

Analysing Interlinked Urban Functions through Mobility Motifs

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Summary

This paper presented a work on mining mobility patterns using smart-card data. In particular, we investigated the interlinked urban functions from sequences of individuals' daily trips. A spatiotemporal network approach is introduced with workflow and related data analysis specified. Using London Underground as a case study, the analytical result shows a universal pattern and spatial heterogeneity. Statistically, there is a universal pattern of mobility motif distribution, which is consistent with previous works using mobile and surveyed data. When extend the analysis to spatial dimension, relations between motifs and urban functions can be identified.

KEYWORDS: Network analysis, motifs, urban mobility, smart-card data, urban functions

1. Introduction

Analysing and modelling urban mobility patterns has long been researched, due to its wide range of application from transit service, urban planning [1, 2], city management [3, 4] to the evolution of epidemics [5, 6]. The emerging new type of mobility data, such as smart-card data, mobile phone, social media data, are generated from human agents with fine granularity and has brought new opportunities to this field. The aspects we are particularly keen to comprehend are:

(1) In which way are urban functional zones inter-connected through individual's daily trip sequence?

(2) Is there a universal pattern of motifs in public transportation? What is the statistical distribution of different mobility motifs?

(3) What is the spatial distribution of different mobility motifs? How does the local context matter?

We aim to push forward the study of mobility patterns to include spatial dimensions and link it to urban planning issues. In sum, our work contributes to a better understanding of urban complexity and modelling of urban flows.

2. Method

A workflow is presented in Figure 1. In general, smart-card data is used for extracting motifs, and POI data and O-D data is combined to describe the feature of land use around each underground stations. There are three steps in the workflow: Firstly, individual network are constructed from trip records. Secondly, we extract motifs from networks. Thirdly, census data of work-home trips and POI data are combined as feature vectors to describe the corresponding urban functions of stations. Combining extracted motifs and clustered urban functions, we perform further analysis of individual mobility network to identify how people move among different functional zones.

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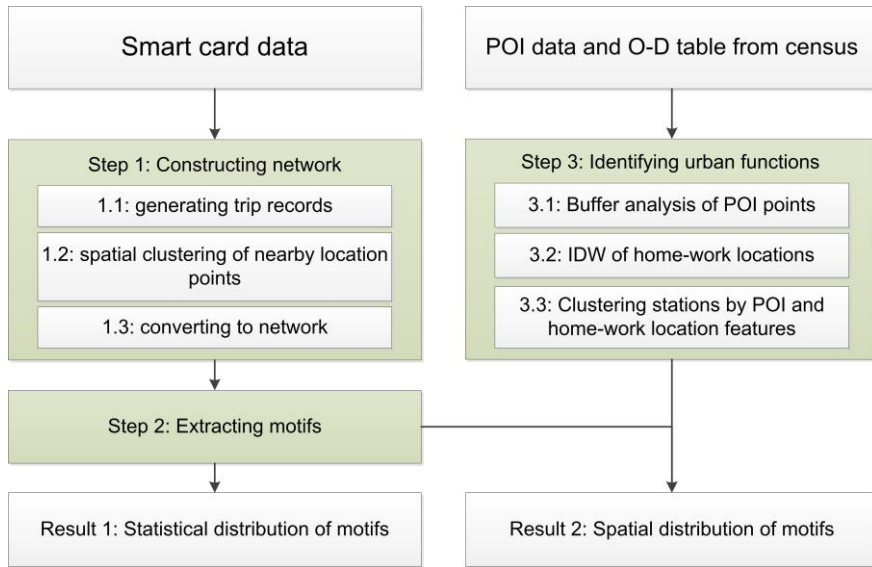


Figure 1. Experiment design.

3. Result

Without any post-selection of motif types, all types of two and three nodes motifs are presented in Figure 2 (bottom), which shows the statistical distribution of motifs.

