A cognitive learning model for dynamic activity-travel patterns

Sehnaz Cenani*, Theo A. Arentze, Harry J. P. Timmermans

Eindhoven University of Technology, Department of the Built Environment, Urban Planning Group, Eindhoven, 5600 MB, the Netherlands

Abstract

As individuals travel and receive information about the urban and transport environment through information and communication technologies, they will update their mental representation of the built environment, which in turn may influence their activity-travel choices. Thus, in this paper, we propose a model that simulates probabilities based on individual observations in the built environment, explain our model framework, and then present the results of the simulations that are designed to test the face validity of the model.

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1. Introduction

Spatial knowledge acquisition increases over time with exposure to the built environment. When individuals move to an unfamiliar environment, they begin to gain spatial knowledge rapidly. Exposure to an unfamiliar environment causes individuals to develop a representation of their immediate surroundings. An examination of the relevant literature suggests that activity-travel models [1, 2], which have achieved a growing interest in the transportation research community, do not systematically include the development of dynamic cognitive maps and their relationship with different facets of activity-travel behavior [e.g., 3, 4, 5, 6, 7, 8]. The study of the relationship between activity-travel behavior and the development of dynamic cognitive maps seems an under-researched, but potentially important topic for transportation and urban planning. The development of dynamic activity-based models [e.g., 9, 10], which is now high on the international research agenda, should explore the possibility of including cognitive learning of urban and transportation networks, because individual and household travel decisions are based on imperfect and incomplete assumptions, which are nonlinearly related to the objective attributes of the spatial environment. A cognitive learning model for dynamic activity-travel patterns
is a potentially important step in developing such dynamic activity-based models of travel demand. As individuals travel and receive information about urban and transport networks, they will update their mental representation of the built environment, which in turn may influence their activity-travel choices. Arentze and Timmermans [11] developed a model of observation that is derived from existing Bayesian theories of perception updating, and following their study, we propose a model that simulates probabilities based on individual observations in the built environment.

The outline of this paper is structured as follows: The following section describes the proposed model. Then, the next section explains the implementation of the model and presents the results of the simulations that are designed to test the face validity of the model. Finally, the last section draws some conclusions.

2. Model

The model proposed here is one of the layers of a large-scale multi-agent model that is capable of handling short-term, mid-term and long-term dynamics [10]. The model simulates dynamic activity-travel patterns of individuals and households. Daily scheduling decisions are dependent on the state of the agent and, at the same time, implementing a schedule can change an agent’s state. After having implemented the schedule, an agent updates its knowledge about the transport network, transport modes and route network, and develops habits for implementing these activities (e.g., habitual routes). At the start of each day, the agent generates a schedule and during the day it executes the schedule in space and time. When there is an unexpected event, the agent will make adaptations to its schedule (within-day re-planning). At any decision moment during the implementation process, the memory will receive the perception results of the observations made so far and probabilities will be updated. Also, at the end of the day, probabilities will be updated according to observations made during travelling and conducting activities at locations, simulating learning especially through exploration and/or encountering unexpected events during the day.

Several biases can be observed between the real world and the world perceived by the individual. Drawing from findings in the spatial cognition literature [12, 13, 14], the proposed model includes mechanisms for such distortions. Since mental maps are generally distorted and incomplete, the system is divided into two fundamental parts: the physical environment (real world) and the mental environment (the world depends on the agent’s perception). We should emphasize that forgetting is in line with learning. Therefore, we include limited memory retention in our model framework as well. The model uses the implemented activity-travel schedule that includes transport mode, activity location and route choices, and after each trip, the agent makes an observation and updates its mental map.

2.1. Learning through observation

In this section, we explain a model that simulates probabilities based on observation while implementing an activity-travel schedule. Given that an observed state does not have to be identical to the true state, Arentze and Timmermans [11] represent an observation of some attribute of some link $X = \{x_1, x_2, \ldots, x_n\}$ by a separate variable $Y = \{y_1, y_2, \ldots, y_n\}$, where $y_1, y_2, \ldots, y_n$ denote observed states. They indicate that uncertain observations means that the probability of $Y = y_s$ given that $X = x_s$ is not necessarily one and the probability of $Y = y_s$ given that $X \neq x_s$ is not necessarily zero. When an observation is made, the probabilities are computed according to the Bayesian method [11]:

$$P(x_s | y_u) = \frac{P(y_u | x_s)P(x_s)}{\sum_{s'=1}^{n} P(y_u | x_{s'})P(x_{s'})} \forall s$$

(1)
where:
\[ P(x_i) \] is the initial probability for \( x_i \);
\[ P(x_i|y_u) \] is the updated probability after observation \( Y = y_u \);
\[ P(y_u|x_i) \] is the probability of observation \( Y = y_u \) given \( X = x_i \);
\( n \) is the number of possible values of \( X \) and \( Y \).

