Inferring characteristics of urban structure through the variability in human mobility patterns

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Summary

The polycentric city model has gained popularity in spatial planning policy, since it is believed to overcome some of the problems often present in monocentric metropolises, ranging from congestion to difficult accessibility to jobs and services. However, the concept 'polycentric city' has a fuzzy definition and as a result, the extent to which a city is polycentric cannot be easily determined. Here, we leverage the fine spatio-temporal resolution of smart travel card data from multiple cities to infer urban polycentricity by examining how a city departs from a well-defined monocentric model.

KEYWORDS: Urban spatial structure, Smart card data, Polycentricity, Complexity, Mixture models.

Extended abstract

The rapid urban growth and the recent developments in transport infrastructure and information technologies have led to the emergence of new forms of urban structure, more sophisticated than the traditional monocentric cities (Zhong et al., 2014). In particular, the polycentric city model has gained popularity in spatial planning policy, since it is believed to overcome some of the problems often present in monocentric metropolises, ranging from congestion to difficult accessibility to jobs and services (Ahlfeldt and Wendland, 2013; Anas et al., 2000; Huai et al., 2021). However, the concept of 'polycentric city' has a fuzzy definition and as a result, the extent to which a city is

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polycentric cannot be easily determined (Davoudi, 2003; Green, 2007; Kloosterman and Musterd, 2001; Meijers, 2008; Rauhut, 2017).

Here, we leverage the fine spatio-temporal resolution of smart travel card data to infer urban polycentricity by examining how a city departs from a well-defined monocentric model. In particular, we analyse the human movements that arise as a result of sophisticated forms of urban structure by introducing a novel probabilistic approach which captures the complexity of these human movements. We focus on London (UK) and Seoul (South Korea) as our two case studies, and we specifically find evidence that London displays a higher degree of monocentricity than Seoul, suggesting that Seoul is likely to be more polycentric than London.

In our methodology, we first define the "nucleus" of each city as the station with the highest number of smart-card tap-outs. We then consider the network structure of the public transport system in order to measure the length of the journeys as a network distance between stations. Our working hypothesis is: "If a city was perfectly monocentric, most of the socioeconomic activity that requires travel on the public transport system would be concentrated around the nucleus. Consequently, the average length of the journeys taken to a given station would be approximately equal to the length of the shortest path between the nucleus and the destination station". In reality, the perfectly monocentric city does not exist and this is captured in Figure 1, where each data point corresponds to a destination station. The x-coordinate represents the length of the shortest path between the nucleus and the destination station, measured as the minimum number of stations that need to be visited to travel from the origin to the destination stations. The y-coordinate represents the average length of the journeys terminating at each station. If the cities were perfectly monocentric, the data points would be lying exactly on the $y = x$ line, but Figure 1 shows that this is not the case neither for London or Seoul.

Poisson mixture models allow us to model the variability of the length of journeys terminating at each station with greater precision. For example, a 2-component Poisson mixture model assumes a bi-modal distribution for the length of the journeys terminating at each station. We refer to the components corresponding to the shortest and longest journey lengths as the proximal and distal components respectively. Figure 2 shows the relationship between the means of the proximal and distal components corresponding to a given station and the network distance between that station and the nucleus. As the network distance between a destination station and the nucleus becomes larger, there is no significant increase in the proximal mean, since it remains around 5 and never above 10. The effect is strikingly obvious in the case of Seoul, suggesting that this city departs from the hypothesised monocentric behaviour more than London. These observations are likely to be the consequence of the existence of other socioeconomic centres, closer to the destination station, where passengers prefer to travel to carry out some socioeconomic activities at a more local level. In contrast, the distal component displays a significant linear growth. The distal component captures long-distance, city-wide journeys from stations that are possibly close to the nucleus, to stations that are in the peripheral regions of the city

Even though the methodology described above can be expanded to Poisson mixture models with more components, we recommend keeping the number to 2 or 3 as a good trade-off between capturing the detail in the data variability whilst keeping the components meaningful without over-

