

Modelling the Dynamic Formation of Activity Location Choice-Sets

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Abstract:

This paper develops a framework for modelling the dynamic formation of location choice-sets. The proposed framework integrates three key concepts, namely aspiration, activation and expected utility. Aspirations are defined at the level of attributes of choice alternatives and represent an individual's beliefs about performance levels that potentially can be achieved. Activation levels are defined at the level of choice alternatives and represent the ease with which an alternative can be retrieved from memory and, hence, the degree of awareness of an alternative. Finally, expected utility represents an individual's evaluation of a choice alternative based on his/her current beliefs about attributes of the alternative. In the proposed system, all these cognitions - aspirations, activations and beliefs – are conditional upon context variables and subject to cognitive and social learning. Based on principles of Bayesian learning, re-enforcement learning and social comparison theories, the framework specifies functions for experience-based learning, extended and integrated with social learning.

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1 Introduction

Transportation research has a long tradition in developing and applying choice models to predict transport mode, destination and route choice behaviour. Many models have been developed to predict single choice facets. Recently, more complex activity-based models that can deal with multiple facets of activity-travel patterns in a more integral fashion have been proposed (see Timmermans, *et al.*, 2002 for an overview).

Although the theoretical underpinnings of these activity-based models differ, they have in common the assumption that individuals will choose within their choice sets the alternative they prefer, sometimes subject to a set of constraints (Ben-Akiva and Boccara, 1995; Pellegrini, *et al.*, 1997, Cascetta and Papola, 2001). In most of these models, however, the construction and composition of individual choice-sets is not explicitly modelled. Choice-sets are typically assumed given or derived on the basis of some arbitrary rule (Swait and Ben-Akiva, 1987; Thill and Horowitz, 1997; Swait, 2001). The delineation of choice-sets is particularly important in large-scale micro-simulation systems, which are receiving increasing attention in activity-based travel-demand modelling and integrated land-use – transportation systems. As expected, knowing the choice-set from which a location is selected significantly decreases the complexity and may improve the performance of these large-scale systems (Shocker, *et al.*, 1991). In this context, the choice-set refers to the set of discrete locations known by the individual, which is a subset of the universal choice-set that consists of all alternatives available to the decision maker. Known means that the individual knows not only the physical location, but also the attributes that are potentially relevant for evaluation under specific contextual conditions in the activity-travel decision-making process. Note that this definition differs from commonly used terminology in marketing, where a distinction is made between awareness, evoked set, consideration-set and choice-set (Timmermans and Golledge, 1990). We can refine our framework along these lines, but that is beyond the goal of the present paper.

In this paper, we will develop a conceptual framework for the formation of dynamic location choice-sets. It lays the conceptual foundation for the longer-term dynamics of the FEATHERS models (Arentze, *et al.*, 2006a; Janssens, *et al.*, 2006), which is best viewed as an extension of Aurora (Joh, *et al.*, 2005). We assume that individuals conduct activities to satisfy specific needs and try to organise their activities and travel in time and space in some satisfactory way, influenced by their cognition of the environment. If the environment is stationary, one might assume that as a result of repeated trials some Pareto optimum or steady state will be established: activity-travel patterns are stabilized and become habitual. However, in reality, the space-time environment is non-stationary and individuals' needs may change as well, as a result of, for example, changes in socio-demographics. Furthermore, critical incidents may imply that individuals are triggered to change their behaviour. Under these circumstances, the actual performance of the transport and land-use system for an individual may decrease below some critical level – the aspiration level of the individual, leading him/her to search for alternatives such that the expectations regarding his/her activity-travel pattern can be achieved. In addition, an individual's cognition of the environment may change as a result of new information from media, actual travel and social contacts, which may prompt him/her to adjust the aspiration level and actively explore new locations. Thus, choice-set formation is conditional upon the context and dynamic in the sense that choice-sets are updated each time an individual has executed an activity-travel schedule or when new information becomes available.

These considerations lead to the following three core parts of the proposed conceptual framework of modelling the dynamic process: (1) an aspiration level associated with the

choice-set that in combination with evaluation results determines whether the individual will start exploring or persist in habitual behaviour, (2) an activation level of each location alternative that determines whether or not the alternative is included in the choice-set in the next time step and, (3) an expected (utility) function that allows an individual to evaluate each location alternative given current beliefs about the attributes of the location (including travel time). Each of these elements is dynamic.

In the following, we will first identify key drivers that trigger changes in choice behaviours and describe how they are integrated in the decision making process. To depict mechanisms that influence such changes, we continue with describing their functions for cognitive updating based on principles of re-enforcement and Bayesian learning. Then, we extend the system to incorporate social learning that involves social adaptation and information transfer. We complete with a conclusion and discussion for future research.

