Chapter 7
Revealing Taxi Driver's Mobility Intelligence through His Trace

Liang Liu
Massachusetts Institute of Technology, USA

Clio Andris
Massachusetts Institute of Technology, USA

Assaf Biderman
Massachusetts Institute of Technology, USA

Carlo Ratti
Massachusetts Institute of Technology, USA

ABSTRACT

This study develops a methodology for the analysis of taxi drivers' operation behavior in a real urban environment. The research objective is to spatially and temporally quantify, visualize, and examine taxi drivers' operational behavior and skill (as measured by income), which the authors call 'mobility intelligence'. For the first time, taxi drivers' different operation strategies were systematically analyzed through their daily activity traces. Routes and economic behavior data were collected with the use of Global Positioning System (GPS) and a set of spatiotemporal analysis tools were developed. Drivers are categorized by their daily income into top drivers and ordinary drivers. A 3D clustering technique is used to quantitatively analyze the spatiotemporal patterns for top driver and ordinary driver. Also, fractal analysis is employed to quantify tortuosity of movement paths and to explore how top and ordinary drivers operate on different spatial scales at different times, where the primary focus is to reveal top driver mobility intelligence.

INTRODUCTION

In recent years, the deployment of pervasive technologies and their ability to track movement in cities has led to a massive increase in the volume of records of people's spatial traces. These records serve as digital footprints of individual mobility patterns. Also, geo-located websites and services provide new sources of real-world human activity data. For example, Rattenbury et al. (2007) and Girardin et al. (2008) used geo-tagging patterns of

DOI: 10.4018/978-1-61520-769-5.ch007

Copyright © 2010, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

posted photographs in the popular photo hosting website, *Flickr*, to automatically detect interesting real-world events and draw conclusions about the flow of tourists in a city. In addition, as city-wide urban infrastructure like buses, taxis, subways, public utilities, and roads become digital, these datasets can be used as framework for tracking flows through space and time. Some have capitalized on this technology by using cellular network data to study city dynamics and human mobility (Ratti et al., 2006; Reades et al. 2007; and González et al. 2008). Also McNamara et al. (2008) used data collected from an RFID-enabled subway system to predict co-location patterns amongst mass transit users. These sources of data are ever-expanding and offer large, underexplored opportunities to understand physically-based interactions with the real world.

Recognizing human behavior and understanding a user's mobility from his digital footprints are critical issues in pervasive computing systems. In this chapter, we introduce a novel methodology to measure taxi drivers' ability to earn the most profit by their continuous GPS traces and activity (carrying passenger or not). First, we classify the taxi drivers into top drivers and ordinary drivers by calculating their earnings, earnings rank and 'eigenactivities'; then we compare the spatial-temporal distribution and client frequency of top drivers and ordinary drivers to find why top drivers earn more than ordinary drivers.

It is intuitive that a taxi driver wants to make the most money in the least amount of time. Because of the fare rate system and desire for continuous revenue, a driver hopes to pick up many passengers whose destinations are in places where there are more potential customers for a new pick up, to perpetuate a chaining of constant business. There are several commonsense assumptions about this operation behavior:

- **Assumption 1:** Taxi drivers prefer areas with the most potential customers.
- **Assumption 2:** A taxi, once occupied by a customer at origin zone, will move to the customer's destination zone via the shortest path. Once a customer ride is completed, the taxi becomes vacant and cruises either in the same zone or goes to other zones to seek its next customer. In doing this, each taxi driver is assumed to attempt to minimize his/her expected search time required to meet the next customer.

Assumption 1 reflects the observed behavior of many taxi drivers to aggregate at railway stations, hotels and other places of interest for visitors. Assumption 2 also follows economic intuition, and is bolstered by other scientific urban taxi services models. (See Wong, K. et al. 2001, 2002, 2005; Wong, S. et al. 1998; and Yang et al., 1998, 2001, 2002, 2005a, 2005b).

These assumptions are not definitive, as there are several prevailing arguments about their validity. For assumption 1: An area that is attractive to customers will also be attractive to competition from other taxi drivers and incur increased waiting time and congestion. In some sense, passenger demand levels and time spent in traffic is a tradeoff. As for assumption 2, most of the taxi fare systems are based on trip distance. In order to maximize his revenue, a taxi driver may not always take the shortest path. Bearing these assumptions in mind, our goal is to uncover the difference in taxi driver performance based on when and where they operate in order to reveal what decisions the top driver makes to perform the best.

Next, we introduce the research area and data description. After, we describe how to classify taxi drivers according to income and how to find common features among top drivers. Finally we compare the spatiotemporal operation patterns of top drivers and ordinary drivers to understand the difference and conclude with an outlook on future work.

14 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:
www.igi-global.com/chapter/revealing-taxi-driver-mobility-intelligence/42393

Related Content

Designing Mobile Learning Smart Education System Architecture for Big Data Management Using Fog Computing Technology
Muhammad Adnan Kaim Khani, Abdullah Ayub Khan, Allah Bachayo Brohiand Zaffar Ahmed Shaikh (2022). *The International Journal of Imaging and Sensing Technologies and Applications (pp. 1-23).*
www.irma-international.org/article/designing-mobile-learning-smart-education-system-architecture-for-big-data-management-using-fog-computing-technology/306653

A Review on Conservation of Energy in Wireless Sensor Networks
Oluwadara J. Odeyinka, Opeyemi A. Ajibola, Michael C. Ndinechi, Onyebuchi C. Nosiriand Nnaemeka Chiemezie Onuekwusi (2020). *International Journal of Smart Sensor Technologies and Applications (pp. 1-16).*
www.irma-international.org/article/a-review-on-conservation-of-energy-in-wireless-sensor-networks/281600

MICROMEGAS
(2014). *Innovative Applications and Developments of Micro-Pattern Gaseous Detectors (pp. 60-75).*
www.irma-international.org/chapter/micromegas/108172

Optimization of C5.0 Classifier With Bayesian Theory for Food Traceability Management Using Internet of Things
Balamurugan Souprayen, Ayyasamy Ayyanarand Suresh Joseph K (2020). *International Journal of Smart Sensor Technologies and Applications (pp. 1-21).*
www.irma-international.org/article/optimization-of-c50-classifier-with-bayesian-theory-for-food-traceability-management-using-internet-of-things/272125

Robust Localization Using Identifying Codes
Moshe Laifenfeld, Ari Trachtenbergand David Starobinski (2009). *Localization Algorithms and Strategies for Wireless Sensor Networks: Monitoring and Surveillance Techniques for Target Tracking (pp. 321-347).*
www.irma-international.org/chapter/robust-localization-using-identifying-codes/25590