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EMPIRICAL ESTIMATION OF AGENT SHOPPING PATTERNS FOR SIMULATING PEDESTRIAN MOVEMENT

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Abstract: A multi-agent model to simulate pedestrian route choice and activity scheduling behavior is under development. In this model, the simulation of movement patterns is embedded in a more comprehensive model of activity scheduling and choice behavior. This paper reports the estimation result for one component of the model: the probability of successfully completing an activity in a store. We assume that the probability of a successful completion is a function of among others availability and predictability of the product. To estimate this probability function, survey data were collected and the results of the estimations will be discussed.

Keywords: pedestrian modeling, data collection, multi-agent system, micro-simulation

1. INTRODUCTION

Modeling pedestrian flows have recently gained strong interest because predicting such behavior is of great public interest. Several models of pedestrian modeling have been developed since the 1990s. For example, cellular automata have been developed to simulate evacuation and escape behavior (e.g. Blue et al., 1999; Kukla et al., 2001; Schelhorn et al., 1999; Helbing et al., 2000; Hoogendoorn et al., 2001; Meyer-König et al., 2001; Cavens et al., 2005). More recently, pedestrian following models (e.g. Hoogendoorn et al., 2002; Teknomo, 2002), walking behavior models (e.g. Daamen et al., 2003; Daamen, 2004) and pedestrian behavior models (e.g. Borgers, et al., 2004, 2005; Kitazawa et al., 2004; Masuda et al., 2005) have been developed.

Several years ago we started a research project to develop a multi-agent system for network decision analysis that in principle can be used to various types of agents who have to make decisions in a network (Dijkstra et al., 2002a); pedestrian movement is just one example. The term network decision analysis is used to encompass all design and decision problems that involve predicting how individuals make choices when moving along a network such as streets and corridors in a building.

Thus a multi-agent model differs from other models of pedestrian movement in at least one important way; the actual movement of pedestrians is only a small component of the approach. This is in contrast with most previous models with a primarily focus on movement rules, lane forming and hazardous situations. The focus of our approach differs in the sense that we have primarily activity scheduling, destination and route choice in mind when developing the model. Points of departure were the earlier attempts that have focused on destination choice and route choice (e.g. Borgers et al., 1986a, 1986b). The actual microscopic movement was not addressed in these models. Our goal was to combine activity scheduling, destination and route choice behavior, and microscopic movement. We assume that destination and route choice decisions are influenced by motivation, activity scheduling, store awareness, signaling intensity of stores, and store characteristics. The domain of our model is simulating pedestrian movement in a shopping environment. This implies that the often very simple rules to simulate pedestrian movement are probably not very useful to predict the complex dynamics of pedestrian shopping behavior. Therefore, the conceptualization of the model (Dijkstra, et al, 2002, 2004) consists of a set of behavioral principles and mechanisms that are used to simulate pedestrian behavior. The conceptualization underlying the model is discussed in detail in Dijkstra et al. (2002). To summarize, we assume that an agent has an agenda of activities it intends to complete during a shopping trip. This involves choosing a sequence of destinations and a path through the environment. During movement however pedestrians may become aware of stores, conceptualized as a function of signaling intensity of the store and pedestrian awareness. This will reflecting that a pedestrian will consider hereby that store and then enter to conduct the planned / unplanned activity. A pedestrian may or may not successfully complete the activity, leading to a possible rescheduling of the agenda.

These several components of the model are more empirically estimated. In a previous paper (Dijkstra et al., 2005), we have reported the results of the signaling - awareness component. In this paper, we will report the results of a sub-model predicting the probability of a successful completion of an activity.

The paper is organized as follows. First in section 2, we will discuss the behavioral model to predict a successful completion of an activity at a store. Then, in section 3, we will describe the data collection. Section 4 will discuss the estimation results. We will finish with a brief discussion.

