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Estimation of trip travel time distribution using a generalized Markov chain approach

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A B S T R A C T

The increasing availability of opportunistic and dedicated sensors is transforming a once data-starved transport field into one of the most data-rich. While link-level travel time information can be derived or inferred from this data, methods for estimation of trip travel times between an origin and a destination pair are still evolving and limited, especially in the context of probability distribution estimation. This paper proposes a generalized Markov chain approach for estimating the probability distribution of trip travel times from link travel time distributions and takes into consideration correlations in time and space. The proposed approach consists of three major components, namely state definition, transition probabilities estimation and probability distribution estimation. A heuristic clustering method, based on Gaussian mixture models, has been developed to cluster link travel time observations with regard to their homogeneity and underlying traffic conditions. A transition probability estimation model is developed as a function of link characteristics and trip conditions using a logit model. By applying a Markov chain procedure, the probability distribution of trip travel times is estimated as the combination of Markov path travel time distributions weighted by their corresponding occurrence probabilities. The link travel time distribution is conditioned on the traffic conditions of the current link that can be estimated from historical observations. A moment generating function based algorithm is used to approximate the Markov path travel time distribution as the sum of correlated link travel time distributions conditional on traffic conditions. The proposed approach is applied in a transit case study using automatic vehicle location data. The results indicate that the method is effective and efficient, especially when correlations and multimodal distributions exist.

1. Introduction

Knowledge of travel times is crucial at many levels of transportation planning and management. Network-wide travel time information provides inputs for impact assessment of strategic and operational instruments. Information of link travel times can reveal problematic locations where targeted strategies can be introduced to improve service reliability performance. In addition, disseminating information on travel time reliability to system users is a key component of addressing urban mobility issues, since it can aid travellers to make informed travel decisions (Kuhn et al., 2013).

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The increasingly available automated collection technique provides ample of vehicle trajectory data at a large spatiotemporal scale. Many studies have proposed algorithms to extract or infer link travel times from this data, but yet research on the estimation of trip travel times, especially the probability distribution of travel times, between any origin-destination (OD) pairs is still evolving and rather limited. Previous studies on estimations of parameters of travel time distribution (TTD) (e.g. mean and standard deviation) used a Markov Chain methodology (Yeon et al., 2008; Ramezani and Geroliminis, 2012; Hunter et al., 2013b) and assumes the link travel times are independent conditional on link traffic conditions. However, empirical evidence in our case study reveals that the conditional independence assumption is not always appropriate. Besides, the existing studies adopt static transition probabilities under different situations (e.g. constant for a given time period) and estimate them from empirical counts of transitions, which constraints their ability to generalize to a large range of applications in terms of accuracy and data availability.

To address these gaps, this paper proposes a generalized Markov chain (GMC) approach for estimation of trip TTDs between arbitrary OD pairs at arbitrary times from link or segment TTDs. This study builds on Ramezani and Geroliminis (2012)'s work by adopting a flexible, model based Markov Chain component structure, proposing a new Markov path TTD estimation algorithm explicitly incorporating conditional dependence between link travel times, designing a logit formulation based model to dynamically estimate transition probabilities, and providing a thorough comparison with the state of art methodologies using transit automatic vehicle location (AVL) data. In addition, the proposed GMC model is modular with all methodology components being able to be characterized as explanatory models, which is important for use under situation when data sample is limited, especially for urban road networks.

The remainder of the paper is organized as follows: Section 2 presents the related literature on the estimation of travel times. The research problem and definitions are provided in Section 3. Following these, the TTD estimation framework is proposed in Section 4, as along with description of detailed methodologies. The performance is validated in Section 5 using transit AVL data, from which any OD travel time is directly extracted. Finally, the main conclusions and future research potential are summarized.

2. Literature review

Methods on the estimation and prediction of travel times can be generally classified into two categories, namely analytical and data-driven. Analytical models explore the physical relationship between travel times and other traffic variables (traffic flow, occupancy, signal phase plans, etc.) (Geroliminis and Skabardonis, 2011). Data-driven models estimate travel times by combining potential factors that can be easily implemented and show a promising performance in practice (Fei et al., 2011). Among the most applied data-driven techniques are parametric and nonparametric regression (Chang et al., 2010), Kalman filter (Cathey and Dailey, 2003), machine learning (Chun-Hsin et al., 2004; Yu et al., 2011; Van Lint et al., 2005), Bayesian (van Hinsbergen et al., 2009) and hybrid methods (Van Lint, 2008; Ma et al., 2014). Most of these studies focus on the estimation of expected travel times, which can be used as an indication of congestion levels once compared with free flow travel times for planning applications (van Hinsbergen et al., 2009) or to aid users in making smart travel decisions (Brakewood et al., 2015).

Travel time variability caused by the inherent network randomness in the context of supply, demand and service performance is important to consider (Jenelius, 2012). Reduction of travel time variability decreases commuting stress and uncertainty of making travel decisions, e.g. departure time choices (Fosgerau and Engelson, 2011). Many statistical scalar indexes have been used to characterize variability, including variance, percentiles and confidence intervals (Khosravi et al., 2011a,b; Li and Rose, 2011; Jenelius and Koutsopoulos, 2013; Pattanamekar et al., 2003). A common limitation is that the scalar indexes cannot fully characterize the stochastic features of travel times without an assumption on the shape of distribution. They can only provide incomplete information since the features of distributions may be missed, e.g. skewness and multimodality (van Lint et al., 2008).

Probability distributions contain maximum information that captures the stochastic characteristics of travel times (Du et al., 2012). Many studies on travel time reliability have attempted to fit mathematical distributions to travel times at different network levels (Clark and Watling, 2005; Hollander and Liu, 2008; Fosgerau and Fukuda, 2012). For many applications, e.g. trip planning, trip travel time information is of more interest (Bhat and Sardesai, 2006). The trip TTDs can be derived or inferred using archived data of direct observations for the same OD pairs under similar trip conditions, e.g. time period. One problem is that the archived database requires the full coverage of all OD pairs that travellers might take. Note that the OD pairs are not restricted to the major planning zones, but can be any locations in the network. Furthermore, with data from mobile sources, it is likely that for many OD pairs very few or no samples were observed directly. An effective approach for estimating trip TTDs between arbitrary OD pairs at arbitrary times is from individual link TTDs. Link and segment travel times can be derived directly (e.g. transit AVL data) or estimated from the increasingly available but sparse opportunistic sensor data, e.g. vehicular GPS, Automatic Number Plate Recognition (ANPR), and mobile phone data (Zheng and Van Zuylen, 2013; Rahmani and Koutsopoulos, 2013; Jenelius and Koutsopoulos, 2015; Hellinga et al., 2008; Kazagli and Koutsopoulos, 2013). Given the known link TTDs, the challenge is how to estimate trip TTDs by taking into consideration of the spatiotemporal correlations between link travel times.

For the estimation of the mean and variance of trip travel times, the Space Time Autoregressive Integrated Moving Average (STARIMA) model was proposed by Pfeifer and Deutrch (1980). The model can capture the spatiotemporal relationships