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Identification of communities in urban mobility networks using multi-layer graphs of network traffic

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ABSTRACT

This paper proposes a novel approach to identify the pockets of activity or the community structure in a city network using multi-layer graphs that represent the movement of disparate entities (i.e. private cars, buses and passengers) in the network. First, we process the trip data corresponding to each entity through a *Voronoi* segmentation procedure which provides a natural null model to compare multiple layers in a real world network. Second, given nodes that represent Voronoi cells and link weights that define the strength of connection between them, we apply a community detection algorithm and partition the network into smaller areas independently at each layer. The partitioning algorithm returns geographically well connected regions in all layers and reveal significant characteristics underlying the spatial structure of our city. Third, we test an algorithm that reveals the unified community structure of multi-layer networks, which are combinations of single-layer networks coupled through links between each node in one network layer to itself in other layers. This approach allows us to directly compare the resulting communities in multiple layers where connection types are categorically different.

1. Introduction

Does a consistent community structure exist in the city-scale, and does it differ from one entity to another? This study aims to answer this question by building graphs of mobility patterns for disparate entities (e.g., buses, bus passengers and cars) and revealing their pockets of activity in a city network. The underlying characteristics of a city structure, such as spatial borders, commercial/residential areas and accessibility of transportation network, influences individual travel behaviours and aggregated patterns that result from them. For instance, natural and artificial boundaries (e.g. river, train tracks) define social and spatial organisation of a city and largely affect the physical or perceived distance between nearby locations. Additionally, how the city centres, shopping districts or school zones interact with the neighbouring areas illustrates the framework in which mobility patterns are formed. Nevertheless, as urban forms are quite dissimilar for each entity (e.g. public transport network vs. car network), resulting aggregated patterns and activity pockets might differ significantly.

The influence of city structure on travel patterns has been a long standing question in the area of geography (Handy, 1996). However, these studies had limited conclusions due to unavailability of large-scale data sets and proper mathematical techniques (Yue et al., 2014). These limitations have now been overcome with achievements in sensor technologies and advances in network theory methods. A large variety of data sources has been used in the literature as a proxy for travel patterns; circulation of bank notes (Brockmann et al., 2006; Thiemann et al., 2010), cell phone tower data (Toole et al., 2015; Çolak et al., 2016), transit smart card transactions (Sun et al., 2013; Zhong et al., 2014; Alsger et al., 2018; Zhao et al., 2018), passenger flights (Guimera et al., 2005), call

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detail records (Iqbal et al., 2014; Alexander et al., 2015), taxi trips (Liu et al., 2015a), census household surveys (Saberi et al., 2016), etc. Among them, big mobility data collected from passive sources such as smart cards, cell phones, GPS devices, enable us to accurately and cost-effectively model the flows of people and vehicles around the city (Bar-Gera, 2007; Pelletier et al., 2011; Chen et al., 2014). The rise of big mobility data has also made it possible to investigate the relations between travel patterns and city structure from a time geography perspective (Liu et al., 2015b; Chen et al., 2016).

Travel flows and mobility patterns resulting from them have been largely exploited in the context of network theory or complex networks. Analysing human mobility patterns, understanding spatial distribution of activity and how these are intertwined with each other has been largely studied and discussed from a complex network theory perspective, and worthwhile insights into the way cities and people are organized have been reported in the literature (Brockmann et al., 2006; Gonzalez et al., 2008; Barthélemy, 2011). Spatial structure of mobility graphs is, in fact, essential to understanding the interactions between neighbourhoods, identifying the infrastructure needs and improving the operational aspects. Such structures can be revealed by partitioning the network into natural groups of nodes, or, in other words, by detecting *communities*. In the field of complex networks, *communities* refer to groups of nodes, within each of which nodes are connected more densely and between which nodes are connected more sparsely. And, *community detection* is the process of identifying the underlying community structure in a given graph by dividing the network into groups of nodes with dense connections internally and sparser connections between groups (Fortunato, 2010). Consequently, this technique provides sub-structures of a network that represent natural partitions or functional units of the system. Community detection has been applied on a global scale to determine airport clusters (Guimera et al., 2005), on national scale to understand whether administrative boundaries affect human communication patterns (Ratti et al., 2010) and on city-scale to reveal sub-regions and examine urban structure (Zhong et al., 2014, 2015; Liu et al., 2015a). Note that these studies focus on a single data source (e.g., phone records, transit smart card) and unveil the spatial structure from a particular interaction perspective. Nevertheless, spatial networks, especially transportation networks, are multi-domain, multi-layer structures where partitioning at each layer might take different forms.

In this study, using movement data from three sources, i.e. bus GPS observations, smart card transactions and roadside Bluetooth detector records, we build three layers of graphs indicating the movement patterns for buses, bus passengers and cars, respectively. We then identify the community structure in these graphs from a layer-by-layer and a multi-layer perspective, and compare the divisions across the three layers to unveil the interactions between them and to expose the underlying spatial structure. A major contribution of this paper is the development of a unified network that shares the same node set across different layers, thereby allowing the construction of mobility graphs that represent trajectories from disparate sources in a common form and thus enabling the comparison of community structures across layers. To the best of our knowledge, this work is the first attempt to build a multi-layer transportation framework and investigate community detection problem across the layers. Our findings, revealing comparable features of the network organisation in the bus and passenger layers and the dependency of the movement patterns on the chosen transportation mode, provide insights for the planning and design of transportation systems. Another major contribution is the construction of the supply graph (e.g., bus movements) which represents the service provided by the public transport vehicles. In the demand graphs (e.g., passenger and car layers), the interaction between nodes is defined by a single link between origin and destination points, whereas the same points hardly represent any activity in the supply networks. The approach we follow here can be further exploited in the context of layered complex networks to facilitate the description and analysis of supply networks (Kurant and Thiran, 2006). This will be further discussed in the next section.

The rest of the paper is organized as follows. In Section 2, we briefly describe the data sets, explain the processing step which is necessary to map different sources of data on the same network and outline the applied community detection techniques. In Section 3, we present the properties of the resulting graphs, discuss the results of the layer-by-layer and the multi-layer community detection and study the interactions between the layers. In Section 4, we provide a discussion and conclude the paper.

2. Methodology

A comprehensive analysis of mobility patterns at the city-scale requires the consideration of multiple entities, e.g. people/vehicles using/representing distinct transportation modes. Therefore, this study exploits multiple sources of mobility data, builds analogous graphs of movement patterns for each entity and identifies the community structures.

2.1. Study network and data

All the data sets employed in this paper are collected from the Brisbane metropolitan area, Australia between 6am-10am on Tuesday, 22/09/2015. The list of the data sets is as follows:

- bus trajectory data containing GPS traces,
- bus passenger trajectory data constructed from smart card transactions,
- car trajectory data obtained from roadside Bluetooth detection records.

The bus trajectory data were obtained from archived data of real-time bus tracking information in General Transit Feed Specification - Realtime (GTFS-RT) format, provided by TransLink (Brisbane's sole transit agency). A total of 4,945 bus trajectories were obtained. An example of bus trajectory data is shown in the top left of Fig. 2.

For the bus passenger data, *go* card (Brisbane's smart card system) transaction records were used, where each transaction represents a single *trip*, the act of travelling from point A to point B with no transfers. Each transaction provides the information on the