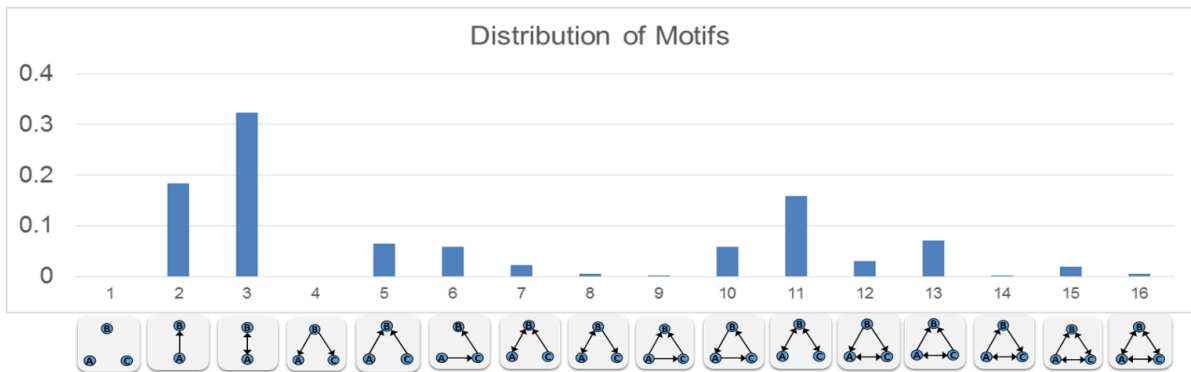


Figure 2: Distribution of motifs.

Note: Two nodes motifs can also be considered as two nodes with a third node disconnected.

When applying our rules of valid network, a few types of motifs are removed from further analysis. For instance, in type 7, there is a one-direction edge between node c and node b, which means that there is no journey back (from node c), which actually may happen in reality. In Figure 3, results of UG London is from our analysis, whereas the other results are recreated from [7]: we only select the information about 2, 3 and 4 nodes type of motifs because they match with our interest. For a fair comparison, values have been adjusted according to the percentage of the selected type of motifs to the total. For instance, the original percentage of the two nodes motif in survey 1 is 39%, divided by 0.75 is then 51%. 0.75 is the portion of selected 8 motifs in the total results. It shows that motifs detected from smart-card data follow very similar distributions, especially in comparison to the survey data from Paris. Our analysis is complementary to the previous studies, adding a new type of travel data. Furthermore, it proves that the universal patterns of urban mobility motifs may also be applied to the modeling and simulation of public transportation.

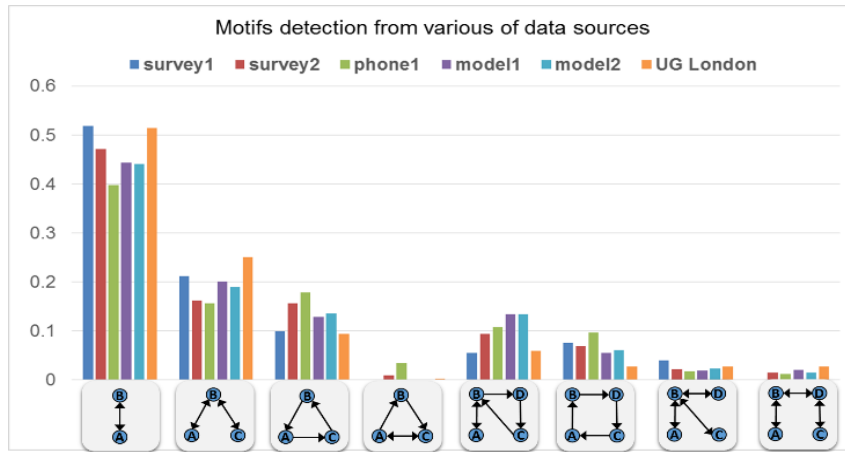


Figure 3: Distribution of motifs comparing to previous work using other data sets.

We then first look at the residential-related trip stations. A query condition is set as from where people leave earlier than 10:00 am and return after 4:00 pm. In addition, in Figure 4 (a), we map the relation of each station to residential locations by measuring how many people use a specific station as the ‘closest’ one to their homes with color coded. The number is counted as number of different card id from all motif types. Most of the top 20 stations are also railway stations, connecting local LU line to railway lines as. They function as important transport hubs, The statistical map on the top shows a negative exponential-like distribution with an outlier at the tail. The outlier (colored in green) is composed of the top three stations – King’s Cross, Victoria and Waterloo, which are railway stations as indicated. In terms of the most visited third location. Figure 4 (b) which shows a map of the third most visited locations and the distribution of counts at each station. Contrarily to. Figure 4 (a), there is a spatial concentration in the central area, where retails and restaurants are densely distributed and highly accessible by correspondingly densely distributed LU stations, like Oxford Circus.