2 The model

The basic assumption is that an individual (simulated agent) acts based on behavioural principles and mechanisms. (S)He holds beliefs (knowledge) about the environment during a certain life course, has preferences and basic needs, leading to plans, agendas and schedules. (S)He carries out those plans, agendas and schedules in time and space. When a deviation exists between his/her expectation and aspiration an individual may start exploring his/her environment for new alternatives. Thus, (s)he learns about the environment and the consequences of his/her actions, in this case the choice of activity locations, and is able to adapt to changing circumstances and improve less effective behaviour. Based on experiences, an individual forms habits, reinforces memory traces, updates beliefs about attributes of locations and routes, discovers the conditions under which certain states of the environment are more likely than others, and in so doing makes sense of the world around him/her. Moreover, through social contacts individuals exchange information and adjust aspirations, which may trigger actions to explore new alternatives. Thus, for an individual, the composition of the location choice-set for a specific activity under certain conditions is dynamic. The alternatives within the choice-set will be expanded with newly discovered alternatives and reduced with old ones that are discarded or no longer retrievable from memory.

Consequently, we assume that, there are three core drivers that trigger changes through out the dynamic process: an *aspiration* level that reflects expectations of what can be achieved, an *activation* level that represents the degree of awareness, and an *expected utility* that represents subjective evaluations of alternatives given current knowledge. In this section, we give a more detailed description of these drivers and indicate how they work together to result in the location choice, in the proposed conceptual model.

2.1 Drivers

An aspiration level is an individual's goal for the outcome of the decision (Payne, et al., 1980; Patricia and Susan, 1998). In theory, aspirations could be defined either at the level of choice alternatives (a bundle of attributes) or individual attributes. We assume that it is more plausible to define aspiration at the level of attributes as it is on that level that an individual may determine goals that give direction to exploration processes (e.g., find alternative stores with a lower price level rather than find stores that have higher utility for my purposes). Defined for an attribute, an aspiration serves as a subjective reference point, which determines

what qualifies as a satisfactory outcome for that attribute. An aspiration level is individual and, in case of a dynamic attribute, context-specific and, in the context of this paper, associated with location attributes. The outcome of a comparison between aspiration and actual or expected outcome given current knowledge provides a measure of an individual's satisfaction and willingness to explore new alternatives. A possible discrepancy between the expected outcomes derived from the alternatives within the current choice-set and the individual's aspiration levels may trigger the individual to switch from habitual behaviour to a conscious choice mode.

Generally, aspiration levels are context dependent. For example, satisfaction or tolerance about the crowdedness encountered at shopping locations may vary by day-of-the-week and shopping location's category type. Aspiration levels can relate to both (quasi)-static attributes and dynamic attributes (which may fluctuate as a function of the behaviour of all individuals in the system). Formally, we denote the set of current aspiration values as $A = \{A_k\}$, where $A_k = (c_k, e_k)$, $e_k = (e_{1k}, e_{2k}, \dots, e_{jk})$, e_{1k} represents the aspiration value of the first attribute under the k -th condition, and $c_k = (c_{1k}, c_{2k}, \dots, c_{lk})$ defines the k -th condition as a set of states of the condition variables considered.

Table 1A shows an arbitrary example of (quasi)-static attributes while Table 1B gives an example with dynamic attributes. The first two columns show activity and location type combinations as condition variables, and the rest columns show attribute variable outcomes, which in this case are the aspiration levels of each attributes under concern. Table 1A assumes that several (Quasi)-static attributes, including for which goods stores are present, price level, and parking space, may have a role in determining whether an outcome is satisfactory or not. In this table, there are three types of shopping locations. The table represents the following notions. A big shopping centre is expected to have all types of goods present at a medium price level and offers sufficient parking space. A medium sized shopping centre is expected to have daily goods and semi-daily goods present at a medium price level and again provides sufficient parking space. Finally, a small shopping centre is not expected to provide durable goods and ample parking space, but it is anticipated to have a low price level. Table 1B represents aspirations regarding a dynamic attribute, namely crowdedness, assuming that day-of-the-week and time-of-the-day are condition variables that may have an influence in defining what is considered a satisfactory outcome for a shopping centre. As the example shows, large crowds in the weekend during peak hours will not jeopardise a satisfactory outcome for a big shopping centre and small crowds will be fine for non-peak hours; while on workdays, not more than medium crowdedness is acceptable for peak hours and no crowds is considered attainable for non-peak hours. In sum, the table allows one to determine the aspiration level for crowdedness for any given situation defined in terms of the activity type, location type, day-of-the-week and time-of-the-day.

