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Editorial

Human-Centric Data Science for Urban Studies

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Abstract: Due to the wide-spread use of disruptive digital technologies like mobile phones, cities have transitioned from data-scarce to data-rich environments. As a result, the field of geoinformatics is being reshaped and challenged to develop adequate data-driven methods. At the same time, the term "smart city" is increasingly being applied in urban planning, reflecting the aims of different stakeholders to create value out of the new data sets. However, many smart city research initiatives are promoting techno-positivistic approaches which do not account enough for the citizens' needs. In this paper, we review the state of quantitative urban studies under this new perspective, and critically discuss the development of smart city programs. We conclude with a call for a new anti-disciplinary, human-centric urban data science, and a well-reflected use of technology and data collection in smart city planning. Finally, we introduce the papers of this special issue which focus on providing a more human-centric view on data-driven urban studies, spanning topics from cycling and wellbeing, to mobility and land use.

Keywords: urban data science; smart cities; geoinformatics

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1. Introduction

Disruptive technological advances over the past two decades, such as mobile phones and online social networks, have fundamentally changed how we see the world. Although digital technologies have profoundly transformed social interaction, the proclaimed "death of geography" [1] has not come to fulfillment: More people than ever live in urban areas, underlining the significance of cities as hubs of social activity [2]. However, our lives increasingly take place in virtual spaces, including social networks, digital communities, and online messengers, ultimately without requiring any personal interaction in physical space.

As a result of this transformational development, the scientific community has faced a transition from a data-scarce to a data-rich urban environment [3], which gave birth to urban informatics and reshaped geoinformatics through the increased application of data-driven approaches. These new approaches necessitate the development of new methods for data acquisition, storage, and analysis, including unsupervised machine-learning algorithms or semi-supervised learning systems, among others.

Additionally, in the past decade, the concept of "smart cities" has been driven by the idea of an ICT-infused city; that is, an urban system enriched with a number of different information technologies to support urban management and planning. However, many smart city research initiatives are promoting techno-positivistic approaches which do not account enough for the citizens' needs [4,5].

This special issue "Human-Centric Data Science for Urban Studies" focuses on this challenge and provides a more human-centric view of smart cities.

2. Creating Value from Massive Urban Data Sets

IT-based planning approaches of the last decade have arisen from the aims of different stakeholders to create value out of the exploding amount of individually-generated data sets in cities. This variety of novel massive data sets is generated by different sources and for different reasons, including:

- **Geo-social network data.** With the rapid rise of social networks, we have witnessed a paradigm shift in human communication, but even more so in the availability of real-time data that reflect urban processes. These data stem from geo-social networks like Twitter, Foursquare, Facebook, Flickr, YouTube, and many others [6]. Apart from the data's inherent spatial and temporal nature (geolocation plus timestamp), there is an increasing focus on analyzing the semantic content of social media posts: Semantic richness allows for the extraction of relevant information, such as sentiments, opinions, or observations [7].
- **Wearable sensor data.** Recently, research efforts capitalizing on new developments in physiological sensing have been flourishing, particularly in deriving emotions from physiological parameters. These efforts are driven by the increasing availability of a variety of affordable wearable sensors that measure a broad range of physiological parameters, such as heart rate, galvanic skin response, or skin temperature [8]. These new low-cost wearables are increasingly used in scientific studies in a variety of areas like health research [9], well-being assessment, extraction of emotion information [10], spatial emotion analysis, and stress detection [11]. However, as a new research field, caution has to be exercised as some research efforts in this direction have used wearable physiological sensors without prior investigation of the sensor's exact quality parameters; i.e., how accurately a sensor actually measures a given parameter or how reliable a sensor is at producing continuously high-quality measurement results.
- **Mobile phone data.** Additionally to traditional call details records, modern smartphones record high-frequency x-detail records that include internet/app activities and continuous GPS positions [12]. The recent wide spread of mobile phone technology, therefore, allows tracking both the detailed movements and socio-economic activities of the majority of a city's inhabitants and its visitors [13]. This extensive insight into the lives of individuals implies unprecedented opportunities for computational social science [14,15], while at the same time posing new fundamental challenges to privacy [16].
- **Transport and mobile sensor data.** The digitalization of private and public transport services now allows tracking of citizens in the public transportation system, such as through the London Oyster card [17], and analyzing/visualizing entire taxi systems and transportation fleets [18,19]. Further, detailed records are being generated by novel mobility sharing systems, from car and bicycle sharing to e-stroller and ride sharing. Custom sensors, installed on vehicles, can provide the potential to sense ecological urban variables and the sentiments of city dwellers in unprecedented detail [20]. All these developments have led to an explosion in data-driven research on human mobility [21].
- **Volunteered geographic information.** OpenStreetMap (OSM) has become a vital source for urban analysis. Its geospatial accuracy, completeness, and semantic comprehensiveness [22] allow for supporting decisions in a number of academic and real-world use cases through high-quality and up-to-date information about urban features [23,24].
- **Economic transactions.** Credit card transactions allow one to study cities from a spending behavior perspective [25]; detailed individual economic information allows street-level insights into segregation [26].