2. PROBABILITY OF COMPLETING AN ACTIVITY AT A STORE

A multi-agent model is assumed for simulating pedestrian movement. The basic behavioral principles of this model are described elsewhere (Dijkstra et al., 2002a). In this model a shopping environment with agents representing pedestrians is considered. Each agent i is supposed to carry out a set of activities A_i. That is, agents are supposed to purchase a set of goods, become involved in window-shopping, and in possibly conduct other activities such as having a lunch, etc. Thus, agents each with their own activity agenda make a trip in the shopping environment. This activity agenda is time-dependant and the activities have their priorities. We assume that the completion of an activity is a key decision point, where agents will adjust, if necessary, their activity schedule and anticipated time allocation to the activities not yet completed. Agents need to decide which stores to choose in what order, and which route to take, subject to time and institutional constraints. When moving over a network such as the streets in an inner-city center, we assume that agents have perceptual fields. Perceptual fields, which guide which stores an agent will perceive varies according to the agent's awareness threshold and the signaling intensity of the store. Face validity for this assumption was provided in Dijkstra et al. (2005).

When stores are signaled and become included in an agent's perceptual field, the agent has to decide whether or not to act and visit the store. This is called the activation of the agent. We assumed that activation is defined and depends among others on agent's personal characteristics, motivation, familiarity with a store, suitability to conduct a visit, and the agent's consideration set. A consideration set is a set of stores that an agent considers in performing a particular activity. If an agent is not familiar with a store, the activation of the agent towards this store will be lower. Similarly, activation will be equal to zero if the store is not suited to conduct any of the activities that are still scheduled to be completed. Figure 1 shows the conceptual model for visiting a store.

Figure 1 Influence of personal and store characteristics on store visiting

If an agent becomes activated, it will gradually move to the store. The model then simulates the duration of window-shopping, if any, the probability and duration of an actual visit to the store, the probability of successfully completing the activity at the store. We assume that the probability of a successful completion is a function of availability and predictability of the product, the urgency of completing the activity, the familiarity of the store to the agent, the duration of the visit, and the attractiveness of the store. In particular

$$p_{iaj} = \frac{\exp(\beta_1 X_{1aj} + \beta_2 X_{2aj} + \beta_3 u_{ia} + \beta_4 \eta_{ij} + \beta_5 \Delta_{ij} + \beta_6 \Theta_{ij})}{1 + \exp(\beta_1 X_{1aj} + \beta_2 X_{2aj} + \beta_3 u_{ia} + \beta_4 \eta_{ij} + \beta_5 \Delta_{ij} + \beta_6 \Theta_{ij})} \quad (1)$$

where,

p_{iaj} is the probability that agent i will buy a product and with that completing activity a at store j

X_{1aj} is the available assortment of products for completing activity *a* at store *j*

X_{2aj} is the predictability of a product for completing activity *a* at store *j*

u_{ia} is the urgency that agent *i* will buy a product for completing activity *a*

η_{ij} is the familiarity of store *j* to agent *i*

Δ_{ij} is the duration of the visit of store *j* by agent *i*

Θ_{ij} is the attractiveness of store *j* for agent *i* for conducting activity *a*

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are parameters to be estimated

After the activity is completed, the remaining activities are reconsidered, possibly rescheduled and the simulation continues.

3. DATA COLLECTION

Data were required to estimate the parameters of the model predicting the probability that an agent will complete an activity at a store. The test ground for the application of the model is the city center of Eindhoven. Figure 2 shows the main shopping street of Eindhoven.

Figure 2 Main Shopping Street

Data were collected in October 2006 by interviewing shoppers at several stores along the main shopping street. Besides personal characteristics, shoppers were interviewed about their product expectations, familiarity with the store and urgency to buy the expected product. After the visit, they were interviewed again and asked whether expectations were fulfilled and whether their occupying completed their activity.

The response was 570 complete questionnaires. The stores were random selected almost along the main shopping street and evenly distributed. Table 1 shows the number of selected store locations for each store category. The number of store locations of the specific store category is larger because of the difficulty acquiring a sufficient number of respondents within a convenient period. Tables 2 thru 5 show descriptive results. Hereby, tables 2 thru 4 presents the distribution of stores with respectively store familiarity, store attraction and available assortment. Tables 5 and 6 refers to product predictability and the urgency for buying the product. Table 7 shows the duration of a visit in the regarding store.

