets mentioning Syria. The results show Ukraine and Iran as other locations of concern across this collective of tweets. While this example focuses only on the data and metadata contained in tweets, the general method of heterogeneous network mining can be applied to explore any forms of connection across data of multiple forms (Janowicz et al. 2012).

Conclusions

Big data, while a potential resource that might enable new understanding of place and interconnections among places has the potential to be used for a wide variety of applications, not all of which will be viewed positively by everyone. Cresswell

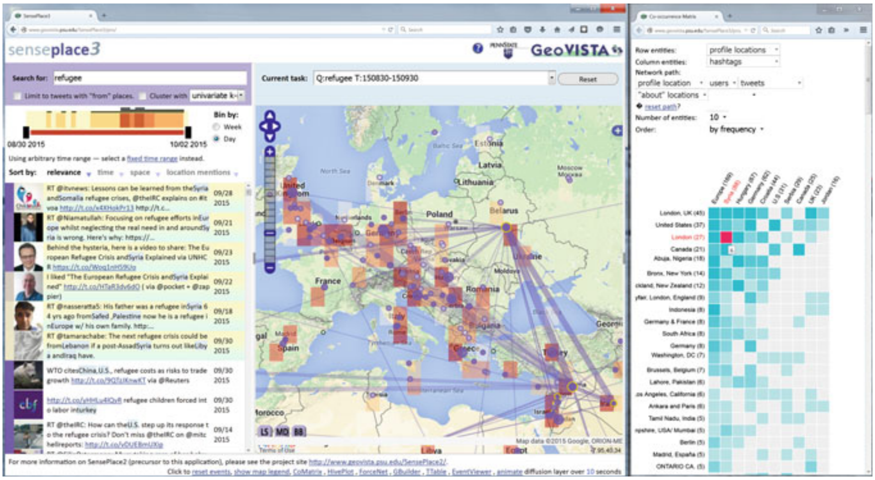

Fig. 1 SensePlace 3 results for tweets that mention "refugee", with a heterogeneous network constraint that identifies the subset of these tweets by individuals with London as their profile location and "Syria" as a term in the tweet text

(2014), for example, quotes Sui and Goodchild (2011) on the start of attempts in GIScience to formalize place in ways that can support application of GIScience methods and tools. He takes a rather critical view, highlighting the ways in which this formalization may be used "in sometimes sinister ways" that include politicians targeting swing voters, supermarkets interrogating shopping habits, and police/security forces sifting personal information in the hope of finding links between crime and place.

It is, of course, important for those of us who develop big data analytical methods to consider the cons as well as the pros of the tools we create. That puts privacy-preserving analytics at the top of the list for important research initiatives as we work to shift the attention of GIScience away from a space-only perspective to one that includes attention to place and the context within which human (and other) activity occurs.

If we can develop methods that minimize the dangers of big data while leveraging the potential, there is an opportunity to address a wide array of place-based challenges for science and society that were impractical to consider prior to the advent of place-aware big data.

I end with two suggested research challenges at the interface of big data, gVA, and place. Research is needed: (1) to integrate advances in methods and technologies that address dynamic, heterogeneous (unstructured + structured), and massively interconnected data to understand place and connections among places at multiple scales; and (2) to create a science of "placial analytics"[1] that addresses place as deeply as GIScience has addressed space thus far.

Acknowledgements Examples in Section "Data Variety" were derived as part of the GeoTxt project, in collaboration with Jan Wallgrün, Morteza Karimzadeh, and Scott Pezanowski; A portion of this research was supported by the Visual Analytics for Command, Control, and Interoperability Environments (VACCINE) project, a center of excellence of the Department of Homeland Security, under Award #2009-ST-061-CI0001. See also: Wallgrün, Jan Oliver, Morteza Karimzadeh, Alan M. MacEachren, Frank Hardisty, Scott Pezanowski, and Yiting Ju. 2014. "Construction and First Analysis of a Corpus for the Evaluation and Training of Microblog/Twitter Geoparsers." GIR'14: 8th ACM SIGSPATIAL Workshop on Geographic Information Retrieval, Dallas, TX.

References

Agarwal, P. (2005). Operationalising "sense of place" as a cognitive operator for semantics in placebBased ontologies. In A. G. Cohn & D. M. Mark (Eds.), *Lecture notes in computer science* (pp. 96–114).