This variety of such new large-scale datasets have led to a previously unknown situation in urban science; namely, the transformation from data-scarce to data-rich research environments, implicating both unprecedented potential and challenges for research.

3. Challenges in Human-Generated Urban Data Analysis

Human-generated data are created in non-standardized processes with uncertain characteristics, including social media posts, subjective personal observations, or from wearable sensors. Their analysis with geospatial analysis methods is still a major challenge. This challenge comes from the data's noisy characteristics with respect to location uncertainty, temporal uncertainty, semantic ambiguity, or lack of structure. In fact, these kinds of data are not designed and captured to serve a specific purpose with clearly defined syntactic and semantic content, as opposed to traditional Geodata. Thus, currently available analysis methods may be inadequate to be applied to human-generated data. To tackle this issue, new cross-disciplinary methods have to be developed, complementing single-disciplinary approaches. These joint efforts will allow for uncovering latent patterns through analyzing human-generated data, and for drawing more profound conclusions from the analysis results to shape real-world processes; i.e., to use human-generated data in urban planning and decision-making, with a strong connection to developments in the field of urban geography [27].

Further issues include the fact that social media users and posts are not uniformly distributed across all age groups and education levels, and are thus not representative of the entire population [28,29]. Moreover, the geolocation of social media posts is not necessarily the actual location of the observation of a real-world phenomenon even though they are often considered in-situ reports. Location uncertainties may also arise from geospatial inaccuracies in the measurement devices or through user-defined locations. The same applies to temporal uncertainty—it is often not entirely clear whether users refer to past, current, or future events [30]. Finally, only a smaller percentage (typically between 1% and 10%) of all social media posts contain an explicit geolocation [29], further biasing the dataset. From a semantic viewpoint, social media posts contain a large portion of slang words, abbreviations, emoticons, irregular punctuation, "yoof speak," or other words that cannot be found in standard dictionaries [31]. All these limitations reduce or eliminate the usability of currently available analysis methods.

4. Approaches to Analyzing Human-Generated Urban Data

The quantitative and computational analyses of cities started with geoinformatics in the 1970s, when computers enabled geographers to apply efficient automated analyses to geospatial data. The focus on computational aspects and large-scale data sets from new sources developed into urban computing/informatics in the early 21st century, attracting computer scientists. More recently, additional approaches have emerged from different communities, such as complex systems, developing a physics-inspired "Science of Cities" approach by applying quantitative methods and network formalisms to understand the structure, dynamics, and development of cities and their infrastructural networks [32–34].