Moreover, it is easy to imagine that individuals within similar social demographic class or belonging to the same social network may have similar aspiration levels since they communicate to each other and may adapt their aspirations based on social comparison (as explained later).

Besides the references that will be used to judge a situation and define what counts as a satisfactory outcome, individuals also have the ability to memorize situations and outcomes (i.e., events). People memorize events at least partly context dependent, that is, certain contextual conditions automatically activate particular memory traces that lead to particular levels of awareness. For example, consider an individual who occasionally drops by a supermarket to buy daily goods on the way home from work, and this particular supermarket is one out of three supermarkets that (s)he knows. By known, we mean that (s)he could

retrieve it from his/her memory. In this case, the origin location (work or home) and time-of-the-day at the moment of shopping are contextual conditions on which the awareness of the supermarket for buying daily goods will depend at the moment a location choice is determined. Activation level of a location alternative is the indicator of the strength of such a memory trace, and hence reflects the ease with which it can be retrieved from memory. As such, an activation level is associated with each alternative in the current choice-set for each specific contextual condition, for example, defined in terms of type of activity (i.e. purpose of the trip), the previous activity location (i.e. origin location of the trip), day-of-the-week and time-of-the-day.

By repeatedly performing certain behaviour under same situational conditions, individuals develop habits. By forming and following habits, individuals can reduce mental effort involved in constantly evaluating choice alternatives and making choices. By saving cognitive resources for the operation, habits help individuals conserve mental resources and time, and free them for other tasks. Habits have been described as learned and scripted behaviours and are capable of being automatically activated by the situational conditions that normally precede the behaviour. As such, the activation level of a location represents the degree of an individual's habit of choosing that location under certain contextual conditions. In our framework, habitual behaviour involves that individuals consistently select from a choice-set the alternative with the highest activation level under the given condition at the moment a choice is to be made. In turn, we define the choice set in a given choice situation as the locations that are retrievable from memory in that situation (i.e., condition). Formally, let q be the number of relevant condition variables, $W_i^t(z_m)$ be the activation level of an alternative i under condition m , where $z_m = (z_{1m}, z_{2m}, \dots, z_{qm})$ represents the states of the q condition variables under condition m , ω be a minimum activation level for memory retrieval ability. Then, the choice-set is defined as $\Phi^t(z_m) = \{L_i \mid W_i^t(z_m) \geq \omega\}$. Note that, as implied by this equation, the definition of a choice-set may vary between situations.

Table 2 shows an arbitrary example of an activation level pattern for shopping locations. The left-hand side shows contextual conditions, and the right-hand side shows the outcome, which in this case is the activation level of each location. The table assumes that day-of-week, origin location, and time-of-day are condition variables that may have an impact. In this example, there are three shopping locations. The table structure is based on the following notions. Shopping centre 1 and 2 are located close to home, and shopping centre 3 is located close to work. An individual most often goes shopping on Saturday during peak hours from home to shopping centre 1, while sometimes on Wednesday (s)he also visits shopping centre 3 after work during non-peak hours. Once in a while, (s)he visits shopping centre 2 from home on Saturday during non-peak hours. In sum, the table allows one to determine the activation level for any given location, if current conditions on variables including day-of-the-week, origin location, and time-of-the-day are known.

The attractiveness of a location is in general influenced by values of its attributes. Depending on the targeted need underlying the activity, the attributes that should be evaluated may be different. For example in case of shopping, the variety of stores is important for entertainment and purchase purposes, while a social need requires some familiarity with the location. Furthermore, the intention of resting attracts attention to spatial layout, while economic considerations emphasize quality and price. Thus, the impact of location may be diverse, that is, the combination of location and activity needs determines the utility of a location.

Moreover, some of the attributes are (quasi)-static, while others are dynamic. The (quasi)-static attributes reflect characteristics of the location that are in short term constant, for example the size category, price level, parking space, and presence of stores for certain goods in a shopping centre. We assume that an individual will learn all the (quasi)-static attributes of a location simply through observing them after implementing an activity at that location. This knowledge will keep constant, and only change when the physical conditions are changed externally, for example, after a renovation of the shopping centre. Table 3A gives an arbitrary example of a current state of knowledge of an individual regarding (quasi)-static attributes matrix of shopping locations.