According to Equation (1), the updated probability, \( P(x_i|y_u) \), becomes the initial probability in the next observation. Similar to Arentze and Timmermans’ assumption [11], a node probability table (NPT) defines for each configuration of states of the parent node a probability distribution across the possible states of the node concerned. The NPT characterizes the probabilities of observed states under each assumption of the real state of the attribute observed. The ONPT is a version of the NPT linked to an observation, which indicates the perception of the observation of an agent.

To use Equation (1), Arentze and Timmermans [11] proposed a method to specify the ONPT of an observation as a function of the state of the agent and variables of the field of vision that is applicable here as well. Their method assumes that observation accuracy is composed of two factors, namely sensitivity and bias. They propose to use a logit model defined as follows:

\[
P(y_u|x_i) = \frac{\exp(\theta \beta_{us})}{\sum_{s=1}^{n} \exp(\theta \beta_{us'})} \forall u, s
\]

where \( \beta_{us} \) are observation-bias parameters and \( \theta \) is the observation-sensitivity parameter. Keeping sensitivity \( (\theta) \) constant, an increase in \( \beta_{us} \) leads to a higher probability of observing \( u \) while \( s \) is the case. Observation bias would be absent if, for all \( u \), \( \beta_{uu} > 0 \) and \( \beta_{us} = 0, \forall s \not= u \).

Since \( \theta \) sets the scale of the parameters, it is natural to use a zero-one scale for the bias parameters, whereby \( \beta_{uu} = 1 \) and \( \beta_{us} = 0 \) for states \( x_u \) and \( x_s \) that are considered to be least easily confused with each other for the attribute considered. On the other hand, we assume that the sensitivity parameter is a function of a range of factors which we here specify as:

\[
\theta_{jk} = f(a_k, D_{jk}, V_{jk})
\]

where \( jk \) is some attribute \( k \) of link \( j \), \( a \) is the amount of attention the agent pays to attributes of type \( k \), \( D_{jk} \) is the shortest (straight-line) distance between position of the observer and observed object on link \( j \), \( V_{jk} \) is the visibility of the object from the current position of the observer. To give some examples, sensitivity is higher if attention for the attribute is high, distance is short, and the view is not blocked by a building. The interaction between the purpose of the trip and the attribute type has a possible impact on the amount of attention. For example, when the purpose of the trip is exploration or wayfinding, observation sensitivity will be high for landmarks. As another example, when the trip purpose is shopping, attention will be higher for attributes related to presence of stores. For illustration purposes, a basic specification was assumed for the function used to predict thetas:
\[ \theta_{jk} = z - (b * D_{jk}) \]  

(4)

where \( b \) has a value on the interval 0 and 1. The closer \( b \) is to zero, the smaller the speed of forgetting (\( z = 5 \)). Since we assume that all activity locations and landmarks are visible at all times, both attention (\( a \)) and visibility (\( V_{jk} \)) do not affect the sensitivity parameter, therefore sensitivity depends only on distance (\( D_{jk} \)).

We assume an agent traveling on a road network and making observations about attributes (e.g., distance, visibility, attention, etc.) of activity locations (points) such as a grocery store, a day-care center or a post office. As a result, during the implementation of the activity-travel schedule, the agent will acquire spatial knowledge in terms of attributes of activity locations. We assume the following elements of this process:

- Links and points that were not known yet are added and links and points that did have a representation in the mental map have their memory strength increased (reinforcement of the memory trace),
- Probabilities of links and points are updated (for the newly added ones as well as existing ones) based on observation,
- Sequences of links traveled are grouped as chunks and added (when not yet existed) or reinforced (when already existed),
- Landmarks are identified as anchor points and added or reinforced.

In brief, we compute attribute learning of activity locations (perception updating of each visible point) by means of calculating the sensitivity using Equation (4), deriving the ONPT using Equation (2), then simulating an observation (draw the observed state from the ONPT given the true state of attribute \( jk \)), and finally updating the probabilities using Equation (1).