With respect to the analysis of human-generated data, the high degree of uncertainty, including textual ambiguities, positional and temporal inaccuracies, and semantic irregularities, requires new analysis methods to be developed. Concretely, unsupervised self-learning systems and semi-supervised machine learning techniques seem to be a promising avenue [7,35] for several reasons: First, they reduce or eliminate the need for a priori knowledge with respect to linguistic structures, geospatial correlations, or semantic meaning. Second, it is possible to incorporate the geospatial dimension into the analysis process, in many cases in a simple fashion without having to modify the original method. This step is essential because many machine-learning algorithms have originally not been designed for handling and analysing geospatial data. Third, machine learning methods have the power to deal with large amounts of data in that data-driven approaches can be applied to mine latent, unanticipated patterns in human-generated data [7].

While all these approaches have their merits, they often neglect human complexity. Therefore it is high time to push beyond disciplinary boundaries, for an urban data science [36] that combines approaches from geography, computer science, physics, social sciences, and more, in an anti-disciplinary way. To increase democratic participation, citizen science should also be welcomed.

The variety of large-scale datasets, sensing technologies, geo-participation initiatives, collaborative mapping tools, and data science approaches have the potential to help us with gaining a better understanding of urban processes and converting them into concrete urban planning and management actions.

5. Urban Planning for Humans, Not for Technological or Entrepreneurial Self-Interest

Human-generated data constitute a valuable source of information for modern, citizen-centric urban planning. Unfortunately, urban planning is often still a closed communication process between local governmental actors, and not an open, transparent procedure that integrates, discusses, and considers the requirements of citizens and civic interest groups. In an ideal planning workflow, all arguments should be collected, weighed against each other, and discussed in workshops or other open formats to gather opinions and needs from citizens. This broad discussion procedure necessitates an equally broad understanding of the citizens' needs and related urban processes. At the same time, care must be taken to avoid obstructing bold sustainable policy making, to reach societal goals without getting stuck in "NIMBYism" (Not In My BackYard) [37,38].

The goal of a human-centric urban data science is value creation for citizens. This objective implies an approach to smart city programs with reasonable skepticism, to scrutinize the motives of commercial and political stakeholders, and to actively repulse actors who install or abuse technology to benefit their own interests at the cost of citizens, especially regarding vulnerable demographics. Of course such a distinction is not black and white: profit-generating technology is not necessarily in conflict with usefulness for city dwellers. However, a constant open dialogue is necessary to ensure benefit for all citizens.

For example, most cities and their planning processes turned car-centric in the 20th century [39]. To undo this massive damage to urban livability (and the global climate), more and more cities are starting to take note of the principles of transport justice [40], refocusing on walkability [41] and sustainable transport such as cycling [42], creating economic benefits for society as a whole [43]. To combat the political inertia countering such efforts and to plan in a sustainable way, urban planning stakeholders must become more aware of internal biases like elite projection [44] and of the system dynamics of path-dependence [45].

Further, we agree with Hollands [5] that the label "smart city" is problematic as it easily comes with the danger of masking—if not creating—increased socio-economic inequality: "while smart cities may fly the banner of creativity, diversity, tolerance, and culture, the balance appears to be tipped towards appealing to knowledge and creative workers, rather than using IT and arts to promote social inclusion" ([5], p. 312). To the contrary, technology and data collection have the potential to be used for social good [46]—but their application must start with people rather than a blind belief that they will automatically transform and improve cities [5,47]. In any case, a human-centric urban data science must actively reject the ongoing erosion of democratic processes in unreflectingly implemented "smart cities", and it must reject the abuse of technology and data collection for surveillance capitalism [48].

6. The Contributions of This Special Issue

This special issue explores several of the mentioned data sets, issues, and challenges in 24 research papers. Contributors to the special issue cover a spectrum of methods spanning sentiment analysis, machine learning, network science, phone data, and mobility analysis, and classical spatial analysis. A variety of human-centric topics is covered:

Cycling. Four issue papers focused on cycling, exploring the stress challenges experienced in urban environments by the vulnerable demographic of cyclists [49–52]. Werner et al. [49] and

Pajarito and Gould [52] focused on improving livability through cycling, investigating cyclists' stress sensations through route analysis. Pritchard et al. [50] also studied cycling stress, but considered a mix of indicators for assessing bicycle level of service. Zhang et al. [51] took a different approach, leveraging public bicycle-sharing data and machine learning methods to identify land use.