Dynamic attributes, such as crowdedness and travel time, are subjective and uncertain, and may be dependent on contextual variables. We assume that for each dynamic attribute, X_j , the individual uses some classification, denoted as $X_j = \{x_{j1}, x_{j2}, \dots, x_{jN}\}$, where x_{j1} - x_{jN} represent possible states of X_j , and specifies his/her beliefs regarding location i based on his/her current knowledge as a probability distribution across X_j denoted as $P_i(X_j)$, which sums up to 1. The degree of uncertainty is given by the degree of uniformity of $P_i(X_j)$. The more evenly the probabilities are spread across possible states, the larger the uncertainty is, and vice versa. For example, consider again the crowdedness of a shopping location. This is a dynamic attribute of a location and therefore may involve uncertain knowledge. An individual could choose four states for crowdedness as {no, little, medium, very}, and specifies his/her beliefs regarding each shopping location i as a probability distribution across these four states.

In addition, the individual may discover that probabilities of states are conditional upon certain contextual variables. For example, the individual may discover that probabilities of crowdedness of a shopping location depend on day-of-the-week and time-of-the-day (e.g. peak hours and non-peak hours). Learning that some variables have an impact on outcome-states means extending unconditional probabilities $P^t(X_j)$ to obtain conditional probabilities $P^t(X_j|C)$, where C stands for one or more variables. Table 3B shows an arbitrary example of knowledge about the dynamic attribute of crowdedness for a shopping location.

A utility function allows the individual to evaluate each location alternative given his/her current beliefs about the attributes of the location (including travel time) and his/her preferences. Using probabilities of the types $P^t(X_j|C)$ to describe the knowledge of the individual, the expected utility equation can be expressed as below:

$$EU_i^t(c_k) = EU_i^{static} + EU_i^{dynamic}(c_k) \quad (1)$$

$$EU_i^{static} = \beta X_i \quad (2)$$

$$EU_i^{dynamic}(c_k) = \sum_j \sum_n \beta_j x_{jn} P_{ij}^t(x_{jn}|c_k) \quad (3)$$

Where EU_i^t is the expected utility of location i at time t , βX_i is the expected partial utility of location i for static attributes and preference, and $\beta_j x_{jn} P_{ij}^t(x_{jn}|c_k)$ is the expected partial utility of location i under possible states x_{jn} with probabilities $P_{ij}^t(x_{jn}|c_k)$ and preference β_j regarding dynamic attribute j . $c_k = (c_{1k}, c_{2k}, \dots, c_{lk})$ represents the values of relevant condition variables under the k -th condition. Thus, expected utility takes into account current beliefs regarding state probabilities as well as an individual's preferences. Of course, static attributes could also be dealt with by these equations, namely as the special case where the believed state has a probability of 1.

2.2 Making a choice

In the assumed choice making process, individuals go through a mental process to arrive at a choice. They start with implementing their habitual behaviour that requires least mental effort, and carry on with conscious choice that asks for more effort only if the habitual choice is not satisfactory, until they find a choice that is satisfactory. As the aspiration levels are the standards for determining whether an outcome is acceptable, they will try to find the alternative that meets the requirements within a tolerance threshold. Figure 1 schematically shows the main steps of the decision making process by which the model arrives at a location choice.

The tolerance threshold is a predefined and individual specific parameter that reflects a characteristic of the individual. A large tolerance threshold indicates the individual strongly dislikes the mental effort involved to make better actions and is sooner happy with the current situation. Vice versa, a small threshold implies that on the one hand the individual is stricter in what is found acceptable, and on the other hand the individual may have a higher propensity to explore. In general, the larger an individual's threshold is, the higher the probability will be that the individual is satisfied with the expected performance of the current choice-set. Being satisfied with the current situation means less desire to take a risk, invest effort, and change behaviour, and consequently, also that it is less likely to explore and possibly make better choices in the future.

As implied by the definition of action level, the alternative that has the highest activation level in the choice-set is the one that is most easily retrieved from memory and requires the smallest amount of mental effort for an individual. In order to determine the level of satisfaction with the habitual choice, the location with the highest activation level is compared to aspiration levels. We assume that if dissatisfaction (i.e. the difference between aspiration and expected level) regarding at least one attribute exceeds the tolerance threshold, an individual will switch to another mode of behaviour and start searching consciously for better alternatives. On the other hand, if this threshold is not exceeded, we assume that no active search will take place and that the individual will exhibit habitual behaviour that leads to executing the choice that has the highest activation level.