Agnew, J. (2011). *Space and place*. London: The Sage Handbook of Geographical Knowledge (pp. 316–330).

Agnew, J. A., & Duncan, J. S. (2014). *The power of place (RLE Social & Cultural Geography): Bringing together geographical and sociological imaginations*. Routledge.

Alexander, C. (2002). *The nature of order an essay on the art of building and the nature of the universe: Book I-the phenomenon of life* (p. 119). Berkeley, California: The Center for Environmental Structure.

Andrienko, G., Andrienko, N., Bak, P., Keim, D., & Wrobel, S. (2013). *Visual analytics of movement*. Springer Science & Business Media.

Andrienko, G., Andrienko, N., Keim, D., MacEachren, A. M., & Wrobel, S. (2011). Challenging problems of geospatial visual analytics. *Journal of Visual Languages and Computing, 22*(4), 251–256.

Andrienko, N., Andrienko, G., Fuchs, G., & Jankowski, P. (2015). Scalable and privacy-respectful interactive discovery of place semantics from human mobility traces. *Information Visualization, 15*(2), 117–153.

Andriole, S. (2015). Unstructured data: The other side of analytics. *Forbes*. http://www.forbes.com/sites/steveandriole/2015/03/05/the-other-side-of-analytics/print/

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis, 27,* 93–115.

Bennett, B., & Agarwal, P. (2007). Semantic categories underlying the meaning of 'place'. In *International Conference on Spatial Information Theory* (pp. 78–95). New York: Springer.

Bharti, N., Tatem, A. J., Ferrari, M. J., Grais, R. F., Djibo, A., & Grenfell, B. T. (2011). Explaining seasonal fluctuations of measles in Niger using nighttime lights imagery. *Science, 334*(6061), 1424–1427.

[1]placial rather than platial since place is from the old French place and medieval Latin placea (place, spot)—source: http://www.etymonline.com (earlier Latin used platea (courtyard, open space; broad way, avenue) and Greek used plateia (broad way); for comparison, spatial is from the Latin spatium + al (room, area, distance, stretch of time + of or relating to)); analytics rather than analysis since the latter is the activity while analytics, from the Ancient Greek ἀναλυτικά (ànalytiká, is "science of analysis")—source: https://en.wiktionary.org.

Carmona, M. (2003). *Public places, urban spaces: The dimensions of urban design*. Amsterdam: Routledge.

Cervone, G., Sava, E., Huang, Q., Schnebele, E., Harrison, J., & Waters, N. (2016). Using Twitter for tasking remote-sensing data collection and damage assessment: 2013 Boulder flood case study. *International Journal of Remote Sensing, 37*(1), 100–124.

Charlton, M., Fotheringham, S., & Brunsdon, C. (2006). *Geographically weighted regression. NCRM/006, National University of Ireland Maynooth*, Maynooth, Co. Kildare, IRELAND.

Cresswell, T. (2014). *Place: An introduction*. Chichester, West Sussex: Wiley.

De Blij, H. (2008). *The power of place: Geography, destiny, and globalization's rough landscape*. Oxford, UK: Oxford University Press.

Duncan, J. S., & Ley, D. (1993). *Place/culture/representation*. New York, NY: Routledge.

Edwardes, A. J., & Purves, R. S. (2007). Eliciting concepts of *place* for text-based image retrieval. In *Proceedings of the 4th ACM Workshop on Geographical Information Retrieval* (pp. 15–18). ACM, Lisbon, Portugal.

Egenhofer, M., & Herring, J. R. (1990). A mathematical framework for the definition of topological relationships. In *Proceedings of the 4th International Symposium on Spatial Data Handling* (vol. 2, pp. 803–813).

Ellard, C. (2015). *Places of the heart: The psychogeography of everyday life*. New York: Bellevue Literary Press.

Goodchild, M. F. (2011). Formalizing place in geographic information systems. In L. M. M. Burton, S. A. P. Matthews, M. Leung, S. P. A. Kemp, & D. T. T. Takeuchi (Eds.), *Communities, neighborhoods, and health. Social disparities in health and health care* (pp. 21–33). New York: Springer.

Gustafson, P. E. R. (2001). Meanings of place: Everyday experience and theoretical conceptualizations. *Journal of Environmental Psychology, 21*(1), 5–16.

Hardy, D., Frew, J., & Goodchild, M. F. (2012). Volunteered geographic information production as a spatial process. *International Journal of Geographical Information Science, 26*(7), 1191–1212.

