Modeling and Calibrating Transition Rules in Urban Cellular Automata

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Introduction

Urban CA researchers are facing several challenges, such as, model structures, transition rules and model calibration and valiation (Clarke 2004, Xie and Batty 2004). Transition rules and model structures are usually application-dependent. Although some CA models have been argued to be generic in nature (White *et al.*1997, Wu 1998, Batty *et al.* 1999), these models are substantially different in their forms. The variations are due to the existence of many possible ways of defining the transition rules and model structures. For instance, Batty and Xie (1994) deployed the nested neighborhood space and a distance decay function from the seed of development to determine transition probability. White and Engelen (1993) developed a predetermined parameter matrix to control the development probability. Wu and Webster (1998) defined transition rules on the basis of multicriteria evaluation (MCE) method. However, it is controversial how to evaluate the appropriateness of a transition rule selection in the context of fitting to a specific application.

Objectives and Approach

The purpose of this paper is to illustrate a new approach, Multinomial Logit Modeling, to model and calibrate urban CA transition rule. Multinomial Logit Model (MLM) has played an important role in spatial analysis and modeling in the fields such as landscape change, travel study and urban and regional planning (Stynes and Peterson 1984, McMillen 1989, Gabriel and Rosenthal 1989, Dale et al 1993, Waddle 2000, Finnie 2004 Prashker and Bekhor 2004). MLM provides a detailed representation of the complex aspects of demands, based on strong theoretical justifications. Discovering a suitable solution for a specific application calls for both a considerable knowledge about the topics under exploration and a strong ability to apprehend the methodological and theoretical background of the model (Luce 1959, Ben-Akiva and Lerman 1985, Anderson et al. 1992, DeMaris 1992, Greene 1997, Jaccard 2001, Ben-Akiva and Bierlaire 2003).

A technical convenience of applying MLM in urban CA models is the explicit probabilities generated from MLM. Applying MLM to historical data, we can directly determine the probabilities of the population mobility as well as the building change (Waddell 2000, Xie and Batty 2004). We can model household's or building's dynamics, producing corresponding possibilities, e.g. move out/move in/stay for households.

We are developing a calibration procedure to validate MLM through applying the IPF (Iterative Proportional Fitting) method. The regional predictions of demographic and socioeconomic changes at the census geography by regional government agencies will be distributed to CA neighborhoods through IPF and to examine the sensitivity of MLM and CA models.

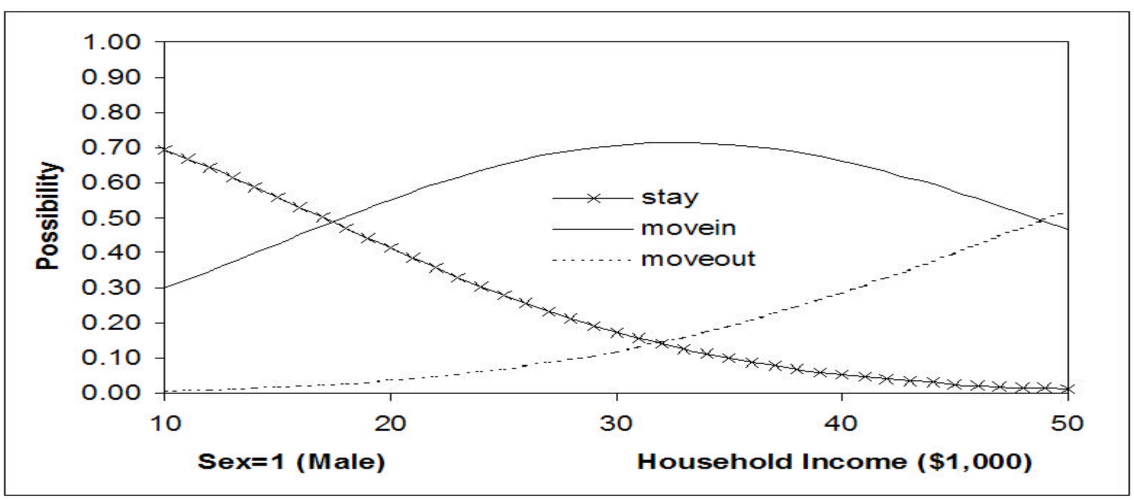
Some Preliminary Results

Household and Building Mobility Model can be summarized by the following conceptual models:
Household_MLM = f(socioeconomic attributes $<S_1, S_2, S_{3,...}>$, GeographicLocation)
Building_MLM= f(physical environment factors$<P_1, P_2, P_{3,...}>$, GeographicLocation)
An output of preliminary results of Household Mobility Model, which is based on two attributes (household income and sex of household head), is shown below,

Parameter Estimates

VAR(a)		B	Std. Error	Wald	df	Sig.	Exp(B)	Interval for Exp(B) Lower Bound	Upper Bound
movein	Intercept	-3.624	0.780	21.610	1	0.000			
	income	0.117	0.024	23.826	1	0.000	1.124	1.072	1.178
	sex	2.630	0.647	16.524	1	0.000	13.877	3.904	49.324
moveout	Intercept	-6.324	1.009	39.276	1	0.000			
	income	0.183	0.027	46.548	1	0.000	1.200	1.139	1.265
	sex	2.217	0.737	9.048	1	0.003	9.178	2.165	38.907

a. The reference category is: stay.



Conclusion

Through integrating the multinomial logit model to model the demand-supply core of the urban model, external geo-demographic and geo-economic models can be linked to land supply suitability potentials. Hence, CA-based urban modeling becomes more applicable in urban planning process and more generic in land development decision-making, by incorporating the geography, demographics and socio-economics of the real city into the modeling and simulation.

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