We make a distinction between exploitation and exploration as alternative non-habitual modes of choice making. We assume that when acting in a conscious mode, an individual will first be engaged in exploitation and search within his/her current choice-set (i.e. retrieve alternatives from his/her memory that have a lower awareness) for a better alternative under current conditions. With exploitation, the individual calculates the expected utilities (equation 3) of all the alternatives within the choice-set given current knowledge of the environment and the given conditions, and compares the attributes of the one that has the highest expected utility with aspiration levels. When for none of the attributes dissatisfaction exceeds the threshold, we assume that no active exploration of new alternatives will happen and the individual will choose the location that has the highest expected utility. If for at least one attribute there is a mismatch that exceeds the tolerance threshold, the individual will start to explore new alternatives that might solve the mismatch. We call this exploration. Thus, search is not random, but rather directed. The attribute causing dissatisfaction will guide the individual in what to search for.

Exploration is a process by which new alternatives can enter the choice-set. The probability of a location to be discovered is modelled as a function of attractiveness of the location regarding the attributes that are not satisfied by the alternatives within the current

choice-set. Because individuals are uncertain in this situation due to limited information, we propose to use the Boltzmann model (see Sutton and Barto 1998) to calculate discover probabilities across the universal choice set of locations and simulate outcomes of search processes:

$$P(L_i^t) = \frac{\exp(V_i^t / \tau)}{\sum_i \exp(V_i^t / \tau)} \quad (4)$$

where V_i^t is a utility measure of location i and τ is a parameter determining the degree of uncertainty in the selection of new locations. The larger the value of the τ parameter is the more evenly probabilities are distributed across alternatives and, hence, the higher the uncertainty is, and vice versa. The parameter can be interpreted as the general (lack of) quality of information sources available to the individual, such as social network, public and local media and own observations during travel. V_i^t is a utility calculated based on true levels of attributes of locations. Note that the utility depends on the objective of the search: by including only those attributes that are dissatisfactory in the current best choice, V_i^t reflects the focus of the search. Furthermore, a disutility of travel distance is included in the function for V_i^t for two reasons: (1) the longer the travel distance is, the less likely information about the location is available and, (2) the longer the travel distance is, the less likely the location will be considered by the individual because of the higher generalized travel costs.

Having defined the discover probability distribution across locations across the universal choice set, Monte Carlo simulation will be used to select a new location that will be tried and may be added to the choice-set. Once tried, the new location receives an activation level reflecting memory trace strength and is subject to the same updating and learning process as other alternatives in the choice-set, as will be explained later.

In addition, a mental effort counter is included to prevent an individual from getting trapped in continuous and endless exploration. We assume that the individual will keep a record of how many consecutive times (s)he already tried exploring a new location under the same contextual conditions. Every time a choice is made through exploration, it will add 1 unit of mental effort. A habitual choice or an exploitation choice will break the chain of incrementing the score and restore it back to 0. We assume that when the mental effort involved in search for a better alternative is built up and exceeds a predefined threshold, instead of continuing exploring, the individual will avoid further frustration by lowering the aspiration level (realising that the current aspiration level is not realistic). Therefore, in the choice process, before engaging in exploration, the system will check whether the accumulated mental effort exceeds this threshold. If this threshold is not exceeded, the individual will continue exploring. When it is exceeded, the individual will replace the current aspiration levels with the attributes levels of the alternative that currently has the highest expected utility, to assure a relatively optimal outcome and maintain high aspiration levels for future choices. As a consequence of choosing it, the activation level of this alternative will be increased.

As a consequence of the above mechanisms, an individual arrives at a selection of a single alternative location each time an activity is to be carried out. Depending on aspiration levels, this alternative could be the one that has the highest activation level (habitual choice), the one that has the highest expected utility (conscious exploitation choice), or the one that was newly discovered (conscious exploration choice).

3 Experience-based learning

Central to our dynamic process is the notion that choices are contingent upon the outcome of previous choices. By repeatedly making decisions, an individual acquires knowledge (learns) about the environment and thereby forms expectations about attributes of the environment. It should be noted that adaptation and learning processes involve two operations. One concerns updating an individual's perception of the environment. Through repeated experience, individuals will update their expectation of attributes of locations (and routes), which are considered relevant for making choices, and discover conditions having an influence on outcomes. The other operation concerns the formation of habits to avoid the needless repetition of effortful memory retrieval and evaluation tasks. In this section, we will consider these two processes in turn, starting with habit formation.