Hubbard, P., & Kitchin, R. (2010). *Key thinkers on space and place*. Beverly Hills: Sage.

Hubert, L. J., Golledge, R. G., & Costanzo, C. M. (1981). Generalized procedures for evaluating spatial autocorrelation. *Geographical Analysis, 13*(3), 224–333.

Janowicz, K., Scheider, S., Pehle, T., & Hart, G. (2012). Geospatial semantics and linked spatiotemporal data–past, present, and future. *Semantic Web, 3*(4), 321–332.

Jenkins, A., Croitoru, A., Crooks, A. T., & Stefanidis, A. (2016). Crowdsourcing a collective sense of place. *PLoS ONE, 11*(4), e0152932.

Keim, D., Kohlhammer, J., Ellis, G., & Mansmann, F. (Eds.). (2010). *Mastering the information age: Solving problems with visual analytics*. Goslar, Germany: Eurographics Association.

Keim, D. A., Krstajic, M., Rohrdantz, C., & Schreck, T. (2013). Real-time visual analytics for text tsreams. *Computer, 46*(7), 47–55.

Klippel, A., Yang, J., Wallgrün, J.O., Dylla, F., & Li, R. (2012). *Assessing similarities of qualitative spatio-temporal relations. Spatial Cognition VIII* (pp. 242–261). New York: Springer.

Kohlhammer, J., May, T., & Hoffmann, M. (2009). Visual analytics for the strategic decision making process. *GeoSpatial Visual Analytics*, 299–310.

Kraft, T., Wang, D. X, Delawder, J., Dou, W., Yu, L., & Ribarsky, W. (2013). Less after-the-fact: Investigative visual analysis of events from streaming twitter. In B. Geveci, H. Pfister & V. Vishwanath (Eds.), *IEEE symposium on large-scale data analysis and visualization (LDAV)* (pp. 95–103), Citeseer.

Langran, G. (1992). *Time in geographic information systems. Technical topics in geographic information systems*. London: Taylor & Francis.

Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., et al. (2015). Social sensing: A new approach to understanding our socioeconomic environments. *Annals of the Association of American Geographers, 105*(3), 512–530.

Madia, K. (2015). *Embracing real-time, streaming analytics in the insight economy, blogs*. IBM, IBM Big Data & Analytics Hub.

Malik, A., Maciejewski, R., Jang, Y., Oliveros, S., Yang, Y., Maule, B., et al. (2012). A visual analytics process for maritime response, resource allocation and risk assessment. *Information Visualization, 13*(2), 93–110.

Martin, D. (1998). Optimizing census geography: The separation of collection and output geographies. *International Journal of Geographical Information Science, 12*(7), 673–685.

Massey, D. (2013). *Space, place and gender*. New York: Wiley.

Massey, D. B. (1994). *Space, place, and gender*. Minneapolis: University of Minnesota Press.

Mennis, J. L., Peuquet, D. J., & Qian, L. J. (2000). A conceptual framework for incorporating cognitive principles into geographical database representation. *International Journal of Geographical Information Science, 14*(6), 501–520.

Monroe, B. L. (2013). The five Vs of big data political science introduction to the virtual issue on big data in political science. *Political Analysis, Virtual Issue*, *19*(5), 66–86.

Morison, B. (2002). *On location: Aristotle's concept of place*. Oxford Aristotle Studies: Clarenden Press, Oxford, Oxford. 194.

Nairn, K., Kraftl, P., & Skelton, T. (eds.) (2016). *Space, place and environment. Geographies of children and young people* (vol. 3). New York: Springer.

Nelson, J. K., Quinn, S., Swedberg, B., Chu, W., & MacEachren, A. M. (2015). Geovisual analytics approach to exploring public political discourse in Twitter. *ISPRS International Journal of Geo-Information, 4*(1), 337–366.

Peuquet, D. J. (1988). Representations of geographic space: Toward a conceptual synthesis. *Annals of the Association of American Geographers, 78*(3), 373–394.

Pezanowski, S., MacEachren, A. M., Savelyev, A., & Robinson, A. C. submitted. *SensePlace3: A geovisual framework to analyze place-time-attribute information in social media.*

Pred, A. (1984). Place as historically contingent process: Structuration and the time- geography of becoming places. *Annals of the AAG, 74*(2), 279–297.

