New approaches to measure the spatial structure(s) of cities

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Summary

This paper uses mobile phone data for the city of Amsterdam to study the distribution of activity over space and time. The extent to which we can empirically learn about the spatial structure of cities is limited by the technology and data available at given point in time. Using new sources of data that did not exist only a few years ago and recent statistical approaches that exploit them in a fuller fashion, we are able to obtain a representation of the changing spatial structure of the city over the course of a year, a week and a day.

KEYWORDS: Urban spatial structure, space-time statistics, mobile phone data, big data, urban form.

1 Introduction

Our understanding of the spatial structure of cities has been shaped by the type of data available at each moment. Traditionally, researchers looking at the spatial distribution of activity within cities have relied on official sources. These datasets have a high degree of accuracy and representativeness but a low temporal resolution, usually being collected once every ten years in censuses. This degree of coarseness likely hide many patterns of relevance that are lost in-between observations, limiting how much we can learn about human activity within cities. In recent years, several technological advances have given rise to multiple new sources of data that promise to fill many of the gaps left by traditional datasets (Arribas-Bel, 2014). In this paper, we use mobile phone data for the city of Amsterdam to study the distribution of activity over space and time. We begin with the analysis presenting insights that one would expect to obtain from traditionally aggregated data to then move on to much finer disaggregation of mobile phone usage. Taking advantage of these new data also require modification in the methodological approaches and, to this end, we adopt not only traditional tools from spatial analysis but more modern space-time approaches. This additional layer of detail allows us get insights about the changing shape of activity within the same city,

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within a day and a within a week, that would have been missed if only a traditional dataset was available.

There is a longstanding literature in quantitative geography and urban economics focusing on the measurement and study of the spatial structure of cities (Anas et al., 1998). Most of this works relies almost exclusively in some form of official data, be it census or transportation datasets, provided by official agencies at a spatial and temporal aggregated level. Initial approaches such as that outlined in Giuliano and Small (1991) were highly influential and, although relied on simple and often ad-hoc measures, seeded the way for more sophisticated analysis. In the early 2000's, McMillen (McMillen, 2001, McMillen and Smith, 2003, McMillen, 2004) significantly advanced the field by including more advanced methods based on non-parametric techniques such as geographically weighted regression (GWR). In more recent years, the efforts have been split between sophisticating the methods further (e.g. Redfearn, 2007) and applying them in empirical contexts that substantially broaden the scope of the areas covered (e.g. Lee, 2007, Arribas-Bel and Sanz-Gracia, 2014).

Urban analysis based on data from mobile phone operators or other big data sources provides new opportunities to urban analysis as it enables researchers to model and gain a deeper understanding of the pulse of the city (Batty, 2010). Analysis using the above data do not focus on the physical form of cities, but on human activity and most importantly, on how citizens use cities. Researchers have now the ability to utilise such data due to pervasiveness of digital technologies which resulted to huge pools of human behavioural data. Urban analysts are now able to use such data as a tool to understand the structure of cities (Louail et al., 2014). The value added of such data is related with their granularity both in terms of space and time. The latter enables researchers to study the dynamics of urban structure and how cities are perceived and used by citizens over time. The results of such research can support urban planning and generate new opportunities for the management of cities. For instance, according to Ahas and Mark (2005) geo-located data from mobile phone operators can be utilized in monitoring the usage of transport infrastructure, in studying and quantifying the temporal dimensions and the dynamics of urban space, and in planning and designing transportation and transport infrastructure.

This paper draws upon a fast developing research domain which utilises data from mobile phone operators in analysing and modeling cities. The main lesson from this research strand is data from mobile phone operators offers the possibility to study micro- and macro-behaviors and truly reflect human behavior given the fact that data is becoming more and more available (Calabrese et al., 2014, p. 25:4). In other words, such data reflect the collective behaviour of people (Calabrese et al., 2010). In another paper, Reades et al. (2009) identified a strong relationship between human activity and aggregated mobile phone usage using the city of Rome as a case study. More recent, Sevtsuk and Ratti (2010) used data for mobile phone activity as a proxy to model population distribution over time and space and Jacobs-Crisioni et al. (2014) employed such data to assess the impact of land-use density and mix on urban activity patterns.

2 Data

The data used for this paper has been provided by one of the major mobile phone operators in The Netherlands. It is an aggregated dataset of individual mobile phone activity and includes telecommunication counts at the level of the GSM (Global System for Mobile Communications) zones on an hourly basis for 2010. 815 such zones are included in the analysis which represent the coverage areas of GSM antennas. These zones are represented by irregular polygons which vary in shape and size, the design of which supports the function of the GSM network. For instance, smaller GSM zones can be observed in the centre of Amsterdam as this is a busier area and therefore GSM antennas accommodate smaller areas. In regards to the telecommunications counts, the main focus of the paper lies on the number of Erlangs. This is a measure of telecommunication activity: 1 Erlang can consist of either one phone call of 60 minute duration or of two 30 minute phone calls (Sevtsuk and Ratti, 2010).

