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An exploratory study of instance-based learning for route choice with random travel times

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A B S T R A C T

Availability of individual-level longitudinal data provides the opportunity to better understand travelers' day-to-day learning behavior, enabling more accurate predictions of traffic patterns in a network with random travel times. In this paper, an instance-based learning (IBL) model that can capture the recency, hot stove and payoff variability effects embedded in travelers' day-to-day learning processes is developed for route-choice based on the power law of forgetting and practice. Experiments based on synthetic datasets show that the true parameter values of the IBL model can be consistently retrieved and the model can potentially predict different traffic patterns compared to non-learning models. The IBL model is compared with a baseline learning model using an experimental dataset of repeated route-choice. Estimation results show that the IBL model reveals higher sensitivity to perceived travel time and achieves better model fit. Cross validation experiments suggest that the forecasting ability of the IBL model is consistently better than the baseline learning model. Practical considerations for choice modeling are further discussed.

1. Introduction

1.1. Motivations and literature overview

Travel times are inherently uncertain, due to random disruptions such as incidents and bad weather, and random behavior of travelers. The psychological literature has distinguished two types of decision under uncertainty/risk. The first is decision from description, where the probabilistic distribution of the payoff for each option is explicitly described to the decision maker, e.g., a 50% chance of winning $100 and a 50% chance of losing $20. Bounded-Rational theories, such as Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), have been applied to study decision under description and travel choice modeling, e.g., Ben-Elia and Shiftan (2010) and Gao et al. (2010). The second type is decision from experience, where the uncertain outcomes of chosen actions are experienced by instead of described to decision makers. Past studies have shown that decision from experience and decision from description can result in very different, sometimes even opposite risk attitudes (Barron and Erev, 2003; Erev and Barron, 2005; Rakow and Newell, 2010).

Route-choice decision making is a typical example of decision from experience. Travelers make route-choice decisions based on

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their knowledge about the environment that is mainly learned through experience and constrained by their cognitive capabilities. The decision-making process is dynamic and involves information acquisition and assimilation. For example, a newcomer to a city follows a GPS device's recommendation. However, once becoming a seasoned resident, she can recall past experience and connect existing route segments to form a new route even if the destination is new. The process of learning about the decision environment is indispensable in understanding travelers' route-choice behavior and predicting the overall resulting traffic patterns. Meanwhile, the ever-increasing availability of smartphones and other portable sensors provides individual-level longitudinal data to help improve and validate route learning and choice models.

Most econometric route-choice models focus on cross-sectional analysis of route-choice behaviors, e.g., Path-Size Logit (Ben-Akiva and Ramming, 1998; Ben-Akiva and Bierlaire, 1999), C-Logit (Cascetta et al., 1996), Cross-Nested Logit Vovsha and Bekhor (1998), and Logit Mixture (Ramming, 2001; Bekhor et al., 2002; Frejinger and Bierlaire, 2007). Travel time variability, if considered, is usually static and travelers are assumed to have the same knowledge of travel time distribution, such that the temporal relation between the current choice and past experience are ignored (see e.g., Abdel-Aty et al., 1995; Bates et al., 2001; Lam and Small, 2001; Liu et al., 2004; Gan and Bai, 2014; Tilahun and Levinson, 2001; Carrion and Levinson, 2012; Fosgerau, 2015).

A number of studies have been conducted since the route-choice learning model was first introduced to the transportation research community. Some studies focus on theoretical analysis of the convergence properties of the models and thus impose relatively strong assumptions on learning and choice behavior without considering travelers' actual cognitive capacity (Horowitz, 1984; Cascetta and Cantarella, 1991; Yang and Zhang, 2009). Most empirical studies are conducted using experimental data on single-origin-destination (OD) networks with two or three routes and minimum overlapping (Avineri and Prashker, 2005; Bogers and van Zuylen, 2005; Ben-Elia and Shiftan, 2010; Lu et al., 2011, 2014), with the exception of a series of studies by Mahmassani and collaborators where there are successive switching options between three parallel routes (Mahmassani and Liu, 1999). Some simulation studies deal with more general networks, but the critical problem of spatial knowledge acquisition and its impact on route-choice in a realistic network setting is not properly addressed (Ben-Akiva et al., 1991; Emmerink et al., 1995; Jha et al., 1998; Ben-Elia and Avineri, 2015).

The weighting scheme of past experience has evolved along with learning models over time. Horowitz (1984) proposed using a weighting scheme to quantify the relative importance of the recent and distant travel experience, yet no specific psychological theories was referred to validate the weighting scheme. Later on, both Chang and Mahmassani (1988) and Iida et al. (1992) found that the more recent travel experience is more important than distant travel experience. However, they did not explicitly analyze how travelers develop perceptions of travel time variability. More recent learning models often embed perception updating mechanisms to quantify the weighting scheme of past experience. The dominant descriptive models in the literature (in contrast to a normative model such as Bayesian updating) speculate that the perceived travel time at time t is a convex combination of the perceived travel time and experienced travel time at time $t-1$ (Ben-Akiva et al., 1991; Emmerink et al., 1995; Nakayama et al., 2001; Avineri and Prashker, 2005; Bogers and van Zuylen, 2005; Lu et al., 2014). The convex combination updating is equivalent to an assumption of exponential decay of memory, which is inconsistent with the psychological theory that human memory decay follows a power function rather than an exponential function (Wickelgren, 1976; Newell and Rosenbloom, 1981; Anderson and Schooler, 1991; Rubin and Wenzel, 1996).

To sum up, learning models that are able to sufficiently utilize the individual-level longitudinal data to precisely capture travelers' day-to-day learning process following psychological findings are in great demand for more accurate traffic pattern predictions.

1.2. Background of instance-based learning theory

The instance-based learning theory (IBLT) was developed to explain decision making in complex and dynamic situations, where individuals make repeated choices attempting to maximize gains over the long run (Gonzalez and Lebiere, 2005; Gonzalez et al., 2003). An instance is broadly defined by the context, decision, and outcome of a previous choice that is encoded in the declarative memory (i.e., memories that can be consciously recalled such as facts and verbal knowledge). Learning resides in the activation mechanism that relies on the frequency and recency of past choices, i.e., more recent and frequent instances are more active in memory. According to the IBLT, a decision-making process contains the stages of matching, evaluation, selection and execution. In the matching stage, based on their levels of activation, instances that are relevant to the current decision context are retrieved and blended to produce perceptions of options. Memory decay is captured by the power law of forgetting.

IBLT is often implemented within the Adaptive Control of Thought-Rational (ACT-R) cognitive architecture (Anderson and Lebiere, 1998), which incorporates a set of mechanisms that can be used to develop models of learning and performance. The different mechanisms used to retrieve instances, evaluate alternatives, and apply feedback are central to IBLT. A number of models have been implemented within the ACT-R architecture and demonstrated close approximations to human decision making in multiple tasks (Gonzales and Lebiere, 2005; Lebiere et al., 2007; Martin et al., 2004). More recent models have been implemented to account for repeated choices (Lebiere et al., 2007; Stewart et al., 2009). An IBL model implemented in the ACT-R architecture was the winner of a competition of predicting repeated binary lottery choice decisions (Erev et al., 2010). Since the aforementioned models are limited by the complexity of the ACT-R architecture, later on, Lejarraga et al. (2012) proposed a simplified version of the winning IBL model, where the decision context is not utilized in instance retrieval.

1.3. Contributions and paper organization

As preferable as the aforementioned IBL models are in accounting for decision making in dynamic environments, they are all