3.1 Updating activation levels

A mechanism similar to reinforcement learning will be used for updating activation levels to simulate memory process. In line with evidence in cognitive psychology (Anderson, 1983), the basic assumptions are that an alternative that has higher utility stays longer in memory, and that memory is reinforced when an alternative is chosen and memory decays if it is not chosen. Every time a location is chosen, the activation level of that location will be incremented to simulate the strengthening of a memory trace. The reinforcement rate is an increasing function of the experienced utility of the chosen location which in turn is a function of the location's attributes (as before). Limited memory retention capacity is simulated in the system by a parameter that determines rate of decay over time. If one alternative has not been chosen for some time, its activation level will decrease. When its activation level drops below some predefined threshold, it will be removed from the current choice-set to reflect the limited human ability of memory retrieval.

Formally, the strength of a memory trace of a particular activity location i in the choice-set is modelled as follows:

$$W_i^{t+1}(z_m) = \begin{cases} W_i^t(z_m) + \gamma U_i^t(z_m) & \text{if } I_i^t = 1 \\ \lambda W_i^t(z_m) & \text{otherwise} \end{cases} \quad (5)$$

where $W_i^t(z_m)$ is the strength of the memory trace (awareness) of location i at time t under a configuration of conditions z_m and $I_i^t = 1$, if the location was chosen at time t , and $I_i^t = 0$, otherwise, $0 \leq \gamma \leq 1$ is a parameter representing a recency weight, which is relevant only when the location is chosen; and $0 \leq \lambda \leq 1$ is a parameter representing the retention rate. $U_i^t(z_m)$ is the experienced utility attributed to location i that is calculated based on experienced states of the attributes of location i , including both (quasi)-static and dynamic variables. The calculation (based on a utility function similar to the one represented by equation (1)), uses observed states of the dynamic attributes, such as crowdedness and travel time.

Thus, at each time step the strength is reinforced or decays depending on whether the location has been chosen in the last time step. The coefficients γ and λ determine the size of reinforcement and memory retention respectively and are parameters of the system.

Based on the current value of memory strength, the system determines whether or not the item is included in the choice-set in the next time step based on the simple rule stating that

it is included if it exceeds a threshold level and is not included, otherwise. This rule can be written in the following general form:

$$\Phi'(z_m) = \{L_i | W_i'(z_m) \geq \omega\} \quad (6)$$

3.2 Updating beliefs

We assume that individuals make personal observations and update their beliefs of their environment based on these observations in order to be able to make better predictions about what can be expected in the next time step. Each time a location is chosen when an activity is implemented, the individual updates beliefs $P'(X_j|C)$, where C is the condition or, if multiple condition variables are involved, the condition configuration experienced. Learning implies two processes: parameter learning and structural learning. The first process involves incrementally updating the conditional belief distributions across the possible states for each observed attribute of the location after experiencing the actual states. The second process is aimed at discovering the conditions that have an influence on the likelihood of states of the system. Thus, the second process determines the form of the conditional probabilities that are kept up to date through the first process. This is done by periodically reconsidering splitting or merging condition states based on condition variables to update a tree structure that better predicts states based on observed outcomes. In the field of Bayesian Networks, the two processes are generally known as parameter and structural learning respectively.

We will adopt the approach proposed by Arentze and Timmermans (2003). In their approach, a method of parameter learning is used that is derived from Bayesian principles. Moreover, for structural learning, the proposed approach assumes a process of incrementally splitting and merging conditions based on events experienced in the past and stored in memory using some split criterion. In specific, the problem can be defined as a well-known problem considered by decision tree induction methods, namely as the problem of finding the most efficient way of splitting a set of known observations on predictor variables into partitions c_k that are as homogeneous as possible in terms of a response variable. For example in case of estimating the crowdedness of a location, the state of crowdedness is the response variable and time-of-the-day and day-of-the-week serve as predictor variables. Then, the problem is to split the sample of observations on the condition variables such that observations within partitions are as homogeneous as possible in terms of crowdedness. Different criteria for finding the best splits, such as Chi-square or expected information gain can be used for this problem. Condition variables that are not significant in the current time step may become so at some next moment in time when more observations have been stored. Therefore, splitting and merging operations are periodically reconsidered. For more detail, readers are referred to Arentze and Timmermans (2003). The result of a structural learning step, generally, is that subsequent parameter learning is based on a new belief structure. The new conditional probabilities can be derived from the event base in a straight-forward way.

4 Social learning

Individuals are not isolated from each other, but participate in social networks. Participation in social networks may lead to adaptation of aspirations and diffusion of knowledge, which in turn may trigger changes in activity-travel choice behaviour. Modelling the dynamic formation of social contacts between individuals based on social links is beyond the scope of this paper (for a possible model of these processes, see Arentze and Timmermans, 2006b). In

this section, we consider social links as given and focus on the impacts of social interactions on individuals' aspiration levels and knowledge about activity locations.