3 Methods

More detailed data both in space and time do not automatically translate into more detailed insights. To leverage the full power and advantages of mobile phone data, it is necessary to include methodologies that recognize such degree of detail and are able to cope with it. To show this in an intuitive way, we adopt an incremental approach that begins with cross-section spatial methods applied to a completely time-aggregated version of the dataset. In particular, we use the widely adopted local indicators of spatial association (LISAs, e.g. Anselin, 1995). This stage is meant to show what a traditional analysis would be able to find and thus represents a benchmark against new insights will be compared. We then begin to dissaggregate the data over more fine-grained temporal scales. First we calculate similar LISA maps for hourly slices over a day and over a week. These allow to start thinking about the idea of an evolving spatial structure, hidden to traditional approaches. Finally we embrace the space-time nature of mobile phone data by adopting some of the more recent statistical techniques such as Kulldorff's scan statistics (Kulldorff et al., 2005, Kulldorff, 2014).

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5 Biography

Dani Arribas-Bel is lecturer in Human Geography at the University of Birmingham. He is interested in quantitative spatial methods and urban analysis. In particular, he is interested in how the computational advances and explosion of data witnessed in the last decades can contribute to the understanding of the spatial structure of cities. He is also involved in the open-source community, mostly as a core developer of the scientific library of advanced spatial analysis PySAL.

Emmanouil Tranos is lecturer in Human Geogrpahy at the University of Birmingham. He is an economic geographer focusing primarily on digital geographies. He has published on issues related with the spatiality of the Internet infrastructure, the economic impacts that this infrastructure can generate on space and the position of cities within spatial, complex networks. Recently, he has been focusing on the use of big data of high spatio-temporal resolution (e.g. mobile phone data) in urban and regional analysis.

References

Ahas, R. and Mark, Ü. (2005). Location based servicesnew challenges for planning and public administration? *Futures*, 37(6):547–561.

Anas, A., Arnott, R., and Small, K. (1998). Urban spatial structure. *Journal of Economic Literature*, 36(3):1426–1464.

Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographical Analysis*, 27(2):93–115.

Arribas-Bel, D. (2014). Accidental, Open and Everywhere: Emerging Data Sources for the Understanding of Cities. *Applied Geography*, 49:45–43.

Arribas-Bel, D. and Sanz-Gracia, F. (2014). The validity of the monocentric city model in a polycentric age: Us metropolitan areas in 1990, 2000 and 2010. *Urban Geography*, 35(7):980–997.

Batty, M. (2010). The pulse of the city. *Environment and Planning B: Planning and Design*, 37(4):575–577.

Calabrese, F., Di Lorenzo, G., and Ratti, C. (2010). Human mobility prediction based on individual and collective geographical preferences. In *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, pages 312–317. IEEE.

Calabrese, F., Ferrari, L., and Blondel, V. D. (2014). Urban sensing using mobile phone network data: A survey of research. *ACM Computing Surveys (CSUR)*, 47(2):25.

Giuliano, G. and Small, K. (1991). Subcenters in the Los Angeles Region. *Regional Science and Urban Economics*, (21):163–182.

Jacobs-Crisioni, C., Rietveld, P., Koomen, E., and Tranos, E. (2014). Evaluating the impact of land-use density and mix on spatiotemporal urban activity patterns: an exploratory study using mobile phone data. *Environment and Planning A*, 46(11):2769–2785.

Kulldorff, M. (2014). Satscan v 9.3: Software for the spatial and space-time scan statistics. Technical report.

Kulldorff, M., Heffernan, R., Hartman, J., Assunçao, R., and Mostashari, F. (2005). A space–time permutation scan statistic for disease outbreak detection. *PLoS medicine*, 2(3):e59.

Lee, B. (2007). "Edge" or "Cdgeless Cities"? Urban Spatial Structure in US Metropolitan Areas, 1980 to 2000. *Journal of Regional Science*, 47(3):479–515.

Louail, T., Lenormand, M., Cantú, O. G., Picornell, M., Herranz, R., Frias-Martinez, E., Ramasco, J. J., and Barthelemy, M. (2014). From mobile phone data to the spatial structure of cities. *arXiv preprint arXiv:1401.4540*.

McMillen, D. (2001). Nonparametric employment subcenter identification. *Journal of Urban Economics*, 50(3):448–473.

McMillen, D. (2004). Employment densities, spatial autocorrelation, and subcenters in large metropolitan areas. *Journal of Regional Science*, 44(2):225–244.

McMillen, D. and Smith, S. (2003). The number of subcenters in large urban areas. *Journal of Urban Economics*, 53(3):321–338.

Reades, J., Calabrese, F., and Ratti, C. (2009). Eigenplaces: analysing cities using the space-time structure of the mobile phone network. *Environment and Planning B: Planning and Design*, 36(5):824–836.

Redfearn, C. L. (2007). The topography of metropolitan employment: Identifying centers of employment in a polycentric urban area. *Journal of Urban Economics*, 61(3):519–541.

Sevtsuk, A. and Ratti, C. (2010). Does urban mobility have a daily routine? learning from the aggregate data of mobile networks. *Journal of Urban Technology*, 17(1):41–60.