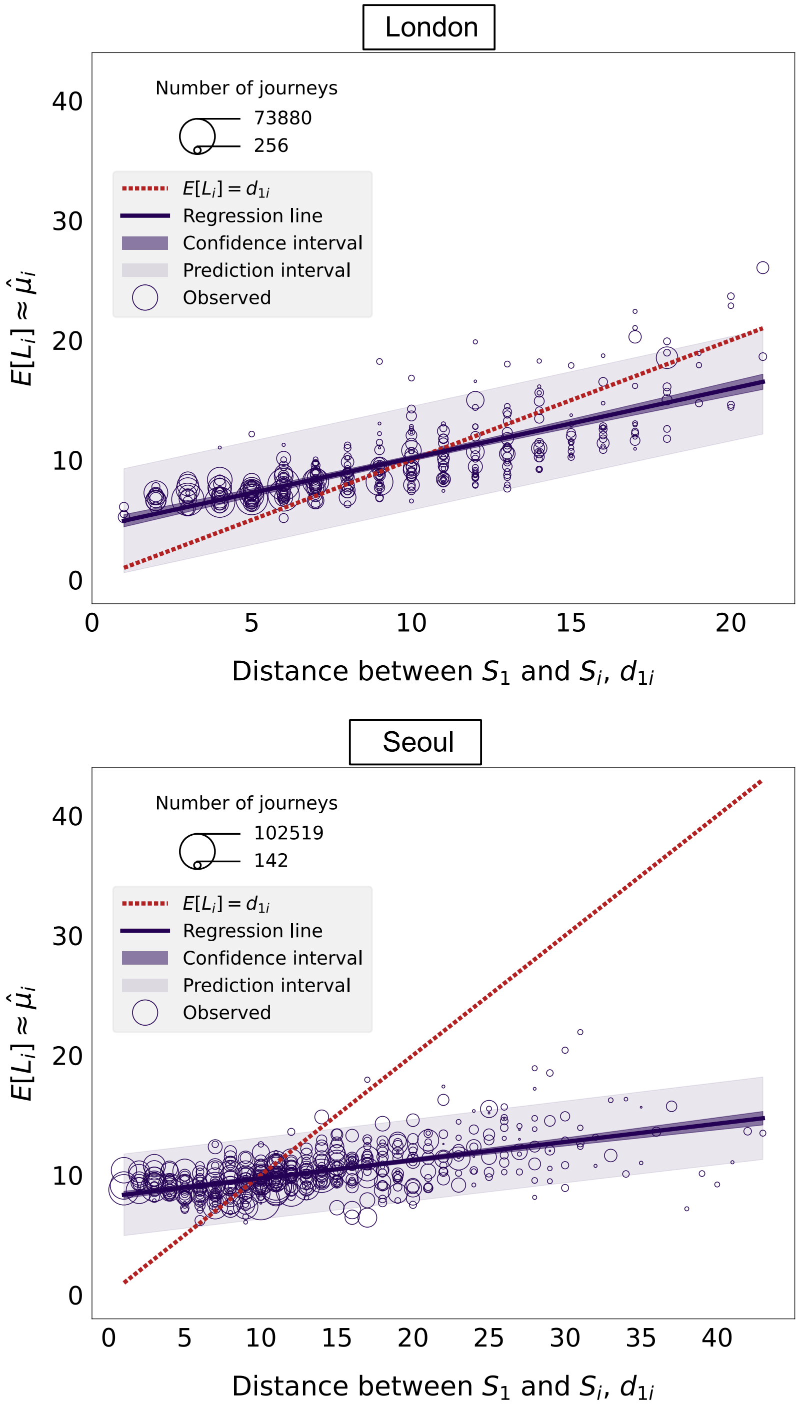

Figure 1: Relationship between the mean of the distribution of lengths of journeys terminating at each station and the (network) distance between the nucleus and a given destination station.