Wellbeing. Five issue papers focused on another aspect of urban human wellbeing: comfort [53–55] and crime [56,57]. The former contributions focused on sentiment analysis; the latter two used spatial and machine learning methods, respectively. Kovács-Győri et al. [53] classified parks and their visitors in London using spatiotemporal and sentiment analysis of Twitter data, going beyond traditional spatial proximity analysis. Nouman et al. [54] prototyped a mobile environmental sensor toolkit to asses outdoor comfort using data mining and sensing techniques. Bielik et al. [55] performed an empirical study to assess trade-offs in a variety of urban design parameters—social, psychological, and energetic—on planning the fundamental elements of urban form: the street network and the building massing. Concerning crime, Xiao et al. [56] analyzed the travel patterns of residential burglars in a Chinese city, disentangling origin and destination effects, while Lin et al. [57] explored different machine learning algorithms demonstrating the importance of geographic feature design for improving performance and explanatory ability in grid-based crime prediction.

Mobile phones. Two studies exploited mobile phone technology for urban research purposes [58,59]. Cottineau and Vanhoof [58] followed a computational social science approach and related massive call data records with socioeconomic census data in France, unveiling the potential for detailed insights into urban socioeconomic organization. Osaba et al. [59] used a completely different method, deploying a smartphone-based system of human behavior analysis in a "senseable space".

Mobility. Five issue papers analyzed human mobility related issues from various human-centric perspectives [60–64]: railway and public transport, emergencies, nursing equity, and crowd flows. Zheng et al. [60] developed machine learning techniques to efficiently recognize modes of driving railway trains. Maeda et al. [64] created an index based on human mobility data, making it possible to predict the influence of urban development on future residential movements. Li and Zhou [61] proposed a multiobjective rescue routing model for urban emergency logistics under travel time reliability, critical for urban emergency logistics during disasters. Hu et al. [62] performed a multi-modal trip network analysis to assess the spatial equity of nursing homes in Changchun, finding heterogeneous hot spots. Finally, Zhou et al. [63] develop a neural network model to predict crowd mobility at transportation hubs such as metro/bus/bike stations.

Street networks. Three issue papers used a network science approach to street network analysis [65–67]. Yang et al. [67] analyzed changes in the spatio-temporal characteristics of the spatial-interaction networks of Beijing, finding specific changes in connections, which play a vital role in understanding urban spatial heterogeneity. Agryzkov et al. [66] proposed a new centrality measure for complex networks based on PageRank to establish a ranking of nodes considering the importance of some dataset associated to the network, evaluated on a street network. Hacar et al. [65] analyzed OpenStreetMap road data to characterize the behavior of OpenStreetMap contributors, finding that more experienced contributors make for more detailed contributions.

Land use. Five issue papers studied a mix of human-centric spatial topics related to land use [68–72]: housing, business, vegetation, gender, and digital signage. Wang et al. [68] used regression models to explore the factors affecting housing prices and changes of urban space prices, observing a particular trajectory of urban development. Sánchez-Martín et al. [69] performed hotspot analysis and outlier analysis to group accommodation businesses not only using their spatial proximity but their lodging capacity. Zhang et al. [70] quantified the temporal and spatial patterns of impervious surfaces over a timespan of 10 years, with important implications for the study of regional environmental and economic development. Lei et al. [71] used location data from Weibo users to study the human dynamics of the spatial-temporal characteristics of gender differences in Beijing's Olympic Village in June 2014, finding gender-specific differences in spatial land use patterns. Finally, Zhang et al. [72]

focused on a spatial analysis of the case of digital signage in Beijing, with the potential to enhance the sustainable management of digital signage.

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