International Journal of Transportation Science and Technology xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

International Journal of Transportation Science and Technology

journal homepage: www.elsevier.com/locate/ijtst

Constructing activity–mobility trajectories of college students based on smart card transaction data

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ARTICLE INFO

Article history:
Received 28 February 2017
Received in revised form 23 July 2017
Accepted 29 August 2017
Available online xxxx

Keywords:
Activity–mobility patterns
Activity-travel behavior
Spatio-temporal behavior
Smart card transactions

ABSTRACT

In this research, we use UB card as a convenient source of combined smart transaction data in order to define a campus-wide model for constructing students' activity–mobility trajectories in time–space dimension. UB Card is a student's official ID at the University at Buffalo and is used across campus for various activities including Stampedes and Shuttles (on-campus bus system), facilities access, library services, dining, shopping, and etc. Two activity–mobility trajectory construction algorithms are developed. The base algorithm constructs students' activity–mobility patterns in space–time dimension using a set of smart card transaction data points as the only inputs. The modified individualized algorithm constructs activity–mobility patterns with prior knowledge of students' previous patterns as they have similar patterns for certain days of the week. A database of 37 students' travel survey and UB card transactions that contains a period of 5 days have been used to illustrate the results of the study. Three measures of errors have been proposed to capture the time allocation, location deviation, and activity sequences. These errors present an acceptable accuracy (12–25% error ranges for activity types and average 0.04–0.16 miles of error for location predictions) and show the potential of inferring activity–mobility behaviors based on smart card transaction type data sets.

1. Introduction

Novel sensing technologies can help us observe human mobility and activity behavior at a finer spatio-temporal resolution unimaginable before. For transportation research, information from these data collection technologies such as mobile phones (Calabrese et al., 2011; González et al., 2008), smartphones (Pelletier et al., 2011), GPS devices (Jiang et al., 2009), social media (Hasan et al., 2013), and smart card transactions (Kusakabe and Asakura, 2014; Hasan et al., 2013) can be used to improve the modeling of mobility and activity behavior. Traditionally, travel surveys have been used to understand individual activity and mobility choices. These surveys contain comprehensive and detailed information of people's daily routines including their trips, travel purposes, time and location of all visited places, transportation modes, activity types, etc. However, conducting these surveys are excessively expensive, time consuming and limits the result to a small number of people on a few selected days.

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http://dx.doi.org/10.1016/j.ijtst.2017.08.003
2046-0430/

With the ubiquitous uses of IT technologies and devices, passive data collection technologies have started to provide longitudinal information on individual activity–mobility patterns at a massive scale (Blondel et al., 2012; de Montjoye et al., 2014). However, data provided from these devices may contain limited and/or incomplete information. For instance, a Global Positioning System (GPS) device installed in a car can collect detailed trajectories of movements reducing the amount of resources required to collect such information (Herrera et al., 2010). However, information on various important aspects of travel behavior including activity purposes, transportation modes, and participating individual(s) are missing from such datasets.

Thus a major challenge of utilizing the massive information from ubiquitous devices is how to infer individual trajectories from incomplete datasets. Although studies have started to use ubiquitous data sources for modeling activity–mobility patterns, existing methods do not account for missing information in trajectories. Thus data mining techniques are needed to reconstruct user trajectories.

In this paper, we present a heuristic method to construct the activity–mobility trajectory of an individual given a set of discrete transaction type data points. To test our methods, we use smart card transactions data at the University of Buffalo (UB). The constructed trajectories will help to characterize student activity–mobility patterns which will benefit campus facility and transportation management and planning authorities to have a better insight of student behavior dynamics leading to a better decision making process. Moreover, insights on student mobility patterns around the campus will help managers to make strategic decisions on various applications such as emergency evacuation, special event management, spread of diseases and viruses, or campus-wide marketing.

Trajectory data mining techniques presented in this paper will help to advance our knowledge about individual activity–mobility patterns. In particular, this paper highlights the potential of using comprehensive smart card transaction type data which is becoming more available and powerful for travel behavior modeling. A key advantage of using smart card transaction data is its ability to infer some level of contextual information (i.e., activity types) that are not easily found from other passively collected data (e.g., mobile phones, wifi, GPS, etc.) and less bias in sampling compared to social media data. Examples of smart card data include public transport smart card transactions for ticketing purposes (Sun et al., 2012; Hasan, 2013) and credit card transactions (Lenormand et al., 2014; de Montjoye et al., 2015).

The inferred activity–mobility pattern provides information for many applications in urban dynamics. For instance, learning individual routines will help city managers to act more dynamically making better decisions about the location and time of service facilities, events, and predict traffic for specific location and time. In addition, activity–mobility patterns can provide useful information to control the spread of diseases among individuals as they move in public spaces and therefore can be used to design activity/zone shutdown and warning systems to mitigate the situation.

2. Literature review

In the last few years, human mobility and activity patterns have been widely studied using various emerging datasets. Passive data collection technologies offer many advantages: they often require a relatively low degree of user compliance, they are free of user collection errors and more reliable- and often more detailed with respect to times, geographic locations and routes than travel digital survey methods (Rieser-Schüssler, 2012). New information technologies such as Global Positioning System (GPS), mobile phone data, social media and smart card data have revolutionized modeling human mobility patterns. Most of new activity–mobility patterns and Origin–Destination matrices adopted one or more type of new technologies. Here we discuss some of the most important data sources that have been used to construct human mobility patterns.

2.1. Social media

Recently social media datasets have been widely adopted towards understanding human mobility patterns. With the advent of location-based services in social media, people are able to share their location in their virtual social networks such as Facebook, Twitter, and Foursquare etc. These new sources of data provide geo-location information about human movements which can be used for understanding human activity–mobility patterns. Rashidi et al. (2017) have recently reviewed the potential of social media data for modeling travel behavior.

Noulas et al. (2011) presented a large-scale study of user behavior in Foursquare and used a dataset of 700 thousands used for a period of 100 days to analyze user check-in dynamics, demonstrating how it reveals meaningful spatio-temporal patterns and offer the opportunity to study both user mobility and urban spaces. Hasan et al. (2013) presented an application of check-in data collected from social media to analyze urban activity–mobility patterns. They categorized individual activity patterns by finding the timing distribution of visiting different places depending on activity category and explored the frequency of visiting a place with respect to the rank of place in individual visitation records. Hasan and Ukkusuri (2014, 2015) analyzed large-scale geo-location data from social media to infer individual activity patterns. They proposed a data-driven modeling approach based on topic modeling to classify patterns in individual activity choices.

2.2. Mobile phones and WiFi

Mobile phone data is another useful source of information for constructing mobility patterns. Smartphones record the GPS position in predefined time intervals along with the mobile phone antennas, WiFi stations and Bluetooth devices it