4.1 Social comparison

According to social comparison theory, people often obtain information about their performance by comparing themselves to others (Festinger, 1954). Social comparison theory posits that people are generally motivated to evaluate their opinions and abilities and that one way to satisfy this need for self-evaluation is to compare themselves to others. Information gathered from these social comparisons can then be used to provide insights into one's capacities and limitations, which may motivate them to achieve higher goals since people are motivated to maintain or increase positive self-evaluation.

Following this theory, we assume that when two individuals P_1 and P_2 meet, individual P_1 will evaluate and update his/her aspiration levels based on the best performances of individual P_2 , if P_2 belongs to the reference group of P_1 . More specifically, for each contextual condition of which individual P_1 has defined aspiration levels, P_1 will ask P_2 's best performance. Individual P_2 will provide as feedback the attribute information of the alternative that has the highest expected utility within his/her choice-set under the corresponding conditions, since this alternative reflects his/her highest possible achievement given his/her current knowledge.

After receiving the information from individual P_2 , individual P_1 first makes a decision on whether or not (s)he will change his/her aspiration levels. For this, P_1 compares the expected utility that is calculated using attributes values from individual P_2 's answer and his/her own preferences with the expected utility that is derived from his/her current aspiration levels. We assume that only if a positive discrepancy between the two expected utilities exist (i.e., $U(P_2) > U(P_1)$) which exceeds a tolerance threshold of P_1 , then P_1 is willing to update his/her aspiration levels; we say the individual is in an updating mode. If the discrepancy is not positive or the threshold is not exceeded, we assume that no adjustment will take place implying that P_1 will leave his/her aspiration levels unchanged. We assume that when in an updating mode, P_1 will upgrade the aspiration levels on those attributes on which the alternative conveyed by P_2 has the better value. Note that, updating aspiration levels may lead to a switch from a habitual to a conscious choice mode, which in turn may lead to exploration of new alternatives and, hence, adaptation of the person's choice-set.

4.2 Knowledge transfer

Besides social comparison, when two individuals P_1 and P_2 meet, P_1 will also update his/her knowledge by integrating the new information provided by P_2 . In the system, P_2 presents a list of all the locations (s)he knows to P_1 . After receiving the list from P_2 , P_1 checks the list with his/her knowledge to find out if the list of P_2 includes alternatives that are new to him/her. Each location alternative that is unknown to P_1 activates P_2 to provide further information about the attributes levels of the location. Then, P_1 checks whether there are constraints (e.g. opening times, travel time) that limit the use of the new alternative, and add the new known alternative to condition-dependent choice-sets, if any, for which the new alternative is appropriate. When added to a choice-set, the new alternative is specified according to the attribute information conveyed by P_2 and the activation level is initialized. Once added, the new location is subject to the same selecting, updating and learning processes as other alternatives within the choice-set.

In sum, social contacts provoke social learning that not only provides stimuli for adjusting aspiration levels, but may also trigger changes in terms of adding new locations to existing choice-sets.

5 Conclusion and discussion

This paper has outlined the conceptual framework that will be used to model the dynamic process of individuals' activity location choice in a micro-simulation system. The framework considered dynamic formation of the choice-set. It integrates cognitive learning and social learning. In the proposed approach, cognitive learning focuses on updating beliefs about a non-stationary environment that will impact the expected utility of alternatives and habit formation, while social learning emphasizes on deriving and updating aspirations that may trigger re-evaluating currently known alternatives (exploitation) or search for new alternatives (exploration). As such, it provides a modelling approach for distinguishing habitual choice, exploitation choice and exploration choice.

The framework presented in this paper provides a first step towards a fully operational model of dynamic formation of location choice-sets. In principle, the framework can be extended to a more complex system as we further explore in more detail how and to what extent social interactions influence people's behaviour that could be incorporated in defining and updating aspiration levels, as well as how people compose their expected outcome and make satisfaction evaluation. Before that, we plan to first implement the current model and conduct an illustrative case study showing how this model can be integrated in an agent-based micro-simulation to model dynamic decision making under uncertainty. We intend to report on such implementations and results of some theoretical analyses of dynamic formation of location choice sets as revealed in simulations in the near future.