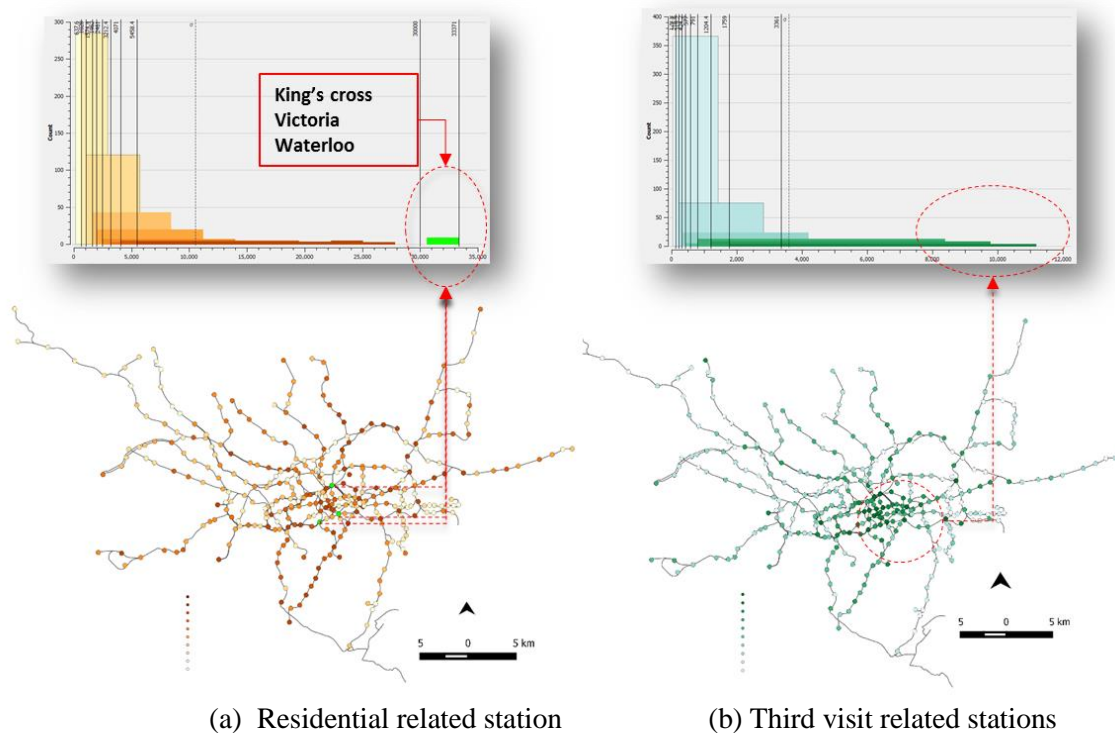


Figure 4: Mapping functional locations extracted from spatial motifs across the city.

Note: Colour denotes the number of passengers using the station for the stated purpose. The darker the color, the higher the usage rate. It is classified into 10 scales in quantile mode.

4. Discussion

Information extracted from automatically generated human mobility data could give us a good profile of city's dynamics and citizen's lifestyles. Here, we investigated the interlinked urban functions from the sequences of trips. This is an important topic because travel plan and activity diary are essential for transport planning, and the embedded information of spatial interaction is a crucial element in urban planning. Results of our case study shows: (1) a universal pattern. Statistically, there is a universal pattern of mobility motif distribution, which is consistent with previous works conducted using other types of transport data. Our results prove the existence of similar patterns in public transportation. (2) Spatial heterogeneity. We extend the analysis to spatial dimensions and look at the travel purpose of trips from various stations and the heterogeneity of types of motifs in different urban areas.

There are several aspects could be improved. 1) The coverage of the data. Due to the incompleteness of bus records, this paper used only underground data, of which the spatial resolution is much lower. 2) A temporal dimension could be added to investigate the change of urban functionality during period of days. For that, we need a longer period of data. 3) We would like to further enhance and verify the preliminary results presented in this paper with improved motif detection methods, and expand the motif analysis to cover more types of motifs.

5. Biography

Dr Chen Zhong is Lecturer in Spatial Analysis at King's College London. Her research interests include spatiotemporal data analysis, transport and land use planning.

Dr Ed Manley is Lecturer in Smart Cities at University College London. His research focuses on the use of big, new datasets to analyse human behaviour in urban areas at a highly granular scale.

Patrizia Sulis is a PhD candidate at the Centre for Advanced Spatial Analysis, UCL. Her research investigates medium and small scale urban dynamics analysing spatial big data. She holds a MSc in Urbanism from the Delft University of Technology.

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