Table 1: The number of store locations for each store category

	# store locations	distribution	Total
Clothes	5	37,34,17,17,6	108
Shoes	5	26,19,18,10,12	85
Health & Body	4	40,27,17,8	92
Department store	4	87,38,26,8	159
Other (specific)	9	33,17,16,13,12,10,9,8	126

Looking at tables 2 thru 4, the shoe category is striking in all these cases. Apparently shoe stores are less well-known; visitors are less familiar with them and therefore have less strong notion about assortment.

Table 2: Familiarity with store (% within store category)

	Good	Moderate	Not so good
Clothes	82,4	13,9	3,7
Shoes	37,7	37,6	24,7
Health & Body	92,4	6,5	1,1
Department store	91,2	6,3	2,5
Other (specific)	54,0	34,9	11,1

Table 3: Store attraction (% within store category)

	Good	Reasonable	More or less acceptable
Clothes	40,7	32,4	46,9
Shoes	24,7	31,8	43,5
Health & Body	41,3	28,3	30,4

Department store	49,7	30,2	20,1
Other (specific)	44,4	30,2	25,4

Table 4: Available assortment (% within store category)

	Good	Sufficient	Inadequate
Clothes	45,4	46,3	8,3
Shoes	35,3	49,4	15,3
Health & Body	68,5	26,1	5,4
Department store	62,3	31,4	6,3
Other (specific)	58,7	34,1	7,2

Table 5: Product predictability (% within store category)

	Yes	No
Clothes	57,4	42,6
Shoes	64,7	35,3
Health & Body	78,3	21,7
Department store	80,5	19,5
Other (specific)	84,1	15,9

Tables 6 and 7 shows the duration of a visit for the health & body store is less than the other store categories. This is also valid for the urgency of buying a product. This store category is especially convenient for buying some necessary small goods that takes little time. Table 7 shows the striking effect of using a fitting-room on the duration for the clothes store category.

Table 6: Urgency for buying a product (% within store category)

	Yes	No
Clothes	18,5	81,5
Shoes	22,4	77,6

Health & Body	41,3	58,7
Department store	28,3	71,7
Other (specific)	29,4	70,6

Table 7: Duration of visit (% within store category)

	> 15 min	5–15 min	< 5 min
Clothes	64,8	25,9	9,3
Shoes	24,7	48,2	27,1
Health & Body	9,8	70,7	19,5
Department store	29,6	49,1	21,3
Other (specific)	33,3	42,9	23,8

Examination of a possible correlation between familiarity of a store and store attractiveness for the store categories shoes and other, we found a significant statistic result at 0.05 level for the correlation in case of ‘Shoes store’. In case of ‘Other stores’, for the correlation there was no significant statistic result.

4. ESTIMATION RESULTS

The dichotomous response variable is whether the concerning activity has a successful evidence by buying a product. It means whether a product has been brought. As expressed by equation (1) the explanatory variables are the familiarity of the store, the available assortment of a product, the predictability of a product, the urgency of buying a product, the attractiveness of a store and the duration of a visit. SPSS was applied to determine the parameters in the equation; dummy coding was used to represent these variables.

Running SPSS for the first time, some curiosities shows up by excessive parameter outcomes. For some variables level indications must be adapted such as the duration of visit with respect to clothes category. In that case, we assign two levels respectively > 15 min and ≤ 15 min.

Table 1 presents the distribution of types of stores and the familiarity of the respondents with the visited store. It shows the percentage of respondents that is familiar with the store is very high. It seems for most store types that familiarity is less important in the proposed equation (1). Examination of a possible correlation between familiarity of a store and store attractiveness for the store categories shoes and other, we found a significant statistic result at 0.05 level for the correlation in case of 'Shoes store'. In case of 'Other (specific) stores', there was no significant statistic result.

As expressed by equation (1) the probability of a successful completion of an activity depends on the familiarity of a store. As mentioned in the previous paragraph, this familiarity only plays a role for the store category 'Other'. In case of store categories, this variable is not included. Another interesting point is the level determination of the duration of visiting a store.