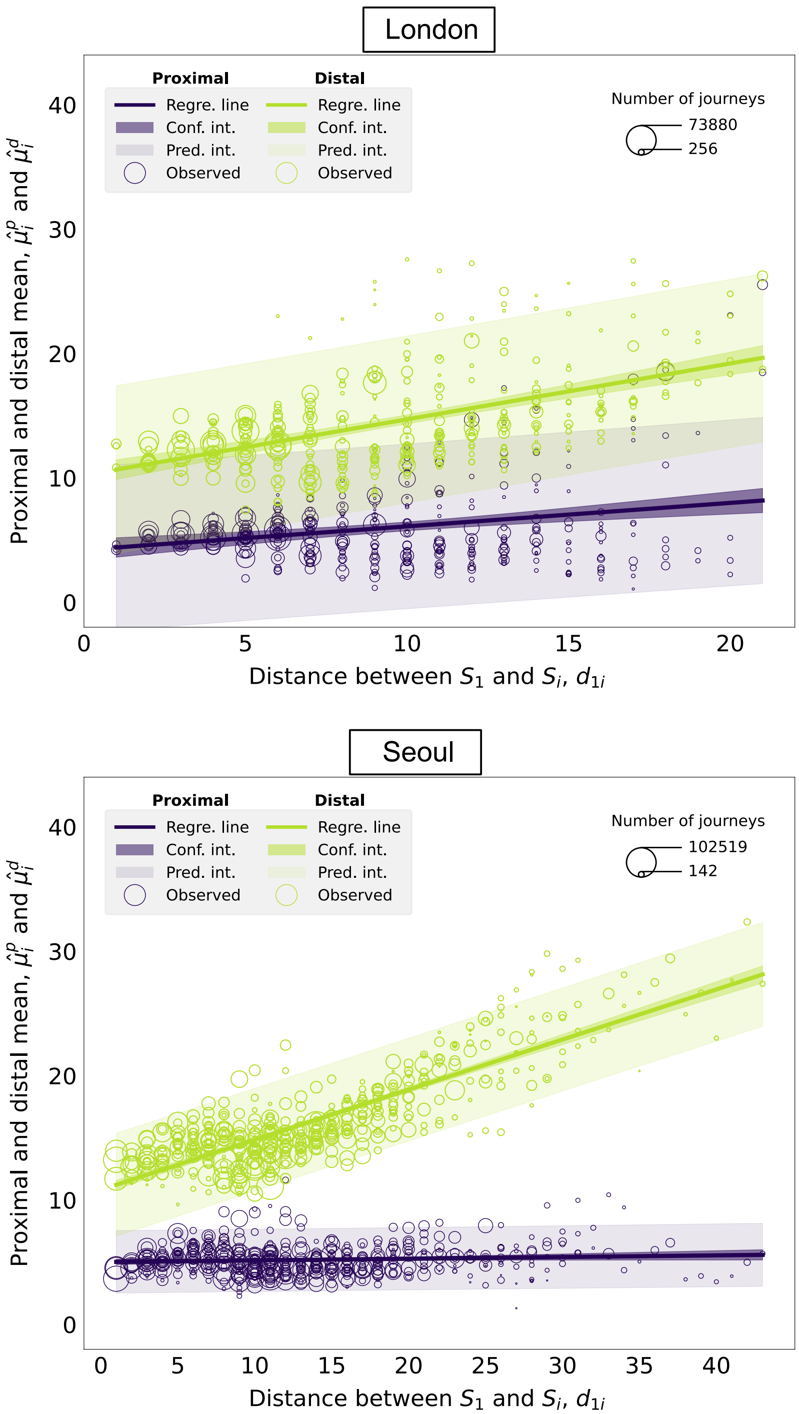

Figure 2: Relationship between the mean of the distribution of lengths of journeys terminating at each station and the (network) distance between the nucleus and a given destination station.

complicating the model. In fact, the model with 3 components yields a lower value of the Bayesian Information Criterion, suggesting that this model should be selected over the two-component model. Furthermore, it should be noted that by performing a sensitivity analysis, we can show that similar results hold for other choices of nuclei.

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Biography

Carmen Cabrera-Arnau is a Lecturer in Geographic Data Science at the University of Liverpool and a member of the Geographic Data Science Lab. Her research is about the development of mathematical models to uncover patterns displayed by socioeconomic data in the context of urbanisation.

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References

Ahlfeldt, G. & Wendland, N. (2013). How polycentric is a monocentric city? Centers, spillovers and hysteresis. *Journal of Economic Geography*, *13*(1), 53–83 `https://EconPapers.repec.org/RePEc:oup:jecgeo:v:13:y:2013:i:1:p:53-83`.

Anas, A., Arnott, R., & Small, K. (2000). The panexponential monocentric model. *Journal of Urban Economics*, *47*(2), 165–179 https://EconPapers.repec.org/RePEc:eee:juecon:v:47:y:2000:i:2:p:165-179.

Davoudi, S. (2003). EUROPEAN BRIEFING: Polycentricity in European spatial planning: from an analytical tool to a normative agenda. *European Planning Studies*, *11*(8), 979–999, https://doi.org/10.1080/0965431032000146169 https://doi.org/10.1080/0965431032000146169.

Green, N. (2007). Functional polycentricity: A formal definition in terms of social network analysis. *Urban Studies*, *44*(11), 2077–2103, https://doi.org/10.1080/00420980701518941 https://doi.org/10.1080/00420980701518941.

Huai, Y., Lo, H. K., & Ng, K. F. (2021). Monocentric versus polycentric urban structure: Case study in Hong Kong. *Transportation Research Part A: Policy and Practice*, *151*, 99–118, https://doi.org/https://doi.org/10.1016/j.tra.2021.05.004 https://www.sciencedirect.com/science/article/pii/S0965856421001300.

Kloosterman, R. C. & Musterd, S. (2001). The polycentric urban region: Towards a research agenda. *Urban Studies*, *38*(4), 623–633, https://doi.org/10.1080/00420980120035259 https://doi.org/10.1080/00420980120035259.

Meijers, E. (2008). Measuring polycentricity and its promises. *European Planning Studies*, *16*(9), 1313–1323, https://doi.org/10.1080/09654310802401805 https://doi.org/10.1080/09654310802401805.

Rauhut, D. (2017). Polycentricity – one concept or many? *European Planning Studies*, *25*(2), 332–348, https://doi.org/10.1080/09654313.2016.1276157 https://doi.org/10.1080/09654313.2016.1276157.

Zhong, C., Arisona, S. M., Huang, X., Batty, M., & Schmitt, G. (2014). Detecting the dynamics of urban structure through spatial network analysis. *International Journal of Geographical Information Science*, *28*(11), 2178–2199, https://doi.org/10.1080/13658816.2014.914521 https://doi.org/10.1080/13658816.2014.914521.