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Personalized travel time estimation for urban road networks: A tensor-based context-aware approach

Kun Tang[a,b,c], Shuyan Chen[a,b,c,*], Aemal J. Khattak[d]

[a] Jiangsu Key Laboratory of Urban ITS, Southeast University, Nanjing 210096, China
[b] Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, Southeast University, Nanjing 210096, China
[c] School of Transportation, Southeast University, Nanjing 210096, China
[d] Department of Civil Engineering, University of Nebraska-Lincoln, 330E Whittier Research Center, 2200 Vine Street, Lincoln, NE 68583-0851, United States

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ABSTRACT

Urban travel time estimation is of significant importance at many levels of traffic operation and transportation management. This paper develops a tensor-based context-aware approach to dynamically provide personalized travel time estimation from a citywide perspective, using sparse and large-scale GPS trajectories. This novel model is comprised of four major components: map matching, travel time tensor construction, context-aware feature extraction, and travel time tensor factorization. First, GPS trajectories are map-matched onto the road network. Then, travel times of different drivers on different road segments in different time slots are modeled with a 3-order tensor. Following these, three categories of context features, i.e., historical, geographical and spatial-temporal features, are extracted to capture the contextual information of travel time and traffic condition in the road network. Finally, an objective function is devised to factorize travel time tensors with context features collaboratively. In addition, a gradient-based algorithm is developed to find an optimal solution for the context-aware estimation model. The novel model incorporates both the spatial correlation between different road segments and the deviation between different drivers, as well as the fine-grain temporal correlation between different time slots and the coarse-grain temporal correlation between recent and historical traffic conditions. The proposed model is applied in a real case on the urban road network of Beijing, China, based on the sparse and large-scale GPS trajectories collected from over 32,000 drivers in a period of 2 months. Empirical results on extensive experiments demonstrate that the proposed model provides an effective and robust approach for citywide personalized travel time estimation, and outperforms the competing methods.

1. Introduction

With increasing population and migrations to cities, many urban road transportation systems are congested resulting in reduced efficiency of transportation system and detrimental effects on the ecological environment. To tackle these issues, knowledge of travel time from a citywide perspective is of great importance at many levels of traffic management and operations. Through accurate travel time information, individuals can make better travel choices (Miranda & Conceição, 2016), fleet management companies can operate dispatch system more efficiently, traffic management departments can find problematic locations and then introduce a revised traffic control scheme to improve the efficiency of transportation, traffic policy-making agencies can analyze travel demand and assess the effects of policies and regulations, such as congestion charges (Jenelius & Koutsopoulos, 2013).

Recently, the GPS devices installed in vehicles and smartphones carried by occupants of motor vehicles have served as opportunistic sensors for travel time data collection (Sanaullah, Quddus, & Enoch, 2016). Although a number of well-designed models are available for urban travel time estimation based on GPS data (Rahmani, Koutsopoulos, & Jenelius, 2017; Woodard et al., 2017), these models have limitations such as adoption of traffic analysis models, based on limited number of data-rich highways or small urban areas, focused only on average travel time, and ignoring contextual information. To make up for these limitations, this paper proposes a purely data-driven approach, i.e., the tensor-based context-aware model, to dynamically provide personalized travel time estimation from a citywide perspective, based on the sparse and large-scale GPS trajectories. This novel approach incorporates both the spatial correlation between different road segments and the deviation between different drivers, as well as the coarse-grain

* Corresponding author.
E-mail addresses: kuntang_seu@seu.edu.cn (K. Tang), chenshuyan@seu.edu.cn, 13995724445@qq.com (S. Chen), khattak@unl.edu (A.J. Khattak).

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temporal correlation between recent and historical traffic conditions and the fine-grain temporal correlation between different time slots. The contributions of this work are as follows.

1) Tensor-based travel time modeling. We model travel times of different drivers on different road segments in different time slots with a 3-order tensor.
2) Contextual features extraction and utilization. We extract several categories of contextual information, including historical, geographical and spatial-temporal context features, to estimate travel time accurately.
3) Context-aware and collaborative estimation model. We devise an objective function to factorize tensors and contextual features collaboratively.
4) Tensor factorization algorithm. We develop a gradient-based algorithm to find an optimal solution for the proposed context-aware estimation model.
5) Evaluation. We evaluate the proposed model by extensive experiments of the real case study in Beijing, China, based on the sparse and large-scale GPS trajectories.

The remainder of this paper is organized as follows. Section 2 presents a review of related literature on travel time estimation. The problem statement and definitions are provided in Section 3 while in Section 4 the methodology of the proposed model is discussed. Experimental results of the case study in Beijing, China are reported in Section 5. In the final section, conclusions and future research direction are presented.