For each store category the model was estimated. Table 8 presents the estimated parameters of the variables.

Table 8: Estimated parameters

	Store category									
	Clothes		Shoes		Department Store		Health & Body		Specific	
	B.	Sig.	B.	Sig.	B.	Sig.	B.	Sig.	B.	Sig.
Available assortment										
Good	2.481	.008	2.725	.030			1.106	.319	2.967	.003
Sufficient	1.376	.138	1.849	.124			.122	.920	2.885	.004
Available assortment										
Good					1.299	.013				
Product predictability										
Yes	.283	.539	.550	.414	.356	.556	1.524	.027	-1.585	.030
Product urgency										
Yes	1.158	.027	1.094	.071	.878	.078	.520	.420	1.226	.014
Familiar with store										
Good									1.195	.013
Duration of visit										

> 15 min			.891	.283	1.154	.101	.449	.706	-.480	.469
5-15 min			.377	.610	.685	.218	.793	.305	-.808	.198
Duration of visit										
> 15 min	1.831	.000								
Store attraction										
Good	-.143	.812	-.682	.361	.085	.888	-.477	.557	.191	.765
Reasonable	-.194	.741	.740	.270	.689	.300	-.535	.530	-.175	.775
Constant	-3.205	.003	-4.014	.002	-.521	.531	-.674	.554	-1.199	.221

Table 8 shows some worth mentioning patterns. The available assortment is a significant variable except for the specific stores. Duration of the Clothes category is significant and less important for the other store categories. Familiarity of a store plays a significant role in case of specific stores; these stores are more unusual to visit and for visiting such a store some familiarity with that kind of stores is advisable. The impact of store attraction is small. Maybe, this will be influenced by the overall perception of the store with regard to their appearance. Closer examination of store attraction with respect to expectations and findings about some characteristics like service, assortment, quality and sphere maybe distinguish store attraction.

To assess the goodness of fit of the estimated model we have used McFadden's Rhosq.; Table 9 presents the results.

Table 3: McFadden's RhoSq.

	Store category				
	Clothes	Shoes	Department Store	Health & Body	Specific
Significance	.198	.290	.455	.435	.287

Table 3 shows that the results of McFadden's Rhosq. are reasonable up to good, so we can conclude the model fits the data quite well.

5. DISCUSSION

In this paper we presented we presented the results of a model predicting the probability of completing an activity at a store. It was hypothesized that this probability is a function of the available assortment of a store and some other factors. The results of the estimation are interpretable and the goodness of fit satisfies.

We mentioned that the store attraction is not clear. Further examination would be desirable to get more distinction and therefore better results. This would improve the applicability of the model.

The probability of successful completing an activity is one of the behavioral principles. In this paper, we have not worked out the underlying equation of activation of an agent that causes the gradually movement of an agent to a store. This will be explained elsewhere.

The underlying equations of behavioral principles will be used in the simulation to predict, using Monte Carlo simulation, whether an individual store will be visited and whether an activity will be successful completed. Other information in the system, such as an activity agenda, consideration set and triggering window shopping will be linked to the process of entering the store and shopping. We plan to report about the overall behavioral principles in future publications.

REFERENCES

Blue, V.J. and Adler, J.L. (1999) Bi-directional emergent fundamental pedestrian flows from cellular automata microsimulation. In A. Ceder (ed.) **Transportation and Traffic Theory: Proceedings of the International Symposium on Traffic Theory.** Pergamon, London.

Borgers, A. and Timmermans, H.J.P. (1986a) A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas, **Geographical Analysis, Vol. 18, No. 2,** 115-128.

Borgers, A. and Timmermans, H.J.P. (1986b) City centre entry points, store location patterns and pedestrian route choice behaviour: a micro-level simulation model, **Socio-Economic Planning Sciences, 20,** 25-30.

Borgers, A. and Timmermans, H.J.P. (2004) Simulating pedestrian route choice behaviour in urban & retail environments. **Proceedings Walk21.** Copenhagen, June 2004. (cd-rom)

Borgers, A. and Timmermans, H.J.P. (2005) Modeling pedestrian behaviour in downtown shopping areas, **9th Computers in Urban Planning & Urban Management Conference CUPUM '05.** London, June 2005.

