Mobile Cyber-Physical Systems for Smart Cities

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ABSTRACT

Nowadays, rapid urbanization leads to severe urban challenges, e.g., congestion and energy consumption, related to human mobility. To address them, it is essential to (i) measure and predict human mobility based on data from urban infrastructure, and (ii) intervene and alter human mobility with novel services on urban infrastructure, i.e., a Cyber-Physical System approach. However, both existing mobility models and resultant services are built upon the interaction of residents with single infrastructure (e.g., taxis) or multiple infrastructures from *single domains* (e.g., transportation), which are limited by their homogeneous nature. Fortunately, cross-domain infrastructures and their data from the latest infrastructure expansion enable us to explore real-time interactions between residents and infrastructures across domains. In this talk, we will introduce some of our recent work under cross-domain interactions.

KEYWORDS

Cyber-Physical Systems, Human Mobility, Smart Cities

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1 INTRODUCTION

Given the rapid urbanization, the interactions of urban residents and infrastructures (e.g., transportation and telecommunication) have been becoming ubiquitous in urban environments[33]. Understanding and utilizing such ubiquitous interactions would be key to show various urban phenomena, e.g., traffic congestion, air quality, energy consumption. In this talk, we focus on a concrete urban phenomenon, i.e., real-time human mobility, based on ubiquitous infrastructure-resident interactions[31]. In particular, we aim to study the human mobility under well-developed infrastructures to support multi-modal mobility, e.g., cars, taxis, metros, buses, bikes[29] at urban scale in real time, which is essential to many city services including transportation management [42], urban planning [40], and emergency response [22]. A common feature of these services is to explore data collected when residents interact with infrastructures in the physical world and improve these infrastructure with data-driven decision making, i.e., a Cyber-Physical System (CPS) approach based on infrastructure-resident interactions [29].

2 CHALLENGES AND OPPORTUNITIES

The real-time human mobility is extremely challenging to model and utilize because it requires *large spatial* coverage and *fine temporal* coverage across different *modes*. To address this challenge, we argue that these seemingly-untraceable human mobility can be quantified by their interactions with infrastructures. Most literature along this line has been focusing on fine-grained mobility to design models and services based on infrastructures and their data [3], e.g., cellphones [44], smartcards [34], taxis [25], buses [41], and subways [22]. However, their common drawback is that they only capture incomplete, biased, and noisy mobility with *single infrastructures* [33]. Some of our recent work has been focusing on multiple infrastructures to address the drawback of single infrastructures based on infrastructure integration [17] [4], showing the potential of infrastructure diversities. However, their key drawback is that they are mostly based on multiple infrastructures from *single domains*, e.g., transportation [17] or telecommunication [4]. Admittedly, these multiple single-domain infrastructures indeed provide some diversity [39], but they are still limited by their inherent homogeneous nature [9]. The historical reason for this limitation is that researchers have been constrained by the capability of observing infrastructure-resident interactions across domains through cross-domain data in a timely and low-cost fashion [33].

Under recent Data Revolution [3], many cities around the world upgrade their infrastructures and consolidate large-scale real-time infrastructure data (collected for billings and performance testings) across different domains to understand and improve cities' efficiency [38]. Compared to single-domain infrastructures, exploring cross-domain data presents an unprecedented opportunity to revolutionize human mobility modeling [29].

3 RESEARCH VISION

In our recent work, we have been exploring a framework for mobility modeling and resultant services based on Cross-domain Infrastructure resident Interaction. Its key novelty is the *cross-domain philosophy* where these cross-domain data (e.g., cellphone logs, vehicle GPS, smartcard transactions) present detailed mobility phenomena from complementary perspectives [32]. In particular, this framework has two kinds of key research tasks as in Fig. 1.

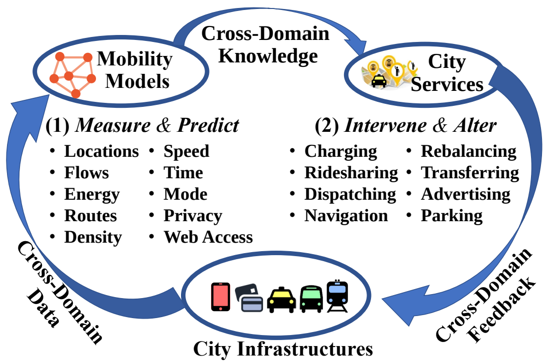

Fig 1: Cross-Domain Modeling Framework

(1) Measuring and predicting Mobility by Mobility Models. We have been exploring various metrics to quantify human mobility based on cross-domain data from city infrastructure in terms of locations [19] [17], flows [33] [31] [39] [29] [25] [26], energy [11], routes [43], density [4], speed [38] [36] [30] [9] [40], time [3] [20], modes [44], privacy [1], web access [2] [8] [10], by different statistical and machine learning models. These mobility models will provide *cross-domain knowledge* for novel city services.

(2) Intervening and altering mobility by City Services. We design and evaluate a few urban services including electric vehicle charging [13] [14] [21] [12], ridesharing [35] [37] [28] [27], bike rebalancing [15] [16], centralized dispatching [18] [7] [41] [42], distributed navigation [24] [23], transit transferring [22], advertising [34] [5], parking [6], based on various Optimization, Control Theory and Learning techniques. These city services provide positive *cross-domain feedback* to improve city infrastructures.

Based on these two sets of work, a closed-loop optimization can be formulated where the improved infrastructures will generate new cross-domain data, which will update our mobility models to produce new cross-domain knowledge and then update our services to produce new feedback to further improve the infrastructures.

In this talk, we will highlight a few projects with some new challenges and opportunities under this cross-domain framework.

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BIOGRAPHY OF SPEAKER

Desheng Zhang is an Assistant Professor at the Department of Computer Science, Rutgers University. Desheng is interested in bridging Cyber-Physical Systems (as known as Internet of Things under some context) and Data Science in extreme-scale data-intensive urban infrastructure from an interdisciplinary perspective. He is focused on the life cycle of data-driven urban systems, from mobile data collection, to cross-domain data fusion, heterogeneous model integration, visual data analytics, system optimization and application deployment. He positions his research on real-time interactions of cross-domain urban systems, i.e., transportation (e.g., taxis, buses, trucks, subways, bikes, personal & electric vehicles), telecommunication (e.g., cellphones, Wi-Fi), payment (e.g., smartcards and toll collection), social networks (e.g., check-in and app logs), and geography (e.g., road networks). He has been investigating platforms across 8 cities on 3 continents with 100 thousand app users, 500 thousand vehicles, 10 million phones, 16 million smartcards, and 100 million residents involved. Desheng has been regularly publishing in top CS conferences including UbiComp, MobiCom, SenSys, WWW, and has been honored with 7 best paper/thesis/poster runnerup awards.