Appendices

Table 1A Aspiration level for (quasi)-state attributes of shopping locations

Table 1B Aspiration level for dynamic attributes of shopping locations

Table 2 Activation level of shopping locations

Table 3A (Quasi)-state attributes of shopping locations

Table 3B Dynamic attributes of a shopping location

Figure 1 The choice making model

Activity	Location category	Store for daily goods present	Store for semi-durable goods present	Store for durable goods present	Price level	Parking space
Shopping	Big	1	1	1	Medium	1
Shopping	Medium	1	1	0	Medium	1
Shopping	Small	1	1	0	Low	0

Activity	Location category	Contextual condition		Crowdedness
		Time of day	Day of week	
Shopping	Big	Peak hour	Weekend	Very
Shopping	Big	Non-peak hour	Weekend	Little
Shopping	Big	Peak hour	Workday	Medium
Shopping	Big	Non-peak hour	Workday	No
Shopping	Medium	Peak hour	Weekend	Medium

Table 2 Activation level of shopping locations					
Contextual condition				Outcome	
Activity	Day-of-week	Origin location	Time-of-day	Location	Activation level
	*				
	*				
	*				
Shopping	Wednesday	Work	Non-peak	Shopping centre 1	10
				Shopping centre 2	10
				Shopping centre 3	80
	*				
	*				
	*				
Shopping	Saturday	Home	Peak	Shopping centre 1	100
				Shopping centre 2	20
				Shopping centre 3	10
Shopping	Saturday	Home	Non-peak	Shopping centre 1	30
				Shopping centre 2	60
				Shopping centre 3	10

Table 3A (Quasi)-Static attributes of shopping locations						
Location ID	Location category	Store for daily goods present	Store for semi-durable goods present	Store for durable goods present	Price level	Parking space
1	Big	1	1	1	high	1
2	Medium	1	1	0	low	1
3	Medium	0	1	1	middle	0
4	Small	1	1	0	high	1
5	Small	1	0	0	low	0

Table 3B Dynamic attributes of a shopping location						
Location ID	Contextual condition		Crowdedness (Percentage)			
	Time of day	Day of week	No	Little	Medium	Very
1	Peak hour	Weekend	10	10	30	50
	Non-peak hour	Weekend	20	20	30	30
	Peak hour	Workday	30	30	20	20
	Non-peak hour	Workday	50	30	20	0

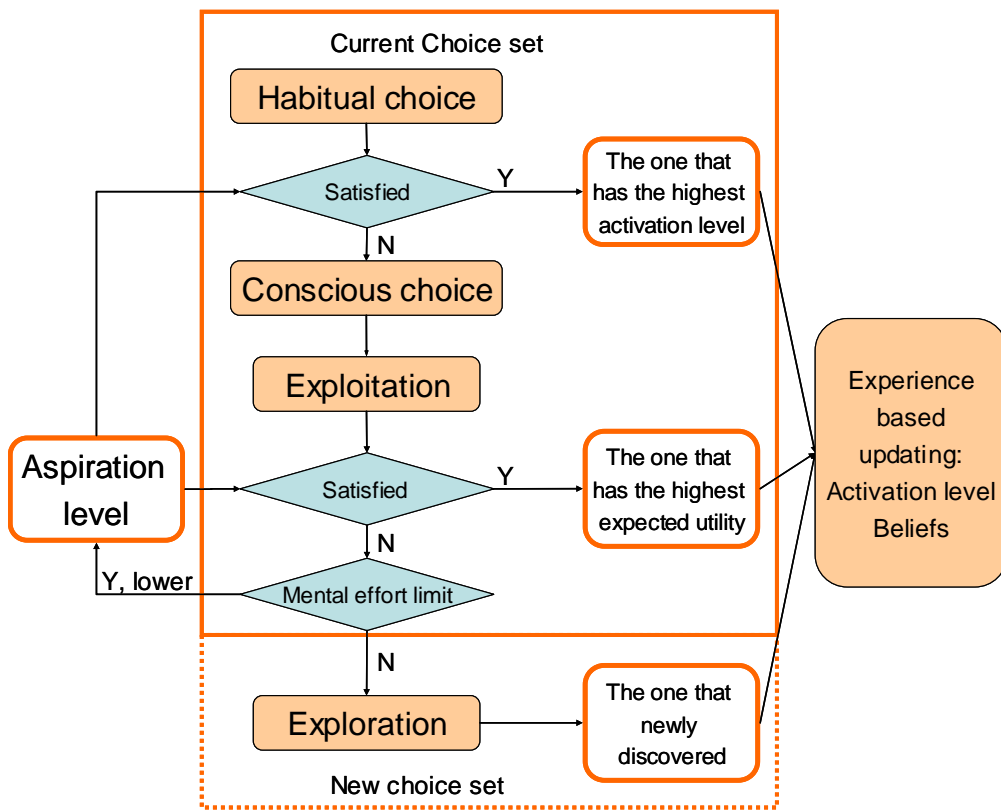


Figure 1 The choice making model

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