2.2. Forgetting

Forgetting processes run in the opposite direction as perception updating processes. It follows from the foregoing that three cases of memory retention need to be distinguished [15]:

- Link/point attributes that have discrete states (categorical variables),
- Link/point attributes that have values on a continuous scale,
- Point and link objects.

Following our above notions, in this paper, we model forgetting of attributes of points (activity locations) as a step-wise return to a-priori probabilities [11]:

\[ P_{jks}^{t+1} = P_{jks}^t + \alpha^t_{jk} \left( P_{ks}^0 - P_{jks}^t \right) \]  

(5)

where \( P_{jks}^t \) is the probability that attribute \( X_k \) has value \( x_s \) at time \( t \), \( P_{ks}^0 \) is the level of the probability prior to all observations made (during the life of the agent) and \( \alpha \) is a step-size parameter. It is immediately clear that the probabilities, also after decay, still sum up to one. Typically, this decay will mean that the entropy in the probability distribution increases, but this is not necessarily the case. In general, probabilities return to their a-priori values so that, entropy returns to the value it had before learning.
3. Implementation

3.1. Data

The activity-travel schedule of a fictional newcomer is designed for illustration purposes. For the purpose of illustration, the first three months of a newcomer was taken into consideration. It is assumed that the fictional newcomer lives in Eindhoven, the Netherlands. According to his/her activity-travel schedule, the individual works five days a week (full-time), and every day before and after the work, he/she goes to the day-care center to drop-off and pick-up his/her child. Once a week, on Wednesdays after work, he/she goes to grocery shopping. Friday nights, after work, he/she goes to non-grocery shopping or a restaurant, or participates in some social activities. On Saturdays, he/she goes to grocery shopping and conducts several recreational, leisure and social activities. The first Sunday of each month is assumed as “Shopping Sunday”, and sometimes he/she goes to the city center for several activities. On weekends, he/she usually participates in recreational activities, has guests, visits friends, or sometimes he/she stays at home. Note that activity-travel schedule of each day starts at home and ends at home. Given that the agent is a newcomer, learning the city and the road network is essential. Additionally, it is assumed that he/she travels with his/her private vehicle. Route choice is not in the scope of this study and is assumed that the agent consults a navigation system and chooses the shortest path between origin and destination points. In addition, destination (activity locations), transport mode and route choices are managed elsewhere in the model system. Table 1 illustrates the activity categories used in the simulations. Each activity location is located in one of the six land-use types (i.e., industry, residential, commercial, green, mixed commercial and residential, other), and the agent’s a-priori probabilities about availability of specific facilities are dependent on these land-use types [11].

Table 1. Activity categories

<table>
<thead>
<tr>
<th>ID</th>
<th>Activity category</th>
<th>Subcategory</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Home</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Work</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Volunteering</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Education</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Grocery shopping</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Non-grocery shopping</td>
<td>Clothing or footwear; drugstore items; electronics; household items; flowers; books; other</td>
</tr>
<tr>
<td>7</td>
<td>Service</td>
<td>Bank; post office; hairdresser; health</td>
</tr>
<tr>
<td>8</td>
<td>Pick-up/drop-off family members</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Leisure</td>
<td>Eating out; cinema; theatre; bar, café, disco; museum; concert, show; sports</td>
</tr>
<tr>
<td>10</td>
<td>Recreation</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Social</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Helping family</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Waiting</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Other</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Unspecified</td>
<td></td>
</tr>
</tbody>
</table>
As an example, Table 2 indicates random values of the NPT related to the availability of each activity location in six land-use types. For instance, an agent has a-priori knowledge that a grocery store can be found with a higher probability in a commercial area than a residential area but he/she knows that it is almost impossible to find a grocery store in an industrial area. These values represent a-priori knowledge of an individual. Since, individuals may have different assumptions about how urban areas are structured because of their experiences or occupations; this a-priori knowledge may be different for other individuals and cities.