Quinn, S., & Yapa, L. (2015). OpenStreetMap and food security: A case study in the city of Philadelphia. *The Professional Geographer, 68*(2), 271–280.

Ratti, C., Sobolevsky, S., Calabrese, F., Andris, C., Reades, J., Martino, M., et al. (2010). Redrawing the map of Great Britain from a network of human interactions. *PLoS ONE, 5*(12), e14248.

Relph, E. (1976). *Place and placelessness, 1*. Pion.

Richardson, M., Kamalski, J., Huggett, S., & Andrew, P.… Courtesy of In, e.b. (2012). The fundamental interconnectedness of all things. In K. Börner & M. J. Stamper (Eds.), *Courtesy of Elsevier Ltd. In "8th iteration (2012): science maps for kids," places & spaces: Mapping science. curated by the cyberinfrastructure for network science center*, http://scimaps.org

Robinson, A. C. (2011). Supporting synthesis in geovisualization. *International Journal of Geographical Information Science, 25*(2), 211–227.

Roche, S., & Rajabifard, A. (2012). Sensing places' life to make city smarter. In *Proceedings of the ACM SIGKDD International Workshop on Urban Computing* (pp. 41–46). Beijing, China: ACM.

Savelyev, A., & MacEachren, A. M. (2014). Interactive, browser-based information foraging in heterogeneous space-centric networks. In G. Andrienko et al. (Eds.), *Workshop on geovisual analytics: Interactivity, dynamics, and scale, in conjunction with GIScience 2014*. Vienna: Austria.

Savelyev, A., & MacEachren, A. M. in preparation. Interactive, browser-based information foraging in heterogeneous space-centric networks.

Scheider, S., & Janowicz, K. (2014). Place reference systems. *Applied Ontology, 9*(2), 97–127.

Sui, D., & Goodchild, M. (2011). The convergence of GIS and social media: Challenges for GIScience. *International Journal of Geographical Information Science, 25*(11), 1737–1748.

Sun, Y., & Han, J. (2012). Mining heterogeneous information networks: Principles and methodologies. *Synthesis Lectures on Data Mining and Knowledge Discovery, 3*(2), 1–159.

Thomas, J. J., & Cook, K. A. (Eds.). (2005). *Illuminating the path: The research and development agenda for visual analytics*. Los Alamos, CA: IEEE Computer Society.

Tomaszewski, B., Blanford, J., Ross, K., Pezanowski, S., & MacEachren, A. M. (2011). Supporting geographically-aware web document foraging and sensemaking. *Computers, Environment and Urban Systems, 35*(3), 192–207.

Tomaszewski, B., & MacEachren, A. M. (2012). Geovisual analytics to support crisis management: Information foraging for geo-historical context. In *Information Visualization (invited extension of paper originally published in proceedings of IEEE VAST 2010)* (vol. 11 (4), pp. 339–359).

Tuan, Y.-F. (1977). *Space and place: The perspective of experience*. Minneapolis: University of Minnesota Press. 226.

Vasardani, M., & Winter, S. (2016). Place properties. In H. Onsrud & W. Kuhn (Eds.), *Advancing geographic information science: The past and next twenty years* (pp. 243–254). Needham, MA: GSDI Association Press.

Wang, X., Miller, E., Smarick, K., Ribarsky, W., & Chang, R. (2008). Investigative visual analysis of global terrorism. *Computer Graphics Forum, 27*(3), 919–926.

Winter, S., & Freksa, C. (2012). Approaching the notion of place by contrast. *Journal of Spatial Information Science, 2012*(5), 31–50.

Wojcik, S. P., Hovasapian, A., Graham, J., Motyl, M., & Ditto, P. H. (2015). Conservatives report, but liberals display, greater happiness. *Science, 347*(6227), 1243–1246.

Woodcock, C. E., & Strahler, A. H. (1987). The factor of scale in remote sensing. *Remote Sensing of Environment, 21*(3), 311–332.

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Lu, F., Chen, J., et al. (2016). Another tale of two cities: Understanding human activity space using actively tracked cellphone location data. *Annals of the American Association of Geographers, 106*(2), 489–502.

Yang, X., Ye, X., & Sui, D. Z. (2016). We know where you are: In space and place-enriching the geographical context through social media. *International Journal of Applied Geospatial Research (IJAGR), 7*(2), 61–75.