2. Literature review

Travel time estimation in urban road network has always been regarded as a key fundamental component in intelligent transportation systems (ITSs) (Lee, Tseng, & Tsai, 2009). Over the past few decades, a number of well-designed models have been developed for urban travel time estimation. These models assist in many levels of traffic operation and management, and improve the efficiency of transportation ranging from signal coordination to route guidance (Braaten, Gjønnes, Hvattum, & Tirado, 2017; Janssens, Caris, & Ramaekers, 2009). According to the type of method utilized (Lint & Hinsbergen, 2012), the existing approaches for urban travel time estimation can be roughly classified into four categories: Naïve, parametric, non-parametric and hybrid models.

1) Naïve approach. Naïve approaches refer to the models that provide estimation directly based on the used data and the exact physical relationships, e.g., historical average and speed vs. volume to capacity ratio relation. These models are independent of both the model structure and parameters. Due to the easy implementation and low computational effort, they are widely used in practice. However, the accuracy is generally low. For example, by combining Naïve methods with nonparametric approaches, Nikovski, Nishiuma, Goto, and Kumazawa (2005) presents an experimental comparison of several methods for travel time estimation.
2) Parametric approach. Parametric approaches (Ma, Koutsopoulos, Ferreira, & Mesbah, 2017; Zhan, Hasan, Ukkusuri, & Kamga, 2013), e.g., analytical models and traffic simulation models, formulate travel time with a fixed model structure. These models are constructed based on a set of model assumptions and are described with a set of model parameters. Suffering from the model assumptions that are taken to fit the formulation, parametric models usually perform poorly when the traffic condition fluctuate remarkably or road network settings are complex. For example, Jenelius and Koutsopoulos (2013) present a statistical model consisting of network model and observation model for travel time estimation in urban road network, based on the low frequency GPS trajectories collected from probe vehicles.
3) Non-parametric approach. In contrast, non-parametric approaches (Fan, Su, Nien, Tsai, & Cheng, 2017; Rahmani, Jenelius, & Koutsopoulos, 2015), e.g., data analysis-based methods and neural network techniques, utilize the algorithms of machine learning and data mining for travel time analysis. These approaches are mostly data-driven models and discover the patterns and knowledge within the data through analyzing the data itself. Travel time are formulated in an implicit way, rather than a dedicated analysis model which heavily relies on the personal experience and intuition. It has been proven that non-parametric models are generally more effective for many transportation applications. For example, Zheng and Van Zuylen (2013) presented a three-layer neural network model to estimate the complete link travel times based on the sparse data obtained from probe vehicles.
4) Hybrid approach. Hybrid approaches (Allström et al., 2016; Zhan, Ukkusuri, & Yang, 2016) refer to the models that fuse the aforementioned approaches at levels of model structure or decision, such as ensemble learning models and model fusion approaches. Benefiting from the advantages of multiple models, hybrid approaches are general more effective than the approaches that learn a model alone. For example, by combining a well-established theory of traffic flow through signalized intersections and a machine learning framework, Hofleitner, Herring, Abbeel, and Bayen (2012) proposed a hybrid modeling framework for estimating and predicting arterial travel times using streaming GPS probe data.

In summary, a number of approaches have been developed for travel time estimation in urban context. Although these approaches have their own merits in some situations, they possess certain limitations as follows. First, traffic analysis-based approach is primarily adopted. Due to the complexity of the signalized urban network, explicitly modeling travel time with an analytical traffic model is not easy (Fontem, Melouk, Keskin, & Bajwa, 2016; Wang & Lin, 2017). To provide accurate and reliable travel time based on the limited information form sparse GPS trajectories, more elaborate travel time modeling approach have to be sought. Second, considering only some data-rich roads or small areas. Since drivers travel in urban network with different trip purposes, travel time on any road segment in the road network is possible to be queried by the drivers. It is very essential to model travel times from a citywide perspective. Third, focusing only on the average travel time. Travel time on a road is not only affected by the road attributes and network traffic condition, but also depends on the driver. Travel times of different drivers through the same segment may differ significantly from each other. Consequently, it is more practical to provide personalized travel times for different drivers. And finally, ignoring the contextual information. Travel time of a road segment is highly correlated with the contextual information at the time of interaction, such as the interest of points around the road, traffic condition on the network, and traffic patterns in history and so on. Extracting and utilizing these contextual features can help improve estimation accuracy.

3. Problem statement and definitions

To facilitate the description of the proposed methodology, some definitions utilized hereafter are introduced.

Definition 1. Context-aware. The context is any information that can be used to characterize the situation of an entity (Yang, Guo, Ma, & Jensen, 2015). It includes any information available at the time of interaction, such as people, location, time of the day, traffic condition and so on. A model is context-aware if it is able to extract, interpret and utilize the context, and adapt its functionality to the current context.