Table 2. NPT related to availability of activity locations dependent on land-use types

<table>
<thead>
<tr>
<th>Activity locations</th>
<th>Probability (Yes)</th>
<th>Industry</th>
<th>Residential</th>
<th>Commercial</th>
<th>Green</th>
<th>Mixed</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grocery store</td>
<td>0</td>
<td>0.20</td>
<td>0.50</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Non-grocery store</td>
<td>0</td>
<td>0</td>
<td>0.50</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Service</td>
<td>0</td>
<td>0</td>
<td>0.50</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Leisure</td>
<td>0</td>
<td>0.20</td>
<td>0.50</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Recreation</td>
<td>0</td>
<td>0.40</td>
<td>0</td>
<td>0.75</td>
<td>0.20</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Social</td>
<td>0</td>
<td>0.85</td>
<td>0</td>
<td>0</td>
<td>0.50</td>
<td>0.20</td>
<td></td>
</tr>
</tbody>
</table>

The difference between the predicted probability and a-priori probability for an activity location or a landmark represents the level of knowledge about that activity location or landmark. As implied by Equation (5), if no observations are made for a long time, probabilities will return to their initial values. The initial state of the mental map of an agent assumes that he/she knows the land-use type of each activity location and a-priori probabilities for these attributes are derived from the NPTs (see Table 2). The specification of each NPT is based on the assumption that the agent has accurate knowledge about conditional probabilities. The NPT supports the case of an individual who just moved into a new city, yet has enough information through a map or a navigation device, of how the area is structured in terms of land-use types.

3.2. Results

At present, the model considers attribute learning and limited forgetting of activity locations, and the a-priori probability of each activity location derives from the NPTs (see Table 2). Equation (4) is used to predict thetas \((b = 0.01\) and \(z = 5\)) and in addition to the steps of the perception updating explained at the end of the section 2.1, if an agent does not make any observation about the attributes of activity locations, then the forgetting is computed using Equation (5) \((\alpha = 0.01)\). Additionally, we used a basic setting for the logit model to calculate the ONPT for a given observation; all \(\beta_{us}\) are assumed zero for off-diagonal cells \((u \neq s)\) and one for the diagonal cells \((u = s)\).

Figure 1 shows the daily predicted probabilities for several activity locations during the implementation of an activity-travel schedule of 90 consecutive days, and the main specification is consistent with a facility is present at the activity location (point) and the agent makes observations about the attributes of these activity locations. Figure 1a represents the predicted probabilities of two frequently used activity locations, which are home (P1) and work (P3). As the agent visit these locations, due to the observation, it continuously updates the probabilities about these locations. Thus, the probabilities stay close to 1. Figure 1b indicates predicted probabilities of two grocery stores. Here, the agent learns the second grocery store (P35) later than the first one (P4). When the agent does not visit these activity locations, we observe a decrease in values, and after the visit, the values increase again. As long as the agent visits these activity locations (points), it does not forget and the values remain close to 1. In Figure 1c, 1d and 1e, the graphs show the predicted probabilities of two non-grocery stores (P5 and P9; clothing store and flower store), two service locations (P13 and P14; post office and hairdresser) and two leisure locations (P16 and P40; both of them are restaurants), respectively.
Fig. 1. the daily predicted probabilities for (a) home and work; (b) two grocery stores; (c) two non-grocery stores; (d) two service locations; (e) two leisure locations
The last three graphs represent similar activity-travel behavior; therefore we will explain one of them as an example. In Figure 1d, we notice that the agent visits both activity locations once, and then it never visits them again. In another word, at first we detect an increase because of the observation, and afterwards as the agent never make an observation about the attributes of these activity locations, the agent starts to forget and as a result the values decrease. In long-term, if the agent does not visit these locations ever again, the probabilities will return to their initial states. In sum, our results revealed that, as we expected, the frequently visited activity locations retain in the memory longer than the less visited activity locations.

4. Conclusions

In this paper, we proposed a model of cognitive learning for dynamic activity-travel patterns of individuals with limited memory retention. The model uses the implemented activity-travel schedule, and the route choice is handled by another model. As explained in the previous section, according to this model, an agent travels with his private vehicle, consults a navigation system and uses the shortest path between origin and destination points. After having implemented the schedule, an agent will update the probabilities based on the perception results of the observations.

This paper presents the results of the simulations that are designed to test the face validity of the model. As a future scenario, we intend to analyze the effects of individual preferences on route choices. Some routes can be more attractive (e.g., scenic route, route with shopping alternatives, recommended route by a social contact) or less attractive (e.g., non-secured route, traffic congestion, etc.) than other routes. Accordingly, the agent may choose routes based on its preferences. As we integrate our model into the Supernetwork model, an agent will be able to choose different routes in its daily activity-travel schedule. Additionally, we will be able to include sub-paths when an agent prefers park-and-ride or public transport. Thus, given that transport modes affect our route choices, as another potential scenario, we intend to explore the effects of transport mode choices on spatial learning.

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