Cavens, D. and Schmid, W.A. (2005) Behavioural modelling of pedestrians with an agent-based system, **9th Computers in Urban Planning & Urban Management Conference CUPUM '05.** London, June 2005.

Daamen, W. and Hoogendoorn, S.P. (2003) Controlled experiments to derive walking behaviour, **European Journal of Transport and Infrastructure Research, Vol. 3, No. 1,** 39-59.

Daamen, W. (2004) Modelling Passenger Flows in Public Transport Facilities. **Trail thesis series.** Delft University Press, Delft.

Dijkstra, J., Timmermans, H.J.P. (2002a) Towards a multi-agent model for visualizing simulated user behaviour to support the assessment of design performance,

Automation in Construction, 11, 135-145.

Dijkstra, J., Jessurun, A.J. and Timmermans, H.J.P. (2002b) Simulating pedestrian activity scheduling behaviour and movement patters using a multi-agent cellular automata model, **Proceedings of the Transportation Research Board Conference**. Washington, January 2002.

Dijkstra, J., Timmermans, H. and de Vries, B. (2004) Data requirements for the Amanda model system. In J.P. van Leeuwen and H.J.P. Timmermans (eds.) **Developments in Design & Decision Support Systems in Architeccture and Urban Planning.** Eindhoven University of Technology, Eindhoven.

Dijkstra, J., Timmermans, H. and de Vries, B. (2005) Modelling behavioural aspects of agents in simulating pedestrian movement, **9th Computers in Urban Planning & Urban Management Conference CUPUM '05.** London, June 2005.

Helbing, D., Farkas, I.J. and Viscek, T. (2000) Simulating dynamical features of escapic panic, **Nature, 407,** 487-489.

Hoogendoorn, S.P., Bovy, P.H.L and Daamen, W. (2001) Microscopic pedestrian wayfinding and dynamics modelling. In M. Schreckenberg and S.D. Sharma (eds.) **Pedestrian and Evacuation Dynamics**, Springer, Berlin.

Hoogendoorn, S.P. and Daamen, W. (2002) Extracting microscopic pedestrian characteristics from video data. **Proceedings of the Transportation Research Board Conference.** Washington, January 2002.

Kitazawa, K. and Batty, M. (2004) Pedestrian behaviour modelling – An application to retail movements using genetic algorithms. In J.P. van Leeuwen and H.J.P. Timmermans (eds.) **Developments in Design & Decision Support Systems in Architeccture and Urban Planning.** Eindhoven University of Technology, Eindhoven.

Kukla, R., Kerridge, J., Willis, A. and Hine, J. (2001) PEDflow: development of an autonomous agent model of pedestrian flow. **Proceedings of the Transportation Research Board Conference.** Washington, January 1999.

Masuda, H. and Arai, T. (2005) An agent-based model of evacuation in a subway station, **9th Computers in Urban Planning & Urban Management Conference CUPUM '05.** London, June 2005.

Meyer-König, T., Klüpfel, H. and Schreckenberg, M. (2001) Assessment and analysis of evacuation processes on passenger ships by microscopic simulation. In M. Schreckenberg and S.D. Sharma (eds.) **Pedestrian and Evacuation Dynamics,** Springer, Berlin.

Schelhorn, T., O'Sullivan, Hcklay, M. and Thurstain-Goodwin (1999) STREETS: an agent-based pedestrian model. **Computers in Urban Planning and Urban Management.** Venice, July 1999.

?? Schultz, M., Lehmann, S. and Fricke, H. (2005) A discrete microscopic model for pedestrian dynamics to manage emergency situations in airport terminals. In N. Waldau, P. Gattermann, H. Knoflacher and M. Schreckenberg (eds.) . **Pedestrian and Evacuation Dynamics 2005,** Springer, Berlin.

Teknomo, K. (2002) Microscopic pedestrian flow characteristics: Devlopement of an image processing data collection and simulation model. **PhD Thesis. Graduate School of Information Sciences,** Tohoku.