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Final Report

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Project Title:

A Spatial Learning Model for the Micro-Simulation of Travel Dynamics

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Problem Addressed

The objective of this project is to develop and calibrate a computational process model of spatial learning, for the micro-simulation of travel dynamics where individual travelers' decision-making is simulated. Travel decisions are usually made in large spatial environment, and therefore spatial knowledge is an important moderator in the decision-making process. Priori research in environmental psychology, geography and artificial intelligence has shown that spatial knowledge is usually incomplete, distorted, and idiosyncratic depending on personal experience. The assumption of complete and precise spatial knowledge in all current travel micro-simulation models is thus problematic. This project aims at closing the gap between theory and practice by enhancing a computational process model of spatial learning using tracking data over a multi-month period. The model, once incorporated in an overall travel micro-simulation framework, can potentially improve the realism and policy sensitivity of the simulation.

Approach and Methodology

Model Specification
We develop an econometric instance-based learning (IBL) model for route choice in a general network based on the power law of forgetting and practice, which is able to capture the recency effect, hot stove effect and payoff variability effect embedded in travelers' day-to-day learning process. A path is composed of multiple segments and spatial experience happen at the segment level with trips from multiple ODs. Due to the idiosyncrasy nature of learning, system-wide traffic prediction based on learning models requires storage of a copy of network attributes for each simulated traveler. On one extreme, if experience is coded at the link level for each traveler, the model will become intractable fairly quickly. On the other extreme, if experience from all travelers is blended in a single collective memory, the important issue of spatial knowledge heterogeneity is ignored which potentially lead to misunderstanding of route choice behaviors. We propose a model that trades off model realism with tractability. In a general road network, a particular day's experience is the vehicle trajectory. A major road segment generally contains a number of links (e.g., a stretch of highway between two major interchanges, an arterial road between two neighborhood centers). Experience on a major road segment is stored in a traveler's memory and is individual-specific. Experience on minor road links from all travelers is stored in a collective memory and is not individual-specific. The trajectory does not need to cover the complete major road segment that defines the instance, and prorated travel time will be used if only part of the segment is traversed. The underlying assumption is that human beings tend to use categorization to simplify knowledge representation. Spatial knowledge from one OD is naturally carried over to another OD through experience on common major road segments.

Synthetic Data Generation
We use a two-OD network in the Greater Boston area to lay the groundwork for model estimation and prediction. OD1 is a work trip from home in Watertown to Massachusetts General Hospital in Boston, with two path alternatives Path 1 and Path 2. Path 1 is an 8.4-mile local path that is composed of two major road segments Soldiers Field Road and Storrow Drive, landmarked by the Beacon Street Bridge, Boston University Bridge, and Longfellow Bridge. Path 2 is an 8.8-mile path with a considerable portion of toll road, which is defined by the access to/egress from the Massachusetts Turnpike. OD2 is an occasional recreational trip from a friend's house in Brookline to the New England Aquarium in Boston with two path alternatives Path 3 and Path 4. The major road segments of Path 3 are defined by Commonwealth Avenue and Storrow Drive, and Path 4 contains two major road segments of Route 9 and Downtown Boston. Although the recreational trip is an

entirely new OD to the traveler, its overlap with the regular work trip Path 1 (Storrow Drive passing the Hatch Shell) alters her perception of travel time distribution of Path 3. A synthetic dataset is generated following a postulated true model, the IBL model with spatial knowledge carryover.

Model Estimation and Prediction
The true model is estimated to show that true parameters can be recovered. Two simplifying models are also estimated. A mixed Logit model that assumes travelers' full information of the underlying travel time distributions is estimated for OD1. To show that failure to carry over learned knowledge can lead to estimation and prediction biases, we estimate a no-carryover learning model that does not consider travelers' familiarities with Path 1 when traveling on OD2.

Conclusions and Recommendations

Estimation results show that the true parameter values can be consistently retrieved. A mixed Logit model that assumes no learning and full knowledge of the network, and a learning model that ignores spatial knowledge carryover are estimated with the same data set. These two simplifying models yield significantly biased parameter estimates and value-of-time (VOT). Prediction results made by the estimated models show that the full-knowledge and no-carryover learning models are potentially inadequate in assessing the impact of travel time variability on route choice in three aspects: 1. They predict more random route choice; 2. They underestimate the sensitivity of path shares and experienced travel times to the objective travel time variability; 3. The path share standard deviations of the two simplifying models are insensitive to the objective travel time variability.

It is recommended that route choice model should consider the idiosyncrasy of spatial knowledge to the extent possible, through an explicit learning model.

Outcomes

Journal Publications
Tang, Y. and Gao, S. Endogeneity due to Missing Observations in a Learning Model for Travel Choice. *Transportation Research Record*. Submitted.

Conference Proceedings

Tang, Y. and Gao, S. An Exploratory Study of Instance-based Learning for Network Route Choice. The 94th Annual Meeting of Transportation Research Board Compendium of Papers DVD. Paper #15-5503. Washington, DC, Jan. 11-15, 2015.

Conference Presentations

Tang, Y. and Gao, S. An Exploratory Study of Instance-based Learning for Network Route Choice. The 5th International Choice Modeling Conference (ICMC), Austin, Texas, May 10-13, 2015.

Tang, Y. and Gao, S. An Exploratory Study of Instance-based Learning for Network Route Choice. The 94th Annual Meeting of Transportation Research Board, Washington, DC, Jan. 11-15, 2015.